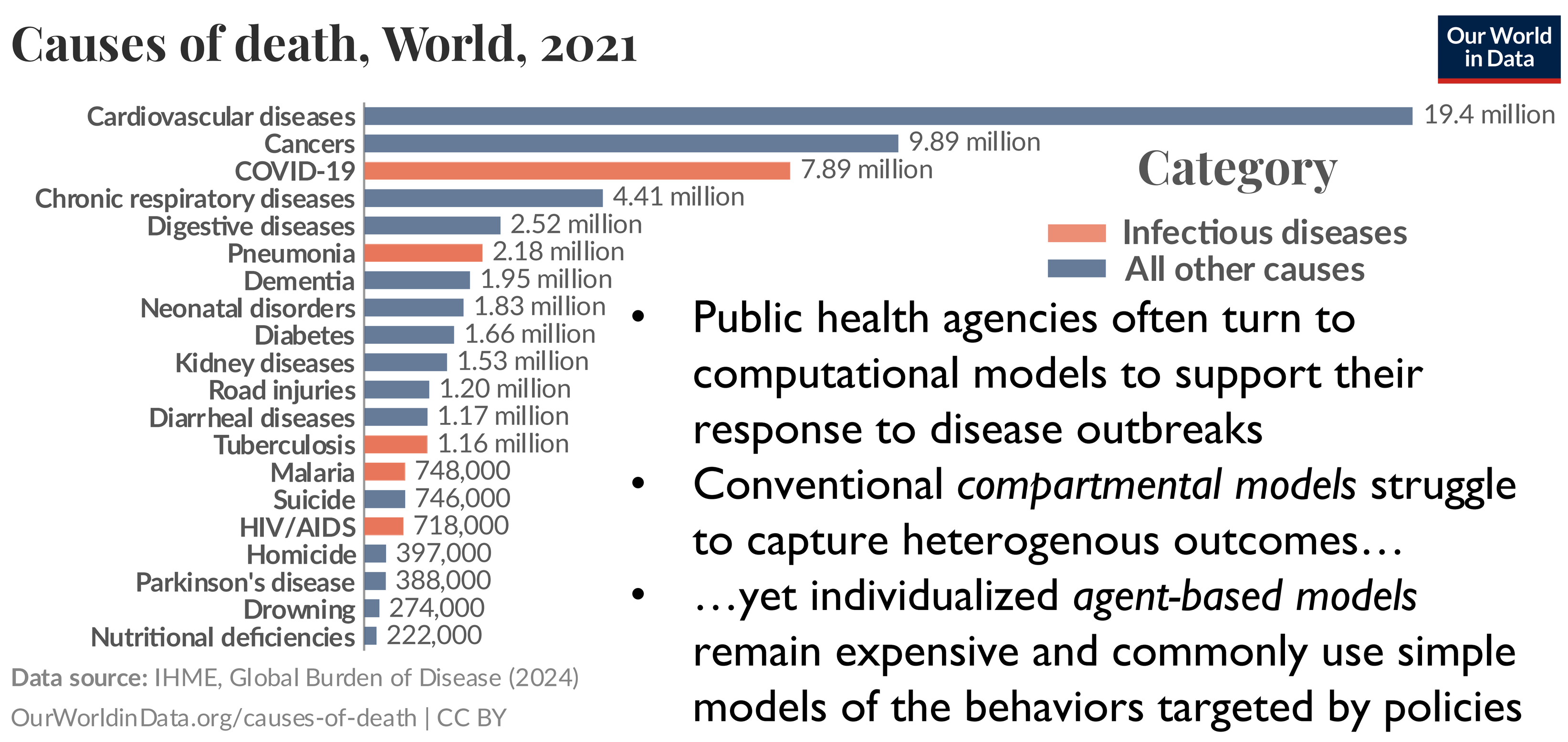
Scaling an Agent-based Epidemic Simulation on Realistic Social Contact Networks

UNIVERSITY OF MARYLAND

Joy Kitson and Abhinav Bhatele
Department of Computer Science, University of Maryland

PARALLEL SOFTWARE AND SYSTEMS GROUP

Motivation



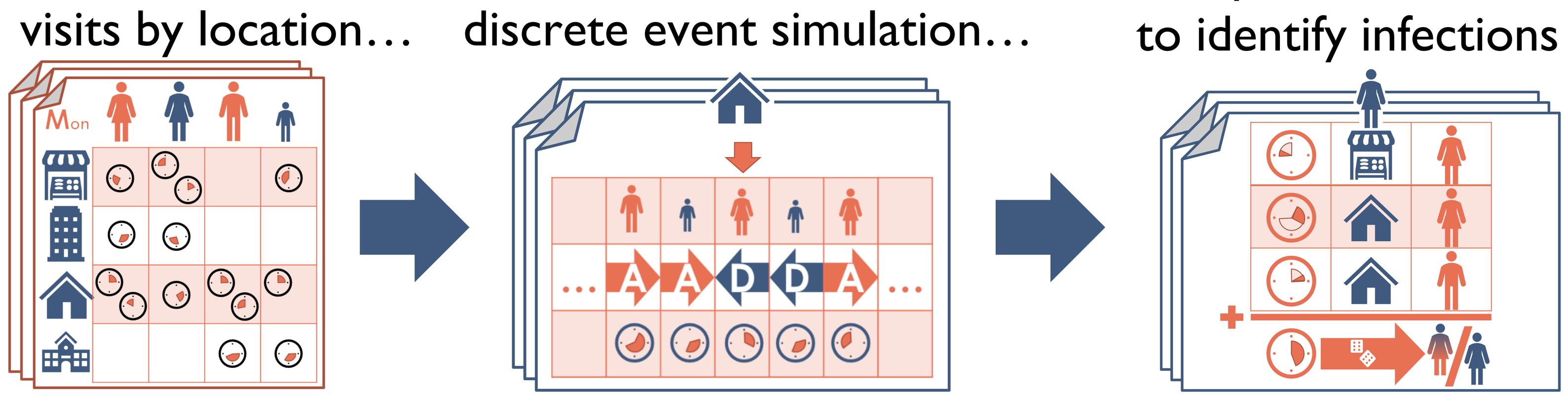
- Public health agencies often turn to computational models to support their response to disease outbreaks
- Conventional *compartmental models* struggle to capture heterogenous outcomes…
- …yet individualized *agent-based models* remain expensive and commonly use simple models of the behaviors targeted by policies

Scaling Agent-Based Models

We model disease spread through a bipartite person-location network, which specifies where each person is at any given time.

Disease Spread Algorithm

1. Distribute daily visits by location…
2. Determine contacts via discrete event simulation…
3. sum up infection risks to identify infections

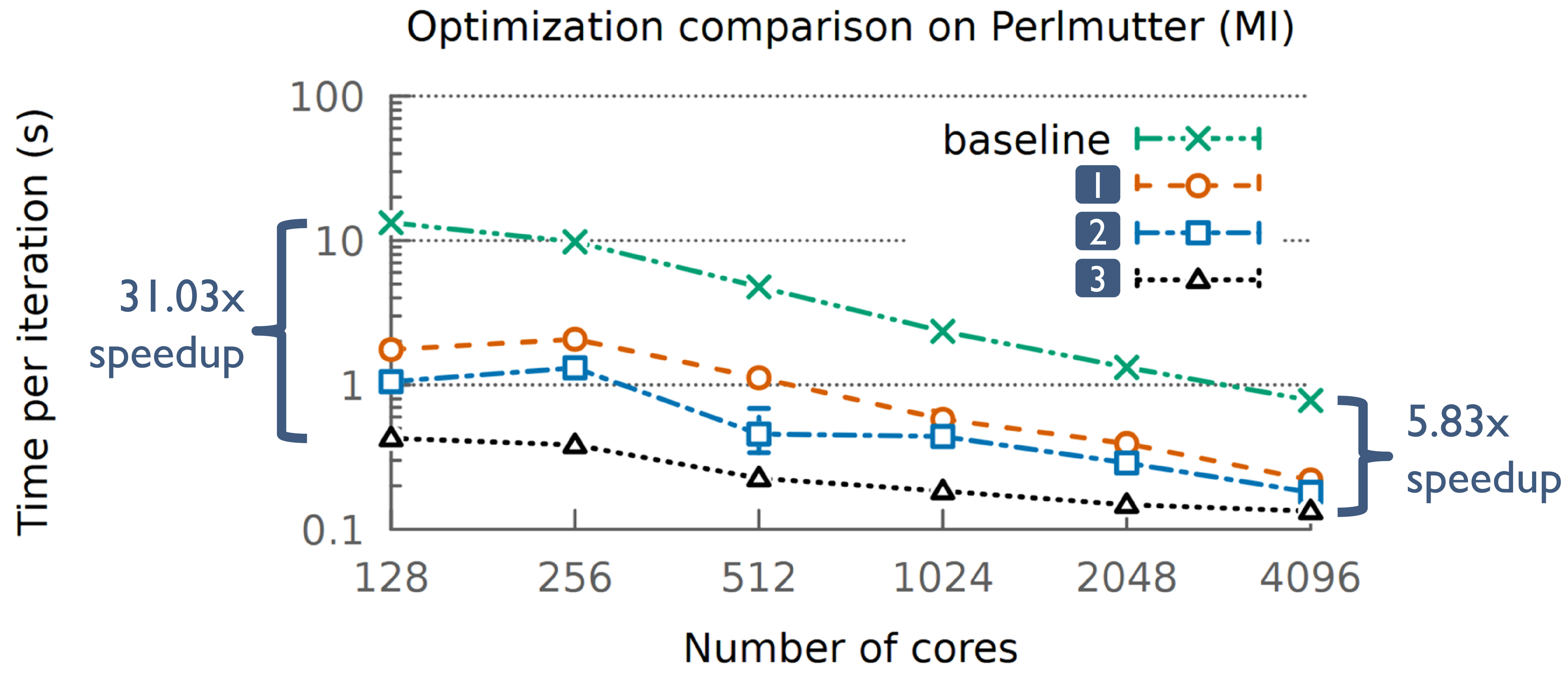


Key Optimizations

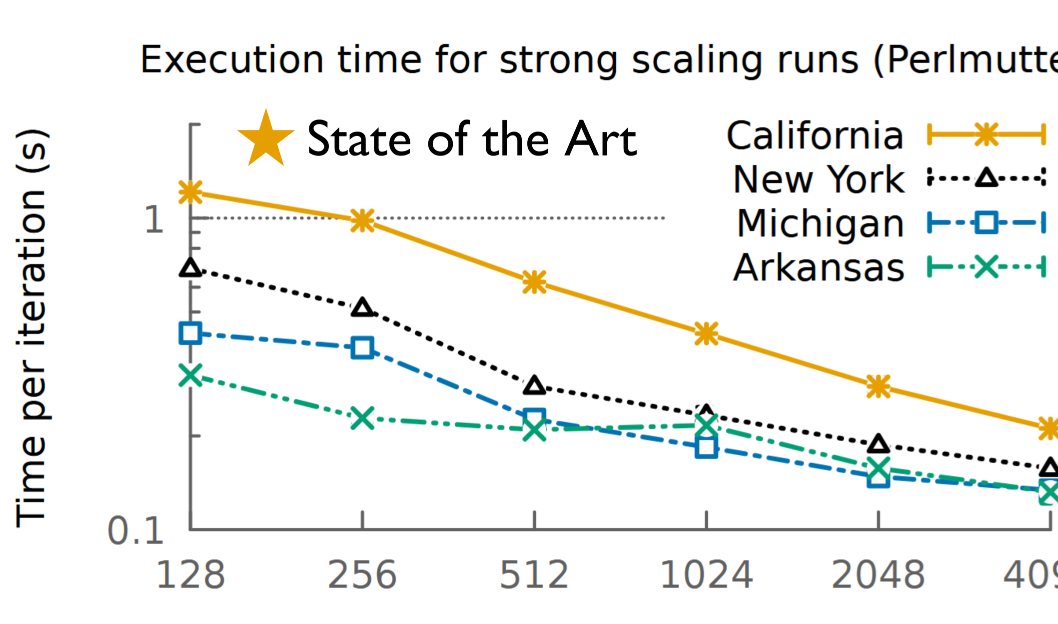
1
Problem: Load Imbalance
Solution: Sort locations by ZIP-code, then use prefix sum on visit counts to assign to processes

2
Problem: Unneeded DES evaluations
Solution: Only compute DES for locations with infectious visitors

3
Problem: Inefficient communication
Solution: Store visits with locations and only send update to people's disease status



Scaling Performance



	Visits	People	Locations
California	164M	35.5M	24.5M
New York	88.3M	18.1M	18.0M
Michigan	44.4M	9.34M	16.3M
Arkansas	12.8M	2.75M	13.2M

Overall, we see a 2.2x speedup over the state of the art (EpiSimdemics) on 1.53x fewer cores

Modeling Behavior

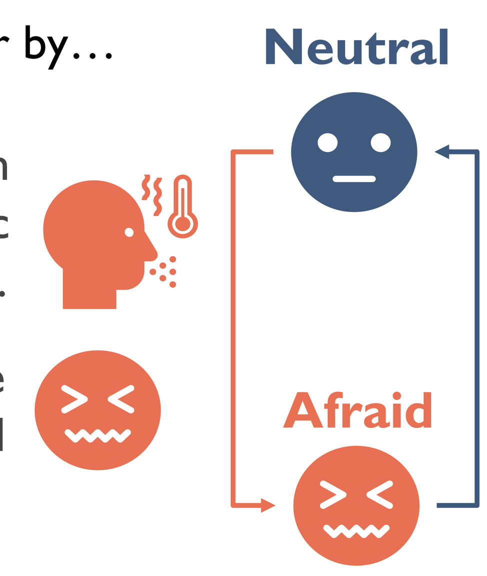
- What-if scenarios make purely data-driven models difficult to use in practice, as there is no ground truth to compare against
- Instead, we need to incorporate a mechanistic model of how people adopt protective behaviors directly into our simulation
- Our model is based on the spread of fear of a disease alongside the disease itself, with fear causing people to take protective measures

Coupling Fear and Disease Spread

People can gain fear by…

…interacting with symptomatic people…

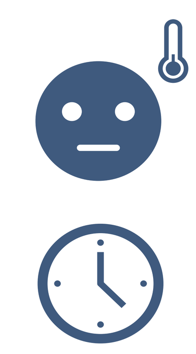
…or those who are already afraid



People can lose their fear by…

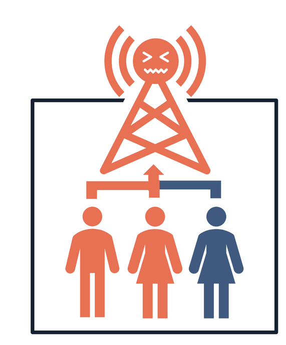
…interacting with neutral people who recovered from symptomatic infection…

…or over time

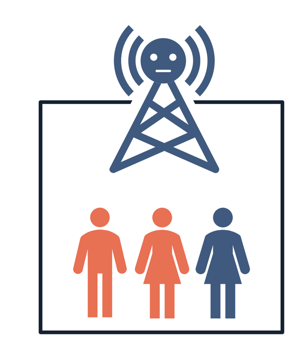


Fear can also spread via regional broadcaster media…

…which start spreading fear when enough of their employees become afraid…

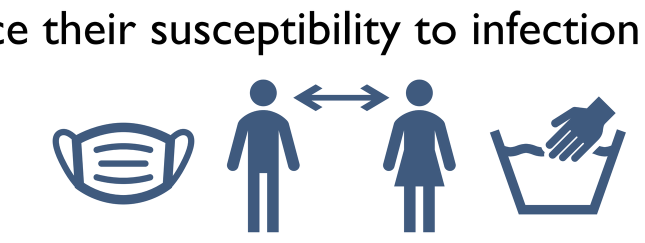


…and switch to countering fear spread once local cases fall



While afraid, people may:

1. Reduce their susceptibility to infection



2. Withdraw from everyday activities

Comparing Scenarios

We investigated one baseline scenario…

1 agents only withdraw when hospitalized

…and five with fear-based withdrawals:

2 withdraw when afraid and symptomatic

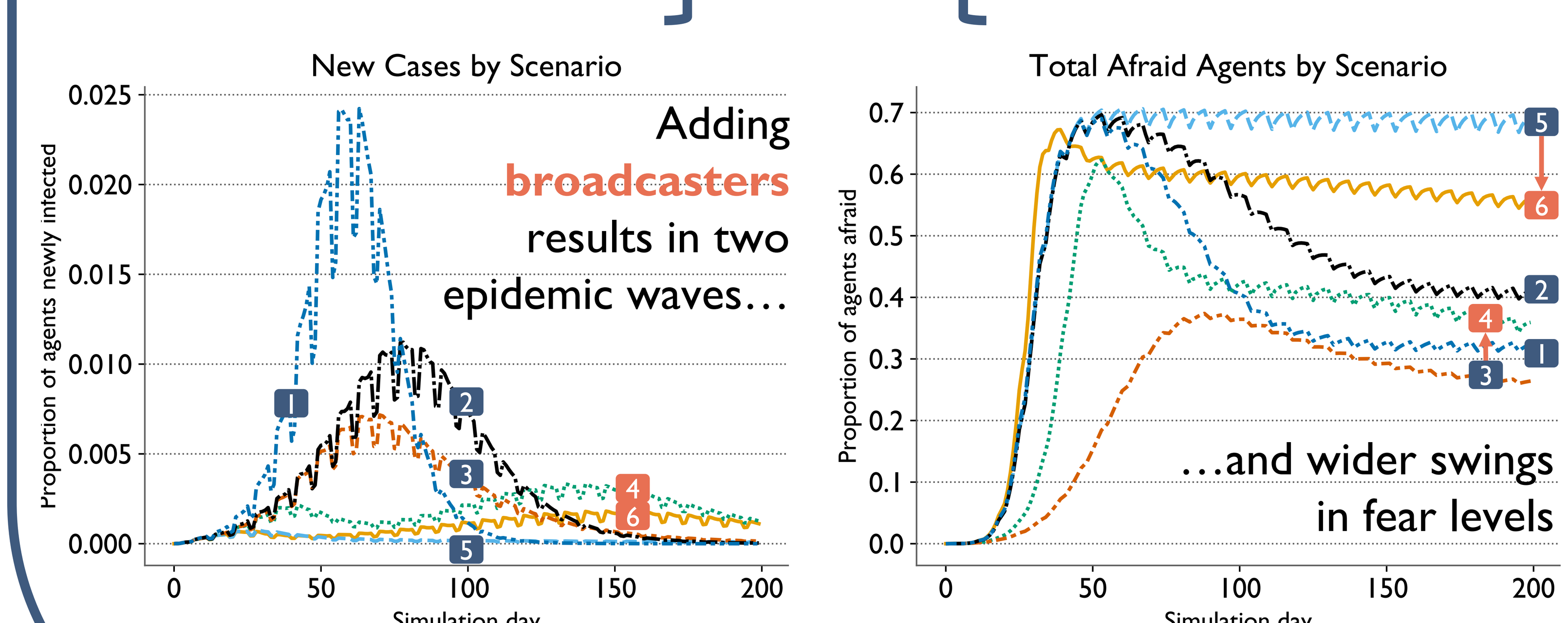
3 a chance to withdraw purely due to fear

4 fear also spreads through broadcasters

OR

5 agents have a reduced susceptibility when afraid

6 fear also spreads through broadcasters



Conclusion

1. Presented an individualized model of infectious disease spread
2. Implemented three key optimizations to that model and demonstrated their benefits
3. Introduced a model of individualized dynamic behaviors based on the spread of fear of a disease alongside the disease itself, and compared fear spread scenarios

Future Work

1. Extend the fear spread model to arbitrary social networks, which can include long distance connections (e.g. through social media)
2. Optimize the implementation of the fear spread model

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