
Co-evolving Complex Networks: Epidemics in Social and Wireless Networks

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These slides are a slightly extended version of the invited presentation given on March 02 2009 at Miami USA. A few additional slides are included to make the talk more self contained. Additionally, the last few slides contain a list of references that readers might find useful.

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SIAM Annual Conf on Computational Science and Engineering (CSE'09)

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Preparing for pandemics

■ 1918 Pandemic

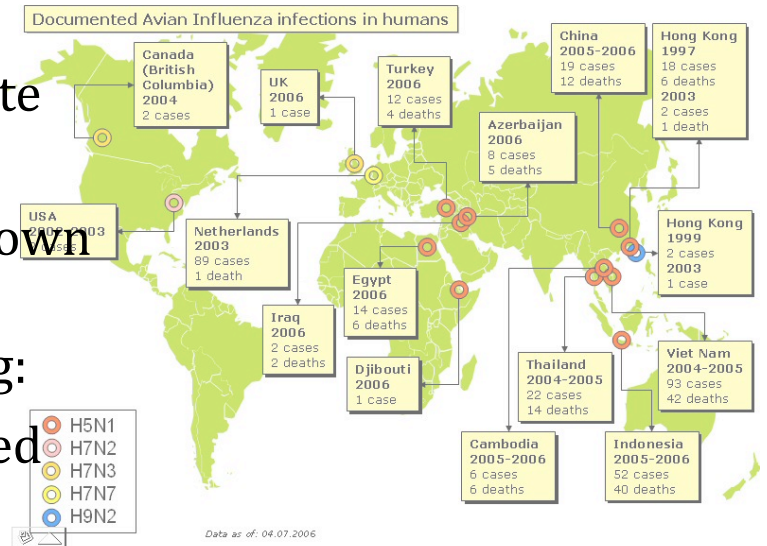
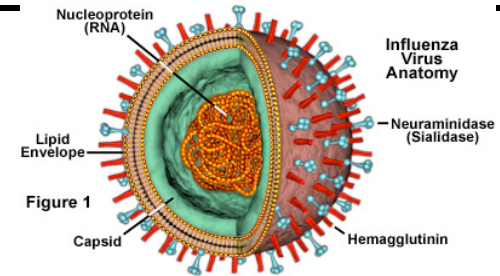
- 50 million deaths in 2 years (3-6% world pop)
- Every country and community was effected

■ Good news

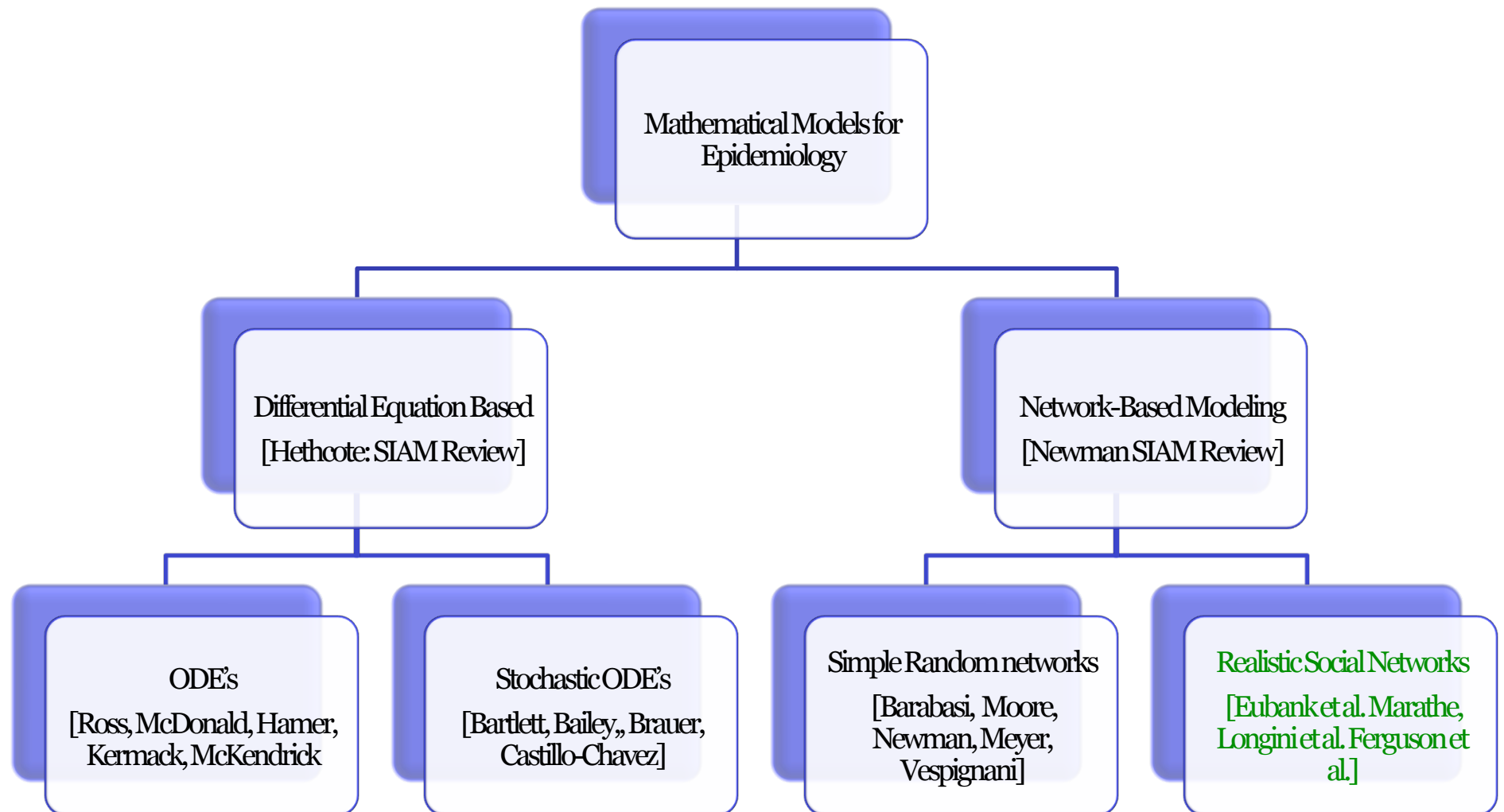
- Pandemic of 1918 lethality is currently unlikely
- Governments better prepared and coordinated : e.g. SARS epidemic

■ But ..

- Planning and responding to even a moderate outbreak is challenging:
 - inadequate vaccines/anti-virals, unknown efficacy, hard logistics issues
- Modern trends further complicate planning:
 - increased travel, immuno-compromised populations, increased urbanization



Models in Mathematical/Computational Epidemiology



Simdemics: High resolution network-based modeling

1. Create a synthetic population
 - Sampling Contingency Tables, Assignment Problems
2. Derive a social contact network G
 - Assign activities (CART Trees), locations (Gravity models), Construction and analysis of large networks
3. Create a model of disease transmission
 - Design probabilistic timed finite state automata based on data
4. Simulate disease spreads over G
 - Simulation of a diffusion process
5. Study effect of interventions: co-evolution of G , behavior, policy and disease progression
 - Markov decision processes (MDP) and n -way games

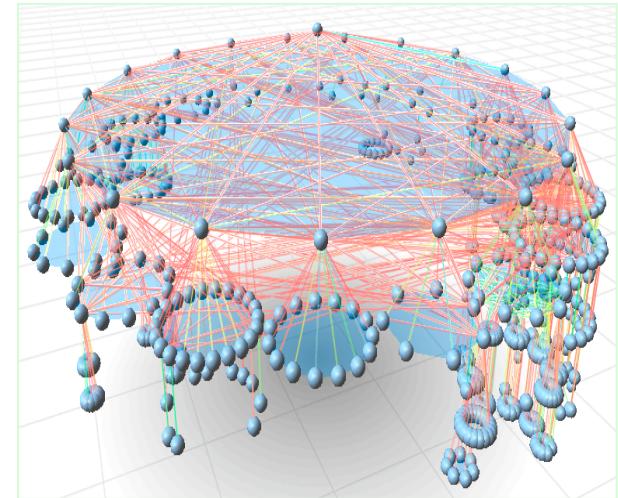
Eubank, Marathe et al. Nature'04, SODA, Scientific American, DIMACS, Longini et al. PNAS 06, Science 05, Ferguson et al. Nature 05, 06.

Practical Usefulness

- *White House Homeland Security Council for smallpox mass vaccination*
 - Do we need mass vaccination? How do we protect critical workers?
- Top-Off 2 outcome analysis
 - Socio-economic analysis of interventions
- Multi-sector disruption -- NISAC DHS Study
 - Situational awareness and coordination with multiple infrastructures
- *Federal Influenza Plan: OHS & DHHS -- NIH MIDAS project*
 - TLC: Targeted Layered Containment, Importance of Social Distancing
- *Pandemic Planning for National Guard Preparedness: DoD*
 - Impact of layered interventions for force projection: Public versus military health epidemiology
- Pandemic Preparedness for Medcom: DoD
 - Can we develop general guidelines for military populations?
- DHHS Medkit study
 - Use of markets in conjunction with public stockpiles to distribute A/V

Difficulty: Very Large Co-evolving Networks

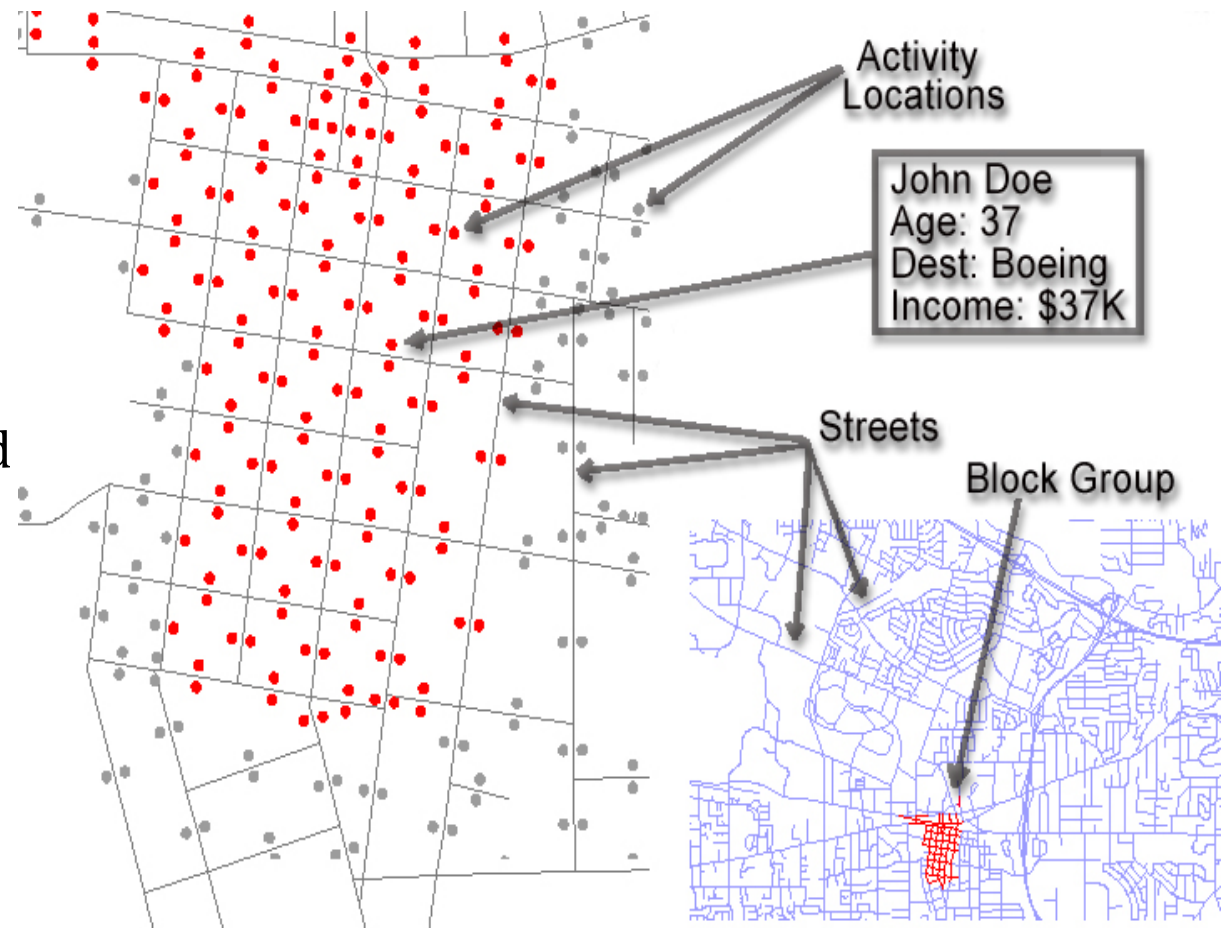
- Network has to be synthesized: Data is sparse, incommensurate
 - Need new methods for information fusion: Currently using 34 databases
- Large Complex Large Networks
 - >100GB input data: 300M people , 22Billion edges, 100M locations, 1.5B daily activities
 - Irregular Network: Dimension reduction techniques do not apply
 - Co-evolving behaviors, networks and disease spread
- Large experimental design \Rightarrow multiple configurations
 - 5000 run study not unusual



Unique challenge for researchers in HPC, Data and Network Science

Step 1: Synthetic populations

- Who, where, what, when: *People*
 - Individuals
 - Household structure
 - Statistically identical to U.S. Census
 - Assigned to Home and Activity Locations



Beckman et al. Transportation Science, NISS technical reports, Barrett et al. TRANSIMS technical reports

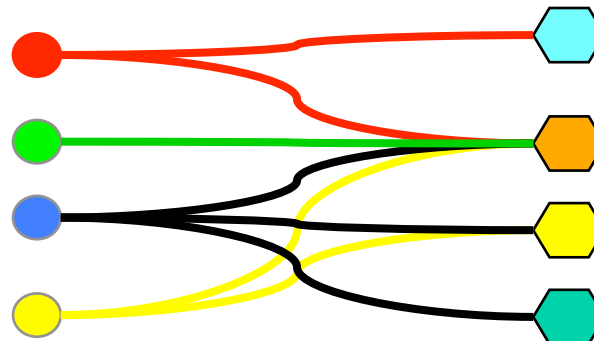
Step 2: Urban dynamic social contact network

- Demographically match schedules
- Assign appropriate locations by activity and distance
- Determine duration of interaction
- Generate social network



People Vertex:

- age
- household size
- gender
- income ..



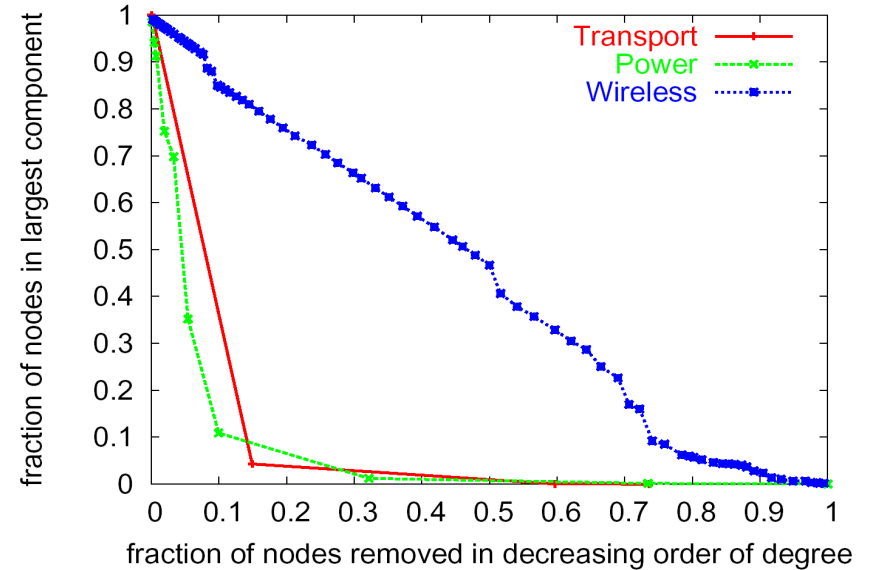
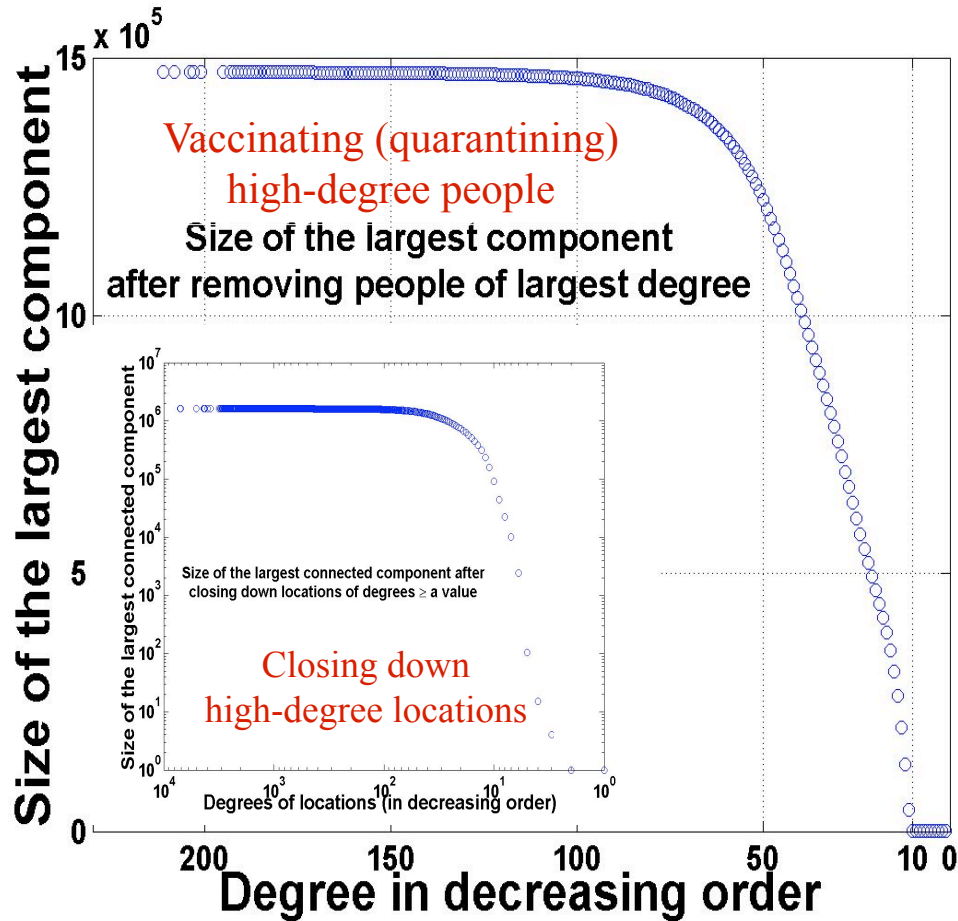
Location Vertex:

- (x,y,z)
- land use .
- Business type

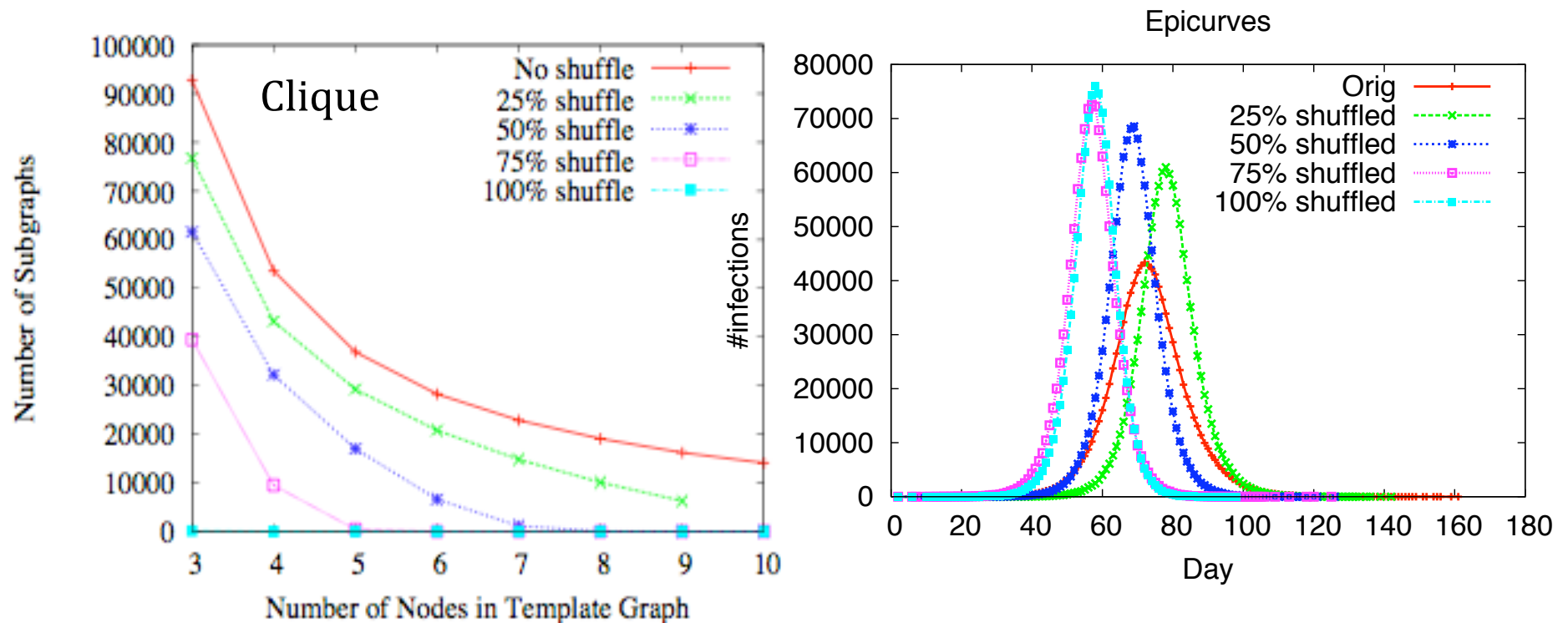
Edge labels

- activity type: shop, work, school
- (start time 1, end time 1)
- (start time 2, end time 2)

Social Contact Networks are not easy to shatter



Realistic Social Contact network differ from “simple” random networks



Portland Network:

- Cliques within same age group (0-19).
- Such new measures can *only be produced* by Simdemics like models

Research Questions: Relational Networks

- **Question 1:** Efficient algorithms for pattern matching in relational networks
 - Extracting relational structures as the network evolves due to interventions: *sparsification* (rather than densification) of the network
- **Question 2:** Models and algorithms for embedding detailed sub-networks
 - Often times one has detailed information about certain sub-networks, e.g. critical workers, --- public health versus critical worker health
 - E.g. embedding more detailed networks of schools and universities
- **Question 3:** Integrating new information to improve the quality of synthetic networks
 - Cell-phone based movement data

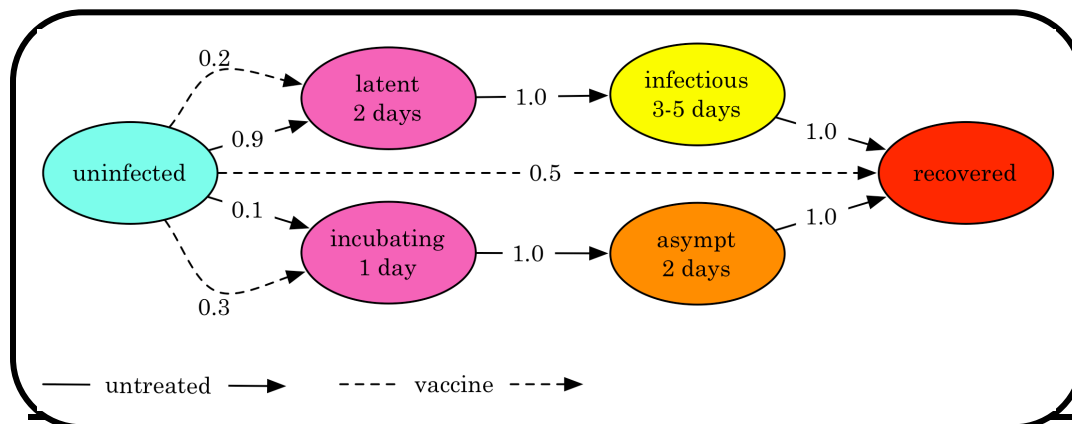
Step 3. Within Host Disease Models



Disease can be spread from one person to another.

The probability of transmission can depend on:

- type of disease
- duration and type of contact
- person's characteristics
 - age, health state, etc.

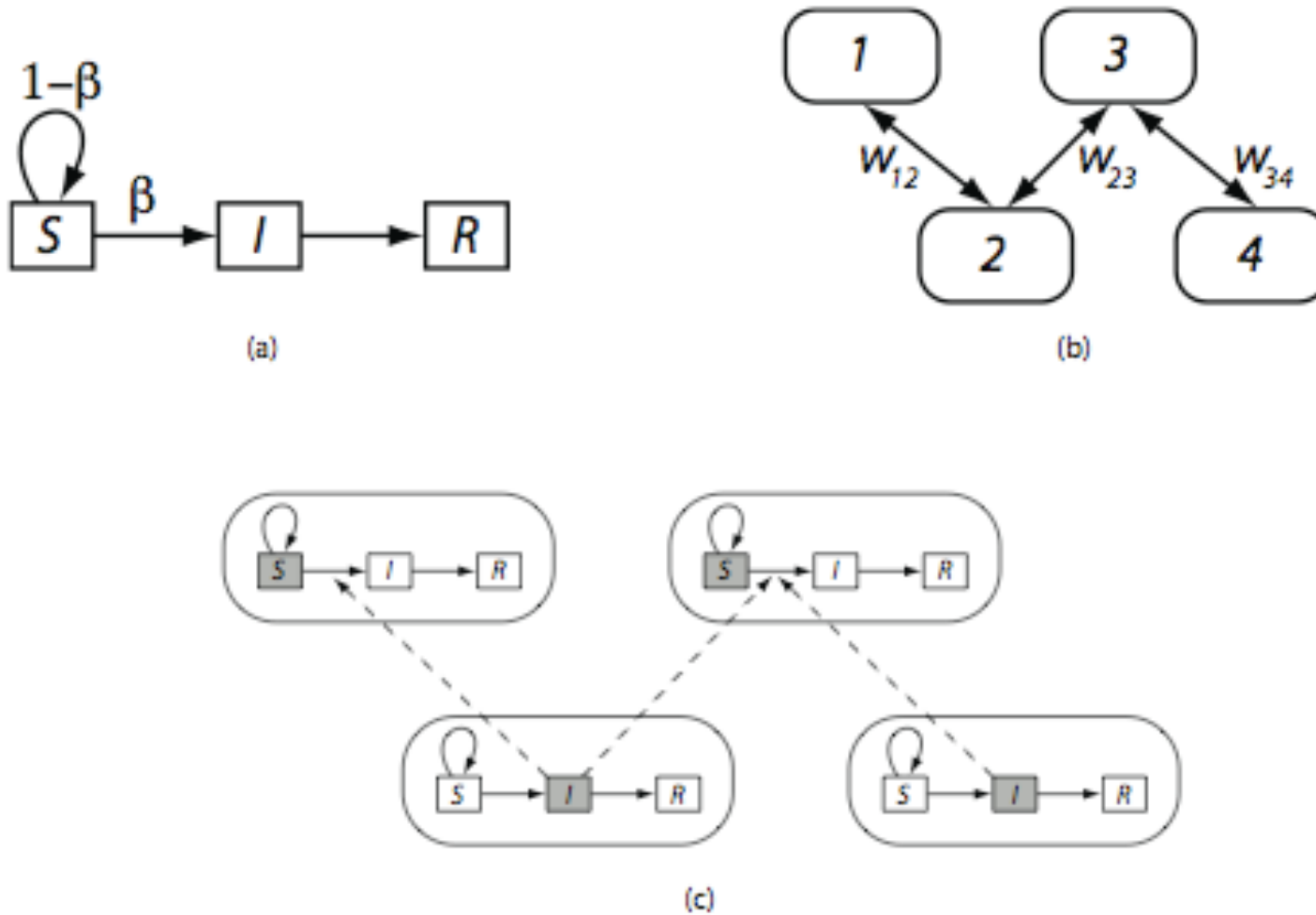


Within host model:
Probabilistic timed
transition systems (PTTS)

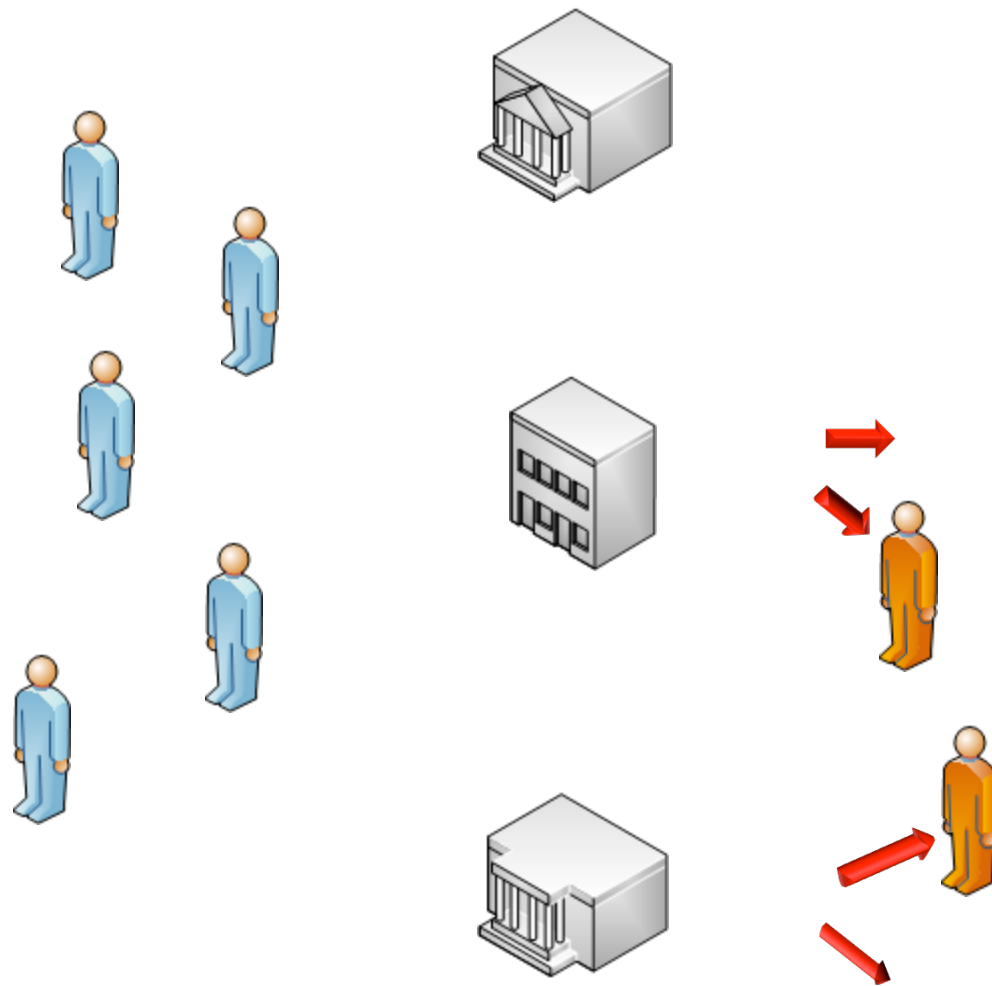
Three Simulations Disease Transmission

| Distinguishing Features | EpiSims (Nature'04) | EpiSimdemics (SC'09) | FastDiffuse |
|--|------------------------------|---|---|
| <i>Solution Method</i> | Discrete Event Simulation | Interaction-Based Simulation | Combinatorial +discrete time |
| <i>Performance 180 days 9M hosts & 40 proc.</i> | ~40 hours | 2 hours | Few minutes |
| <i>Co-evolving Social Network</i> | Can work | Works Well | Works <i>only</i> with restricted form |
| <i>Disease transmission model</i> | Edge as well as vertex based | Edge as well as vertex based (e.g. threshold functions) | Edge based, independence of infecting events |

Step 4: Model for disease transmission



EpiSimdemics Algorithm



Generate the population

Set initial infections

Based on activities move the people to the locations

Compute interactions among the people at the locations

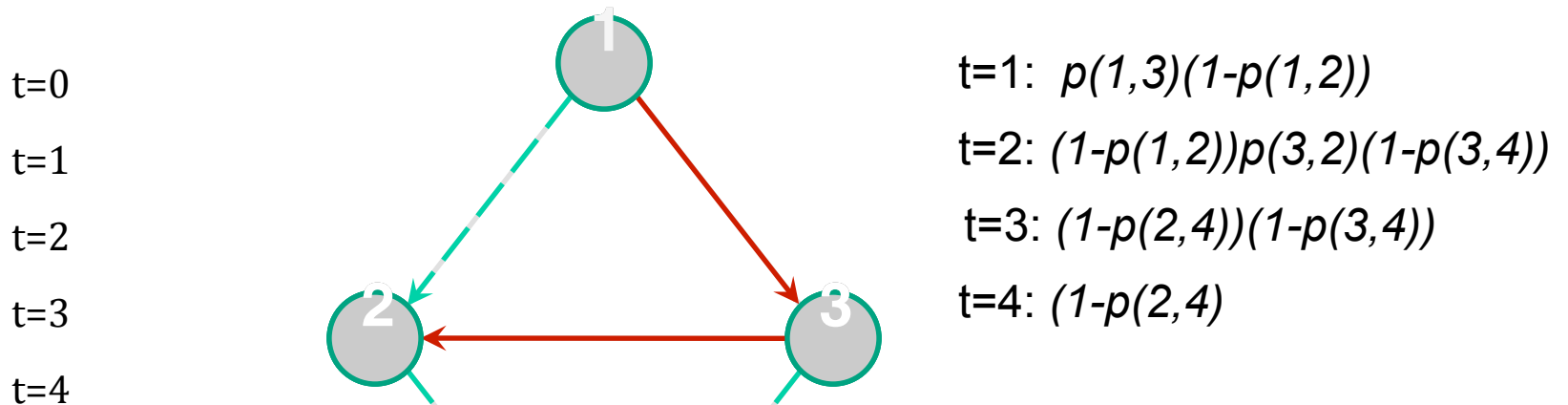
Some exposed people may become infected






After their activities, the people are moved back to their home PE

Update state of person at his home PE

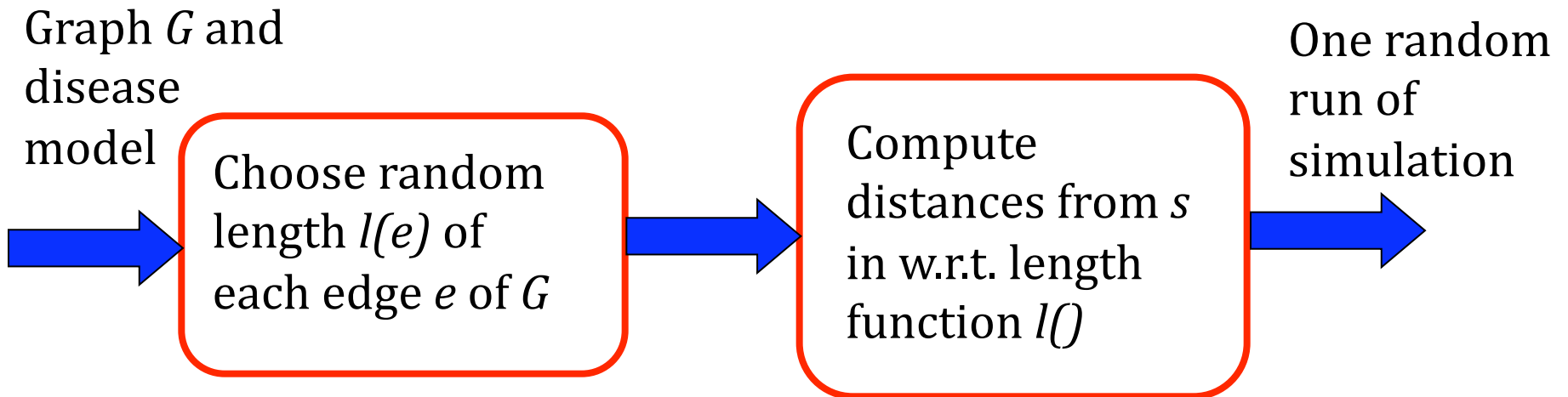
Percolation Based Viewpoint of Disease Transmission

$$p_S(\mathbf{R}) = p(1,3)p(3,2)(1 - p(1,2))^2(1 - p(2,4))^2(1 - p(3,4))^2$$



-  Susceptible
-  Infectious during 1st and 2nd step
-  Recovered
-  transmission
-  No transmission

Algorithm FastDiffuse



random length for edge $e=(u,v)$:

$$l(e) = \begin{cases} i \in \{1, \dots, S(u)\}, & \text{with probability } (1 - p(e))^{i-1} p(e); \\ \infty, & \text{with probability } (1 - p(e))^{S(u)}. \end{cases}$$

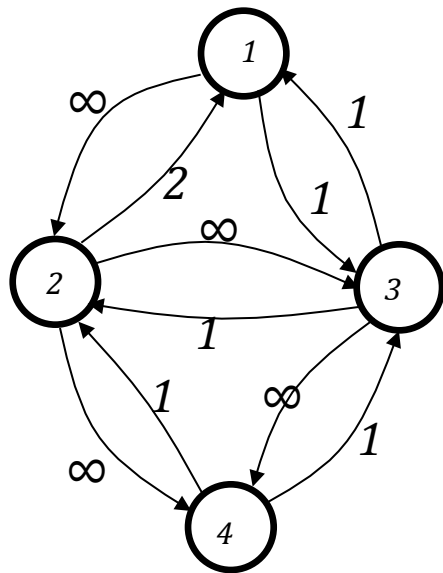
$$V_t = \{v : \text{dist}_\ell(s, v) = t\}$$

$$I = \{e = (u, v) : \ell(e) = \text{dist}_\ell(s, v) - \text{dist}_\ell(s, u)\}$$

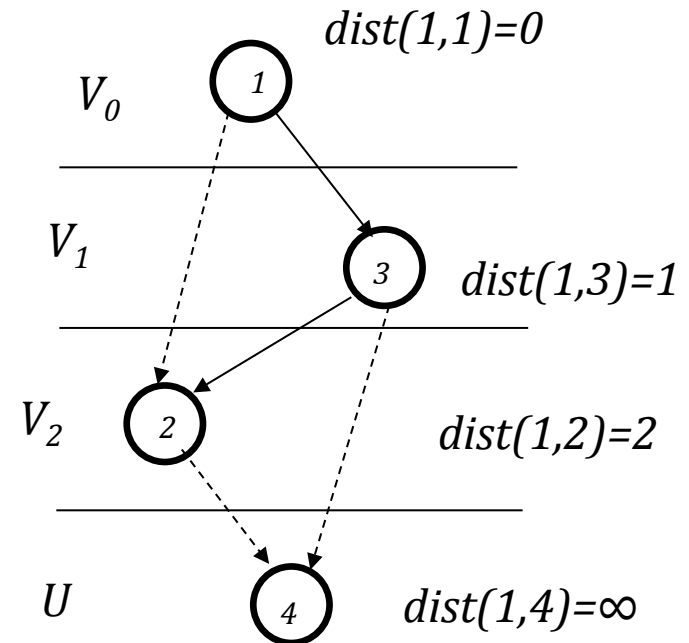
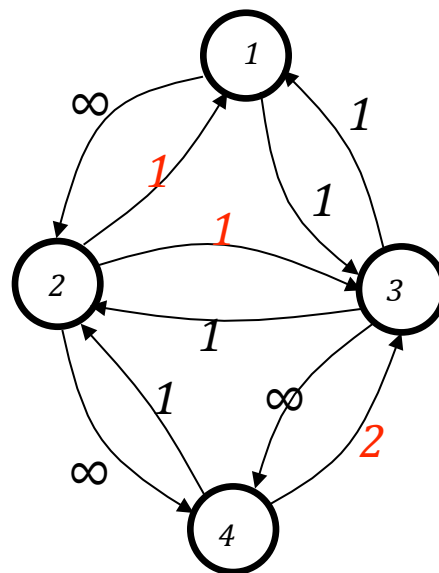
$p(e)$ = transmission prob. on edge e
 $S(u)$ = infectious duration of node u

Correctness and Efficiency: FastDiffuse

$$prob = p^6(1-p)^9$$



$$prob = p^7(1-p)^7$$



$$I = \{ (1,3), (3,2) \}$$

Same output

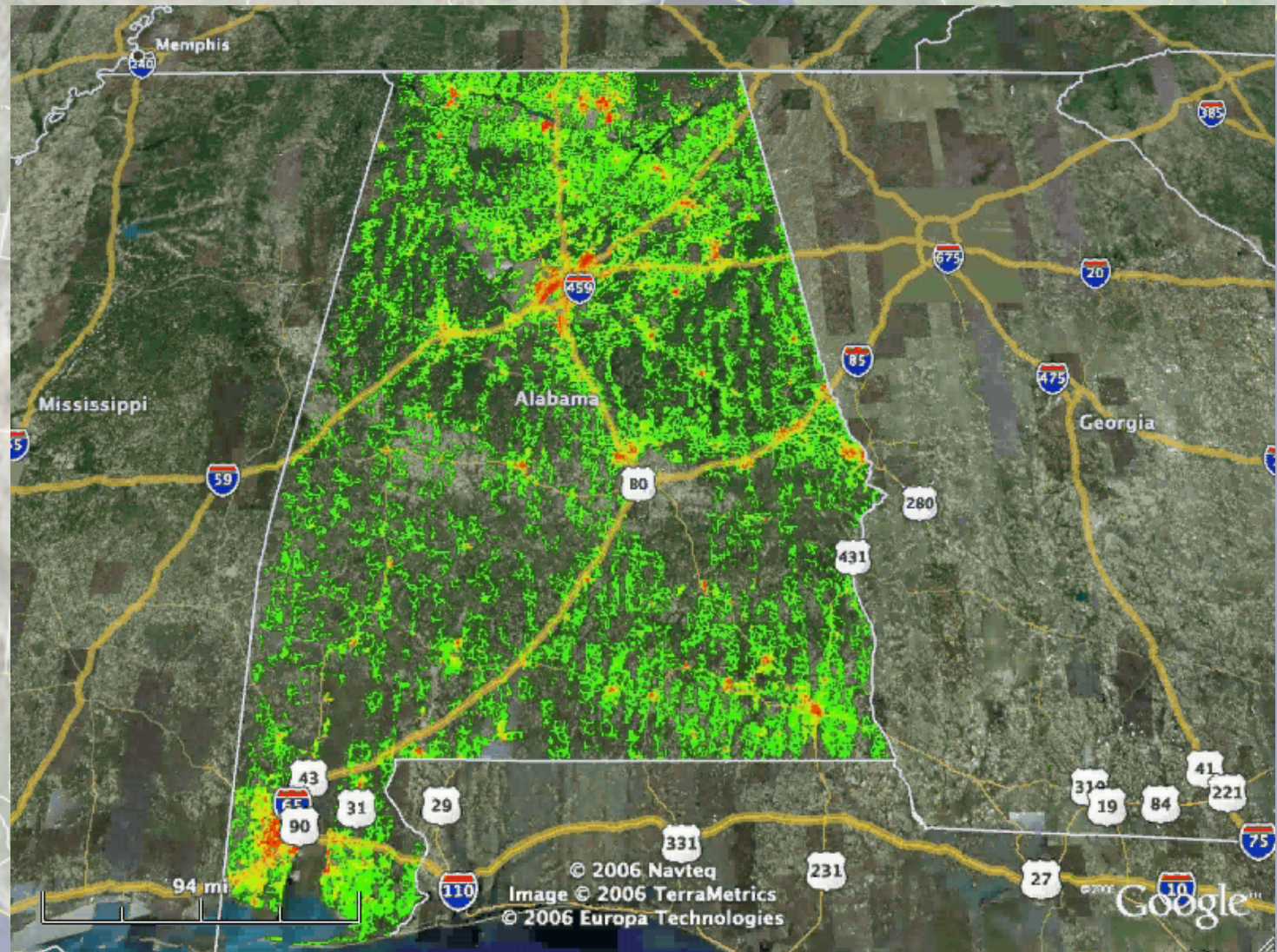
$$R = ((V_0, V_1, V_2, U), I)$$

Theorem:

- FastDiffuse simulates a DES and runs in linear time

Visualizing the spatio-temporal diffusion

Spatial and Temporal details on spread of disease at this scale and fidelity

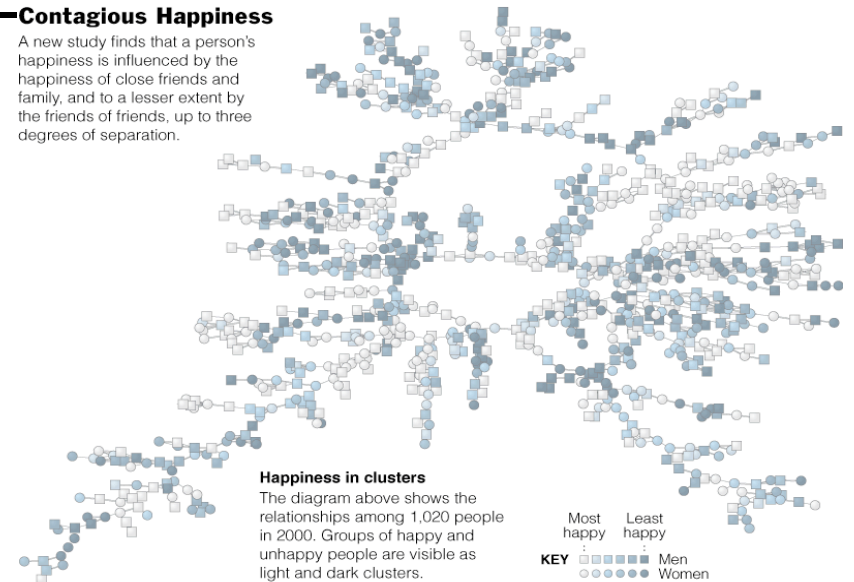


Research Questions: Faster Algorithms & Generalized Diffusions

- **Question 3: Scale and Speed**
 - Peta-scale systems & global populations
 - Animal/Birds disease: e.g. avian influenza, foot and mouth
- **Question 4: Generalized diffusions**
 - Generalized contagion models: (e.g. Dodds and Watts)
 - Other social processes (e.g. fads, ideas, viral marketing, financial cascades...)
 - Similar ideas might be applicable to happiness, obesity and smoking

Contagious Happiness

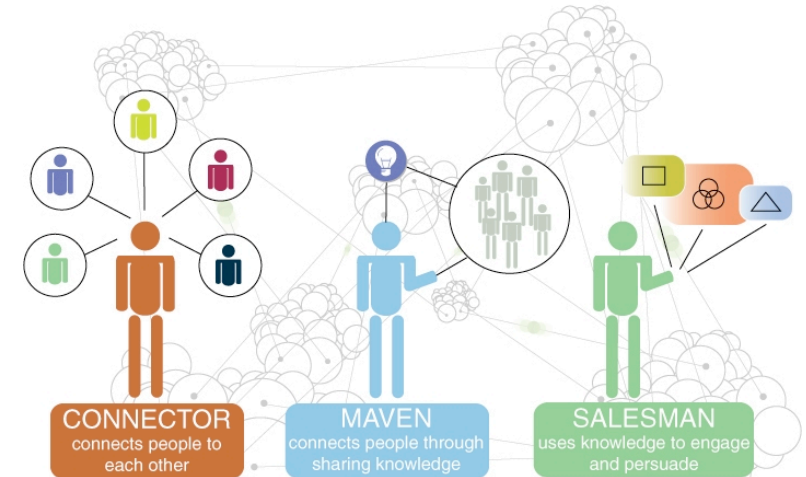
A new study finds that a person's happiness is influenced by the happiness of close friends and family, and to a lesser extent by the friends of friends, up to three degrees of separation.



Sources: James H. Fowler; Nicholas A. Christakis; BMJ

THE NEW YORK TIMES

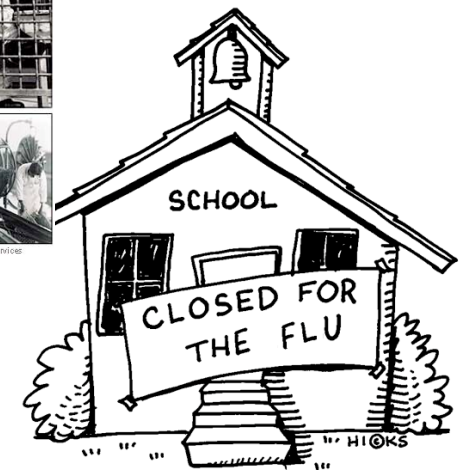
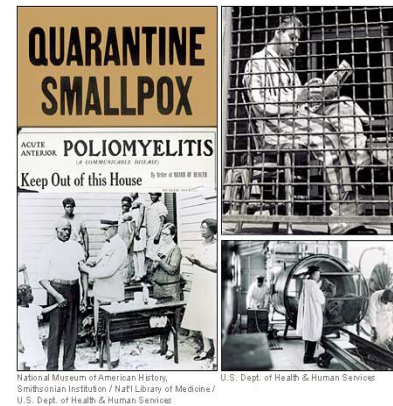
The Tipping Point + The Social Media Network



http://h10068.www1.hp.com/blogpost/tipping_pt.jpg

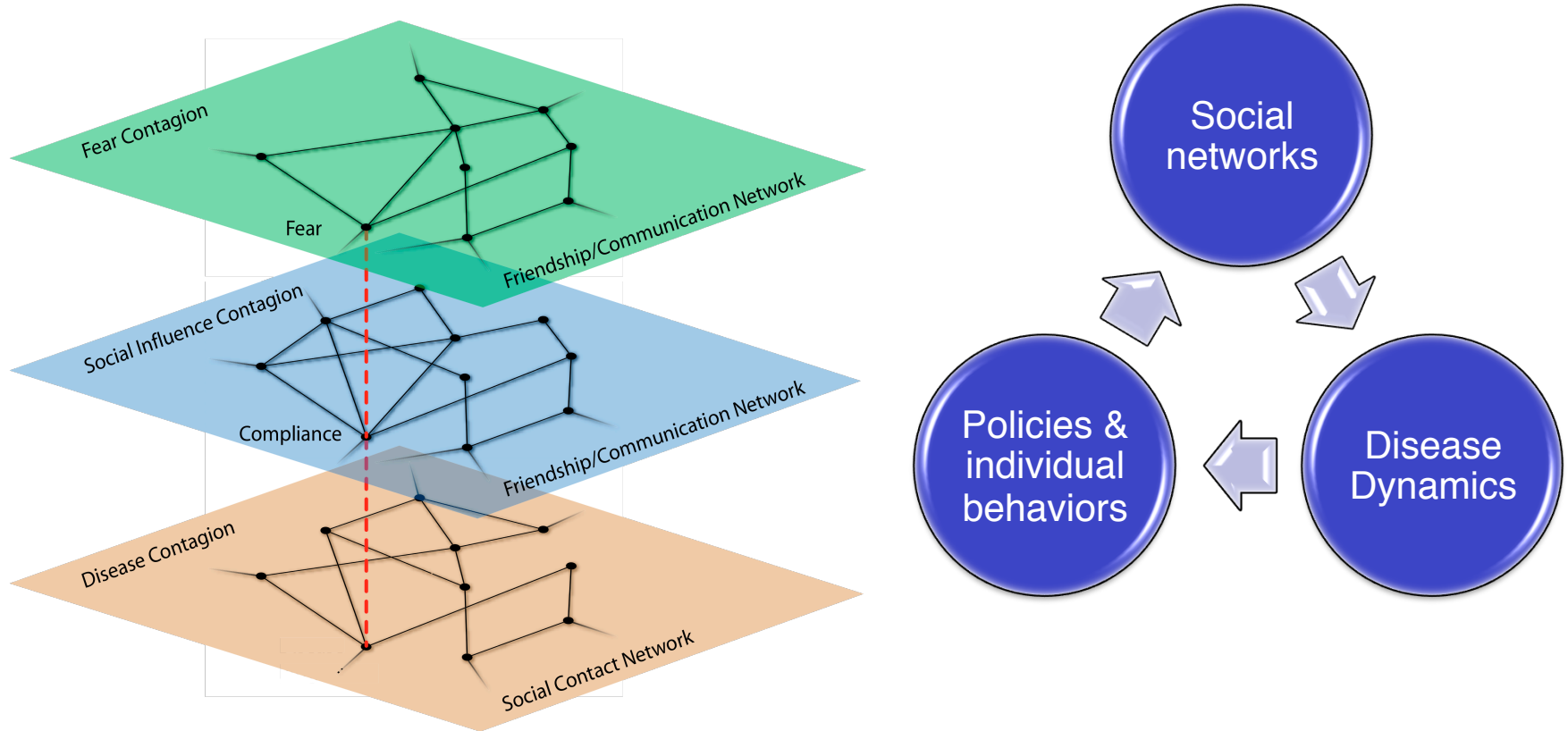
Step 5: Study Effects of Interventions

- Specifying a Situation (Scenario)
 - E.g. How to represent cascading failures?
- Kinds of Interventions
 - PI: Vaccines and Anti-viral, Anti-biotic
 - NPI: Social distancing, quarantining
- Specifying an Intervention
 - When, where, whom & how much
- Cost Functions
 - Human suffering averted
 - Time gained (delay of exponential growth)
 - Resource constraints



Mathematical Model: POMDP & n -way games

Interventions: Partially Observable Markov Decision Process (POMDP)

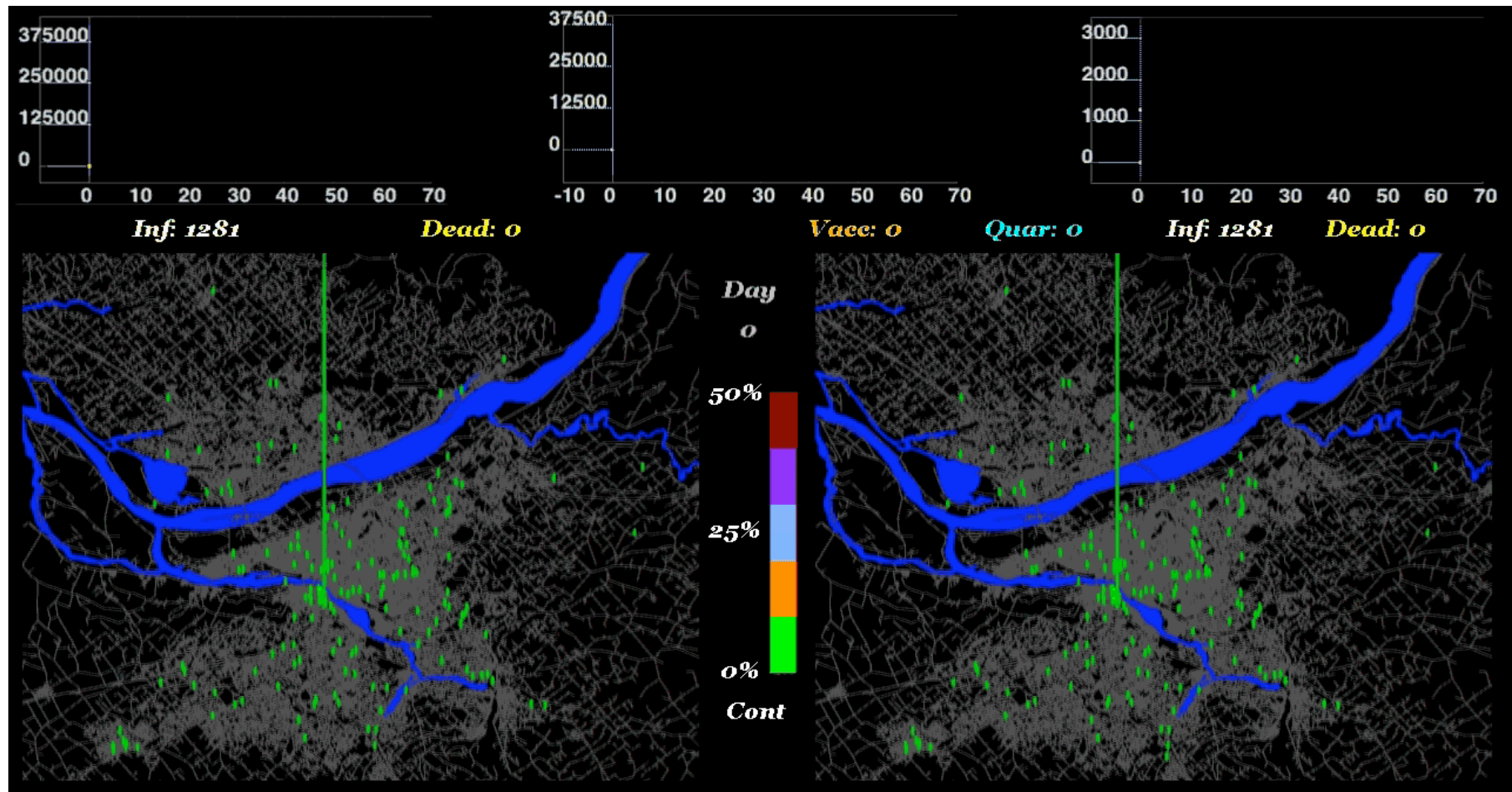


- Behaviors and Disease dynamics can be cast as generalized reaction diffusion: Leads to coupled networks
- Co-evolving dynamical systems

Step 5 Mathematical Model: POMDP & n -way games

- Partially Observable Markov Decision Process (POMDP)
 - Useful in modeling sequential decision making, e.g. policies
 - POMDP is exponentially larger than the natural problem representation (coupled dynamical system)
 - Capture the co-evolution of social network & actions
- Mechanics
 - Each step decision maker makes partial observations
 - Interventions based on the observation (NPI or PI: vaccinate)
 - Changes network structure or individual attributes, behaviors
 - Disease advances by one or more steps
 - Compute Cost (based on action, system state), e.g. #people infected

Effects of early detection and targeted interventions (Nature'04)



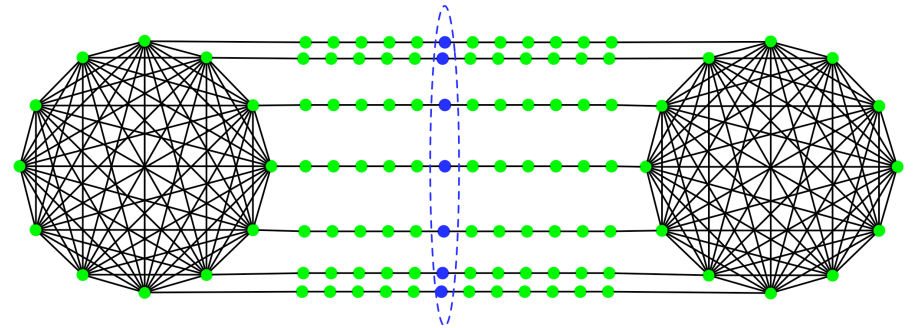
Case Study: Co-evolution of network, public policy and individual behavior

Interventions

- **Static Non-Adaptive Interventions**
 - Vaccination/AV = Static changes to social network
 - Useful as a general precautionary measure and when vaccines are very effective
- **Policy based triggered interventions**
 - School closure = One time dynamic change triggered by an event
- **Modify Individual Behavior (Decisions made by individuals)**
 - Improve individual adherence = Continuous changes to network dependent on disease status

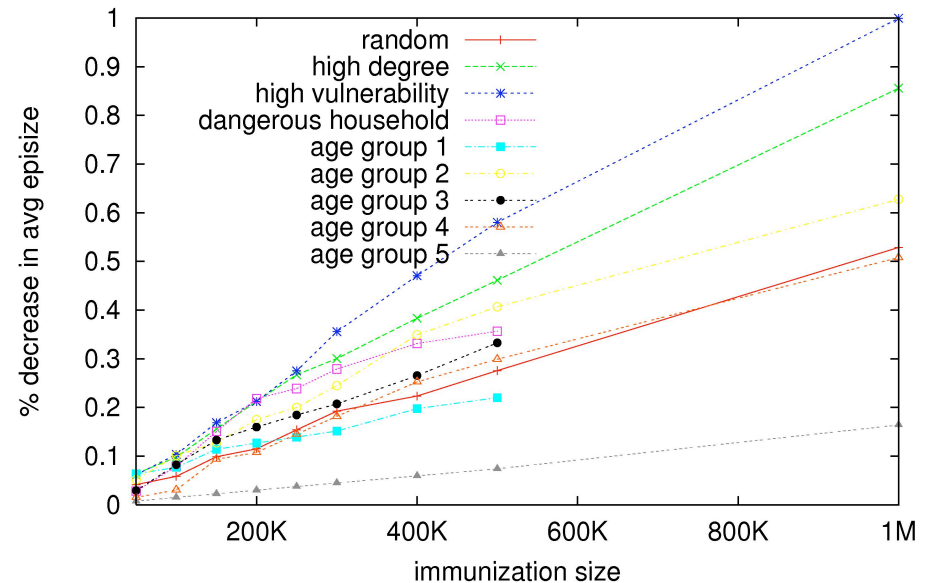
Vulnerable versus Critical Individuals

- Vulnerability(v): $\Pr(v = \text{infected})$
- Criticality(v): reduction in epidemic size when the node is vaccinated
- Vulnerability \neq Criticality.
- Criticality and vulnerability of a node do not depend only on demographics or contacts (degree)
- Vaccinating vulnerable nodes is effective



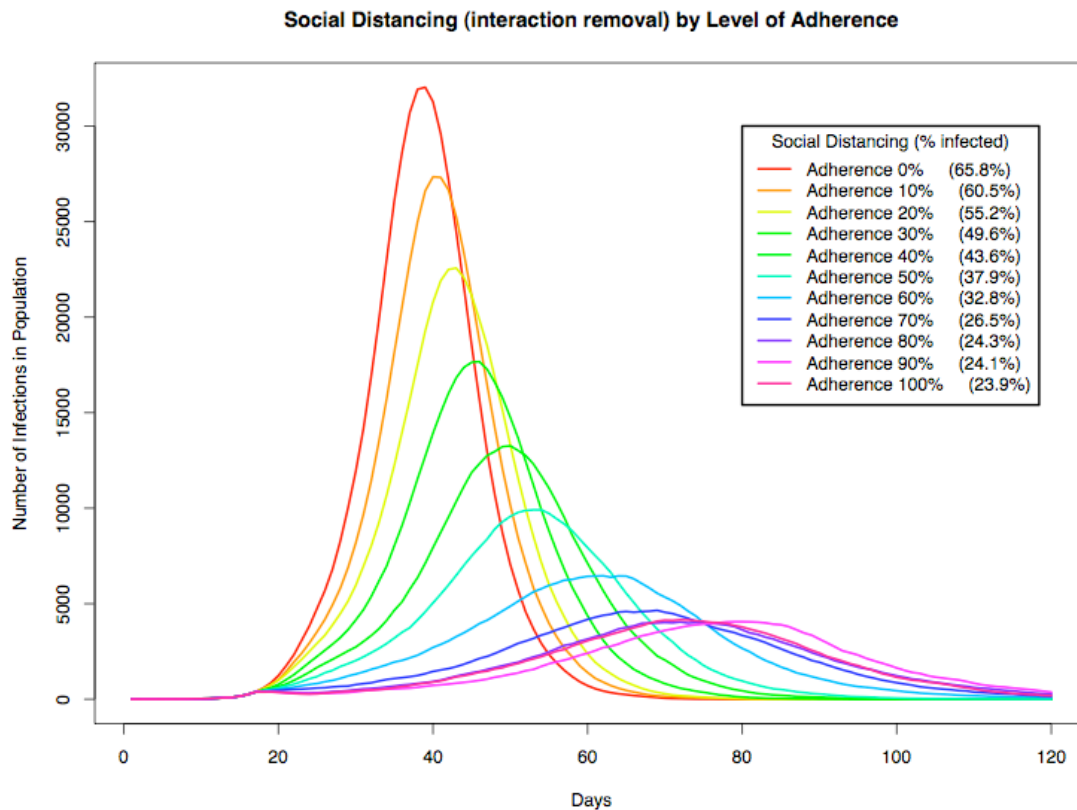
Blue nodes are highly critical but not very vulnerable

Percentage Decrease in Average Epidemic Size vs Immunization Size
 $\tau=0.000048$



Triggered Policy + Individual behavior: curtailing non-essential activities

- A triggering event causes a proportion of the population to eliminate non-essential activities



| Proportion Changing Behavior | Final Attack Rate |
|------------------------------|-------------------|
| 0% | 66% |
| 10% | 61% |
| 20% | 55% |
| 30% | 50% |
| 40% | 44% |
| 50% | 38% |
| 60% | 33% |
| 70% | 27% |
| 80% | 24% |
| 90% | 24% |
| 100% | 24% |

DIDACTIC: HPC Services Based Epidemiological Planning Environment

Analyst can focus on delivering results rather than
becoming a computing expert

Simple User Interface to Set up Experiments

Highly resolved parameters

Experiments Analyses Triggers User Manual Feedback About

bryan Logout

Name **i** Demo_Vax_SDS_50 Description: Vax = 0, 25,50 SDS=50 SDG=none Replicates **i** 25

Status **i** completed Total Cells **i** 3

Owner **i** sample Simulated Days **i** 200

Region **i** Alabama View

Disease Model **i** Catastrophic flu View

Initial Conditions **i** Saday View

Enabled Interventions **i** Vaccinate Antiviral Social Distance Close Work Close School

Vaccinate Antiviral Social Distance Close Work **Close School**

Close Schools **i**

Subpopulation **i**

- all
- preschool
- school-age
- adult
- senior
- Tier 1
- Tier 2
- Tier 3
- Critical Workers

View

Compliance **i**

% Value **i** 50

Sweep

Initial % Value **i**

Final % Value **i**

Increment **i**

Trigger **i**

0.5 percent

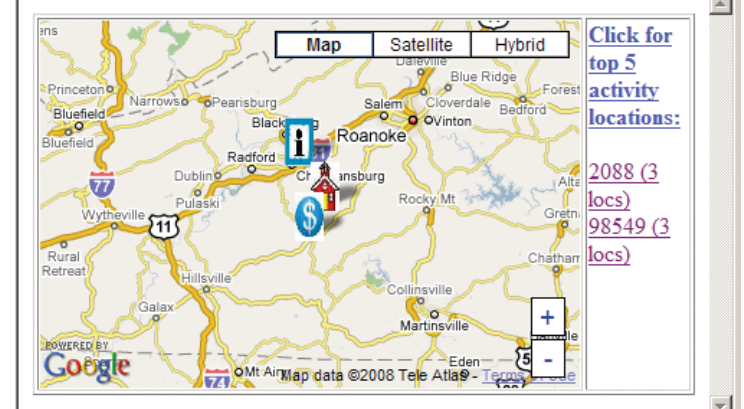
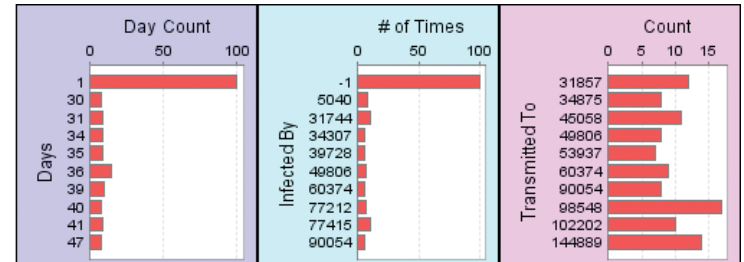
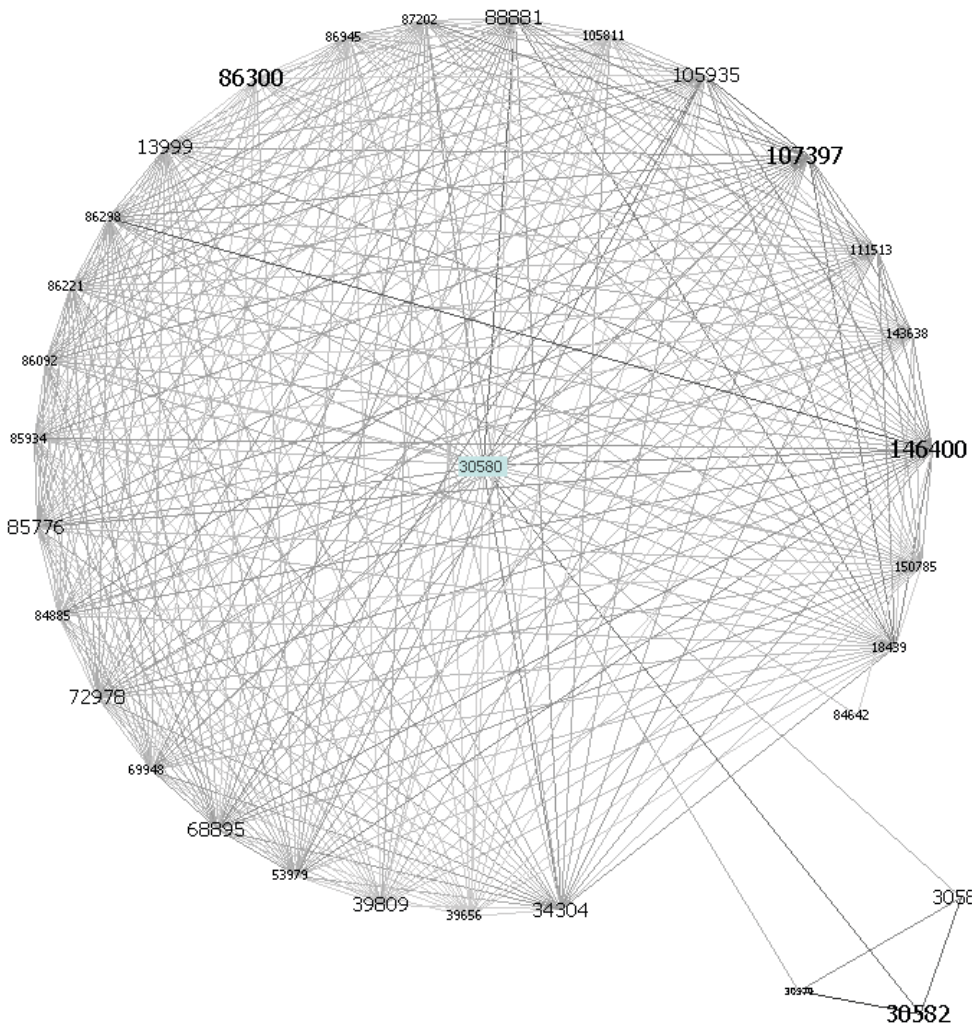
Sweep

Edit Triggers

Done Save Discard Unsaved Changes Show Cells

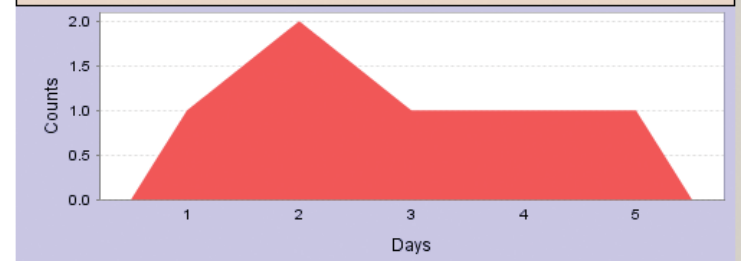
- Population
- Disease
- Initial conditions
- Interventions
 - Type
 - Efficacy
 - Compliance
 - Timing
 - Subpopulation

Visual Analytics Support



To clear the list of Ids above click here: [Clear List](#)

Select Epidemic Id:



Wireless Epidemics

Wireless Epidemics

- Ubiquity of smart digital devices have amplified opportunities for malware attacks
- 20.7 million devices shipped in US in 2007
 - China, India together have approx 1 Billion devices
- First generation worms like Cabir, Mabir, CommWarrior
 - No significant damage, but attacks are predicted to increase
- Wireless Epidemic can bring human epidemics closer to Internet epidemics
 - Spatial diffusion

From "Malware goes mobile," Mikko Hypponen, Scientific American, 2006



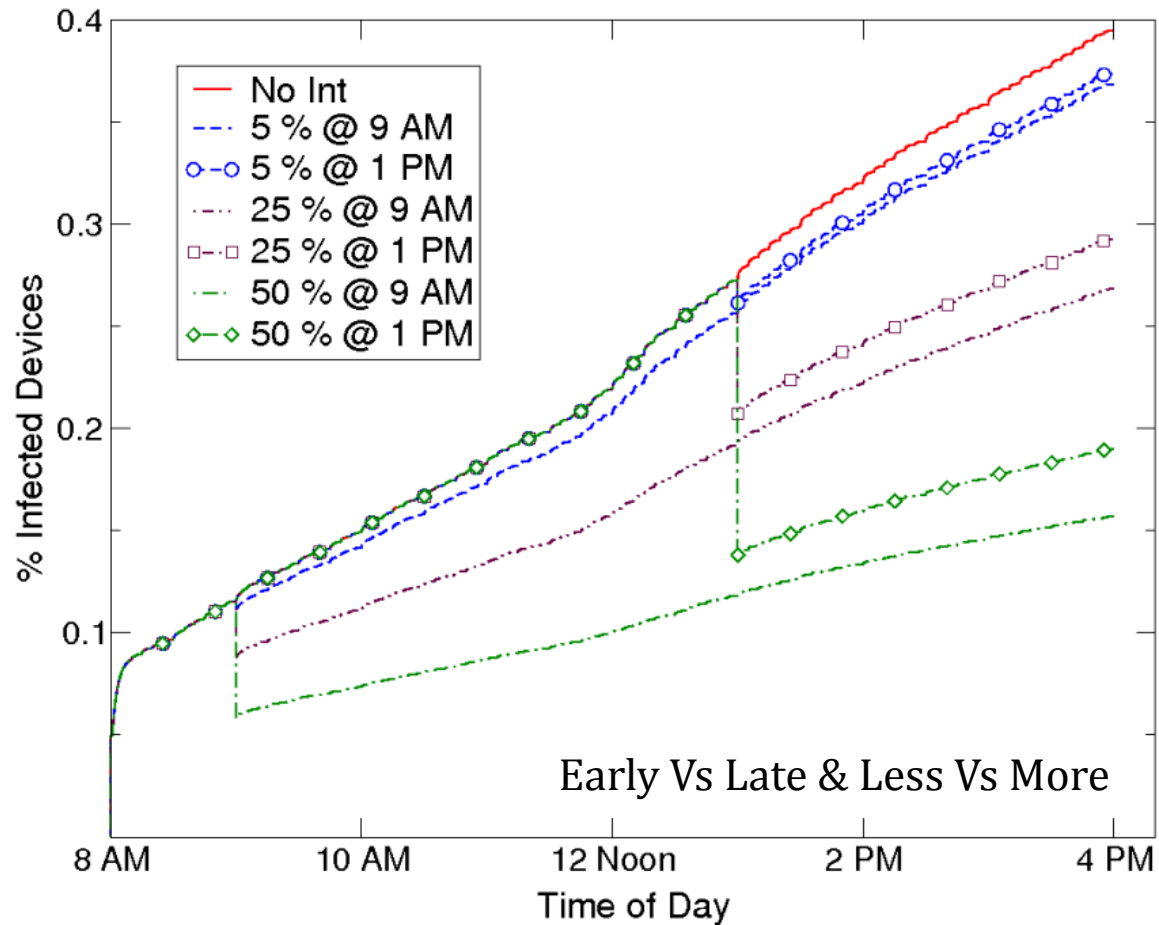
Models

- Classical Approaches
 - Exact simulation studies (NS-2)
 - Use detailed worm models, small sized networks, simple mobility models (e.g. Random Waypoint)
 - 24-48 hours for 50 node simulation !
 - Classical ODE studies
- EpiNet: Scalable Networked Models
 - Detailed models for mobility, device assignment and activity
 - Realistic coupled social + wireless networks !
 - Provably approximate representations of Blue tooth worms
 - HPC based methods for scalability



From "The Wireless Epidemic,"
John Kleinberg, Nature, 2007

Effect of Interventions



Solution: Better late than never & a stitch in time saves nine !

Conclusions and Summary

- **Simdemics: Network-based Computational Epidemiology**
 - Highly resolved, captures complex social and epidemic interactions
 - Case Studies demonstrate practical usefulness and guide R&D
 - Extensions to wireless epidemics
 - HPC, Network and Data Science, Algorithms all play crucial role
- **Suggests new directions for future research**
 - Information extraction from relational networks
 - Understanding other social diffusion processes (e.g. economic contagion)

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