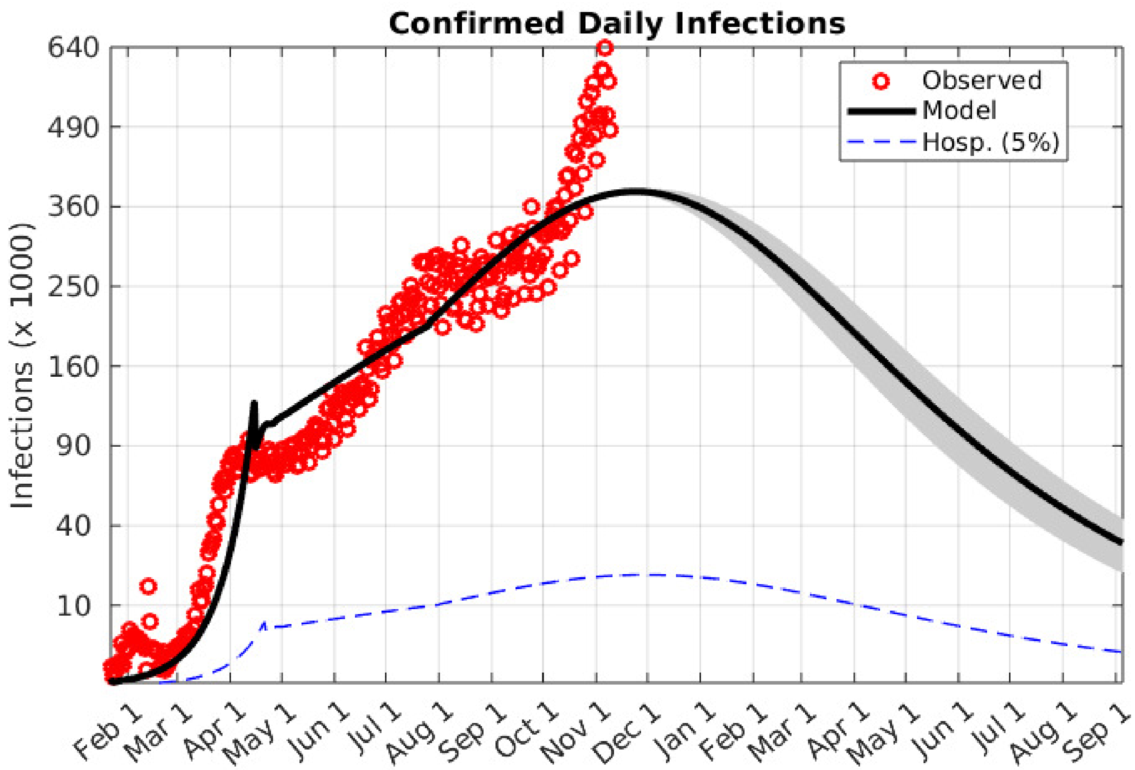
AI and ML for Predicting COVID-19

Malik Magdon-Ismail,
Computer Science, Rensselaer.

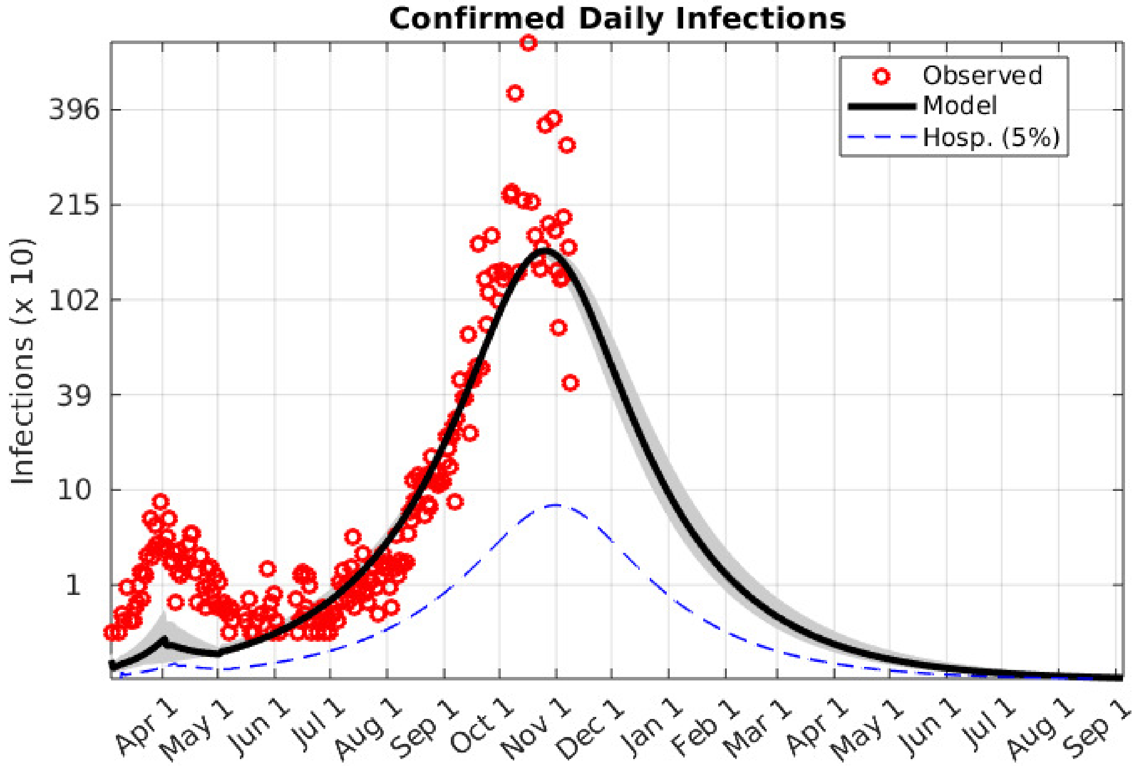
Shout-Out:
Rensselear IDEA
J. Hendler, K. Bennet, J. Erickson, MANY good students.

World ~ 8 billion

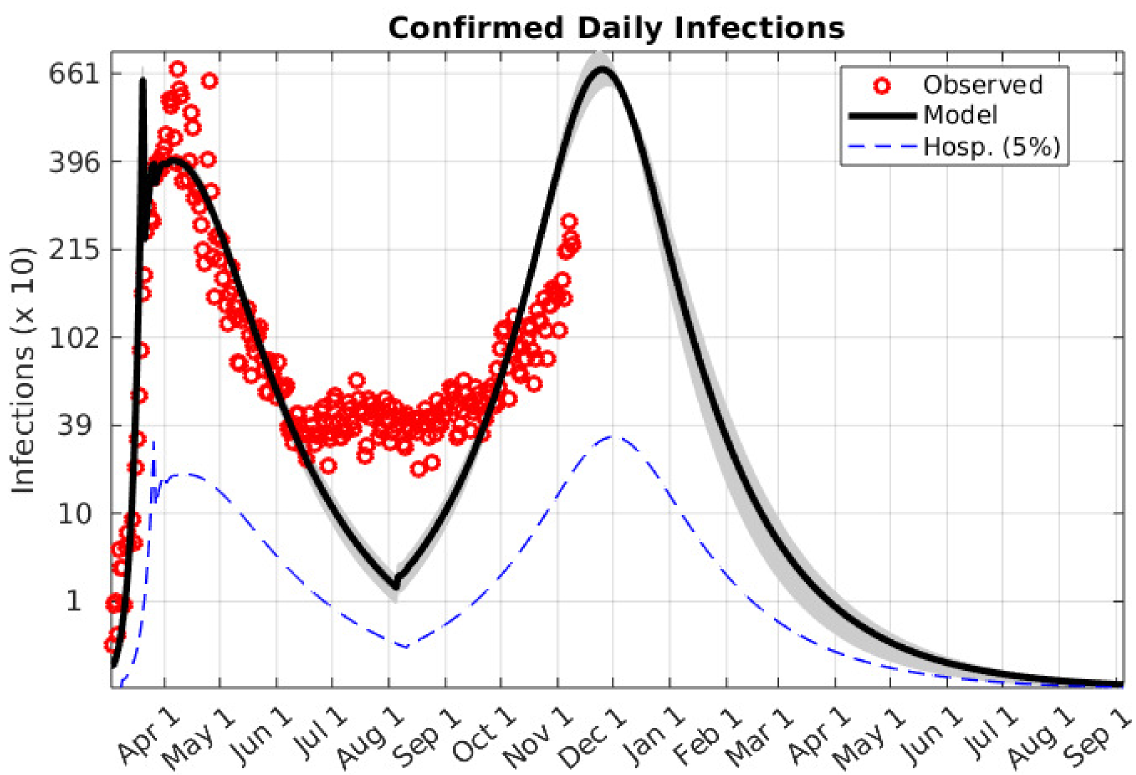


Scales of COVID-19

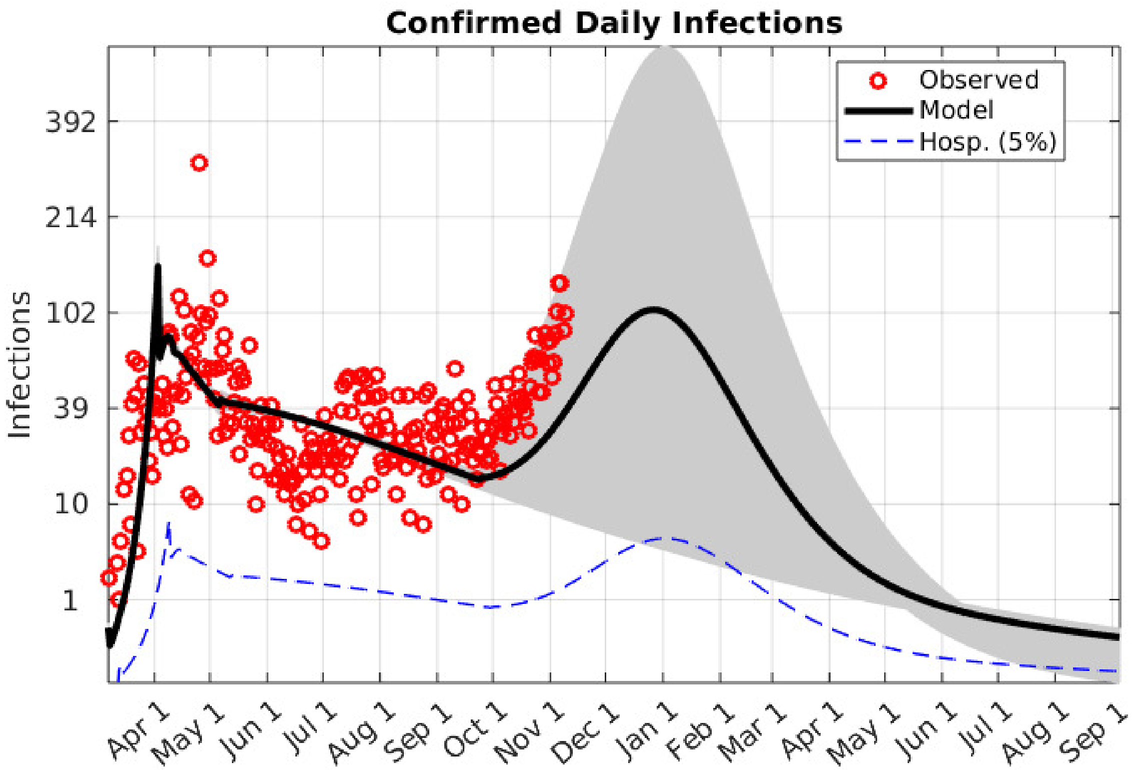
USA ~ 330 million



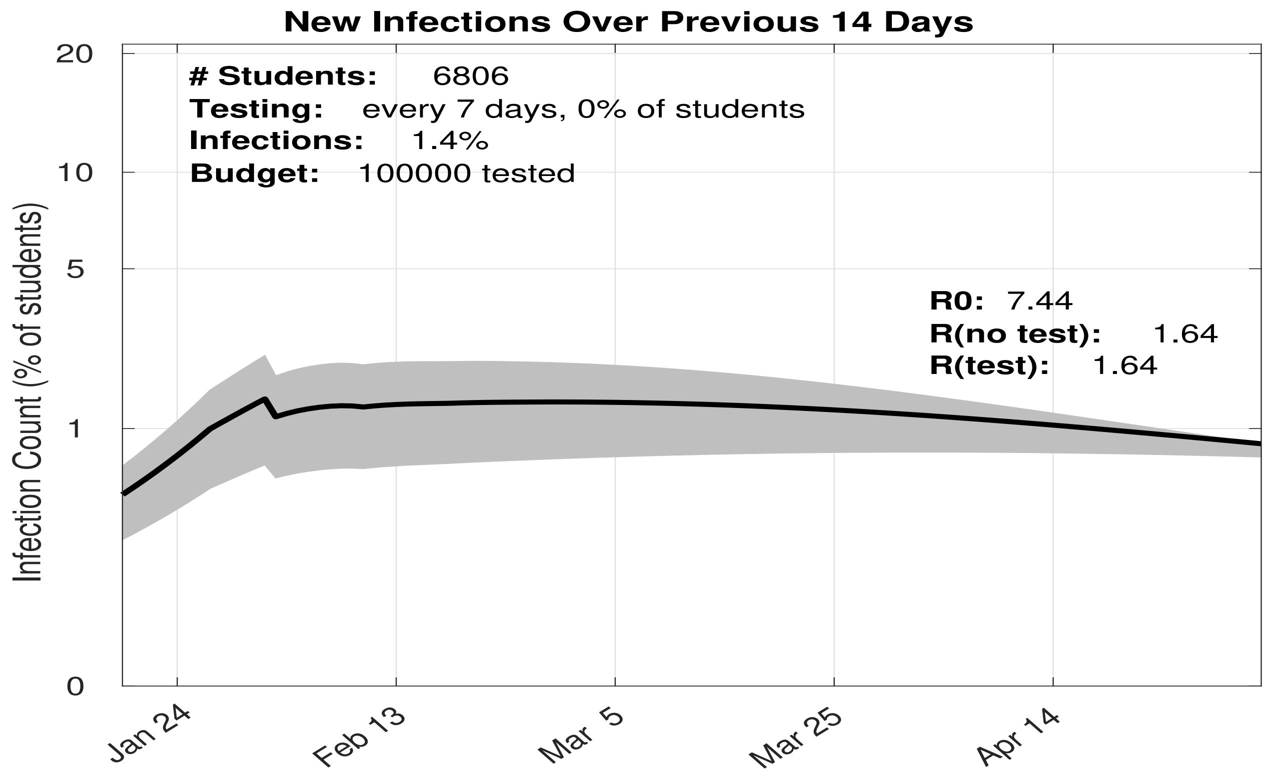
NY State ~ 20 million



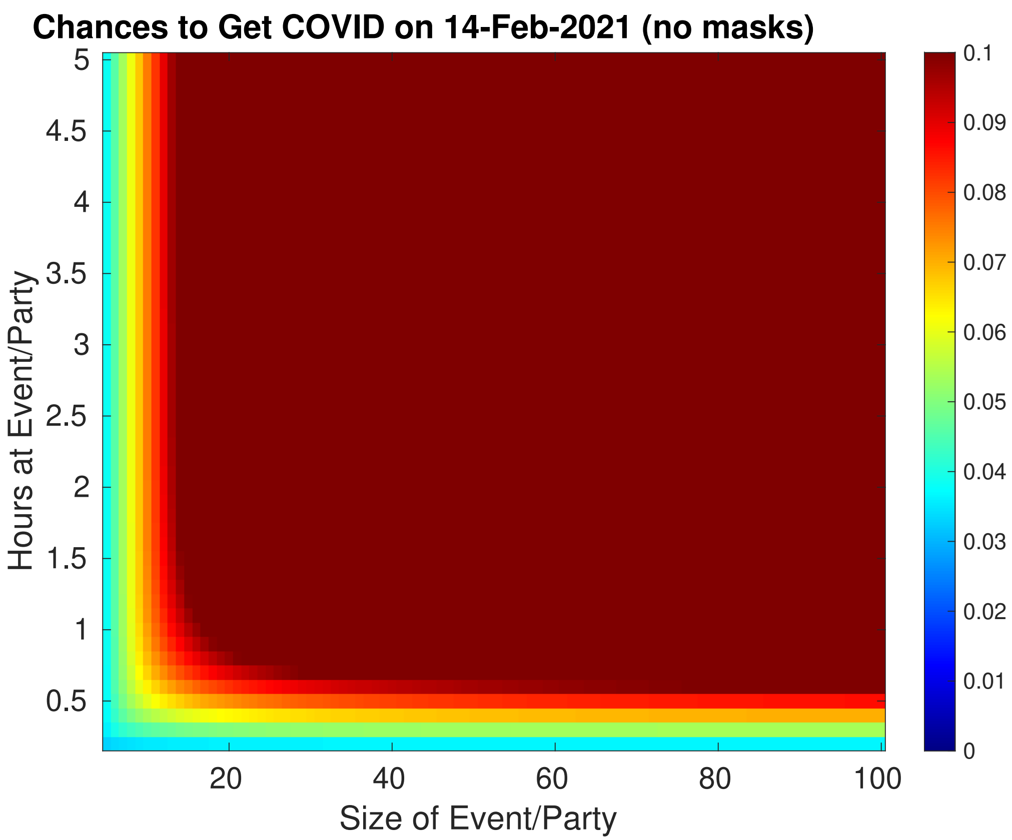
Albany/Troy/Cap Dist ~ 1 million



Rensselaer ~ 10 thousand

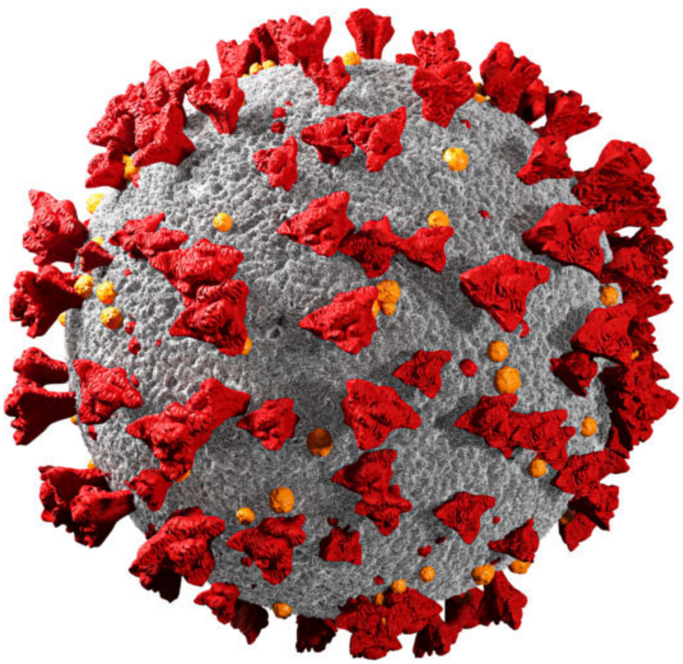


Party at Rensselaer ~ 20



Scales of COVID-19

vaccines, virology, genomics



Two Sides of COVID Modeling

Epidemiological Modeling

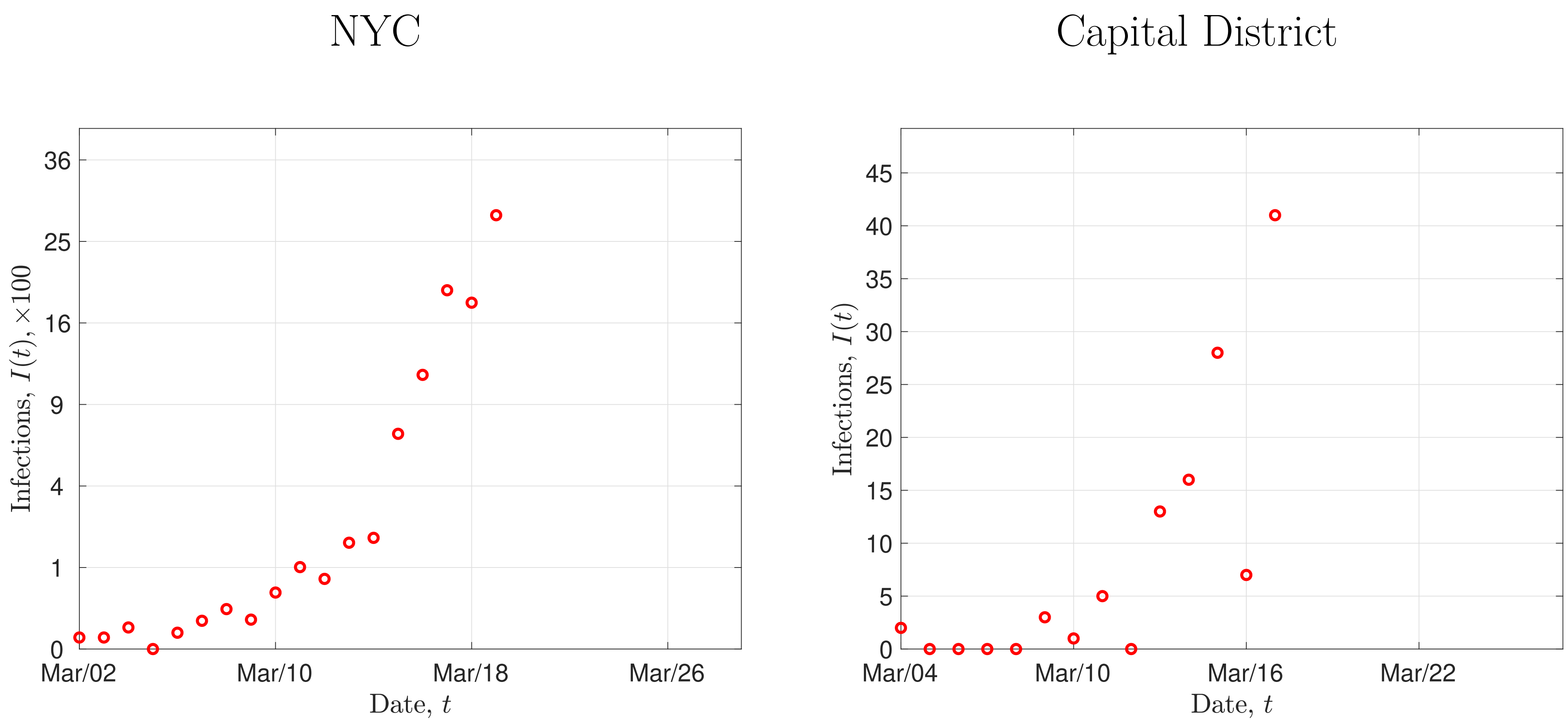
Harvard-model, Imperial-model, UW-model, Your-model, My-model, . . .

AI and Machine Learning Prediction

What the data says vs. What we think ought to be.

Engineering success vs. Biological correctness.

The Race To Predict Ventilator Demand



Infection counts: very noisy dirty data.

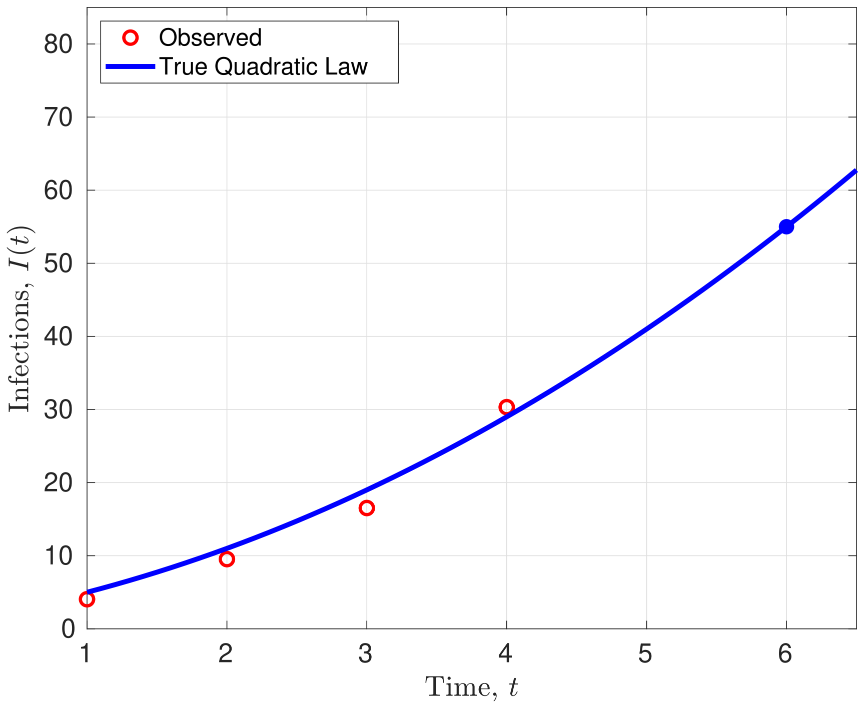
Predictions must be local: mobility patterns, density, social distancing, weather, ...

- Smaller regions: more noisy; more sparse.

A Easier Example

True "biological" law: quadratic growth.

Quadratic Fit + Extrapolate



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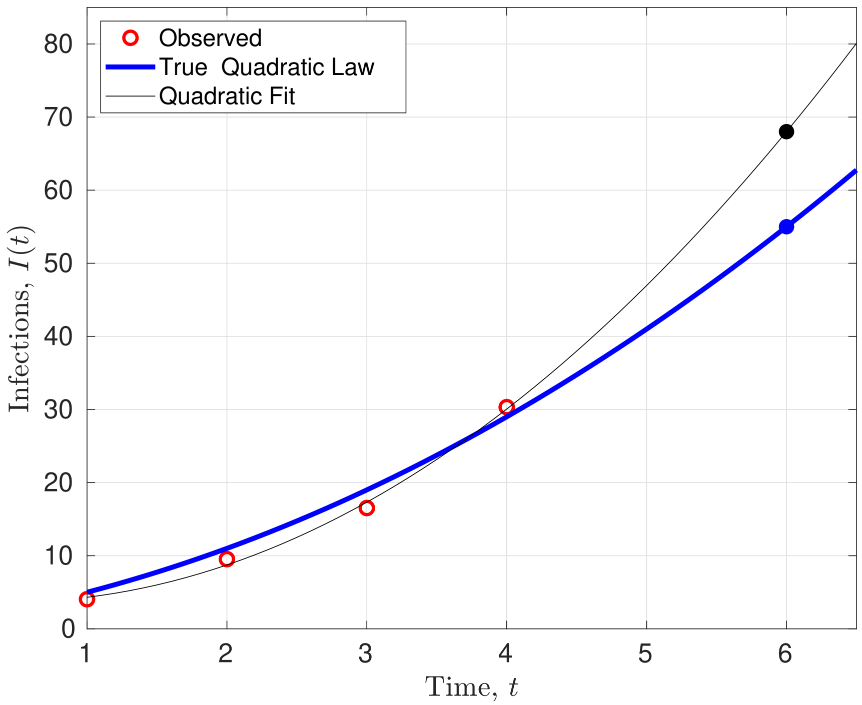

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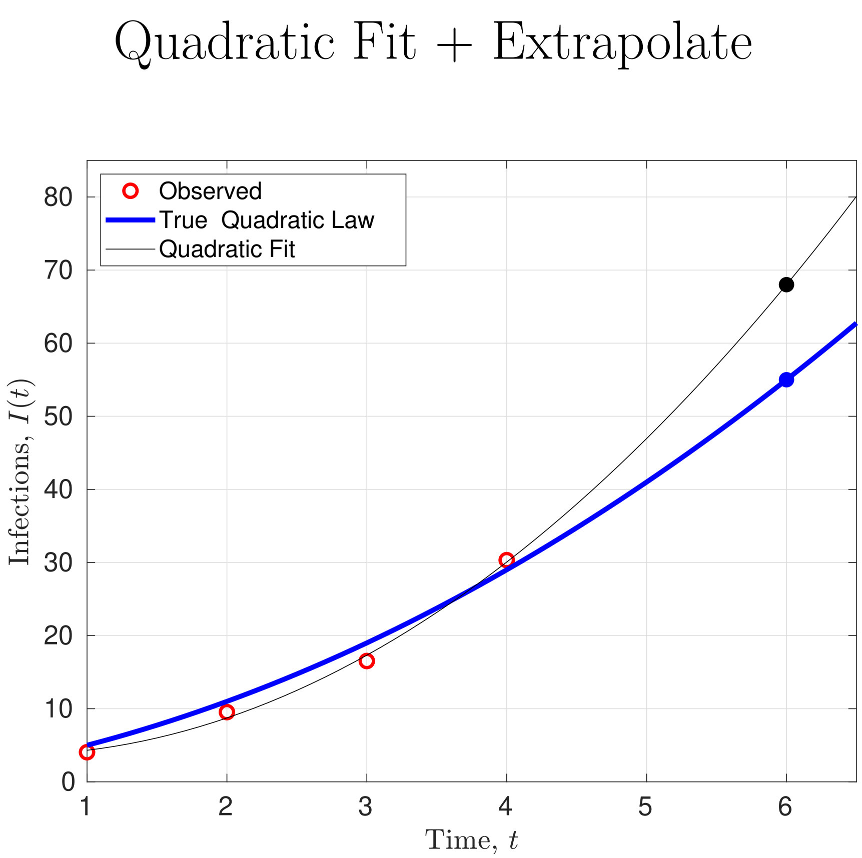

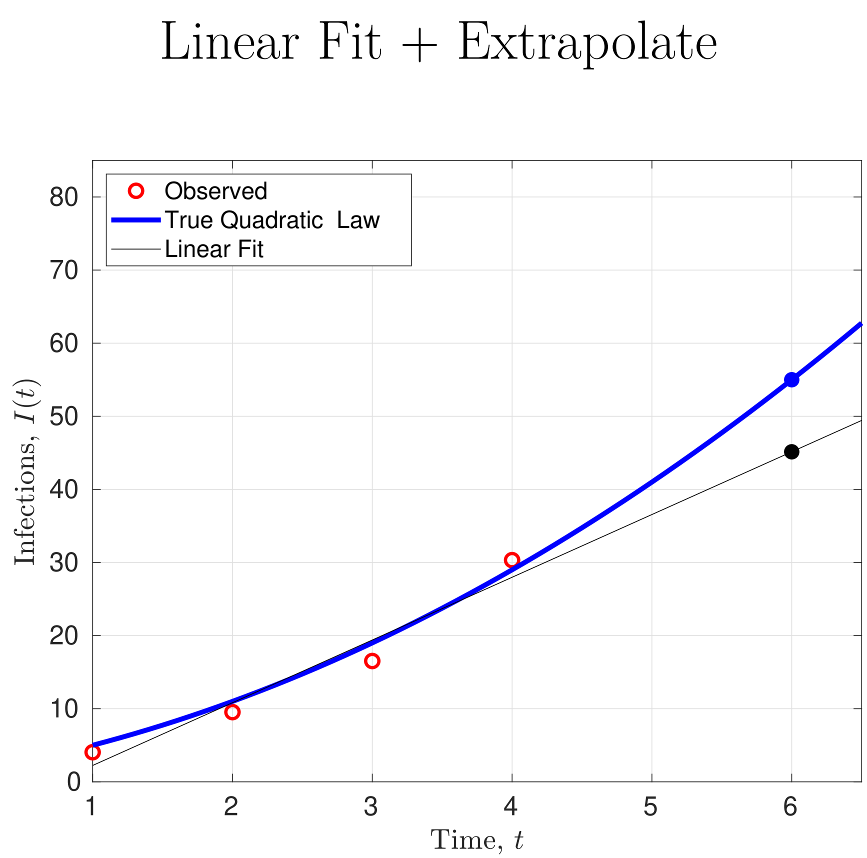

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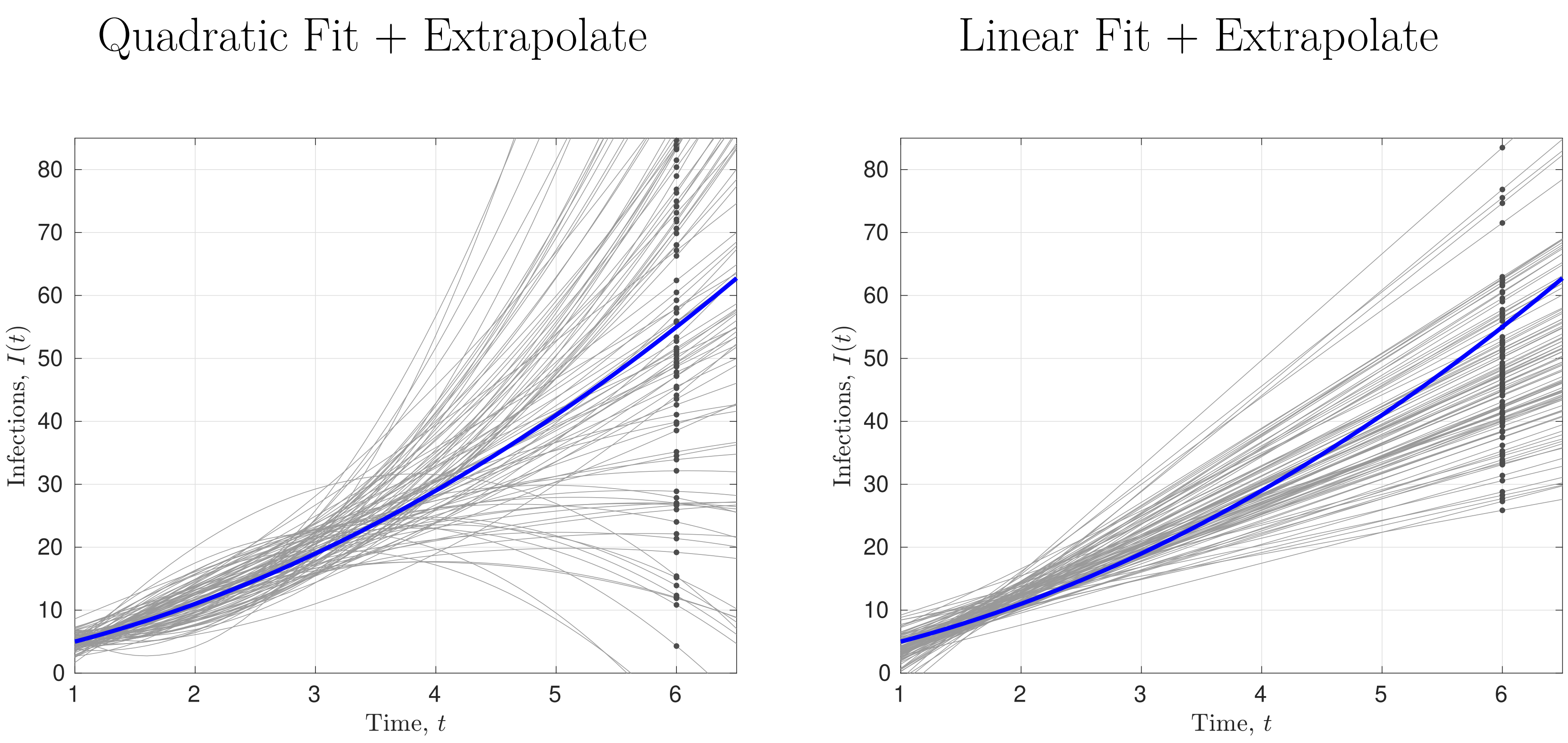


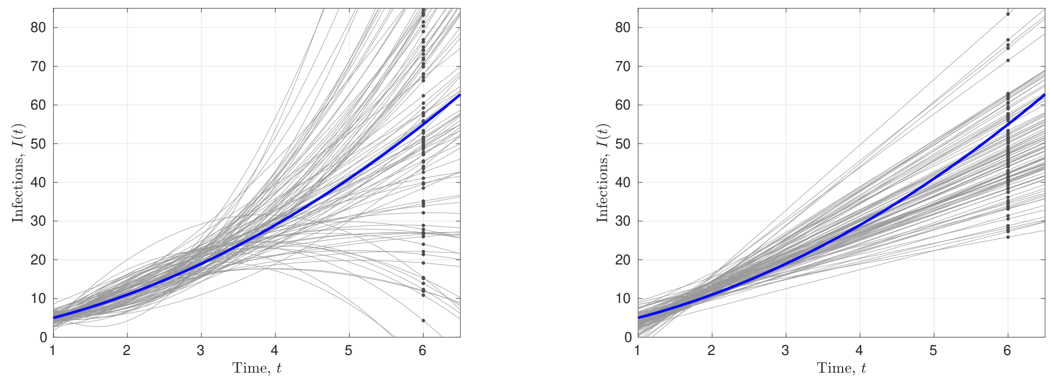
$E_{\text{out}} \approx 34$

$E_{\text{out}} \approx 14$ ✓

A Stunning Nugget From The Theory of Learning

When there is noise,

Simpler can be better than correct.



What we would like to learn versus what we *can* learn.

The data determines what we can learn

Harvard-model, Imperial-model, UW-model, Your-model, My-model, . . .

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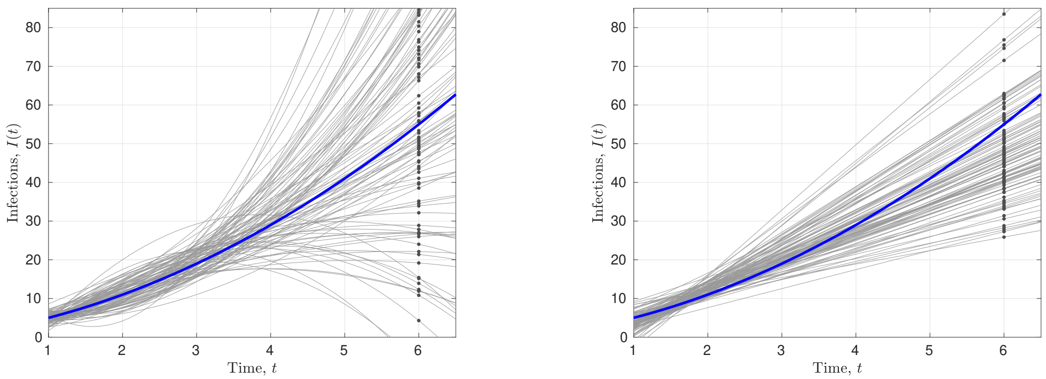
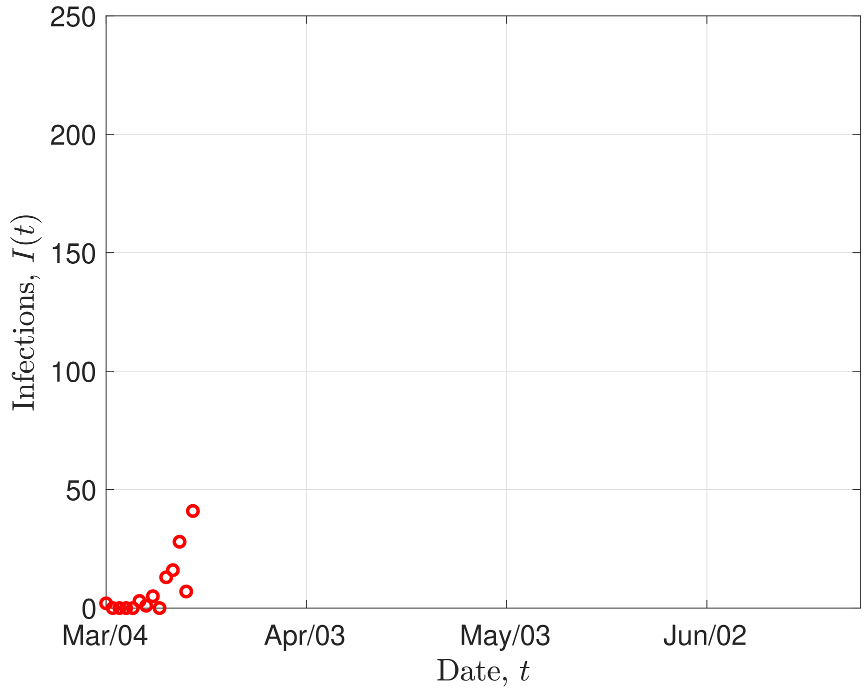


What we would like to learn versus what we *can* learn.

The data determines what we can learn

Harvard-model, Imperial-model, UW-model, Your-model, Simple–robust–adaptable model, . . .

Let's Predict For The Capital District



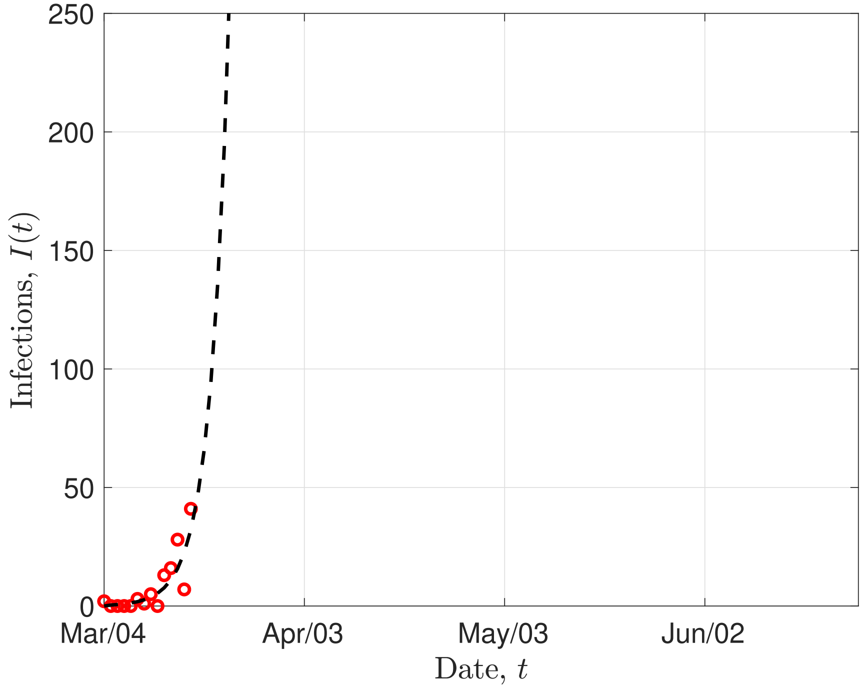
How quickly is it spreading?

How large is the pasture?

Capital District $\sim$ 1M.

- Extrapolation is hard.

Let's Predict For The Capital District



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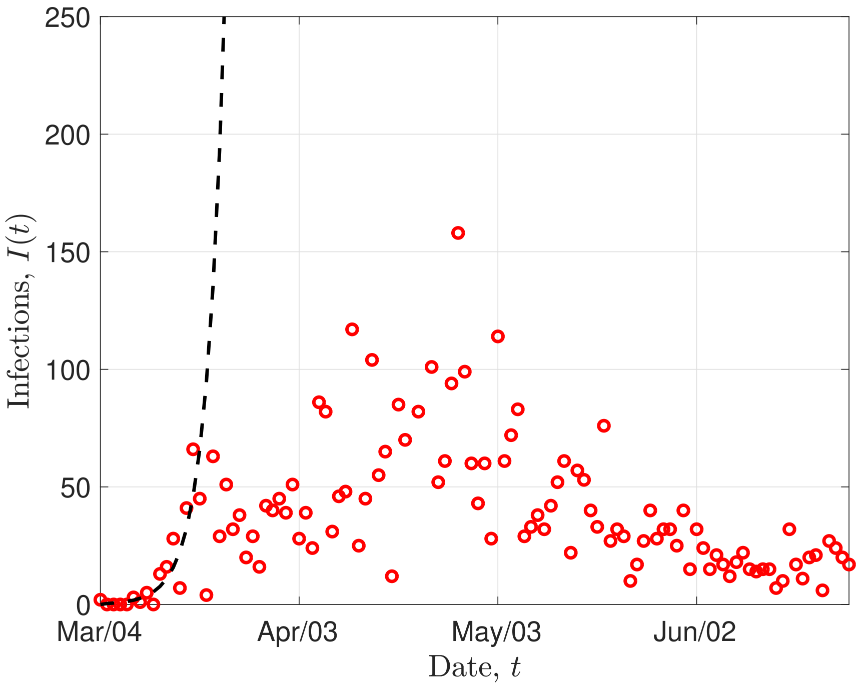

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Disaster!

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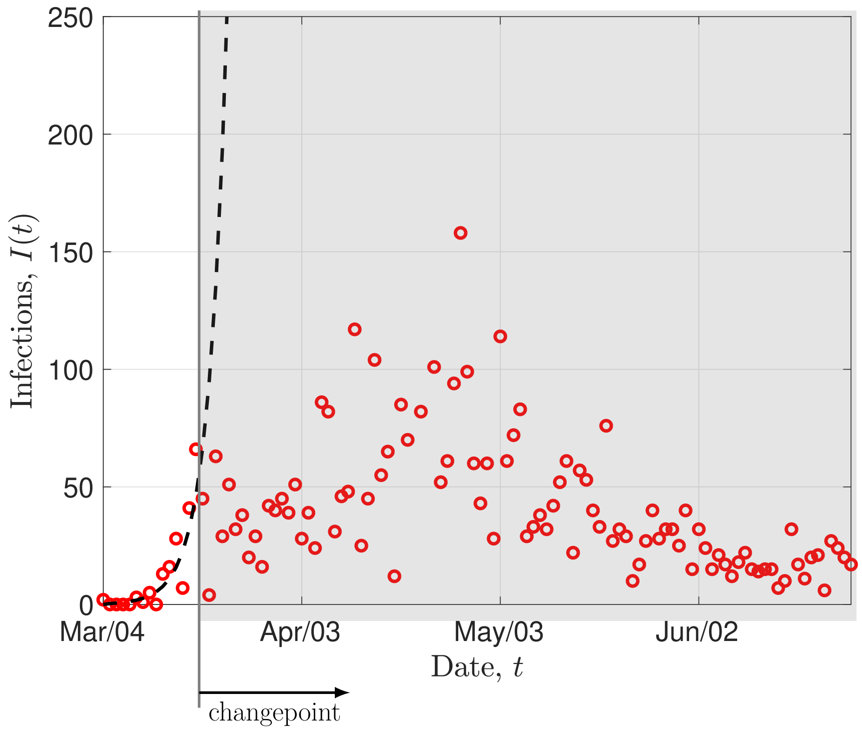


How quickly is it spreading?

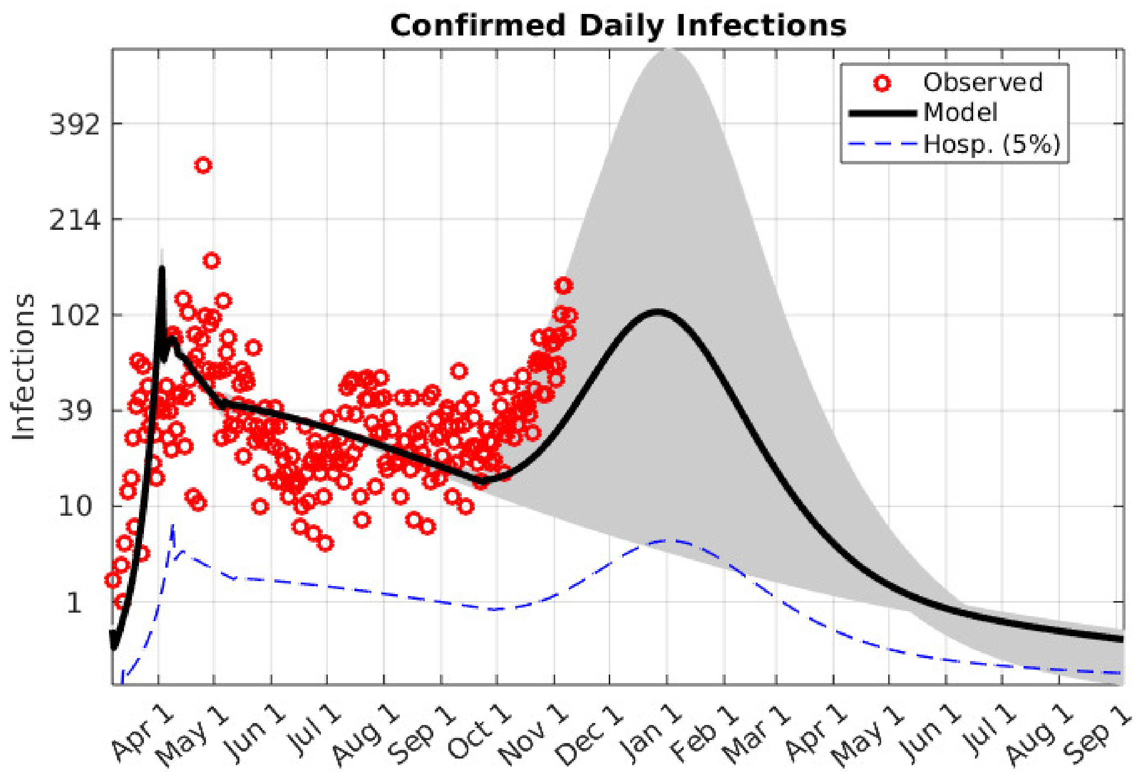
How large is the pasture?

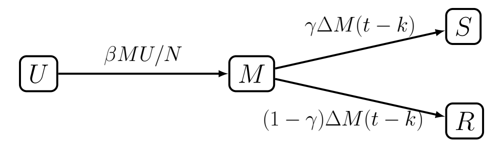
Capital District $\sim$ 1M.

- Extrapolation is hard.
- Changepoints make it impossible.

Disaster!

Keep It Simple, Really Simple. But, Adaptive



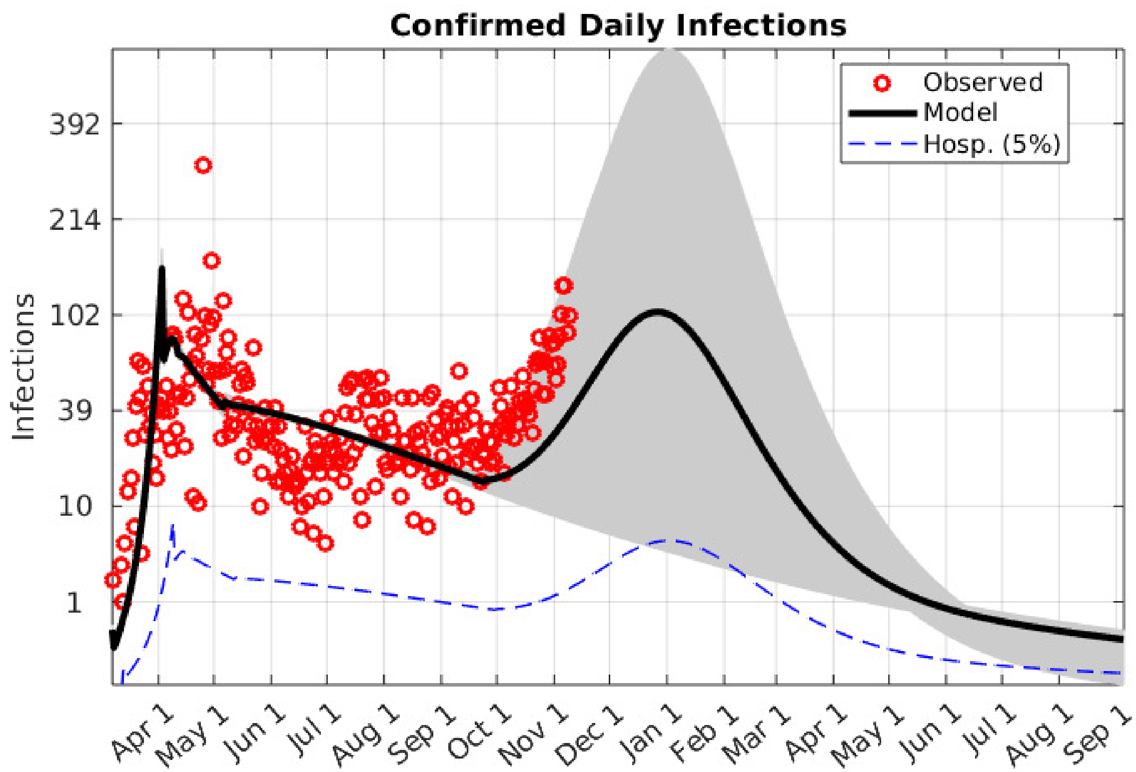


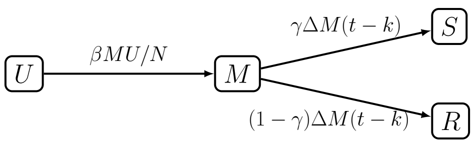
U: Uninfected.
M: Contagious.
S: Symptomatic.
R: Recovered.

Parameters:
N, β, α, γ.
Robust changepoints.

1
2
3

Keep It Simple, Really Simple. But, Adaptive





U: Uninfected.
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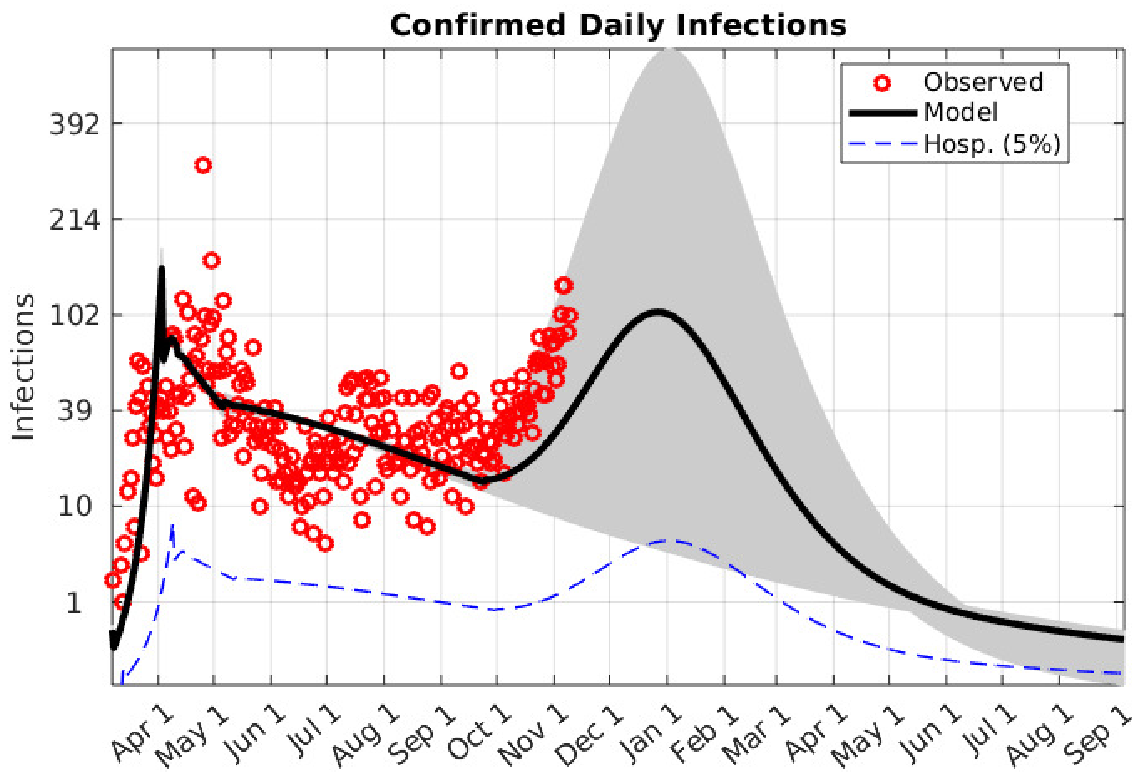
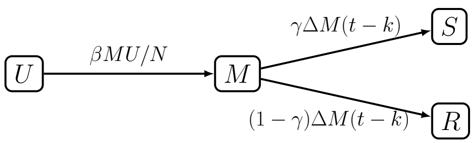
Robust changepoints.

1. Robustly determine changepoints.
2.
3.

Keep It Simple, Really Simple. But, Adaptive





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1. Robustly determine changepoints.
2. Robustly fit. Gray is uncertainty.
3.

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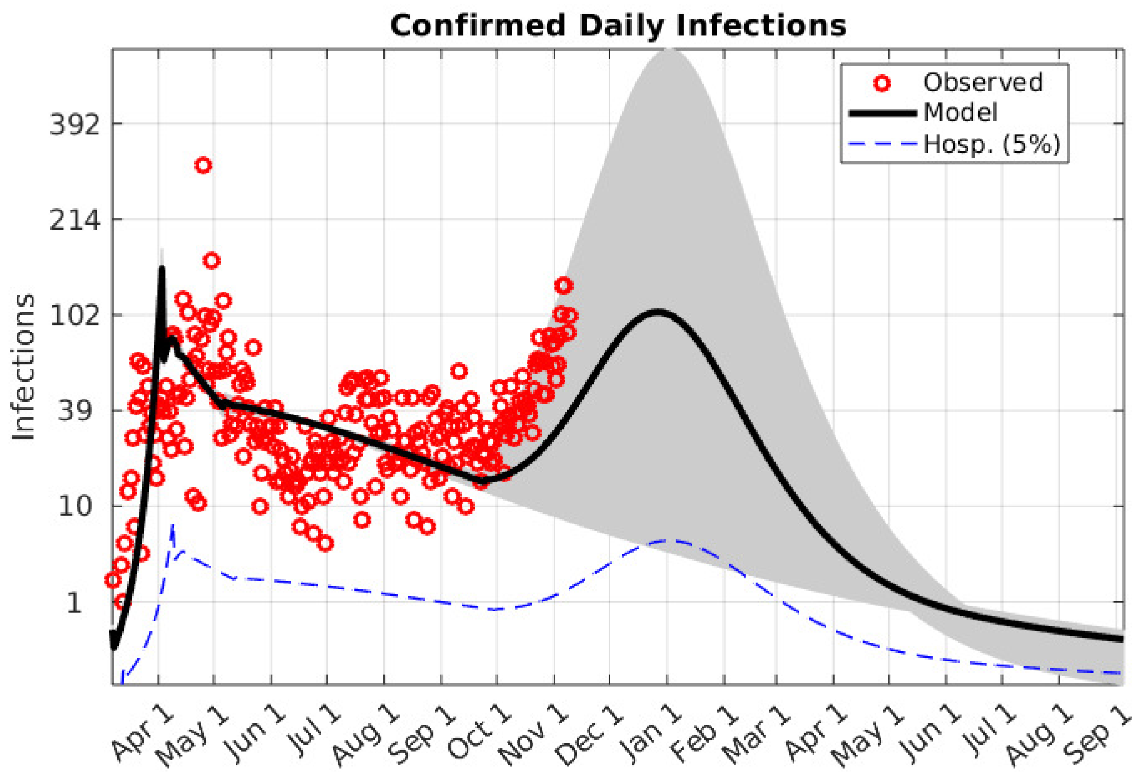

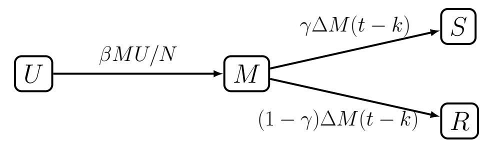

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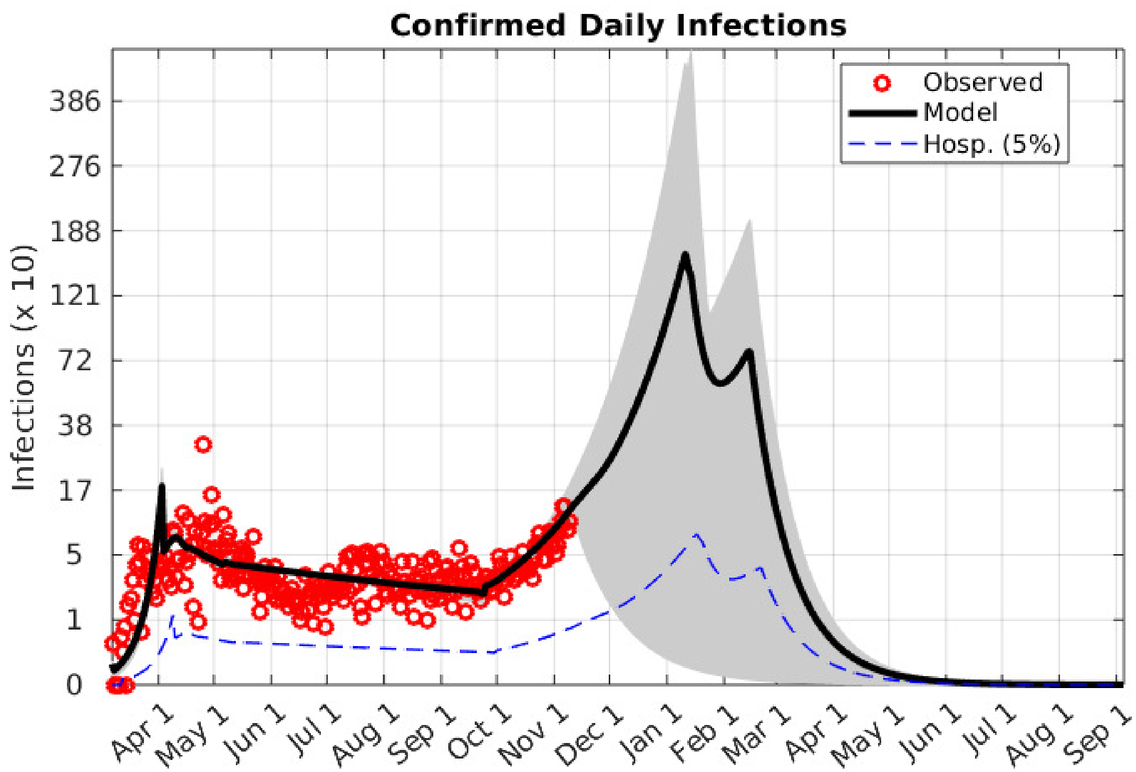
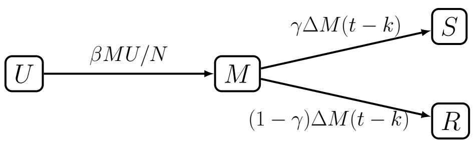
3. State persists across changepoints.

Keep It Simple, Really Simple. But, Adaptive





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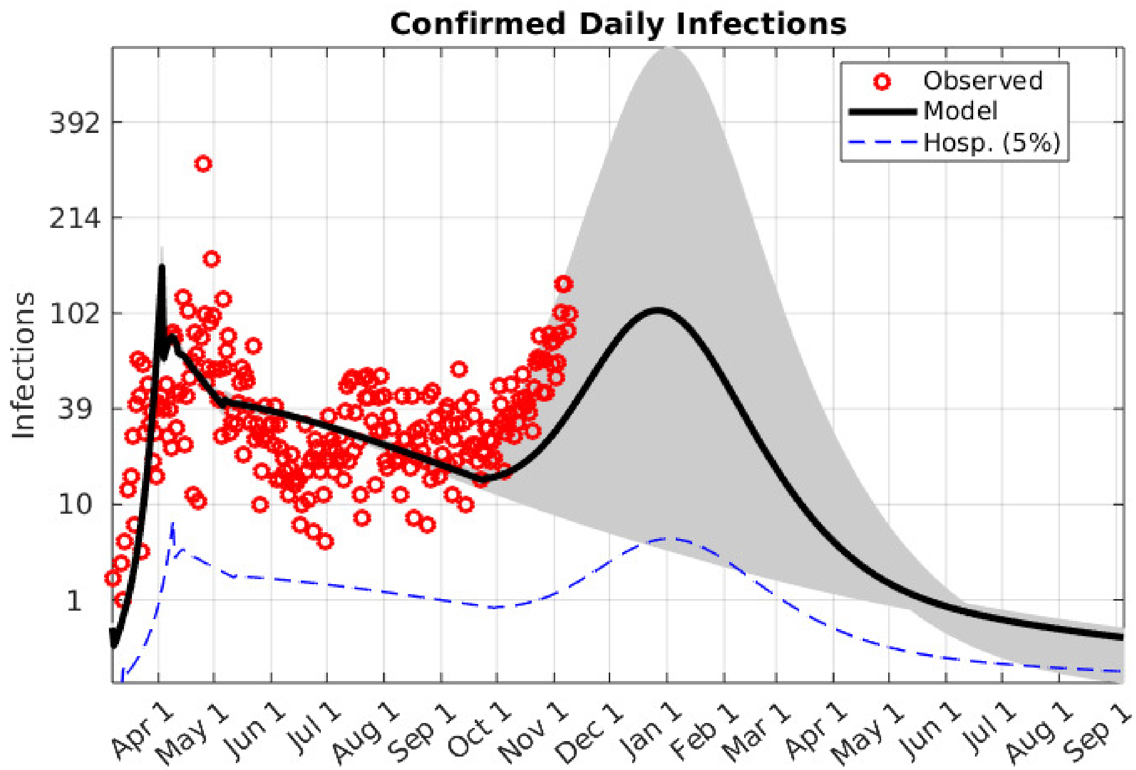
How: Even simpler analytic model pre-calibrates.

Keep It Simple, Really Simple. But, Adaptive



$$\begin{tikzcd} & & S \\ U \arrow[r, "\beta MU/N"] & M \arrow[ur, "\gamma\Delta M(t-k)"] \arrow[dr, "(1-\gamma)\Delta M(t-k)"'] & \\ & & R \end{tikzcd}$$

U: Uninfected.
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Parameters:
N, β, α, γ.
Robust changepoints.

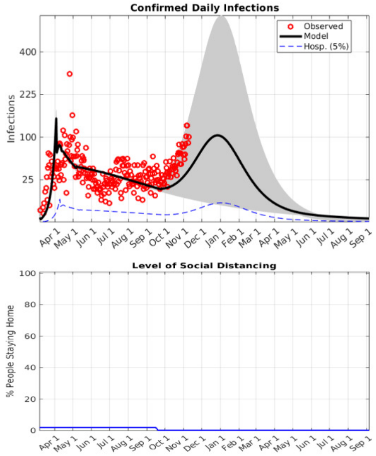
- **We get current state:**

  Infected and contagious. Immune. Social distancing.

- **Predictions assuming stabilized behavior.**

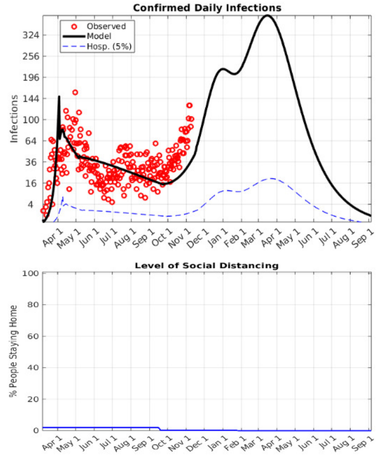
Capital District

Status Quo (Model picks Social Distancing)



population	908,843
confirmed infections	9,406
total infections (model)	52,680
infectious (model)	0.2317%
immunity (model)	5.5646%
fatalities	295
fatality rate (model)	0.56%
confirmed infections, Dec 31	13,435
total infections, Dec 31	84,453
infectious, Dec 31	0.5521%
immunity, Dec 31	8.7402%
fatalities, Dec 31	473

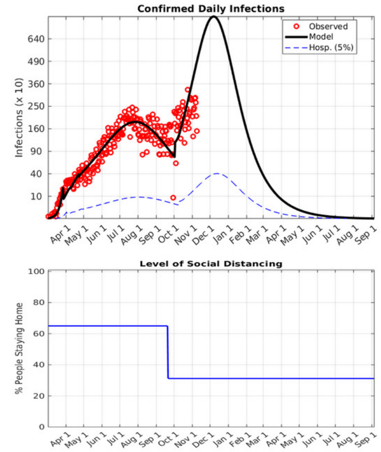
Phased Open (target 500 daily infections)



population	908,843
confirmed infections	9,406
total infections (model)	52,680
infectious (model)	0.2317%
immunity (model)	5.5646%
fatalities	295
fatality rate (model)	0.56%
confirmed infections, Dec 31	16,152
total infections, Dec 31	109,048
infectious, Dec 31	1.2001%
immunity, Dec 31	10.7985%
fatalities, Dec 31	611

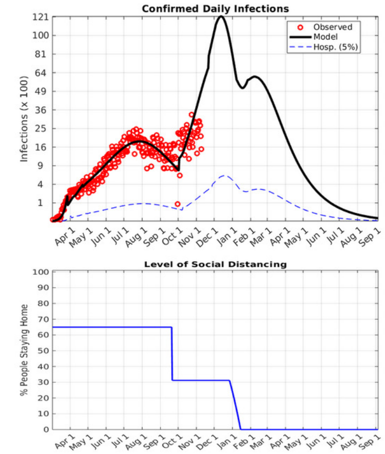
North Carolina

Status Quo (Model picks Social Distancing)



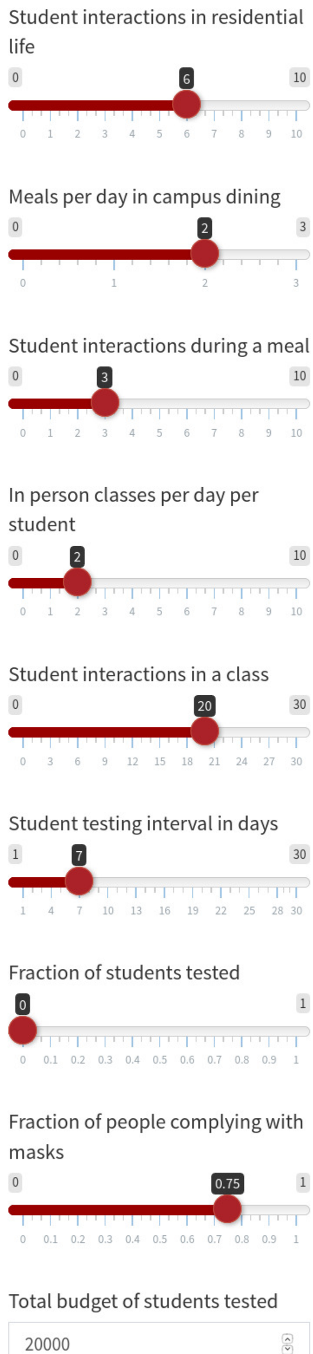
population	10,488,084
confirmed infections	294,857
total infections (model)	1,902,553
infectious (model)	3.4063%
immunity (model)	14.7339%
fatalities	4,615
fatality rate (model)	0.2426%
confirmed infections, Dec 31	660,205
total infections, Dec 31	3,645,433
infectious, Dec 31	2.6067%
immunity, Dec 31	32.1512%
fatalities, Dec 31	8,843

Phased Open (target 9325 daily infections)



population	10,488,084
confirmed infections	294,857
total infections (model)	1,902,553
infectious (model)	3.4063%
immunity (model)	14.7339%
fatalities	4,615
fatality rate (model)	0.243%
confirmed infections, Dec 31	788,645
total infections, Dec 31	4,402,542
infectious, Dec 31	3.7023%
immunity, Dec 31	38.2743%
fatalities, Dec 31	10,680

All US Counties. All Countries.



Who's bringing covid to campus?

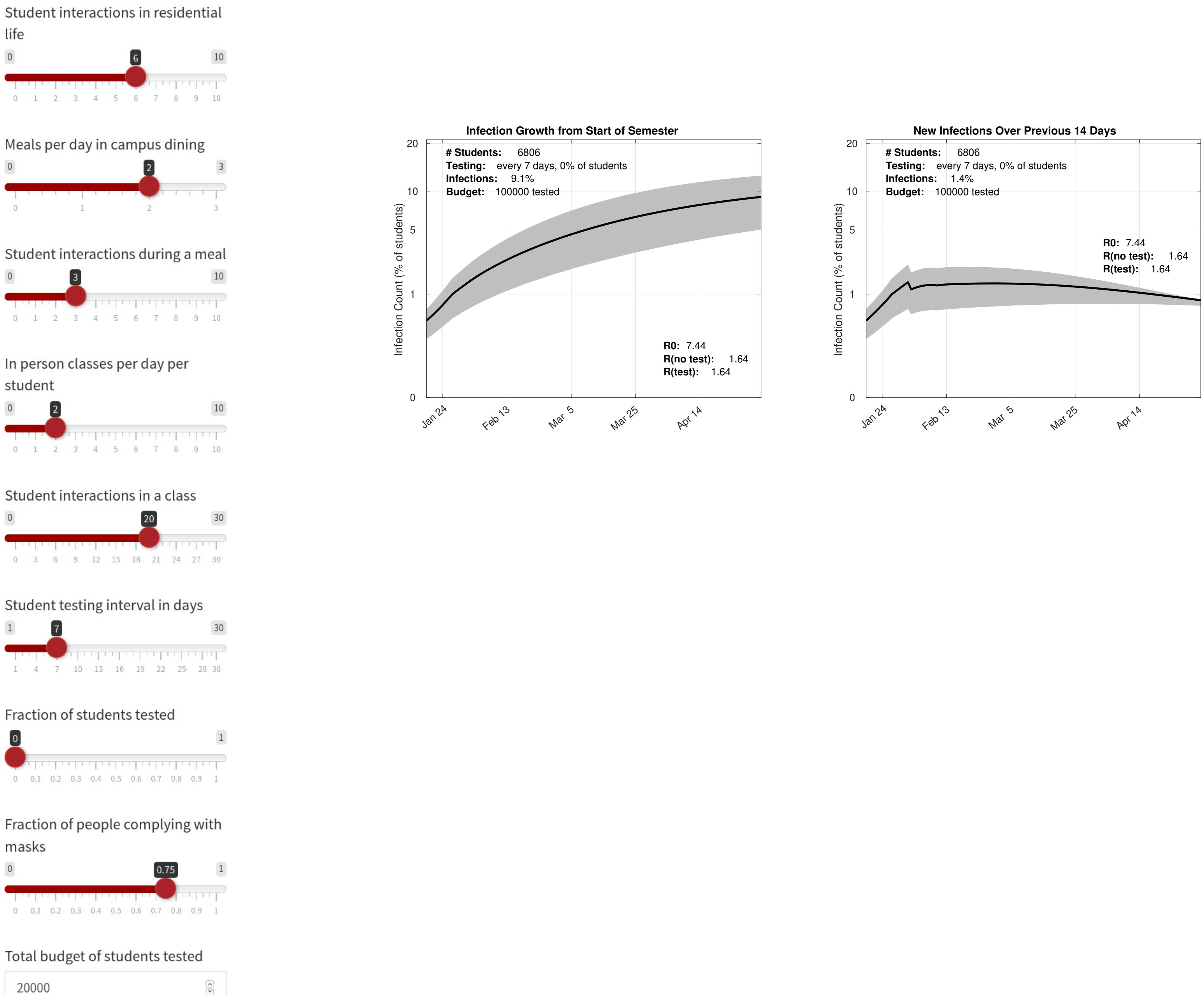
Ambient county infection rate?

COVID-War-Room

Jan 19:

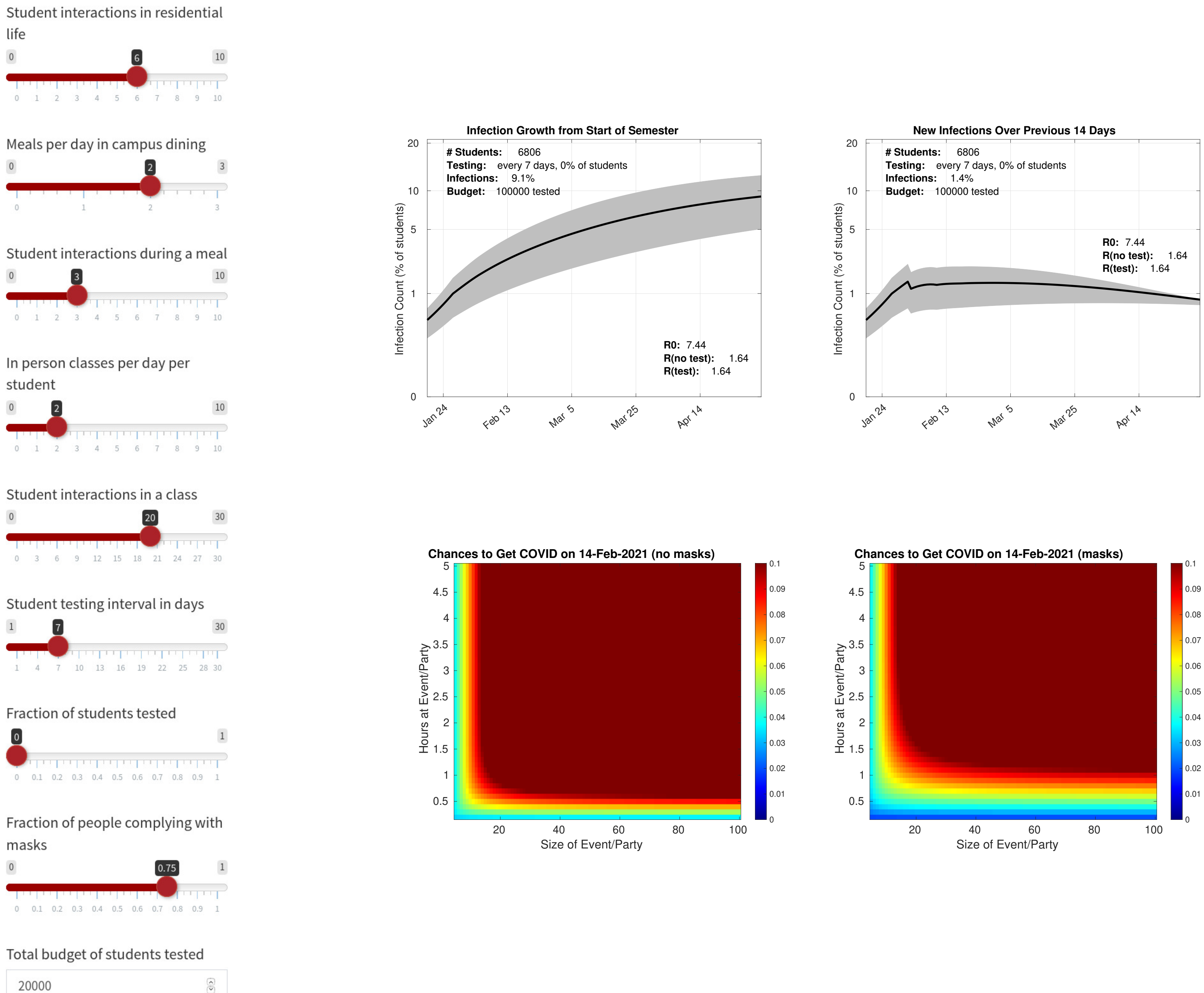
∼24 cases,

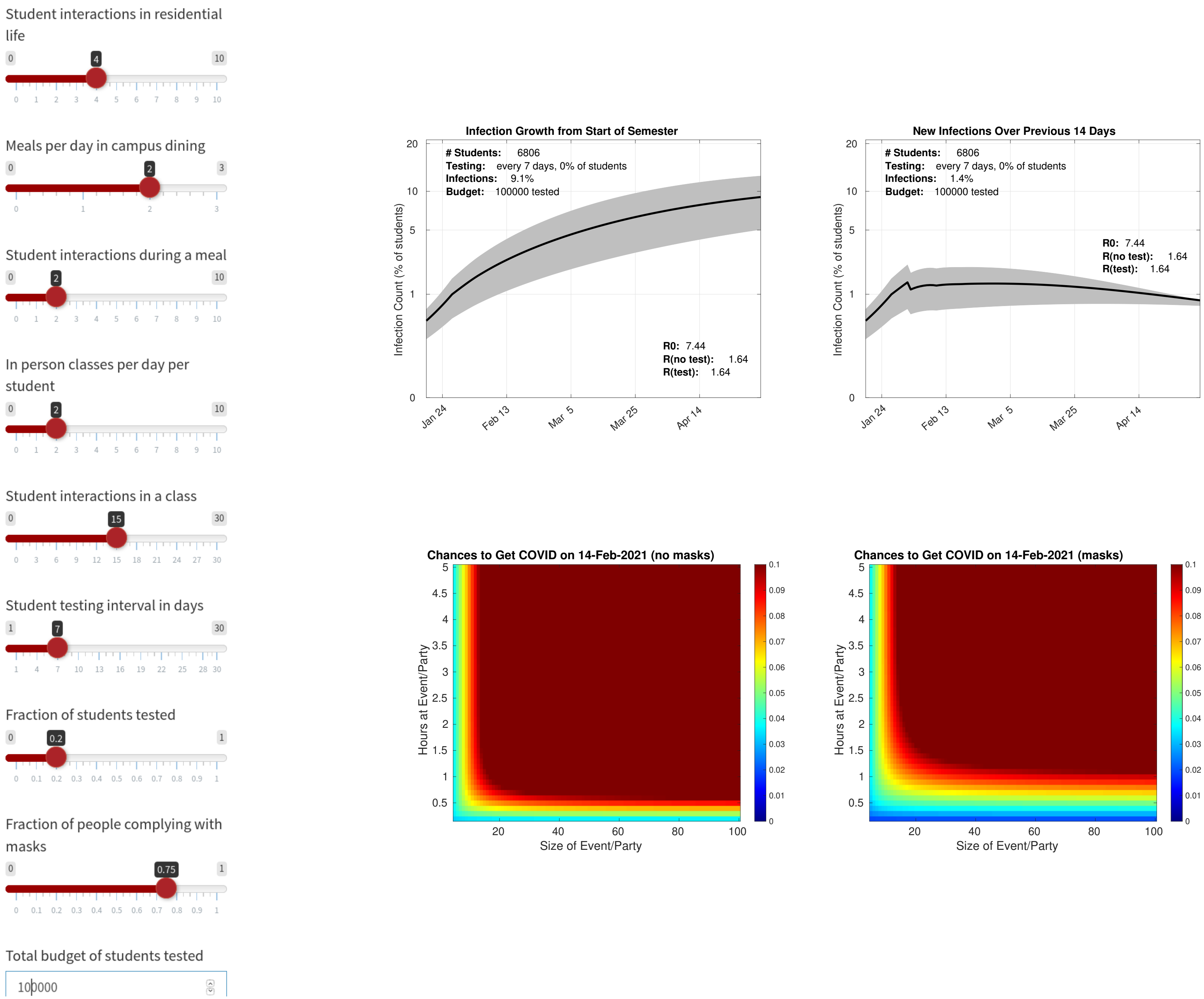
∼20% immunity.



Student interactions in residential life
6
Meals per day in campus dining
2
Student interactions during a meal
3
In person classes per day per student
2
Student interactions in a class
20
Student testing interval in days
7
Fraction of students tested
0
Fraction of people complying with masks
0.75
Total budget of students tested
20000
Infection Growth from Start of Semester
Students: 6806
Testing: every 7 days, 0% of students
Infections: 9.1%
Budget: 100000 tested
R0: 7.44
R(no test): 1.64
R(test): 1.64
Infection Count (% of students)
Jan 24
Feb 13
Mar 5
Mar 25
Apr 14
New Infections Over Previous 14 Days
Students: 6806
Testing: every 7 days, 0% of students
Infections: 1.4%
Budget: 100000 tested
R0: 7.44
R(no test): 1.64
R(test): 1.64

COVID-Back-To-School




Student interactions in residential life
4
Meals per day in campus dining
2
Student interactions during a meal
2
In person classes per day per student
2
Student interactions in a class
15
Student testing interval in days
7
Fraction of students tested
0.2
Fraction of people complying with masks
0.75
Total budget of students tested
100000
Infection Growth from Start of Semester
Students: 6806
Testing: every 7 days, 0% of students
Infections: 9.1%
Budget: 100000 tested
R0: 7.44
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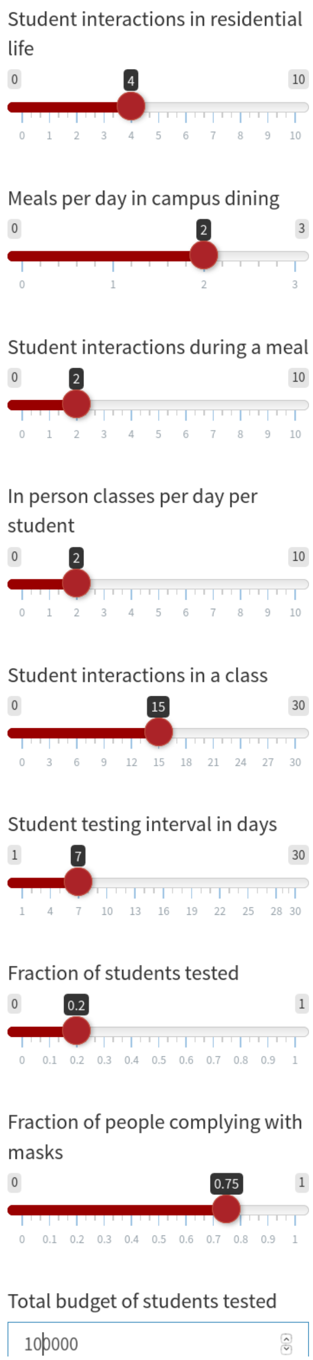
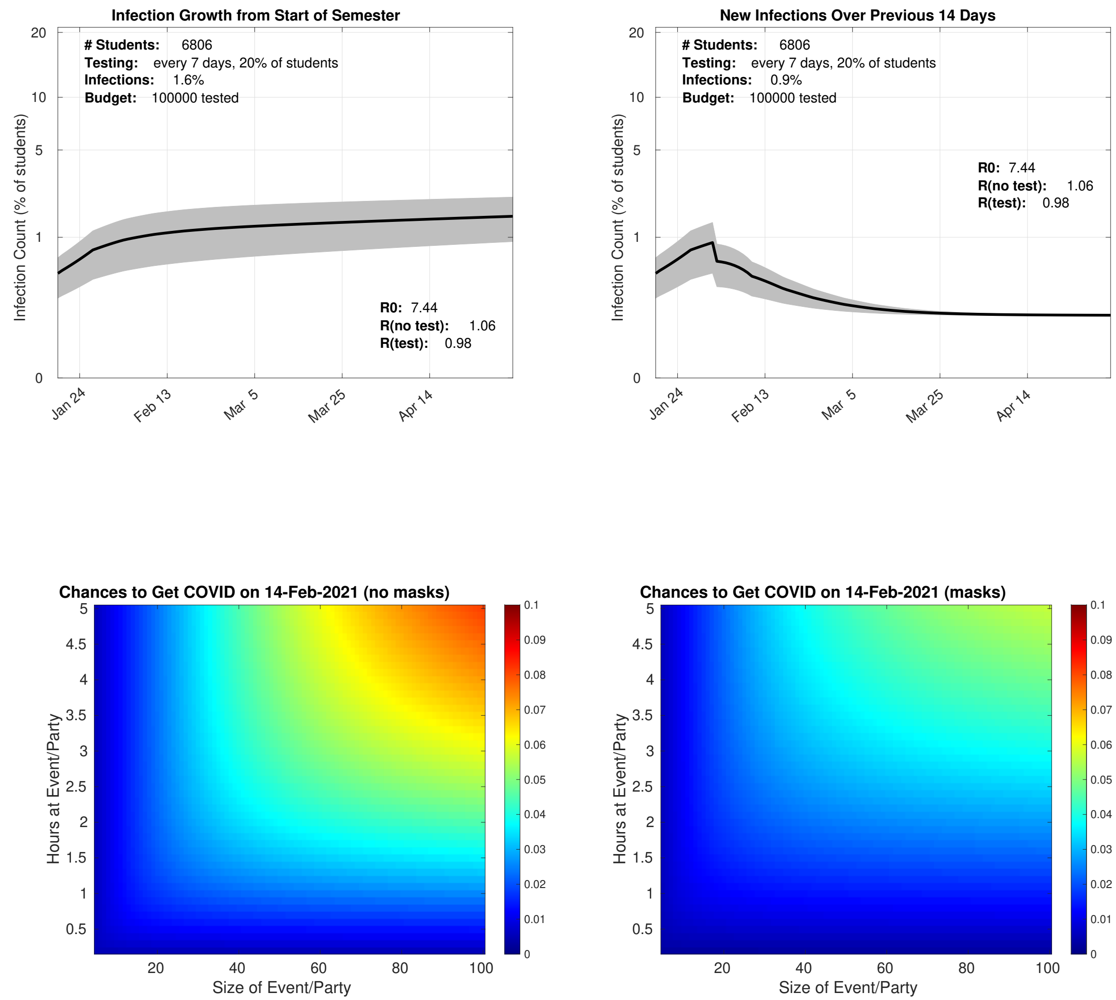
R(test): 1.64
Chances to Get COVID on 14-Feb-2021 (no masks)
Chances to Get COVID on 14-Feb-2021 (masks)
Hours at Event/Party
Size of Event/Party

COVID-Back-To-School

https://covidspread.idea.rpi.edu





Rensselaer: $1.5\% \approx 60$. 18 infections so far.

Tools to Policy

We have tools to model spread at all scales.

In policy making, all scales are relevant. Decisions should take a holistic view.

- The spread of COVID is just one factor that influences these decisions.
- . . .

I really enjoyed giving this talk