Network-Informed Intervention Strategies for Pandemic Response

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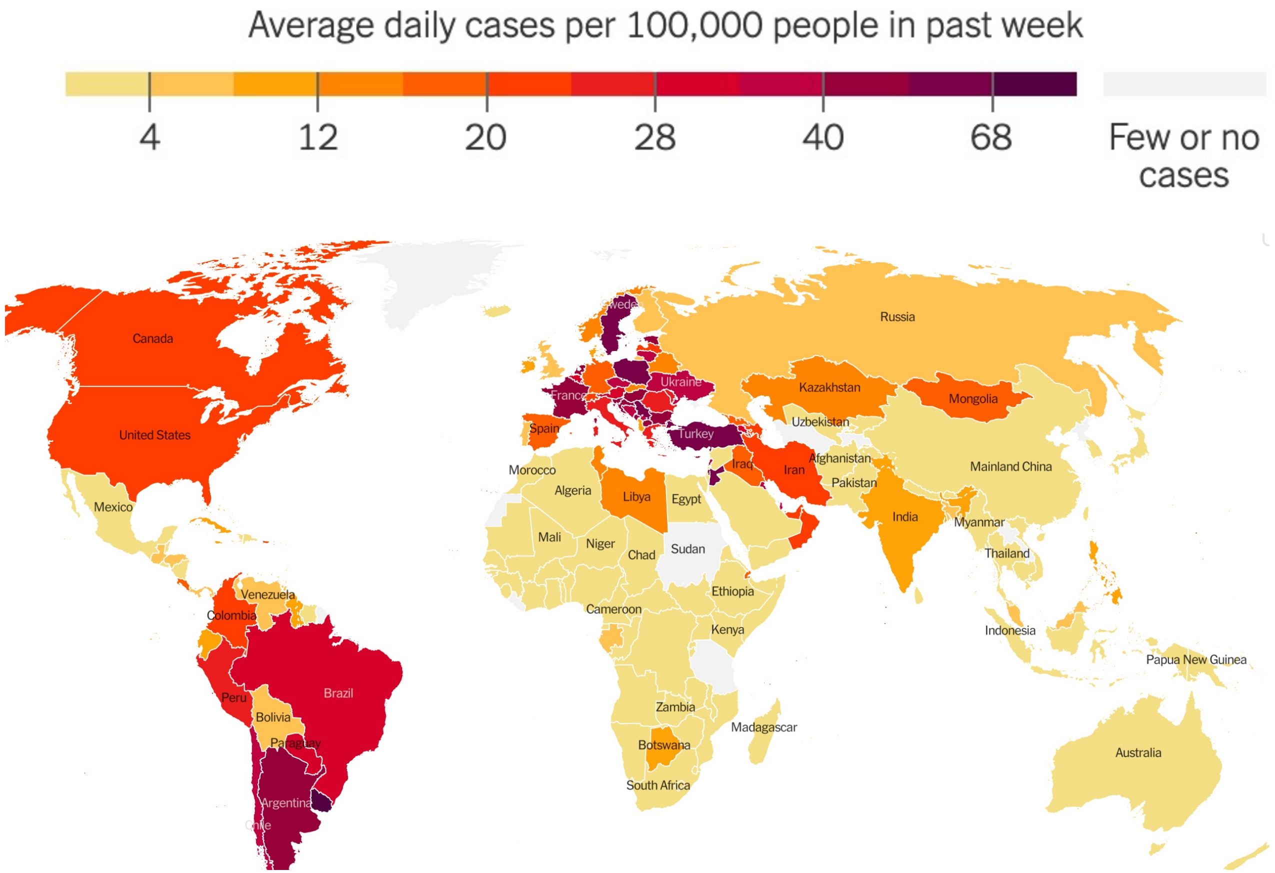
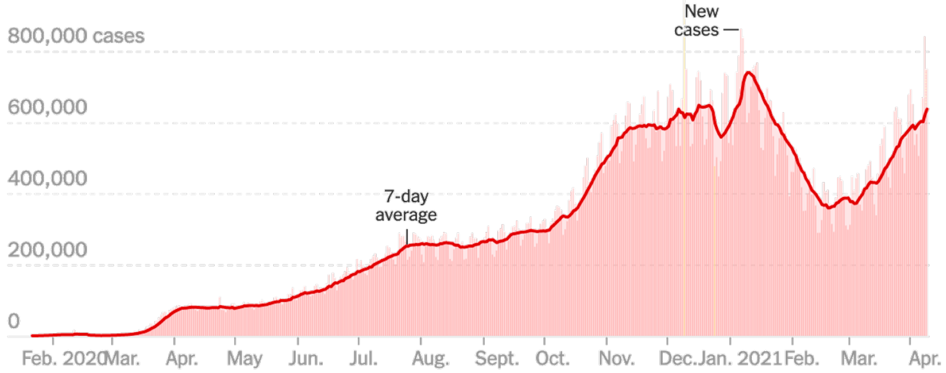
COVID-19 Pandemic





	TOTAL REPORTED	ON APRIL 9	14-DAY CHANGE
Cases	134.6 million+	749,008	+19%
Deaths	2.9 million+	13,498	+19%

COVID-19 is causing devastating human and economic losses at global scale

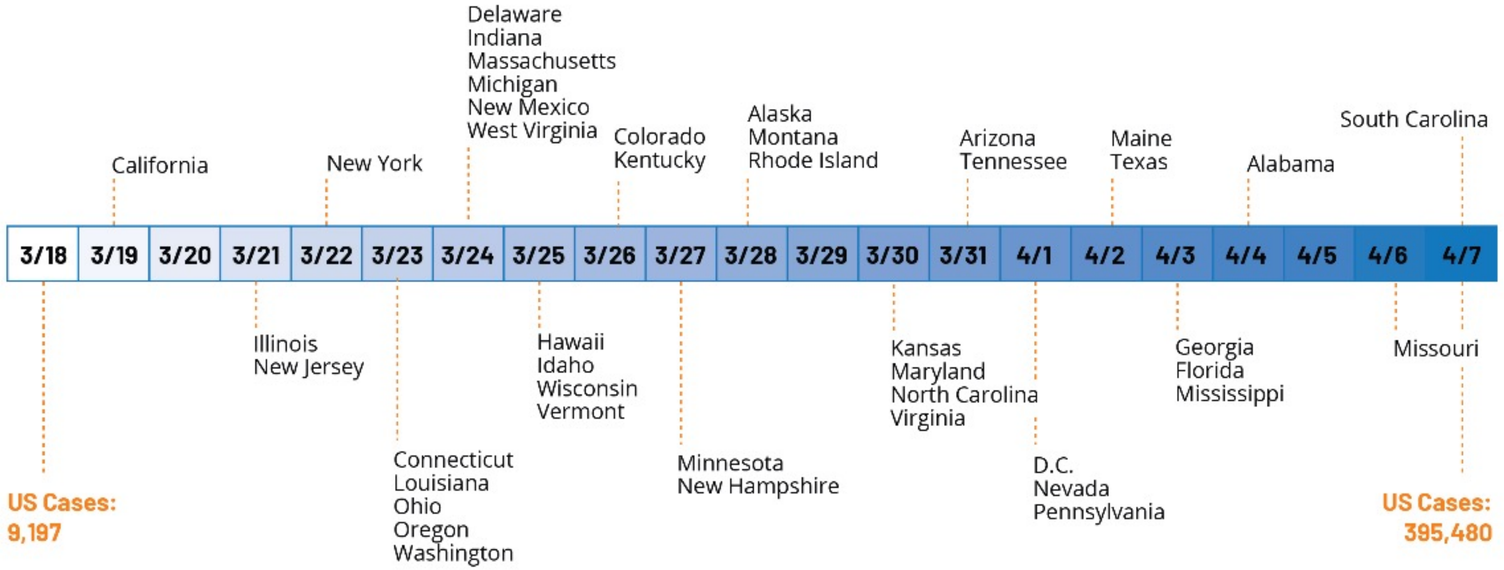
https://www.nytimes.com/interactive/2020/world/coronavirus-maps.html

Why is Control of Pandemics Difficult?

COVID revealed that we don't have good NPI strategies

- Uncoordinated state responses
- Severe, one-size-fits-all strategies do not respect discrepancies in local resources
- Responses do not adapt to changing conditions (new strains, new outbreaks, vaccination)

Timeline of state stay-at-home orders

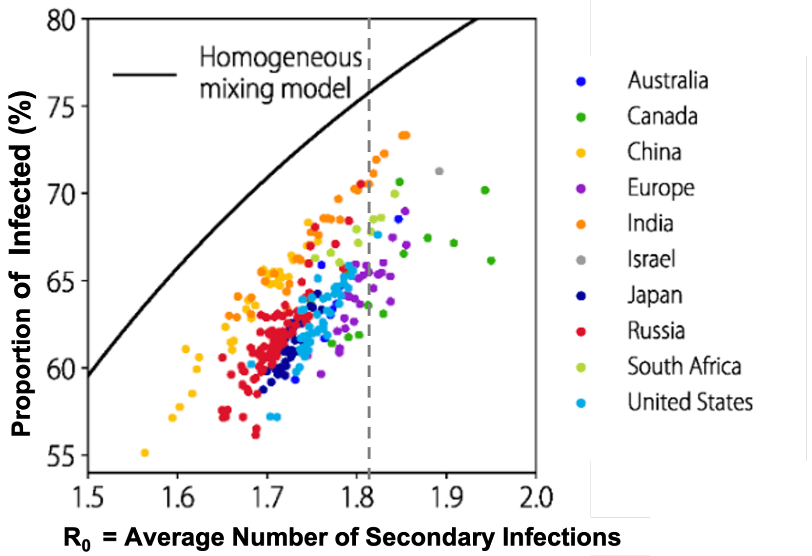


We lack systems that identify contextual, effective, lower-cost pandemic mitigation strategies

NPI = Non-pharmaceutical interventions https://www.kff.org/policy-watch/stay-at-home-orders-to-fight-covid19/

Importance of Complex Network Modeling

Complex Network Effects



Same local effects lead to heterogenous meso-scale and global scale effects

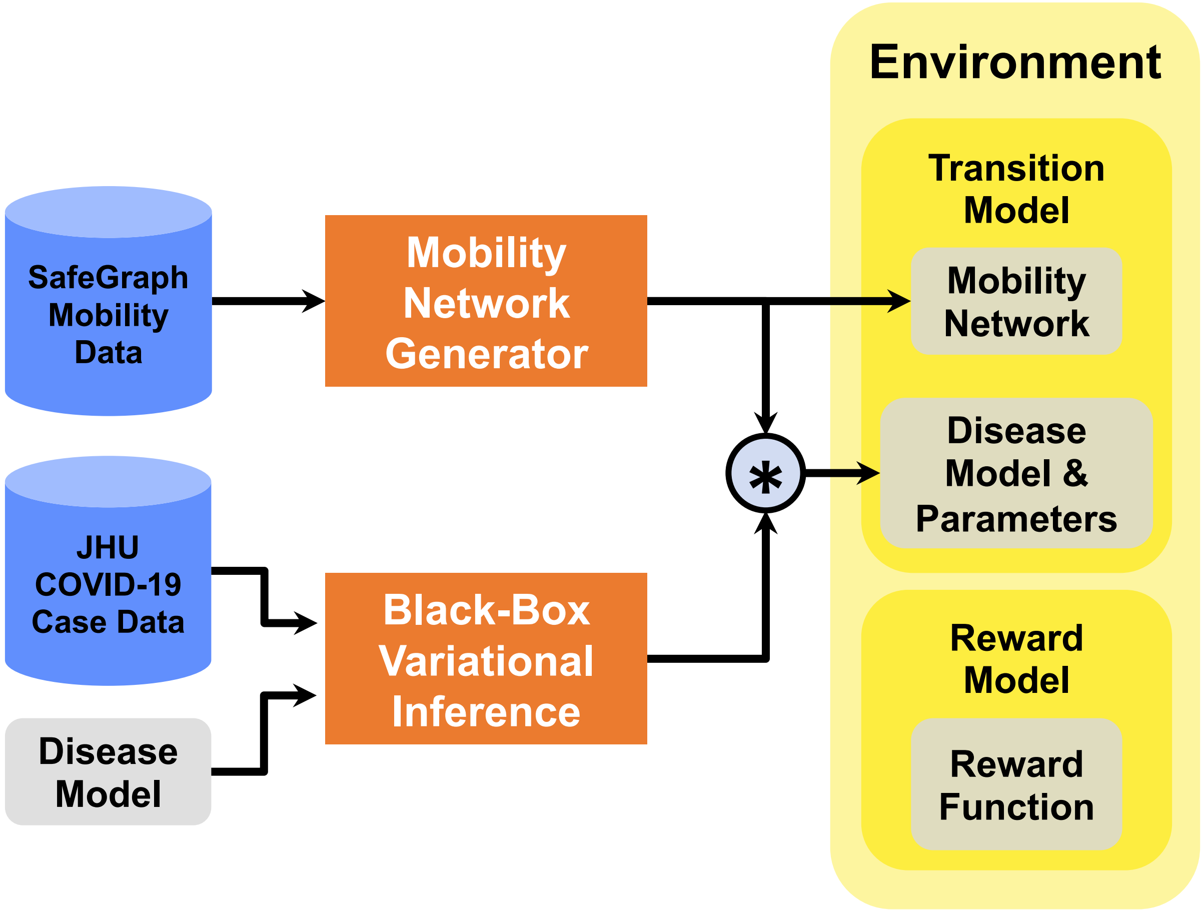
Incorporating network effects is crucial for realistic modeling of diseases

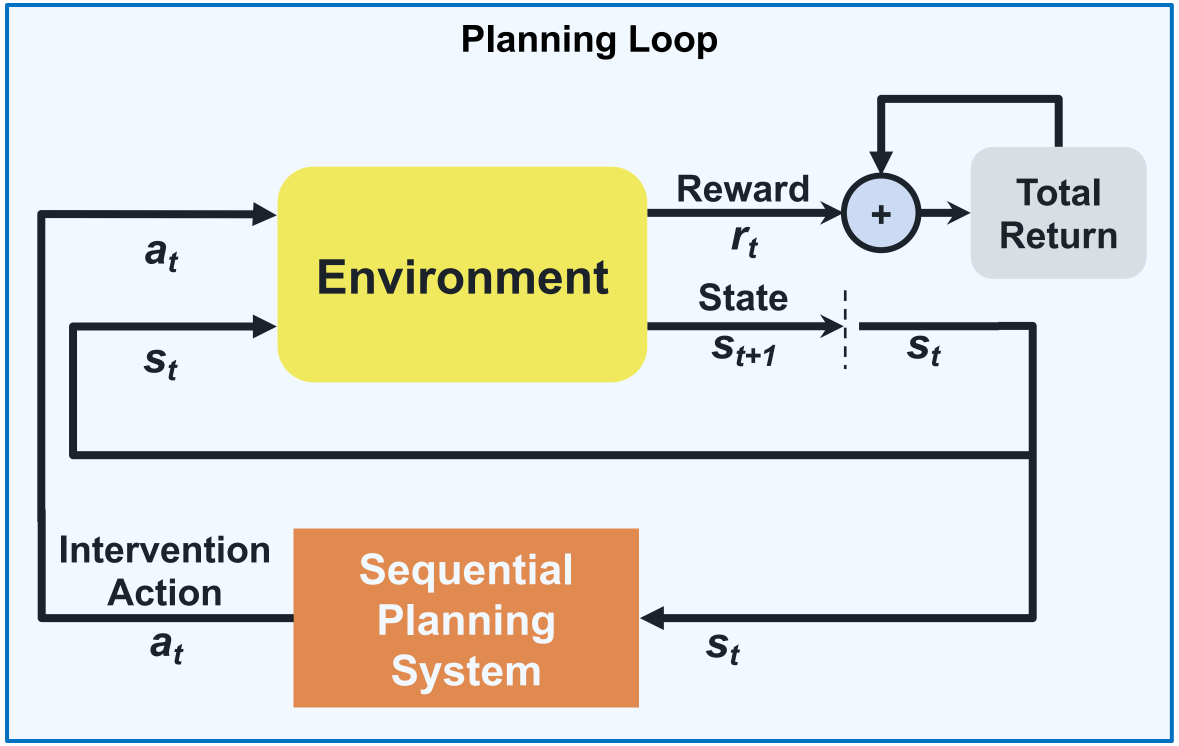
- Models that ignore underlying networks produce inaccurate predictions leading to poor evaluation and public distrust
- Evaluating intervention strategies with inaccurate models is insufficient at best, dangerous at worst
- Realistic simulations allow adaptively finding new strategies through simulated trial and error

High-resolution models are necessary for realistic simulation and evaluating intervention efficacy

Left figure adapted from Mistry D. et al., "Inferring high-resolution human mixing patterns for disease modeling", 2020

Courses of Actions over Incomplete Networks (COANET)



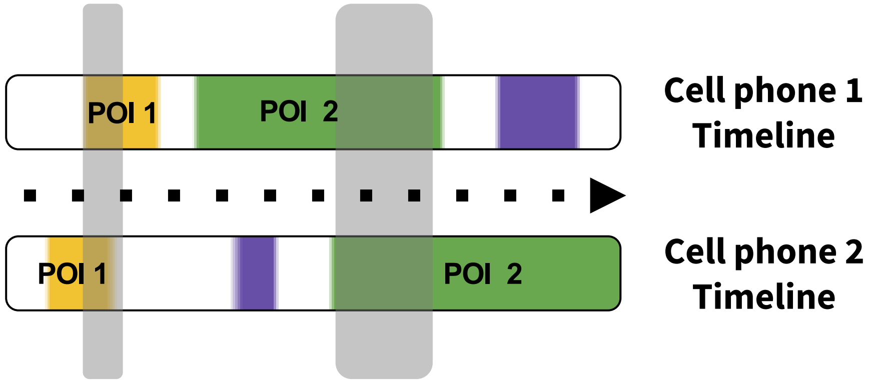


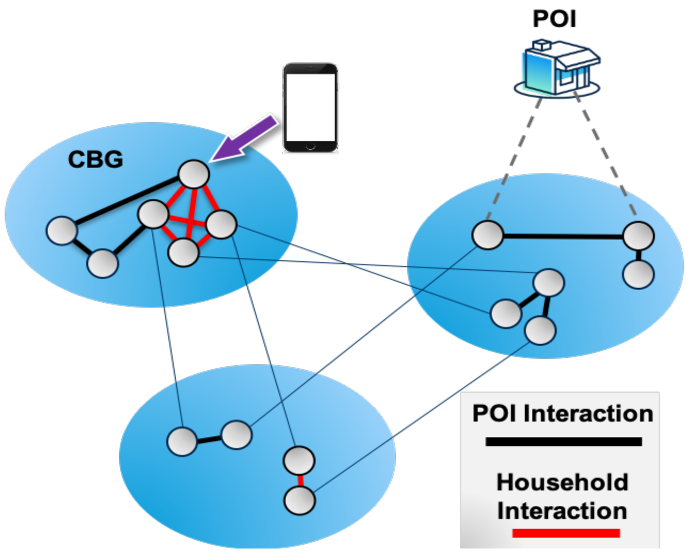
Outline

- Network SEIR model
- Sequential Planning Algorithm
- Results and Discussion

Contact Networks as Stochastic Block Models

- **Device to points-of-interests (POI) location data from opt-in smartphone devices[1]**
- **Each smartphone device is mapped to a "home" Census Block Group (CBG)**
- **Leverage a DCSBM[2] network model to simulate geographically structured contact patterns**
  - Nodes are individuals; stochastic blocks are CBGs
  - Edges represents different types interactions (household, POI co-location)
  - POI interaction probability is based on shared (correlation) POI visit counts, household interaction probability is set to 1
  - Weight of interactions captures the duration of co-location



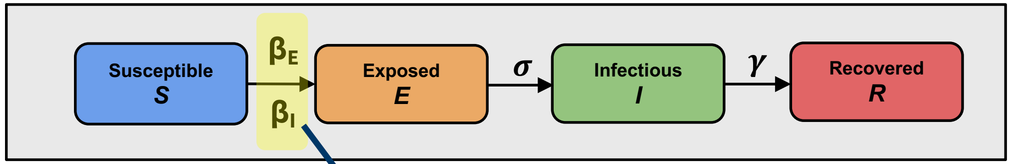


[1] Safegraph: https://www.safegraph.com/ [2] DCSBM: Degree Corrected Stochastic Block Model: https://en.wikipedia.org/wiki/Stochastic_block_model

Incorporating Networks into SEIR Modeling

Compartmental Models:

$$\frac{dS}{dt} = -\frac{\beta SI}{N} \qquad \frac{dE}{dt} = \frac{\beta SI}{N} - \sigma E$$

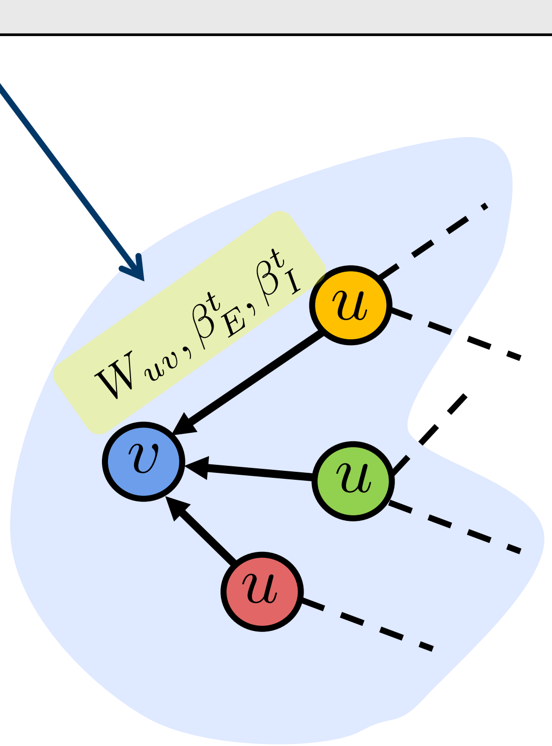


Network-based Model: Network-SEIR

- **Exponential model of node interactions**

$$P(v \text{ becomes exposed} \mid u \text{ is exposed }) = 1 - e^{-W_{uv}\beta_E}$$

$$P(v \text{ becomes exposed} \mid u \text{ is infected }) = 1 - e^{-W_{uv}\beta_I}$$



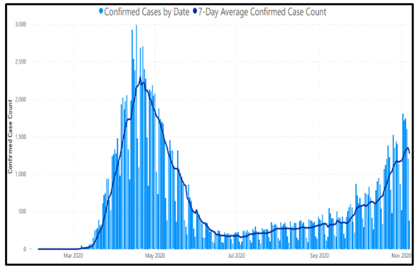
- **Local neighborhood determines probability of exposure**

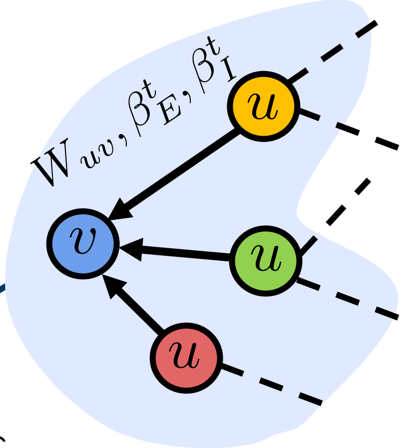
$$P(v \text{ becomes exposed}) = 1 - e^{-\sum_{u \in N_E} W_{uv}\beta_E - \sum_{u \in N_I} W_{uv}\beta_I}$$

Estimating GraphSEIR Parameters from Data

Fit network-level parameters directly to data using probabilistic programming

JHU Reported Infection Counts





$$p(\beta \mid \text{data}) = \frac{\overbrace{p(\text{data} \mid \beta)\; p(\beta)}}{p(\text{data})}$$

Black-box Variational Inference (BBVI)

$$\begin{aligned}\phi^* &= \arg\min_{\phi} \ \mathrm{KL}(q_\phi(\,\cdot\,) \,||\, \underbrace{p(\,\cdot \mid \mathit{data})}_{\textbf{intractable}}) \\ &= \arg\max_{\phi} \ \mathscr{L}(\phi) \leftarrow \textbf{tractable surrogate objective (ELBO)}\end{aligned}$$

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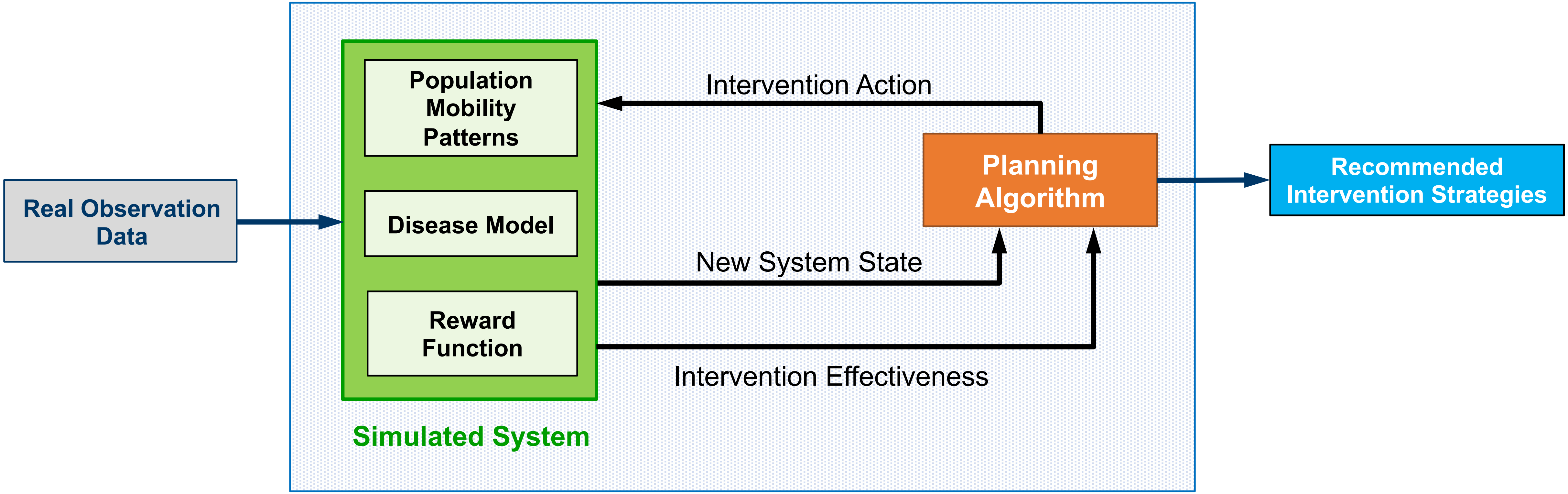
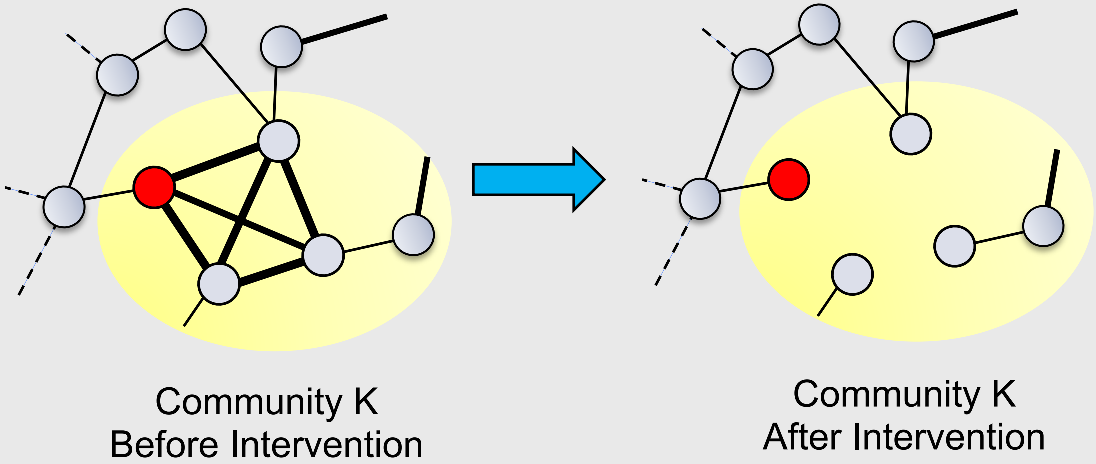
Pandemic Control via Reinforcement Learning



COANET System Overview

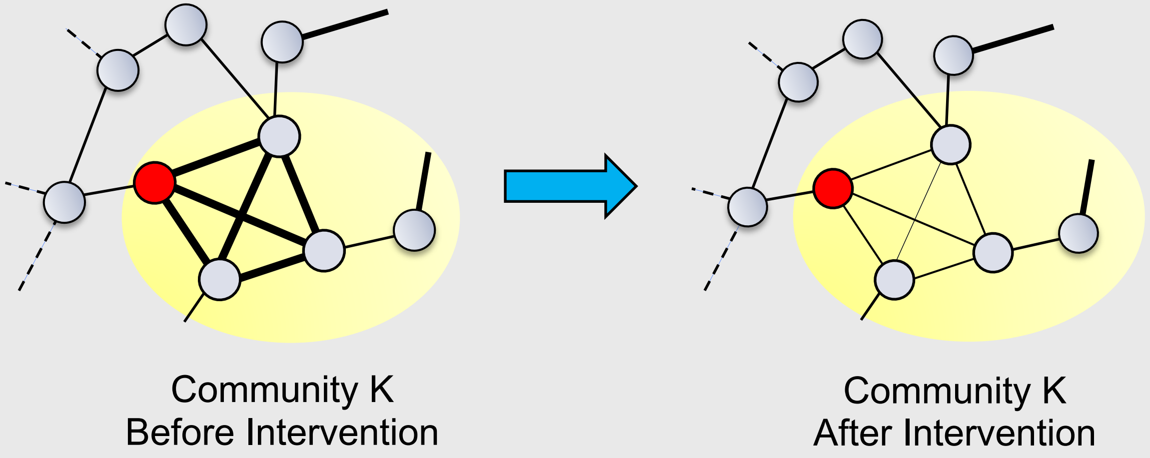
Action Space

Action 1: Enforce stay-at-home action in community K with a given intensity strength



Network Sparsification

Action 2: Enforce mask-wearing in community K with a given effectiveness strength



Reduction of disease spread

- **Jitter Suppression:** Actions must have a minimum active duration
- **Prioritization:** Limit actions to top ranked communities by network centrality and disease prevalence
- **Feasibility:** Allow only one, single community action per timestep

Reward Function

- **Reward function intuitions**
  - Maximizing susceptible individuals rewards limiting disease spread
  - Policy scale represents relative disruptiveness of intervention
  - Total policy cost is proportional to number of impacted individuals
  - Policy change cost penalizes changes in interventions to capture public “policy fatigue”

$$r = \frac{1}{N}\left(S(G) - \sum_{i=1}^{|C|} \left(\alpha_{sh} s_{sh,i} |c_i| + \alpha_{mw} s_{mw,i} |c_i| \right) + \alpha_{a \neq 0} |c_i| \right)$$

Susceptible Individuals	**Policy Scale Parameters**	**Policy Severities**	**Community Sizes**	**Policy Change Cost**

N: Population Size $\quad$ c_i: Community being intervened

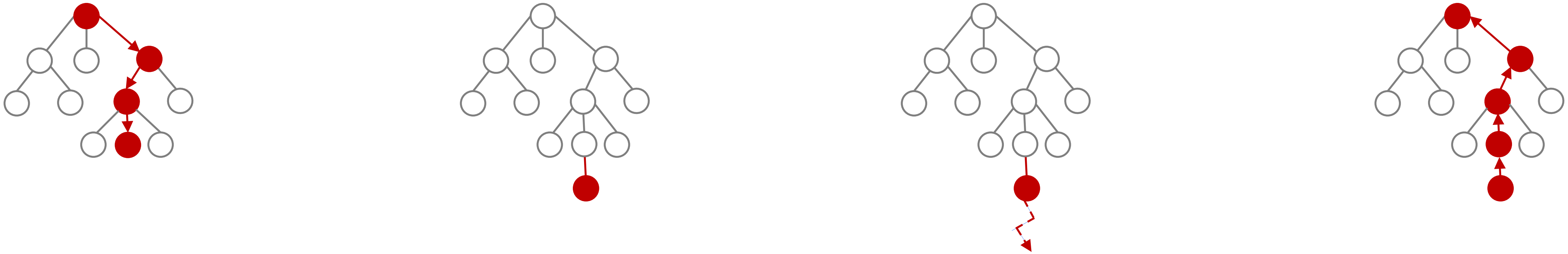
Monte Carlo Tree Search (MCTS) Algorithm

State-action tree with

Q (s, a) - the estimated expected return of taking action *a* from state *s*
N (s, a) - how often we have visited state-action pairs in the tree

Run continuously in the allotted time

Selection → **Expansion** → **Simulation** → **Backpropagation**



Repeatedly select optimally-promising* state-action pairs deeper in the tree

At a leaf node, instantiate a new node

Perform a "rollout" simulation to a specified depth, following a heuristic policy to get Q (s, a)

Backpropagate Q (s, a) and increment N (s, a) along the simulation's (s, a) path

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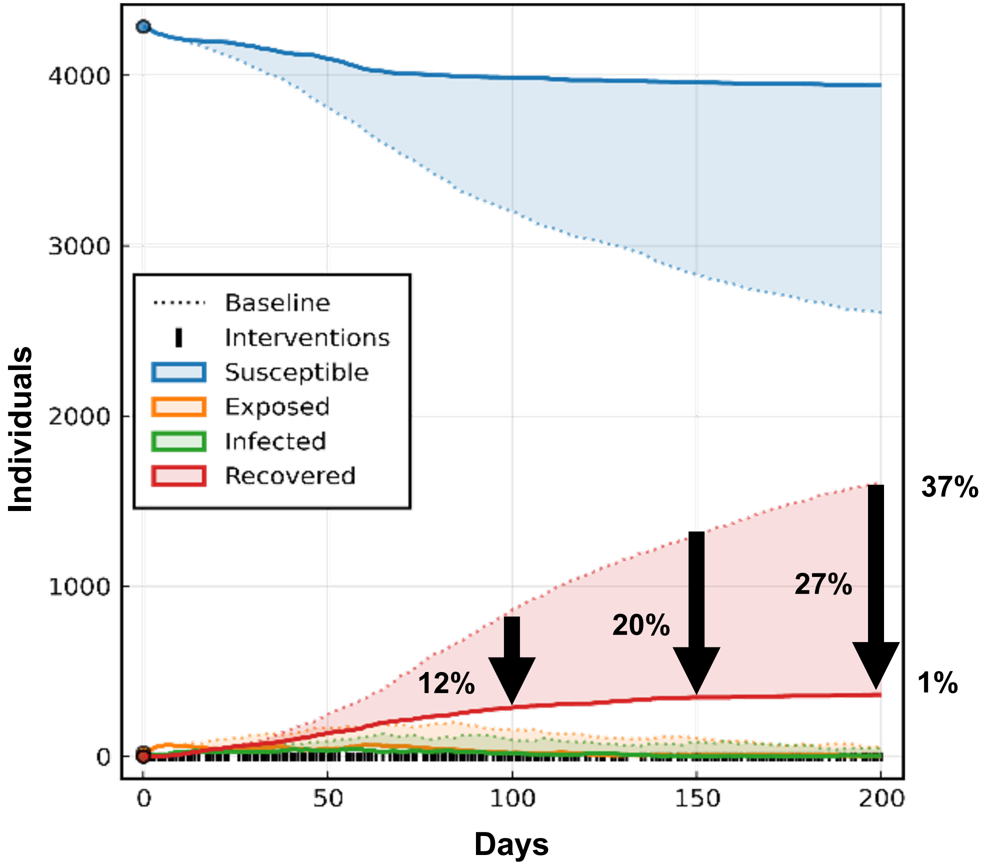
Controllability of COVID-19

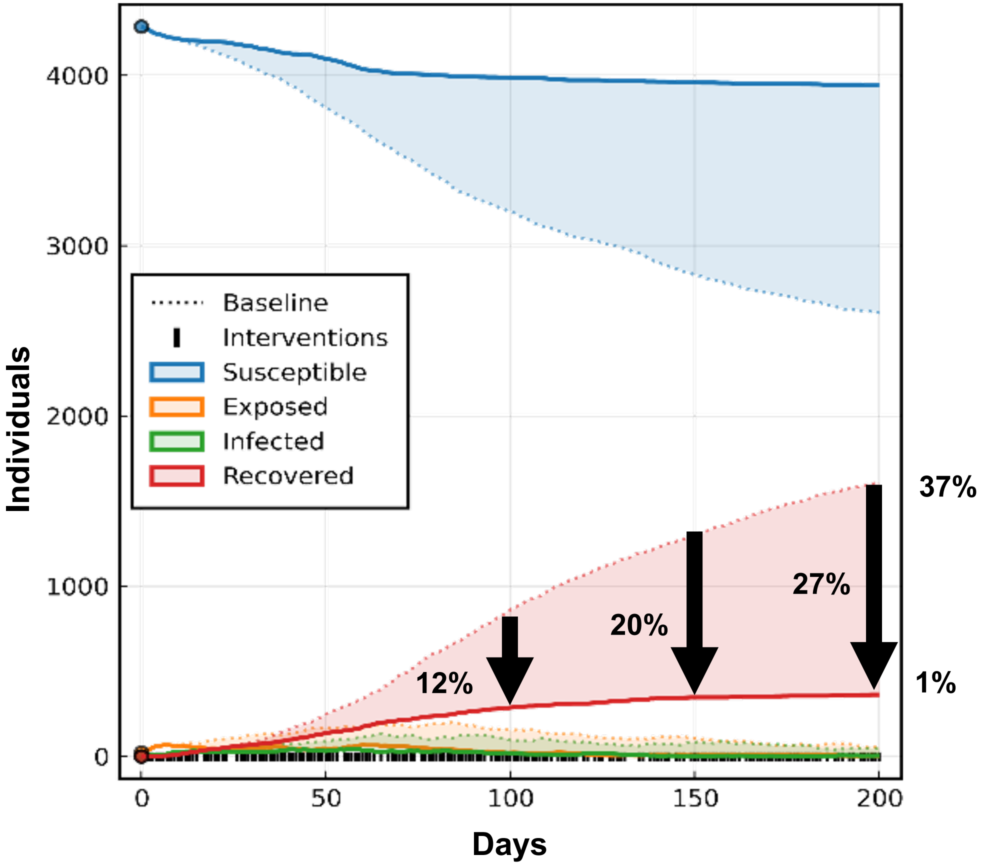
Uniform initial infection spread



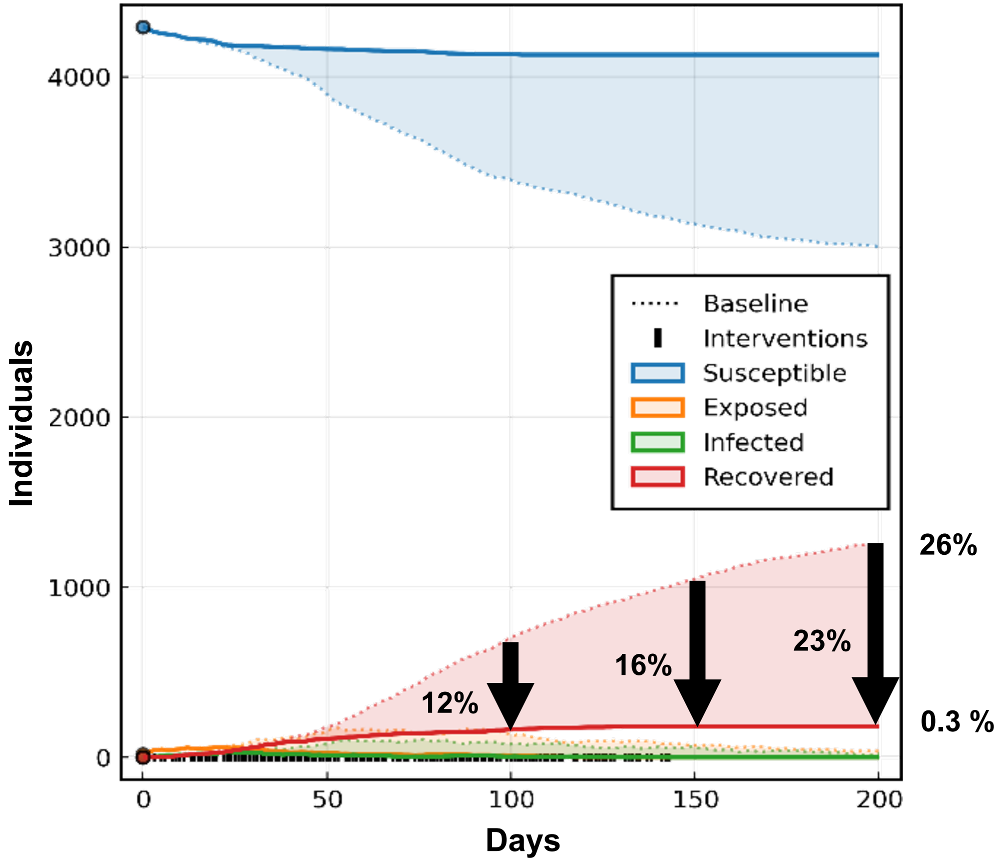
Planning leads to more effective and targeted control

Controllability of COVID-19

Uniform initial infection spread



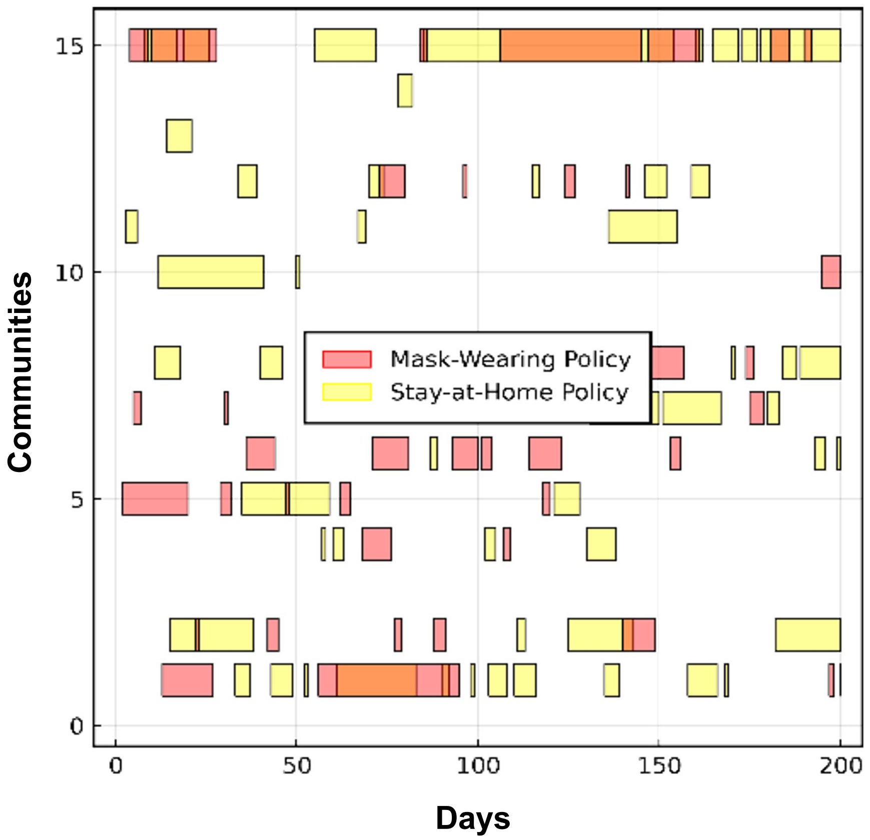
Initial infection spread in 2 census blocks



The more localized the initial conditions the more effective the control

Controllability of COVID-19

Uniform initial infection spread



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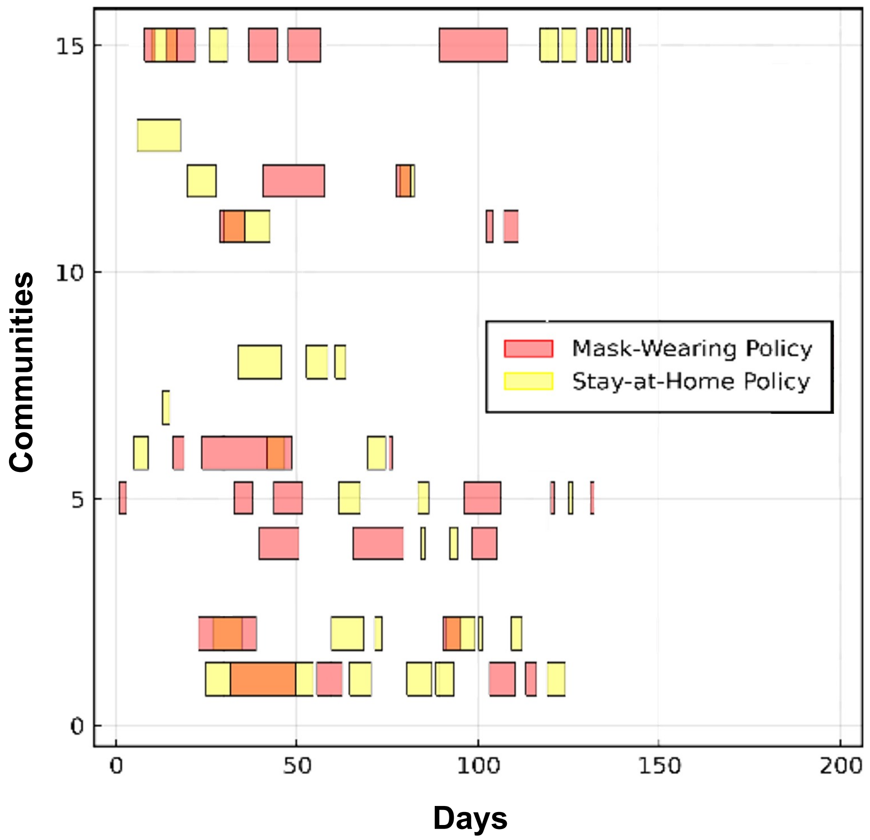
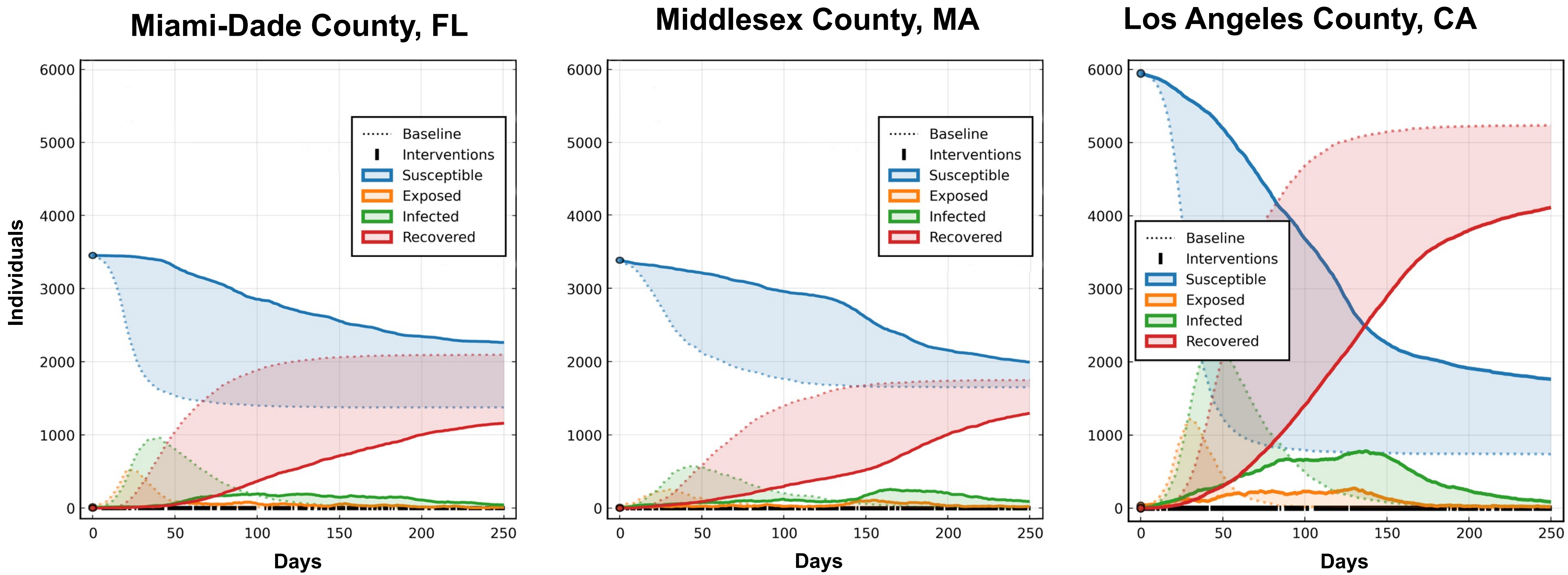


Adaptive strategies are non-trivial – COANET finds no universal lockdown required

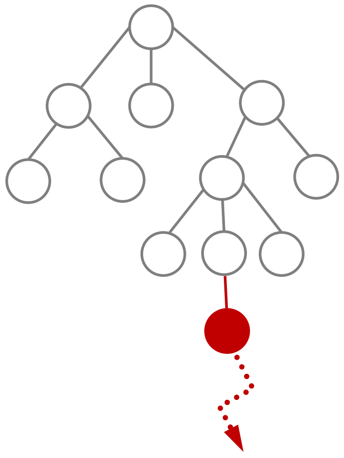
Control Effectiveness in Different Geographic Regions



Our system customizes control strategies to different geographic regions and maintain effectiveness

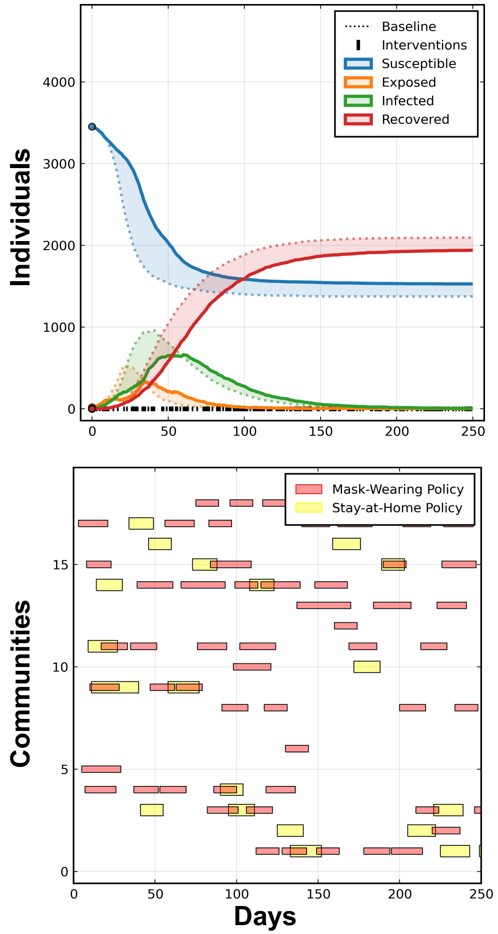
Effects of Longer Lookaheads

Simulation



Actions are evaluated by simulating disease forward in time

2 week lookahead



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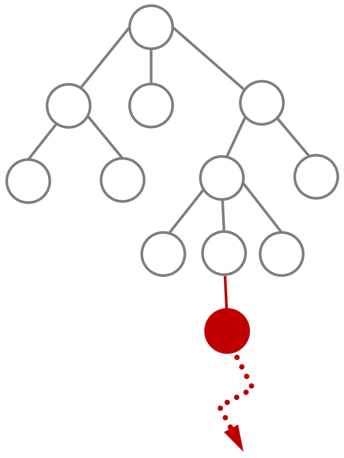

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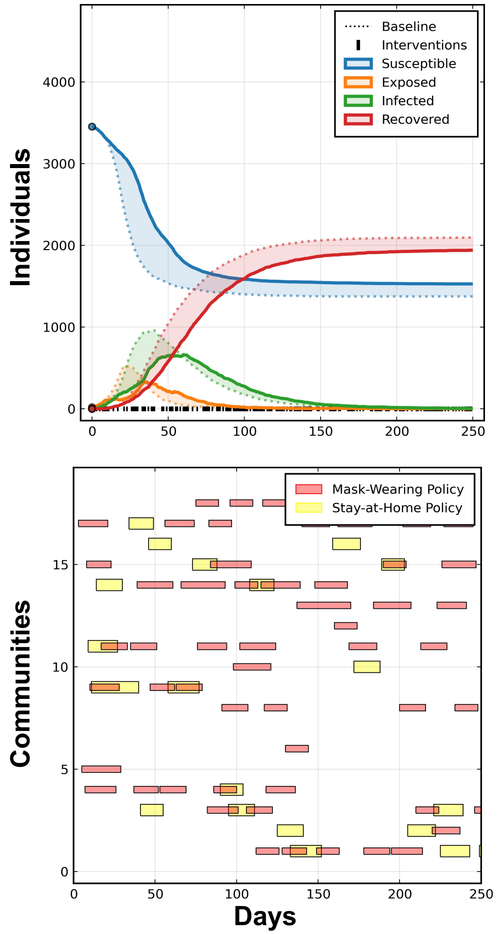
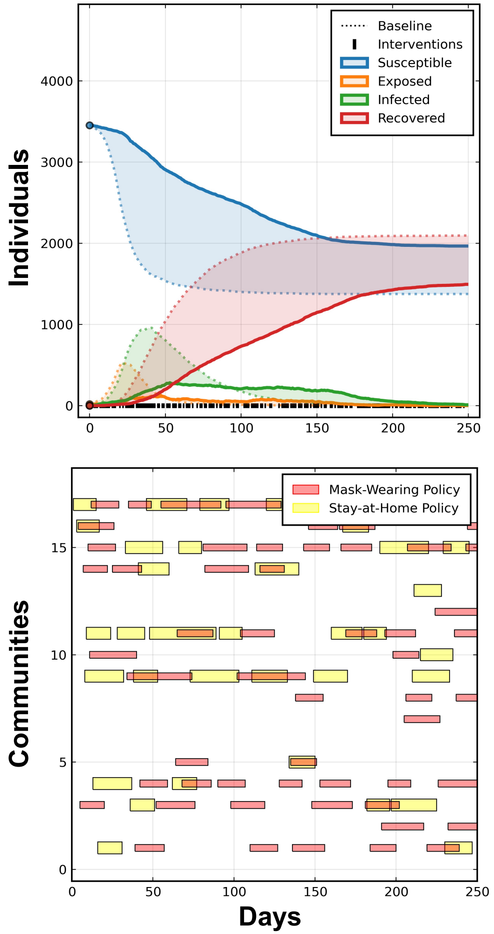
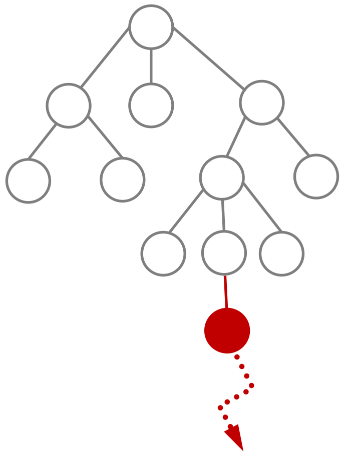


4 week lookahead



Effects of Longer Lookaheads

Simulation



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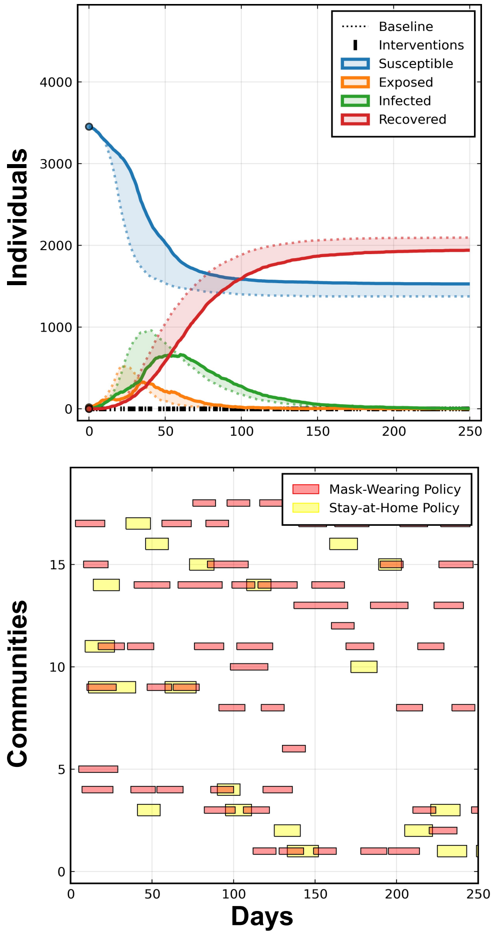
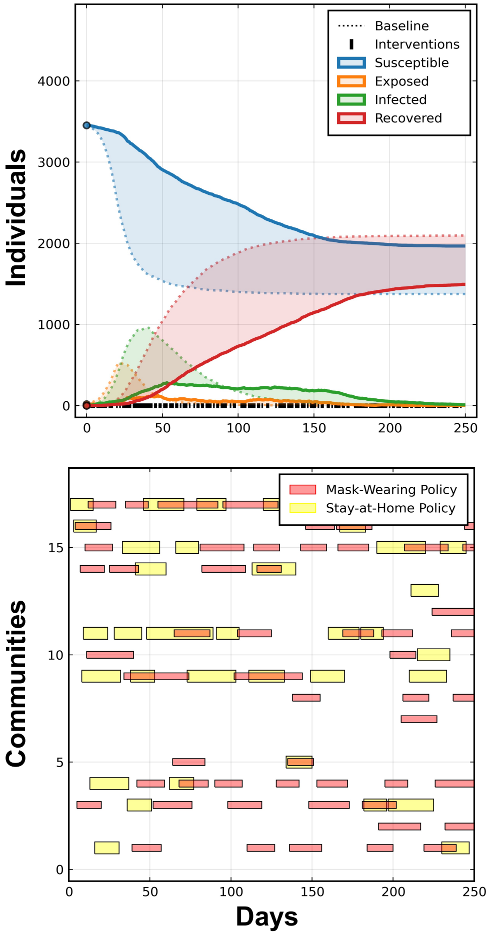
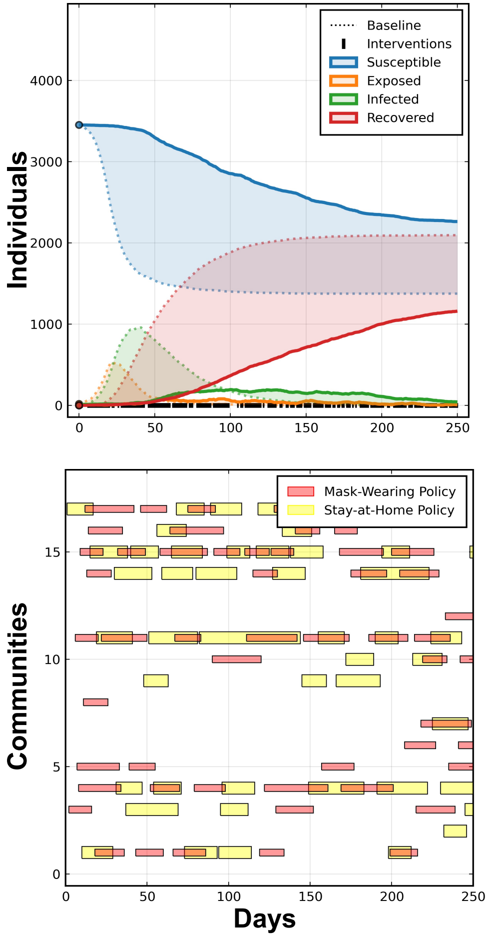
2 week lookahead



4 week lookahead



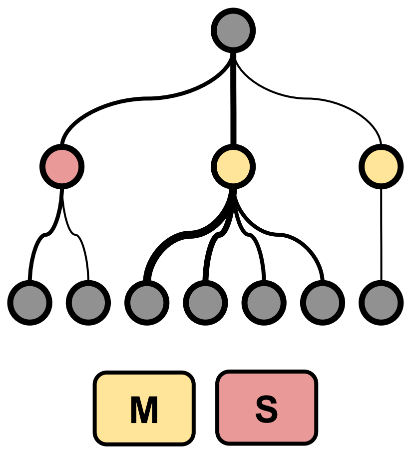
6 week lookahead



COANET identifies a minimum, required 3-4 week lookahead time for effective planning

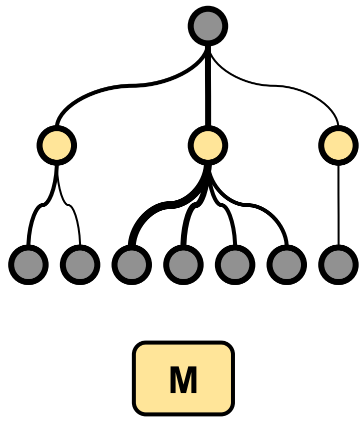
Comparison With Baseline Approaches

MCTS Planner with Mask-Wearing and Stay-at-Home Actions

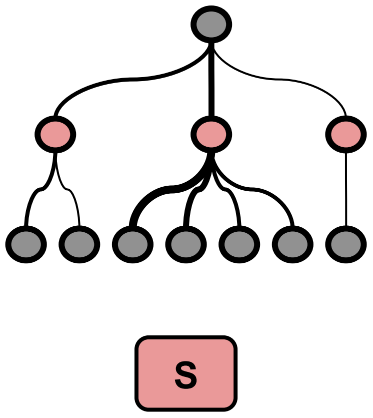


Our Approach

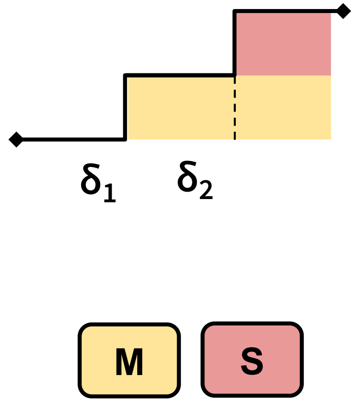
MCTS Planner with Mask-Wearing Actions Only



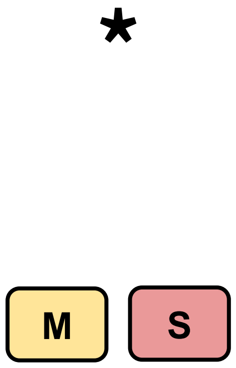
MCTS Planner with Stay-at-Home Actions



Global Threshold Policy

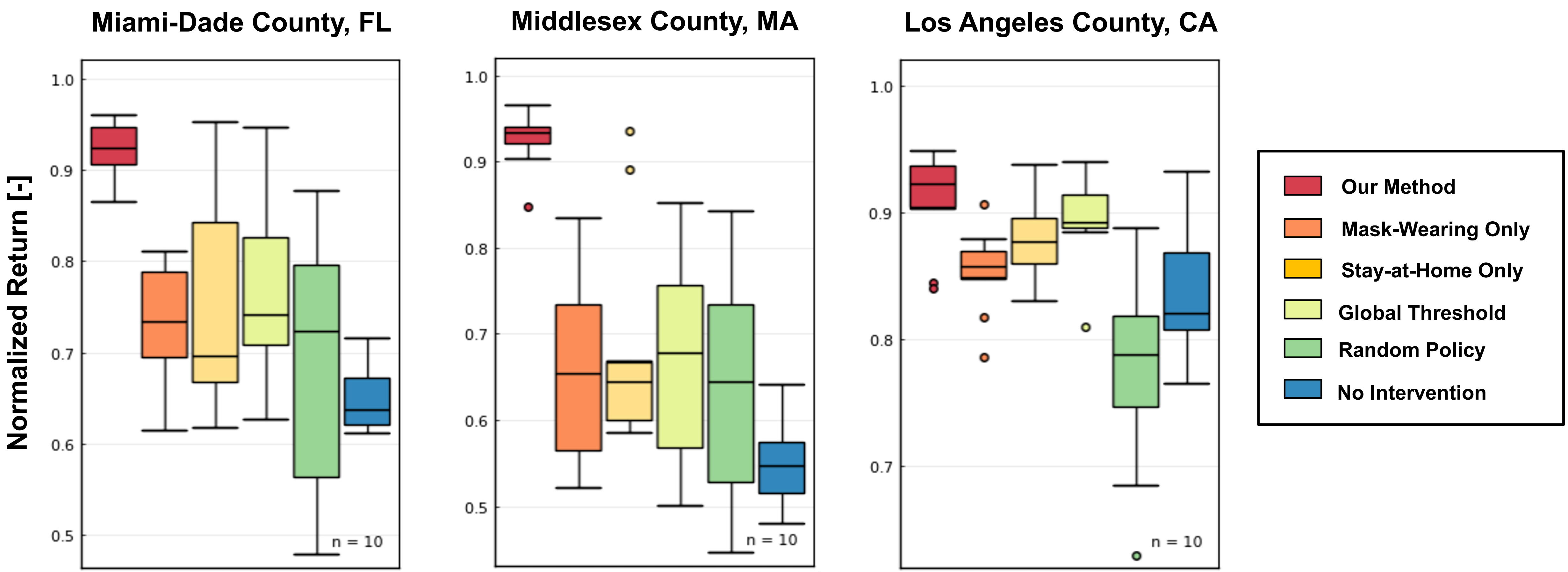


Random Policy



Evaluate the performance of our adaptive planner against several baseline heuristics

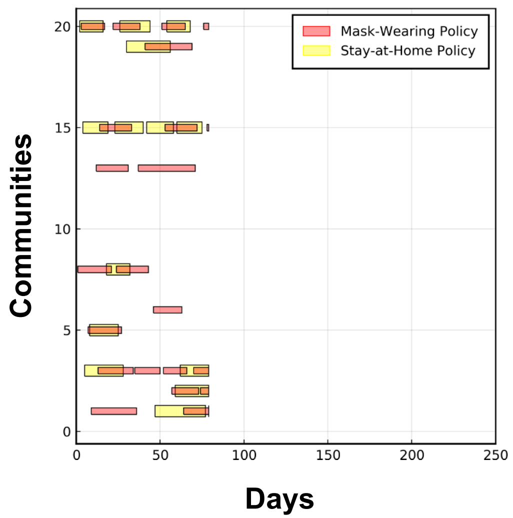
Performance Comparison With Baselines



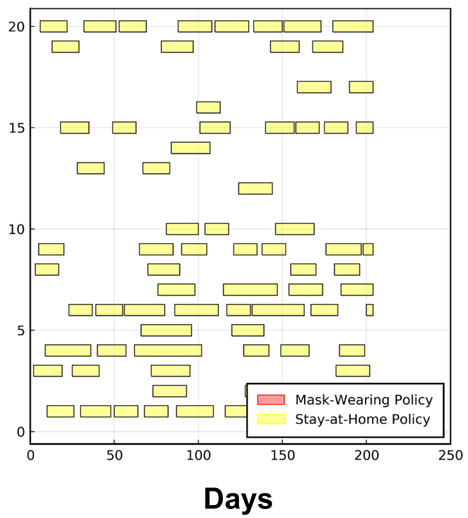
Our planner achieves 1) higher cumulative return and 2) lower variance

Middlesex County, MA Results

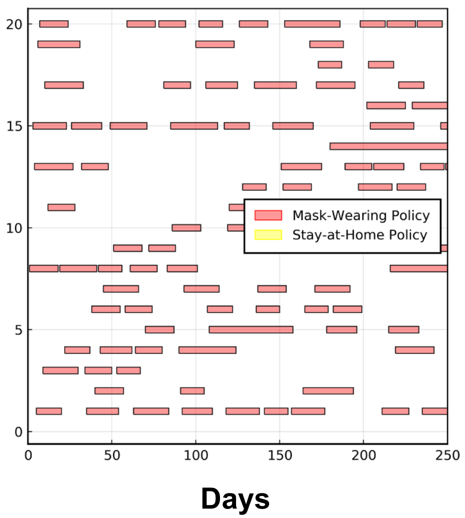
Our Approach



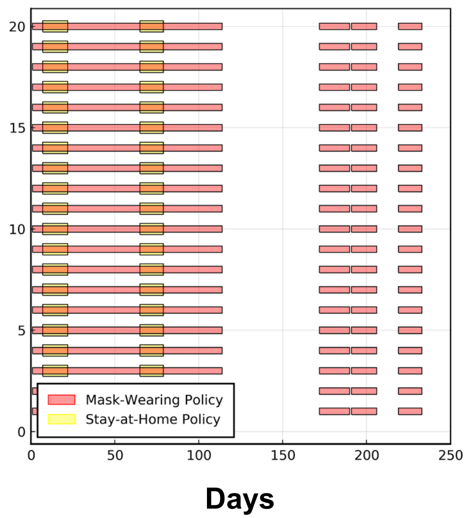
Stay home-Only



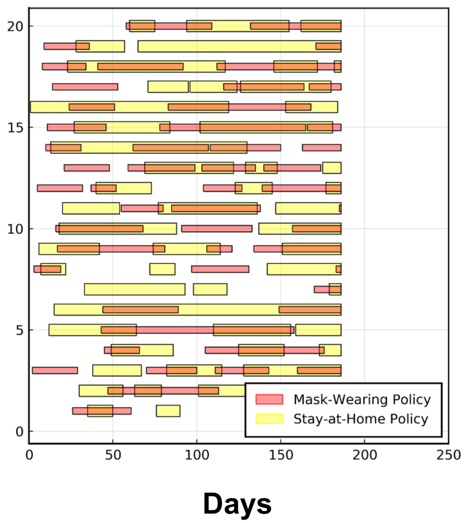
Mask-Only



Global Threshold

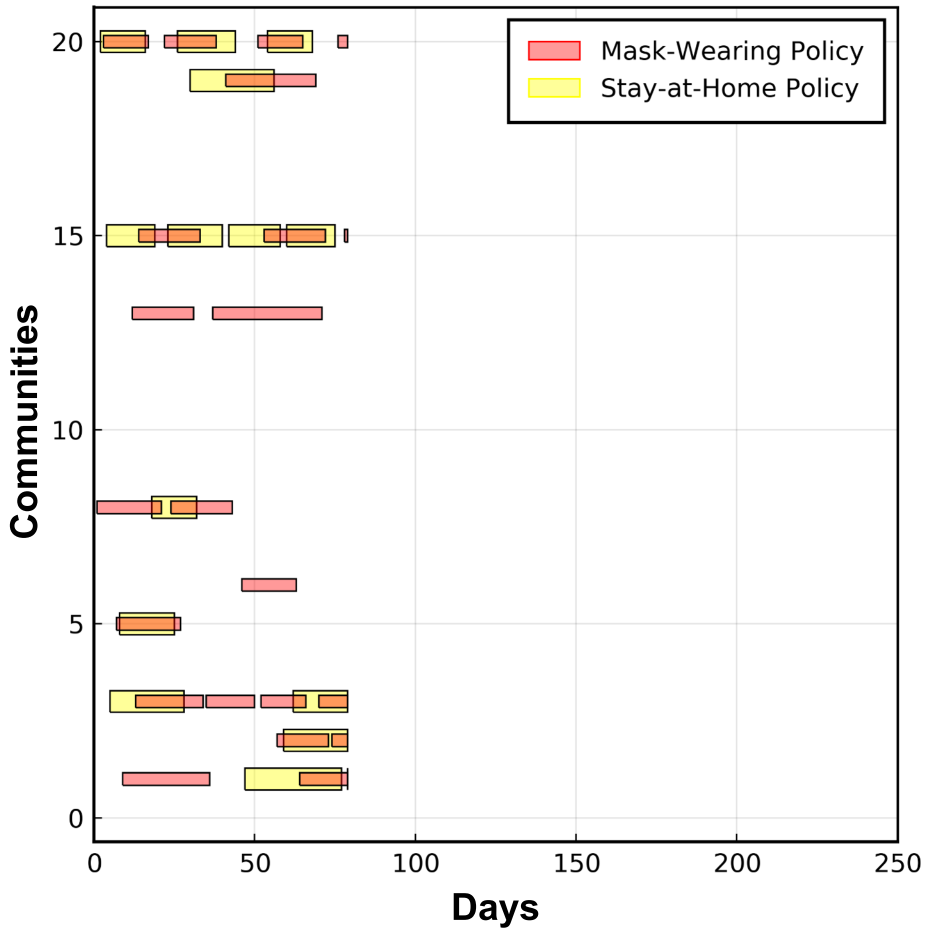


Random Action

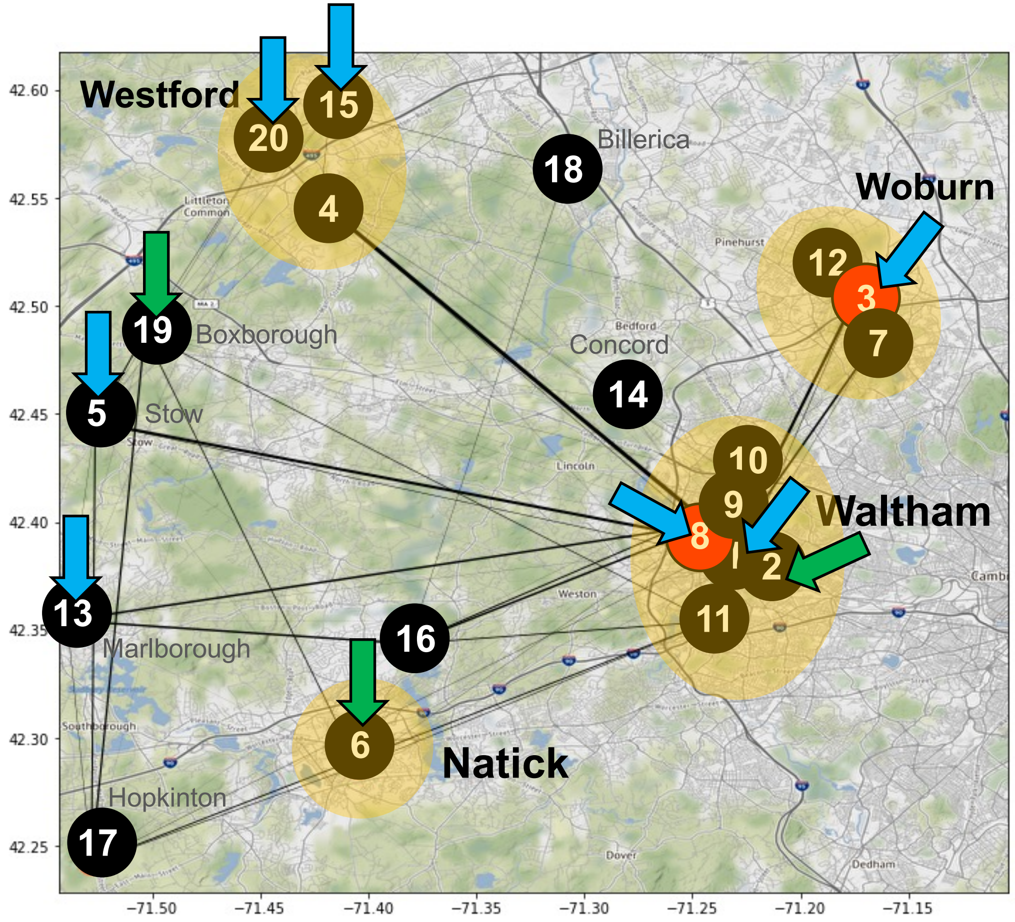


Our planner identifies much more targeted interventions while achieving higher cumulative reward

Exploring Learned Intervention Policies



Middlesex County, MA



Our planner offers a sandbox environment for exploring and inferring canonical intervention strategies

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Ongoing Work and Future Directions

Interpretability and Usability

- Analyze planner output to identify canonical, simple strategies
- Characterization of topological effects on planning decisions
- Develop usable dashboard that assists with analyzing planner outputs

Scalability

- Efficient and specialized network heuristics for reducing state/action spaces
- Engineering cloud computing and GPU acceleration for scalability
- Distributed hierarchical planning over complex networks

Realism and Performance Improvement

- Designing and fusing offline and online training environments
- Probabilistic programming applied to various system components (topology, control)
- Planning with partial observability and lack of compliance

References

- K. Menda, L. Laird, M. J. Kochenderfer, R. S. Caceres, **“Explaining COVID-19 Outbreaks with Reactive SEIRD Models”,** Scientific Reports 2021, under review, https://doi.org/10.1101/2021.02.09.21251440.

- N. Smedemark-Margulies, R. Walters, H. Zimmermann, L. Laird, N. Kaushik, R. S. Caceres and J. van de Meent, **“Inference in Network-based Epidemiological models with probabilistic programming”,** ICLR Workshop on AI for Public Health, 2021.

- R. B. Alexander, L. Laird, N. Kaushik. C. Vanderloo, N. Smedemark-Margulies, R. Walters, H. Zimmermann, L. Torres, R. S. Caceres, J. van de Meent, T. Eliassi-Rad, M. J. Kochenderfer, **“Adaptive Intervention Strategies for Epidemic Control on Population Topologies”,** in preparation.

- N. Kaushik, R. S. Caceres, L. Laird, C. Vanderloo, L. Torres, T. Eliassi-Rad, **“Network-based modeling of mobility patterns and SEIR dynamics to analyze COVID 19**”, in preparation.

Questions

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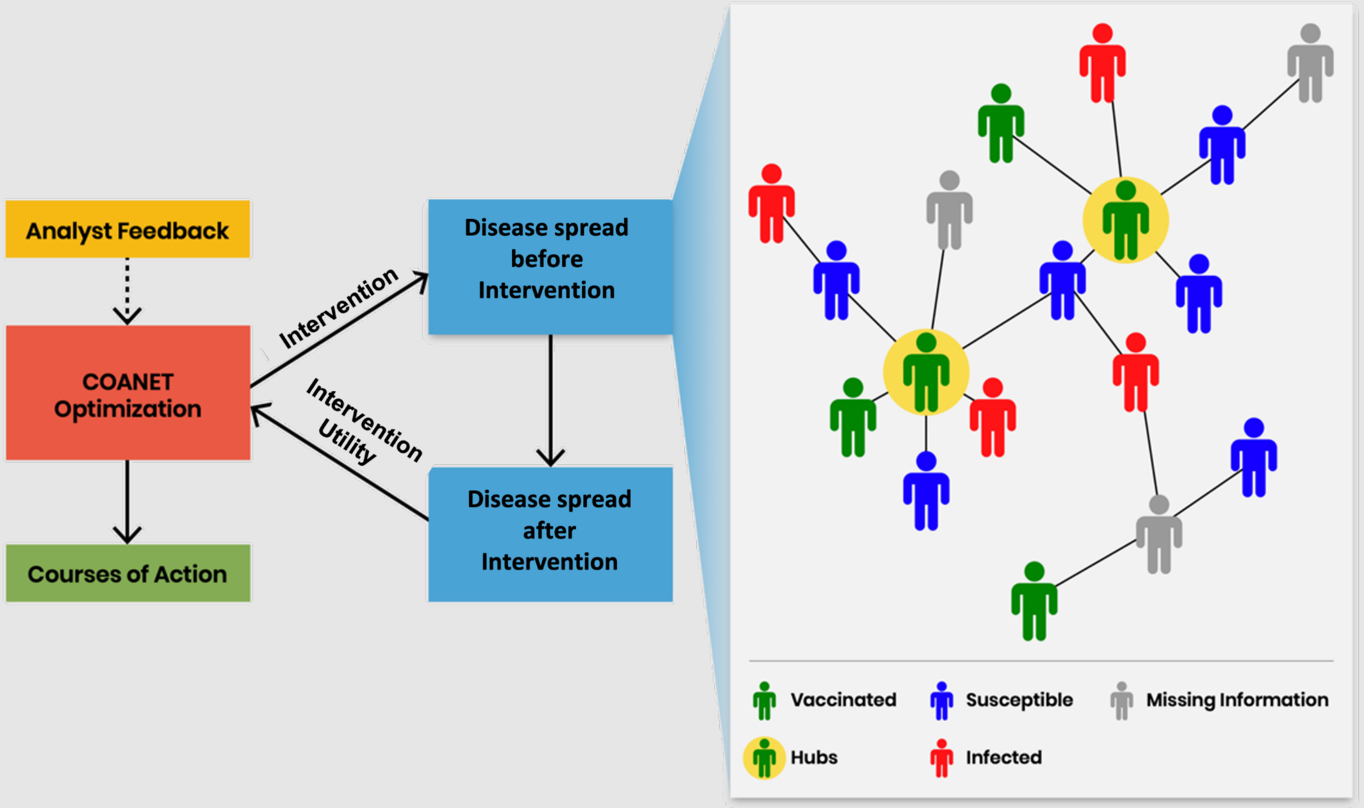
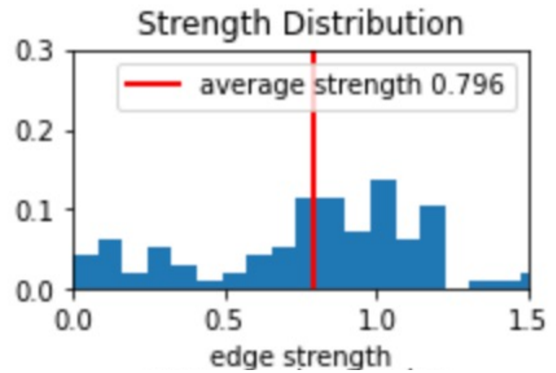


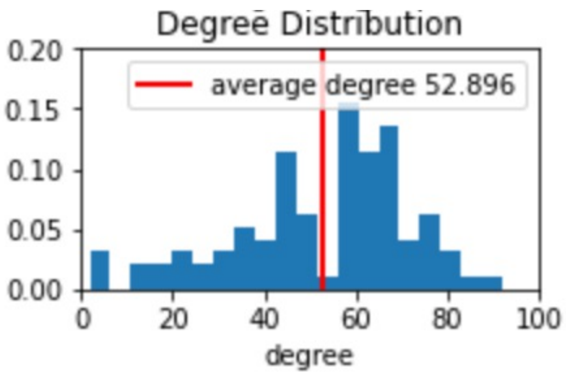
COANET Capability

Backup

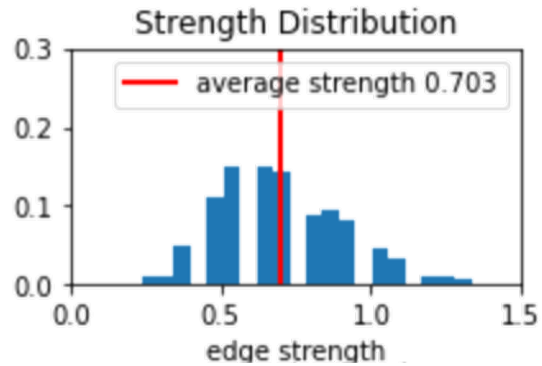
Mobility Networks as Stochastic Block Models

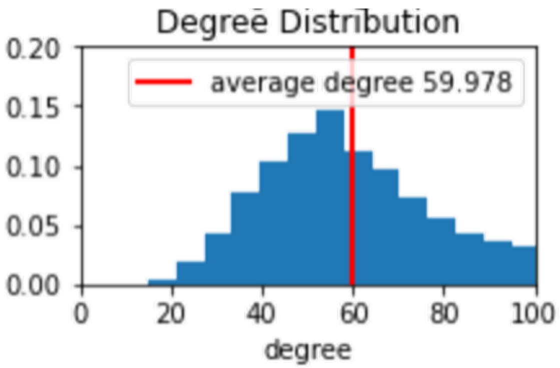
MIT Reality Mining Network[1]



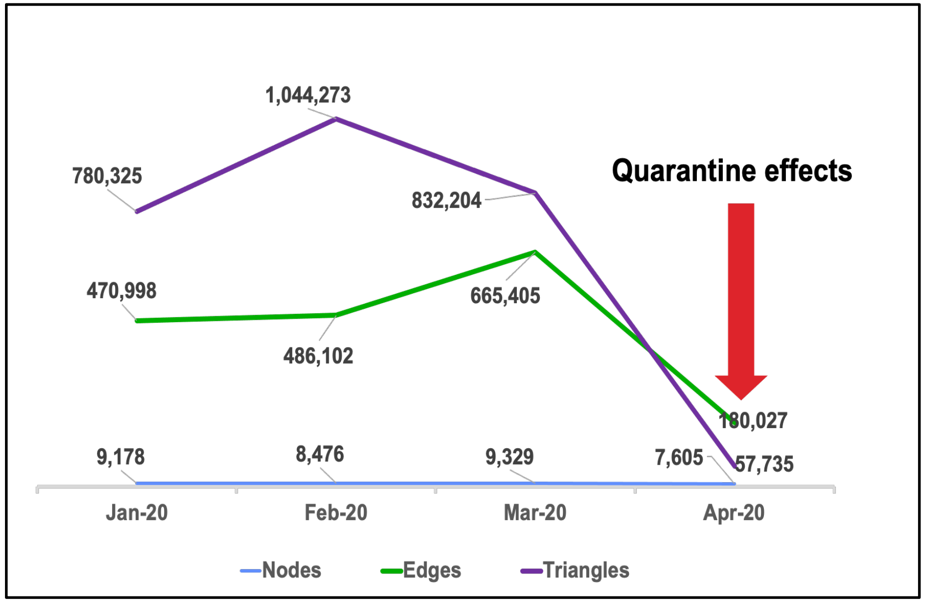


MIT LL Network Snapshot[2]





MIT LL Network over Time



Our model captures contact patterns also observed in other social and mobility networks[1,3,4,5] and reflects observed intervention effects

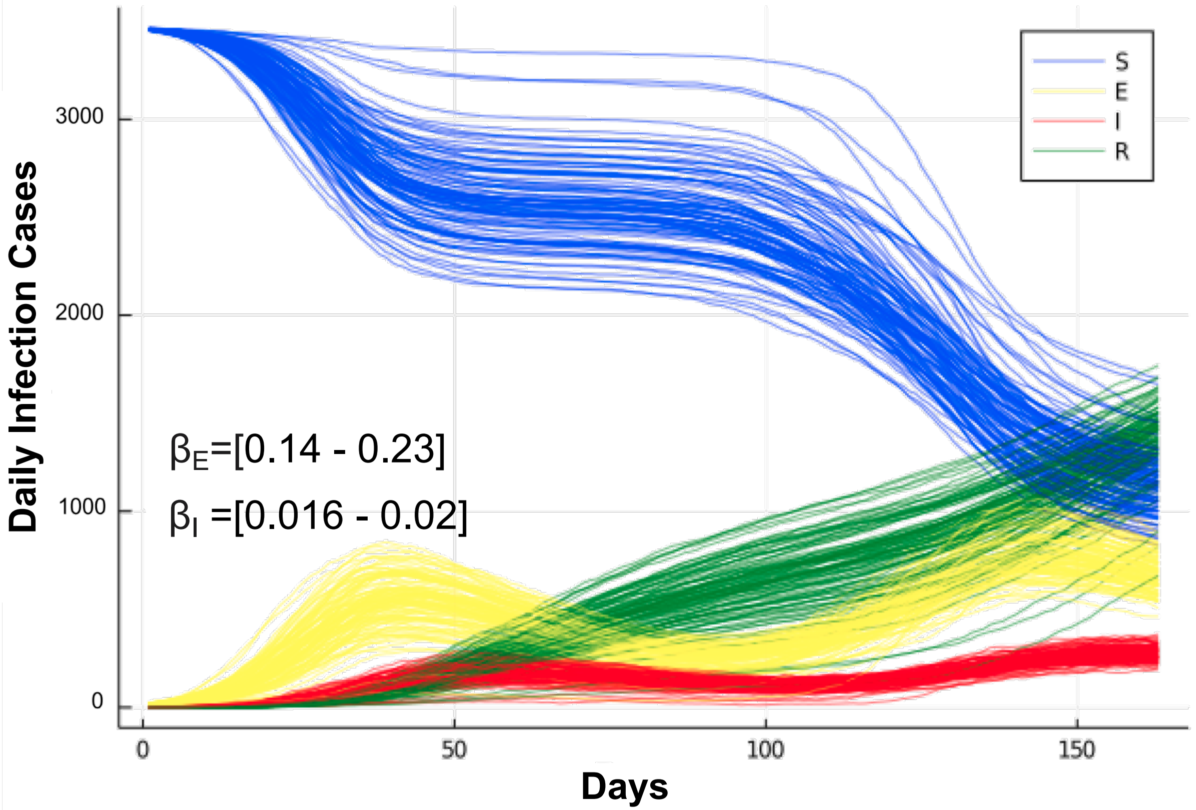
[3] https://www.medrxiv.org/content/10.1101/2020.06.15.20131979v1.full.pdf
[4] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7273304/
[5] https://www.networkscienceinstitute.org/publications/assessing-changes-in-commuting-and-individual-mobility-in-major-metropolitan-areas-in-the-united-states-during-the-covid-19-outbreak

[1] MIT Reality Mining: http://realitycommons.media.mit.edu/realitymining.html
[2] Middlesex Network Snapshot

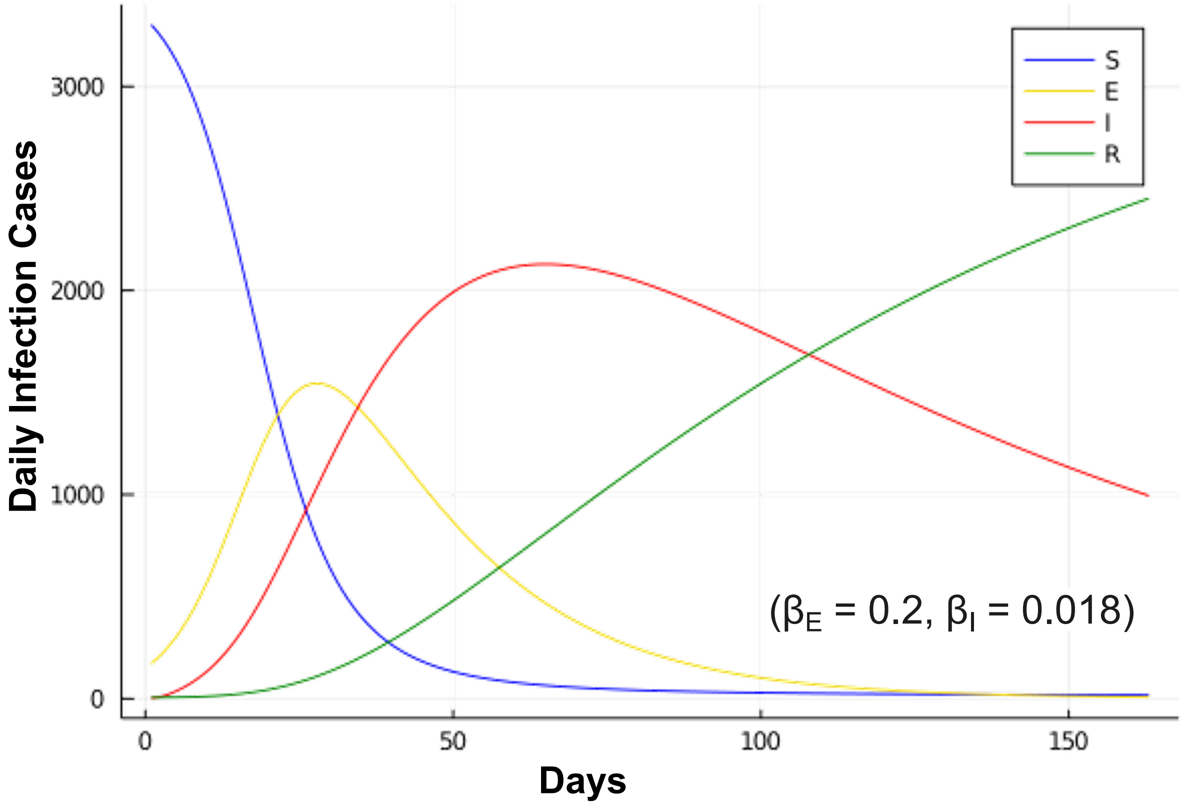
Estimating Network SEIR Parameters from Data

(Probabilistic Programming Approach)

Our Probabilistic Programming Network-SEIR Model



Vanilla SEIR Model



Plots reflect 100 simulated disease trajectories

Using probabilistic programming and network SEIR, we can model more realistic disease progression

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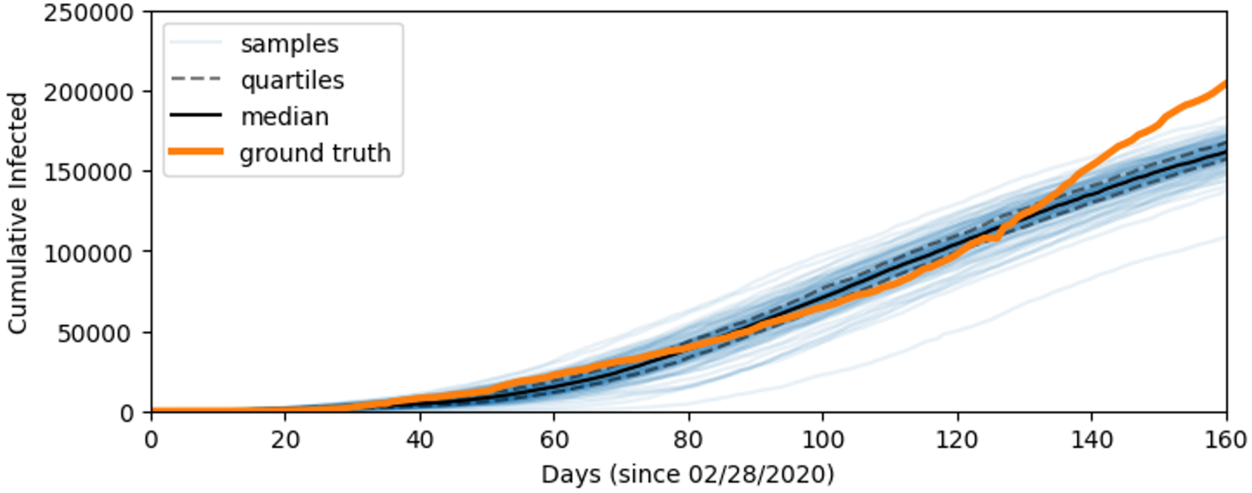
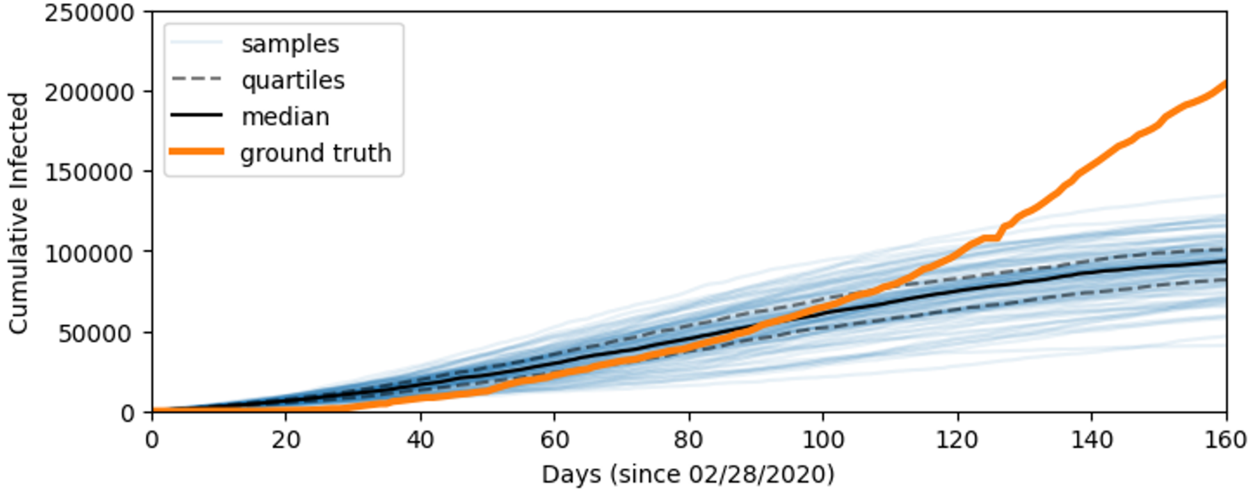
Estimating Network SEIR Parameters from Data
(Probabilistic Programming Approach)

Our Method



R_t-Analytic Baseline



Disease Model	Fitting Method	LA-MDAE	Miami-Dade-MDAE
Compartmental	CE-EM	0.0251	0.0161
Network	R_t-Analytic	0.0075	0.0086
Network	BBVI	**0.0029**	**0.0053**

Using probabilistic programming and network SEIR model allows for a closer fit to data

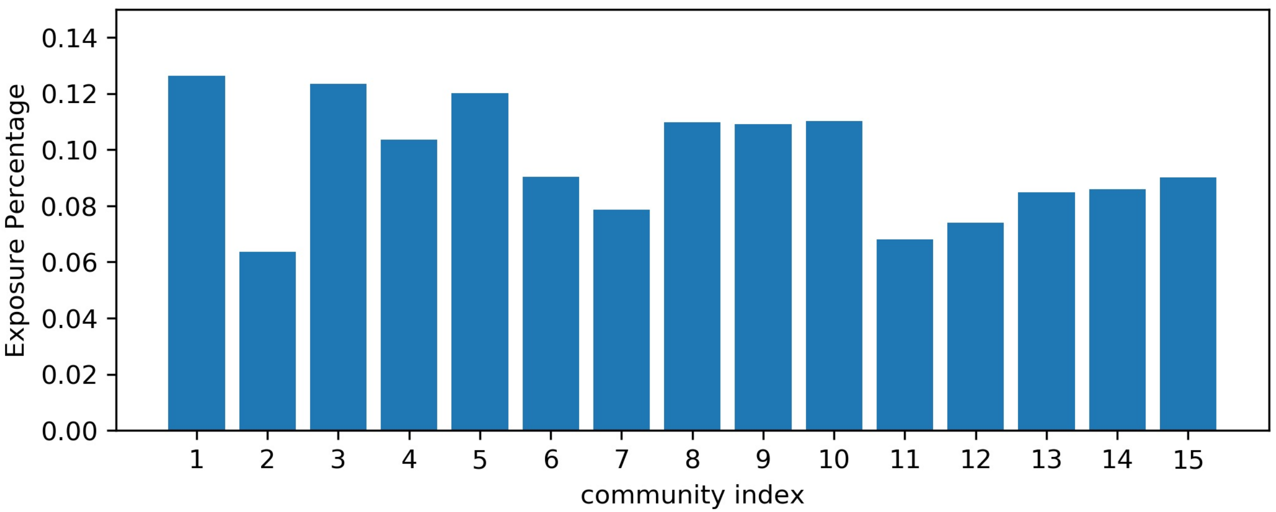
* Network R_t Analytic estimator assumes the network has average constant degree

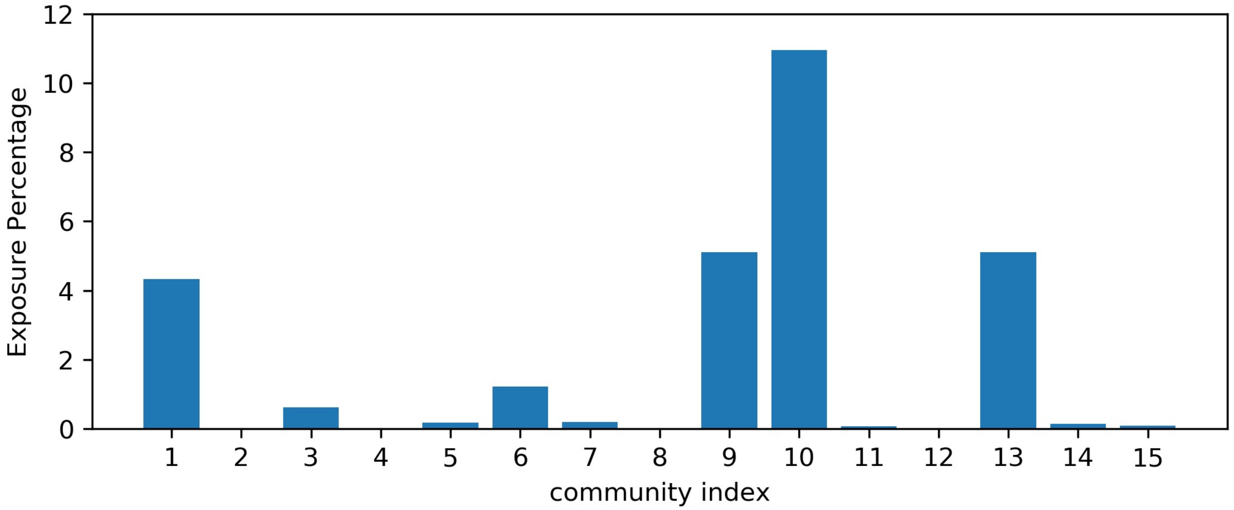
Plots reflect 100 simulated disease trajectories

MDAE: Mean Daily Absolute Error

Inferring Starting Communities

Miami-Dade County, Fl

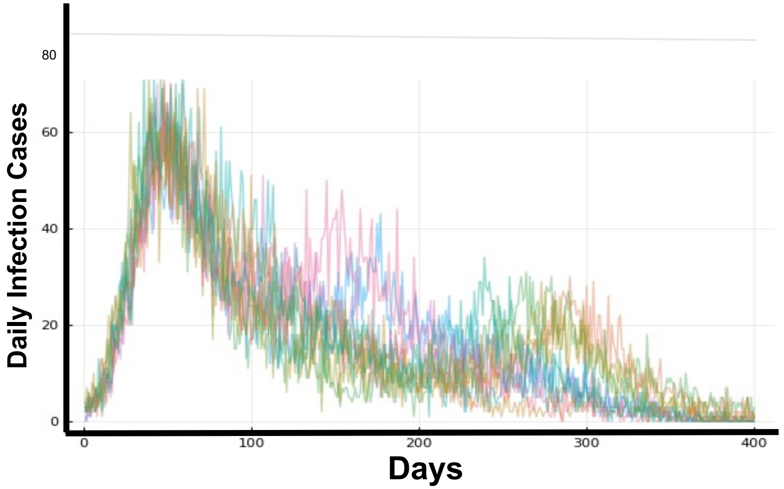




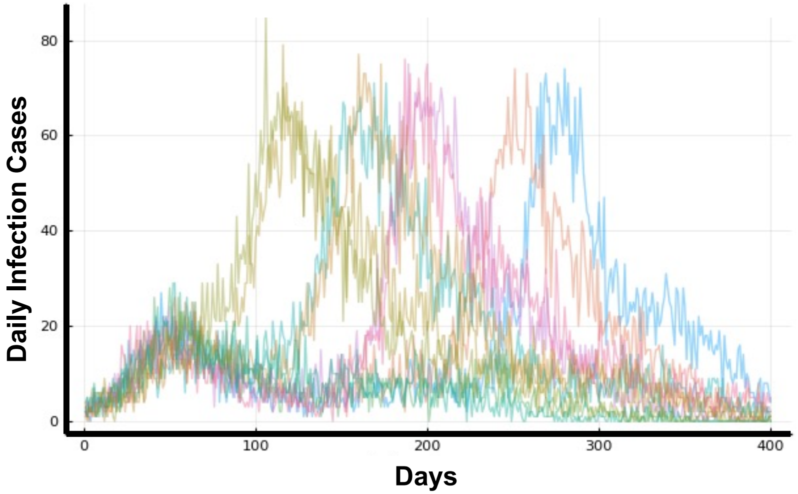
We can identify likely communities where disease could have spread from given observed data

Patterns of Disease Spread

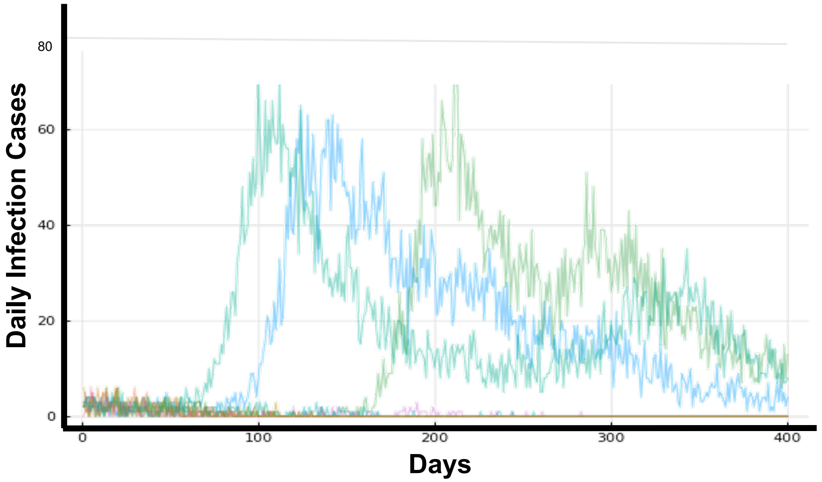
Same geographic area, same initial infections that start in different communities



Consistent Peak & Timing



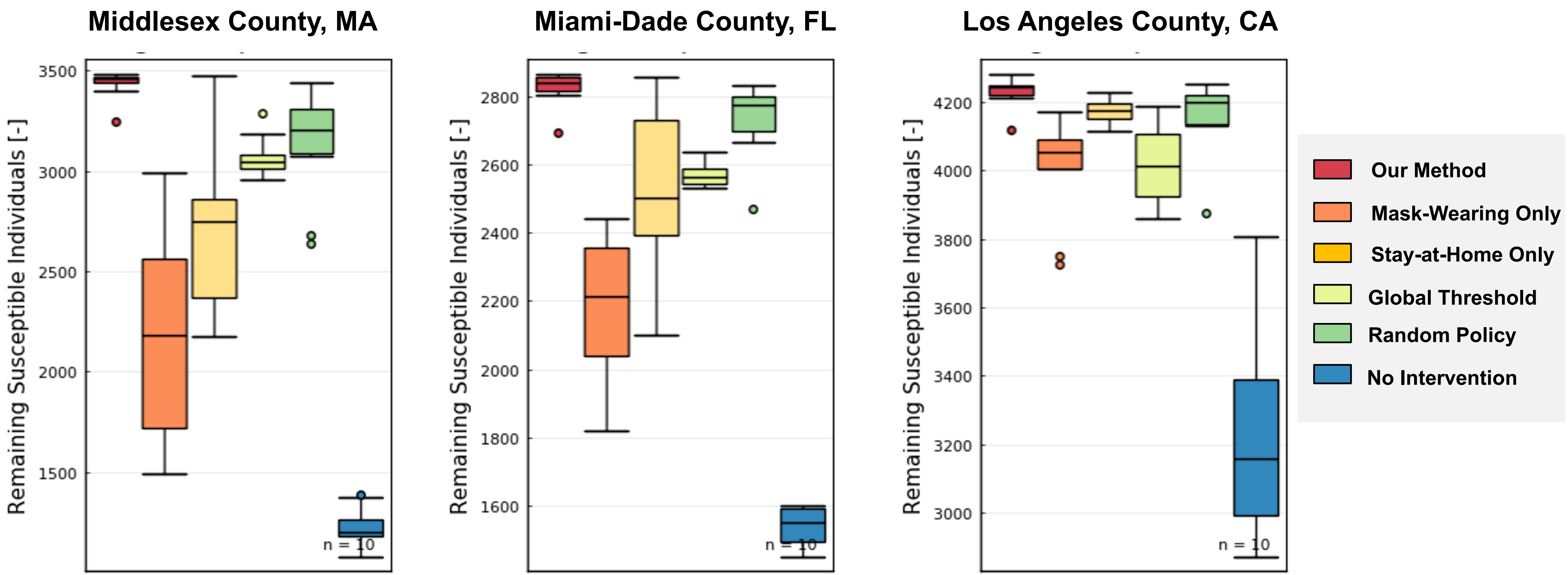
Consistent Peak & Delayed Timing



Inconsistent Peak & Timing

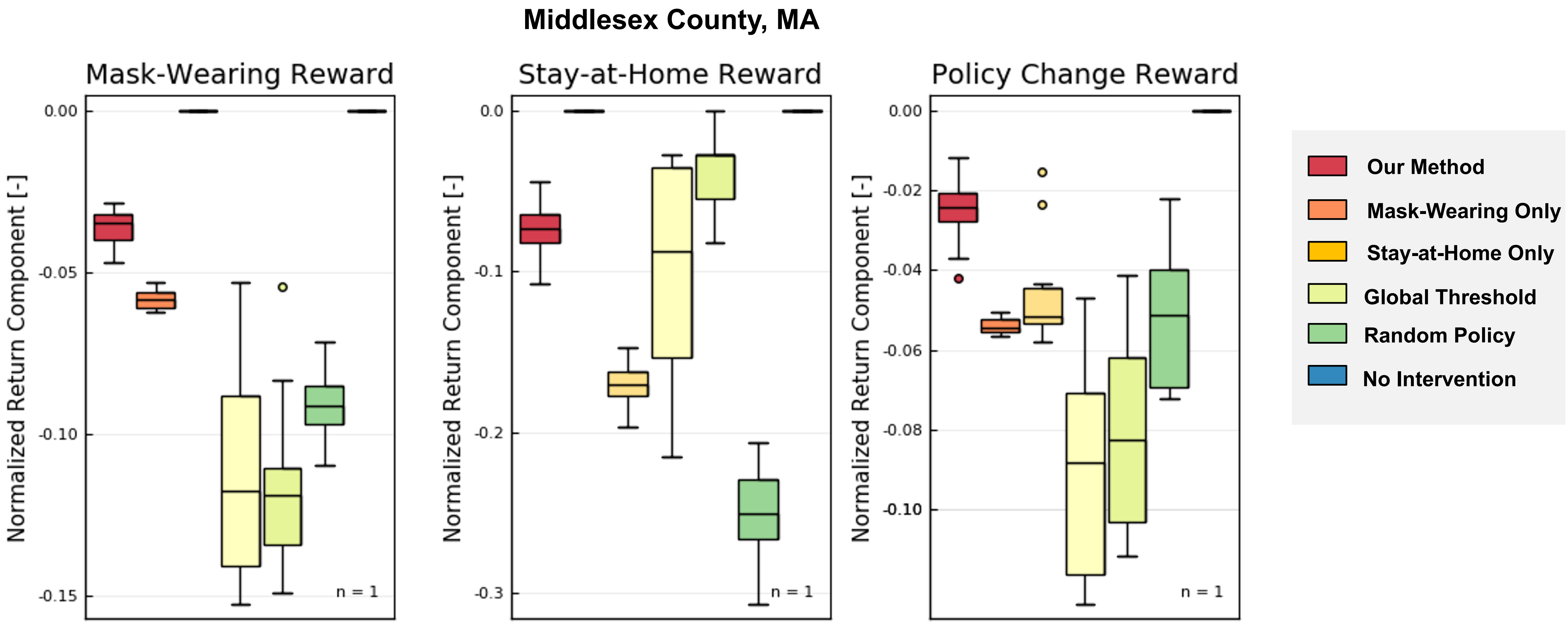
- Our network-SEIR model can simulate super-spreader events (sharper peaks) and recurring outbreaks (multiple peaks) that traditional SEIR models cannot capture
- We observe non-trivial, heterogeneous network effects on the patterns of disease spread

Comparison with Non-Adaptive Heuristics



Our planner leads to a smaller fraction of population being infected

Comparison with Non-Adaptive Heuristics



Our planner finds a good trade-off between the various reward components