Virtual University of Pakistan
FEDERAL GOVERNMENT UNIVERSITY

COMPLETE SLIDES

Modelling and Simulation

CS620

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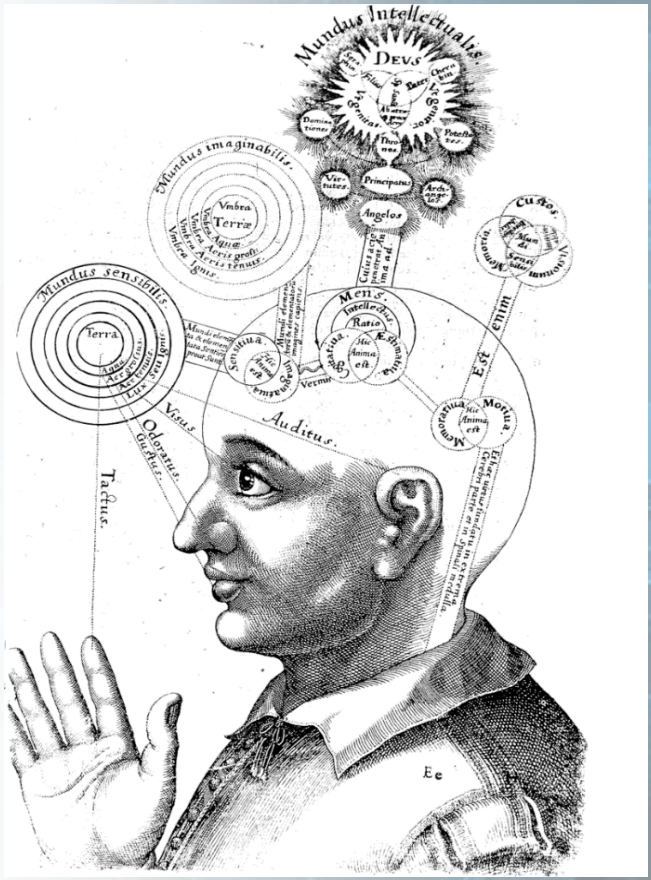
Course Introduction

Overview

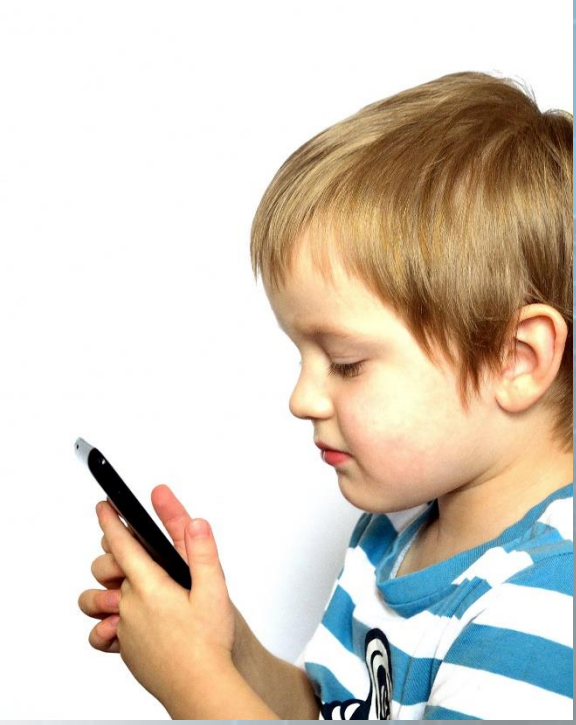
- Modeling & Simulation is an extremely important part of our daily lives.
- Our entire living experience is based on the concept of “Consciousness”
- The state of being aware of and responsive to one's surroundings

Consciousness: Robert Fudd (17th CenturCony)



Modeling Example

What if we show a child a video on a mobile smart phone?



Simulation: What goes on in the brain?

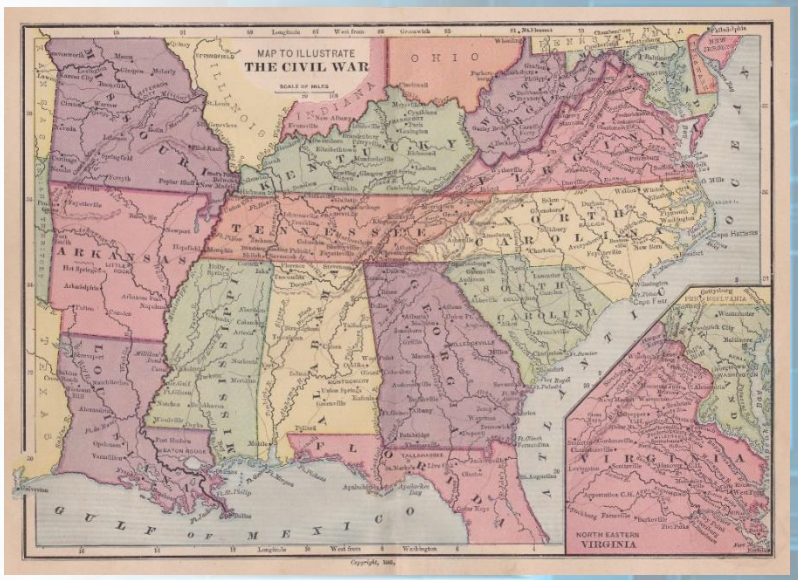
When driving to work:

Questions and thoughts?

If I take this road, will I get there on time?

What is in the mind's eye? Implicit Modeling

Maps: An Example of Explicit Modeling



Examples Problems with Models

Google Maps vs. Open Street Maps

What is This Course About?

- Developing Models
- Executing Simulations
- Analyzing Results
- Calibrating Models
- Verification &

  Validation of Models

Outline: The Big Picture

- Basics of Simulation
- Statistical Models
- Formal Models
- Agent-based Models

Textbooks and Reference Material

- Discrete-Event System Simulation (5th Edition)
  Banks et al.
- An Introduction to Agent-Based Modeling by Wilensky and Rand
- Cognitive Agent-based Computing-I by Niazi and Hussain

Textbooks and Reference Material

- Computer Systems Perf. Evaluation and Prediction by Fortier and Michel
- Software Reliability Modeling Fundamentals and Applications by Yamada

END

Simulation: When is it an Appropriate Tool?

Simulation: When is it an Appropriate Tool?

- In this module, we shall see how simulation can be an **appropriate** tool in certain cases

Differences in Tools

- **Every tool has a different purpose**
- **A hammer cannot be used in place of a pliers or a screw driver**

Analysis of Complex Systems

- Simulation enables the study of, and experimentation with, the internal interactions of a complex system or of a subsystem within a complex system.

Complex System

Defining Changes

- Informational, organizational, and environmental changes can be simulated, and the effect of these alterations on the model's behavior can be observed.

Knowledge from Simulation

- **The knowledge gained during the designing of a simulation model could be of great value toward suggesting improvement in the system under investigation.**

Learning from Change

- **Changing simulation inputs and observing the resulting outputs can produce valuable insight into which variables are the most important and into how variables interact.**

Pedagogical Value

- **Simulation can be used as a pedagogical device to reinforce analytic solution methodologies.**

Trial & Error

- **Simulation can be used to experiment with new designs or policies before implementation, so as to prepare for what might happen.**

Verification of Mathematical Models

- Simulation can be used to verify analytic solutions.

Learning Requirements for a Machine

- **Simulating different capabilities for a machine can help determine the requirements on it.**

Replacement for Training

- Simulation models designed for training make learning possible without the cost and disruption of on-the-job instruction.

Animation of Simulation

- Animation shows a system in simulated operation so that the plan can be visualized.

Visually Understanding Modern Factories

- **The modem system (factory, wafer fabrication plant, service organization, etc.) is so complex that its internal interactions can be treated only through simulation.**

Other reasons!

- Explain (very distinct from predict)
- Guide data collection
- Illuminate core dynamics
- Suggest dynamical analogies
- Discover new questions
- Promote a scientific habit of mind
- Bound (bracket) outcomes to plausible ranges

Other reasons!

- Illuminate core uncertainties.
- Offer crisis options in near-real time
- Demonstrate tradeoffs / suggest efficiencies
- Challenge the robustness of prevailing theory through perturbations
- Expose prevailing wisdom as incompatible with available data

Other reasons!

- Train practitioners
- Discipline the policy dialogue
- Educate the general public
- Reveal the apparently simple (complex) to be complex (simple)

Summary

- **A large number of uses**
- **Additional Reading: Joshua M. Epstein, Why Model?**
- http://jasss.soc.surrey.ac.uk/11/4/12.html

Simulation: When isn't an Appropriate Tool?

Simulation: When isn't an Appropriate Tool?

- In this module, we shall see when simulation may not be the most appropriate tool

Simulation is NOT a Silver Bullet!

- **There is a typical misconception often in graduate students that everything can be, or should be simulated.**
- **Simulation is NOT for everything!**

Banks and Gibson (1997)

- **Banks and Gibson present ten rules for evaluating when simulation is not appropriate**

Rule Number 1

- Simulation should not be used when the problem can be solved by common sense.

Example

- E.g. In an automobile tag facility serving customers who arrive randomly at an average rate of 100/hour and are served at a mean rate of 12/hour.
- To determine the minimum number of servers needed, simulation is not necessary.

Example

- **Just compute 100/12 = 8.33 indicating that nine or more servers are needed.**

Rule Number 2

- Simulation should not be used if the problem can be solved analytically.
- For example, under certain conditions, the average waiting time in the example above can be found from curves that were developed by Hillier and Lieberman [2002].

Rule Number 3

- **Simulation should not be used if it is easier to perform direct experiments.**

Example

- In a fast-food drive-in restaurant it can be less expensive to stage a person taking orders using a hand-held terminal and voice communication to determine the effect of adding another order station on customer waiting time.

Rule Number 4

- **Don’t use simulation if the costs exceed the savings.**
- **If a simulation study costs $20,000 and the savings might be $10,000, simulation would not be appropriate.**

Rule 5 & 6

- **Simulation should not be performed if the resources or time are not available.**

Examples

- If the simulation is estimated to cost $20,000 and there is only $10,000 available, the suggestion is not to venture into a simulation study.
- Similarly, if a decision in needed in two weeks and a simulation will take a month, the simulation study is not advised.

Rule 7

- **Simulation takes data, sometimes lots of data.**
- **If no data is available, not even estimates, simulation is not advised.**

Rule 8

- The next rule concerns the ability to verify and validate the model.
- If there is not enough time or if the personnel are not available, simulation is not appropriate.

Rule 9

- **If managers have unreasonable expectations, if they ask for too much too soon, or if the power of simulation is overestimated, simulation might not be appropriate.**

Rule 10

- Last, if system behavior is too complex or can't be defined, simulation is not appropriate.
- Human behavior is sometimes extremely complex to model.

Summary

- A number of people use simulation just for the sake of simulation
- That makes no sense
- Simulation should be used ONLY if it is the most appropriate tool to use

END

Modeling and Simulation

Advantages and Disadvantages of Simulation

Simulation: Advantages and Disadvantages?

- **In this module, we shall see both sides of the coin: advantages of simulation and also disadvantages**

Simulation is NOT a Silver Bullet!

- Simulation is intuitively appealing to a client because it mimics what happens in a real system or what is perceived for a system that is in the design stage.
- The output data from a simulation should directly correspond to the outputs that could be recorded from the real system.

Simulation is NOT a Silver Bullet!

- Additionally, it is possible to develop a simulation model of a system without dubious assumptions (such as the same statistical distribution for every random variable) of mathematically solvable models.
- For these and other reasons, simulation is frequently the technique of choice in problem solving.

Simulation is NOT a Silver Bullet!

- **For these and other reasons, simulation is frequently the technique of choice in problem solving.**

Simulation vs. Optimization

- In contrast to optimization models, simulation models are "run" rather than solved.
- Given a particular set of input and model characteristics, the model is run and the simulated behavior is observed.

Simulation vs. Optimization

- This process of changing inputs and model characteristics results in a set of scenarios that are evaluated.
- A good solution, either in the analysis of an existing system or in the design of a new system, is then recommended for implementation.

Simulation

- Simulation 'has many advantages, but some disadvantages.
- Pegden, Shannon, and Sadowski [1995] summarize these.

Benefits

- New policies, operating procedures, decision rules, information flows, organizational procedures, and so on can be explored without disrupting ongoing operations of the real system.

Benefits

- New hardware designs, physical layouts, transportation systems, and so on can be tested without committing resources for their acquisition.
- Hypotheses about how or why certain phenomena occur can be tested for feasibility.

Benefits

- Time can be compressed or expanded to allow for a speed-up or slow-down of the phenomena under investigation.
- Insight can be obtained about the interaction of variables.
- Insight can be obtained about the importance of variables to the performance of the system.

Benefits

- Bottleneck analysis can be performed to discover where work in process, information, materials, and so on are being delayed excessively.
- A simulation study can help in understanding how the system operates rather than how individuals think the system operates.

Benefits

- "What if' questions can be answered. This is particularly useful in the design of new systems.

Summary

- **In this module, we have examined various benefits of simulation.**

Disadvantages of Simulation

Disadvantages of Simulation

- Model building requires special training.
- It is an art that is learned over time and through experience.
- Furthermore, if two models are constructed by different competent individuals, they might have similarities, but it is highly unlikely that they will be the same.

Disadvantages of Simulation

- Simulation results can be difficult to interpret
- Most simulation outputs are essentially random variables (they are usually based on random inputs), so it can be hard to distinguish whether an observation is a result of system interrelationships. or of randomness.

Disadvantages of Simulation

- **Simulation modeling and analysis can be time consuming and expensive.**
- **Skimping on resources for modeling and analysis could result in a simulation model or analysis that is not sufficient to the task.**

Disadvantages of Simulation

- Simulation is used in some cases when an analytical solution is possible, or even preferable.
- This might be particularly true in the simulation of some waiting lines where closed-form queueing models are available.

In Defense of . . .

- Vendors of simulation software have been actively developing packages that contain models that need only input data for their operation.

In Defense of . . .

- Such models have the generic tag "simulator" or "template."
- Many simulation software vendors have developed output-analysis capabilities within their packages for performing very thorough analysis.

More defense . . .

- Simulation can be performed faster today than yesterday and will be even faster tomorrow, because of advances in hardware that permit rapid running of scenarios and because of advances in many simulation packages.

More defense . . .

- For example, some simulation software contains constructs for modeling material handling that uses such transporters as fork-lift trucks, conveyors, and automated guided vehicles.

More defense . . .

- Closed-form models are not able to analyze most of the complex systems that are encountered in practice.
- In many years of consulting practice, not one problem was encountered that could have been solved by a closed-form solution.

Summary

- Even when Simulation is the most appropriate tool, it is not without disadvantages.
- Any simulation project must first be analyzed in terms of pros and cons

Areas of Application

Areas of Application

- **In this module, we shall see different areas of application**

Where to Look for Simulation Applications?

- Wintersim conference (WSC) is a great place to look at.
- www.wintersim.org
- In the WSC, we can see:
- Latest in applications, theory, and Tutorials

Technical Societies Co-Sponsoring WSC

- American Statistical Association (ASA),
- Association for Computing Machinery/Special Interest Group on Simulation (ACM/SIGSIM),
- Institute of Electrical and Electronics Engineers: Computer Society (IEEEICS),

Technical Societies Co-Sponsoring WSC

- Institute of Electrical and Electronics Engineers: Systems, Man and Cybernetics Society (IEEEISMCS),
- Institute of Industrial Engineers (IiE),

Technical Societies Co-Sponsoring WSC

- Institute for Operations Research and the Management Sciences: College on Simulation (INFORMS/CS) and
- The Society for Computer Simulation (SCS)

Manufacturing Applications

- Dynamic modeling of continuous manufacturing systems, using analogies to electrical systems
- Benchmarking of a stochastic production planning model in a simulation test bed
- Paint line color change reduction in automobile assembly

Manufacturing Applications

- Modeling for quality and productivity in steel cord manufacturing
- Shared resource capacity analysis in biotech manufacturing
- Neutral information model for simulating machine shop operations

Semiconductor Manufacturing

- Constant time interval production planning with application to work-in-process control
- Accelerating products under due-date oriented dispatching rules
- Design framework for automated material handling systems in 300 mm wafer fabrication factories
- Etc.

Construction Engineering & Project Management

- Impact of multitasking and merge bias on procurement of complex equipment
- Application of lean concepts and simulation for drainage operations maintenance crews
- Building a virtual shop model for steel fabrication
- Simulation of the residential lumber supply chain

Summary

- **Here we have examined a number of industrial application of simulation**

Modeling & Simulation

Military Applications and more

Military Applications

- Frequency-based design for terminating simulations: A peace-enforcement example
- A multi-based framework for supporting military-based interactive simulations in 3D environments
- Specifying the behavior of computer-generated forces without programming

Military Applications

- **Fidelity and validity: Issues of human behavioral representation**
- **Assessing technology effects on human performance through trade-space development and evaluation**
- **Impact of an automatic logistics system on the sortie-generation process**

Military Applications

- **Research plan development for modeling and simulation of military operations in urban terrain**

Logistics, Supply Chain & Distribution Applications

- Inventory analysis in a server-computer manufacturing environment
- Comparison of bottleneck detection methods for AGV systems
- Semiconductor supply-network simulation

Logistics, Supply Chain & Distribution Applications

- Analysis of international departure passenger flows in an airport terminal
- Application of discrete simulation techniques to liquid natural gas supply chains
- Online simulation of pedestrian flow in public buildings

Transportation Modes and Traffic

- Simulating aircraft-delay absorption
- Runway schedule determination by simulation optimization
- Simulation of freeway merging and diverging behavior
- Modeling ambulance service of the Austrian Red Cross.

Transportation Modes and Traffic

- Simulation modeling in support of emergency firefighting in Norfolk
- Modeling ship arrivals in ports
- Optimization of a barge transportation system for petroleum delivery
- Iterative optimization and simulation of barge traffic on an inland waterway

Business Process Simulation

- Agent-based modeling and simulation of store performance for personalized pricing
- Visualization of probabilistic business models
- Modeling and simulation of a telephone call center

Business Process Simulation

- **Using simulation to approximate sub-gradients of convex performance measures in service systems**

Business Process Simulation

- Simulation's role in baggage screening at airports
- Human-fatigue risk simulations in continuous operations
- Optimization of a telecommunications billing system
- Segmenting the customer base for maximum return

Healthcare

- Modeling front office and patient care in ambulatory health care practices
- Evaluation of hospital operations between the emergency department and a medical telemetry unit
- Estimating maximum capacity in an emergency room

Healthcare

- Reducing the length of stay in an emergency department
- Simulating six-sigma improvement ideas for a hospital emergency department
- A simulation-integer-linear-programming-based tool for scheduling emergency room staff

More defense . . .

- Simulation can be performed faster today than yesterday and will be even faster tomorrow, because of advances in hardware that permit rapid running of scenarios and because of advances in many simulation packages.

More defense . . .

- For example, some simulation software contains constructs for modeling material handling that uses such transporters as fork-lift trucks, conveyors, and automated guided vehicles

- Closed-form models are not able to analyze most of the complex systems that are encountered in practice.
- In many years of consulting practice, not one problem was encountered that could have been solved by a closed-form solution

Summary

- We have seen such a wide variety of areas where simulation has applications
- Sky is the Limit!

System and Environment

- In this module, we shall examine the concepts of system and environment

Motivation

- Before we are able to model anything, we need to have some basic concepts.
- There are two basic concepts of importance.
- System
- System Boundary

System

- A system is defined as a group of objects joined together in some regular interaction or interdependence toward the accomplishment of some purpose

Manufacturing Applications

- Dynamic modeling of continuous manufacturing systems, using analogies to electrical systems
- Benchmarking of a stochastic production planning model in a simulation test bed
- Paint line color change reduction in automobile assembly

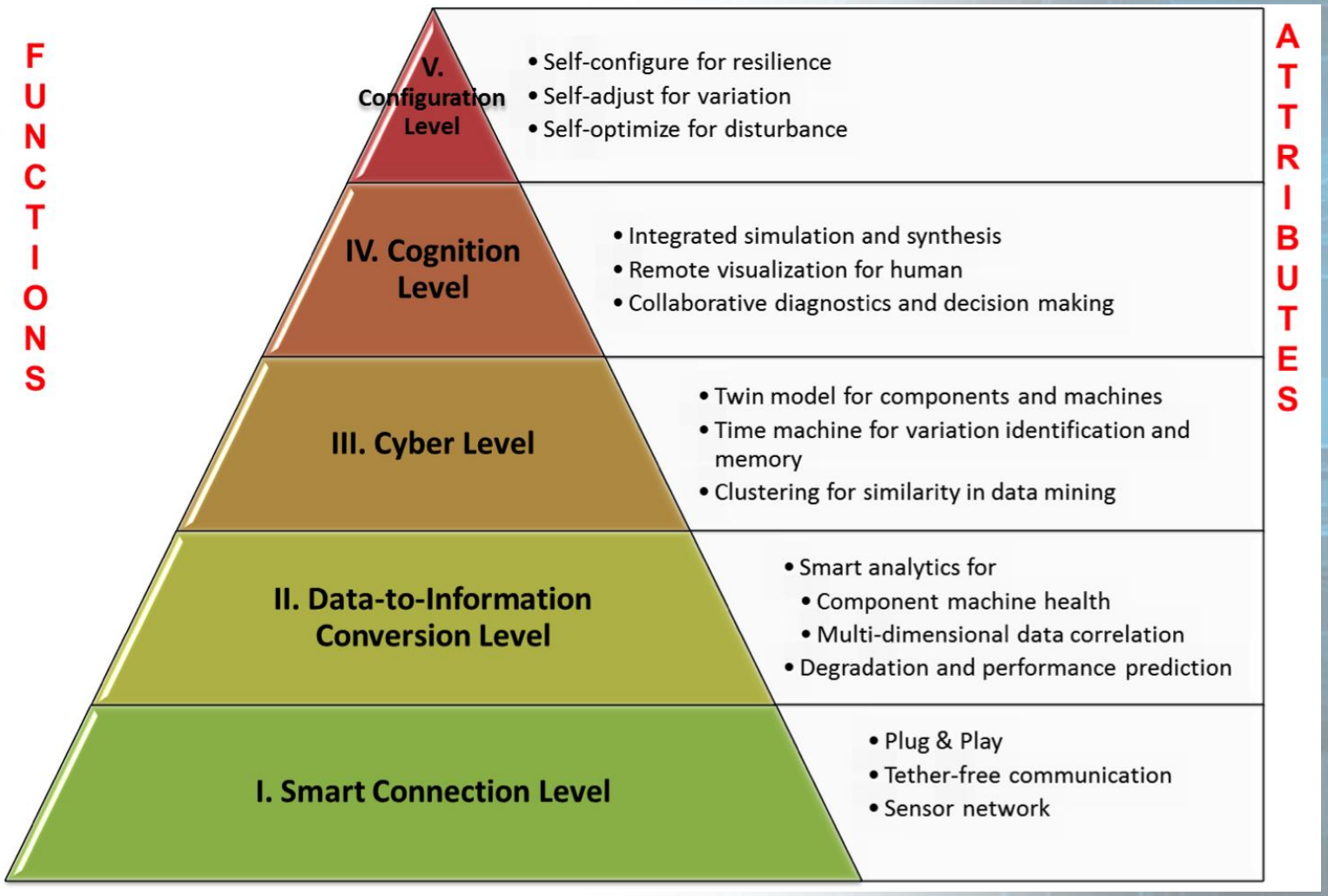
Manufacturing Applications

- Modeling for quality and productivity in steel cord manufacturing
- Shared resource capacity analysis in biotech manufacturing
- Neutral information model for simulating machine shop operations

Example: BMW Car Production System

Example: Aircraft Arresting System

Example: Cyberphysical System



System Environment

- Changes in a "system environment" occur based on changes outside the system

System Boundary

- **Modeling system requires identification of the concept of "System Boundary"**

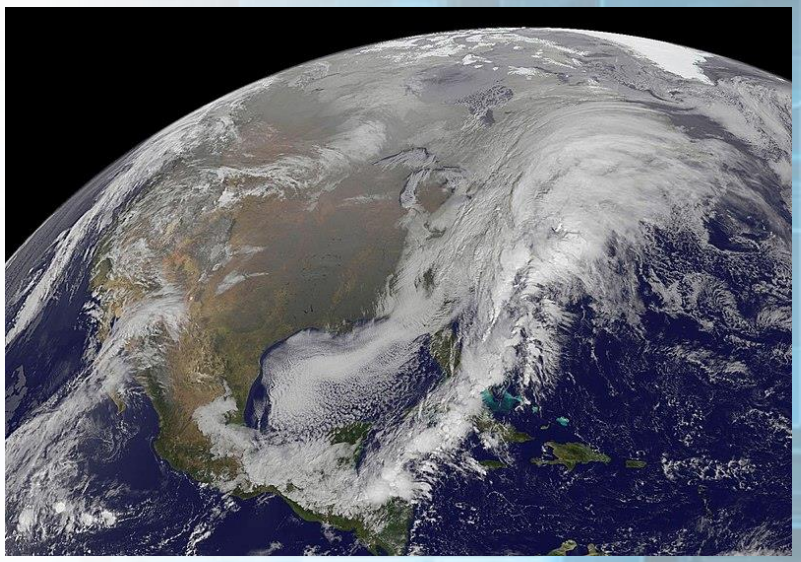
Examples

- In a factory system, arrival of orders can be considered as outside of the influence of the factory.
- Therefore it can be a part of the environment

Examples

- **If the effects of supply on demand are important, then this must be part of the system**

Example: Storm System



Summary

- **In this module, we have started to understand the concept of a system**

Modeling & Simulation

System Concepts

System Concepts

- System: An organized entity made up of interrelated and interdependent parts.
- Boundaries: Barriers that define a system and distinguish it from other systems in the environment.

System Concepts

- **Homeostasis: The tendency of a system to be resilient towards external factors and maintain its key characteristics.**
- **Adaptation: The tendency of a self-adapting system to make the internal changes needed to protect itself and keep fulfilling its purpose.**

System Concepts

- **Reciprocal Transactions: Circular interactions that systems engage in such that they influence one another.**

System Concepts

- **Feedback Loop: The process by which systems self-correct based on reactions from other systems in the environment.**
- **Throughput: Rate of energy transfer between the system and its environment during the time it is functioning.**

System Concepts

- **Microsystem: The system closest to the client.**
- **Mesosystem: Relationships among the systems in an environment.**
- **Exosystem: A relationship between two systems that has an indirect effect on a third system.**

System Concepts

- **Macrosystem: A larger system that influences clients, such as policies, administration of entitlement programs, and culture.**
- **Chronosystem: A system composed of significant life events that can affect adaptation.**

Summary

Here, we have examined various concepts related to systems

Modeling and Simulation

Components of a system

Components of a system

- **In this module, we shall examine the concepts of system components**

Motivation

- **Once we know about system and system boundary, there are some other concepts that we need to define**

Entity and more!

- Any object of interest in the system is called an entity
- An attribute is the property of an entity
- An activity represents a time period of a specific length

State

- Collection of variables necessary to describe the system at any time, relative to the objectives of the study

Event

- Instantaneous occurrence that might change the state of the system

Endogenous vs. Exogenous

- Endogenous is used for activities and events occurring within the system
- Exogenous is used for activities and events occurring in the environment that affect the system

Examples

System	*Entities*	*Attributes*	*Activities*
Banking	Customers	Checking-account balance	Making deposits
Rapid rail	Riders	Origin; destination	Traveling
Production	Machines	Speed; capacity; breakdown rate	Welding; stamping
Communications	Messages	Length; destination	Transmitting
Inventory	Warehouse	Capacity	Withdrawing

Examples

System	*Events*	*State Variables*
Banking	Arrival; departure	Number of busy tellers; number of customers waiting
Rapid rail	Arrival at station; arrival at destination	Number of riders waiting at each station; number of riders in transit
Production	Breakdown	Status of machines (busy, idle, or down)
Communications	Arrival at destination	Number waiting to be transmitted
Inventory	Demand	Levels of inventory; backlogged demands

Summary

- We talked about some basic concepts of systems
- We also discussed some examples

Modeling and Simulation

Discrete vs. Continuous

Discrete and Continuous

- **In this module, we shall examine the concepts of discrete and continuous systems**

Motivation

- **Once we know about system and system boundary, there are some other concepts that we need to define**

How computers handle the real world?

- In the real world, things are complex.
- Measuring the exact values is important for us to develop the most appropriate model

Discrete vs. Continuous

- Computers by themselves are based on digital circuits.
- As such, intrinsically, their internal representation is based on discrete (clear steps)

Event

- Few systems in practice are wholly discrete or continuous, but since one type of change predominates for most systems, it will usually be possible to classify (Law and Kelton , 2009)

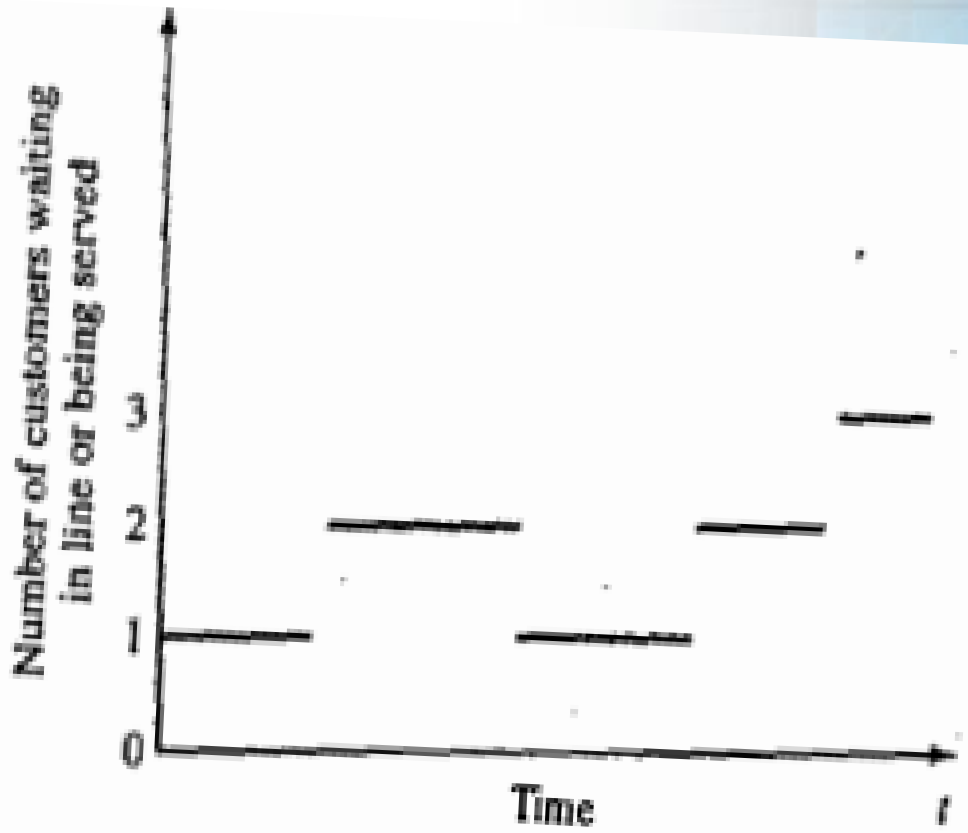
Discrete System

- **A discrete system is one in which the state variables change ONLY at discrete set of points in time.**

Example

- Customer arrival in a bank.
- The state variable ‘Number of customers’ changes only when a customer arrives or when the service is completed.

Example: Discrete System



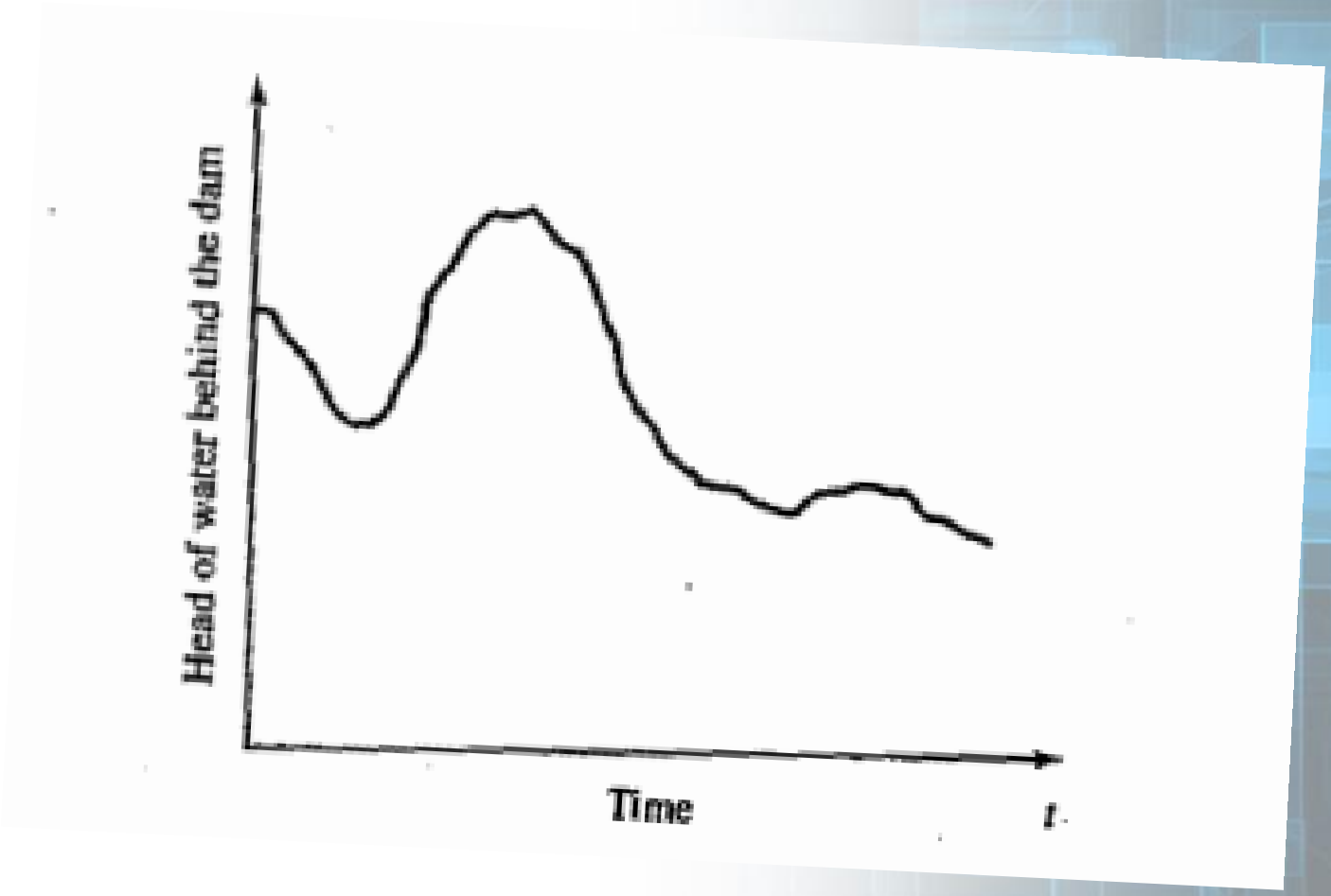
Continuous System

- **A Continuous system is one in which the state variables change CONTINUOUSLY over time.**

Example

- Head of water behind a dam.
- The state variable ‘Head of Water’ changes as rain comes in or dam is emptied etc.

Example: Discrete System



Summary

- We talked about discrete and continuous systems
- We also discussed some examples

Model of a System

- In this module, we shall examine what it means by developing a system model

Motivation

- How do we model a system?

Why Model?

- Sometimes it is of interest to study a system to understand the relationships between its components or to predict how the system will operate under a new policy.

Ideally . . .

- To study the system, it is sometimes possible to experiment with the system itself.
- However, this is not always possible.

Why not the Real System?

- Maybe the new system might not yet exist; it could be in only hypothetical form or at the design stage.
- E.g. Space flight, going to distance planets, rescue system, anything revolutionary etc.

Would Having an Existing System Work?

- Even if the system exists, it might be impractical to experiment with it.
- E.g.
- It may be too costly
- It may be impractical

Example

- Would it make sense to double the unemployment rate to discover the effect of employment on inflation?
- In the case of a bank, reducing the numbers of tellers to study the effect on the length of waiting lines might infuriate the customers so greedy that they move their accounts

Example: Discrete System

- In case of a consulting job for the simulation of a redesigned port in western Australia.
- At $200 millions for a loading/unloading berth, it's not advisable to invest that amount only to find that the berth is adequate or not.

Model: What it is?

- A model is defined as a representation of a system for the purpose of studying the system.
- For most studies, it is only necessary to consider those aspects of the system that affect the problem under investigation.
- These aspects are represented in a model of the system; the model, by definition, is a simplification of the system.
- On the other hand, the model should be sufficiently detailed to permit valid conclusions to be drawn about the real system

Variety of Models: Same System

- A system may need to be described by several models
- Model is described similar to components.

Summary

- We talked about discrete and continuous systems
- We also discussed some examples

Model Types

- In this module, we shall examine different types of models

Motivation

- What are the different model types?

Key Types

- Mathematical
- Physical

Mathematical

- A mathematical model uses symbolic notation and mathematical equations to represent a system.

What is a Simulation Model?

- A special type of Mathematical model
- Simulation models may be further classified as being static or dynamic, deterministic or stochastic, and discrete or continuous.

Monte Carlo Model

- A static simulation model, sometimes called a Monte Carlo simulation, represents a system at a particular point in time.

Dynamic Models

- Dynamic simulation models represent systems as they change over time
- E.g. Simulation of a Bank form 9 AM to 2PM

Deterministic Models

- Simulation models that contain no random variables are classified as deterministic.
- Deterministic models have a known set of inputs, which will result in a unique set of outputs.
- Deterministic arrivals would occur at a dentist's office if all patients arrived at the scheduled appointment time.

Stochastic Models

- A stochastic simulation model has one or more random variables as inputs.
- Random inputs lead to random outputs
- Random Outputs can be considered only as estimates of the true characteristics of a model.
- The simulation of a bank would usually involve random interarrival times and random service times.
- Thus, in a stochastic simulation, the output measures the average number of people waiting, the average waiting time of a customer
- Output must be treated as statistical estimates of the true characteristics of the system.

Discrete vs. Continuous Model Definition

- Discrete and continuous models are defined in an analogous manner.
- However, a discrete simulation model is not always used to model a discrete system, nor is a continuous simulation model always used to model a continuous system.
- Tanks and pipes are modeled discretely by some software vendors, even though we know that fluid flow is continuous.

What if Both?

- In addition, simulation models may be mixed, both discrete and continuous. The choice of whether to use a discrete or continuous {or both discrete and continuous) simulation model is a function of
  - the characteristics of the system
  - the objective of the study.
- E.g. , a communication channel could be modeled discretely if the characteristics and movement of each message were deemed important.
- Conversely, if the flow of messages in aggregate over the channel were of importance, modeling the system via continuous simulation could be more appropriate.

Cont'd

- We shall be studying discrete, dynamic, and stochastic models primarily

Summary

- We have examined the basic types of models and seen how systems can be modeled.

Modeling & Simulation

Discrete Event Simulation

Discrete Event Simulation

- **In this module, we shall examine Discrete Event Simulation**

Motivation

- **Why is Discrete Event Simulation important?**
- **What is it?**

Key Types

- Discrete-event systems simulation is the model-ing of systems in which the state variable changes only at a discrete set of points in time.
- The simulation models are analyzed by numerical methods rather than by analytical methods.

What does it mean?

- Analytical methods employ the deductive reasoning of mathematics to "solve" the model
- For example, differential calculus can be used to compute the minimum-cost policy for some inventory models.

Numerical Methods

- Numerical methods employ computational procedures to "solve" mathematical models.
- In the case of simulation models, which employ numerical methods, models are "run" rather than solved-that is

Numerical Methods

- An artificial history of the system is generated from the model assumptions,
- Observations are collected to be analyzed and to estimate the true system performance measures.

Characteristics of Real World Models

- Real-world simulation models are rather large,
- The amount of data stored and manipulated is vast, so such runs are usually conducted with the aid of a computer.
- However, much insight can be obtained by simulating small models manually.

Summary

- Our key focus is on discrete-event system simulation
- The models of interest are analyzed numerically, usually with the aid of a computer

Steps in a Simulation Study: Planning

Steps in a Simulation Study

- **In this module, we shall examine steps in a Simulation study**

Motivation

- How is a Simulation study conducted?
- What are the steps?

Key Steps

- Problem Formulation
- Setting of Objectives and Overall project plan
- Model Conceptualization

Key Steps

- Data Collection
- Model Translation
- Verification
- Validation

Key Steps

- Experimental Design
- Production Runs and Analysis
- More Runs?
- Documentation and Reporting
- Implementation

Problem Formulation

- Every study should begin with a statement of the problem.
- If the statement is provided by the policymakers, or those that have the problem, the analyst must ensure that the problem being described is clearly understood.

Formulation

- If a problem statement is being developed by the analyst, it is important that the policymakers understand and agree with the formulation.
- There are occasions where the problem must be reformulated as the study progresses.
- In many instances, policy-makers and analysts are aware that there is a problem long before the nature of the problem is known.

Objectives and Project Plan

- **The objectives indicate the questions to be answered by simulation.**
- **Without the objectives, it makes little sense to develop a simulation model**

Objectives

- **The first thing to verify is: Is Simulation the right tool for the problem at hand?**
- **This will be based on the actual problem statement**

If Simulation is the Right Tool . . .

- Assuming that it is decided that simulation is appropriate, the overall project plan should include benchmark Systems evaluation
- i.e. a statement of alternative systems to be considered
- Also, a method for evaluating the effectiveness of these alternatives should be noted.

Project Planning

- It should also include the plans for the study in terms of
- The number of people involved
- The cost of the study
- The number of days required to accomplish each phase of the work
- The results expected at the end of each stage.

Summary

- **We have examined the importance of basic planning and project management**

Steps in a Simulation Study: Conceptualization

Step 2: Model Conceptualization

- The construction of a model of a system is probably as much art as science.
- Pritsker [1998] provides a lengthy discussion of this step.

Step 2

- **Although it is not possible to provide a set of instructions that will lead to building successful and appropriate models in every instance, there are some general guidelines that can be followed" [Morris, 1967].**

Step 2

- The art of modeling is enhanced by
  - An ability to abstract the essential features of a problem
  - To select and modify basic assumptions that characterize the system,
  - To enrich and elaborate the model until a useful approximation results.

Step 2

- **Thus, it is best to start with a simple model and build toward greater complexity.**
- **However, the model complexity need not exceed that required to accomplish the purposes for which the model is intended.**

Step 2

- Violation of this principle will only add to model-building and computer expenses.
- It is not necessary to have a one-to-one mapping between the
- model and the real system.
- Only the essence of the real system is needed.

User Involvement

- It is advisable to involve the model user in model conceptualization.
- Involving the model user will both
  - enhance the quality of the resulting model
  - increase the confidence of the model user in the application of the model.

User Involvement

- **While several models will be presented in the course – only real-world experience can "teach" the art of modeling**

Summary

- **Till now we have taken a look at the first 2 steps of a simulation study.**

Steps in a Simulation Study: Data Collection and Model Translation

Steps in a Simulation Study

- **In this module, we shall continue to examine 2 key steps in a Simulation study**

Data Collection

- **There is a constant interplay between the construction of the model and the collection of the needed input data [Shannon, 1975].**
- **As the complexity of the model changes, the required data elements can also change.**

Data Collection

- Data collection takes a large portion of the total time required to perform a simulation
- It is therefore necessary to begin it as early as possible

Data Collection

- Data collection is usually conducted together with the early stages of model building.
- The objectives of the study dictate, in a large way, the kind of data to be collected.

Example

- In the study of a bank, for example, if the desire is to learn about the length of waiting lines as the number of tellers change, the types of data needed would be
- the distributions of interarrival times (at different times of the day),

Example

- The service-time distributions for the tellers,
- The historic distributions on the lengths of waiting lines under varying conditions.
- See also an excellent discussion by Henderson [2003].)

Model Translation

- Most real-world systems result in models that require a great deal of information storage and computation,
- So the model must be entered into a computer-recognizable format

Model Translation

- We use the term "program" even though it is possible to accomplish the desired result in many instances with little or no actual coding.
- The modeler must decide whether to program the model in a simulation language

Model Translation

- GPSSIH, or to use special-purpose simulation software.
- For manufacturing and material handling, tools include Arena®, AutoMod™, Extend™, Flexsim, MicroSaint, ProModel®, Quest®, SIMUL8®, and WITNESS™

Model Translation

- Simulation languages are powerful and flexible.
- However, if the problem is amenable to solution with the simulation software, the model development time is greatly reduced.

Model Translation

- **Furthermore, most of the simulation-software packages have added features that enhance their flexibility, although the amount of flexibility varies greatly.**

Steps in a Simulation Study: Verification and Validation

Has the Model been Verified?

- Verification pertains to the computer program prepared for the simulation model.
- The basic question is “Is the computer program performing properly?”

Has the Model been Verified?

- With complex models, it is difficult, if not impossible, to translate a model successfully in its entirety without a good deal of debugging

Testing Verification

- **If the input parameters and logical structure of the model are correctly represented in the computer, verification has been completed.**

Validation

- Validation is usually achieved through
  - the calibration of the model,
  - an iterative process of comparing the model against actual system behavior
  - using the discrepancies between the two, and the insights gained, to improve the model.

Validation

- **This process is repeated until model accuracy is judged acceptable**

Validation

- In the example of a bank, data was collected concerning the length of waiting lines under current conditions.
- Does the simulation model replicate this system measure?
- This is one means of validation.

Summary

- Till now we have taken a look at the several steps of the simulation study.
- We have examined how verification and validation are performed.

Steps in a Simulation Study: Experimental Design

Experimental Design

- In this module, we shall continue to examine steps in a Simulation study

Experimental Design

- The alternatives that are to be simulated must be determined.
- Often, the decision concerning which alternatives to simulate will be a function of runs that have been completed and
- analyzed.

Experimental Design

- For each system design that is simulated, decisions need to be made concerning
- the length of the initialization period,
- the length of simulation runs,
- the number of replications to be made for each run.

Production Runs and Analysis

- Production runs, and their subsequent analysis, are used to estimate measures of performance for the system designs that are being simulated.
- There is also possibility to use software to help in this step

Example Software

- E.g. AutoStat (in AutoMod), OptQuest (in several pieces of simulation software), SimRunner (in Pro Model), WITNESS Optimizer (in WITNESS), behavior space in NetLogo etc.

More Runs?

- Given the analysis of runs that have been completed, the analyst determines whether additional runs are needed
- Also what design those additional experiments should follow.

More Runs

- Simulation languages are powerful and flexible.
- However, if the problem is amenable to solution with the simulation software, the model development time is greatly reduced.

More Runs

- Furthermore, most of the simulation-software packages have added features that enhance their flexibility, although the amount of flexibility varies greatly.

Summary

- We have seen how simulation steps can be simplified by means of specific software

Steps in a Simulation Study: Documentation

Documentation and Reporting

- There are two types of documentation:
- Program
- Progress.

Documentation

- Program documentation is necessary for numerous reasons.
- If the program is going to be used again by the same or different analysts, it could be necessary to understand how the program operates.
-

Documentation Benefits

- This will create confidence in the program, so that model users and policymakers can make decisions based on the analysis.
- Also, if the program is to be modified by the same or a different analyst, this step can be greatly facilitated by adequate documentation.

Documentation Benefits

- One experience with an inadequately documented program is usually enough to convince an analyst of the necessity of this important step.

Documentation Benefits

- Another reason for documenting a program is so that model users can change parameters at will in an effort to learn the relationship in
  - input parameters and
  - output measures of performance
- or to discover the input parameters that optimize some output measure of performance.

Frequency of Progress Reports

- Progress reports should be frequent (monthly, at least)
- They help even those not involved in the day to day operation to keep abreast
- The awareness of these others can often enhance the successful completion of the project by surfacing misunderstandings early, when a problem can be solved easily.

Summary

- We have seen how progress reports can be used in a study

Steps in a Simulation Study: Logs and Reports

Project Log

- Musselman also suggests maintaining a project log
- It can contain
  - a comprehensive record of accomplishments,
  - change requests,
  - key decisions,
  - Any other items of importance.

Reporting Deliverables

- Musselman suggests frequent deliverables.
- These may or may not be the results
- of major accomplishments.
- His maxim is that "it is better to work with many intermediate milestones than with one absolute deadline."

Possible Reports

- Possibilities prior to the final report include
- a model specification,
- Prototype demonstrations
- Animations
- training results,
- intermediate analyses,

Project Reports

- Program documentation,
- Progress reports
- Presentations etc.
- He suggests that these deliverables should be timed judiciously over the life of the project

The Final Report

- The result of all the analysis should be reported clearly and concisely in a final report.

The Final Report

- This will enable the model users (now, the decision makers) to review
  - the final formulation
  - the alternative systems that were addressed,
  - the criterion by which the alternatives were compared

The Final Report

- the results of the experiments, and
- the recommended solution to the problem.

The Final Report

- Furthermore, if decisions have to be justified at a higher level, the final report should provide
  - a vehicle of certification for the model user/decision maker
  - add to the credibility of the model and of the model-building process.

Finally: Implementation

- The success of the implementation phase depends on how well the previous 11 steps have been performed.
- It is also contingent upon how thoroughly the analyst has involved the ultimate model user during the entire simulation process.

Implementation

- If the model user has been thoroughly involved during the model-building process and if the model user understands the nature of the model and its outputs, the likelihood of a vigorous implementation is enhanced [Pritsker, 1995].

Implementation

- Conversely, if the model and its underlying assumptions have not been properly communicated, implementation will probably suffer, regardless of the simulation model's validity.

Summary

- Till now we have taken a look at the various steps of the simulation study.
- To Summarize there are 4 key phases in a simulation study

Steps in a Simulation Study: Phases Overview

Phase I

- Phase I consists of Problem Formulation and an Orientation/discovery Period
- The initial statement of the problem is usually quite "fuzzy," the initial objectives will usually have to be reset, and the original project plan will usually have to be fine-tuned.

Phase I

- **These recalibrations and clarifications could occur in this phase, or perhaps will occur after or during another phase (i.e. , the analyst might have to restart the process).**

Phase II

- It involves model building and data collection
- This includes steps 3 (Model
- Conceptualization), 4 (Data Collection), 5 (Model 'Translation), 6 (Verification), and 7 (Validation).

Phase II

- A continuing interplay is required among the steps.
- Exclusion of the model user during this phase can have dire implications at the time of implementation.

Phase III

- Once we are done with the basic simulation experiments, it is imperative to involve the end user for exiting the case study.
- This is a continuing step.

Summary

- **We have seen how typical case studies are structured in the form of different phases**

Modeling & Simulation

Simulation Case Studies

Simulation Case Studies

- In this module, we shall see an overview of various case studies

Variety of Examples

- We shall be taking a look at a couple of examples.
- The variety will include hands on as well as spreadsheet examples.
- Key objective: Take a look at Discrete Event Simulation and also descriptive statistics for prediction of system performance

General Steps

- Every simulation that we observe will be based on 3 key steps
- The idea is to examine the examples using a methodological approach

First Step

- Determine the characteristics of each of the inputs to the simulation.
- Quite often, these are modeled as probability distributions, either continuous or discrete.

Second Step

- Construct a simulation table.
- Each simulation table is different, for each is developed for the problem at hand.

Example: Simulation Table

- An example of a simulation table is shown in Table.
- In this example, there are p inputs, xij,j= l, 2, .. . , p,
- One response yi for each of repetitions (or, trials)
- i =1, 2, . . . , n.
- Initialize the table by filling in the data for repetition 1

Table

Repetitions	Inputs						Response
	x_{i1}	x_{i2}	$\cdots$	x_{ij}	$\cdots$	x_{ip}	y_i
1							
2							
3							
.							
.							
.							
n							

Step 3

- For each repetition i, generate a value for each of the p inputs, and evaluate the function
- Calculate a value of the response yi.

Step 3

- The input values may be computed by sampling values from the distributions chosen in step 1
- A response typically depends on the inputs and one or more previous responses.

Step 3

- Also, if the program is to be modified by the same or a different analyst, this step can be greatly facilitated by adequate documentation.
- One experience with an inadequately documented program is usually enough to convince an analyst of the necessity of this important step.

Overview of Examples

- Queueing
- Inventory
- Reliability
- Network analysis.
- The two queueing examples provide
  - single-server
  - two-server system

First Example Overview

- **The first of the inventory examples involves a problem that has a closed-form solution;**
- **What it means is that the simulation solution can be compared to the mathematical solution.**

Second Inventory Example

- **The second inventory example pertains to the classic order-level model .**

More examples

- Next, there is an example that introduces the concept of random normal numbers
- Also, there is a model for the simulation of lead-time demand.
- The examples conclude with the analysis of a network.

Summary

- In this module, we have examined how simulation examples give us a clear picture of how to do simulations
- We also took a look at the type of examples that we shall be examining in our next module

Modeling and Simulation

Basics of Spreadsheet Simulation

Basics of Spreadsheet Simulation

- In this module, we shall see an overview of spreadsheet simulation
- We shall also take a look at simulating randomness

How to Simulate Randomness

- Almost every simulation we encounter needs at least one random variable
- E.g. Coin Toss (Head vs. Tail)

Another Example: Queue

- **Arrival and departure rate**

Taking a Step Back: What is Random?

- In the real world, the number of factors involved in any event are so numerous that it can be very difficult to predict such events.
- In a computer, this can be very hard to generate.
- Hence the concept of "pseudo randomness"

General Steps

- Generate a number between 0 and 1 – referred to as the "random number"
- "Random variable" is any randomly generated quantity with a specified statistical distribution.
- A method of generating a sequence of random numbers is called a Random Number Generator (RNG)

Important Statistical Properties

- Number should be uniformly distributed between 0 and 1
- Subsequent numbers should be statistically independent of all previous numbers

VBA in MS Excel

- We use the RAND formula = RAND()
- More complex formulas can be used e.g. IF(RAND() <= 0.5, 0.1)
- Here IF checks the first condition and if true, returns the second one

VBA in MS Excel

- Another option is RANDBETWEEN()
- Rnd01
- Discrete Uniform(min, max)
- DiscreteEmp(rCumProb, rValues)
- Uniform(low, high)
- NORMSINV(Rnd01())
- For manual simulation, we can use coin toss or dice (Impractical for anything large however)

Summary

- **In this module, we have examined the basics of simulation in spreadsheet**

Modeling and Simulation

Simulating a Coin Toss

Simulating a Coin Toss

- In this module, we shall see how we can simulate a coin toss using Excel

The Problem

- We want to simulate a sequence of 10 coin tosses.
- Coin is a “fair” coin
- Fair means same chance of heads vs. tail

Type of Simulation: Monte Carlo Simulation

- There are no events
- No clock times being tracked

Description: Solutions

- The spreadsheet example has 4 solutions.
- Two use RAND() and other two use Rnd01 function

Simulation

Example 2.1: Coin Tossing (with 4 Solutions)

Click the button, or hit the F9 key, to recalculate the spreadsheet and generate a new trial.

Generate New Trial

Coin	Probability	Cumulative Probability
Head	0.50	0.50
Tail	0.50	1.00

You may change the Example by changing any of the values with a green background.

Frequency of Heads and Tails	
Bins	Frequency
H	7
T	3

Seed for Random Numbers 12345

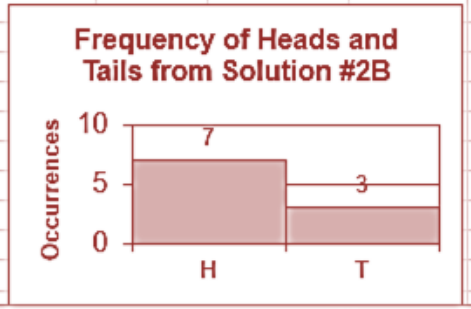
Reset Seed & Run

Reset Seed sets the RN seed. then runs a new trial.

Number of Tosses = 10

NOTE: Solution #2B is the recommended solution.

	Solution #1A		Solution #1B		Solution #2A		Solution #2B
Toss	RAND( )	Solution using RN from Col C	Solution using RAND( )	Toss	Rnd01( )	Solution using RN from Col G	Solution using Rnd01( )
1	0.3030427	H	H	1	0.2822478	H	H
2	0.4531398	H	H	2	0.7593559	T	T
3	0.4340458	H	T	3	0.3890941	H	H
4	0.5977018	T	T	4	0.8293307	T	H
5	0.5955604	T	H	5	0.8633085	T	H
6	0.3717375	H	H	6	0.0461711	H	H
7	0.7097325	T	T	7	0.6850743	T	H
8	0.2652147	H	T	8	0.5623563	T	T
9	0.6304771	T	H	9	0.6297657	T	T
10	0.9020576	T	H	10	0.7395675	T	H



One Trial | Experiment | Explain

Summary

- **In this module, we have examined how we can use VBA to simulate a coin toss.**

Modeling and Simulation

Simulating a Random Service Time

Simulating a Random Service Time

- In this module, we shall see how we can simulate a Random service time

The Problem

- We want to simulate a set of discrete values from continuous variables.
- Callers are assigned 3 different times with different probabilities.
- 3 with a probability of 30%
- 6 with a probability of 45%
- 10 with a probability of 25%

Type of Simulation: Monte Carlo Simulation

- There are no events
- No clock times being tracked

Description: Solution

- **The spreadsheet example converts the continuous number to discrete using cumulative probability**

Simulation

Example 2.2: Random Service Times for an Information Service

the button, or hit the F9 key, to recalculate the spreadsheet and generate a new

Generate New Trial

Service Time	Probability	Cumulative Probabilit
3	0.30	0.30
6	0.45	0.75
10	0.25	1.00

You may change the Example by changing any of the values with a green background.

Frequency of Heads and Tails	
Bins	Frequency
3	4
6	15
10	6

Seed for Random Numbers 12345

Reset Seed & Run

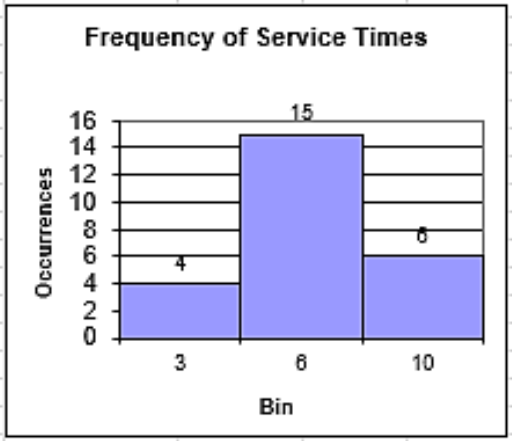
Number of Callers = 25

The "Reset Seed & Run" button sets the RN seed and generates a new trial using that seed.

Simulation Table

Step	Activity
Caller	Service Time
1	10
2	6
3	6
4	6
5	3
6	6
7	10
8	10
9	6
10	3
11	3
12	3
13	6
14	6
15	6
16	6
17	6
18	6
19	6
20	10
21	6
22	10

=DiscreteEmp($D$7:$D$9,$B$7:$B$9)



Summary

- In this module, we have examined how we can use Excel VBA functions to simulate a discrete distribution.
- The key idea is to assign limits based on cumulative probability for each value

Modeling and Simulation

Simulating a Random Arrival Time

Simulating a Random Arrival Time

- In this module, we shall see how we can simulate a Random Arrival time

The Problem

- **We want to simulate a random interarrival time (Time between successive arrivals) and compute arrival times of customers or other entities**

Interarrival Time

- Interarrival times and service times are examples of simulation-generated time durations
- These are called activity times or activities

Simulation Clock

- Simulation clock is a key component in a dynamic discrete-event simulation.
- Clock times represent the time of occurrence of an event
- E.g. arrival, service beginning, completion etc.

Simulating a Random Arrival Time

- Telephone calls to a Telephone Info service occur at random times
- These are defined by a discrete distribution with values 1, 2, 3, or 4 min – all equal probability.
- Goal is to generate both interarrival times and arrival times

Simulating a Random Arrival Time

- Dynamic here means time-based – with system state changing over time
- Dynamic event-based means model tracks progression of event occurrences over time

Simulation Details

- Simulation is based on the "Uniform" discrete distribution
- Uniform means all events have equal probabilities
- VBA Function Discrete Uniform()
- The function takes 2 arguments – minimum and maximum values

Simulation Clock

- Simulation clock is a key component in a dynamic discrete-event simulation.
- Clock times represent the time of occurrence of an event
- E.g. arrival, service beginning, completion etc.

Example2.3ArrivalTimes.xls

Example 2.3: Random Arrival Times for an Information Service

lick the button, or hit the F9 key, to recalculate the spreadsheet and generate a new tria

Generate New Trial

Interarrival Times (minutes)	
Minimum	1
Maximum	4

You may change the Example by changing any of the values with a green background (and adjusting the frequency counts, if necessary).

Frequency of Heads and Tails	
Bins	Frequenc
1	5
2	12
3	4
4	4

Number of Callers =	25	Seed for Random Numbers	12345

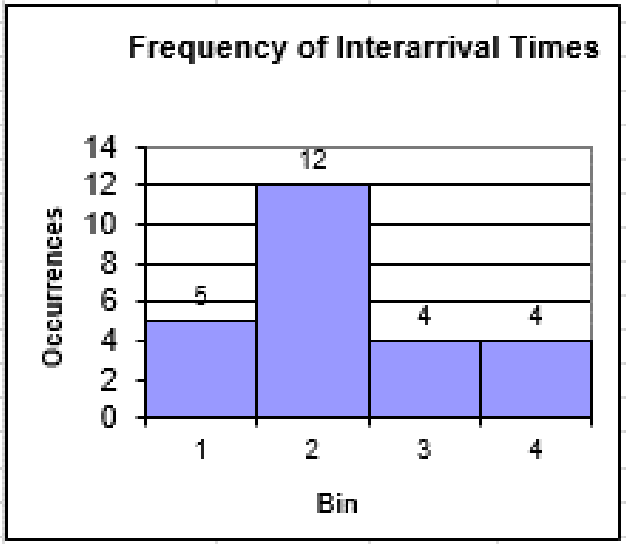
Reset Seed & Run

The "Reset Seed & Run" button sets the RN seed and generates a new trial using that seed.

Simulation Table

Step	Activity	Clock
Caller	Interarrival Time	Arrival Time
1	4	0
2	2	2
3	2	4
4	3	7
5	2	9
6	2	11
7	2	13
8	1	14
9	2	16
10	2	18
11	2	20
12	3	23
13	2	25
14	4	29
15	2	31
16	1	32
17	3	35
18	4	39

Interarrival times are generated using a uniform random number generator between the specified minimum and maximum values (integer values only).
Click "Generate New Trial" repeatedly to observe how much a small sample of size 25 varies from uniform.



Summary

- In this module, we have examined how we can use Excel VBA functions to simulate events such as interarrival times and arrival times.
- The key idea is to use a discrete uniform distribution

Modeling and Simulation

Framework for Spreadsheet Simulation

Framework for Spreadsheet Simulation

- **In this module, we shall examine a framework for Spreadsheet simulation**

Motivation

- We have seen several examples of simulation.
- Can we convert those examples into a framework?

Definitions

- First of all, model developer must define:
  - Model Inputs
  - System States
  - Model outputs

What are Inputs

- Inputs are the exogenous variables that are (usually) defined independently of other system characteristics
- E.g. Probability of heads in a coin toss
- Service times

What are Inputs

- Interarrival time distribution in a queuing system
- Demand distribution in an inventory model

Implications of Input Variables

- These input specifications are useful
- They can help generate:
- Random activity times and other random variables
- Whereas other inputs may be constants
- E.g. policy or decision parameters

Output variables

- They compute measures of system performance (also known as model responses)
- E.g. an output could be:
- An individual customer's waiting time (in a queue)
- The cost of an individual transaction in an inventory system

Associated Responses

- Associated responses could be:
- Average wait time in a queue
- Average cost per unit time in an inventory system

Summary

- In this module, we have examined a generic framework for developing simulation models (spreadsheet-based)
- It essentially follows a step-by-step procedure

Modeling and Simulation

Framework: Simulation

Table Design

Simulation Table Design

- Each sim table is custom designed for the problem at hand.
- Each column can have various types

Column Types

- An activity time associated with the input
- Any other random variable defined by an input
- A system state
- An event or clock time of an event
- Model output
- Sometimes, a model response

General Guidelines: Input

- Input Characteristics
- Probability distributions
- Constants

General Guidelines: Activities

- Activities
- Events
- System states
- Sorting the relevant from the irrelevant

General Guidelines: Model Responses

- Summary performance measures
- Correlate with objectives and specific questions

General Guidelines: Model Outputs

- Determine the outputs needed to compute the model response

General Guidelines: Simulation Table

– **Construct the simulation table**

Repetitions	Inputs						Response
	x_{i1}	x_{i2}	...	x_{ij}	...	x_{ip}	y_i
1							
2							
3							
.							
.							
.							
n							

General Guidelines: Simulation Table

- For each step i, generate a value for each activity.
- Next, calculate the system states
- Finally calculate the outputs

General Guidelines: Simulation Table

- In the end, use the outputs to compute the model responses or measures of performance

Summary

- In this module, we have examined a generic framework for developing simulation models (spreadsheet-based)
- It essentially follows a step-by-step procedure

Modeling and Simulation

Framework Using Discrete-Event Simulation: General Idea

General Principles

- This Module develops a common framework for the modeling of complex systems by using discrete-event simulation
  - It covers the basic building blocks of all discrete-event simulation models: entities and attributes, activities, and events

Discrete-event Simulation

- In Discrete-event Simulation,
  - A system is modeled in terms of-its state at each point in time; of the entities that pass through the system
  - And the entities that represent system resources; and of the activities and events that cause the system state to change.

Discrete-event Simulation

- Discrete-event models are appropriate for those systems for which changes in system state occur only at discrete points in time

Summary

- **This Module introduces and explains the fundamental concepts and methodologies underlying all discrete-event simulation packages.**

Modeling and Simulation

Framework Using Discrete-event Simulation-I

Concepts In Discrete-event Simulation

- This section expands on these concepts and proposes a framework for the development of a discrete-event model of a system.
- The major concepts are illustrated by examples

Concepts In Discrete-event Simulation

- The major concepts are briefly defined
  - System : A collection of entities (e.g., people and machines) that interact together over time to accom-plish one or more goals.

Concepts In Discrete-event Simulation

- **Model**: An abstract representation of a system, usually containing structural, logical, or mathematical relationships that describe a system in terms of state, entities and their attributes, sets, processes, events, activities, and delays.

Concepts In Discrete-event Simulation

- **System state**: A collection of variables that contain all the information necessary to describe the system at any time.
- **Entity**: Any object or component in the system that requires explicit representation in the model (e.g., a server, a customer, a machine).

Concepts In Discrete-event Simulation

- **Attributes**: The properties of a given entity (e.g., the priority of a waiting customer, the routing of a job through a job shop).

Concepts In Discrete-event Simulation

- List: A collection of (permanently or temporarily) associated entities, ordered in some logical fashion (such as all customers currently in a waiting line, ordered by "first come, first served," or by priority).

Concepts In Discrete-event Simulation

- **Event:** An instantaneous occurrence that changes the state of a system (such as an arrival of a new customer).

Concepts In Discrete-event Simulation

- **Event notice**: A record of an event to occur at the current or some future time, along with any associated data necessary to execute the event; at a minimum, the record includes the event type and the event time.

Concepts In Discrete-event Simulation

- **Event list: A list of event notices for future events, ordered by time of occurrence; also known as the future event list (FEL).**

Summary

- Here we have discussed some basic concepts related to a framework for DES

Modeling and Simulation

Framework For Discrete-event Simulation-II

Concepts In Discrete-event Simulation

- This section continues to expand on the framework concepts

Concepts In Discrete-event Simulation

- **Activity**: A duration of time of specified length (e.g., a service time or interarrival time), which is known when it begins (although it may be defined in terms of a statistical distribution).

Concepts In Discrete-event Simulation

- **Delay:** A duration of time of unspecified indefinite length, which is not known until it ends (e.g., a customer's delay in a last-in-first-out waiting line which, when it begins, depends on future arrivals).

Concepts In Discrete-event Simulation

- **Clock:** A variable representing simulated time, called CLOCK in the examples to follow

Different Simulation, Packages Use Different Terminology

- Different simulation, packages use different terminology for the same or similar concepts-for example, lists are sometimes called sets, queues, or chains. Sets or lists are used to hold both entities and event notices

The Entities On A List Are Always Ordered By Some Rule

- The entities on a list are always ordered by some rule, such as first-in-first-out or last-in-first-out, or are ranked by some entity attribute, such as priority or due date. The future event list is always ranked by the event time recorded in the event notice

An Activity Typically Represents A Service Time

- An activity typically represents a service time, an interarrival time, or any other processing time whose duration has been characterized and defined by the modeler. An activity's duration may be specified in a number of ways:

Activity's Duration

- 1. **Deterministic:** For example, always exactly 5 minutes;
- 2. **Statistical:** For example, as a random draw from among 2, 5, 7 with equal probabilities;

Activity's Duration

- **3. A function depending on system variables and/or entity attributes-for example, loading time for an iron ore ship as a function of the ship's allowed cargo weight and the loading rate in tons per hour.**

Duration Of An Activity is Computable

- However it is characterized, the duration of an activity is computable from its specification at the instant it begins. Its duration is not affected by the occurrence of other events (unless, as is allowed by some simulation packages, the model contains logic to cancel an event)

Summary

- **Here we have given some additional concepts related to DES**

Modeling and Simulation

Framework For Discrete-event Simulation-III

Concepts In Discrete-event Simulation

- This section discusses keeping track of activities

To Keep Track Of Activities

- For example, if the current simulated time is CLOCK = 100 minutes and an inspection time of exactly 5 minutes is just beginning, then an event notice is created that specifies the type of event (an end-of-inspection event), and the event time (100 + 5 = 1 0 5 minutes)

Conditional Wait

- A delay is sometimes called a conditional wait, an activity an unconditional wait.
- The completion of an activity is an event, often called a primary event, that is managed by placing an event notice on the FEL.

Conditional Or Secondary Event

- The completion of a delay is sometimes called a conditional or secondary event, but such events are not represented by event notices, nor do they appear on the FEL.

Systems Considered Here Are Dynamic

- The systems considered here are dynamic, that is, changing over time. Therefore, system state, entity attributes and the number of active entities

Systems Considered Here Are Dynamic

- The contents of sets, and the activities and delays currently in progress are all functions of time and are constantly changing over time. Time itself is represented by a variable called CLOCK

Example 3.1: Call Center, Revisited

- Consider the Able-Baker call center system of Example 2.2. A discrete-event model has the following components:
- System state
  - Lq (t): the number of callers waiting to be served at time t;

System State

- **La (t): 0 or 1 to indicate Able as being idle or busy at time t;**
- **Lg (t): 0 or 1 to indicate Baker as being idle or busy at time t.**

Entities

- **Entities:**
  - **Neither the callers nor the servers need to be explicitly represented, except in terms of the state variables, unless certain caller averages are desired**

Events

- **Events:**
  - **Arrival event;**
  - **Service completion by Able;**
  - **Service completion by Baker.**

Summary

- This Module deals exclusively with dynamic, stochastic systems (i.e., involving time and containing random elements) that change in a discrete manner

Modeling and Simulation

Framework For Discrete-event Simulation-IV

Activities

- Activities
  - Interarrival time, defined in Table 2.11;
  - Service time by Able, defined in Table 2.12;
  - Service time by Baker, defined in Table 2.13.

Delay

- **Delay:**
  - **A caller's wait in queue until Able or Baker becomes free .**
- **The definition of the model components provides a static description of the model.**

Prototype System Snapshot At Simulation Time t

Clock	*System state*	*Entities and attributes*	*Set 1*	*Set 2*	...	*Future event list, FEL*	*Cumulative statistics and counters*
t	$(x, y, z, \ldots)$					$(3, t_1)$ – Type 3 event to occur at time t_1 $(1, t_2)$ – Type 1 event to occur at time t_2 ⋮ ⋮	

Prototype system snapshot at simulation time t.

Some Questions That Need Answers Include

- How does each event affect system state, entity attributes, and set contents?
- How are activities defined (i.e., deterministic, probabilistic, or some other mathematical equation)?
- What event marks the beginning or end of each activity?

Some Questions That Need Answers Include

- What is the system state at time 0? What events should be generated at time 0 to prime the model that is, to get the simulation started?
- Which events trigger the beginning (and end) of each type of delay? Under what conditions does a delay begin or end?

Discrete-event Simulation

- A discrete-event simulation is the modeling over time of a system all of whose state changes occur at discrete points in time-those points when an event occurs .

Discrete-event Simulation

- A discrete-event simulation (hereafter called a simulation) proceeds by producing a sequence of system snapshots (or system Images) that represent the evolution of the system through time

Summary

- **This Module presents further concepts of DES**

Modeling and Simulation

The Event Scheduling

Time Advance Algorithm

The Event Scheduling/Time Advance Algorithm

- The mechanism for advancing simulation time and guaranteeing that all events occur in correct chronological order is based on the future event list (FEL)
- This list contains all event notices for events that have been scheduled to occur at a future time.

Scheduling A Future Event

- Scheduling a future event means that,
  - At the instant an activity begins, its duration is computed or drawn as a sample from a statistical distribution;
  - And that the end-activity event, together with its event time, is placed on the future event list

Random Breakdowns Or Random Arrivals

- In the real world, most future events are not scheduled but merely happen
  - such as random breakdowns or random arrivals. In the model, such random events are represented by the end of some activity, which in tum is represented by a statistical distribution

FEL Is Ordered By Event Time

- At any given time t, the FEL contains all previously scheduled future events and their associated event times (called t1;t2)
- The FEL is ordered by event time,

Imminent Event

- meaning that the events are arranged chronologically-that is, the event times satisfy

$$t < t_1 \leq t_2 \leq t_3 \leq \cdots t_n.$$

- Time t is the value:
  - of CLOCK, the current value of simulated time. The event associated with time t 1 is called the imminent event

Imminent Event

- Imminent event; that is, it is the next event that will occur
- After the system snapshot at simulation time CLOCK= t has been updated, the CLOCK is advanced to simulation time CLOCK= t1 the imminent event notice is removed from the FEL, and the event is executed

Execution Of The Imminent Event

- Execution of the imminent event means that a new system snapshot for time t1 is created, one based on the old snapshot at time t and the nature of the imminent event

Execution Of The Imminent Event

- At time t1, new future events may or might not be generated, but if any are, they are scheduled by creating event notices and putting them into their proper position on the FEL

Execution Of The Imminent Event

- After the new system snapshot for time t 1 has been updated, the clock is advanced to the time of the new imminent event and that event is executed. This process repeats until the simulation is over.

Summary

- To summarize the discussion, when using the *Event-scheduling Approach*, a simulation analyst concentrates on events and their effect on system state

Modeling and Simulation

The Event Scheduling Time Advance Algorithm-II

Event-scheduling/Time-advance Algorithm

- The sequence of actions that a simulator (or simulation language) must perform to advance the clock and build a new system snapshot is called the *Event-scheduling/Time-advance Algorithm*, whose steps are listed in Advancing simulation time and updating system image

Old System Snapshot At Time t

Old system snapshot at time t

CLOCK	System state	...	Future event list	...
t	(5, 1, 6)		(3, t_1) – Type 3 event to occur at time t_1 (1, t_2) – Type 1 event to occur at time t_2 (1, t_3) – Type 1 event to occur at time t_3 . . . (2, t_n) –Type 2 event to occur at time t_n	

Event-scheduling/time-advance algorithm

Step 1. Remove the event notice for the imminent event (event 3, time t_1) from FEL.
Step 2. Advance CLOCK to imminent event time (i.e., advance CLOCK from t to t_1).
Step 3. Execute imminent event: update system state, change entity attributes, and set membership as needed.
Step 4. Generate future events (if necessary) and place their event notices on FEL, ranked by event time. (Example: Event 4 to occur at time t^*, where $t_2 < t^* < t_3$.)
Step 5. Update cumulative statistics and counters.

Advancing simulation time and updating system image.

New System Snapshot At Time t1

New system snapshot at time t_1

CLOCK	*System state*	. . .	*Future event list*	. . .
t_1	(5, 1, 5)		$(1, t_2)$ – Type 1 event to occur at time t_2 $(4, t^*)$ – Type 4 event to occur at time t^* $(1, t_3)$ – Type 1 event to occur at time t_3 . . . $(2, t_n)$ – Type 2 event to occur at time t_n	

Advancing simulation time and updating system image.

List Processing

- The length and contents of the FEL are constantly changing as the simulation progresses, and thus its efficient management in a computerized simulation will have a major impact on the efficiency of the computer program representing the model. The management of a list is called list processing

Cancellation Of An Event

- The major list processing operations performed on a FEL are removal of the imminent event, addition of a new event to the list, and occasionally removal of some event (called *Cancellation of an Event*). As the imminent event is usually at the top of the list, its removal is as efficient as possible.

Removal And Addition Of Events From The FEL

- The removal and addition of events from the FEL is illustrated in Advancing simulation time and updating system image.
  - Event 3 with event time t1 represents, say, a service completion event at server 3

Removal And Addition Of Events From The FEL

- **Since it is the imminent event at time t, it is removed from the FEL in step 1 of the *event-scheduling/time-advance algorithm*:**

Removal And Addition Of Events From The FEL

- When event 4 (say, an *Arrival Event*) with event time t* is generated at step 4, one possible way to determine its correct position on the FEL is to conduct a *top-down* search:

If $t^* < t_2$,	place event 4 at the top of the FEL.
If $t_2 \le t^* < t_3$,	place event 4 second on the list.
If $t_3 \le t^* < t_4$,	place event 4 third on the list.
	⋮
If $t_n \le t^*$,	place event 4 last on the list.

Least Efficient Way To Maintain The FEL

- The least efficient way to maintain the FEL is to leave it as an unordered list (additions placed arbitrarily at the top or bottom), which would require at step 1 (of a Figure) complete search of the list for the imminent event before each clock advance

Summary

- To summarize the discussion, when using the *Event-scheduling Approach*, a simulation analyst concentrates on events and their effect on system state

Modeling and Simulation

The Event Scheduling Time Advance Algorithm-III

Exogenous Events

- If t = O, then the state (5, I, 6) might represent the initial number of customers at three different points in the system
- An *Exogenous Event* is a happening "*outside the system*" that impinges on the system

Exogenous Events

- An important example is an arrival to a queueing system
- At time 0, the first arrival event is generated and is scheduled on the FEL (meaning that its event notice is placed on the FEL).
- The interarrival time is an example of an activity

Exogenous Events

- When the clock eventually is advanced to the time of this first arrival, a second arrival event is generated. First, an interarrival time is generated, a*;
- It is added to the current time, CLOCK= t; the resulting (future) event time, t +a* = t*, is used to position the new arrival event notice on the FEL

Bootstrapping

- This method of generating an external arrival stream is called bootstrapping ; it provides one example of how future events are generated in step 4 of the event scheduling time-advance algorithm.

The Event Scheduling Time Advance Algorithm II

- The method of generating an external arrival stream is called bootstrapping
- Bootstrapping is illustrated in Figure given. The first three interarrival times generated are 3.7, 0.4, and 3.3 time units.

Bootstrapping

- The end of an interarrival interval is an example of a primary event.
- A second example of how future events are generated is provided by a service completion event in a queueing simulation

Service Completion

- When one customer completes service, at current time CLOCK= t, if the next customer is present, then a new service time, s*, will be generated for the next customer.

Service Completion

- The next Service completion event will be scheduled to occur at future time $t^* = t + s^*$, by placing onto the FEL a new event notice, of type service completion, with event time t^*

Summary

- To summarize the discussion, when using the *Event-scheduling Approach*, a simulation analyst concentrates on events and their effect on system state

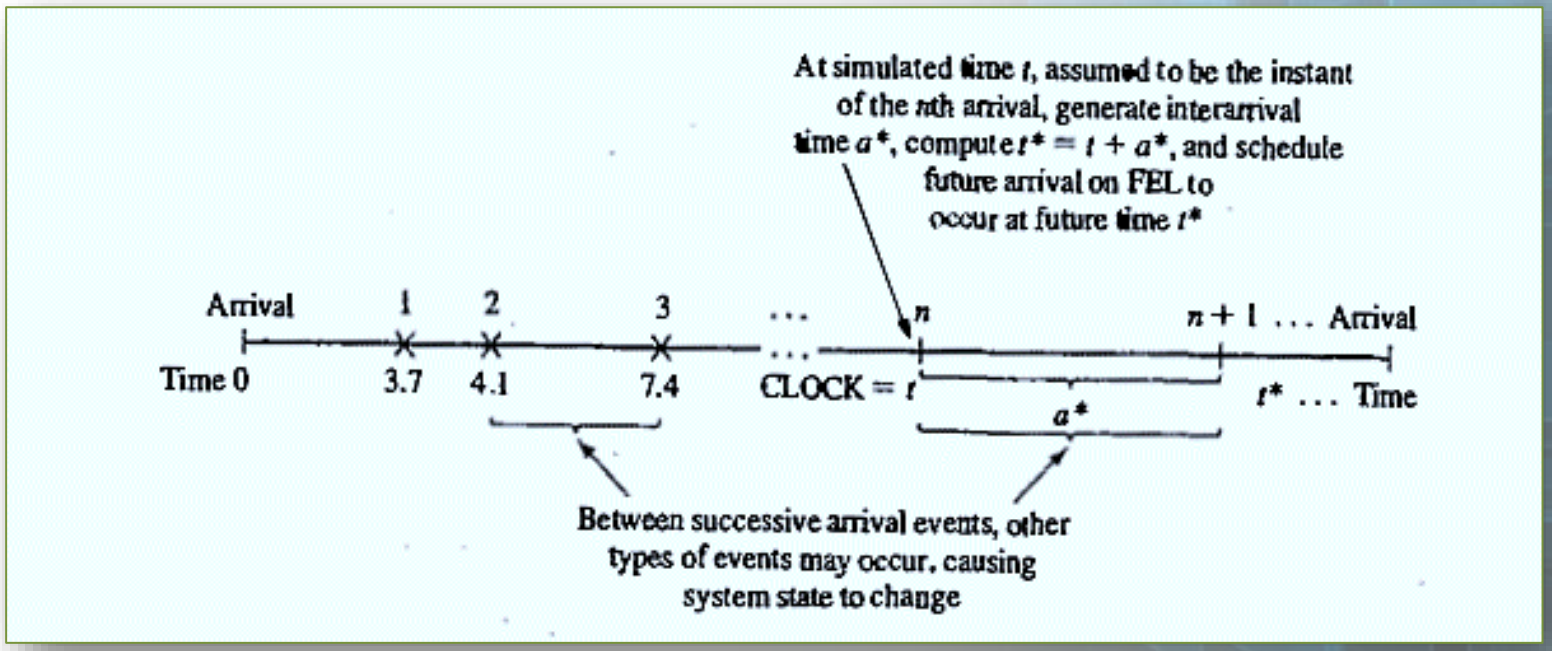
Modeling and Simulation

The Event Scheduling Time Advance Algorithm-IV

Service Completion

- Beginning service is a conditional event because its occurrence is triggered only on the condition that a customer is present and a server is free
- Service completion is an example of a primary event

Generation Of An External Arrival



Generation of an external arrival stream by bootstrapping.

Runtimes And Downtimes

- A third important example is the alternate generation of runtimes and downtimes for a machine subject to breakdowns.
- At time 0 , the first runtime will be generated, and an end-of-runtime event will be scheduled.

Stopping Event, E

- Every Simulation must have a stopping event, here called E, which defines how long the simulation will run.
- There are generally two ways to stop a simulation

Stopping Event, E

1. At time 0, schedule a stop simulation event at a specified future time TE'.
   - Thus, before simulating, it is known that simulation will run over the time interval[0, TE]. Example: Simulate a job shop for TE -40 hours.

Stopping Event, E

- Run length TE is determined by the simulation itself.
- Generally, TE is the time of occurrence of some
- specified event E. Examples: T E is the time of the l00th service completion at a certain service center

Stopping Event, E

- TE is the time of break down of a complex system. TE is the time of disengagement or total kill (whichever _ occurs first) in a combat simulation. TE is the time at which a distribution center ships the last carton in a day's orders.

Summary

- To summarize the discussion, when using the *Event-scheduling Approach*, a simulation analyst concentrates on events and their effect on system state

World Views-I

World Views

- When using a simulation package or even when doing a manual simulation, a modeler adopts a world view or orientation on for developing a model.

The Most Prevalent World View

- The most prevalent world views are
  - The event-scheduling world view,
  - The process-interaction world view,
  - The activity-scanning world view

Simulation Model In Terms of Analyst

- When using a package that supports the process-interaction approach, a simulation analyst thinks in terms of processes.

Simulation Model In Terms of Analyst

- The analyst defines the simulation model in terms of :
  - Entities or objects
  - And their life cycle as they flow through the system, demanding resources and queueing to wait for resources

Life Cycle

- A process is the life cycle of one entity.
- This life cycle consists of various events and activities.
- Some activities might require the use of one or more resources whose capacities are limited.

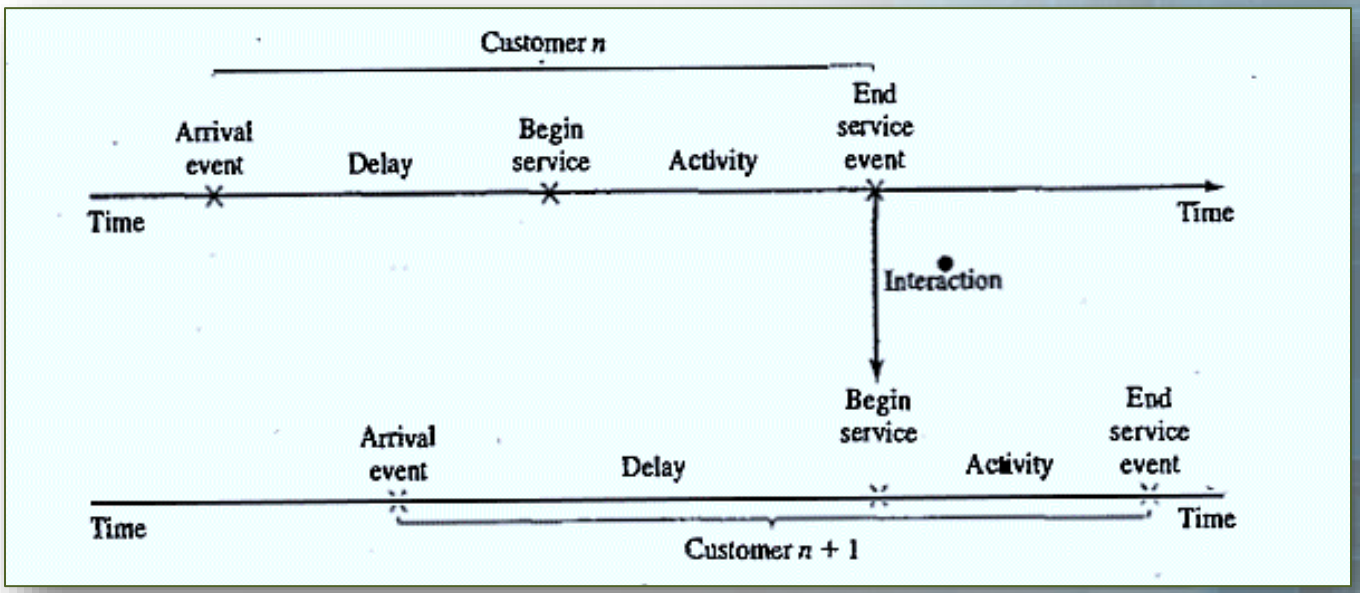
End Service Event

- In more precise terms, a process is a time-sequenced list of
  - Events
  - Activities
  - Delays
- Including demands for resources, that define the life cycle of one entity as it moves through a system

Customer Process

- An example of a "customer process" is shown in Following Figure.
- In this figure, we see the interaction between two customer processes as customer n + 1 is delayed until the previous customer's "end service event" occurs.

Two Interacting Customer Processes In A Single-server Queue



Two interacting customer processes in a single-server queue

Activity-scanning Approach

- The pure activity-scanning approach has been modified (and made conceptually somewhat more complex) by what is called the three-phase approach

Summary

- In this module we learnt Proponents claim that the activity scanning and three-phase approaches are particularly good at handling complex resource problems in which various combinations of resources are needed to accomplish different tasks.

Summary

- These approaches guarantee that all resources being freed at a given simulated time will all be freed before any available resources are reallocated to new tasks.

World Views-II

Three-phase Approach

- The three-phase approach, which combines some of the features of event scheduling with activity scanning to allow for variable time advance and the avoidance of scanning when it is not necessary, but keeps the main advantages of the activity-scanning approach.

Duration Zero Time Units

- In the three-phase approach, events are considered to be activities of duration zero time units. With this definition, activities are divided into two categories, which are called B and C.

B activities & C activities

- **B activities**:
  - Activities bound to occur; all primary events and unconditional activities.
- **C activities**:
  - Activities or events that are conditional upon certain conditions-being true

B-type Activities

- The B-type activities and events can be scheduled ahead of time, just as in the event-scheduling approach.
- This allows variable time advance.
- The FEL contains only B-type events. Scanning to learn

C-type Activities

- C-type activities can begin or C-type events occur happens only at the end of each time advance, after all B-type events have completed.

Three-phase Approach

- In summary, with the three-phase approach, the simulation proceeds with repeated execution of the 3 phases until it is completed;
- Phase A :
  - Remove the imminent event from the FEL and advance the clock to its event time.

Three-phase Approach

  - Remove from the FEL any other events that have the same event time.
- Phase B:
  - Execute all B-type events that were removed from the FEL. (This could free a number of resources or otherwise change system state.)

Three-phase Approach

- **Phase C :**
  - **Scan the conditions that trigger each C-type activity and activate any whose conditions are Smet.**
  - **Rescan until no additional C-type activities can begin and no events occur.**

Summary

- In this module we learnt Proponents claim that the activity scanning and three-phase approaches are particularly good at handling complex resource problems in which various combinations of resources are needed to accomplish different tasks.

Summary

- These approaches guarantee that all resources being freed at a given simulated time will all be freed before any available resources are reallocated to new tasks.

Modeling and Simulation

Manual Simulation
Using
Event Scheduling

Manual Simulation Using Event Scheduling

- **In the conducting of an event-scheduling simulation, a simulation table is used to record the successive system snapshots as time advances.**

Single-Channel Queue

- Example 3 3: Single-Channel Queue
- Reconsider the grocery store with one checkout counter that was simulated in (previous example) by an ad hoc method.
- The system consists of those customers in the waiting line plus the one (if any) checking out.

Single-Channel Queue

- A stopping time of 60 minutes is set for this example. The model has the following components:

Model's Component

System state $(LQ(t), LS(t))$, where $LQ(t)$ is the number of customers in the waiting line, and $LS(t)$ is the number being served (0 or 1) at time t.

Entities The server and customers are not explicitly modeled, except in terms of the state variables.

Events

Arrival (A);
Departure (D);
Stopping event (E), scheduled to occur at time 60.

Event notices

(A, t), representing an arrival event to occur at future time t;
(D, t), representing a customer departure at future time t;
(E, 60), representing the simulation stop event at future time 60.

Activities

Interarrival time, defined in Table 2.6;
Service time, defined in Table 2.7

Delay Customer time spent in waiting line.

Event Type, Event Time

- The event notices are written as (event type, event time).
- In this model, the FEL will always contain either two or three event notices.
- The effect of the arrival and departure events was first shown in previous Figures and is shown in more detail in next Figures .

Simulation Table

- The simulation table for the checkout counter is given in Table 3.1.
  - The reader should cover all system snapshots except one, starting with the first,

Simulation Table

– and attempt to construct the next snapshot from the previous one and the event logic in figure below and the interval time and service time will be identical to those used in table below:

Interarrival Times	1	1	6	3	7	5	2	4	1…
Service Times	4	2	5	4	1	5	4	1	4…

The simulation table for the checkout counter

Summary

- **Here we have examined the basics of manual simulation**

Execution Of The Arrival Event

- **Initial conditions are that the first customer arrive at time 0 and begin service. This is reflected in table 3.1**

Simulation Table for Checkout Counter

Table 3.1 Simulation Table for Checkout Counter (Example 3.3)

	System State				Cumulative Statistics	
Clock	*LQ(t)*	*LS(t)*	*Future Event List*	*Comment*	*B*	*MQ*
0	0	1	(A, 1) (D, 4) (E, 60)	First A occurs ($a^* = 1$) Schedule next A ($s^* = 4$) Schedule first D	0	0
1	1	1	(A, 2) (D, 4) (E, 60)	Second A occurs: (A, 1) ($a^* = 1$) Schedule next A (Customer delayed)	1	1
2	2	1	(D, 4) (A, 8) (E, 60)	Third A occurs: (A, 2) ($a^* = 6$) Schedule next A (Two customers delayed)	2	2
4	1	1	(D, 6) (A, 8) (E, 60)	First D occurs: (D, 4) ($s^* = 2$) Schedule next D (Customer delayed)	4	2
6	0	1	(A, 8) (D, 11) (E, 60)	Second D occurs: (D, 6) ($s^* = 5$) Schedule next D	6	2

(continued overleaf)

Simulation Table for Checkout Counter

Table 3.1 *(continued)*

	System State				Cumulative Statistics	
Clock	*LQ(t)*	*LS(t)*	*Future Event List*	*Comment*	*B*	*MQ*
8	1	1	(D, 11) (A, 11) (E, 60)	Fourth A occurs: (A, 8) ($a^* = 3$ Schedule next A (Customer delayed)	8	2
11	1	1	(D, 15) (A, 18) (E, 60)	Fifth A occurs: (A, 11) ($a^* = 7$) Schedule next A Third D occurs: (D, 11) ($s^* = 4$) Schedule next D Customer delayed	11	2
15	0	1	(D, 16) (A, 18) (E, 60)	Fourth D occurs: (D, 15) ($s^* = 1$) Schedule next D	15	2
16	0	0	(A, 18) (E, 60)	Fifth D occurs: (D, 16)	16	2
18	0	1	(D, 23) (A, 23) (E, 60)	Sixth A occurs ($a^* = 5$) Schedule next A ($s^* = 5$) Schedule next D	16	2
23	0	1	(A, 25) (D, 27) (E, 60)	Seventh A occurs: (A, 23) ($a^* = 2$) Schedule next Arrival Sixth D occurs: (D, 23)	21	2

Execution Of The Arrival Event

- b the s stem snap shot at time zero (CLOCK = 0), with LQ = 0) = 0, LS(0) = 1, and both a departure event and arrival event on the FEL
- The simulation is scheduled to stop at time 60. Only two statistics, server utilization and maximum queue length, will be collected

Server Utilization

- Server utilization is defined by total server busy time (B) divided by total time (Te).
- Total busy time B, and maximum queue length, MQ will be accumulated as the simulation progresses
- A column headed “comments” is included to aid the reader

Server Utilization

- (a* and s* are the generated interarrival and service times, respectively.)
- As soon as the system snapshot at times CLOCK =0 is complete , the simulation begins. At time 0, the imminent event is (A,1).
- The CLOCK is advanced to time 1 , and (A, 1)is removed from the FEL

Execution of the arrival event

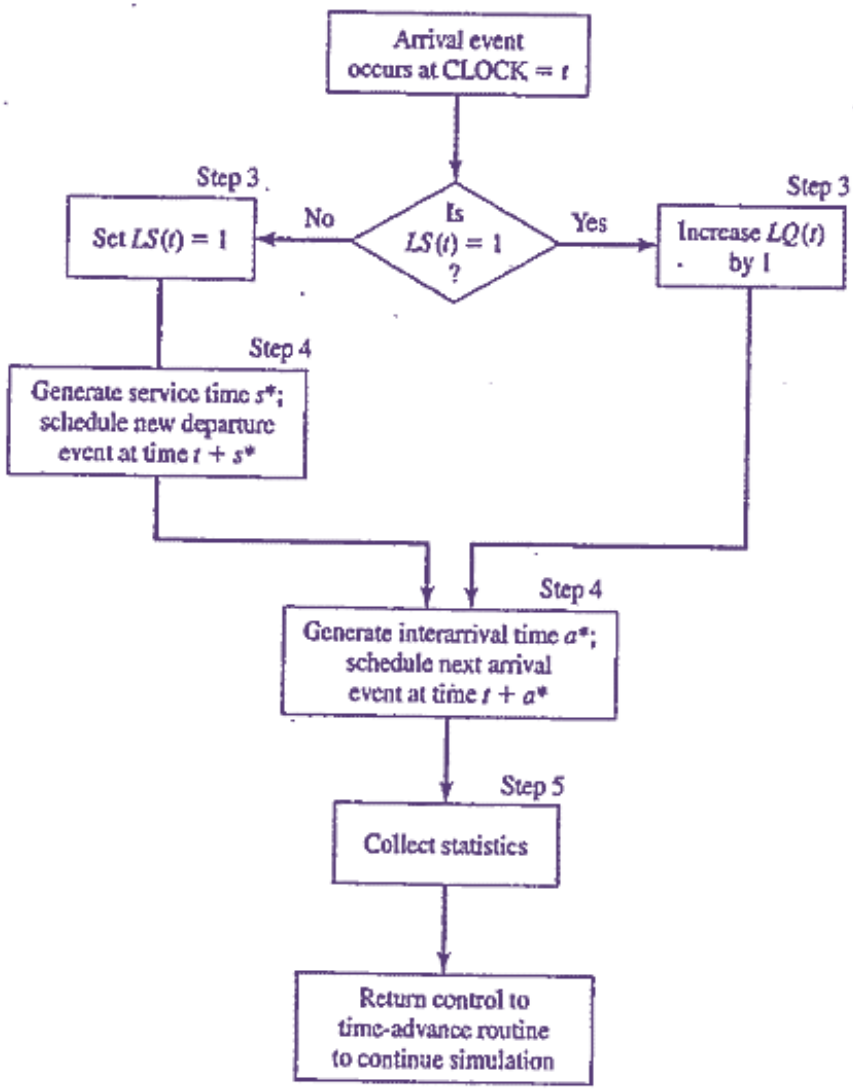


Figure 3.5 Execution of the arrival event.

Execution of the departure event

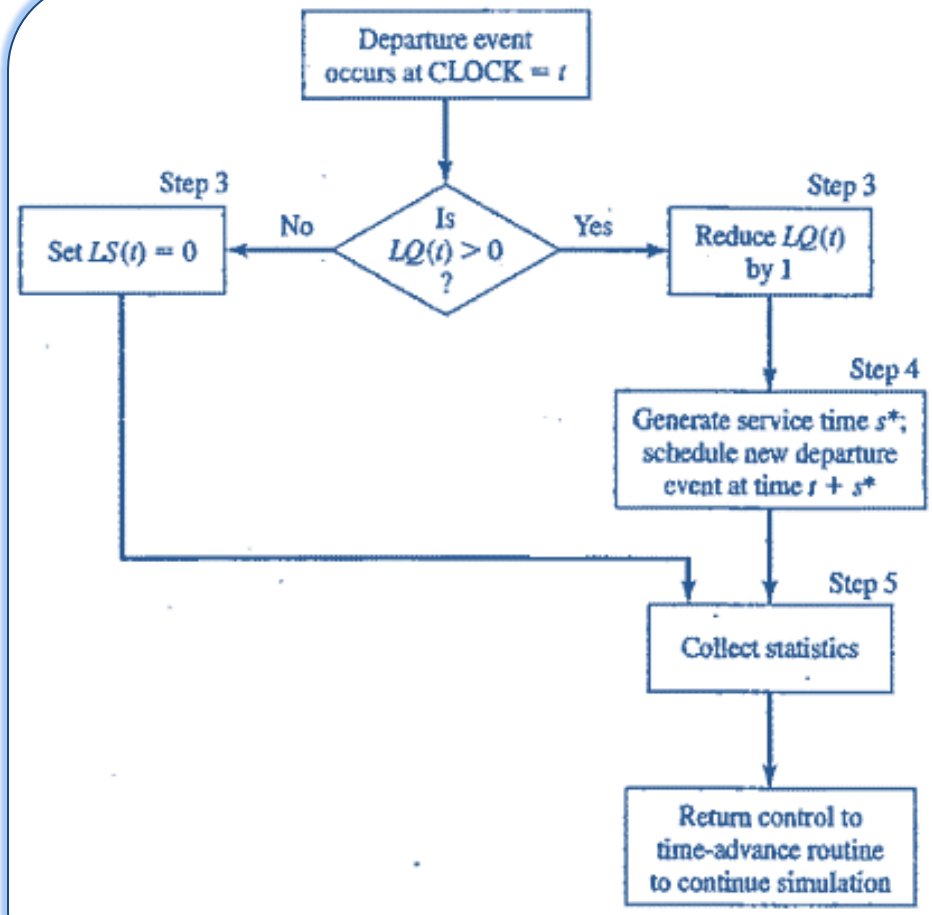


Figure 3.6 Execution of the departure event.

Simulation for Checkout Counter

- The simulation in Table 3.1 covers the time interval {0,23]. At simulated time 23, the system empties, but the next arrival also occurs at time 23.
- The server was busy for 21 of the 23 time units simulated, and the maximum queue length was two.

Simulation for Checkout Counter

- This simulation is, of course, too short to draw any reliable conclusions.
- Exercise 1 asks the reader to continue the simulation and to compare the results with those in Example 2.1.

Simulation for Checkout Counter

- Note that the simulation table gives the system state at all times, not just the listed times.
- For example, from time 11 to time 15, there is one customer in service and one in the waiting line.

The Dump-Truck Problem

- Six dump trucks are used to haul coal from the entrance of a small mine to the railroad. Figure 3.7 provides a schematic of the dump-truck operation. Each truck is loaded by one of two loaders. After a loading, the truck immediately moves to the scale, to be weighed as soon as possible.

The Dump-Truck Problem

- Both the loaders and the scale have a first-come-first-served waiting line (or queue) for trucks.
- Travel time from a loader to the scale is considered negligible. After being weighed, a truck begins a travel time (during which time the truck unloads) and then afterward returns to the loader queue.

The Dump-Truck Problem

- **The distributions of loading time, weighing time, and travel time are given in Tables 3.3, 3.4, and 3.5, respectively, together with the random digit assignment for generating**

Summary

- **Here we have examined the details of manual simulation**

Manual Simulation Using Event Scheduling-II

Execution Of The Arrival Event

- **Initial conditions are that the first customer arrive at time 0 and begin service. This is reflected in table 3.1**

Simulation Table for Checkout Counter

Table 3.1 Simulation Table for Checkout Counter (Example 3.3)

	System State				Cumulative Statistics	
Clock	*LQ(t)*	*LS(t)*	*Future Event List*	*Comment*	*B*	*MQ*
0	0	1	(A, 1) (D, 4) (E, 60)	First A occurs ($a^* = 1$) Schedule next A ($s^* = 4$) Schedule first D	0	0
1	1	1	(A, 2) (D, 4) (E, 60)	Second A occurs: (A, 1) ($a^* = 1$) Schedule next A (Customer delayed)	1	1
2	2	1	(D, 4) (A, 8) (E, 60)	Third A occurs: (A, 2) ($a^* = 6$) Schedule next A (Two customers delayed)	2	2
4	1	1	(D, 6) (A, 8) (E, 60)	First D occurs: (D, 4) ($s^* = 2$) Schedule next D (Customer delayed)	4	2
6	0	1	(A, 8) (D, 11) (E, 60)	Second D occurs: (D, 6) ($s^* = 5$) Schedule next D	6	2

(continued overleaf)

Simulation Table for Checkout Counter

Table 3.1 *(continued)*

	System State				Cumulative Statistics	
Clock	*LQ(t)*	*LS(t)*	*Future Event List*	*Comment*	*B*	*MQ*
8	1	1	(D, 11) (A, 11) (E, 60)	Fourth A occurs: (A, 8) ($a^* = 3$ Schedule next A (Customer delayed)	8	2
11	1	1	(D, 15) (A, 18) (E, 60)	Fifth A occurs: (A, 11) ($a^* = 7$) Schedule next A Third D occurs: (D, 11) ($s^* = 4$) Schedule next D Customer delayed	11	2
15	0	1	(D, 16) (A, 18) (E, 60)	Fourth D occurs: (D, 15) ($s^* = 1$) Schedule next D	15	2
16	0	0	(A, 18) (E, 60)	Fifth D occurs: (D, 16)	16	2
18	0	1	(D, 23) (A, 23) (E, 60)	Sixth A occurs ($a^* = 5$) Schedule next A ($s^* = 5$) Schedule next D	16	2
23	0	1	(A, 25) (D, 27) (E, 60)	Seventh A occurs: (A, 23) ($a^* = 2$) Schedule next Arrival Sixth D occurs: (D, 23)	21	2

Execution Of The Arrival Event

- b the s stem snap shot at time zero (CLOCK = 0), with LQ = 0) = 0, LS(0) = 1, and both a departure event and arrival event on the FEL
- The simulation is scheduled to stop at time 60. Only two statistics, server utilization and maximum queue length, will be collected

Server Utilization

- Server utilization is defined by total server busy time (B) divided by total time (Te).
- Total busy time B, and maximum queue length, MQ will be accumulated as the simulation progresses
- A column headed “comments” is included to aid the reader

Server Utilization

- (a* and s* are the generated interarrival and service times, respectively.)
- As soon as the system snapshot at times CLOCK =0 is complete , the simulation begins. At time 0, the imminent event is (A,1).
- The CLOCK is advanced to time 1 , and (A, 1)is removed from the FEL

Execution of the arrival event

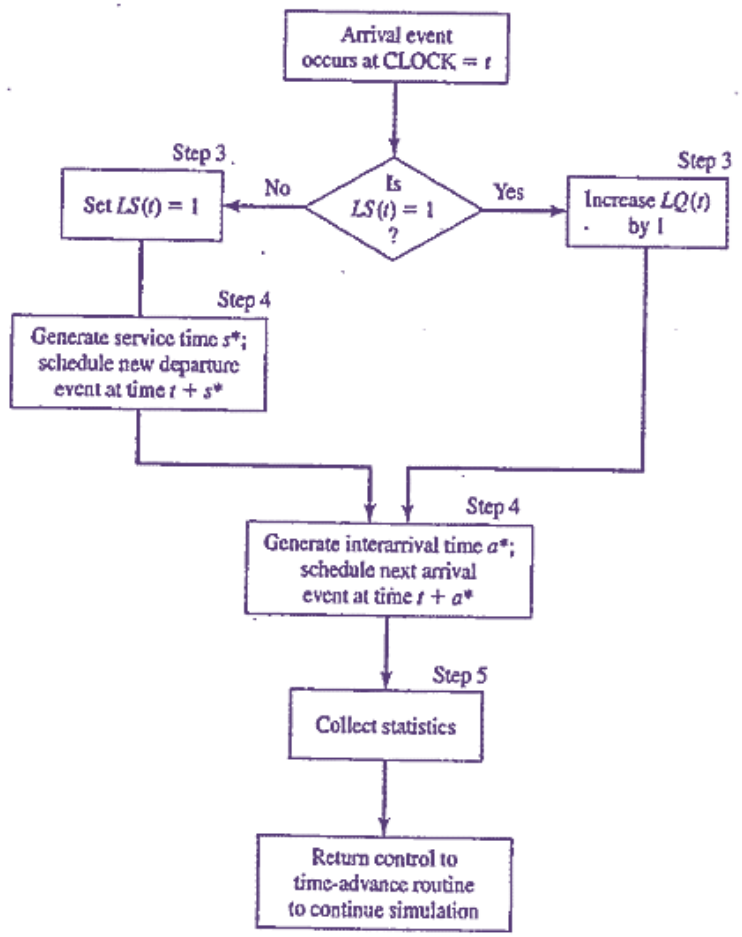


Figure 3.5 Execution of the arrival event.

Execution of the departure event

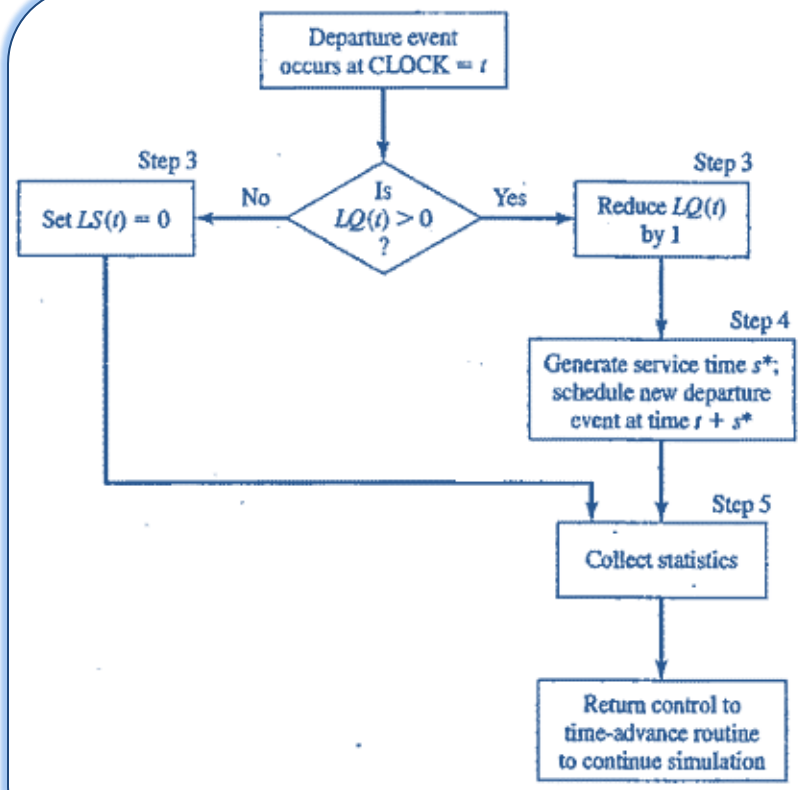


Figure 3.6 Execution of the departure event.

Summary

- **Here we have examined the details of manual simulation**

Simulation for Checkout Counter

- The simulation in Table 3.1 covers the time interval {0,23]. At simulated time 23, the system empties, but the next arrival also occurs at time 23.
- The server was busy for 21 of the 23 time units simulated, and the maximum queue length was two.

Simulation for Checkout Counter

- This simulation is, of course, too short to draw any reliable conclusions.
- Exercise 1 asks the reader to continue the simulation and to compare the results with those in Example 2.1.

Simulation for Checkout Counter

- Note that the simulation table gives the system state at all times, not just the listed times.
- For example, from time 11 to time 15, there is one customer in service and one in the waiting line.

The Dump-Truck Problem

- Six dump trucks are used to haul coal from the entrance of a small mine to the railroad. Figure 3.7 provides a schematic of the dump-truck operation. Each truck is loaded by one of two loaders. After a loading, the truck immediately moves to the scale, to be weighed as soon as possible.

The Dump-Truck Problem

- Both the loaders and the scale have a first-come-first-served waiting line (or queue) for trucks.
- Travel time from a loader to the scale is considered negligible. After being weighed, a truck begins a travel time (during which time the truck unloads) and then afterward returns to the loader queue.

The Dump-Truck Problem

- **The distributions of loading time, weighing time, and travel time are given in Tables 3.3, 3.4, and 3.5, respectively, together with the random digit assignment for generating**

Summary

- **Here we have examined the details of manual simulation**

Manual Simulation
Using
Event Scheduling-III

Simulation for Checkout Counter

- The simulation in Table 3.1 covers the time interval {0,23]. At simulated time 23, the system empties, but the next arrival also occurs at time 23.
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Summary

- **Here we have examined the details of manual simulation**

Modeling and Simulation

Statistical Models in Simulation

"Review Of Terminology And Concepts"

Discrete Random Variable

- Discrete random variables
  - Let X be a random variable. If the number of possible values of X is finite, or countably infinite, X is called a discrete random variable
  - The possible values of X may be listed as xi, x2, …

Discrete random variables

- In the finite case, the list terminates; in the countably infinite case, the list continues indefinitely.

Example # 1

- The number of jobs arriving each week at a job shop is observed. The random variable of interest is X, where
  - X = number of jobs arriving each week
- The possible values of X are given by the range space of X, which is denoted by Rx
  - Here Rx = { 0, 1, 2, . }

Example

- Let X be a discrete random variable. With each possible outcome xi in R, a number p(xi) = P(X = xi) gives the probability that the random variable equals the value of xi.

Example (Probability Distribution)

- The numbers p(xi) , i = I, 2.., must satisfy the following two conditions :

1. $p(x_i) \geq 0$, for all i
2. $\sum_{i=1}^{\infty} p(x_i) = 1$

- The collection of pairs (x., $p(x_i)$), i = 1, 2, ... is called the probability distribution of X, and p(x,) is called the probability mass function (pmf) of X

Example # 2

- Consider the experiment of tossing a single die. Define X as the number of spots on the up face of the die after a toss.
  - Then Rx = { 1, 2, 3, 4, 5, 6}
- Assume the die is loaded so that the probability that a given face lands up is proportional to the number of spots showing.

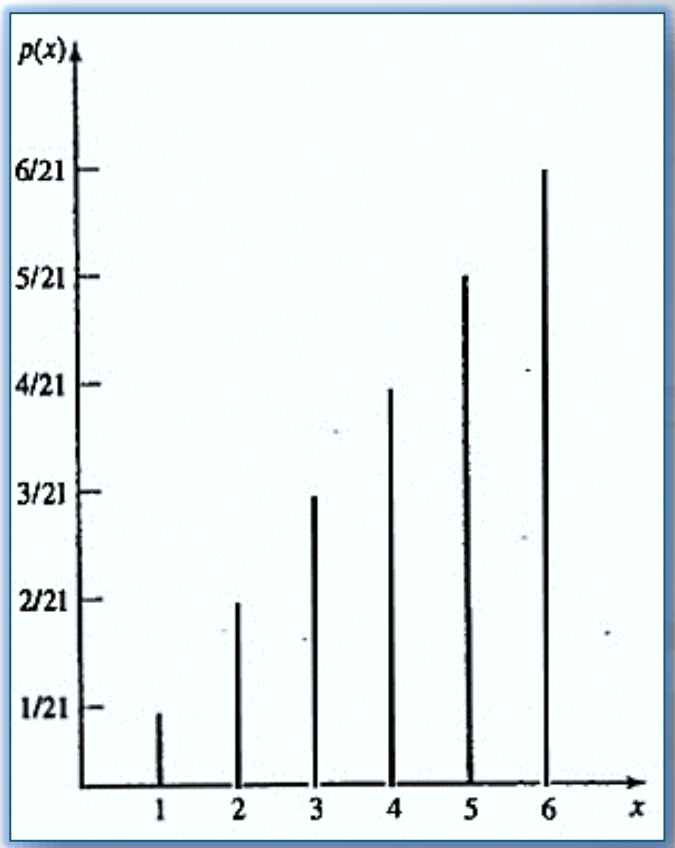
Example

- The *Discrete Probability Distribution* for this random experiment is given by

x_i	1	2	3	4	5	6
$p(x_i)$	1/21	2/21	3/21	4/21	5/21	6/21

- The conditions stated earlier are satisfied-that is, p(xi) ≥ 0 for i = 1, 2, ... , 6 and $\sum_{i=1}^{\infty} p(x_i) =$ 1/21 + .. + 6/21 = 1

Probability Mass Function For Loaded-die Example



Probability mass function for loaded-die example.

Summary

- **In this Module we have seen about more properties of a random variable i.e. Probability Distribution and probability mass function**

Modeling and Simulation

Review of Terms-I

Continuous Random Variable

- If the range space R_x of the random variable X is an interval or a collection of intervals, X is called a *Continuous Random Variable*. For a continuous random variable X, the probability that X lies in the interval [a , b] is given by

$$P(a \le X \le b) = \int_a^b f(x)\,dx \qquad (5.1)$$

Continuous Random Variable

a. $f(x) \geq 0$ for all x in R_X

b. $\int_{R_X} f(x)dx = 1$

c. $f(x) = 0$ if x is not in R_X

- As a result of Equation (5.1}, for any specified value
  - x_0, $P(X = x_0) = 0$, because

$$\int_{x_0}^{x_0} f(x)\,dx = 0$$

Continuous Random Variable

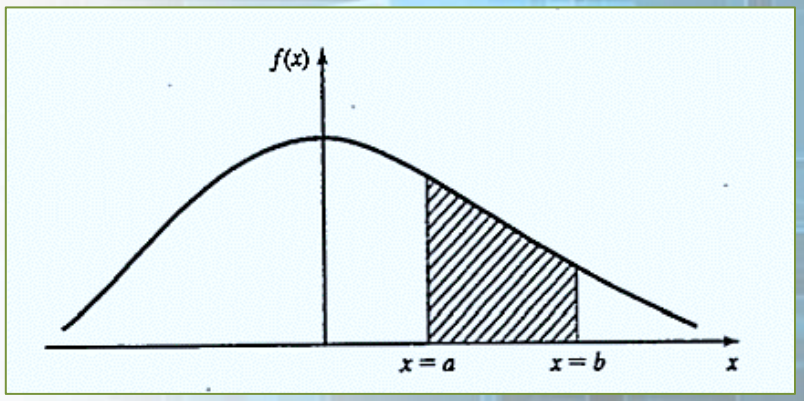
- **P(X = x0) = 0 also means that the following equations hold:**

$$P(a \le X \le b) = P(a < X \le b) = P(a \le X < b) = P(a < X < b)$$

- **The graphical interpretation of Equation** $P(a \le X \le b) = \int_a^b f(x)\,dx$ **is shown in Figure**

Graphical Interpretation

- **The shaded area represents the probability that X lies in the interval [a, b]**



Graphical interpretation of $P(a < X < b)$.

Example

- The life of a device used to inspect cracks in aircraft wings is given by X, a continuous random variable assuming all values in the range x ≥0. The pdf of the lifetime, in years, is as follows:

$$f(x) = \begin{cases} \frac{1}{2}e^{-x/2}, & x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

pdf

- pdf is shown graphically in below in Figure . The random variable X is said to have an exponential distribution with mean 2 years

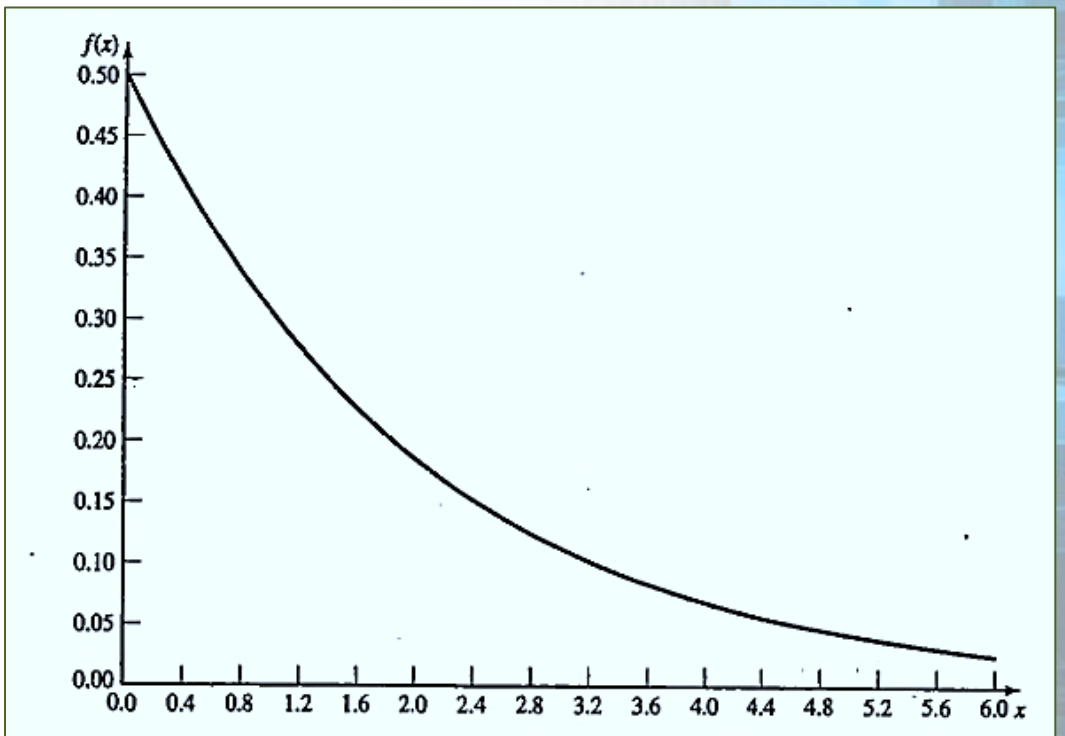


Figure 5.3 pdf for inspection-device life.

Probability Of Life Of The Device

- **The probability that the life of the device is between 2 and 3 years is calculated as**

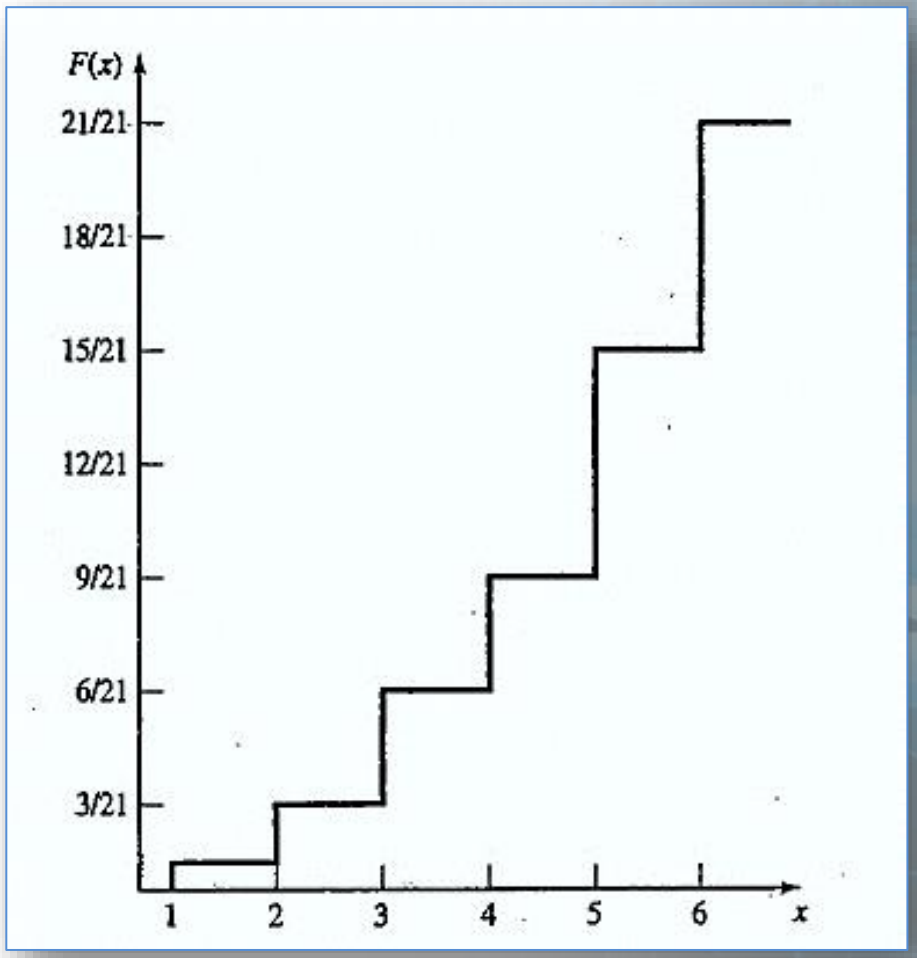
$$P(2 \le X \le 3) = \frac{1}{2}\int_2^3 e^{-x/2}dx$$
$$= -e^{-3/2} + e^{-1} = -0.223 + 0.368 = 0.145$$

Summary

- **In This Module we discussed about Continuous Random Variable and its probability of occurrences in time interval [a, b]**

Review of Terms-III

Cdf For Loaded-die Example



cdf for loaded-die example.

Expectation

- **An important concept in probability theory is that of the expectation of a random variable.**
- **If X is a random variable, the expected value of X, denoted by E(X), for discrete and continuous variables is defined as follows:**

$$E(X) = \sum_{\text{all } i} x_i p(x_i) \qquad \text{if } X \text{ is discrete} \qquad (5.6)$$

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx \qquad \text{if } X \text{ is continuous} \qquad (5.7)$$

nth Moment Of X

- The expected value E(X) of a random variable X is also referred to as the mean, μ , or the first moment of X.
- The quantity $E(X^n), n \geq 1,$ is called the nth moment of X, and is computed as follows:

Variance of X

The variance of a random variable, X, denoted by $V(X)$ or $\mathrm{var}(X)$ or σ^2, is defined by

$$V(X) = E[(X - E[X])^2]$$

A useful identity in computing $V(X)$ is given by

$$V(X) = E(X^2) - [E(X)]^2$$

- **The mean E(X) is a measure of the central tendency of a random variable. The variance of X measures the expected value of the squared difference between the random variable and its mean.**

Variance of X

- Thus, the variance,
  - V(X), is a measure of the spread or variation of the possible values of X around the mean E(X). The standard deviation, σ, is defined to be the square root of the variance σ^2

Mean And The Standard Deviation

- **The mean, E(X), and the standard deviation** $\sigma = \sqrt{V(X)}$ **have same units**

Thus,

$$V(X) = 21 - \left(\frac{91}{21}\right)^2 = 21 - 18.78 = 2.22$$

and

$$\sigma = \sqrt{V(X)} = 1.49$$

Example

- **The mean and variance of the life of the device described in Example 5.3 are computed as follows:**

$$E(X) = \frac{1}{2}\int_0^\infty x e^{-x/2} dx = -x e^{-x/2}\Big|_0^\infty + \int_0^\infty e^{-x/2} dx$$

$$= 0 + \frac{1}{1/2} e^{-x/2}\Big|_0^\infty = 2 \text{ years}$$

Example

- **To compute V(X) from Equation (5.10), first compute $E(X^2)$ from Equation (5.9) as follows:**

Thus,

$$E(X^2) = -x^2 e^{-x/2}\Big|_0^\infty + 2\int_0^\infty x e^{-x/2}\,dx = 8$$

giving

$$V(X) = 8 - 2^2 = 4 \text{ years}^2$$

and

$$\sigma = \sqrt{V(X)} = 2 \text{ years}$$

Summary

- In this Module we discussed about Cumulative Distribution Function of random variable X and its properties (e.g.) Standard Deviation Mean and Variance

Review of Terms-IV

The Mode

- The Mode is used in describing several statistical models that appear in this chapter

The Mode (Discrete case)

- In the discrete case, the mode is the value of the random variable that occurs most frequently.

The Mode (Continuous case)

- In the continuous case, the mode is the value at which the pdf is maximized
- The mode might not be unique

Bimodal

- **If the modal value occurs at two values of the random variable, the distribution is said to be *Bimodal***

Summary

- In this module we discussed Mode is used in describing several statistical models

Useful Statistical Models

Useful Statistical Models

- Numerous situations arise in the conduct of a simulation where an investigator may choose to introduce probabilistic events
- In an inventory model, the time between demands and the lead times (time between placing and receiving an order) can be probabilistic

Useful Statistical Models

- In a *reliability model*, the time to failure could be probabilistic. In each of these instances, the *simulation analyst* desires to generate random events and to use a known statistical model if the underlying distribution can be found

Queueing systems

- In the queueing examples, interarrival- and service-time patterns were given. In these examples, the times between arrivals and the service times were always probabilistic, as is usually the case.

Queueing systems

- However, it is possible to have a constant interarrival time (as in the case of a line moving at a constant speed in the assembly of an automobile), or a constant service time (as in the case of robotized spot welding on the same assembly line).

Queueing systems

- **The following example illustrates how probabilistic interarrival times might occur.**

Example # 1

- Mechanics arrive at a centralized tool crib as shown in Table 5.1. Attendants check in and cheek out the requested tools to the mechanics. The collection of data begins at 10:00 A.M. and continues until 20 different interarrival times are recorded.

Example

- Rather than record the actual time of day, the absolute time from a given origin could have been computed.
- Thus, the first mechanic could have arrived at time zero, the second mechanic at time 7:13 (7 minutes, 13 seconds), and so on.

Table (Arrival Data)

Table 5.1 Arrival Data

Arrival Number	*Arrival (Hour:Minutes::Seconds)*	*Interarrival Time (Minutes::Seconds)*
1	10:05::03	—
2	10:12::16	7::13
3	10:15::48	3::32
4	10:24::27	8::39
5	10:32::19	7::52
6	10:35::43	3::24
7	10:39::51	4::08
8	10:40::30	0::39
9	10;41::17	0::47
10	10:44::12	2::55
11	10:45::47	1::35
12	10:50::47	5::00
13	11:00::05	9::18
14	11:04::58	4::53
15	11:06::12	1::14
16	11:11::23	5::11
17	11:16::31	5::08
18	11:17::18	0::47
19	11:21::26	4::08
20	11:24::43	3::17
21	11:31::19	6::36

Summary

- In this Module we discussed about useful Statistical models and relation between distribution of time arrivals and number of arrivals per time period

Useful Statistical Models-II

Example # 2

- Another way of presenting interarrival data is to find the number of arrivals per time period.
- Here, such arrivals occur over approximately 11/2 hours; it is convenient to look at l0-minute time intervals for the first 20 mechanics.

Example

- In the second time period, two mechanics arrived, and so on. The results are summarized in Table 5.2.
- This data could then be plotted in a histogram, as shown in Figure 5.5.

Table (Arrivals in Successive Time Periods)

Table 5.2 Arrivals in Successive Time Periods

Time Period	*Number of Arrivals*	*Time Period*	*Number of Arrivals*
1	1	6	1
2	2	7	3
3	1	8	3
4	3	9	2
5	4	—	—

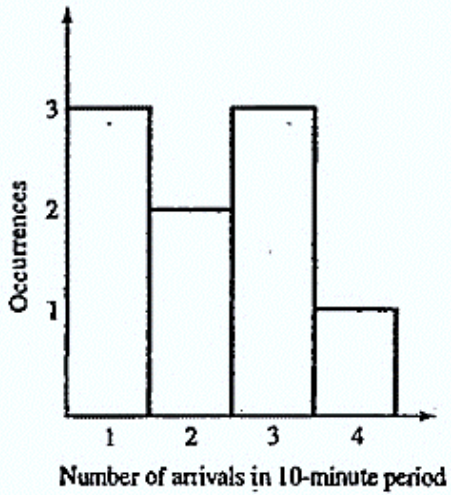


Figure 5.5 Histogram of arrivals per time period.

Distribution Of Time

- The distribution of time between arrivals and the distribution of the number of arrivals per time period are important in the simulation of waiting-line systems.

Distribution Of Time

- "Arrivals" occur in numerous ways; as machine breakdowns, as jobs coming into a job shop, as units being assembled on a line, as orders to a warehouse, as data packets to a computer system, as calls to a call center, and so on

Summary

- In this Module we discussed about useful Statistical models and relation between distribution of time arrivals and number of arrivals per time period

Why Agent-Based Modeling?

Agent-based Modeling

- Before we discuss why *Agent-based Modeling* is important, we briefly describe what agent-based modeling is.
  - An agent is an autonomous computational individual or object with particular properties and actions.

Agent-based Modeling

- Agent-based modeling is a form of computational modeling whereby a phenomenon is modeled in terms of agents and their interactions
- In the past two decades,
- scientists have increasingly used agent-based modeling methods to conduct their research

ABM

- ABM is a species of computation, growing up alongside the maturation of computer technology.
- The combination of large data, cheap computation, and high connectivity allows agent-based models to be constructed with millions of individual agents

Agent-based Representations

- **Agent-based representations are easier to understand than mathematical representations of the same phenomenon.**
  - **This is because agent-based models are constructed out of individual objects**

Agent-based Representations

- and simple rules for their movement of behavior, as opposed to equational models that are constructed from mathematical symbols.

Individual Agents

- In thinking about individual agents, we can make sense of them by projecting our bodily experience onto the agents.
- Thus, the language and concepts we use in agent-based modeling is much closer to natural language and our natural thinking.

Step To Presenting This Conceptualization

- As a first step to presenting this conceptualization, we look back historically at changes to representational tools and practices used in science and the significant benefits they had for both scientists and learners.

Summary

- The main argument of this introductory module is
  - That ABM is a transformative representational technology that enables us to better understand familiar topics

Summary

- And analyze hitherto unexplored topics; and enable a democratization of access to computational tools for making sense of complexity and change

Modeling and Simulation

A Thought Experiment

A Thought Experiment

- Imagine a country (let ' s call it Foo) where people represented numbers as the Romans did, using symbols such as MCMXLVIII.
- Fooian scientists worked laboriously to quantify and more accurately calculate basic science such as planetary motion and dynamical forces.

Number Of Different Approaches

- **Business people had great difficulties with their financial calculations, tradespeople struggled with their measurements, and consumers labored to assess their purchases.**

Number Of Different Approaches

- Educational researchers and policymakers in this imaginary country were very concerned with the difficulty of learning to handle numbers,
- They worked hard to make these skills accessible to more of their citizens.
- They engaged in a number of different approaches.

Name The Sort Of Innovation

- A first step is to name the sort of innovation associated with the shift from Roman to Hindu-Arabic representations of number
- It is not sufficient,
  - for example, to say that we have a new approach to learning and working with numbers

Structuration

- By Structuration we mean :
  - The encoding of the knowledge in a domain as a function of the representational infrastructure used to express the knowledge.

Restructuration

- A change from one structuration of a domain to another resulting from such a change in representational infrastructure we call a restructuration .

Examples Of Restructuration

- **The development of Arabic numerals and the transformation of kinematics via algebra were empowering and democratizing, enabling significant progress in science and widening the range of people who could make sense of previously formidable topics and skills**

Summary

- If the problems with which we struggle today could be so transformed, think of the new domains we could enter and conquer.
- This Module was about the
  - “who can do what, ”

Complex Systems and Emergence

Complex Systems and Emergence

- What areas are widely thought to be difficult for people to comprehend and potentially ripe for restructuration? One such area is complex systems.
- Its very name suggests that it is a difficult area for comprehension.

Complex Systems and Emergence

- **However, even if the level of complexity in our life remained constant over the ages, our continual quest for knowledge would ultimately lead us to study complex systems.**

From Simple to Complex System

- As we gain facility and more complete understanding of simple systems, we naturally progress to trying to make sense of increasingly complex systems.

Simple Population Dynamics Models

- Simple population dynamics models,
  - For example, make the implicit assumption that all members of a species are the same,
  - But later, it becomes important to explore the manifold complexity of the food web

Simple Population Dynamics Models

- And how each individual interacts with every other individual.

- Thus, our need to understand more complex systems is also a natural result of the growth of human knowledge.

Complex Systems Theory

- Complex systems theory develops principles and tools for making sense of the world ' s complexity and defines complex systems:
  - as systems that are composed of multiple individual elements that interact with each other

Complex Systems Theory

- yet whose aggregate properties or behavior is not predictable from the elements themselves.

Emergent Phenomenon

- Through the interaction of the multiple distributed elements an “ emergent phenomenon ” arises.
- The phenomenon of emergence is characteristic of complex systems.
- The term “ emergent ” was coined by the British philosopher and psychologist G. H. Lewes

Emergence

- Since Lewes ' s time, scholars have struggled with how to best define emergence
- For our purposes, we define emergence as :
  - The arising of novel and coherent structures, patterns, and properties through the interactions of multiple distributed elements .

Features Of Emergence

- Important features of emergence include:
  - The global pattern ' s spontaneous arising from the interaction of elements,
  - And the absence of an orchestrator or centralized coordinator — the system " self-organizes. "

Macrostructures Are Emergent

- Structure (or rules) at the micro-level leads to ordered pattern at the macro-level.
  - Because the macrostructures are emergent, composed of many elements, they are dynamic,
  - And perturbing them often results in them dynamically reforming

Summary

- **In This Module we discussed about complex systems theory which is ever finding more complex systems that may at first seem irreducible but are found to be self-organized or evolved rather than intelligently designed by a designer.**

Modeling and Simulation

Understanding Complex Systems and Emergence

Understanding Complex Systems and Emergence

- **We have said that understanding complex systems and emergence is hard for people.**

Fundamental And Distinct Challenges

- Emergence, in particular, presents two fundamental and distinct challenges.
  - The first difficulty lies in trying to figure out the aggregate pattern when one knows how individual elements behave.

Integrative Understanding

- We sometimes call the first fundamental and distinct challenge "integrative" understanding,
  - As it parallels the cumulative integration of small differences in calculus.

Fundamental And Distinct Challenges

- A second difficulty in fundamental and distinct challenge arises
  - when the aggregate pattern is known and one is trying to find the behavior of the elements that could generate the pattern

Differential Understanding

- We sometimes call the second fundamental and distinct challenge a "differential" understanding (aka compositional understanding),
  - As it parallels the search in calculus for the small elements that produce an aggregate graph when accumulated

Summary

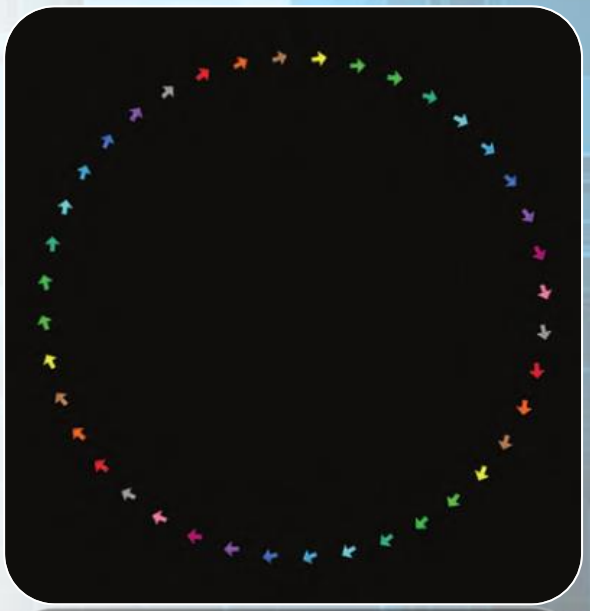
- **In this Module we have discussed about why it is hard to understand complex systems and emergence**

Modeling and Simulation

Example 1:
Integrative Understanding

Integrative Understanding

- **Figure presents a system composed of a few identical elements following one rule.**



Some arrows moving clockwise around a circle of radius 20.

Integrative Understanding

- Each element is a small arrow.
- We imagine a clock ticking and at each tick of the clock the arrows follow their rule.
- We initialize the system so that each individual arrow starts on a circle (of radius 20 units).
- We start them all facing clockwise on the circle.

Integrative Understanding

- Now, we give them one movement behavior (or rule).
- At every tick of the clock, they move forward 0.35 units then turn right one degree.
- As the clock ticks, they continue to move and turn, move and turn, moving clockwise along the circle

Integrative Understanding

- Now suppose that we slightly alter these rules.
  - Instead of moving forward 0.35 units, we have them move 0.5 units while still turning one degree. What will be the aggregate pattern that we see??

Integrative Understanding

- In fact, the pattern that emerges is a pulsating circle.
  - All the arrows stay in a circle, but the circle changes its radius,
  - First expanding, then contracting
  - And repeating this cycle forever.

Summary

- **In this Module we analyzed certain pattern of agents and their behavior while changing factors**

Example 2:

Differential Understanding

Differential Understanding

- **There are many coherent, powerful, and beautiful patterns we observe in the world. What accounts for their prevalence? How do they originate?**

Differential Understanding

- The secret to understanding the formation of these patterns is to understand
  - That they are emergent, arising from the interactions of distributed individual elements.

Flocking Of Birds

- One such prevalent (and often beautiful) pattern is the flocking of birds.
  - Birds fly together in many different formations, from the classic V formation of goose flocks to the large, very dense flocks of starlings that resemble insect swarms.

How And Why Do Birds Flocks Emerge?

Flock of geese flying in a classic V formation.

Deterministic-centralized Mindset

- In the 1980s and early ’ 90s, Wilensky and Resnick interviewed people from a wide range of backgrounds, asking them to explain how such patterns arise.

Cognitive Pattern

- The results suggested a phenomenon, or cognitive pattern, called the deterministic-centralized mindset, or DC mindset.
  - The pattern stemmed from two main empirical findings:

Empirical Findings (The D Component)

1. Most subjects did not see any role for randomness in creating these structures, randomness was seen as destructive of pattern, not a force for creating pattern (the D component);

Empirical Findings (The C Component)

Most subjects described these patterns as arising from the actions of a centralized controller or orchestrator (the C component).

Summary

- In this module we have discussed that in the past two decades, researchers have found that emergent phenomena are endemic to the natural and social worlds and that using an emergent lens to make sense of complex patterns is a vital need in a twenty-first-century world.

Differential Understanding-II

Thinking In Levels

- In further analyses of the interviews, Wilensky and Resnick (1999) identified a key component of the DC mindset and an obstacle to thinking about emergent phenomena:
- The problem of " thinking in levels. "

Emergent phenomena's two levels

- Emergent phenomena can be described as existing on
  - at least two levels: the level of the individual elements (cars, birds, people, etc.); and the
  - level of system or aggregate patterns (flocks, traffic jams, housing patterns, etc.).

Emergent phenomena's two levels

- Most people fail to distinguish between these levels, instead " slipping " between levels to attribute the properties of one level to the other

Appearance Of Stability

- The appearance of stability often leads people to conclude that the individual elements of the flock (the birds) are stable and have a consistent place in the flock.

Complex Phenomena

- **Wilensky and Resnick also showed a host of examples where this levels slippage interfered with both integrative and differential understanding of complex phenomena in the natural and human social worlds.**

Summary

- In this module we have discussed that in the past two decades, researchers have found that emergent phenomena are endemic to the natural and social worlds and that using an emergent lens to make sense of complex patterns is a vital need in a twenty-first-century world.

Modeling and Simulation

Agent-Based Modeling as Representational Infrastructure for Restructurations

Agent-Based Modeling for Restructurations

- With the aid of new computer-based modeling environments, we can simulate complex patterns and better understand how they arise in nature and society.
- Whereas in many areas of science we have relied on simplified descriptions of complexity

Agent-based modeling

- Agent-based modeling is a computational methodology that enables one to model complex systems.
- As the name suggests, agent-based models are composed of agents:
  - computational entities that have properties, or state variables and values

Agents

- Agents usually also have a graphical component so you can see them on the computer screen.
  - An agent can represent any element of a system.

Gas Molecule Agent

- A gas molecule agent, for instance, might have properties such as
  - " Mass " with value 30 atomic mass units,
  - "Speed " with value 10 meters per second,
  - and " Heading " with a value of the angle it is facing

A Sheep Agent

- A sheep agent, by contrast, might have properties such as
- “ speed ” with value 3 mph,
- “ weight” with value 30 lbs.,
- and fleece with a value of “ full ” (a discrete-textual rather than numerical value).

Agents Also Have Rules Of Behavior

- In addition to their properties, agents also have rules of behavior.
  - A gas molecule agent might have a rule to collide with another molecule;
  - A sheep agent might have a rule to eat grass if there is grass available nearby

Universal Clock

- In an agent-based model, we imagine a universal clock.
- When the clock ticks, all agents invoke their rules.
- If the conditions of the rules are satisfied, (e.g., they are at the edge of a box, or grass is nearby), they enact the behavior (i.e., bounce or eat grass)

Summary

- In this module we discussed While different fields have different degrees of structuration inertia, there is no end to the domains of application for ABM.
- However, differences in structuration inertia render some fields more easily adaptable to ABM restructuration than others.

Modeling and Simulation

Agent-Based Modeling as Representational Infrastructure for Restructurations

Agents And Rules

- The goal of agent-based modeling is to create agents and rules that will generate a target behavior.
- Sometimes the rules are not well known, or you just want to explore the system's behavior.

ABM's Enable Restructurations Of Complex Systems

- We contend that ABM 's enable restructuration of complex systems so that the
  - (a) understanding of complex systems can be democratized and
  - (b) the science of complex systems can be advanced.

NetLogo

- The computer language used in this text, NetLogo (Wilensky, 1999), was developed by Uri Wilensky for these express purposes.
  - It is a general-purpose agent-based modeling language designed to be “ low-threshold ”
  - but also “ high-ceiling ”

Turtle

- NetLogo calls its prototypical agent a “ turtle. ”
- NetLogo was first developed in the late 1990s, and it is now in use by hundreds of thousands of users worldwide.

Netlogo To Construct And Explore Models

- Thousands of scientific papers have utilized NetLogo to construct and explore models in a wide variety of disciplines.
- It has also been employed by policymakers to model policy choices, business practitioners to model business decisions

Summary

- In this module we discussed While different fields have different degrees of structuration inertia, there is no end to the domains of application for ABM.
- However, differences in structuration inertia render some fields more easily adaptable to ABM restructuration than others.

Modeling and Simulation

Example:

Predator-Prey Interactions

Predator-Prey Interactions

- To illustrate the potential power of widespread agent-based modeling literacy and restructuration,
- we will look briefly at two examples derived from different content domains:
  - predator-prey interactions
  - the spread of forest fires

Predator-Prey Interactions

- Let us start with the study of predator-prey interactions.
- This domain is often first introduced qualitatively in high school, then quantitatively at the university level

Lotka-volterra Differential Equations

- In its quantitative form, the population dynamics of a single predator and prey are introduced by the classic Lotka-Volterra differential equations, a pair of coupled differential equations that proceed as follows:

Lotka-volterra Differential Equations

- **Lotka-Volterra differential equations**

$$\frac{d\mathrm{Pred}}{dt} = K_1 * \mathrm{Pred} * \mathrm{Prey} - M * \mathrm{Pred}$$

$$\frac{d\,\mathrm{Pr}\,ey}{dt} = B * \mathrm{Pr}\,ed * K_2 * \mathrm{Pr}\,ed * \mathrm{Pr}\,ey$$

  - **The first equation says that the number of predators increases as**

First DFE

- Predators interact with prey

  (by fixed constant K1)
- and decreases by a constant mortality rate (M).

Second DFE

- The second equation says that the number of prey
- Increase by a constant birthrate (B) and
- Decreases in interaction with predators (by a fixed constant K 2).

Summary

- In This module we described
  - In general, exploring complementary approaches to a single problem provides us with deeper insight.

Summary

- If multiple different approaches find a similar pattern of behavior at different levels of analysis, then there is better confirmation of the underlying result.

Modeling and Simulation

Example:

Predator-Prey Interactions

Agent-based Representation Of Predator And Prey

- **An agent-based representation of predator and prey, such as the one illustrated, would typically employ simple algorithmic models.**

An agent-based Wolf Sheep Predation model.

Agent-based Representation Of Predator And Prey

- They might give each predator and prey a store of energy that is depleted when they move and increased when they eat.
  - If their energy dips too low, they die.
  - If it is high enough, they might reproduce.

Agent-based Representation Of Predator And Prey

- And when they move, if they encounter food (which, for the predator, is the prey), they eat it
- These instructions are explicitly stated in an easy-to-read language that instructs each agent in how to behave, and accompanies the visual model.

Explicit Mechanism

- This kind of representation makes its mechanisms explicit; as such, they are usually quite understandable by even young children.
- They also can be challenged more easily and tested.
- We will explore such predator-prey models in detail

Advantages To Agent-based Representations

- There are many advantages to agent-based representations.
- First, it does not require knowing calculus.
- Requiring calculus to be able to reason about predator-prey interactions sets the entry threshold quite high.

Advantages To ABM Representations

- The content of the predator-prey model can be made quite accessible to a non-calculus audience through ABM.
- Agent-based models can serve as powerful complements to equation-based models.
- They are particularly effective entry points into scientific domains.

Disadvantage Of ABM Representation

- AMB also have some disadvantages as compared to equations. For an expert, an equation can more compactly represent a phenomenon than can an ABM.
- Moreover, when the equation is solvable, it enables the direct calculation of results without the need to run a model.

Disadvantages of ABM

- **We now know from the works of biologists such as Gause (1936) that the equational model is less accurate than an ABM in the isolated predator-prey situation for which it was intended.**

Disadvantages of ABM

- **In particular, the equational model underrepresents extinctions, since the model uses real numbers to represent the population densities.**

Summary

- In This module we described
  - In general, exploring complementary approaches to a single problem provides us with deeper insight.

Summary

- If multiple different approaches find a similar pattern of behavior at different levels of analysis, then there is better confirmation of the underlying result.

Modeling and Simulation

Example:

Forest Fires

Forest Fire

- Our second example is about the spread of a forest fire.
- It typically falls under the subject matter of physics, described in terms of two classic partial differential equations.
  - Classic heat equation
  - Spread of a forest fire

Classic Heat Equation

- **The first is the classic heat equation,**
  - **which describes the distribution of heat in a given region over time, where theta represents the thermal diffusivity of the material through which the heat is traveling.**

$$\frac{dH(x,t)}{dt} = \theta \frac{d^2 H(x,t)}{dx^2}$$

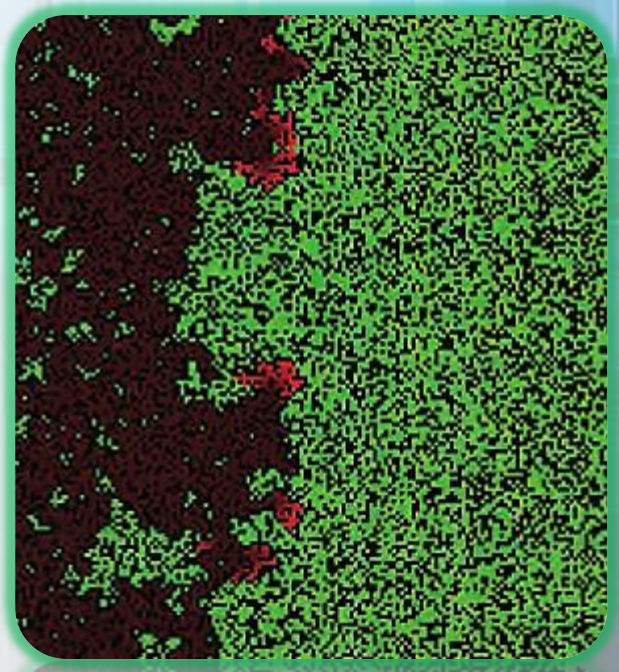
The Spread Of A Forest Fire

- **The second equation physicists use to describe :**
  - **The spread of a forest fire treats the fire as if it were a potentially turbulent fluid, thus using the Reynolds equation of fluid flow.**

$$\frac{dU_i}{dt} + U_j \frac{dU_i}{dX_j} = \frac{1}{\rho}\frac{dP}{dx_i} + v\frac{d^2U_i}{dx_j dx_j} - \frac{d}{dx_j}\overline{u_i^t}\,\overline{u_j^t}$$

ABM Approach To Modeling Forest Fires

- **Contrast these two equations with the ABM approach to modeling forest fires (illustrated in figure below),**



ABM Approach To Modeling Forest Fires

- This would typically model the environment as a grid of cells with trees occupying certain cells.
- Modeling the spread of fire consists simply of giving rules to the cells that are on fire as to when to spread to neighboring tree cells.

ABM Approach To Modeling Forest Fires

- A very simple ABM of forest fire spread would not correctly model a particular fire,
  - But it does give insight into the dynamics of any fire and once we know the details of a particular fire,
  - we can add in whatever data or rules that apply to the situation.

ABM Provides Several Representational Benefits

- ABM methods are starting to be used to model and fight real forest fires
- The restructuration of these systems using ABM provides several representational benefits.

ABM uses Discrete than Continuous Representations

- They make use of discrete rather than continuous representations,
  - which are more easily comprehensible, more closely match real-world situations and require much less formal mathematics to employ.

Summary

- In this Module we discussed how ABM is more preferable than any mathematical equations
- 'Agent-based models' are now used in the professions to do research in medicine and law and by policymakers to help them explore effects of alternative policies.

Summary

- There is still much work to do to establish the representational infrastructure and the science of ABM.
- What is needed is widespread literacy in agent-based modeling

Modeling and Simulation

What Is Agent-Based Modeling?

Ants (Foraging For Food)

- The ant opens her eyes and looks around. There are many of her siblings nearby, but there is no food.
- The ant is hungry, so she heads out from the ant colony and starts to wander around.
- She sniffs a little to the left and a little to the right,

Ants (Foraging For Food)

- and still she cannot smell any food. So she keeps wandering.
- She passes by several of her sisters, but they do not interest her right now;
  - she has food on her mind.
- She keeps wandering. Sniff! Sniff!
- She gets a whiff of some of that delightful pheromone stuff.

Ants (Foraging For Food)

- She heads in the direction of the strongest pheromone scent;
  - in the past there has been food at the end of that trail.
- Sure enough, as the ant proceeds along the trail, she arrives at some delicious food.

Ants (Foraging For Food)

- She grabs some food and heads back to the colony, making sure to drop some pheromone along the way.
- On the way back, she runs into many of her sisters, each sniffing her way along pheromone trails, repeating the same process they will carry out all day.

Model Of Ant Behavior

- What we have just fancifully described is an ant foraging for food.
- The opening paragraph of this Module is in itself a model of ant behavior.

Model

- By a model ,
  - we mean an abstracted description of a process, object, or event.
- Models can take many distinct forms.
- However, certain forms of models are easier to manipulate than other forms.

Textual Description

- The textual description in our first paragraph cannot easily be manipulated to answer questions about the ant colony ' s behavior

  — for example, what would we see if all the ants in the colony followed the behavior we described ?

Textual Model Is Not Sufficiently Generative

- It is difficult to extrapolate from the textual description of one ant to a description of an ant colony.
- The textual model is not sufficiently generative to answer such questions.
- It is a fixed description — always " behaving " the same

Summary

- In this module we have described that the methodology of ABM :
  - Encodes the behavior of individual agents in simple rules so that we can observe the results of these agents ’ interactions.

Summary

- **This technique can be used to model and describe a wide variety of processes, phenomena, and situations**

Modeling and Simulation

What Is Agent-Based Modeling?

Computational Model

- One way to make the preceding model more generalizable and gain insight into the behavior of an ant colony would be to implement the model in a
  - computational form

Computational Model

- A computational model is a model :
  - that takes certain input values, manipulates those inputs in an algorithmic way, and generates outputs.

Computational Model

- In computational form, it would be easy to run the “ Ants ” model
  - with large numbers of ants and to observe the model’s outputs given many possible different inputs.

Model implementation

- We use the term model implementation to refer to this process of transforming a textual model
  - into a working computational simulation
    - (written in some form of computer " code ")

Conceptual Model

- **Besides textual models, there are other forms of conceptual models that describe processes, objects, or events but are not computational;**
  - **conceptual models can also be diagrammatic or pictorial.**

Agent

- By the word agent , we mean an autonomous individual element of a computer simulation.
- These individual elements have properties, states, and behaviors.

Agent (Ant)

- The ant is an agent.
- It has properties such as:
  - Its appearance and its rate of movement.
- It has characteristic behaviors such as:
  - Moving, sniffing, picking up food, and dropping pheromone.

Agent (Ant)

- It has states such as whether or not it is carrying food (a binary state)
- and whether it can sense how much pheromone is in the environment around it (a multi-valued state).

Agent-based modeling (ABM)

- **Agent-based modeling (ABM) is a computational modeling paradigm that enables us to describe how any agent will behave.**
- **it is most useful when describing these phenomena as complex systems .**

Summary

- In this module we have described that the methodology of ABM :
  - Encodes the behavior of individual agents in simple rules so that we can observe the results of these agents ’ interactions.

Summary

- **This technique can be used to model and describe a wide variety of processes, phenomena, and situations**

Creating the Ant Foraging Model

Ant Foraging Model

- Many biologists and entomologists have observed ants in the wild (Hölldobler & Wilson, 1998 ; Wilson, 1974)
- And have described how ants seemed to form trails to and from food sources and their nest.

Complex System

- The study of complex systems has become an important scientific frontier.
- By the term complex system we mean a system composed of many distributed interacting parts .
- The field of complex systems or complexity science arose in the mid-1980s

Complex System

- It was born out of a variety of disparate fields from economics to physics to ecology.
- Complex systems science provides a set of tools and frameworks for viewing phenomena.

Complex System

- Any phenomenon can be viewed as a complex system, and choosing when to do so depends on assessing when it is most useful to use the lens and/or methodologies of complex systems.

Complexity Science

- One important methodology of complexity science is agent-based modeling.
- The history of agent-based modeling and complex systems is explored

Ant Foraging Model (Hypothesis)

- After an ant finds food, it goes back to the nest, drops the food off, and communicates to the queen ant, and this queen ant tells the other ants where the food is and sends them off to collect it.
- Suppose a researcher notices :

Ant Foraging Model (Hypothesis)

- that the food-finding ant never communicates with any kind of “ boss ” ant before leaving the nest again,
- so the researcher might reason that food gathering was not working through a centralized leader or controller but rather through distributed control

An Other Hypothesis

- Another hypothesis that could be advanced is that perhaps the ant did not communicate with a central leader,
- But rather simply communicated with other ants, and those other ants were able to “ diffuse ” the information about the food source throughout the nest.

An Other Hypothesis

- There is reason to believe such a hypothesis might be true, since bees work in a similar way;
- when a bee finds a food source, it returns to the hive and conducts a complicated dance that tells the other bees where to find the food (Gould & Gould,1988)

An Other Hypothesis

- However, though ants do have some methods of communicating information directly (Hölldobler & Wilson, 1998)
- Most species do not communicate the exact route to a food source in this way.

Summary

- In this module we explored about ant's behavior and have described about different Hypothesis , By the end of chapter 3, you will be able to make substantive modifications to this model,(Ant Foraging Model)

Creating the Ant Foraging Model-II

Basic Hypothesis

- Now that we have a basic hypothesis (in the form of a textual model) that describes the behavior of the ant,
- how do we implement the model so that we can test out this hypothesis
- We also check if our computational model adequately models nature?

Implemented Model

- The first step is to create a more algorithmic description of the preceding textual model.
- This is just another model itself, but one that is more easily translated into an implemented model.

Set Of Rules

- Here is one set of rules that an individual ant could follow in order to operate in accordance with the model described earlier.
- We describe the rules from the point of view of an individual ant.
  1. If I am not carrying food, I check if there is food where I am;

Set Of Rules

- if there is, I pick it up; if there isn't food right here,
- I try to sense a pheromone trail nearby; if I find one, then I face " uphill " along the pheromone gradient toward its strongest source.

Set Of Rules

2. If I am carrying food, I turn back toward the nest and drop pheromone on the ground below me.
3. I turn randomly a small amount and move forward a step.

NetLogo

- These rules are easily implemented in a computer language.
- There are many computer languages in use for many purposes,
  - but only a few are especially tailored to work with agent-based modeling.
- One of these is NetLogo (Wilensky, 1999a).

NetLogo

- NetLogo is both a modeling language and an integrated environment designed to make agent-based models easy to build.
- In fact, NetLogo is so easy to use that, rather than describe algorithms and models in pseudo-code,

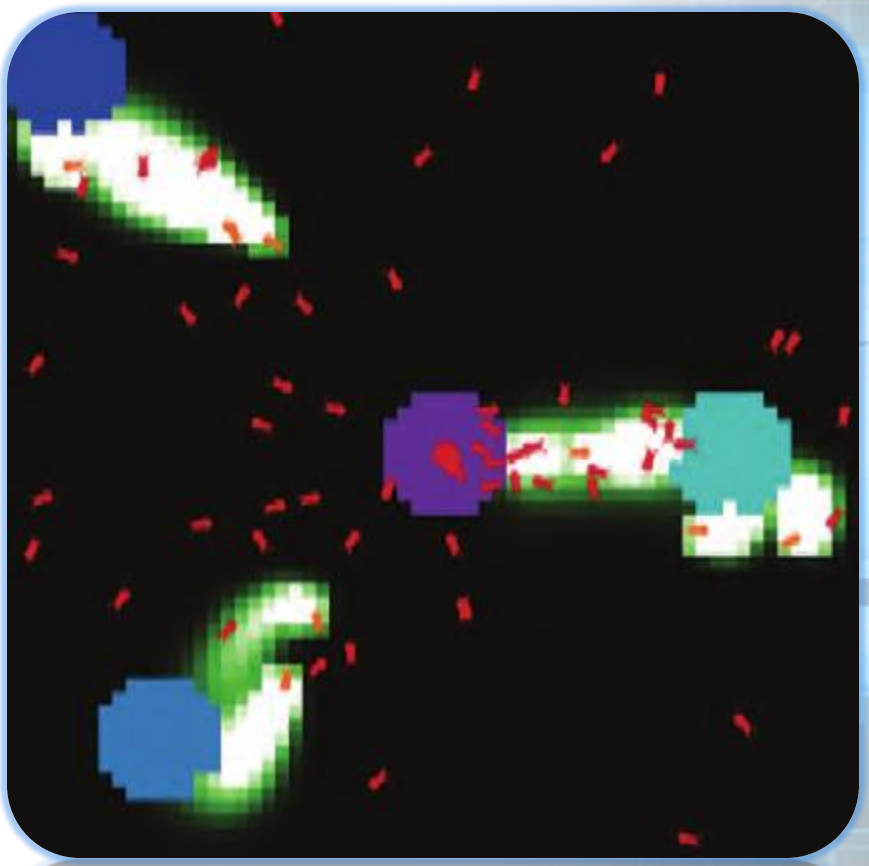
NetLogo code:

- throughout this course we will use NetLogo instead.
- Describing the preceding rules in the NetLogo language is straightforward.
- Here, for example, is one translation of rules 1 – 3 into NetLogo code:

NetLogo code:

```
If not carrying-food? [ look-for-food ]      ;; if not carrying food, look for it
if carrying-food? [ move-towards-nest ]      ;; if carrying food turn back towards the nest
wander                                       ;; turn a small random amount and move forward
```

NetLogo “ Ants ” model of foraging behavior



NetLogo “Ants” model of foraging behavior.

Summary

- **In this module we have explored how to model the ant's behavior and have described it using different hypotheses**

Creating the Ant Foraging Model-III

NetLogo Videos

Forest Fire

Results and Observations (Ant Model)

- If we look closely at the model running, we observe that initially the ants wander around at random.
- Then some ants will wander into a nearby food source.

Results and Observations

- Once they find that food source, they will start to bring food back to the nest, laying a pheromone trail beneath them.
- If just one lone ant finds the food source, the pheromone trail will not be strong enough for other ants to follow it;

Results and Observations

- As more and more ants find the food source, the trail will become stronger and stronger.
- The ants as a group appear to exploit food sources in an optimal manner.
- That is, they first gather food from the nearest food source, then the second nearest, and so on.

Results and Observations

- This appears to be a conscious plan of the ant colony; but as we know from the ant rules, this is not the case.
- In fact, as you observe the model closely, you will note that sometimes ants operate almost at cross-purposes with other ants

Results and Observations

- Ants create additional pheromone trails to farther food sources and distracting some of the ants that are currently harvesting the closer food source.
- When the food source has been completely consumed, the ants no longer lay pheromone;

Summary

- In this Module we have seen Ant's behavior model. Having run and used the model, it may seem obvious that these low-level rules can create these rich and optimal global patterns.

Results & Observations From The Ant Model-I

Exploration & Exploitation

- This optimal exploitation of food sources could be placed within a larger context.
- In many ways, the colony of ants seems to balance exploration and exploitation (Dubins & Savage, 1976

Exploring The Environment

- In any situation in which an entity is operating in an unknown environment, the entity must spend some time exploring the environment to understand how its actions affect its rewards

Exploiting The Environment

- And some time exploiting the environment , that is taking actions that it knows have produced the best rewards in the past.

Balances Exploration And Exploitation

- By allocating a large number of ants to exploit the current nearest food source while other ants continue to explore, the ant colony as a whole successfully balances exploration and exploitation.

Emergent Phenomenon

- The “ trails, ” “ optimal, ” and “ balance ” behavior of the ants is not coded into any of the ants but is instead an emergent phenomenon of the model (Holland, 1998 ; Anderson, 1972 ; Wilensky & Resnick, 1999).

Summary

- In this module we have seen Ant's behavior model. Having run and used the model, it may seem obvious that these low-level rules can create these rich and optimal global patterns.

What Good Is an Ant Model?

What Good Is an Ant Model?

- The Ant model is our first example of an agent-based model.
- Now that we have gone through the process of understanding how a model of ant foraging works,
- what knowledge have we gained from that process and how can we profitably use the model?

Eight Main Uses For Agent-based Models

- Description,
- Explanation,
- Experimentation,
- Providing Sources Of Analogy,

Eight Main Uses For Agent-based Models

- Communication/Education,
- Providing Focal Objects Or Centerpieces For Scientific Dialogue,
- As Thought Experiments,
- Prediction.

A Model Is Descriptive

- A model is descriptive of a real-world system.
- Granted, it is a simplification of the real world and does not contain all of the details and inconsistencies that are present in the real world.

A Model Is Descriptive

- **Models that are not coarse-grained descriptions are useless as descriptions because they are indistinguishable from the real world and therefore do not assist in our understanding of complex systems (Korzybski, 1990)**

Models Are Explanatory

- **Models are explanatory in that they point out the essential mechanisms underlying a phenomenon.**
- **They can function as a proof that hypothesized mechanisms are sufficient to account for an observation.**

Models Are Explanatory

- Models provide us with a proof of concept that something is possible.
- For example, once we built the Ants model and observed the results, we proved that an ant colony could exhibit characteristics such as “ trails, ” “ optimality, ” and “ balance ” without a centralized

Summary

- We have been discussing the Ants model and its results for some time now.
- This model is one example of an agent-based model.
- But there is a wide diversity of models that are called agent-based models

What Good Is an Ant Model?-II

Key function of ABMs

- A key function of ABMs is to explicate the power of the emergence.
- In general, it is difficult for people to understand how such simple rules can lead to complex observed phenomena, and ABMs make this connection explicit

Models Facilitate Experimentation

- Models can be run repeatedly to note variations in their dynamics and in their outputs.
- Some models have very little variation from run to run.
- Others exhibit path dependency and can therefore vary tremendously from run to run.

Experimentation

- Model parameters can be varied to see their effect on model behavior and outputs.
- For example, in the Ants model, we could change the evaporation rate of the pheromone and see what effect that has on the performance of the ants

Experimentation

- **Alternatively, we could model the return to nest behavior in more detail, by placing a sun in the environment and have the ants calculate their path back based on the sun.**

Effects of modifications on system

- Thus agent-based models enable us to easily examine different mechanisms and attributes of a system and see what effect those modifications have on the overall behavior of the system.

Model's Behavior Classification

- **By varying these different attributes or parameters and observing their effect on the behavior of the system, we can classify model behavior into output regimes , or characteristic output behaviors of the model.**

Models Provide Us With Analogies

- **Since models are simplifications of reality, they enable us to find similarities with other such simplifications even if the modeled phenomena are apparently very different.**

Models Provide Us With Analogies

- **In this way, we can apply reasoning gained in one domain of knowledge to other knowledge domains.**

Models Provide Us With Analogies

- For instance, in 1996, Schoonderwoerd, extending Dorigo's work on ant colonies as optimization devices, found that the problem of ants efficiently finding food sources is similar to the problem of packets on networks efficiently seeking out their destinations (Schoonderwoerd et al., 1996).

Summary

- **We have discussed various benefits of Agent-based Models**

What Good Is an Ant Model?-III

Communication And Education

- Agent-based models can be used as a vehicle for communication and education .
- We can show the model to people who have never seen an ant colony before and they can explore how ant colonies behave.

Communication And Education

- Models provide us with an educational tool that encapsulates
- knowledge that may not be readily available from real world observation.
- Moreover, an agent based model allows us to expand beyond static knowledge, enabling learners to conduct experiments much as scientists do.

Communication And Education

- **If someone has a hypothesis as to how a particular mechanism works, they can implement that mechanism and see whether it can account for observed behavior.**

Thought Experiments

- **Models can sometimes present new phenomena that are not necessarily about some real-world phenomenon, but are thought experiments on possible computations.**

Prediction

- A common conception of computer modeling is that its major purpose is prediction .
- It is true that we often use modeling to think about possible future scenarios, and to the extent that any modeling tool can be used for discussing the future, agent-based modeling can be used in this way

Predictions Depend On..

- However, like any modeling tool, an agent-based model's predictions depend on the accuracy of its input data.
- This is especially true when the events we are interested in are the results of complex systems, for which small changes in inputs can often lead to very different results.

Model To Predict The Outcome Of A System,

- Many times, while modelers may claim to want to use a model to predict the outcome of a system,
- Such as an ant colony, they actually use the model to describe past patterns of behavior,.

Prediction

- Such as what food source was first eaten, and to explain future patterns that might arise, such as how ants might move around on the landscape.
- Sometimes modelers start off motivated by generating predictions but end up finding greater power for explanation and description

Summary

- We have been discussing the Ants model and its results for some time now.
- This model is one example of an agent-based model.
- But there is a wide diversity of models that are called agent-based models

What is Agent-based Modeling?

The Reality of Agents

- Agents vs. Objects
- Why agent-based modeling is so intuitive?

What is an Agent?

- **An agent is an autonomous individual or object with particular properties, actions, and possibly goals.**

What is the environment?

- The environment is the landscape on which agents interact and can be geometric, network-based, or drawn from real data.
- The interactions that occur between these agents or with the environment can be quite complex.

What about the interactions?

- The interactions that occur between these agents or with the environment can be quite complex.
- Agents can interact with other agents or with the environment

What about the interactions?

- **Not only can the agent's interaction behaviors change in time, but so can the strategies used to decide what action to employ at a particular time.**

ABM vs. Other Modeling Forms

- The most common form of scientific models is the equation form.
- One distinction is that because ABM models individuals it can model a heterogeneous population
- Equational models typically must make assumptions of homogeneity.

ABM vs. Other Modeling Forms

- Furthermore, when you model individuals, the interactions and results are typically discrete and not continuous.
- Continuous models do not always map well onto real-world situations.

ABM vs. Other Modeling Forms

- For instance, equation-based models of population dynamics treat populations as if they are continuous quantities
- In fact they are populations of discrete individuals.

ABM vs. Other Modeling Forms

- When simulating population dynamics it is very important to know if you have a sustainable population.
- After all, a wolf population cannot continue if there are fewer than two wolves left

ABM vs. Other Modeling Forms

- In reality, a millionth of a wolf cannot exist and certainly cannot reproduce, but it can result in increased wolf population in EBMs.
- The mismatch between the continuous nature of EBMs and the discrete nature of real populations causes this " nano-wolf " problem (Wilson, 1998).

Summary

- **Here we have compared ABMs with EBMs**

Randomness vs. Determinism

Randomness

- One important feature of agent-based modeling, and of computational modeling in general, is that it is easy to incorporate randomness into your models

Benefits of Randomness

- Many equation-based models and other modeling forms require that each decision in the model be made deterministically.
- In agent-based models this is not the case
- Instead, the decisions can be made based on a probability.

Example of Randomness

- For instance, in the Ants model, as the ants move around the landscape, their decisions are not completely determined; instead, at each time step they change their heading a small amount based on a random number.

Ant Model and Randomness

- As a result, each ant follows a unique, irregular path.
- In reality, ants might be affected by small changes in elevation, the presence or absence of twigs and stones, and even the light of the sun.

Other cases

- **Finally, there are often times when we simply do not know enough about how a complex system works in order to build a completely deterministic model.**

Other cases

- In many of these cases the only type of model that we can build is a model with some random elements. Agent-based modeling
- Or other modeling forms that allow you to incorporate random features are essential to studying these kinds of systems.

Summary

- **Here, we have analyzed the benefits of randomness**

When is ABM beneficial?

ABM Benefits

- **Agent-based modeling has some benefits over other modeling techniques, but, as with any tool, there are contexts in which it is more useful than others.**

ABM Benefits

- **ABM can be used to model just about any natural phenomenon (e.g., you could describe any phenomenon by describing the interaction of its subatomic particles).**

ABM Benefits

- However, there are some contexts for which the cost of building an ABM exceeds the benefits, and there are other times when the benefits are extraordinary given the costs.

Examples

- Some problems with large number of homogenous agents are often better modeled (i.e., they will provide more accurate solutions to aggregate problems faster) using an aggregate solution like mean field theory or system dynamics modeling (Opper & Saad, 2001 ; Forrester, 1968).

Examples

- **For instance, if you are concerned about the temperature in a room, then tracking every individual molecule and its history is not necessary.**

General Rules

- On the other hand, if a problem has only a handful of interacting agents, then you usually do not need to bring to bear the full power of ABM and instead can write detailed equations describing the interaction — two billiard balls colliding, for example, does not require ABM

General Rules

- **As a rule of thumb, agent-based models are most useful when there are a medium number (tens to millions) of interacting agents (Casti, 1995).**

Summary

- **Here, we have analyzed the benefits of randomness**

Tradeoffs of ABM

ABM Tradeoffs

- **Agent-based modeling has some benefits over other modeling techniques, but, there are also tradeoffs**

ABM Tradeoffs

- Sometimes agent-based modeling is not the right tool for the job.
- For example, ABM can be computationally intensive.
- Simulating thousands or millions of individuals can require great computing power.

ABM Tradeoffs

- Equation-based models, by contrast, are often very simple to run and essentially just require repetitive mathematical calculations.
- This is true only for simple equation-based models

ABM Tradeoffs

- **Numerically solving complicated equation-based models may take as much computational time as agent-based models.**

Still ABM may be Better

- The computational expense of running an ABM is a price one pays for having the benefits of rich individual-level data.
- The additional computational power needed for running ABMs is the same power that allows the tracking and development of rich histories of individuals.

Example

- For example, in the Ants model we could write a simple equation that describes the rate at which food is gathered based on its distance from the nest.
- However, through ABM, we are able to observe the behavior of the individual ants and
- understand how they form trails to the food source.

Other cases

- **ABM does require us to gain an understanding of the microbehavior of a system, but without modeling the microbehaviors, ABM would not provide as elaborate a model as it does.**

Other cases

- **While ABM does require us to know or guess about the individual-level mechanisms operating, it does not require knowledge of the aggregate level mechanism.**

Summary

- **Here, we have analyzed the tradeoffs of ABMs**

Tradeoffs of ABM

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Summary

- **Here, we have analyzed the tradeoffs of ABMs**

Creating Simple Agent-Based Models: Life-I

Overview

- Toy Models are very important
- “Real world” is better understood as a thought experiment
- Game of Life is an interesting first model

Toy Models?

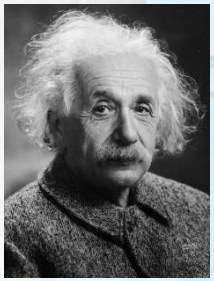
- Humans learn by using toys
- Abstract Models can be made for the real world

Thought Experiments

- Science is filled with thought experiments

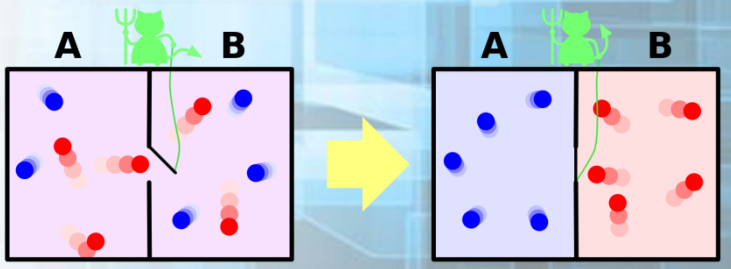
Physics: Thought Experiments

- **Physics**



More Thought Experiments

- **Maxwell's Demon**



Game of Life: History

- British Mathematician John Horton Conway – 1970
- A cellular automaton
- It was made popular by a columnist “Martin Gardner”

http://adeptis.ru/vinci/m_part3_3.html

Game of Life

- The game is played on a large grid, such as a checkerboard or graph paper.
- Let ’ s say we are playing on a square grid with 51 squares 1 (or “ cells ”) on a side.
- Each cell can be either “ alive ” or “ dead. ”

Game of Life

- This is called the “ state ” of the cell.
- Every cell is surrounded by eight “ neighbor ” cells.
- The grid is considered to “ wrap around ” so that a cell on the left edge has three (3) neighbor cells on the right edge and, similarly, a cell on the top edge has three (3) neighbor cells on the bottom edge.

Game of Life

- There is a central clock. The clock ticks establish a unit of time.
- In the game of Life, the unit of time is called a generation.
- More generally, in agent-based models, the unit of time is referred to a tick.
- Whenever the clock ticks, each cell updates its state

Rules of Life

- (1) If the cell has less than two (2) alive neighbors, it dies.
- (2) If it has more than three (3) alive neighbors, it also dies

Rules of Life

- (3) If it has exactly two (2) alive neighbors, the cell remains in the state
- (4) If it has exactly three (3) alive neighbors, the cell becomes alive if it is dead, or stays alive if it is already alive

Summary

- We have seen how Toy Models can be an important exercise
- We have looked at the history and rules of the Game of Life

END

Life-II

Overview

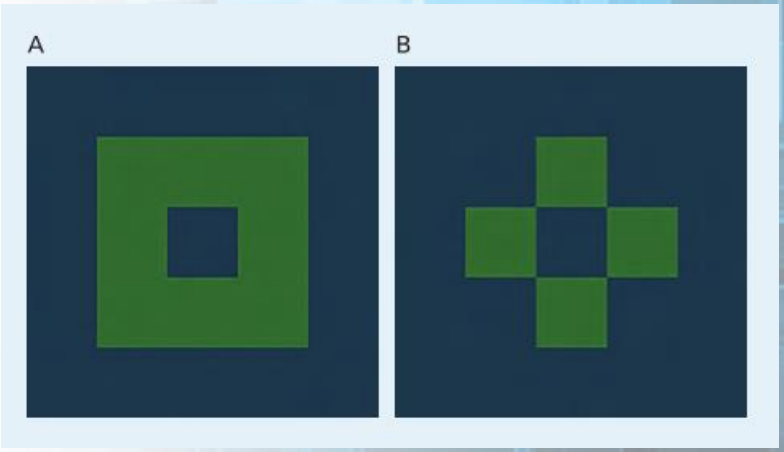
- Game of Life is interesting to code
- It is developed using NetLogo patches
- Overview of implementation

Game of Life

- Game of Life involves a Cellular Automaton
- Every cell is a square
- Every cell has neighbors

Cell: Neighbors

- A. Moore Neighborhood
- B. Von Neumann Neighborhood



Understanding the rules

- Each cell checks the state of itself and its eight surrounding neighbors and then sets itself to either alive or dead.
- If there are less than two alive neighbors, then the cell dies.

Understanding the rules

- If there are more than three alive neighbors, the cell dies.
- If there are 2 alive neighbors, the cell remains in the state it is in.
- If there are exactly three alive neighbors, the cell becomes alive.
- This is done in parallel and continues forever.

Understanding the Code

- **patches-own [live-neighbors]**

Code of Life

```
to setup
  clear-all
  ask patches [
    ;; create approximately 10% alive patches
    set pcolor blue - 3 ;; dark blue cells are dead
    if random 100 < 10 [
      set pcolor green ;; green cells are alive
    ]
  ]
  reset-ticks
end
```

Code of Life

```
to go
  ask patches [
    ;; each patch counts its number of green neighboring patches
    ;; and stores the value in its live-neighbors variable
    set live-neighbors count neighbors with [ pcolor = green ]
  ]
  ask patches [
    ;; patches with 3 green neighbors, turn (or stay) green
    if live-neighbors = 3 [ set pcolor green ]
    ;; patches with 0 or 1 green neighbors turn (or stay) dark blue (from isolation)
    if live-neighbors = 0 or live-neighbors = 1  [ set pcolor blue - 3 ]
    ;; patches with 4 or more green neighbors turn (or stay) dark blue (from overcrowding)
    if live-neighbors >= 4 [ set pcolor blue - 3 ]
    ;; patches with exactly 2 green neighbors keep their color
  ]
  tick
end
```

Summary

- We have seen the importance of toy models
- We have examined game of life
- We have seen how to start coding in NetLogo using patches

END

Modeling & Simulation

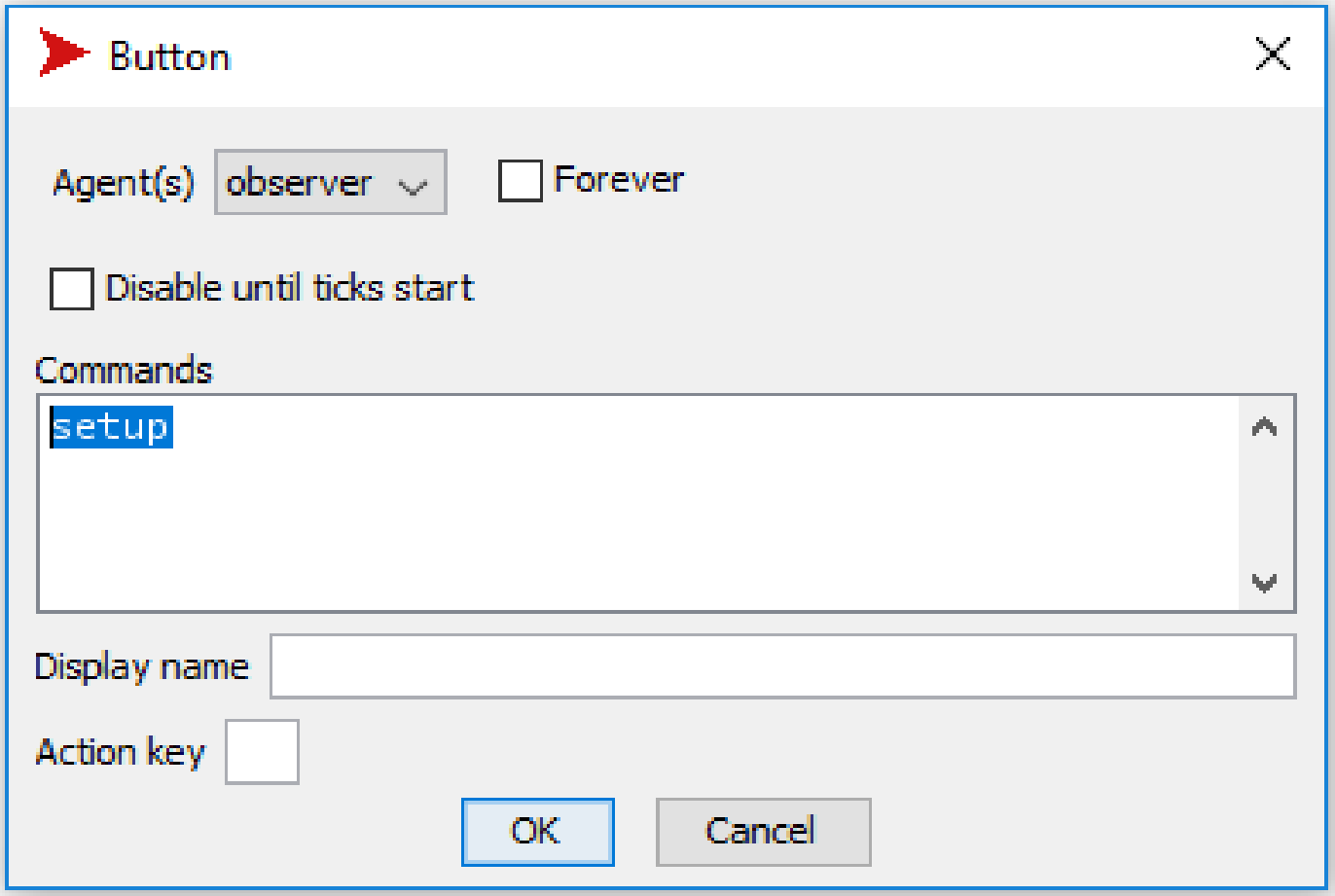
Life-III

Overview

- Observing how Game of Life Works
- Examining emergent patterns

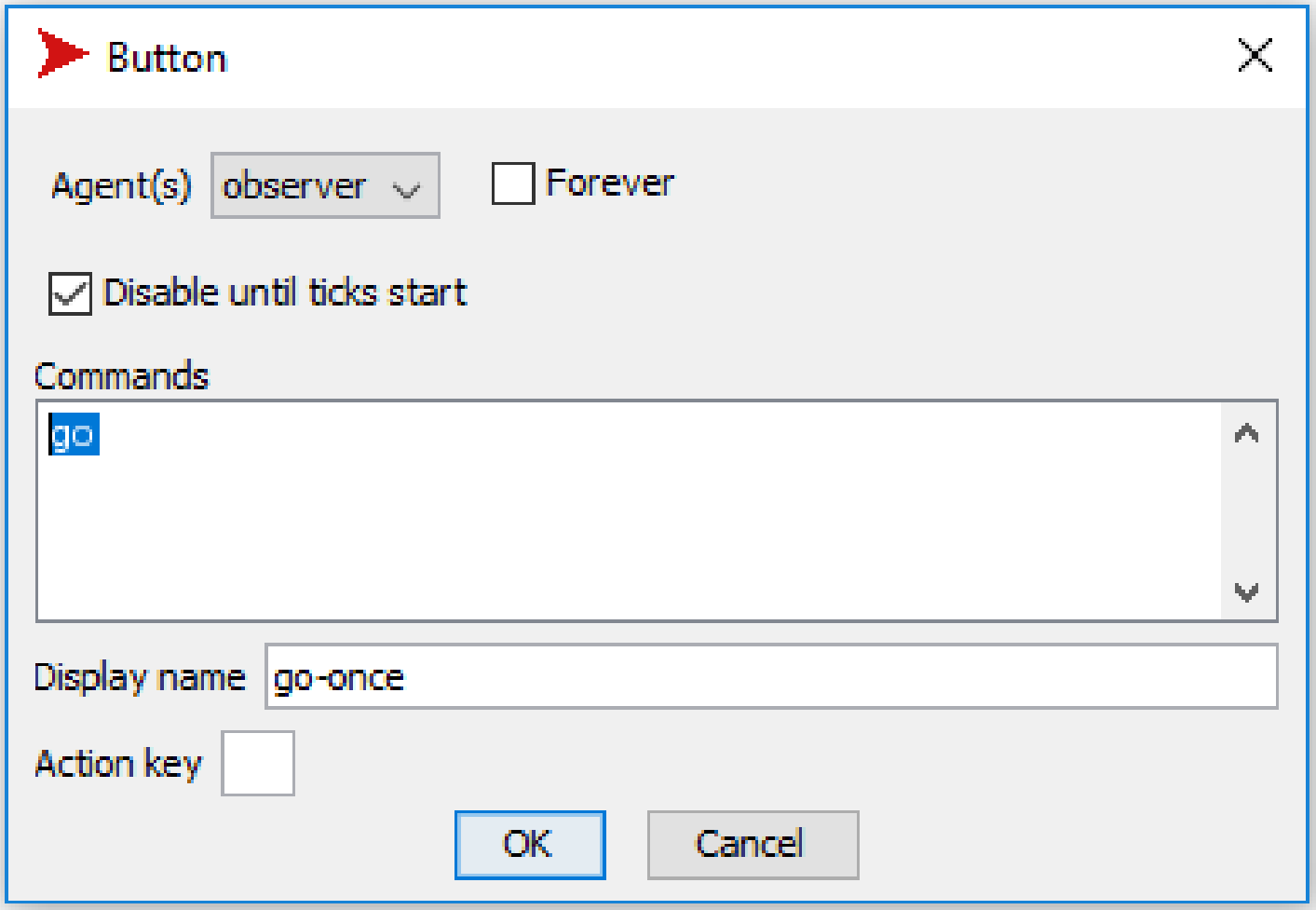
User Interface

- **Adding a Button**



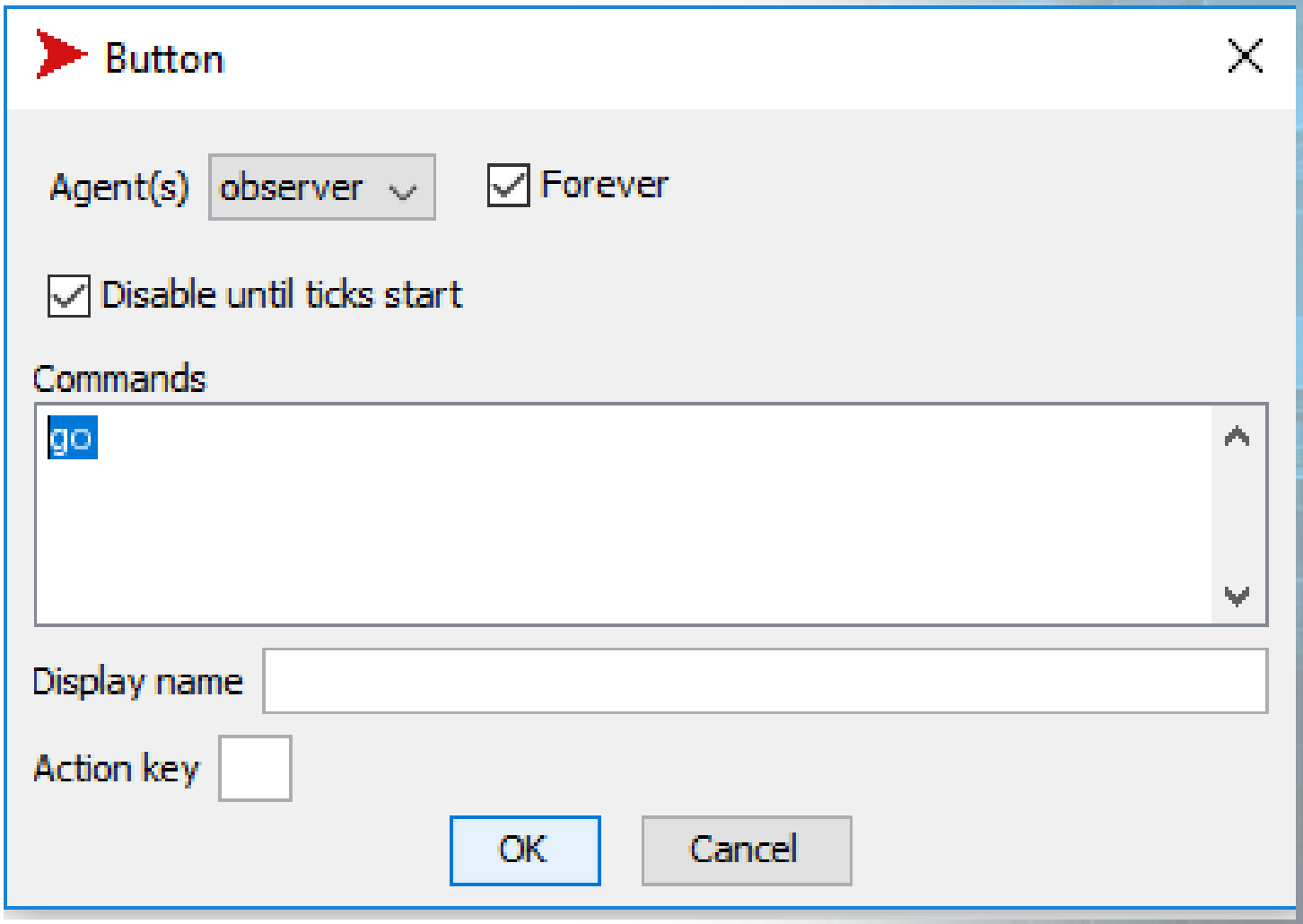
Go-Once button

- **Add another button**



Go button

- **Add yet another button**

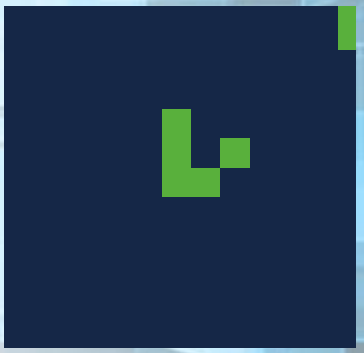


Understanding the Output

Simulation of Life

Understanding the Output

- **Emergent Pattern: Glider**



Output

- Another emergent pattern

Summary

- We have examined outcome from the game of life
- We have seen how emergent patterns emerge unexpectedly

END

Simple Economy-I

Overview

- Understand how economy model works
- Learn about more ABM concepts

Simple Economy

- In spite of being primarily of interest to Computer Sciences, there has been a growing interest in the use of ABM in the social sciences.

Why ABM in Other Sciences?

- Agent-based methods may be particularly valuable in the social sciences
- Mathematical descriptions often do not offer sufficient descriptive power
- Heterogeneous agents help a lot in developing an understanding

Organizations

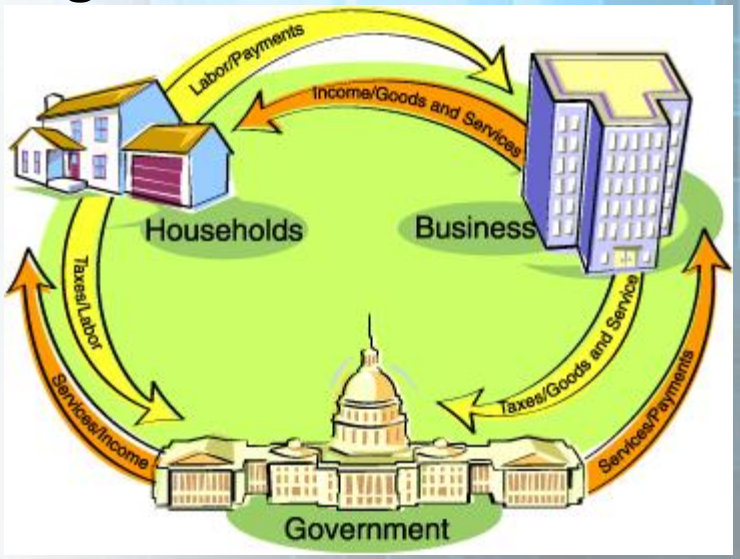
- Complex Systems Social Sciences Association (CSSSA)
- World Congress on Social Simulation (WCSS)

Others

- American Education Research Association (AERA),
- Marketing Science,
- Eastern Economics Association
- American Association of Geographers (AAG)
- These have hosted sessions on the intersection of agent-based modeling and social science.

Economics Using ABM

- Economies consist of heterogeneous actors such as buyers and sellers
- There is a natural mapping of ABM methods to economics.
- Figure credit: Wikimedia



Economics Using ABM

- In 1996, the economists, Josh Epstein and Robert Axtell published a book
- It depicted a world titled SugarScape
- This world was populated by economic agents

Simple Economy Description

- A very simple economics model that has some surprising results.
- Suppose you have a fixed number of people, say 500, each starting out with the same amount of money, say $100.

Simple Economy Description

- At every tick, each person gives one of his or her dollars to any other person at random.
- What will happen to the distribution of money?
- An important constraint is that the total amount of money remains fixed, so no one can have less than zero money.

Simple Economy Description

- If you run out of money, you cannot give any away until you get some back.
- Refining the question a little further:
- Is there a stable limiting distribution of the money?
- If so, what is it? For instance, will all the wealth be concentrated in a few hands or will it be equitably distributed?

Simple Economy Intuition

- Intuitively, we can think about the model
- There should be a limiting flat distribution
- The reasoning:
  - No person starts off with an advantage
  - Selection of people to whom money is transferred is random,
  - No person should have much of an advantage over any others.

Simple Economy Intuition

- Thus, the resulting wealth distribution should be relatively flat
- Everyone should wind up with roughly the same amount of money he or she started with.

Alternate Intuition

- **Wealth will be normally distributed**

Summary

- We have examined the role of ABM in the social science
- We have seen how economics can benefit from ABM
- We have seen the basis of the “Simple Economy” model

END

Simple Economy-II

Overview

- Go in more detail about the “Simple Economy” model
- Understand the code for Simple Economy

Simple Economy

```
turtles-own [ wealth ]

to setup
  clear-all
  create-turtles 500 [
    set wealth 100
    set shape "circle"
    set color green
    set size 2

    ;; visualize the turtles from left to right in ascending order of wealth
    setxy wealth random-ycor
  ]
  reset-ticks
end
```

Simple Economy

```
to go
  ;; transact and then update your location
  ask turtles with [ wealth > 0 ] [ transact ]
  ;; prevent wealthy turtles from moving too far to the right
  ask turtles [ if wealth <= max-pxcor [ set xcor wealth ] ]
  tick
end

to transact
  ;; give a dollar to another turtle
  set wealth wealth - 1
  ask one-of other turtles [ set wealth wealth + 1 ]
end

to-report top-10-pct-wealth
  report sum [ wealth ] of max-n-of (count turtles * 0.10) turtles [ wealth ]
end

to-report bottom-50-pct-wealth
  report sum [ wealth ] of min-n-of (count turtles * 0.50) turtles [ wealth ]
end
```

Summary

- We have examined the implementation of the Simple Economy Model
- We have seen how turtles can be used to develop a model

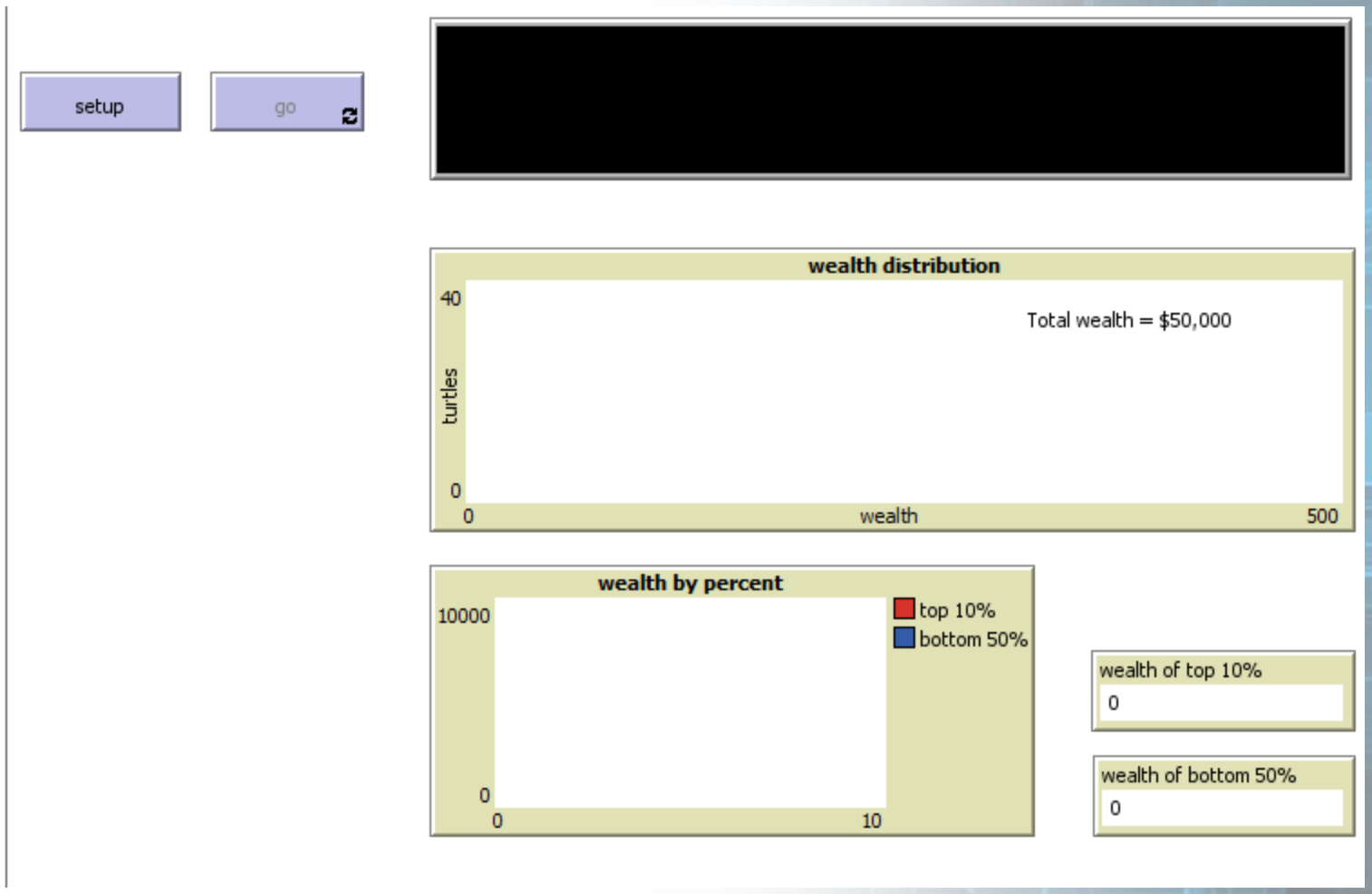
END

Simple Economy-III

Overview

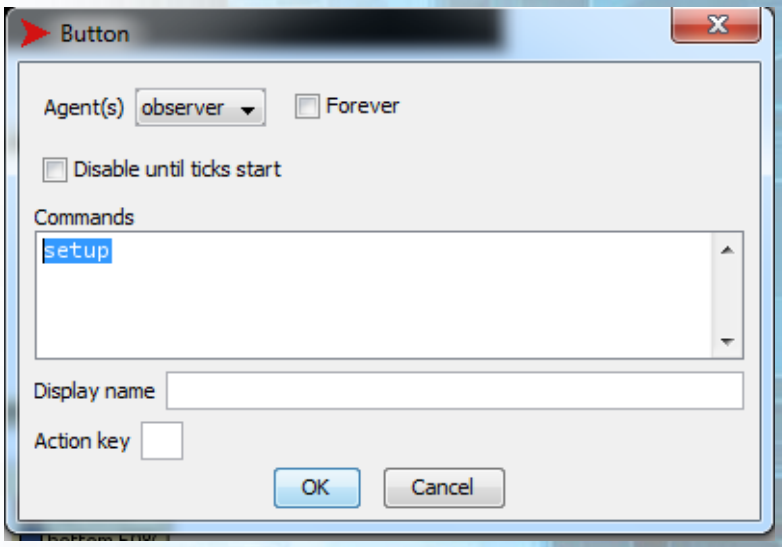
- Understanding the User Interface of Simple Economy
- Understand the execution of Simple Economy

Simple Economy



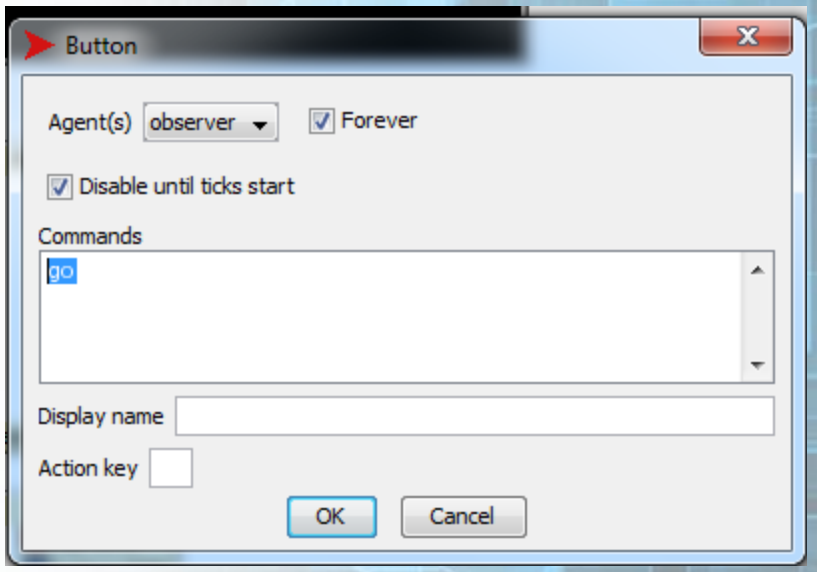
Simple Economy

- **First we add a button**



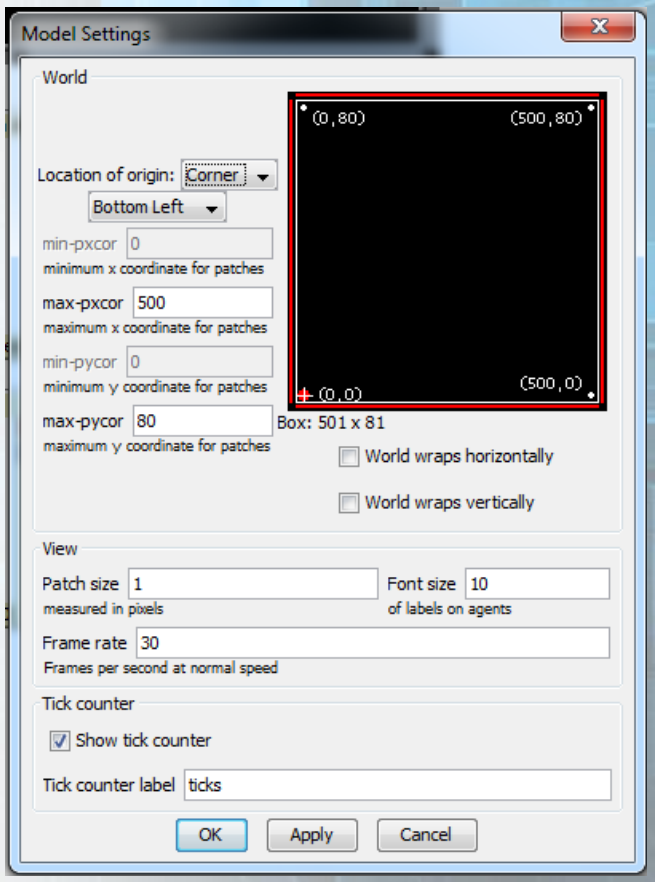
Simple Economy

- **Another button**



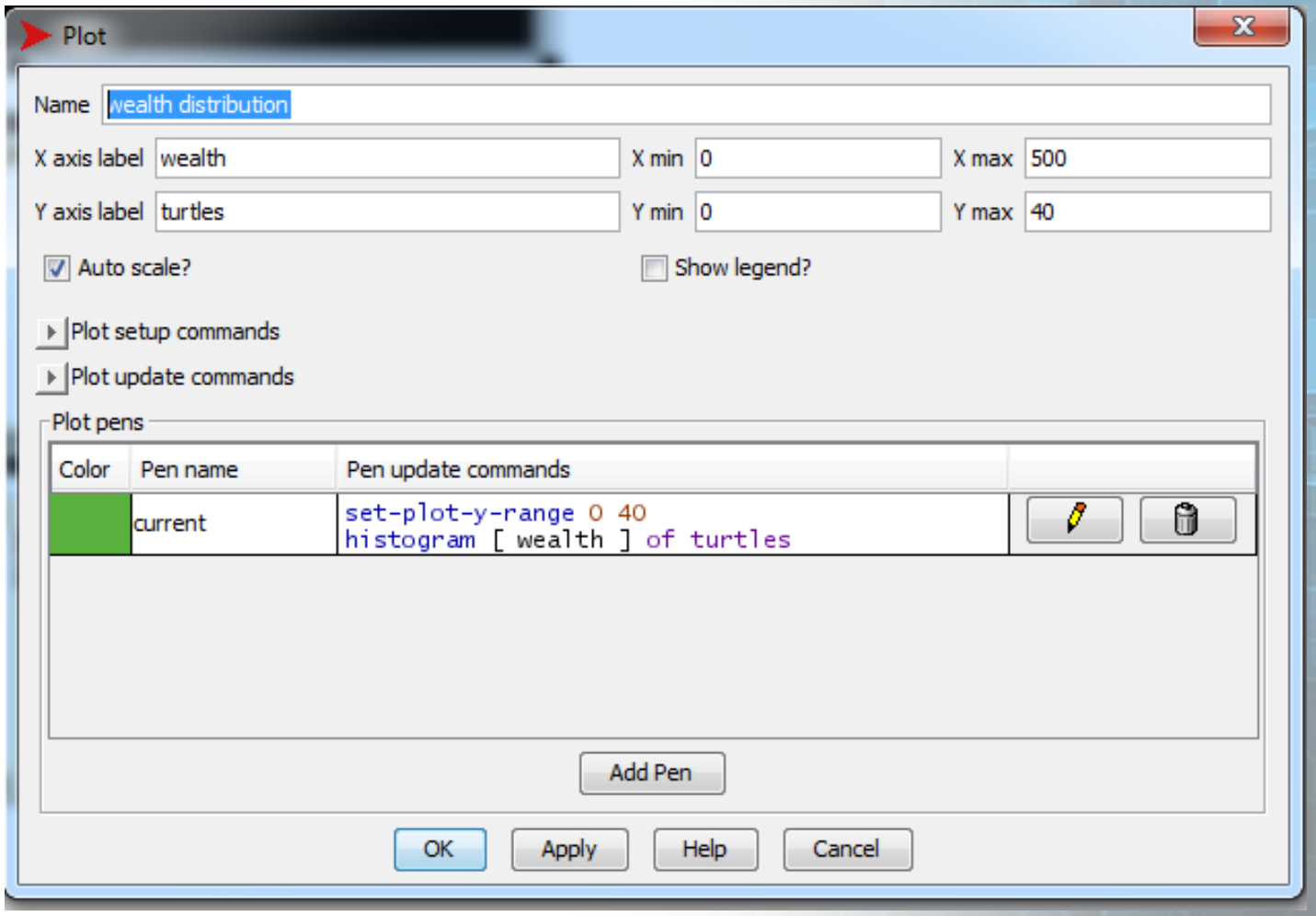
Simple Economy

- **Next, let us adjust the world settings**



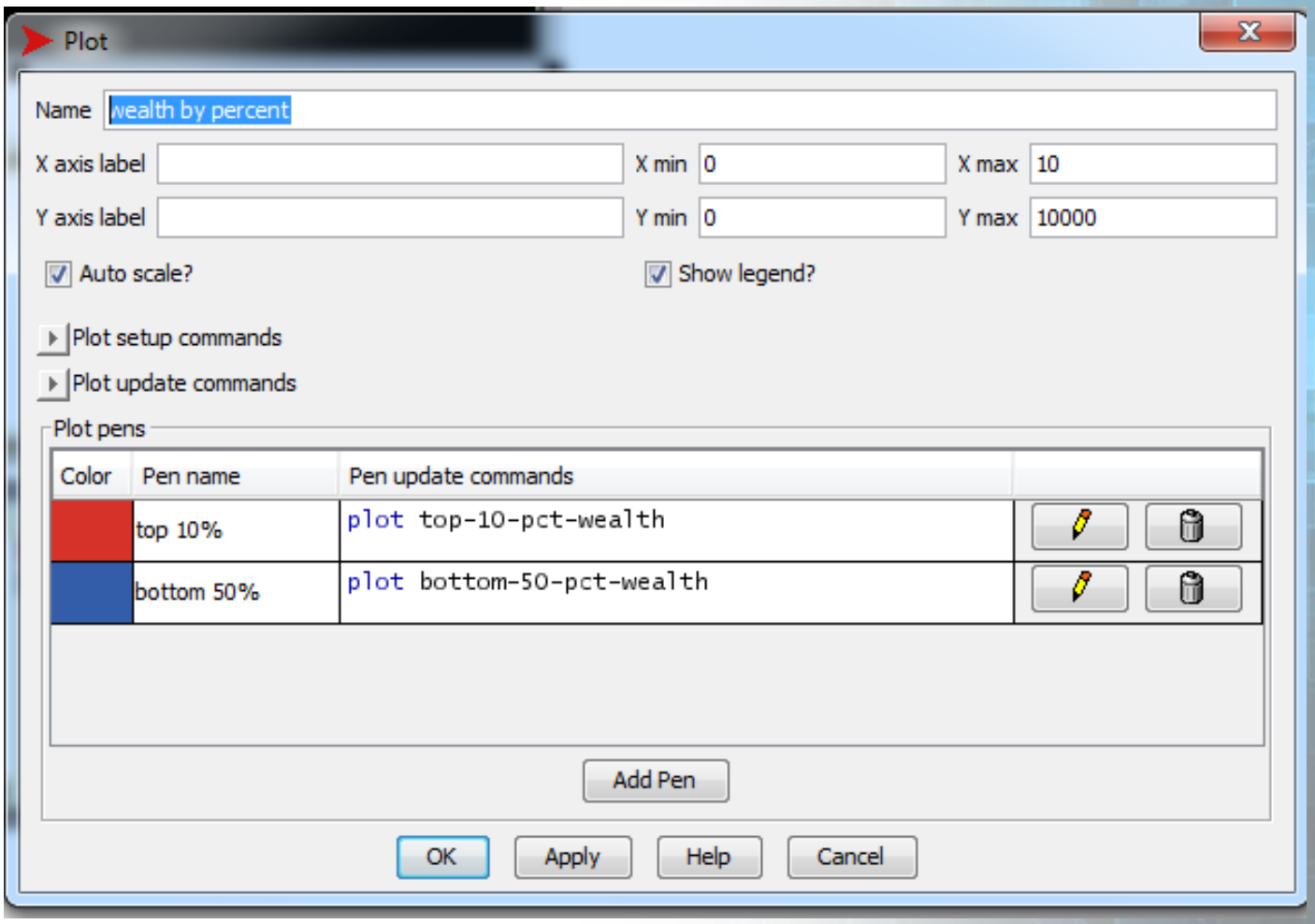
Simple Economy

- **Now, we add a plot**



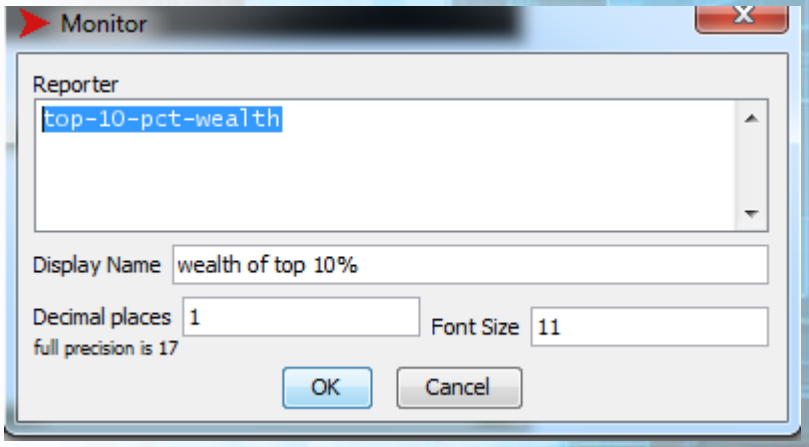
Simple Economy

- **Now, we add another plot**



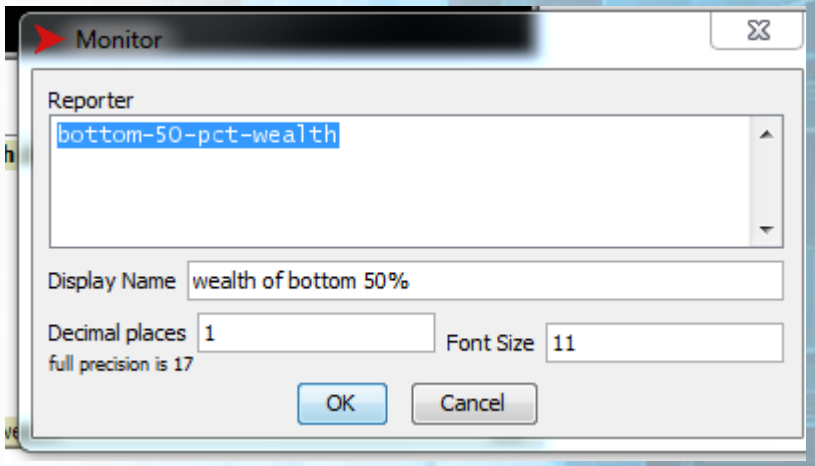
Simple Economy

- **Now, we add a monitor**



Simple Economy

- **Now, we add another monitor**



Summary

- We have examined the design of the User interface for the Simple Economy Model

END

Simple Economy-IV

Overview

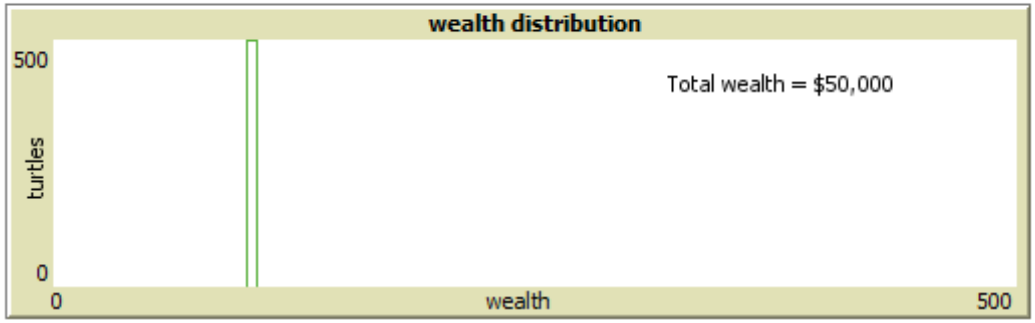
- **Understand the Complexity dynamics of the Simple Economy Model**

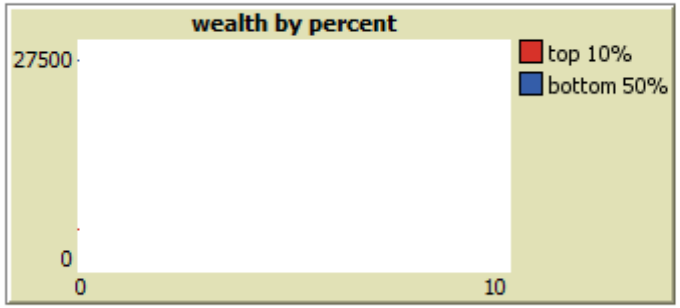
Simulation Run

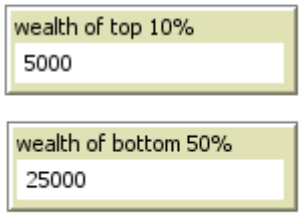
- Let us see how this works in NetLogo

Running the Model

- **Let us see the initial conditions**

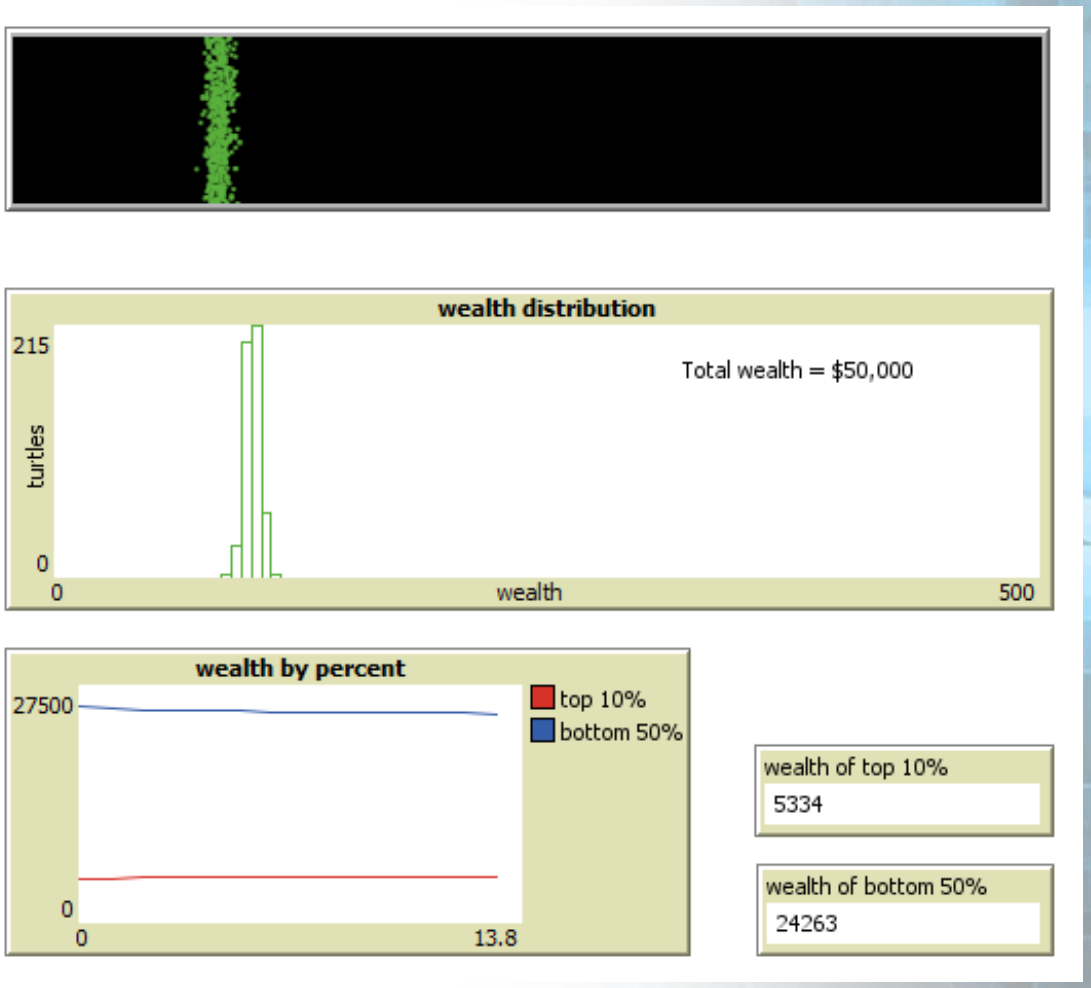






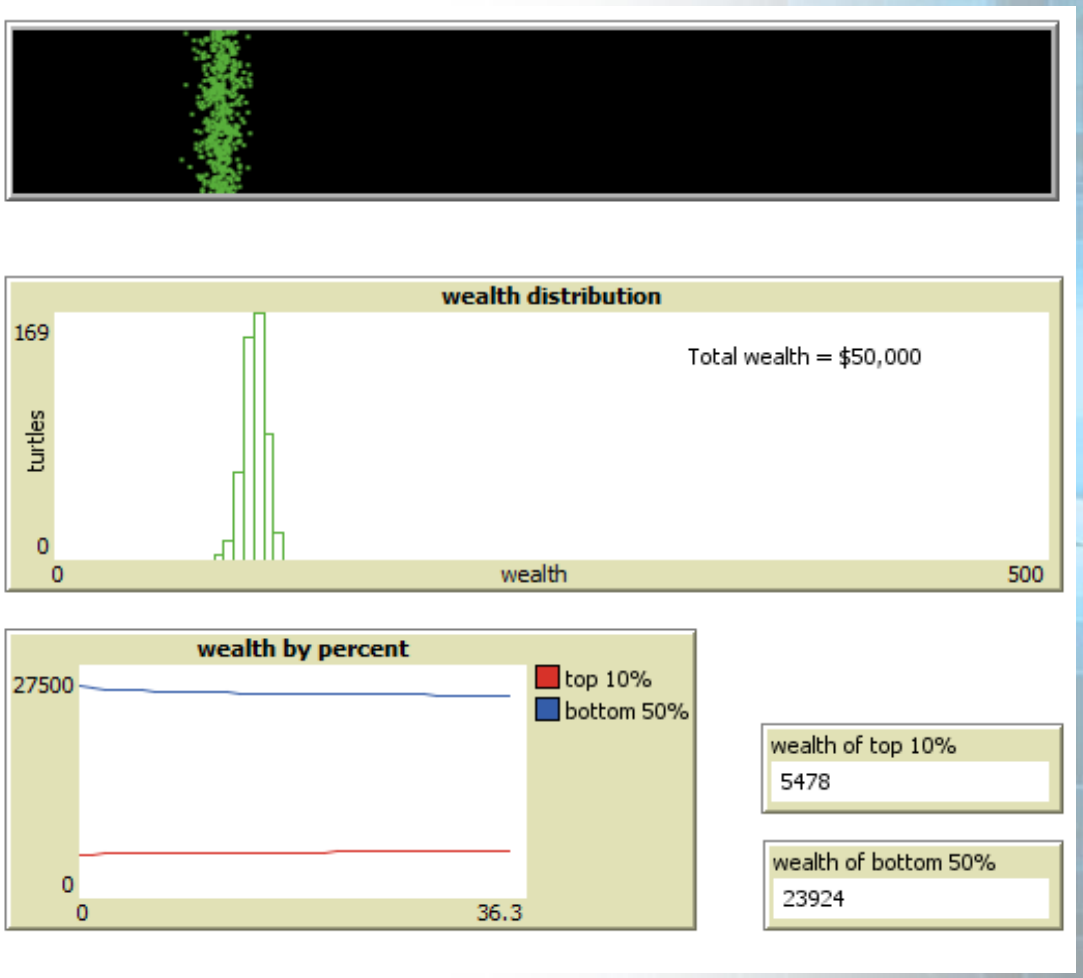
Running the Model

- **After running**



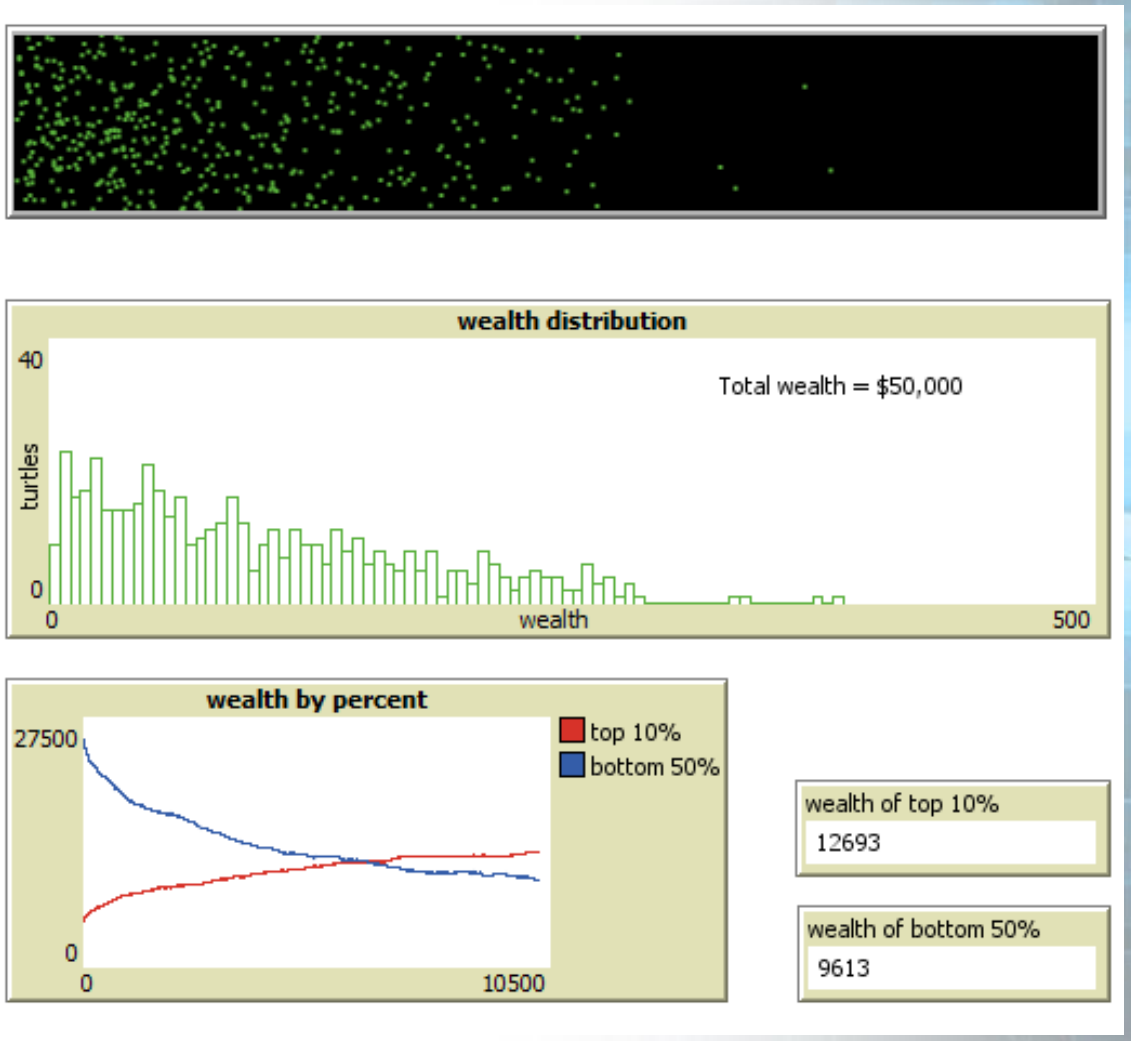
Running the Model

- **After running**



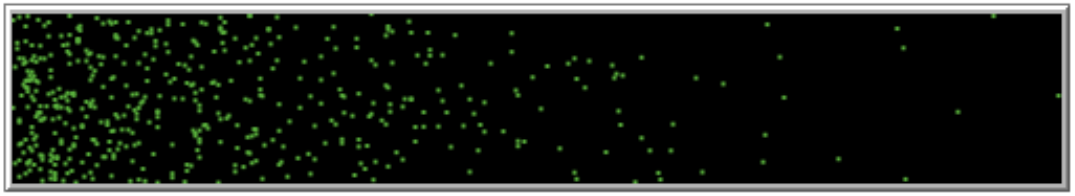
Running the Model

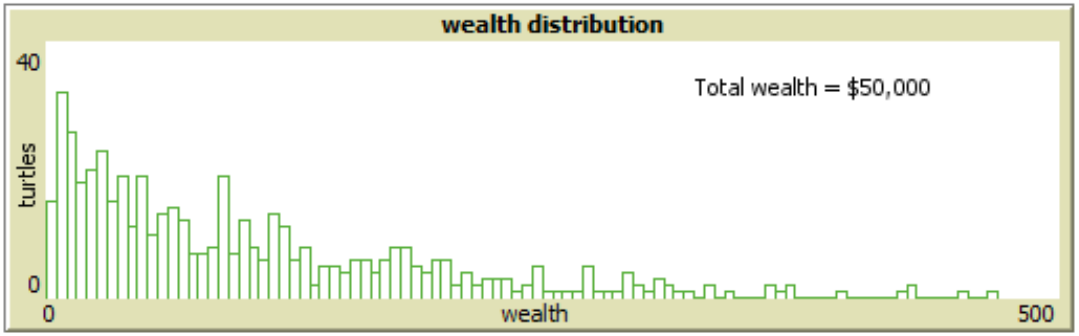
- **After long run: 10,000**

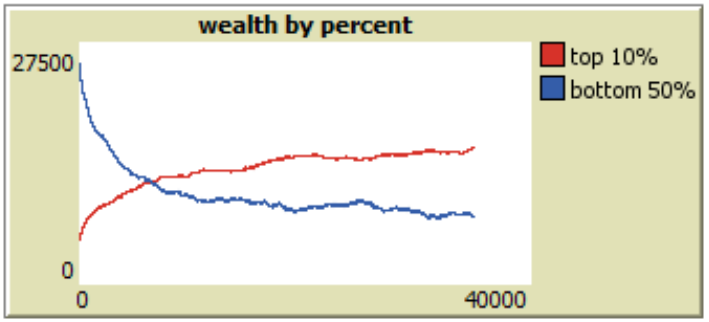


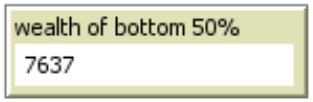
Running the Model

- **After long run: 35,000**









Understanding Results

- We can see that the distribution is not at all flat.
- There are a few very wealthy individuals and many poor agents.

Understanding Results

- At this time step in this model run, the wealth of the top 10 percent of the agents is a total of $12,633, or an average of $253 per person
- Whereas the total wealth of the entire bottom 50 percent is only $10,166, or an average of $41 per person.

Understanding Results

- The crossover point at which the wealth of the top 10 percent of all agents exceeded the wealth of the bottom half, or 50 percent, of all agents was at 5,600 ticks.

Understanding Results

- If we run it for 25,000 more ticks, the gap continues to grow and now the top 10 percent have more than twice as much in total (and more than 10 times as much per individual) than the bottom 50 percent.

Understanding Results

- The distribution of money eventually converges to a stationary distribution.
- This distribution has been shown to be exponential, which means that there is great inequality in monetary wealth.

Understanding Results

- **The key condition that creates this stationary distribution is the conservation of money.**

Summary

- We have examined the Execution of the Simple Economy Model
- We have seen how surprising results can appear in relatively simple models

END

Modeling & Simulation

Econophysics

Overview

- **Understand the basis of Complexity dynamics of the Simple Economy Model**

The basis

- The distribution we have just seen in the Simple Economy model is an instance of a broader class of models
- In these models a conserved quantity is exchanged in a closed system.

The basis

- The great nineteenth-century Austrian physicist Ludwig Boltzmann first examined such models when he worked out the physics of gas molecules in a box.
- He imagined these molecules as “ billiard balls ” moving and colliding.

The basis

- When they collide, they change speed and direction,
- Because of the conservation of energy, the total energy after a collision remains the same.

The basis

- He derived an equation, now known as the Boltzmann equation , for the distribution of the energies of the billiard balls

The basis

- He solved the equation to show that their energies formed a stationary exponential distribution
- It is known as Boltzmann distribution, the Boltzmann-Gibbs distribution, and the Maxwell-Boltzmann distribution.

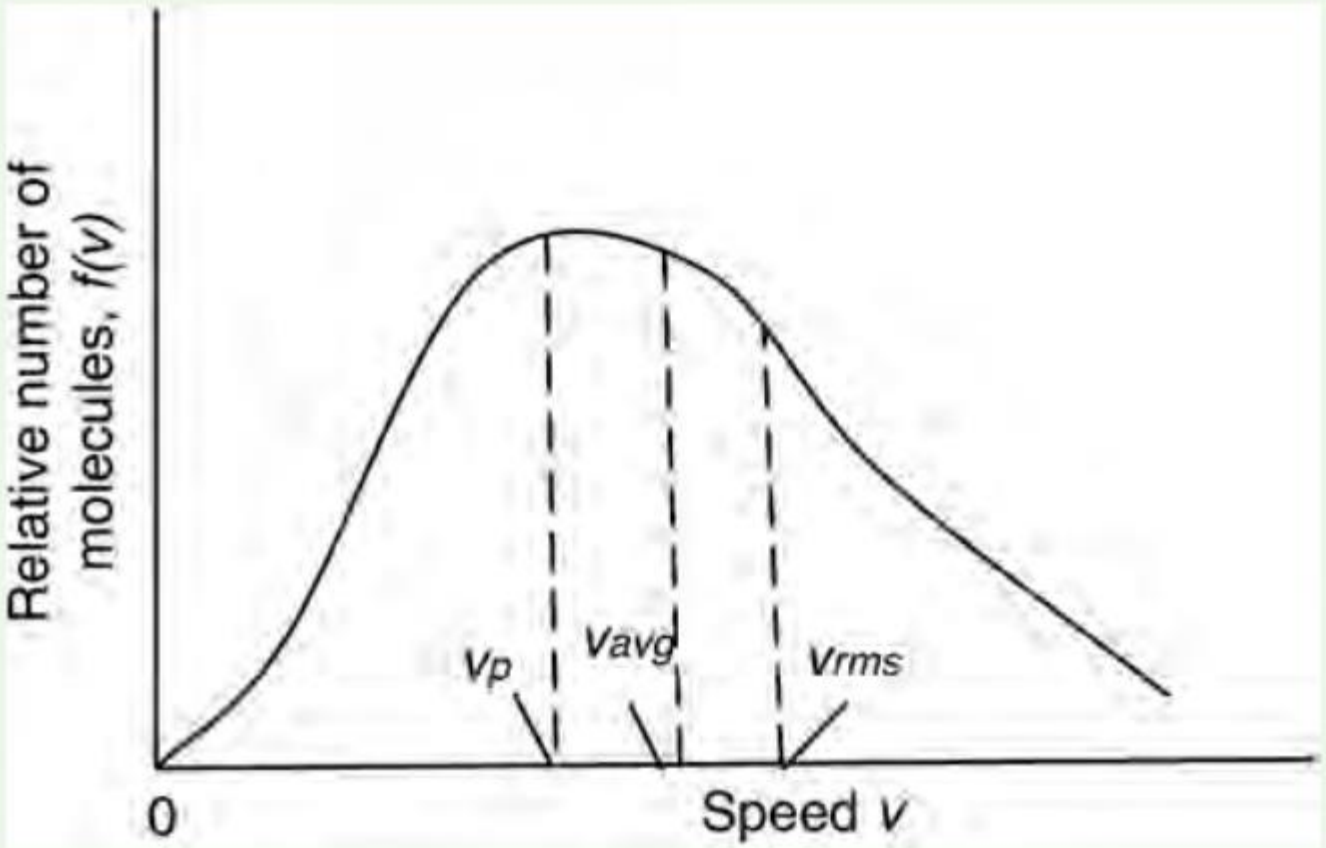
The basis

- The Boltzmann distribution is a central component of statistical mechanics.
- Statistical mechanics uses probability theory to understand the thermodynamic behavior of systems composed of a large number of particles.

The basis

- In many ways, agent-based modeling can be seen as extending this perspective to content domains beyond physics.

The basis



Recent Work

- In recent years, theories and methods from physics have been applied to economics.
- The physicist Gene Stanley (1996) coined the term “ econophysics ” for this interdisciplinary research field.

Recent Work

- In their 2000 paper, Dragulescu and Yakovenko describe several variants of the kind of monetary exchange that we have explored in this model.

Recent Work

- They show that if agents are allowed to go into debt (subject to a fixed credit limit), there is still a stationary exponential distribution
- However in this case it results in even greater inequality.

Recent Work

- A more specific term for what we are modeling is monetary wealth .

Recent Work

Dragulescu and Yakovenko caution:

It is tempting to identify the money distribution with the distribution of wealth. However, money is only one part of wealth, the other part being material wealth. Material products have no conservation law: They can be manufactured, destroyed, consumed, etc. Moreover, the monetary value of a material product (the price) is not constant. The same applies to stocks, which economics textbooks explicitly exclude from the definition of money. So, in general, we do not expect the Boltzmann-Gibbs law for the distribution of wealth.

Summary

- We have examined the basis of complex results in the Simple Economy Model
- We have seen how concepts from one domain can be used in a completely different domain

END

NetLogo: Agentsets and Lists

Overview

- Understand some commonly used NetLogo concepts

Understanding Complex Results

- Understanding complex results often requires advanced modeling techniques
- E.g. in Simple economy, we have seen complex results

Understanding Complex Results

- Some of these results need correlation with the real world
- Empirical studies have shown that wealth distribution in most countries is not distributed exponentially,
- Instead it follows a power law known as the Pareto distribution (Pareto, 1964).

Understanding Complex Results

- This distribution is even more unequal than an exponential distribution.
- Power law distributions arise in a surprising number of contexts
- They are typically associated with preferential attachment processes (Barabási, 2002)
- The amount received is proportional to the existing amount.

Lists and Agentsets

- To model such complexity we often need advanced programming concepts
- Some of the most used constructs (data structures) in NetLogo are:
- Agentsets
- Lists

Lists and Agentsets

- An agentset is a set of agents.
- Agentsets can have turtles, patches, or links, but they cannot mix agent types.
- You can ask an agentset to perform some commands.
- NetLogo comes with three special agentsets built in: “ turtles, ” “ patches, ” and “ links”

Lists and Agentsets

- What makes agentsets so powerful is that you can create your own agentsets
- For example, an agentset of all the red turtles,
- Or an agentset of all the patches in the upper right quadrant.

Lists and Agentsets

- Agentsets are always in random order.
- So if you ask an agentset, several different times, to execute some commands, each time the order in which the agents take turns executing the commands will be different.

Lists and Agentsets

- Lists are ordered collections of data.
- We can have a list of numbers
- A list of words, even a list of lists, also even a list of agents.
- Since they are in a list, these agents will have a particular order, so you can use the list to execute their commands in any order you might like.

Summary

- We have examined the basis of complex results in the Simple Economy Model
- We have seen how concepts from one domain can be used in a completely different domain

END

Exploring and Extending Agent-Based Models

Overview

- Understand how we do not have to develop models from scratch
- Understand how existing models can be extended easily

Part of the inhumanity of the computer is that, once it is competently programmed and workin smoothly, it is completely honest.

—Isaac Asimov

The perfect journey is never finished, the goal is always just across the next river, round the shoulder of the next mountain. There is always one more track to follow, one more mirage to explore.

—Rosita Forbes

Sailors on a becalmed sea, we sense the stirring of a breeze.

—Carl Sagan

Characteristic Features

- There are four characteristic features of agent-based modeling:

1. Simple rules can be used to generate complex phenomena
2. Randomness in individual behavior can result in consistent patterns of population behavior

Characteristic Features

3. Complex patterns can “ self-organize ” without any leader orchestrating the behavior
4. Different models emphasize different aspects of the world

Characteristic Features

- Simple rules can be used to generate complex phenomena
- Many of the models that we will look into have very simple rules that do not require complex mathematical formulas or a deep understanding of the knowledge domain that they are attempting to model.

Characteristic Features

- **Nonetheless, they are able to reproduce complex phenomena that are observed in the real world.**

Characteristic Features

- For instance, a model of fire spread may have only a simple rule to describe fire spread from one tree to another
- Still it may have interesting things to say about how likely a fire is to spread across an entire forest.

Characteristic Features

- Randomness in individual behavior can result in consistent patterns of population behavior
- It is easy to misunderstand this

Characteristic Features

- E.g. Seeing an ordered population level behavior such as a flock of birds, it is easy to assume that there must be deterministic processes that govern the behavior of the individuals (Wilensky & Resnick, 1999)

Characteristic Features

- Many times the individual level rules are quite simple
- The rules do not necessarily tell the bird where to position itself in the flock.

Characteristic Features

- Instead, the rules often contain a certain amount of nondeterminism and are robust to perturbations in the initial conditions.
- Despite the stochastic nature, they can still result in the generation of predictable high-level behavior like the flocking of birds.

Summary

- We have a couple of characteristic features of ABM

END

Characteristic Features of ABM

Overview

- Understand some more characteristic features of ABMs

No Leader Needed!

- Complex patterns can “ self-organize ” without any leader orchestrating the behavior

No Leader Needed!

- Nature has surprises in store
- A population of individuals, each following very simple rules, can “ self-organize, ” generating complex and beautiful patterns without any orchestrator or centralized controller

Different Models – different aspects

- Different models emphasize different aspects of the world.

Different Models – different aspects

- Finishing a model does not mean that the work is all done
- Even after we have completed a good working model of a particular phenomenon, we are not done with the modeling process.

Different Models – different aspects

- Every model foregrounds certain aspects of the world
- It also backgrounds other aspects.
- This is the idea behind abstraction and narrowness of focus

Different Models – different aspects

- There can be many models of the same phenomenon
- They each may have something interesting to say about the way the world works

Different Models – different aspects

- For instance, a model of residential location preferences may emphasize
- How likely is it for a person is to move into a neighborhood based on how she likes the other people in the neighborhood.

Different Models – different aspects

- Such a model may have very interesting things to say about how urban populations develop,
- However it may say nothing about school districts, location of retail businesses, or development of parks
- All of these are also affected by residential location preferences.

Summary

- We have a examined some very interesting characteristic features of ABM
- Understanding these features allows us to reuse and extend existing models rather than develop them from scratch

END

Modeling & Simulation

Fire Model

Overview

- Understand the dynamics of the Forest Fire Model

Forest Fire

Credit: Pixabay

Forest Fire

- Why study Forest fires?
- Forest fires are inherently an extremely complex phenomena
- Some countries have developed a complex mathematical index to predict them.
- The mathematical model (Fire Weather Index) involves a very large number of variables

Tipping Points

- Different models emphasize the concept of tipping points.
- Threshold or tipping point

Forest Fire

- A tipping point occurs when a small change in one parameter results in a large change in an outcome.
- Good example – forest fire

Forest Fire

- This simple model is highly sensitive to one parameter.
- When observing the resultant outcome of whether or not a fire will burn from one side of a forest to another (percolate), the output is mainly dependent on the percentage of the ground that is covered by trees

Forest Fire

- As this parameter increases, there will be little to no effect on the system for a long time,
- Then all of a sudden the fire will leap across the world.
- This is a “ tipping point ” in the system

Benefits of Knowing

- First, if you know a system exhibits a tipping point, you know that continuing to put effort into the system, even if you are not seeing any results yet, may yet bear fruit.

Benefits of Knowing

- Second, if you know where the tipping point is, and if you know how close you are to it, then you can determine whether or not it is worth putting additional effort into the system.

Benefits of Knowing

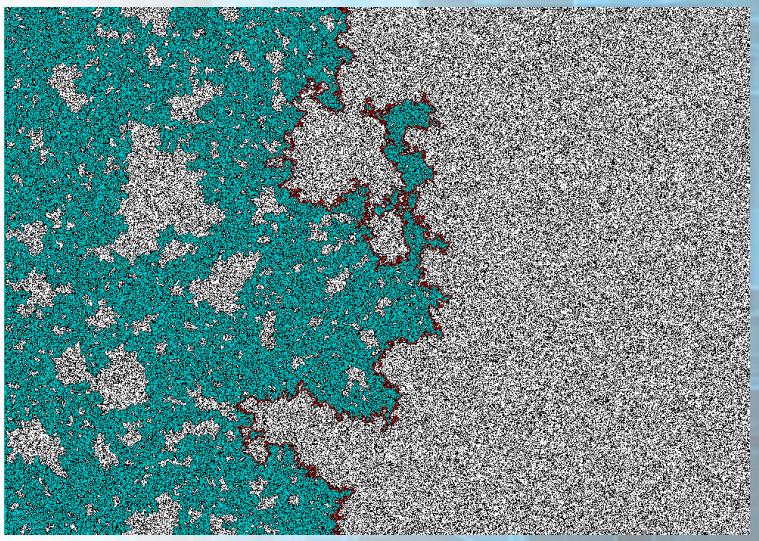
- If far away from the tipping point, then it might not be worthwhile trying to change the state of the system
- Whereas if close to the tipping point it may take only a small amount of effort to make a big change in the state of the system.

Forest Fire Model

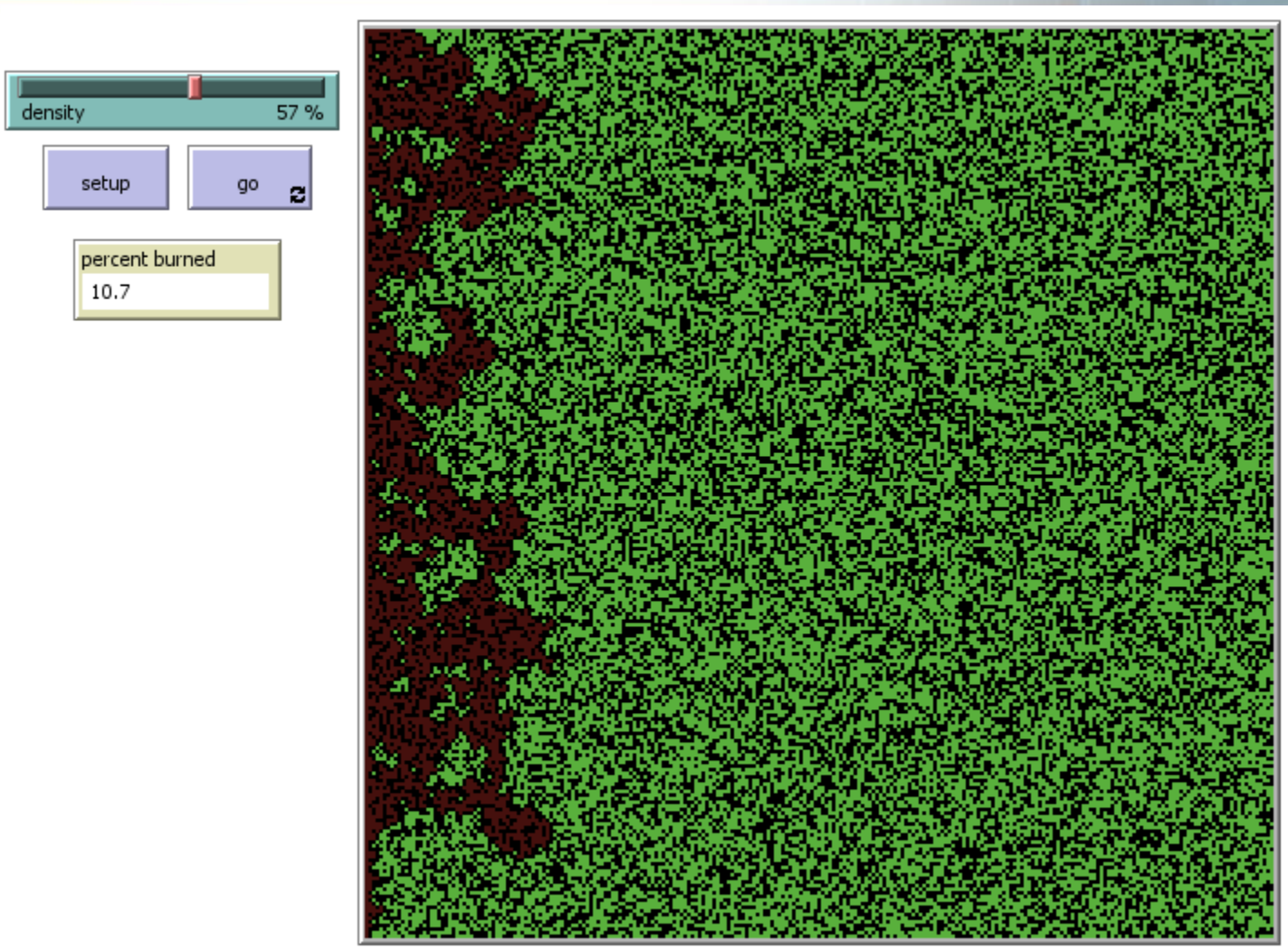
- The Fire model arose from a number of independent efforts to understand percolation phenomena.
- In percolation, a substance (such as oil) moves through another material (such as rock), which has some porosity.

Forest Fire Model

- Percolation
- Credit: Wikimedia Commons



Forest Fire Model



Summary

- We have a examined the basics of Forest Fire model

END

Fire Model: Basic Model

Overview

- Understand the code of the Forest Fire Model

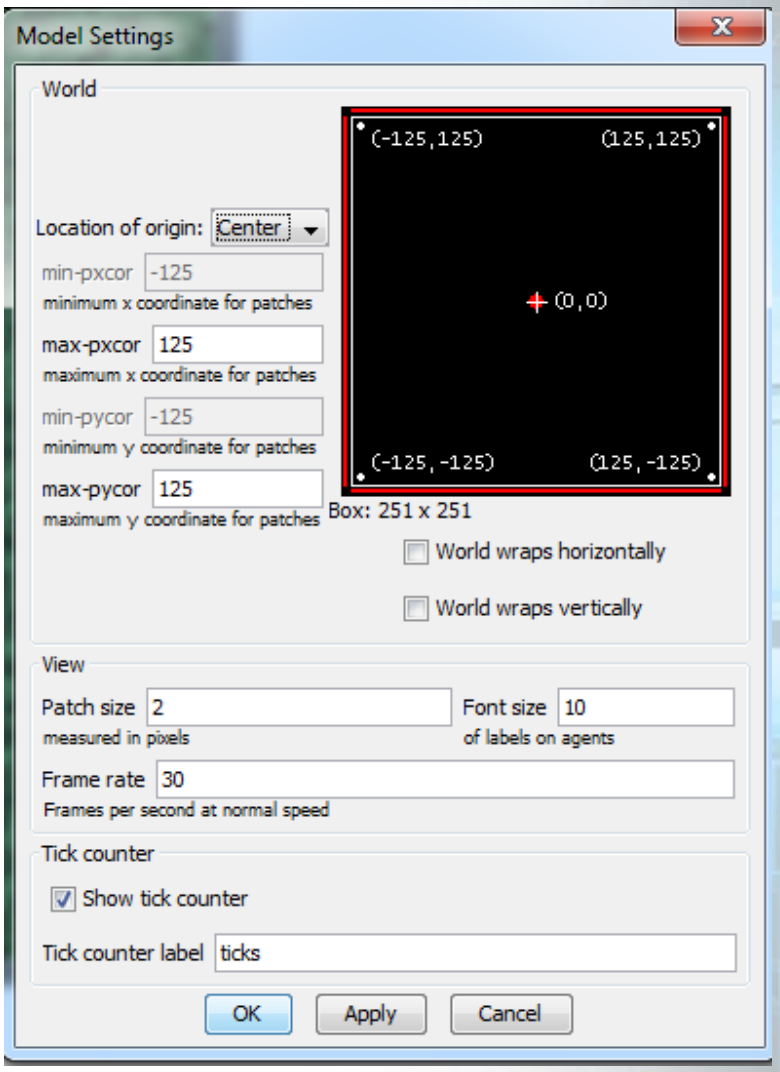
Forest Fire Model

```
globals [
  initial-trees   ;; how many trees (green patches) we started with
]

to setup
  clear-all
  ;; make some green trees
  ask patches [
    if (random 100) < density [
      set pcolor green
    ]
    ;; make a column of burning trees at the left-edge
    if pxcor = min-pxcor [
      set pcolor red
    ]
  ]
  ;; keep track of how many trees there are
  set initial-trees count patches with [pcolor = green]
  reset-ticks
end
```

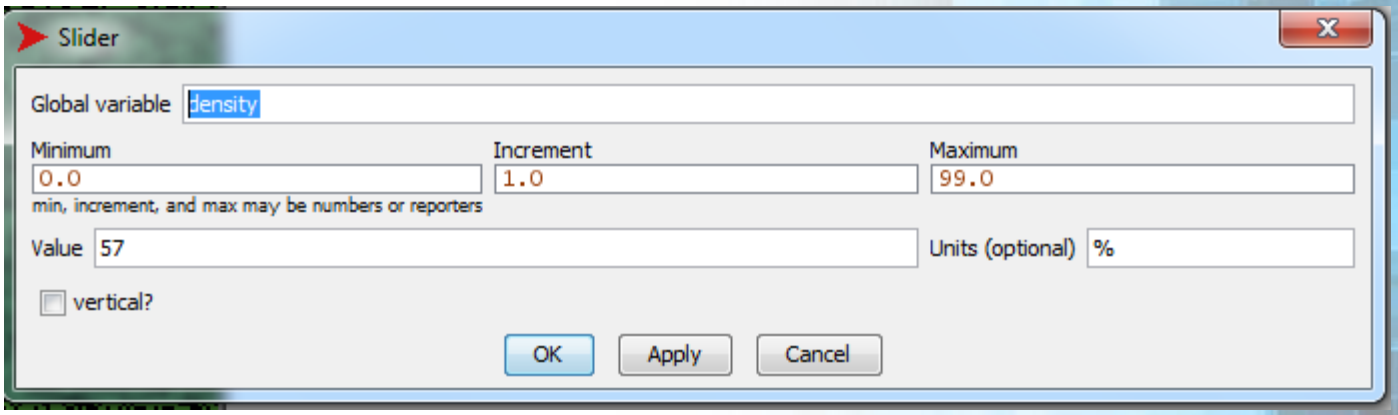
Forest Fire Model

```
to go
  ;; stop the model when done
  if all? patches [ pcolor != red ] [
    stop
  ]
  ;; ask the burning trees to set fire to any neighboring non-burning trees
  ask patches with [ pcolor = red ] [ ;; ask the burning trees
    ask neighbors4 with [pcolor = green] [ ;; ask their non-burning neighbor trees
      set pcolor red ;; to catch on fire
    ]
    set pcolor red - 3.5 ;; once the tree is burned, darken its color
  ]
  tick ;; advance the clock by one “tick”
end
```

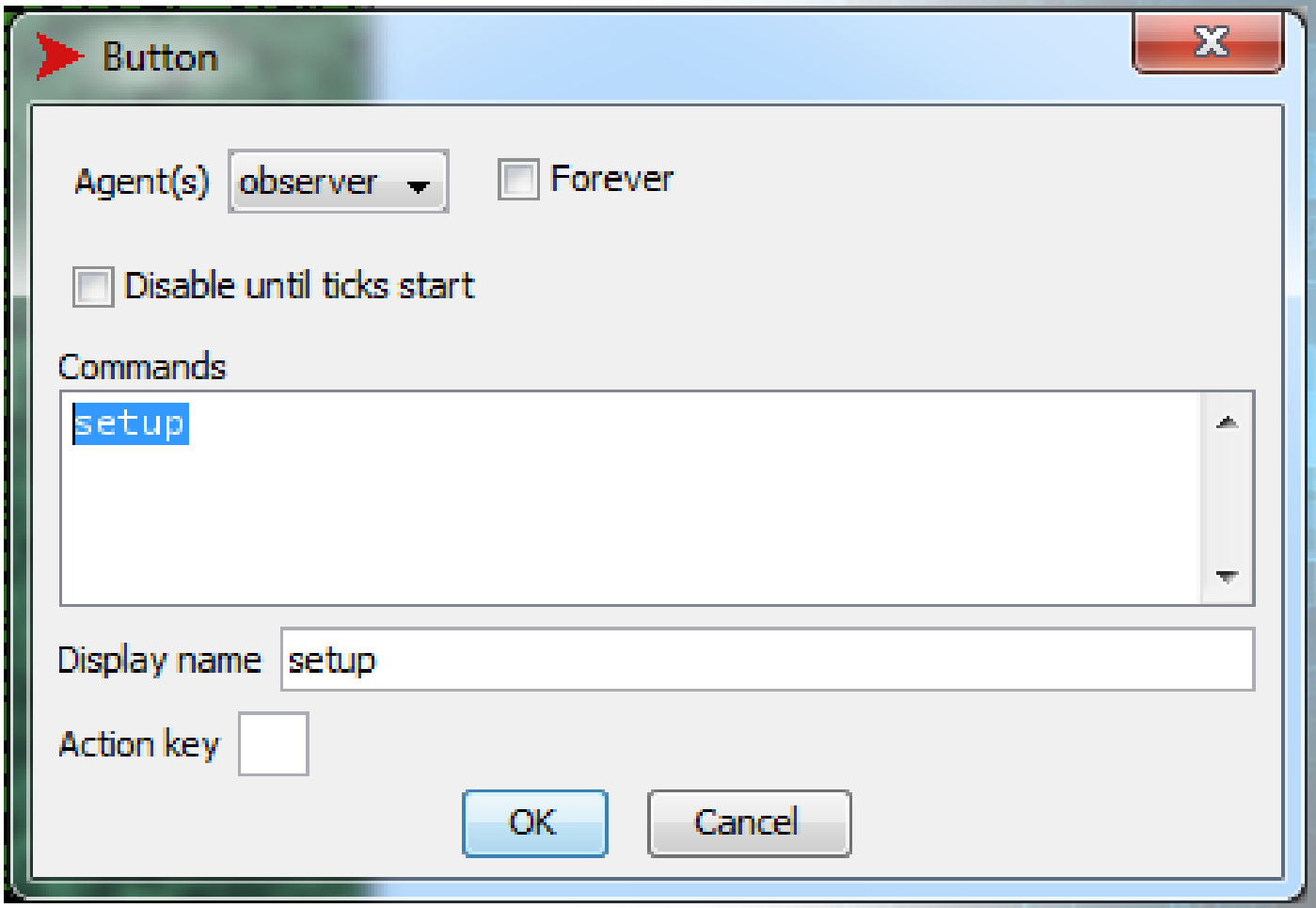
Forest Fire


Model Settings
World
Location of origin: Center
min-pxcor -125
minimum x coordinate for patches
max-pxcor 125
maximum x coordinate for patches
min-pycor -125
minimum y coordinate for patches
max-pycor 125
maximum y coordinate for patches
(-125,125)
(125,125)
(0,0)
(-125,-125)
(125,-125)
Box: 251 x 251
World wraps horizontally
World wraps vertically
View
Patch size 2
measured in pixels
Font size 10
of labels on agents
Frame rate 30
Frames per second at normal speed
Tick counter
Show tick counter
Tick counter label ticks
OK
Apply
Cancel

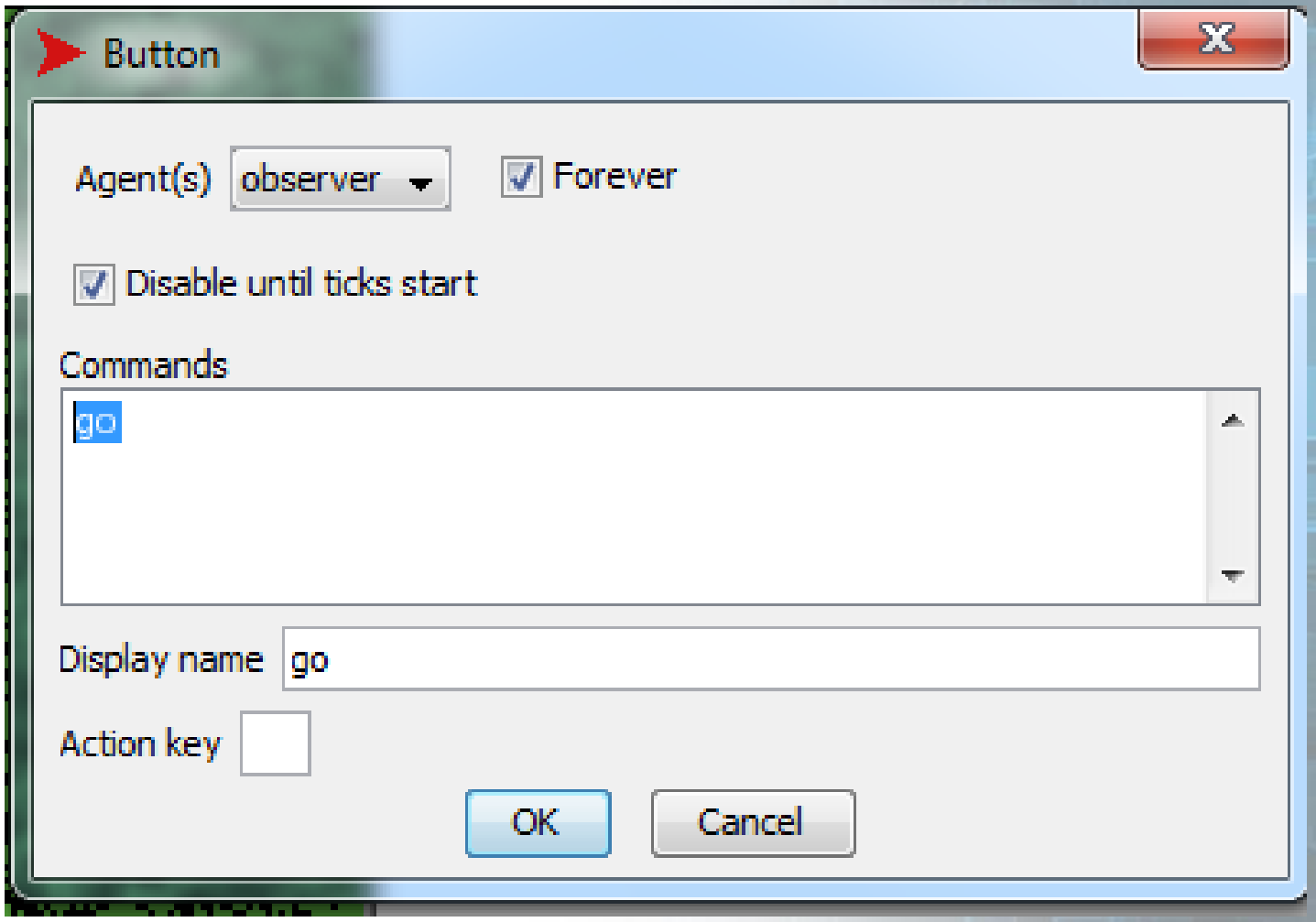
Forest Fire


Slider
Global variable
density
Minimum
0.0
Increment
1.0
Maximum
99.0
min, increment, and max may be numbers or reporters
Value
57
Units (optional)
%
vertical?
OK
Apply
Cancel

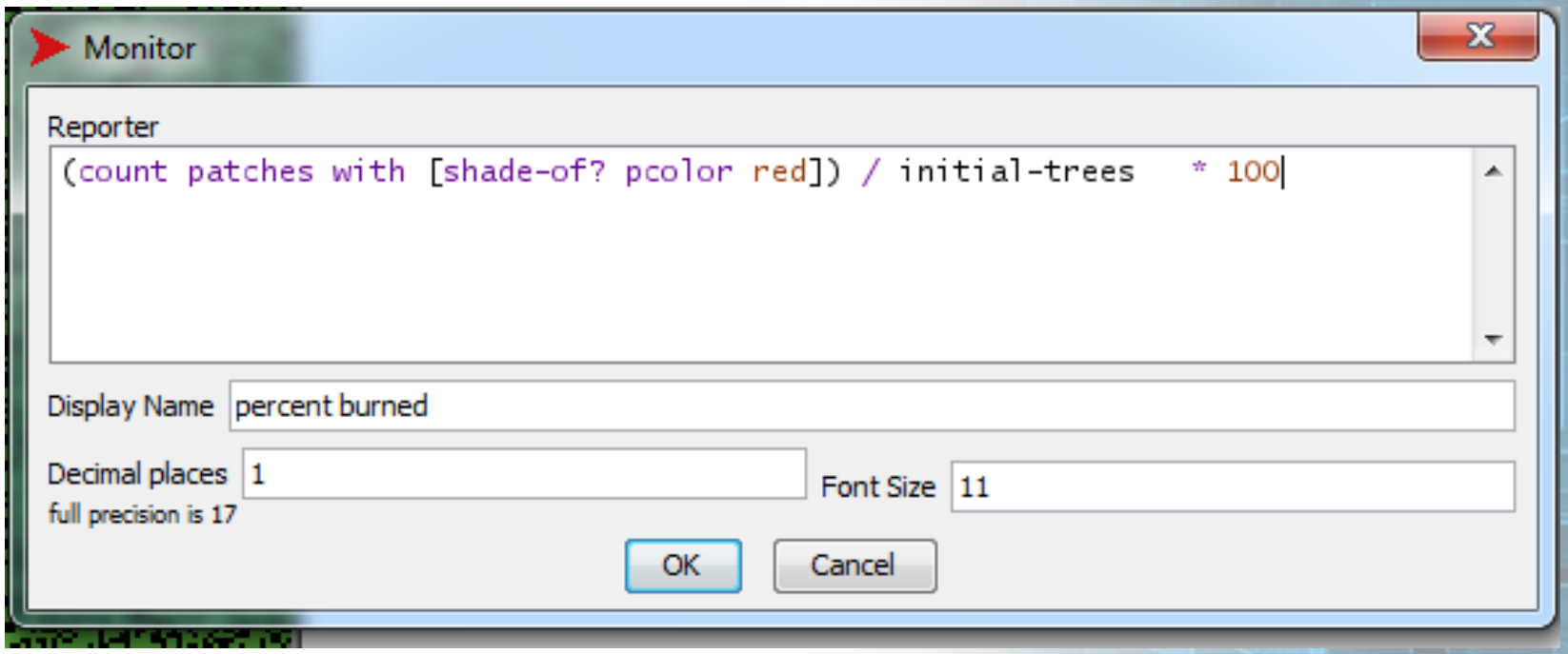
Forest Fire


Button
Agent(s)
observer
Forever
Disable until ticks start
Commands
setup
Display name
setup
Action key
OK
Cancel

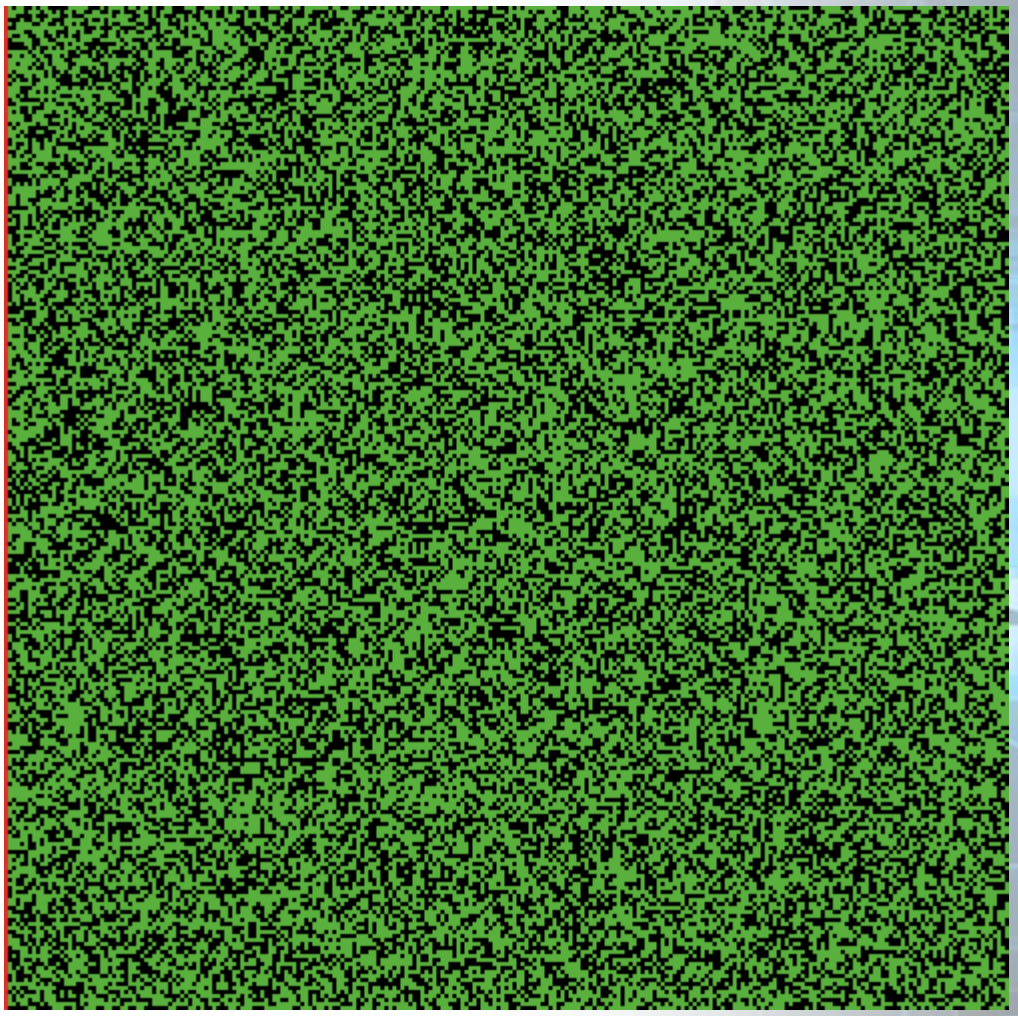
Forest Fire


Button
Agent(s)
observer
Forever
Disable until ticks start
Commands
go
Display name
go
Action key
OK
Cancel

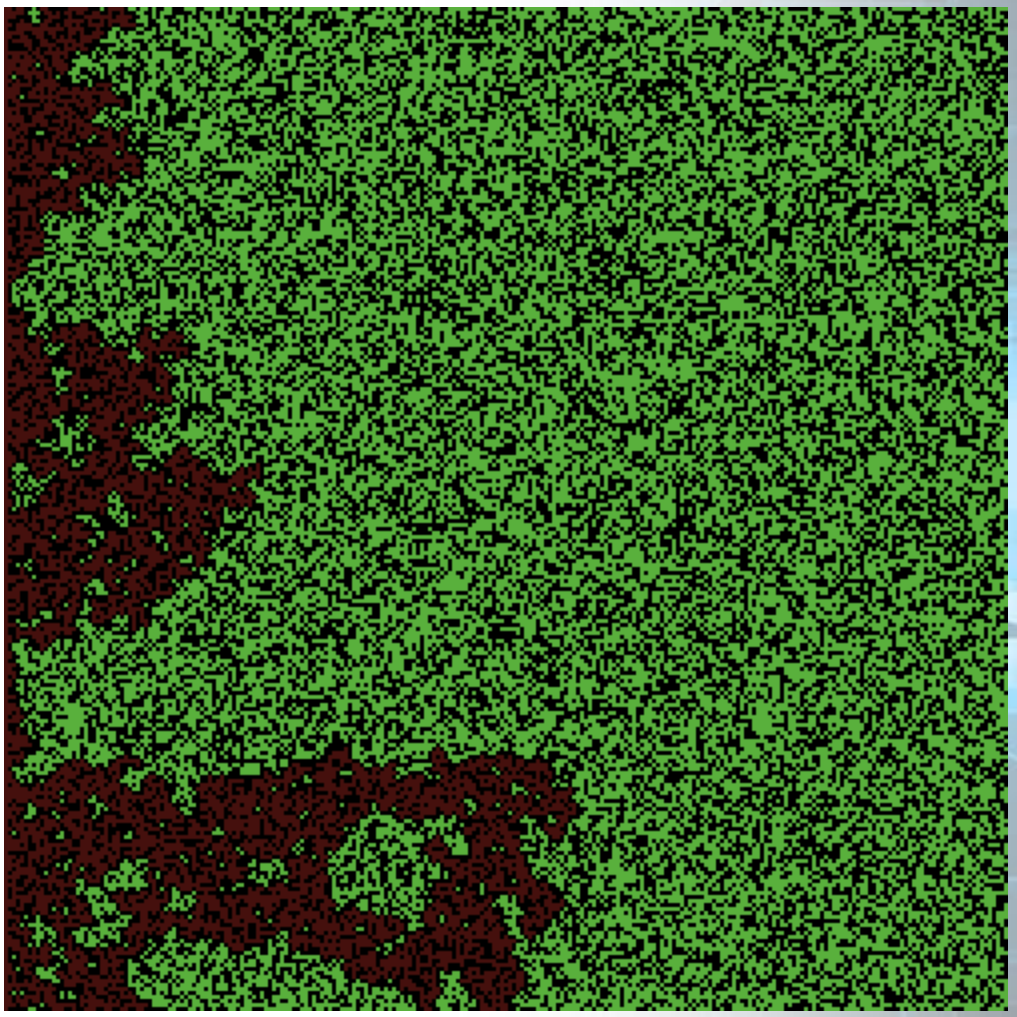
Forest Fire


Monitor
Reporter
(count patches with [shade-of? pcolor red]) / initial-trees * 100
Display Name
percent burned
Decimal places
1
full precision is 17
Font Size
11
OK
Cancel

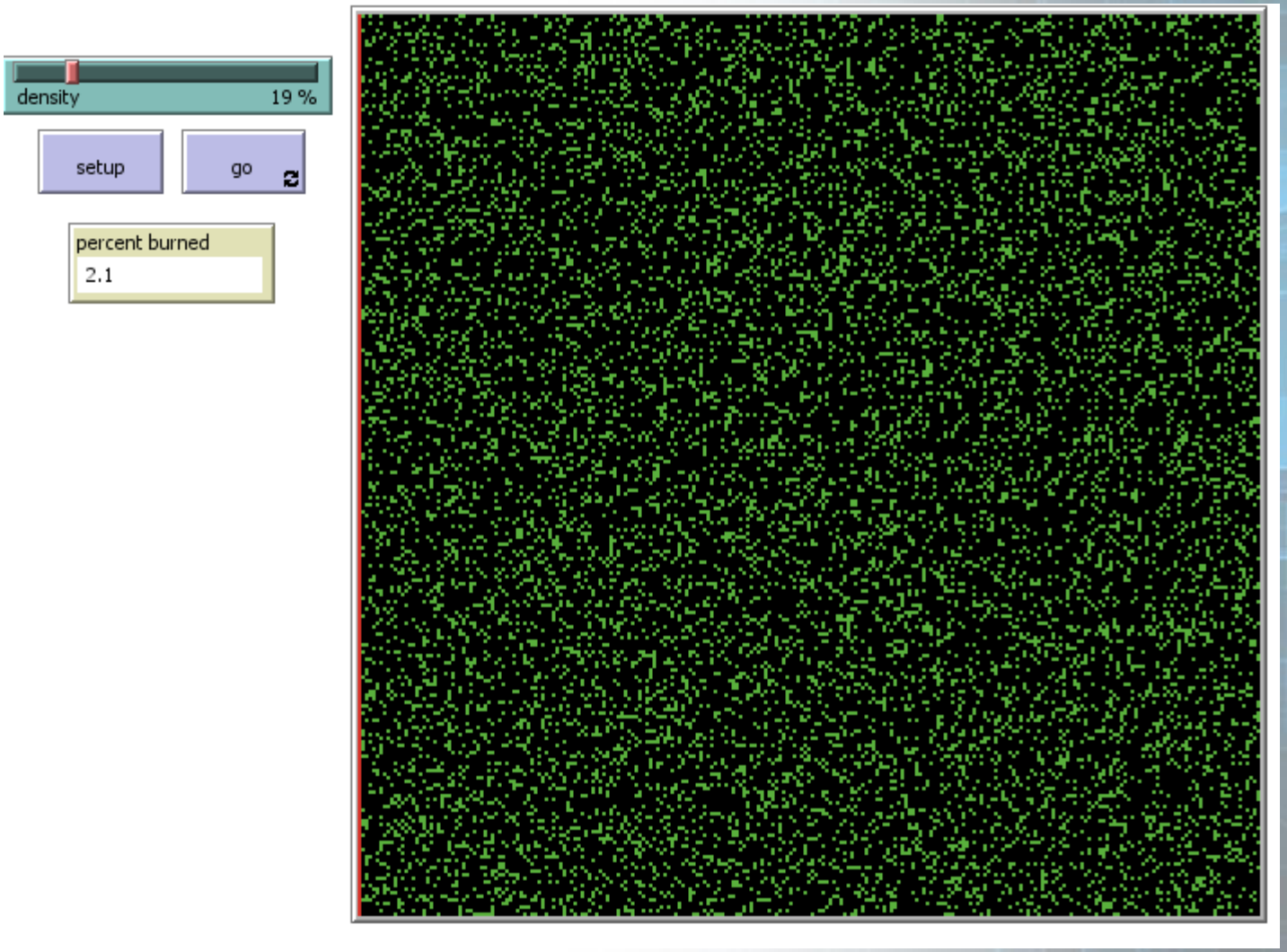
Forest Fire: Initial



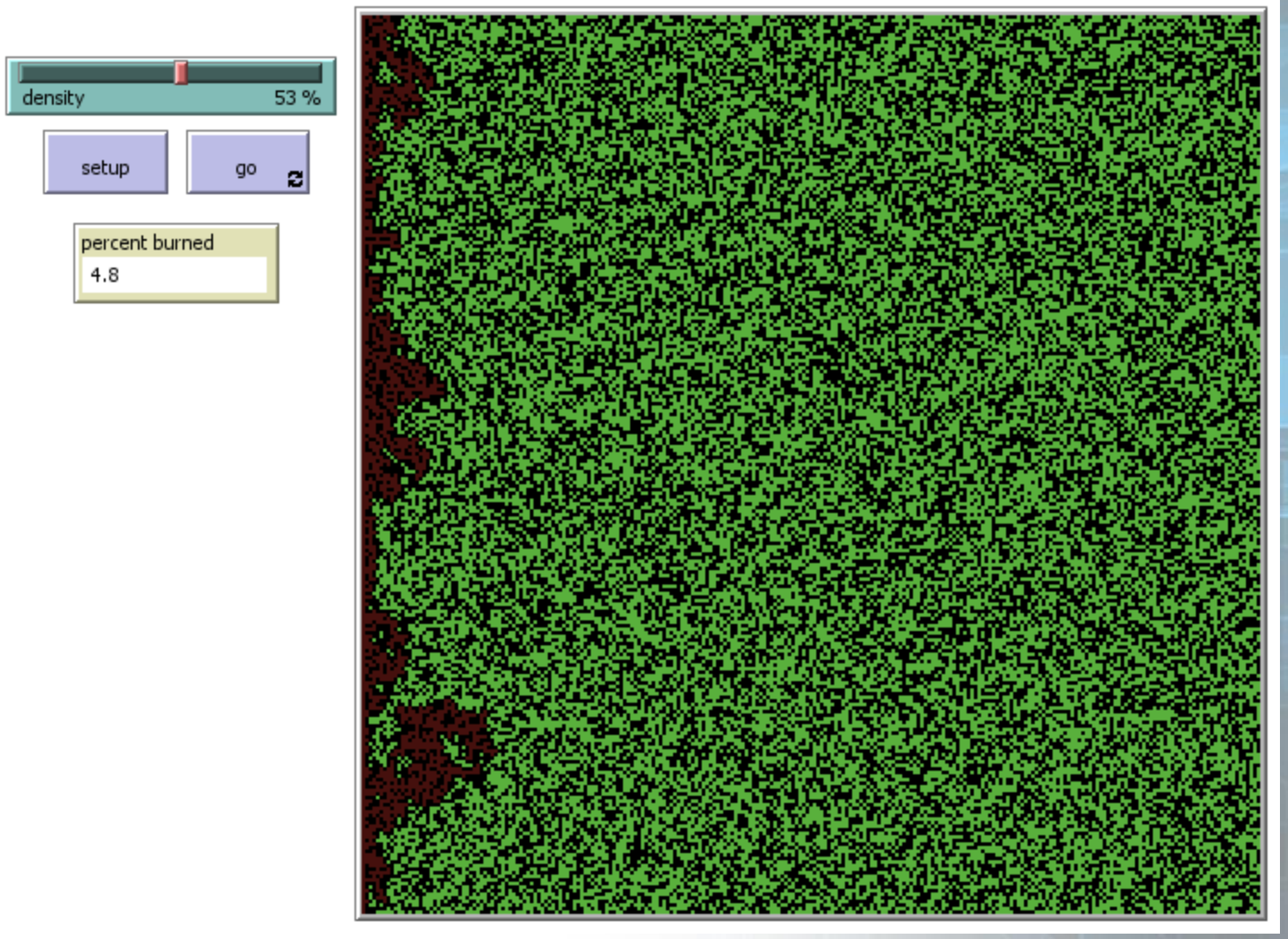
Forest Fire: Final



Another Run: 19% cover



Another Run: 53% cover



Summary

- We have a examined the code and various runs of the Forest Fire model

END

First Extension: Probabilistic Transitions

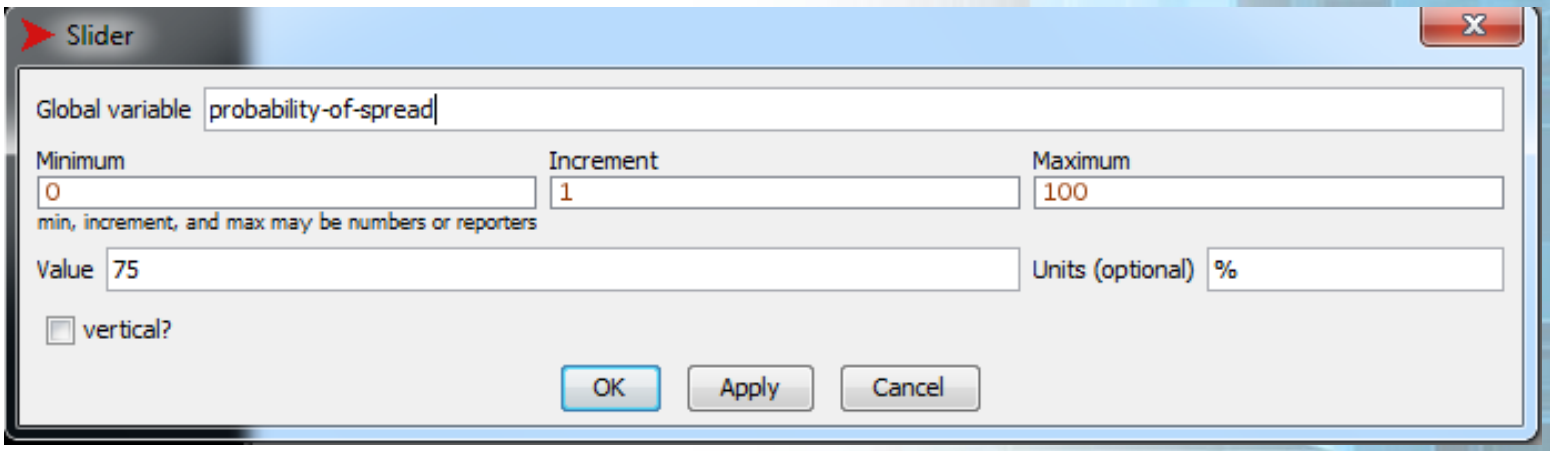
Overview

- Make changes in the original model to make it more realistic

Fire in the Real World

- Fire is not simple at all
- In the real world, it rather it jumps to another tree based on a variety of factors such as wind
- E.g. the type of wood, even how close the branches are to each other.
- See more complex extended models in the work given here: https://tinyurl.com/muazniazi

Fire Model Extension



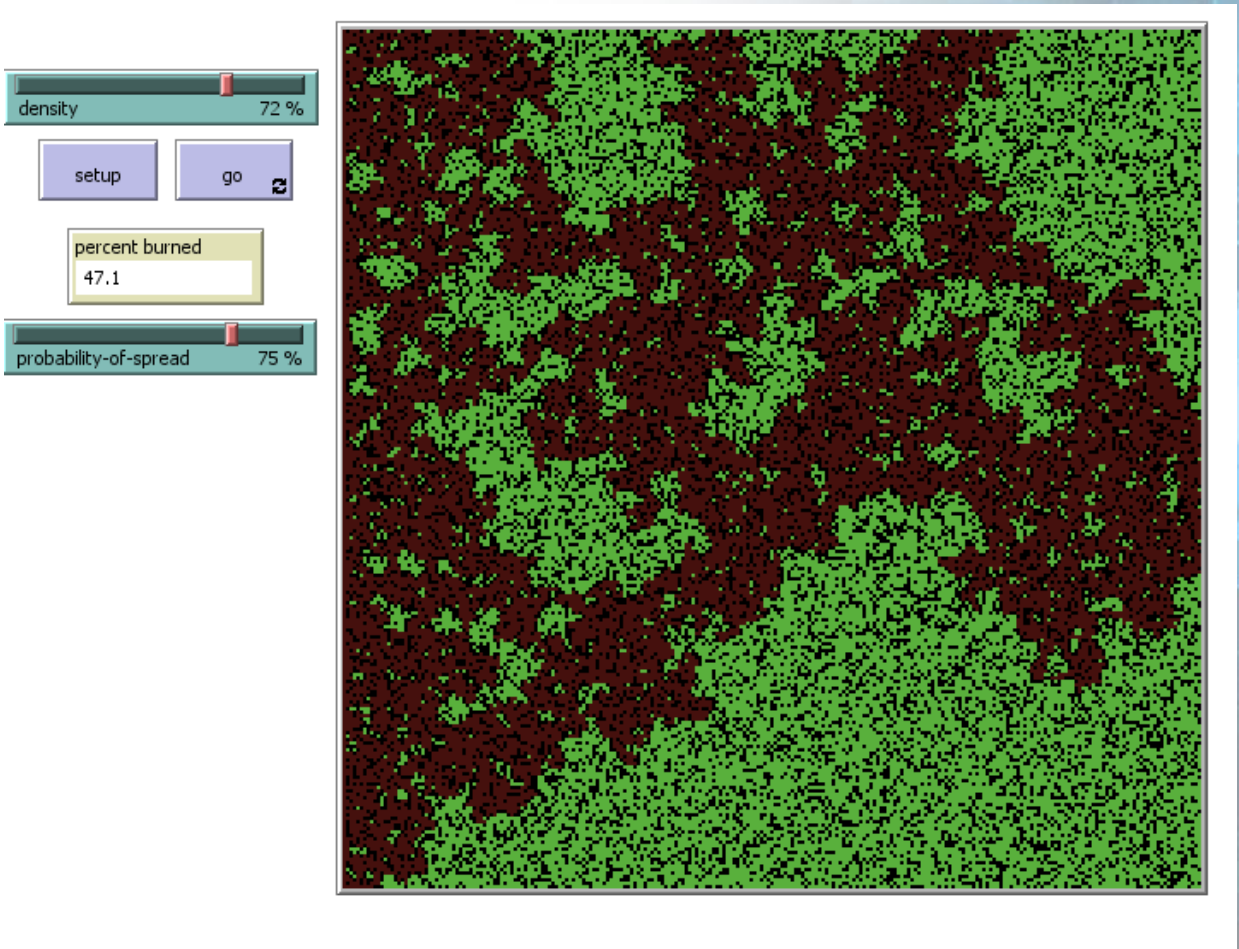
Model Code

```
to go
  ;; stop the model when done
  if all? patches [ pcolor != red ] [ stop ]

  ;; ask the burning trees to set fire to any neighboring non-burning trees
  ask patches with [ pcolor = red ] [ ;; ask the burning trees
    ask neighbors4 with [ pcolor = green ] [ ;; ask their non-burning neighbor trees
      ;; only burn if a random draw is greater than the probability of spread
      if random 100 < probability-of-spread [ set pcolor red ] ;; to catch on fire
    ]
    set pcolor red - 3.5 ;; once the tree is burned, darken its color
  ]
  tick ;; advance the clock by one "tick"
end
```

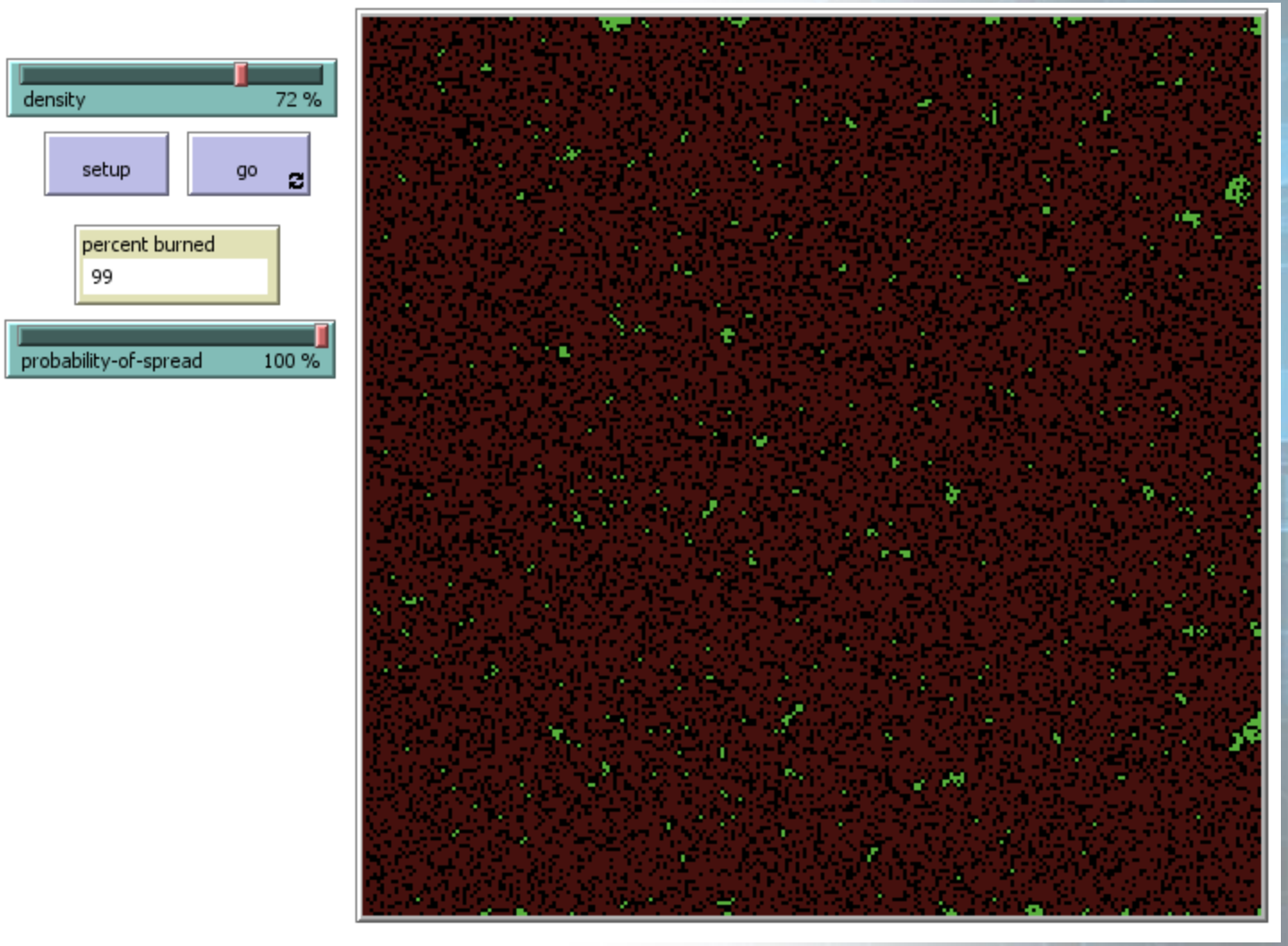
Results

- Try setting both the DENSITY and the PROBABILITY-OF-SPREAD parameters to a variety of values.
- We can reproduce the results of the original model by setting the PROBABILITY-OF-SPREAD slider to 100 percent.

New Model


density
72 %
setup
go
percent burned
47.1
probability-of-spread
75 %

Replication of Old Model



Summary

- We have a examined how minor changes in a model can help make complex changes in the outcome
- Also, we have seen how to make models more realistic

END

Second Extension: Adding Wind

Overview

- Make changes to add new parameter of Wind

Commands

- In NetLogo, commands and reporters tell agents what to do.
- A command is an action for an agent to carry out, resulting in some effect.
- A reporter is a set of instructions for computing a value, which the agent then “ reports ” to whoever asked it.

Commands

- Typically, a command name begins with a verb, such as “ create, ” “ die, ” “ jump, ” “ inspect, ” or “ clear. ”
- Most reporter names are nouns or noun phrases.

Commands

- For example, “ forward ” is a command, it tells a turtle agent to carry out a movement
- But “ heading ” is a reporter, it tells the agent to report the angle it is facing.

Built-in

- Many commands and reporters are built into NetLogo,
- We can create new ones in the Code tab.
- Commands and reporters built into NetLogo are called primitives.
- The
- NetLogo Dictionary has a complete list of built-in commands and reporters.

User Generated

- We can create your own commands and reporters by defining them in procedures.
- Each procedure has a name, preceded by the keyword to or to-report, depending on whether it is a command procedure or a reporter procedure.

User Generated

- The keyword end marks the end of the procedure.
- It can be useful to notice that reporters are colored purple and commands are colored blue in NetLogo ’ s automatic syntax highlighting.

User Generated

- Sometimes an input to a primitive is a command block (zero or more commands inside square brackets, e.g., [forward 10 set color red])
- Or a reporter block (a single reporter expression inside square brackets, e.g., the Boolean reporter [color = red]).

Second Extension

- Sometimes we can take an ABM for which we used a probability to model a suite of mechanisms and refine it so that some of those mechanisms are modeled in a more physical way.
- E.g. Our first extension hides a host of possible mechanisms in the PROBABILITY-OF-SPREAD.

Second Extension

- Wind is a good example of a process that we can model more specifically.
- We can think of the effect of wind on a fire as increasing the chance of fire spread in the direction it is blowing, decreasing the chance of fire spread in the direction it is not blowing,

Second Extension

- Also, wind will have little effect on fire spread that occurs perpendicular to the direction of its movement
- Of course, this too is an oversimplification — there are often local effects of wind, such as turbulence
- However, all models are simplifications anyways

Second Extension Code

```
to go
  ;; stop the model when done
  if all? patches [ pcolor != red ] [ stop ]
  ;; each burning tree (red patch) checks its 4 neighbors.
  ;; If any are unburned trees (green patches), change their probability
  ;; of igniting based on the wind direction
  ask patches with [ pcolor = red ] [
    ;; ask the unburned trees neighboring the burning tree
    ask neighbors4 with [ pcolor = green ] [
      let probability probability-of-spread
      ;; compute the direction from you (the green tree) to the burning tree
      ;; (NOTE: “myself” is the burning tree (the red patch) that asked you
      ;; to execute commands)
      let direction towards myself
      ;; the burning tree is north of you
      ;; so the south wind impedes the fire spreading to you
      ;; so reduce the probability of spread
```

Second Extension Code

```
if direction = 90 [
  set probability probability - west-wind-speed
]
;; the burning tree is south of you
;; so the south wind aids the fire spreading to you
;; so increase the probability of spread
```

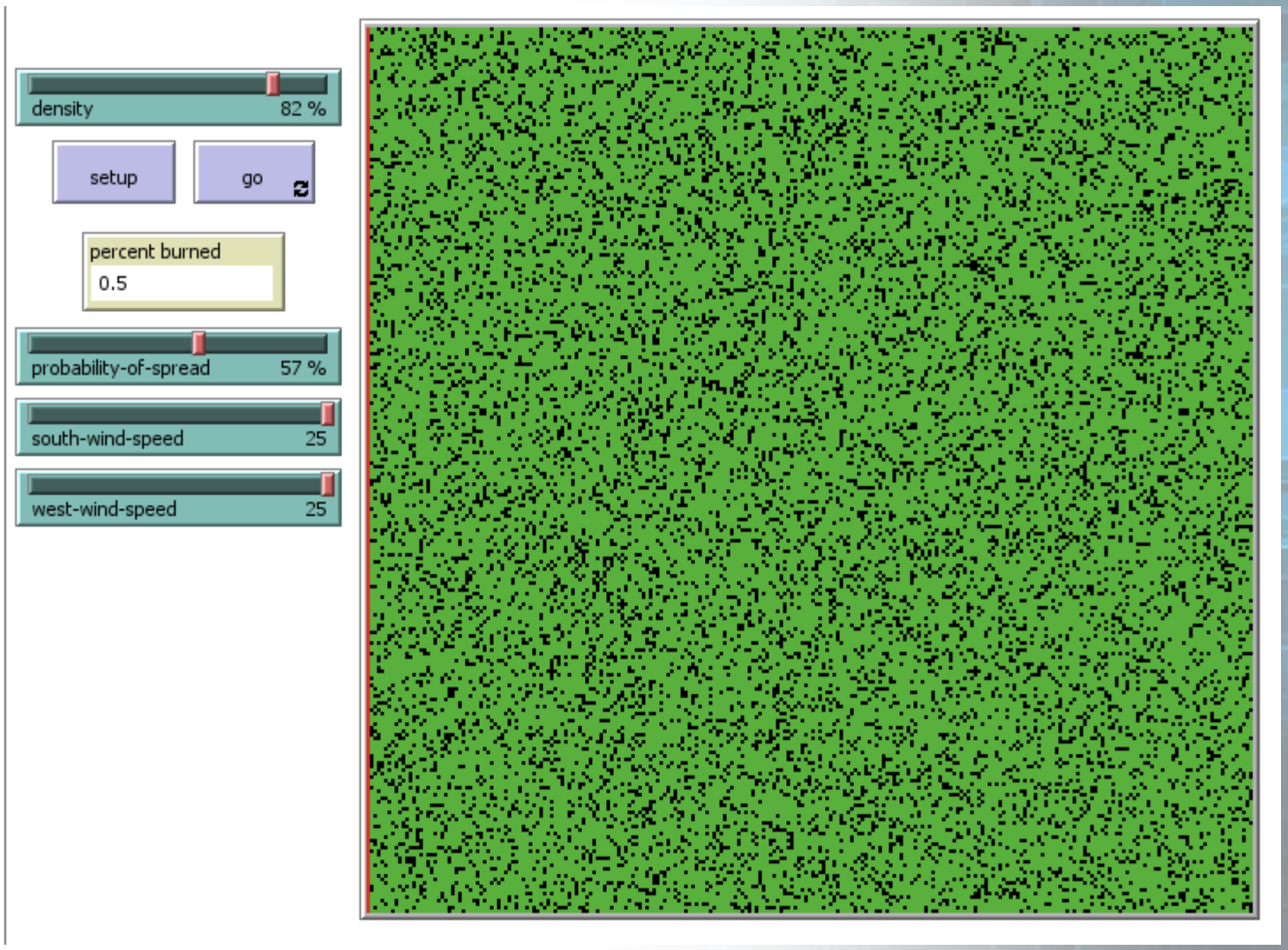
Second Extension Code

```
  if direction = 180 [
    set probability probability + south-wind-speed
  ]
  ;; the burning tree is west of you
  ;; so the west wind aids the fire spreading to you
  ;; so increase the probability of spread
  if direction = 270 [
    set probability probability + west-wind-speed
  ]
  if random 100 < probability [
    set pcolor red ;; to catch on fire
  ]
]
set pcolor red - 3.5 ;; once the tree is burned, darken its color
```

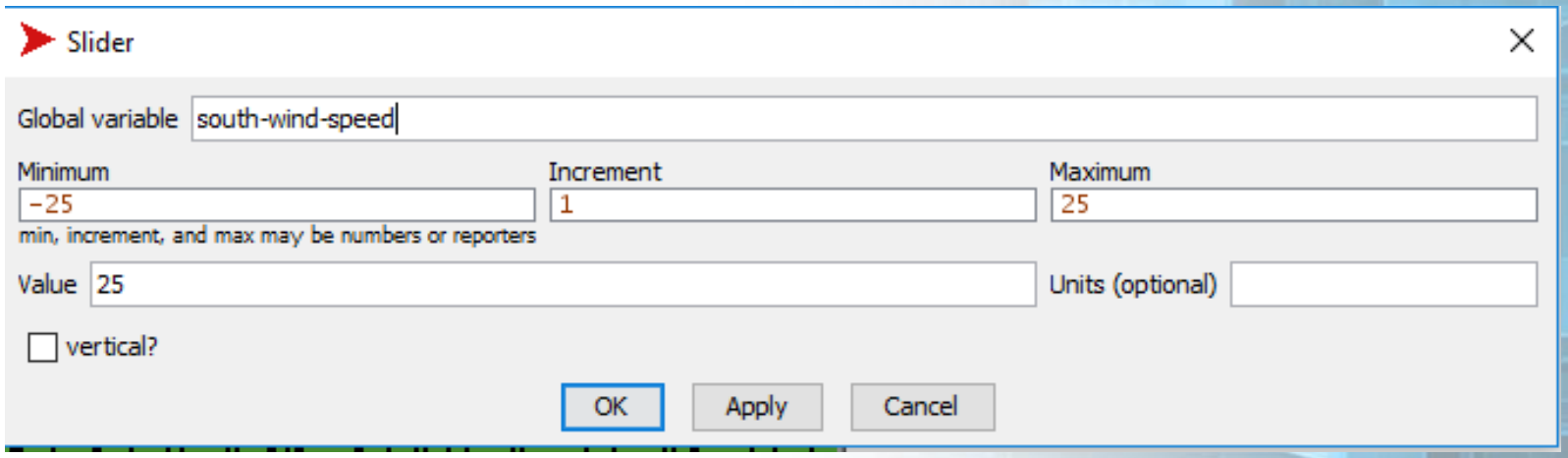
Understanding the Code

- Essentially, what it does is modify the probability of spread, increasing it in the direction of the wind and decreasing it in the opposite direction

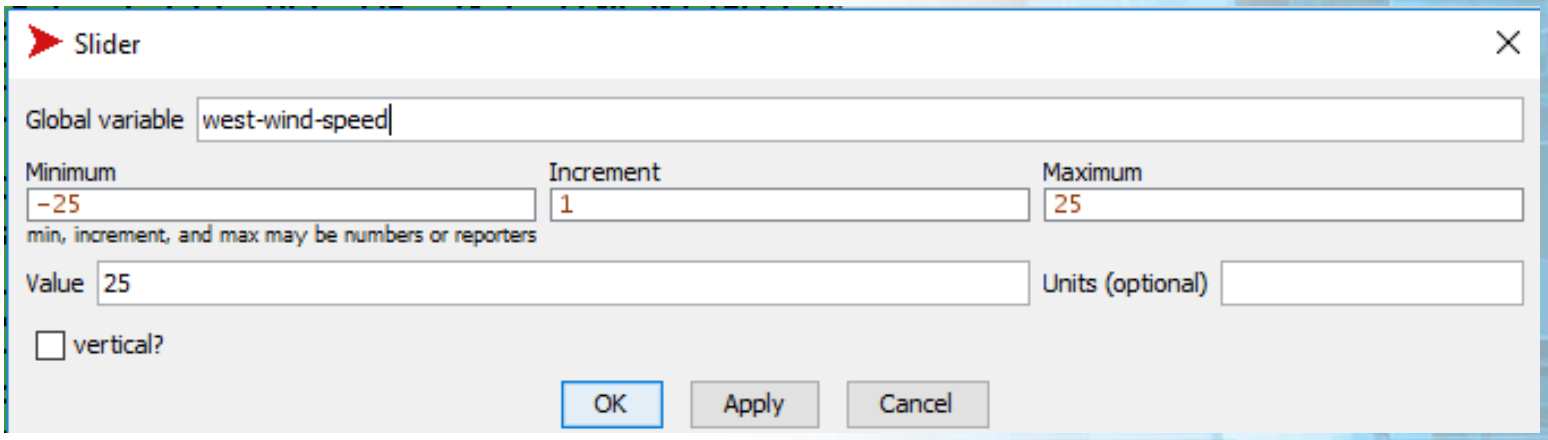
New UI


density
82 %
setup
go
percent burned
0.5
probability-of-spread
57 %
south-wind-speed
25
west-wind-speed
25

Understanding the Code



Understanding the Code



Second Extension

- Also, wind will have little effect on fire spread that occurs perpendicular to the direction of its movement
- Of course, this too is an oversimplification — there are often local effects of wind, such as turbulence
- However, all models are simplifications anyways

Second Extension

- Also, wind will have little effect on fire spread that occurs perpendicular to the direction of its movement
- Of course, this too is an oversimplification — there are often local effects of wind, such as turbulence
- However, all models are simplifications anyways

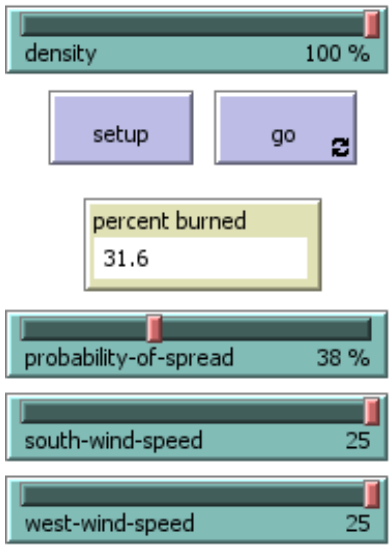
Interesting Results

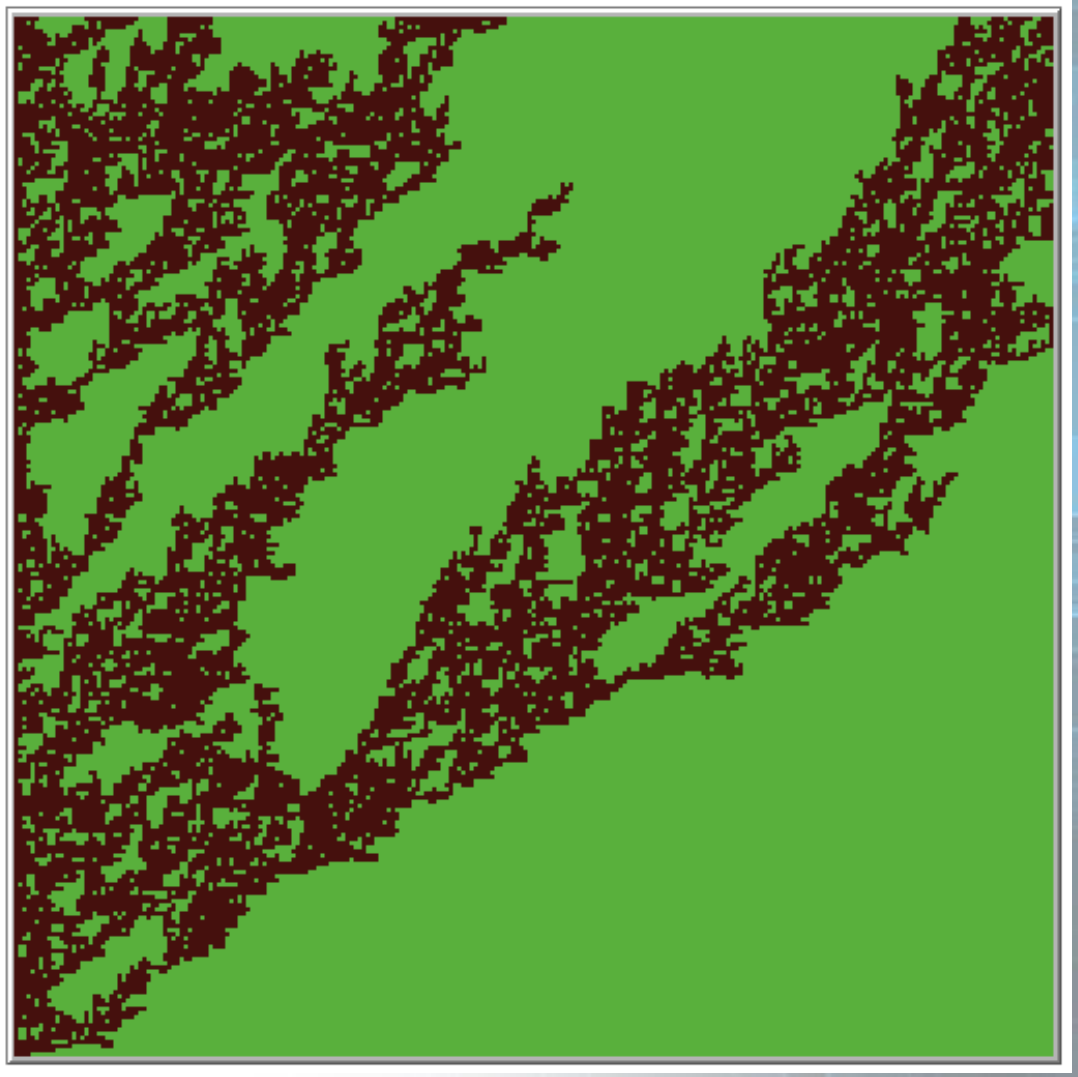
- This modification can lead to quite interesting patterns of spread.
- For example, set the density at 100 percent, and make the wind blow strong from the south and west.
- At the same time, set the PROBABILITY-OF-SPREAD fairly low, say around 38 percent.

Interesting Results

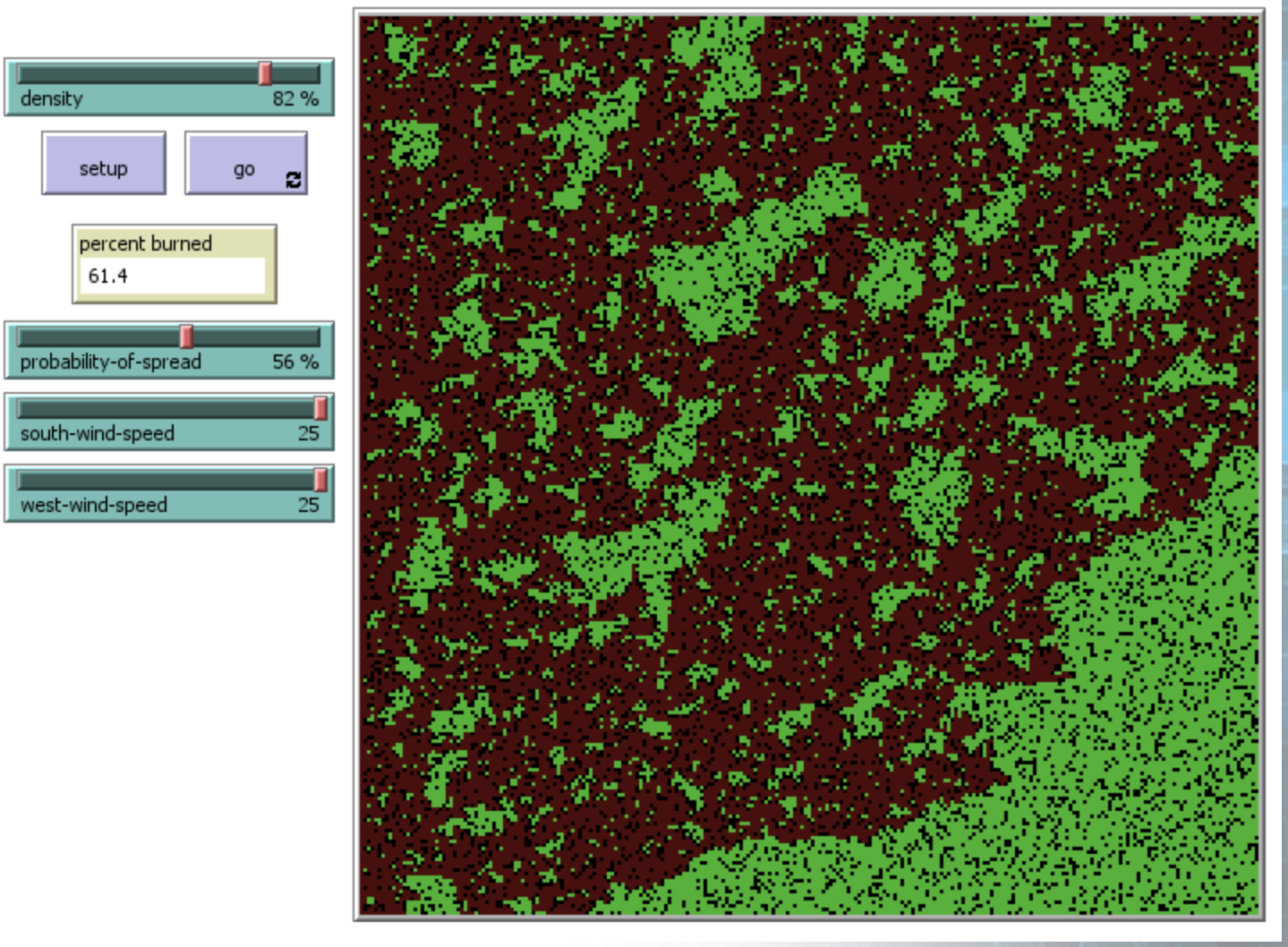
- This creates a triangular spread, and, all else being equal, the fire should spread to the northeast.

Interesting Results





Interesting Results



Summary

- We have a examined how we can make intelligent changes in a model
- This helps us predict and replicate complex phenomena in the real world

END

Modeling & Simulation

Third Extension:
Allow Long-Distance Transmission

Overview

- Make changes to add support for long jumps
- Understand how Exploratory Agent-based Modeling (EABM) works

Exploratory Agent-basd Modeling

- Cognitive Agent-based Computing Framework by Niazi and Hussain presents detailed instructions on how to build Agent-based Models
- One of the key techniques in developing standard models is to build models and gradually improve them over time

Third Extension

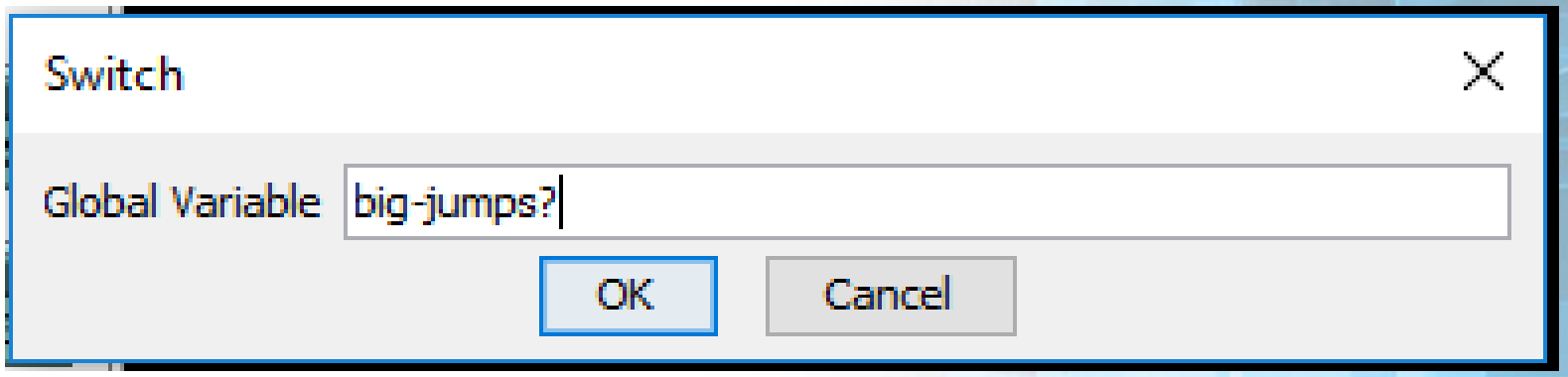
- . We add a Boolean (TRUE or FALSE) switch labeled BIG-JUMPS?
- Switches in NetLogo provide a way to have direct control over variables that can only be true or false.

Third Extension

- One way to model fire jumping due to wind would be to ignite a new fire at some distance in the direction of the wind.

Third Extension

Third Extension Code

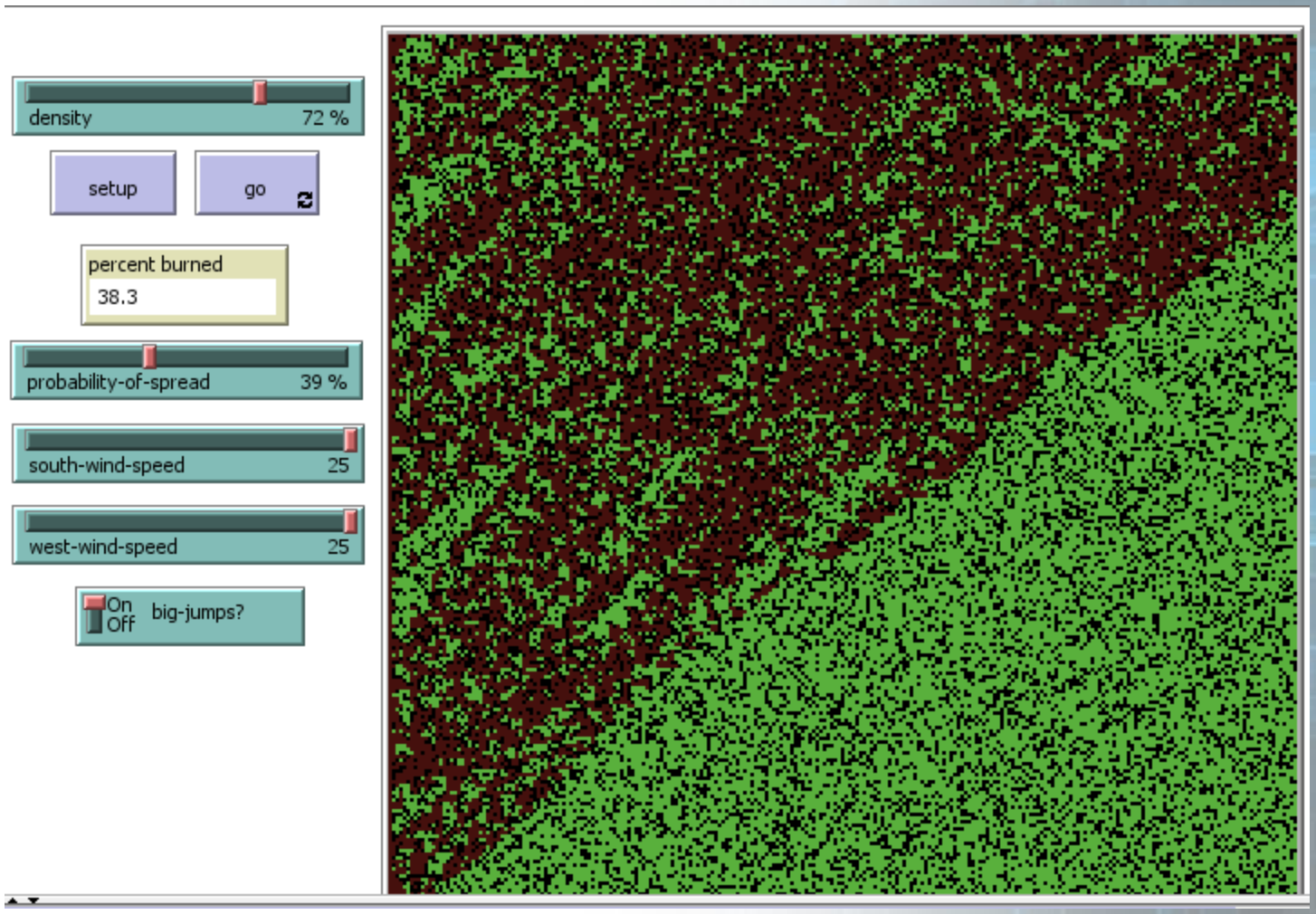


Understanding the Code

- **Here we see the major changes in the code**

```
if random 100 < probability [
  set pcolor red ;; to catch on fire
  ;; if big jumps is on, then sparks can fly farther
  if big-jumps? [
    let target patch-at (west-wind-speed / 5) (south-wind-speed / 5)
    if target != nobody and [ pcolor ] of target = green [
      ask target [
        set pcolor red ;; to ignite the target patch
      ]
    ]
  ]
```

Effects of jumps



Fire Model: Summary

- We have seen how EABM can be used to develop and extend a model
- There are three different changes
- Each adds something interesting

Fire Model: Summary

- The final change to the model points out that the measure we were observing (whether or not the fire made it to the right edge of the world) might not even be the measure we want to observe.

Fire Model: Summary

- As we change the fire spread mechanisms, other
- measures such as “ percent burned ”
- These may become more important. may or may not have tipping points.

Fire Model: Summary

- This illustrates an important feature of tipping points.
- They are defined by an input and an output measure.
- A model does not have a tipping point in and of itself — the tipping point is relative to the choice of inputs and output
- measures.

Summary

- We have a learnt about another extension of the fire model
- We have seen how EABM can be used to extend models
- We have developed a basic understanding of modeling complex phenomena in the real world

END

The Diffusion-Limited Aggregation (DLA) Model

Overview

- Understand the The Diffusion-Limited Aggregation (DLA) Model

DLA Model

- As demonstrated with the Fire Simple model, it is possible to think about inanimate objects (such as trees) as agents.
- We can reconceptualize atoms and molecules as agents, and then developing procedural rules to describe how these agents interact.

DLA Model

- In many physical processes from the creation of clouds, to snowflakes, to soot, smoke, and dust, particles aggregate in interesting ways

DLA Model

DLA Model

- Diffusion-limited aggregation (DLA) is an idealization of this process,
- It was first examined as a computational model in the early eighties (Witten & Sander, 1981 , 1983).

DLA Model

- DLA models were able to generate patterns that resemble many found in nature
- These include crystals, coral, fungi, lightning, and growth of human lungs, as well as social patterns such as growth of cities (Garcia-Ruiz et al., 1993; Bentley & Humphreys, 1962; Batty & Longley, 1994).

DLA Model

- This model starts with a large number of red particle agents and one green patch in the center.
- The green patch at the center of the screen is stationary

DLA Model

- When we press GO, all of the red particles move randomly by “ wiggling ” left and right (resulting in a small random turn)
- Each also moves forward one step.

DLA Model

- After a particle moves, if any of its neighbors (i.e., nearby patches) are green, the particle dies, turning the patch it is on green
- The particle can do so because all turtles have direct access to the variables of the patch they are on.

DLA Model

- If you let the model run long enough, you will get an interesting fractal-like pattern forming from the green patches

NetLogo Model Simulation

- Simulation

NetLogo Model

```
to setup
  clear-all
  ;; start with one green "seed" patch at the center of the world
  ask patch 0 0 [
    set pcolor green
  ]
  create-turtles num-particles [
    set color red
    set size 1.5 ;; easier to see
    setxy random-xcor random-ycor
  ]
  reset-ticks
end
```

NetLogo Model

```
to go
  ask turtles [
    ;; turn a random amount right and left
    right random wiggle-angle
    left random wiggle-angle
    forward 1
    ;; if you are touching a green patch
    if any? neighbors with [ pcolor = green ] [
      set pcolor green ;; turn your own patch green
      die ;; and then die
    ]
  ]
  tick
end
```

Summary

- We have a learnt about the NetLogo DLA Model
- We have also developed further understanding of modeling complex phenomena in the real world

END

First Extension: Probabilistic Sticking

Overview

- We apply Exploratory Agent-based Modeling to extend the DLA model

DLA Model

- The DLA Simple model has very simple rules.
- The code consists of only two procedures
- Both of them are very small, yet these two procedures can generate many interesting results.

DLA Model

- After you run the model for a while, you will realize that it always produces thin and
- wispy types of structures.
- Often the “ stems ” and “ trunks ” of the structures are only a single patch wide.

DLA Model

- This is because as soon as a particle touches anything green it will stop moving.
- It is much more likely that it will touch something toward the edge of the structure rather than near the interior of the structure.

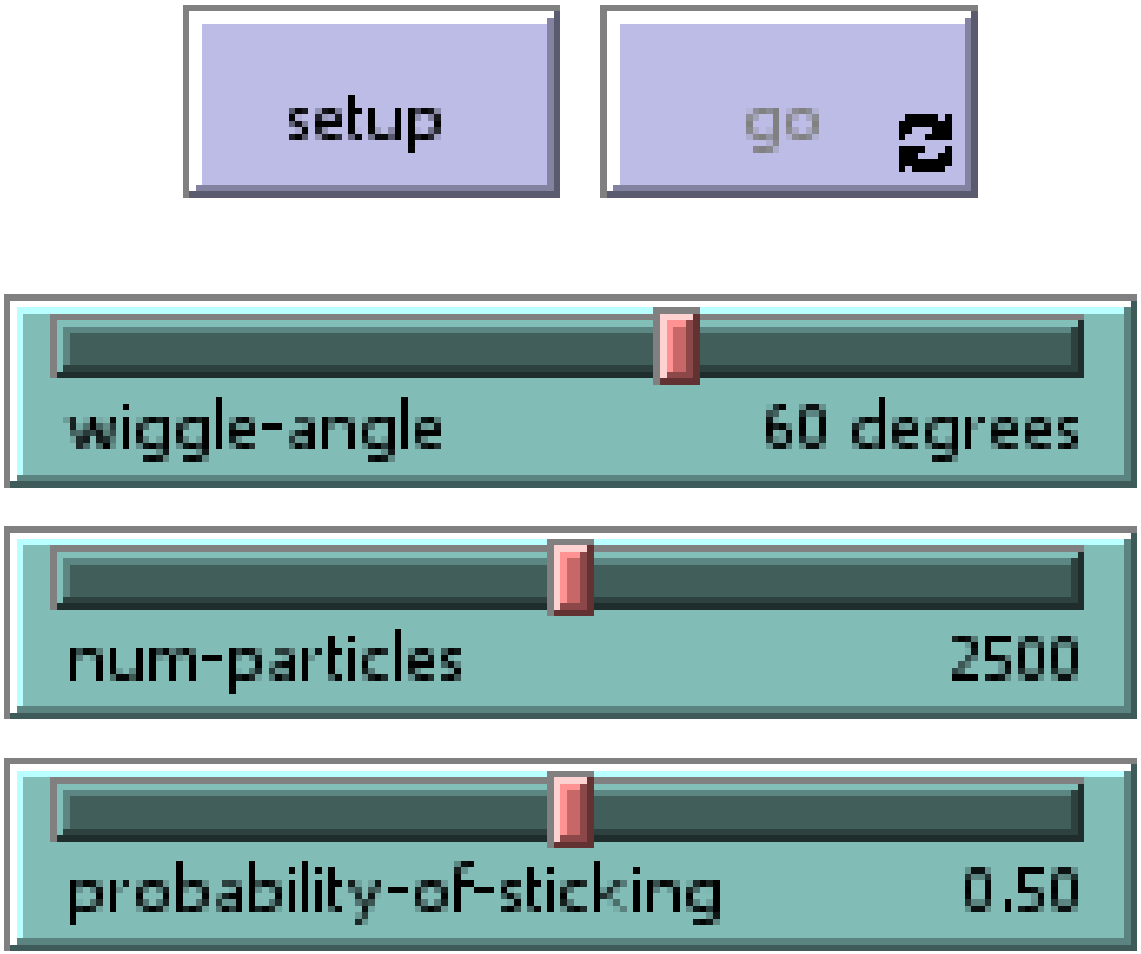
DLA Model

- However, we can change this.
- One way to think of this system is that if a particle comes into contact with a stationary object, then it becomes stationary itself with 100 percent probability.

DLA Extension

- What if we decrease this probability?
- That is exactly what we will do in this extension.
- We will allow the user to control the probability of a particle becoming stationary.

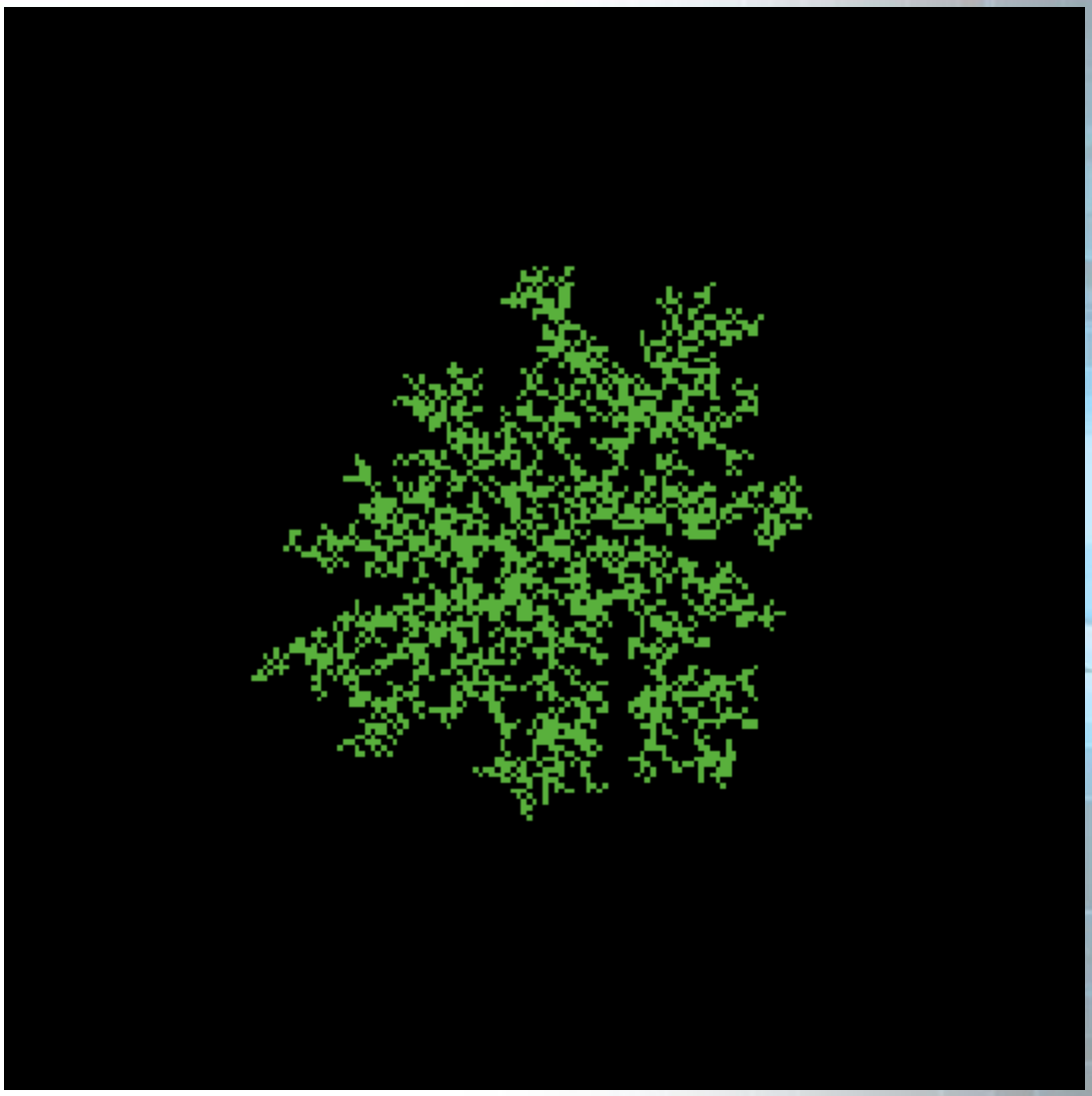
DLA Extension



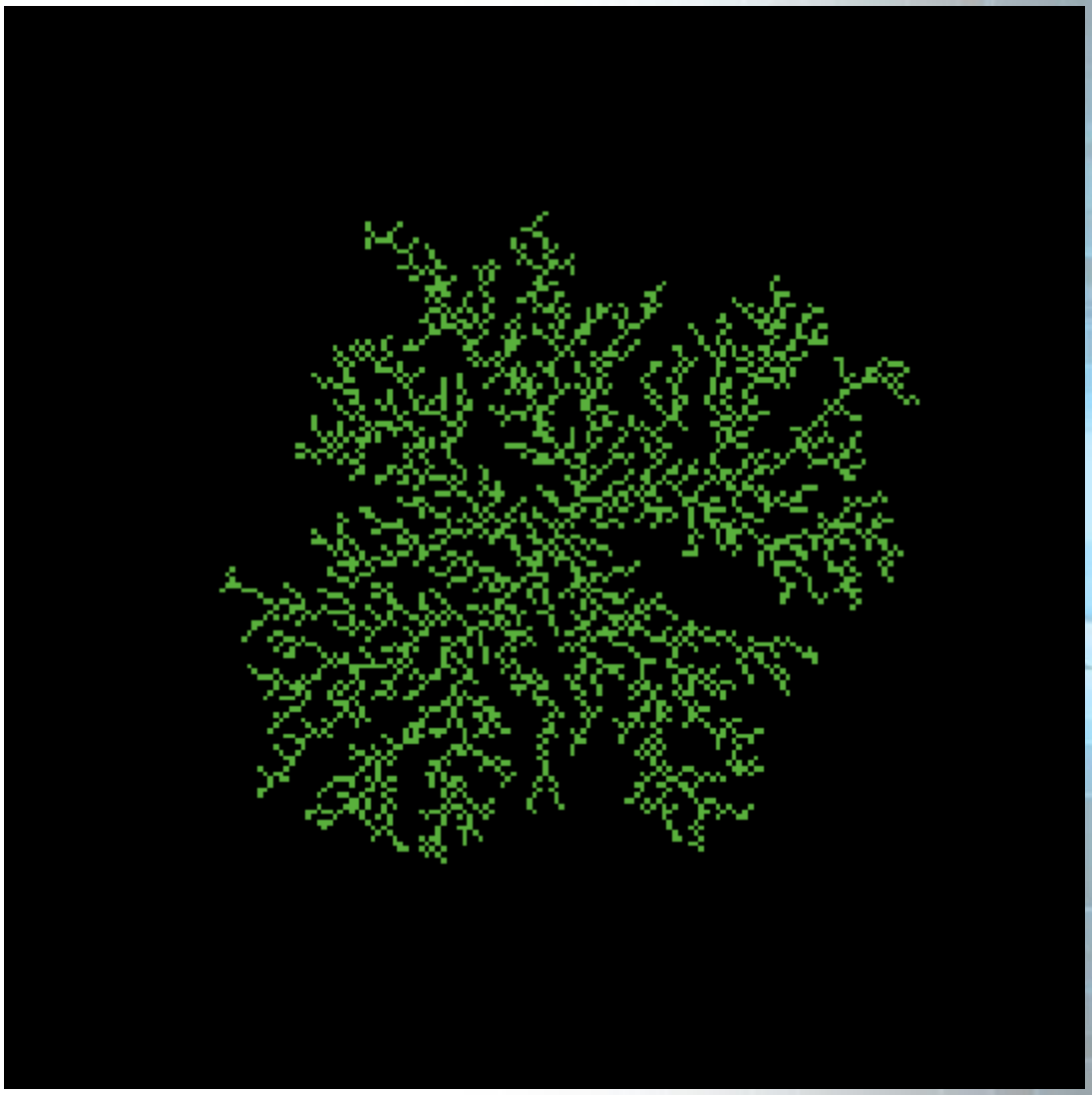
DLA Extension

```
to go
  ask turtles [
    ;; turn a random amount right and left
    right random wiggle-angle
    left random wiggle-angle
    forward 1
    if any? neighbors with [ pcolor = green ]
      and pcolor = black
      and random-float 1.0 < probability-of-sticking [
      set pcolor green
      die
    ]
  ]
  tick
end
```

DLA Extension



DLA Extension: Original Replication



Summary

- We have seen how EABM can be used to extend the original DLA model
- Credits: Uri Wilensky book

END

Second Extension: Neighbor Influence

Overview

- We apply Exploratory Agent-based Modeling to extend the DLA model further by adding the influence of neighbors

DLA Extension

- One commonly explored extension to the DLA model is to explore how the probability of sticking is related to the number of neighbors that are already stationary (the green patches) (Witten & Sander, 1983).

DLA Extension

- If a particle is moving, it is more likely that it will stick somewhere if two or three of its neighbors are at rest than if just one of its neighbors is at rest.

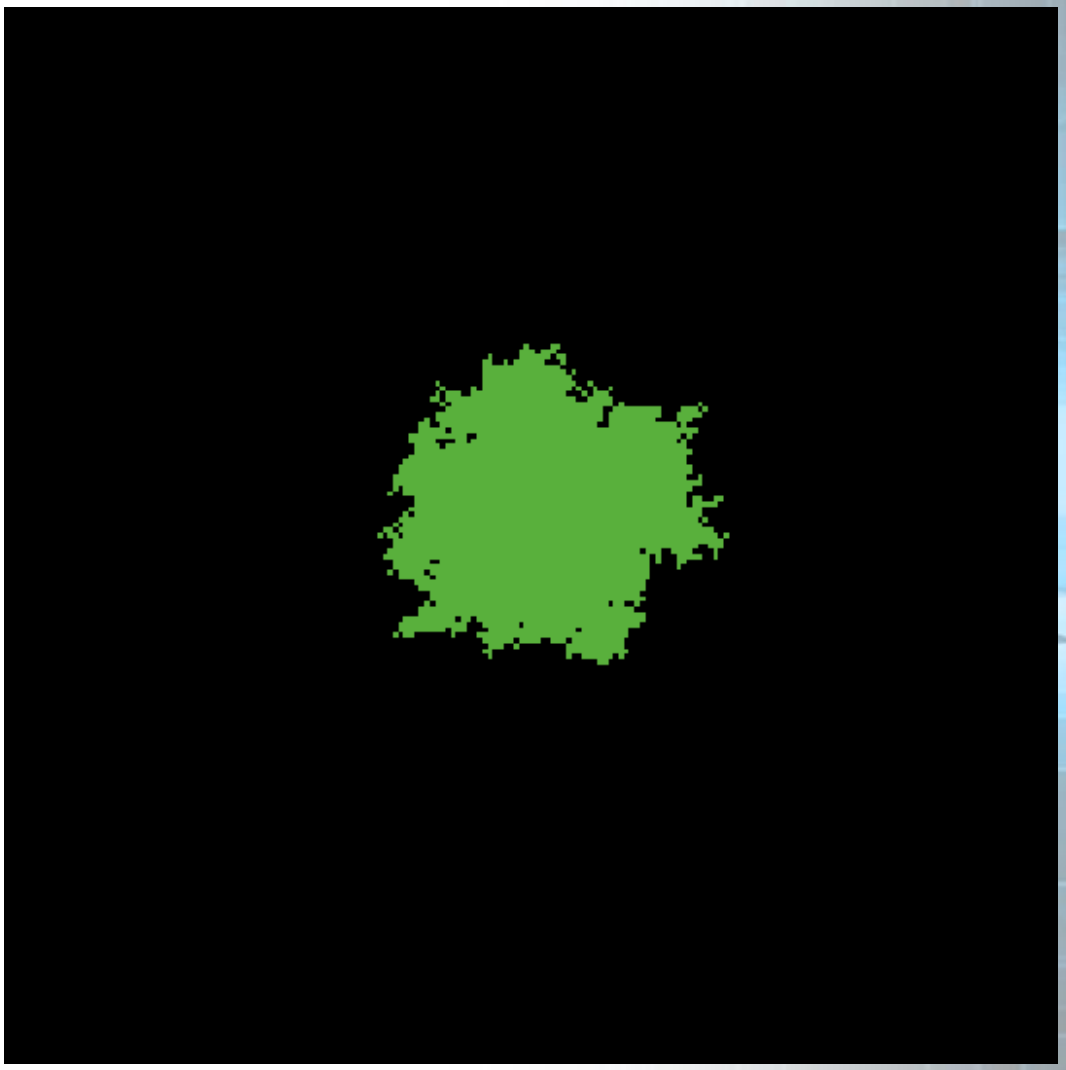
DLA Extension

- **This can be done by first adding a switch NEIGHBOR-INFLUENCE?**

DLA Extension

```
to go
  ask turtles [
    right random wiggle-angle
    left random wiggle-angle
    forward 1
    ;; if neighbor-influence is TRUE then make the probability proportionate
    ;; to the number of green neighbors, otherwise use the slider as before
    let local-prob probability-of-sticking
    if neighbor-influence? [
      ;; increase the probability of sticking the more green neighbors there are
      set local-prob probability-of-sticking * (count neighbors with [ pcolor = green ] / 8)
    ]
    if any? neighbors with [ pcolor = green ]
      and pcolor = black
      and random-float 1.0 < local-prob [
      set pcolor green
      die
    ]
  ]
  tick
end
```

DLA Extension



Simulation Results

- When we run the model with this change in the code, we notice
- (1) that it takes much longer to form a structure because there is a much lower probability of a mobile particle stopping,

Simulation Results

- (2) the structures that emerge are very thick and almost bloblike.
- In addition there are many fewer one patch-wide branches, because the probability of stopping when in contact with only one other stationary patch is very small.

Summary

- We have seen how EABM can be used to further extend the original DLA model
- Credits: Uri Wilensky book

END

Third Extension: Different Aggregates

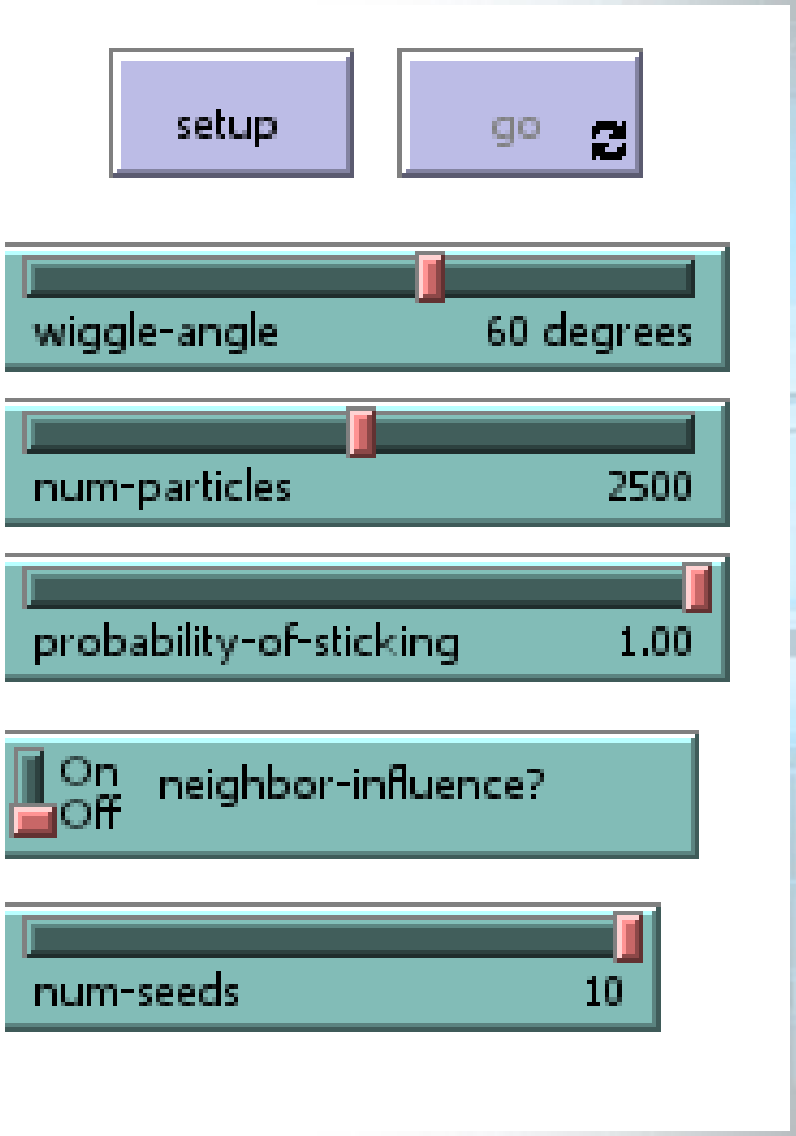
Overview

- We now apply Exploratory Agent-based Modeling to extend the DLA model further by adding the capability of different aggregates

DLA Extension 3

- The previous two extensions have concentrated on deciding how a particle should stop when it is moving
- There is another way that we can control how a particle stops.
- We can simply give it more places to stop at the beginning.

DLA Extension 3



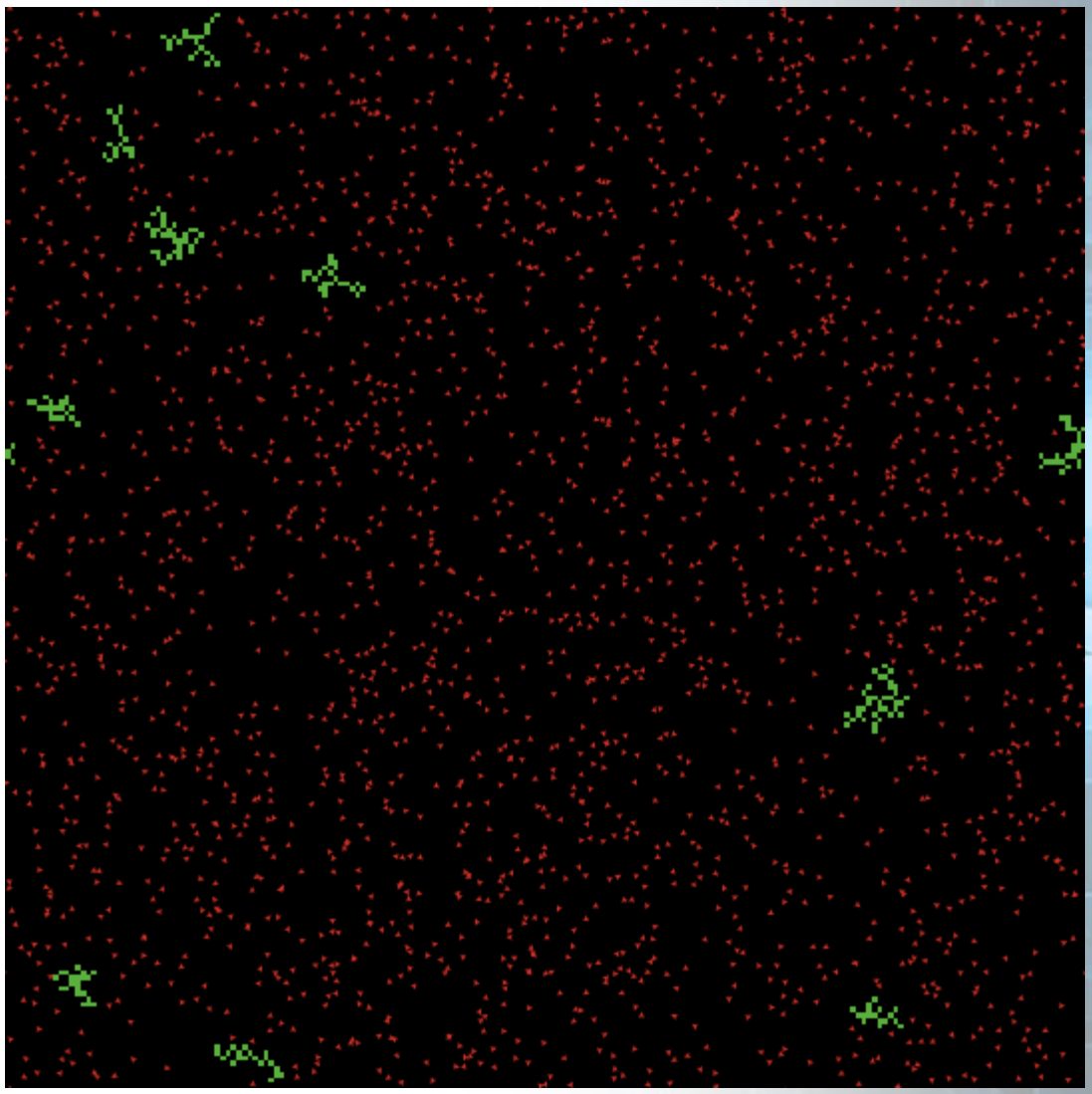
DLA Extension 3

```
to setup
  clear-all
  ;; start with NUM-SEEDS green patches as “seeds”
  ask n-of num-seeds patches [
    set pcolor green
  ]
  create-turtles num-particles [
    set color red
    set size 1.5 ;; easier to see
    setxy random-xcor random-ycor
  ]
  reset-ticks
end
```

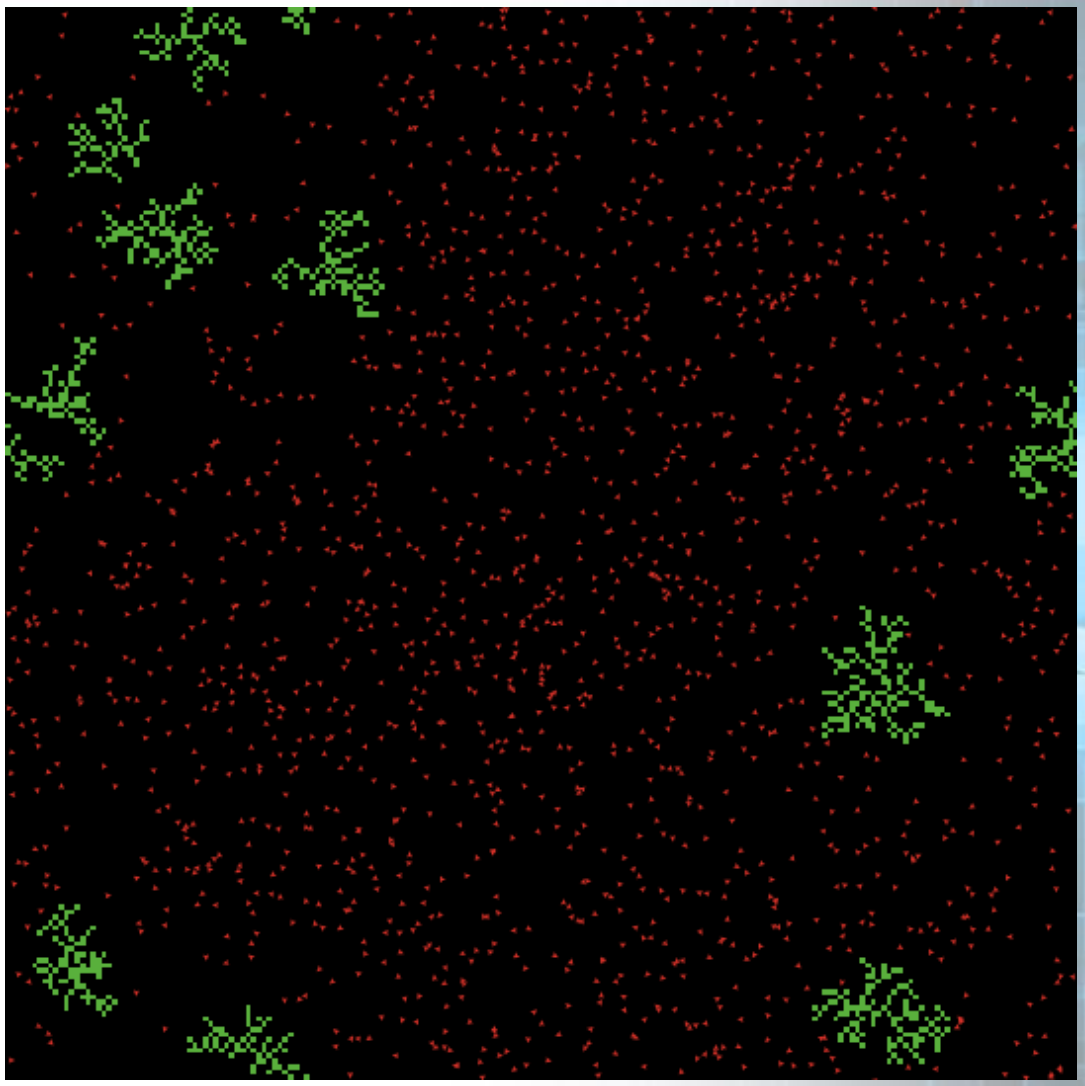
Simulation Results

- When we run the model with this change in the code, we notice multiple seeds
- However, it does not replicate the original results
- The seed may not be at the center

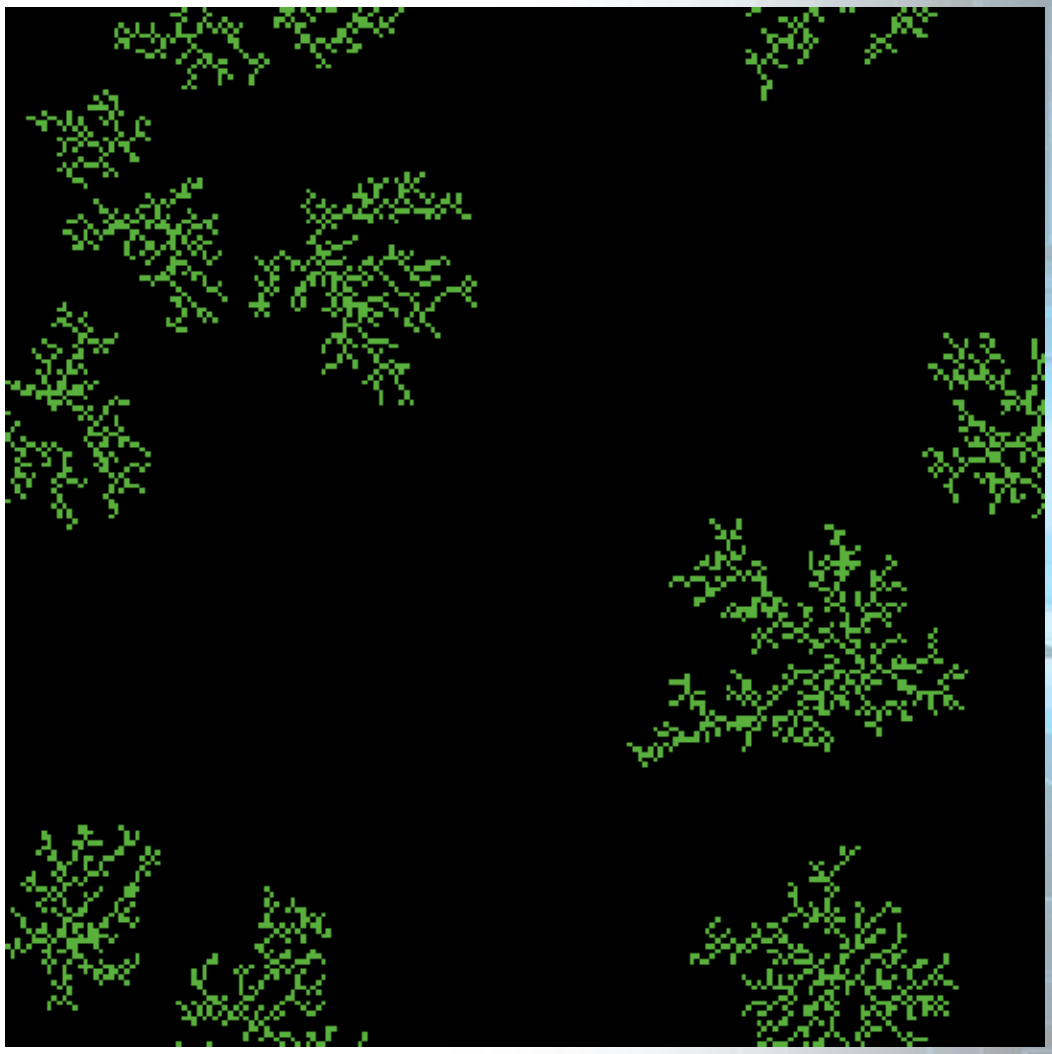
Simulation Results



Simulation Results



Simulation Results



Summary

- We have seen how EABM can be used to further extend the original DLA model by adding the option of multiple seeds
- Credits: Uri Wilensky book

END

Segregation Model

Overview

- Here, we understand the basics of the so-called "Segregation" model

Fundamental Approaches to ABM

- There are two fundamental approaches to starting to build an agent-based model.
- The first approach, more common in science contexts, is to start with a known phenomenon to be modeled.

Fundamental Approaches to ABM

- This approach is called phenomena-based modeling.
- Typically phenomena-based modeling is linked with an aggregate pattern, termed a reference

Fundamental Approaches to ABM

- Another way to begin is to start with some simple rules and play them out to see what patterns develop.
- This approach is sometimes referred to as exploratory modeling

Fundamental Approaches to ABM

- Both ways can be classified under Exploratory agent-based modeling (EABM).
- EABM with Standard Reference
- EABM with Pure Exploration
- Often times a combination of these is used

Schelling Model

- Thomas Schelling took a more exploratory modeling approach with his Neighborhood Tipping model (1971).

Schelling Model

- Schelling wondered what would happen if you
- assume that everyone in the world wanted to live in a place where at least a reasonable fraction of their neighbors were like themselves,

Schelling Model

- i.e., they have an aversion to being an
- extreme minority (which he called weakly prejudiced; see Anas, 2002).

Schelling Model

- He explored this model using a checkerboard as a grid,
- Pennies to represent one race and dimes to represent another.
- He counted by hand the number of pennies surrounding each dime and divide by the number of neighbors surrounding that dime.

Schelling Model

- If this value exceeded a certain threshold value, he would move the dime to a random empty location on the board.
- He repeated this process hundreds of times and observed the outcome.

Summary

- We have seen how EABM can be used to develop Agent-based Models
- We have looked at the basis of Schelling's work
- Credits: Uri Wilensky book

END

Description of the Segregation Model-I

Overview

- Here, we understand the details of the so-called "Segregation" model

Schelling Model

- What surprised Schelling about this was that even at low levels of the threshold, he would still see groups of pennies and groups of dimes together in dense clusters.

Schelling Model

- This global segregation occurred despite the relative tolerance of each individual.

Schelling Model

- There was no single individual in the Schelling model who wanted a segregated neighborhood, but the group as a whole moved toward segregation.
- Schelling described this as “ macrobehavior ” derived from “ micromotives ” (1978).

Schelling Model

- At the time when Schelling introduced this model, it was very controversial for several reasons.
- First, it was widely believed at the time that housing segregation was caused by individuals being prejudiced.

Schelling Model

- Schelling ’ s work seemed to be “ excusing ” people from prejudice, saying that prejudice itself is not the cause of segregation.
- The cause of segregation is an emergent effect of the aggregation of people’s weak prejudice.

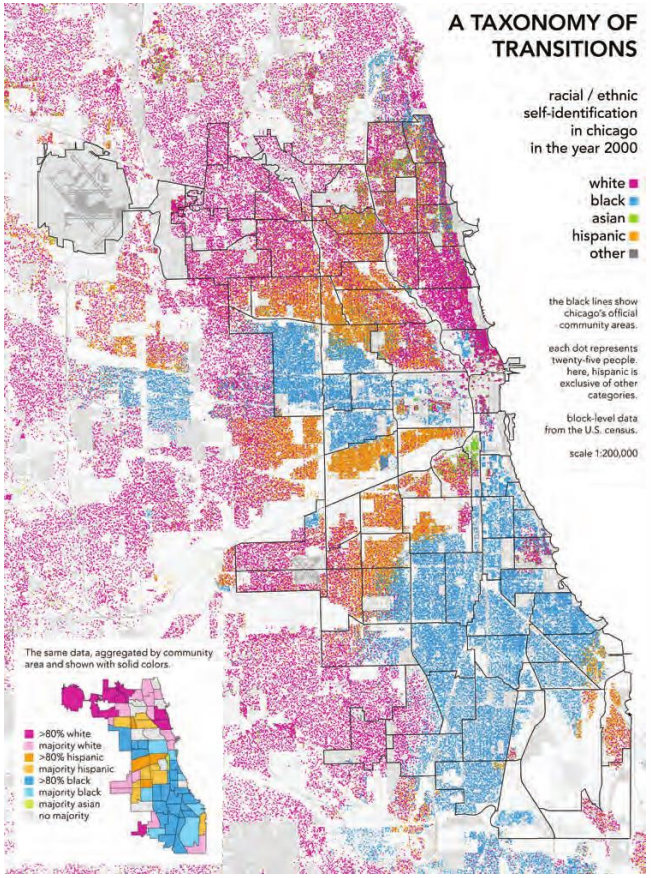
Schelling Model

- But Schelling ’ s point was not to excuse people for their prejudice, his model demonstrates that prejudice is not a “ leverage point ” of the housing system.

Schelling Model

- Another controversial aspect of Schelling ’ s model is that it modeled the people as behaving with very simple rules.
- Critics argued that “ people are not ants ” ;

Schelling Model



- A map of Chicago with each dot representing twenty-five people.
- By representing the data at this finer level than traditional maps that aggregate demographics are mapped at a high level, Rankin illustrates nuances of segregation much like ABM enables us to explore nuances of individual-level behavior.

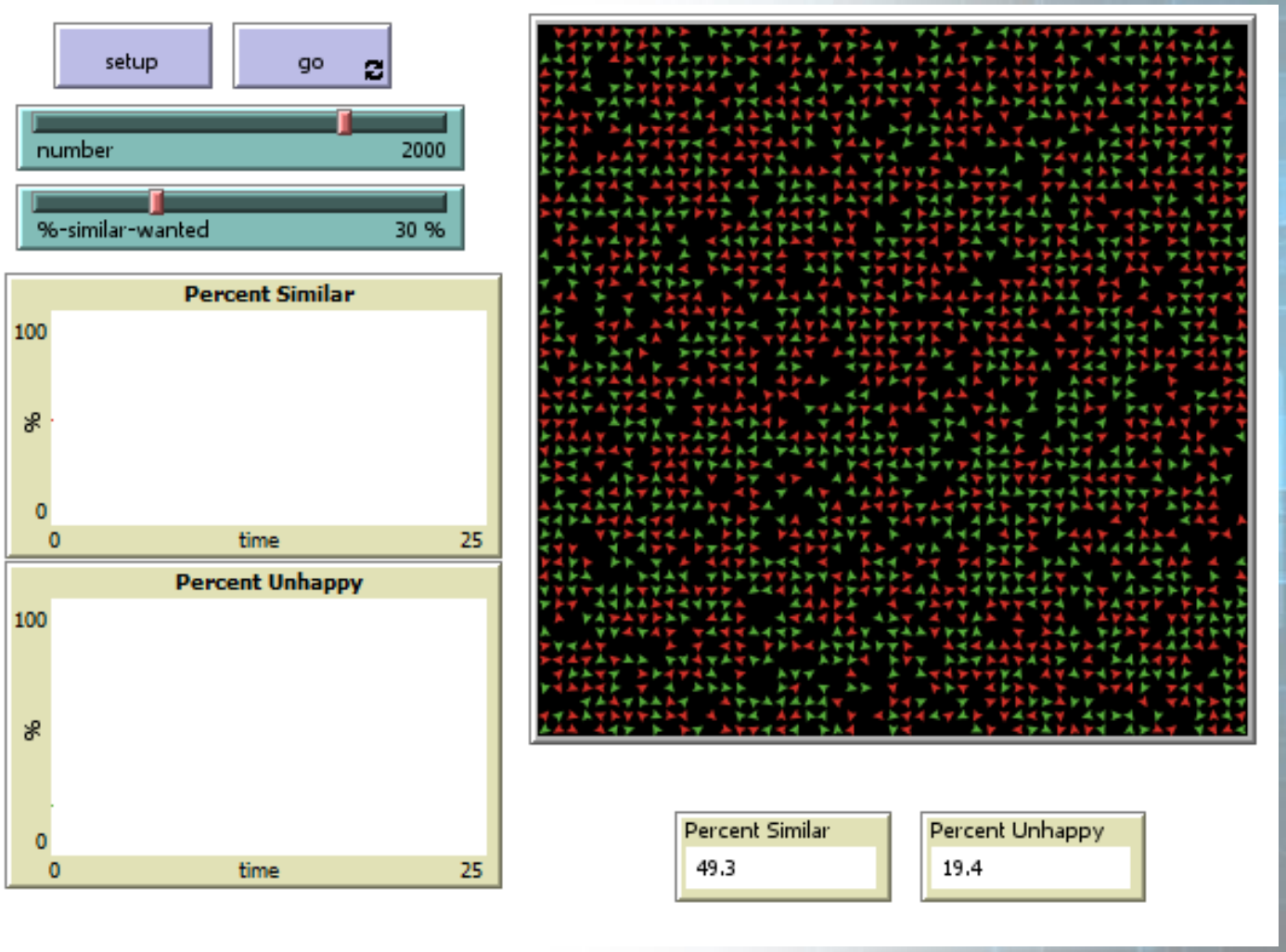
Schelling Model

- Schelling was awarded the Nobel Prize in economics in 2005.
- To this day, it remains controversial how much of human behavior can be modeled with simple rules.

Schelling Model

- Schelling was awarded the Nobel Prize in economics in 2005.
- To this day, it remains controversial how much of human behavior can be modeled with simple rules.

Schelling Model



Summary

- We have seen the details of Schelling Model
- Credits: Uri Wilensky book

END

Description of the Segregation Model-II

Overview

- Here, we understand the details of the so-called "Segregation" model

Schelling Model

```
globals [
  percent-similar  ;; on the average, what percent of a turtle's neighbors
                   ;; are the same color as that turtle?
  percent-unhappy  ;; what percent of the turtles are unhappy?
]
```

Schelling Model

```
turtles-own [
  happy?          ;; for each turtle, indicates whether at least %-similar-wanted percent of
                  ;; that turtle's neighbors are the same color as the turtle
  similar-nearby  ;; how many neighboring patches have a turtle with my color?
  total-nearby    ;; sum of previous two variables
]
```

Schelling Model

```
to setup
  clear-all
  ;; create a turtle on NUMBER randomly selected patches.
  ;; note that slider's maximum value is 2500 which is a
  ;;little less than the total number of patches
  ask n-of number patches [
    sprout 1
  ]
  ask turtles [
    ;; make approximately half the turtles red and the
    ;;other half green
    set color one-of [ red green ]
  ]
  update-turtles
  update-globals
  reset-ticks
end
```

Summary

- We have seen the details of Schelling Model
- Credits: Uri Wilensky book

END

Simulation of the Segregation Model

Overview

- Here, we understand the simulation of the so-called “Segregation” model

Schelling Model

```
to go
  if all? turtles [ happy? ] [ stop ]
  move-unhappy-turtles
  update-turtles
  update-globals
  tick
end

to move-unhappy-turtles
  ask turtles with [ not happy? ]
    [ find-new-spot ]
end

to find-new-spot
  rt random-float 360
  fd random-float 10
  if any? other turtles-here
    [ find-new-spot ]          ;; keep going until we find an unoccupied patch
  setxy pxcor pycor  ;; move to center of patch
end
```

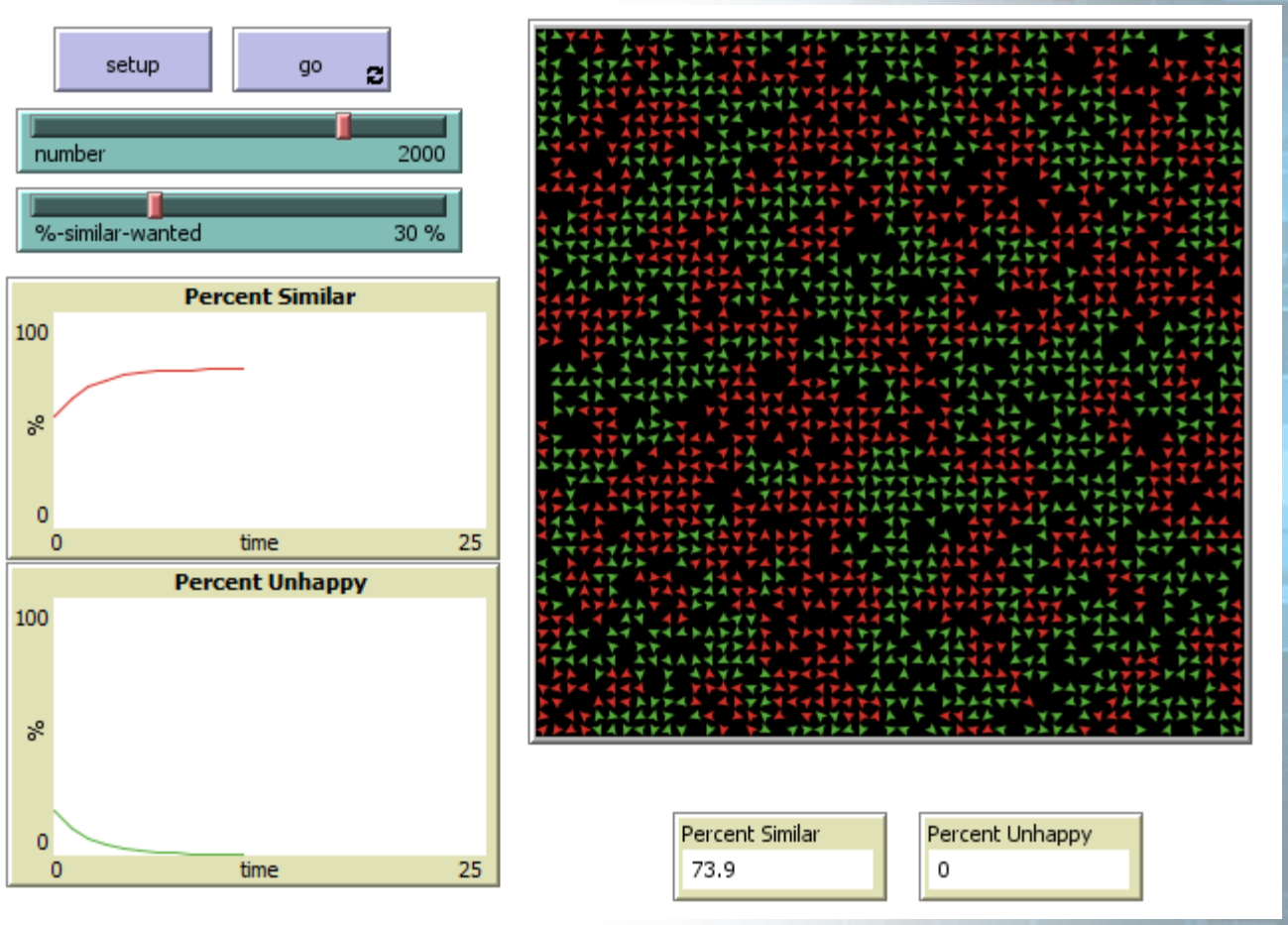
Schelling Model

```
to setup
  clear-all
  ;; create a turtle on NUMBER randomly selected patches.
  ;; note that slider's maximum value is 2500 which is a
  ;;little less than the total number of patches
  ask n-of number patches [
    sprout 1
  ]
  ask turtles [
    ;; make approximately half the turtles red and the
    ;;other half green
    set color one-of [ red green ]
  ]
  update-turtles
  update-globals
  reset-ticks
end
```

Schelling Model

```
to update-turtles
  ask turtles [
    ;; in next two lines, we use "neighbors" to test the eight patches
    ;; surrounding the current patch

    ;; count the number of my neighbors that are the same color as me
    set similar-nearby count (turtles-on neighbors)
      with [color = [color] of myself]

    ;; count the total number of neighbors
    set total-nearby count (turtles-on neighbors)

    ;; I'm happy if there are at least the minimal number of same-colored neighbors
    set happy? similar-nearby >= ( %-similar-wanted * total-nearby / 100 )
  ]
end

to update-globals
  let similar-neighbors sum [similar-nearby] of turtles
  let total-neighbors sum [total-nearby] of turtles
  set percent-similar (similar-neighbors / total-neighbors) * 100
  set percent-unhappy (count turtles with [not happy?]) / (count turtles) * 100
end
```

Schelling Model



Summary

- We have seen the details of Schelling Model
- Credits: Uri Wilensky book

END

First Extension: Adding Multiple Ethnicities

Overview

- Here, we understand the extension to the "Segregation" model

Schelling Model

- One simple extension to this model is to add a third, fourth, and even fifth ethnicity.
- This can be done by modifying the SETUP code.

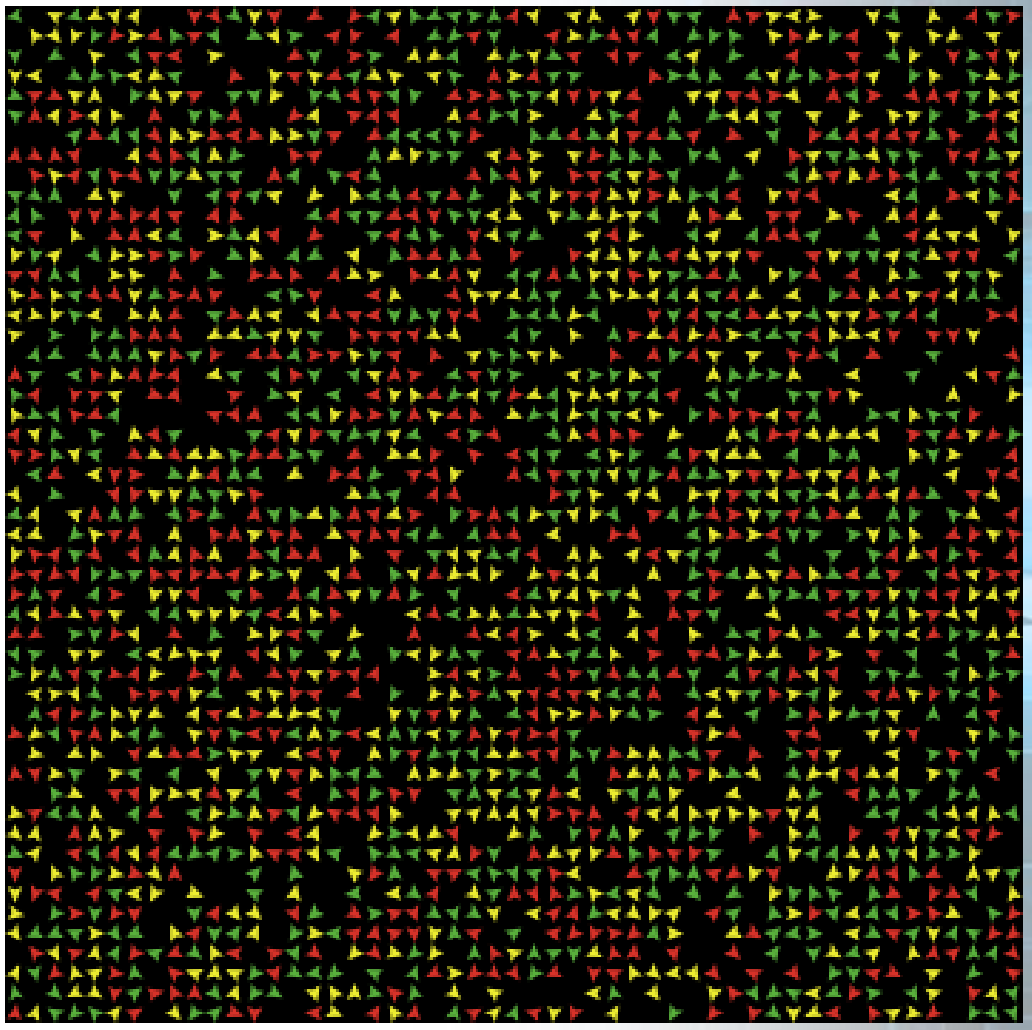
Schelling Model

```
globals [
percent-similar    ;; on average, what percent of a turtle's neighbors
                                                ;; are the same color as that turtle?
    percent-unhappy  ;; the percent of the turtles that are unhappy
    colors                                ;; a list of colors we use to color the turtles
]
```

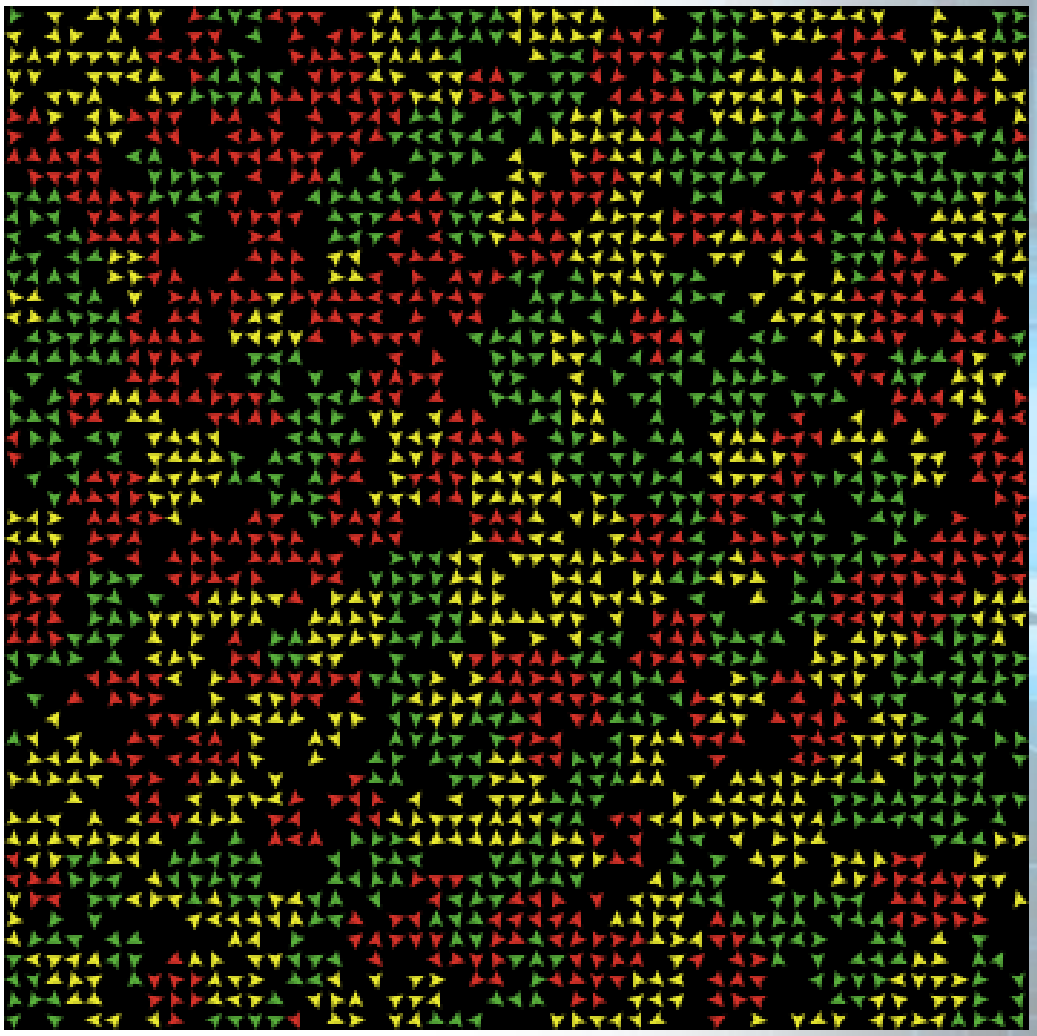
Schelling Model

```
to setup
  clear-all

  set colors [ red green yellow blue orange ]

  ;; create a turtle on NUMBER randomly selected patches.
  ;; note that slider's maximum value is 2500 which is a little less than the total number
  ask n-of number patches [
    sprout 1
  ]
  ;; assign a color to each turtle from our list of colors
  ask turtles [
    set color (item (random number-of-ethnicities) colors)
  ]

  update-turtles
  update-globals
  reset-ticks
end
```

Schelling Model



Schelling Model



Summary

- We have seen the details of Schelling Model
- Credits: Uri Wilensky book

END

Second Extension: Allowing Diverse Thresholds

Overview

- Here, we understand a further extension to the “Segregation” model

Schelling Model

- In the original version of Schelling ' s model, every agent in the world had exactly the same similarity threshold.
- This meant that every agent had the same level of tolerance for having other ethnicities in its neighborhood.

Schelling Model

- Although relaxing this assumption might have been difficult to enact with a checkerboard, it is straightforward to do using an ABM language.

Schelling Model

```
turtles-own [
  happy?                ;; for each turtle, indicates whether at least
  ;;%-similar-wanted percent of
                        ;; that turtle's neighbors are the same color as the turtle
  similar-nearby        ;; how many neighboring patches have a turtle with my color?
  total-nearby          ;; sum of previous two variables
  my-%-similar-wanted ;; the threshold for this particular turtle
]
```

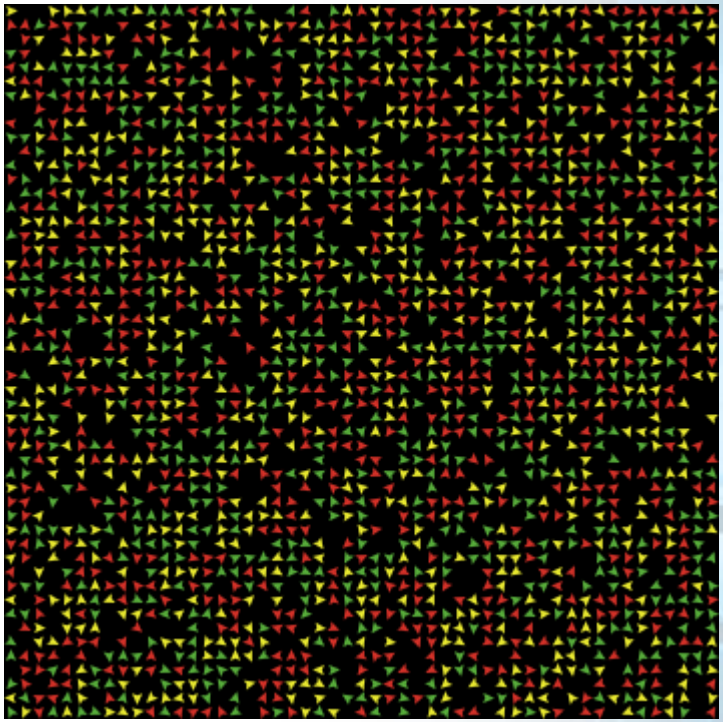
Schelling Model

```
;; assign a color to each turtle from the list of our colors
;; and assign an individual level of %-similar-wanted
ask turtles [
  set color (item (random number-of-ethnicities) colors)
  set my-%-similar-wanted random %-similar-wanted
]
```

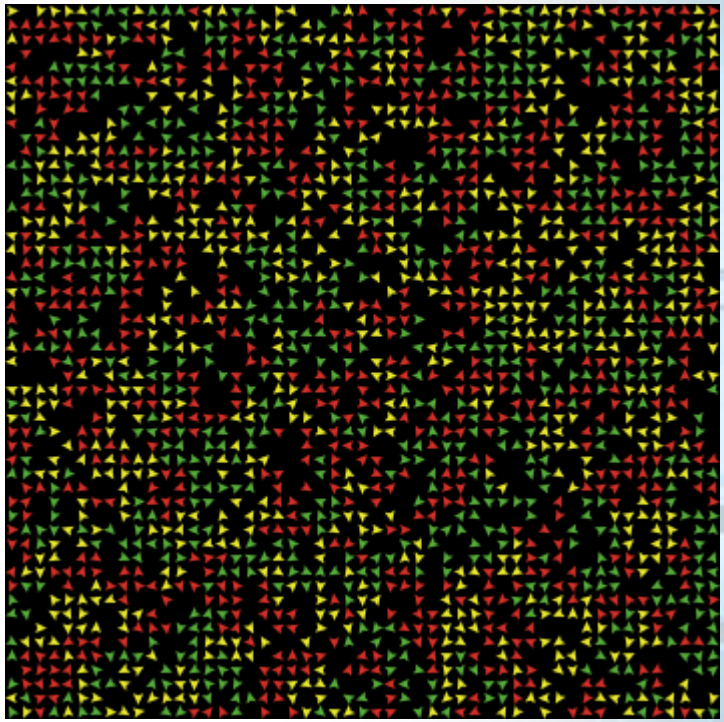
Schelling Model

```
;; I'm happy if there are at least the minimal number of same-colored neighbors
set happy? similar-nearby >= ( my-%-similar-wanted * total-nearby / 100 )
```

Schelling Model



Schelling Model



Summary

- We have seen another extension of Schelling Model
- Credits: Uri Wilensky book

END

Third Extension: Adding Diversity-Seeking Individuals

Overview

- Here, we understand an extension to allow for diversity-seeking individuals in the "Segregation" model

Schelling Model

- Another simplification that the original segregation model makes about the world is that individuals are concerned about too much diversity
- However no agents actively seek diversity in their neighborhoods

Schelling Model

- Although relaxing this assumption might have been difficult to enact with a checkerboard, it is straightforward to do using an ABM language.

Schelling Model

```
turtles-own [
  happy?                ;; for each turtle, indicates whether at least
  ;;%-similar-wanted percent of
                        ;; that turtle's neighbors are the same color as the turtle
  similar-nearby        ;; how many neighboring patches have a turtle with my color?
  total-nearby          ;; sum of previous two variables
  my-%-similar-wanted ;; the threshold for this particular turtle
]
```

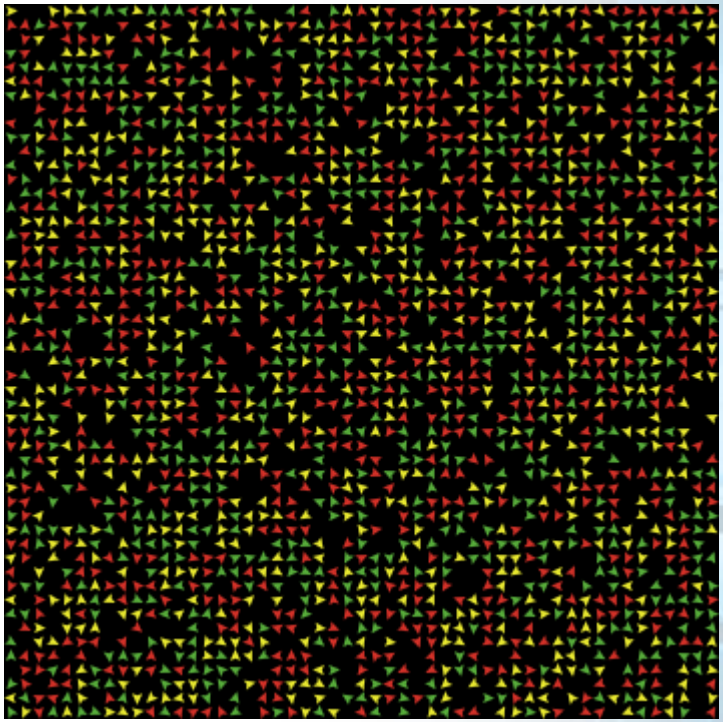
Schelling Model

```
;; assign a color to each turtle from the list of our colors
;; and assign an individual level of %-similar-wanted
ask turtles [
  set color (item (random number-of-ethnicities) colors)
  set my-%-similar-wanted random %-similar-wanted
]
```

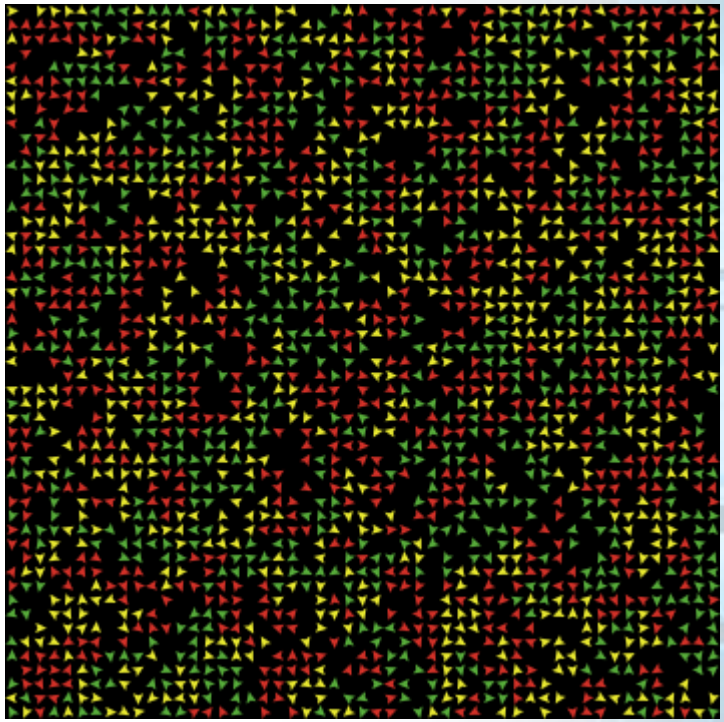
Schelling Model

```
;; I'm happy if there are at least the minimal number of same-colored neighbors
set happy? similar-nearby >= ( my-%-similar-wanted * total-nearby / 100 )
```

Schelling Model



Schelling Model



Summary

- We have seen another extension of Schelling Model
- Credits: Uri Wilensky book

END

Modeling and Simulation

Advanced Urban Modeling Applications

Overview

- **Here, we understand a Advanced Urban Modeling Applications**

Modeling Of Urban Landscapes.

- **Agent-based modeling has frequently been used for the modeling of urban landscapes.**

“ Residential Preference ”

- The Segregation model described earlier can be seen as one particular example of what are generally called
- “Residential Preference” models, which are a major component of urban modeling systems

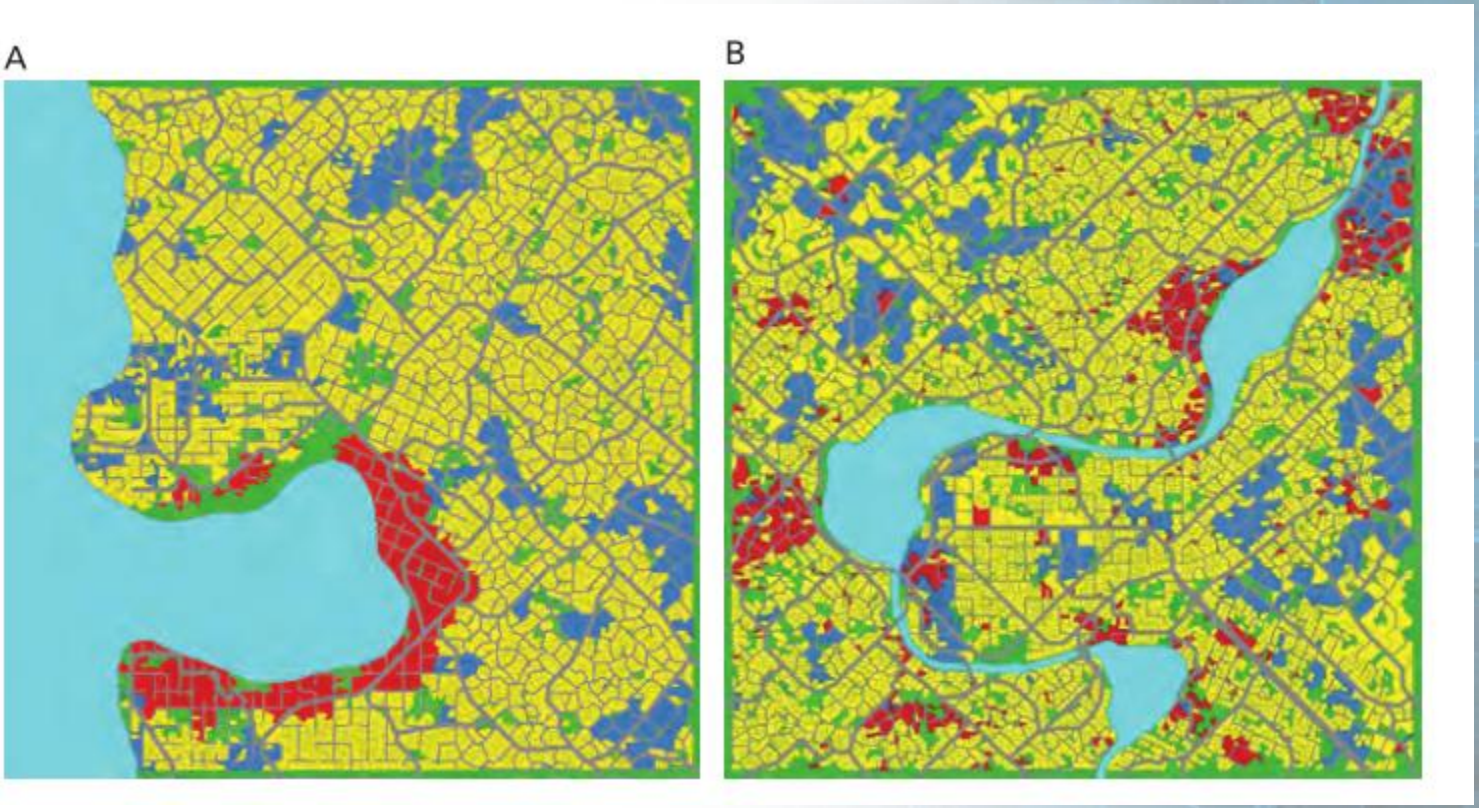
CITIES project

- These models can be combined with commercial, industrial, and governmental models of urban policy to create an integrated model of a city.
- One such example is the CITIES

CITIES project

- CITIES project carried out by the Center for Connected Learning and Computer-Based Modeling at Northwestern University
- The goal of the CITIES project was to procedurally develop realistic cities that could be used as tools in education and exploration

CITIES model in Net Logo (Lechner et al., 2006).



Goal Of Urban Modeling

- **Another goal of urban modeling is to explore the ecological impact of cities and their footprint on the environment.**

SLUCE Project

- The SLUCE project at the University of Michigan built several models of residential and tract development to explore land-use policies and their effect on the surrounding environs in southeastern Michigan (Brown et al., 2005 ; Rand et al., 2003).

Summary

- We have seen how Agent Based Modeling can be used for Advanced Urban Modeling Applications
- Credits: Uri Wilensky book

Modeling and Simulation

The El Farol Model

&

Description of the El Farol Model

Overview

- **Here, we understand *the El Farol model*, and we will add additional reporters to this model.**
- **In this way we can gain *new information from the model* that was not previously available.**

The El Farol Model

- The El Farol model uses “ lists ” and mathematical regression, but the modifications we will make to this model do not require knowledge of how these particular methods work

Description of the El Farol Model

- W. Brian Arthur was an Irish economist who, was a pioneer of using complexity methods in economics
- Arthur posed the El Farol Bar problem as an exploration of bounded rationality and inductive reasoning

" Optimal ” Equilibrium

- **Traditional neoclassical economics presupposes that humans are completely rational:**
  - **that is, they have *access to perfect information* and *maximize their utility in every situation***
- **When *each agent behaves* this way the aggregate can achieve an *optimal equilibrium***

El Farol Bar

- On Canyon Road in Santa Fe, New Mexico, there is a bar called the El Farol.
- This bar was popular with researchers from the Santa Fe Institute, including Arthur

El Farol Bar

- **One night each week, the El Farol had live Irish music, and Arthur enjoyed going on these nights, but occasionally it got crowded, and he did not enjoy it on those nights.**
  - ***Arthur wondered, how do people decide if they should go to the bar or not?***

Arthur's hypothesis

- Arthur hypothesized that one way to model this situation would be to give each agent a bag of strategies.
- Each of these strategies would be some rule of thumb about what the attendance was that week, e.g.

Strategies

- *“ twice last week ’ s attendance, ”*
  “ half the attendance of two weeks ago, ”

– **or**

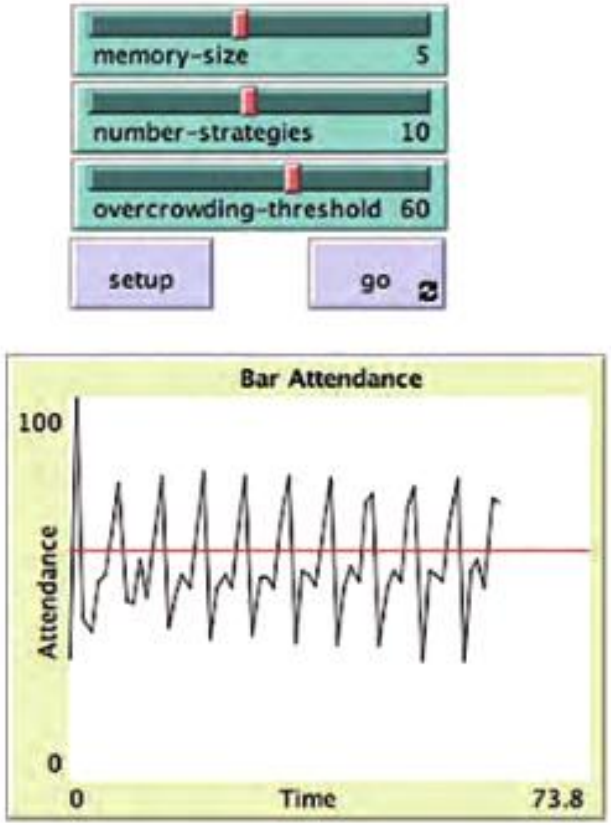
- *“ an average of the last three weeks attendance.”*

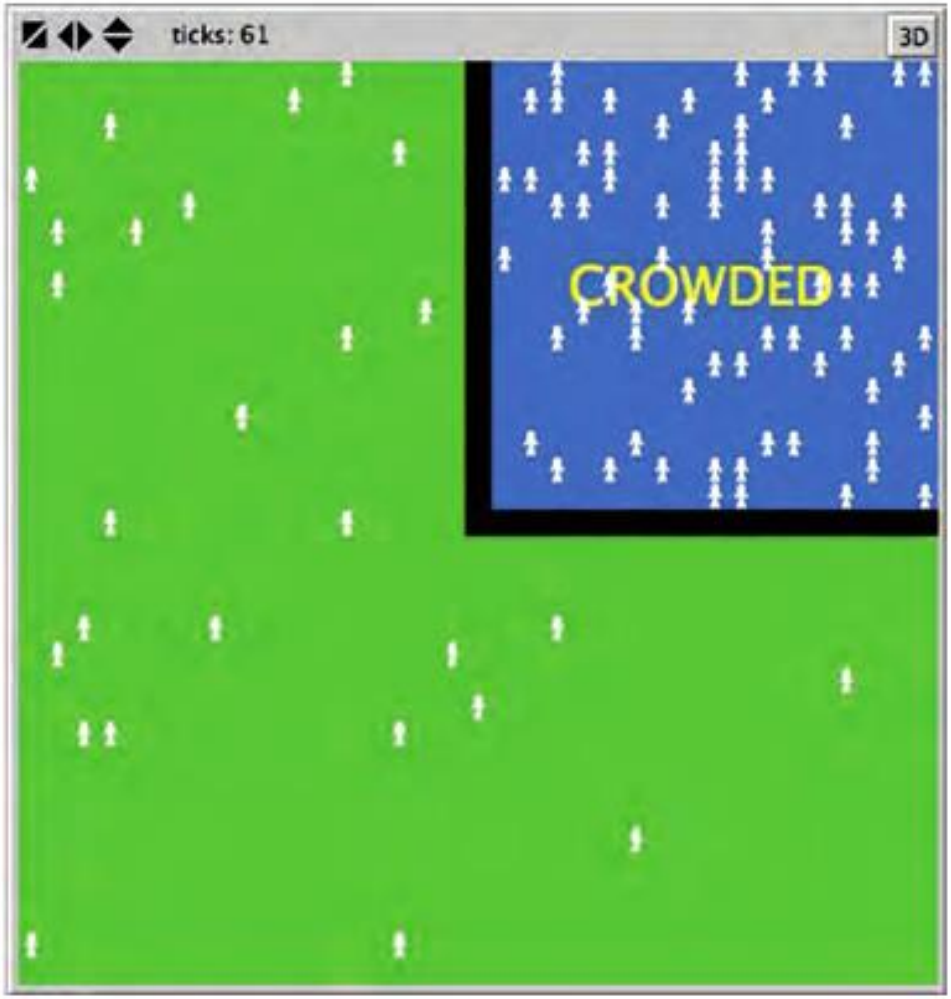
– **The agents would use whichever strategy would have worked the best to predict this coming week ’ s attendance**

NetLogo Model

- This model is available in the NetLogo models library under Sample Models > IABM Textbook > Chapter Three > El Farol
- This model has a few controls. You can adjust the MEMORY-SIZE of the agents, which controls how many weeks of attendance they remember.

The El Farol model





Summary

- In this Module we have seen The El Farol model
- This model was a good example of how you do not need to understand every part of an agent-based model in order to work with it
- Credits:
  - Uri Wilensky book

Modeling and Simulation

First Extension:

Color Agents That Are More Successful Predictors

Overview

- Here, we understand about First Extension of El Farol model and will see how to further modify it in order to understand :
  - Are some agents better at deciding when the bar will not be crowded than others?

Color Agents That Are More Successful Predictors

- The original model tells you how many agents are attending the bar, and you can get the visual reference of them moving to and from the bar,
- But there is nothing in this model to indicate which agents are better at choosing good times to attend the bar.

Add a Property to Each Agent

- In order to find this out, Are some agents better at deciding when the bar will not be crowded than others?
- We first need each agent to keep track of how often they go to the bar when it is not crowded; to do this, we add a property to each agent.

REWARD

- We will modify the turtles ' properties to add one additional item, REWARD:
- We are calling this new property REWARD, since the agents get rewarded if they attend the bar when it is not crowded.
- Now we have to initialize this property, since each agent will start with reward of 0.

Initialize The REWARD To 0

```
turtles-own [
    strategies          ;; list of strategies
    best-strategy ;; index of the current best strategy
    attend?                 ;; true if the agent currently plans to attend the bar
    prediction          ;; current prediction of the bar attendance
    reward                  ;; the amount that each agent has been rewarded
]
```

```
;; create the agents and give them random strategies
create-turtles 100 [
    set color white
    move-to-empty-one-of home-patches
    set strategies n-values number-strategies [random-strategy]
    set best-strategy first strategies
    set reward 0
    update-strategies
]
```

Update The Reward

- We also need to update the reward whenever the agent goes to the bar and it is not crowded.
- The word CROWDED is displayed on a patch in the bar
- We want to update the reward of turtles who attend the bar when this condition is not true, so we can make this IF statement

Update The Reward

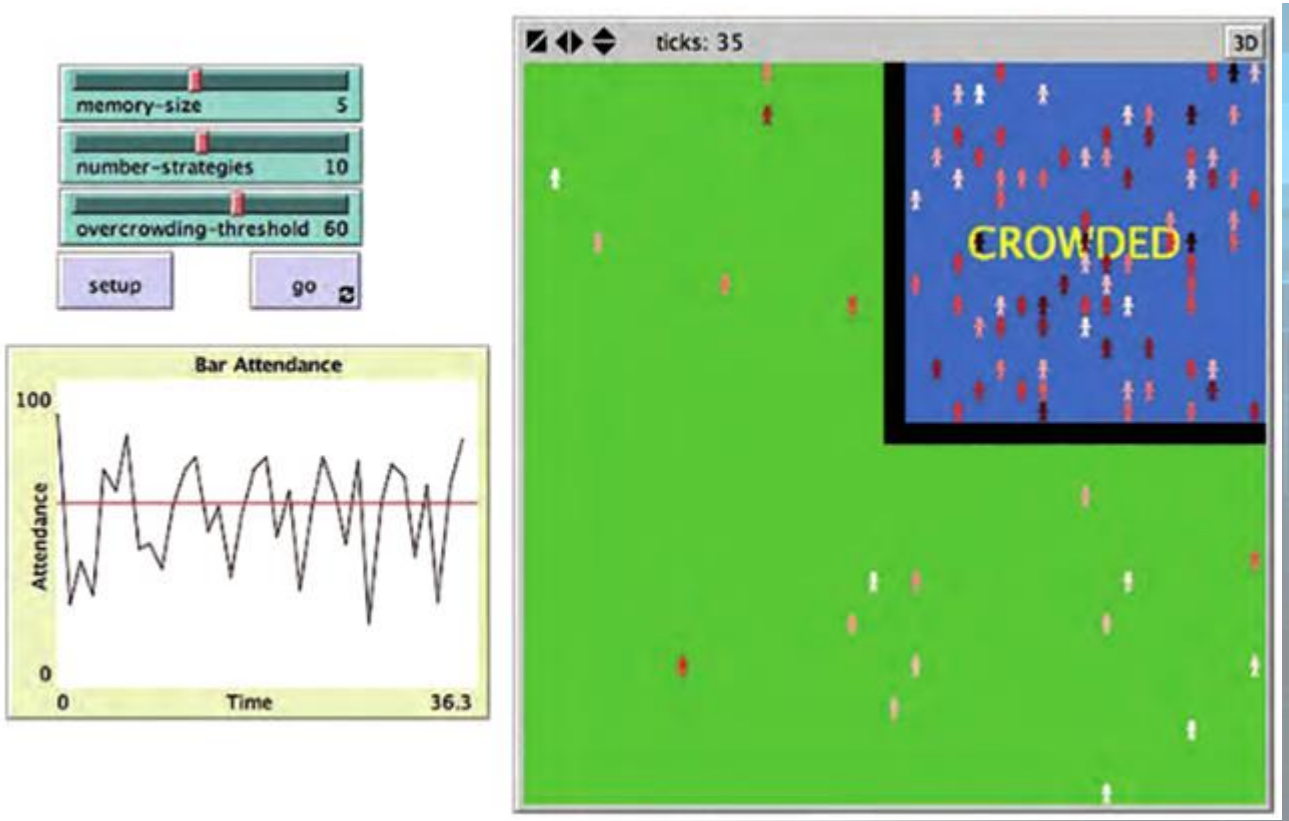
```
ifelse attendance > overcrowding-threshold [
    ask crowded-patch [ set plabel "CROWDED" ]
]
[   ;; if the bar is not overcrowded, reward the turtles that are attending
    ask turtles with [ attend? ] [
        set reward reward + 1
    ]
]
```

SCALE-COLOR

- NetLogo has a command called SCALE-COLOR that allow you to do this, we can set each agent ’s color to a shade of a color based on their reward.
- In this case, the darkest agents will be the one with the lowest reward, and the lightest agents will be the ones with the most reward

El Farol model: first extension

```
ask turtles [
        set prediction predict-attendance best-strategy sublist history 0 memory-size
        ;; set the Boolean variable
        set attend? (prediction <= overcrowding-threshold)
        set color scale-color red reward (max [ reward ] of turtles + 1) 0
    ]
```



Summary

- The first extension enables us to visually see which agents are doing better at going to the bar when it is not crowded
- Credits: Uri Wilensky book

Third Extension:
Histogram Reward Values

Overview

- Here, we understand are the agents distributed uniformly across reward levels or are many agents at the minimum value and many agents at the maximum value with few agents in between?
- To find out an answer to this question, we are going to add another plot to the El Farol model.

Distribution Of Rewards

- In this model we will need to use the plot widget ’s “ Plot update commands ” feature.
- To do this we first need to create a new plot in the Interface tab.
- In the configuration for this plot, we can give the plot the name “ Reward Distribution, ”

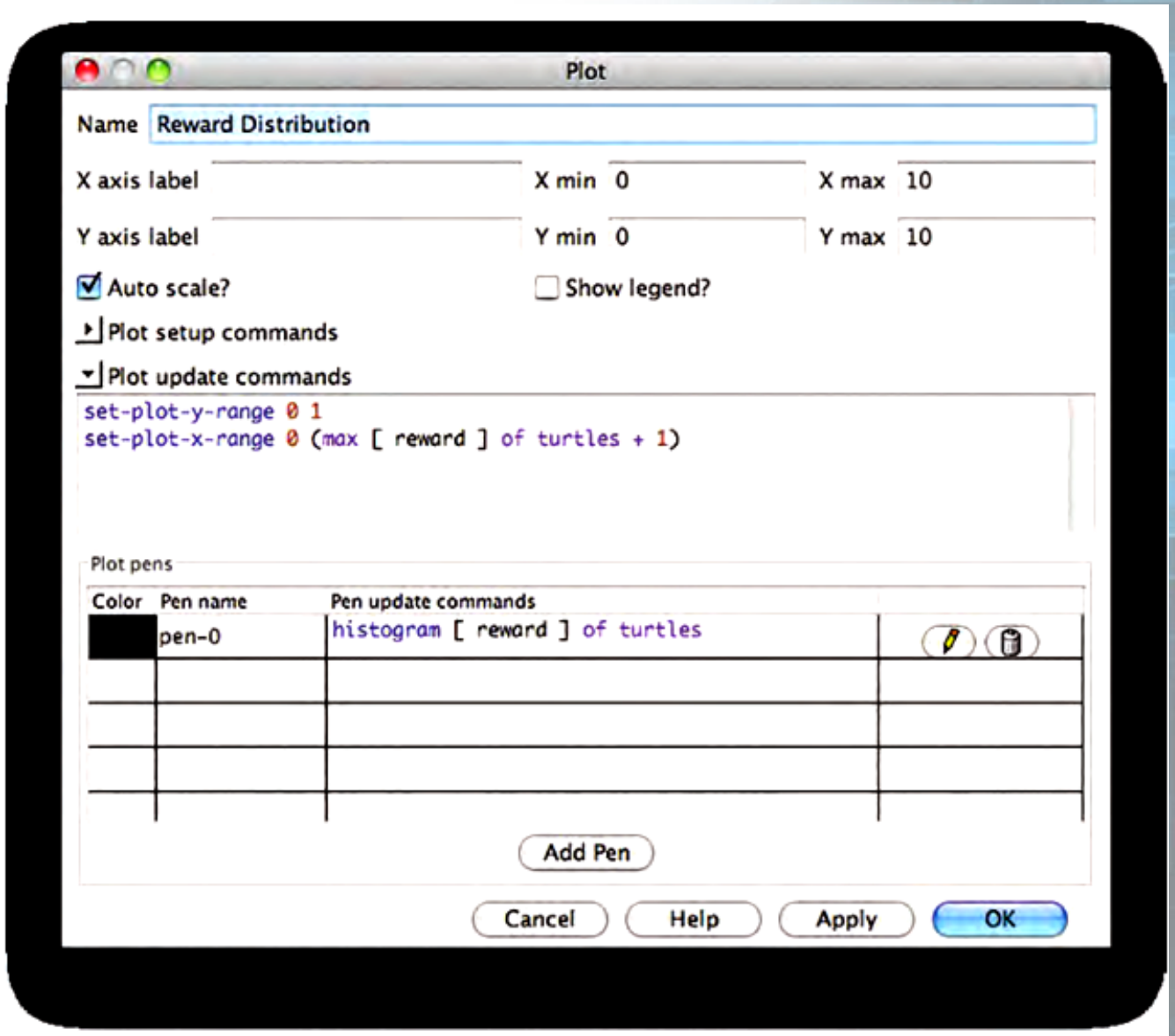
Histogram of the REWARDs

- **Change the Mode of the pen to *"Bar"* by clicking on the pencil in the first row of the Plot pens table.**
- **We tell the pen to display a histogram of the distribution by putting the following code in " *Pen update commands.* "**
  - ***histogram [reward] of turtles***

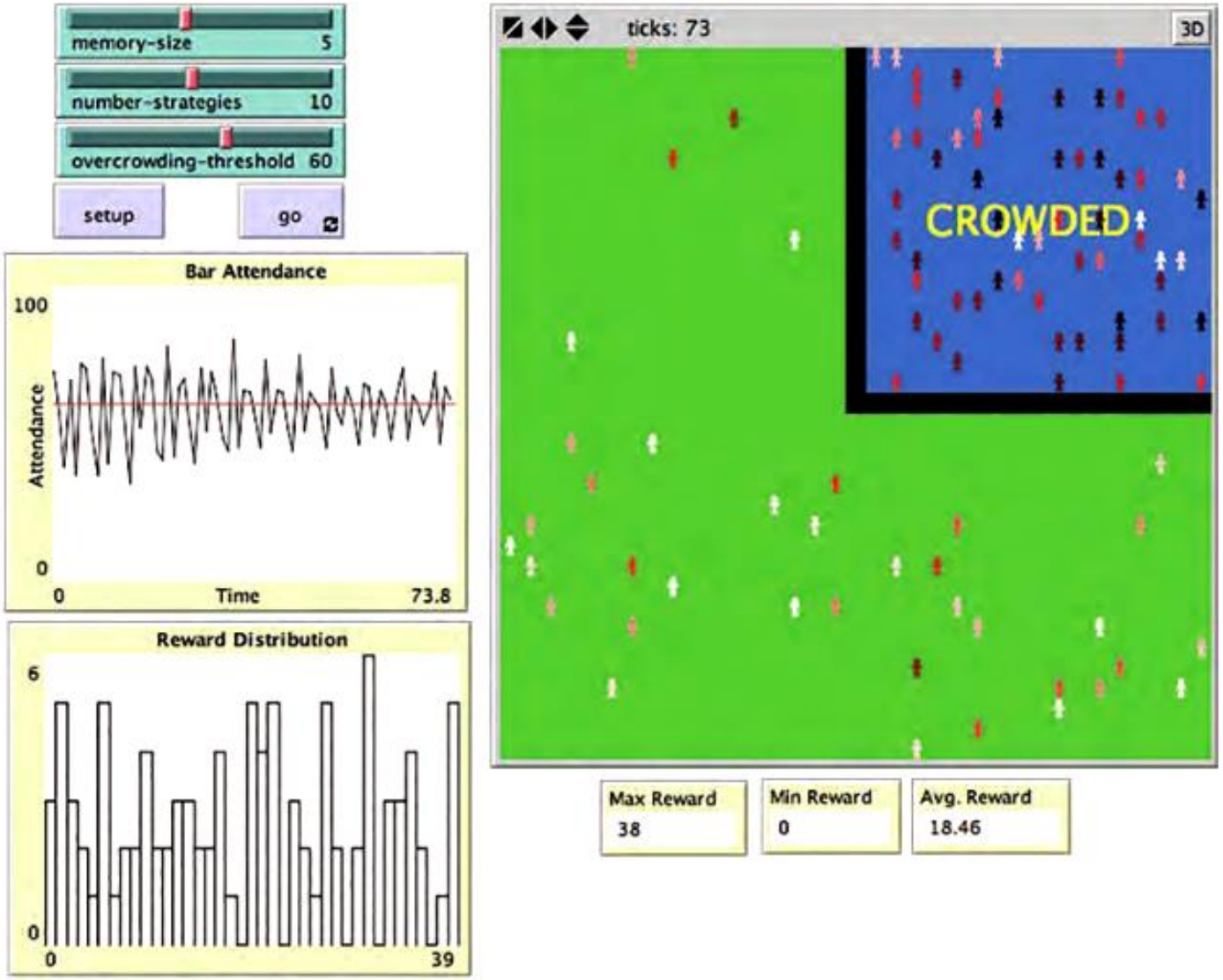
Histogram

- If we ran the model in this state, we would see a histogram drawn. However, the axes of the plot would not update correctly.
- Thus, we must enter the following under " Plot setup commands. "
  - set-plot-y-range 0 1
  - set-plot-x-range 0 (max [reward] of turtles + 1)

Histogram


Plot
Name
Reward Distribution
X axis label
X min
0
X max
10
Y axis label
Y min
0
Y max
10
Auto scale?
Show legend?
Plot setup commands
Plot update commands
set-plot-y-range 0 1
set-plot-x-range 0 (max [reward] of turtles + 1)
Plot pens
Color
Pen name
Pen update commands
pen-0
histogram [reward] of turtles
Add Pen
Cancel
Help
Apply
OK

El Farol model: third extension



Summary

- **We have seen when we run the model over time, you will see it start out similar to a normal distribution, but the *distribution will quickly change with a few groups of individuals maintaining large rewards* and many more having a lower reward.**
- **Credits: Uri Wilensky book**

Modeling and Simulation

Advanced Modeling Applications

Overview

- **Here we understand the Advanced Modeling Applications**

Machine learning

- Machine learning enables the creation of powerful agent-based models where the agents not only change their actions over time, but also their strategies, i.e.,
  - the agents change the way they decide to take actions

Minority Game

- The *El Farol model* has also been idealized into the *Minority Game* which has been studied by *physicists and economists* because it provides insights into *complex systems*.
- For instance, *both El Farol and the Minority Game* can be seen as a crude approximation for financial markets

Economic Model

- The El Farol model is also one example of an economic model.
- The Artificial Stock Market is an early agent-based economic model
- This model attempted to simulate the stock market

Economic Models In NetLogo

- There are several other economic models in the NetLogo models library, such as the Oil Cartel model and the Root Beer Supply Chain
- Both of these models are interesting because they make use of the HubNet facility that is also provided with NetLogo.

HubNet

- HubNet (Wilensky & Stroup, 1999c) is a NetLogo feature that enables Participatory Simulations, which is a simulation method where humans control agents in an agent-based model

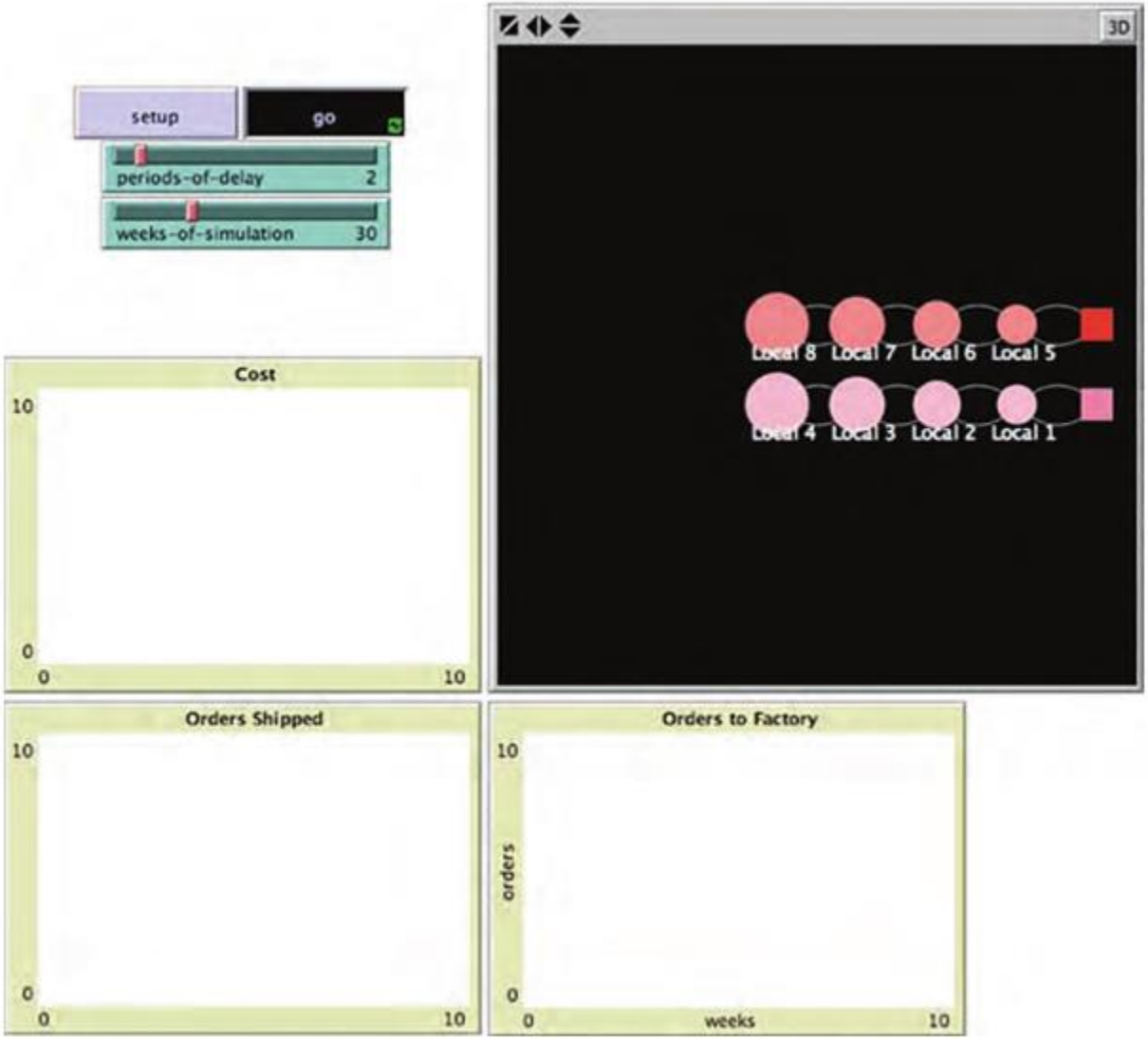
Tools To Extend NetLogo Models

- In the Fire model extensions and in the DLA extensions, we have seen that it is often useful to extend a model by replacing deterministic rules by probabilistic rules.
- Conversely, as we saw in modeling wind and long distance transmission in the Fire model

Tools To Extend NetLogo Models

- It is sometimes useful to replace a probabilistic rule with an agent-based mechanism that generates the probabilities.
- And with each change to the model, we need to consider whether we also need to design a new metric for measuring model performance

NetLogo HubNet Root Beer Game model.



Summary

- We have illustrated how to extend four different models, each in three different ways, and we have explored how these models relate to some of the key concepts of ABM.
- Credits: Uri Wilensky book

Modeling and Simulation

Creating Agent-Based Models

Overview

- **Here we will understand about how to design and build our own model from the ground up.**

First Step Of Devising A Question

- **This Module is intended to take you from the first step of devising a question or area you want to explore, all the way through designing, and building your model, to refining your question and revising your model, to analyzing your results and answering your question.**

Sequence of Steps

- **The sequence of steps are presented here in linear order, but in reality these steps fold back on each other and are part of an iterative exploration and refinement of the model and motivating question.**

Three Main Sections

- To facilitate the process, this module and other modules are broken into three main sections:

1. Designing your model will take you through the process of determining what elements to include in your model,
2. Building your model,

Three Main Sections

- **Building your model will demonstrate how to take a conceptual model and create a computational object**
- **(3) Examining your model will address how to run your model, create some results, and analyze those results to provide a useful answer to your motivating question.**

Model Of An Ecological System

- Throughout this chapter we will be designing, building, and examining a simple model of an ecological system.
- The basic question that we will be addressing is: " How do the population levels of two habitat-sharing animal species change over time? "

Wolf Sheep Simple model

- **For our purposes in this chapter, we will call this model the Wolf Sheep Simple model.**

Summary

- In this chapter More important, the components that we will be developing in this model are basic components utilized in most ABMs.
- Credits: Uri Wilensky book

Modeling and Simulation

Designing Your Model

Overview

- Here in this Module we will understand about many ways of designing an agent-based model.
- Which you choose will depend on many factors including the type of phenomenon to be modeled, your level of knowledge of the content domain, your comfort with NetLogo coding

Phenomena-based Modeling

- We consider two major categories of modeling:
  - phenomena-based modeling and exploratory modeling
- In phenomena-based modeling , you begin with a known target phenomenon
- Typically, that phenomenon has a characteristic pattern,

Reference Patterns

- A *characteristic pattern*, known as a *reference pattern* .
- Examples of *reference patterns* might include common housing segregation patterns in cities, spiral-shaped galaxies in space, leaf arrangement patterns on plants, or oscillating population levels in interacting species.

Goal Of Phenomena-based Modeling

- The goal of phenomena-based modeling is to create a model that will somehow capture the reference pattern
- In ABM, this translates to finding a set of agents, and rules for those agents, that will generate the known reference pattern.

Exploratory Modeling

- The second core modeling form is exploratory modeling.
- This form is perhaps less common in equational contexts than it is in ABM
- In exploratory modeling with ABM, you create a set of agents, define their behavior, and explore the patterns that emerge.

Formulate Research Question

- Another distinction in modeling methodology is to what degree we specify a question to be answered by a model.
- At one end of the spectrum, we formulate a specific research question (or set of questions) such as " How does a colony of ants forage for food? "

Designing The Conceptual Model

- A third dimension is the degree to which the process of designing the conceptual model is combined with coding your model.
- In some cases, it is advisable to work out the entire conceptual model design in advance of any coding of the model. This is referred to as top-down design.

Top-down design

- In a top-down design, the model designer will have worked out the types of agents in the model, the environment they reside in, and their rules of interaction before writing a single line of code.

Bottom-up Design

- In bottom-up design, you choose a domain or phenomenon of interest with or without specifying a formal question.
- Using this approach, you would then start writing code relevant to that domain, building the conceptual model

Design Principle

- We will emphasize the top-down approach.
- Throughout the design process there is one major principle that we will use
- We call this the ABM design principle :
  - Start simple and build toward the question you want to answer

Components Of Design Principle

- There are two main components of this principle
- The first is to begin with the simplest set of agents and rules of behavior that can be used to explore the system you want to model.

1st Components

- " Everything should be made as simple as possible, but not simpler. "
- In the case of ABM, this means making your model as simple as possible given that it must provide you with a stepping-stone toward your final destination

2nd Component

- Second, always have your question in mind, which means not adding anything to your model that does not help you in answering your question
- This core ABM design principle is useful in several ways

Verification

- Another virtue of the ABM design principle is that, by keeping the model simple, you make it both more understandable and easier to verify.
- Verification is the process of ensuring that a computational model faithfully implements its target conceptual model.

Simpler Conceptual Model

- A simpler conceptual model leads to a simpler model implementation, which makes it easier to verify the model.
- Starting simple and building up also facilitates the process of just-in-time results.

Identifying a Question

- We will start by identifying a question we want to explore, which is required by the ABM design principle (top-down version).
- After that we will discuss what the agents in our models are and how they can act. Then we move on to the environment and its characteristics.

Summary

- In this Module we have seen what happens in an individual time step of the model.
- Finally, we discuss what measures we will be using to answer our question
- Credits: Uri Wilensky book

Modeling and Simulation

Choosing Your Questions

Overview

- **Here, we understand why Choosing a question may seem to be a separate issue from model design?**

Natural Progression

- **The natural progression seems to be:**
  - ***First*** **choose a question,**
  - ***Second*** **build a model to answer that question.**
- **In many instances we will need to refine our questions when we start to think about it in an agent based way.**

Wolf Sheep Simple model

- Our original question for the Wolf Sheep Simple model was:
  - " How do the population levels of two species change over time when they coexist in a shared habitat? "
- We will now evaluate whether this question is one that is amenable to ABM

ABM For Making Sense Of Systems

- Agent-based *modeling is particularly useful for making sense of systems* that have a number of interacting entities, and therefore have *unpredictable results*.
- As we discussed in chapter 1, there are certain problems and questions that are more amenable to ABM solutions

Consider A Different Modeling Method

- If our primary question of interest violates our guidelines, it may be an indication that we should consider a different modeling method.
- For example, we might be interested in examining the dynamics of two very large populations under the assumption

Assumption

- The *assumption* that the species are homogenous and well-mixed (no spatial component or heterogeneous properties) and that the population level of each species is simply dependent on the population level of the other species.

EBM vs. ABM

- **If that is the case then we could have used an *equation-based model instead of an agent-based model* since EBM's work well for large homogeneous groups, and as we mentioned in previous chapters there is a classic EBM for this situation known as the *Lotka-Volterra differential***

Conceptualize The Agents

- ***ABM will be more useful*** **to us if we are thinking of the agents as heterogeneous with spatial locations. This affects how we conceptualize the agents.**
- **One aspect of the animals that is likely to be relevant to our question is how they make use of their resources.**

Agent's Interaction With Environment

- **A third guideline is to consider whether the aggregate results are dependent on the *interactions of the agents* and on the *interaction of the agents with their environment*.**
- **For example, if one species is consuming another then the results will be dependent on agent interaction.**

Time Dependent Processes

- **Yet another guideline is that agent-based modeling is most useful for modeling *time dependent processes*.**
- **In the Wolf Sheep Simple model, our core interest lies in examining *how population levels change over time.***

Summary

- In This Module we understood question " Can we find model parameters for two species that will sustain positive population levels in a limited geographic area when one species is a predator of the other
- Credits: Uri Wilensky book

A Concrete Example

Overview

- **Now that we have identified our research question in detail here we will understand how it can be useful to consider a particular context for this research question.**

Phenomena-based Agent-based Models

- Earlier, we discussed reference patterns as a source of phenomena-based agent-based models.
- Sometimes that reference pattern is the original inspiration for the model.

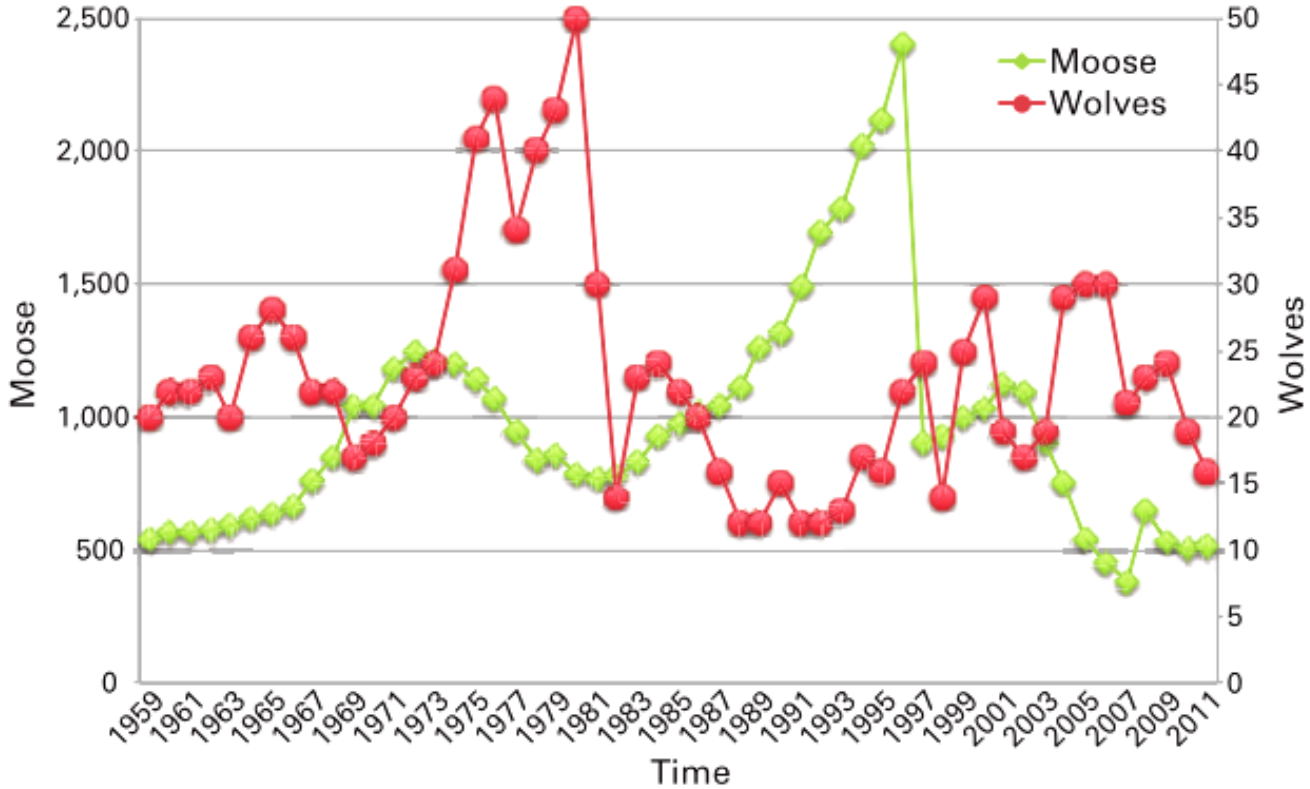
Refined Research Question

- **we have refined our research question enough that we seek out a reference pattern that will help us test whether our model is a valid answer to the question.**

Predator-prey Relations

- In the case of the predator-prey relations, there is a famous case of cohabiting small predator-prey populations in a small geographic area.
- This is the case of fluctuating wolf and moose populations in Isle Royale, Michigan.

Wolf And Moose Populations In Isle Royale



Five decades of fluctuating wolf and moose populations at Isle Royale. Note that when the wolf population peaks, the moose population is at a low point and, similarly, when the moose population peaks, the wolf population is at a low point.

Populations Exhibit a Rough Oscillation

- As we can see in the data from Isle Royale, the wolf and moose populations in Isle Royale have been sustaining themselves for more than fifty years without either species going extinct.
- The populations also exhibit a rough oscillation, with moose at a low when wolves peak and vice versa.

Reference Pattern

- **We can refine our research question to:**
  - ***" Can we find model parameters for two species that will sustain oscillating positive population levels in a limited geographic area when one species is a predator of the other and the second species consumes resources from the environment? "***

Summary

- In this Module we have introduce you to classic examples of predator-prey modeling and to try to reproduce the oscillating sustained pattern of population levels.
- Credits: Uri Wilensky book

Choosing Your Agents

Overview

- **Now that we have identified and contextualized our driving research question, Here we will understand that we can begin to design the components that will help us answer it.**

What Are The Agents In The Model?

- The first question we should ask ourselves is:
- What are the agents in the model? When designing our agents, we want to choose those components of our model that are autonomous and have properties, states, and behaviors that could possibly have bearing on our question.

Agent Overload

- we must be careful to avoid agent overload
- Depending on the perspective one takes, almost any model component could be considered an agent.
- However, a model that is designed with an excess of agent types can quickly become unmanageable.

Entities Relevant to Research Question

- When choosing what are to be the agents in a model, it is important to concentrate on those autonomous entities which are most relevant to our research question.
- A related issue is the " granularity " of the agent. Every entity is composed of multiple smaller entities.

What is The Right Level of Entity to Choose?

- Should our agent be molecules or atoms? Body organs or cells? Some agents can be treated as mass properties.
- If we want to model a field of grass, we might not want to model every blade of grass, but instead choose “ clumps ” of grass as our agents.

Granularity Of Each Agent in temporal scale

- It is important that the granularity of each agent be at roughly the same level.
- For instance in the temporal scale, if you are modeling the sheep actions at the level of days of activity, but the grass minute by minute, that can be difficult to reconcile.

Granularity of Each Agent In Physical Scale

- **In the physical scale, if there is more grass than the sheep can consume then you will not see many interesting behaviors since grass will not serve as a limiting condition.**

Proto-agents

- By the term proto-agent, we mean agents that do not have individual properties, states, or behaviors but instead inherit some or all of their characteristics from a global agent type.
- For example, in the Wolf Sheep Simple model we might desire to have a human hunter who interacts with the other two species.

Create a Simpler Proto-agent

- **There is no need to build the hunter as a full agent at the start; instead we can create a simpler proto-agent that has the ability to kill off a random percentage of the population.**

Three Agent Types

- We model the predators, which we will call wolves, and the prey, which we will call sheep, and the resources the sheep consume, grass.
- We could have added many other agents to this model.
- However, by choosing just wolves, sheep, and grass, we stick to the ABM design principle.

Summary

- Here we have seen We have the two simple mobile agent types, and one stationary agent type to model the environment, and those are the minimal set of agents necessary to answer our question of what parameters will allow two populations to coexist in a limited geographic area.
- Credits: Uri Wilensky book

Choosing Agent Properties

Overview

- Here we will understand that Agents have properties that distinguish them from other agents.
- It is important to determine these properties in advance so we can conceptualize the agent and design the agents' interaction with each other and with the environment.

Wolf Sheep Simple model

- In the Wolf Sheep Simple model we give the sheep and wolves three properties each:
  - An energy level, which tracks the energy level of the agent,
  - A location, which is where in the geographic area the agent is,

Three Properties

- A heading, which indicates the direction the agent is currently moving or would be moving

- The energy property is not merely describing temporary energy (such as whether an animal is fresh or fatigued).

Energy Property

- Rather,“ energy ” incorporates some notion of the amount of “ vitality ” in a creature, abstracting away the messy details of metabolism, calorie storage, or starvation, and condensing it all into a single measure.

Adding Additional Properties

- We could add additional properties and some of them might be useful for future extensions.
- For instance, we could add a movement speed and allow different agents to move at different speeds, or an offense/defense capability that affects the ability of the individual.

Summary

- Here in this Module we have seen the behavior that each of these two agent types exhibit in wolf sheep model
- Further we will see what makes agents different from each other?
- Credits : Uri Wilensky

Modeling and Simulation

Choosing Agent Behavior

Overview

- Here we will understand how it is important to determine what kind of behavior the agents can exhibit.
- These behaviors are necessary to describe how agents interact with each other and the environment.

Wolf Sheep Simple Model

- In the Wolf Sheep Simple model, sheep and wolves share many common behaviors.
  - They both have the ability to turn randomly, move forward, reproduce and die.
- However, sheep and wolves differ

Differentiates The Two Agents

- Sheep have the ability to consume grass and wolves have the ability to consume sheep.
- This differentiates the two species/agent types from each other.
- Of course, once again there are many other behaviors we could prescribe for these agents.

Differentiates The Two Agents

- For instance, we could give sheep the ability to huddle in herds to defend against wolf attacks, or the ability to fight back.
- The wolves could have the ability to move at different speeds from a walk to a run or to chase sheep.

Differentiates The Two Agents

- The behaviors we have described (moving, reproducing, eating, and dying) are reasonable choices for a simple model that can address our research question.
- For the grass clump agents, we give one simple behavior, the ability to grow.

Summary

- Here we have seen how agents have different behaviors from each other so we can easily propose our research question on basis of their differentiated properties
- Credits : Uri Welinsky

Choosing Parameters of the Model

Overview

- **Here we will understand about what is the next step to define what attributes of the model we will be able to control through parameters.**

Several Possible Parameters Of Interest

- There are several possible parameters of interest in the Wolf Sheep Simple model.
  - For instance, we will want to be able to control the number of initial sheep and wolves.
- This will enable us to see how different values of the initial population levels affect the final population levels.

Possible Parameters

- Another factor to control is how much energy it costs an agent to move.
- Using this parameter, we can make the landscape more or less difficult to traverse, and thus simulate different types of terrain.

Parameters For Controlling The Energy

- Related to the cost of movement is the energy that each species gains from food.
- Thus, we choose to have parameters for controlling the energy gained from grass and the energy gained from sheep.

Homogenous Parameters

- we will need a parameter for the grass re-growth rate.
- There are many other parameters that we could have included in this model.
- The parameters we chose are homogenous across the model.
- In other words, one sheep will gain the same energy from grass as any other sheep.

Heterogeneous Parameters

- However, we could make this model more heterogeneous by drawing the energy gain for each sheep from a normal distribution, and have two model parameters that control the mean and variance of the energy gain.

Add Parameters to Control Aspects

- We could also add parameters to control aspects that we are currently planning to specify as constant values in the code.
- For example, we did not create a parameter to control the speed of the agents.

Summary

- Here we have seen how to create some parameters that enable us to control the model, so that we can easily examine different conditions.
- Credits : Uri Welinsky

Summary of the Wolf Sheep Simple Model Design

Overview

- **Now that we have gone through the major design steps, we can create a summary document that describes our model design.**

Wolf Sheep Simple model Summary

- The Wolf Sheep Simple model can be described in the following way:
  - Driving Question *Under what conditions do two species sustain oscillating positive population levels in a limited geographic area when one species is a predator of the other and the second species consumes limited but regenerating resources from the environment?*

Agent

- **Agent Types:**
  - Sheep, Wolves, Grass
- **Agent Properties:**
  - Energy, Location, Heading (wolf and sheep), Grass-amount (grass)
- **Agent Behaviors:**
  - Move, Die, Reproduce (wolf and sheep), Eat-sheep (wolf only), Eat-grass (sheep only), Re-grow (grass)

Parameters

- **Parameters:**
  - **Number of Sheep, Number of Wolves, Move Cost, Energy Gain From Grass, Energy Gain From Sheep, Grass Re-growth Rate**
- **Time Step :**
  - **1. Sheep and Wolves Move**
  - **2. Sheep and Wolves Die**
  - **3. Sheep and Wolves Eat**
  - **4. Sheep and Wolves Reproduce**
  - **5. Grass Re-grows**

Measures

- **Measures:**
  - **Sheep Population versus Time, Wolf Population versus Time**
- **For instance, if you are using *the top-down design process* then you might look over the following set of questions and write down answers to them as a provisional guide**

Set Of Questions

- What part of your phenomenon would you like to build a model of?
- What are the principal types of agents involved in this phenomenon?
- In what kind of environment do these agents operate? Are there environmental agents?
- What properties do these agents have (describe by agent type)?

Set Of Questions

- What actions (or behaviors) can these agents take (describe by agent type)?
- How do these agents interact with this environment or each other?
- If you had to define the phenomenon as discrete time steps, what events would occur in each time step, and in what order?

Bottom-up Approach

- A more bottom-up approach would not start with these questions.
- Instead, you might know only that you want to build some kind of ecological model and could begin by creating some sheep and have them spread out in the world.

Implementing Some Behaviors

- In order for the sheep to eat, you might decide to add grass to the model.
- Having sheep eat grass provokes the question, “ What eats sheep? ” Therefore, you modify the model to include wolves, as predators for the sheep.
- This process allows the wolf sheep model to be designed

Summary

- In this Module we summarizes Wolf Sheep Module in few steps
- Credits : Uri Welinsky

Modeling and Simulation

Examining a Model

Overview

- Here we will examine the model in detail We did not calibrate our model from real-world data, so the parameter values themselves are not important.
- But, discovering that there exist model parameters that exhibit our reference pattern gives us insight into the natural phenomenon we were trying to model

Parameters of two Species

- **We have partially answered our research question:**
  - ***What parameters of two species will sustain oscillating positive population levels in a limited geographic area when one species is a predator of the other and the second species consumes limited but re-growing resources from the environment?***

Observing the Behavior Of Model Once

- Just observing the behavior of this model once does not provide us with a robust answer.
  - First, because many components of our model are stochastic in nature, there is no guarantee that the model when run again with the exact same parameters will exhibit the same behavior.

Observing the Behavior Of Model Once

- Second, we have found one set of parameters that allow wolves and sheep to exist, but are there other parameter settings?

- A more general answer would allow us to make statements about ranges of parameters, and relationships between parameters, that allow both the wolves and the sheep to survive.

Variety of Parameter Settings

- If we run the model many times with a variety of parameter settings, this will create a lot of data.
- Thus, to give us even a simple answer to our question, we really need to examine multiple runs across multiple different parameter settings and summarize this data in a useful way

Summary

- Here we have seen how to examine model.
- We will explore data analysis in greater detail in next modules, but before we leave the Wolf Sheep Simple model, we will perform a basic analysis, in order to develop a preliminary answer to our question.
- Credits : Uri Wilensky

Modeling and Simulation

Multiple Runs

Overview

- **Here we will understand Whenever you have a model that has stochastic components, it is important to run the model several times so that you can be certain you have correctly characterized the behavior of the model.**

Anomalous Behavior

- If the model is run only once, you might happen to see anomalous behavior that is not what the model usually produces.
- For instance, in the Wolf Sheep Simple model it might be possible to run the model and arrive at a state i.e.

Anomalous Behavior

- In which there is simply one wolf and one sheep, and the sheep produces a second sheep often enough to keep the wolf fed, but not often enough to produce three sheep.

Run the Model Multiple Times

- It is important to run the model multiple times so that you can characterize the normal/average behavior of the model and not the aberrant behavior of the model

BehaviorSpace Tool

- **NetLogo provides you with the BehaviorSpace tool *(Wilensky & Shargel, 2002)* that enables you to run a model for several iterations with the same (or different) parameter settings and collect the results.**

Number of Time Steps

- One additional consideration when performing multiple runs is how many time steps to run the model for.
- Since we want to be able to compare the results across different random number seeds, it is useful to hold the number of time steps we run the model constant.

Summary

- Here we have seen how it is important to run the model several times to ensure that you have correctly characterized the behavior of the model.
- Credits : Uri Wilensky

Predator-Prey Models: Additional Context

Overview

- **Here we will understand how parameter settings effects the population what is relationship between pray and predators depending upon parameter settings**

Predator-prey Interaction

- Lotka and Volterra has designed way to study ecologies and population dynamics in a concrete way
- They developed a system of equations to describe a two species predator-prey interaction.

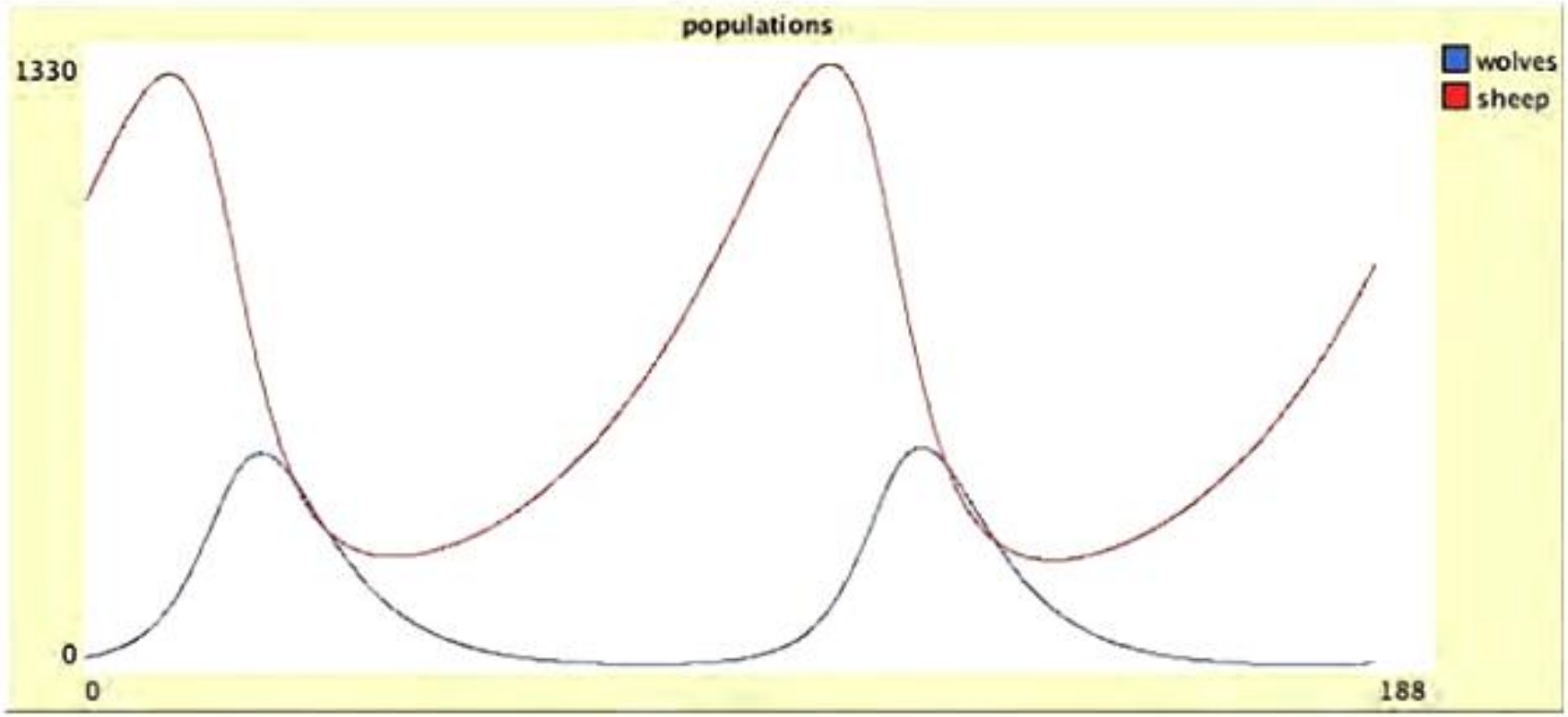
Lotka-Volterra equations

- These simple equations showed that you could meaningfully model ecological systems with just a few parameters.
- And once you have a model of a system you can start to explore options for perturbing the system into favorable states.

Lotka-Volterra equations

- The general result of the Lotka-Volterra equations is that predators and prey populations move in cycles.
- Depending on the parameter settings, if the two populations are equal at the start, then the predators will begin consuming the prey; this will result in a decrease of the prey population.

Lotka-Volterra relationship



Lotka-Volterra relationship (Wolf Sheep Predation System Dynamics model)

Prey and Predator Population

- Eventually, the prey will die off to the point where predators cannot find any more prey to eat.
- This will in turn cause predators to die off because they have no prey to feed on

Prey and Predator Population

- As the prey population increases it will become easier for the predator population to find them and the predator population will increase as well.
- This, in turn, results in the prey population's decreasing trend, and the whole process begins again.

Lotka-Volterra Equations

- The Lotka-Volterra equations have been a standard way of describing the fluctuations in predator and prey populations
  - They are differential equations
  - They represent a continuous model of population change

“ Nano-sheep Problem ”

- **The phenomenon is so common in differential equation-based modeling that it is sometimes referred to as the “ nano-sheep problem ” in specific reference to the wolf-sheep/predator-prey model**

“ Nano-sheep Problem ”

- The problem is that nano-sheep (i.e., a millionth of a sheep) do not exist: Sheep either exist or do not exist, and therefore modeling them with a continuous distribution can be problematic
- To rectify the nano-sheep problem, biologists have created agent-based models of predator-prey relationships

Classic Lotka Volterra differential equations

$$\frac{dx}{dt} = \alpha x - \beta xy$$

$$\frac{dy}{dt} = \delta xy - \gamma y$$

- x is the number of prey, y is the number of predators, and α , β , γ , and δ are parameters describing the interactions of the two species.

Gause Work

- In 1934, Gause showed that indeed for isolated predator and prey (with no other competing species) the agent-based model was more accurate in its predictions — indeed, extinctions happen much more frequently than the Lotka-Volterra equations predict.

Summary

- Here we have seen parameter settings are very important factors to control the population
- Credits : Uri Wilensky

Modeling and Simulation

Advanced Modeling Applications

Overview

- **Here we will understand some Advanced Modeling Applications of ABM**

Modeling of Food Webs

- One use of agent-based models in ecological systems is the modeling of food webs
- This combines ABM with another new complex systems methodology, network analysis

Structure of Ecological Interactions

- **By understanding both the structure of ecological interactions via network analysis and the process of animal interactions via ABM, researchers gain a deeper insight into overall ecological systems**

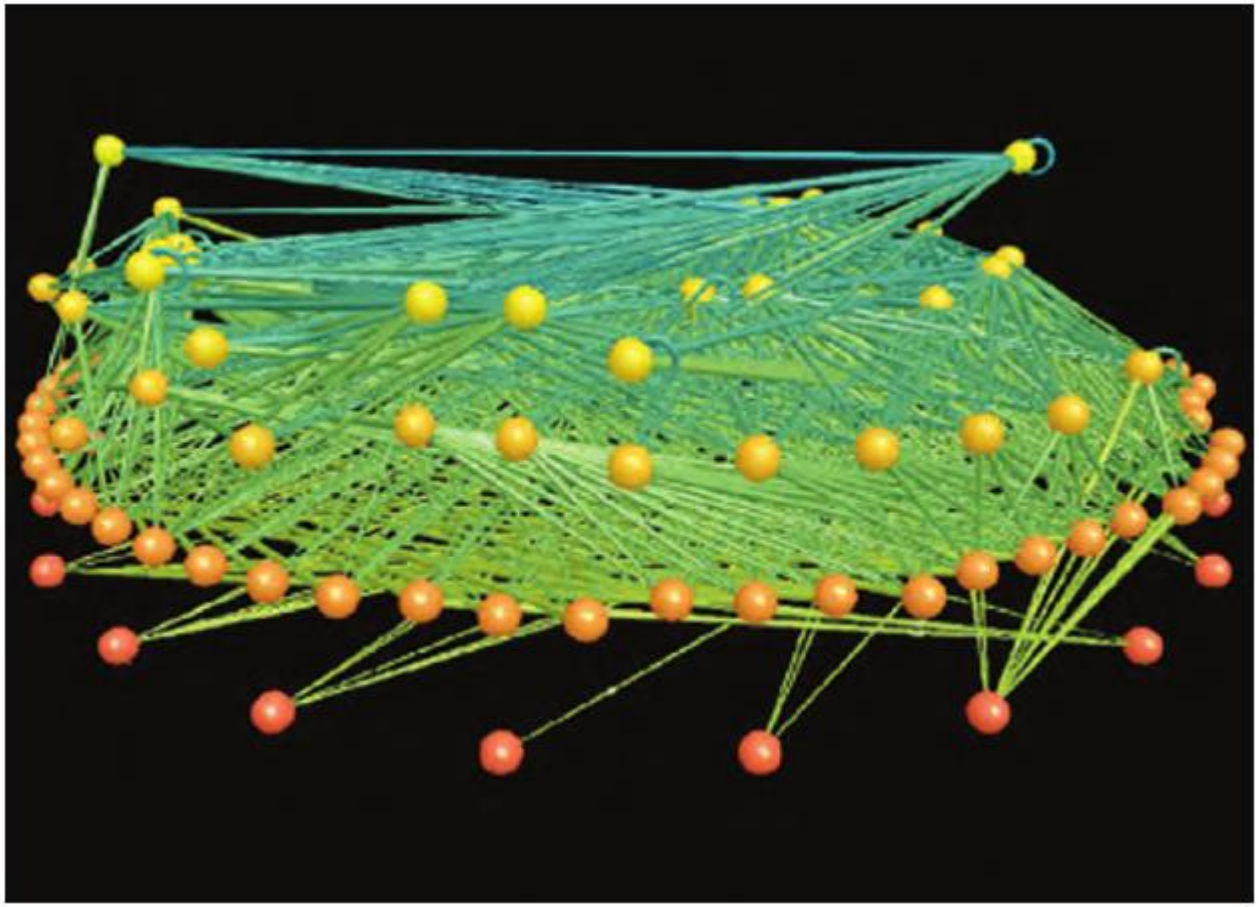
ABM and Ecological Modeling

- **Another particularly interesting application of ABM and ecological modeling has been in doing prescriptive design of engineered systems to ameliorate human interventions in the environment.**

Modeling Of Fish Populations

- Weber and his colleagues have done significant modeling of fish populations, and then examined the effect of various fish ladders near dams on salmon populations
- Agent-based modeling has been frequently used to model evolution of organisms

Little Rock Lake food web



ABM Approach as Natural Selection

- Evolution lends itself well to the ABM approach as natural selection and other evolutionary mechanisms can be thought of as computational algorithms.
- Models can be used to try to understand adaptation and speciation in the historical record

Summary

- In this module we have seen some Advance modeling application Moreover, as we will see in next modules mechanisms inspired by evolution can be employed as methods of machine learning
- Credits : Uri Wilensky

The Components of Agent-Based Modeling

Overview

- **Here we will understand about Components of ABM**

Components of ABM

- The main components of any ABM are
  - Agents ,
  - Environment ,
  - And Interactions.
- Agents are the basic ontological units of the model, while the environment is the world in which the agent lives

Distinction Between Agents and Environment

- The distinction between agents and environment can be fluid, as the environment can sometimes be modeled as agents.
- Interactions can occur either between agents or between agents and the environment.

Agent Actions

- Agent actions can also occur internally, directly affecting only the agent's internal state
- The environment is not merely passive; it can also act autonomously
  - For instance, in the models we discussed, the grass re-grows on its own.

Observer/User Interface

- The observer is an agent itself, but one that has access to all of the other agents and the environment
- The observer asks agents to carry out specific tasks.

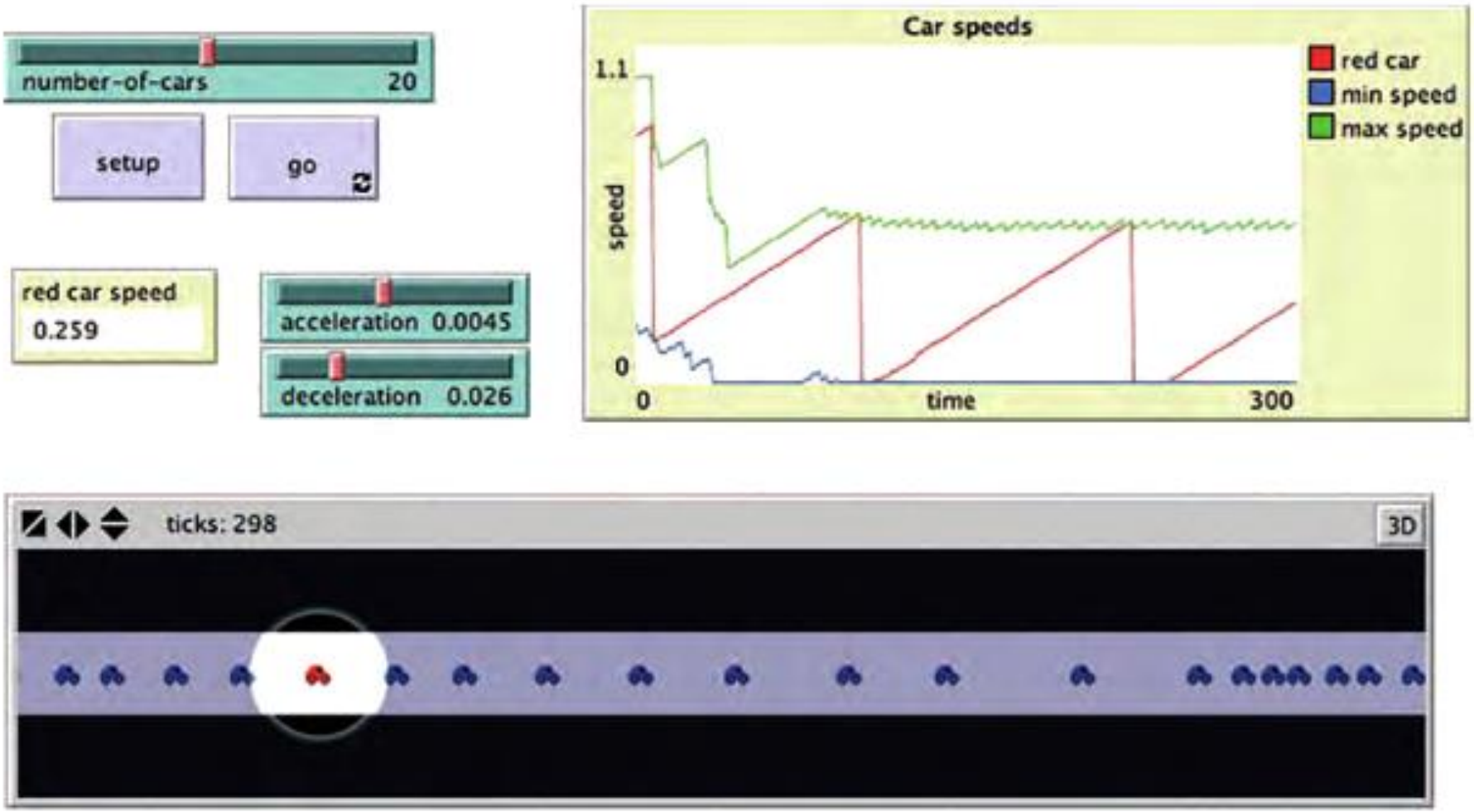
User Interface

- Users of agent-based models can interact with the agents by way of the User Interface, which enables the user to tell the observer what the model should do

Schedule

- The Schedule, is what the observer uses to tell the agents when to act.
- The Schedule often involves user interaction as well.
- In NetLogo models, the interface typically includes SETUP and GO buttons.
- The user presses SETUP and then GO to schedule these events to occur.

Traffic Basic model



Summary

- Here we have introduced basic components of ABM ,
- We will now describe each of these five components in further depth
- Credits : Uri Wilensky

Modeling and Simulation

Agents

Overview

- Agents are the basic units of agent-based modeling
- Here we will understand about, how it is important to choose the design of your agents carefully ?

Properties and Actions

- The two main aspects that define agents are
  - The properties that they have
  - And the actions (sometimes called behaviors or methods) that they can execute

Properties and Actions

- Agent properties are the internal and external state of the agents — their data and description
- Agent behaviors or actions are what the agents can do
- Besides these two main agent attributes, there are also several issues that are related to agent design

“ Grain-size ”

- First is the issue of agent “ grain-size ”:
  - which is most effective for the chosen model? For example, if you are modeling a political system, do want to model the individual actors or, instead, the political institutions or even each nation’s government as a single entity?

Agent Cognition

- A second factor to consider is agent cognition.
- How much capability do the agents have to observe the world around them and make a decision? Do they act in a
- stimulus-response fashion? Or do they plan out their actions?

Proto-agents and Meta-agents

- Some special types of agents:
  - Proto-agents, which are not fully specified agents;
  - Meta-agents, composed of other agents.

Summary

- Here we have introduced about what is an Agent? Next we will see in detail about its properties and behavior
- Credits : Uri Wilensky

Modeling and Simulation

Properties & Behaviors

Overview

- Agent properties describe an agent's current state, the items that you see when you inspect an agent
- Besides items that define the state of an agent (properties), it is also necessary to define how the agent can behave (the actions it can take)

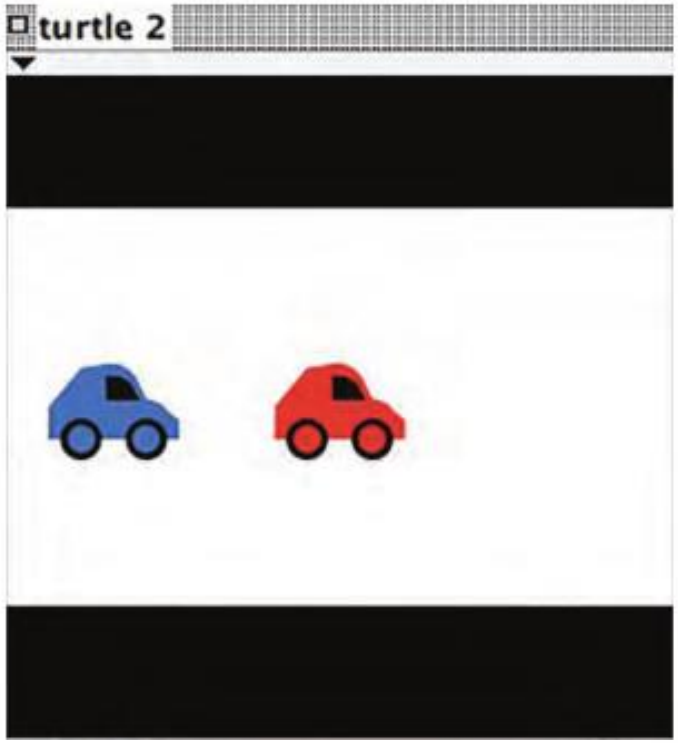
NetLogo

- In NetLogo, turtles and links have COLOR as a property, while patches have PCOLOR as a property.
- Likewise, turtles have XCOR and YCOR as properties, while patches have PXCOR and PYCOR
- The turtle can just execute SET COLOR PCOLOR to set its color

Link Properties

- Patches cannot directly access turtle or link properties, because a patch could have 0, 1 or many links or turtles on it
- Therefore, you must specify which turtle or link you are referring to when accessing their properties

Agent Properties for the Traffic Basic Model



Agent Properties for the Traffic Basic Model

- For this model, SPEED describes the current speed of the car, SPEED-LIMIT is the maximum speed of the car and SPEED-MIN, its minimum speed.
- When the Traffic Basic model starts up, all of these properties are set in the SETUP-CARS procedure:

```
set speed 0.1 + random-float .9
set speed-limit 1
set speed-min 0
```

Initialized Agent Properties

- We have initialized agent properties by setting them to constant values or to statistical distributions.
- Other ways to initialize agent properties are to set the values from a list or from a data file.
- Properties define an agent ’s current state, but they can also change to reflect how the state changes

Behaviors (Actions)

- An agent's actions or behaviors are the ways in which the agent can change the state of the environment, other agents, or itself
- In NetLogo, there are many behaviors that are predefined for the agents
  - It includes actions like FORWARD, RIGHT, LEFT, HATCH, DIE, and MOVE-TO.

Traffic Basic model

- In the Traffic Basic model, the agents have two additional behaviors that they can carry out —
- SPEED-UP-CAR and SLOW-DOWN-CAR — both of which modify the agents 'speed:

```
;; turtle procedure
to slow-down-car
  set speed speed - deceleration
end

;; turtle procedure
to speed-up-car
set speed speed + acceleration

end
```

Summary

- Behaviors are the basic way for agents to interact with the world while Action define an agent ’ s current state
- Here we have seen it is also necessary to define how the agent can behave (the actions it can take).
- Crtedits : Uri Wilensky

Modeling and Simulation

Collections of Agents

Overview

- **Here we will understand in detail about the Collections of Agents**

Types of Agents

- Agents are typically divided into three main types:
- Mobile agents:
  - That can move about the landscape
- Stationary agents:
  - That cannot move at all
- Connecting agents:
  - That link two or more other agents

NetLogo

- In NetLogo, turtles are mobile agents, patches are stationary agents, and links are connecting agents.
- From a geometric standpoint, turtles are generally treated as shapeless area-less points, although they may be visualized with various shapes and sizes).

Patches and Turtles

- A primary difference between patches and turtles is that patches cannot move.
- Patches also take up a defined space/area in the world;
  - Thus, a single patch can contain multiple turtle agents on it. Links are also unable to move themselves.

Links

- Links are often used to represent the relationship between turtles.
- They can also represent the environment
- In some ABM toolkits, the environment is passive and does not have the full capabilities of an agent.

Breeds of Agents

- Besides these three predefined agent-types, modelers can also create their own types of agent called breeds.
- The breed of an agent designates the category or class to which the agent belongs.
- Different breeds of agents are required if different agents have different properties or actions.

Wolf and sheep

- These two breeds had the same set of properties, it was useful to create two breeds because each had different characteristic actions —
- Wolves eat sheep, while sheep eat grass
  - breed [sheep a-sheep]
  - breed [wolves wolf]

Properties That Breeds Have

- We can define the properties that breeds have:
  - turtles-own [energy]
- We could give the wolves a “fang-strength” property and the sheep a “ wooliness ” property
  - sheep-own [wooliness]
  - wolves-own [fang-strength]

Sets of Agents

- **Breeds are particular *collections of agents* where the collections are defined by the kinds of properties and actions of their agents**
- **NetLogo uses the term *agent set* to designate an unordered collection of agents**

Traffic Basic model

- **We could create a set of all the agents that have a speed over 0.5**
  - ***let fast-cars turtles with [speed > 0.5]***
- **We can ask all of the turtles that have a high speed to set their size bigger so they are easier to see**
  - ***let fast-cars turtles with [speed > 0.5] ask fast-cars [set size 2.0]***

“ let ” and “Ask” statement

- The “ let ” statement above collects the fast cars into an agent set
- In the following example, all of the agents are asked with the same ASK command, so the order in which the turtles take actions will be random

```
ask turtles [
    ifelse speed > 0.5 [
set size 2.0
]
[
    set size 1.0
    ]
]
```

TURTLES-ON PATCH-AHEAD

- **Another method for creating agent sets is on the basis of their location**

```
let car-ahead one-of turtles-on patch-ahead 1
        ifelse car-ahead != nobody
            [ slow-down-car ]
```

- **TURTLES-ON PATCH-AHEAD 1 creates an agent set of all of the cars in the patch in front of the current car.**

Agent-sets and Lists

- Agent sets and lists are both variables that can contain one or many other variables
- We can then add numbers, strings, and even turtles to the list

```
;; we put items at the start of the list
set a-list fput 1 a-list
set a-list fput “and” a-list
set alist fput turtle 0 a-list
show a-list
;; prints [(turtle 0) “and” 1
```

No-turtles

- **no-turtles is an empty turtle agent-set (i.e., an agent-set containing no turtles), so by setting an-variable to no-turtles, we specify that this variable is of the type agent-set**
- **we can then add turtles to it by using the turtle-set reporter:**

```
;; this adds turtle 0 to the agentset
set an-agentset (turtle-set turtle 0)
;; this adds turtle 1 and turtle 2 to the agentset
set an-agentset (turtle-set an-agentset turtle 1 turtle 2)
show an-agentset
;; prints (agentset, 3 turtles)
```

Ordered List

- We would need to create an ordered list, and order them by whatever parameter we think determines their advantage.
- *set a-list sort-on [information] turtles*
- A-list now contains all turtles sorted by information in ascending order.

Foreach Command:

- we can use the foreach command:
  - foreach a-list [ask ? [ ]]
- The “ ? ” is a special variable that takes on the value of each element of the list.
- So this code will iterate through each turtle in the list

Agent-sets and Computation

- Once you ask an agent-set to perform an action, all the agents collected at that moment (and only those agents) will perform the action
- If one agent's (agent A) action causes another agent (agent B) in the agent-set to no longer satisfy the collection criteria, B will still perform the action

Agent-set Ordering model

```
to setup
    clear-all
    create-turtles 100 [
       set size random-float 2.0
       forward10
    ]
end

to go
    ask turtles [
       set color blue
       ]
    ask turtles with [ size < 1.0 ] [
       ask one-of turtles with [size > 1.0] [
           set size size - 0.5
       ]
       set color red
    ]
    print count turtles with [ color = red ]
    print count turtles with [ size < 1.0 ]
end
```

The bolded code has the potential to change the set of agents with size < 1.0 by making some agents smaller, thereby changing the agent-set defined in the first ASK

Agent-set Efficiency model

```
;; GO-1 sets red patch labels to a small random number and
;; green patch labels to a larger random number
to go-1
    if any? patches with [ pcolor = red] [
       ask patches with [ pcolor = red] [
              set plabel random 5 ;; red patches are labeled 0-4
       ]
    ]
    if any? patches with [ pcolor = green] [
       ask patches with [ pcolor = green] [
              set plabel 5 + random 5 ;; green patches are labeled 5-9
       ]
    ]
    tick
end
```

Look at the GO-1 procedure above from the Agent-set Efficiency model This code computes each of the two agent-sets PATCHES WITH [PCOLOR = RED] and PATCHES WITH [PCOLOR = GREEN] twice

Agent-set Efficiency model

```
;; GO-2 has the same behavior as go-1 above. But it is more efficient as it
computes each of the patch agentsets only once.
to go-2
 let red-patches patches with [ pcolor = red ]
 let green-patches patches with [ pcolor = green ]
 if any? red-patches [
     ask red-patches [
    set plabel random 5
    ]
]
if any? green-patches [
    ask green-patches [
    set plabel 5 + random 5
    ]
]
 tick
end
```

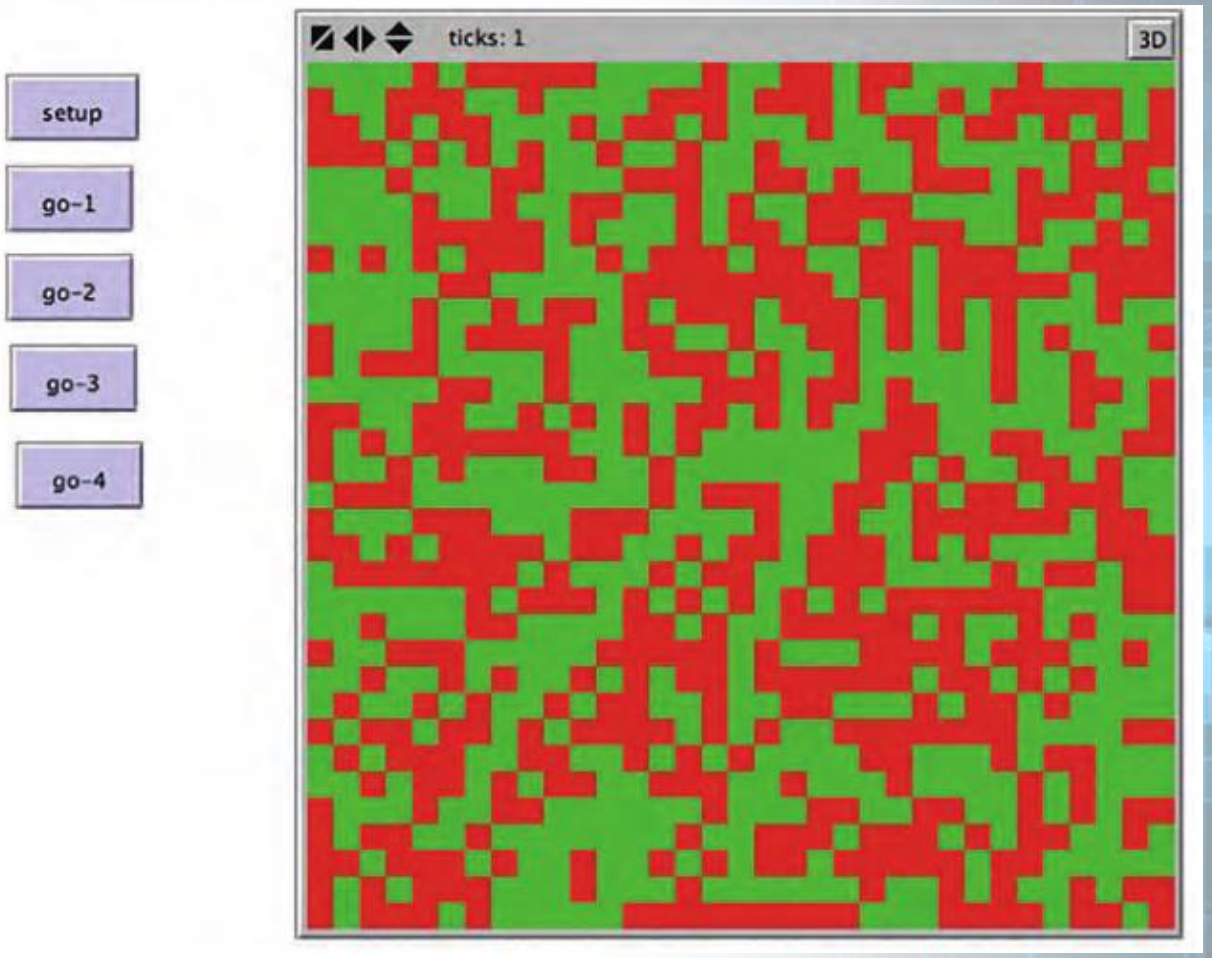
***The procedure GO-2 above has the same behavior as GO-1, but it is more efficient in that it computes each of those agent-sets only once*.**

Pernicious Issue

```
;; GO-3 shows what happens if patch colors are changed "on the fly"
to go-3
    if any? patches with [ pcolor = red] [
       ask patches with [ pcolor = red] [
              set pcolor green
       ]
    ]
    if any? patches with [ pcolor = green] [
       ask patches with [ pcolor = green] [
              set pcolor red
       ]
    ]
    tick
end
```

A more pernicious issue arises if we change just one line of GO-1 and GO-2: If you run this code, you might expect to get a picture that looks like next figure that is, you expect red patches to turn green and vice versa

Constructing Agent-sets at the Outset



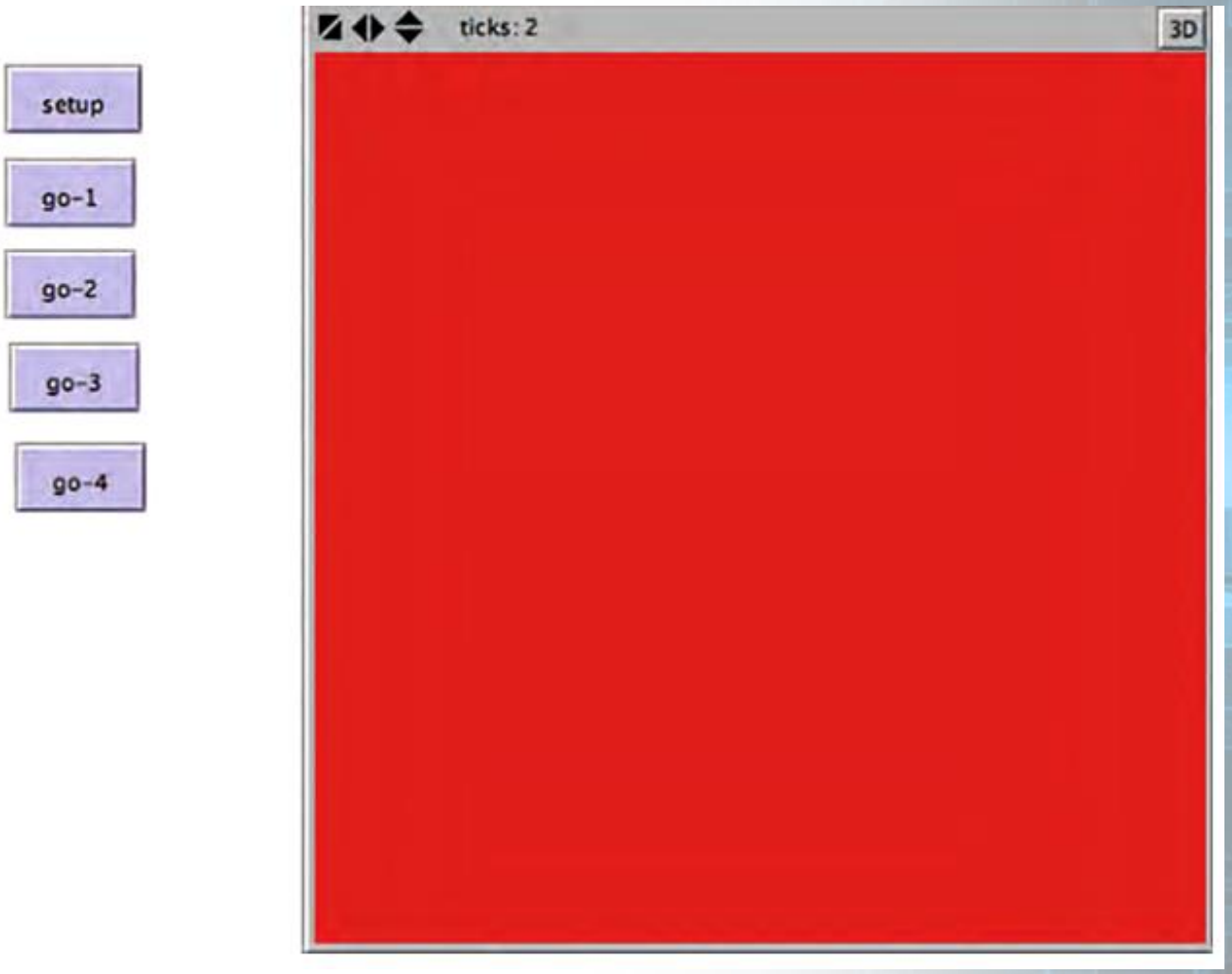
This is another example of the ordering issue The first " if statement " turns the patches green, so by the time the second " if statement " is executed, all the patches are green and therefore then turn red.

Constructing Agent-sets at the Outset

```
;; GO-4 shows what happens if you keep track, at the outset, of which patches
;; are red and which are green
to go-4
        let red-patches patches with [pcolor = red]
        let green-patches patches with [pcolor = green]
        if any? red-patches [
            ask red-patches [
                set pcolor green
            ]
        ]
        if any? green-patches [
            ask green-patches [
                set pcolor red
            ]
        ]
    tick
end
```

By computing the agent-sets ahead of time, as in GO-4, you are not only using more efficient code but are also ensuring that the green-patches agent-sets you ask to execute the instructions are the same green-patches agent-sets as at the start of the procedure and not the set of green patches that result from the first " if-statement, "

Unintended Outcome



Constructing agent-sets after the model state has changed, results in unintended outcome.

Summary

- Here in this module we have seen all different collections of agents in detail
- Credits : Uri Wilensky

The Granularity of an Agent

Overview

- **Here we will understand about One of the first considerations when designing an agent-based model is at what granularity should you create your agent — at what level of complexity is the agent you are modeling.**

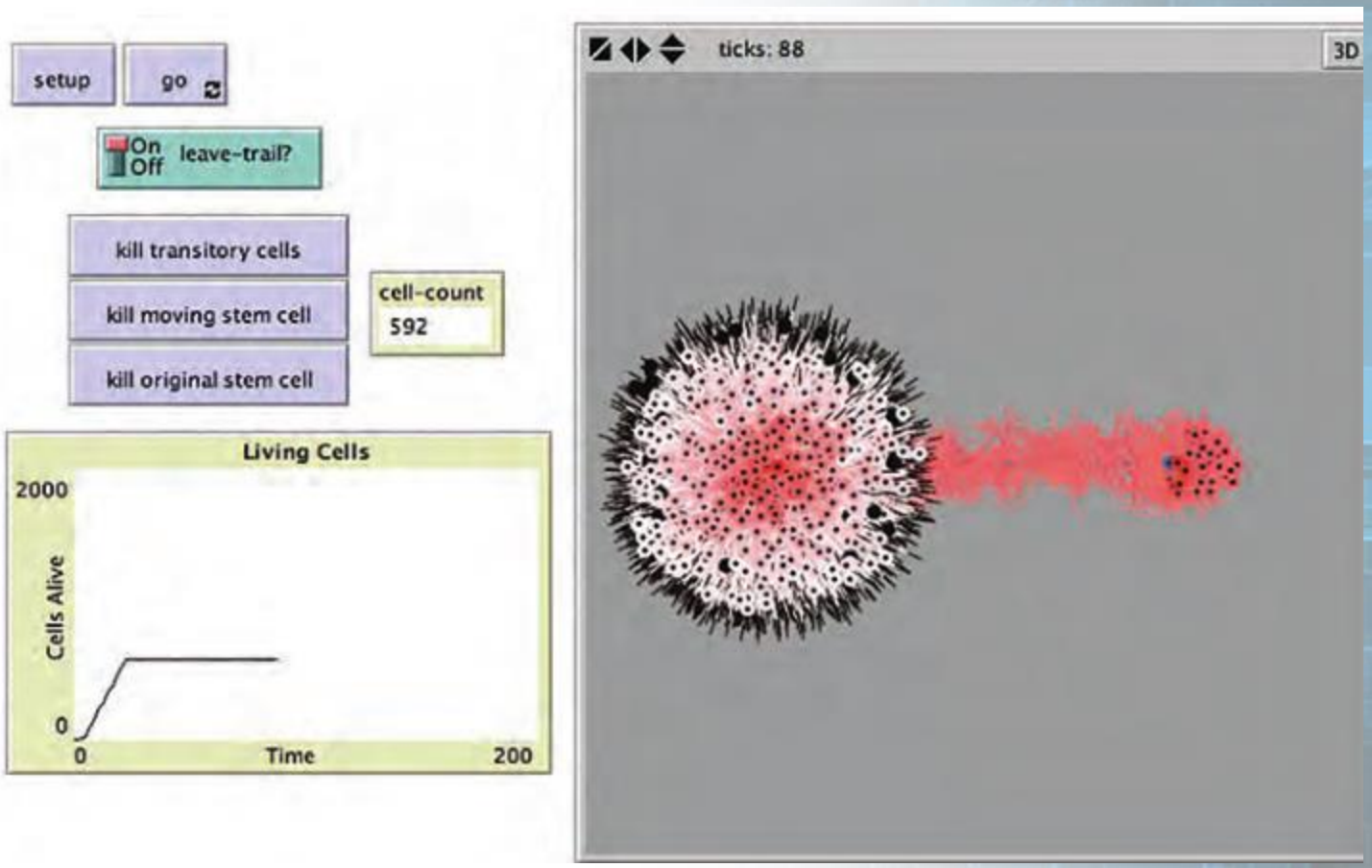
Level of Complexity for the Agents

- How do you choose the level of complexity for the agents in your model?
- The guide-line is to choose agents such that they represent the fundamental level of interaction that pertains to your question about the phenomenon.

Tumor Model

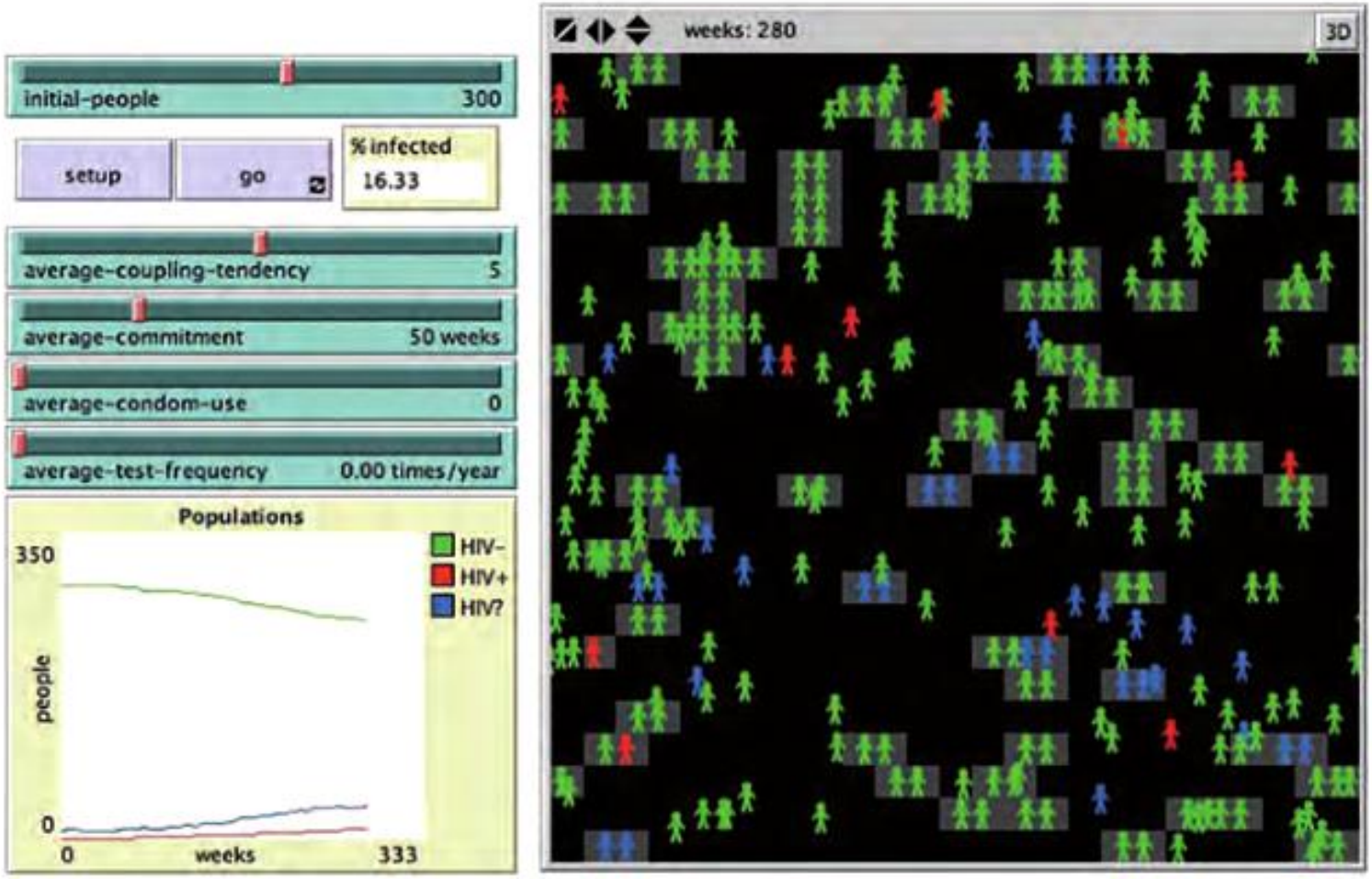
- For instance, if you look at the *Tumor model* the agents are cells within the human body, since the research question the model examines is how tumor cells spread
- However, even though the *AIDS model* is also concerned with disease, the basic agents are humans instead of cells.

NetLogo Tumor model



http://ccl.northwestern.edu/netlogo/models/Tumor (Wilensky, 1998b).

NetLogo AIDS model



http://ccl.northwestern.edu/netlogo/models/AIDS (Wilensky, 1997a).

Question Of Concern

- **The AIDS model is more concerned with how the disease spreads between humans instead of how it spreads within the human body.**
- **In the Tumor model, the *question of concern* is how cells interact to create cancer.**

Choices Of Granularity

- **These two models highlight the relationship between the question being investigated, the interactions being modeled, and the resulting choices of granularity for the agents.**

Level Of Complexity

- **Both individual cells and groups of cells can be valid choices for the level of complexity of these agents, and deciding between them will depend on details of the question you are asking as well as considerations of computational complexity**

Summary

- Here we have seen Choosing the appropriate granularity for your agents can make your models much easier to create, as it allows you to ignore unnecessary aspects of the phenomena being modeled and instead focus on the interactions of interest.
- Credits : Uri Wilensky

Modeling and Simulation

Agent Cognition

Overview

- Here we will understand about how do agents examine their properties and the world around them to decide what actions to take?
  - This question is resolved by a decision-making process called agent cognition

Types Of Agent Cognition

- Several types of agent cognition:
  - Reflexive agents ,
  - Utility-based agents
  - Goal-based agents ,
  - And adaptive agents

Reflexive agents

- Reflexive agents are built around very simple rules. They use if-then rules to react to inputs and take actions
- For instance, the cars in the Traffic Basic model are reflexive agents. If you look at the code that controls their actions, it looks like this:

Traffic Basic Model are Reflexive Agents

```
let car-ahead one-of turtles-on patch-ahead 1  ;;choose a car on the patch ahead
ifelse car-ahead != nobody [  ;; if there is a car ahead
    slow-down-car car-ahead ;; set car speed to be slower than car ahead
]
[   ;; otherwise, speed up
    speed-up-car ;; increase speed variable by the acceleration
]
;; ….
fd speed
```

This code says that if there are cars ahead, then slow down below the speed of the car in front; if there are not any cars ahead, then speed up. This is the most basic form of agent cognition

Utility-based Form of Agent Cognition

- We could elaborate Traffic Basic model by giving the cars gas tanks and fuel efficiencies based on the speed they are going.
- We could then have the cars change their speeds in order to improve their fuel efficiencies.

Utility-based Form of Agent Cognition

- As a result, the agents might have to speed up and slow down at different times than they currently do to minimize their gas usage while still not causing accidents.
- Giving the agents this type of decision-making process would give them a utility-based form of agent cognition

Implementation Of Model Of Agent Cognition

- To implement this model of agent cognition, we need to start by replacing our SPEED-UP-CAR procedure with a new procedure that accounts for the car ’s fuel efficiency.
- We want the ADJUST-SPEED-FOR-EFFICIENCY procedure to maintain the same speed if the car is at the maximally fuel efficient speed

ADJUST-SPEED-FOR-EFFICIENCY

```
;; choose a car on the patch ahead
let car-ahead one-of turtles-on patch-ahead 1
ifelse car-ahead != nobody [ ;; if there is a car ahead
    slow-down-car car-ahead  ;; set car speed to be slower than car ahead
]
[ ;; otherwise, adjust speed to find ideal fuel efficiency
    adjust-speed-for-efficiency ]
```

The car would still need to slow down if it was about to crash into the car in front of it. As such, the true utility function includes an exception that gives a utility of 0 to any action that results in a crash. As a result, we can leave the first part of the code that slows the car before it crashes,

ADJUST-SPEED-FOR_EFFICIENCY

```
;; car procedure
to adjust-speed-for-efficiency
 if (speed != efficient-speed) [ ;; if car is at efficient speed, do nothing
        if (speed + acceleration < efficient-speed) [
;; if accelerating will still put you below the efficient speed then accelerate
            set speed speed + acceleration
       ]                                          ;;
;; if decelerating will still put you above the efficient speed then decelerate
        if (speed - deceleration > efficient-speed) [
            set speed speed - deceleration
       ]
    ]
end
```

we can leave the first part of the code that slows the car before it crashes and just add ADJUST-SPEED-FOR_EFFICIENCY when there is no car directly ahead, as illustrated in the code above from the Traffic Basic Utility model

Utility Functions

- In the language of utility functions, each car agent is minimizing a function f, defined by:

$$f(v) = |v - v^*|$$

- where v is the current velocity of the car and v* is the most efficient velocity. The constraint that is described in the code is that the v cannot be adjusted arbitrarily,

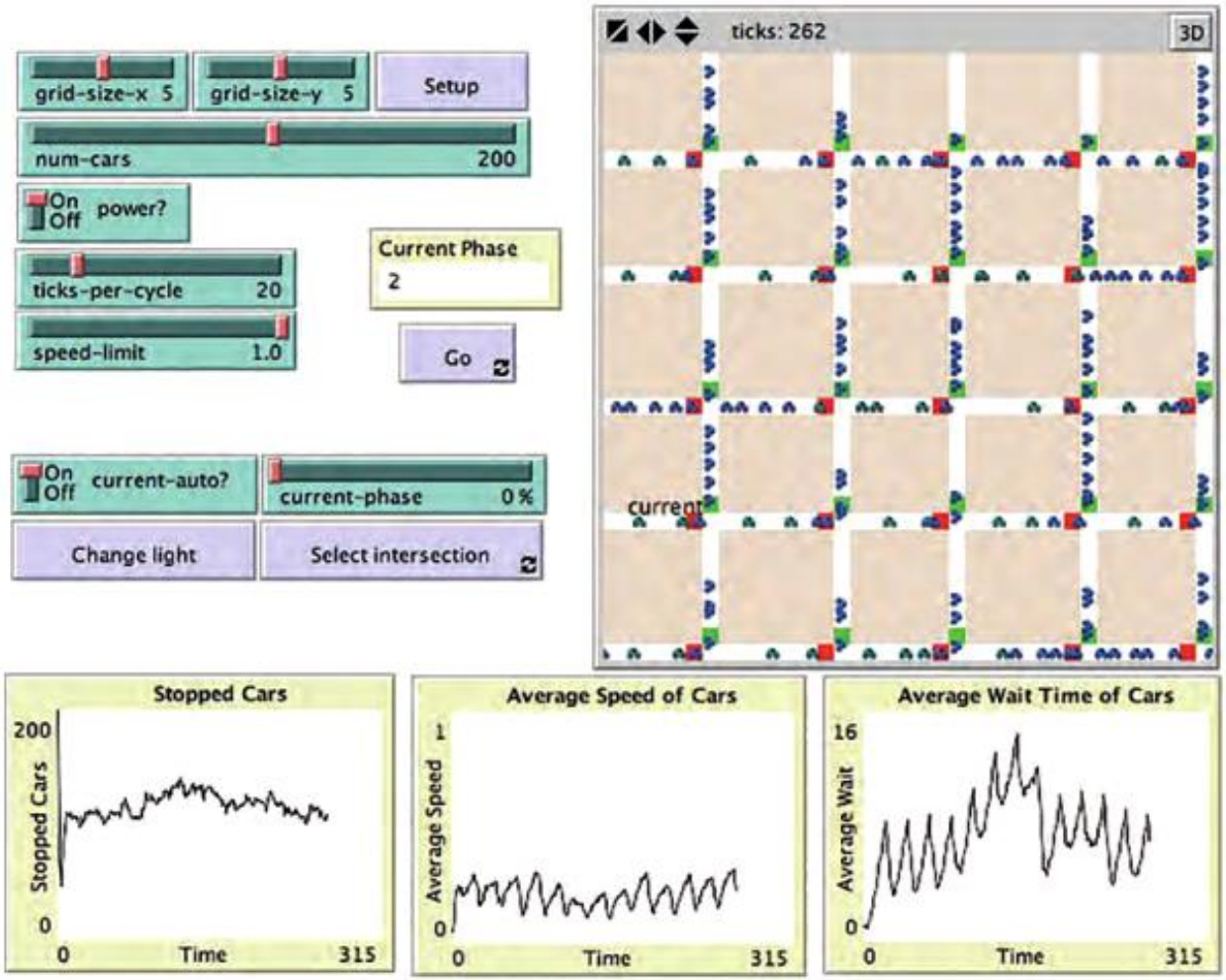
Goal-based Agents

- **Imagine that each car in the Traffic Grid model from the social sciences section of the NetLogo models library has a home and a place of work, with the goal of moving from home to work in a reasonable amount of time.**

Goal-based Agents

- **Now, not only do the agents have to be able to speed up and slow down, but they also have to be able to turn left and right**
- **In this version of the model, the cars are *goal-based agents* , since they have a goal (getting to and from work) that they are using to dictate their actions.**

Traffic Grid model



http://ccl.northwestern.edu/netlogo/models/TrafficGrid (Wilensky, 2002b).

Implement The Goal-based

- To implement the goal-based version of the model, we start by defining the procedure that the cars will use to navigate between their two desired destinations
- The car check if it is right next to its goal
- It does this by choosing candidate patches to move to (adjacent patches on the road) and then selecting the candidate closest to its goal

Implement The Goal-based

```
;; establish goal of driver
to-report next-patch
;; if I am going home and I am next to the patch that is my home
;; I turn around and head towards work (my goal is set to “work”)
if goal = house and (member? patch-here [neighbors4] of house) [
        stay set goal work
    ]
;; if I am going to work and I am next to the patch that is my work
;; I turn around and head towards home (my goal is set to “home”)
    if goal = work and (member? patch-here [neighbors4] of work) [
        stay set goal house
    ]
;; CHOICES is an agentset of the candidate patches which the car can
;; move to (white patches are roads, green and red patches are lights)
let choices neighbors with [pcolor = white or pcolor = red or pcolor = green]
          ;; choose the patch closest to the goal, this is the patch the car will move to
    let choice min-one-of choices [distance [goal] of myself]
;; report the chosen patch
    report choice
end
```

Now, we have goal-directed car agents in the grid

Adaptive Agent

- An agent that can change its strategy based on prior experience is an adaptive agent .
- Unlike conventional agents, which will also do the same thing when presented with the same circumstance, adaptive agents can make different decisions if given the same set of inputs

Traffic Basic model

- **In the Traffic Basic model, cars do not always take the same action;**
  - ***They operate differently based on the cars around them by either slowing down or speeding up***
- **To be truly adaptive, agents need to be able to change not only their actions in time, but also their strategies.**

Example Of Adaptive Cognition

- For instance, the agent could have observed that in the past that, when there was a car five patches ahead of it,
- It braked too quickly, even though it could have waited longer to brake without hitting the other car.

Example Of Adaptive Cognition

- In the future, it could change its rule for braking to brake only when a car is four patches ahead.
- This agent is now an adaptive agent because it not only modifies its actions , but also, its strategies .

Summary

- Besides the basic types of cognition that we have discussed, there are also more advanced methods of giving cognition to agents. One of the best ways to do this is by combining agent-based modeling with machine learning
- Credits : Uri Wilensky

Other Kinds of Agents

Overview

- Here we will Understand about two other special kinds of agents that deserve at least a brief mention.
  - The first type are meta-agents,
  - The second is proto-agents

Meta-Agents

- All those“ agents ”which are composed of other agents are called meta agents
- For instance, if we have selected a human to be the agent, he or she is actually composed of many subagents, with these subagents in turn being different depending on how you view the human.

Meta-agents and Sub-agents

- Agents can also be both meta-agents and subagents at the same time.
- For instance, organs are composed of cells and are meta-agents.
- However, they also play a compositional role in the systems of the human body and are thus subagents.

Meta-agent Appears to be a Single Agent

- From the perspective of another meta-agent, a meta-agent appears to be a single agent.
- If a person meets another person, they do not (usually) directly interface with the heart or the lungs (unless the meeting takes place at the surgical table).
- Instead, they interface with the person as a whole.

Modeling Agents and Their Interactions

- When we think of modeling agents and their interactions, we have to determine what level of granularity we want to describe the agent behaviors
- However, we always have the option of refining our model by converting agents

Proto-Agents

- Sometimes, though, it can be desirable to create agents that, rather than having their own properties or behaviors, are instead placeholders for future agents.
- We call these agents proto-agents

Example of Proto-agent

- For instance, if you were creating a model of residential location decision making, you would have residents as agents;
  - However, since where a resident lives is greatly influenced by places of employment and services (e.g., grocery stores and restaurants

Example of Proto-agent

- Keeping these agents as proto-agents early on means that when you add in the more richly detailed versions to the model, you do not have to go back and revise your resident agents.
- Instead, you can use the interaction events that they had already been using to interface with the service center proto-agents.

Summary

- **Both meta-agents and proto-agents provide a way to initially create a simpler model and late elaborate upon that model as we continue to refine it.**
- **Credits : Uri Wilensky**

Modeling and Simulation

Environments

Overview

- **Here we will understand in detail about how to design the environment of the agent-based model**

Environment

- The environment consists of the conditions and habitats surrounding the agents as they act and interact within the model.
- The environment can affect agent decisions, and, in turn, can be affected by agent decisions.

Environment Can Affect Agent

- For instance, in the Ants model the ants leave pheromone in the environment that changes the environment, and in turn changes the behavior of the ants.
- There are many different kinds of environments that are common in ABMs

Implementation of an Environment

- The environment itself can be implemented in a variety of ways.
- First, the environment can be composed of agents such that each individual piece of the environment can have a full set of properties and actions.

NetLogo

- In NetLogo, this is the default view of the environment :
  - The environment is represented by the agent-set of patches.
- This allows different parts of the environment to have different properties and act differently based on their local interactions.

Summary

- Here we have discussed about environment and its implementation on agent-set
- Credits : Uri Wilensky

Modeling and Simulation

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Summary

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- Credits : Uri Wilensky

Modeling and Simulation

Network-Based Environments

Overview

- **Here we will understand about Network-Based Environments**

Link

- A link is defined by the two ends it connects, which are frequently referred to as nodes
- We will use the network/node/link vocabulary throughout Module
- In NetLogo, links are their own agent-type.

lattice networks

- lattice graphs can also be called lattice networks , with the property that each position in the network looks exactly like every other position in the network
- ABM environments usually do not implement lattice environments as networks for both conceptual and efficiency reasons

Random Networks

- Besides the regular networks described earlier, the three most common network topologies are random , scale-free , and small-world
- In random networks , each individual is randomly connected to other individuals.

Random Networks

- For example, if you had a model of agents moving around a large room and connected every agent in the room to another agent based on which agent had the next largest last two digits of their social security number, you would probably create a random network.

A Random Network

- Here we show one simple methods for creating a random network.
- This code is also in the Random Network model in the chapter 5 subfolder of the IABM Text-book folder of the NetLogo models library:

Code for creating a random network

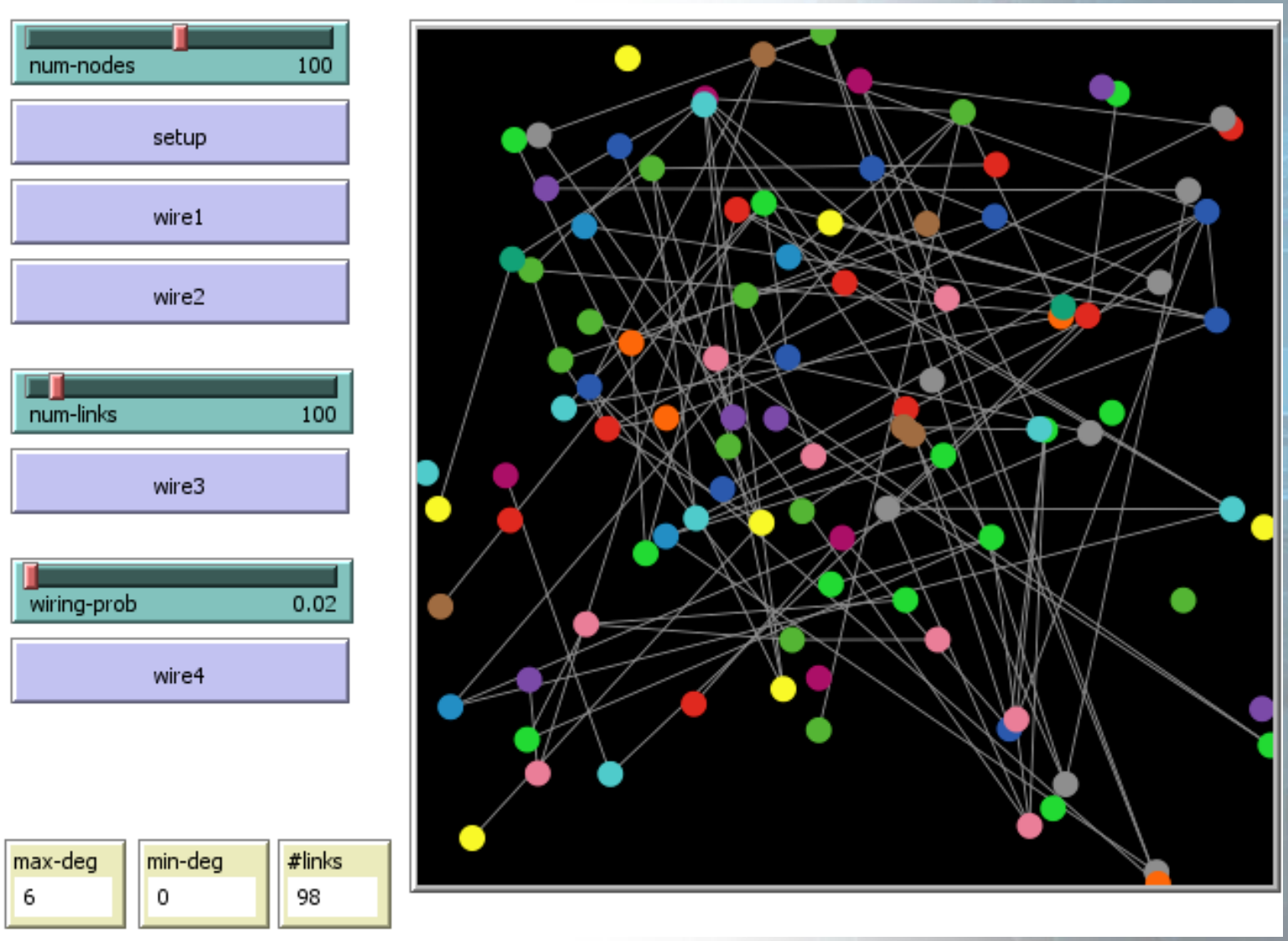
```
;; Create nodes.
to setup
  clear-all
  create-turtles num-nodes [
    set shape "circle"
    setxy random-xcor random-ycor
  ]
  reset-ticks
end

;; Ask each node to create a link with a random other node.
;; Results in "just under" NUM-NODES links because no new link is created
;; if a node tries to connect to a node with which it is already linked.
to wire1
  ask links [ die ]
  ask turtles [
    create-link-with one-of other turtles
  ]
end

;; Pick a random node and ask it to create a link with a random other node.
;; Results in "just under" NUM-NODES links because no new link is created
;; if a node tries to connect to a node with which it is already linked.
to wire2
  ask links [ die ]
  repeat num-nodes [
    ask one-of turtles [
      create-link-with one-of other turtles
    ]
  ]
end

;; This is the classic Erdős-Rényi random network.
;; It uses WHILE to ensure we get NUM-LINKS links.
to wire3
  ask links [ die ]
  if num-links > max-links [ set num-links max-links ]
  while [ count links < num-links ] [
```

Random Network model



Scale-free Networks

- **Scale-free networks have the property that any sub network of the global network has the same properties as the global network**
- **A common way to create this type of *network is by adding new nodes and links to the system so that extant nodes with a large number of links are more likely to receive new connections***

Preferential Attachment

- This technique is sometimes called preferential attachment , since nodes with more connections are attached to preferentially.
- This method for network creation tends to produce networks with central nodes that have many radiating links;

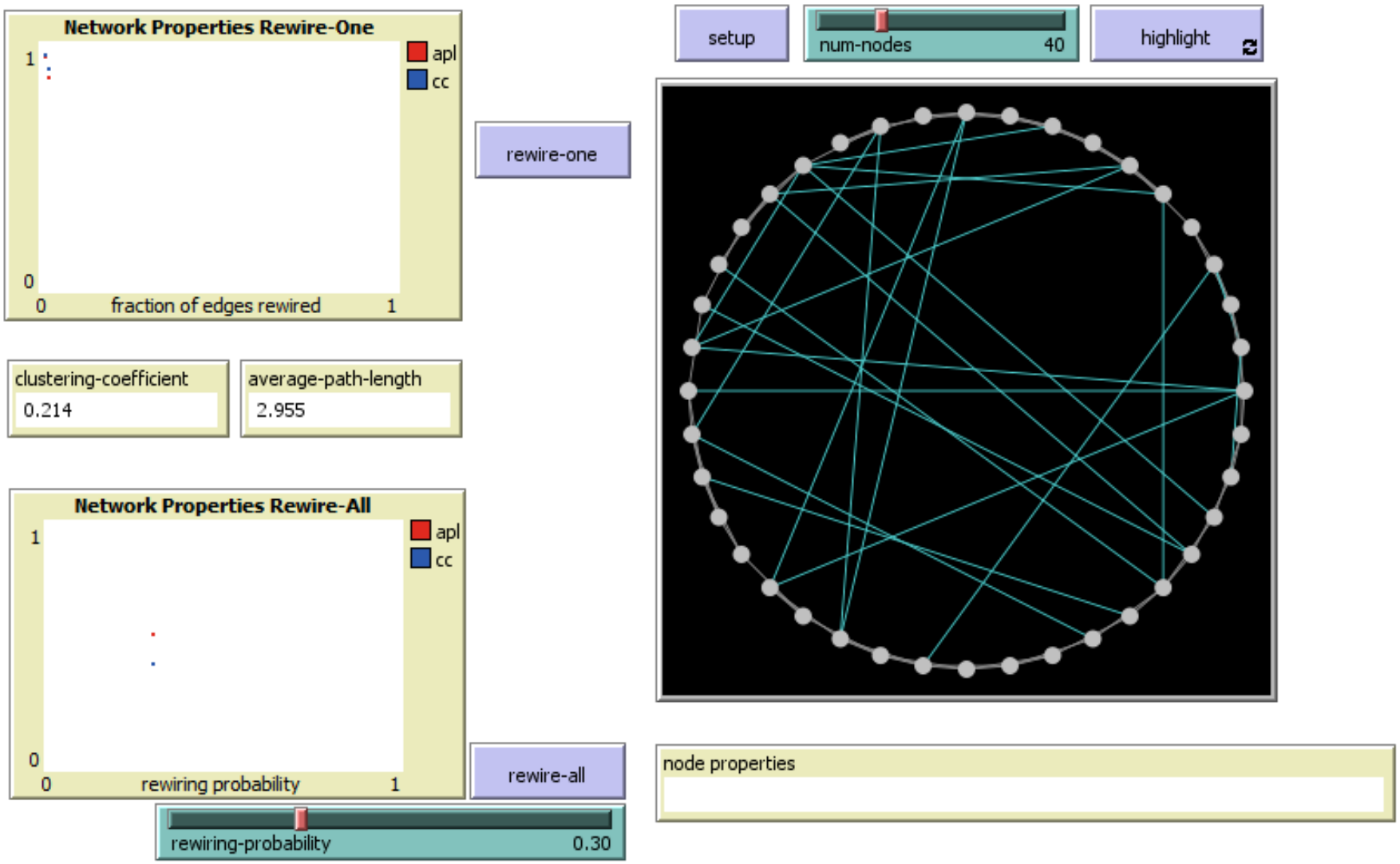
Small-world Network

- The final standard network topology is known as a small-world network.
- Small-world networks are made up of dense clusters of highly interconnected nodes joined by a few long distance links between them.

Small-world model

- **Small-world networks are sometimes created by starting with regular networks**
- **There are many ways to characterize networks.**
- **Two commonly used ways are average path length and clustering coefficient**
- ***The average path length is the average of all the pair wise distances between nodes in a network*.**

Small-world model



Small-World model in the Networks section of the NetLogo models library (Wilensky, 2005a)

Average Path Length

- The average path length is the average of all the pair wise distances between nodes in a network.
- In other words, we measure the distance between every pair of nodes in the network and then average the results.
- Average path length characterizes how far the nodes are from each other in a network.

Clustering Coefficient of a Network

- The clustering coefficient of a network is the average fraction of a node's immediate neighbors who are also neighbors of the node's other neighbors
- In networks with a high average clustering coefficient, any two neighboring nodes tend to share many of their neighbors in common,

Summary

- NetLogo also includes a special extension, the network extension, for creating, analyzing, and working with networks.
- This extension enables full integration of network theory methods into ABM.
- Credits : Uri Wilensky

Modeling and Simulation

Special Environments

Overview

- **Here we will understand about two of the most interesting topologies involve the use of 3D worlds and Geographic Information Systems (GIS).**

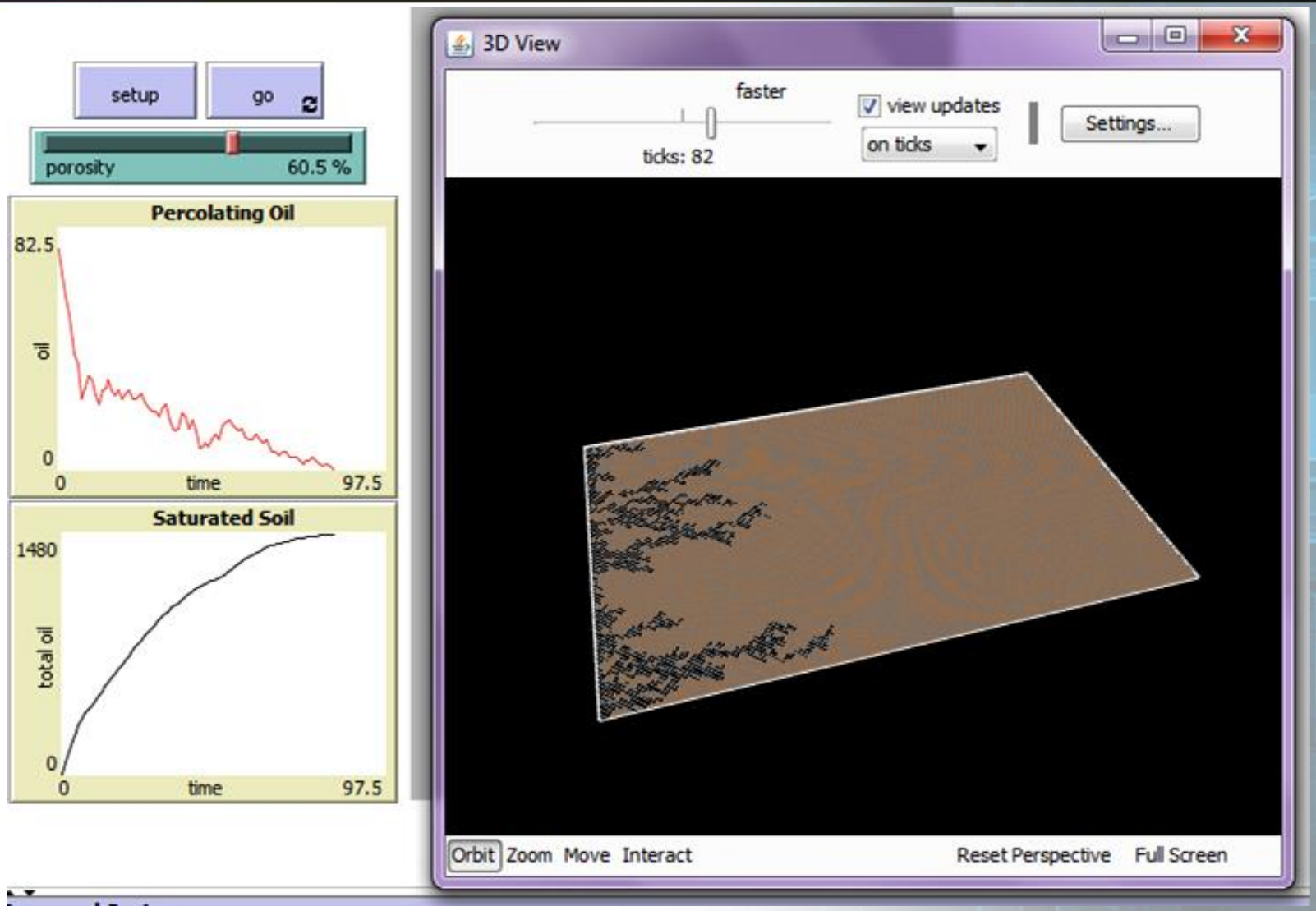
3D Worlds

- 3D environments enable model developers to explore complex systems which are irreducibly bound up with a third dimension as well as sometimes increasing the apparent physical realism to their models.
- There is a version of NetLogo called NetLogo 3D

Working With 3D Worlds

- Working with 3D worlds is not much different from working with 2D worlds.
- Although, using a 3D world does require additional data and commands.
- For instance, agents now have a Z coordinate, and new commands are needed to manipulate this new degree of freedom.

Percolation 3D



There is a three-dimensional version of the Percolation model

Code for PERCOLATE procedure in 2D

```
to percolate
    ask current-row with [pcolor = red] [
        ;; oil percolates to the two patches southwest and southeast
        ask patches at-points [[-1 -1] [1 -1]]
            [ if (pcolor = brown) and (random-float 100 < porosity)
                [ set pcolor red ] ]
        set pcolor black
        set total-oil total-oil + 1
    ]
    ;; advance to the next row
    set current-row patch-set [patch-at 0 -1] of current-row
end
```

The code for the PERCOLATE procedure in 2D Percolation looks like this:

Code for PERCOLATE procedure in 3D

```
to percolate
    ask current-row with [pcolor = red] [
       ;; oil percolates to the four patches one row down in the z-coordinate and
    ;; southwest, southeast, northeast, and northwest
       ask patches at-points [[-1 -1 -1] [1 -1 -1] [1 1 -1] [-1 1 -1]]
           [ if (pcolor = black) and (random-float 100 < porosity)
              [ set pcolor red ] ]
       set pcolor brown
       set total-oil total-oil + 1
    ]
    ;; advance to the next row
    set current-row patch-set [patch-at 0 0 -1] current-row
end
```

Notice that in the 2D version, the code has each patch look at patches that are below, left, and right of the patch. This will change in the 3D version. In 3D Percolation (Wilensky& Rand, 2006), PERCOLATE looks like this:

The difference between 3D percolate and 2D

- The only difference between the 3D percolate and its 2D counterpart is that instead of percolating a line of patches at a time, We percolate a square of patches.
- As a result, each patch must ask four patches below it (in a cross shape) to percolate, not just two as it does in the 2D version.

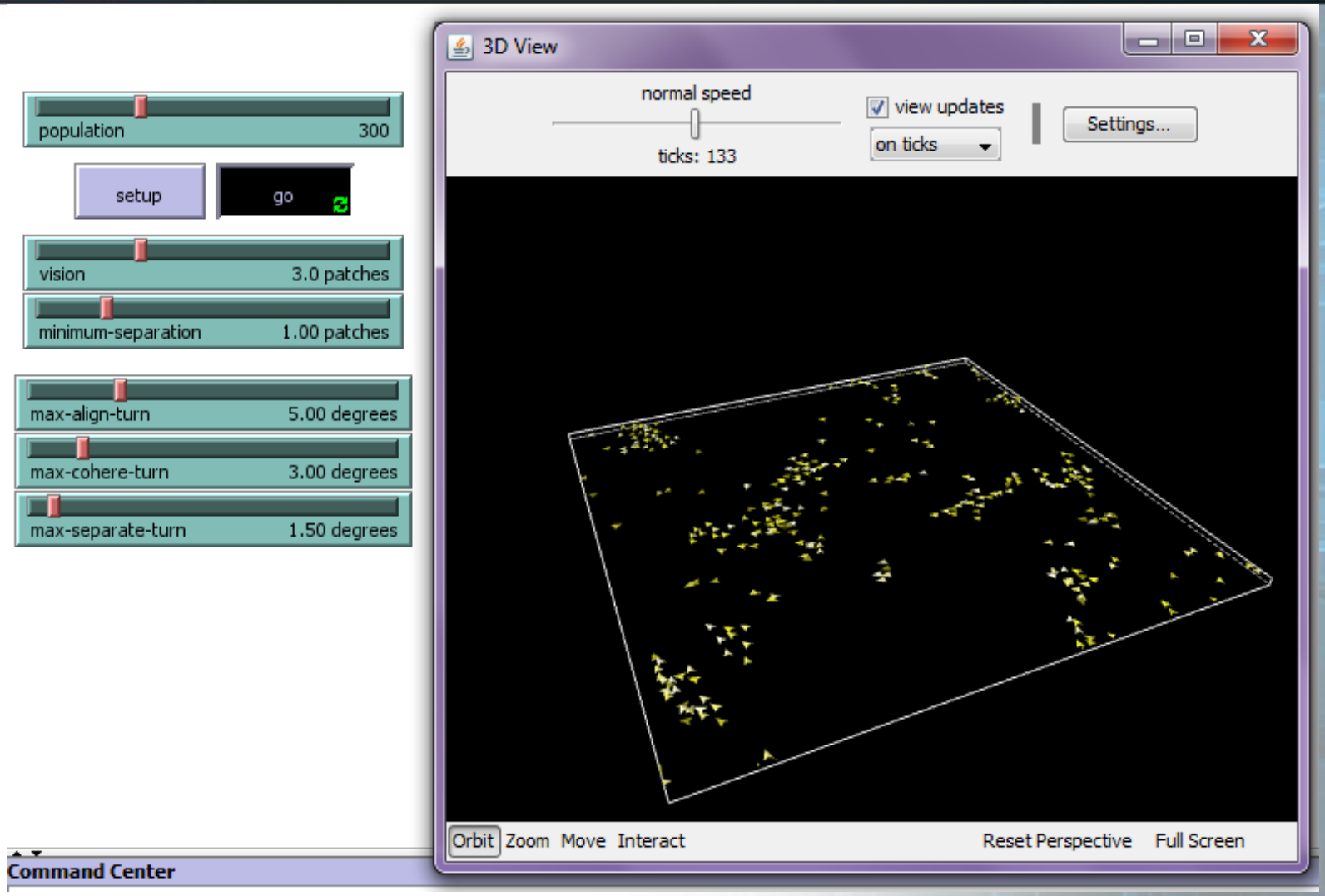
GIS-Based

- Geographic Information Systems (GIS) are environments that record large amounts of data that are related to physical locations in the world.
- GISs are widely used by environmental scientists to organize data and make decisions about any large area of land.

GIS Tools And Techniques

- GIS tools and techniques allow for a more in-depth exploration of the pattern of a complex system.
- Agents moving on a GIS terrain may be constrained to interact on that terrain.
- Thus, GIS can serve as an interaction topology

The 3D model, Flocking 3D



Where does ABM fit in to this picture? GIS can provide an environment for an ABM to operate in.

Summary

- Using the NetLogo GIS extension is the preferred method of importing large amounts of GIS data into a NetLogo model
- Credits: Uri Wilensky

Modeling and Simulation

Observer/User Interface

Overview

- **Now that we have talked about the agents, the environments, and the interactions that occur between agents and environmental attributes, here we will discuss who controls the running of the model**

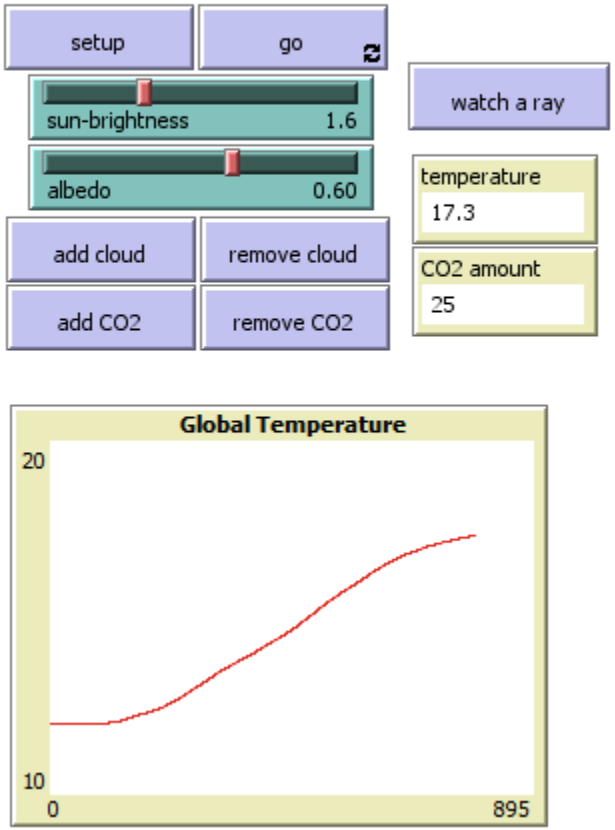
Observer

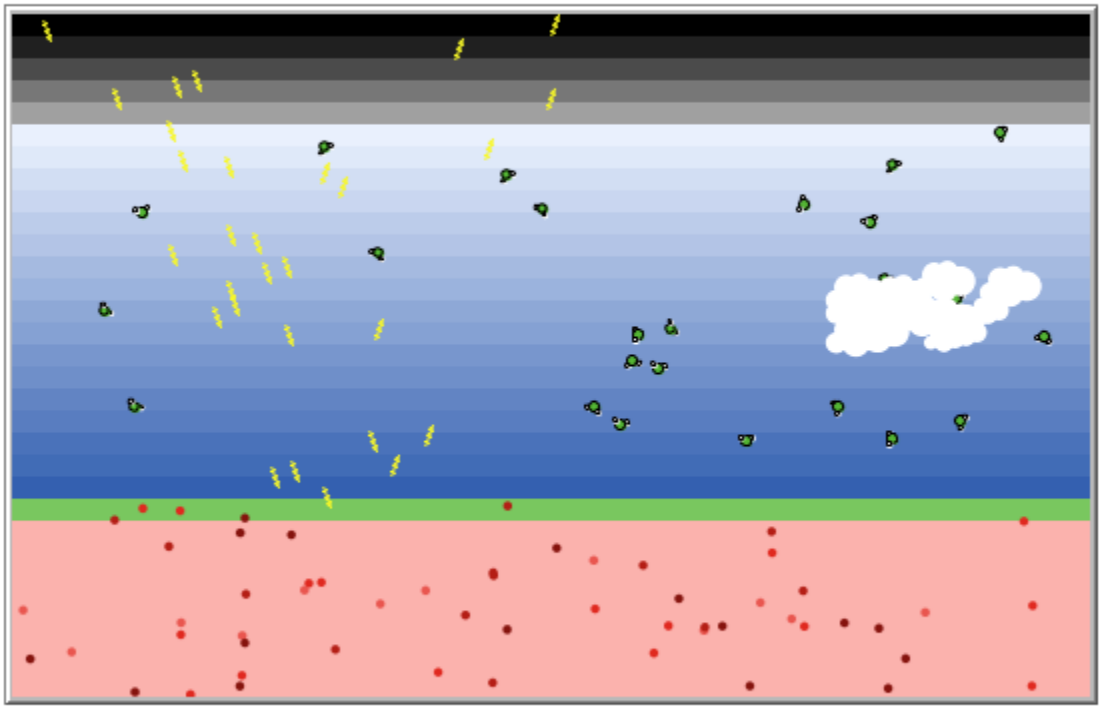
- The observer is a high-level agent that is responsible for
  - Ensuring that the model runs and proceeds according to the steps developed by the model author.
  - The observer issues commands to agents and the environment,

Properties Specific to the observer

- The only properties that one could consider to be specific to the observer are those relating to the perspective from which the modeled world is viewed
- In NetLogo the view may be centered on a specific agent

Climate Change model





In NetLogo the view may be centered on a specific agent, or focusing a highlight on a certain agent, using the FOLLOW, WATCH, or RIDE commands

User Input and Model Output

- **ABMs require a control interface or a parameter group that allows the user to setup different parameters and settings for the ABM**
- **The most common control *mechanism is a button* , which executes one or more commands within the model**
  - ***if it is a forever button it will continue***

Command Center

- The command center is a very useful feature of NetLogo, as it allows the user to interactively test out commands, and manipulate agents and the environment.
- The *input controls include* sliders, switches, choosers, and input boxes.
- The *output controls consist* of monitors, plots, an output area, and notes.

Sliders, Switches & Input Boxes

- Sliders enable the model user to select a particular value from a range of numerical values
- Switches enable the user to turn various elements of a model off or on
- Input boxes are more free-form, allowing the user to input text that the model can use

Monitors , Plots & Notes

- Monitors display the value of a global variable or calculation updated several times a second.
- Plots provide traditional 2D graphs enabling the user to observe the change of an output variable over time
- Notes enable the modeler to place text information on the Interface tab

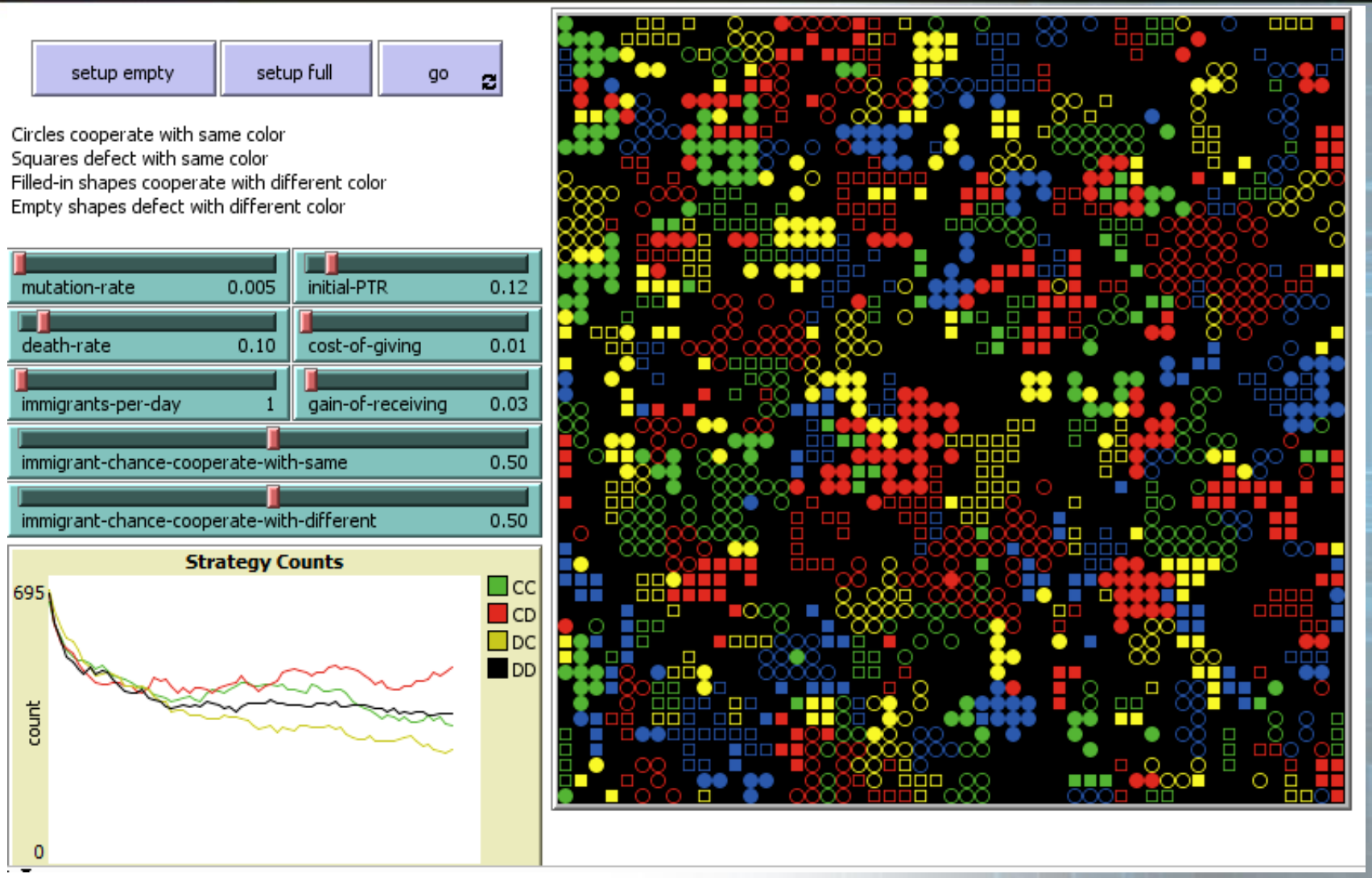
Visualization

- Visualization is the part of model design concerned with how to present the data contained in the model in a visual way
- There are three guidelines that should be kept in mind whenever designing the visualization of an ABM:
  - Simplify, Explain, and Emphasize

Guidelines for Designing Visualization

- **Simplify the visualization:**
  - ***Make the visualization as simple as possible***
- **Explain the components:**
  - ***If a model is to be useful it is necessary that anyone viewing the model can easily understand what it is saying***
- **Emphasize the main point :**
  - ***A model visualization should emphasize the main points and interactions***

NetLogo Ethnocentrism model



This model uses the shape of agents to visualize agent strategy

Batch vs. Interactive

- **When user can interact as the model is running This kind of spur-of-the-moment control is called interactive running**
- **In contrast to interactive running, *another type of user running of a model is called batch running* With batch running, instead of controlling the model directly, *the user writes a script to run the model many times***

Summary

- When designing the user interface for your model, it is important to keep in mind that some users are going to want to be able to interact with your model
- Credits : Uri Wilensky

Modeling and Simulation

Schedule

Overview

- In NetLogo, there is no single identifiable object that can be identified as " the schedule. "
- We will first discuss the common SETUP/GO idiom which is employed in almost all agent-based models, and then move on to discuss some of the subtler issues concerning scheduling in ABMs.

Schedule, SETUP and GO

- The schedule is a description of the order in which the model operates
- There is usually an initialization procedure that creates the agents initializes the environment, and readies the user interface

SETUP and GO

- In NetLogo initialization procedure is usually called *SETUP* and it executes whenever a user presses the SETUP button on a NetLogo model
- For instance, in Traffic Basic the SETUP procedure looks

```
to setup
    clear-all
    ask patches [ setup-road ]
    setup-cars
    watch sample-car
end
```

Main Loop

```
to go
;; if there is a car right ahead of you, slow down to a speed below its speed
    ask turtles [
         let car-ahead one-of turtles-on patch-ahead 1
         ifelse car-ahead != nobody
              [   slow-down-car car-ahead]
              ;; otherwise, speed up
              [ speed-up-car ]
    ;; don't slow down below speed minimum or speed up beyond speed limit
         if speed < speed-min [ set speed speed-min ]
         if speed > speed-limit [ set speed speed-limit ]
         fd speed ]
    tick
end
```

The other main part of the schedule is what is often called the main loop, or in NetLogo, the GO procedure.

Traffic Basic the GO procedure looks like above code:

Asynchronous vs. Synchronous Updates

- **If a model uses an *Asynchronous* update schedule,**
  - **This means that when agents change their state, that state is immediately seen by other agents.**
- **In a *Synchronous* update schedule changes made to an agent are not seen by other agents until the next clock tick**
  - **That is, all agents update simultaneously.**

Sequential vs. Parallel Actions

- **Sequential actions involve only one agent acting at a time while Parallel actions are those in which all agents act independently.**
- **In NetLogo sequential action is the standard behavior for agents.**

Sequential vs. Parallel Actions

- For the agents to act truly in parallel, you would need parallel hardware so that the actions of each agent would be carried out by a separate processor.
- There is an intermediate solution.
  - *Simulated concurrency* uses one processor to simulate many agents acting in parallel

Summary

- After completing these Modules, you have learned how to use simple agent-based models, extend an ABM, and build your own agent-based model, while familiarizing yourself with the components of an agent-based model.
- Credits : Uri Wilensky

Analyzing Agent-Based Models

Overview

- **Here, we will understand details on how to analyze Agent-based Models.**

Analyzing Agent-Based Models

- We have examined, modified, and built models from scratch.
- Question: How can we employ ABMs to produce new and exciting results about the domain?

Analyzing Agent-Based Models

- **Specifically:**
- **What kind of results are produced by an ABM?**
- **Advantages and Disadvantages of comparative techniques**
- **Often times, it is better to consider the analysis method *before* building an ABM**

Analyzing Agent-Based Models

- Let us examine a disease spread model
- Someone catches a cold and is coughing up a storm, he might infect others.
- Those that he comes into contact with — his friends, co-workers, and even strangers — may catch the cold.

Analyzing Agent-Based Models

- We have examined, modified, and built models from scratch.
- Question: How can we employ ABMs to produce new and exciting results about the domain?

Analyzing Agent-Based Models

Infection Data

Infection Data

Population	50	100	150	200
Time to 100% Infection	419	188	169	127

Analyzing Agent-Based Models

- **Based on these results, we conclude that as the population density increases, the time to full infection dramatically decreases.**

Analyzing Agent-Based Models

Table 6.2
Your Friend's Data

Population	50	100	150	200
Time to 100% Infection	305	263	118	126

Table 6.3
Raw Data

Population	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10
50	419	365	305	318	323	337	432	380	430	359
100	188	263	256	205	206	205	201	181	202	231
150	169	118	163	146	143	167	137	121	140	140
200	127	126	113	111	133	129	109	101	105	133

Analyzing Agent-Based Models

- **The data is inconsistent because most ABM models employ randomness in their algorithms**
- **i.e., the code makes use of a random number generator.**

Summary

- **We have learnt about the analysis of agent-based models.**
- **Credits: Uri Wilensky book.**

Types of Measurements

Overview

- **Here, we will understand about the different types of measurements in an ABM**

Types of Measurements

- **Statistical Analysis of ABM: Moving beyond Raw Data**
- **Statistical results are the most common way of looking at any kind of scientific data**

Types of Measurements

- The general methodology behind descriptive statistics is to provide numerical measures
- These measures summarize a large data set
- Also, describe the data set in such a way that it is not necessary to examine every single value.

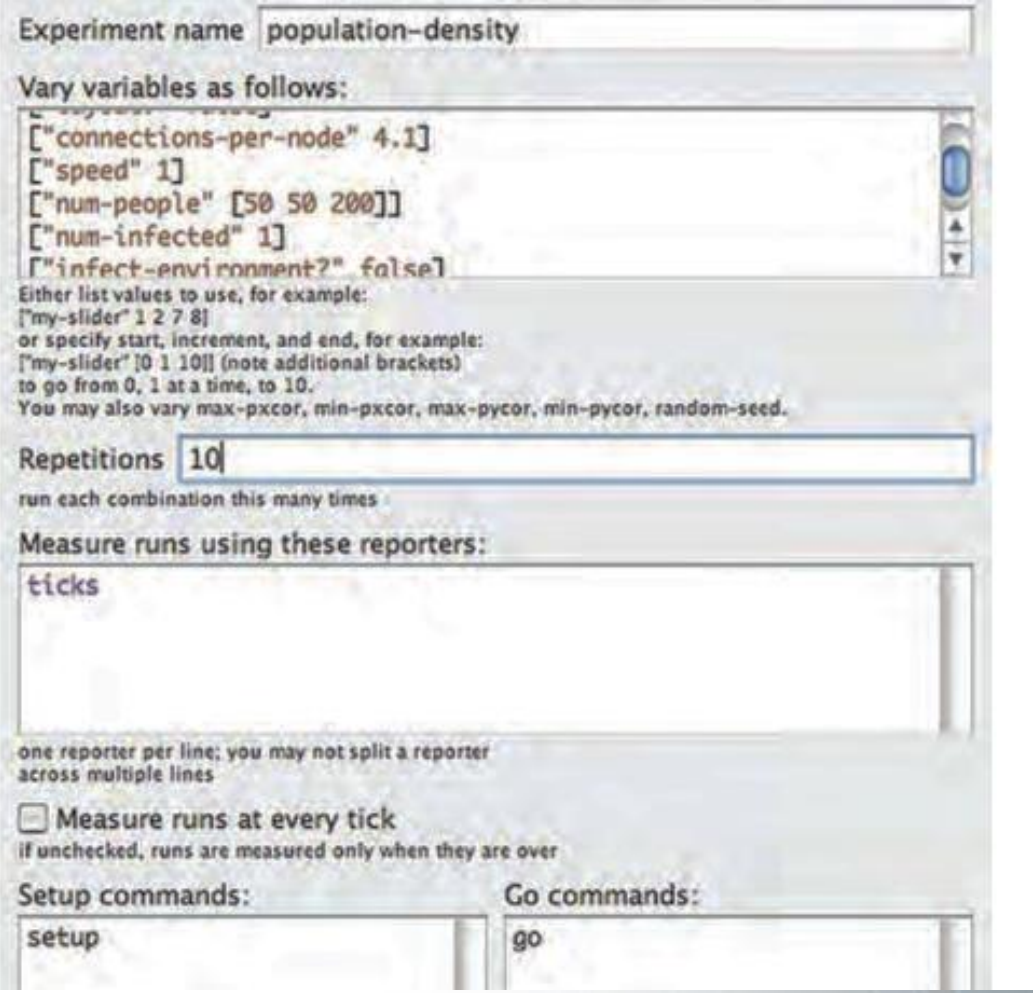
Types of Measurements

Summary Statistics

Population	Mean	Std. Dev.
50	366.8	47.39385802
100	213.8	27.40154091
150	144.4	17.65219533
200	118.7	12.12939497

Types of Measurements

Behavior space experiments



Types of Measurements

BehaviorSpace Data Imported into a Spreadsheet

BehaviorSpace Table data

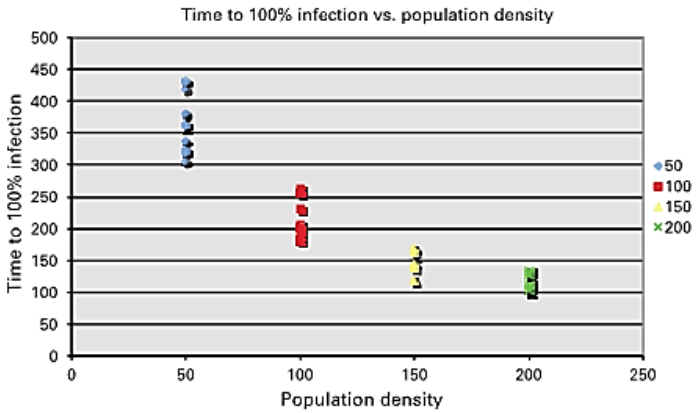
population-density

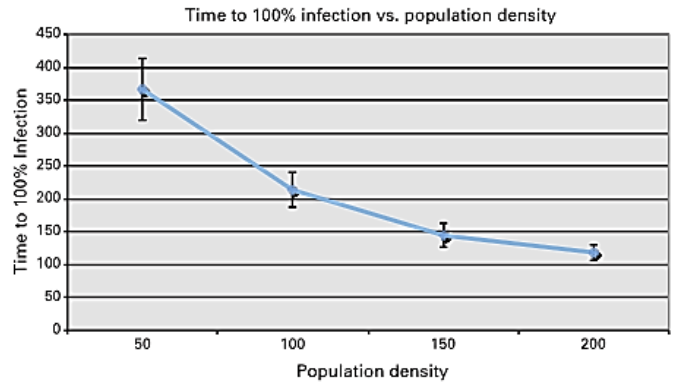
DATE
TIME

[run number]	network?	layout?	connections-per-node	speed	num-people	num-infected	infect-environment?	[tick]	ticks
1	FALSE	FALSE	4.1	1	50	1	FALSE	299	299
2	FALSE	FALSE	4.1	1	50	1	FALSE	432	432
3	FALSE	FALSE	4.1	1	50	1	FALSE	444	444
4	FALSE	FALSE	4.1	1	50	1	FALSE	400	400
5	FALSE	FALSE	4.1	1	50	1	FALSE	467	467
6	FALSE	FALSE	4.1	1	50	1	FALSE	397	397
7	FALSE	FALSE	4.1	1	50	1	FALSE	337	337

Types of Measurements

- **Raw data in graphs**





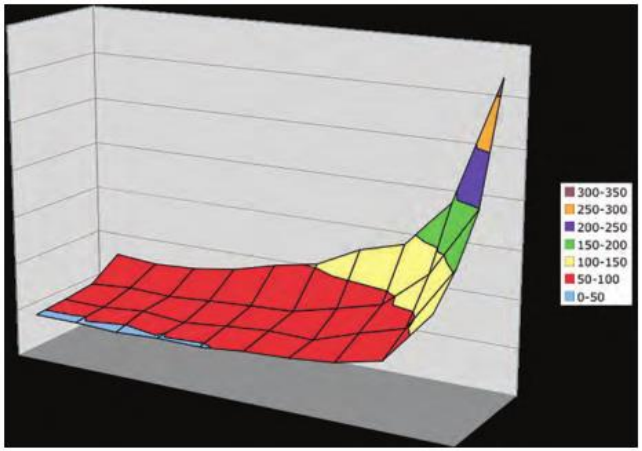


Figure 6.9
3D Chart of NUM-PEOPLE and DISEASE-DECAY versus time to 100 percent infection.

Summary

- **We have learnt about the types of measurements in the analysis of an ABM.**
- **Credits: Uri Wilensky book.**

Modeling and Simulation

Modeling the Spread of Disease

Overview

- **Here we will Model the spread of disease in detail**

Infection Initially Rises Exponentially

- If a cold virus infects someone, that person might spread that disease to five other people (six now infected) before they recover.
- In fact, the rate of infection initially rises exponentially.

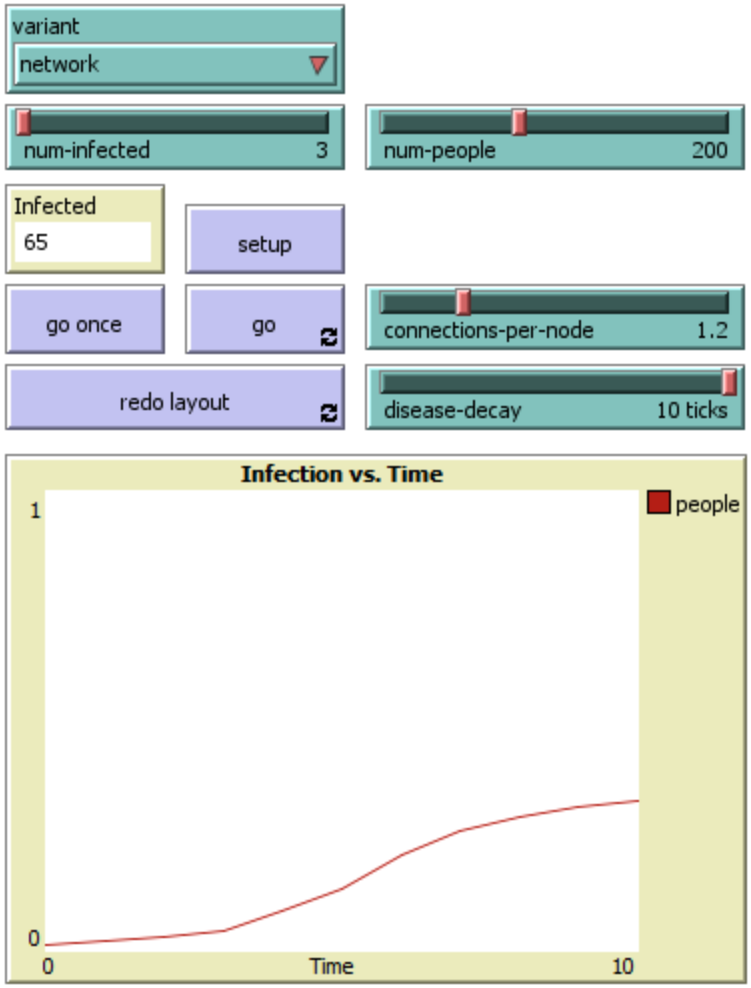
Understanding the Spread of Disease

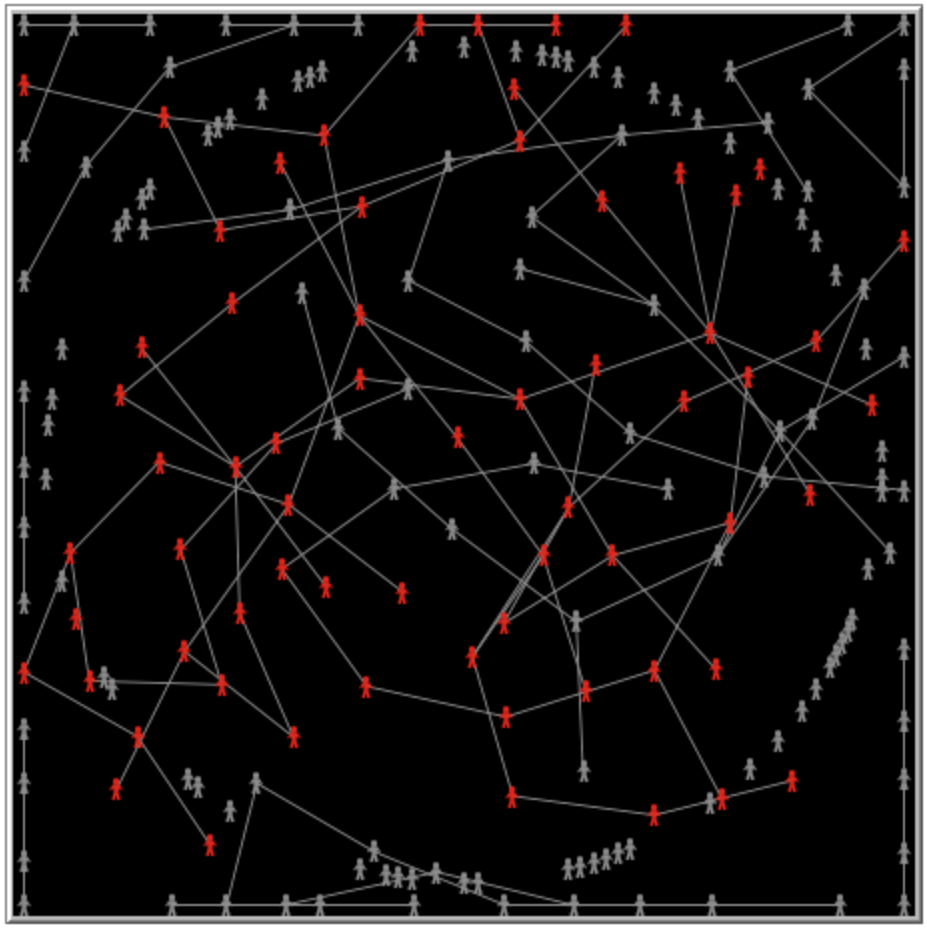
- **Suppose that we are interested in understanding the spread of disease, and we want to build an ABM of such a spread. *How should we go about doing it?***
  - ***First, we need some agents that keep track of whether they are infected with a cold or not***

Initialize the Model

- We need the ability to initialize the model by infecting a group of individuals
- Individuals move around randomly on a landscape and infect other individuals whenever they come into contact with them.

Spread of Disease model





We conclude that as the population density increases, the time to full infection dramatically decreases

In Beginning infection rate increases slowly

- **In the beginning, when *the first person becomes infected, if there are not many other people around, the person has no one to infect*, and thus the infection rate increases slowly.**
- **However, if there are many people around then there will be plenty of infection opportunities**

True Despite the Fact

- **Moreover, at the end of the run, when there are only one or two uninfected agents, they will be more likely to run into someone with an infection if the population count is high.**
- ***This is true despite the fact that the total number of people that need to be infected increases.***

Summary

- To describe these patterns of behavior it makes sense to turn to some statistics
- Credits : Uri Wilensky

Statistical Analysis of ABM: Moving beyond Raw Data

Overview

- Here we will learn about the general methodology behind descriptive statistics that is to provide numerical measures that summarize a large data set and describe the data set in such a way that it is not necessary to examine every single value

A Coin Is Fair

- Suppose we are interested in determining whether a coin is fair
  - (i.e., it is as likely to turn up heads when flipped as it is to turn up tails) then we can conduct a series of experiments where we flip the coin and observe the results.

Means And Standard Deviations

- It is much easier to look at means and standard deviations than it is to examine large series of data
  - (e.g., for HHHHTTHTTT, the observed probability is 0.5, and the expected outcome for ten trials is to observe five heads with a standard deviation of 1.58).

Spread of Disease model

- To apply this technique to our Spread of Disease model in more depth, we can create summary statistics

Summary Statistics

Population	Mean	Std. Dev.
50	366.8	47.39385802
100	213.8	27.40154091
150	144.4	17.65219533
200	118.7	12.12939497

- From these summary results:

Summary Statistics

- We see that the mean time to 100 percent infection declines as the population density increases.
- Another interesting result is that as the population density goes up, the standard deviation goes down.
- This means that the data is less varied.

Confirming Or Rejecting Hypotheses

- These results seem to confirm our original hypothesis that as population density increases the mean time to infection declines.
- Within ABM, statistical analysis is a common method of confirming or rejecting hypotheses

Abms Create Large Amounts Of Data

- **ABMs create large amounts of data (the Spread of Disease model is just a small example), and if we can summarize that data we can examine large amounts of output in an efficient manner.**

ABM toolkits

- Most ABM toolkits give you the basic ability to carry out simple statistical analysis within the package itself
  - (e.g., in NetLogo there are MEAN and STANDARD-DEVIATION primitives). Thus, while the model is running, the ABM itself can generate summary statistics.

Summary

- The NetLogo R extension to conduct analyses with the R statistical package
- Credits : Uri Wilensky

The Necessity of Multiple Runs within ABM

Overview

- When you are trying to collect statistical results from an ABM you should run the model multiple times and collect different results at different points
- Here we will understand how ABM toolkits will provide you with a way to collect the data from these runs automatically

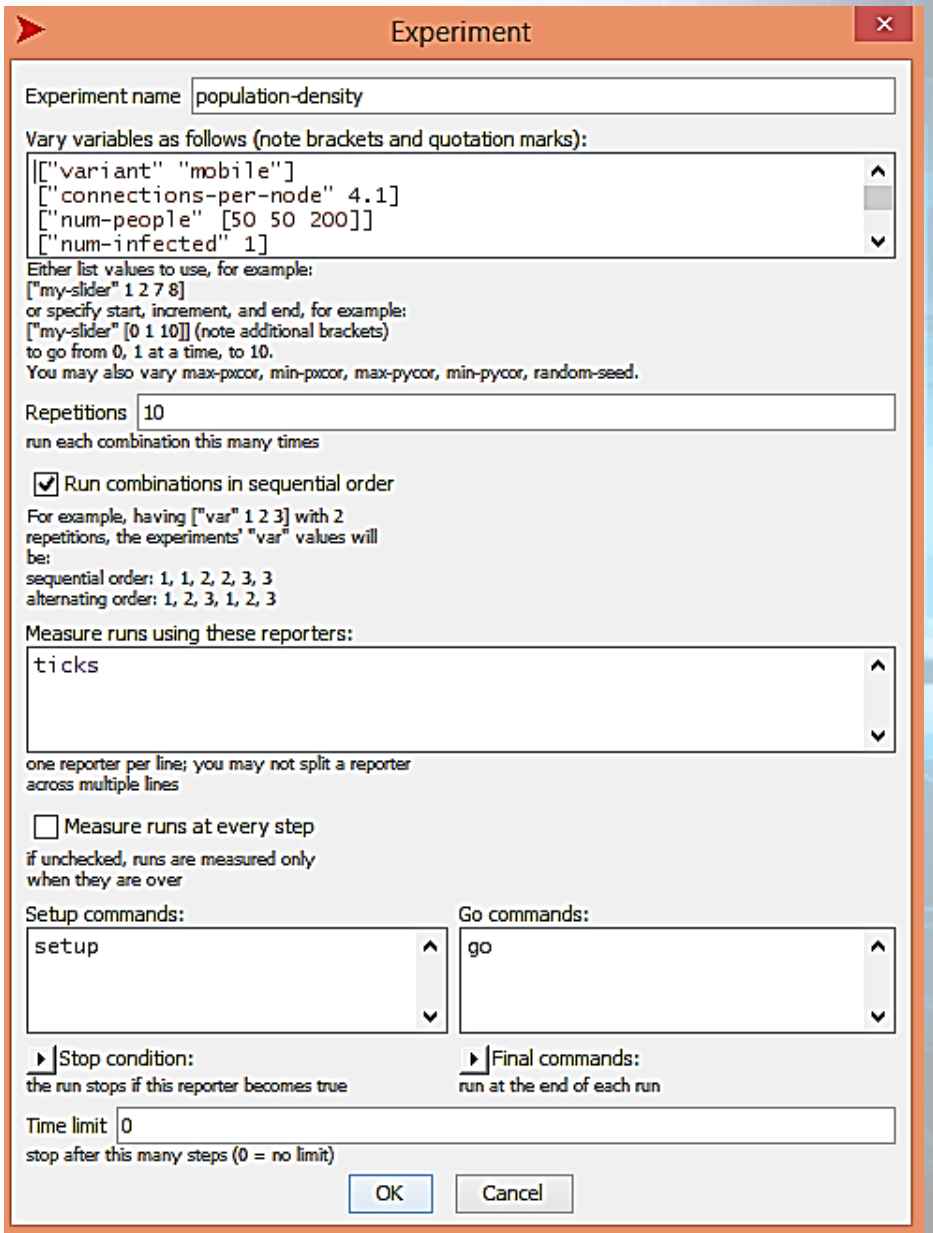
BehaviorSpace

- In NetLogo there is a tool called BehaviorSpace
- ABM toolkits are often full-featured programming languages, allowing you to write your own tools for creating experiments to produce the data sets you want to analyze

Batch Experiment Tool

- These tools will automatically run the model multiple times with multiple different settings and collect the results in some easy to use format like the CSV files mentioned earlier.
- Let us call this experiment “ population density, ”

Setting Up a BehaviorSpace Experiment



Commands

- **The SETUP and GO commands allow you to specify any additional NetLogo code that you need to make the model start and go.**
  - **" Stop condition " allows you to specify special stop conditions for each run, and**
  - **" Final commands " allows you to insert any commands that you want executed between runs of the model**

Manually Running Model Multiple

- **In general in ABM, it is important to carry out multiple runs of your experiments so that you can determine if some result is truly a pattern or just a one-time occurrence.**

Summary

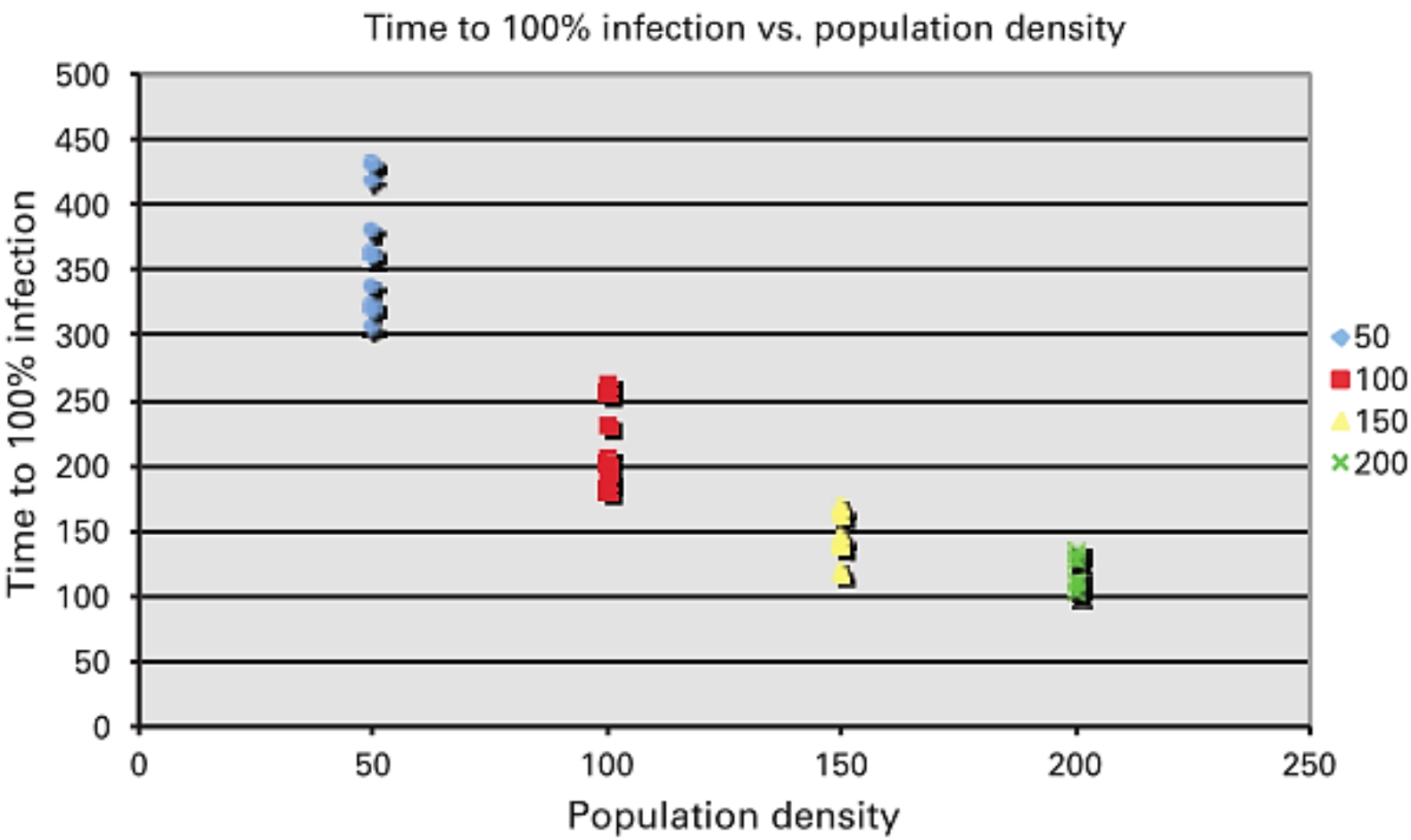
- One common way is to start by manually running your model multiple times, but to get a better sense of the results it is usually much easier to use a batch experiment tool We have illustrated the BehaviorSpace tool, which is the batch experiment tool for NetLogo
- Credits : Uri Wilensky

Using Graphs to Examine Results in ABM

Overview

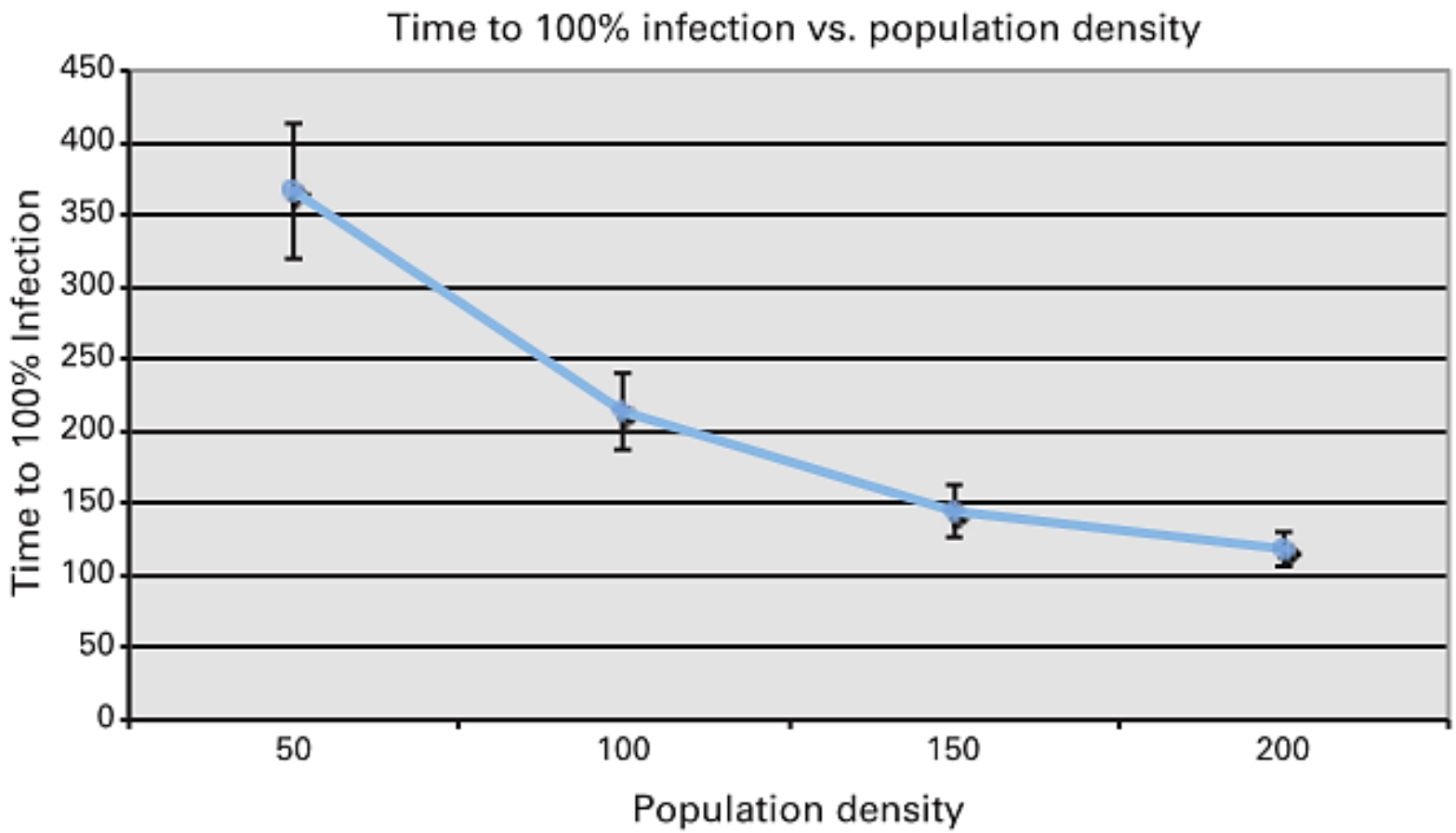
- In NetLogo creating simple graphs is easy to do and will often suffice for simple data analysis.
- But with complex data sets, designing a useful and immediately informative graph can be challenging and is the subject of an extensive body of literature

All Raw Data In a Graph-based Form



We can quickly see how the data is distributed and how the data changes with population density

Summary data

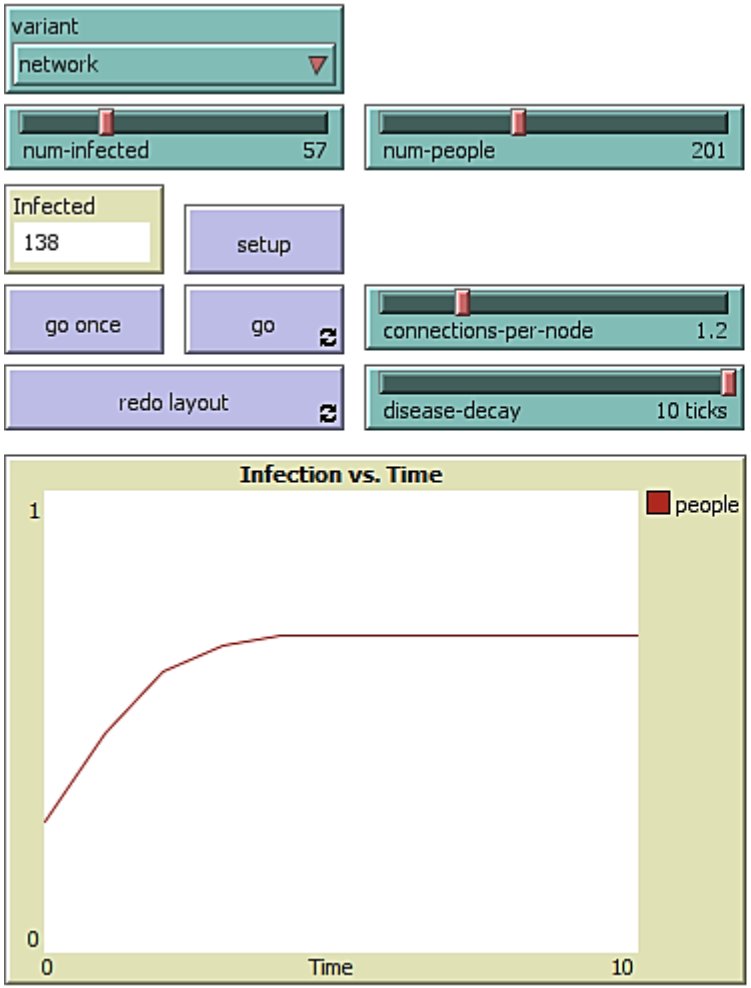


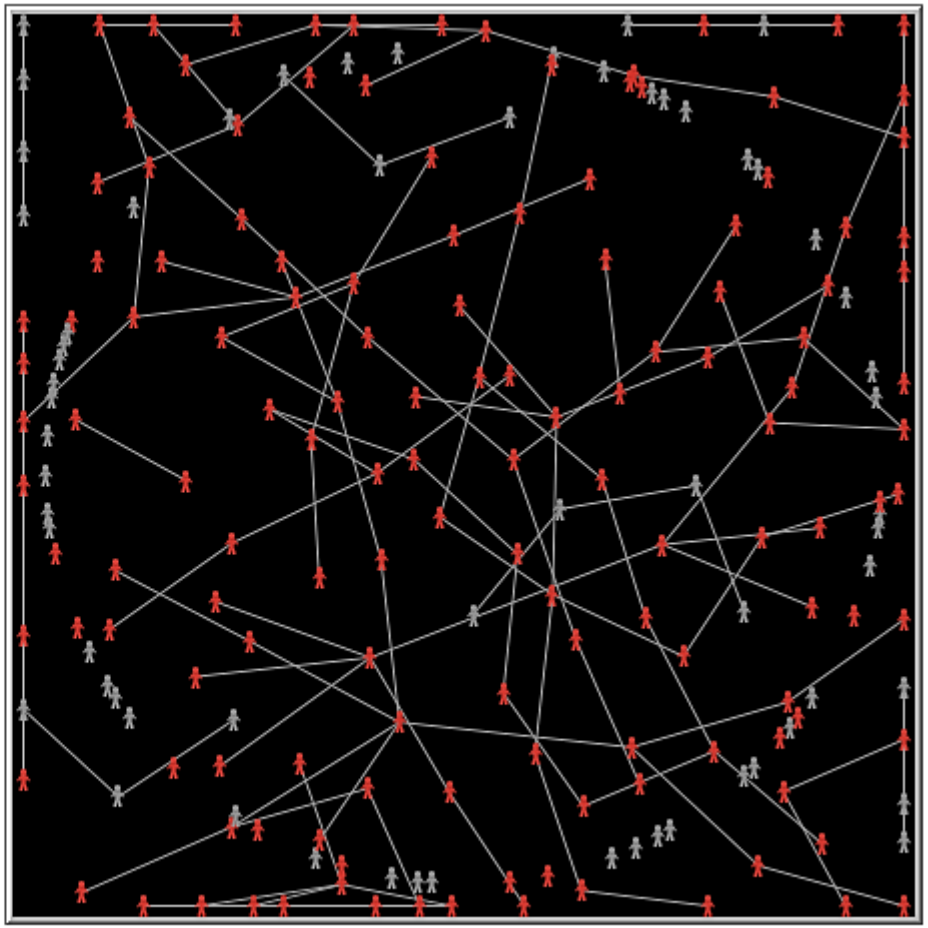
This new figure might not be easier to understand than previous figure, but if there were one hundred data points in previous figure rather than ten data points, then a figure like this one might be very helpful.

Graphs

- **Many ABM toolkits *include capabilities for continually updating graphs and charts* during the running of a model and thus enable you to see the progress of the model temporally**
- **For instance, in the Spread of Disease model there is a graph that *illustrates the change in the fraction of infected agents as time proceeds***

Fraction Infected Versus Time





This is one example of how we can use time series to help understand the behavior of a model.

Summary

- Summary: We have seen the use of graphs in simulation software
- Credits: Uri Wilensky

Analyzing Networks within ABM

Overview

- **Here, we understand the analysis of "networks within ABM"**

Spread of disease model

- Interactions do not occur in physical space.
- But rather across social networks.

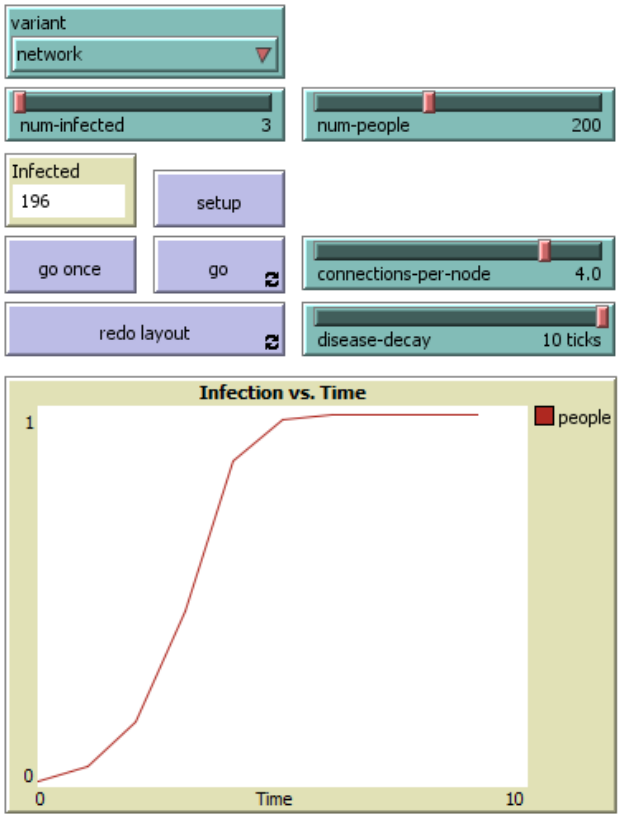
Spread of disease model

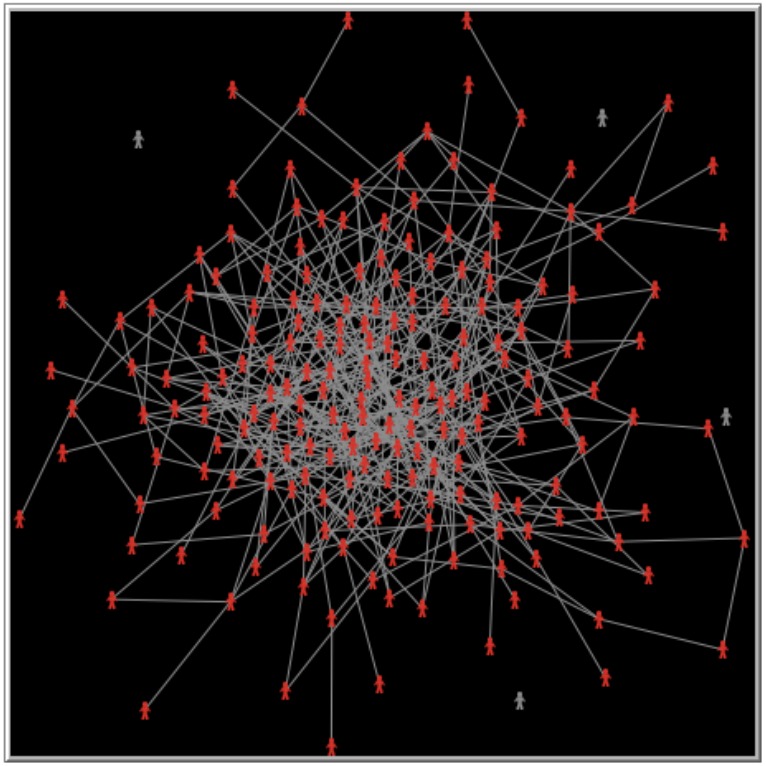
- Some diseases spread only through certain kinds of social networks.
- If we set the chooser to “network” we can explore this.

Spread of disease model

- The property which determines how many connections.
- Each individual has to other individual in the network.
- Known as “connections-per-node”.

Spread of disease model figure





Spread of disease model

- A well known property of random graph is the average number of individuals infected.
- Grows substantially
- The connections-per-node exceeds 1.0
- Forms a giant component in the network.

Spread of disease model

- The property of average path length, which measure the distance between any two nodes in the network.
- Affect the spread of disease in the network.
- Another property is clustering co-efficient.

Spread of disease model

- **Different properties and tools are there to measure and analyze a wide variety of metrices**
- **Associated with social network analysis (SNA).**

Summary

- Each of these network properties can be analyzed as to their effect on the spread of disease.
- Reports and toolkits like UCInet can be used for further examination.
- Credits: Uri Wilensky book.

Modeling and Simulation

Environmental Data and ABM

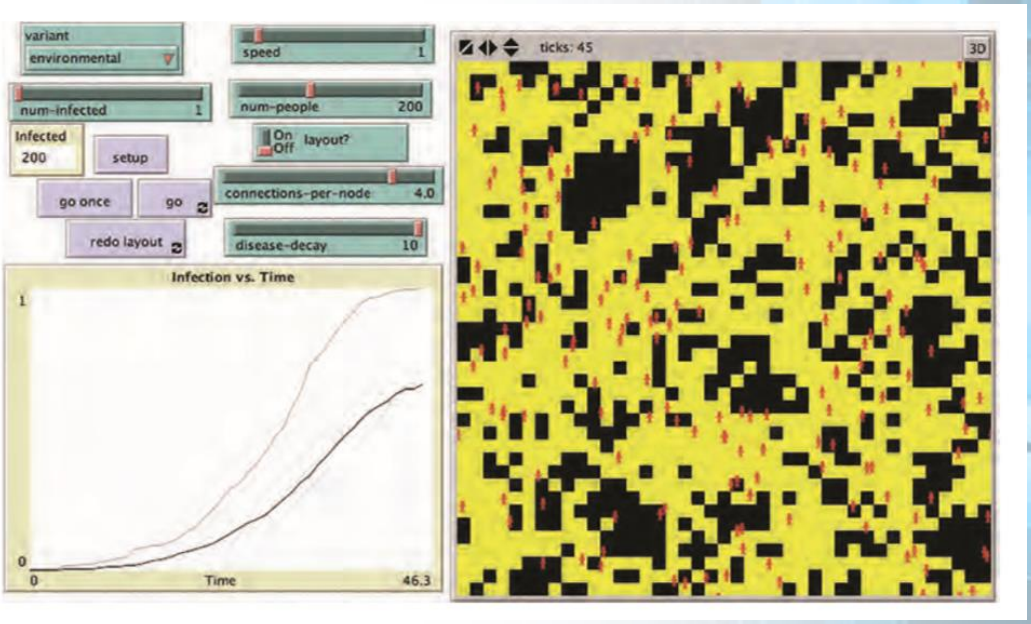
Overview

- **In this section we are going to see agent-to-environment and environment-to-agent transmission.**

Environmental data and ABMs

- **Spread of disease model for examining.**
- **Environmental interaction effect.**

Environmental data and ABMs



Environmental data and ABMs

- **The path below any agent will become yellow.**
- **Change the rate if DISEASE-DECAY 0 to 10 at a single time intervals**

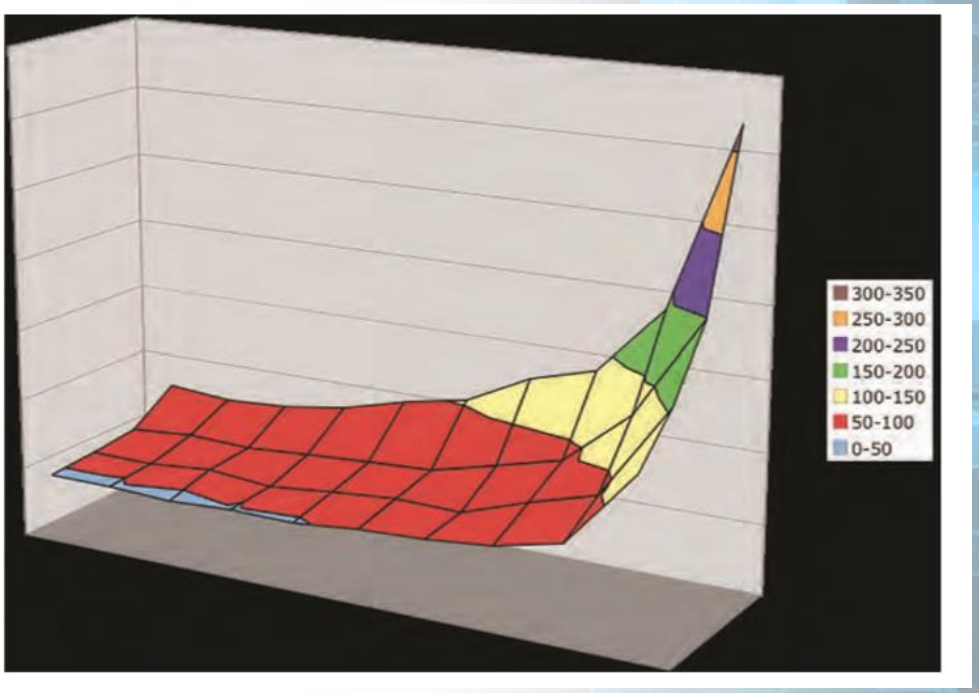
Environmental data and ABMs

- A long DIESEASE-DECAY might have negligible over having a small DISEASE-DECAY.
- Investigating using behaviour space.

Environmental data and ABMs

- **A Powerful aspect of ABMs is that it also shows us the pattern of infection.**

Environmental data and ABMs



Environmental data and ABMs

- **Leaving long stringy patterns of environmental infection.**

Summary

- We have seen the working of environmental data and ABMs.
- Credits: Uri Wilensky book

Correctness of a Model

Overview

- **Here, we understand the about the "correctness of a model"**

Correctness of a Model

- **Output relating the concerned issue must be accurate.**
- **Model accuracy is evaluated through validation, verification and replication.**

Correctness of a Model

- **Implemented model corresponds to, and explains, some phenomenon in the real world.**

Correctness of a Model

- **Model verification: determining whether an implemented model corresponds to the target conceptual model.**
- **Make sure that the model has been implemented correctly.**

Correctness of a Model

- **Model replication is the implementation by one researcher or group of researchers of a conceptual model previously implemented by someone else.**

Correctness of a Model

- **Set of results from a model that corresponds to the real world is not sufficient.**
- **Multiple runs are often needed to confirm that a model is accurate.**

Summary

- **Verification, validation, and replication collectively underpin the correctness, and thus utility, of a model.**
- **Credits: Uri Wilensky book.**

Modeling and Simulation

Verification

Overview

- **Here, we understand the role of “Verification” in Correctness of a Model.**

Verification

- In larger models, the code can be difficult to understand as it evolves over time.
- Verification ensures the elimination of “bugs” from the code.

Verification

- The process of debugging becomes more difficult for complex models.
- Keep the process easy and simple.

Verification

- **Build the model simply to begin with.**
- **It will be easier to verify.**

Verification

- **Expand the complexity of the model as necessary.**
- **This incremental approach makes it easy to verify the additional components.**

Verification

- Even if all the components are verified, it is still possible that the system isn't.
- Complications may arise from the interaction between model components.

Summary

- **Throughout the section , we examined the issue of verification of a model in the context of a simple ABM.**
- **Credits: Uri Wilensky book**

Modeling and Simulation

Communication

Overview

- **Here, we understand need of "communication" for Correctness of Model.**

Communication

- Sometimes a team of people builds a model.
- Other team members actually implement the model.
- Verification becomes critical.

Communication

- Communication is critical to ensure that the implemented model is correct.
- It is essential.

Communication

- In the voting model.
- Political scientists differentiate between Moore and Van Neumann neighborhoods.
- Small world network and hexagonal versus a rectangular grid.

Communication

- In an ideal situation, the model author and the implementer is the same person which averts the sort of communication errors.
- But when it isn't then there is often room for human error and misunderstanding.

Communication

- In the past it was difficult to be expert model implementer and model author.
- However, low-threshold ABM languages, such as NetLogo is narrowing the gap between author and implementer.

Summary

- We have seen how communication play an important role in the correctness of a model.
- How communication can fill the gap between the implementor and the author of the model.
- Credits: Uri Wilensky book.

Modeling and Simulation

Describing Conceptual Models

Describing Conceptual Models

Overview

- **Here, we will understand how "Describing Conceptual Model" play a role in correctness of a model.**

Describing Conceptual Models

Conceptual Models

- **Implementing the voting model.**
- **We may realize that we didn't understand completely when we talked to political scientist.**

Describing Conceptual Models

Conceptual Models

- Describing how we plan to implement the model.
- We and political scientist have same conceptual model in mind.
- This document is “Describing conceptual model”.

Describing Conceptual Models

Conceptual Models

- **Describe the model in more formal terms.**
- **Pictorial description of the model using flowcharts.**

Describing Conceptual Models

Conceptual Models

- **Convert the flowcharts into pseudo-code**
- **The goal of pseudo-code is to serve as a midway point between natural language and programming language.**

Describing Conceptual Models

Pseudo-Code

```
Voters have votes = {0, 1}

For each voter:
    Set vote either 0 or 1, chosen with equal probability
Loop until election
    For each voter
       If majority of neighbors' votes = 1 and vote = 0 then set vote 1
       Else If majority of neighbors' votes = 0 and vote = 1 then set vote 0
       If vote = 1: set color blue
       Else: color = green
    Display count of voters with vote = 1
    Display count of voters with vote = 0
End loop
```

Describing Conceptual Models

Conceptual Models

- **Other methods are UML, choosing a language similar to pseudo-code and NetLogo.**

Describing Conceptual Models

Summary

- We have learnt about processes involve in describing conceptual model which include flowcharts, pseudo-code, UML and NetLogo.
- Credits: Uri Wilensky book

Modeling and Simulation

Verification Testing

Verification Testing

Overview

- **Here, We will discuss and understand how we can use "Verification Testing" for the Correctness of a Model.**

Verification Testing

Implementation

- **When implementing the design into code we follow ABM core design principle.**

Verification Testing

Setup Code

```
patches-own
[
    vote ;; my vote (0 or 1)
    total ;; sum of votes around me
]

to setup
    clear-all
    ask patches [
           if (random 2 = 0) ;; half a chance of this
           [ set vote 1 ]
       ]
    ask patches [
       if (random 2 = 0) ;; half a chance of this
           [ set vote 0 ]
    ]
    ask patches [
       recolor-patch
    ]
end

to recolor-patch ;; patch procedure
    ifelse vote = 0
       [ set pcolor green ]
       [ set pcolor blue ]
end
```

Verification Testing

To Check Setup

```
to check-setup
    let diff abs ( count patches with [ vote = 0 ] - count patches
with [ vote = 1 ] )
    if diff > .1 * count patches [
       print "Warning: Difference in initial voters is greater than 10⁴%."
    ]
end
```

Verification Testing

To Check Setup

```
to setup
    clear-all
    ask patches [
            set vote random 2     ;; 0 or 1, with equal probability
    ]
    ask patches [
       recolor-patch
    ]
    check-setup
end
```

Verification Testing

Unit Testing

- This verification technique is a form of unit testing.
- We can modify the code without disrupting previous code.

Verification Testing

NetLogo Code

```
to go
    ask patches [
       set total (sum [vote] of neighbors)
    ]
    ;; this is equivalent to count neighbors with [vote = 1]
    ;; use two ask patches blocks so all patches compute "total"
    ;; before any patches change their votes
    ask patches [
       ifelse vote = 0 and total >= 4 [
           set vote 1
       ]
           [if vote = 1 and total <= 4 ] [
               [set vote 0
           ]
           recolor-patch
       ]
       tick
       end
```

Verification Testing

Summary

- We understand how incremental approach makes it easy to implement to model correctly.
- Then we write our code into NetLogo for verification purpose.
- Credits: Uri Wilensky book

Modeling and Simulation

Beyond Verification

Beyond Verification

Overview

- **Here, we will learn about the beyond verification using agent-based modelling.**

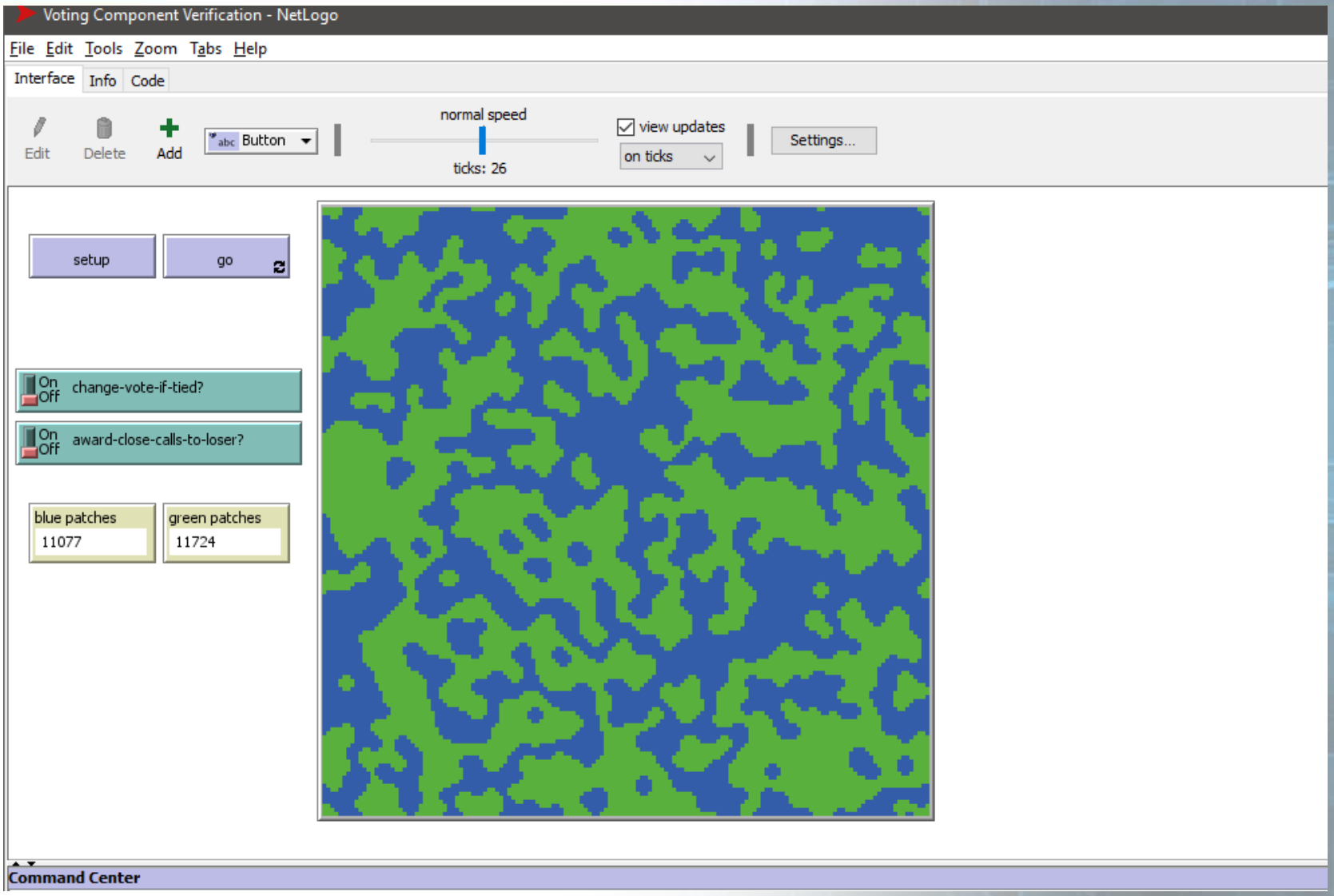
Beyond Verification

- **Sometimes results are not produced to what the implementers and authors hypothesized.**
- **Results of modelling confuse the scientists.**

Beyond Verification

- Jagged edges due to tie votes.
- Design the model that neighbours do not change their votes if tied.
- Switch called CHANGE VOTE IF TIED.

Beyond Verification



Beyond Verification

```
patches-own [
  vote   ;; my vote (0 or 1)
  total  ;; sum of votes around me
]

to setup
  clear-all
  ask patches [
    set vote random 2 ;; set vote to either 0 or 1
    recolor-patch
  ]
  reset-ticks
  check-setup
end

to go
  ;; keep track of whether any patch has changed their vote
  let any-votes-changed? false
  ask patches [
    set total (sum [ vote ] of neighbors)
  ]
  ;; use two ask patches blocks so all patches compute "total"
  ;; before any patches change their votes
  ask patches [
    let previous-vote vote
    if total < 3 [ set vote 0 ] ;; if majority of your neighbors vote 0, set your vote to 0
    if total = 3 [
      ifelse award-close-calls-to-loser?
```

Beyond Verification

```
        [ set vote 1 ]
        [ set vote 0 ]
    ]
    if total = 4 and change-vote-if-tied? [
      set vote (1 - vote) ;; invert the vote
    ]
    if total = 5 [
      ifelse award-close-calls-to-loser?
        [ set vote 0 ]
        [ set vote 1 ]
    ]
    if total > 5 [ set vote 1 ] ;; if majority of your neighbors vote 1, set your vote to 1
    if vote != previous-vote [ set any-votes-changed? true ]
    recolor-patch
  ]
  ;; if the votes have stabilized, we stop the simulation
  if not any-votes-changed? [ stop ]
  tick
end

to recolor-patch  ;; patch procedure
  ifelse vote = 0
    [ set pcolor green ]
    [ set pcolor blue ]
end

;; This procedure checks to see if the SETUP procedure sets up the model with roughly
;; equal numbers of blue and green patches
to check-setup
  ;; count the difference between the number of green and the number of blue patches
  let diff abs (count patches with [ vote = 0 ] - count patches with [ vote = 1 ])
  if diff > .1 * count patches [
    print "Warning: Difference in initial voters is greater than 10%."
  ]
end


; Copyright 2008 Uri Wilensky.
```

Beyond Verification

- **Switch AWARD CLOSE CALLS TO LOSER?**
- **With both switches on, we have a different outcome.**

Beyond Verification

```
to go
  ask patches
    [ set total (sum [vote] of neighbors) ]
  ;; use two ask patches blocks so all patches compute "total"
  ;; before any patches change their votes
  ask patches
    [ if total > 5 [ set vote 1 ]
      if total < 3 [ set vote 0 ]
      if total = 4
        [ if change-vote-if-tied?
          [ set vote (1 - vote) ] ] ;; switch vote
      if total = 5
        [ ifelse award-close-calls-to-loser?
          [ set vote 0 ]
          [ set vote 1 ] ]
      if total = 3
        [ ifelse award-close-calls-to-loser?
          [ set vote 1 ]
          [ set vote 0 ] ]
      recolor-patch ]
  tick
end
```

Beyond Verification

summary

- We have seen the details of beyond verification.
- Credits: Uri Wilensky book

Modeling and Simulation

Sensitivity Analysis and Robustness

Sensitivity Analysis and Robustness

Overview

- **Here, we will understand the sensitive analysis and robustness**

Sensitivity Analysis and Robustness

- **Sensitivity analysis.**
- **Creating the parameter to test the hypothesis of initial balance in one direction.**
- **Using BehaviourSpace running the experiment varying from 25 to 75 percent increment.**

Sensitivity Analysis and Robustness

- **Two conditions:**
- **If no voter switch vote in the last step the model will stop.**
- **The model will stop after one hundred times the steps have executed.**

Sensitivity Analysis and Robustness

```
patches-own
[
  vote   ;; my vote (0 or 1)
  total  ;; sum of votes around me
]

to setup
  clear-all
  ask patches [
    ifelse random 100 < initial-green-pct
      [ set vote 0 ]
      [ set vote 1 ]
    recolor-patch
  ]
  reset-ticks
  check-setup
end

to go
  ;; keep track of whether any patch has changed their vote
  let any-votes-changed? false
  ask patches [
    set total (sum [ vote ] of neighbors)
  ]
  ;; use two ask patches blocks so all patches compute "total"
  ;; before any patches change their votes
```

Sensitivity Analysis and Robustness

```
]
;; use two ask patches blocks so all patches compute "total"
;; before any patches change their votes
ask patches [
  let previous-vote vote
  if total < 3 [ set vote 0 ] ;; if majority of your neighbors vote 0, set your vote to 0
  if total = 3 [
    ifelse award-close-calls-to-loser?
      [ set vote 1 ]
      [ set vote 0 ]
  ]
  if total = 4 and change-vote-if-tied? [
    set vote (1 - vote) ;; invert the vote
  ]
  if total = 5 [
    ifelse award-close-calls-to-loser?
      [ set vote 0 ]
      [ set vote 1 ]
  ]
  if total > 5 [ set vote 1 ] ;; if majority of your neighbors vote 1, set your vote to 1
  if vote != previous-vote [ set any-votes-changed? true ]
  recolor-patch
]
```

Sensitivity Analysis and Robustness

```
  ;; if the votes have stabilized, we stop the simulation
  if not any-votes-changed? [ stop ]
  tick
end

to recolor-patch  ;; patch procedure
  ifelse vote = 0
    [ set pcolor green ]
    [ set pcolor blue ]
end

;; This procedure checks to see if the SETUP procedure sets up the model with
;; roughly expected numbers, given the value of the initial-green-pct slider
to check-setup
  let expected-green (count patches * initial-green-pct / 100)
  let diff-green (count patches with [ vote = 0 ]) - expected-green
  if diff-green > (.1 * expected-green) [
    print "Initial number of green voters is more than expected."
  ]
  if diff-green < (- .1 * expected-green) [
    print "Initial number of green voters is less than expected."
  ]
end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```
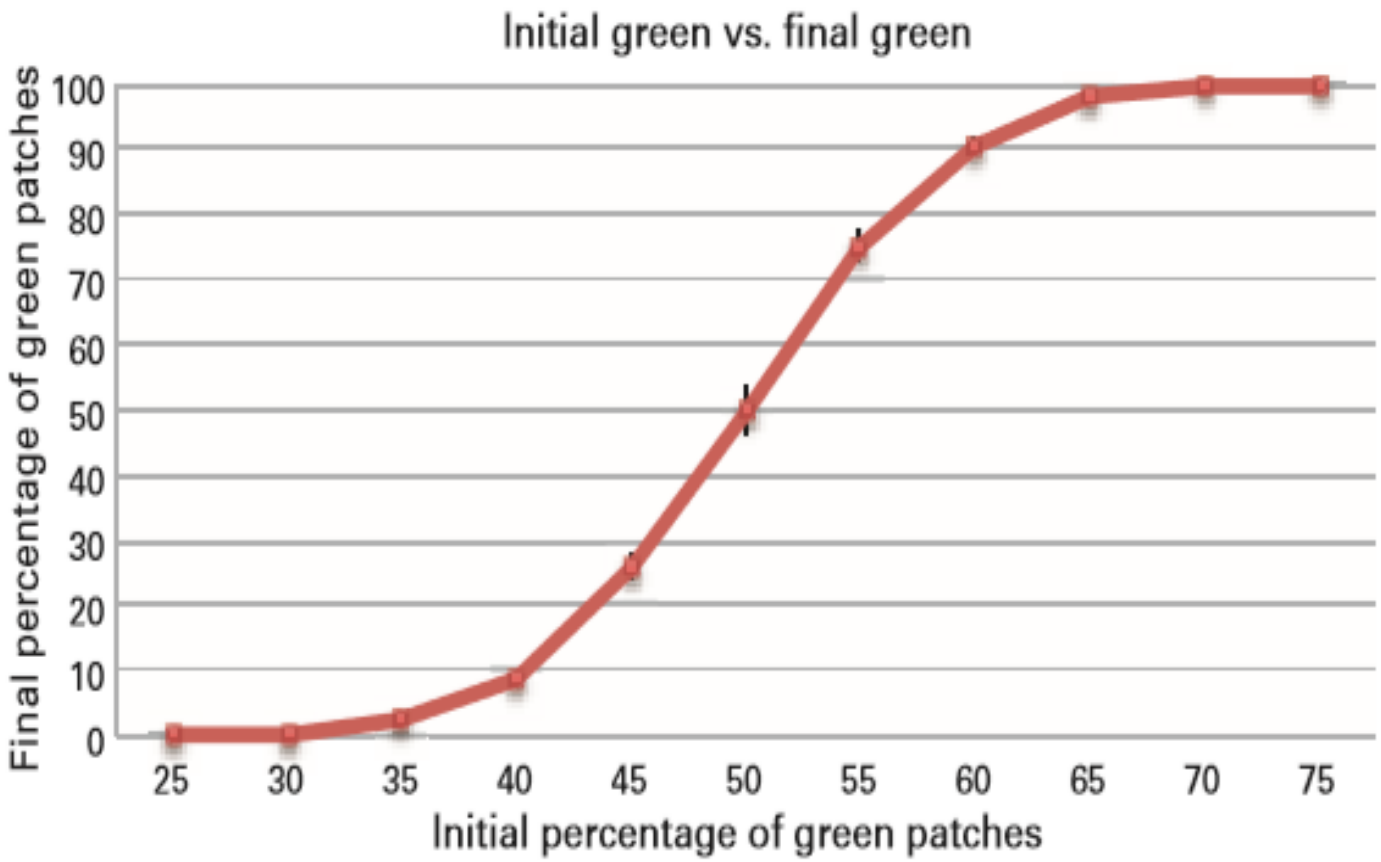

Sensitivity Analysis and Robustness



Sensitivity Analysis and Robustness

- **Past research methodologies for sensitivity analysis.**
- **Active Nonlinear Testing.**

Sensitivity Analysis and Robustness

Summary

- We have seen the details of Sensitivity Analysis and Robustness
- Credits : Uri Wilensky book

Modeling and Simulation

Verification Benefits and Issues

Verification Benefits and Issues

Overview

- **Here, we are going to look verification benefits and issues.**

Verification Benefits and Issues

- **Understanding the cause of unexpected outcomes.**
- **Impact of small changes.**

Verification Benefits and Issues

- Implemented model corresponds to the conceptual model.
- Model's low level rules.
- Understanding the mechanisms.

Verification Benefits and Issues

- **A bug in the code can produce surprising results.**

Verification Benefits and Issues

- **Understanding the operating of the model.**
- **A verification process is not binary.**

Verification Benefits and Issues

Summary

- We have seen the verification benefits and issues.
- Credits: Uri Wilensky book

Modeling and Simulation

Validation

Validation

Overview

- **Here: we will see the validation of agent based modeling.**

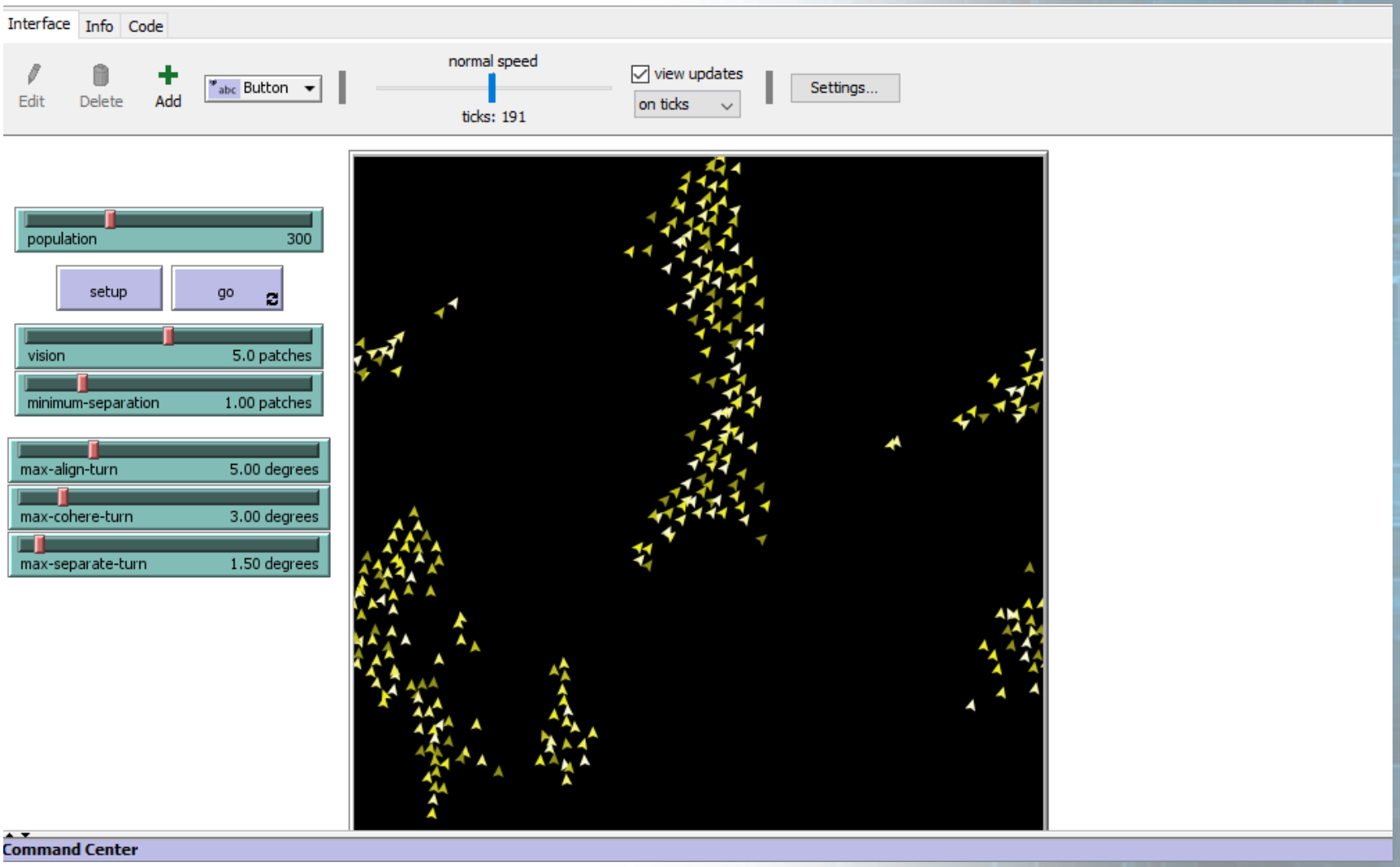
Validation

- **Corresponding between implemented model and reality.**

Validation

- Two axis.
- Macrovalidation.
- Face validation.
- Flocking model.
- A classical agent based model.

Validation


Interface
Info
Code
Edit
Delete
Add
Button
normal speed
ticks: 191
view updates
on ticks
Settings...
population 300
setup
go
vision 5.0 patches
minimum-separation 1.00 patches
max-align-turn 5.00 degrees
max-cohere-turn 3.00 degrees
max-separate-turn 1.50 degrees
Command Center

Validation

```
turtles-own [
  flockmates         ;; agentset of nearby turtles
  nearest-neighbor   ;; closest one of our flockmates
]

to setup
  clear-all
  create-turtles population
    [ set color yellow - 2 + random 7  ;; random shades look nice
      set size 1.5  ;; easier to see
      setxy random-xcor random-ycor
      set flockmates no-turtles ]
  reset-ticks
end

to go
  ask turtles [ flock ]
  ;; the following line is used to make the turtles
  ;; animate more smoothly.
  repeat 5 [ ask turtles [ fd 0.2 ] display ]
  ;; for greater efficiency, at the expense of smooth
  ;; animation, substitute the following line instead:
  ;;   ask turtles [ fd 1 ]
  tick
end
```

Validation

```
to flock  ;; turtle procedure
  find-flockmates
  if any? flockmates
    [ find-nearest-neighbor
      ifelse distance nearest-neighbor < minimum-separation
        [ separate ]
        [ align
          cohere ] ]
end

to find-flockmates  ;; turtle procedure
  set flockmates other turtles in-radius vision
end

to find-nearest-neighbor ;; turtle procedure
  set nearest-neighbor min-one-of flockmates [distance myself]
end

;;; SEPARATE

to separate  ;; turtle procedure
  turn-away ([heading] of nearest-neighbor) max-separate-turn
end

;;; ALIGN

to align  ;; turtle procedure
  turn-towards average-flockmate-heading max-align-turn
end
```

Validation

```
;;; ALIGN

to align  ;; turtle procedure
  turn-towards average-flockmate-heading max-align-turn
end

to-report average-flockmate-heading  ;; turtle procedure
  ;; We can't just average the heading variables here.
  ;; For example, the average of 1 and 359 should be 0,
  ;; not 180.  So we have to use trigonometry.
  let x-component sum [dx] of flockmates
  let y-component sum [dy] of flockmates
  ifelse x-component = 0 and y-component = 0
    [ report heading ]
    [ report atan x-component y-component ]
end

;;; COHERE

to cohere  ;; turtle procedure
  turn-towards average-heading-towards-flockmates max-cohere-turn
end

to-report average-heading-towards-flockmates  ;; turtle procedure
  ;; "towards myself" gives us the heading from the other turtle
  ;; to me, but we want the heading from me to the other turtle,
  ;; so we add 180
  let x-component mean [sin (towards myself + 180)] of flockmates
  let y-component mean [cos (towards myself + 180)] of flockmates
  ifelse x-component = 0 and y-component = 0
    [ report heading ]
    [ report atan x-component y-component ]
end
```

Validation

```
;;; HELPER PROCEDURES

to turn-towards [new-heading max-turn]  ;; turtle procedure
  turn-at-most (subtract-headings new-heading heading) max-turn
end

to turn-away [new-heading max-turn]  ;; turtle procedure
  turn-at-most (subtract-headings heading new-heading) max-turn
end

;; turn right by "turn" degrees (or left if "turn" is negative),
;; but never turn more than "max-turn" degrees
to turn-at-most [turn max-turn]  ;; turtle procedure
  ifelse abs turn > max-turn
    [ ifelse turn > 0
        [ rt max-turn ]
        [ lt max-turn ] ]
    [ rt turn ]
end


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```

Validation

summary

- We have understand the validation of agent based model.
- Credits: Uri Wilensky book.

Modeling and Simulation

Macrovalidation vs. Microvalidation

Macrovalidation vs. Microvalidation

Overview

- **Here, we will understand difference between "macrovalidation and microvalidation" and their role in validation of a model.**

Macrovalidation vs. Microvalidation

- ABM's are built from agents hence we can directly compare them with those that exist in the real world.
- For instance, we can ask whether the agents have properties similar to real birds in flocking model.

Macrovalidation vs. Microvalidation

- **There are some limitation e.g. real birds can fly in three dimensions , but our bird agents move in two dimension only.**
- **However, these limitations doesn't make our model invalid.**

Macrovalidation vs. Microvalidation

- **we can also build the flocking model in three dimensions and examine the resultant flocks to see if they are relevantly different from the 2D flocks.**

Macrovalidation vs. Microvalidation

- **The other major avenue of validation is to investigate the relationship between the global properties of the model and the flocking patterns of real birds, a process called macrovalidation.**

Macrovalidation vs. Microvalidation

Macrovalidation

- By showing that our model corresponds to the macro-level phenomenon, we further validate that our model is descriptive of real world systems.

Macrovalidation vs. Microvalidation

Conclusion

- **Macrovalidation tells you if you have captured the important parts of the system, whereas microvalidation tells you if you ’ve captured the important parts of the agent ’s individual behavior.**

Macrovalidation vs. Microvalidation

Figure.

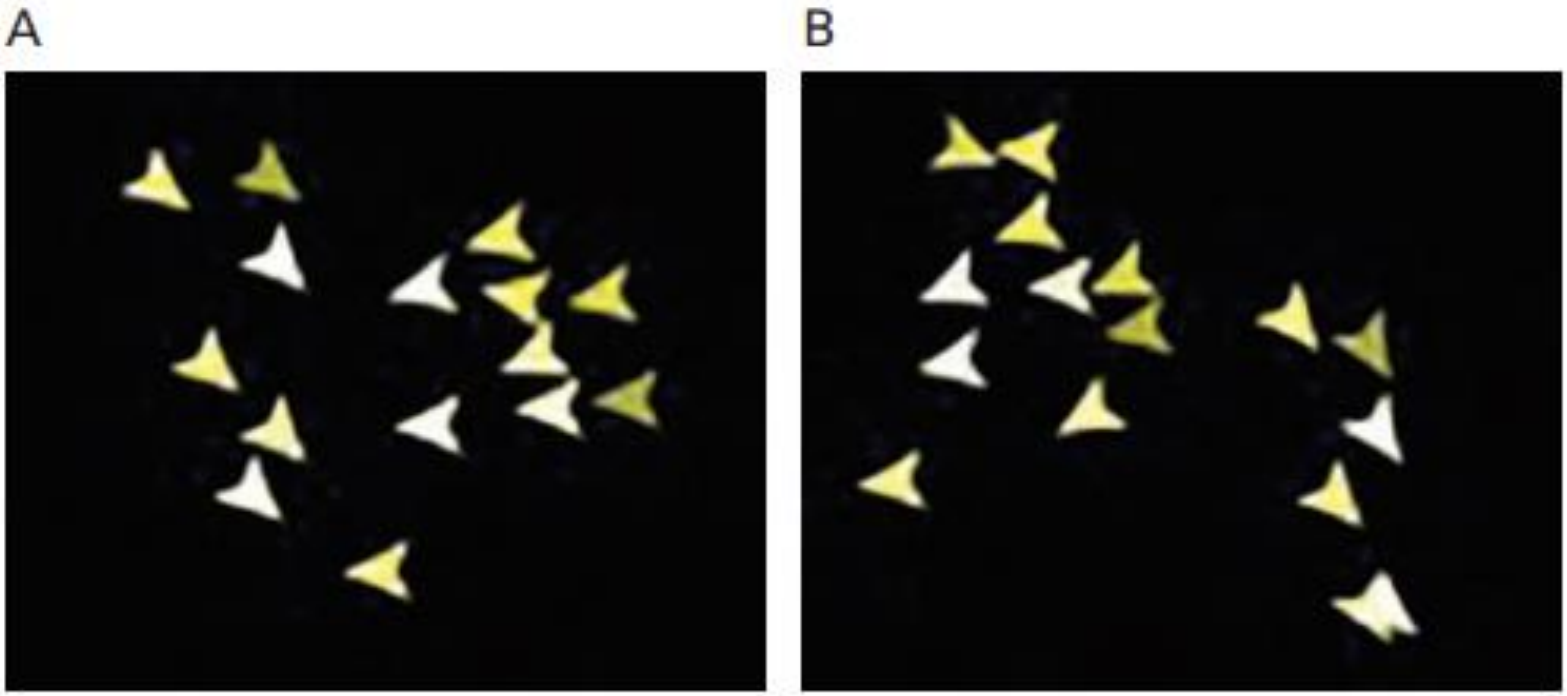


Figure 7.9
Two mini-flocks (A) before and (B) after a collision.

Macrovalidation vs. Microvalidation

Summary

- We understand how macrovalidation and microvalidation compares to each other.
- Credits: Uri Wilensky book.

Modeling and Simulation

Face Validation

vs.

Empirical Validation

Face Validation vs Empirical Validation

Overview

- **Here we will discuss how “face validation” is different from “empirical validation”.**

Face Validation vs Empirical Validation

Face Validation

- **Face validation is the process of showing that the mechanisms and properties of the model look like mechanisms and properties of the real world.**

Face Validation vs Empirical Validation

Empirical Validation

- Empirical validation is making sure that the model generates data.
- Correspond to similar patterns of data in the real world.

Face Validation vs Empirical Validation

Face Validation

- Face validity can exist at both micro and macro levels.
- Determining whether the birds in the model correspond to real birds is face microvalidity.
- While determining if the flocks correspond to the appearance of real flocks is face macrovalidity.

Face Validation vs Empirical Validation

Empirical Validation

- Empirical validation sets a higher bar.
- Data produced by the model must correspond to empirical data derived from the real-world.
- measures and numerical data generated both by the model and the actual phenomenon.

Face Validation vs Empirical Validation

Empirical Validation

- Inputs and outputs in " the real world " are often poorly defined.
- It is hard to isolate and measure parameters from a real-world phenomenon.

Face Validation vs Empirical Validation

Empirical Validation

- **The process of finding the parameters and initial conditions that cause the model to match with real-world data is called calibration.**

Face Validation vs Empirical Validation

Summary

- We understand together, these four types of validation (micro-face, macro-face, micro-empirical, and macro-empirical) characterize the majority of validation efforts carried out.
- Credits: Uri Wilensky book

Modeling and Simulation

Validation Benefits and Questions

Validation Benefits and Questions

Overview

- **Here, we will understand Why is it important to validate a model.**

Validation Benefits and Questions

- **A valid model can be useful for extracting general principles about the world.**
- **Changing the mechanisms and parameters can often help predict what might occur in the real world.**

Validation Benefits and Questions

- **A model is not either valid or invalid:**
- **A model can be said to be more or less valid based upon how closely it has been compared to the real process it is modeling.**

Validation Benefits and Questions

- **A model is never inherently valid.**
- **Its validity comes from the context of what it is being used for.**

Validation Benefits and Questions

- **Something in the model corresponds to something in reality.**
- **The user compare his observation's with real world and use it as the basis of his validation.**

Validation Benefits and Questions

Summary

- Here, we understand about the benefits of validation and question it arises.
- Credits: Uri Wilensky book.

Modeling and Simulation

Replication

Replication

Overview

- Here, we will understand about the "Replication".

Replication

- **Model replication is the implementation by one researcher or group of researchers of a conceptual model previously implemented by someone else.**

Replication

- Scientists must publish the details of how the experiment was conducted.
- Then subsequent teams of scientists carry out the experiment themselves to ascertain.

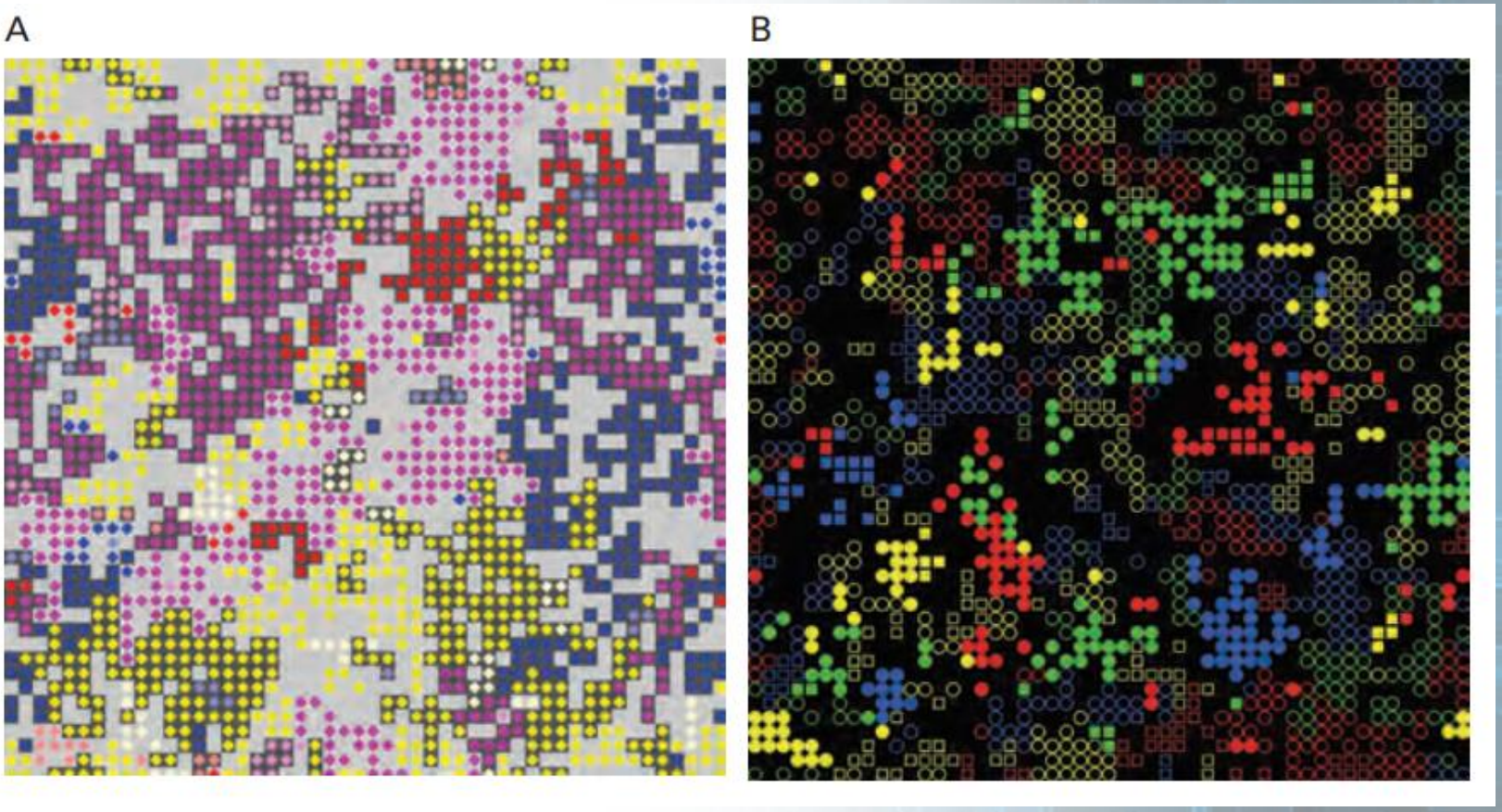
Replication

- Replicating a physical experiment strengthens original results.
- Comparing both the experimental setup and ensuing results.
- Replicating a computational model serves this same purpose.

Replication

- Replicating a computational model increases our confidence.
- New implementation of the model has yielded the same results as the original.

Replication



Replication

- This model includes a mechanism for inheritance of strategies.
- The model suggests that “ ethnocentric ” behavior can evolve under a wide variety of conditions.
- Even when there are no native “ ethnocentrics ”.

Replication

- Here we understand about the basic concepts of replication and how it is useful for the correctness of a model.
- Credits: Uri Wilensky book

Replication of Computational Models: Dimensions and Standards

Overview

- **Here, we will understand about the "Replication of Computational Models: Dimensions and Standards".**

Replication

- **Replication refers to the creation of a new implementation of a conceptual model based on the previous implementation.**

Dimensions

- An original model and replicated model can differ across at least six dimensions.
- Time
- Hardware
- Languages
- Toolkits
- Algorithms
- Authors

Successful Replication

- **A successful replication is one in which the replicators are able to establish that the replicated model creates outputs sufficiently similar to the outputs of the original.**

Replication Standard

- **The criterion by which the replication ’s success is judged is called the replication standard.**
- **Different replication standards exist for the level of similarity between model outputs.**

Categories of Replication Standard

- There are three categories of replication standard.
- Numerical identity
- Distributional equivalence.
- Relational alignment.

Data

- ABMs usually produce large amounts of data.
- much of which is usually irrelevant.
- Data that are central to the conceptual model should be measured and tested during replication.

Summary

- Here, we understand about dimensions of conceptual model like time, hardware, toolkit, language, algorithms and author.
- Then we discussed about replication standard and its categories.
- Credits: Uri Wilensky book

Modeling and Simulation

Benefits of replication

Overview

- **We are going to see the benefits of replication in this section.**

Benefits of Replication

- **Advances scientific knowledge.**
- **Model verification.**
- **Model validation.**
- **Shared understanding.**

Benefits of Replication

- Shared understanding.
- Creation of sets of terms, idioms and best practices.
- Communicate about model.

Benefits of Replication

- Model verification.
- Distinct implementations. producing same results.
- Conceptual model grows by capturing confidence.
- Correction made if there is any difference found in implemented model and replication.

Benefits of Replication

- Model validation.
- Correspondence between the outputs.
- Validation of a model on the basis of output closer to real-world.
- Reevaluating the original mapping.
- Researchers investing and getting interested in it through replication

Benefits of Replication

- Describing the modeling process through developing a language.
- Culture of replication fosters.
- "mean" and "standard deviation" applying them to tests, overtime, replication of ABM experiment to understand "time step" and "shuffled lists".

Summary

- **Here, we understand the benefits of replication in modeling.**
- **Credits: Uri Wilensky book.**

Modeling and Simulation

Recommendations For Model Replicators

Overview

- **Here, we will learn about recommendations for model replicators.**

Recommendations for model replicators

- **RS is to produce the level of precision to establish hypothesis regularity.**
- **Examples : “numerical identity”, “distributional equivalence” and “relational alignment”.**

Recommendations for model replicators

- **How detailed the description of the conceptual model is in the original paper or to communicate with authors or original model.**

Recommendations for model replicators

- **Beneficial to delay the contact with original author until after first attempt to recreate the original model.**
- **Differences between public conceptual model and an implementation can be interesting and resulting in new discoveries.**

Recommendations for model replicators

- Becoming familiar with the toolkit in which original model was written.
- Better understanding of original model.
- Replicator understands the subtler working.
- Deliberately implementing a strategy.

Recommendations for model replicators

- **Obtain the source code of original model.**
- **Effective for illuminating discrepancies in the two model implementations.**

Recommendations for model replicators

- **Groupthink**
- **Unconsciously adopting some of the practices of the original model developer.**

Recommendations for model replicators

Table 7.1
Details to be included in published replications. For each category, sample options to choose from are listed.

Categories of Replication Standards:
Numerical Identity, Distributional Equivalence, Relational Alignment
Focal Measures:
Identify particular measures used to meet goal
Level of Communication:
None, Brief email contact, Rich discussion and personal meetings
Familiarity with Language/Toolkit of Original Model:
None, Surface understanding, Have built other models in this language/toolkit
Examination of Source Code:
None, Referred to for particular questions, Studied in-depth
Exposure to Original Implemented Model:
None, Reran original experiments, Ran experiments other than original ones
Exploration of Parameter Space:
Examined results from original paper, Examined other areas of the parameter space

Summary

- We have understand the recommendation for model replicators in modeling.
- Credits: Uri Wilensky book.

Modeling and Simulation

Recommendations for Model Authors

Overview

- **Here, we will understand the recommendations for the model authors.**

Recommendations for the model authors

- Research paper should be well specified.
- Complete source code for the model may not sufficient.
- Model authors must make their source code publicly available or at least the “pseudo code”.

Recommendations for the model authors

- To what extent the model developer presents a sensitivity analysis.
- Small modification to the original model can effect results drastically.
- These sensitive differences should be published by the authors.

Recommendations for the model authors

- Original author may not be the original implementer.
- Implementation will not be veridical.
- Model authors implement their own models using “ low-threshold ” and toolkits.

Recommendations for the model authors

- **Authors to examine their conceptual models through the lens of a potential model replicator.**

Summary

- **We have understand the recommendations for model authors in modelling.**
- **Credits: Uri Wilensky book**

END

Modeling and Simulation

Complex Adaptive Systems

Overview

- **Here, we will understand the basics about complex adaptive systems (CAS).**

Complex Adaptive Systems

- Complexity
- Adaptation
- Systems

Complex Adaptive Systems

- **The systems approach is an old concept.**
- **The approach stands on the assumption that breaking down of a complex concept into simple easy to understand units helps in better understanding of the complexity.**
- **Ludwig von Bertalanffy first proposed it as 'General System Theory'**

Complex Adaptive Systems

- A system is a delineated part of the universe which is distinguished from the rest by an imaginary boundary. (NECSI)
- Properties of the system, the properties of the universe excluding the system which affect the system and the interactions / relationships.

Complex Adaptive Systems

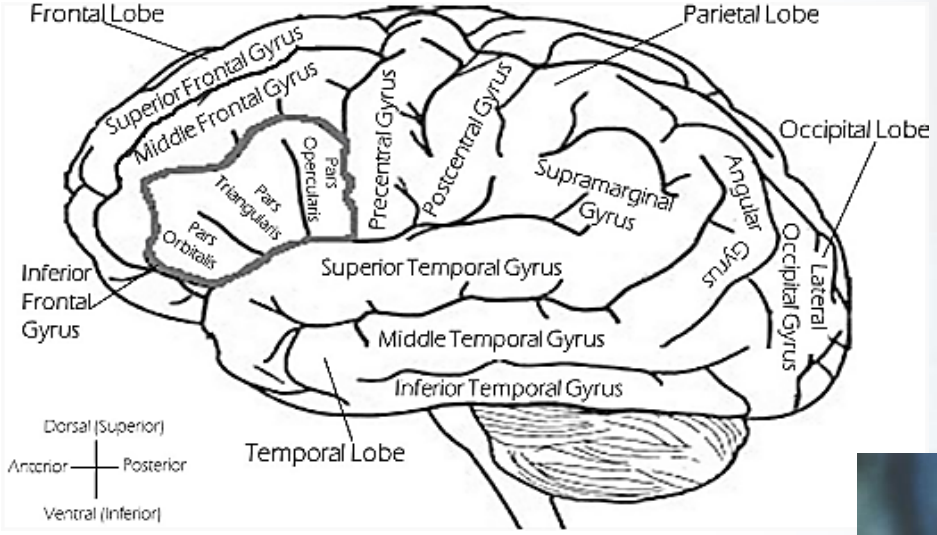
- **An adaptive system (or a complex adaptive system, CAS) is a system that changes its behavior in response to its environment.**
- **The adaptive change that occurs is often relevant to achieving a goal or objective. (NECSI)**

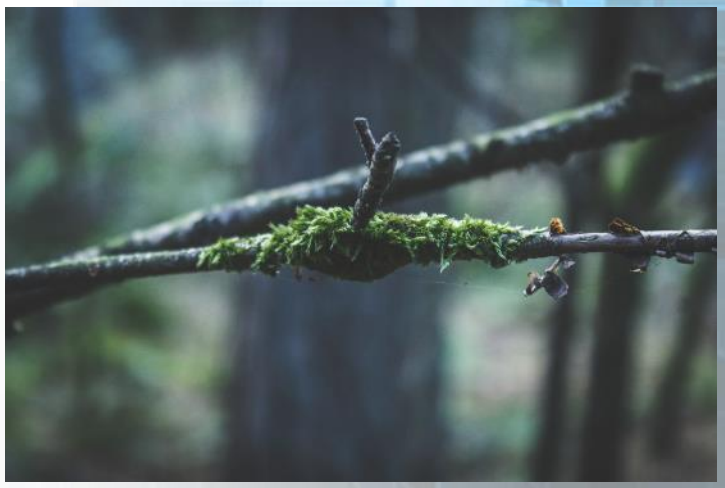
Complex Adaptive Systems

- Complexity is:
- ...the (minimal) length of a description of the system.
- ...the (minimal) amount of time it takes to create the system.
- Here the length of a description is measured in units of information.

Complex Adaptive Systems

Examples





Summary

- **We have learnt about the basic ideas of Complex Adaptive Systems.**
- **Credits: Uri Wilensky Book.**

Modeling and Simulation

History

Overview

- **Here, we will understand about the historical perspective of CAS**

History

- **Started with the concepts of General Systems Theory**

History

- **Biologists focused primarily on individual cells**

History

- **Social Scientists focused on connections**

History

- **John Holland and cas/CAS**

Summary

- **We have learnt about the historical perspective of CAS.**
- **Credits: Niazi & Hussain book.**

Modeling and Simulation

Complexity

Overview

- **Here, we will understand about the basic ideas of complexity**

Complexity

- **Disambiguation from Computational Complexity**

Complexity

- **Nonlinearity**
- **Large number if variables**

Complexity

- Chaos theory
- The term "chaos" is popularly used to refer to disorder or confusion.
- In science, chaos is an important conceptual paradox that has a precise mathematical meaning:
- A chaotic system is a deterministic system that is difficult to predict.

Complexity

- A deterministic system is defined as one whose state at one time completely determines its state for all future times.
- So what does it mean for a chaotic system to be difficult to predict?
- Butterfly effect

Summary

- **We have learnt about the basics of Complexity in CAS.**
- **Credits: Niazi and Hussain book.**

Modeling and Simulation

Adaptation

Overview

- **Here, we will understand about adaptation in CAS.**

Adaptation

- **Adaptive changes in interactions**

Adaptation

- **Who changes**

Adaptation

- **What changes**

Adaptation

- **When changes**

Adaptation

- **How changes**

Summary

- **We have learnt about the adaptation in CAS.**
- **Credits: Niazi and Hussain book.**

Modeling and Simulation

Systems Approach

Overview

- **Here, we will understand about the Systems approach.**

Systems Approach

- **Concept of a System - boundaries**

Systems Approach

- Many systems can be correlated
- Example: Life/Humans/Society

Systems Approach

- **Whole vs. parts**

Systems Approach

- **Reductionist vs. Wholistic approach**

Summary

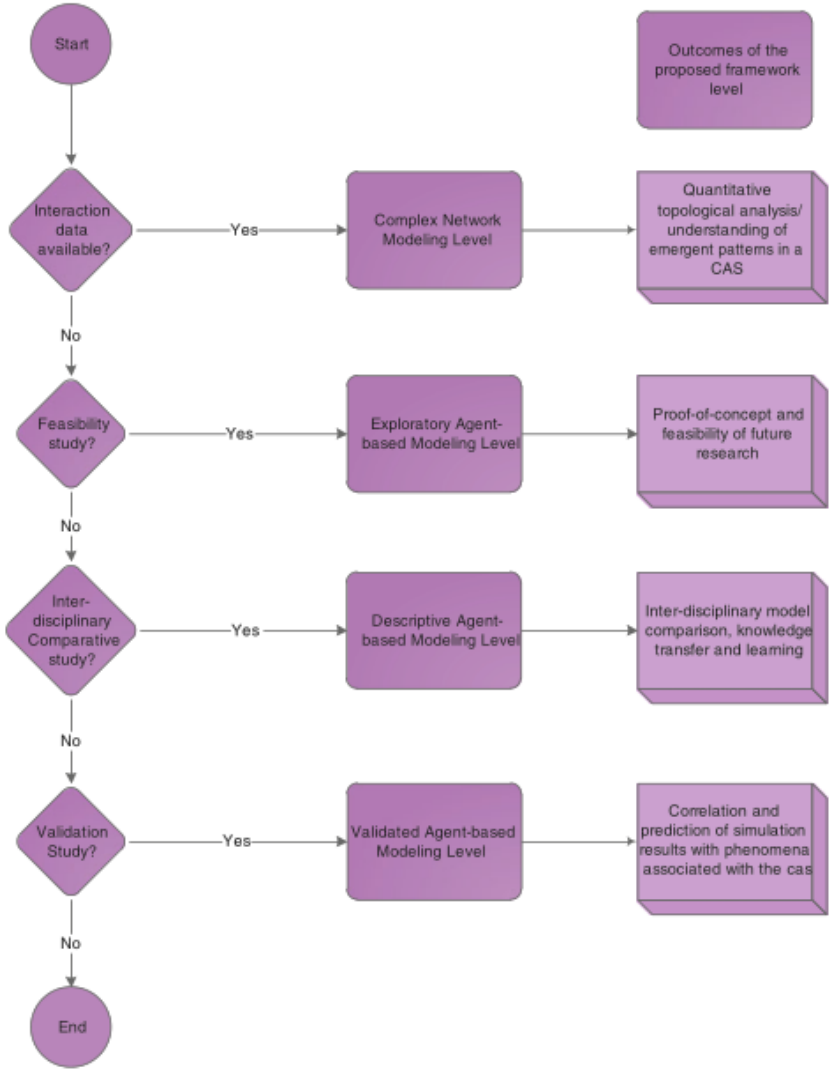
- We have learnt about the systems perspective of things.
- Credits: Niazi and Hussain book.

Modeling of CAS

Overview

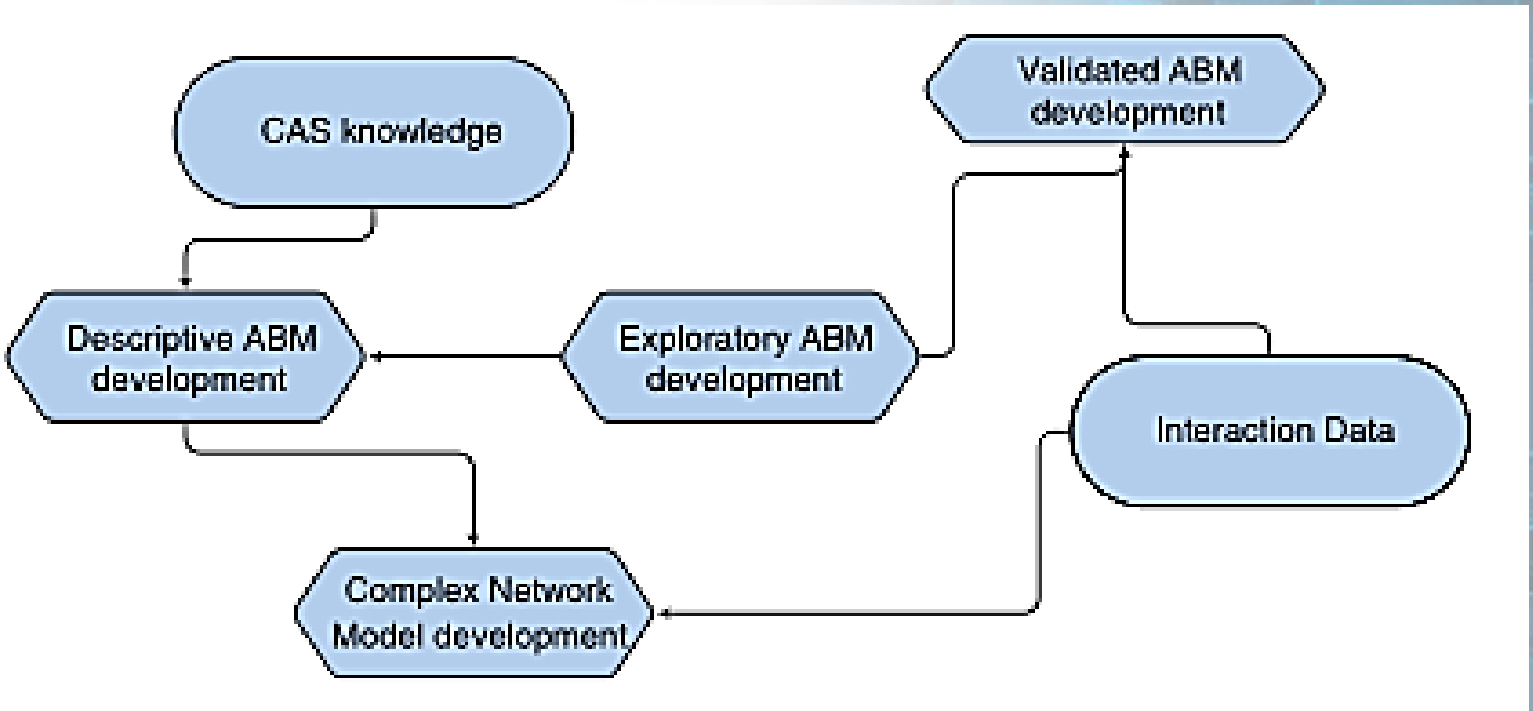
- **Here, we will understand about the problems encountered in modeling of CAS.**

Modeling of CAS



- **Cognitive Agent-based (CABC) Framework**

Modeling of CAS



Summary

- We have learnt about the modeling of CAS using CABC framework
- Credits: Niazi and Hussain book.

Modeling and Simulation

Agent-based Approach

Overview

- **Here, we will understand about the agent-based approach to modeling**

Agent-based Approach

- Agent – something that acts
- There is a concept of agent in domains as distinct as:
- AI/CS/Robotics
- Sociology (Individual)
- Biology
- Ecology
- Etc.

Agent-based Approach

- CABC framework has 3 levels for Agent-based modeling
- Exploratory Agent-based modeling (EABM)
- Descriptive Agent-based Modeling (DREAM)
- Validated Agent-based Modeling (VOMAS-based Modeling or VABM)

Agent-based Approach

- **Exploratory ABM**

Agent-based Approach

- **DREAM**

Agent-based Approach

- Virtual Overlay Multiagent System (VOMAS)
- Validated Agent-based Modeling

Summary

- We have learnt about various approaches for modeling using Agents and the CABC framework.
- Credits: Niazi and Hussain book.

Complex Network-based Modeling

Overview

- **Here, we will understand about complex networks/graphs and modeling using the CABC Level 1**

Complex Network-based Modeling

- What is a graph?
- Graph/Network
- Same entity different terms in different domains

Complex Network-based Modeling

- **Network = weighted graph**

Complex Network-based Modeling

- Different aspects of modeling using networks
- Labels
- arcs/lines
- Directed/Undirected
- Centrality-based
- Ego
- Sentiment graphs
- Community Detection

Complex Network-based Modeling

- Key benefits
- Very well-defined
- Lot of free tools
- Lot of community support
- Well-defined mathematical models

Complex Network-based Modeling

- Cons
- Difficult to figure out
- Difficulty in graph mining – lack of expertise in the community
- Missing data can be very difficult
- Requires complete data
- Complexity in deciding data boundaries

Summary

- We have learnt about complex-network modeling using the CABC framework
- Credits: Niazi and Hussain book.

Modeling and Simulation

Cognitive Agent-based Computing Framework

Overview

- **Here, we will understand how to put modeling and simulation to use employing the CABC framework.**

Cognitive Agent-based Computing Framework

- **Data and Models**
- **How much data is needed**

Cognitive Agent-based Computing Framework

- **Why choose Agent-based Modeling?**

Cognitive Agent-based Computing Framework

- **Why choose Complex network modeling?**

Cognitive Agent-based Computing Framework

- **When to choose EABM?**

Cognitive Agent-based Computing Framework

- **When to choose DREAM?**

Cognitive Agent-based Computing Framework

- **When to choose VOMAS?**

Summary

- We have learnt about putting the CABC framework to work.
- Credits: Niazi and Hussain book.

Modeling and Simulation

Useful Statistical Models

Overview

- **Here, we will learn about the useful statistical models.**

Useful Statistical Model

- The models that are useful in the case of limited data are:
- Queueing systems.
- Inventory and supply-chain systems.
- Reliability and maintainability.
- Limited data.
- Other distributions.

Queueing Systems

- Simulation solved the waiting line problems.
- Interval and service time patters were given in queuing examples.
- In these examples service and arrival time was probabilistic.
- But it is possible to have constant arrival time and constant service time.

Queueing Systems

- "Arrivals" can occur due to many reasons like machine break downs.
- Exponential distribution used to simulate the random exponential distribution of services.
- For special cases truncated normal distribution can be utilized.

Inventory and supply-chain systems

- Three random variables
- Number of units demanded per order or per time period.
- Time between demands.
- Lead time.
- Simple inventory systems have constant demand and lead time constant or zero.

Inventory and supply-chain systems

- **Mathematical tractability based demand and lead time in inventory theory text could be invalid.**
- **Variety of demand patterns are satisfied by geometric, Poisson and negative binomial distributions.**

Reliability and Maintainability

- Failure time is modeled with many distributions.
- When failure occurs randomly model distribution is considered as exponential.
- Modeling standby redundancy required for gamma distribution.

Limited Data

- Three distributions.
- Uniform distribution
- Triangular distribution
- Beta distribution
- Uniform distribution is just a special case of beta distribution

Summary

- Here, we discussed about useful statistical model, queuing systems, Inventory and supply-chain systems, Limited data, Reliability, and maintainability.
- Credits: Jerry Banks book.

Modeling and Simulation

Bernoulli Distribution

Overview

- **Here, we will learn about the Bernoulli distribution.**

Bernoulli Distribution

- Bernoulli trail is one of the simplest experiment you can do in statistic and probability which has one out of two possible outcome.
- Bernoulli distribution is a discrete probability distribution for Bernoulli trail which has one out of two possible outcomes success or fail.

Bernoulli Distribution

- Let us consider an example which consists of n trails and each of which can be a success or a failure.
- $X_j = 1$ if the jth experiment is success
- $X_j = 0$ if its failure.
- N trails and each trail has only two out comes success or failure.

Bernoulli Distribution

$$p(X_1, X_2, \ldots, X_n) = p_1(X_1) \cdot p_2(X_2) \cdot \cdot \cdot p_n(X_n)$$

$$p_j(x_j) = p(x_j) = \begin{cases} p, & x_j = 1, j = 1, 2, \ldots, n \\ 1 - p = q, & x_j = 0, j = 1, 2, \ldots, n \\ 0, & \text{otherwise} \end{cases}$$

- **Success here happens with probability (p) and failure at (p – 1).**
- **X is a discrete random variable. It takes value 1 in case of success and 0 in case of failure.**

Bernoulli Distribution

- **Below is the expected value of random variable X is calculated as:**

$$E(X_j) = 0 \cdot q + 1 \cdot p = p$$

- **Below is the variance of the random variable X is calculated as:**

$$V(X_j) = \left[\left(0^2 \cdot q\right) + \left(1^2 \cdot p\right)\right] - p^2 = p(1-p)$$

Bernoulli Distribution

- We have understand about the Bernoulli distribution.
- Credits: Jerry Banks book.

Modeling and Simulation

Binomial Distribution

Overview

- **Here, we will learn about the binomial distribution.**

Binomial Distribution

- **Binomial distribution is the discrete probability distribution with parameters n and p of the number of successes in the sequence of n independent experiments.**
- **Each n and p with its own boolean-value.**
- **Random variable.**

Binomial Distribution

- **Bernoulli trial's random variable X has binomial distribution:**

$$p(x)=\begin{cases}\binom{n}{x}p^x q^{n-x}, & x=0,1,2,\ldots,n\\ 0, & \text{otherwise}\end{cases}$$

- **This equation is for calculating the probability of a specific outcome with all successes.**

Binomial Distribution

$$P(\overbrace{SSS\ldots\ldots\ldots SS}^{x \text{ of these}}\overbrace{FF\ldots\ldots\ldots FF}^{n-x \text{ of these}}) = p^x q^{n-x}$$

- S = success.
- In first X trials.
- $n - x = \mathrm{f}$ (failures).

Binomial Distribution

$$\binom{n}{x} = \frac{n!}{x!(n-x)!}$$

- $q = 1 - p$
- **This equation shows the required number of successes and failures.**

Binomial Distribution

$$p(x) = \begin{cases} \binom{n}{x} p^x q^{n-x}, & x = 0, 1, 2, \ldots, n \\ 0, & \text{otherwise} \end{cases}$$

- **Again this equation can be used to calculate mean and variance of binomial distribution.**
- **X = sum of independent Bernoulli random variables. Then:**

$$X = X_1 + X_2 + \cdots + X_n$$

Bernoulli Distribution

- Expected value $E(X)$

$$E(X) = p + p + \cdots + p = np$$

- n = total number of experiments.
- p = probability of each experiment getting successful result.
- X = binomially random variable.

Bernoulli Distribution

- Variance $V(X)$

$$V(X) = pq + pq + \cdots + pq = npq$$

- n = total number of experiments.
- p = probability of each experiment getting successful result.
- X = binomially random variable.
- q = probability of failure in each experiment.

Summary

- **We have understand about the Binomial distribution.**
- **Credits: Jerry Banks book.**

Modeling and Simulation

Poisson Distribution

Overview

- **Here, we will learn about the Poisson distribution.**

Poisson Distribution

- **A discrete frequency distribution that gives the probability of independent events occurring in a fixed interval of time is known as the Poisson distribution.**

Poisson Distribution

$$p(x) = \begin{cases} \dfrac{e^{-\alpha}\alpha^{x}}{x!}, & x = 0, 1, \ldots \\ 0, & \text{otherwise} \end{cases}$$

- X = 0,1,2,3,….
- $e = 2.71828$
- $a =$ mean number of successes in the given time interval or region of space.
- $a > 0$

Poisson Distribution

$$E(X) = \alpha = V(X)$$

- **This is the important property of Poisson distribution that is mean and variance is equal to α.**

Poisson Distribution

$$F(x) = \sum_{i=0}^{x} \frac{e^{-\alpha}\alpha^{i}}{i!}$$

- **This is the cumulative distribution function.**

Summary

- **We have understand the Poisson distribution.**
- **Credits: Jerry Banks book.**

Modeling and Simulation

Uniform Distribution

Overview

- **Here, We will understand “Uniform Distribution” also known as “rectangular distribution”.**

Uniform Distribution

- **The uniform distribution is a continuous distribution.**
- **It takes values within a specified range.**

Uniform Distribution

- **Probability density function for a uniform distribution always take a random number on [0,1].**

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

Uniform Distribution

- **Consider a random variable X on the interval [a, b] distributed uniformly. The, equation is given by:**

- $\boldsymbol{X = a + (b - a)R}$

Uniform Distribution

- $X = a + (b - a)R$
- For the derivative of function.
- First, compute the cdf of variable X.
- Second, set $F(x) = R$ on the range of X.
- Third, solve the equation $\mathrm{F}(x)$ in terms of R for X.

Uniform Distribution

- **Step 1:**
- **The cdf for the equation is :**

$$F(x) = \begin{cases} 0 & : x < 0 \\ x & : 0 \leq x < 1 \\ 1 & : x \geq 1. \end{cases}$$

- **If X takes only discrete values 0 and 1 then:**

$$F(x) = \begin{cases} 0 & : x < 0 \\ 1/2 & : 0 \leq x < 1 \\ 1 & : x \geq 1. \end{cases}$$

Uniform Distribution

- **Step 2:**
- **Set**

$$F(x) = (X-a)(X-b)R$$

- **Step 3:**
- **Solve for X in terms of R which proves.**

$$X = a + (b-a)R$$

Summary

- **Here, we understood about the fundamentals of Uniform Distribution.**
- **Credits, Discrete Event System Simulation, Jerry Banks.**

Modeling and Simulation

Exponential Distribution

Overview

- **Here, we will understand About "Exponential Distribution".**

Exponential Distribution

- **The Exponential Distribution is a continuous valued probability distribution.**
- **Takes positive real values and λ which controls the shape of the distribution.**

Exponential Distribution

- **The probability density function**

$$f(x;\lambda) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0, \\ 0 & x < 0. \end{cases}$$

- **This can also be defined as right-continuous Heaviside step function.**

$$f(x;\lambda) = \lambda e^{-\lambda x} H(x)$$

- **Here λ is called the rate parameter.**

Exponential Distribution

- **The cumulative distribution function**

$$F(x;\lambda) = \begin{cases} 1 - e^{-\lambda x} & x \geq 0, \\ 0 & x < 0. \end{cases}$$

- **This can also be defined as heaviside step function**

$$F(x;\lambda) = (1 - e^{-\lambda x})H(x)$$

- **Here λ is the number of occurrences per time unit.**

Exponential Distribution

- **Step 1:**
- **Compute the cdf of random variable x given**

$$F(x) = 1 - e^{-\lambda x},\ x \geq 0.$$

- **Step 2**
- **Set $F(x) = R$ on the range of x which becomes as.**

$$1 - e^{-\lambda x} = R \text{ on the range } x \geq 0.$$

Exponential Distribution

- **Step 3**
- **Solve the equation $F(X) = R$ for X in terms of R as follows.**

$$1 - e^{-\lambda X} = R$$
$$e^{-\lambda X} = 1 - R$$
$$-\lambda X = \ln(1 - R)$$
$$X = -\frac{1}{\lambda}\ln(1 - R)$$

- **Here, X is called random-variate generator.**

Exponential Distribution

- **Step 4**
- **Generate uniform random numbers to compute desired random variates.**

$$X_i = F^{-1}(R_i)$$

- **For exponential case.**

$$X_i = -\frac{1}{\lambda}\ln(1 - R_i)$$

Exponential Distribution

- **If $\boldsymbol{i = 1, 2, 3}$ … replace $\boldsymbol{1 - Ri}$ with $\boldsymbol{R_i}$ as follows.**

$$X_i = -\frac{1}{\lambda} \ln R_i$$

- **Which proves that both R_i and $\mathbf{1} - R_i$ are uniformly distributed on [0, 1].**

Summary

- We understand about "Exponential Distribution"
- Credits, Discrete Event System Simulation, Jerry Banks.

Triangular Distribution

Overview

- **Here, we will discuss about “Triangular Distribution”.**

Triangular Distribution

- **A triangular distribution is a continuous probability distribution with a probability density function shaped like a triangle defined by**
- **The minimum value $\boldsymbol{a}$**
- **The maximum value $\boldsymbol{b}$**
- **The peak value c**
- **Where $\boldsymbol{a} < \boldsymbol{b}$ and** $a \leq c \leq b$

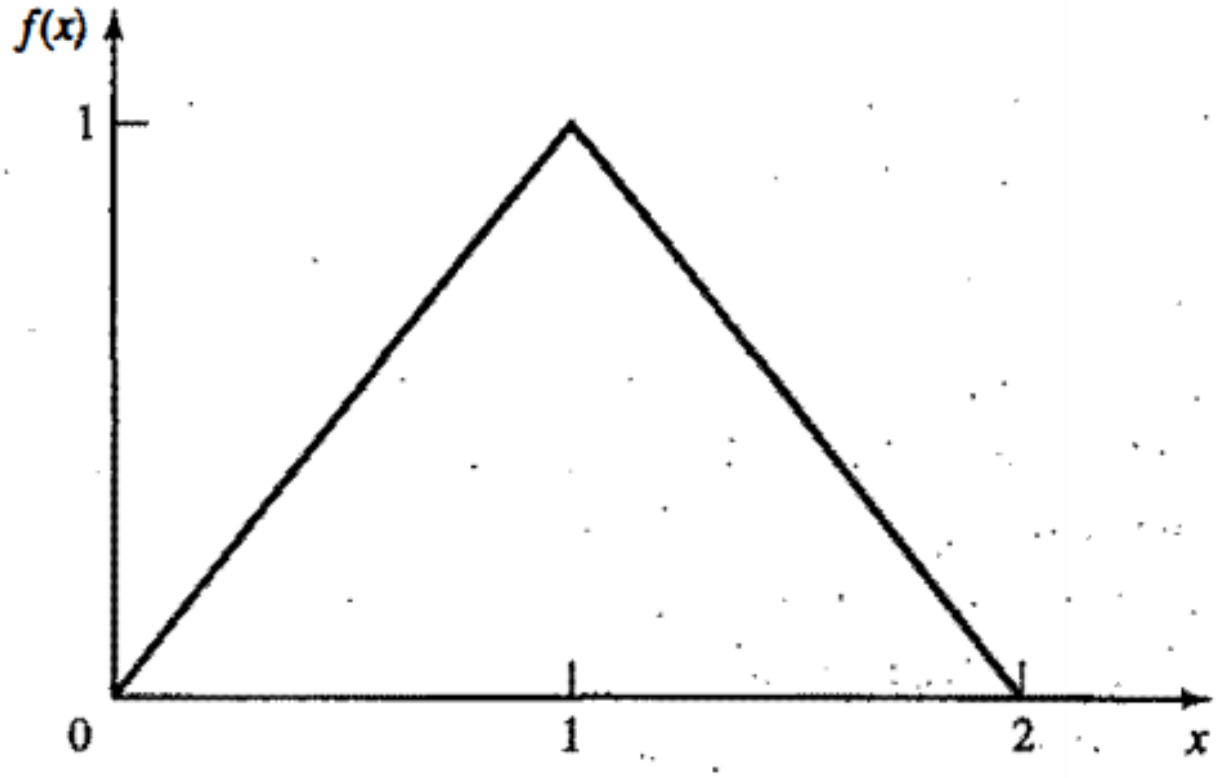
Triangular Distribution

- **Probability density function with variable X**

$$f(x)=\begin{cases} x, & 0 \le x \le 1 \\ 2-x, & 1 < x \le 2 \\ 0, & \text{otherwise} \end{cases}$$

- **Where endpoints are $(0, 2)$ and mode at 1.**

Triangular Distribution



Triangular Distribution

- **Its cumulative distribution function is given as :**

$$F(x) = \begin{cases} 0, & x \le 0 \\ \dfrac{x^2}{2}, & 0 < x \le 1 \\ 1 - \dfrac{(2-x)^2}{2}, & 1 < x \le 2 \\ 1, & x > 2 \end{cases}$$

Triangular Distribution

- **For** $0 \leq X \leq 1$:

$$R = \frac{x^2}{2}$$

- **Which implies that**

$$x = \sqrt{2R}$$

Triangular Distribution

- **For** $1 \leq X \leq 2$:

$$R = 1 - \frac{(2 - X^2)}{2}$$

- **Which implies that**

$$x = 2 - \sqrt{2(1 - R)}$$

Triangular Distribution

- **Thus X is generated as:**

$$X = \begin{cases} \sqrt{2R}, & 0 \le R \le \frac{1}{2} \\ 2 - \sqrt{2(1-R)}, & \frac{1}{2} < R \le 1 \end{cases}$$

Summary

- **Here, we have understood the basics of Triangular Distribution, its pdf, and cdf.**

CHARACTERISTICS OF QUEUEING SYSTEMS

Overview

- **Here, we will learn about characteristics of queueing systems.**

CHARACTERISTICS OF QUEUEING SYSTEMS

- **Customers and servers are the key elements of a queueing system.**
- **A Customer is anything that visits a facility and requires some service.**
- **Servers the service provider.**

CHARACTERISTICS OF QUEUEING SYSTEMS

- **Not every time the customer visits the service facility.**

CHARACTERISTICS OF QUEUEING SYSTEMS

Table 6.1 Examples of Queueing Systems

System	*Customers*	*Server(s)*
Reception desk	People	Receptionist
Repair facility	Machines	Repairperson
Garage	Trucks	Mechanic
Tool crib	Mechanics	Tool-crib clerk
Hospital	Patients	Nurses
Warehouse	Pallets	Fork-lift Truck
Airport	Airplanes	Runway
Production line	Cases	Case-packer
Warehouse	Orders	Order-picker
Road network	Cars	Traffic light
Grocery	Shoppers	Checkout station
Laundry	Dirty linen	Washing machines/dryers
Job shop	Jobs	Machines/workers
Lumberyard	Trucks	Overhead crane
Sawmill	Logs	Saws
Computer	Jobs	CPU, disk, CDs
Telephone	Calls	Exchange
Ticket office	Football fans	Clerk
Mass transit	Riders	Buses, trains

Summary

- **We have learnt about the characteristics of the Queueing systems.**
- **Credits: Jerry Banks books.**

Modeling and Simulation

The Calling Population

Overview

- **Here, we will learn about the calling population.**

The Calling Population

- Calling population is the population of potential customers.
- Finite or infinite.
- Example of the bank having five machines and each machine is a customer and worker is its server.

The Calling Population

- Infinite calling population when the system has a large population of potential.
- Examples are banks and restaurants.

The Calling Population

- Arrival rate is the main difference between the finite and infinite population models.
- Infinite population system is not affected by the arrival rate.
- The Finite system depends on the no of customers waiting and being served.

Summary

- **We have learnt about the calling population and what are effects of finite and infinite population.**
- **Credits: Jerry Banks book.**

Modeling and Simulation

System Capacity

Overview

- **Here, we will learn about the system capacity.**

System Capacity

- Every queueing system has some capacity.
- They have different number of customers entering the system.

System Capacity

- **There is a limit for every queueing system to hold the number of customers.**
- **If the entering system finds the capacity full it will return to the calling population.**

System Capacity

- Some systems have unlimited capacity
- Like tickets sold for a concert to students and many students can wait to purchase them.

System Capacity

- **In limited systems, there is a distinction in arrival time and effective arrival time.**

Summary

- **We have learnt about the system capacity.**
- **Credits: Jerry Banks book.**

Modeling and Simulation

The Arrival Process

Overview

- **Here, we will learn about the arrival process.**

Arrival Process

- For infinite population models the arrival process characterized in terms of interarrival times of successive customers.
- Probability distribution is used to characterize the interarrival times when arrival is occurred in random time.

Arrival Process

- Poisson arrival process is the most important for random arrivals.
- If A_n = inter-arrival
- Between n-1(customer) and
- n(customer) then
- A_n is exponentially distributed with mean $1/\lambda$ time units.

Arrival Process

- **The arrival rate is λ customers per time unit.**
- **So the number of arrivals in a time interval of length t has Poisson distribution with mean λt customers.**
- **In restaurants and banks the Poisson arrival process has been employed successfully.**

Arrival Process

- Scheduled arrival is the second arrival class.
- Inter-arrival could be either constant or constant plus or minus a small random amount to represent early or late arrivals.

Arrival Process

- Third situation occurs when one customer is always present in the queue.
- So we do not have an idle server.

Arrival Process

- For finite population the arrival process is different.
- We define the customer as pending when he is out of the queue system and a member of potential calling population.

Arrival Process

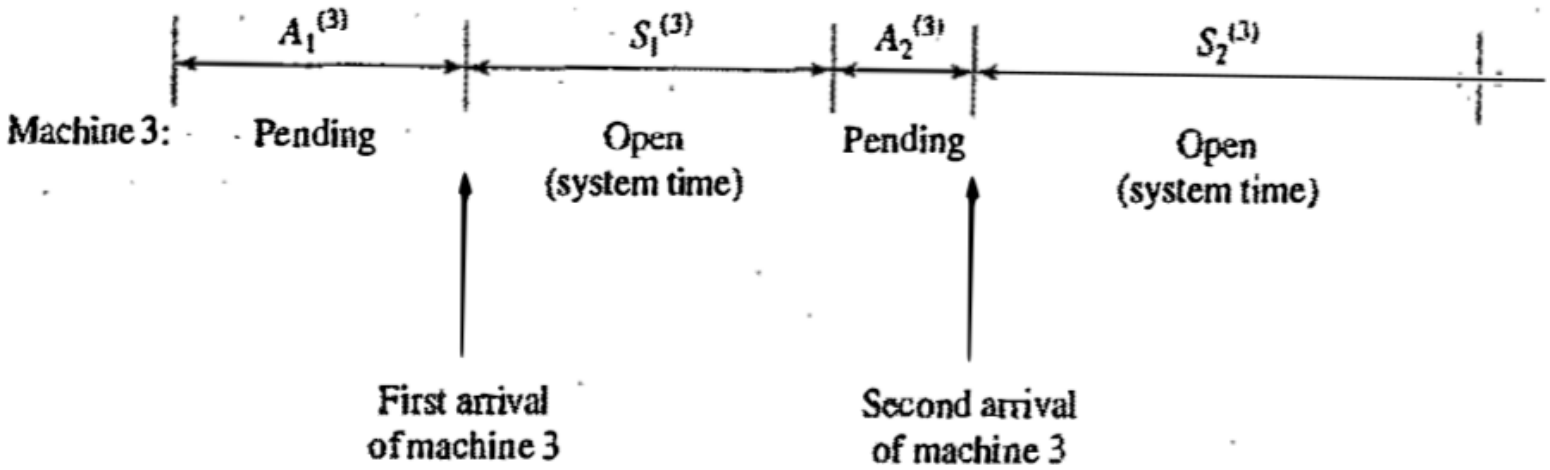


Figure 6.2 Arrival process for a finite-population model.

Arrival Process

- **Important application of finite population model is machine repair problem.**

Summary

- **We have learnt about the finite and infinite arrival processes.**
- **Credits: Jerry Banks book.**

QUEUE BEHAVIOR AND QUEUE DISCIPLINE

Overview

- **Here, we will learn about the Queue behavior and Queue discipline.**

Queue Behavior

- **The actions of the customer while waiting in the queue system for his service is known as the queue behaviour.**
- **The customers can baulk, renege or jockey.**

Queue Discipline

- The logical ordering of the customers in a queue and determining that which customer should come for service when the server is free.
- FIFO, LIFO, SIRO, SPT and PR are some common queue disciplines.

Summary

- We have learnt about the Queue behavior and Queue discipline.
- Credits: Jerry Banks book.

Modeling and Simulation

Service Times and the Service Mechanism

Overview

- **Here, we will learn about the Service Times and the Service Mechanism.**

Service Times and the Service Mechanism

- Service times of successive arrivals are denoted by S_1 S_2…..
- Their duration can be random or constant.
- This latter case is characterized as a sequence of random or identically distributed variables.

Service Times and the Service Mechanism

- The exponential, Weibull, gamma, lognormal and truncated normal distributions are used for service times.
- Sometimes the services are identically distributed for all same customers. Same type customers can have different service time.

Service Times and the Service Mechanism

- **Number of service centers and interconnecting queues are present in a queue system.**
- **Parallel working servers for each service centre.**

Service Times and the Service Mechanism

- Server = c
- Single server (c = 1)
- Multiple servers ($1<c<\infty$)
- Unlimited servers($c = \infty$)

Service Times and the Service Mechanism

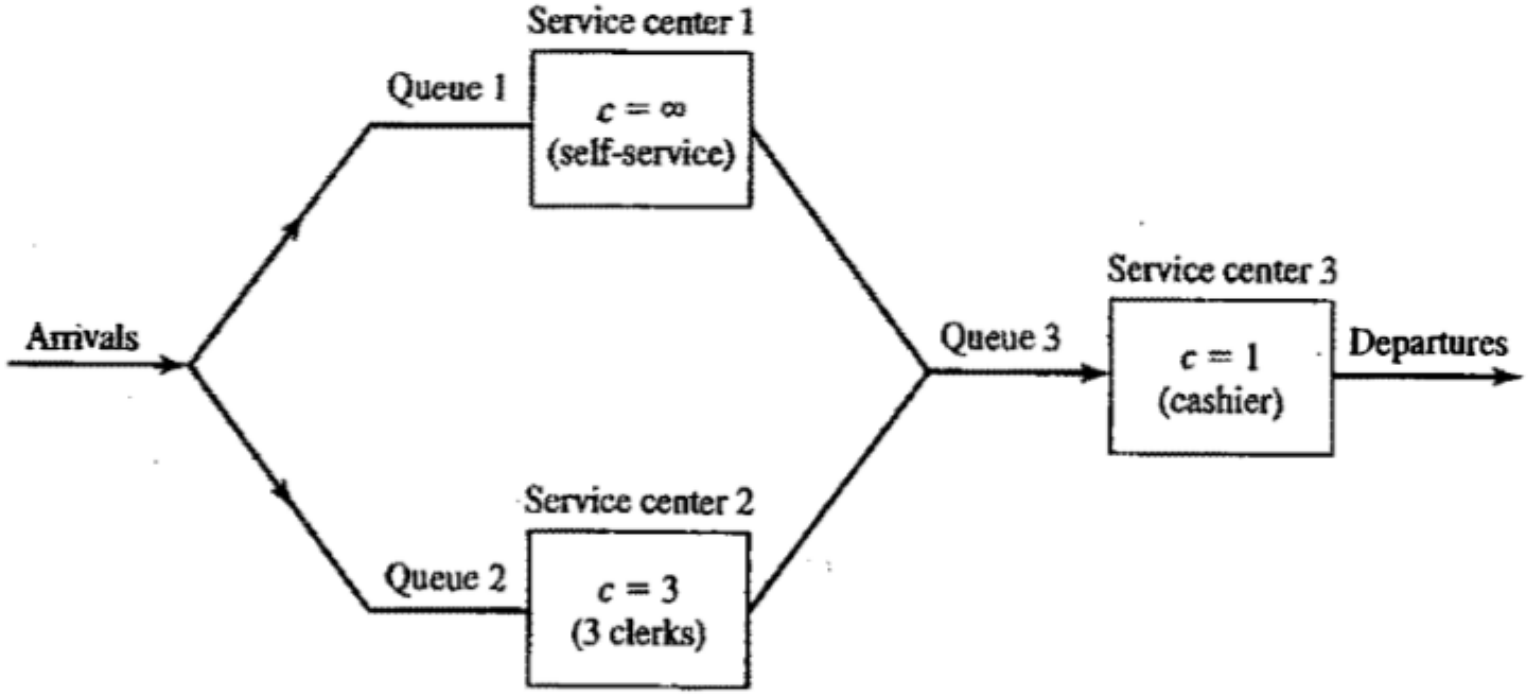


Figure 6.3 Discount warehouse with three service centers.

Service Times and the Service Mechanism

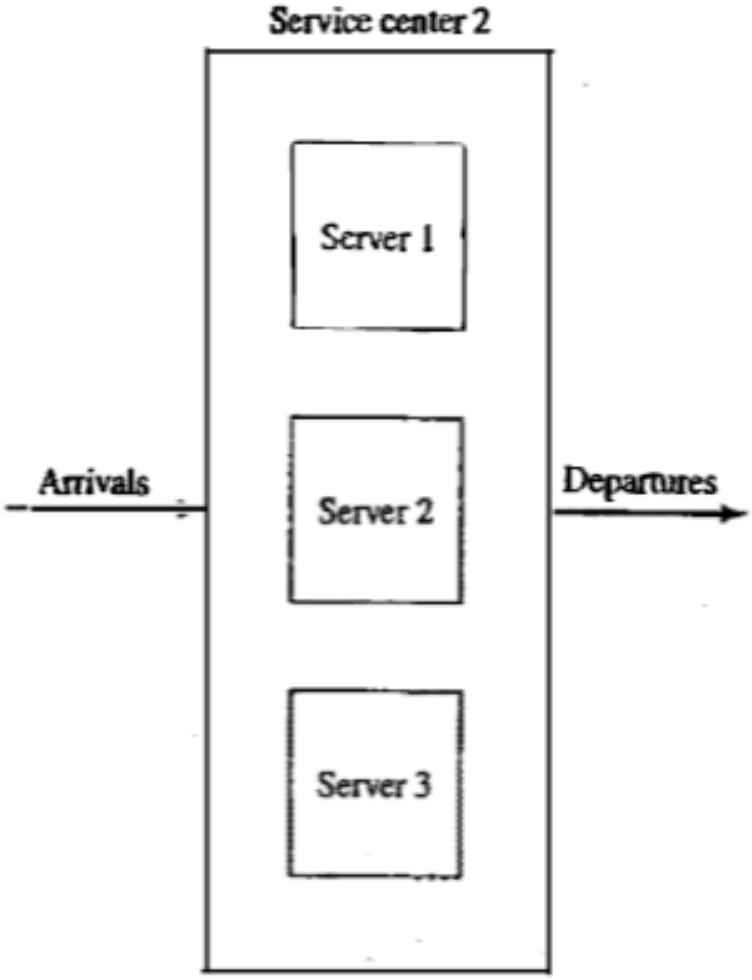


Figure 6.4 Service center 2, with $c = 3$ parallel servers.

Service Times and the Service Mechanism

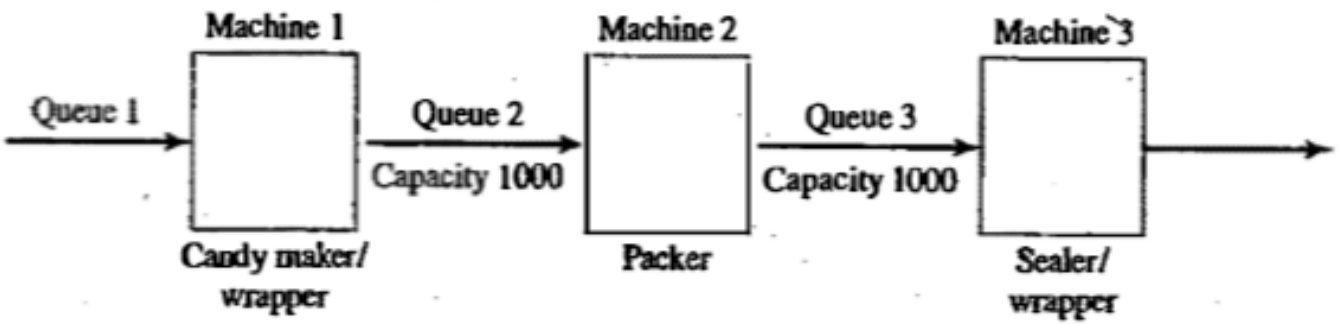


Figure 6.5 Candy-production line.

Summary

- We have learnt about the Service times and the Service mechanism.
- Credits: Jerry Banks book.

Modeling and Simulation

Queueing Notation

Overview

- **Here, we will learn about the Queueing notation.**

Queueing Notation

- Proposed by Kendall [1953]
- For parallel server systems.
- A/B/c/N/K based on this format.
- “A” represents the inter-arrival-time distribution.
- “B” represents the service-time distribution.

Queueing Notation

- "C" represents the number of parallel servers.
- "N" represents the system capacity.
- "K" represents the size of the calling population.

Queueing Notation

- Common symbols for A and B include M (exponential or Markov)
- D (constant or deterministic).
- Ek (Erlang of order k).

Queueing Notation

- PH (phase-type).
- H (hyperexponential).
- G (arbitrary or general)
- GI (general independent).

Queueing Notation

Table 6.2 Queueing Notation for Parallel Server Systems

P_n	Steady-state probability of having n customers in system
$P_n(t)$	Probability of n customers in system at time t
λ	Arrival rate
λ_e	Effective arrival rate
μ	Service rate of one server
ρ	Server utilization
A_n	Interarrival time between customers $n-1$ and n
S_n	Service time of the nth arriving customer
W_n	Total time spent in system by the nth arriving customer
W_n^Q	Total time spent in the waiting line by customer n
$L(t)$	The number of customers in system at time t
$L_Q(t)$	The number of customers in queue at time t
L	Long-run time-average number of customers in system
L_Q	Long-run time-average number of customers in queue
w	Long-run average time spent in system per customer
w_Q	Long-run average time spent in queue per customer

Summary

- **We have learnt about the queueing notation.**
- **Credits: Jerry Banks book.**

Modeling and Simulation

Long-run Measures Of Performance Of Queueing Systems

Overview

- **Here, we will learn about the long-run measures of performance of queueing systems.**

LONG-RUN MEASURES OF PERFORMANCE

- **The primary long-run measures of performance of queueing systems are:**
- **Long-run time-average number of customers in the system (L).**
- **In the queue (LQ).**
- **Long-run average time spent in the system (w).**

LONG-RUN MEASURES OF PERFORMANCE

- In the queue (wQ) per customer.
- Server utilization.
- A Proportion of time that a server is busy (p).
- Waiting line and mechanism is a system.
- System can also be sub-system of queue system.
- “queue” means waiting line alone.

LONG-RUN MEASURES OF PERFORMANCE

- Other measurements include long-run proportion of customer who is delayed longer than t_o time units.
- Customers turned away due to capacity constraints.
- Waiting line containing more than k_o customers.

LONG-RUN MEASURES OF PERFORMANCE

- G/G/c/N/K is defined.
- Their performance relationships and simulation run.
- The two types of estimators are:
- An ordinary sample average.
- A time-integrated sample average.

Summary

- We have learnt about the long-run measures of performance of queueing systems.
- Credits: Jerry Banks book.

Modeling and Simulation

Properties Of Random Numbers

Overview

- **Here, we are going to learn about properties of random numbers.**

Properties of Random Numbers

- **Uniformity and independence are two important statistical properties.**
- **Each sample must be drawn from continuous uniform distribution between 0 and 1.**

$$f(x) = \begin{cases} 1, & 0 \le x \le 1 \\ 0, & \text{otherwise} \end{cases}$$

Properties of Random Numbers

- **The density function and the expected value of R_i is:**

$$E(R) = \int_0^1 x\,dx = \left.\frac{x^2}{2}\right|_0^1 = \frac{1}{2}$$

- **And the variance is:**

$$V(R) = \int_0^1 x^2\,dx - \left[E(R)\right]^2 = \left.\frac{x^3}{3}\right|_0^1 - \left(\frac{1}{2}\right)^2 = \frac{1}{3} - \frac{1}{4} = \frac{1}{12}$$

Properties of Random Numbers

- Generated by a digital computer.
- Individual computation is expensive so computationally efficient method should be used.
- Routine should be portable for different computers and programming languages.

Properties of Random Numbers

- Routine having a long cycle.
- Replicable random numbers.
- Random numbers should closely approximate the ideal statistical properties.

Properties of Random Numbers

- **Techniques to generate random is easy to develop.**
- **Techniques that produce sequences that are independent and uniformly distributed are difficult.**

Summary

- **We have learnt about the properties of the random numbers.**
- **Credits: Jerry Banks book.**

Linear Congruential Method

Overview

- **Here, we will learn about the linear congruential method.**

Linear Congruential Method

- **Widely used technique.**
- **Yields sequences with longer periods.**
- **Produces the sequence of integers.**
- **Between zero and $m - 1$.**

Linear Congruential Method

$$X_{i+1} = (aX_i + c) \bmod m, \quad i = 0, 1, 2, \ldots$$

- x_o = seed.
- a = multiplier.
- c = increment $(c \neq 0)$.
- m = modulus.
- This is called mixed congruential method.
- When c = 0 then known as multiplicative congruential.

Linear Congruential Method

- Interval [0,1] is divided into n classes than expected observation for each interval is N/n .
- N is the total number of observations.
- Observing a value in a particular interval is independent.

Summary

- **We have learnt about the linear congruential method.**
- **Credits: Jerry Banks book.**

Modeling and Simulation

Generation Of Pseudo-random Numbers

Overview

- **Here, we will learn about the generation of pseudo-random numbers.**

Generation Of Pseudo-random Numbers

- False number generation.
- Removes the potential of true randomness.
- Set of random numbers can be replicated.
- Producing numbers between 0 and 1 that simulates the properties of uniform distribution and independence.

Generation Of Pseudo-random Numbers

- Some errors or departures are:
- Not uniformly distributed random numbers.
- Not too high or too low variance.
- Generated numbers might not be continuous valued but are discrete valued.

Generation Of Pseudo-random Numbers

- **Dependence:**
- **Autocorrelation between numbers.**
- **Numbers successively higher or lower than adjacent numbers.**
- **Several numbers above the mean followed by the several numbers below the mean.**

Generation Of Pseudo-random Numbers

- **Departures from uniformity and independence for a particular generation scheme often can be detected by tests.**
- **If detected then dropped in the favour of an acceptable generator.**

Summary

- **We have learnt about the generation of pseudo-random numbers.**
- **Credits: Jerry Banks book.**

Modeling and Simulation

Tests for Random numbers

Overview

- **Here, we will understand about the Tests for Random numbers.**

Tests for Random numbers

- **Two categories:**
- **Uniformity.**

$$H_0: \quad R_i \sim U[0, 1]$$
$$H_1: \quad R_i \nsim U[0, 1]$$

- **H_o denotes numbers distributed uniformly on the interval [0, 1].**

Tests for Random numbers

- **Independence.**

$$H_0: \quad R_i \sim \text{independently}$$
$$H_1: \quad R_i \nsim \text{independently}$$

- **H_o denotes the independent numbers.**

Tests for Random numbers

- **A level of significance α must be stated for each test.**
- **Where α is probability of rejecting the null hypothesis.**

$$\alpha = P(\text{reject } H_0 \mid H_0 \text{ true})$$

Tests for Random numbers

- **Software not specifically developed for simulation comes with random number generator pre-installed**

Tests for Random numbers

- **Additional Tests:**
- **Good's serial test, the median-spectrum test, the run's test and a variance heterogeneity test.**

Summary

- **Here, we understood about the tests for random numbers.**
- **Credits: Jerry banks book.**

Modeling and Simulation

Random Variate Generation

Overview

- **Here, we will understand about the "Random Variate Generation".**

Random Variate

- A random variate is a generated variable using uniformly distributed pseudorandom numbers.
- A random variate can be uniformly or nonuniformly distributed.

Random Variate Generation

- **Modeling activities is unpredictable or indeterminate.**

Random Variate Generation

- **Random Variate Generations explain and illustrate some techniques for generating random**

Random Variate Generation

- **Sometimes there is no availability of random-variate-generation libraries.**
- **It is up to the modeller to create an acceptable routine.**

Random Variate Generation

- This topic includes
- inverse-transform technique
- Acceptance-rejection technique
- Special properties
- The composition method

Summary

- **Here, we understood about Random Variate Generation.**
- **Credits: Jerry banks book.**

Inverse Transform Technique

Overview

- **Here, we will understand about the "Inverse Transform Technique".**

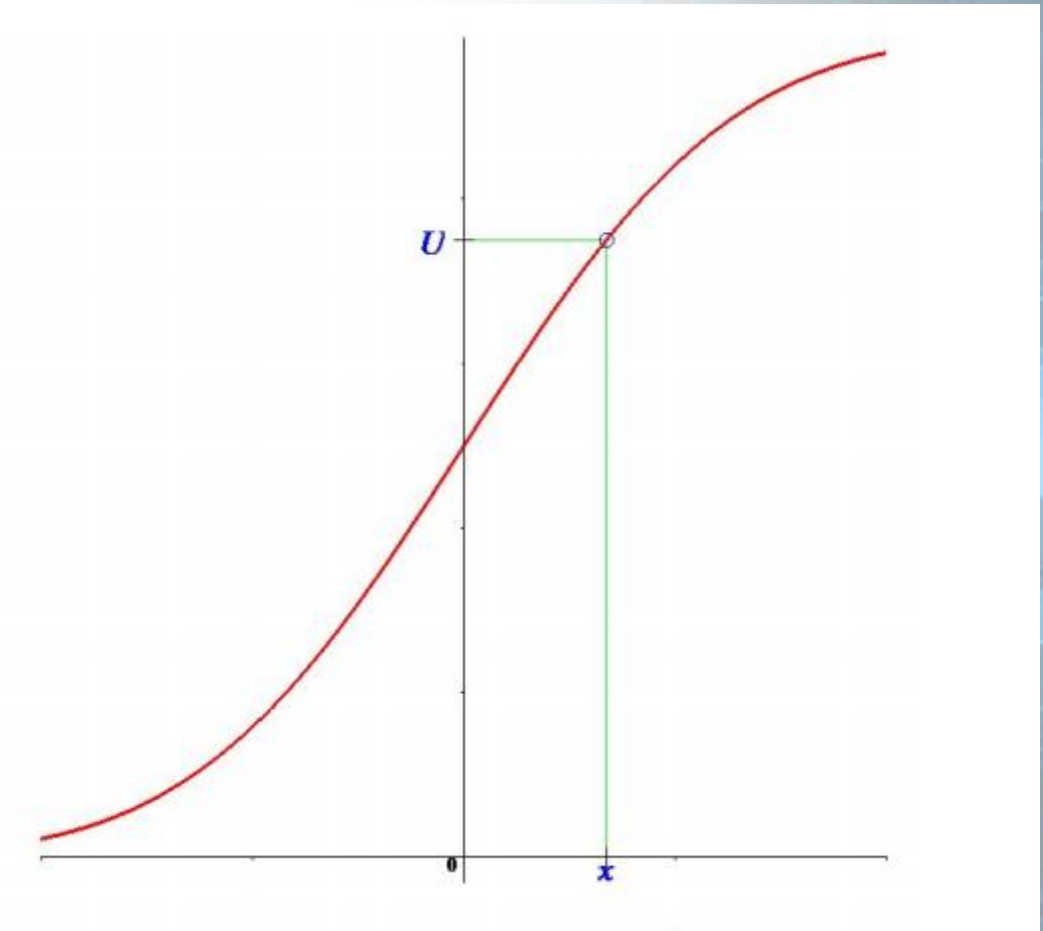
Inverse Transform Technique

- The inverse-transform technique can be used to sample from the exponential.
- The uniform.
- The Weibull.
- The triangular and empirical distributions.

Inverse Transform Technique

- **The basic principle is to find the inverse function of F, F^{-1} such that $FF^{-1} = I$**
- **Where F^{-1} denotes the solution of the equation $r = F(x)$ in terms of γ.**

Inverse Transform Technique



Inverse Transform Technique

- This technique explains:
- Exponential Distribution
- Uniform Distribution
- Weibull Distribution
- Triangular Distribution
- Empirical Continuous Distribution
- Continuous Distribution
- Discrete Distribution

Summary

- **Here, we understood about Inverse Transform Technique.**
- **Credits: Jerry banks book.**

Acceptance Rejection Technique

Overview

- **Here, We will understand “Acceptance Rejection Technique”.**

Acceptance Rejection Technique

- **Acceptance Rejection Technique is a method used to generate random variate using some steps explained next.**

Acceptance Rejection Technique

- **Step 1. Generate a Random Number R.**
- **Step2a. If $R \geq 1/4$ Accept R.**
- **Step2b. If $R \leq 1/4$ Reject R.**
- **If another uniform random variate on [1/4, 1] is needed, repeat the procedure.**

Acceptance Rejection Technique

- **The random variate generated using above methods is indeed uniformly distributed over [1/4, 1].**

Acceptance Rejection Technique

- **Take any** $1/4 \leq a < b \leq 1$ **then**

$$P(a < R \leq b | 1/4 \leq R \leq 1) = \frac{P(a < R \leq b)}{P(1/4 \leq R \leq 1)} = \frac{b-a}{3/4}$$

- **Proves that probability for uniform distribution is on [1/4, 1].**

Acceptance Rejection Technique

- The efficiency of an acceptance-rejection technique rest on reducing the total of rejections.
- Which depends on computer being used.
- The skills of programmer.
- Rejected numbers.

Acceptance Rejection Technique

- The Distributions which operates on acceptance rejection technique are:
- Poisson Distribution
- Nonstationary Poisson process
- Gamma Distribution.

Summary

- Here, we understood about the Acceptance Rejection Technique.
- Credits, Jerry Banks book.

Modeling and Simulation

Other topics in Randomness

Overview

- **Here, we will discuss about “Other topics in Randomness”.**

Special Properties

- **Special Properties are variate generation techniques based on a particular feature of probability distributions.**

Direct Transformation

- Direct transformation is used for the normal and lognormal distributions.
- The cdf is given by:

$$\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt, \qquad -\infty < x < \infty$$

- Box and Muller made this method and is easy to program in scientific programming languages.

Convolution Method

- **The probability distribution of a sum of two or more independent random variables is called convolution method.**

Convolution Method

- This method uses two random variables.
- Sum them and generate a new random variable.
- This technique can be applied on Erlang and Binomial variates.

More Special Properties

- The other relationship among distributions include relation between gamma and beta distribution.
- We can generate beta variates, using two gamma variates with acceptance-rejection technique.

Summary

- **Here, We understood about the Special Properties, Direct transformation, convolution method and other special properties.**
- **Credits: Jerry banks book.**

Data Collection

Overview

- **Here, we will discuss about “Data Collection”.**

Data Collection

- **The relation between construction of the model and the collection of needed input data is constant.**

Data Collection

- **The required data elements changes with complexity of the model.**
- **Time taking nature of data collection.**

Data Collection

- **Which type of data is to be collected is dictated by the objectives of study.**

Summary

- **Here, We understood about the Data Collection.**
- **Credits: Jerry banks book.**

Identifying the Distribution with Data

Overview

- **Here, we will understand About "Identifying the Distribution with Data".**

Identifying the Distribution with Data

- **Data distribution are graphical methods.**

Identifying the Distribution with Data

- These methods are used for selecting input distribution families.
- The specific distribution is often specified by estimating its parameters.

Summary

- **We understood about Data Distribution and how data parameters are selected.**
- **Credits, Jerry Banks book.**

Modeling and Simulation

Histograms

Overview

- **Here, we will understand about the "Histograms".**

Histograms

- **Histograms is a powerful technique for identifying how a distribution is shaped.**
- **Histogram is also known as frequency distribution.**

Histograms

- **There are some methods for constructing a histogram.**

Histograms

- 1. Divide the data ranges into intervals of equal width.
- 2. Label the horizontal axis to follow the nominated intervals.
- 3. Find the frequency of occurrences inside each intervals.

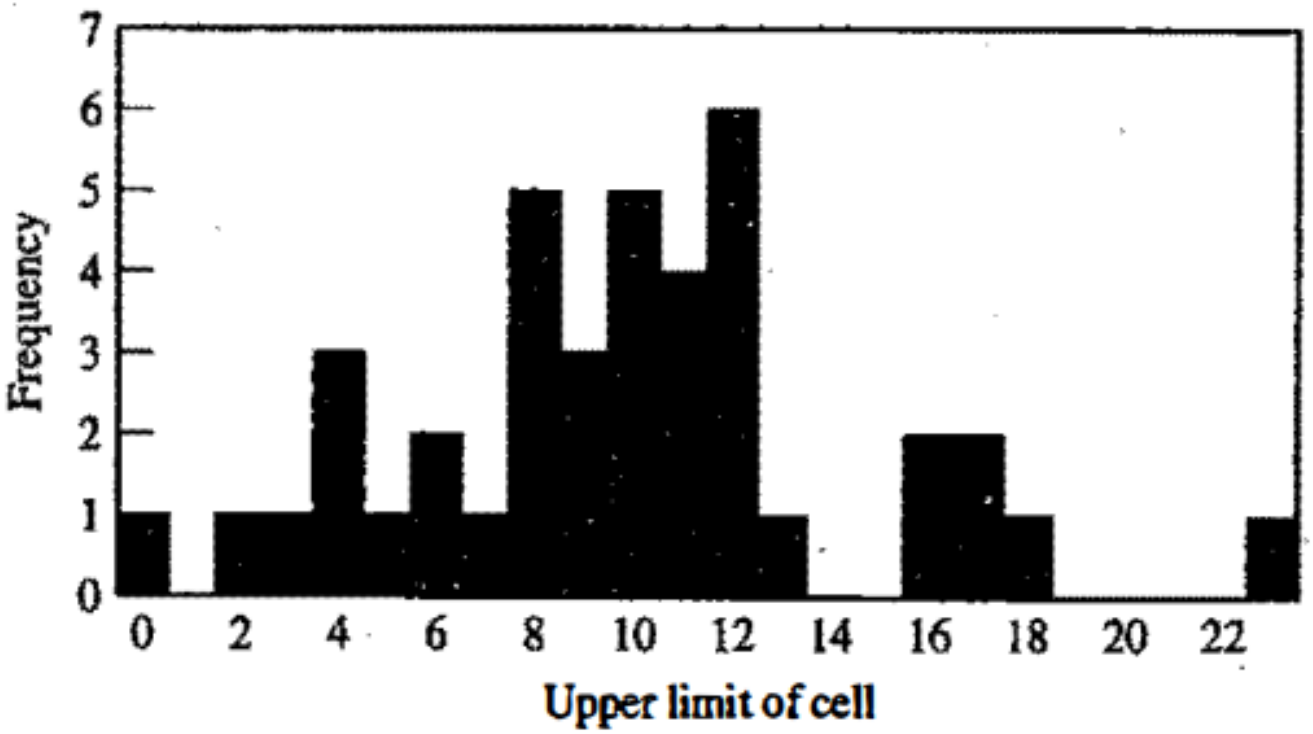
Histograms

- 4. Label the vertical axis to plot total occurrences for every interval.
- 5. Plot the frequencies on the vertical axis.

Histograms

- The number of class intervals is decided by the number of observations.
- Amount of scatter in the data.

Histograms


Frequency
0
1
2
3
4
5
6
7
0
2
4
6
8
10
12
14
16
18
20
22
Upper limit of cell

Summary

- **Here, we understood about the “Histograms”.**
- **Credits: jerry banks book.**

Selecting the Family of Distributions

Overview

- **Here, we will understand about the "Selecting the Family of Distributions".**

Selecting the Family of Distributions

- **The selection of a family of distributions is based on the context for what it is being investigated.**
- **The shape of the histogram.**

Selecting the Family of Distributions

- **The Distributions which are frequently encountered and easy to analyze includes exponential, normal and poison distribution.**
- **Whereas difficult to analyze includes the beta, gamma and Weibull distributions.**

Selecting the Family of Distributions

- Out of many, Here are some examples of distributions which were created on the physical basis.
- Binomial
- Negative Binomial
- Poisson
- Normal
- Lognormal

Selecting the Family of Distributions

- **An input Model is an estimate of reality.**
- **There is no "true" distribution for any stochastic input process.**

Summary

- **Here, we understood about the Family of distributions, its types and input model.**
- **Credits: Jerry banks book.**

Quantile-Quantile Plot

Overview

- **Here, we will understand about the "Quantile-Quantile Plot".**

Quantile-Quantile Plot

- **A Quantile-Quantile is a graphical method for comparison of two probability distributions by plotting their qualities against each other.**

Quantile-Quantile Plot

- **If** $F(\gamma) = P(X \leq \gamma) = q$ **for** $0 < q < 1$
- **Here x is random variable with cdf** F**.**
- ***Q-quantile of*** X ***is value of*** γ ***.***
- ***We write*** $\gamma = F^{-1}(q)$ ***when*** F ***has an inverse.***

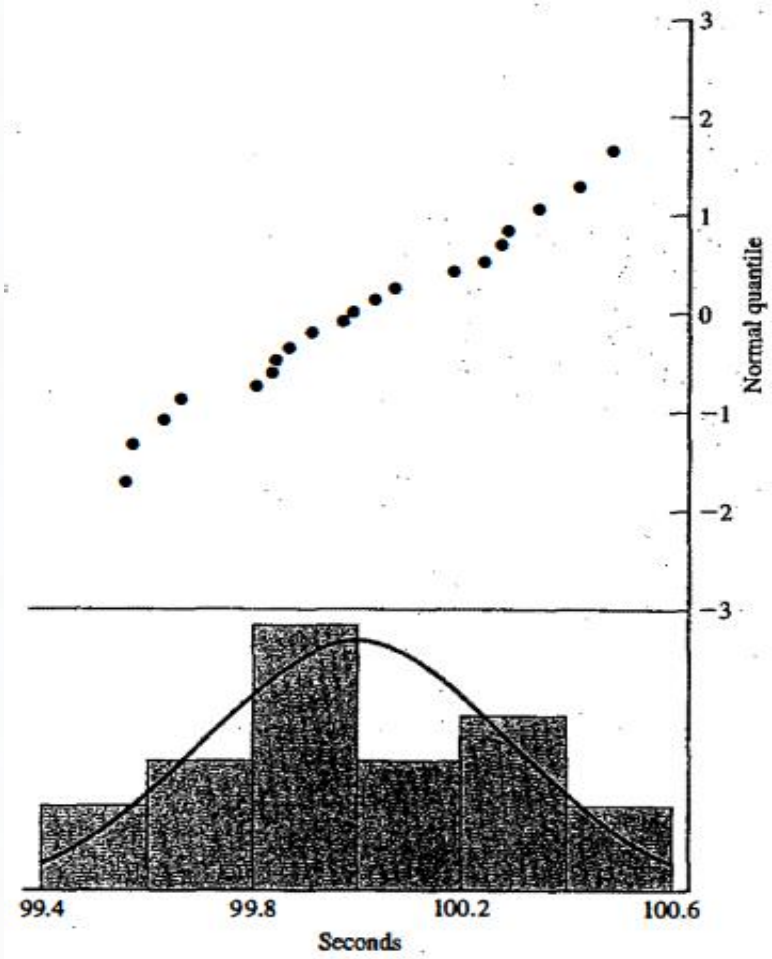
Quantile-Quantile Plot

- **If** $\{x_i, \boldsymbol{i} = 1,2,3 \cdot \cdots n\}$ **and** $\{\boldsymbol{y_j}, \boldsymbol{j} = 1,2,3 \cdot \cdots n\}$
- **Where** $y_1 \leq y_2 \leq \cdots \leq y_n$
- **Let** $\boldsymbol{j}$ **denote the ranking of order**
- $j = 1$**for smallest**
- $j = \boldsymbol{n}$ **for largest**

Quantile-Quantile Plot

- **Then**
- $\boldsymbol{y_j} \approx F^{-1}\left(\frac{j-\frac{1}{2}}{n}\right)$

Quantile-Quantile Plot



Summary

- **Here, we understood about the "Quantile-Quantile Plot".**
- **Credits: jerry banks book.**

PARAMETER ESTIMATION

Overview

- **Here, we will learn about the parameter estimation.**

Parameter Estimation

- **After selecting the family of distribution, the next step is to estimate the parameters of the distribution.**

Parameter Estimation

- **Many useful distribution estimators are described here.**

Parameter Estimation

- **Software packages integrated into simulation languages are available.**

Parameter Estimation

- We have learnt about the parameter distribution.
- Credits: Jerry Banks book.

Modeling and Simulation

Preliminary Statistics: Sample Mean and Sample Variance.

Overview

- **Here, we will learn about the preliminary statistics: sample mean and sample variance.**

Preliminary Statistics

- **To estimate the parameters of a hypothesized distribution.**

Preliminary Statistics

- **When discrete and continuous raw data is available then the following equation is used:**

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}$$

- $\bar{x}$ **= sample mean.**
- $x_1, x_2, \ldots, x_n$ **= observation in a sample of size n.**

Preliminary Statistics

- **The sample variance s^2 is defined as:**

$$S^2 = \frac{\sum_{i=1}^{n} X_i^2 - n\bar{X}^2}{n-1}$$

Preliminary Statistics

- **When discrete or continuous raw data are available following modified equations are used:**

$$\bar{X} = \frac{\sum_{j=1}^{k} f_j X_j}{n}$$

- **Where $\bar{x}$ is the sample mean.**

Preliminary Statistics

- And the sample variance is :

$$S^2 = \frac{\sum_{j=1}^{k} f_j X_j^2 - n\bar{X}^2}{n-1}$$

- Here k is the number of distinct values of X.
- F_j is the observed frequency of the value X_j of X.

Preliminary Statistics

- **When data is discrete or continuous and have been placed in class intervals then the sample mean and the sample variance are approximated from the following equations:**

$$\bar{X} \doteq \frac{\sum_{j=1}^{c} f_j m_j}{n}$$

Preliminary Statistics

- For the sample variance the following equation is used.

$$S^2 \doteq \frac{\sum_{j=1}^{c} f_j m_j^2 - n\bar{X}^2}{n-1}$$

- f_j observed frequency of j_{th} class interval.
- m_j midpoint of j_{th} interval.
- c = number of intervals.

Summary

- We have learnt about the preliminary statistics: sample mean and sample variance.
- Credits: Jerry Banks book.

Modeling and Simulation

Evolution of Computer Systems Architectures

Overview

- **Here, we will learn about the evolution of computer systems architectures**

Evolution of Computer Systems Architectures

- ENIAC was the first computer system with no operating system and was large in size. They used vacuum tubes.
- Early computer doesn’t have a good operating system, databases.
- They doesn’t have any high-level programming language for simplifying program.

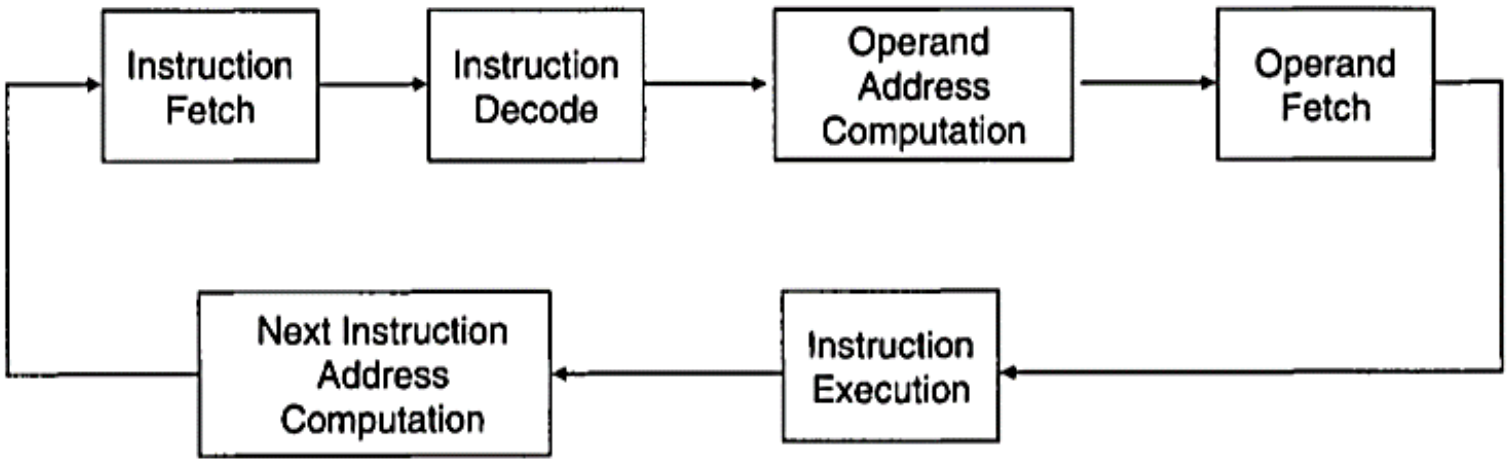
Systems Architecture

- Central Processing Unit.
- Graphics Processing Unit.
- Temporary memory.
- Permanent Memory.
- Input unit.
- Output unit.
- Control element.
- Disk Drives.

CPU Architectures

- Central processing unit.
- CU fetch functions.
- ALU performs functions.
- Registers to store the operands.
- L1, L2, L3 Cache.
- CPU Execution cycle.

Instruction architectures



Instructions and Memory Architectures

- Reduced instruction set computer (RISC).
- Highly optimized instructions.
- Complex instruction set computer (CISC).
- Memory address register.
- Memory data register.

Secondary Storage and Peripheral Device Architecture

- I/O devices control secondary storage.
- Magnetic tape drives.
- Magnetic disk drives.
- Compact optical disk drives.
- Disk jukeboxes.
- High density data storage.

Network Architecture

- Share information and processing capacity in real life.
- Another path to send or receive data.
- Central switching element. Central storage repository.
- Connected using intelligent interface units.

Summary

- We have learnt about the evolution of computer systems architectures.
- Credits: Paul Fortier book.

Modeling and Simulation

Evolution of Database Systems

Overview

- **Here, we will learn about the evolution of database systems.**

Evolution of Database Systems

- Powerful tools to manage information.
- Early computers lag in online data storage.
- System architects have to reply on external storage.
- Initial storage was constructed using simple direct addressing.

Evolution of Database Systems

- File system used coarse semantic means.
- Information Centralization.
- Security.
- Integrity.
- File systems added finer-grained definitions of stored information.

Evolution of Database Systems

- Relational database system was introduced.
- Database must be entered at a specific entry point.
- Must traverse the path leading to the specific item.
- An issue for network is its legacy.

Evolution of Database Systems

- Database system's demise began with development.
- Publication of Codd's relational database model.
- Information can be formed into tables called relations.
- Have to use calculus and algebra to operate.

Evolution of Database Systems

- Concurrent access was not present in early network-based databases.
- The serializability theory and concurrency control led to further improvements in database technology.
- “ACID” properties.

Evolution of Database Systems

- Object-oriented database was developed.
- For application developers to store data and data types efficiently.
- But did not possess some fundamental concepts.

Evolution of Database Systems

- Object relational databases.
- Embraced by the U.S and international venders.
- Next change will be in the area of transactions and transaction processing.
- ACID properties may be altered.

Summary

- We have learnt about the evolution of database systems.
- Credits: Paul Fortier book.

Modeling and Simulation

Evolution of Operating Systems

Overview

- **Here, we will learn about the evolution of operating systems.**

Evolution of Operating Systems

- Operating system is computer's software, firmware, and hardware.
- Interacts at low-level.
- Manage sharing of computer's resources.
- The most privileged of software elements on the system.
- Requires hardware.

Evolution of Operating Systems

- Early coders load the software in a location then make hardware to start processing.
- No automated means to switch between different jobs.
- Monitor or batch operating system provided the solution to transition between processing jobs.

Services of Operating System

- Process and Hardware management.
- Memory management.
- I/O management.
- Inter-process synchronization and communications.
- Resource allocation.
- Protection of system and user resources.

Evolution of Operating Systems

- interrupt service routine checks everything and determines what to perform next.
- Efficient use of computing facilities.
- Convenient interface to user by hiding the details of machine.
- Transparent use of computer resources.

Evolution of Operating Systems

- Improved architectures and instruction execution schemes.
- Improve the performance of the processor.
- Not to depend on a single processor
- Add entire new processors.

Evolution of Operating Systems

- Distributed processors.
- Processors operating system is the single global operating system.
- In one case the entire operating system can be replicated on each site.
- Each processor has a specific function.

Evolution of Operating Systems

- New concepts are still being examined.
- Client/server processing.
- Multiprocessing operating system forum.

Summary

- We have learnt about the evolution of operating systems.
- Credits: Paul Fortier book.

Modeling and Simulation

Evolution of Computer Networks

Overview

- **Here, we will learn about the evolution of computer networks**

Evolution of Computer Networks

- The term network can mean many things.
- In computer it refers to combination of interconnected resources.
- ARPANET was an early computer network.
- A loose coalition of devices that share information.

Evolution of Computer Networks

- All this evolved into internet.
- ARPANET provided early research into communication protocols.
- Greater availability and access to a wider range of devices.
- As more applications were added.

Evolution of Computer Networks

- Information access and manipulation took on greater emphasis.
- As the networks improve new applications arose.
- Remote job execution was added with information exchange.
- But still real-time was not provided.

Evolution of Computer Networks

- They had to develop more advance protocols and network operating systems.
- It was time consuming.
- Local area network was introduced in 1970s.
- LAN became more widely available.

Evolution of Computer Networks

- LAN designs have been produced to fit an extremely wide spectrum of user requirements.
- LAN is widely used in all aspects of society.
- LAN had rapid growth in 1990s and early 2000s.
- LAN can connect a device from anywhere.

Evolution of Computer Networks

- LAN is used to link factory robots.
- LAN provide sensor data, control data and feedback.
- Walt Disney World used LAN for different services.
- Large banks also use LAN for interconnection of their local sites.

Evolution of Computer Networks

- Wireless technology has improved.
- Began in 1970s with Aloha net as foundation.
- Wireless phone network development has opened the door for computer networks.
- More development will be made to provide more applications.

Summary

- We have learnt about the evolution of computer networks.
- Credits: Paul Fortier book.

Modeling and Simulation

Need for Performance Evaluation

Overview

- **Here, we will learn about the need for performance evaluation**

Need for Performance Evaluation

- Selecting a specific computer architecture for an application.
- An operating system.
- A database system.
- A wide area or local area network system.
- If not used properly then decrease productivity.

Need for Performance Evaluation

- Operating system can increase the concurrency access.
- Or can block access.
- A database can provide efficiently sharing information among many applications.
- Or blocking of information by dropping data availably.

Need for Performance Evaluation

- LAN provides means for streamline information processing and eliminate redundancies.
- But it may also deter users from logging on because of link or protocol problems.
- We need to select the computer system mapped to the needs.

Need for Performance Evaluation

- A computer system can be very simple with simple processor etc.
- A computer can be highly elaborate with multiple processors etc.
- A purchaser must decide according to motherboard its using.
- While purchasing the system all this must be kept in mind.

Summary

- We have learnt about the Need for performance evaluation.
- Credits: Paul Fortier book.

Modeling and Simulation

Role of Performance Evaluation in Computer Engineering

Overview

- **Here, we will learn about role of performance evaluation in computer engineering.**

Role of Performance Evaluation in Computer Engineering

- Client/server architectures.
- These systems are from Government, industry and academia.
- There is constant demand for improved reliability and availability.

Role of Performance Evaluation in Computer Engineering

- Present systems provide more features.
- Sharing of resources on global scale.
- Ability to bring computing power to the user.

Role of Performance Evaluation in Computer Engineering

- **The optimal design or selection of computer system is therefore very important.**

Summary

- We have learnt about the role of performance evaluation in computer engineering.
- Credits: Paul Fortier book.

Modeling and Simulation

Overview of Performance Evaluation Methods

Overview

- **Here, we will learn about the overview of performance evaluation methods.**

Overview of Performance Evaluation Methods

- Models provide a tool to define a system.
- Define its problems in a concise fashion.
- This provide an environment to study a system before its existence.
- Developed on the base of theoretical laws and principles.

Overview of Performance Evaluation Methods

- Modeling is better if:
- Physical laws are available.
- Pictorial representation is possible.
- Input/output elements are manageable.
- But we don’t have clear physical laws.

Overview of Performance Evaluation Methods

- Faithful model of a system must be constructed.
- Model a slice of the real-world system.
- Which element is important to understand in faithful system.
- We can say its intuition.

Summary

- We have learnt about the overview of performance evaluation methods.
- Credits: Paul Fortier book.

Modeling and Simulation

Performance Metrics and Evaluation Criteria

Overview

- **Here, we will learn about performance metrics and evaluation criteria.**

Performance Metrics and Evaluation Criteria

- Performance metrics and evaluation criteria is required for systems.
- User must follow a methodology.
- The motivations.
- The environment.
- Technological boundaries.

Performance Metrics and Evaluation Criteria

- Must understand the usage of the system.
- Needs and uses must be defined.
- Must compile a wish list of all potential uses.

Performance Metrics and Evaluation Criteria

- User must know processing requirements.
- Communication transfer.
- Management requirements.
- Define or know why we need something at first priority.

Performance Metrics and Evaluation Criteria

- Checking in which environment the system fits.
- Checking in which technological aspect it fits.
- Connecting to diverse set of company assets.
- Link planned new resources.

Performance Metrics and Evaluation Criteria

- **Need large volume of data for system requirements.**
- **How this data assist in the selection?**
- **Collection of data can be divided in quantitative and qualitative.**

Performance Metrics and Evaluation Criteria

- **Specific performance measures can be derived from one set of data.**
- **Subjective measures can be derived from another.**

Summary

- **We have learnt about the performance metrics and evaluation criteria.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Comparison of Two System Designs

Overview

- **Here, we will understand about the "Comparison of Two System Designs".**

Comparison of Two System Designs

- A simulation analyst can compare two possible configurations.
- Using supply chain inventory system there ordering policies will be compared.

Comparison of Two System Designs

- **Replications is used to analyze the output data.**
- **The mean performance measure for system 'I' will be denoted by** $\theta_i = (\boldsymbol{i} = 1,2)$.

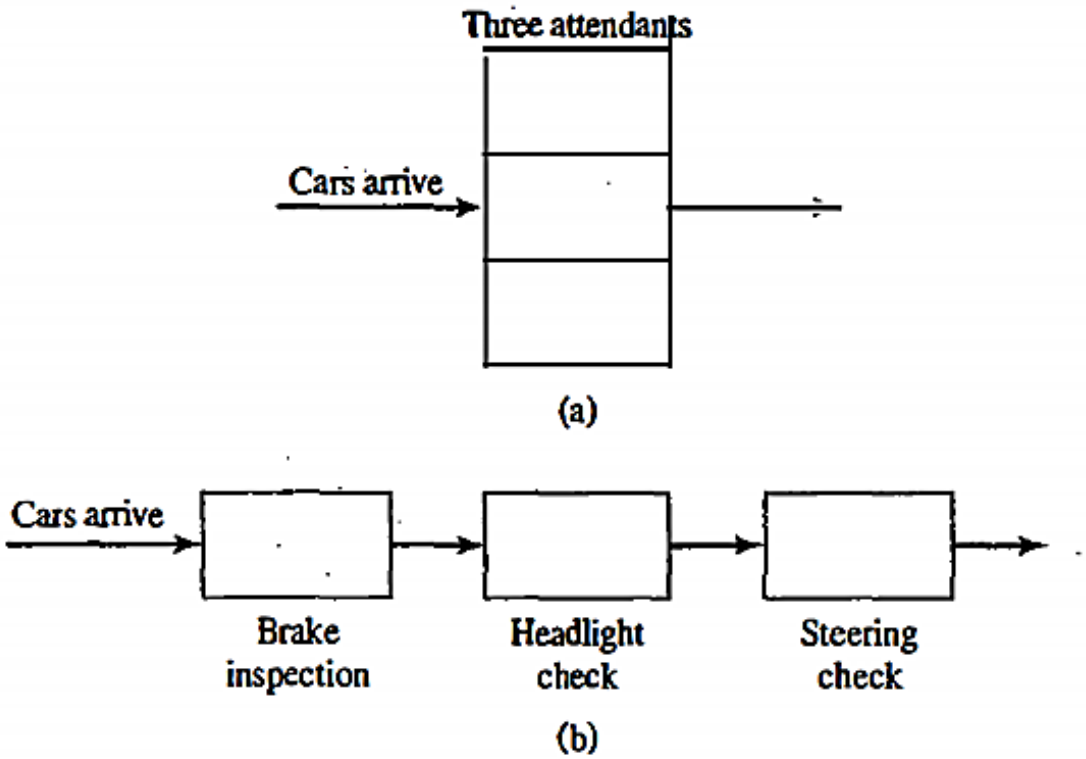
Comparison of Two System Designs

- **The goal of the simulation experiments is to obtain point.**
- **Interval estimates of the difference in mean performance.**
- **Namely** $(\theta_1 - \theta_2)$**.**

Comparison of Two System Designs

- **Inverse Transform Technique**
- **Replications is used to analyze the output data.**
- **The mean performance measure for system 'I' will be denoted by** $\theta_i = (\boldsymbol{i} = 1,2)$.

Comparison of Two System Designs



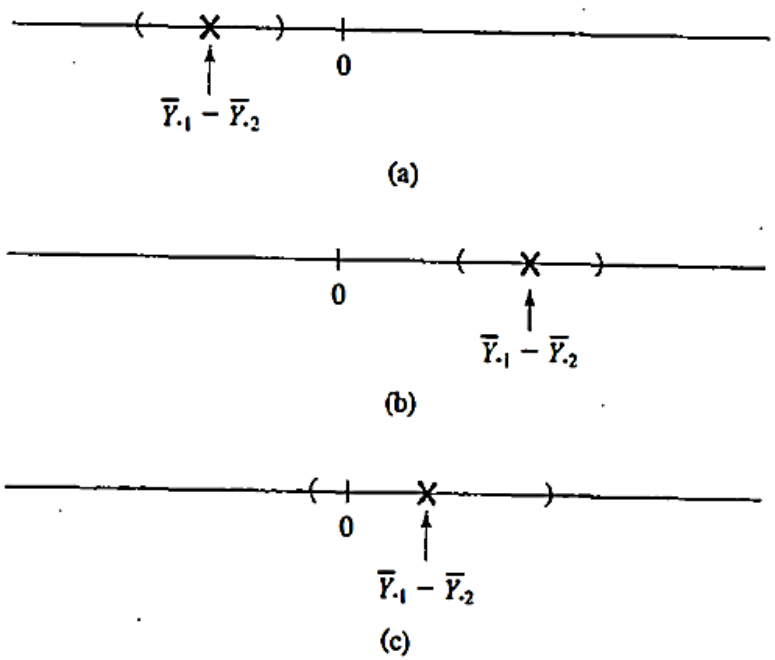
Vehicle Safety Inspection

Comparison of Two System Designs

- **In comparing two systems, number of replications R_i to be made and run length $T_E^{(i)}$ for each model $(\boldsymbol{i} = 1,2)$ is decided.**

Comparison of Two System Designs

System	Replication 1	2	...	R_i	Sample Mean	Sample Variance
1	Y_{11}	Y_{21}	...	$Y_{R1}1$	$\overline{Y}_{\cdot 1}$	S_1^2
2	Y_{12}	Y_{22}	...	$Y_{R2}2$	$\overline{Y}_{\cdot 2}$	S_2^2



Summary

- **Here, we understood about Comparing two system designs.**
- **Credits: Jerry banks book.**

Modeling and Simulation

Independent Sampling with Equal Variances

Overview

- **Here, We will understand "Independent Sampling with Equal Variances".**

Independent Sampling with Equal Variances

- **Independent Sampling refers to different and independent random numbers streams to simulate the two systems.**

Independent Sampling with Equal Variances

- **Acceptance-Rejection**
- **The observations of simulated system 1, $\{Y_{r_1}, r = 1, \cdots, R_1\}$ are all statistically independent of simulated system 2, , $\{Y_{r_2}, r = 1, \cdots, R_2\}$.**
- Y_i **is given by:**

$$V(\bar{Y}_{.i}) = \frac{V(Y_{ri})}{R_i} = \frac{\sigma_i^2}{R_i}, \quad i = 1, 2$$

Independent Sampling with Equal Variances

- **Where $\overrightarrow{Y_1}$ and $\overrightarrow{Y_2}$ are statistically different as:**

$$V(\bar{Y}_{.1} - \bar{Y}_{.2}) = V(\bar{Y}_{.1}) + V(\bar{Y}_{.2})$$
$$= \frac{\sigma_1^2}{R_1} + \frac{\sigma_2^2}{R_2}$$

- **It implies two variances are equal (but unknown in value)** $\sigma_1^2 = \sigma_2^2$.

Independent Sampling with Equal Variances

- **If two-sample-t confidence interval approach is used. The point estimate of the mean difference is:** $\overrightarrow{Y_1}$ - $\overrightarrow{Y_2}$
- **Where** $\overrightarrow{Y_i}$ **is given as:**

$$S_i^2 = \frac{1}{R_i - 1}\sum_{r=1}^{R_i}(Y_{ri} - \overline{Y}_{\cdot i})^2$$
$$= \frac{1}{R_i - 1}\left(\sum_{r=1}^{R_i} Y_{ri}^2 - R_i\overline{Y}_{\cdot i}^2\right)$$

Independent Sampling with Equal Variances

- **Here, S_i^2 is an estimator of variance σ_i^2 . Assuming $\sigma_1^2 = \sigma_2^2 = \sigma^2$ a pool estimate of σ^2 is obtained as:**

$$S_p^2 = \frac{(R_1 - 1)S_1^2 + (R_2 - 1)S_2^2}{R_1 + R_2 - 2}$$

- **Where**
  $\boldsymbol{v} = R_1 + R_2 - 2$

Independent Sampling with Equal Variances

- **The c.i. $\theta_1 - \theta_2$ for with the standard error is computed by:**

$$\text{s.e.}(\overline{Y}_{\cdot 1} - \overline{Y}_{\cdot 2}) = S_p \sqrt{\frac{1}{R_1} + \frac{1}{R_2}}$$

- **The standard error is an estimate of the standard deviation of the point given as:**
  $\sigma\sqrt{1/R_1 + 1/R_2}$.

Summary

- **Here, we understood about the Independent Sampling.**
- **Credits, Jerry Banks book.**

Modeling and Simulation

Independent Sampling with Unequal Variances

Overview

- **Here, we will discuss about "Independent Sampling with Unequal Variances".**

Independent Sampling with Unequal Variances

- **If the assumption of equal variances cannot safely be made, an approximate $\mathbf{100(1-\alpha)\%}$ for $\theta_1 - \theta_2$ can be computed as:**

$$\text{s.e.}(\overline{Y}_{.1} - \overline{Y}_{.2}) = \sqrt{\frac{S_1^2}{R_1} + \frac{S_2^2}{R_2}}$$

Independent Sampling with Unequal Variances

- **Degrees of freedom, v can be as:**

$$v = \frac{(S_1^2 / R_1 + S_2^2 / R_2)^2}{[(S_1^2 / R_1)^2 / (R_1 - 1)] + [(S_2^2 / R_2)^2 / (R_2 - 1)]}$$

- **A minimum number of replications $R_1 \geq 6$ and $R_2 \geq 6$ is recommended for this procedure.**

Summary

- **Here, We understood about Independent Sampling with Unequal Variances.**
- **Credits: Jerry banks book.**

Modeling and Simulation

Common Random Numbers

Overview

- **Here, we will understand About "Common Random Numbers".**

Common Random Numbers

- **CRN means, for each replication, the same random numbers are used to simulate both system.**
- **Therfore, R1 and R2 must be equal, say R1 = R2= R.**

Common Random Numbers

- **The purpose of CRN is to induce positive correlation between y_1 *and* y_2.**
- **A variance reduction in point estimator of mean difference Type equation here. is given by:**

$$V(\bar{Y}_{\cdot 1} - \bar{Y}_{\cdot 2}) = V(\bar{Y}_{\cdot 1}) + V(\bar{Y}_{\cdot 2}) - 2\mathrm{cov}(\bar{Y}_{\cdot 1}, \bar{Y}_{\cdot 2})$$
$$= \frac{\sigma_1^2}{R} + \frac{\sigma_2^2}{R} - \frac{2\rho_{12}\sigma_1\sigma_2}{R}$$

Common Random Numbers

- **Compare variance of $\overrightarrow{Y_1} - \overrightarrow{Y_2}$, call it V_{crn} given as :**

$$V_{CRN} = V_{IND} - \frac{2\rho_{12}\sigma_1\sigma_2}{R}$$

- **Which implies:**

$$V_{CRN} < V_{IND}$$

Common Random Numbers

- To compute a 100(1 - a)% c.i compute the differences:

$$D_r = Y_{r1} - Y_{r2}$$

- Compute Sample mean difference:

$$\bar{\bar{D}} = \frac{1}{R}\sum_{r=1}^{R} D_r$$

Common Random Numbers

- **The sample variance of the difference {D_r} is compute as:**

$$S_D^2 = \frac{1}{R-1}\sum_{r=1}^{R}(D_r - \bar{D})^2$$
$$= \frac{1}{R-1}\left(\sum_{r=1}^{R} D_r^2 - R\bar{D}^2\right)$$

- **Where standard error of $\overrightarrow{Y_1} - \overrightarrow{Y_2}$ is estimated by:**

$$\text{s.e.}(\bar{D}) = \text{s.e.}(\bar{Y}_{.1} - \bar{Y}_{.2}) = \frac{S_D}{\sqrt{R}}$$

Common Random Numbers

- Implementation of common random number.

1. Dedicate a random-number stream to a specific purpose.
2. For system with external arrivals, dedicate one random stream to one of arrival and their attributes.

Common Random Numbers

3. For systems having an entity performing given activities in a cyclic fashion, assign a random-number stream to this entity.
4. If synchronization is not possible use independent steams of random numbers for this subset.

Summary

- We understand about Common Random Numbers.
- Credits, Jerry Banks book.

Confidence Intervals with Specified Precision

Overview

- **Here, we will understand about the "Confidence Intervals with Specified Precision".**

Confidence Intervals with Specified Precision

- **Confidence intervals for the difference between two systems' performance can be achieved in an parallel way.**

Confidence Intervals with Specified Precision

- **If the goal is to obtain error in our estimate $\theta_1 - \theta_2$ to be less than $\pm\,\varepsilon$ then number of replications R should be:**

$$H = t_{\alpha/2,v}\,\text{s.e.}(\bar{Y}_{.1} - \bar{Y}_{.2}) \leq \epsilon$$

Confidence Intervals with Specified Precision

- **Using $R_0 \geq 2$ we obtain an initial estimate.**
- **We solve total number of replication $R \geq R_0$ to achieve half-length criterion.**
- **We make replications $R \geq R_0$ for each system to compute confidence interval and half-length criterion.**

Summary

- **Here we understand about Confidence Intervals with Specified Precision.**
- **Credits: Uri Wilensky book**

Comparison of Several System Designs

Overview

- **Here, we will understand about the "COMPARISON OF SEVERAL SYSTEM DESIGNS".**

COMPARISON OF SEVERAL SYSTEM DESIGNS

- To compare "K" alterative system designs.
- Many different statistical procedures have been developed.
- These are used to analyze simulation data and to draw statistically sound interfaces about parameters θ_i.

COMPARISON OF SEVERAL SYSTEM DESIGNS

- **These procedures are classified as:**
- **Fixed-sample size.**
- **Sequential sampling.**

COMPARISON OF SEVERAL SYSTEM DESIGNS

- **Fixed Sample Size**
- **A predetermined sample size is used to draw inferences via hypothesis tests or confidence intervals.**
- **Example:**
- **The interval estimation of a mean performance measure.**

COMPARISON OF SEVERAL SYSTEM DESIGNS

- Advantages
- An easily estimated or known cost in terms of computer time before running the experiments.
- Can be used when :
- Computer time is limited.
- A pilot study is being conducted.

COMPARISON OF SEVERAL SYSTEM DESIGNS

- **Disadvantages**
- **A strong Conclusion could be impossible.**
- **A hypothesis test may lead to a failure to reject the null hypothesis.**

COMPARISON OF SEVERAL SYSTEM DESIGNS

- **Sequential Sampling**
- **In sequential sampling more and more data are collected until an estimator with a pre-specified precision is achieved.**
- **In two stage procedure, an initial sample estimates additional observations needed to draw conclusions with a specified precision.**

COMPARISON OF SEVERAL SYSTEM DESIGNS

- **Goal of simulation analyst**
- **Estimation of each parameter, θ_i.**
- **Comparison of each performance measure.**
- **All pair wise comparisons.**
- **selection of the best θ_i.**

Summary

- Here, we understood about the "COMPARISON OF SERAL SYSTEM DESIGNS".
- Credits: jerry banks book.

Bonferroni Approach to Multiple Comparisons

Overview

- **Here, we will understand about the "Bonferroni Approach to Multiple Comparisons".**

Bonferroni Approach to Multiple Comparisons

- **If C confidence intervals are computed and that the it_h interval has confidence coefficient $1 - \alpha_i$.**
- **The Bonferroni inequality states that:**

$$P(\text{all statements } S_i \text{ are true}, i = 1, \ldots, C) \geq 1 - \sum_{j=1}^{C} \alpha_j = 1 - \alpha_E$$

Bonferroni Approach to Multiple Comparisons

- Where $\alpha_E = \sum_{j=1}^{C} \alpha_j$ is called overall error probability.
- This is equivalent to:

$$P\text{ (one or more of the } C \text{ confidence intervals does not contain the parameter being estimated)} \leq \alpha_E$$

- Here, a^E provides the upper bound.

Bonferroni Approach to Multiple Comparisons

- **A major advantage of Bonferroni approach is that runs with independent sampling and or common random numbers.**

Bonferroni Approach to Multiple Comparisons

- **The major disadvantage of the Bonferroni approach in making a large number of comparisons is the increased width of each individual interval.**
- **The width of a c.i. is a measure of the precision of the estimate.**

Bonferroni Approach to Multiple Comparisons

- **3 possible ways of using the Bonferroni Inequality when comparing K alterative system designs:**
- **1. Construct a** $100(1-\alpha_i)\%$ **c.i. for parameter** θ_i **, where number of intervals is C = K.**

Bonferroni Approach to Multiple Comparisons

- **2. Compare all designs to one specific design that is:**
- **Construct a** $100(1-\alpha_i)\%$ **c.i. for** $\theta_i - \theta_{\mathbf{1}}$**.**
- **Here, the number of intervals is C = K – 1.**

Bonferroni Approach to Multiple Comparisons

- **3. Compare all designs to each other. That is :**
- **Construct a** $100(1-\alpha_i)\%$ **c.i. for** $\theta_i - \theta_j$.
- **With K designs, the number of intervals is computed as C = K (K – 1) / 2.**

Summary

- **Here, we understood about Bonferroni Approach.**
- **Credits: Jerry banks book.**

Bonferroni Approach to Selecting the Best

Overview

- **Here, We will understand "Bonferroni Approach to Selecting the Best".**

Bonferroni Approach to Selecting the Best

- **Gross Level**
- **If there are K system designs, and the i_{TH} design has expected performance θ_i.**
- **Then , we're interested in best system.**
- **Where "best" means maximum expected performance.**

Bonferroni Approach to Selecting the Best

- Refined
- At a refined level, we are also interesting in knowing how much better the best is relative to alternatives.
- It helps us in choosing a inferior system not deficient by much.

Bonferroni Approach to Selecting the Best

- Difference
- If system design i is the best, then $\theta_i - \max_{j \neq i} \theta_j$ is equal to the difference in performance between the best and the second best.
- If system design i is not the best then, $\theta_i - \max_{j \neq i} \theta_j$ is equal to the difference between system i and the best.

Bonferroni Approach to Selecting the Best

- i^* denote index of the best system.
- Smaller the difference $\theta_i - \max_{j \neq i} \theta_j$ is, the more certain we find the best system.
- If the difference between system i^* and the other is significant, then we try to achieve i^* with high probability.

Bonferroni Approach to Selecting the Best

- **The best system probability should be at least :**

$$1 - \alpha \text{ whenever } \theta_{i^*} - \max_{j \neq i^*} \theta_j \geq \epsilon$$

- **We select best of one of near best if multiple system are within ε of the best.**

Bonferroni Approach to Selecting the Best

- **Achievement**
- **This procedure achieves the desired probability and also forms** $100(1-a)\%$ **confidence intervals for** $\theta_i - \max_{j \neq i} \theta_j$

Summary

- **Here, we understood about Bonferroni Approach to Selecting the Best.**
- **Credits, Jerry Banks book.**

Bonferroni Approach to Screening

Overview

- **Here, we will discuss about “Bonferroni Approach to Screening”.**

Bonferroni Approach to Screening

- When there exist multiple systems and two stage procedure is not possible.
- Then, divide set of systems into the best.
- This is achieved by using screening or subset selection procedure.

Bonferroni Approach to Screening

- Independent sampling with unequal variances
- This promises that stayed subset contains best system.
- With probability $\geq 1 - a$.
- When the data is distributed normally, by independent sampling or CRN is used.

Bonferroni Approach to Screening

- This subset may contain all K systems, only one or some.
- It depends on the number of replications and sample variances.

Bonferroni Approach to Screening

- Procedure
- Specify correct probability selection and sample size.
- Make R replications of the system.
- Calculate the sample and sample variance of the difference.

Bonferroni Approach to Screening

- If bigger is better then retain selected subset system.
- If smaller is better then retain selected subset system.
- All design not retained can be eliminated from further cosiderations.

Summary

- **Here, We understood about Bonferroni Approach to Screening.**
- **Credits: Jerry banks book.**

Modeling and Simulation

Metamodeling

Overview

- **Here, we will understand About "Metamodeling".**

Metamodeling

- **Metamodeling is the process of generating metamodels.**
- **Where metamodel refers to model of a model.**

Metamodeling

- There is a simulation output variable Y.
- It is related to k independent variables.
- Dependent variable Y is random variable.
- Independent variable is design variable.

Metamodeling

- Relation between independent and dependent variable is represented by simulation model.
- Metamodel simplifies this relationship by simpler mathematical function.

Metamodeling

- **This relationship is represented by as function $Y = f(x)$.**
- **Most of the time relationship is unknown.**
- **Function is created using unknown parameter.**
- **Regression analysis estimates this parameter.**

Summary

- **We understand about Metamodeling.**
- **Credits, Jerry Banks book.**

Modeling and Simulation

Simple Linear Regression

Overview

- **Here, we will understand about the "Simple Linear Regression".**

Simple Linear Regression

- **The relationship is between independent variable x and a dependent variable y.**
- **Linear relationship.**
- **Value of y for given x is:**

$$E(Y \mid x) = \beta_0 + \beta_1 x$$

- β_0 **intercept on y axis.**
- β_1 **is the slope.**

Simple Linear Regression

- **Y can be described as:**

$$Y = \beta_0 + \beta_1 x + \epsilon$$

- **ε is random error with mean zero.**
- **This model is commonly called a simple linear regression model.**

Simple Linear Regression

- n **pair of observations** $(y_1, x_1), (y_2, x_2) \ldots (y_n, x_n)$
- β_0 **and** β_1 **estimates the observation.**
- **Sum of squares of the deviation and regression line is minimized.**

Simple Linear Regression

- **The individual observations:**

$$Y_i = \beta_0 + \beta_1 x_i + \epsilon_i,\ i = 1, 2, \ldots, n$$

- $\varepsilon_1, \varepsilon_2$ **... are uncorrelated random variables.**
- ε_i **is given by:**

$$\epsilon_i = Y_i - \beta_0 - \beta_1 x_i$$

- **It shows how** ε_i **is related to** x_i, Y_i **and** $E(Y_i|x_i)$**.**

Simple Linear Regression

- The sum of squares of the deviation is :

$$L = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 x_i)^2$$

- Where L is called least-squares function.
- Rewriting Y_i as:

$$Y_i = \beta_0' + \beta_1 (x_i - \bar{x}) + \epsilon_i$$

- Where:

$$\beta_0' = \beta_0 + \beta_1 \bar{x} \text{ and } \bar{x} = \sum_{i=1}^{n} x_i / n.$$

Simple Linear Regression

- It is often called as Transformed linear regression model.

$$L = \sum_{i=1}^{n} [Y_i - \beta_0' - \beta_1 (x_i - \bar{x})]^2$$

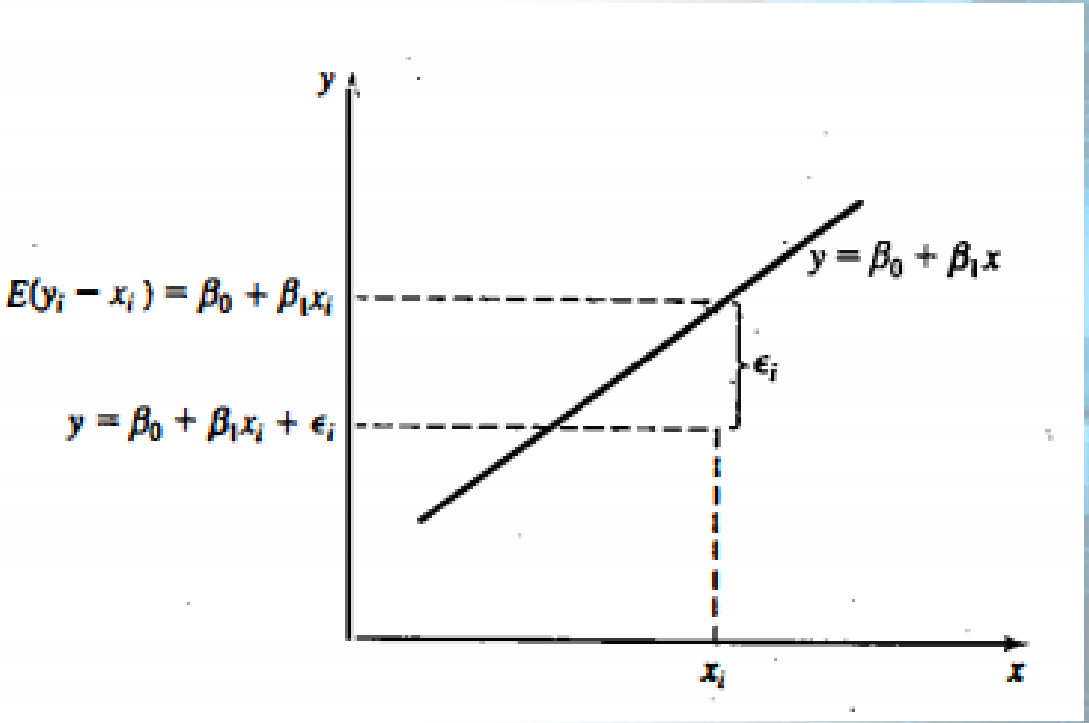
- Taking partial derivatives and setting each to zero.

$$n\hat{\beta}_0' = \sum_{i=1}^{n} Y_i$$

$$\hat{\beta}_1 \sum_{i=1}^{n} (x_i - \bar{x})^2 = \sum_{i=1}^{n} Y_i (x_i - \bar{x})$$

- These are called normal equations.

Simple Linear Regression



Relationship of ε_i 〖 ***to*** x〗$_i$,y_i and $E($ ⊢ Y_i ⊣ | x_i).

Summary

- **Here we understand about Simple Linear Regression.**
- **Credits: Uri Wilensky book**

Testing for Significance of Regression

Overview

- **Here, we will understand about the "Testing for Significance of Regression".**

Testing for Significance of Regression

- **Testing for the significance of regression provides another means for assessing the adequacy of the model.**
- **Error component ε_i is normally distributed.**

Testing for Significance of Regression

- **The adequacy of the model is checked by residual analysis.**
- **Developed by variance properties of and β_0 and β_1.**

Testing for Significance of Regression

- **Alternative hypothesis:**

$$H_0 : \beta_1 = 0$$
$$H_1 : \beta_1 \neq 0$$

- H_0 **indicates no relationship between x and Y.**
- **x is of little value in explaining the variability in Y.**

Testing for Significance of Regression

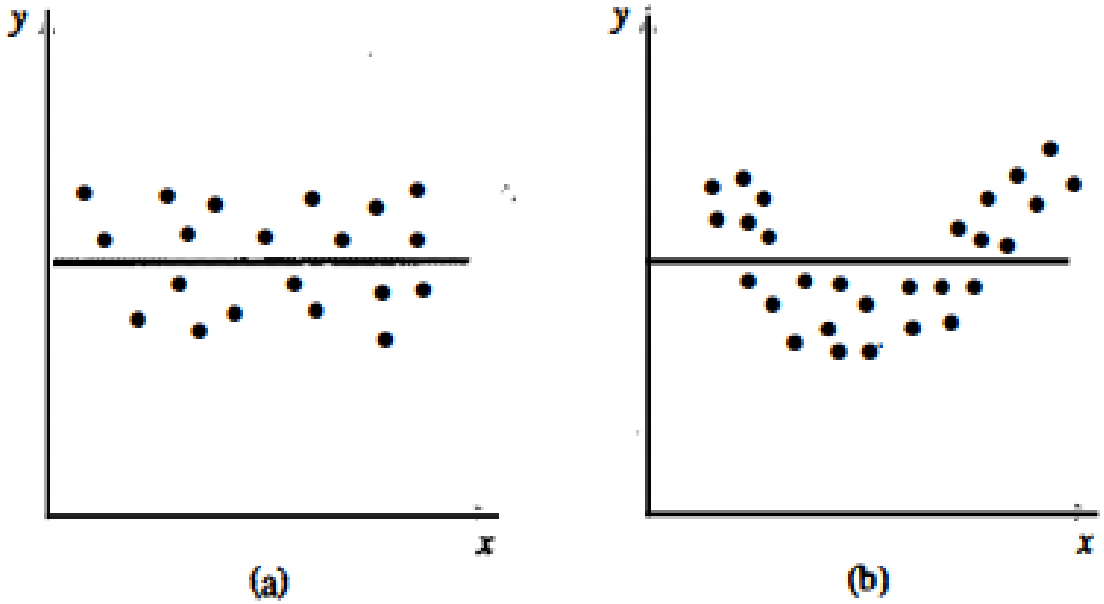


Figure 12.5 Failure to reject $H_0 : \beta_1 = 0$.

Illustration Best Estimator

Testing for Significance of Regression

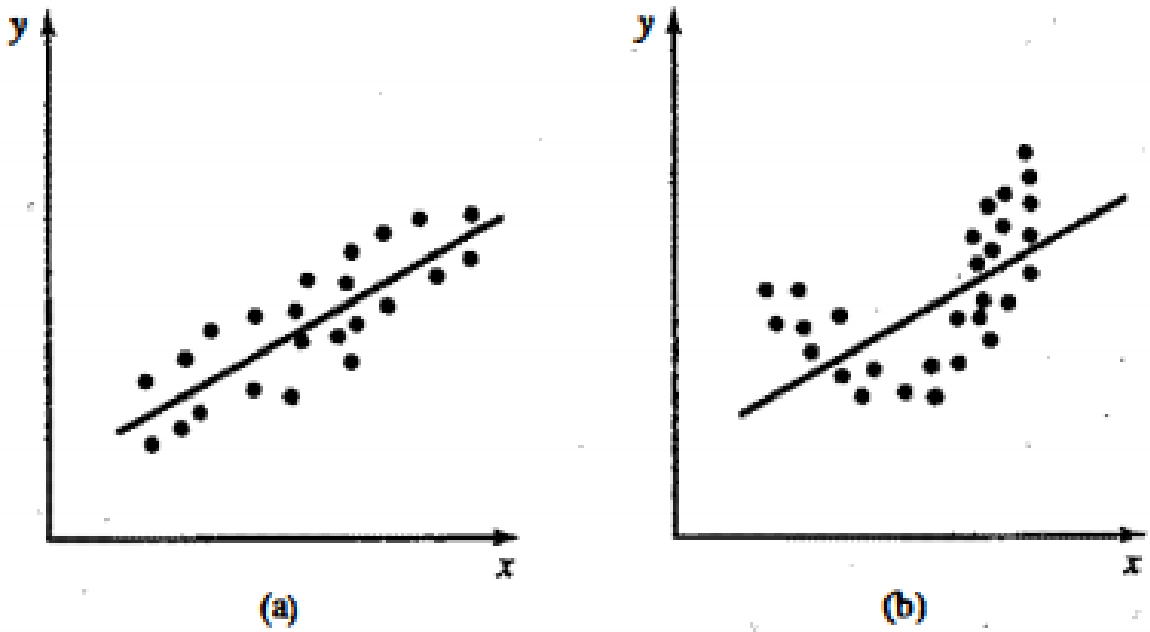


Figure 12.6 $H_0 : \beta_1 = 0$ is rejected.

Illustration Non-linear relationship

Testing for Significance of Regression

- **Testing for Significance of Regression**
- **Statistic for significance of regression:**

$$t_0 = \frac{\hat{\beta}_1}{\sqrt{MS_\varepsilon / S_{xx}}}$$

- MS_ε **is mean squared error given by:**

$$\mathrm{MS}_\varepsilon = \sum_{i=1}^{n} \frac{e_i^2}{n-2}$$

Testing for Significance of Regression

- **The direct method calculates $\sum_{i=1}^{n} e_i^2$.**

$$\sum_{i=1}^{n} e_i^2 = S_{yy} - \hat{\beta}_1 S_{xy}$$

- **Where S_{yy} is corrected sum of squares Y given by:**

$$S_{yy} = \sum_{i=1}^{n} Y_i^2 - \frac{\left(\sum_{i=1}^{n} Y_i\right)^2}{n}$$

Summary

- **Here, we understood about the "Testing for Significance of Regression".**
- **Credits: Jerry banks book.**

What Does 'Optimization via Simulation' Mean?

Overview

- **Here, we will understand about the "Optimization via Simulation".**

Optimization via Simulation

- Optimization is a key tool.
- Well developed algorithms for classes of problems.
- Linear Programming is Most famous.
- Much of optimization deals with performance of design.

Optimization via Simulation

- **In discrete event simulation, result is a random variable.**
- **Let $x_1, x_2 \cdots x_n$ be $\boldsymbol{m}$ controllable design variables.**
- **Let $\boldsymbol{Y}(x_1, x_2 \cdots x_n)$ be observed simulation output performance.**

Optimization via Simulation

- $x_1, x_2 \cdots x_n$ **might denote number of Automated Guided Vehicles.**
- $\boldsymbol{Y}(x_1, x_2 \cdots x_n)$ **could be total Material Handling System acquisition and operation cost.**

Optimization via Simulation

- $\boldsymbol{Y}(x_1, x_2 \cdots x_n)$ **with respect to** $x_1, x_2 \cdots x_n$**.**
- **Y is random variable, so cannot optimize actual value of Y.**
- **Definition of optimization.**

$$\text{maximize or minimize } E(Y(x_1, x_2, \ldots, x_m))$$

Optimization via Simulation

- $\mathbf{E}(\boldsymbol{Y}(x_1, x_2 \cdots x_n))$ is long-run average cost of operating the MHS .
- x_1 AVGs, x_2 load per average, and routing algorithm x_3.
- Formulation of performance measure.

$$Y'(x_1, x_2, x_3) = \begin{cases} 1, & \text{if } Y(x_1, x_2, x_3) \le D \\ 0, & \text{otherwise} \end{cases}$$

Optimization via Simulation

- 1. Combine all of the performance measures into a single measure.
- The most common being cost.
- 2. Optimize with respect to one key performance measure.
- Evaluate with secondary performance measures.

Optimization via Simulation

- **3. Optimize with respect to one key performance measure.**
- **Consider those meeting certain constraints on performance.**
- **Expected cost and cycle time.**

Summary

- **Here, we understood about Optimization via Simulation.**
- **Credits: Jerry banks book.**

Difficulties in Optimization via Simulation

Overview

- **Here, We will understand "Why is Optimization via Simulation Difficult?".**

Difficulties in Optimization via Simulation

- **If design variables are numerous optimization can be difficult.**
- **A diverse collection of design variable types is known as the structure of performance function**
- **The performance can not be evaluated , but can be estimated.**

Difficulties in Optimization via Simulation

- No conclusion with estimates.
- It can frustrate optimization algorithms that try to move in improving directions.
- It can be eliminated using many replications.
- Or using long runs.

Difficulties in Optimization via Simulation

- At each design point that the performance estimate has essentially no variance.
- It causes other designs to be explored.

Difficulties in Optimization via Simulation

- **Standard sampling variability force optimizations are as following.**
- **Guarantee a prespecified probability of correct selection.**
- **Guarantee asymptotic convergence.**

Difficulties in Optimization via Simulation

- **Optimal for deterministic counterpart.**
- **Robust heuristics.**

Difficulties in Optimization via Simulation

- **Robust heuristics are the most common algorithms.**
- **It is found in commercial optimization via simulation software.**

Summary

- **Here, we understood about Bonferroni Approach to Selecting the Best.**
- **Credits, Jerry Banks book.**

Modeling and Simulation

Using Robust Heuristics

Overview

- **Here, we will discuss about “Using Robust Heuristics”.**

Using Robust Heuristics

- It means a procedure that does not depend on strong problem structure.
- Can be applied on decision variables and sampling variability.
- Generic algorithms and tabu search are examples.

Using Robust Heuristics

- There are k possible solutions to the optimization via simulation problem.
- On each iteration a GA operates on a "population" of p solutions.

Using Robust Heuristics

- **Basic Genetic Algo**
- **Set the iteration counter j = 0.**
  $p(0) = \{x_1(0) \ldots x_p(0)\}$
- **Ruin simulation experiments.**
- **Select population p from P(j).**
- **Recombine Solutions via P(j + 1).**
- **Set j = j + 1 and repeat.**

Using Robust Heuristics

- **The G.A can be terminated after some number of iterations.**
- **At termination X* with smallest Y(x) is choosen as best.**

Using Robust Heuristics

- Basic Tabu Search
- Set the iteration counter $j = 0$. select initial x^* in X
- Find solution x' which minimizes $Y(x)$.
- If $Y(x') < Y(x^*)$ then $x^* = x'$.
- Update the list of Tabu and repeat from step 2.

Using Robust Heuristics

- **Tabu search can be terminated when some number of iterations has passed without changing x*.**
- **T.S is fundamentally a discrete-decision-variable optimizator.**

Summary

- **Here, we have understood concepts about Robust Heuristics**
- **Credits: Jerry banks book.**

Random Search: An Illustration

Overview

- **Here, we will understand About “An Illustration: Random Search”.**

Random Search: An Illustration

- Random search provides guaranteed asymptotic converges in certain conditions.
- Convergence can be slow and memory consumptive.
- random search is not a Robust Heuristic.

Random Search: An Illustration

- Random search algorithm requires finite number of possible designs.
- Rule out problem with continuous decision variables.
- Algorithms designed for continuous variable problem is there.

Random Search: An Illustration

- On each iteration, we compare a current solution to a randomly chosen competitor.
- If competitor is better it becomes current good solution.

Random Search: An Illustration

- **Step 1.**
- **Initialize random variables $\mathbf{C}(\boldsymbol{i}) = \mathbf{0}$.**
- **Initial solution $\boldsymbol{i}^0$ and set $\mathbf{C}(\boldsymbol{i}^0) = 1$.**
- **$\mathbf{C}(\boldsymbol{i})$ count number of times $\boldsymbol{i}$ is visited.**

Random Search: An Illustration

- **Step 2.**
- **Chose another solution except i .**
- **Such as each solution has equal chance of being selected.**

Random Search: An Illustration

- **Step 3.**
- **Run two simultaneous experiments.**
- **Use i^0 and i to obtain $Y(i^0)$ and $Y(i\ )$**
- **Set i^0 = i**

Random Search: An Illustration

- **Step 4.**
- **Set** $C(\boldsymbol{i}^0) = C(\boldsymbol{i}^\circ) + 1$
- **If not done go to step 2.**
- **If done, Then select** $x\boldsymbol{i}^*$ **such that** $\boldsymbol{C}(\boldsymbol{i}^*)$ **is largest count.**

Summary

- **We understood about Random search.**
- **Credits, Jerry Banks book.**

Modeling and Simulation

Introduction to performance evaluation

Overview

- **Here, we will see the introduction to performance evaluation.**

Introduction to performance evaluation

- Understanding all elements of the computer system.
- All aspects are important while understanding the issues.
- Realizing the requirements.

Introduction to performance evaluation

- **Computer system must function correctly.**
- **Performing the intended function efficiently.**

Introduction to performance evaluation

- Describing the computer system's design.
- Construction.
- Fielding.
- Life-cycle maintenance.

Summary

- **We have learnt about the introduction to the performance evaluation.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Events

Overview

- **Here, we will understand about the "Events".**

Events

- Time is an important measure.
- Useful if we can measure under computer evaluation.
- An event describes an entity of interest in our system.
- E.g. Clock cycle.

Events

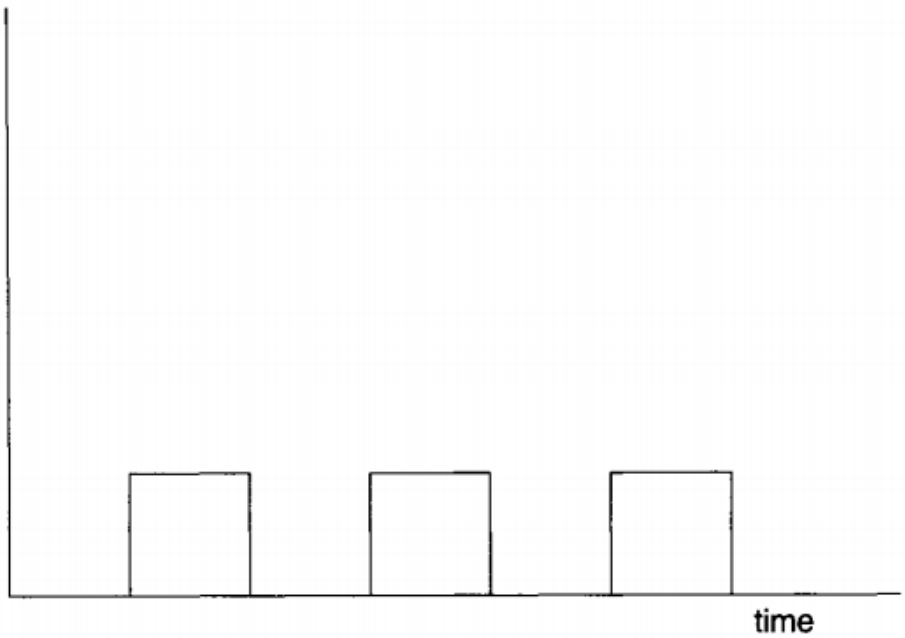


Figure 3.1
Example of a computer clock.

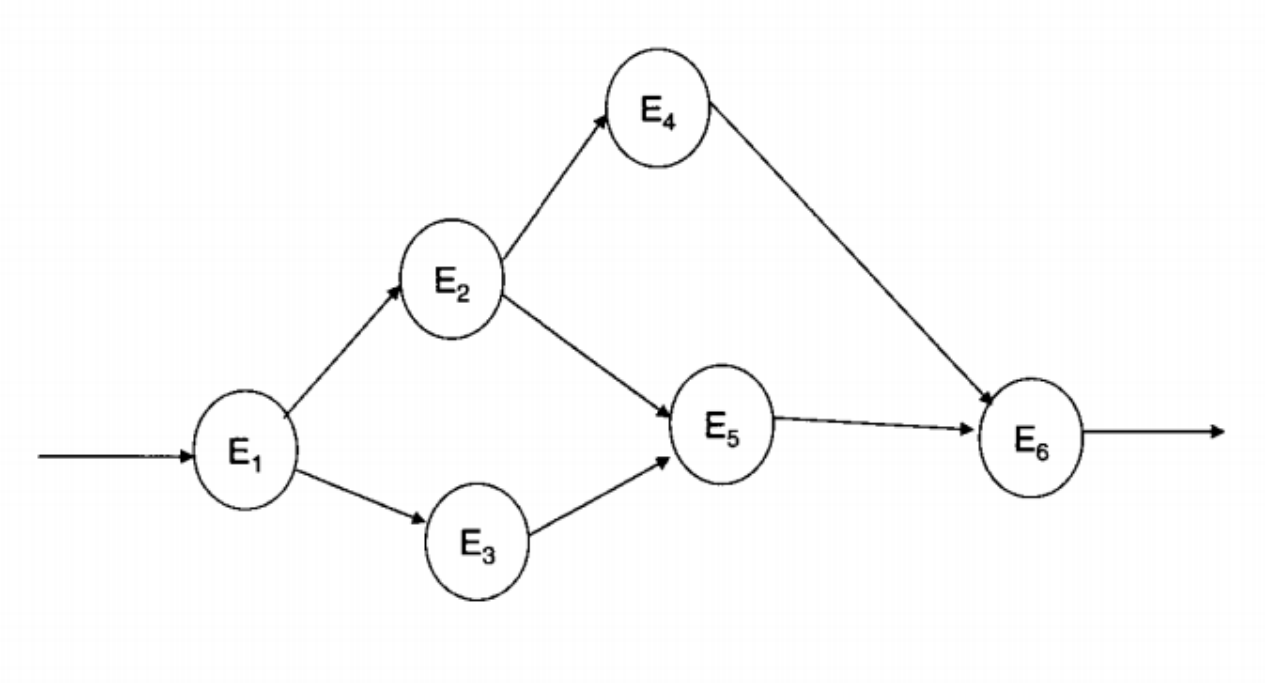
Events

- All events must be controlled.
- Each action is designed to synchronize with other actions.
- Small actions makes larger events.

Events

- System analyst must have understanding of the events.
- And the relationship among different events.

Events



Summary

- **Here we understand about Events.**
- **Credits: Uri Wilensky book**

Modeling and Simulation

Measurements (sampling)

Overview

- **Here, we will learn about the measurements (sampling).**

Measurements (sampling)

- **Events represent all of the real actions that occur in the computer system.**
- **Must know all the possible conditions.**

Measurements (sampling)

- **State is an important concept in any computer system.**

$$S = \{E_1(\text{value}), E_2(\text{value}), E_3(\text{value}), \ldots, E_n(\text{value})\}$$

- **Each event must have valid components.**

Measurements (sampling)

- Primary types of measures are:
- Count a number of items over a given time period.
- Measures all state variables.
- Measures the fraction of time the system is within a state.
- Valid state must reach.

Measurements (sampling)

- Many ways are there to measure system events and decision depends on many factors.
- In hardware monitoring system analyst has ability to add instrumentation.
- Can also use integral test hardware.

Measurements (sampling)

- **The hardware monitoring be designed as an integral component of the system.**
- **Must determine and define all aspects.**

Measurements (sampling)

- Software monitoring requires designers to system hardware elements.
- As well as low level software elements.
- Need to have access to low level operating system calls.

Measurements (sampling)

- **Hybrid monitoring uses the concepts of both software and hardware monitoring.**
- **Synchronization is required.**

Summary

- **We have learnt about the Measurements (sampling).**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Intervals

Overview

- **Here, we will learn about the intervals.**

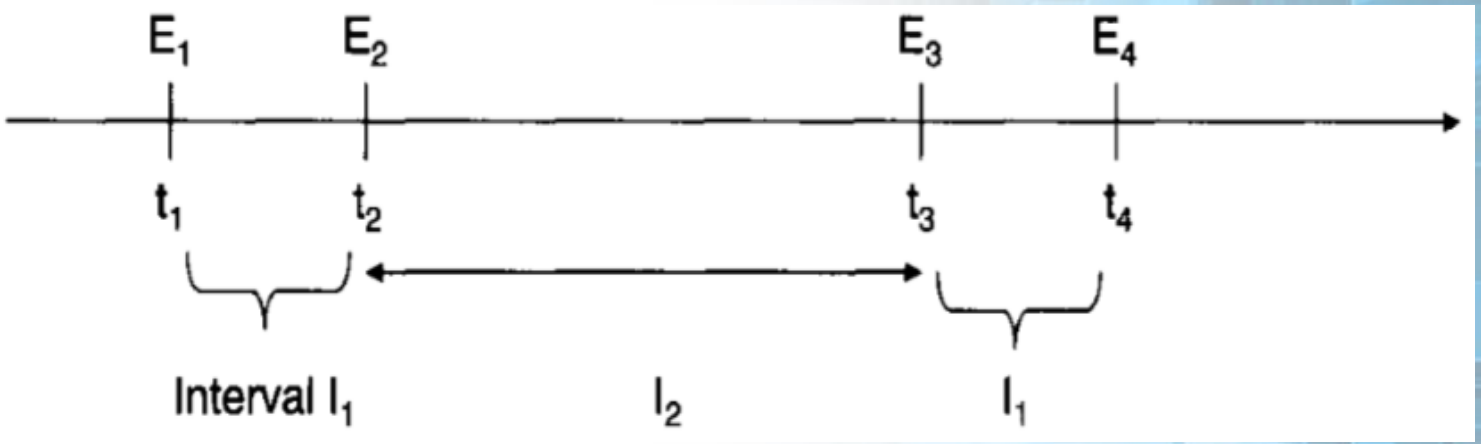
Intervals

- An interval represents a period of time.
- System environment is system clocks.
- Instruction execution cycle.

Intervals

- Intervals are same if they represent the same sequence of events.
- Separate sequence are represented by two intervals then they are unrelated.

Intervals



Summary

- **We have learnt about the Intervals.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Response

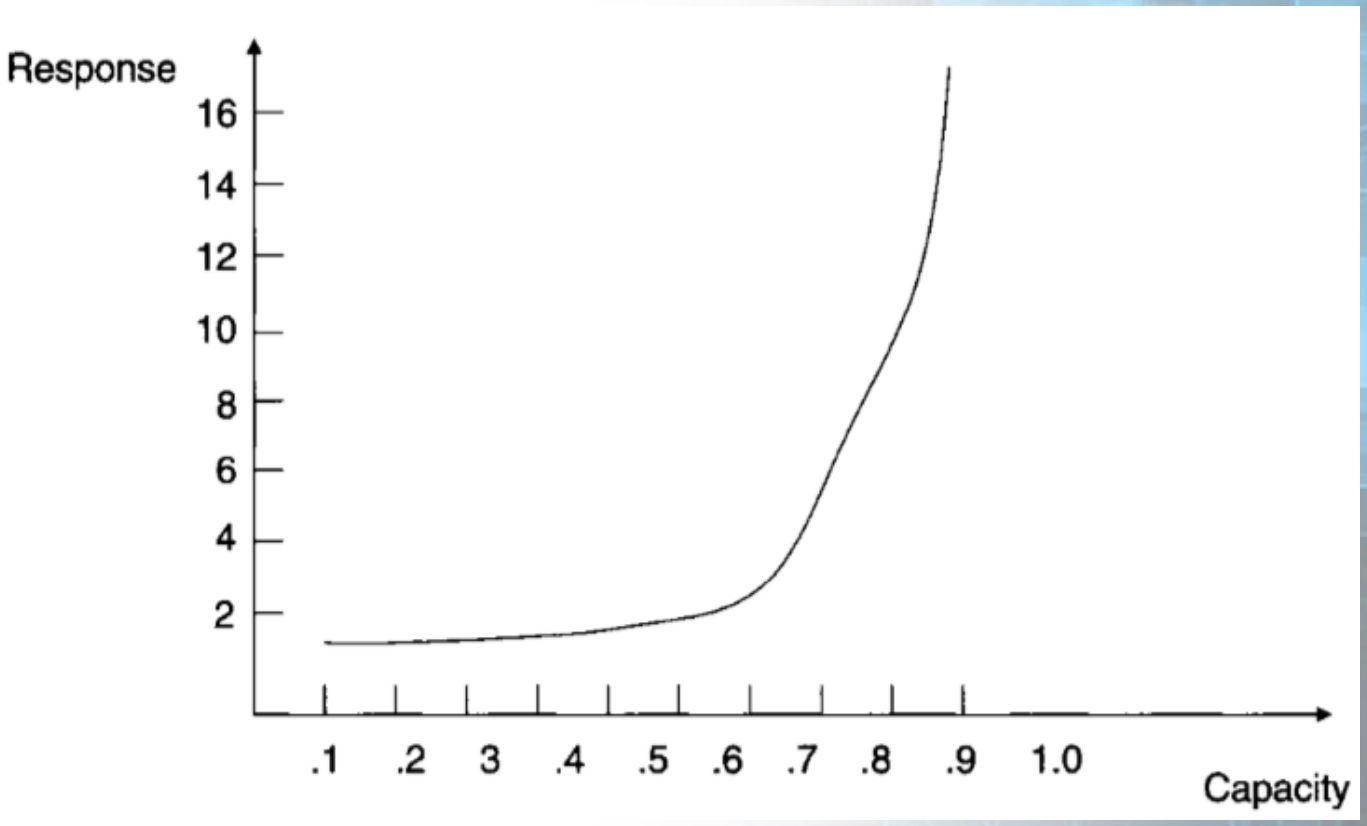
Overview

- **Here, we will learn about the response.**

Response

- Represent a measure of period of time a user or application to wait before task assignment.
- Typical measure may pit the response time.

Response



Response

- Load increases above specific capacity the response increases.
- Study the measurable sequences against system load.
- How these loads impact each other.

Summary

- **We have learnt about the response.**
- **Credits: Paul Fortier book.**

Independence

Overview

- **Here, we will learn about the Independence.**

Independence

- **Occurrence if one dose not influence the outcome of other.**

Independence

- Important concept while evaluating systems.
- Two programs that cannot run concurrently must be consider independent.

Independence

- Running on the same operating system and hardware.
- Cannot interfere each other then they are separate and unrelated.

Independence

- **Important in modeling to define all elements and their relationship.**

Summary

- **We have learnt about the Independence.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Randomness

Overview

- **Here, we will learn about randomness.**

Randomness

- Randomness is a property of an event and its reoccurrence.
- Have no pattern.
- Realization of the property of independence.

Randomness

- Its a mathematical concept.
- External sources can be viewed as random events in systems.

Randomness

- **Important to analyze systems using mathematical concepts.**

Summary

- **We have learnt about the randomness.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Workloads

Overview

- **Here, we will learn about the workloads.**

Workloads

- Simply we can say load.
- Event or event sequences presented to system to model.
- Represent the number of events offered to system for execution.

Workloads

- Arranging the requests and perform them by the system.
- The duration could be endless.
- The load is re-entered after prescribed period of time.

Workloads

- **The database community has developed a set of transactional workloads.**

Summary

- We have learnt about the workloads.
- Credits: Paul Fortier book.

Modeling and Simulation

Problems encountered in model development and use

Overview

- **Here, we will understand about the problems encountered in model development and use.**

Problems encountered in model development and use

- Must start with having concept that what we are doing.
- Determining what to do.
- Two main classes performance assessment.
- First take an existing system and design some experiments.

Problems encountered in model development and use

- Second is either analytical modeling or simultaneous.
- Analyst uses following measures:
- Responsiveness and use levels.
- Mission-ability and dependability.
- Productivity and predictability.

Problems encountered in model development and use

- Analyst must avoid the following mistakes:
- Having no goals.
- Setting biased goals.
- Unsystematic approach to development.
- Choosing of incorrect performance metrics.
- Choosing non-stressful workload.

Problems encountered in model development and use

- **To solve these problems the analyst must ask some questions to himself/herself.**

Summary

- We have learnt about the problems encountered in model development and use.
- Credits: Paul Fortier book.

Modeling and Simulation

A Case Study

Overview

- **Here, we will understand about how to conduct a case study**

A Case Study

- First Step: Define the System that we wish to study
- E.g. Remote pipes vs. Remote Procedures

A Case Study

- **Focus on Services – small and large data transfers**

A Case Study

- Select Metrics
- Rate of access
- Time for Performance
- Resource requirements per service

A Case Study

- **Evaluate the developed model and start over again**
- **Trial and error**

A Case Study

- Conducting our own: Modeling a ? ? ?
- A Bus system
- A railway terminal
- A hospital
- A human cell
- Human brain
- Ecosystem

Summary

- **We have learnt about conducting a case study.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Introduction to Software Reliability

Overview

- **Here, we will understand about software reliability**

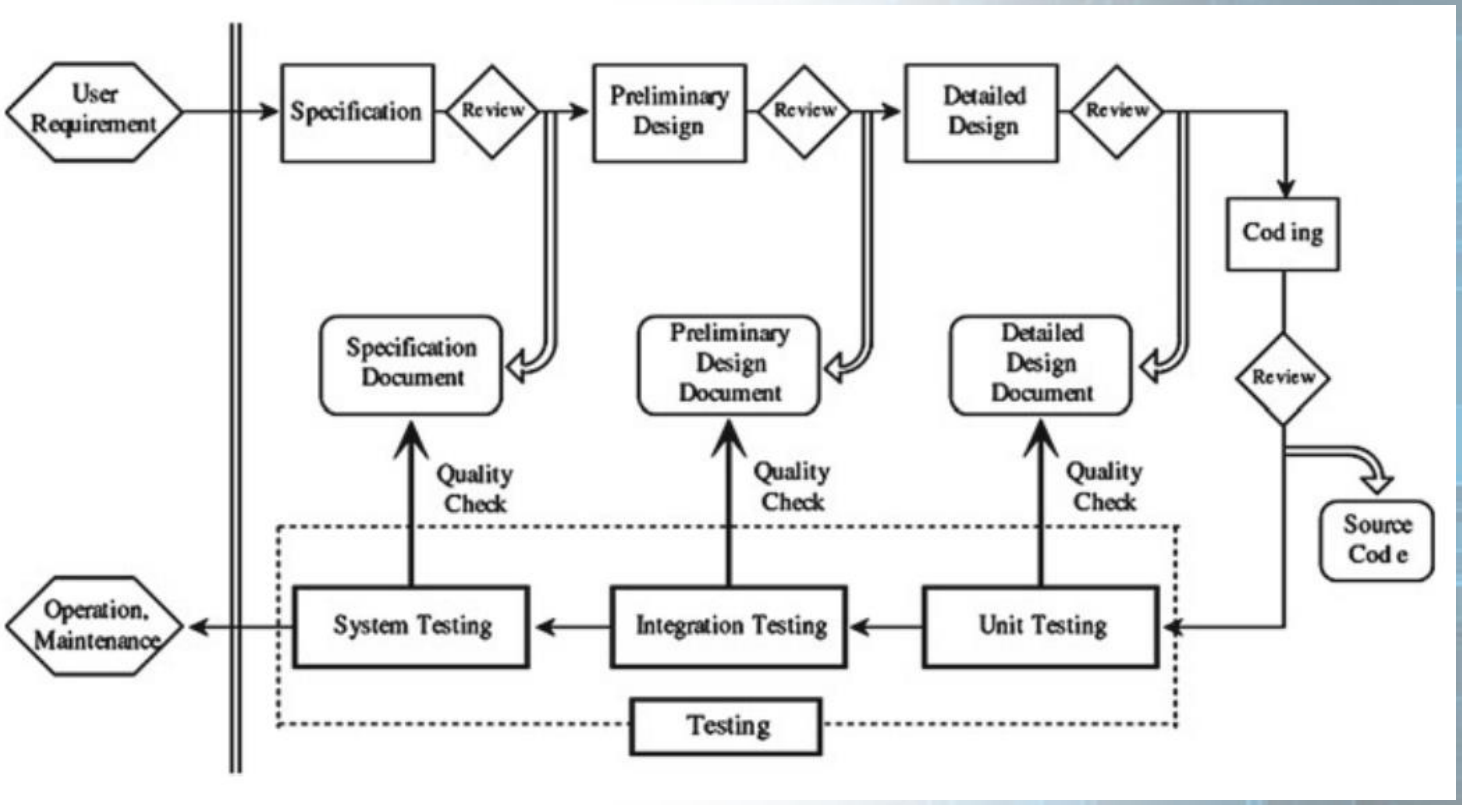
Introduction to Software Reliability

- Software fails on a regular basis
- This is a serious issue
- Especially in case of critical systems – nuclear reactors, patient care etc.

Introduction to Software Reliability

- Problems with X-Ray machine
- Problems with SCUD Missiles
- Problems with rocket launch
- Etc.

Introduction to Software Reliability



Summary

- **We have learnt about software reliability.**
- **Credits: Yamada book.**

Modeling and Simulation

Definitions and Software Reliability Model

Overview

- **Here, we will understand about definitions about reliability**

Definitions and Software Reliability Model

- **Generally, a software failure caused by software faults latent in the system cannot occur except on a specific occasion when a set of specific data is put into the system under a specific condition, i.e. the program path including software faults is executed.**

Definitions and Software Reliability Model

- **A software system is a product which consists of the programs and documents produced through a software development process**

Definitions and Software Reliability Model

- **Software failure is defined as an unacceptable departure of program operation from the program requirements.**
- **The cause of software failure is called a software fault.**

Definitions and Software Reliability Model

- Then, software fault is defined as a defect in the program which causes a software failure.
- The software fault is usually called a software bug.

Definitions and Software Reliability Model

- **Software error is defined as human action that results in the software system containing a software fault**

Definitions and Software Reliability Model

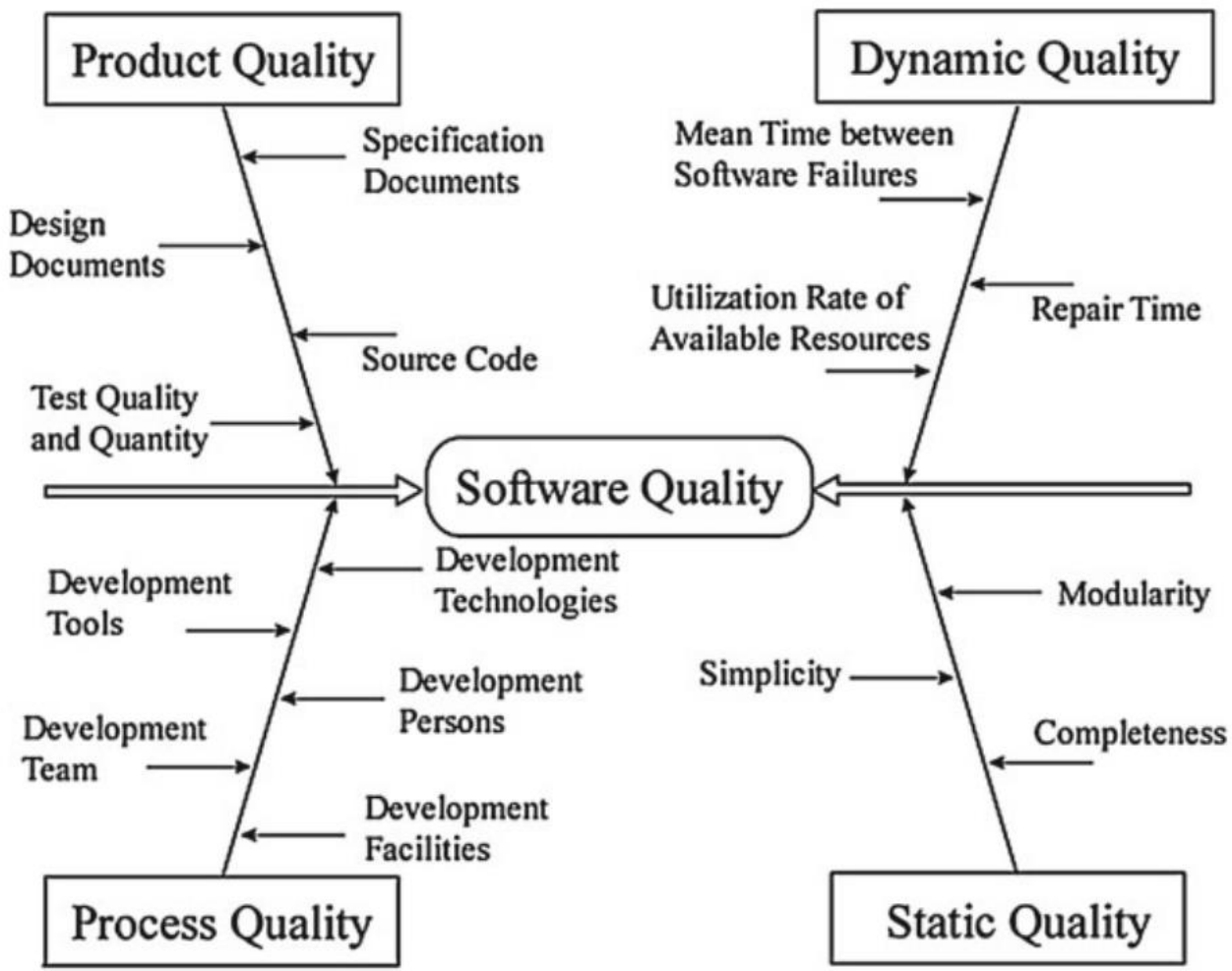
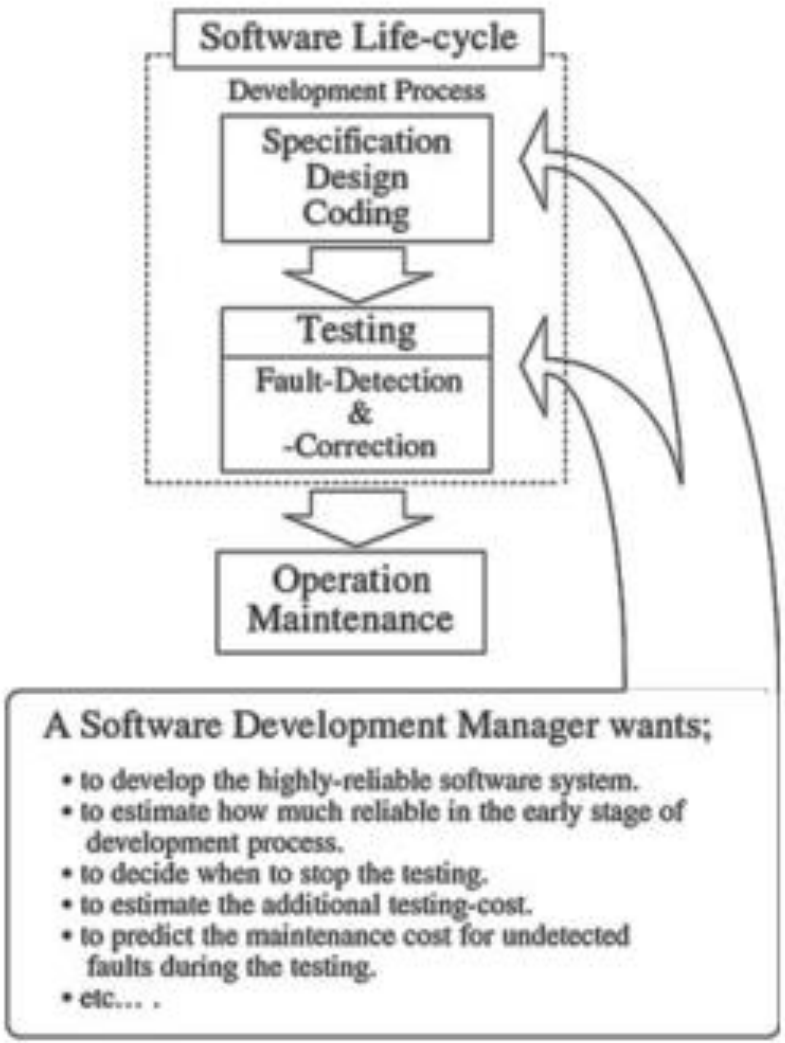


Fig. 1.2 Elements of software quality based on a cause-and-effect diagram

Definitions and Software Reliability Model

Fig. 1.3 Aim of software quality/reliability measurement and assessment



Definitions and Software Reliability Model

Terminologies

- *Software Failure*
  - an unacceptable departure of program operation from the program requirements
- *Software Fault*
  - a defect in the program which causes a software failure (*software bug*)
- *Software Reliability*
  - the attribute that a software system will perform without causing software failures over a given time period under specified conditions
  - measured by its probability

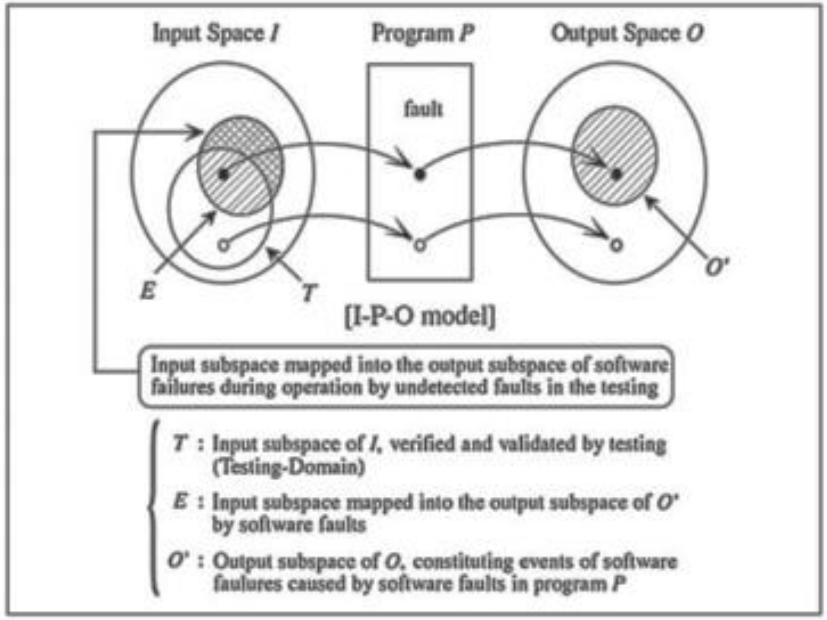


Fig. 1.4 An input-program-output model for software behavior

Definitions and Software Reliability Model

Software Reliability	Hardware Reliability
(1) Software failures can be due to no wearout phenomenon.	(1) Hardware failures can be due to wear.
(2) Software reliability is, inherently, determined during the earlier phase of the development process, i.e. specification analysis and design phases.	(2) Hardware reliability is affected by deficiencies injected during all phases of the development, operation, and maintenance.
(3) Software reliability can not be improved by redundancy with identical versions.	(3) Hardware reliability can be improved by redundancy with identical units.
(4) A verification method of software reliability has not been established.	(4) A testing method of hardware reliability is established and standardized.
(5) A maintenance technology is not established since the market of software products is rather recent.	(5) A maintenance technology is advanced since the market of hardware products is established and the user environment is seized.

Fig. 1.5 Comparison between the characteristics of software reliability and hardware reliability

Summary

- **We have learnt about definitions related to reliability.**
- **Credits: Yamada book.**

Modeling and Simulation

Software Reliability Growth Modeling

Overview

- **Here, we will understand about software reliability growth modeling**

Software Reliability Growth Modeling

- **Generally, a mathematical model based on stochastic and statistical theories is useful to describe the software fault-detection phenomena or the software failure-occurrence phenomena and estimate the software reliability quantitatively.**

Software Reliability Growth Modeling

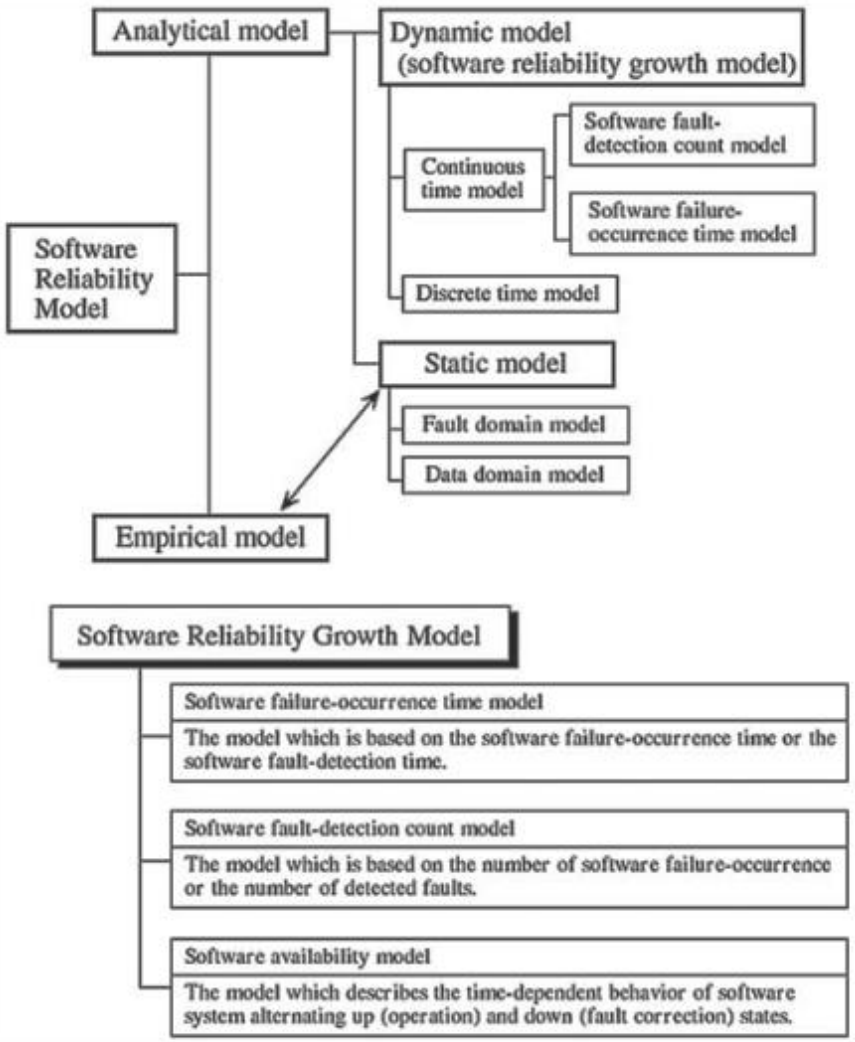


Fig. 1.6 Hierarchical classification of software reliability models

Software Reliability Growth Modeling

$N(t)$	the cumulative number of software faults (or the cumulative number of observed software failures) detected up to time t,
S_i	the ith software-failure occurrence time ($i = 1, 2, \ldots; S_0 = 0$),
X_i	the time-interval between $(i-1)$-st and ith software failures ($i = 1, 2, \ldots; X_0 = 0$).

Software Reliability Growth Modeling

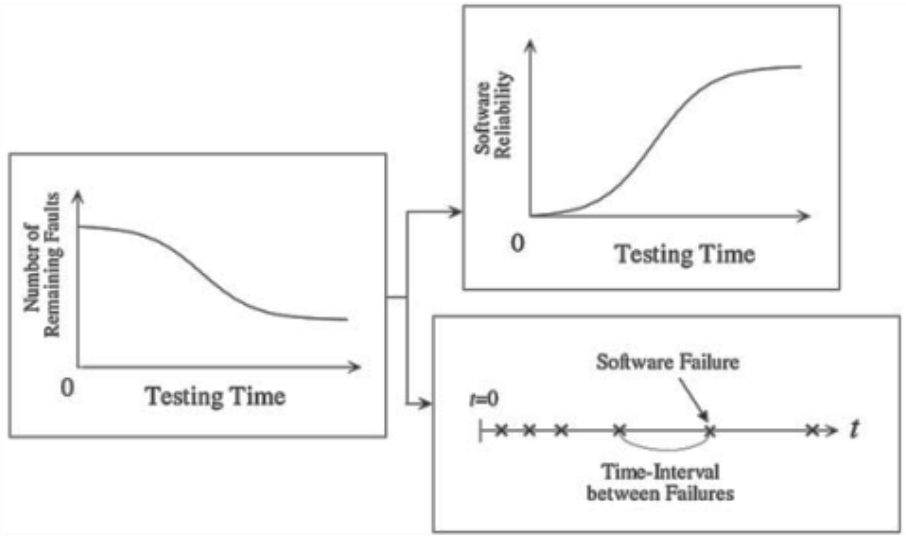


Fig. 1.7 Software reliability growth

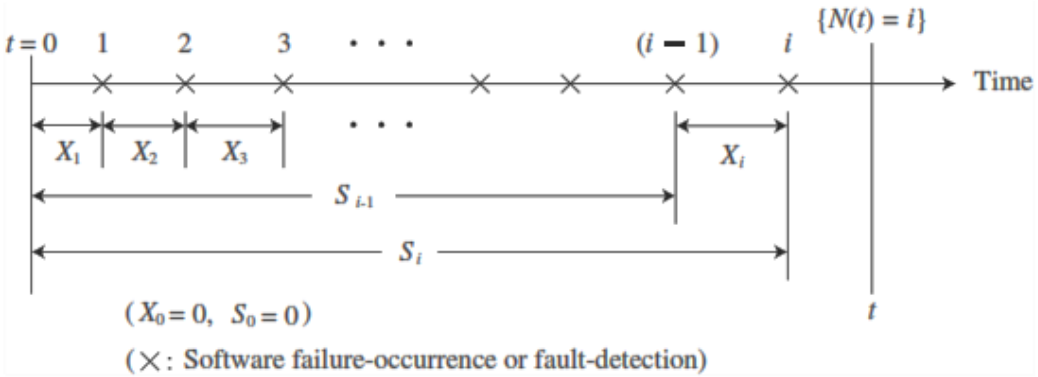


Fig. 1.8 The stochastic quantities related to a software fault-detection phenomenon or a software failure-occurrence phenomenon

Summary

- **We have learnt about software reliability growth modeling.**
- **Credits: Yamada book.**

Imperfect Debugging Modeling

Overview

- **Here, we will understand about imperfect debugging modeling**

Imperfect Debugging Modeling

- **Most software reliability growth models proposed so far are based on the assumption of perfect debugging**

Imperfect Debugging Modeling

- i.e. All faults detected during the testing and operation phases are corrected and removed perfectly.
- However, debugging actions in real testing and operation environment are not always performed perfectly.

Imperfect Debugging Modeling

- For example,
- Typing errors invalidate the fault-correction activity or fault-removal is not carried out precisely due to incorrect analysis of test results

Imperfect Debugging Modeling

- As a result it is preferable to develop an incorrect debugging model.
- This will result in a better estimation of reliability

Summary

- We have learnt about imperfect debugging modeling.
- Credits: Yamada book.

Imperfect Debugging Model with Perfect Correction Rate

Overview

- **Here, we will understand about imperfect debugging model with perfect correction rate**

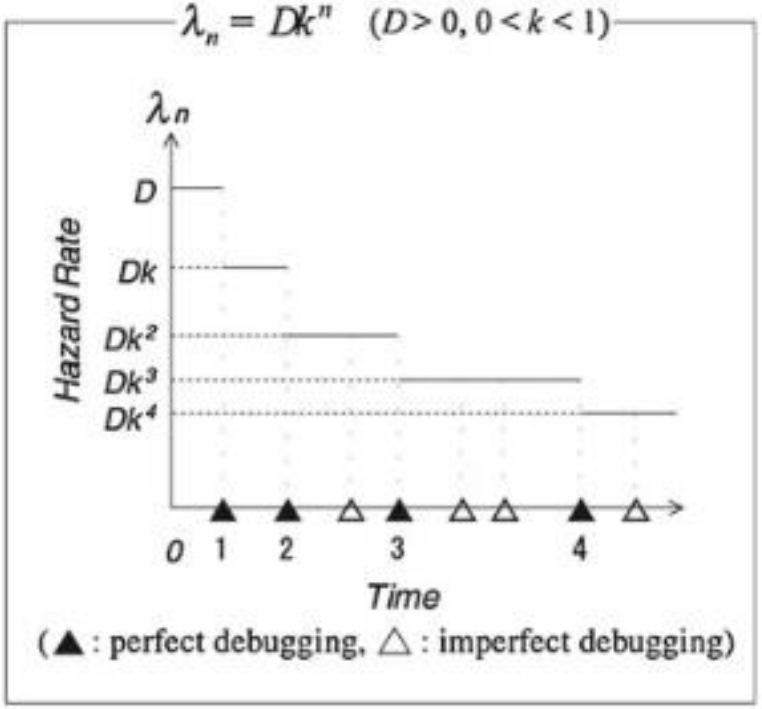
Imperfect Debugging Model with Perfect Correction

- **To model an imperfect debugging environment, the following assumptions are made:**

1. Each fault which causes a software failure is corrected perfectly with probability $p(0 \leq p \leq 1)$. It is not corrected with probability $q(= 1 - p)$. We call p the perfect debugging rate or the perfect correction rate.
2. The hazard rate is given by (1.5) and decreases geometrically each time a detected fault is corrected (see Fig. 1.14).
3. The probability that two or more software failures occur simultaneously is negligible.
4. No new faults are introduced during the debugging. At most one fault is removed when it is corrected, and the correction time is not considered.

Imperfect Debugging Model with Perfect Correction

Fig. 1.14 Behavior of hazard rate



Imperfect Debugging Model with Perfect Correction

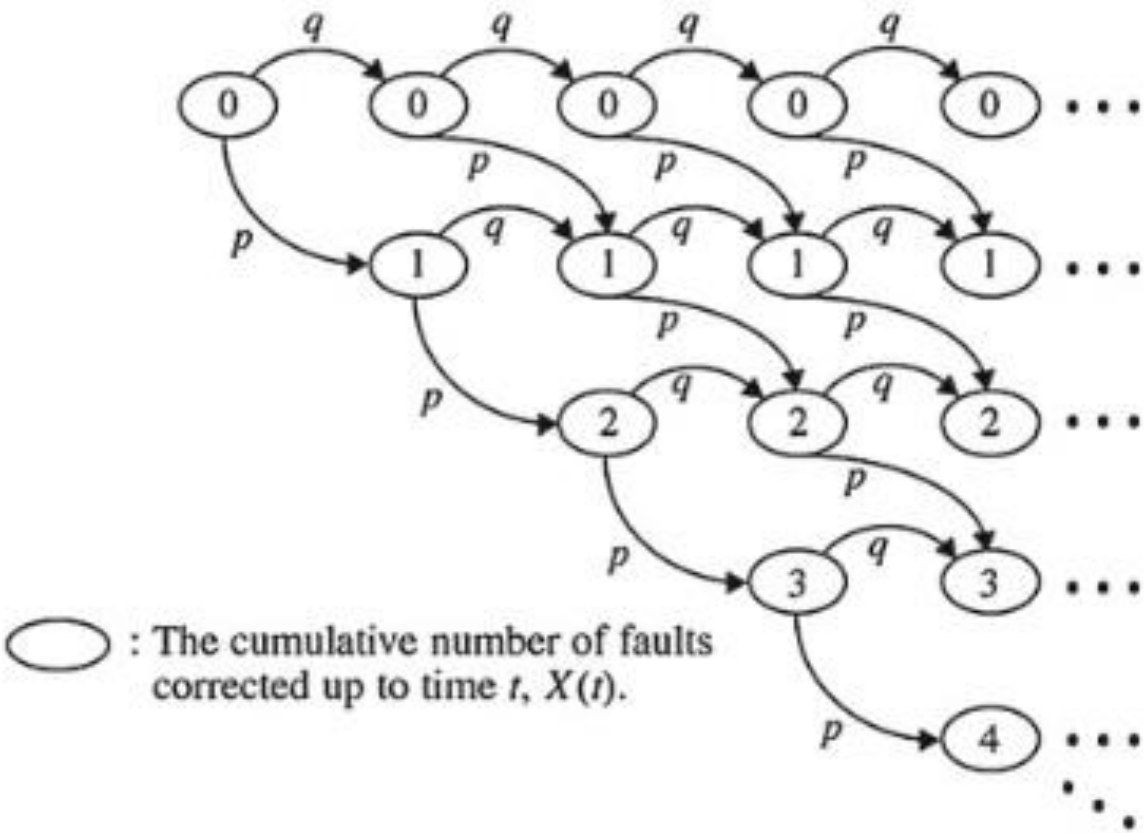


Fig. 1.15 A diagrammatic representation of transitions between states of $X(t)$

Imperfect Debugging Model with Perfect Correction

- Let X (t) be a random variable representing the cumulative number of faults corrected up to the testing time t. Then, X (t) forms a Markov process.
- That is, from assumption 1, when i faults have been corrected by arbitrary testing time t,

Imperfect Debugging Model with Perfect Correction

$$X(t) = \begin{cases} i, & \text{with probability } q, \\ i+1, & \text{with probability } p, \end{cases} \tag{1.14}$$

Summary

- We have learnt about imperfect debugging modeling with correction.
- Credits: Yamada book.

Imperfect Debugging with Introduced Faults

Overview

- **Here, we will understand about imperfect debugging modeling with introduced faults**

Imperfect Debugging with Introduced Faults

- Besides the imperfect debugging factor above in fault-correction activities, we consider the possibility of introducing new faults in the debugging process.
- It is assumed that two kinds of software failures exist in the dynami environment

Imperfect Debugging with Introduced Faults

- **(F1) software failures caused by faults originally latent in the software system prior to the testing (which are called inherent faults)**
- **(F2) software failures caused by faults introduced during the software operation owing to imperfect debugging.**

Imperfect Debugging with Introduced Faults

- In addition, it is assumed that one software failure is caused by one fault
- And that it is impossible to discriminate whether the fault that caused the software failure that has occurred is F1 or F2.

Imperfect Debugging with Introduced Faults

- **As to the software failure-occurrence rate due to F1, the inherent faults are detected with the progress of the operation time.**

Imperfect Debugging with Introduced Faults

- In order to consider two kinds of time dependencies on the decreases of F1, let
- ai(t) = (1,2) denote software failure occurrence rate for F1
- For F2, it is constant (Lambda > 0)

Summary

- We have learnt about imperfect debugging modeling with introduced faults.
- Credits: Yamada book.

Software Availability Modeling

Overview

- **Here, we will understand about software availability modeling**

Software Availability Modeling

- **Recently, software performance measures such as the possible utilization factors have begun to be interesting for metrics as well as the hardware products.**

Software Availability Modeling

- That is, it is very important to measure and assess software availability,
- It is defined as the probability that the software system is performing successfully, according to the specification, at a specified time point

Software Availability Modeling

- **The actual operational environment needs to be more clearly reflected in software availability modeling, since software availability is a customer-oriented metrics.**

Software Availability Modeling

- Software Reliability :

the attribute that software systems can continue to perform and do not cause any software failures *for a given time period*, under a specified environment.

■ *software failure*

[an unacceptable departure from program operation caused by a software fault remaining in the software system.]

- Software Availability :

the attribute that software systems are available and performing *at a given time point*, under a specified environment.

Software Availability Modeling

- Software fails on a regular basis
- This is a serious issue
- Especially in case of critical systems – nuclear reactors, patient care etc.

Summary

- **We have learnt about conducting a case study.**
- **Credits: Paul Fortier book.**

Model Description

Overview

- **Here, we will understand about model description for software availability modeling**

Model Description

- **Assumptions**
- **1. The software system is unavailable and starts to be restored as soon as a software failure occurs, and the system cannot operate until the restoration action is complete**

Model Description

- **2. The restoration action implies debugging activity, which is performed perfectly with probability a**
- **$(0 < a \leq 1)$ and imperfectly with probability $b(= 1 - a)$.**
- **a is the perfect debugging rate**

Model Description

- **One fault is corrected and removed from the software system when the debugging activity is perfect.**

Model Description

- **3. When n faults have been corrected, the time to the next software failure- occurrence and the restoration time follow exponential distributions**

Model Description

4. The probability that two or more software failures will occur simultaneously is negligible

Summary

- **We have learnt about model description.**
- **Credits: Yamada book.**

Software Availability Measures

Overview

- **Here, we will understand about software availability measures**

Model Description

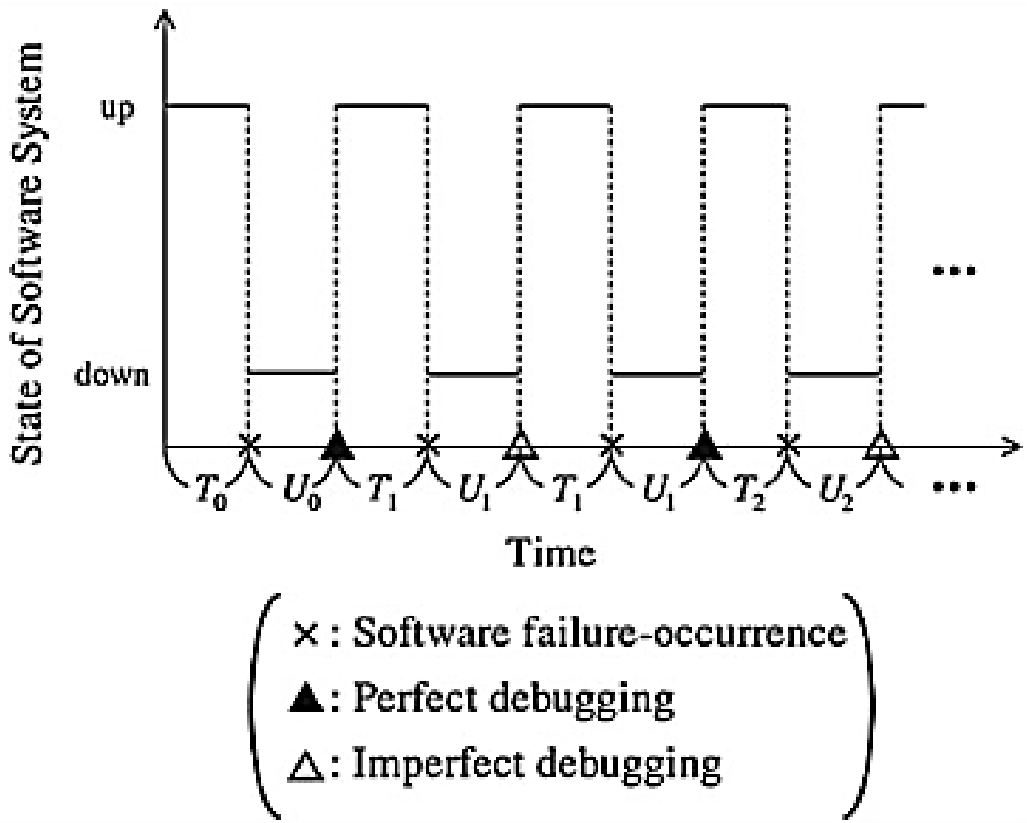
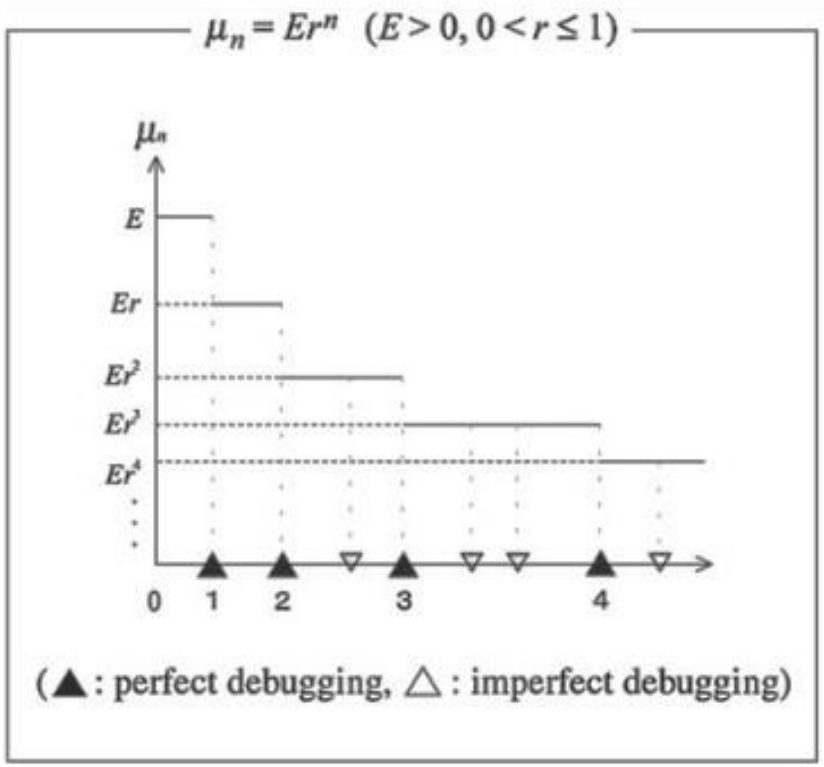


Fig. 1.17 Sample behavior of the software system alternating between up and down states

Software Availability Measures

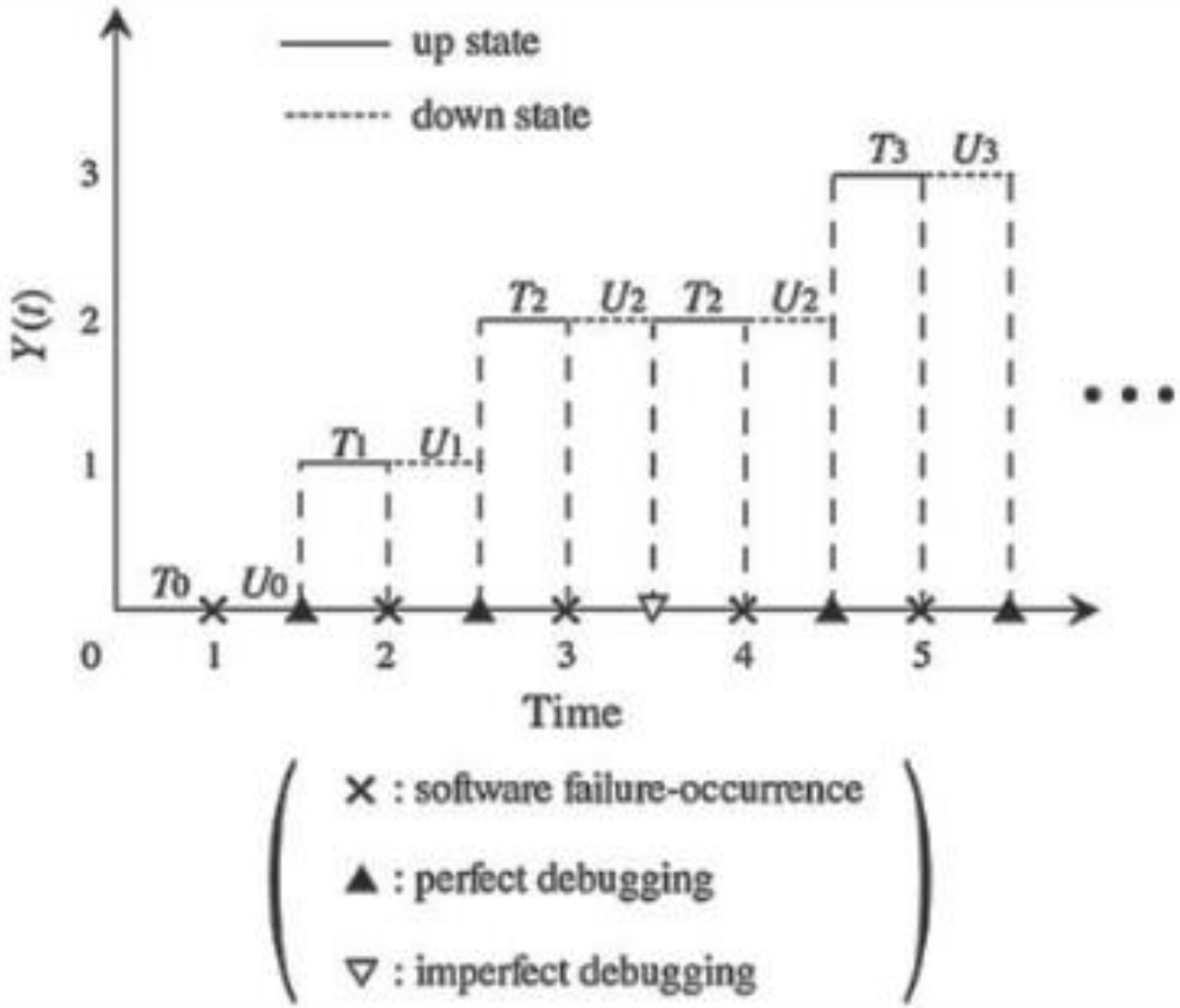


Fault complexity

early-detected : easier to correct.
later-detected : more difficult to correct.

Fig. 1.18 Behavior of restoration rate

Software Availability Measures



Software Availability Measures

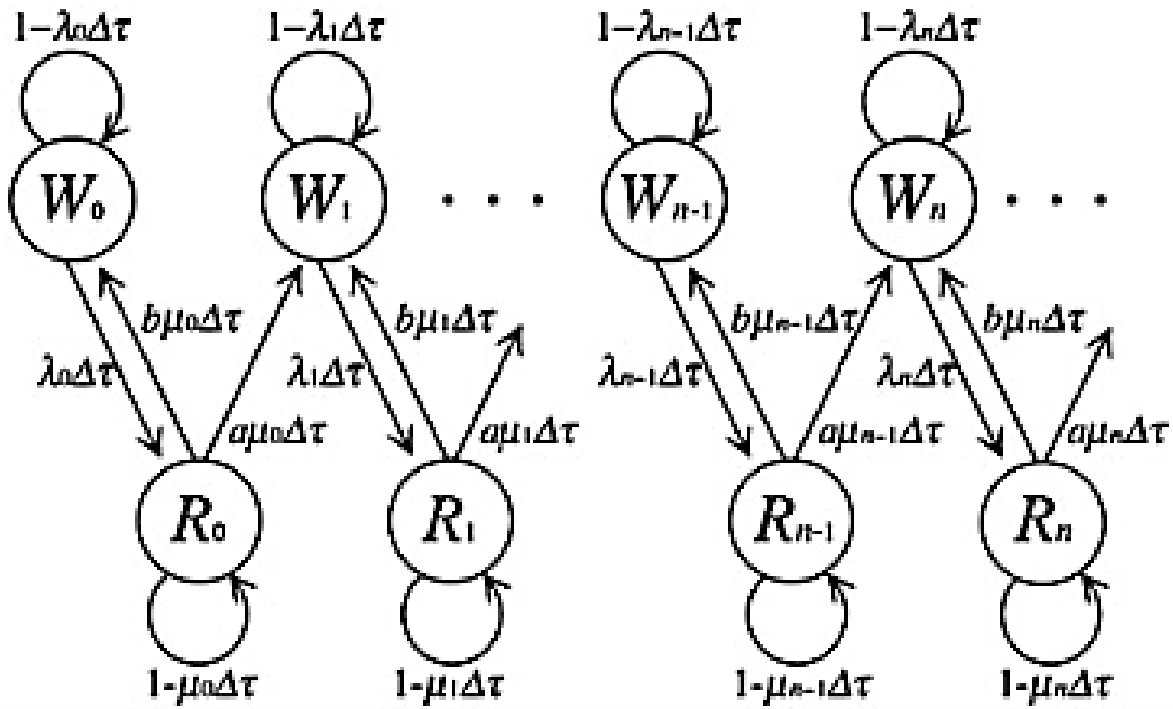


Fig. 1.20 A state transition diagram for software availability modeling

Software Availability Measures

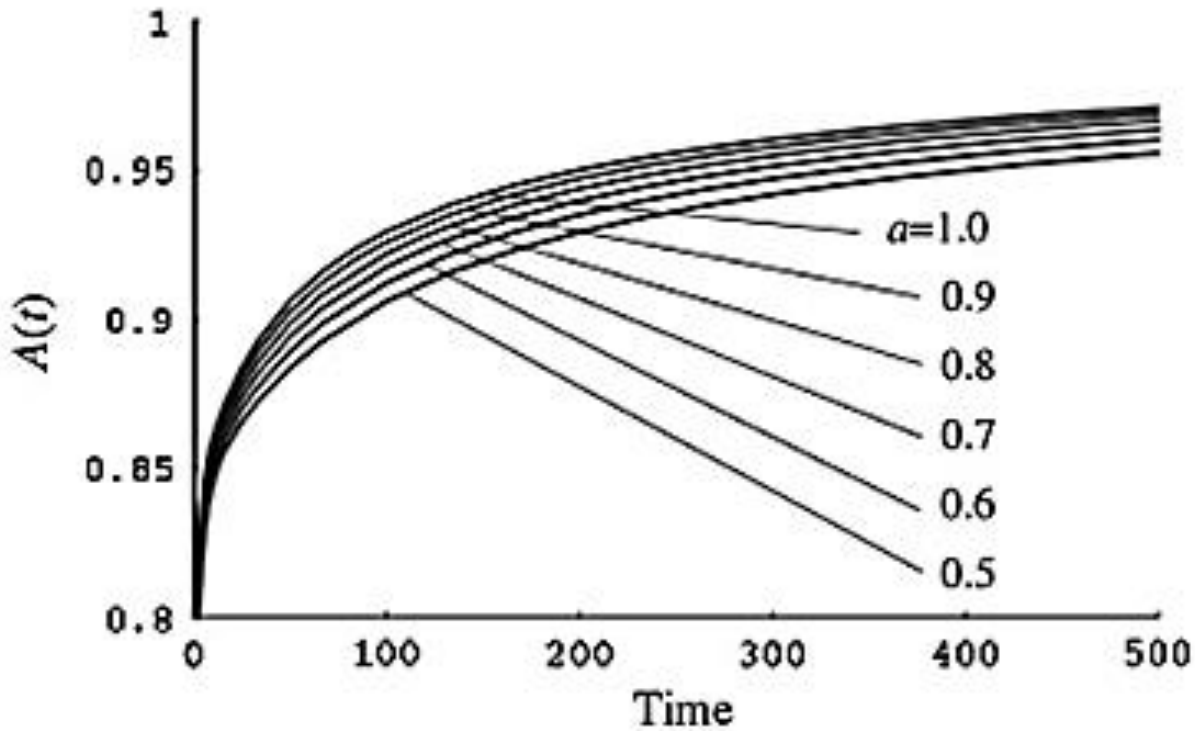


Fig. 1.21 Dependence of perfect debugging rate a on $A(t)$

Software Availability Measures

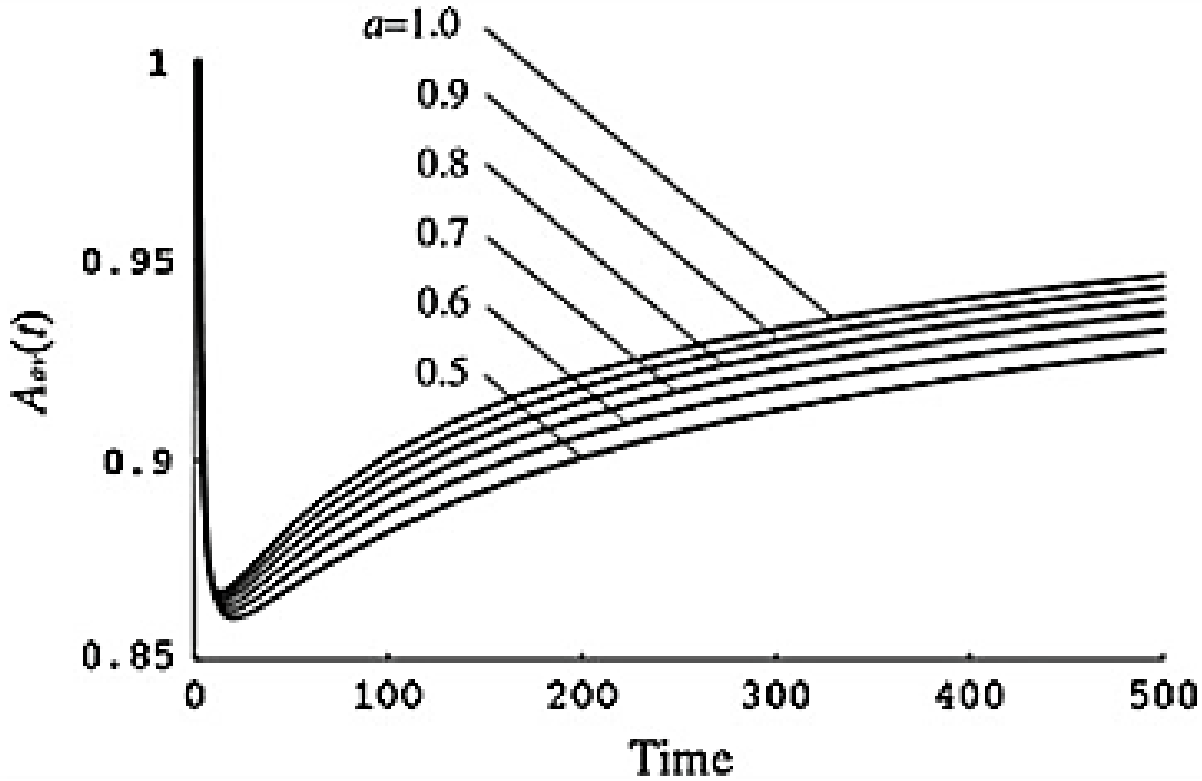


Fig. 1.22 Dependence of perfect debugging rate a on $A_{av}(t)$

Summary

- **We have learnt about software availability measures.**
- **Credits: Yamada book.**

Application of Software Reliability Assessment

Overview

- **Here, we will understand about software reliability assessment**

Application of Software Reliability Assessment

- **It is very important to apply the results of software reliability assessment to manage-ment problems with software projects for attaining higher productivity and quality.**

Application of Software Reliability Assessment

- **We discuss three software management problems as application technologies of soft-ware reliability models.**

Application of Software Reliability Assessment

- Optimal Software Release Problem
- Statistical Software Testing-Progress Control
- Optimal Testing-Effort Allocation Problem

Summary

- We have learnt about conducting a case study.
- Credits: Paul Fortier book.

Optimal Software Release Problem

Overview

- **Here, we will understand about optimal software release issues**

Optimal Software Release Problem

- Recently, it is becoming increasingly difficult for the developers to produce highly reliable software systems efficiently.
- Thus, it has been necessary to control a software development process in terms of quality, cost, and release time.

Optimal Software Release Problem

- **In the last phase of the software development process, testing is carried out to detect and fix software faults, introduced by human work, prior to its release for the operational use.**

Optimal Software Release Problem

- The software faults that cannot be detected and fixed remain in the released software system after the testing phase.
- Thus, if a software failure occurs during the operational phase, then a computer system stops working and it may cause serious damage.

Optimal Software Release Problem

- **If the duration of software testing is long, we can remove many software faults in the system and its reliability increases. However, this increases the testing cost and delays software delivery.**

Optimal Software Release Problem

- In contrast, if the length of software testing is short, a software system with low reliability is delivered and it includes many software faults which have not been removed in the testing phase.
- Thus, the maintenance cost during the operation phase increases.

Optimal Software Release Problem

- It is therefore very important in terms of software management that we find the optimal length of software testing, which is called an optimal software release problem

Optimal Software Release Problem

- These decision problems have been studied in the last decade by many researchers.
- In optimal software release problems we consider both a present value and a warranty period (in the operational phase)

Summary

- **We have learnt about optimal software release.**
- **Credits: Yamada book.**

Statistical Software Testing-Progress Control

Overview

- **Here, we will understand about statistical software testing-progress control**

Statistical Software Testing-Progress Control

- **As well as quality/reliability assessment, software-testing managers should assess the degree of testing-progress.**

Statistical Software Testing-Progress Control

- **We can construct a statistical method for software testing-progress control based on a control chart method**

Statistical Software Testing-Progress Control

- **This method is based on several instantaneous fault-detection rates derived from software**

Statistical Software Testing-Progress Control

The procedure of testing-progress control is shown as follows:

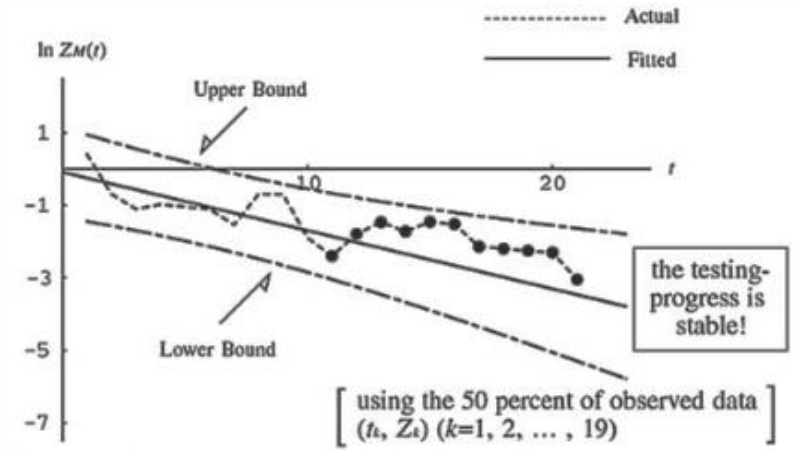
Step 1: An appropriate model is selected to apply and the model parameters are estimated by the method of least-squares.

Step 2: To certify goodness-of-fit of the estimated regression equation for the observed data, we use the F-test.

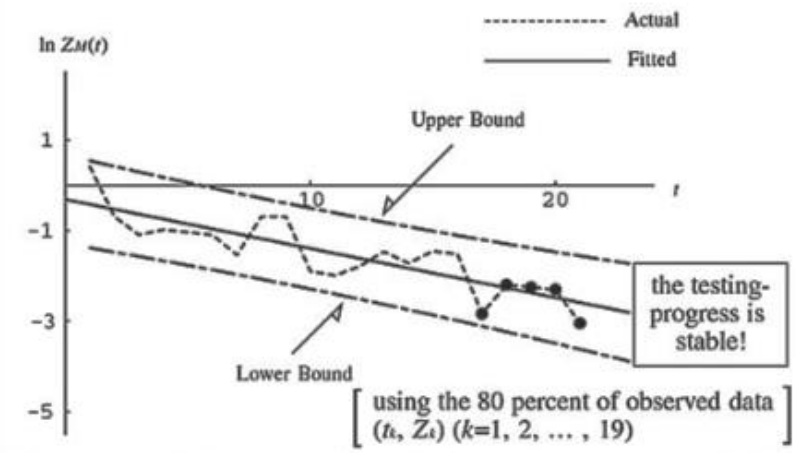
Step 3: Based on the result of the F-test, the central line and upper and lower control limits of the control chart are calculated. The control chart is drawn.

Step 4: The observed data are plotted on the control chart and the stability of the testing-progress is judged.

Statistical Software Testing-Progress Control



[An example of the control chart for the testing-progress control]



[An example of the control chart for the testing-progress control]

Fig. 1.25 Examples of the control chart for the testing-progress control

Summary

- **We have learnt about statistical software testing-progress control.**
- **Credits: Yamada book.**

Optimal Testing-Effort Allocation

Overview

- **Here, we will understand about Optimal Testing-Effort Allocation**

Optimal Testing-Effort Allocation

- We discuss a management problem to achieve a reliable software system efficiently during module testing in the software development process by applying a testing-effort-dependent software reliability growth model

Optimal Testing-Effort Allocation

- We take account of the relationship between the testing-effort spent during the module testing and the detected software faults where the testing-effort is defined as resource expenditures spent on software testing, e.g. manpower, CPU hours, and executed test cases.

Optimal Testing-Effort Allocation

- **The software development manager has to decide how to use the specified testing-effort effectively in order to maximize the software quality and reliability.**

Optimal Testing-Effort Allocation

- That is, to develop a quality and reliable software system, it is very important for the manager to allocate the specified amount of testing-effort expenditure for each software module under some constraints.

Optimal Testing-Effort Allocation

- We can observe the software reliability growth in the module testing in terms of a time-dependent behavior of the cumulative number of faults detected during the testing stage.

Optimal Testing-Effort Allocation

- **Based on the testing-effort dependent software reliability growth model, we consider the following testing-effort allocation problem:**

Optimal Testing-Effort Allocation

- **Based on the testing-effort dependent software reliability growth model, we consider the following testing-effort allocation problem:**

Optimal Testing-Effort Allocation

1. The software system is composed of M independent modules. The number of software faults remaining in each module can be estimated by the model.
2. The total amount of testing-effort expenditure for module testing is specified.
3. The manager has to allocate the specified total testing-effort expenditure to each software module so that the number of software faults remaining in the system may be minimized.

Summary

- We have learnt about Optimal Testing-Effort Allocation.
- Credits: Yamada book.

Modeling and Simulation

Introduction to formal modeling.

Overview

- **Here, we will understand about the "formal modeling".**

Formal modeling

- Petri nets PNs provide graphical tool and notation method.
- Include arrival rate and service rate.
- Individual state information.
- Contention and concurrency.

Formal modeling

- Petri Nets have place in computer systems performance assessment.
- Between analytical queuing theory and computer simulation.

Formal modeling

- System state more complete than analytical models.
- But not as simulations.
- Have fundamental theory but act like simulations.
- Single entities, movement and affect effect of the state of the entire system.

Formal modeling

- Petri Nets was introduced in 1966.
- It describes concurrent systems.
- Followed by continuous improvements.
- Timing of transitions.
- Priority of transitions.

Formal modeling

- Types to Token.
- Colors depicting.
- Analysis tools and modelling aid.

Summary

- Here, we understood about the “Testing for Significance of Regression”.
- Credits: Paul Fortier book.

Basic notation-I

Overview

- **Here, we will understand about the "Basic notation"?**

Basic notation

- Petri Nets provides abstraction and information flow.
- Using four fundamental components.
- Places as Circles.
- Transition as bars.
- Arc as line segments.
- Token as dots.

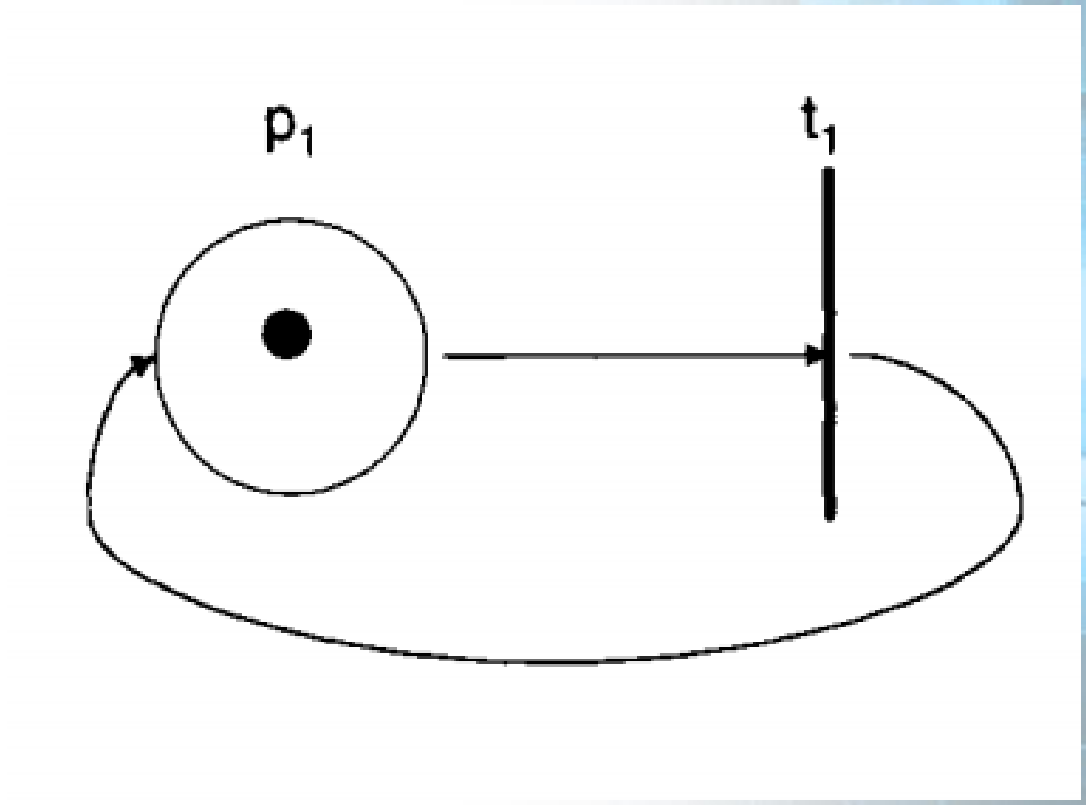
Basic notation

- Places represents useful system components and their state e.g. disk drive.
- Transitions represents events.
- Action of reading an item from disk drive.

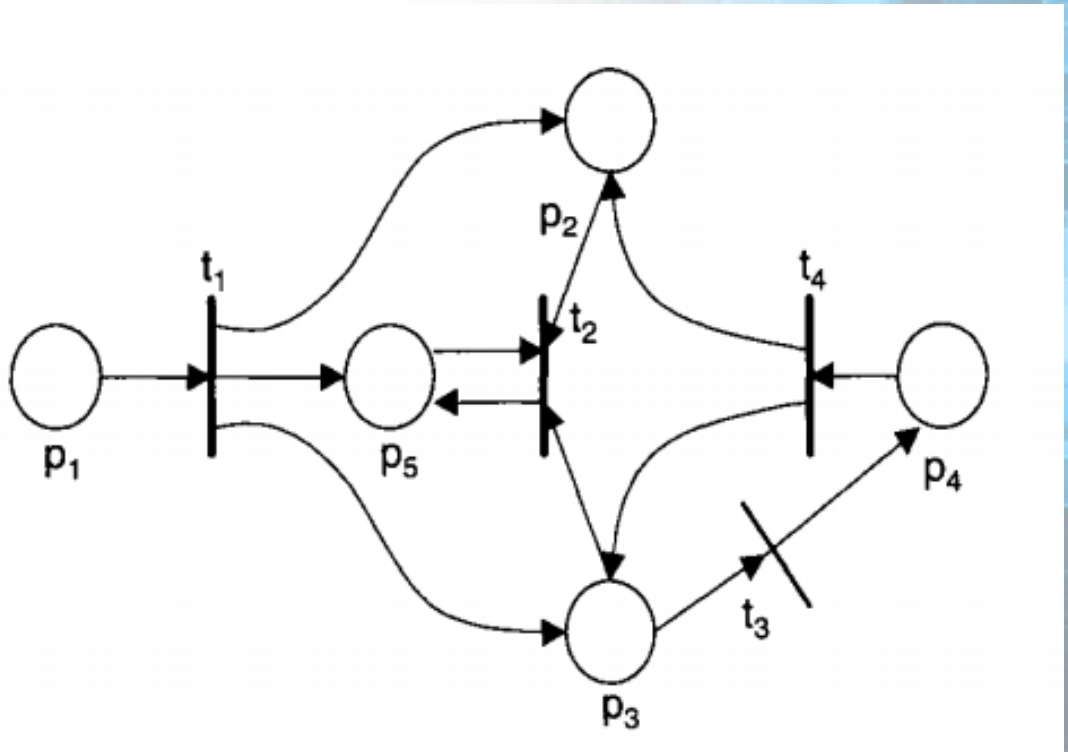
Basic notation

- Arcs represents relationship between transitions and places.
- Proved path for activation of transition.
- Tokens define state of Petri net.

Forever Cycling Petri Net



Petri Net Graphical Representation



Summary

- **Here, we understood about Basic notation.**
- **Credits: Paul Frontier book.**

Basic notation-II

Overview

- **Here, we will understand about the "Basic notation".**

Basic notation-II

Petri Net Dual

- Petri net model also has dual.
- In dual of petri, transitions are changed to places and places to transitions.
- The input becomes output function and output becomes output function.

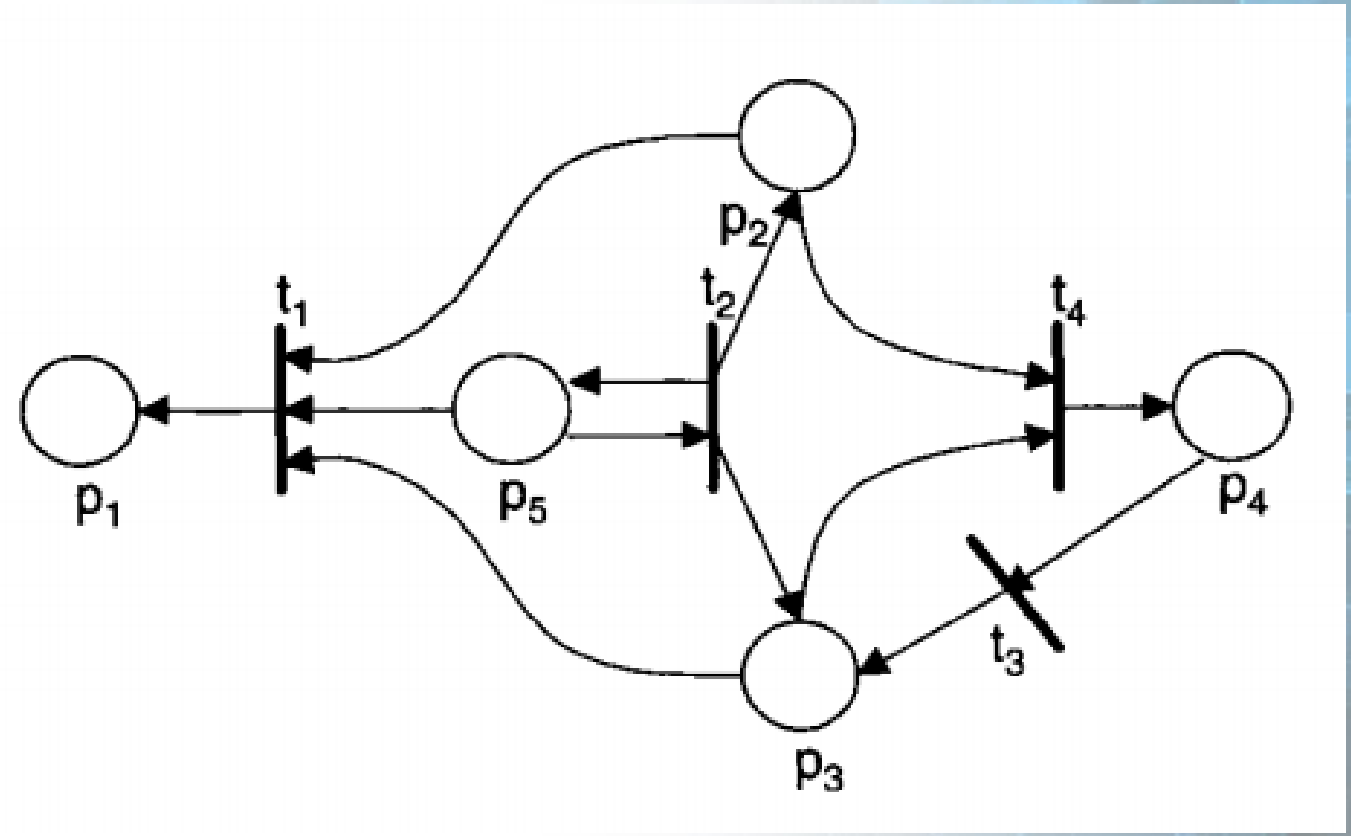
Basic notation-II

Petri Net Inverse

- A petri net model is also defined for inverse.
- Places and transitions are kept same.
- Whereas, input functions switches to output functions.

Basic notation-II

Petri Net Inverse Representation



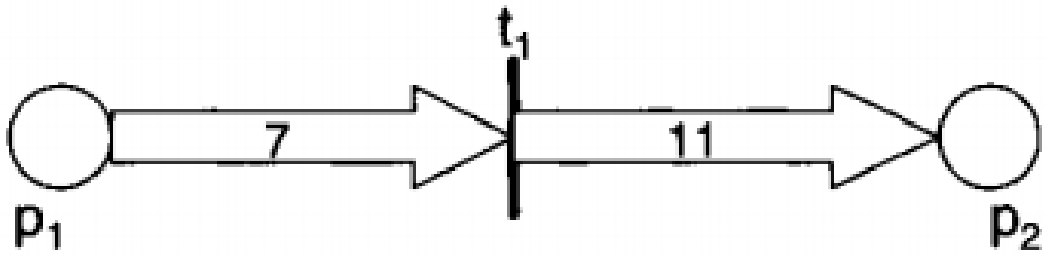
Basic notation-II

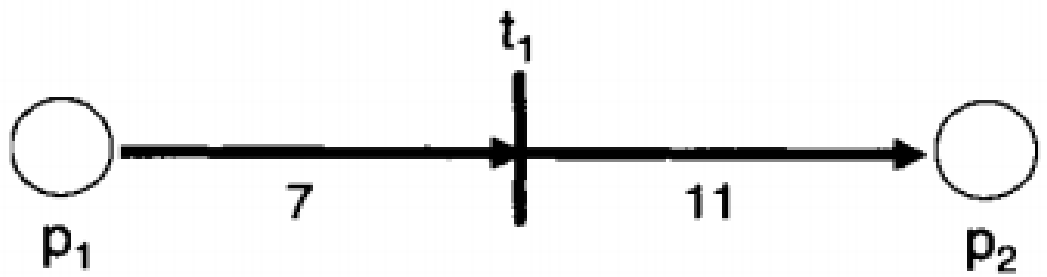
Petri Net Multigraphs

- A petri net model is also defined for Multigraphs.
- It implies there could be several arcs between a single place and a transition.
- Can be represented as:
- Multiple arc as thick arc with numbers inside.
- A bold arc with number attached to it.

Basic notation-II

Basic Petri Net Multigraphs Representation





Basic notation-II

Petri Net State

- A petri net also has a state defined by the cardinality if tokens.
- Represented as function, μ. $\mu : p \rightarrow N$
- μ can be defined as vectors.

$$\mu = (\mu_1, \mu_2, \mu_3, \ldots, \mu_n),$$

Basic notation-II

Petri Net Multigraphs

- **Where.**

$$n = |P| \text{ and each } \mu_i \in N, i = 0, \ldots, n$$

- **Place marking function and vector relation:**

$$\mu(p_i) = \mu_i.$$

- **Petri net structure:**

$$M = (P, T, I, O, \mu_t)$$

- **It represents state of petri net at time t.**

Summary

- **Here, we understood about the “Basic Notaions”.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Classical Petri Nets-I

Overview

- **Here, we will understand about the "Classical Petri Nets"?**

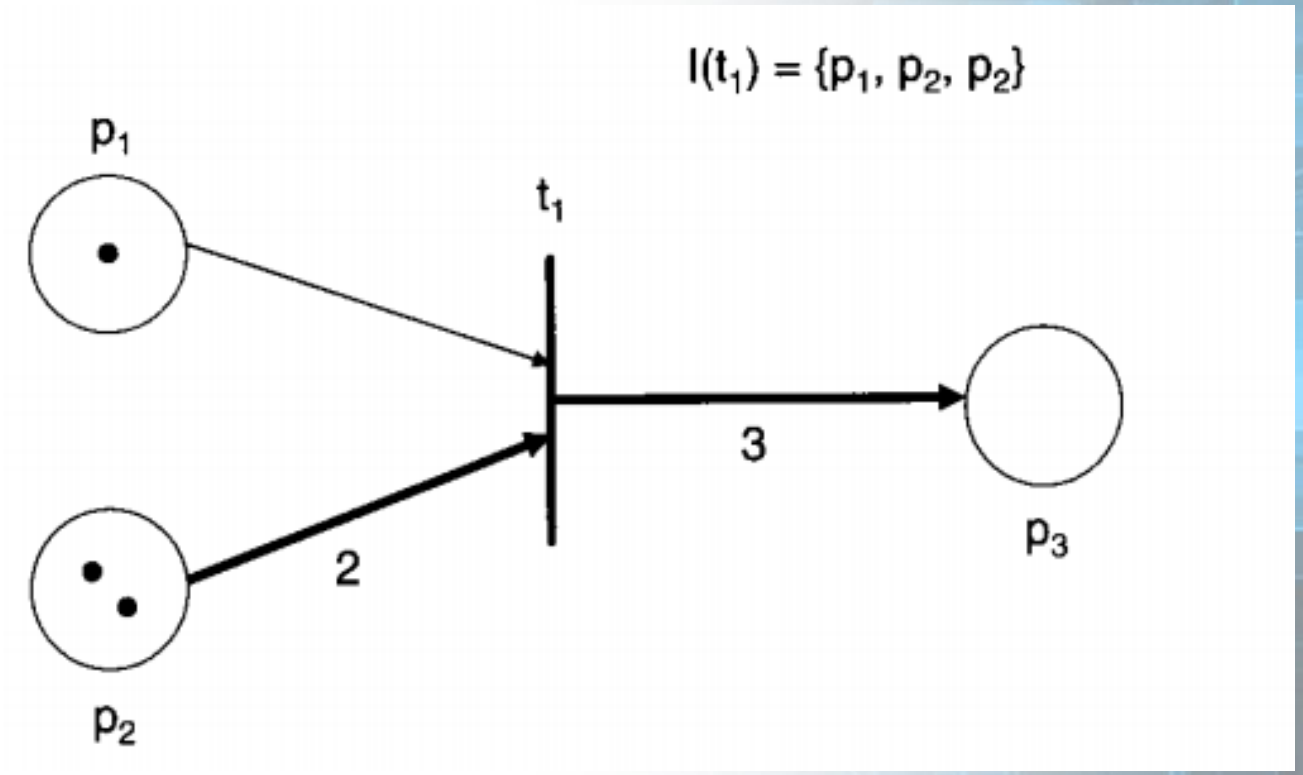
Classical Petri Nets

- By using notations Petri nets can be used in modelling.
- A new petri net state transition notation is required.
- These transitions are helpful in movements.

Classical Petri Nets

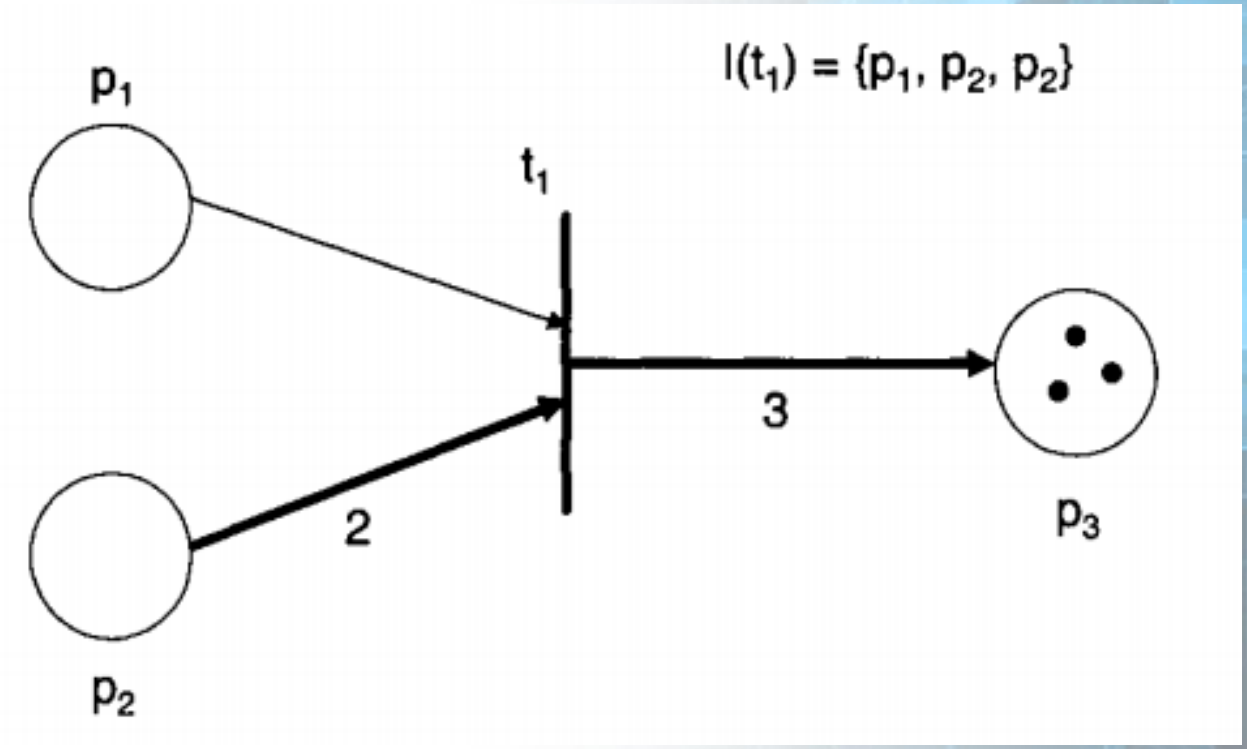
- The exact firing moment can be captured as a clock signal.
- During Clock cycle, all gates start signal execution.
- In petri net all transitions fire once during this cycle.

Classical Petri Nets



Classical Petri Nets

Forever Cycling Petri Net



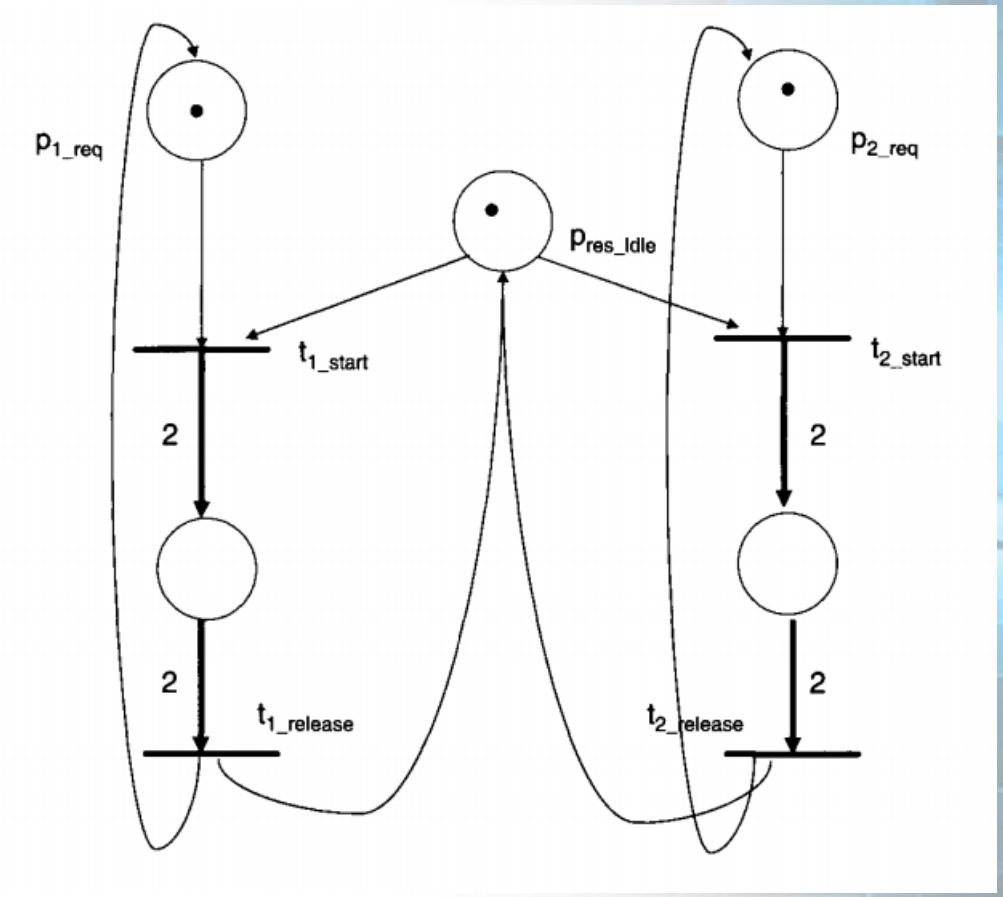
Classical Petri Nets

Petri Net Set Notaion Representation

- Petri nets enables modeling not available through queuing theory.
- Synchronization.
- Conflict.
- Concurrency.
- are not easily defined and modeled by queuing theory.

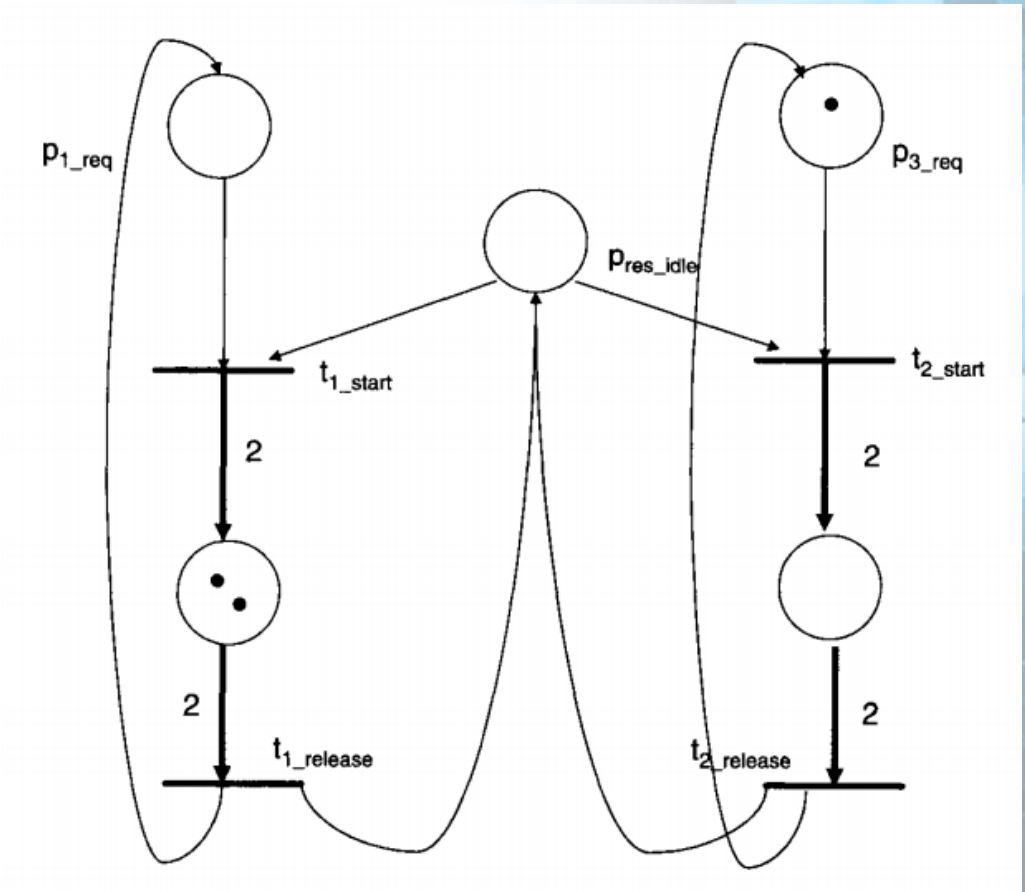
Classical Petri Nets

Resource Sharing



Classical Petri Nets

Allocated Resources



Summary

- **Here, we understood about Classical Petri Nets.**
- **Credits: Paul Frontier book.**

Modeling and Simulation

Classical Petri Nets-II

Overview

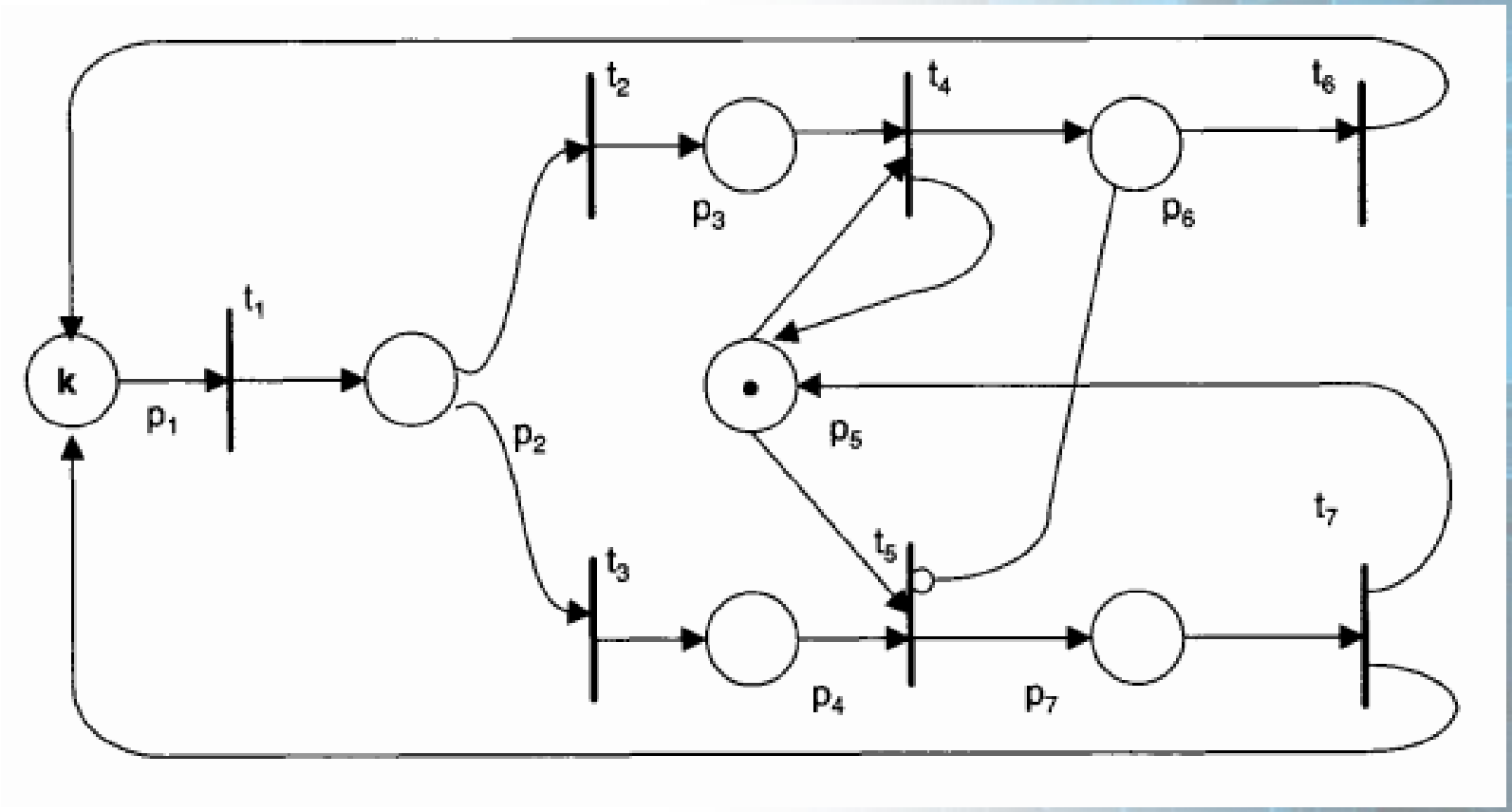
- **Here, We will understand "Classical Petri Nets".**

Classical Petri Nets-II

Classical Petri Nets

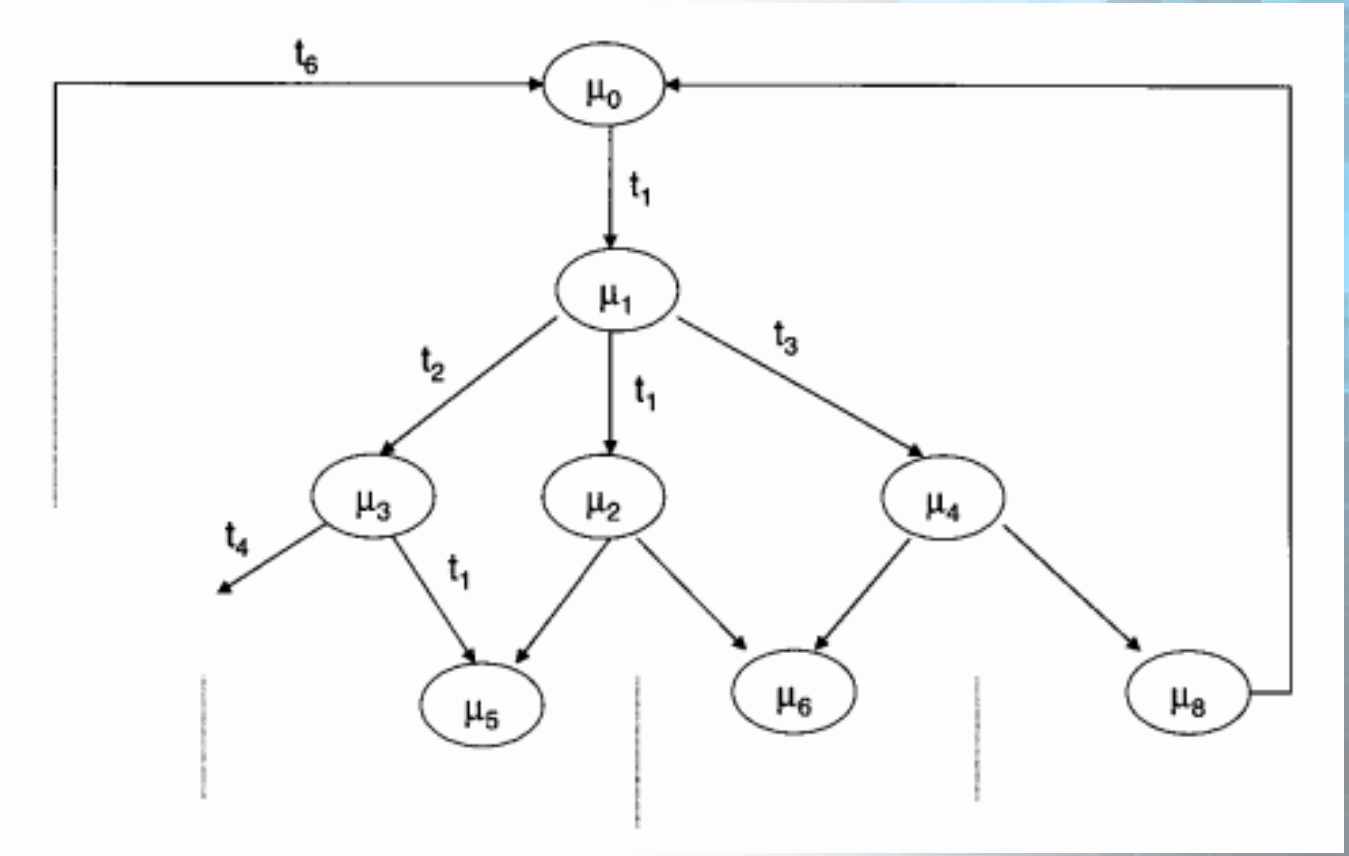
- A Petri net's state, is said to be reachable from some other state, u'.
- There exists some finite number of firings of the Petri net beginning at state u.

Classical Petri Nets-II



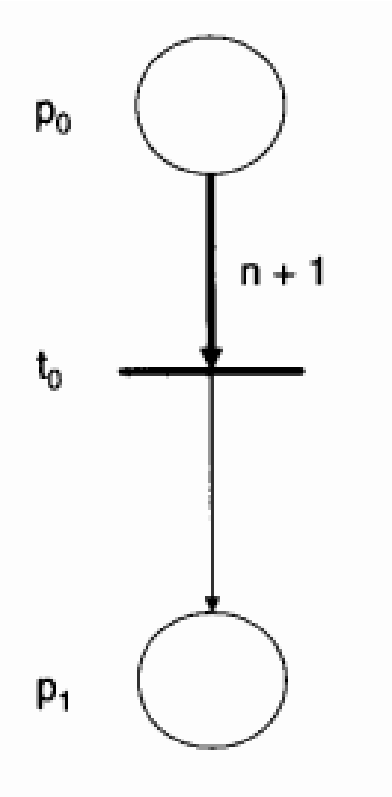
Classical Petri Nets-II

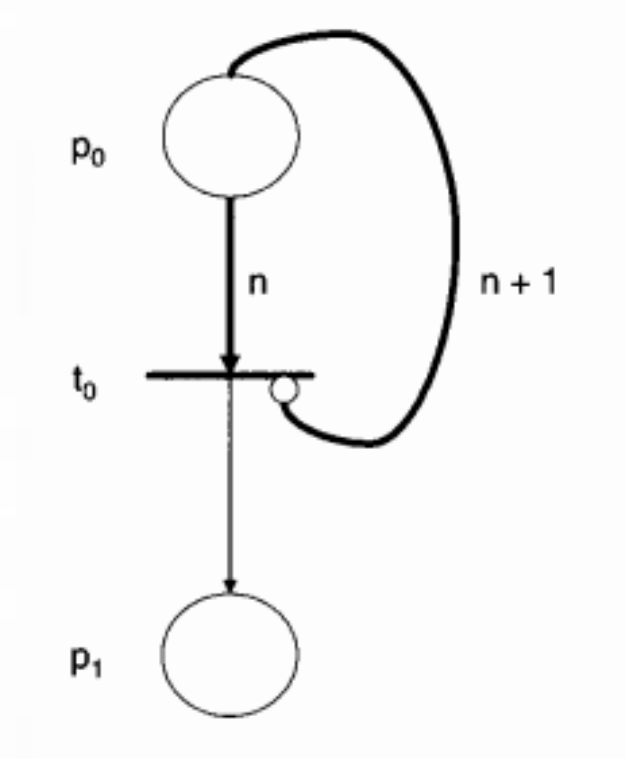
Reachability Graph



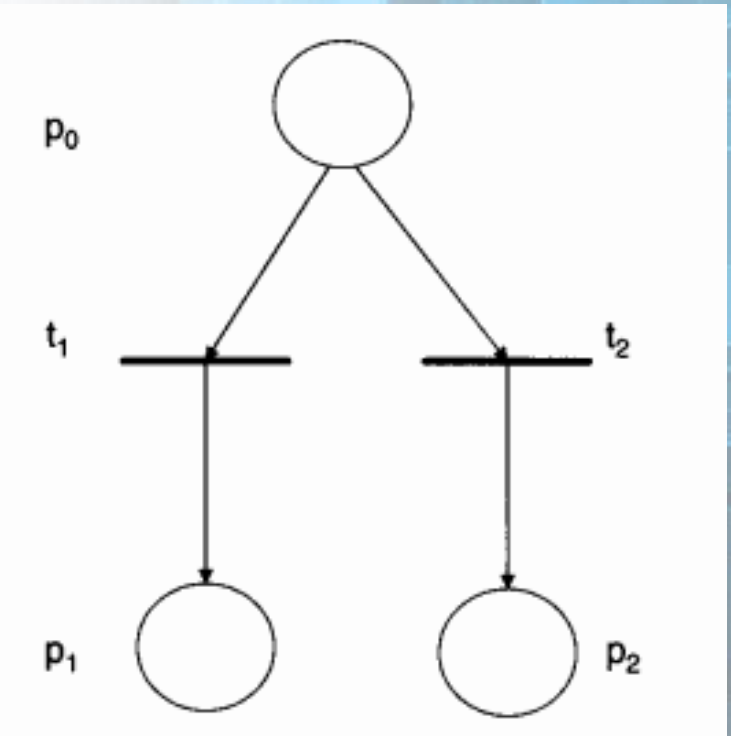
Classical Petri Nets-II

Component Test

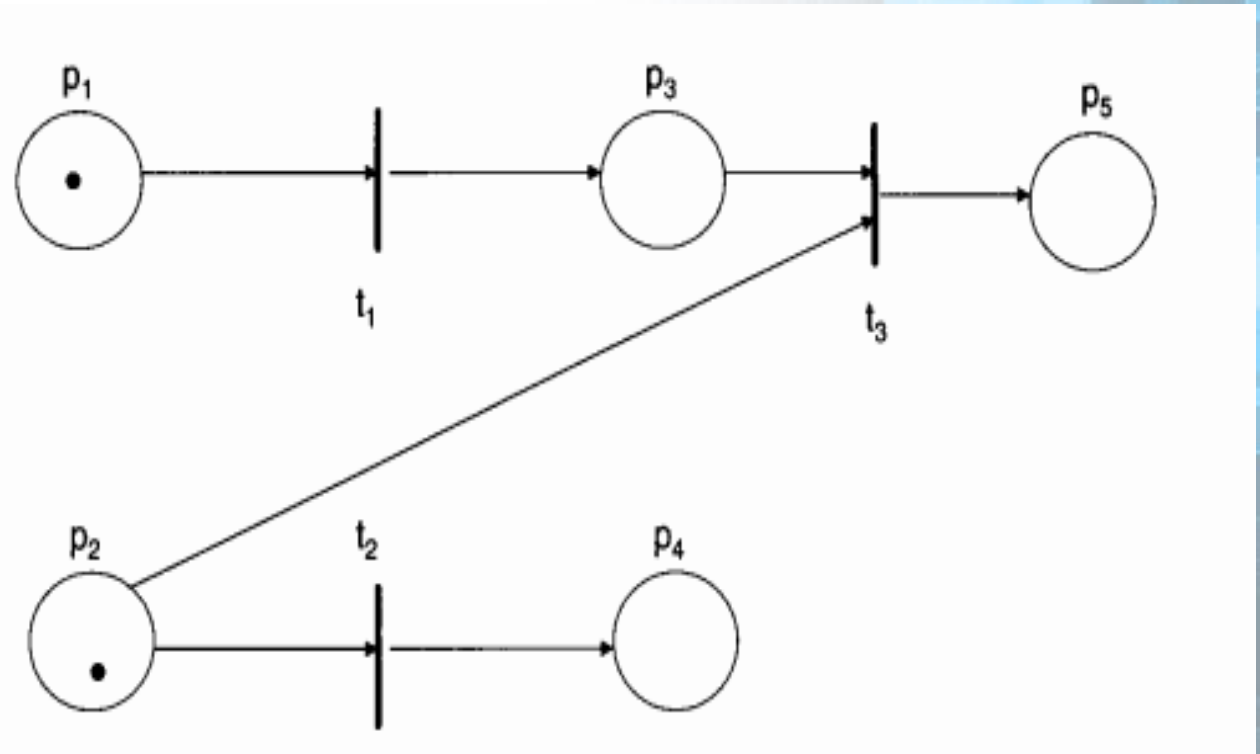




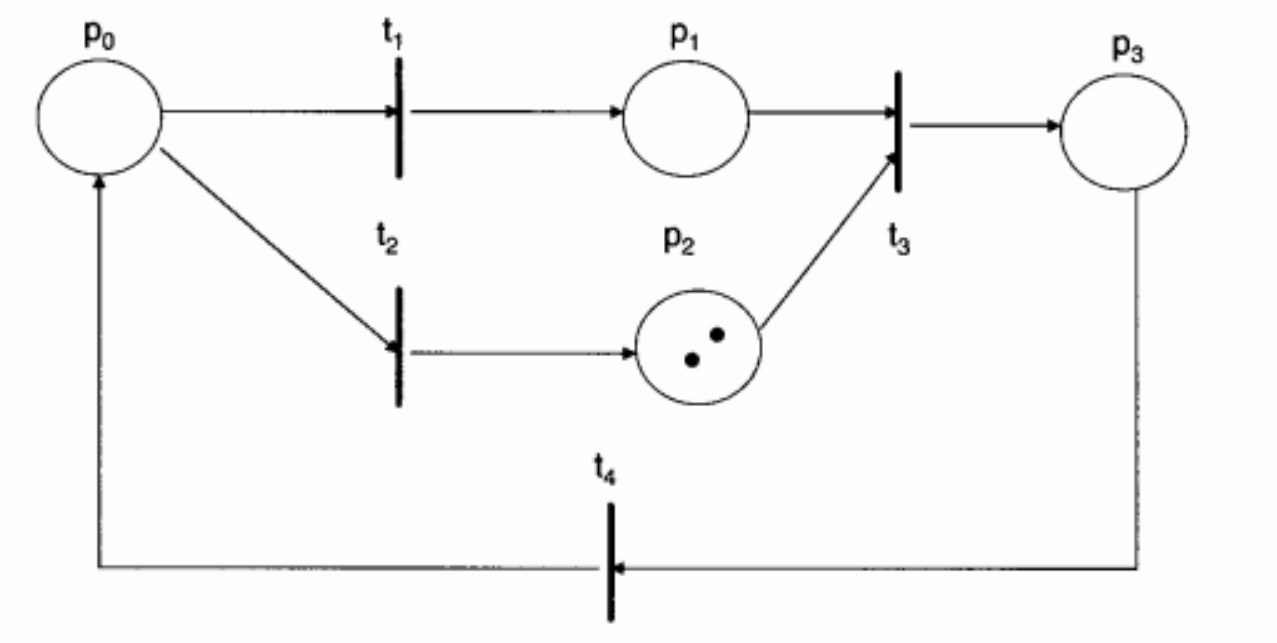
Classical Petri Nets-II



Classical Petri Nets-II



Classical Petri Nets-II



Summary

- **Here, we understood about Classical Petri Nets**
- **Credits, Paul Frontier Book.**

Modeling and Simulation

Timed Petri nets I

Overview

- **Here, we will learn about the timed petri nets.**

Timed Petri nets

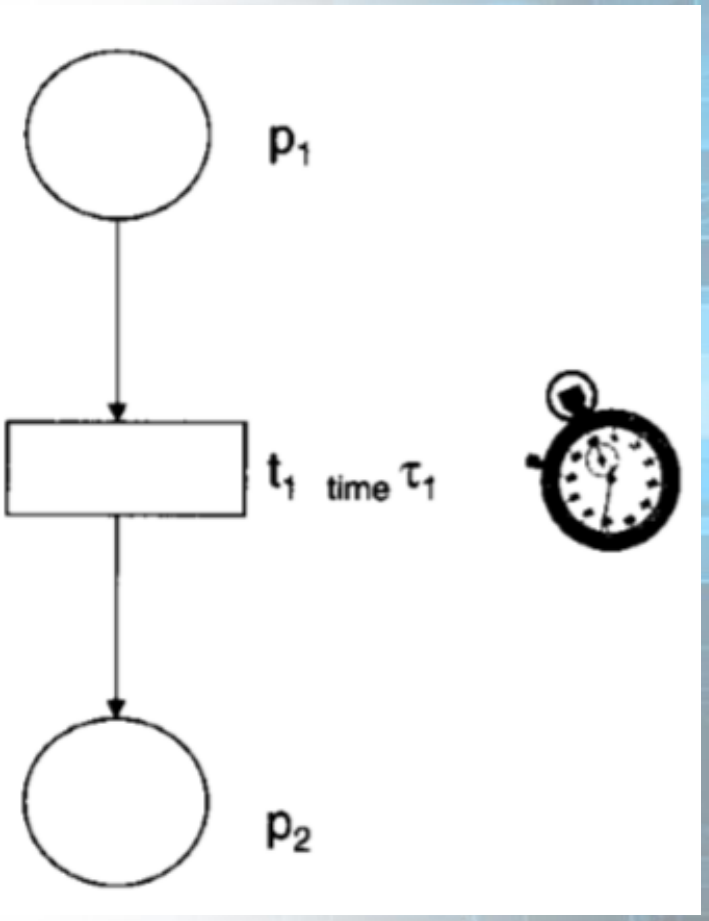
- Every action takes some time to complete.
- Time addition provides Petri net modeler another powerful tool.

Timed Petri nets

- **Time in Petri net modeling is associated with transitions.**

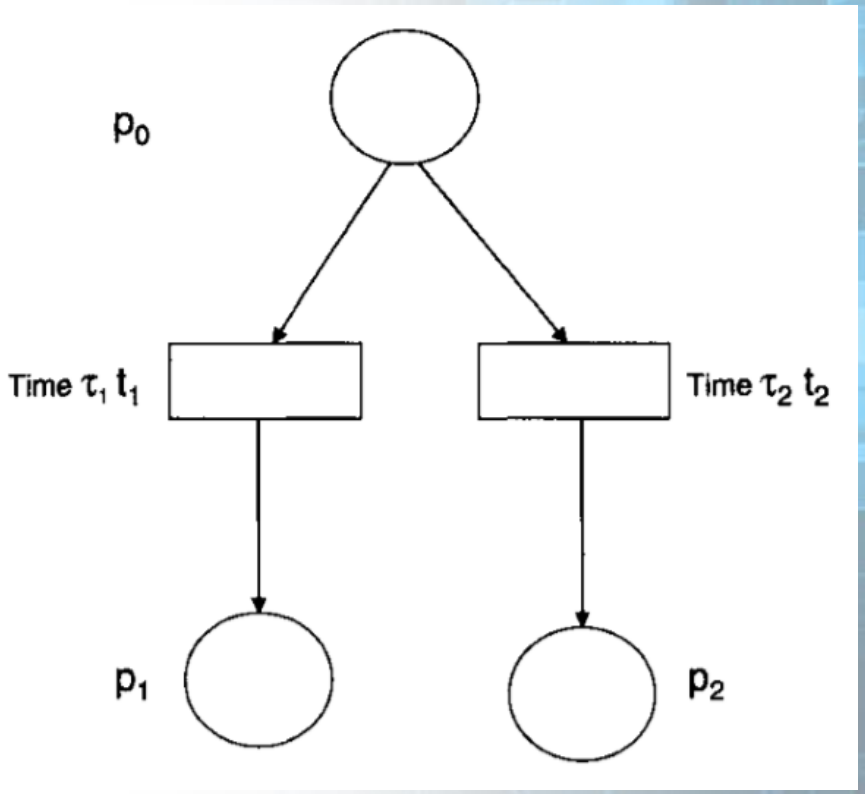
Timed Petri nets

Figure 9.23
Timed Petri net.



Timed Petri nets

Figure 9.24
Timed Petri net with conflict.



Summary

- Here, we have learnt about the two conditions of the timed Petri nets.
- Credits: Paul Fortier book.

Modeling and Simulation

Timed Petri nets II

Overview

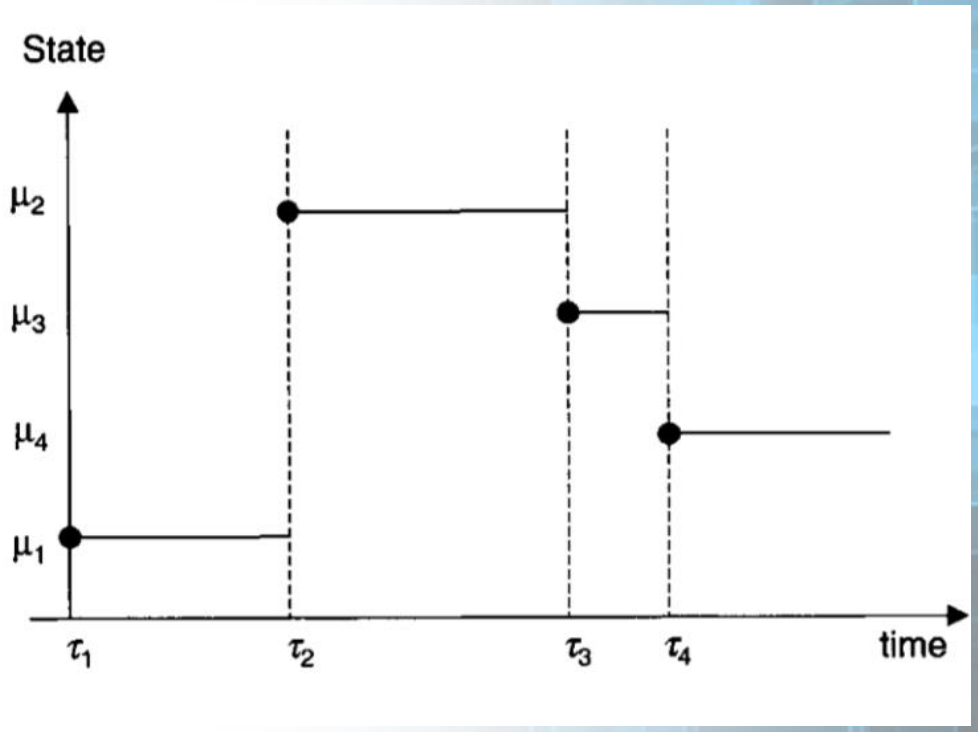
- **Here, we will learn about the timed Petri nets.**

Timed Petri nets

- Some Petri net models have proposed using state transition timing graphs.
- Each state μ is enumerated.
- Time period is set for each state in sequence.

Timed Petri nets

Figure 9.25
State transition timing graph.

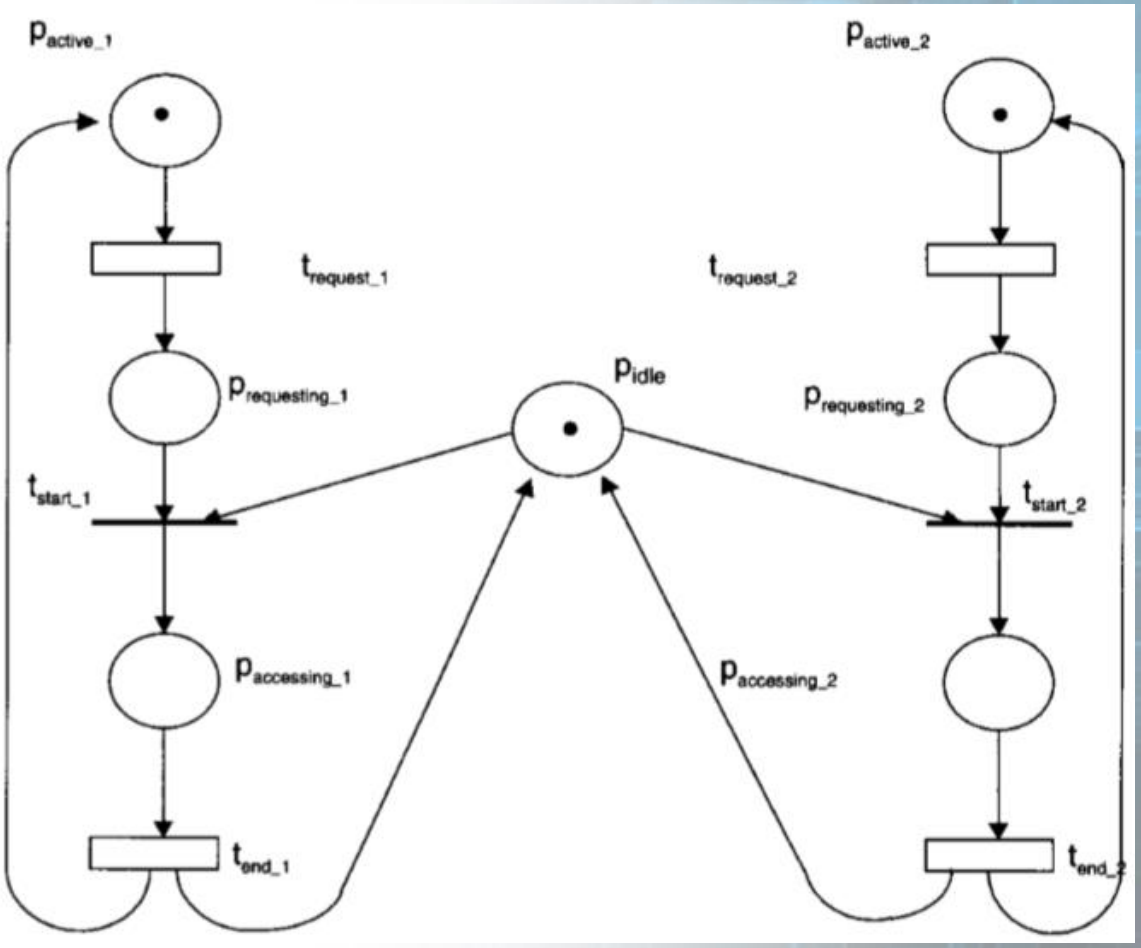


Timed Petri nets

- **Time units can be represented using time transition sequences.**
- $[(\boldsymbol{\tau_1}, \mathbf{t_2}); (\boldsymbol{\tau_2}, \boldsymbol{t_2}); \ldots; (\boldsymbol{\tau_j}, \boldsymbol{t_j}); \ldots]$

Timed Petri nets

Figure 9.26
Timed Petri net with immediate transitions.



Summary

- **We have learnt about the timed Petri nets.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Priority-based Petri nets

Overview

- **Here, we will learn about the Priority-based Petri nets.**

Priority-based Petri nets

- **The Petri net is described by nine tuple.**

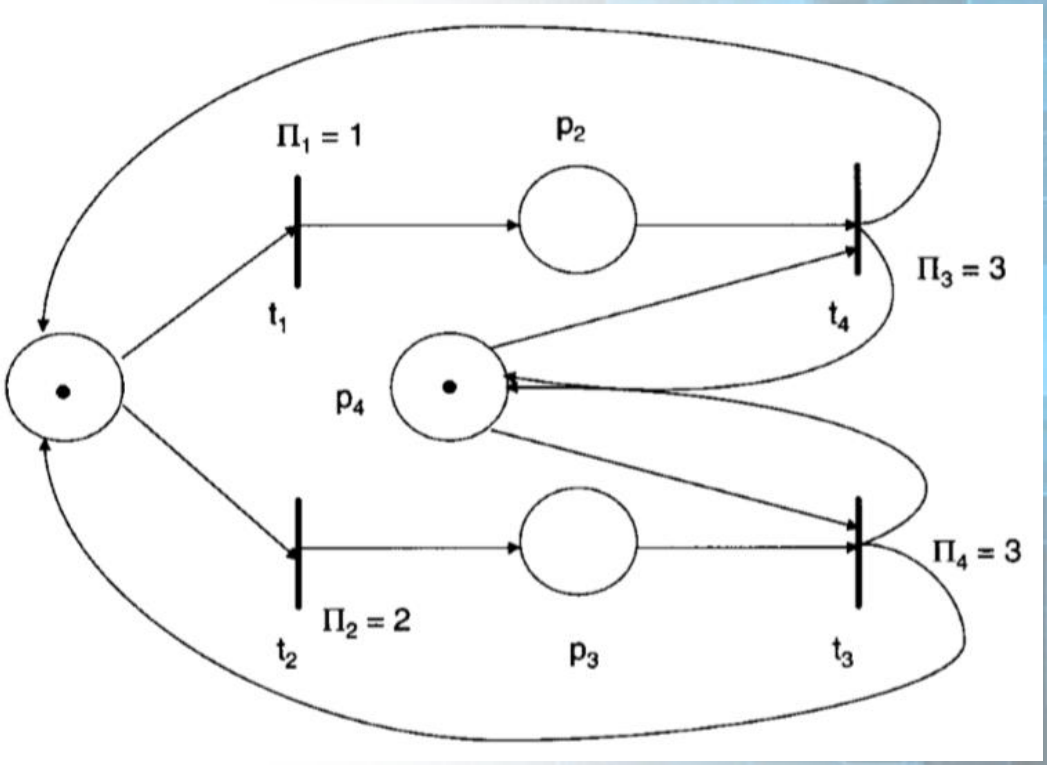
- $$\boldsymbol{M} = \left(\begin{matrix}\boldsymbol{P}, \boldsymbol{T}, \boldsymbol{I}, \boldsymbol{O}, \boldsymbol{H}, \boldsymbol{\Pi}, \mathbf{PAR}, \\ \boldsymbol{Pred}, \boldsymbol{\mu}\end{matrix}\right)$$

Priority-based Petri nets

- **Petri nets are enabled with right amount of tokens.**
- **No additional transitions area enabled.**

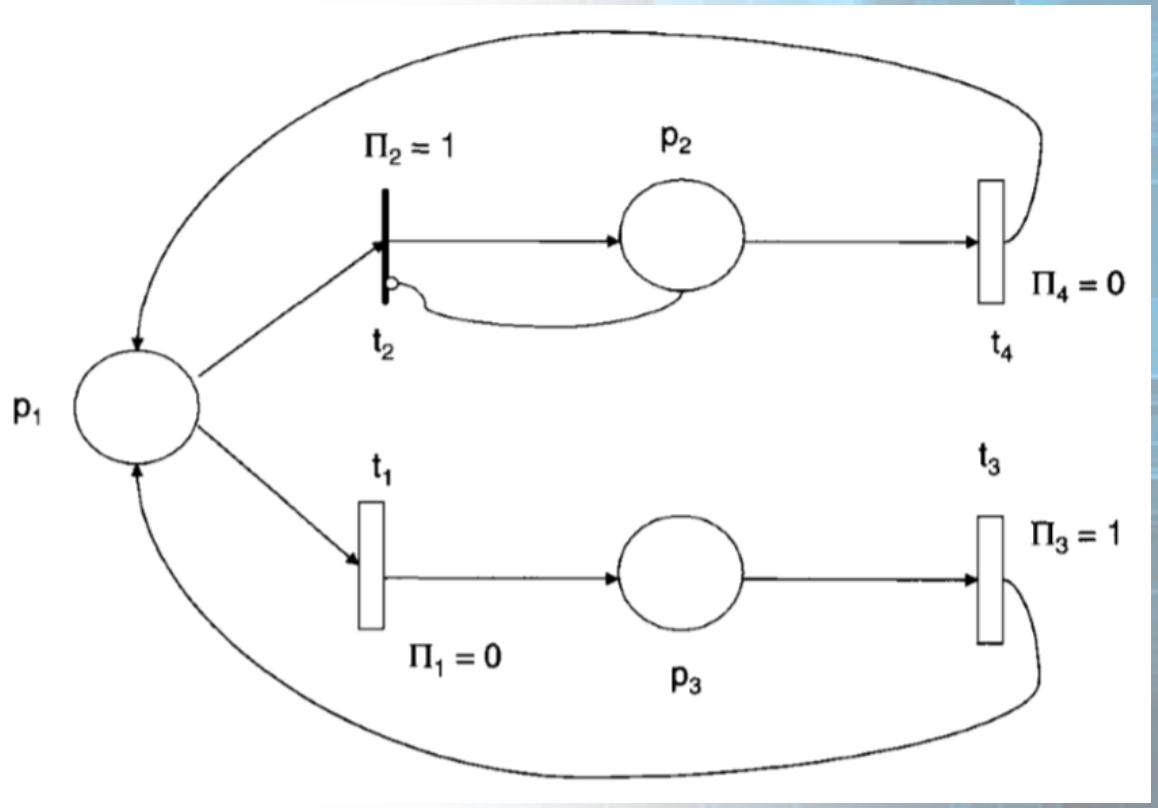
Priority-based Petri nets

Figure 9.27
Priority-based Petri net.



Priority-based Petri nets

Figure 9.28
Timed and priority net.



Summary

- We have learnt about the priority-based Petri nets.
- Credits: Paul Fortier book.

Modeling and Simulation

Colored Petri nets

Overview

- **Here, we will learn about the colored Petri nets.**

Colored Petri nets

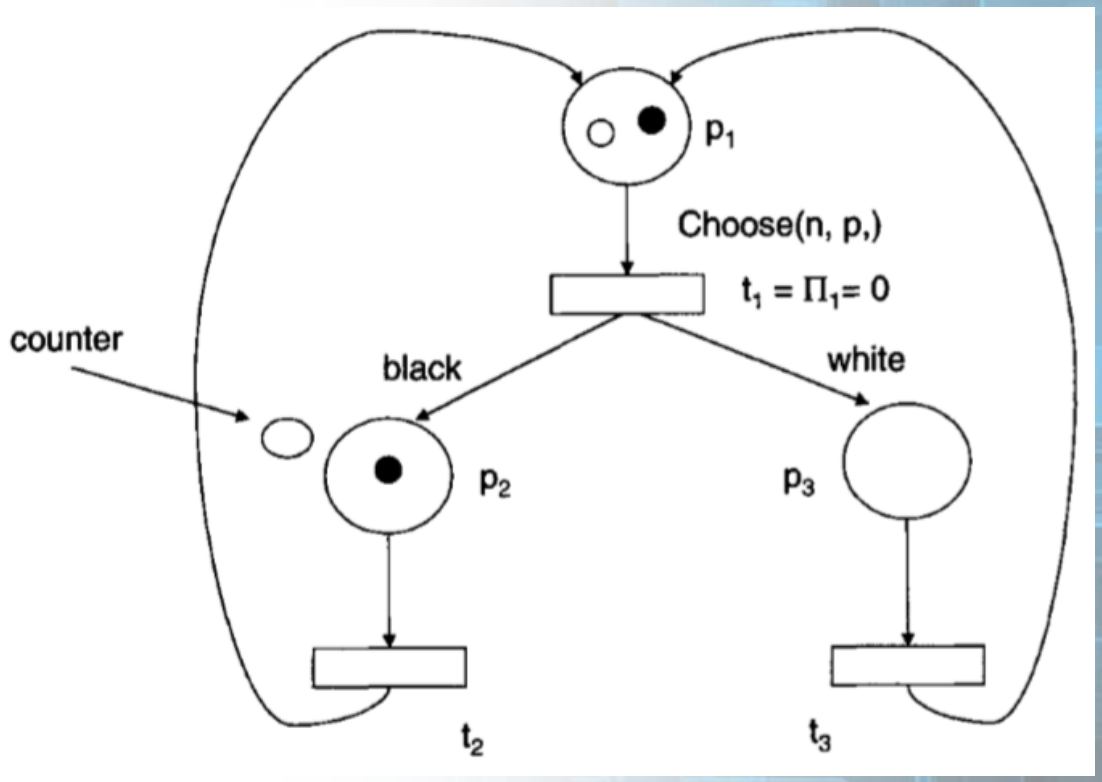
- **Different token types.**
- **Colored tokens are used to represent graphically.**

Colored Petri nets

- Cardinality of the token is represented by all colors.
- All definitions of petri nets can be redefined now.
- And firing rules.

Colored Petri nets

Figure 9.29
Generalized Petri net.



Colored Petri nets

- **We can model about any complex condition in systems.**

Summary

- **We have learnt about the colored Petri nets.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Generalized Petri nets

Overview

- **Here, we will learn about the Generalized Petri nets .**

Generalized Petri nets

- **Rate or weight transition function.**
- $W(t_k \mu)$ **must be defined.**
- $W(t_k)$ **can refer to this when function needs no definition.**
- **This is rate of transition.**

Generalized Petri nets

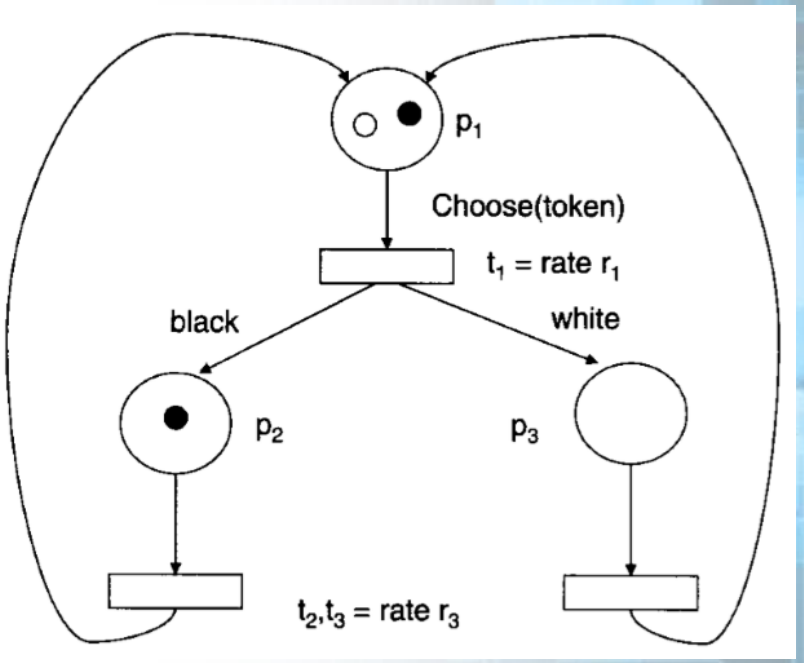
- To compute time to fire transition an exponential function is used.
- Rate must be define.
- Computed timer value is decremented until 0.

Generalized Petri nets

- **System state changes from one state to another.**

Generalized Petri nets

Figure 9.30
Generalized Petri Net.



Generalized Petri nets

- **Each state will not be computed at the same time.**

Generalized Petri nets

- **We have learnt about the generalized Petri nets.**
- **Credits: Paul Fortier book.**

Modeling and Simulation

Formal Spec. Using Z

Overview

- **Here, we will understand about formal specification using Z**

Formal Spec. Using Z

- **Recently, software performance measures such as the possible utilization factors have begun to be interesting for metrics as well as the hardware products.**

Formal Spec. Using Z

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Formal Spec. Using Z

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Formal Spec. Using Z

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Formal Spec. Using Z

- **Recently, software performance measures such as the possible utilization factors have begun to be interesting for metrics as well as the hardware products.**

Summary

- **We have learnt about formal specification using Zed.**
- **Credits: Online.**