Targeting Shutdowns by Repurposing WiFi Logs is More Effective than Moving Classes Online for Controlling COVID-19 on Campuses

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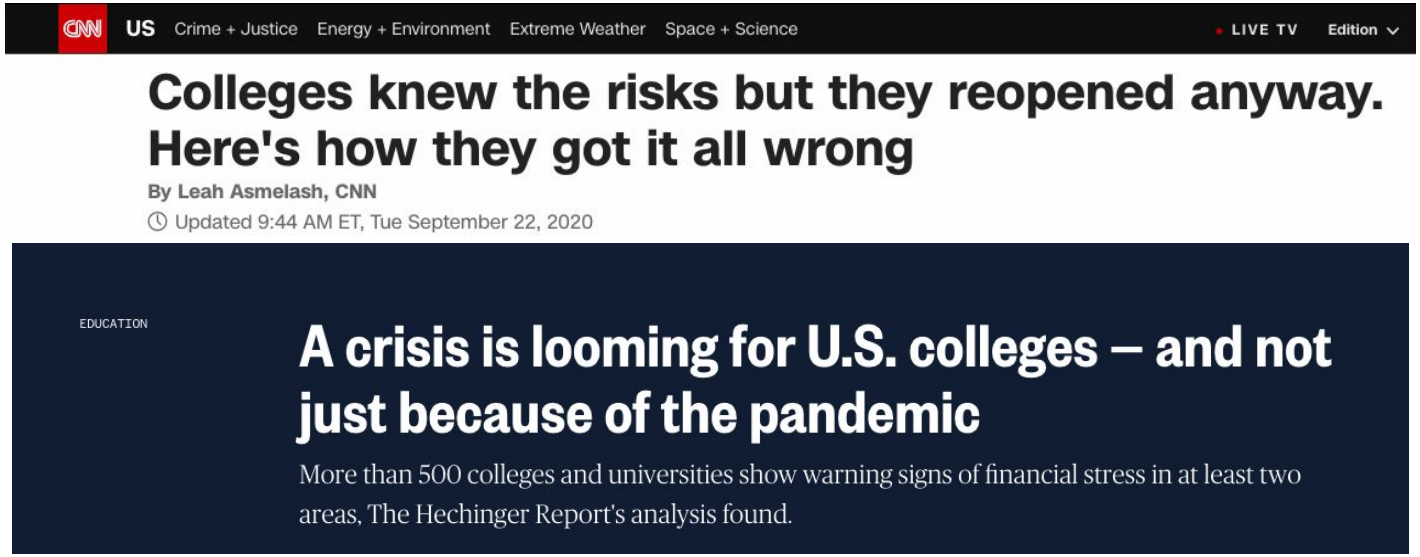
[2]Brown University
[3]Northeastern University

Outline

- ★ Motivation and Goals
- ★ WiFi-based Mobility Data
- ★ Model
  - On-campus agent-based SEIR model with dynamic mobility data
  - Calibration and validation
- ★ Experiments of policies
  - Scenarios
  - Measures of success, impacts, and constraints
- ★ Results
- ★ Further experiment

Motivation

In general, universities are struggling to reopen during the pandemic caused by Covid-19 because ...



Risk of outbreak

Financial Crisis

To reopen, what universities can do?

- Closure policies
  - Move classes online
    - Can be informed by contact networks generated based on course enrollment data ([1], [2])
  - Others
- Others

[1] Borowiak, Molly, et al. "Controlling the spread of COVID-19 on college campuses." *arXiv preprint arXiv:2008.07293* (2020).

[2] Weeden, Kim A., and Ben Cornwell. "The small-world network of college classes: implications for epidemic spread on a university campus." *Sociological science* 7 (2020): 222-241.

Great performance in controlling, is it successful?

- Expensive
  - Shutting down too much locations
  - Force too many students away from campus

- Limitations of course-enrollment data
  - Fail to capture the dynamic mobility pattern of individuals on campus
  - Exclude activities outside the classrooms (gym, residence, non-students...)

Proposed Method

- Leveraging the managed WiFi network on campus can **describe proximity outside courses and residence halls**
  - ➢ WiFi access logs can approximate physical collocation of connected users

Research Aims

- To compare insights of proximity based social networks with assumptions of registration networks

- To design and evaluate efficient policies by simulating disease spread with proximity based networks under reasonable constraints

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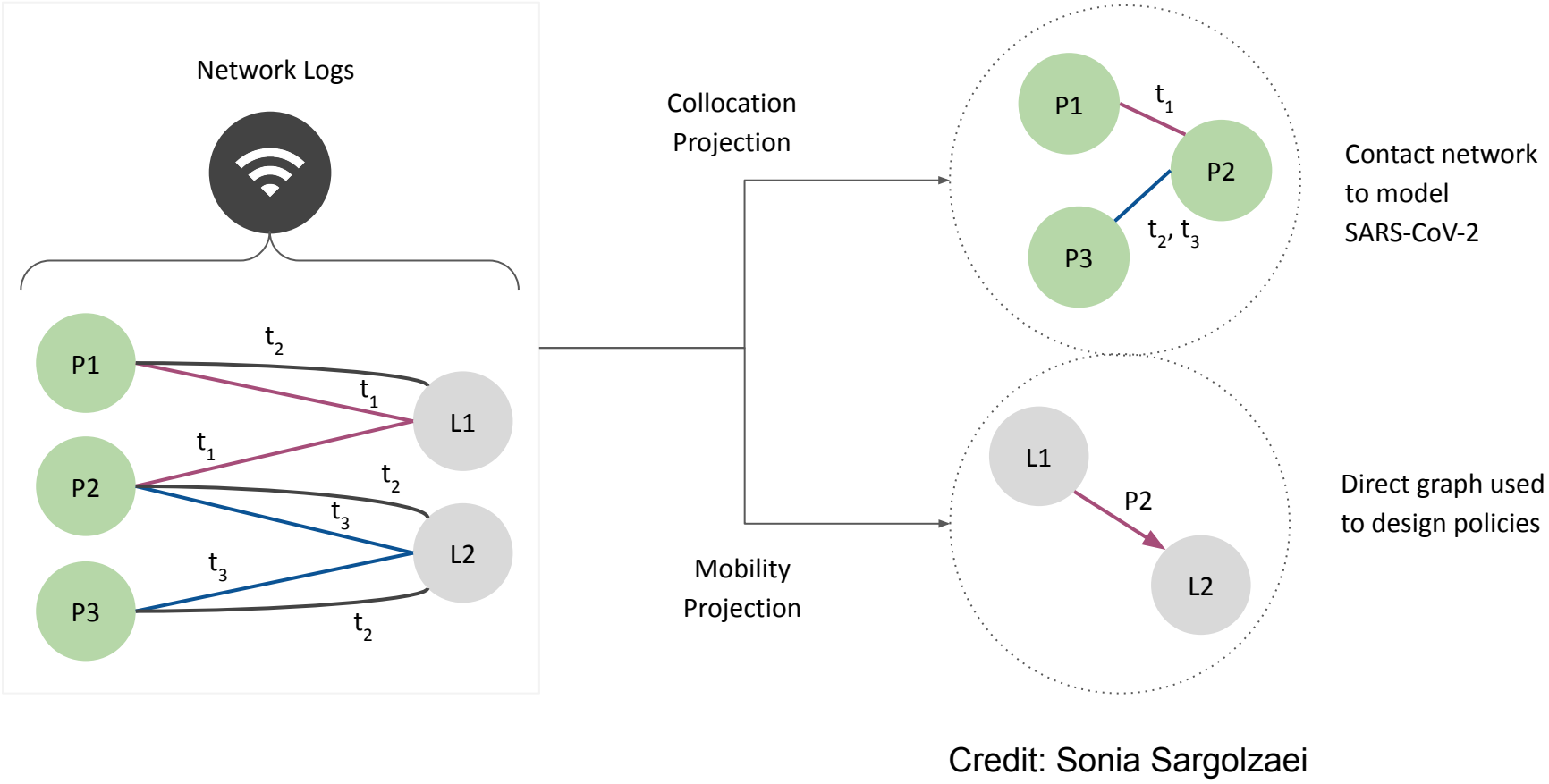
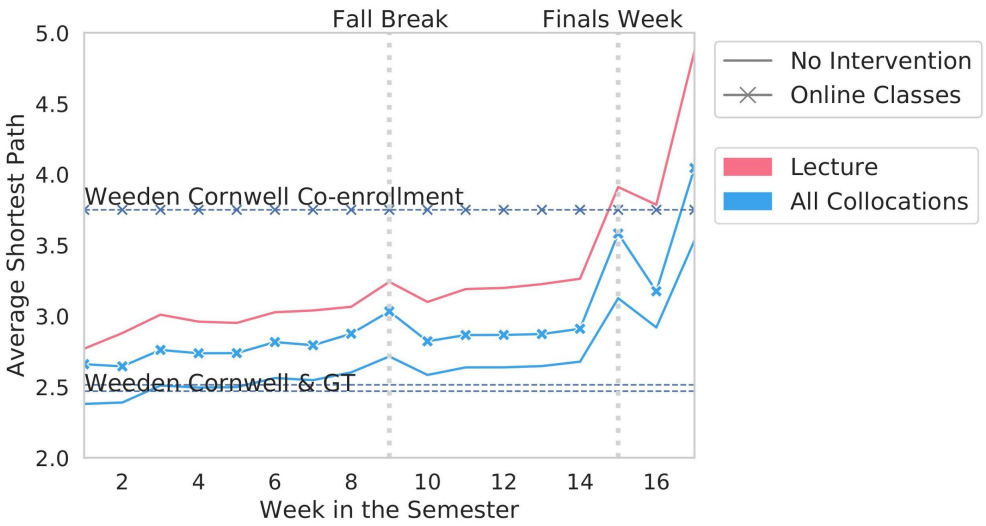
WiFi-based Network Data



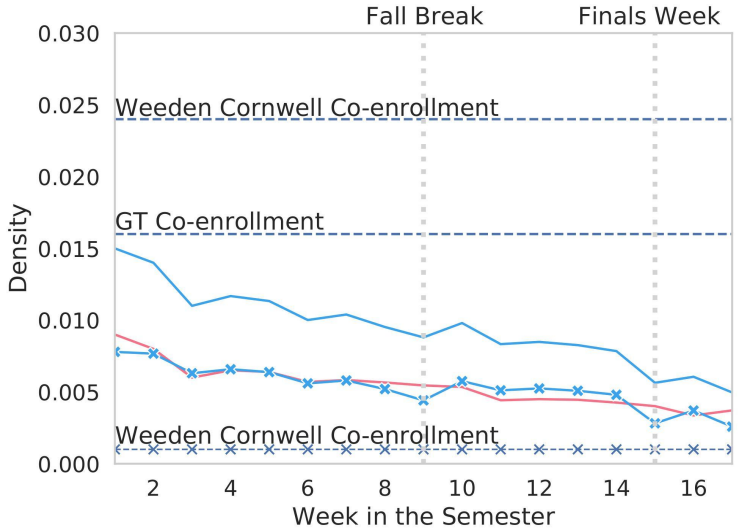
Credit: Sonia Sargolzaei

WiFi-based Mobility Data Vs Course Enrollment Data

Fall 2020 Semester



Fall 2020 Semester



Course enrollment data fails to capture the dynamics of mobility pattern and the inside-outside-classrooms activity as the WiFi-based data

Credit: Sonia Sargolzaei

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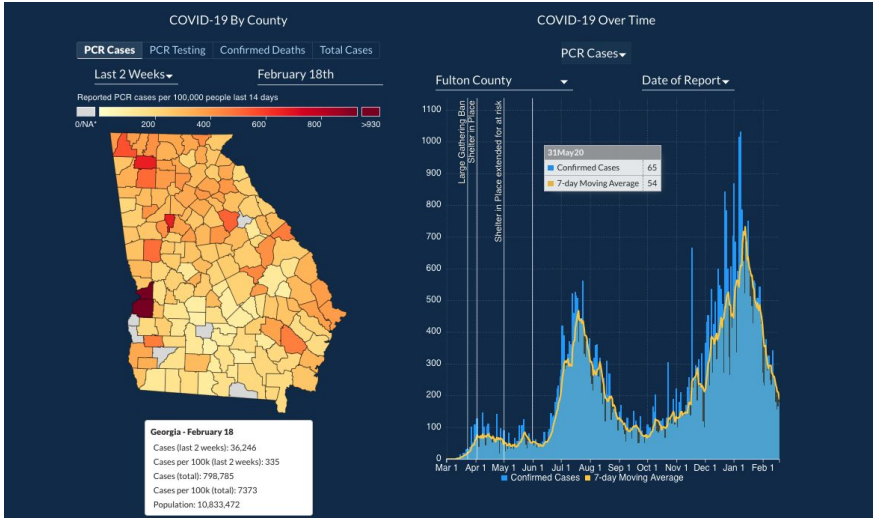
How to model the disease dynamics on campus?

Information refer to ...

- Campus Operation Guideline
  - Surveillance Testing (Asymptomatic)
  - Quarantine in places
  - …
- Surrounding Neighborhood
  - Atlanta
  - Fulton County
  - Georgia
  - ...



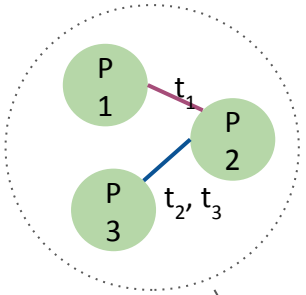
https://health.gatech.edu/tech-moving-forward

https://dph.georgia.gov/covid-19-daily-status-report

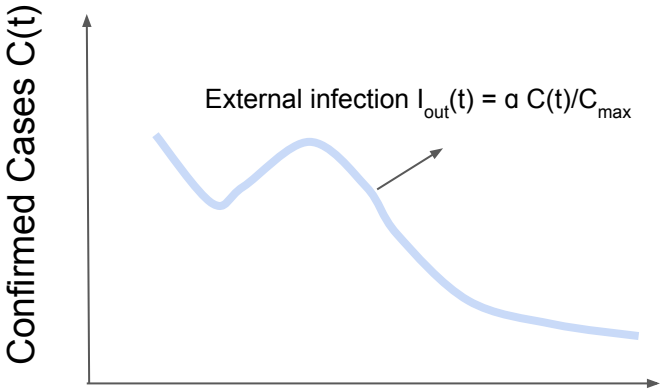
Dynamic SEIR Asymptomatic/Symptomatic Model

Based on the information available, we design an SEIR model

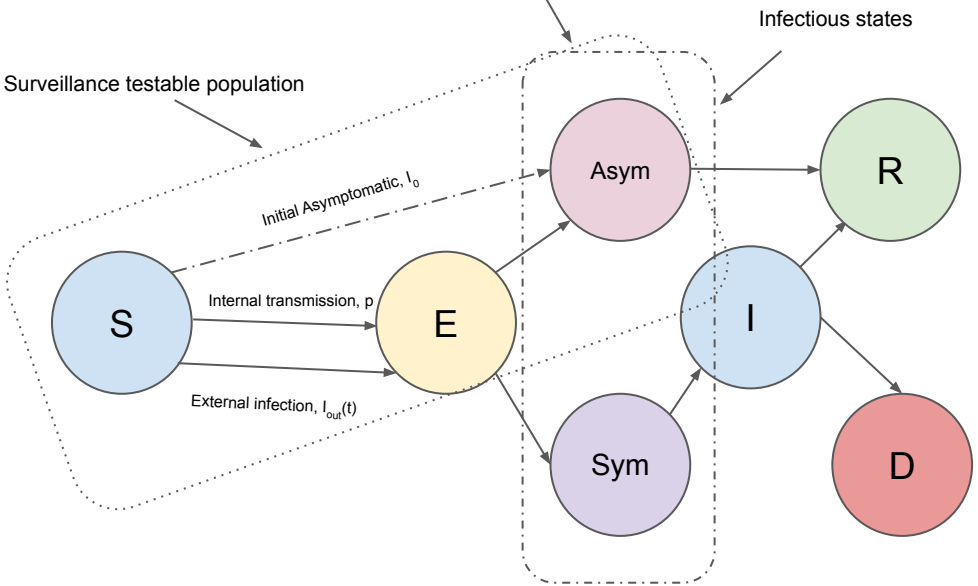
- ★ Using the dynamic collocation as the underline contact network
- ★ Captures asymptomatic transmissions
- ★ Isolate symptomatic individuals
- ★ Bring in external infections from the surrounding neighborhood



Contact network to model SARS-CoV-2



Fulton County



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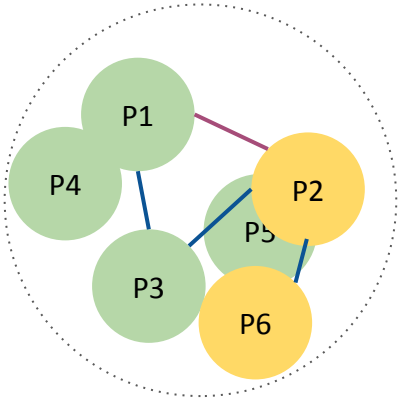
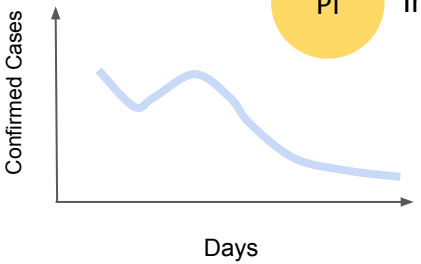
Policies Experiment

Fall 2019 Semester

Collocation Projection Fall 2019



Pi Individual affected by policies

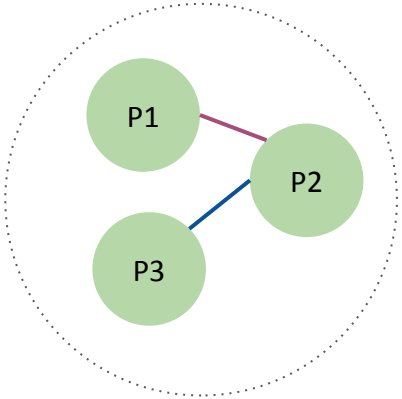


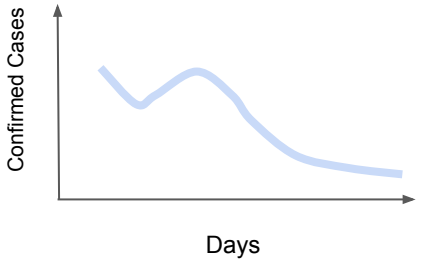
Fulton County Data (Fall 2020) for estimating external infection percentage daily, $I_{out}(t)$

Calibration and Validation

Fall 2020 Semester

Collocation Projection Fall 2020





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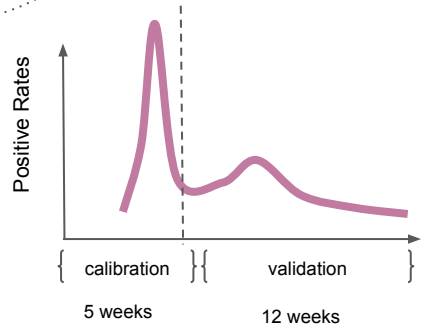
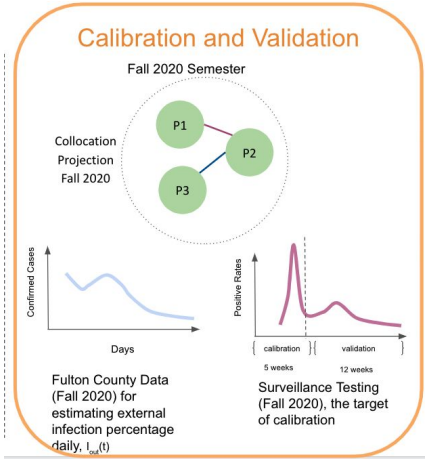


Surveillance Testing (Fall 2020), the target of calibration

Calibration and validation framework

We are going to calibrate the percentage of new asymptomatic cases out of total testable population to the surveillance positive rate



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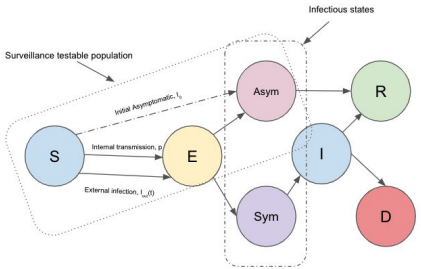

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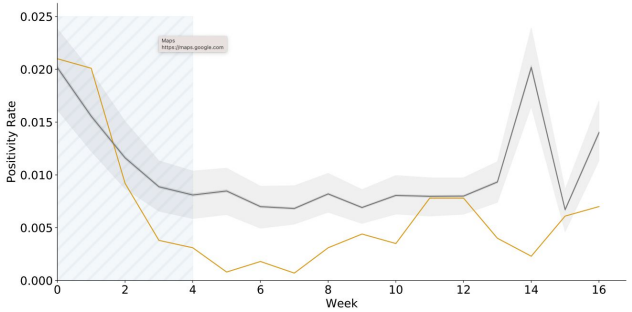

Ranges of optimal parameters

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Policies with Scenarios

We are going to experiment with two policies

- ★ Moving large classes online
- ★ Targeted shutdowns by algorithms (pagerank e.g.)
  - The target policy only use the **first 7 days** of the semester to identify shutdown locations, and it approximates the same **cost** as moving classes online.

Under 3 different scenarios

- ➢ **Persistence**
  - Irrespective of the locations closed, individuals continue their other visiting behaviors
- ➢ **Non-Residential Avoidance**
  - Non-residential students stop all visits to campus if they have at least three courses and the policy forces their entire schedule online
- ➢ **Complete Avoidance**
  - Both residential and non-residential students avoid campus if they have at least three courses and all move online

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Metrics

We compute the following metrics in the process of simulations

- ★ Peak Infections (outcome measure)
- ★ Total Infections (outcome measure)
- ★ Internal Infections (outcome measure)

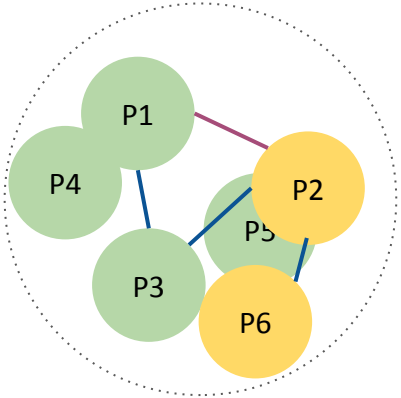
- ❑ Locations affected (cost measure)
- ❑ Students Avoiding % (cost measure)
- ❑ Completely isolated on campus % (measure)

- ➢ Mobility (edges) reduction (constraint)
- ➢ Risk of exposure (worst case)
  - Unique 1-hop neighbors when 2.5% of individuals are randomly sampled to be positive
  - Meaningful for the surveillance test numbers

Policies Experiment

Fall 2019 Semester

Collocation
Projection
Fall 2019



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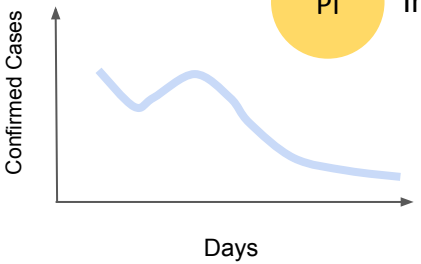

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Calibration and Validation

Fall 2020 Semester

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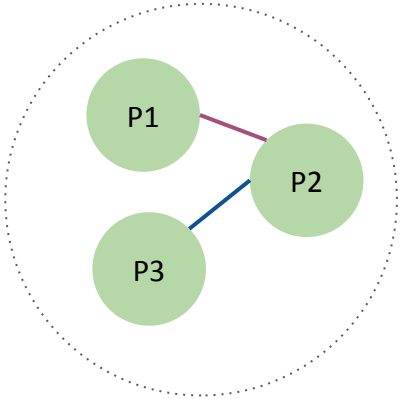

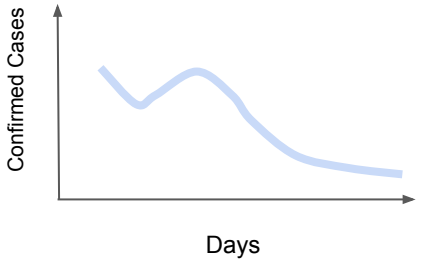

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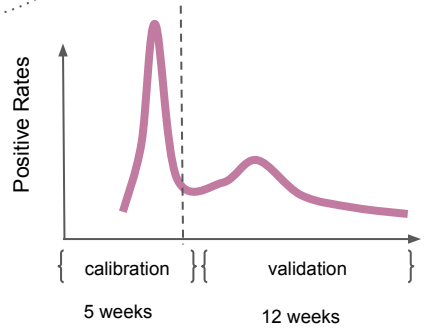

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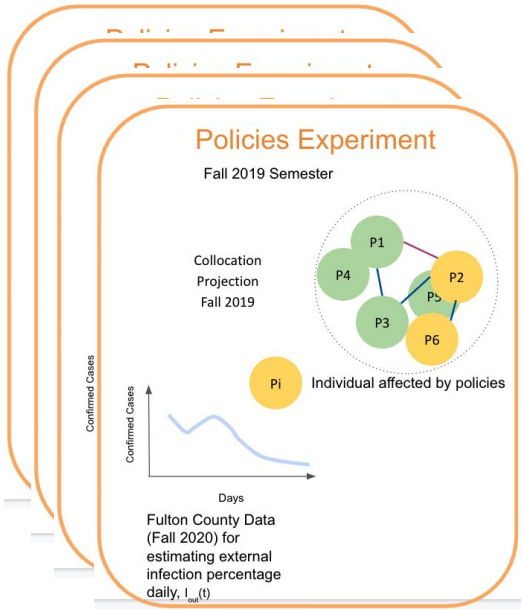

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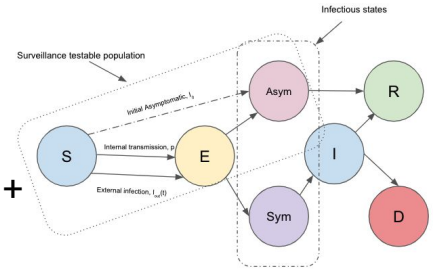

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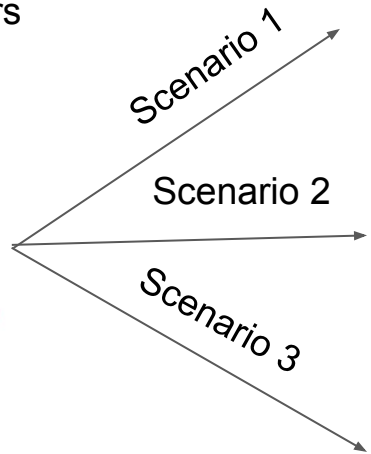

Results

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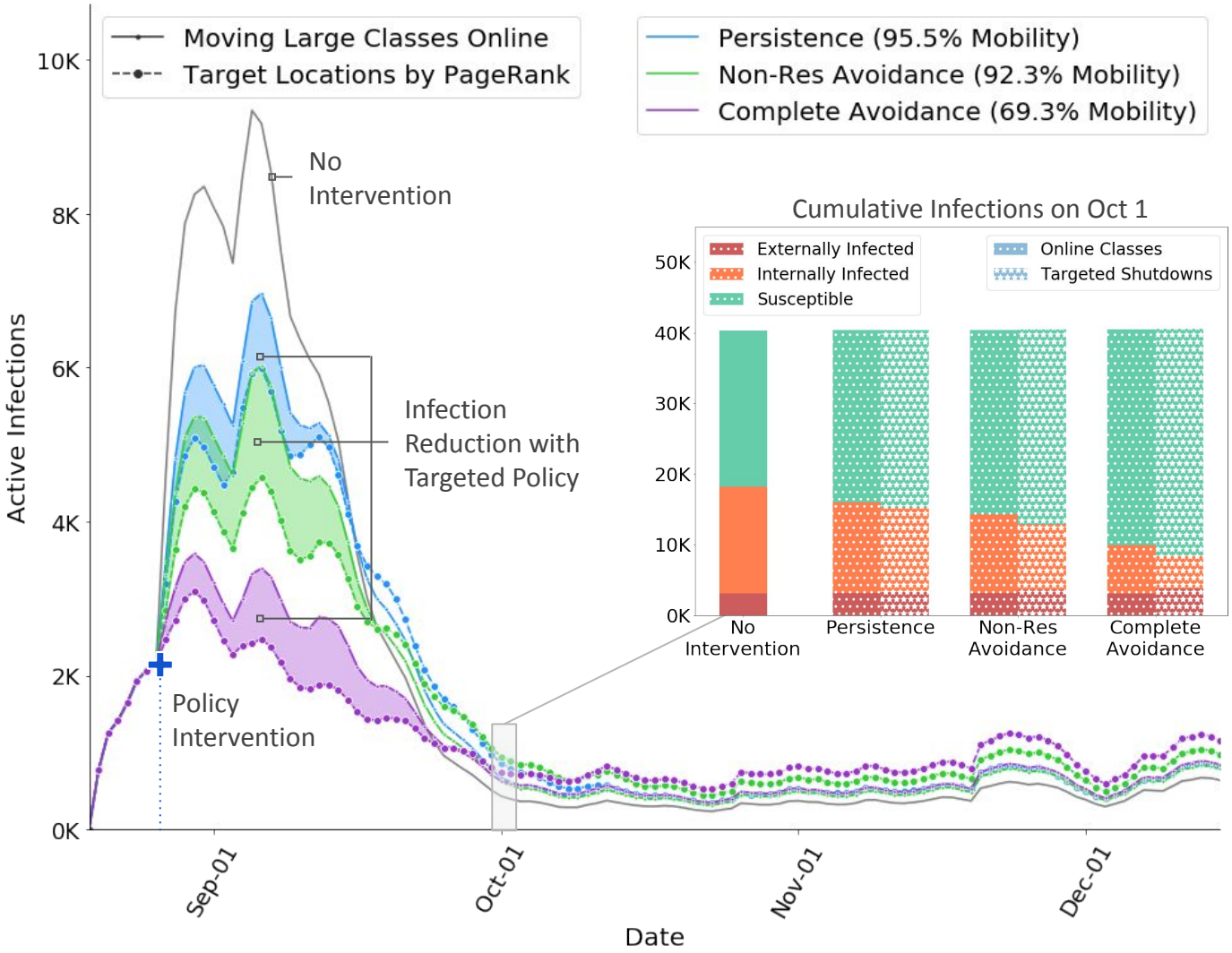
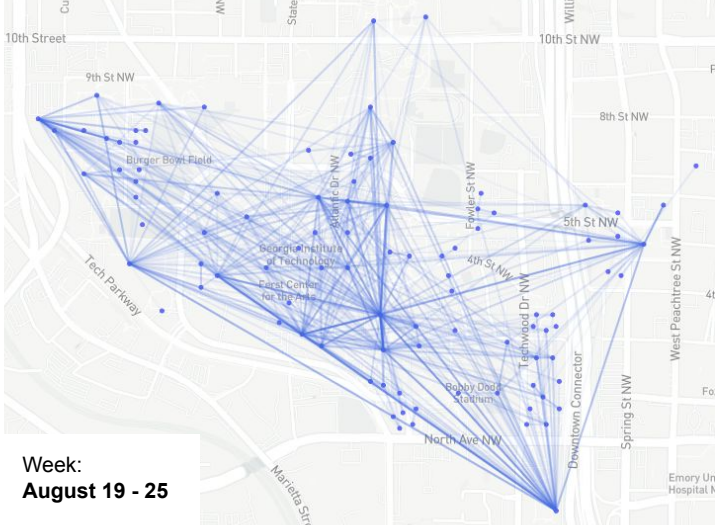
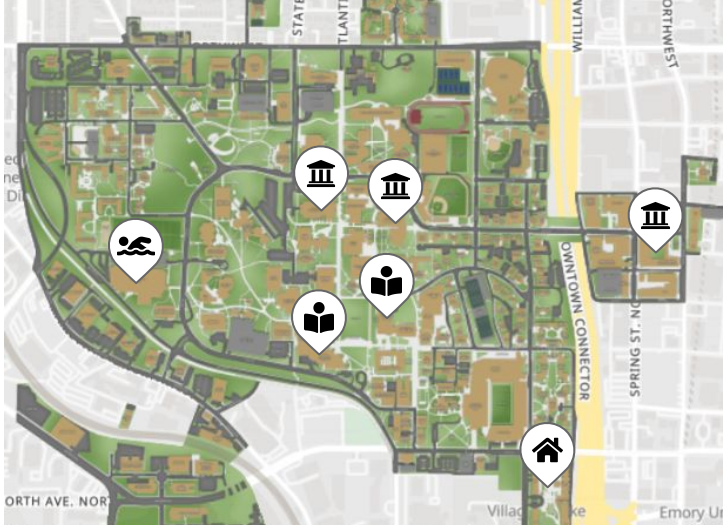

Moving Large Classes Online
Target Locations by PageRank
Persistence (95.5% Mobility)
Non-Res Avoidance (92.3% Mobility)
Complete Avoidance (69.3% Mobility)
No Intervention
Infection Reduction with Targeted Policy
Policy Intervention
Active Infections
10K
8K
6K
4K
2K
0K
Sep-01
Oct-01
Nov-01
Dec-01
Date
Cumulative Infections on Oct 1
Externally Infected
Internally Infected
Susceptible
Online Classes
Targeted Shutdowns
50K
40K
30K
20K
10K
0K
No Intervention
Persistence
Non-Res Avoidance
Complete Avoidance

Credit: Sonia Sargolzaei

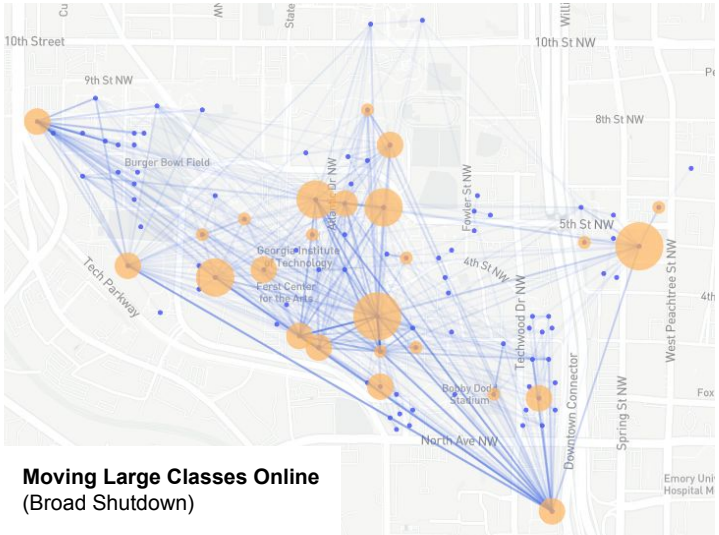


Week:
August 19 - 25

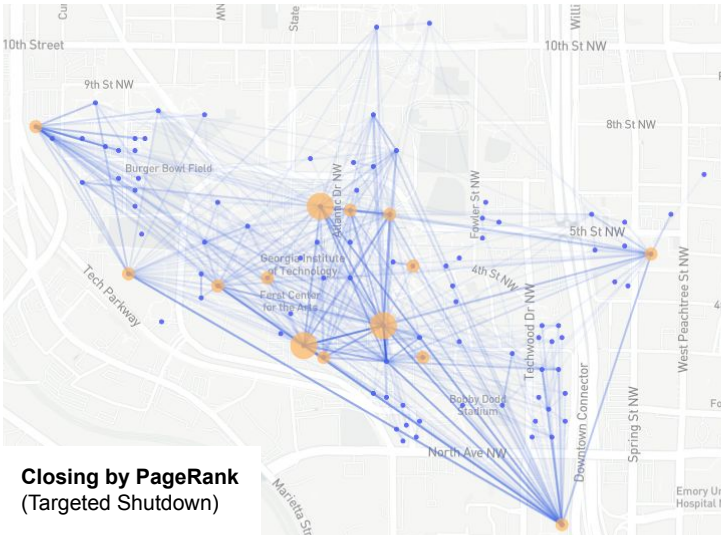


Number of rooms/suites shutdown

- 7+
- 5-6
- 3-4
- 1-2



Moving Large Classes Online
(Broad Shutdown)



Closing by PageRank
(Targeted Shutdown)

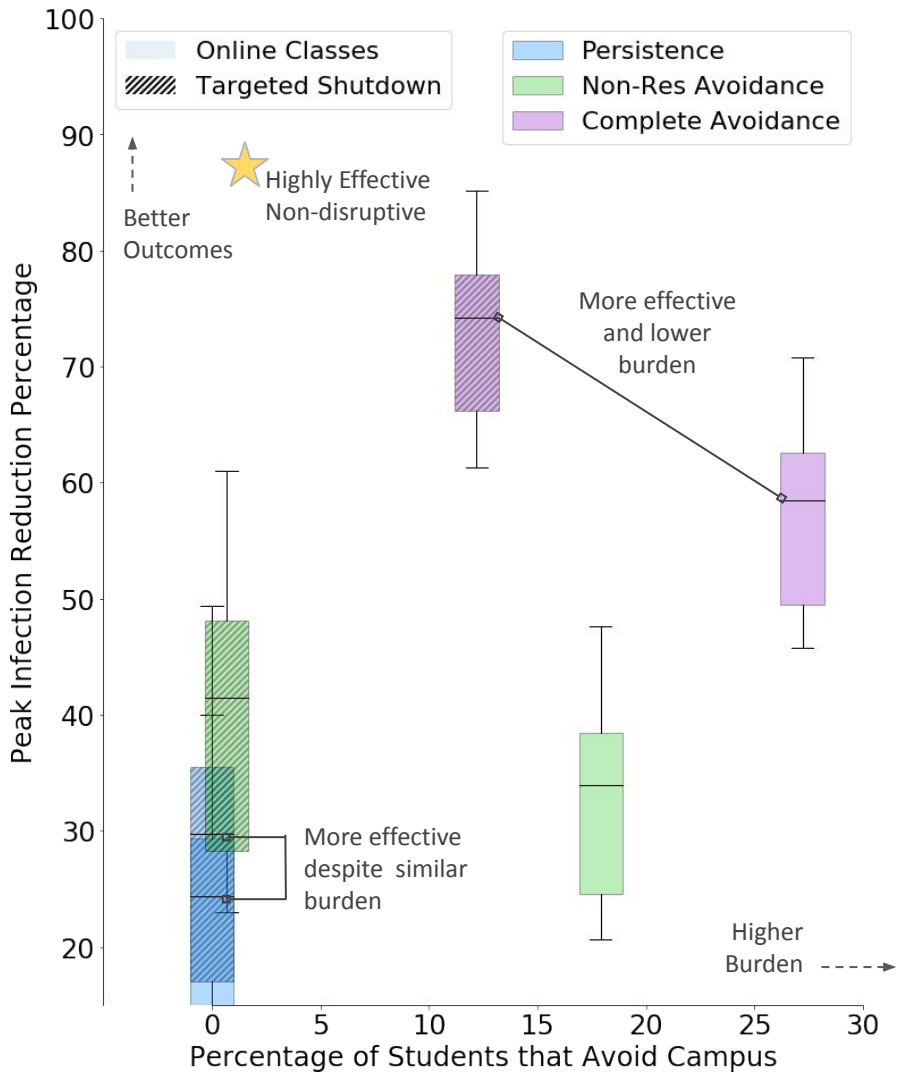

Online Classes
Targeted Shutdown
Persistence
Non-Res Avoidance
Complete Avoidance
Better Outcomes
Highly Effective Non-disruptive
More effective and lower burden
More effective despite similar burden
Higher Burden
Peak Infection Reduction Percentage
Percentage of Students that Avoid Campus
100
90
80
70
60
50
40
30
20
0
5
10
15
20
25
30

Table 1. Comparison of different policies in terms of controlling the disease and impacts on campus

Scenario	Persistence			Non-Res Avoidance			Complete Avoidance		
Policy	Broad	Targeted		Broad	Targeted		Broad	Targeted	
Constraint	-	Mobility (95.5%)	Exposure Risk (18800)	-	Mobility (92.3%)	Exposure Risk (16900)	-	Mobility (69.2%)	Exposure Risk (12700)
Infection Reduction Outcomes									
Peak Infections (%)	25.34(±12)	36.92(±14)**	34.30(±13)**	35.44(±10)	49.33(±11)**	52.19(±10)**	61.62(±7)	69.34(±5)**	64.44(±6)**
Total Infections (%)	6.99(±5)	10.63(±6)**	8.19(±5)**	14.88(±4)	13.96(±6)*	15.67(±6)	33.00(±5)	33.4(±5)	26.94(±5)**
Internal Infections (%)	17.13(±9)	22.62(±11)**	21.01(±11)**	27.58(±8)	35.35(±12)**	39.20(±11)**	54.00(±8)	70.89(±7)**	60.90(±9)**
Impacts to Campus									
Locations Affected	58	18	19	58	38	50	58	192	124
Students Avoiding (%)	0	0	0	17.92	0.68	0.69	27.21	12.2	6.31
Completely Isolated on Campus (%)	6.77	6.47	6.43	7.73	6.85	7.19	9.86	10.04	8.80

Within each scenario, we perform the Kruskal-Wallis H-Test (12) to compare outcomes of targeted policies with moving larger classes online — a type of broad shutdown policy. We find that targeted (p-value: < 0.01:*, < 0.001:**).

Highlights of results

The experimental results inform

- ★ Targeted shutdowns cause greater reduction in peak infections while affecting fewer locations
- ★ Targeted shutdowns lead to comparable reduction in total infections while retaining more students on campus
- ★ Targeted shutdowns cause greater reduction in internal infections without further isolation on campus

Takeaways

To summarize

- ★ WiFi network logs can describe mobility and collocation on campus which gives more insight on contact behavior
- ★ While course enrollment can inform design of policies, the cost is tremendous
- ★ Targeted shutdowns is more efficient and economy

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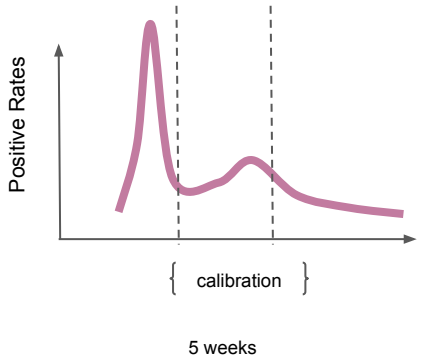
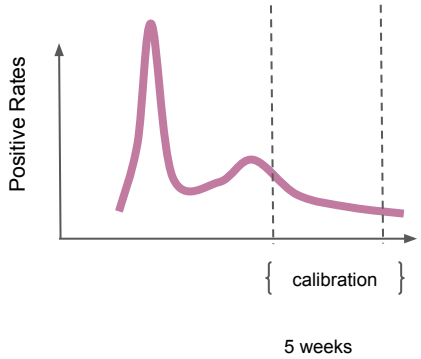
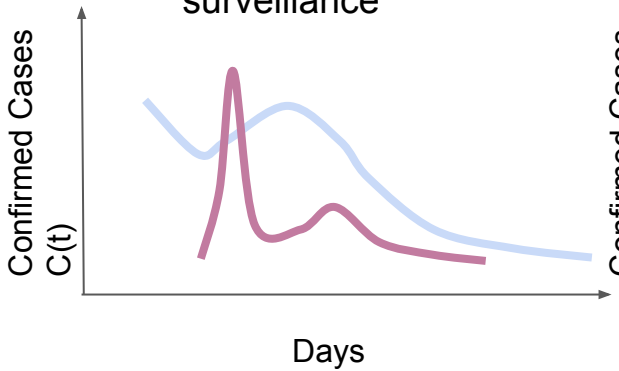
Varying the validation period



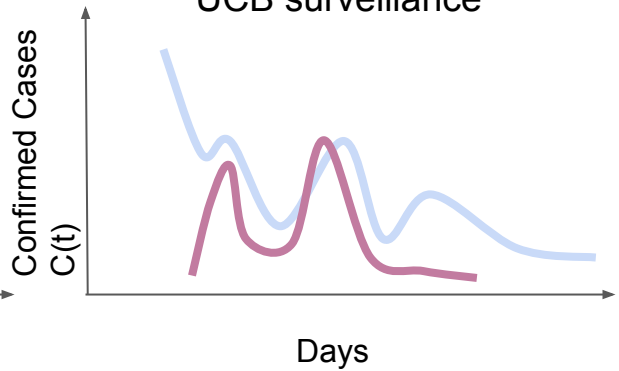


Varying the school surveillance and county

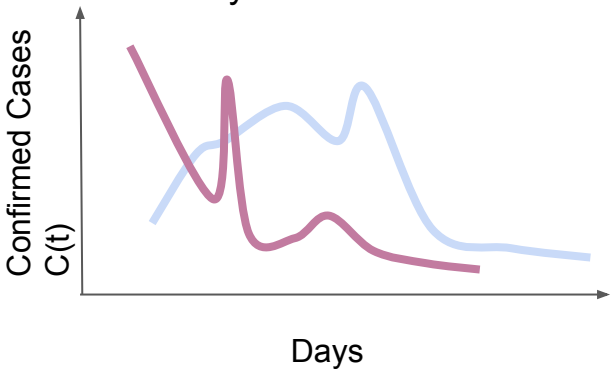
Fulton County + GT surveillance



Surrounding county + UCB surveillance



Other schools + other county



Appendix

Parameters Estimations

Table S2. Model Parameters

Parameter	Definition	Value	Std	Category
p	Transmission probability: For any edge between a *susceptible* and *infectious* individual in the contact network, p is the probability that the *susceptible* person will enter into the *exposed* state. This only dictates internal transmission	0.034	0.007	Estimated
α	Scaling factor of the normalized confirmed cases in the surrounding county(Equation 8). This is the parameter for us to generate $I_{out}(t)$	0.032	0.0032	Estimated
I_0	Probability of *susceptible* persons being *asymptomatic* at day 0	0.012	0.0009	Estimated