Synthetic social habitats for policy and decision making

Workshop on Pedestrian Dynamics and Epidemic Modeling

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Habitat [From Encyclopedia Britanica] ,

A place where an organism or a community of organisms lives, including all living and nonliving factors or conditions of the surrounding environment. Focus on:

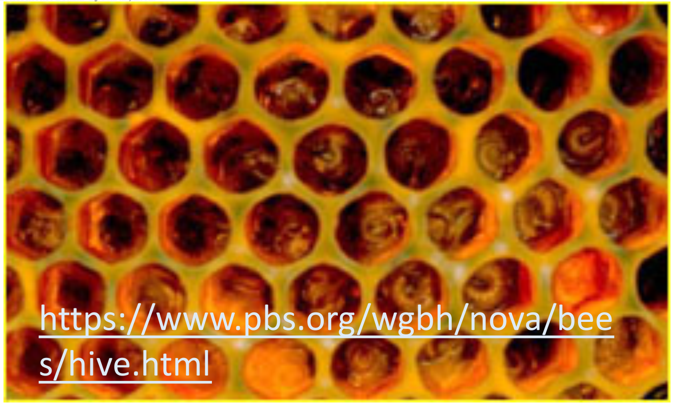
- Engineered environments (e.g. cities, villages, ant hills, termite nests, bee-hives)
- Largely on humans but also on animal, virus and other species (e.g. microbiota in human and animal gut, termite colonies)
- Community as opposed to a single individual


A Metropolis of 200 Million Termite Mounds Was Hidden in Plain Sight

What amount to garbage piles — some are 4,000 years old — are spread over an area the size of Britain in a remote Brazilian forest.

https://www.nytimes.com/2018/11/20/science/termite-mounds-brazil.html

Drone footage of termite mounds across the landscape in northeast Brazil. By Martin, Et Al.



https://www.pbs.org/wgbh/nova/bees/hive.html

The Wisdom of the Hive: The Social Physiology of Honey Bee Colonies, & *Honeybee Ecology: A Study of Adaptation in Social Life,* Thomas D. Seeley. Wilson, Edward O. (1971). *The Insect Societies*. Cambridge.

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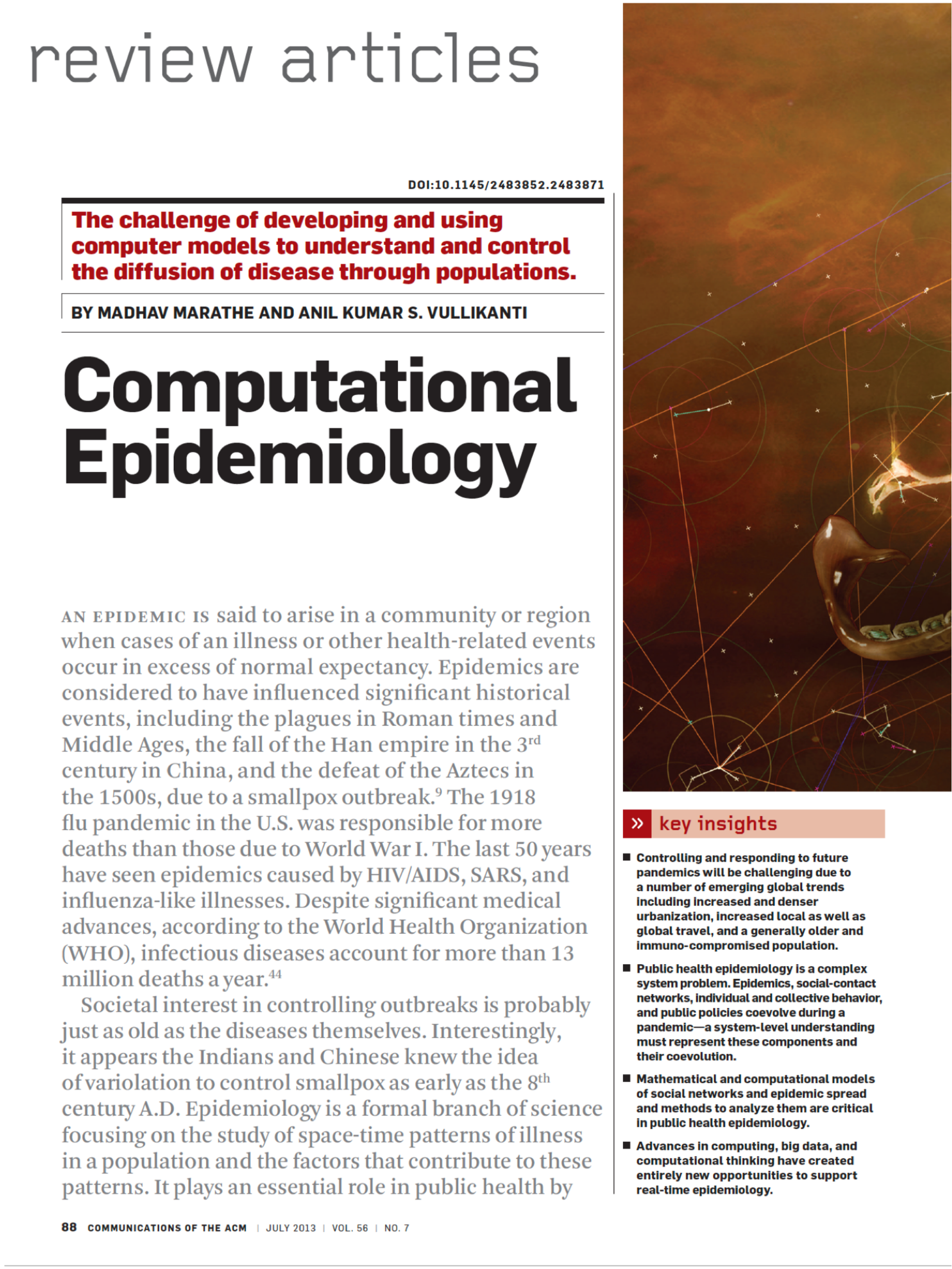
- *Computational Epidemiology*. Tutorial presented at KDD, ICSB, AAAI: Madhav Marathe, Anil Vullikanti and Naren Ramakrishnan: http://ndssl.vbi.vt.edu/supplementary-info/vskumar/kdd-slides.pdf



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The challenge of developing and using computer models to understand and control the diffusion of disease through populations.

BY MADHAV MARATHE AND ANIL KUMAR S. VULLIKANTI

Computational Epidemiology

AN EPIDEMIC IS said to arise in a community or region when cases of an illness or other health-related events occur in excess of normal expectancy. Epidemics are considered to have influenced significant historical events, including the plagues in Roman times and Middle Ages, the fall of the Han empire in the 3rd century in China, and the defeat of the Aztecs in the 1500s, due to a smallpox outbreak.[9] The 1918 flu pandemic in the U.S. was responsible for more deaths than those due to World War I. The last 50 years have seen epidemics caused by HIV/AIDS, SARS, and influenza-like illnesses. Despite significant medical advances, according to the World Health Organization (WHO), infectious diseases account for more than 13 million deaths a year.[44]

Societal interest in controlling outbreaks is probably just as old as the diseases themselves. Interestingly, it appears the Indians and Chinese knew the idea of variolation to control smallpox as early as the 8th century A.D. Epidemiology is a formal branch of science focusing on the study of space-time patterns of illness in a population and the factors that contribute to these patterns. It plays an essential role in public health by

» key insights

- Controlling and responding to future pandemics will be challenging due to a number of emerging global trends including increased and denser urbanization, increased local as well as global travel, and a generally older and immuno-compromised population.
- Public health epidemiology is a complex system problem. Epidemics, social-contact networks, individual and collective behavior, and public policies coevolve during a pandemic—a system-level understanding must represent these components and their coevolution.
- Mathematical and computational models of social networks and epidemic spread and methods to analyze them are critical in public health epidemiology.
- Advances in computing, big data, and computational thinking have created entirely new opportunities to support real-time epidemiology.

Pervasive, Personalized and Precision (P^3) analytics for social-habitats

- **Pervasive:** *Enable decision maker to make decisions at any, place, anytime and any device*
- **Personalized:** *Enable decision maker to get personalized information that reflects her context*
- **Precise:** *The decision maker should have precise information in space, time and context.*

A few real-world applications: 1992-Present

- HPC-based decision support environments since 1992
  - TRANSIMS Program (1992-2001)
  - DHS NISAC Program (2002-present)
  - DoD CNIMS program (2005-present)
- Central focus: rigorous data-driven causal modeling
  - Ensuring models were contextualized and used diverse data sets
  - Over two dozen user defined case studies to support policy analysis and model refinement

Synthetic Population, Network & Information

A Tutorial on Generating Synthetic Populations for Social Modeling

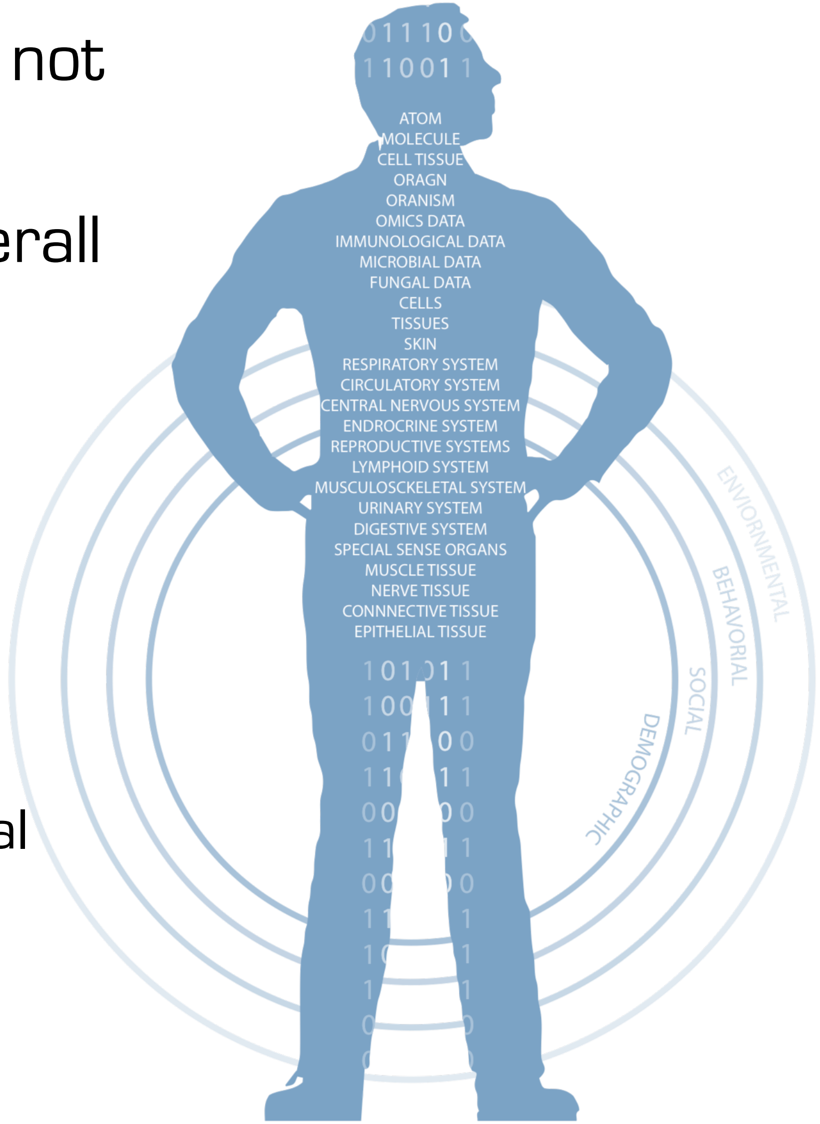
IJCAI 2016, New York City, July 10, 2016 & AAMAS 2016, Singapore, May 9, 2016 and AAMAS 2017, Brazil.

Contains references on the topic as well.

http://people.virginia.edu/~ss7rs/synthetic_population_tutorial/IJCAI_2016_generating_synthetic_populations_for_social_modeling_tutorial.pdf

What is a synthetic agent ?

- A *representation* of elements' and states that is not intended to precisely match any snapshot of the system, but to provide a statistically accurate overall picture:
  - people, places, things
  - cells, cytokines, organs
- A *synthesis* of incommensurate data
- E.g.: A synthetic human agent
  - Can have demographic, social, health, cognitive, cultural attributes
  - These attributes need to be statistically accurate to attributes of humans



Synthetic Populations and Networks

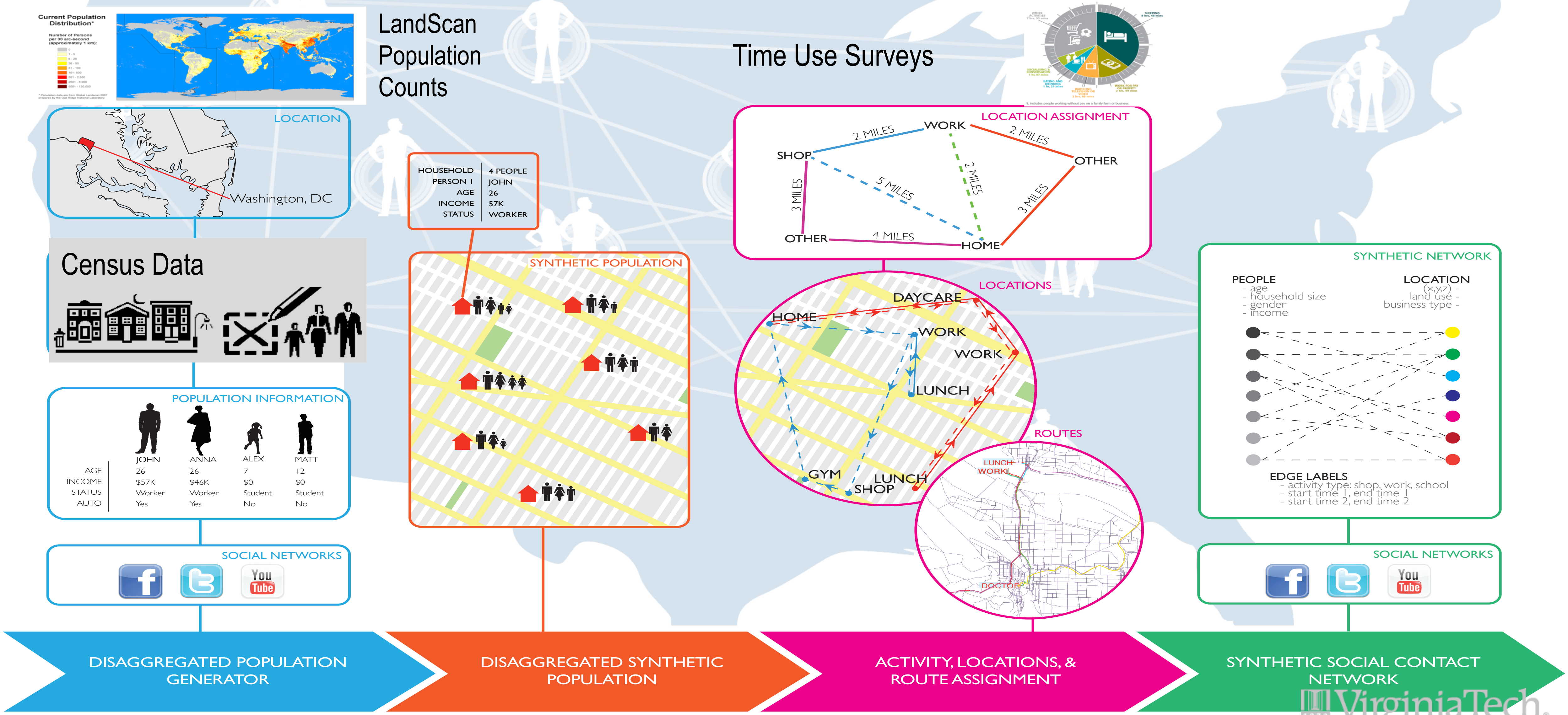
- *Synthetic population:*
  - *set of synthetic agents (e.g. people) that share a common geographic, social or biological characteristic*
  - Sharing can be done at a desired spatial, temporal and social scale.
- Synthetic network:
  - synthetic population with links that capture interactions among the agents
  - Links either physical or a matter of convention
  - Multiple networks are possible over the same synthetic agent collection

Synthesizing realistic synthetic contact networks

- First principles approach for synthesizing social contact networks
- For individuals in a population (representation of individuals):
    - Their demographics (Who)
    - The sequences of activities they do (What)
    - The times they do them (When)
    - The places they do them (Where)
    - The reasons they do them (Why)
- No explicit data sets available for such networks
- Synthesizing public and commercial data sets and expert knowledge
- Can explicitly model impact of behavioral changes
- Input data: Noisy, time lagged, diverse

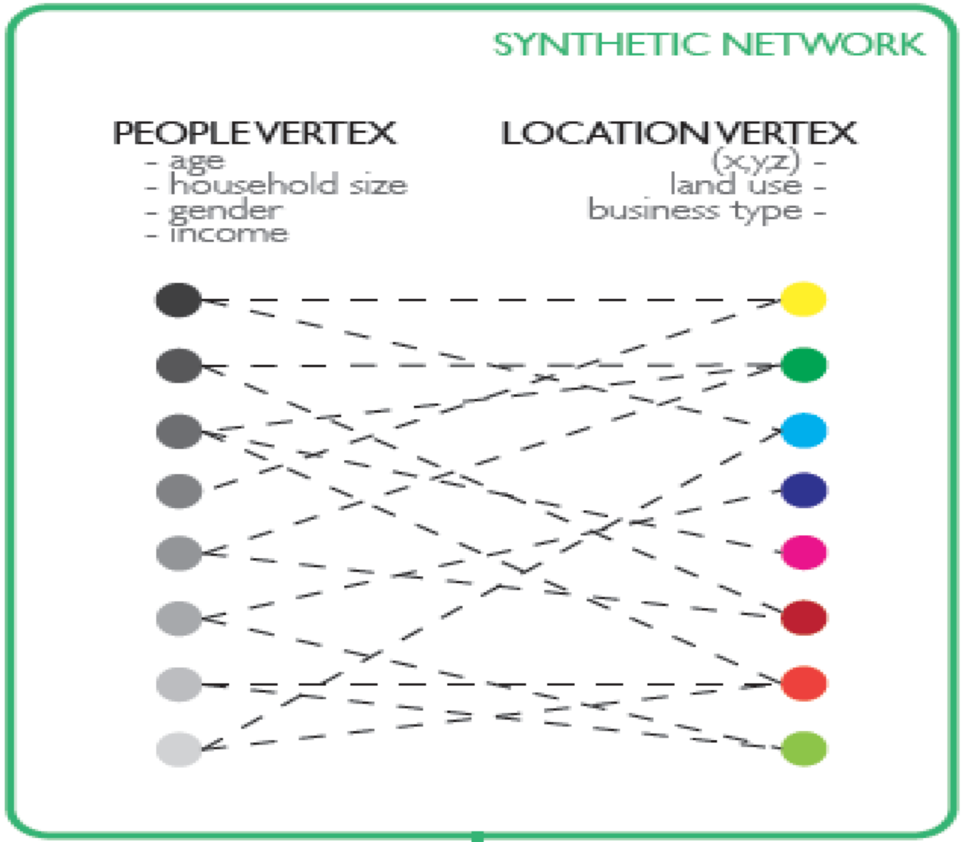
Data sets, documentation at: ndssl.vbi.vt.edu

Constructing synthetic multi-scale synthetic networks at scale

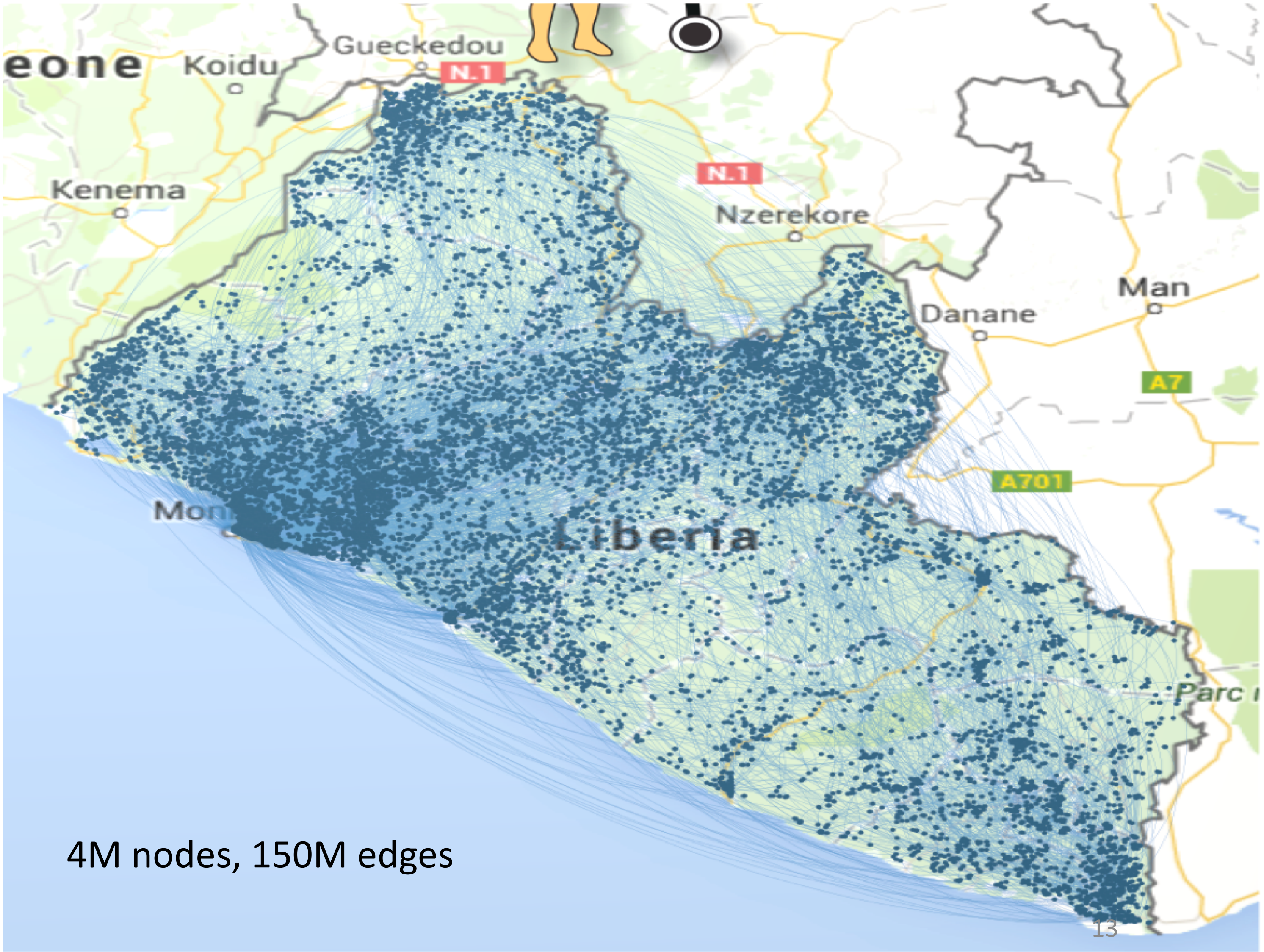


VirginiaTech
Biocomplexity Institute

Yields multi-scale dynamic & relational networks



Edge attributes:
- activity type: shop, work, school
- (start time 1, end time 1)
- (start time 2, end time 2)
- mode taken



4M nodes, 150M edges

Global synthetic information

2GB/M people
Storage

7 Billion
Synthetic individuals

28+ Billion
Interactions

40+
Databases

220 countries
synthetic populations and networks constructed

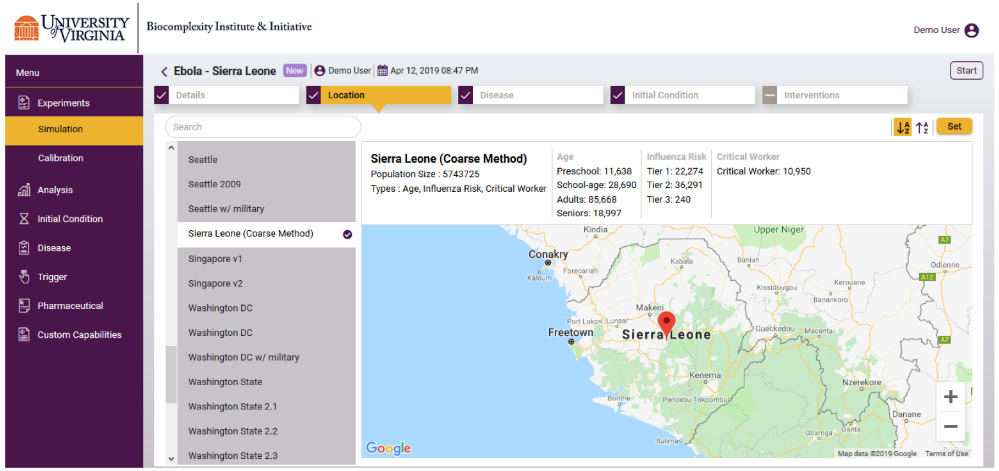
50K+
Files in which data is stored

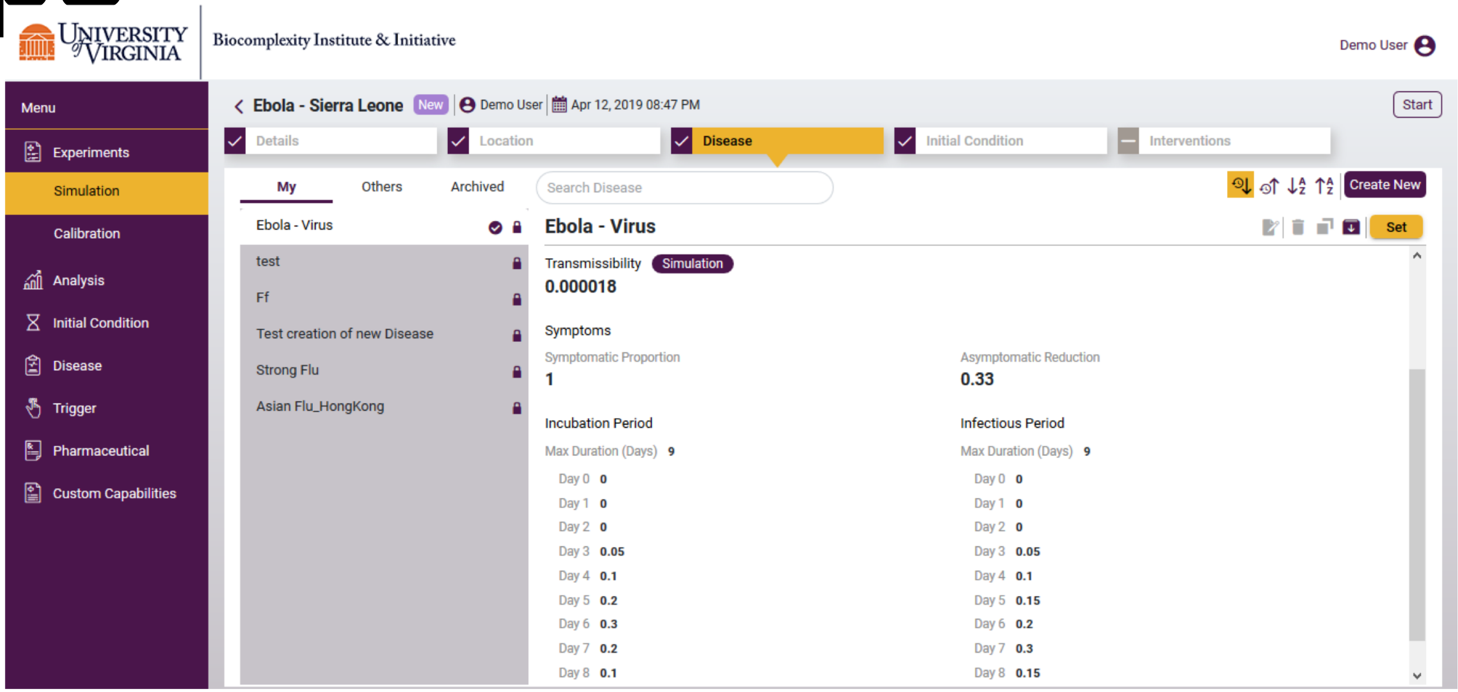
5 Days
Compute time

8TB
Storage

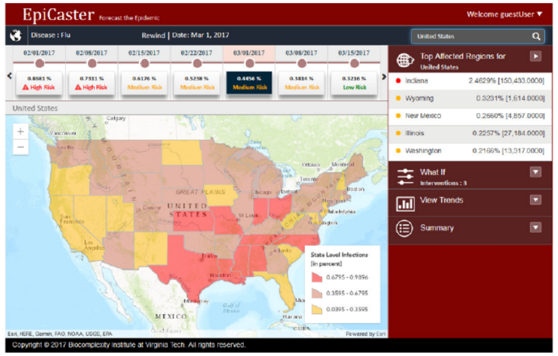
First data driven global synthetic populations and proximity networks

Pervasive webapps

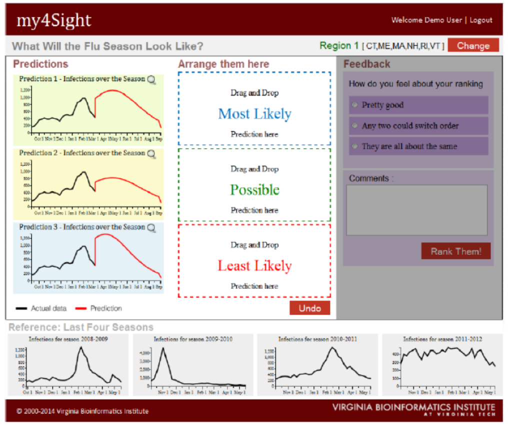




Design, Execute, and Analyze
Agent-based simulations of
Infectious disease spread



a *EpiCaster: spatial visualization*

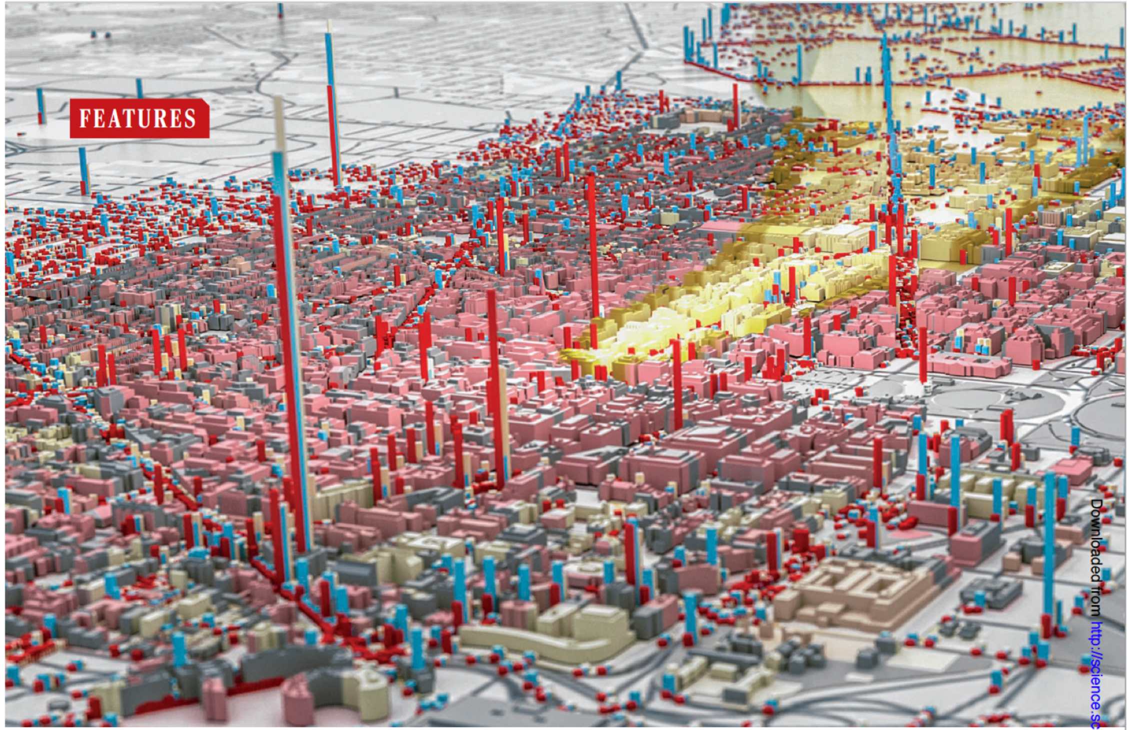


b *My4Sight: model ranking*

c *EpiViewer: concurrent plotting*

https://www.youtube.com/watch?v=8vdo8sX19_I

Reference: Waldrop M (2018) Free Agents: Monumentally complex models are gaming out disaster scenarios with millions of simulated people. *Science*, 360(6385):144-147.



FREE AGENTS

Monumentally complex models are gaming out disaster scenarios with millions of simulated people

By **M. Mitchell Waldrop**

At 11:15 on a Monday morning in May, an ordinary looking delivery van rolls into the intersection of 16th and K streets NW in downtown Washington, D.C., just a few blocks north of the White House. Inside, suicide bombers trip a switch.

Instantly, most of a city block vanishes in a nuclear fireball two-thirds the size of the one that engulfed Hiroshima, Japan. Powered by 5 kilograms of highly enriched uranium that terrorists had hijacked weeks earlier, the blast smashes buildings for at least a kilometer in every direction and leaves hundreds of thousands of people dead or dying in the ruins. An electromagnetic pulse fries cellphones within 5 kilometers, and the power grid across much of the city goes dark. Winds shear the bomb's mushroom cloud into a plume of radioactive fallout that drifts eastward into the Maryland suburbs. Roads quickly become jammed with people on the move—some trying to flee the area, but many more looking for missing family members or seeking medical help.

CREDITS: (IMAGE) DANE WEBSTER, UNIVERSITY OF COLORADO IN DENVER; (DATA) NETWORK DYNAMICS AND SIMULATION SCIENCE LABORATORY (NDSSL)

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