

System Dynamics for Complex Adaptive Systems

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Outline

- Complex Adaptive Systems
- Modeling paradigms
 - System Dynamics
 - Population Growth
 - Epidemiology
 - Agent-based Modeling
 - Strengths/weaknesses of each
- Embedded (Hybrid) Models

Complex Adaptive Systems

“The whole is not only more than but very different than the sum of its parts.”

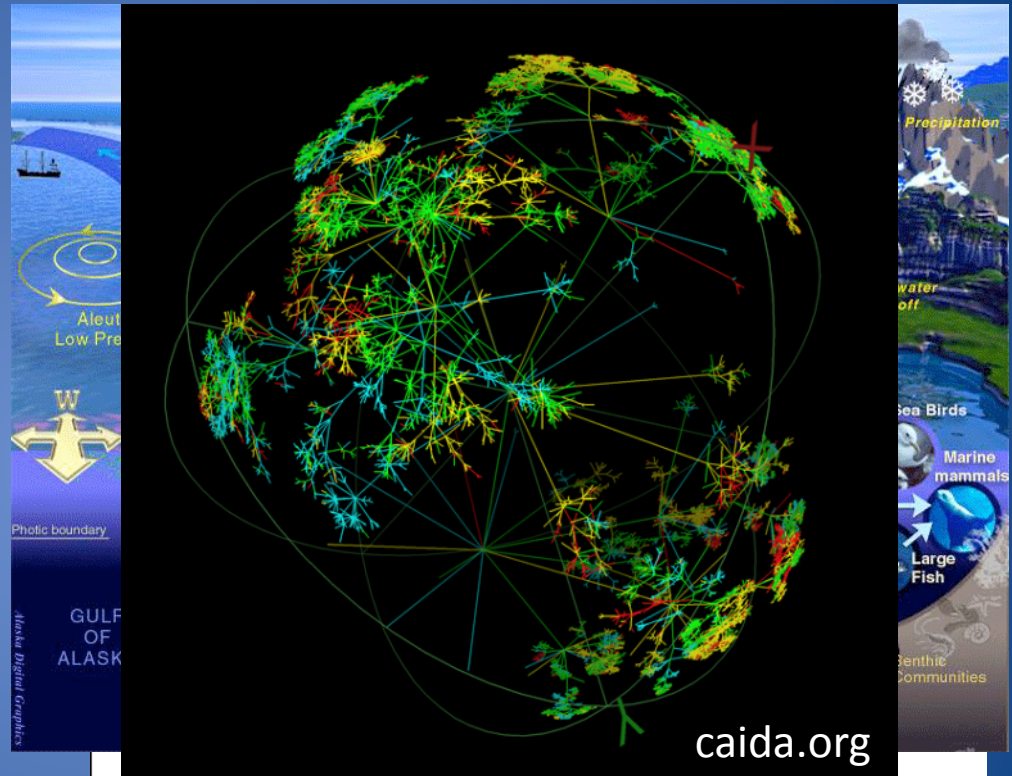
(Anderson, Phil W. 1972. “More is Different.” *Science* 177: 393-96)

- **Dynamic** network of many agents (e.g. cells, species, individuals, firms, nations) acting in parallel, constantly acting and reacting to what the other agents are doing
- **Control** of CAS is dispersed, decentralized
- **Emergent** behaviors (e.g. equilibria, patterns) arise from competition and cooperation among agents

System behavior is unpredictable and the result of decisions made every moment by many individual agents

Complex Adaptive Systems

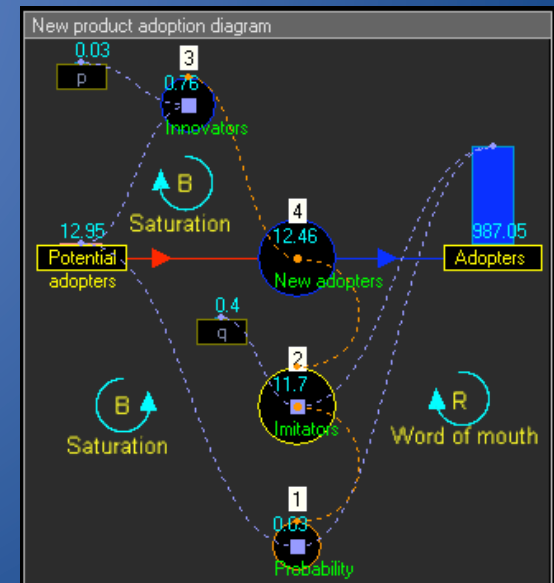
- **Examples:**
 - Energy grids
 - Ecosystems
 - Social diffusion
 - Disease dynamics
 - Politics
 - Supply chain networks
 - Etc.



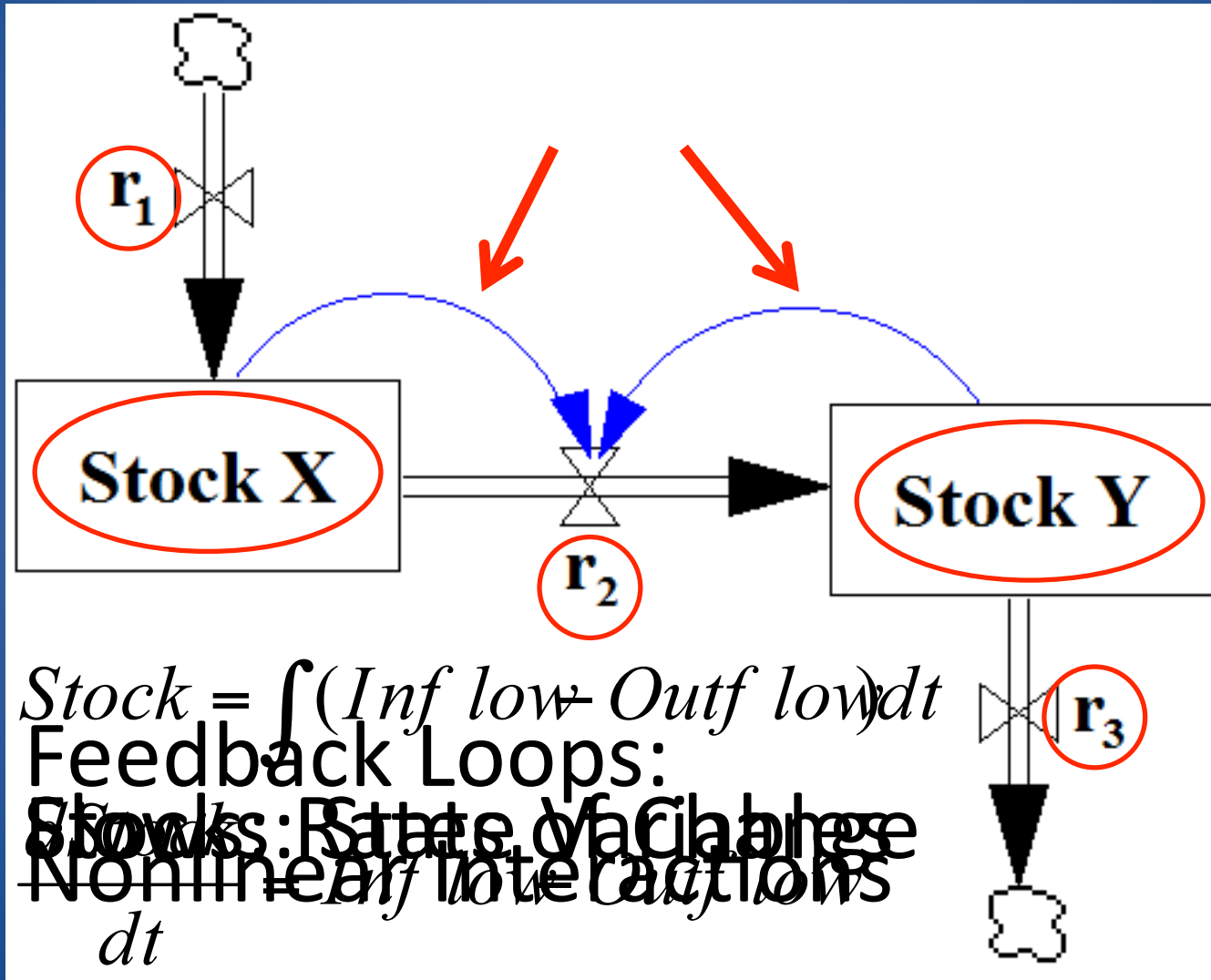
Computational Sustainability to model the **Complex Adaptive Systems** of our world in the hopes of guiding them toward **long-term, sustainable outcomes**

Modeling CAS

- Two basic approaches:
 - Top-down: System Dynamics
 - ODEs, Stock and Flow Diagrams
 - Bottom-up: Agent-based Modeling
 - Cellular Automata, Intelligent Agents



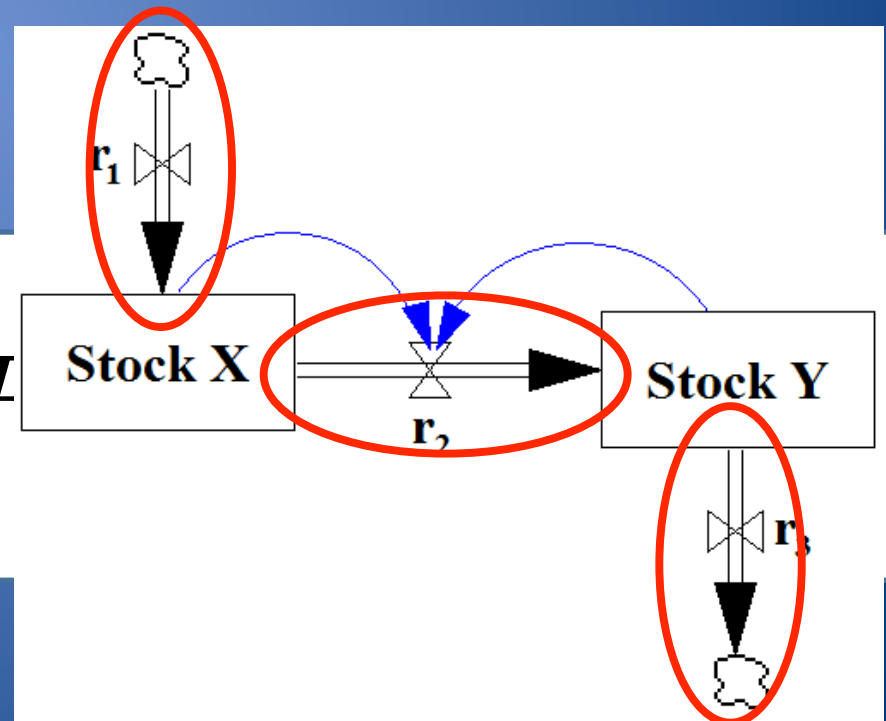
System Dynamics



System Dynamics

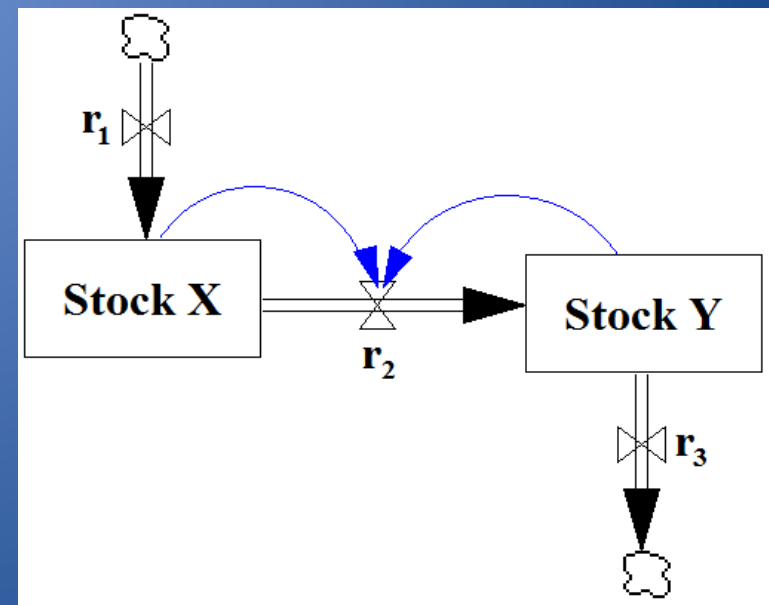
- Flows can be of three types:
 - Generative (F_{gen})
 - Stock-to-Stock (F_{in} , F_{out})
 - Destructive (F_{des})

$$\frac{dStock}{dt} = (F_{gen} + F_{in} - F_{out} - F_{des})$$



System Dynamics

- Discrete systems:
 - Stocks: homogenous groups of well-mixed agents
 - Flows: movement of agents between groups
 - Feedback Loops: nonlinear interactions and effects
 - $r_2 = f(X,Y)$



System Dynamics

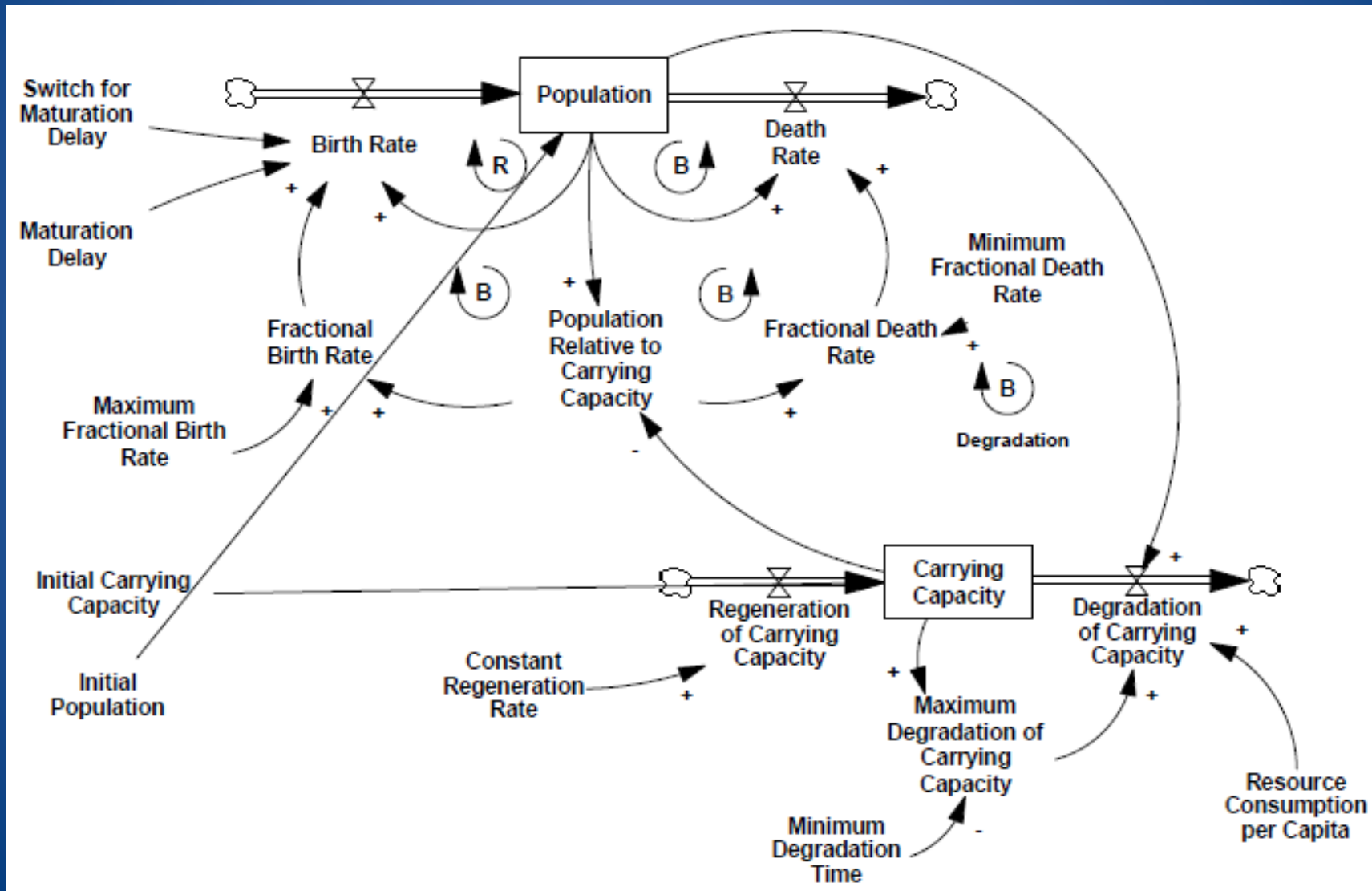
- Example 1: Population Growth

$$\frac{dP}{dt} = rP \left(1 - \frac{P}{K} \right)$$

- P – population size at time t
- r – growth rate
- K – habitat carrying capacity

- Exponential growth when population is small
- Exponential decay when population above K

Population Growth



System Dynamics

- Example 2: Infectious Disease

$$\frac{dS}{dt} = -\beta SI$$

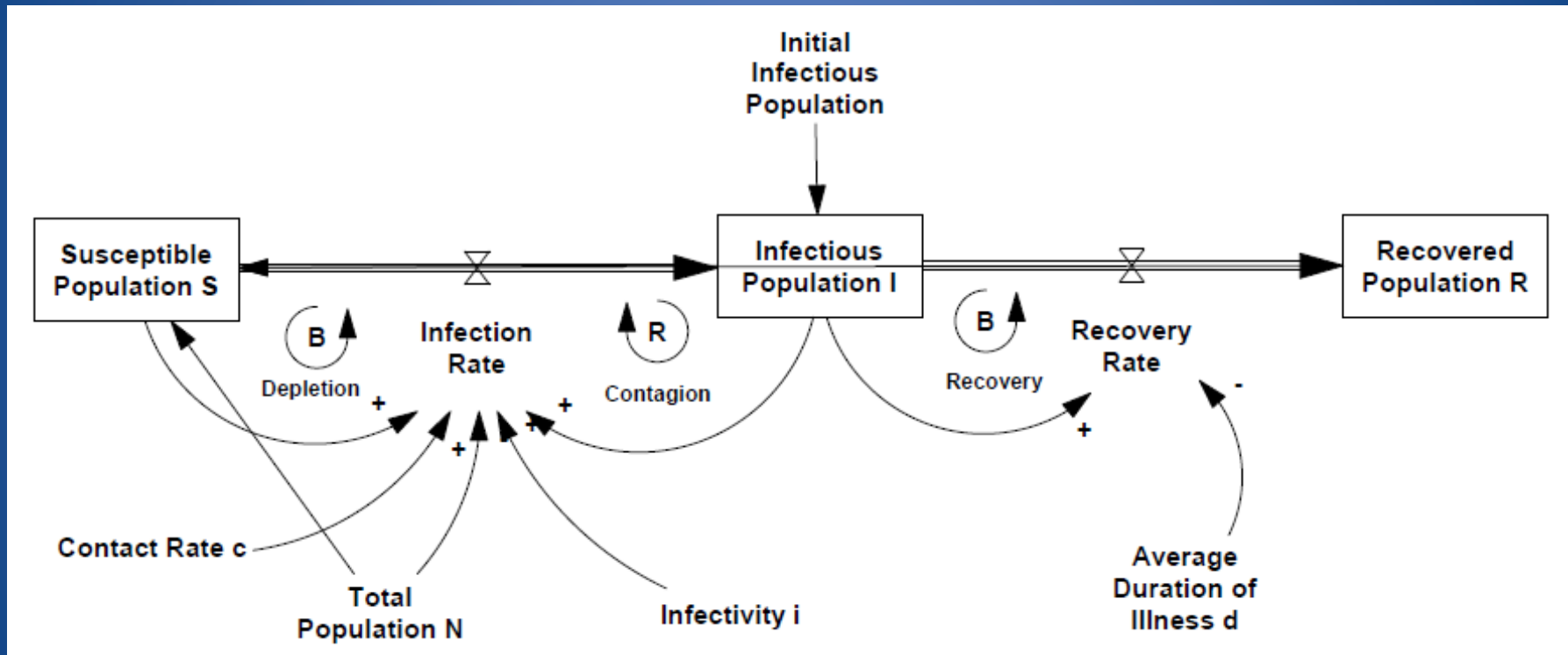
$$\frac{dI}{dt} = \beta SI - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

- S – Susceptible population
- I – Infectious population
- R – Recovered population

- β – Transmission rate
- γ – Recovery rate

Infectious Disease



System Dynamics

- Simulation
 - For most systems of ODEs, analytical solutions do not exist
 - Continuous stock (e.g. money in savings): use numerical methods to approximate solution
 - Discrete stock (e.g. people): use stochastic simulation methods

Stochastic Simulation of ODEs

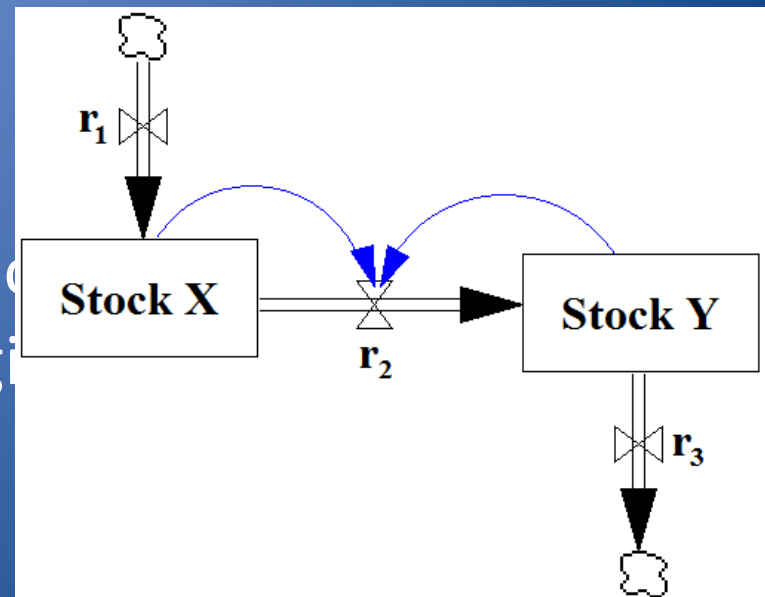
- Assumption: Future state of system depends only on present state, independent of history

→ Continuous Time Markov Chain!

- Time between events Exponentially distributed
- Event occurrences in $[t, t+\Delta t)$ Poisson distributed

Stochastic Simulation of ODEs

- ODEs as CTMCs
 - Flows are interpreted as transition probabilities per unit time
 - Events:
 - $\{X \rightarrow X+1\} \sim \text{Pois}(r_1\Delta t)$
 - $\{(X,Y) \rightarrow (X-1,Y+1)\} \sim \text{Pois}(r_2\Delta t)$
 - $\{Y \rightarrow Y-1\} \sim \text{Pois}(r_3\Delta t)$
 - For Δt small, probability of multiple events per time step is $o(\Delta t^2)$, negligible



Stochastic Simulation of ODEs

Algorithm 1 τ -leap Method

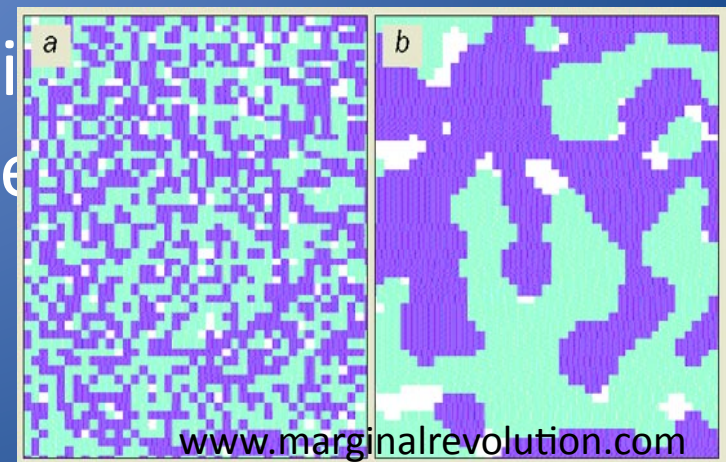
```
while  $Time < MaxTime$  do  
  for all event types  $i$  do  
     $\Delta E_i \leftarrow Poisson(r_i \Delta t)$   
  end for  
  Update size of each stock based on which transition  
  events occur.  
  Randomly select  $\Delta E_i$  agents uniformly from the appro-  
  priate stock and transition according to event  $E_i$ .  
   $Time \leftarrow Time + \Delta t$   
end while
```

System Dynamics

- Strengths:
 - Easy model construction and validation with available data
 - Simulation methods computationally efficient
- Weaknesses:
 - Assumes homogenous and well-mixed population
 - Captures only average behavior
 - Assumes mathematical equations capture all feedback structure in system
 - Assumes macro-level behavior is independent of micro-level behavior
 - Difficult to model certain interventions (actions by outsiders) that influence flows in the model

Agent-Based Modeling

- System modeled as population of heterogeneous agents with evolving state space (e.g. Schelling Segregation Model)
- Agent interactions can cause complex emergent behavior to arise
- Object-oriented programming representing interacting agents

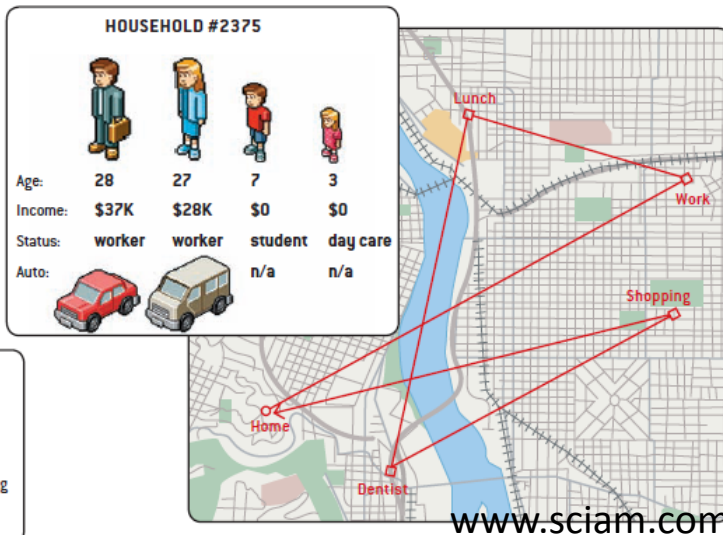


Agent-Based Modeling

- Example: EpiSims
 - Highly detailed
 - Virtual laboratory

SYNTHETIC HOUSEHOLDS

The U.S. Census Bureau provided demographic information, such as age, household composition and income, for the entire city as well as 5 percent of its complete records for smaller study areas of a few square blocks. Through a statistical technique called iterative proportional fitting, these two data sets were combined to create households and individuals with statistically correct demographics and geographic distribution.

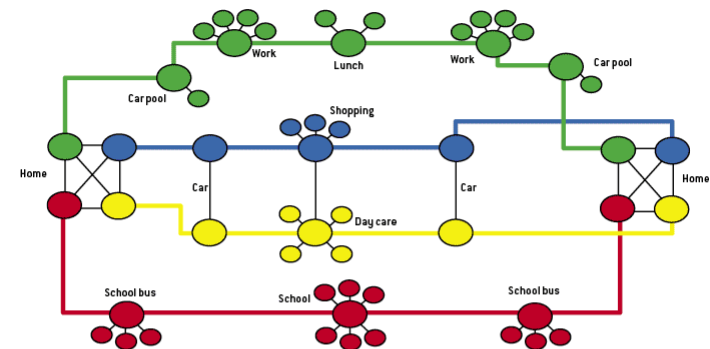


BUILDING SOCIAL NETWORKS

TYPICAL HOUSEHOLD'S CONTACTS

Constructing a social network for a household of two adults and two children starts by identifying their contacts with other people throughout a typical day.

This diagram shows where the household members go and what they do all day but reveals little about how their individual contacts might be interconnected or connected to others.

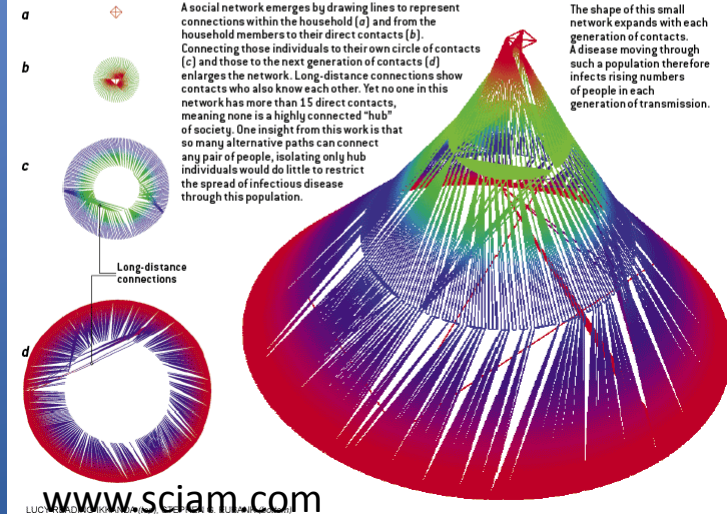


LOCAL SOCIAL NETWORK

A social network emerges by drawing lines to represent connections within the household (a) and from the household members to their direct contacts (b). Connecting those individuals to their own circle of contacts (c) enlarges the network. Long-distance connections show contacts who also know each other. Yet no one in this network has more than 15 direct contacts, meaning none is a highly connected "hub" of society. One insight from this work is that so many alternative paths can connect any pair of people, isolating only hub individuals would do little to restrict the spread of infectious disease through this population.

EXPANDER GRAPH

The shape of this small network expands with each generation of contacts. A disease moving through such a population therefore infects thousands of people in each generation of transmission.



Agent-Based Modeling

- Strengths:
 - Allows sophisticated interactions between agents with heterogeneous state space (e.g. contact network)
 - Yields greater and more intuitive information that can be used by researchers and policymakers
 - More “lifelike” than system dynamics models
- Weaknesses:
 - larger state space means poor computational efficiency
 - Model construction is difficult: hard to link observed behavior to local interactions, capture all critical feedback loops
 - Model calibration, validation, and sensitivity analysis require large amounts of data and time

Embedded (Hybrid) Models

- A complete agent-based model need not be fitted, but individual-level granularity in the model is maintained and heterogeneity in agents can be exploited
- Allows for simulation of novel, complex intervention strategies at the level of agents that might otherwise be difficult or impossible to express succinctly in system dynamics terminology