# Experiences with agent-based modeling & inference for COVID-19: Results and lessons learned

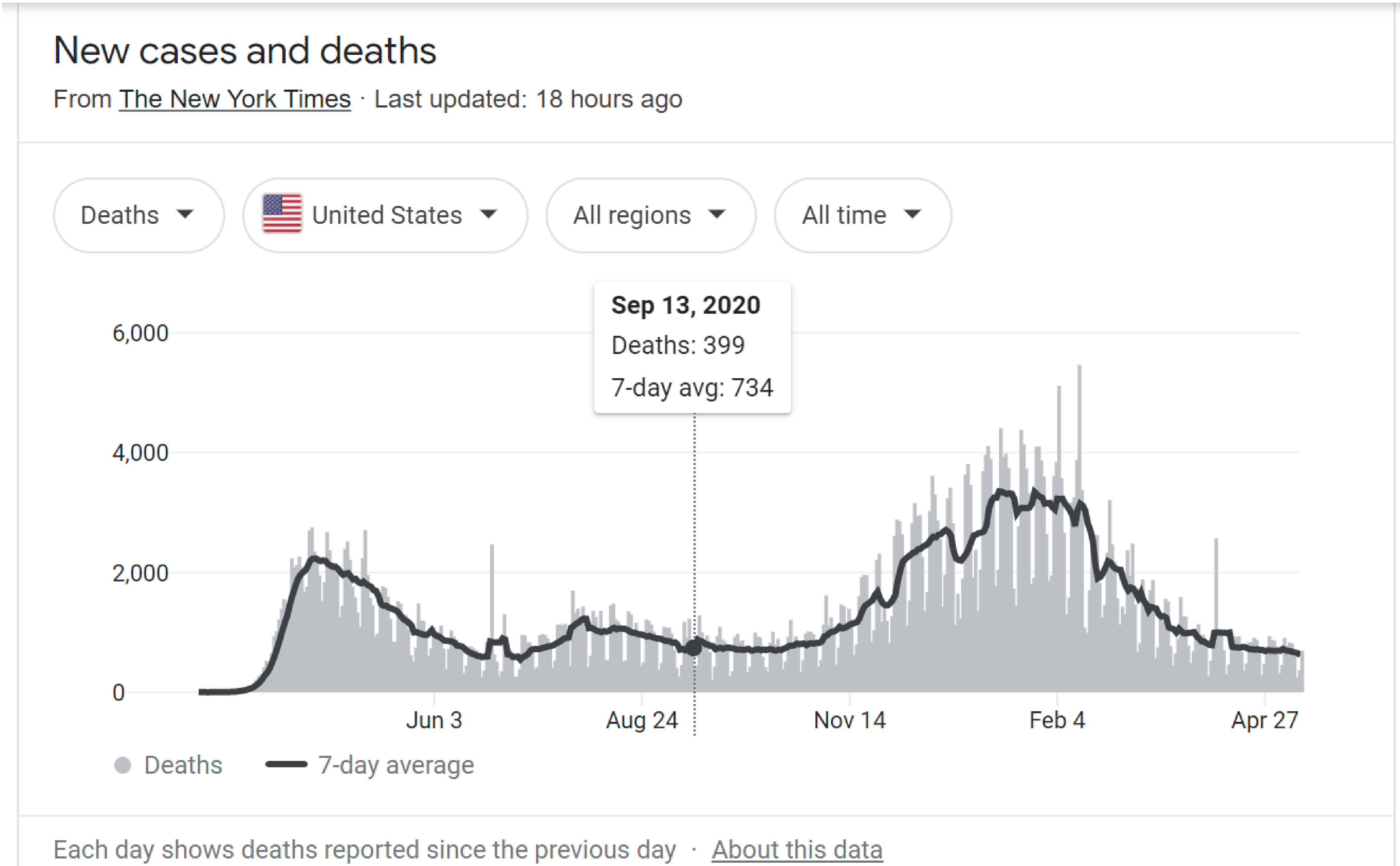
**MILIND TAMBE**

*Director, Ctr for Research on Computation & Society, Harvard University*

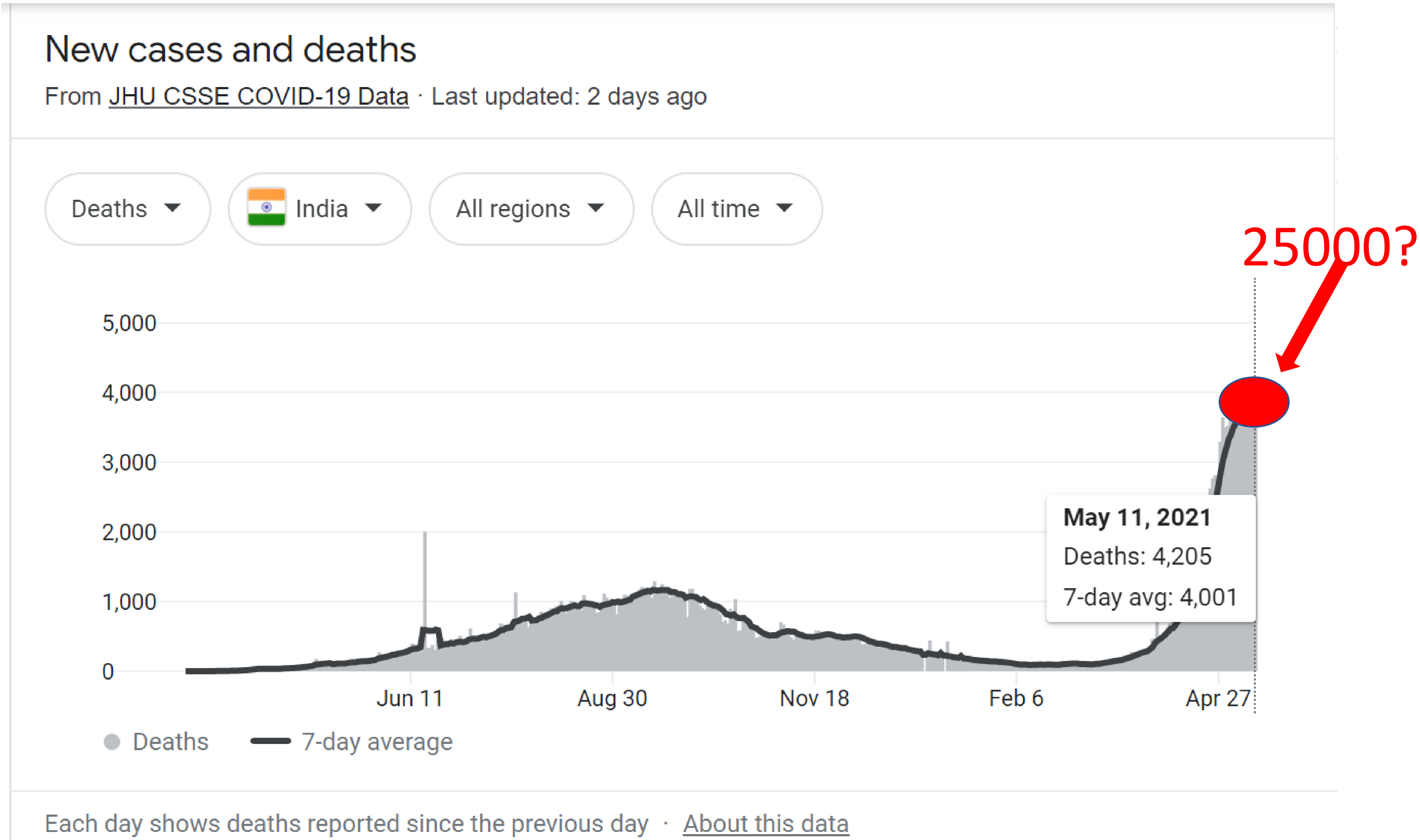
*Director "AI for Social Good", Google Research India*

*@MilindTambe_AI*

# Acknowledging COVID-19 context (US)

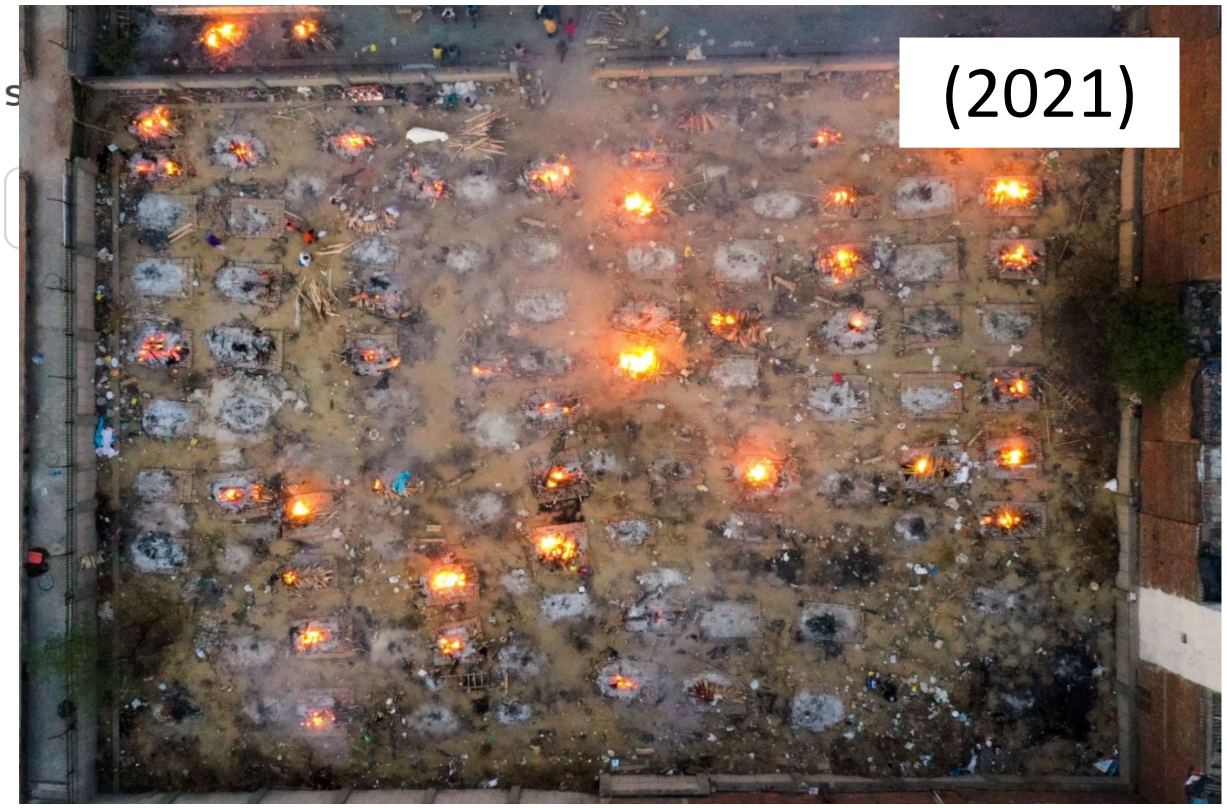


# Acknowledging COVID-19 context (India)



# Acknowledging COVID-19 context (India)

## ‘A hell out here’: COVID-19 ravages rural India




# Outline

- Background “AI for social impact”
- Agent-based modeling for COVID
  - *Modeling COVID-19 dynamics [PNAS, 2020]*
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  - *Contact tracing [Under submission]*
- **Lessons learned**

*Key group members:*
*Bryan Wilder (PhD student)*
*Andrew Perrault (postdoc)*

*Key collaborators:*
*Prof. Maia Majumder (Harvard Medical School)*
*Prof. Michael Mina (Harvard Chan School of Public Health)*

# AI & Multiagent Systems Research for Social Impact

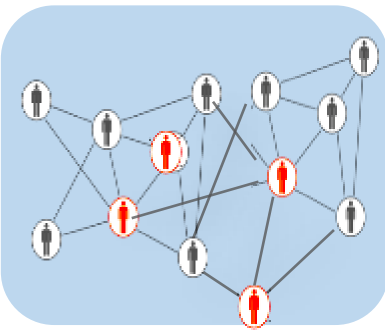

**Public Health**

**Conservation**


**Public Safety and Security**

**Optimize Our Limited Intervention Resources**

# Previous work in Agent-based Modeling




Social Networks & Bandits

Public Health


Green security games

Conservation


Public Safety & Security

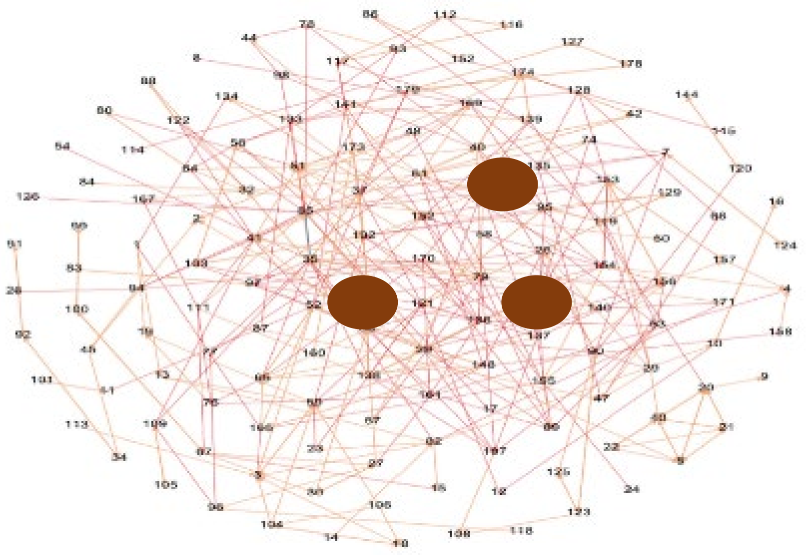

Stackelberg security games

# Information dissemination & behavior change
# Optimizing Limited Intervention (Social Worker) Resources

*Prevent HIV in youth experiencing homelessness: HIV 10x housed population*

- ***Shelters**: Limited number of peer leaders to spread HIV information in social networks*
- *"Real" face-to-face interactions; not Facebook etc*

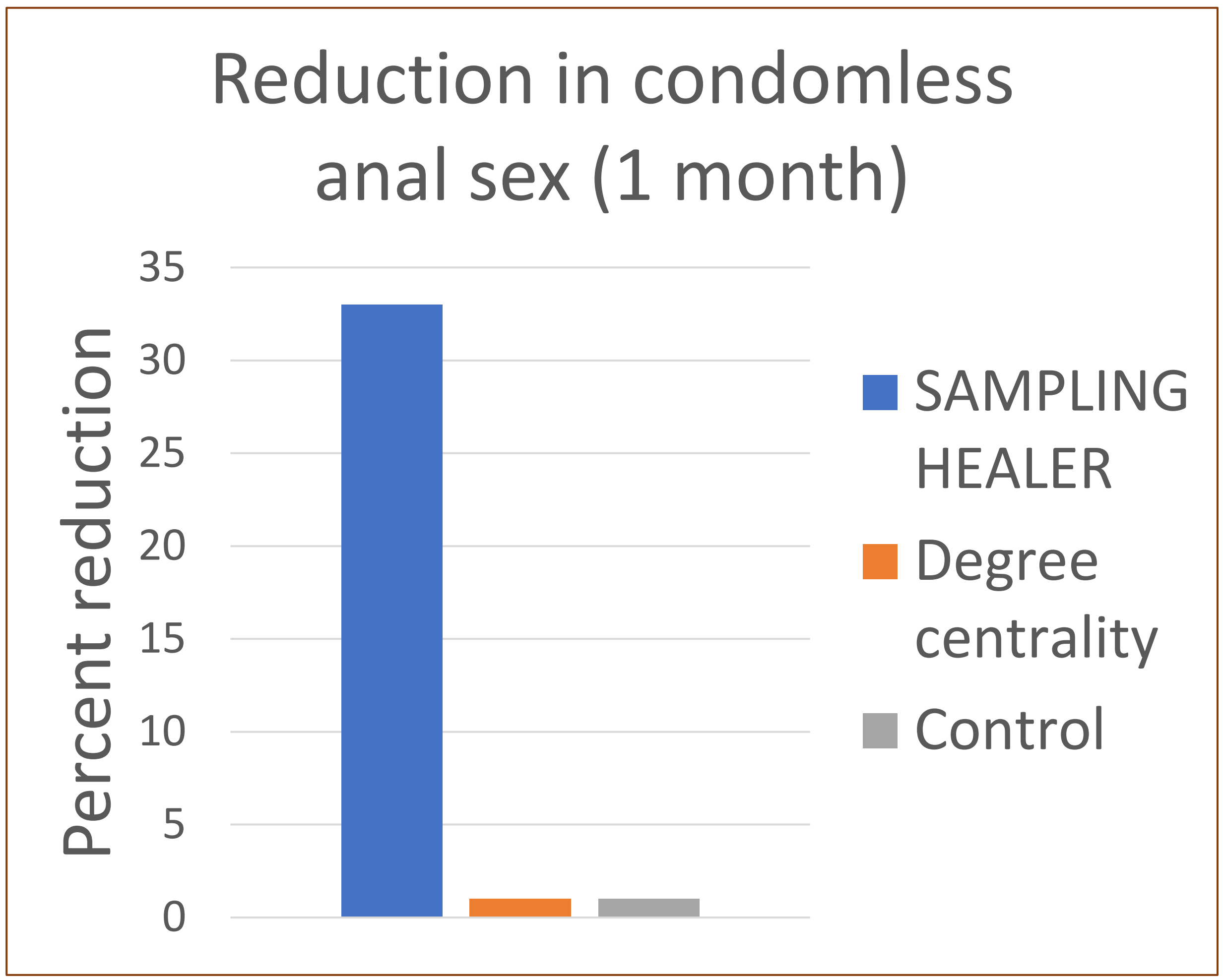

# Influence Maximization in Social Networks

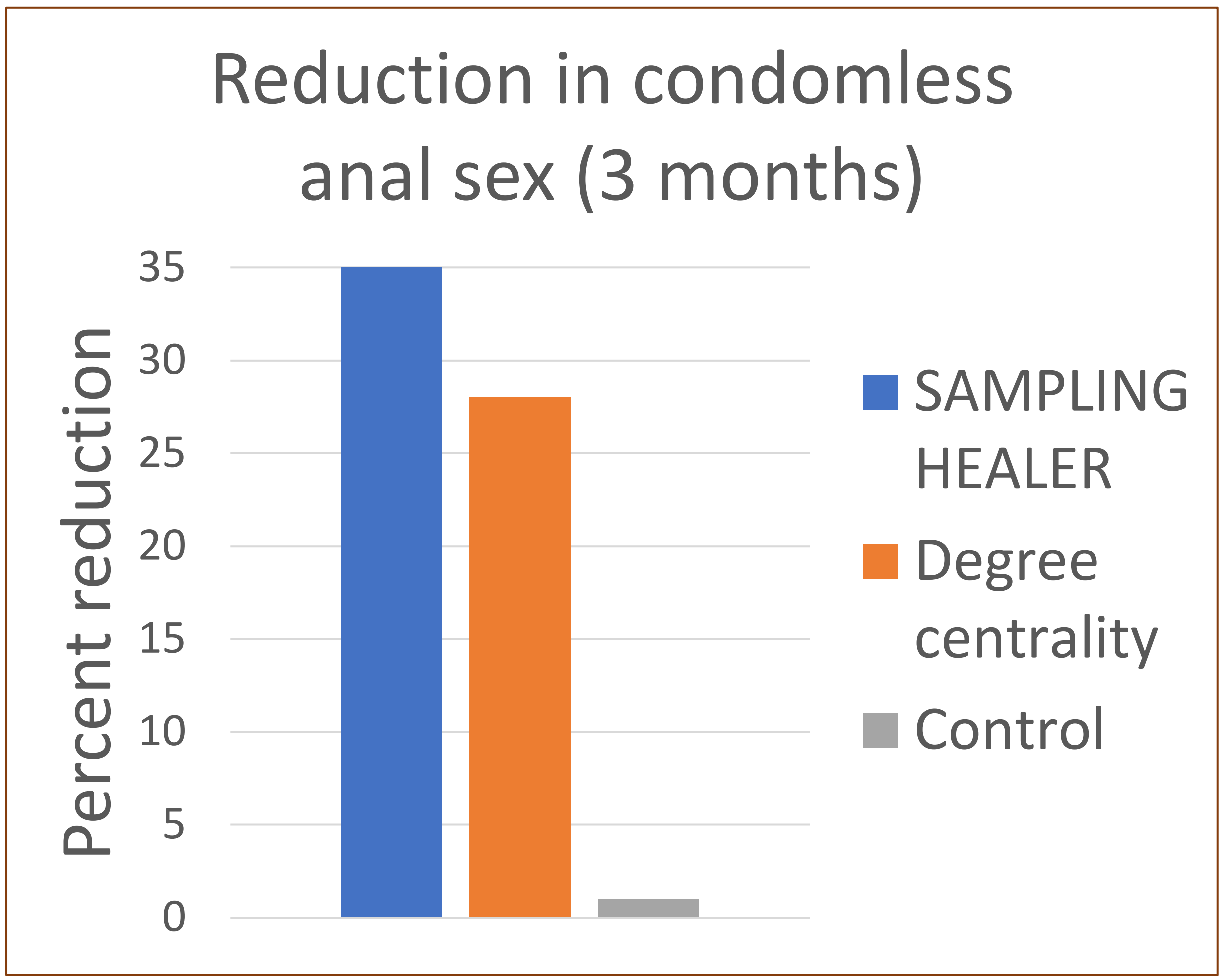


- Given:
  - Social network Graph G
  - Choose K “peer leader” nodes
  - Assume: Independent cascade model of information spread
- Objective:
  - Maximize expected number of influenced nodes
- New algorithm: SAMPLING-HEALER

# Results of 750 Youth Study [with Prof. Eric Rice]
# Actual Change in Behavior?
*(AAAI 2021)*

*First large-scale application of influence maximization for public health*




*Key observation: Pace of AI research vs Field study*

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- **Lessons learned**

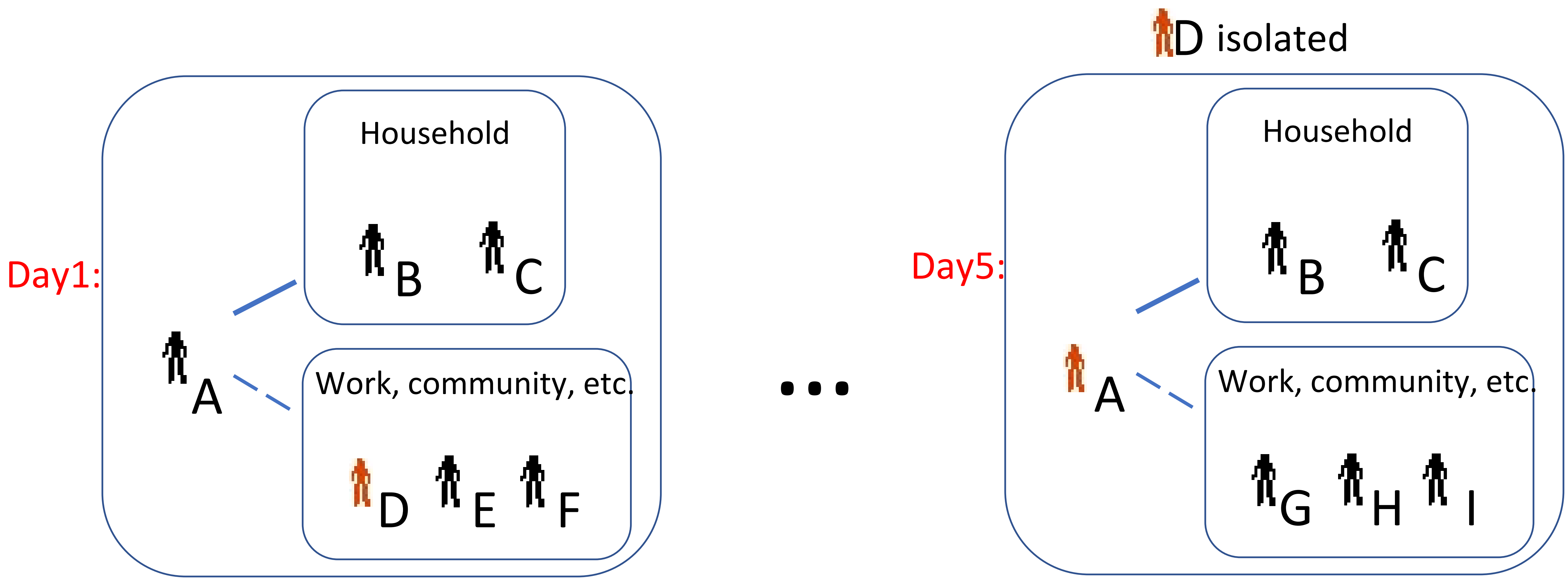
# Background: Agents

- Computer programs simulate individual people

| Agent A |
|---|
| Age: 47 |
| Diabetes: Yes   Hypertension: No |
| Household: Agents B, C |

| Agent H |
|---|
| Age: 35 |
| Diabetes: No   Hypertension: No |
| Household: Agent K |

…



# COVID-19: Agent-based Simulation Model

***Agent-based model:***

- *Families*
- *Co-morbidities*
- *Age distributions*
- *Contact patterns*
- *Bayesian inference over unknowns*

*Key collaborators:*
*Prof. Maia Majumder (Harvard Medical School)*

PNAS Proceedings of the National Academy of Sciences of the United States of America

RESEARCH ARTICLE

## Modeling between-population variation in COVID-19 dynamics in Hubei, Lombardy, and New York City

Bryan Wilder, Marie Charpignon, Jackson A. Killian, Han-Ching Ou, Aditya Mate, Shahin Jabbari, Andrew Perrault, Angel N. Desai, Milind Tambe, and Maimuna S. Majumder

PNAS October 13, 2020 117 (41) 25904-25910; first published September 24, 2020;
https://doi.org/10.1073/pnas.2010651117

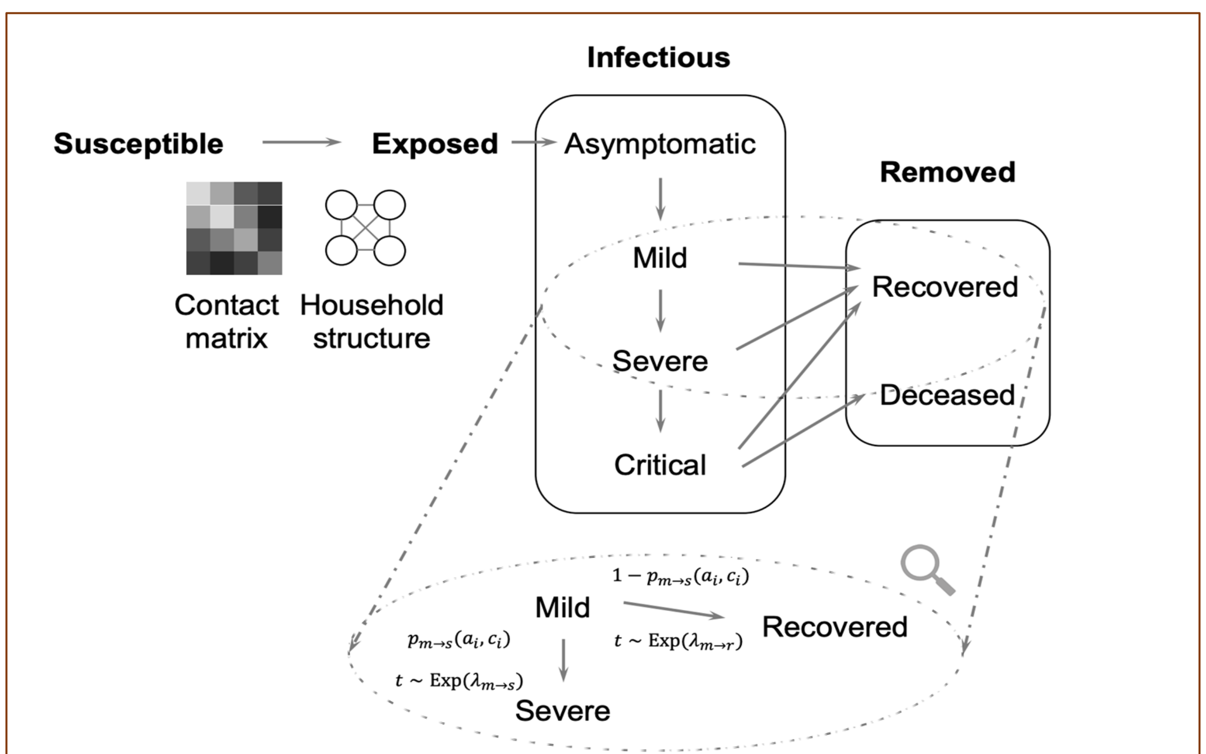



**Fig. 1.** We use a modified SEIR model, where the infectious states are subdivided into levels of disease severity. The transitions are probabilistic and there is a time lag for transitioning between states. For example, the magnified section shows the details of transitions between mild, recovered, and severe states. Each arrow consists of the probability of transition [e.g.,

# Parameter inferences

- Use model to understand variation in dynamics & progression of epidemic

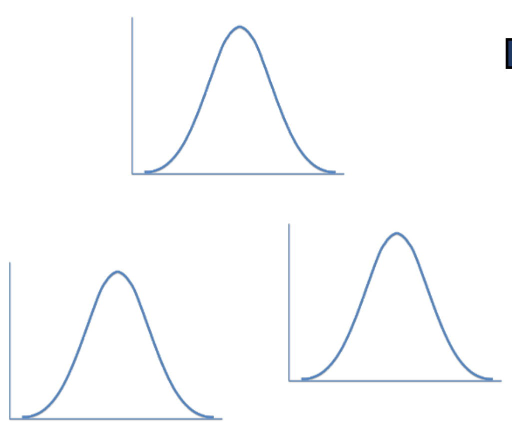
- Two main targets:

  $r_0$: average infections caused by a single infected person
  (in a susceptible population with no interventions)

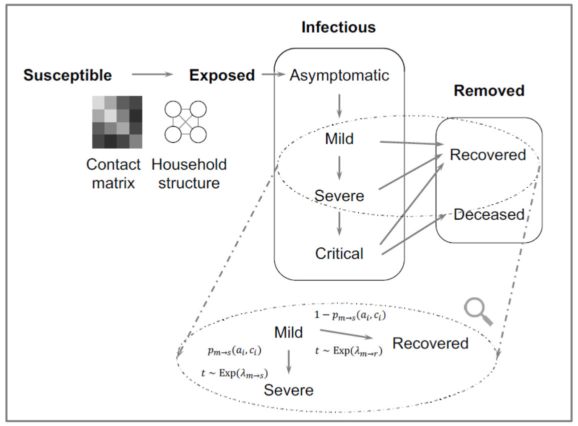
  What fraction of each population was infected in the first wave?

# Bayesian generative model

Sample priors for
$p_{\text{inf}}, t_0, d_{\text{mult}}$

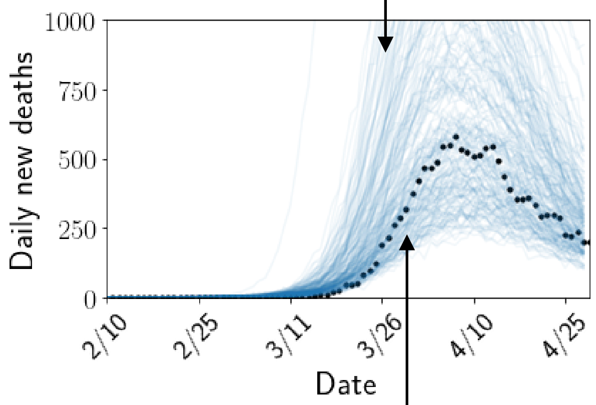


Run model



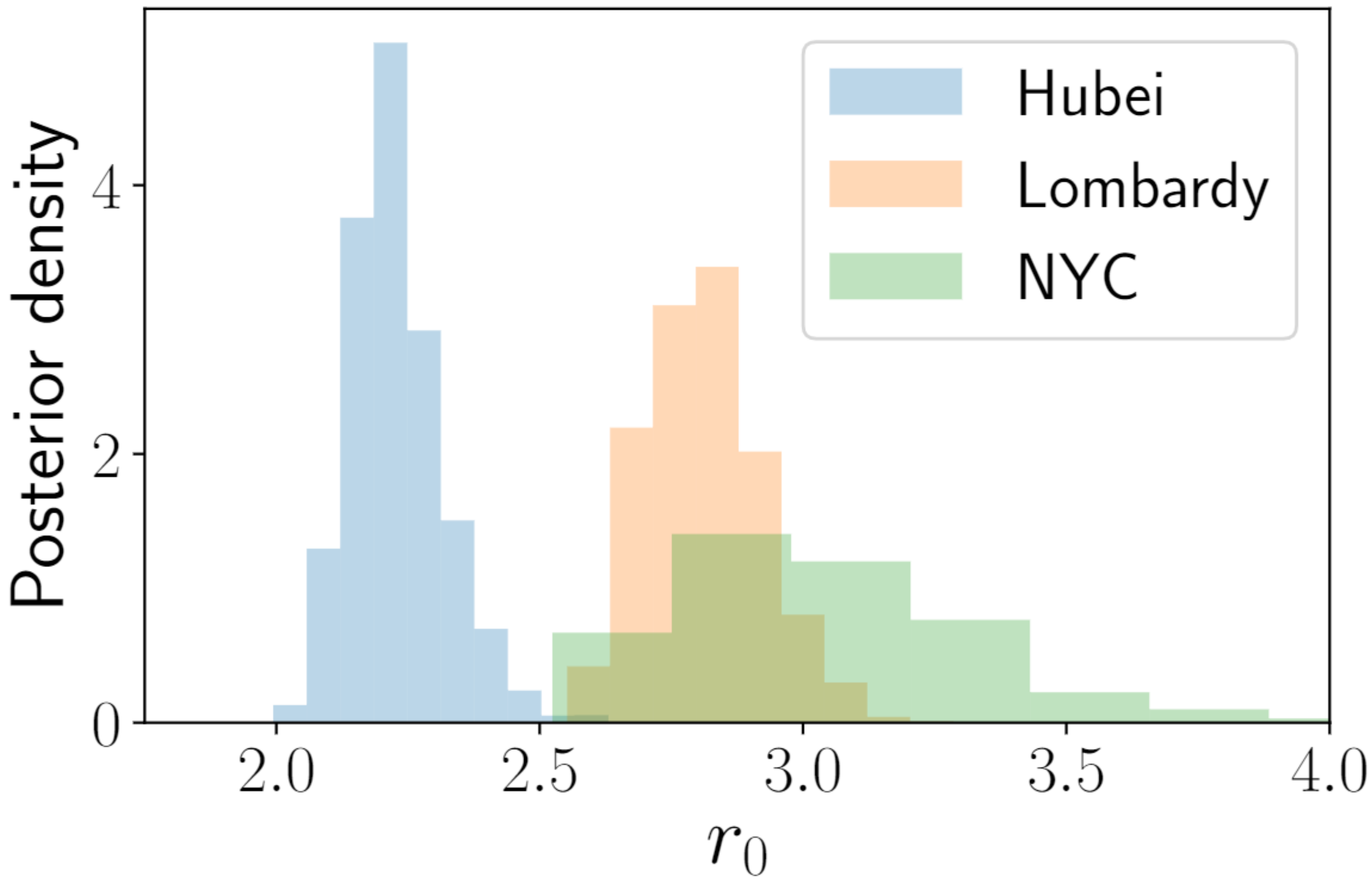

Daily deaths

Samples from model




Reported deaths

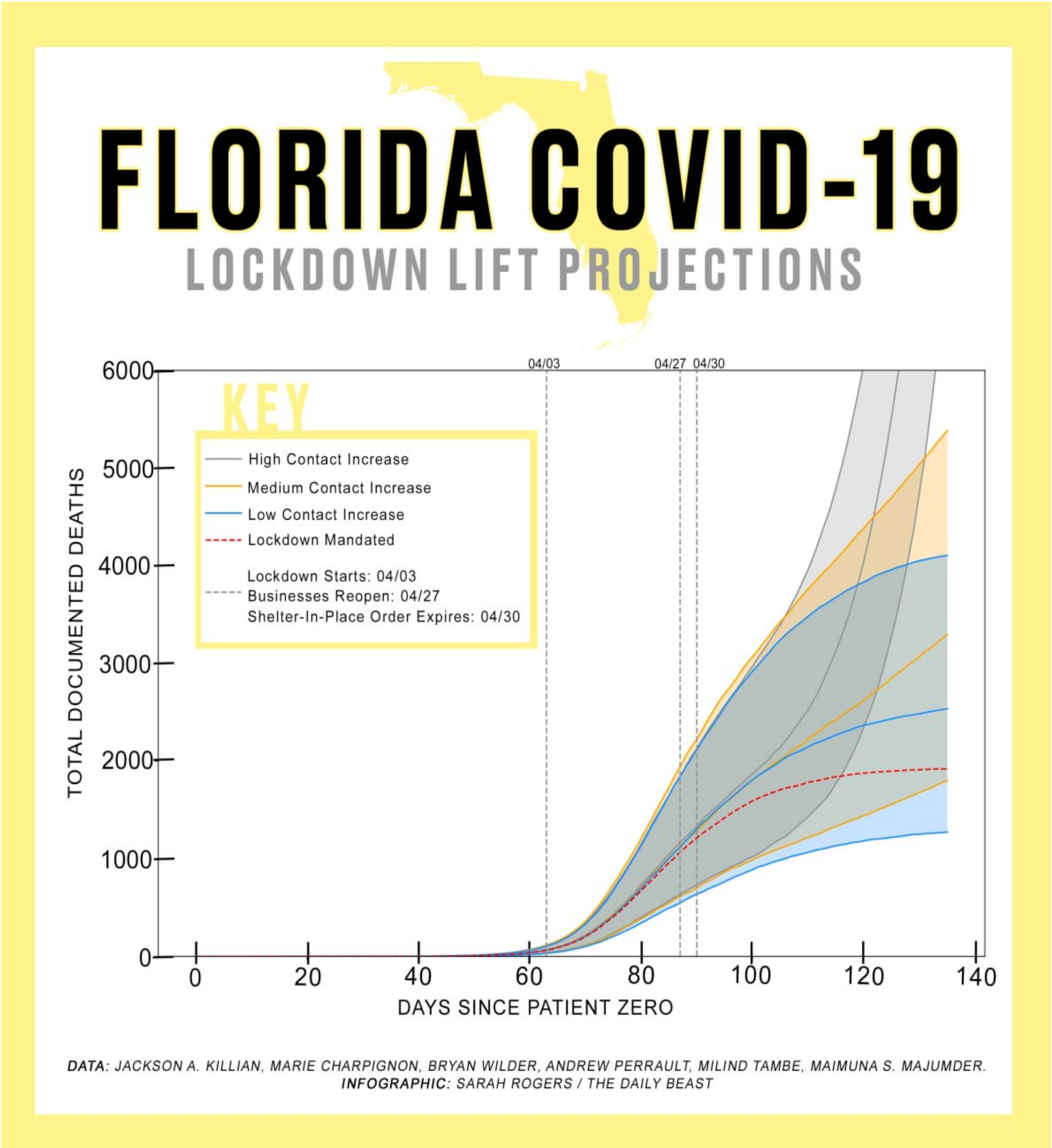
# Results: $r_0$

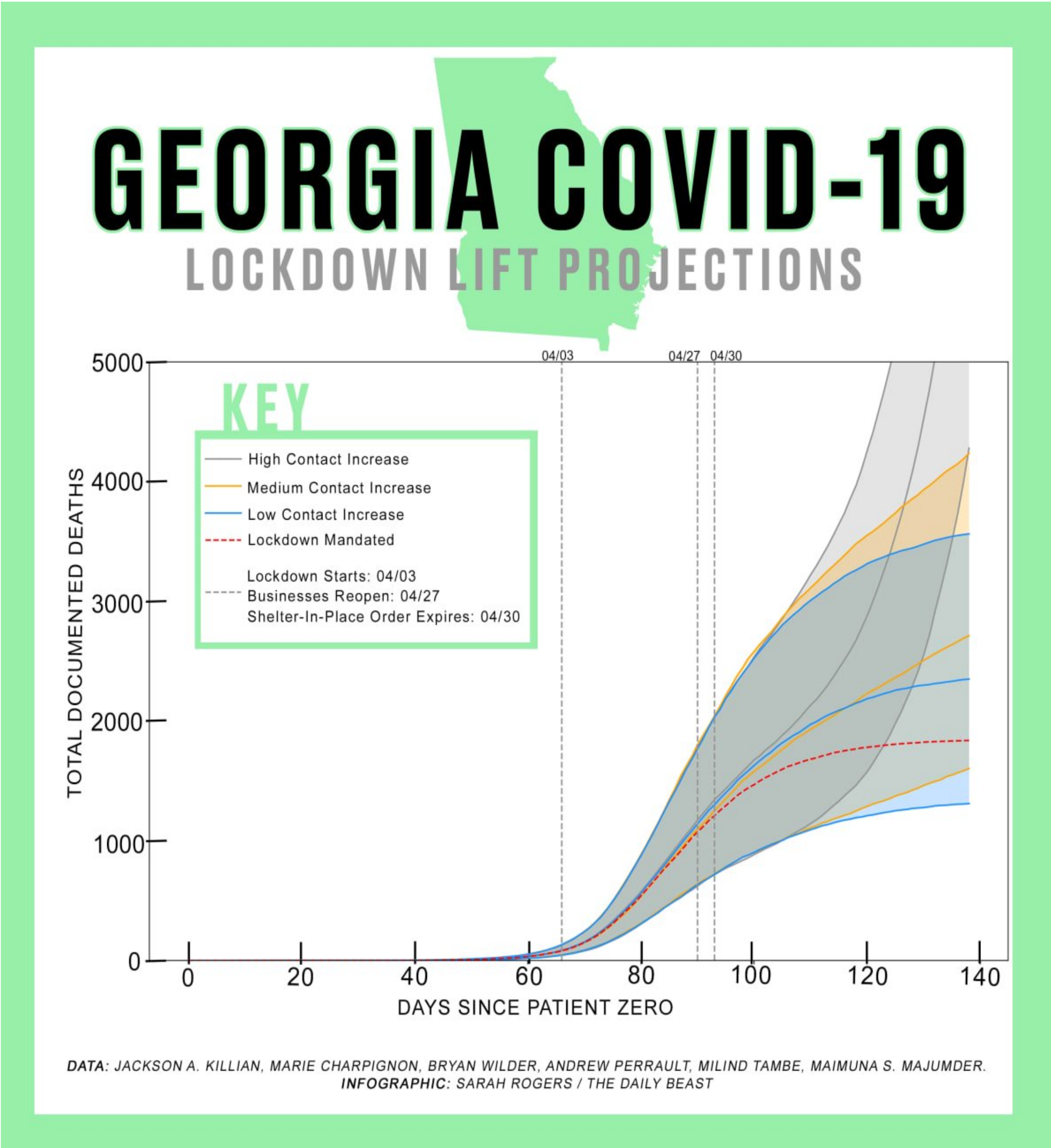



Hubei: 2.21(2.10 - 2.41)
Lombardy: 2.80 (2.66 - 3.01)
NYC: 3.06 (2.65 - 3.59)

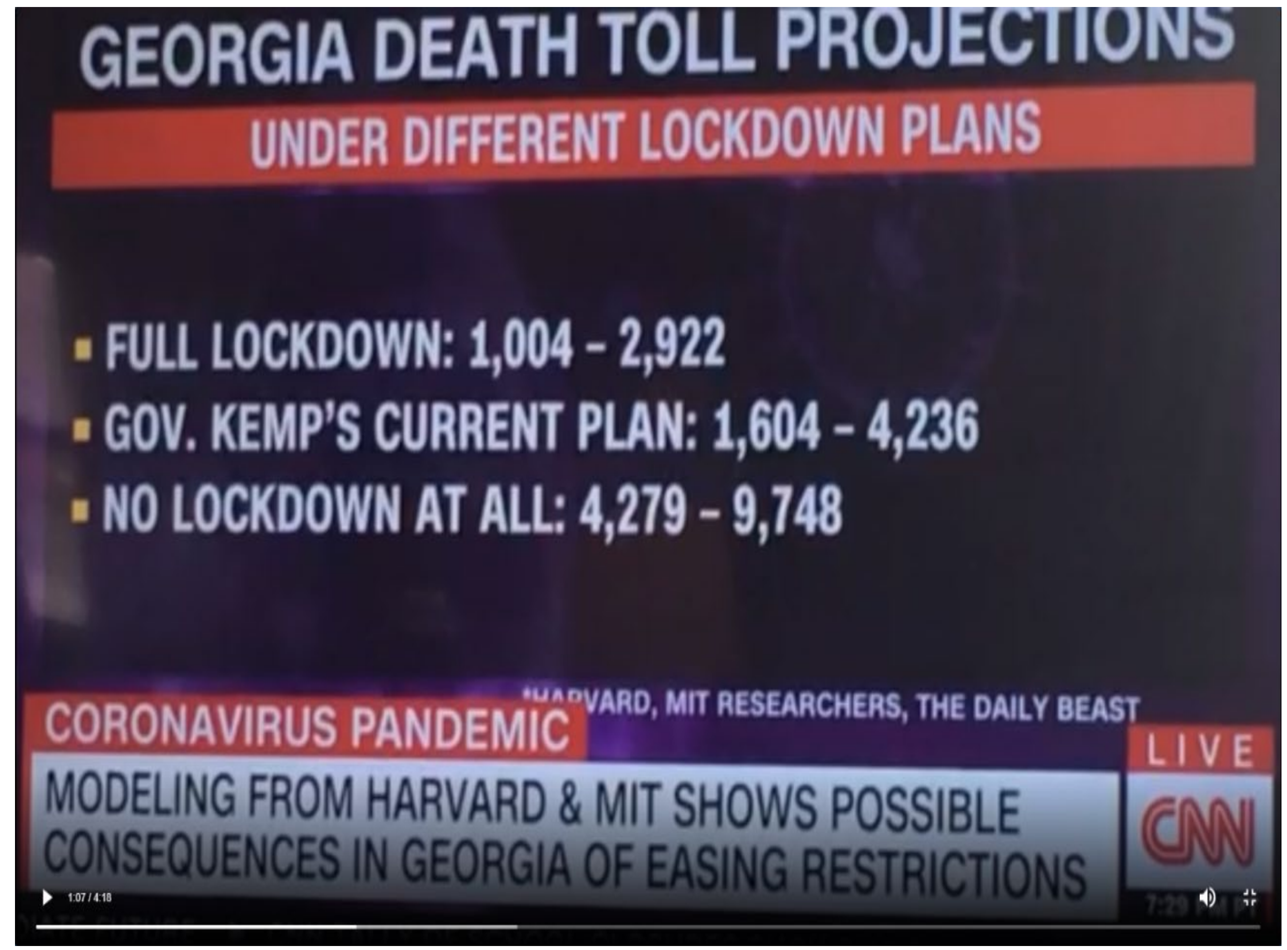
See paper: policy implications for controlling second wave

# COVID-19: Agent-based Simulation Model



# COVID-19: Agent-based Simulation Model Impact


- *Prof. Maia Majumder knew what question to ask*
- *Even if we in AI had the tools to help collaboratively answer that*

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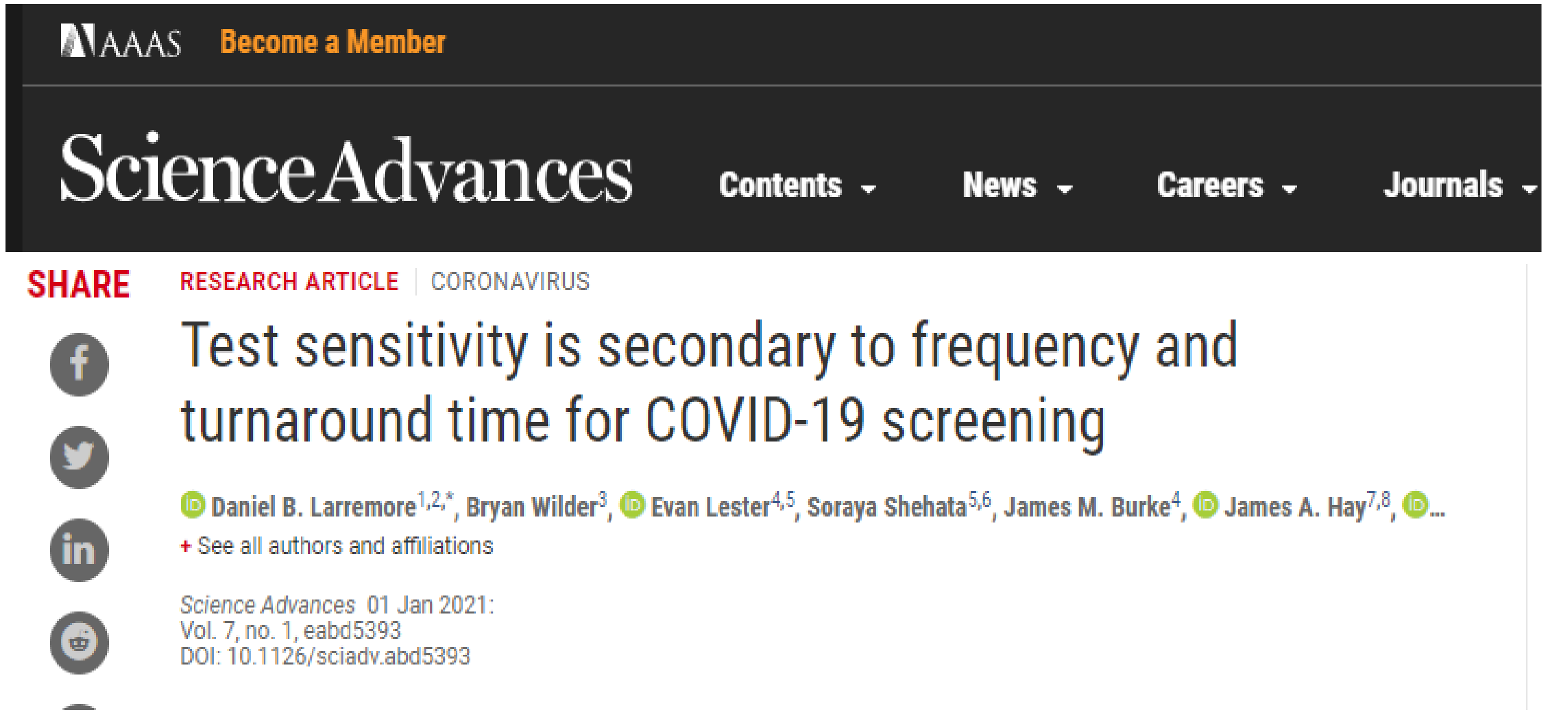
# COVID Testing Policy: Accuracy vs Ease

Range of tests entering market, varying sensitivity/cost:

Quantity vs Quality?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RESEARCH ARTICLE | CORONAVIRUS

Test sensitivity is secondary to frequency and turnaround time for COVID-19 screening

Daniel B. Larremore[1,2,*], Bryan Wilder[3], Evan Lester[4,5], Soraya Shehata[5,6], James M. Burke[4], James A. Hay[7,8], ...

+ See all authors and affiliations

*Science Advances* 01 Jan 2021:
Vol. 7, no. 1, eabd5393
DOI: 10.1126/sciadv.abd5393

- **qRT-PCR (More sensitive):** Detect viral concentration $\mathbf{10^3}$/mL, \$50-100, Slow turnaround
- **Antigen strip (Less sensitive):** Detect viral concentration $\mathbf{10^6}$/mL, \$3-5, Quick turnaround

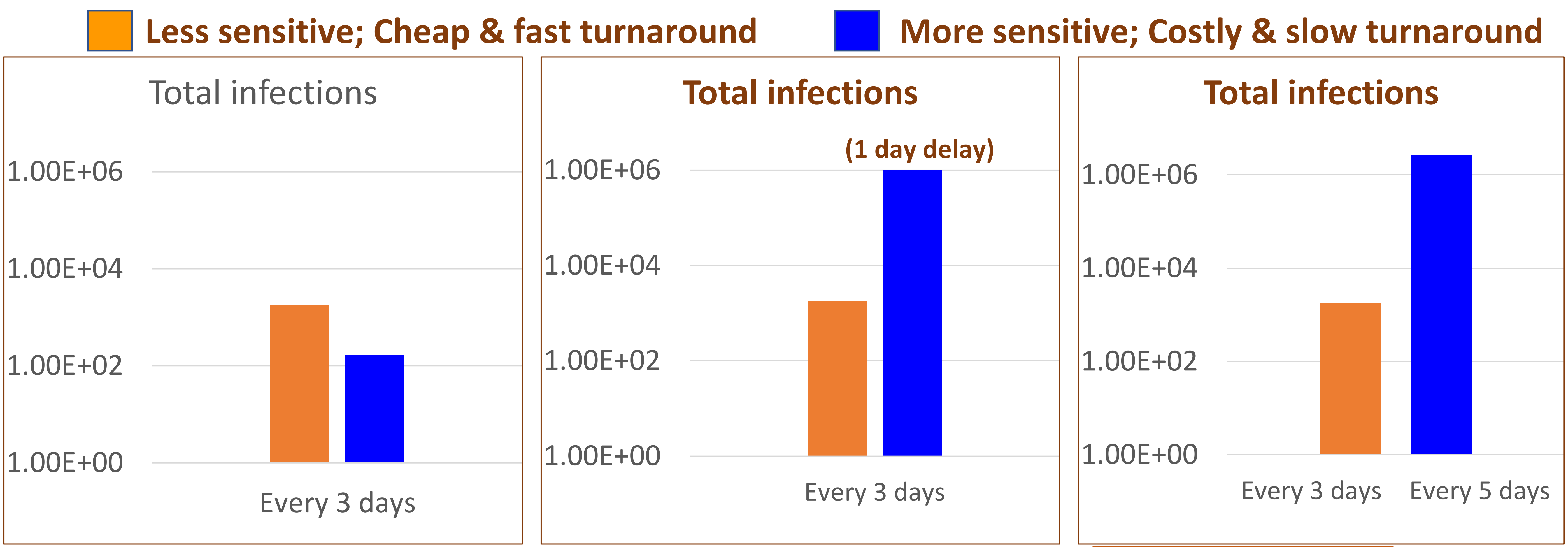
*For campuses like Harvard or others, what is the right testing strategy?*

*Key collaborators:*
*Prof. Michael Mina (Harvard Chan School of Public Health)*

# COVID Testing Policy: Accuracy vs Ease

- **qRT-PCR (More sensitive):** Detect **$10^3$**/mL, \$50-100, Slow turnaround
- **Antigen strip (Less sensitive):** Detect **$10^6$**/mL, \$3-5, Quick turnaround

**Rapid turnaround time & frequency more critical than sensitivity for COVID-19 surveillance**



# Impact: WHO Guidance Reference

Diagnostic testing for SARS-CoV-2

Interim guidance

11 September 2020

World Health Organization

A rapid turnaround time of test results can, in turn, have a positive impact on the outbreak [187, 188]. More studies are needed to fine tune the maximum acceptable time from symptom onset to sample result to have impact on clinical management and outbreak control; currently a maximum of 24 hours is considered reasonable in most settings. As laboratories often have control only over the time between sample arrival and the test result, it is critical to ensure that samples arrive in the laboratory without delay.

# COVID Testing Policy: Impact

- Covered in NYT, WaPo, Time, The Atlantic, The Hill, etc
- Allowed epi collaborators to advocate to FDA/CDC





# COVID Testing Policy: Impact

The Harvard Gazette

HEALTH & MEDICINE

## Approval of at-home tests releases a powerful pandemic-fighting weapon


The Abbott BinaxNOW COVID-19 at-home test was one of two to receive FDA approval this week. The over-the-counter test does not need a prescription.

Courtesy of Abbott

Chan School's Mina says despite vaccination campaign success, diagnostic tools still important

One of them is Michael Mina, assistant professor of epidemiology, who has called on federal regulators for much of the past year to clear the rapid antigen tests, arguing that widespread, frequent use of the diagnostic has the potential to stop outbreaks early and keep case numbers down.

- *Prof. Michael Mina knew what question to ask*
- *Even if we had agent-based models to help collaboratively answer that*

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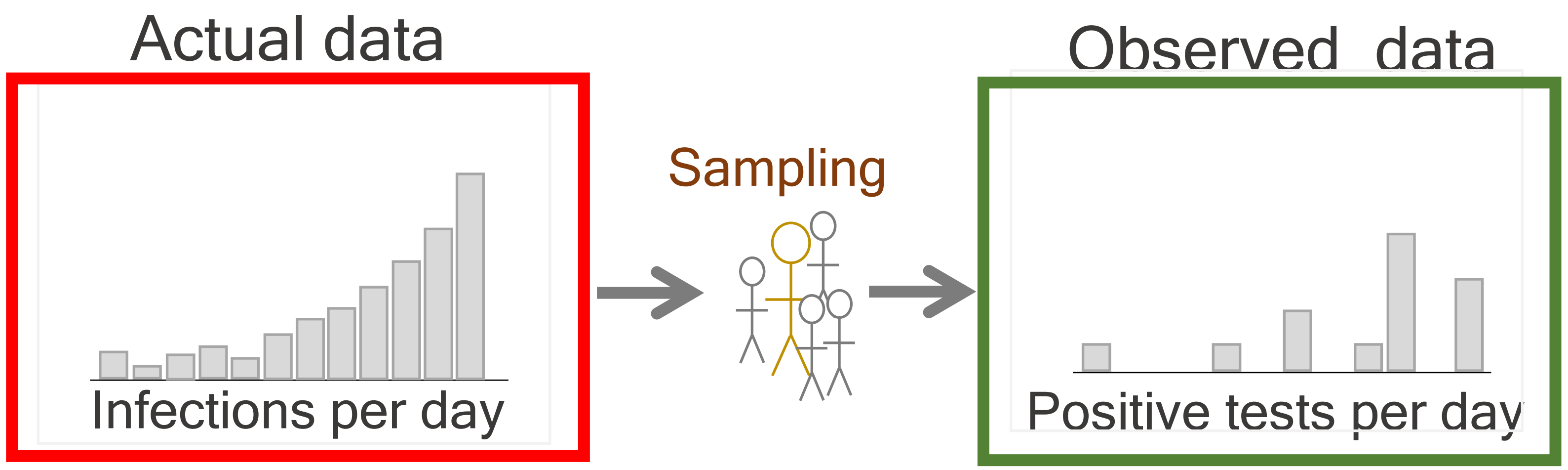
# Detecting Emerging Outbreaks with Partial Observations

Testing at individual colleges or workplaces will yield noisy data



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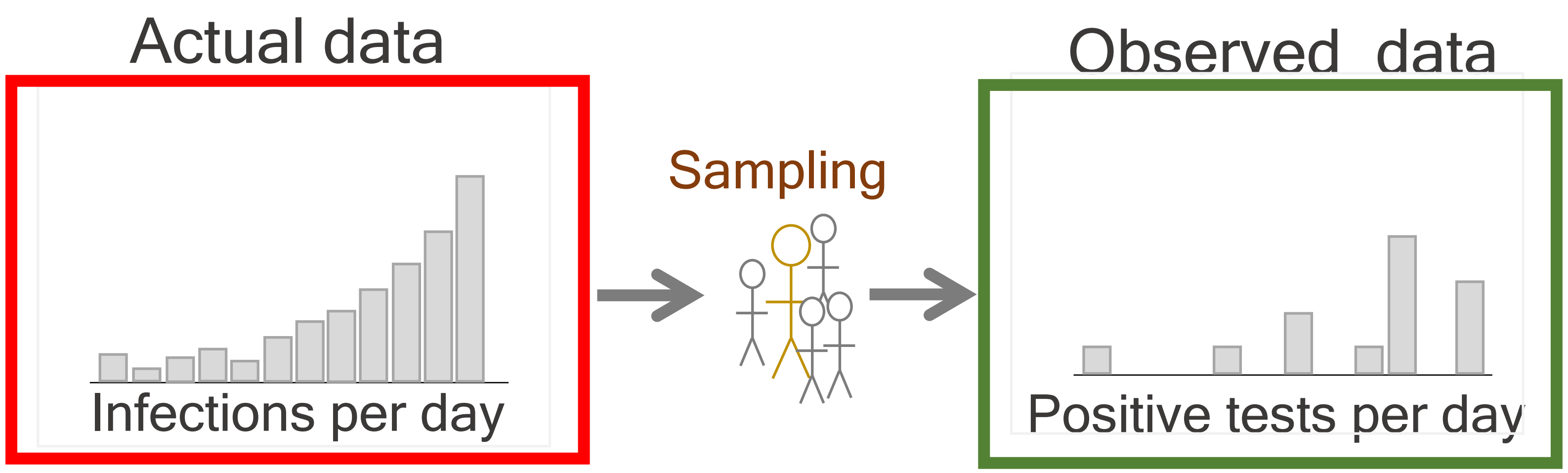


This is an outbreak

Is this an outbreak?

# Detecting Emerging Outbreaks with Partial Observations

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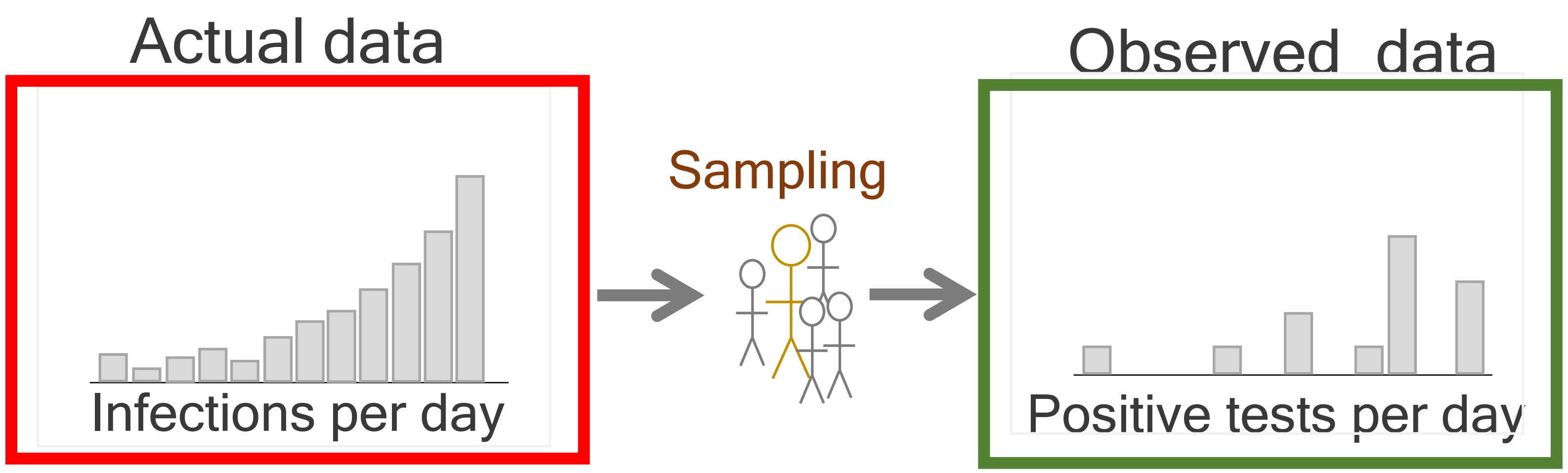
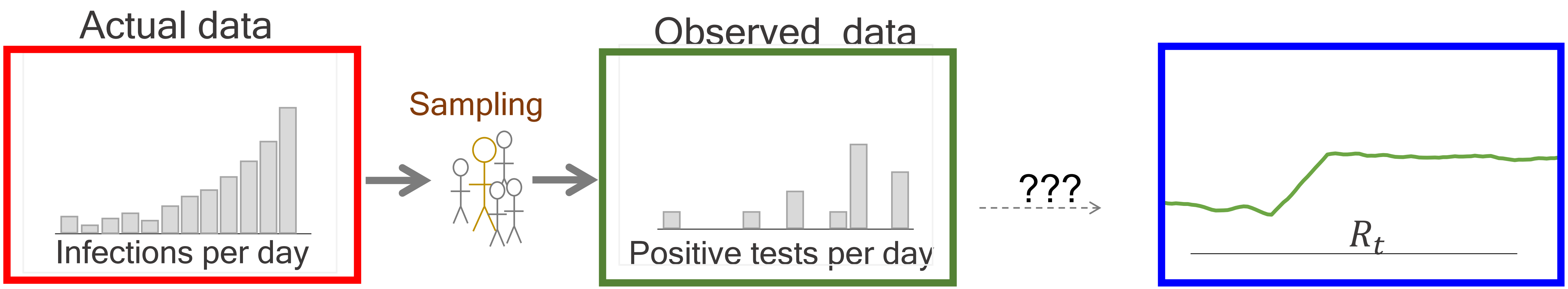



Existing methods look for this… …not this

*How do we detect outbreaks from sparse, noisy test results?*

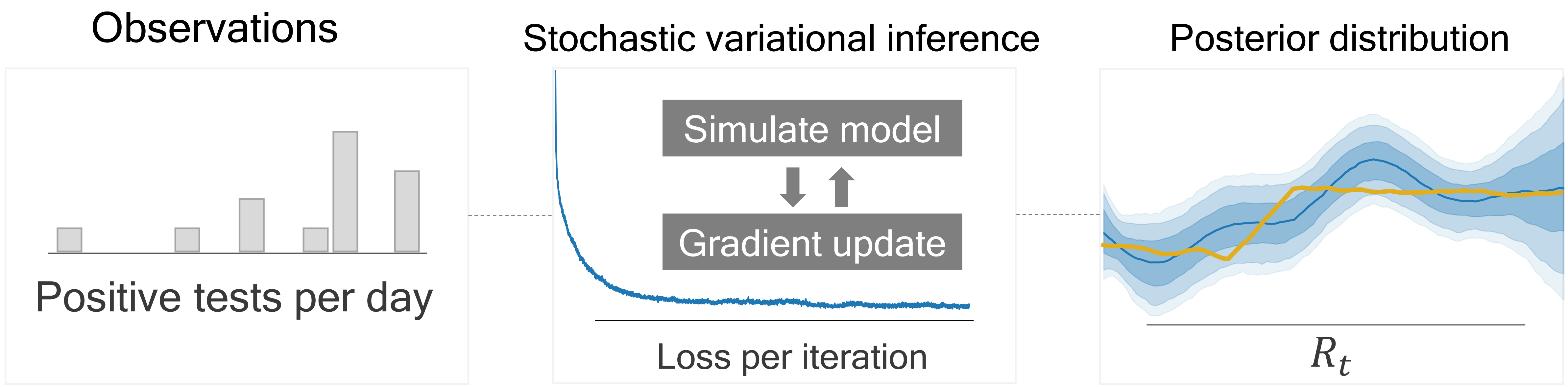
# Detecting Emerging Outbreaks with Partial Observations

Testing at individual colleges or workplaces will yield noisy data



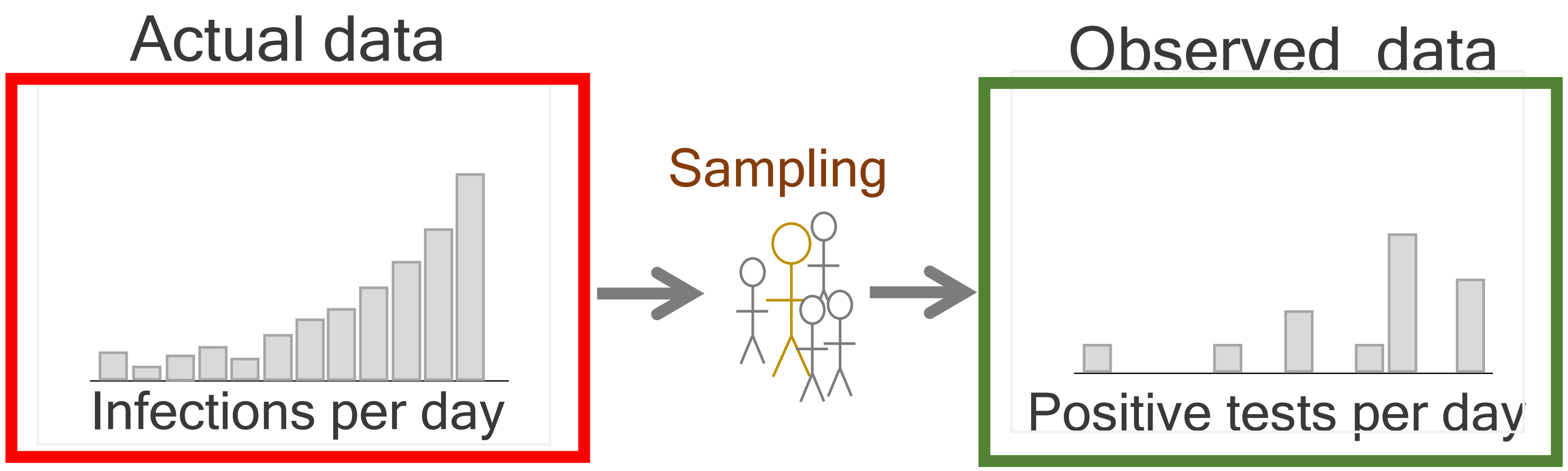

How do we recover the rate at which the epidemic is growing from noisy observations?

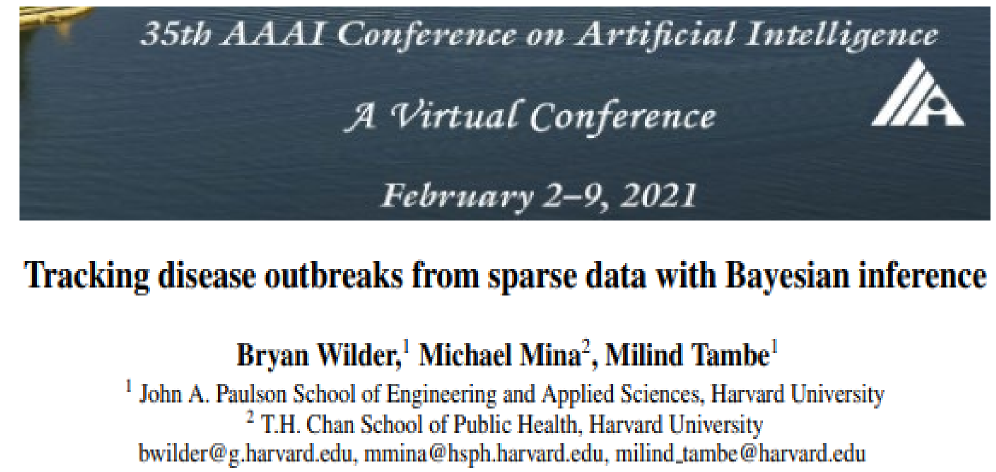
# Approach: inference




- Many, many latent variables in between the case counts and $R$
- Number of daily infections, when each individual is test-positive, who was selected for testing…
- Adds up to 10s-100s of thousands, all discrete!

# Detecting Emerging Outbreaks with Partial Observations





35th AAAI Conference on Artificial Intelligence

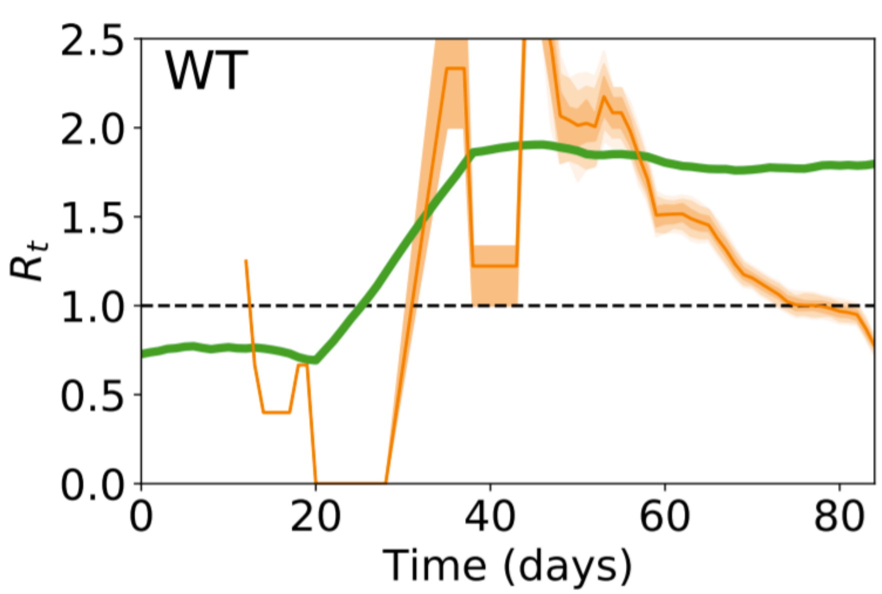
A Virtual Conference

February 2–9, 2021

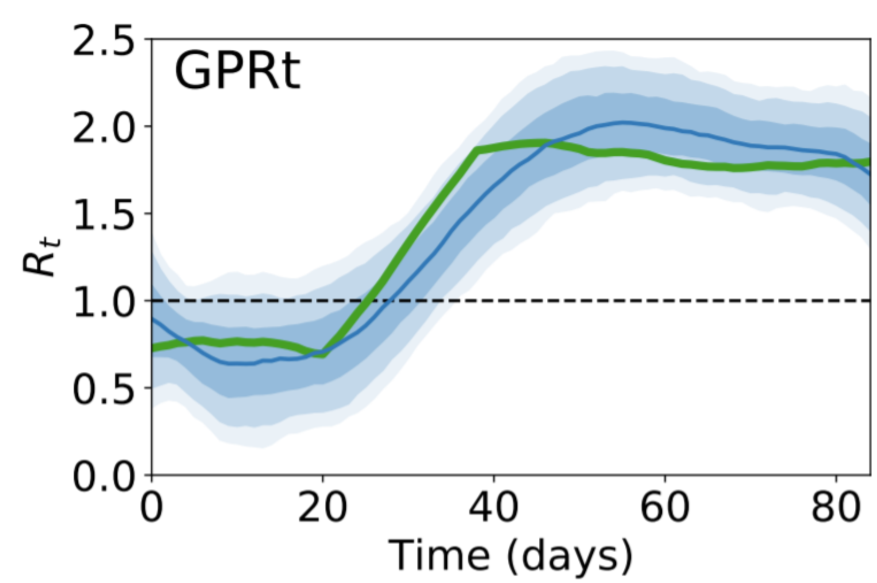
**Tracking disease outbreaks from sparse data with Bayesian inference**


**Bryan Wilder,[1] Michael Mina[2], Milind Tambe[1]**

[1] John A. Paulson School of Engineering and Applied Sciences, Harvard University
[2] T.H. Chan School of Public Health, Harvard University
bwilder@g.harvard.edu, mmina@hsph.harvard.edu, milind_tambe@harvard.edu


*Previous methods return incorrect estimates*




*Our probabilistic tools detect increased transmission from noisy data*

# Detecting Emerging Outbreaks with Partial Observations

- Tracking and responding to epidemics requires new AI methods
- Partial observability is computationally and statistically difficult
- New method: GPRt, for $R_t$ with partial observations
- Greatly improved performance vs standard epidemiological methods

- *Opens up new research directions for AI: Anticipate follow on here*

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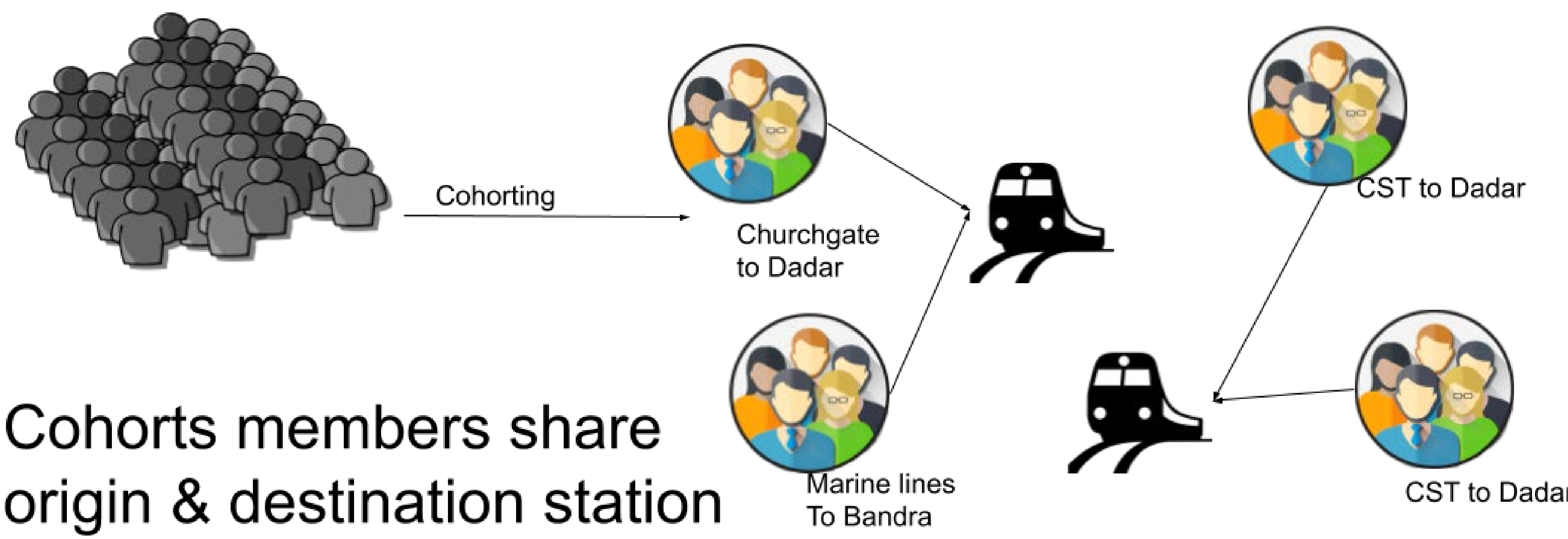
# Reducing the Spread of COVID-19 Using Travel cohorts


**Cohorting to isolate asymptomatic spreaders: An agent-based simulation study on the Mumbai Suburban Railway**

Extended Abstract

Alok Talekar[1], Sharad Shriram[2], Nidhin Vaidhiyan[2], Gaurav Aggarwal[1], Jiangzhuo Chen[3], Srini Venkatramanan[3], Lijing Wang[3], Aniruddha Adiga[3], Adam Sadilek[1], Ashish Tendulkar[1], Madhav Marathe[3], Rajesh Sundaresan[2,4] and Milind Tambe[1]

[1] Google Inc., [2] Indian Institute of Science, Bangalore [3] University of Virginia , [4] Strand Life Sciences

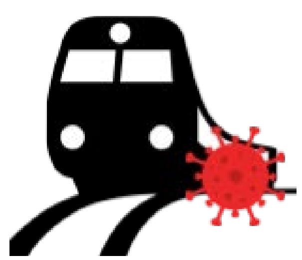



Cohorts members share origin & destination station

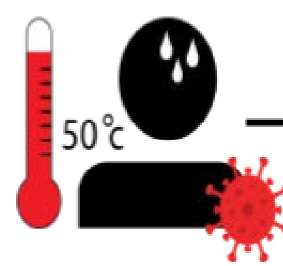
Cohorts members travel together (stay in the same train coach)

# Reducing the Spread of COVID-19 Using Travel cohorts

## Reducing the Spread of COVID-19 Using Travel cohorts



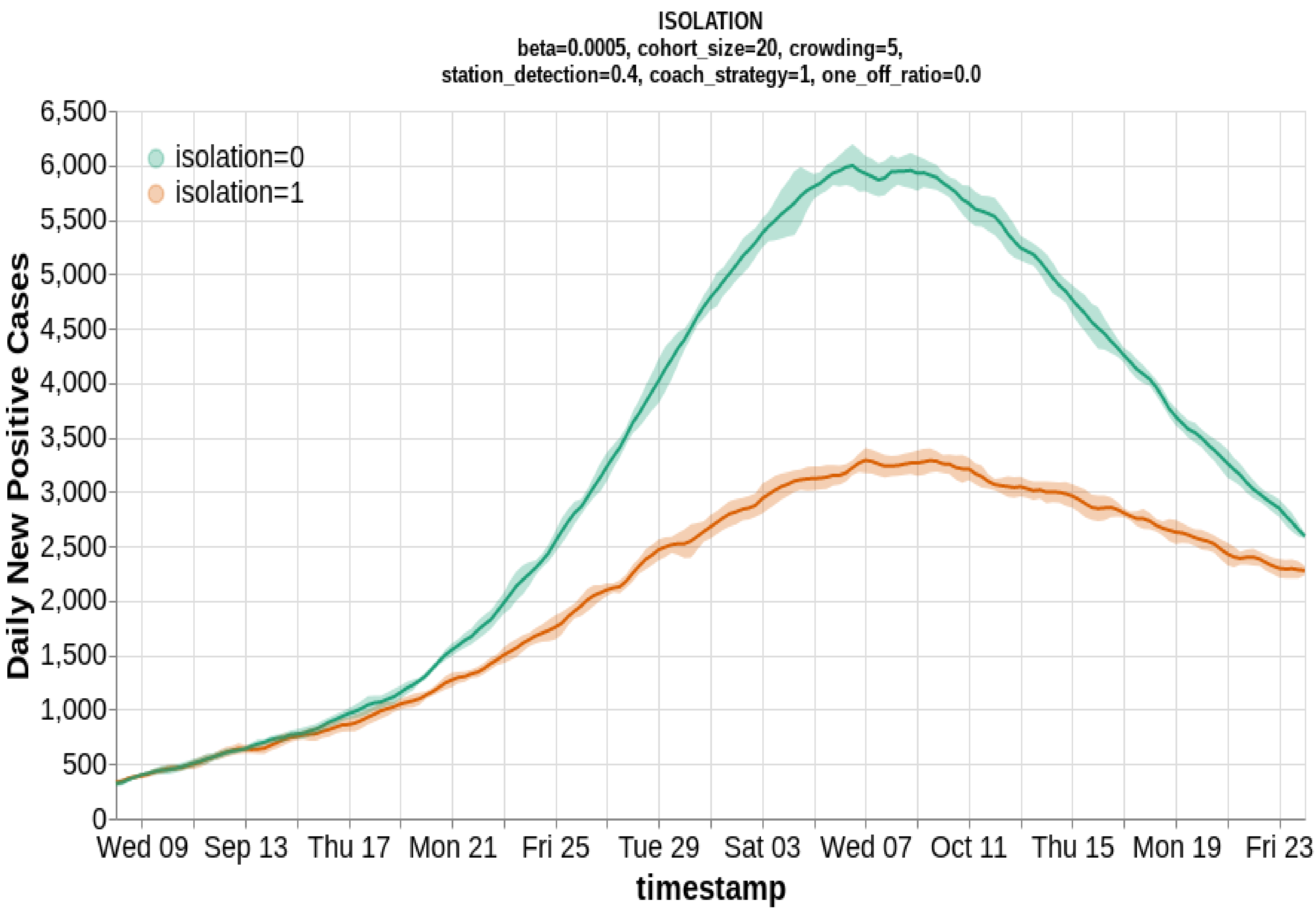
COVID spreads in coaches based on overlap time between travelers.




Screening at stations

If a member is Symptomatic
Quarantine Entire Cohorts

## Reducing the Spread of COVID-19 Using Travel cohorts

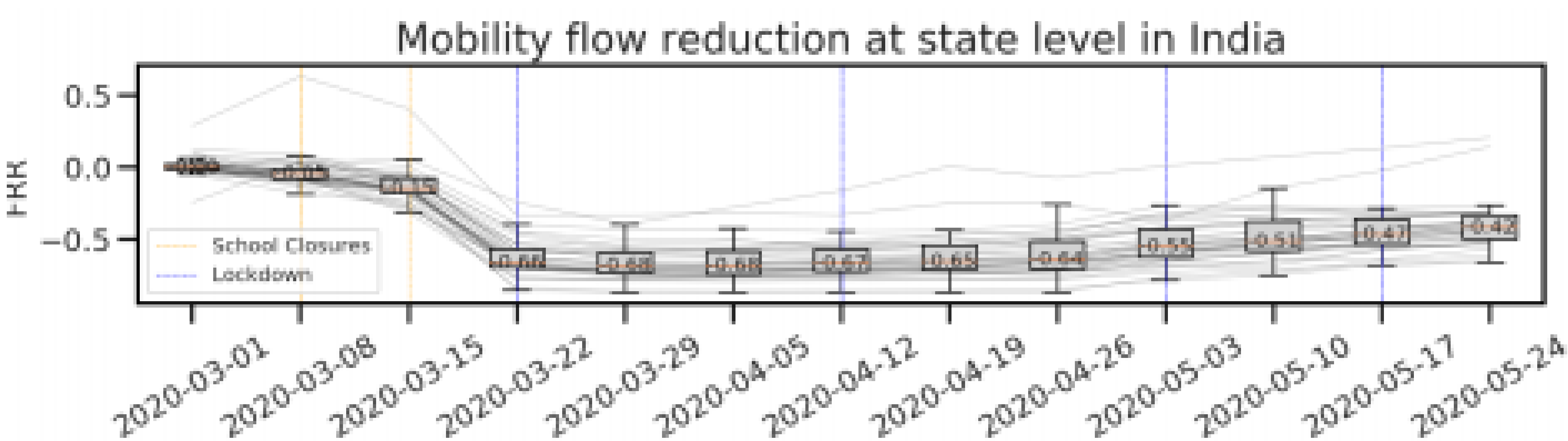



- Isolation ⇒ Require cohort members to quarantine if any member is detected to be infected.
- Better isolation leads to better results.
- No isolation is similar to business as usual.

# COVID-19: Mobility Study

## Interplay of global multi-scale human mobility, social distancing, government interventions, and COVID-19 dynamics

Aniruddha Adiga*, Lijing Wang*, Adam Sadilek*, Ashish Tendulkar*, Srinivasan Venkatramanan, Anil Vullikanti, Gaurav Aggarwal, Alok Talekar, Xue Ben, Jiangzhuo Chen, Bryan Lewis, Samarth Swarup, Milind Tambe, Madhav Marathe†



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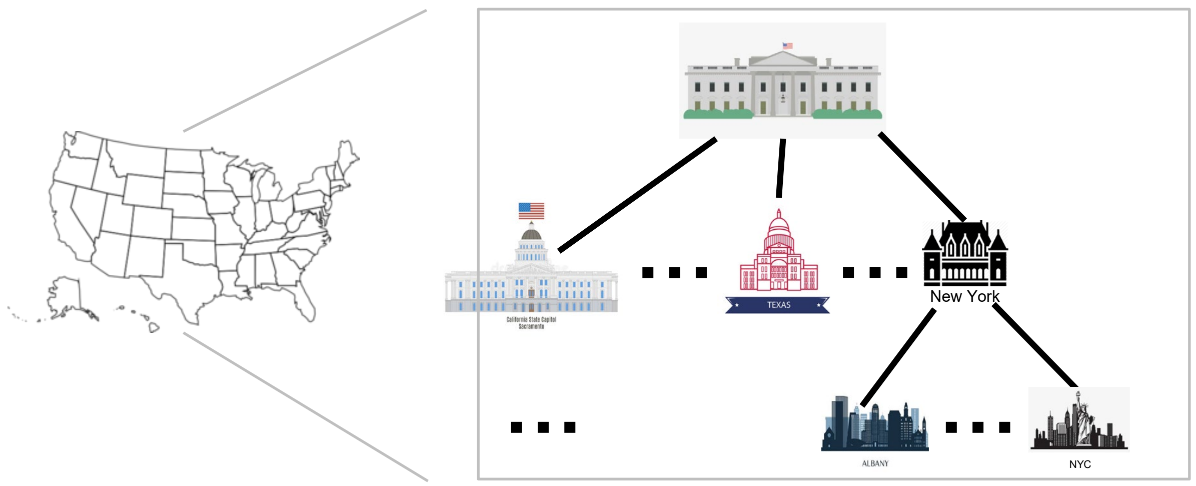
# Decentralized Policy Modeling: A Hierarchical Game

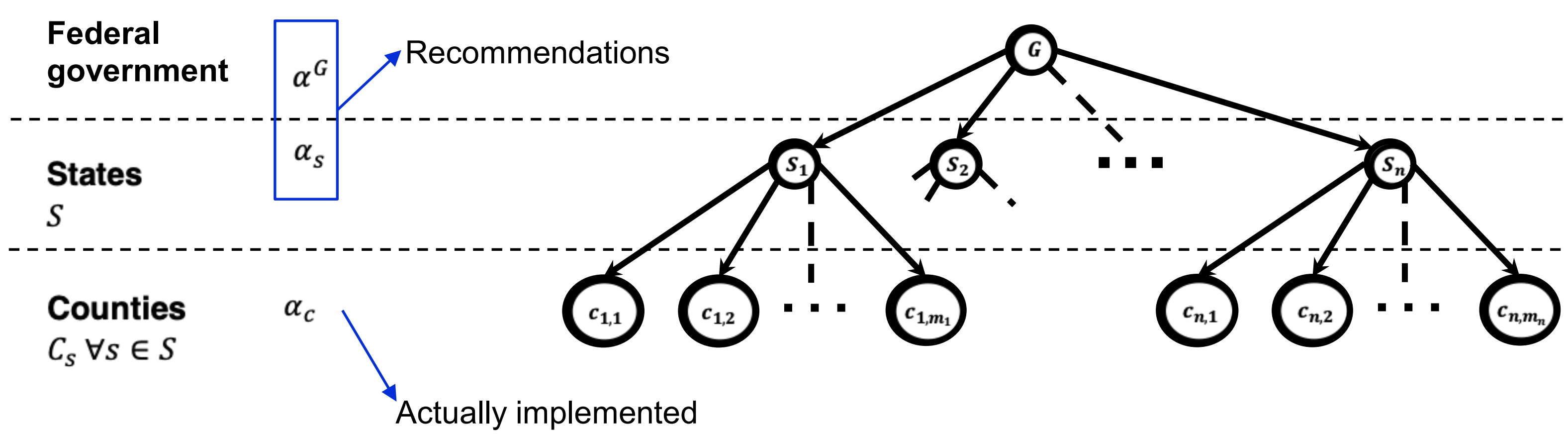



Restricts contact/proximity

Stronger policy → Lower **infection** cost

Stronger policy → Higher **implementation** cost

Negative socio-economic impact (business & manufacturing, mental well-being)




Overall cost = Infection cost + Implementation Cost + Non-compliance cost

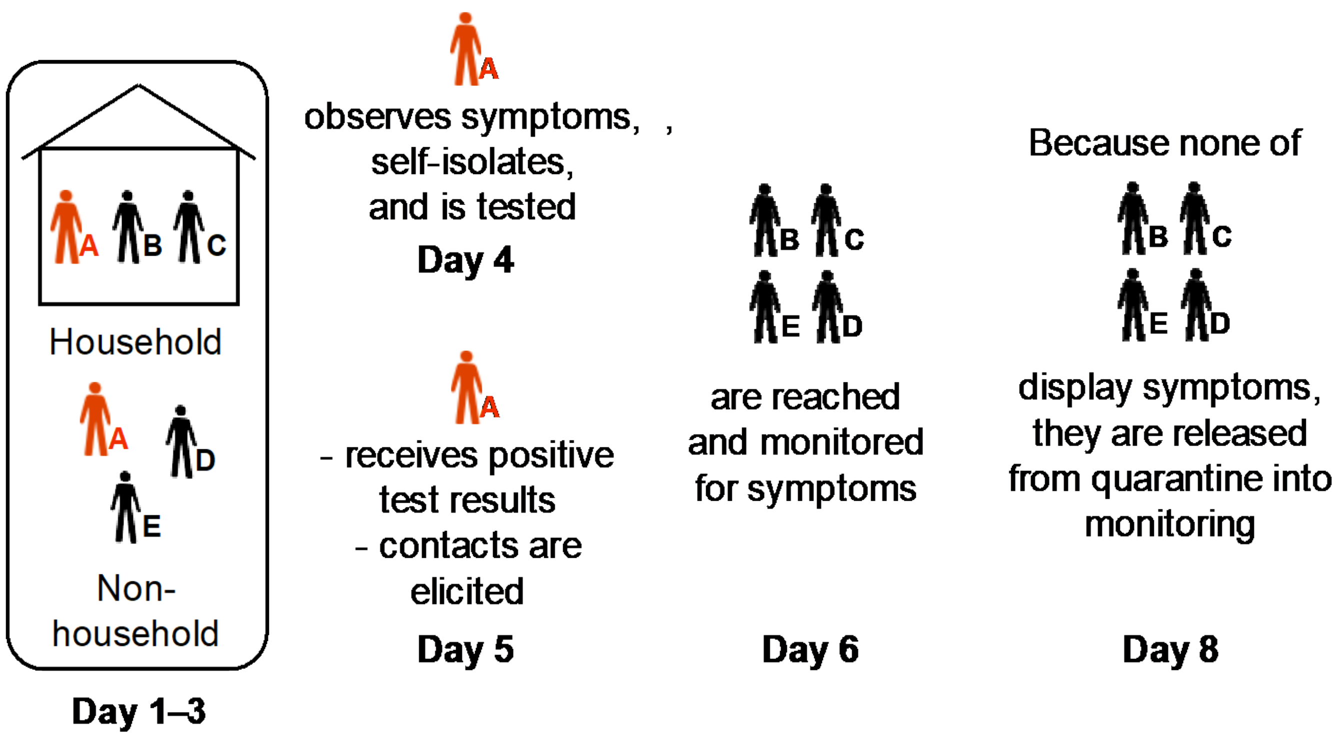
Decentralization: mismatched priorities at different scales

# Surveillance-based release reduces quarantine

- Risk-based quarantine: quarantine clusters whose index case is highly infectious

- Contrast with normal 10-14 day quarantine

- Under submission




**Costs 40% fewer quarantine days**

# Agent-based Modeling & COVID-19

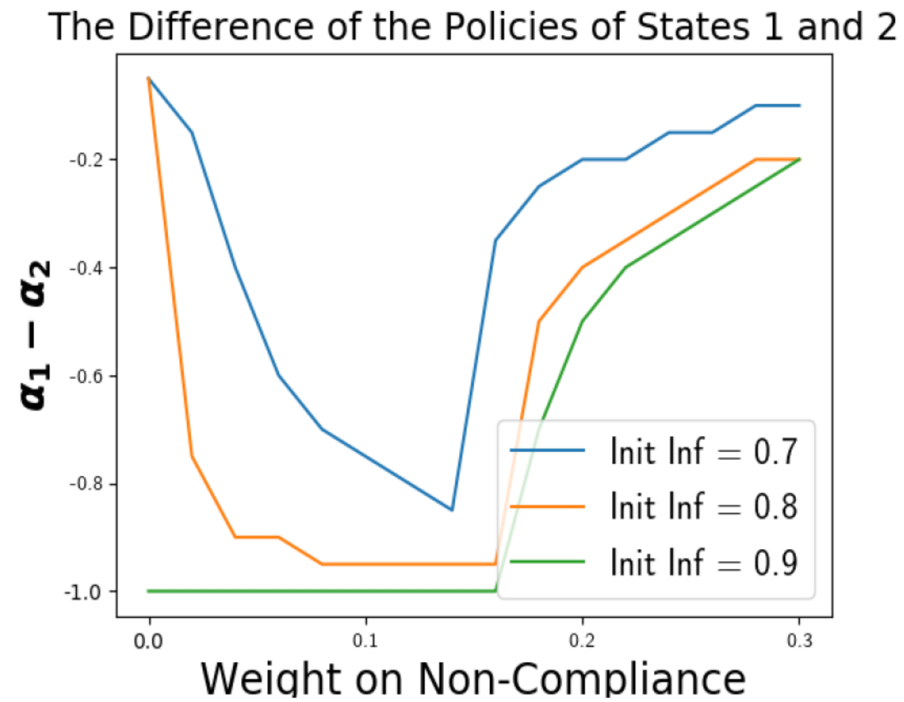
*Key Research Lessons from our collaborations re: COVID-19:*

- Interdisciplinary research: AI researcher have tools to help but not the right questions
- Provided new AI research challenges, e.g., with detection of outbreaks
- AI research at a slower pace vs fast turn around in public health as pandemic progressed
- Not every question asked succeeded in a publication or policy impact (some remain in progress)
- Seed new set of interdisciplinary collaborations between AI & public health in the future
- Lack of data is the norm, should be part of project strategy

@MilindTambe_AI

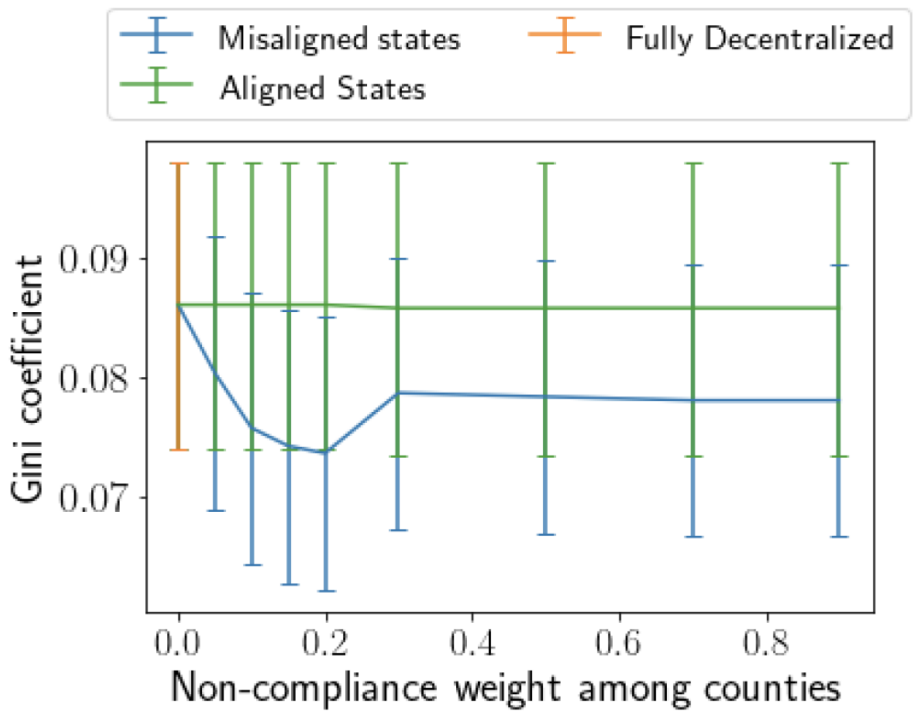
# Decentralized Policy Modeling: A Hierarchical Game

A tool for analyzing the consequences of mismatched priorities and different degrees of decentralization




(a) Counties constrained to comply.

Free-riding




Fairness