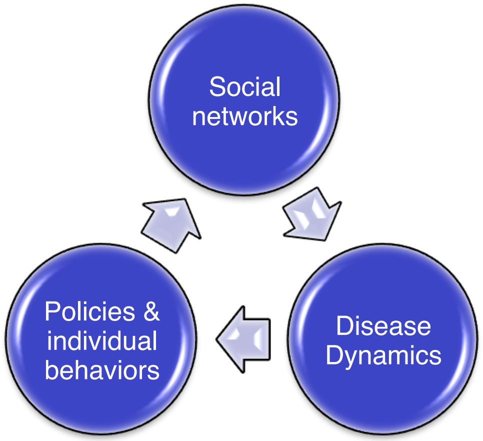
Studying the relationship between individual behavior, public policies, social networks and epidemic processes


Social networks

Disease Dynamics

Policies & individual behaviors

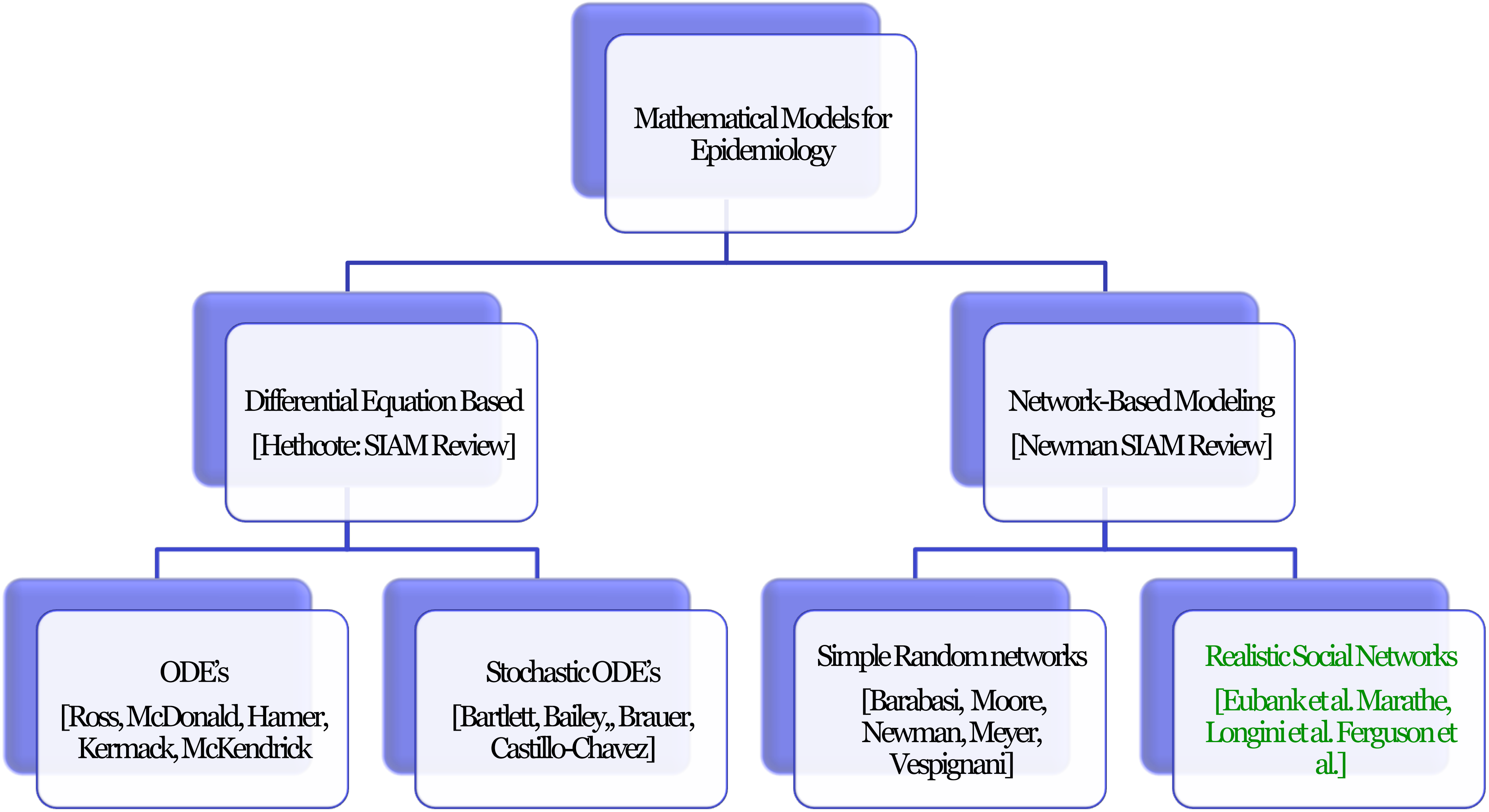
Madhav Marathe
Dept. of Computer Science &
Network Dynamics and Simulation Science Laboratory
Virginia Bioinformatics Institute
Virginia Tech

NDSSL TR-09-074

Acknowledgements: Virginia Tech: Network Dynamics & Simulation Science Laboratory, VBI and our external collaborators

Work funded in part by NIGMS, MIDAS program, CDC Center of Excellence in Medical Informatics, DTRA , NSF HSD, NECO, NETS and OCI programs

Models in Mathematical/Computational Epidemiology



Mathematical Models for Epidemiology

- Differential Equation Based [Hethcote: SIAM Review]
  - ODE's [Ross, McDonald, Hamer, Kermack, McKendrick
  - Stochastic ODE's [Bartlett, Bailey,, Brauer, Castillo-Chavez]
- Network-Based Modeling [Newman SIAM Review]
  - Simple Random networks [Barabasi, Moore, Newman, Meyer, Vespignani]
  - Realistic Social Networks [Eubank et al. Marathe, Longini et al. Ferguson et al.]

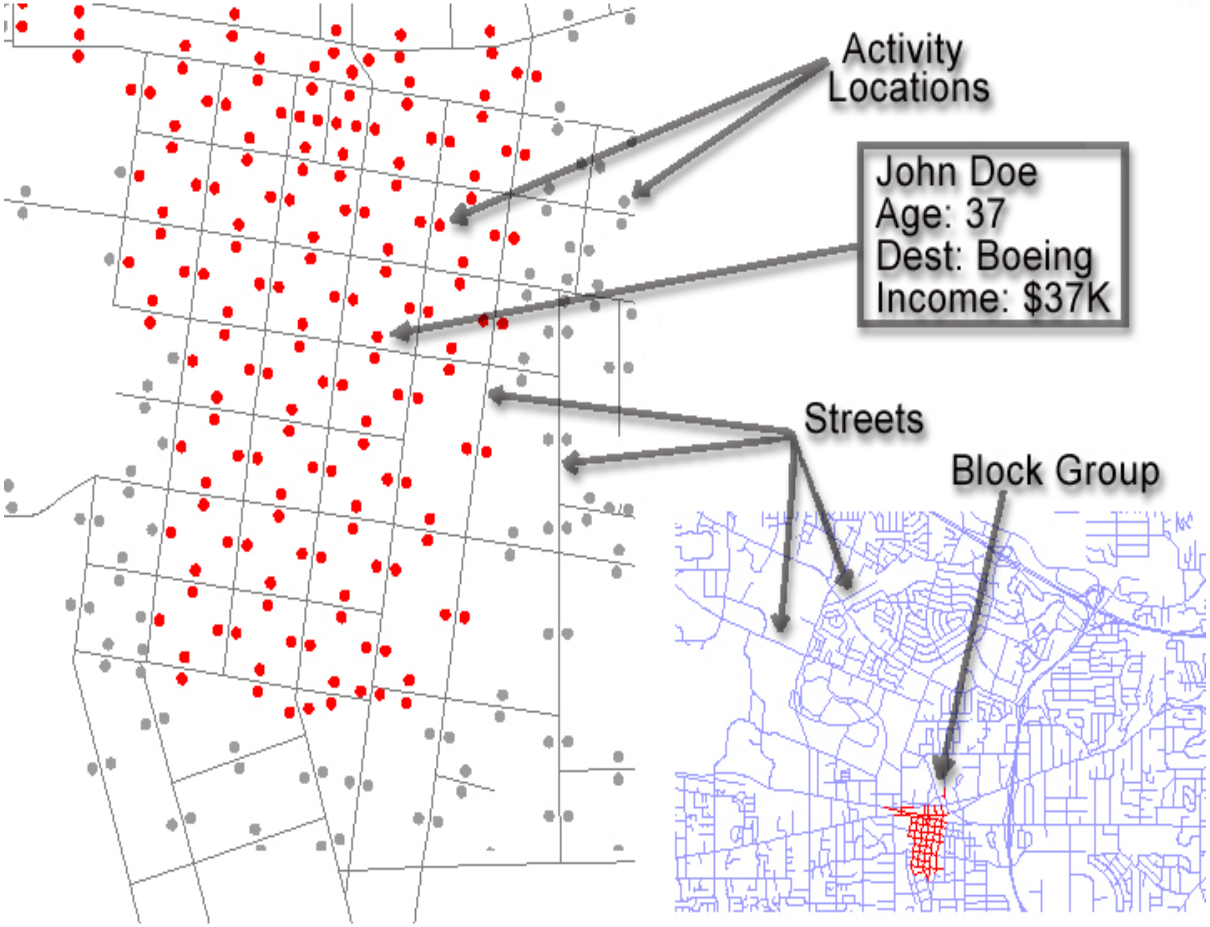
Simdemics: High resolution network-based modeling

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.

Step 1: Synthetic populations

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

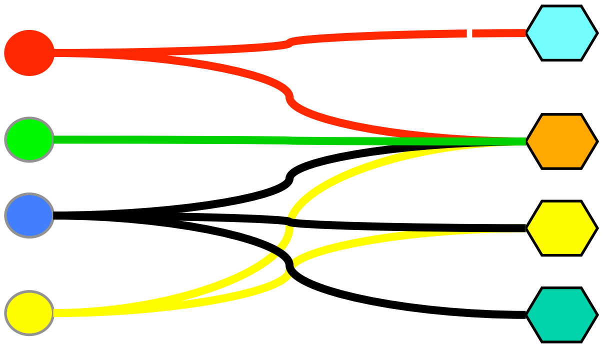


Beckman et al. Transportation Science, NISS technical reports, Barrett et al. TRANSIMS technical reports

Step 2: Urban dynamic social contact network

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

Household:
Single Mother
and Daughter

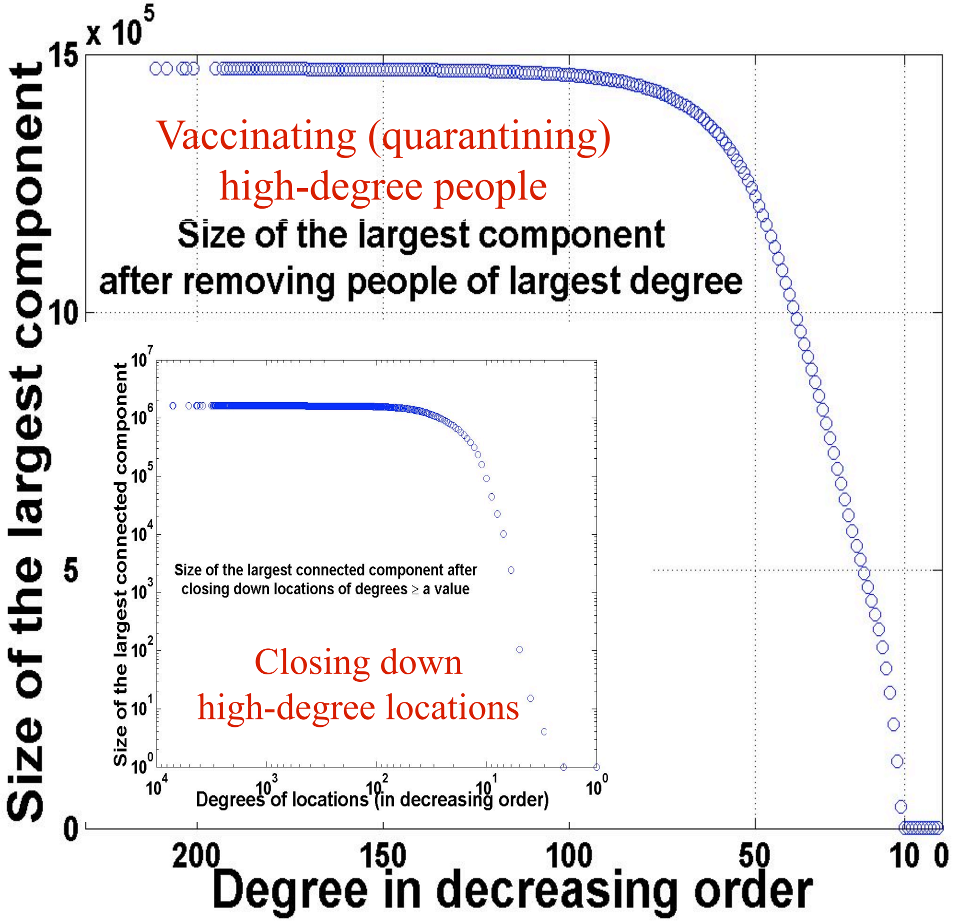


People Vertex:
- age
- household size
- gender
- income ..

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

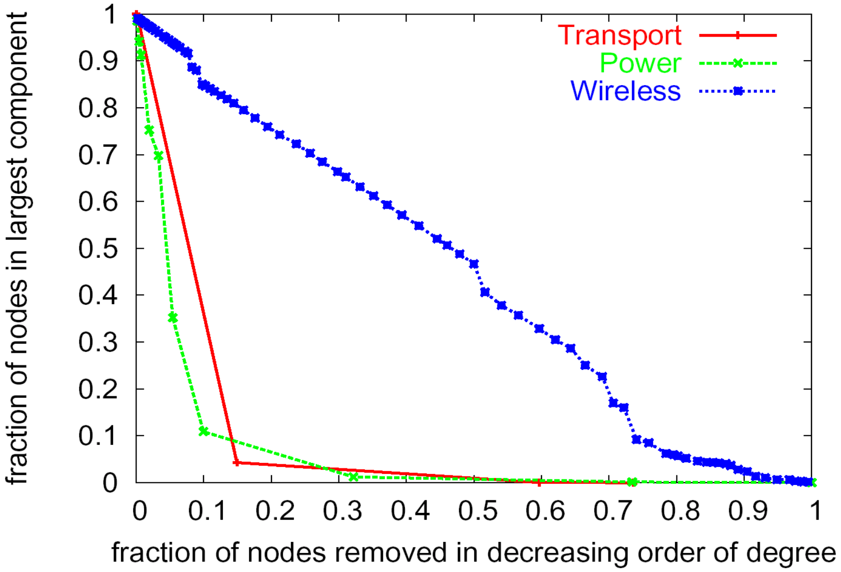


Vaccinating (quarantining) high-degree people

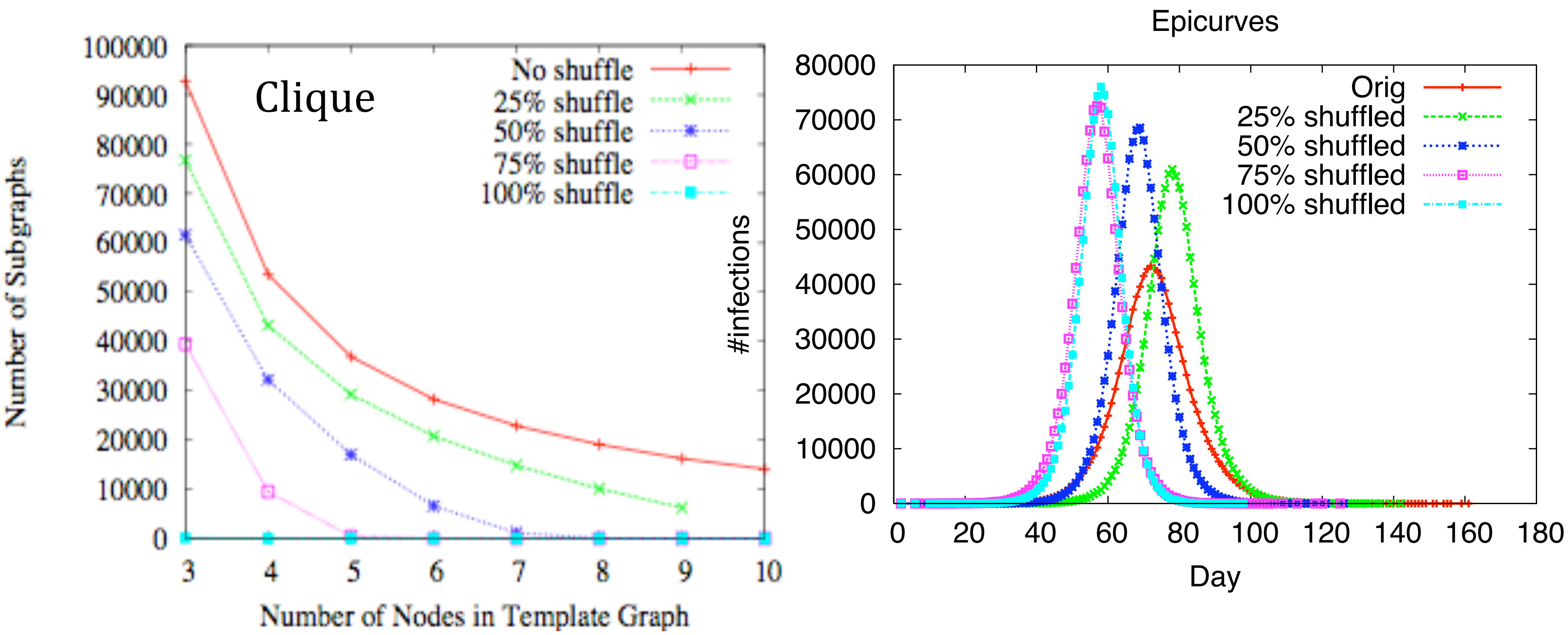
Size of the largest component after removing people of largest degree

Closing down high-degree locations

Size of the largest connected component after closing down locations of degrees ≥ a value



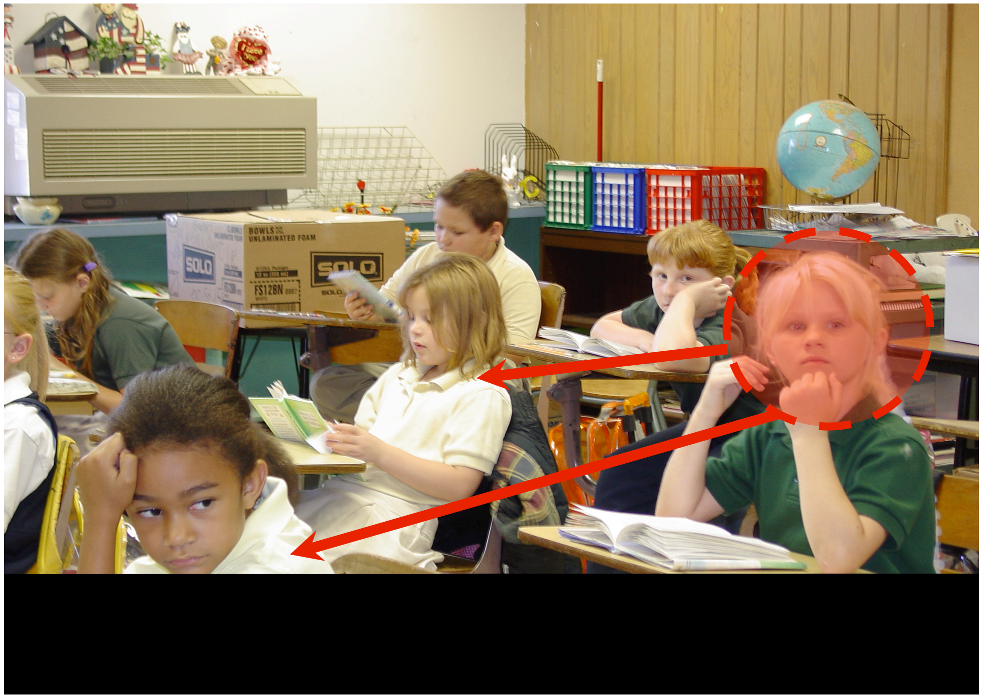
Realistic Social Contact network differ from "simple" random networks



Portland Network:

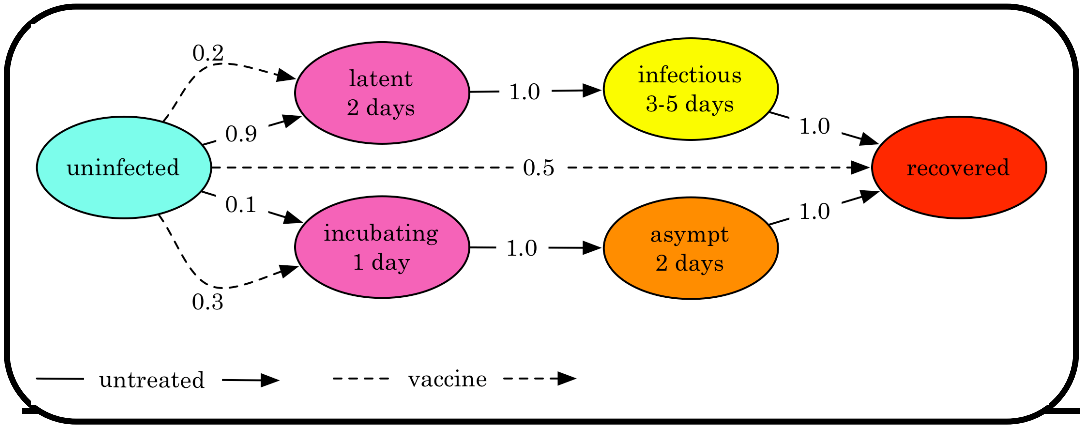
- Cliques within same age group (0-19).
- Simple random graph models cannot produce these structures

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.



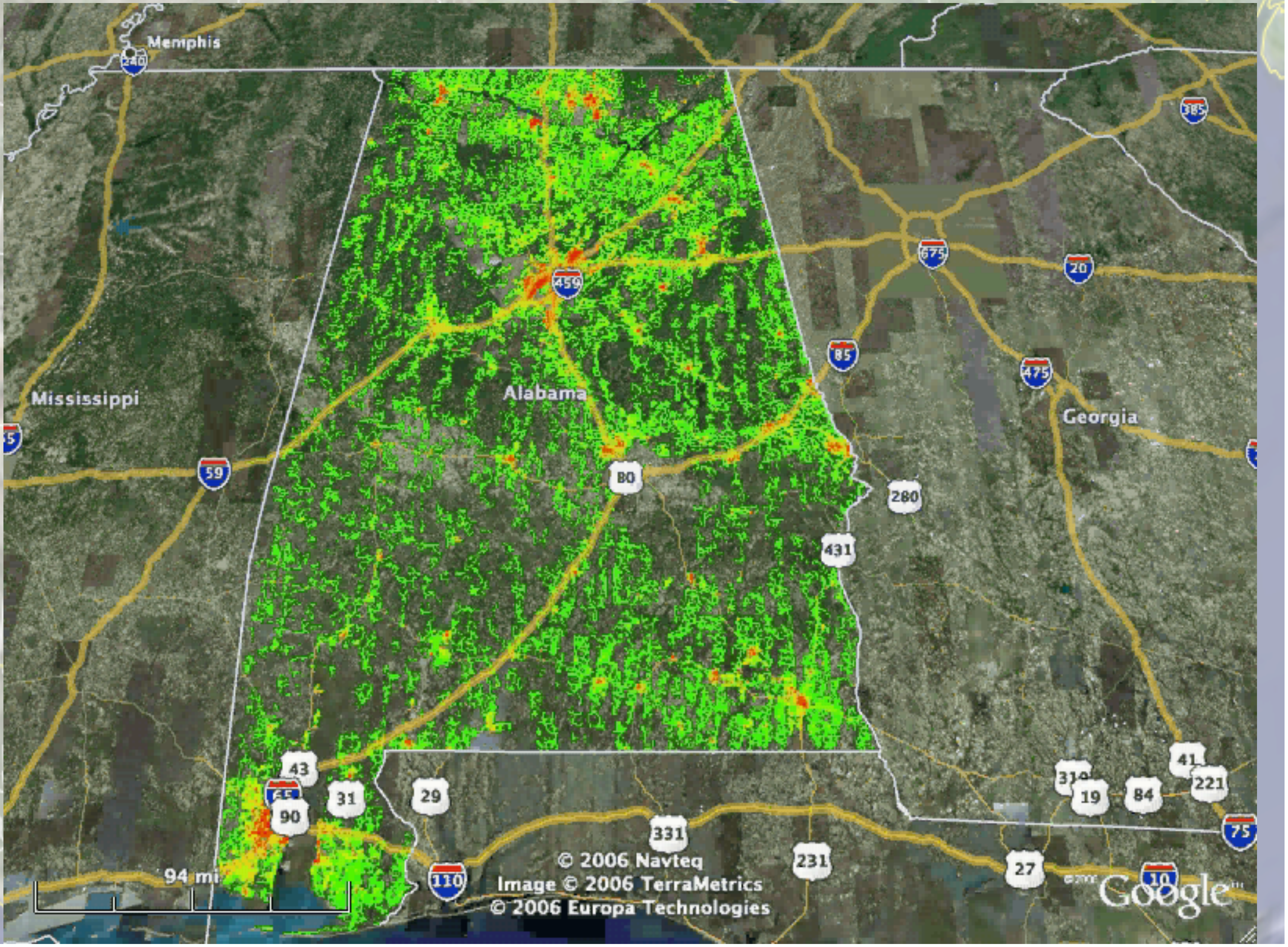
Within host model: Probabilistic timed transition systems (PTTS)

Step 4: Fast Simulations for Disease Spread

Distinguishing Features	**EpiSims (Nature'04)**	**EpiSimdemics (SC'09)**	**EpiFast (ICS' 2009)**
Solution Method	Discrete Event Simulation	Interaction-Based Simulation	Combinatorial +discrete time
Performance 180 days 9M hosts & 40 proc.	**~40 hours**	**2 hours**	**Few minutes**
Co-evolving Social Network	Can work	Works Well	Works ***only*** with restricted form
Disease transmission model	Edge as well as vertex based	Edge as well as vertex based (e.g. threshold functions)	Edge based, independence of infecting events

Visualizing the spatio-temporal diffusion

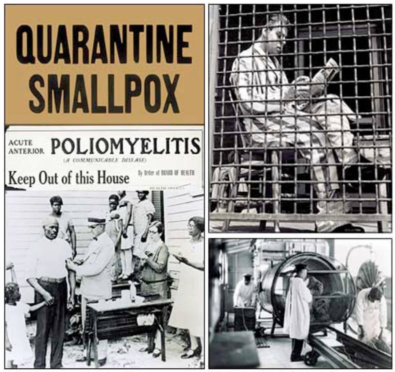
Spatial and Temporal details on spread of disease at this scale and fidelity



© 2006 Navteq
Image © 2006 TerraMetrics
© 2006 Europa Technologies

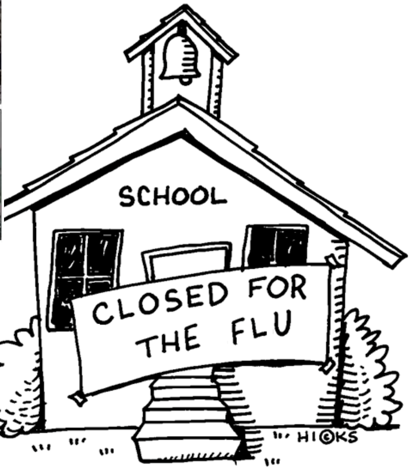
Step 5: Study Effects of Interventions

- 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



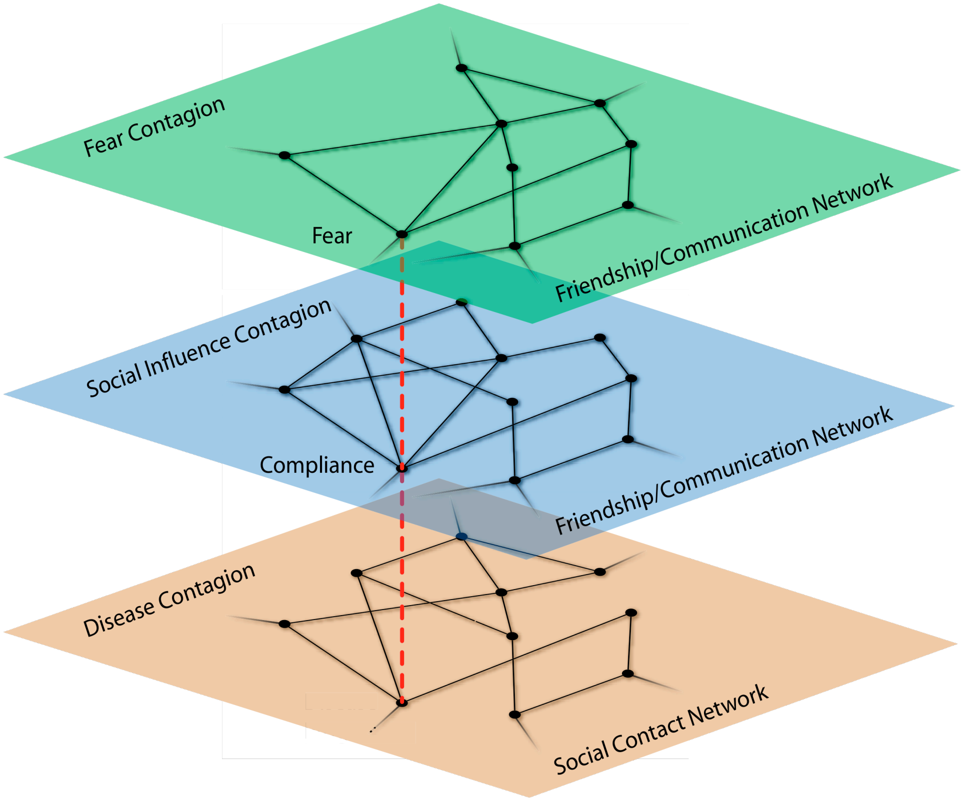
National Museum of American History, Smithsonian Institution / Nat'l Library of Medicine / U.S. Dept. of Health & Human Services

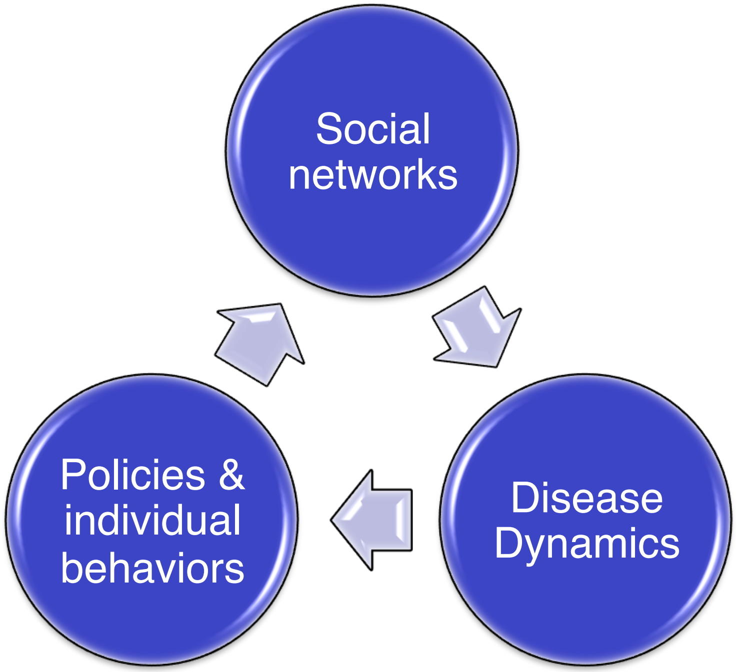
U.S. Dept. of Health & Human Services



Mathematical Model: POMDP & *n*-way games

Interventions: Partially Observable Markov Decision Process (POMDP)



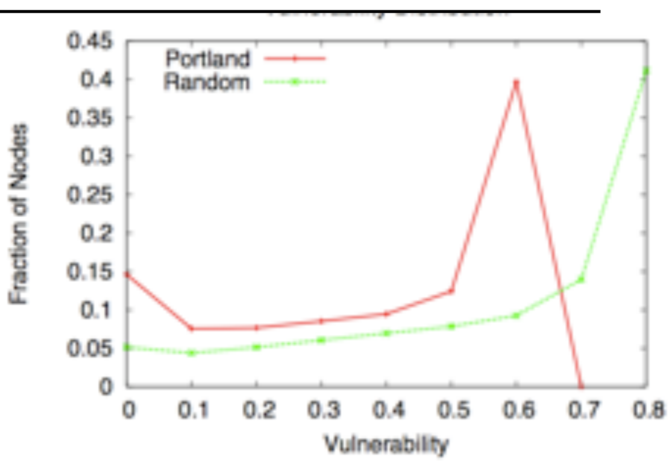


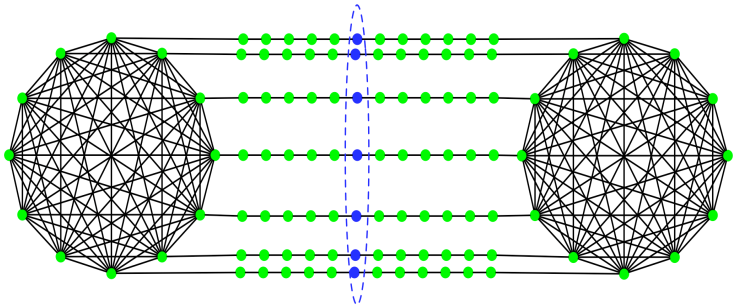
- Behaviors and Disease dynamics can be cast as generalized reaction diffusion: Leads to coupled networks
- Co-evolving dynamical systems

New Network Measures and an application to optimal allocation of PI

Vulnerability and Criticality of nodes

- *V(i)* = Vulnerability of a node *i* = probability of getting infected, if the disease starts at a random node
- Criticality*(v)*: reduction in epidemic size when the node is vaccinated
- *V(i, t)* = Vulnerability of a node *i* at time *t*= probability of getting infected during the first *t* time steps
- Depends on
  - Initial conditions
  - Transmission probability
  - Network structure - not a first order property

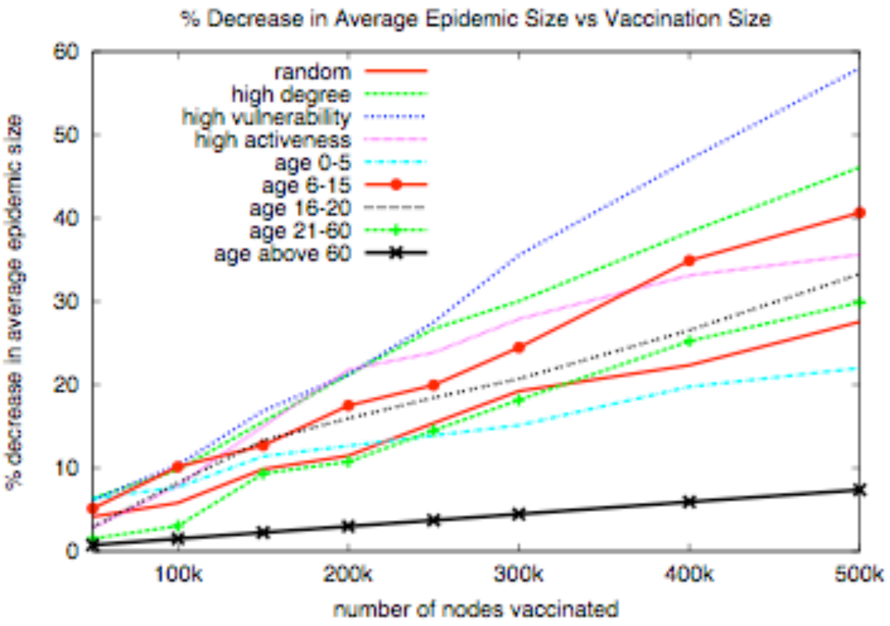


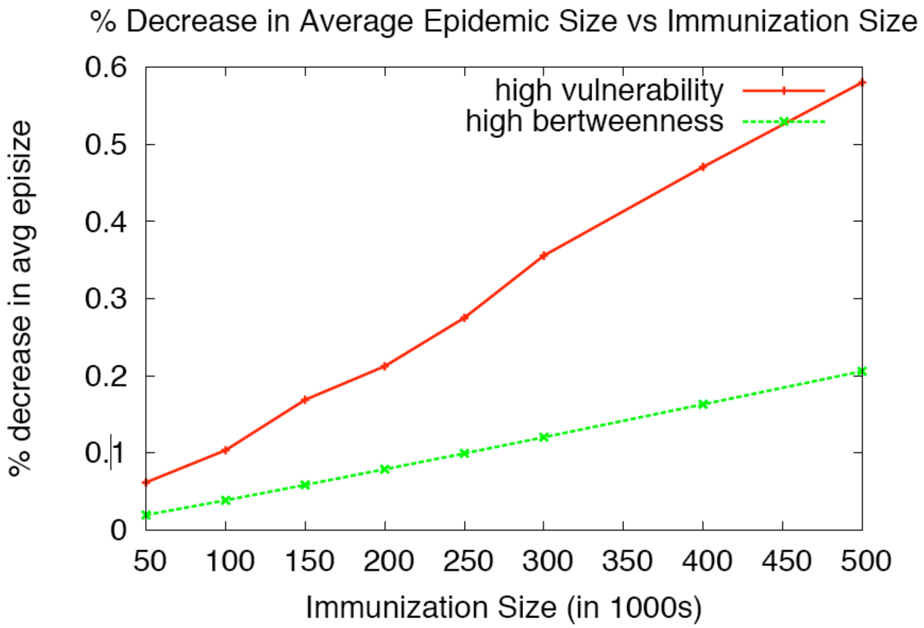


Blue nodes are highly critical but not very vulnerable

Temporal version: probability of

Vaccination based on vulnerability rank order

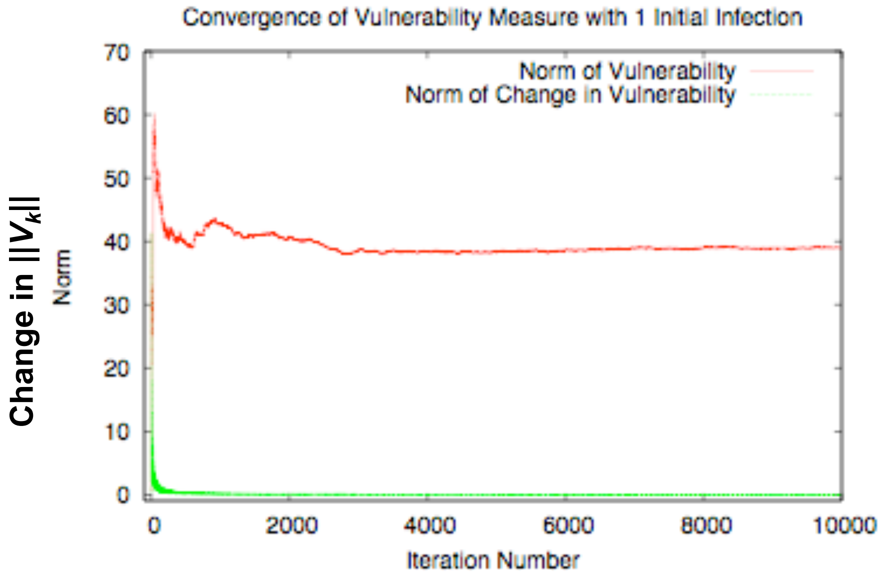


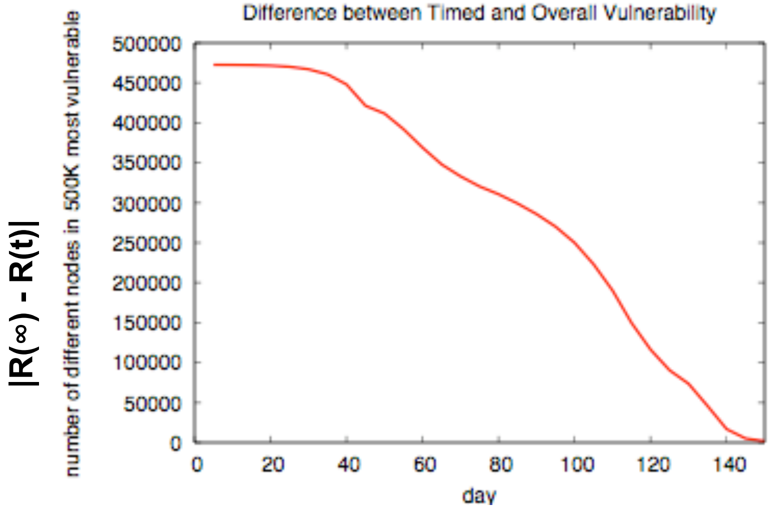


- Contact graph on Chicago, ~ 8 million people
- Highly vulnerable nodes are also most critical for this network

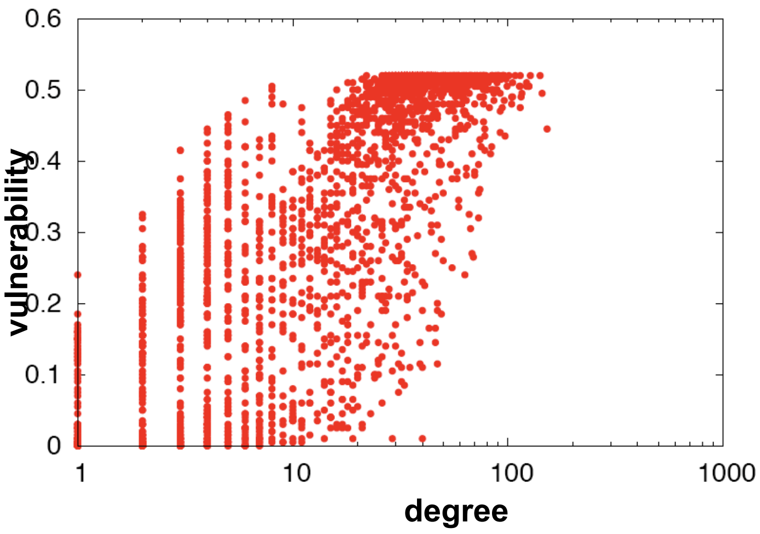
Computing vulnerability

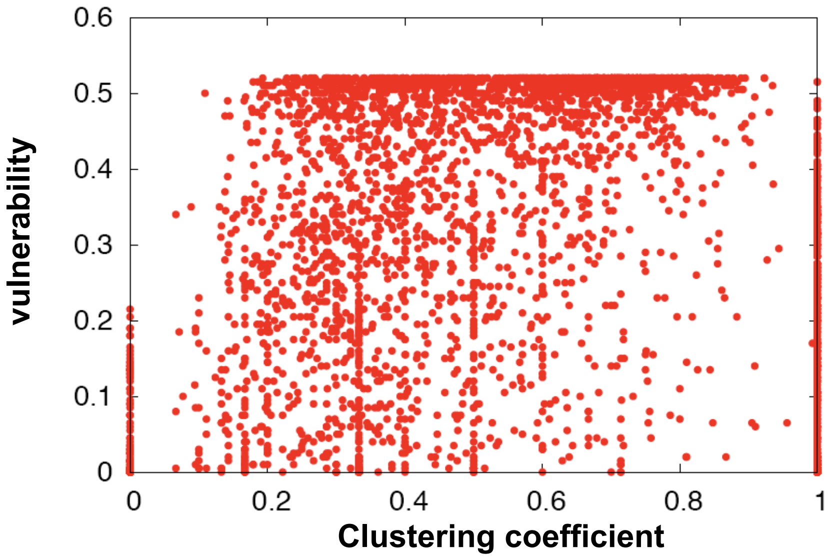
- Monte-carlo samples: each sample by running EpiFast
- $V_k(i)$: probability node i gets infected in k iterations
- $R(\infty)$: top n nodes in vulnerability order, $V(i)$
- $R(t)$: top n nodes in temporal vulnerability order $V(i,t)$

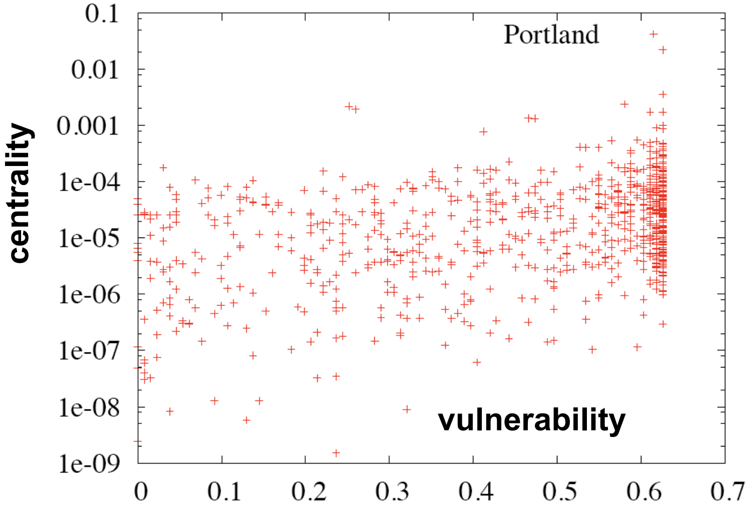




Correlation with static graph measures

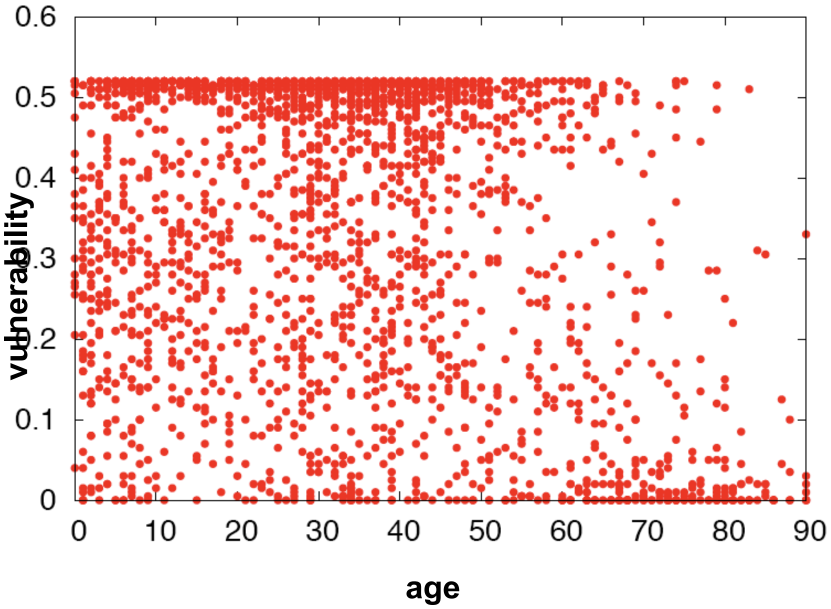


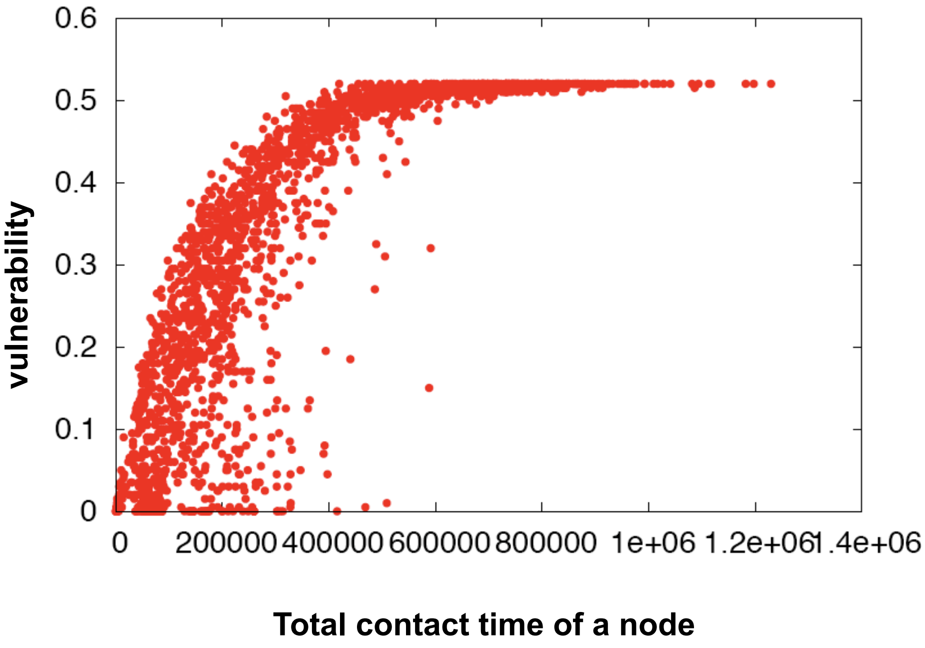




Very little information from static graph measures

Correlations with labels





- ❑ Similar correlations at different transmission probabilities
- ❑ Need better models for individual activities and contact duration

An illustrative case study: allocating and distributing A/Vs through public and private stockpile

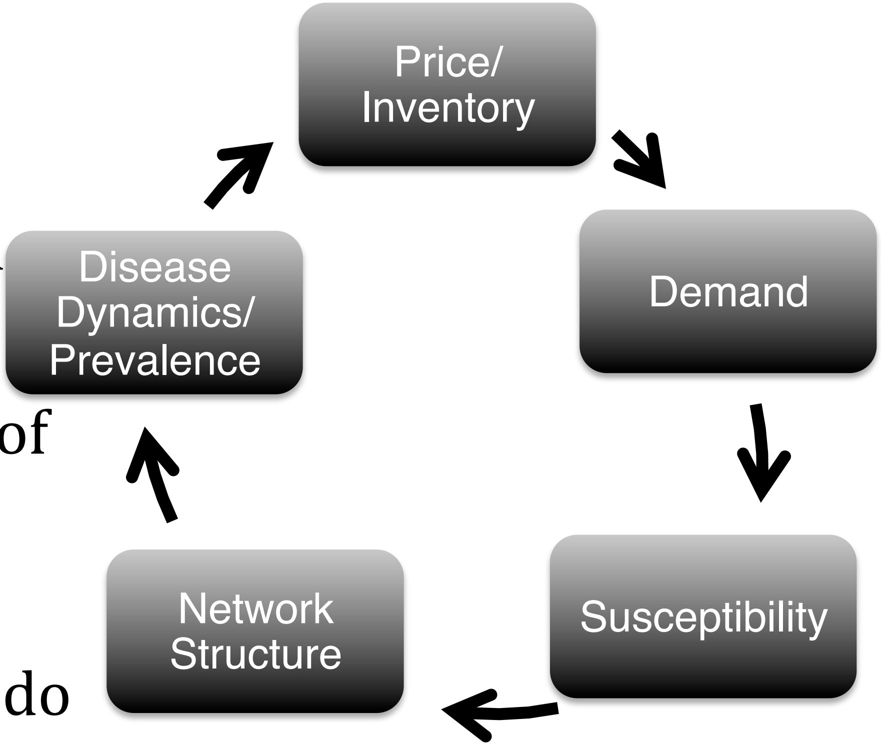
(Marathe et al.)

The problem

Policy Problem: Is there an optimum strategy to partition the scarce AV doses between public stockpile administered through hospitals and private stockpile distributed using a market-mechanism

Measures of Effectiveness: Number of infected, peak infections, cost of recovery, equitable allocation

Additional Scientific Question: How do disease prevalence, individual behavior, network structure, disease dynamics and AV demand co-evolve?


Price/ Inventory

Demand

Susceptibility

Network Structure

Disease Dynamics/ Prevalence

The Setup

- Use Simdemics modeling framework
- All modeling assumptions used in this study are the same as were used for the "MIDAS medkit" study in June 2008
  - Exception 1: Market distribution replaces the pre-assignment of AV kits based on income
  - Exception 2: Self Isolation of households based on prevalence and sick member
  - Exception 3: Disease prevalence used as a mechanism for adaptation
  - Disease model, Reporting, Diagnosis and Distribution Models: Same
- New River Valley population size: 150K
- The total stockpile of AV is 15k (10% of the population size).
- The price of the AV kit can vary between \$50-\$150 (2008 study: 100\$).
- Total household budget for the AV is 1% of the income.
- The private stockpile can be purchased by anyone who can afford it.

Disease Models

- Disease Model:
  - SEIR model is used.
  - Transmissibility (prob. of transmission in every minute of contact between an infectious node and a susceptible node) = 3E-5
  - Incubation and infectious period durations are chosen from distributions, mean = 1.9 and 4.1 days respectively.
  - A/V Efficacy: Susceptible nodes are 87% less likely to get infected; infectious nodes are 80% less likely to transmit the disease.
  - AV treatment and prophylaxis lasts 10 days.

Reporting, Diagonsing and Distribution of Public Stockpile

- Reporting and Diagnosis Model:
  - 2/3 of the infectious are symptomatic and report to the hospital.
  - Remaining 1/3 of the infectious are asymptomatic and 47% less likely to transmit.
  - Only 60% of those who report to the hospital get diagnosed.
  - Misdiagnosed: not sick but diagnosed as sick; In every 12 nodes diagnosed as sick 2 are not sick.
- Distribution
  - The hospital stockpile is distributed to only those diagnosed as infected.
  - There is no direct cost to the people for using the hospital stockpile.

Behavioral models

- [**Isolation based on Prevalence** :] Once the prevalence reaches 0.2%, for individuals diagnosed as infected, with compliance rate 40%, the entire household is isolated at home.
- [**Demand based on Prevalence**:] Total AV supply is 15k: allocated between hospitals and market
  - Hospitals: ***give*** to diagnosed as infected
  - Market: ***sells*** to households according to demand
- Household demand: $D_{t,h} = \frac{B_{t,h}}{P_t}(1 - e^{-\beta x_t})$

  Increases with disease prevalence (x_t)

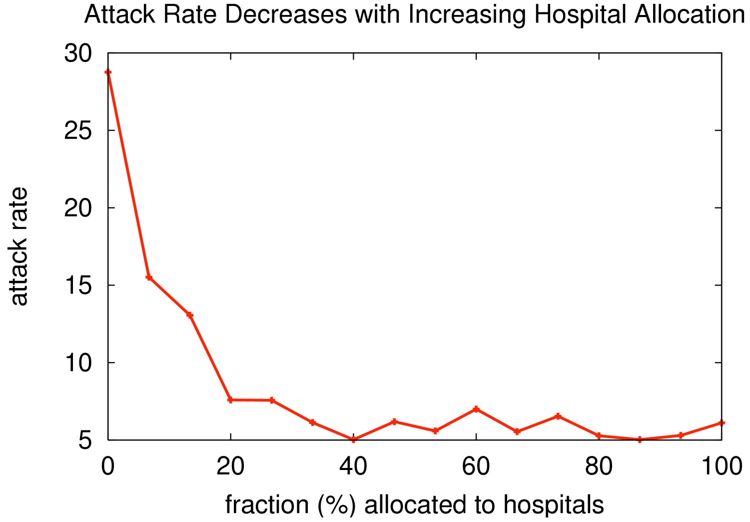
  Increases with household budget ($B_{t,h}$); decreases with price (P_t)

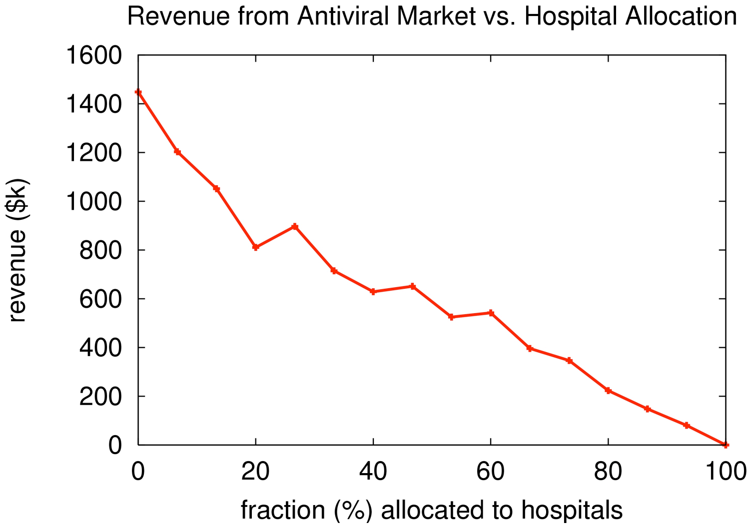
  price is linear in remaining supply

  β reflects risk aversion or prevalence elastic demand to AV.

Suggests an optimal allocation strategy

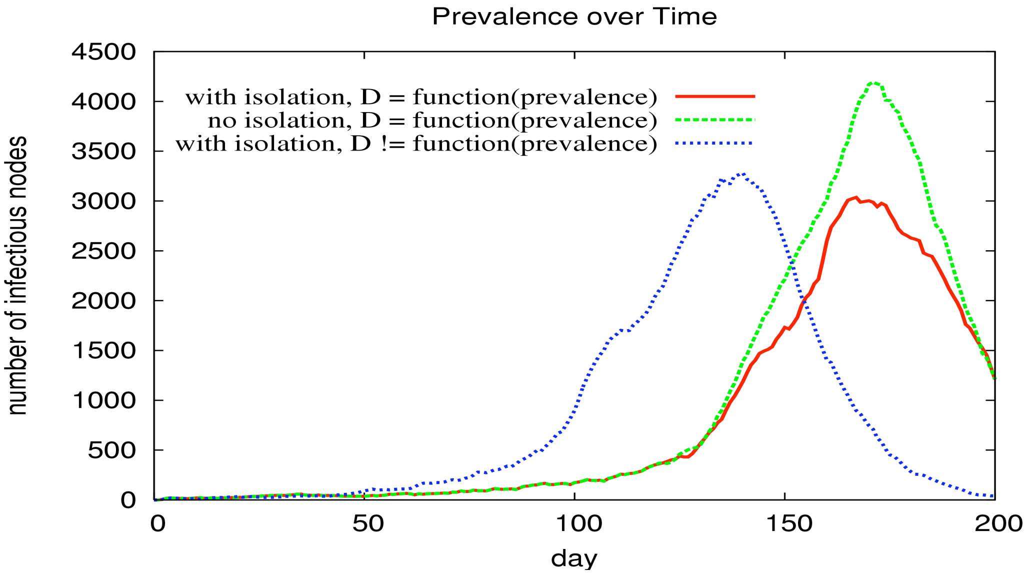
- Suggests optimal allocation strategy of AVs between public and private stockpile
  - Hospitals (public sector) should be given priority
  - If > threshold, the remaining stockpile be distributed via market.
  - Private stockpile useful for individuals who are infectious but not symptomatic
- Optimal split (40% to hospitals, 60% to the market) recovers the cost of antiviral manufacturing if the unit cost is < $42.

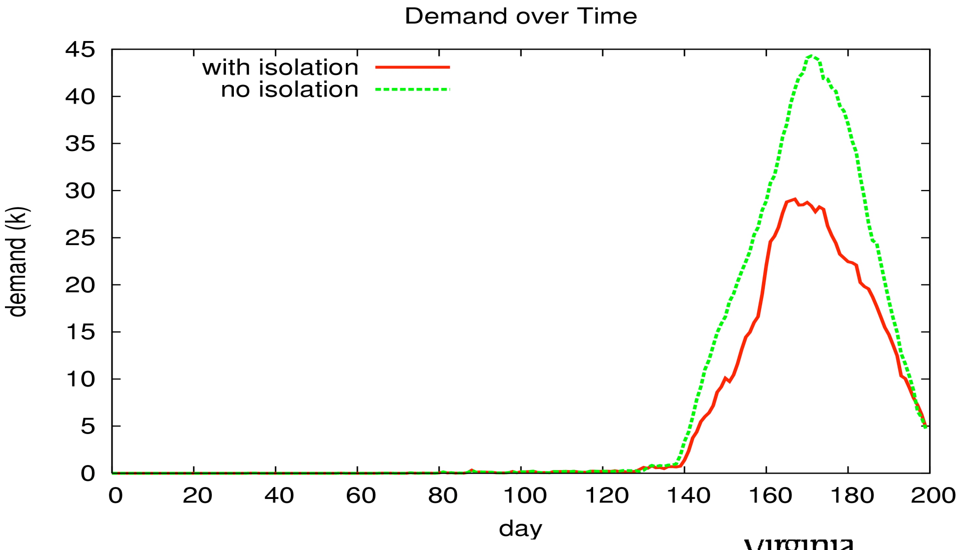




Importance of behavioral modeling

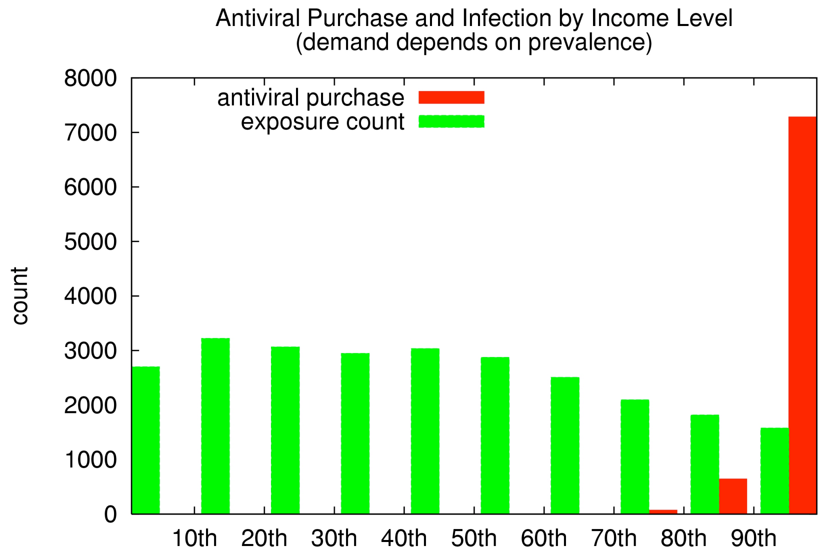
- *Prevalence elastic demand:* Delays the epidemic by about a month
- *Self Isolation triggered by Prevalence and sick member:* reduces the peak of the epidemic and reduces the overall demand

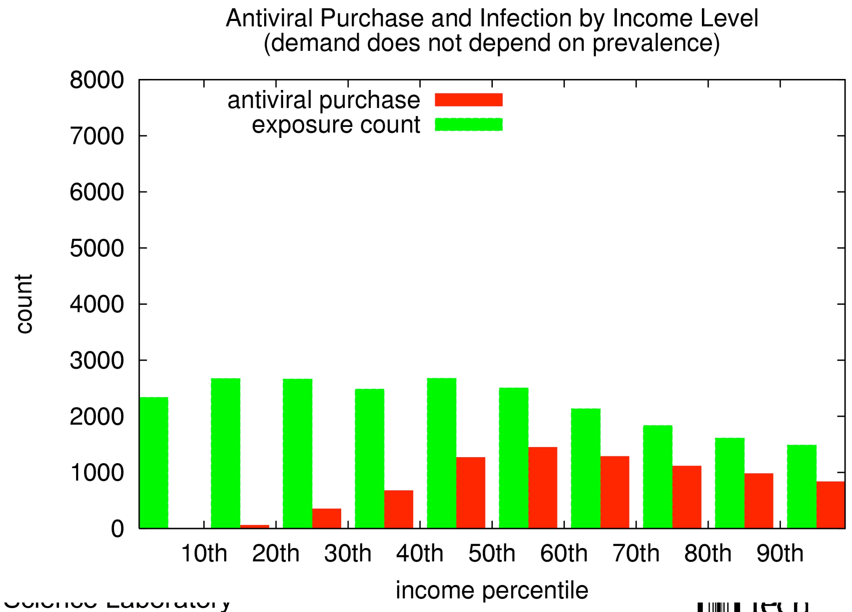




Inequitable allocation & role of government

- Market based distribution is inherently inequitable
  - Prevalence elastic demand creates more inequitable distribution (due to price increase)
- Provides a way for evaluating government subsidy or investment
  - More even distribution possible if price is capped or mechanisms are provided for reimbursing
  - The price range determines the investment needed by the government





A game theoretic view: AV purchase game

- Players: households
- Strategies: {buy antiviral, not to buy}
- Payoff: F (AV cost, expected number of infected household members)
- Information: AV supply (split between hospital and market stockpile) and price, disease prevalence, household budget.

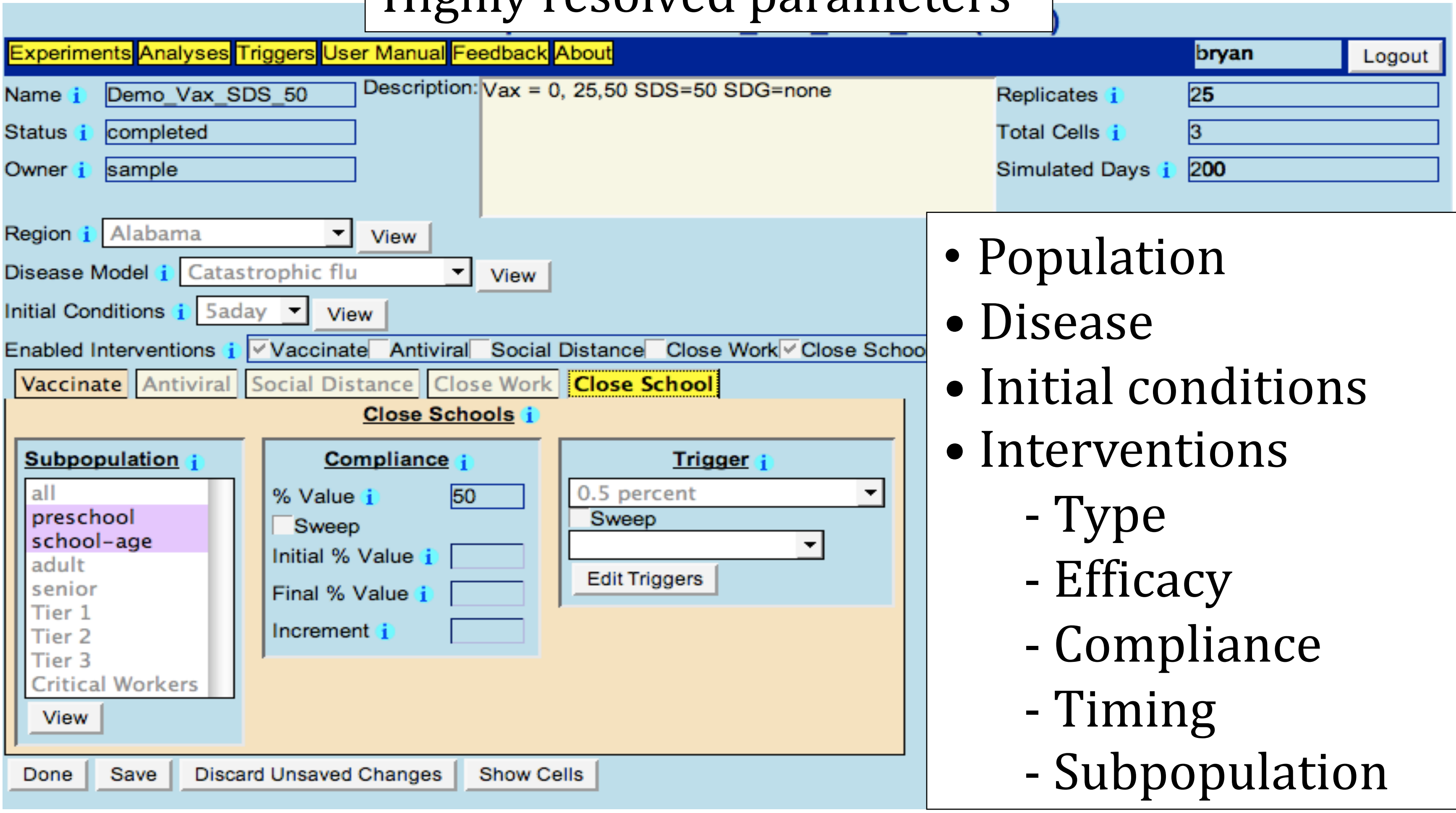
Strategy	Payment	Infection count
buy	$605.98	0.0769
not to buy	$0	0.1692

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



bryan

Name: Demo_Vax_SDS_50

Status: completed

Owner: sample

Description: Vax = 0, 25,50 SDS=50 SDG=none

Replicates: 25

Total Cells: 3

Simulated Days: 200

Region: Alabama

Disease Model: Catastrophic flu

Initial Conditions: 5aday

Enabled Interventions: ☑ Vaccinate ☐ Antiviral ☐ Social Distance ☐ Close Work ☑ Close Schoo

Close Schools

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

Compliance

% Value: 50

☐ Sweep

Initial % Value:

Final % Value:

Increment:

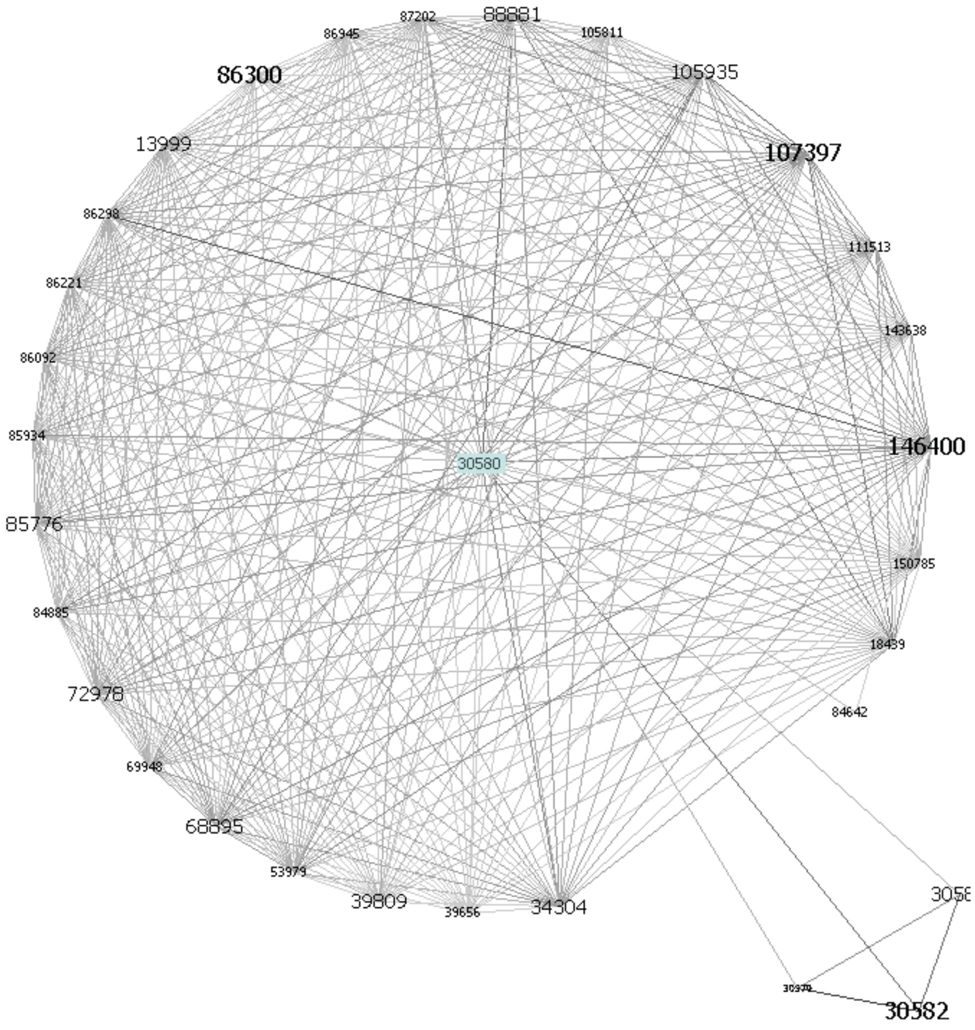
Trigger

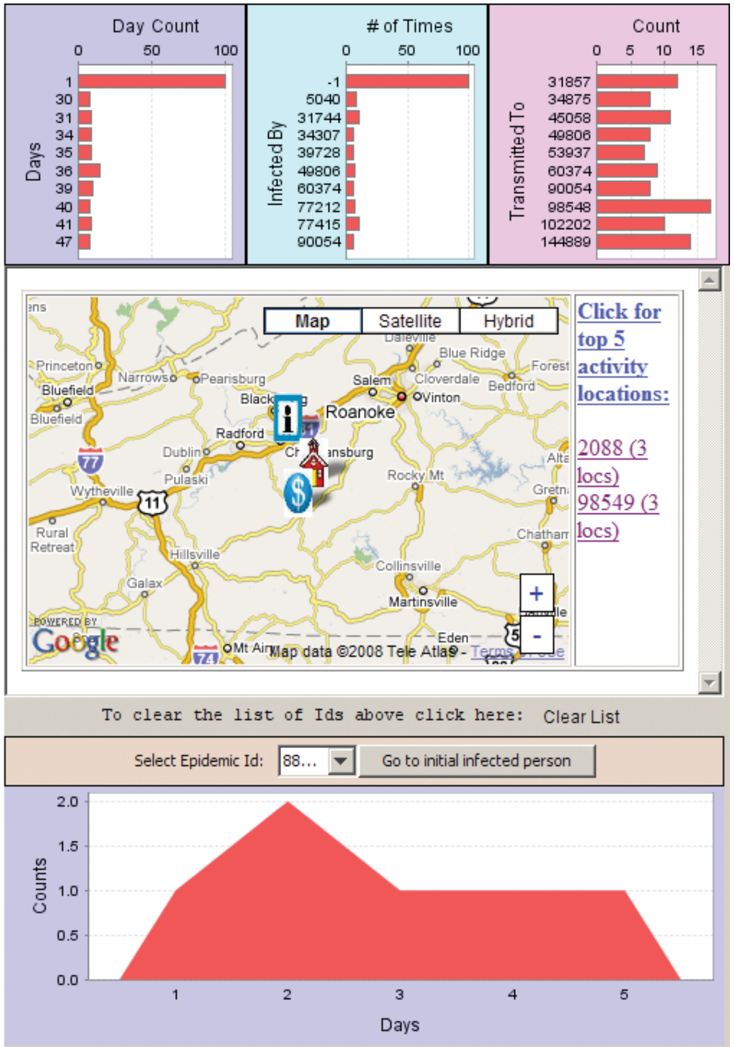
0.5 percent

☐ Sweep

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

Visual Analytics Support





Click for top 5 activity locations:

2088 (3 locs)

98549 (3 locs)

To clear the list of Ids above click here: Clear List

Select Epidemic Id: 88...

Go to initial infected person

Conclusions

- Start towards an integrated HPC-based policy informatics environment to support computational epidemiology that goes beyond simply agent-based disease modeling
  - Easy to use by SMEs, highly scalable and resolved
  - High performance computing grids & web-based services
  - Deployed and used successfully (e.g. during recent H1N1 response)
  - Flexible, realistic and efficient representation of individual behavior and public policy
- Presented a realistic case study to understand public health and economic consequences of AV allocations via public and market mechanisms
  - suggests a split between public and market-based stockpile that is optimal (in terms of the peak, time to peak and cost)
  - Individual behaviors play a crucial role – prevalence elastic demand and isolation is the key.

Summary: 3 take home points

- **Point 1**: Seamless access to powerful computational models for use by subject matter experts (SMEs) is *desirable and possible.*
  - Computing and modeling advances
  - Diversity of interests amongst various stakeholders
  - Yet a desire and need to share information and data during crisis: Social Computing
  - Leads to a qualitative change in the way public policies are supported
- **Point 2**: Models and data sources are increasingly complex and diverse: *Synthetic Information systems* provide a natural and scalable way for model composition and analysis
  - Unified view of models and data
  - Use of context based modeling and reasoning
  - Interactive simulations
- **Point 3**: In realistic situations, individual behavior, social networks, public policy & disease dynamics co-evolve
  - Representing multiple behavioral models & multiple network (MTML) *is now possible*: expressive, easy to use and computationally efficient