Real-Time Pandemic Planning, Prediction and Response



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References

Papers:

- CACM 2014: Computational Epidemiology
- Nature 2004: Modelling disease outbreaks in realistic urban social ٠ networks.
- PNAS 2008: Modeling targeted layered containment of an influenza ٠ pandemic in the United States.
- PNAS 2014: Opinion: Mathematical models: A key tool for outbreak ٠ response.

Tutorials (KDD'14, AAAI'16, ICSB'17): <u>https://covid19.biocomplexity.virginia.edu/publications</u> A Tutorial on Generating Synthetic Populations for Social Modeling, <u>IJCAI 2016</u>, & <u>AAMAS 2016</u>. COVID-19 resource page: <u>https://covid19.biocomplexity.virginia.edu/</u> New NSF Expeditions Project: <u>https://computational-epidemiology.org</u> New NSF Virtual Organization Project: https://prepare-vo.org

review articles

DOI:10.1145/2483852.2483871

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

(WHO), infectious diseases account for more than 13

Societal interest in controlling outbreaks is probably

in a population and the factors that contribute to these

patterns. It plays an essential role in public health by

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

» 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 advances, according to the World Health Organization global travel, and a generally older an uno-compromised population

> Public health epid system problem. Epid mics, social-con networks, individual and collective beh idemic-a system-level underst nust represent these com

Mathematical and computa of social networks and epidemic sprea century A.D. Epidemiology is a formal branch of science and methods to analyze them are critica focusing on the study of space-time patterns of illness

Advances in computing, big data, and computational thinking have crea entirely new opportunities to support

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million deaths a year.44

Modeling for integrated reasoning about situations & actions



 Synthesize available data to produce consistent and meaningful representations of the underlying system

- *Provide* a range of interpretations of incoming measurements
- Evaluate a range of response actions and behaviors
- Monitor effect of intervention responses
- Coordinate understanding among diverse stakeholders
- Usable by analysts and not just computing experts



Adiga, A., et al.. 2020. Data-driven modeling for different stages of pandemic response. Journal of the Indian Institute of Science, pp.1-15.

E.T. Lofgren et al. "Opinion: Mathematical models: A key tool for outbreak response". PNAS, vol. 111, no. 51, 2014.

Human-centered model-based distributed decision making



Individual decision maker

Human-centered model-based distributed decision making



The phases of COVID-19 pandemic



	Phase 1
Questions	 Predict risk of importation Infer disease parameters Evaluate impacts of social distancing
Data Needs	 Clinical studies on disease outcomes Global multimodal traffic Testing and case surveillance
Research Highlights	 Model projections (<i>Imperial, IHME,</i> <i>Northeastern</i>) Undocumented infections (<i>Columbia</i>)

	Phase 1	Phase 2
Questions	 Predict risk of importation Infer disease parameters Evaluate impacts of social distancing 	 Predict risk of resurgence Infer the role of mobility & mask use Evaluate the efficacy of contact tracing
Data Needs	 Clinical studies on disease outcomes Global multimodal traffic Testing and case surveillance 	 Cross-scale intervention measures Local mobility and mixing Behavior and compliance
Research Highlights	 Model projections (<i>Imperial, IHME,</i> <i>Northeastern</i>) Undocumented infections (<i>Columbia</i>) 	 Collaborative ensemble (UMass) Symptom Surveys (CMU) Resource allocation (Yale, UT Austin) Optimal testing (AIM)

	Phase 1	Phase 2	Phase 3
Questions	 Predict risk of importation Infer disease parameters Evaluate impacts of social distancing 	 Predict risk of resurgence Infer the role of mobility & mask use Evaluate the efficacy of contact tracing 	 Predict medical resource demand Infer effect of seasonality Evaluate K-12, colleges reopening
Data Needs	 Clinical studies on disease outcomes Global multimodal traffic Testing and case surveillance 	 Cross-scale intervention measures Local mobility and mixing Behavior and compliance 	 Hospital occupancy statistics Weather and seasonal factors College reopening plans
Research Highlights	 Model projections (<i>Imperial, IHME,</i> <i>Northeastern</i>) Undocumented infections (<i>Columbia</i>) 	 Collaborative ensemble (UMass) Symptom Surveys (CMU) Resource allocation (Yale, UT Austin) Optimal testing (AIM) 	 Digital contact tracing study (<i>Oxford</i>) Susceptibility and climate (<i>Princeton</i>) Mobility reduction impact (<i>Stanford</i>)

	Phase 1	Phase 2	Phase 3	Phase 4
Questions	 Predict risk of importation Infer disease parameters Evaluate impacts of social distancing 	 Predict risk of resurgence Infer the role of mobility & mask use Evaluate the efficacy of contact tracing 	 Predict medical resource demand Infer effect of seasonality Evaluate K-12, colleges reopening 	 Predict variant dominance Infer current seroprevalence Evaluate vaccine rollouts
Data Needs	 Clinical studies on disease outcomes Global multimodal traffic Testing and case surveillance 	 Cross-scale intervention measures Local mobility and mixing Behavior and compliance 	 Hospital occupancy statistics Weather and seasonal factors College reopening plans 	 Seroprevalence surveys Vaccine administration Genomic sequencing
Research Highlights	 Model projections (<i>Imperial, IHME,</i> <i>Northeastern</i>) Undocumented infections (<i>Columbia</i>) 	 Collaborative ensemble (UMass) Symptom Surveys (CMU) Resource allocation (Yale, UT Austin) Optimal testing (AIM) 	 Digital contact tracing study (<i>Oxford</i>) Susceptibility and climate (<i>Princeton</i>) Mobility reduction impact (<i>Stanford</i>) 	 B.1.1.7 US prevalence (Scripps) Vaccine by serostatus (U. Colorado, Harvard)

Challenges for End-to-End Planning, Prediction and Response

From Ecology to Biology to Epidemiology to Sociology

[Zoonosis] Model the evolution of the pathogen in space and time, including its interaction with humans and their immune systems, as well as the effects of interventions.

[Immunological Response] Understand immune response? What is the role of innate and adaptive immunity?

[Vaccine Development and Testing] How effective is the vaccine, how long will the immunity last?

[Viral evolution] How will the virus evolve under selection pressures

[Socio-economics] How will the pandemic interact with social, political and economic aspects

Ebola Virus Ecology and Transmission Ebola virus disease is a zoonotic disease. Zoonotic diseases involve animals and humans Animal-to-Animal Transmission Spillover Event Human-to-Human Transmission Survivor Evidence suggests that bats are the A "spillover event" occurs when an Once the Ebola virus has infected Ebola survivors face new challenges reservoir hosts for the Ebola virus. animal (bat, ape, monkey, duiker) or the first human, transmission of the after recovery. Some survivors human becomes infected with Ebola Bats carrying the virus can transmit it virus from one human to another report effects such as tiredness and to other animals, like apes, monkeys, virus through contact with the can occur through contact with the muscle aches, and can face stigma as and duikers (antelopes), as well as to reservoir host. This contact could blood and body fluids of sick people they re-enter their communities. occur through hunting or preparing or with the bodies of those who the animal's meat for eating. have died of Ebola. ditional funeral practic ealthcare worke CDC ith blood and body fluids

Need: Link models of viral evolution, human immune system, epidemic spread and socio-economic systems

Spatial, temporal and social scales



Organizations (months), Community (days) and individual (days)

•

Need: Multi-scale, multi-theory, multi-level network representations and simulations

Data to decisions and communication



NEED: Context-specific, decentralized information integration and decision making across socio-political scales

Validation and uncertainty quantification (trust and adequacy)

- Retrospective and predictive validity are not as useful in crisis situations when data is limited.
- External Validation
 - validate past predictions
 - update future projections
- Internal Validation
 - ensure structurally correct
- How do we gather and incorporate relevant data in real-time to:
 - actively learn when modeling assumptions cause models to fail to capture real-world dynamics?



Need: New approaches for V&V, UQ and model adaptation for co-evolving networks

Al and High-Performance Computing-Enabled Prediction and Decision Informatics for Real-time Epidemic Science

How do we do it: Data driven-networked epidemiology



Step 1: Build a digital twin of a city/country

How do we do it: Data driven-networked epidemiology



Step 1: Build a digital twin of a city/country

Step 2: Build agent-based simulations of disease propagation

How do we do it: Data driven-networked epidemiology



Step 1: Build a digital twin of a city/country

Step 2: Build agent-based simulations of disease propagation Step 3: Epidemiological workflows using simulation and ML

80+ scientists, staff, and students at UVA and collaborating institutions



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Federal agencies



Commonwealth of Virginia

Primary modeling for planning and response efforts



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EDUCATION

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Your Environmen

Local agencies

 Virginia Hospital and Healthcare Association (comprised of 27-member health systems and 110 community and specialty hospitals)









https://covid19.biocomplexity.virginia.edu/

Weekly updates to state and federal agencies since February 2020

Network Systems Science & Advanced Computing Biocomplexity Institute & Initiative University of Virginia

Estimation of COVID-19 Impact in Virginia

February 17th, 2021 (data current to February 15th – 16th) Biocomplexity Institute Technical report: TR 2021-020

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Literature surveys

https://www.vdh.virginia.gov/coronavirus/covid-19-data-insights/

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continue to decline from the recent peak.

counts remains the further emergence of variants.

· While still high, cases, hospitalizations, and deaths in Virginia

· The most significant obstacle to continued improvement in case

One year into the pandemic, Virginia is performing well compared

to other states on case, death and vaccination rates, but COVID-19 racial/ethnic disparities provide opportunities for improvement.

February 19, 2021

KEY TAKEAWAYS

KEY FIGURES

WEEKLY UPDATE

68 per 100k

Week Ending Jan 24, 2021

39 per 100k

Week Ending Feb 14, 2021

46 per 100k

Cases, Week Ending May 30.

Average Daily Cases

Pandemic Fatique

Days from Onset to Diagnosis and Test Positivity - We

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UVA COVID-19 MODEL WEEKLY UPDATE

VDHURGINIA DEPARTMENT OF HEALTH

THE MODEL

The UVA COVID-19 Model and the weekly results are provided by the UVA Biocomplexity Institute, which has over 20 years of experience crafting and analyzing infectious disease models. It is a (S)usceptible, (E)xposed, (I)nfected, (R)ecovered epidemiologic model designed to evaluate policy options and provide projections of future cases based on the current course of the pandemic. COVID-19 is a novel virus causing a global pandemic and response. The model improves as we learn more about it.

THE PROJECTIONS

The UVA team continues to improve the model weekly. The UVA model uses an "adaptive fitting" methodology, where the model traces past and current trends and uses that information to predict future cases at the local level. The model incorporates projections on the impact of vaccines which will improve over time. Several scenarios are included, including counterfactual "no vaccine" scenarios. The model also includes three "what-if" or planning scenarios. The "Best Past Control" scenario projects what may occur if localities match the lowest rates of transmission seen earlier in the summer. This scenario also includes an optimistic vaccine rollout scenario, meeting public targets. The "Fatigued Control" scenario does the opposite, projecting the highest transmission rates forward and using a pessimistic vaccine rollout scenario. The "New Variants" scenario projects the potential impact of new variants, including a 40% increase in transmission, with the B.1.17 variant becoming dominant in late March.

MODEL RESULTS

The model results are encouraging again this week. All model scenarios show that weekly cases have already peaked at just over 68 average daily cases per 100,000 residents during the week ending January 24th. However, if Virginians relax their behavior as new variants take hold, we could face another smaller peak in the spring, Under the Fatigued Control, Variant B.1.1.7 scenario, cases would reach 46 average daily cases per 100,000 the week ending May 30th. To avoid another peak, we must give vaccines time to have an impact, especially as new variants become more prevalent across the nation. Do your part to stop the spread. Continue to practice good prevention and get vaccinated when eligible.



Model projections
Narrative summaries

https://www.vdh.virginia.gov/coronavirus/covid-19-data-insights/

Reproduction Rate (Based on Confirmation Date) Weekly





Case Detection

Growth Trajectories: 0 Health Districts in Surge



Situation assessment

Literature surveys

Building dashboards

Integrated Solutions:

Accessible and helpful to everyone across the globe, reliable, rich visualizations with easy-to-use interface

COVID-19 Surveillance Dashboard:

1.2 million users worldwide3.7 million views since Feb 3 ,2020

Spatial: 210 Countries, 450 States, 3,200 Counties (USA)

Temporal: Updated multiple times a day since Jan 22, 2020;

Medical Resource Demand Dashboard

https://nssac.bii.virginia.edu/covid-19/usmrddash



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Social distancing survey https://socialdistancing.stanford.edu/



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COVID-19 Mobility Impact Dashboard



Multi-scale, multi-method weekly COVID- 2. 19 forecasting

- Incorporate multiple classes of models:
 - Statistical methods (AR, Kalman filters), deep learning models (LSTM), and Mechanistic meta-population models (SEIR model)

• Ensemble:

- Combine forecasts from multiple methods to produce probabilistic forecasts at county level (performance-based ensemble)
- Bayesian model averaging (instead of model selection) to avoid overconfident inferences & include individual model uncertainty
- Ensemble forecasts usually perform better than individual forecast
- Key observation: All models are useful.



HPC-Grid workflow to compute US medical costs

[1] Daily Incidence data: ~ 3100 counties × 200 days.

[2] A typical design: 2 VHI compliances × 3 lockdown durations $\times 2$ lockdown compliances \times 51 states \times 15 replicates = 9180 simulation instances. Network with 300 million nodes and 7.9 billion edges partitioned across all 50 states [3] Size of *individual* level output data: 12 cells \times 51 states \times 15 replicates multi-million state transitions = approx. multi-billion entries (3TB). [4] Size of aggregate output data: 12 cells × 51 states \times 15 replicates \times 365 days \times 90 health states \times 3 counts = ~1 billion entries (2.5GB).

Scalable Epidemiological Workflows to Support COVID-19 Planning and Response D. Machi, et al. IPDPS 2021, Scientific Reports, 2020



Lessons learned

- Work closely with stakeholders
 - Build models that are explainable, transparent
- Be agile and flexible
 - Each situation is new and comes with unique challenges: requires constant model adaptation
- Unusual effectiveness of transdisciplinary team science
 - Working in teams is critical skills, perspective and collaboration matters
- Social, political and economic considerations are increasingly important
- Communicating scientific results in such situation needs to be thoughtful and deliberate

Concluding remarks and key takeaways

An effective strategy to reduce the global burden of epidemics must:

- **Detect** timing and location of occurrence.
- Anticipate public reaction to an outbreak.
- **Develop** actionable interventions that enable targeted and effective responses.

Needed advances

- **Real-time collection** and updating of data, models in rapidly changing environments.
- Incorporate social and behavioral components in the models
- Models that are scientifically effective, explainable & operational.

New looming challenges

- Climate Change
- Anti-microbial resistance
- Synthetic pathogens
- Infodemics and role of social media
- Urbanization& increased global transactions
- Expectation of timely information

Some Background Information