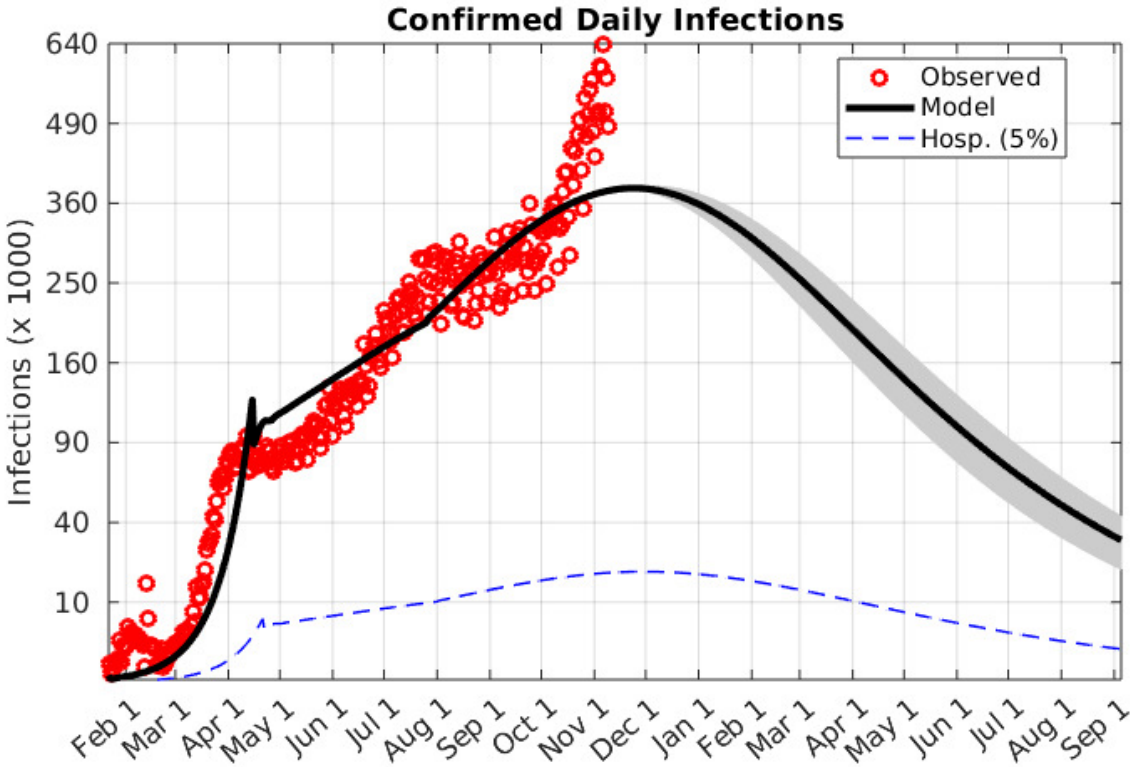
AI and ML for Predicting COVID-19

Malik Magdon-Ismail,
Computer Science, Rensselaer.

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

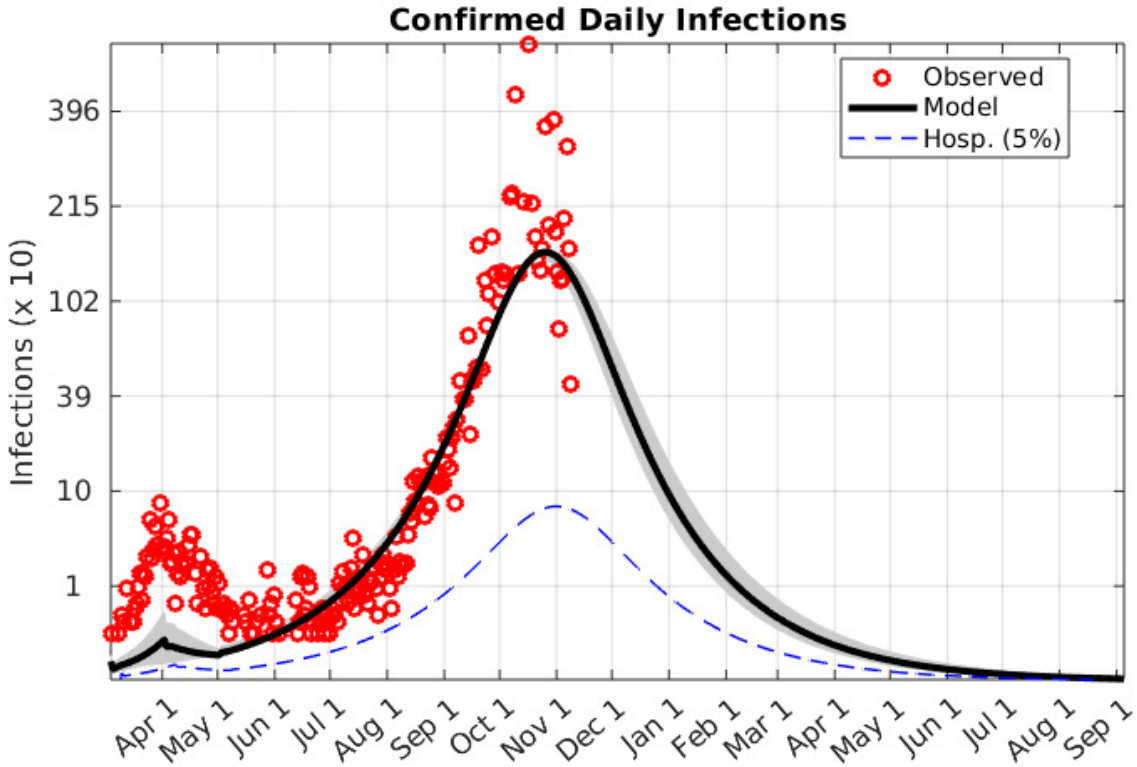
Scales of COVID-19

World ~ 8 billion



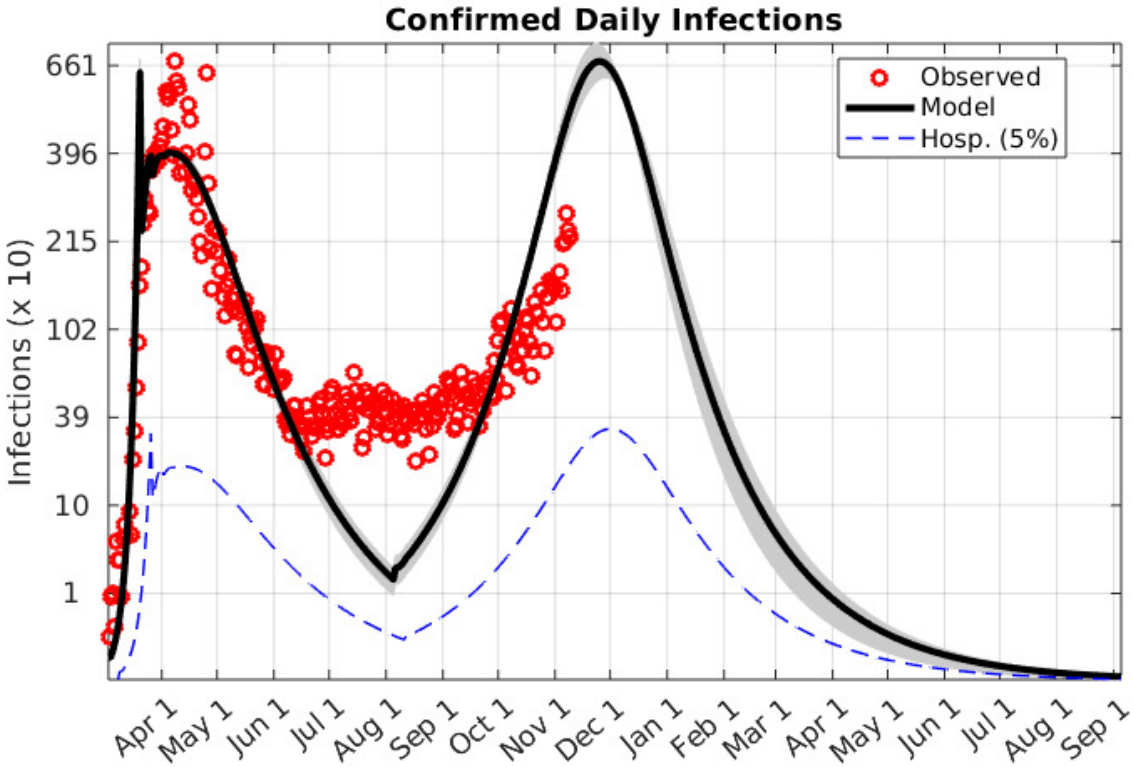
Scales of COVID-19

USA ~ 330 **million**



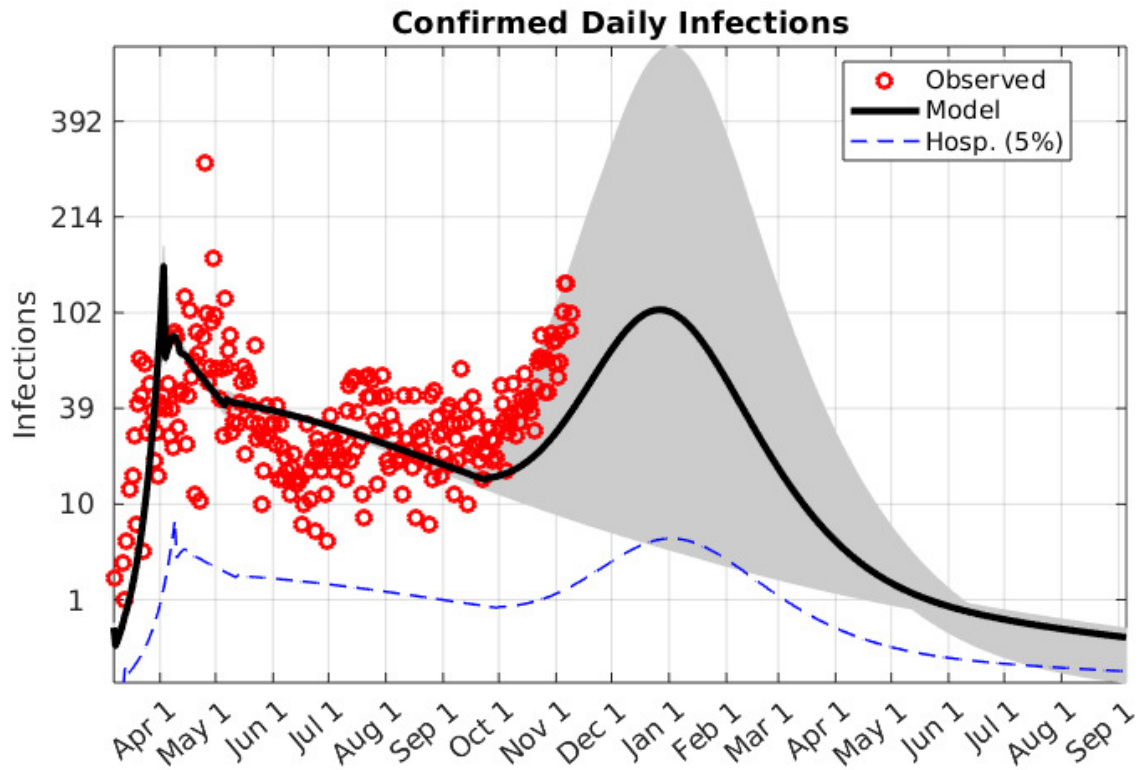
Scales of COVID-19

NY State ~ 20 million



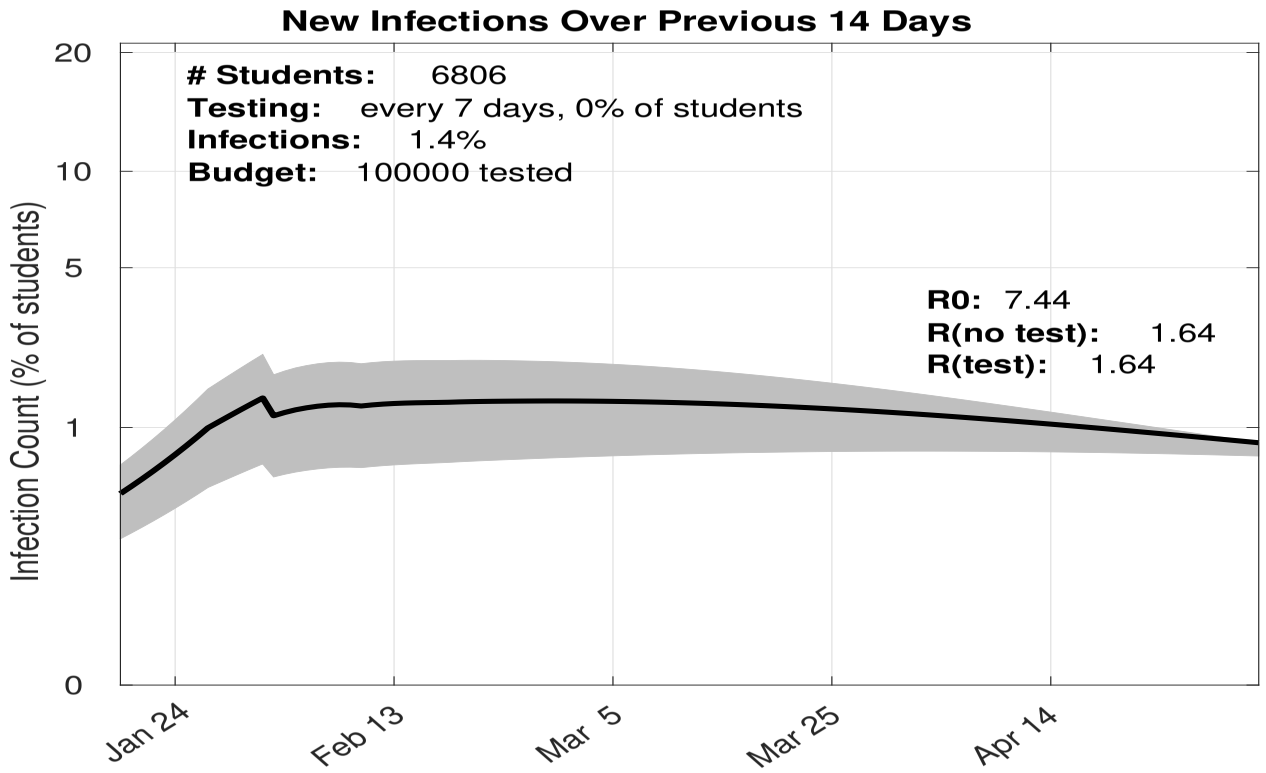
Scales of COVID-19

Albany/Troy/Cap Dist ~ 1 million



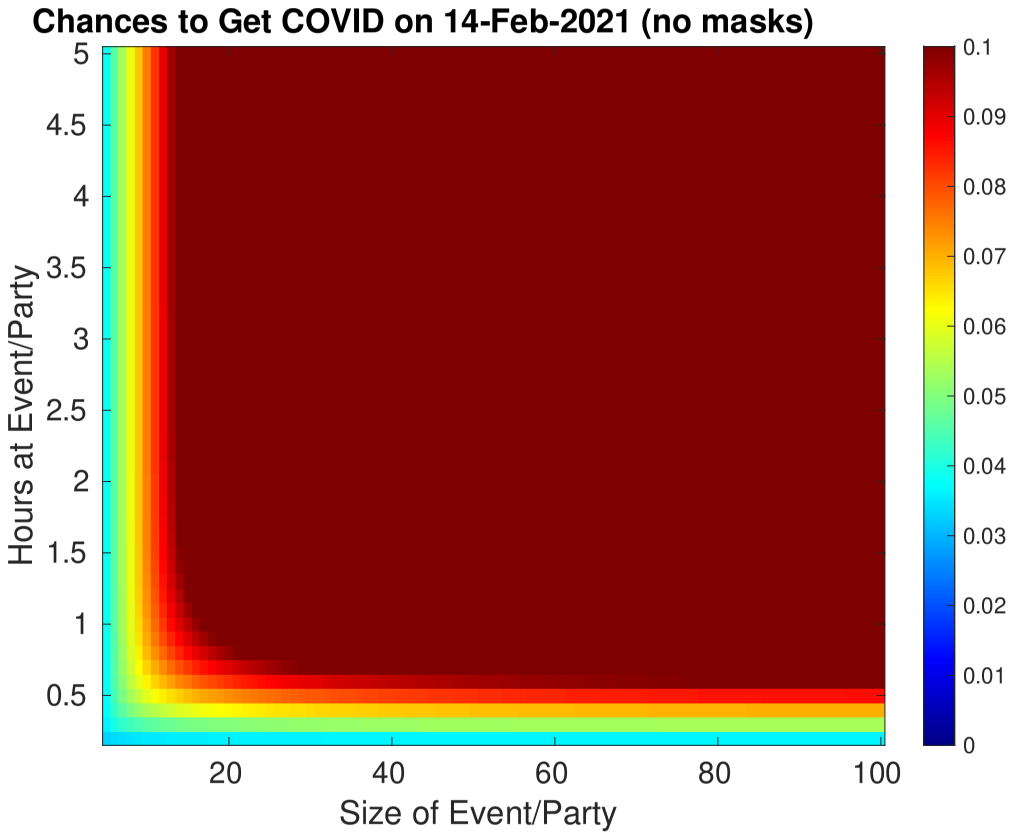
Scales of COVID-19

Rensselaer ~ 10 thousand



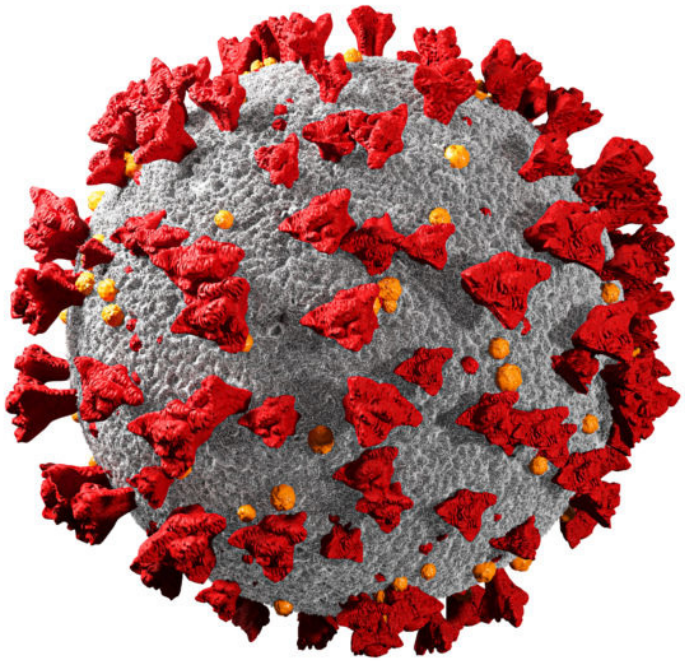
Scales of COVID-19

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, ...

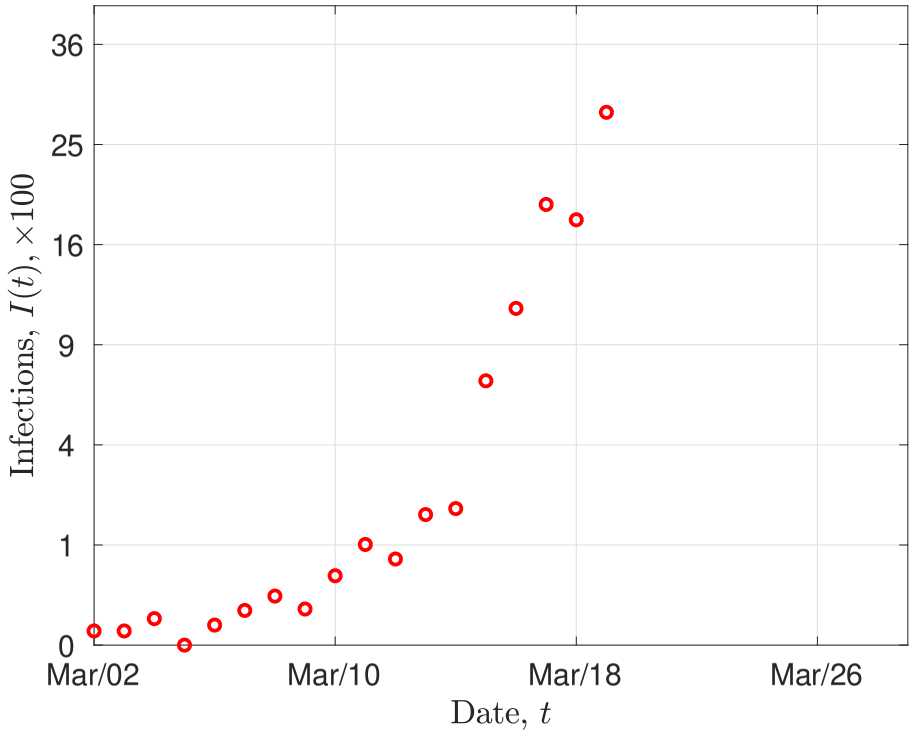
AI and Machine Learning Prediction

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

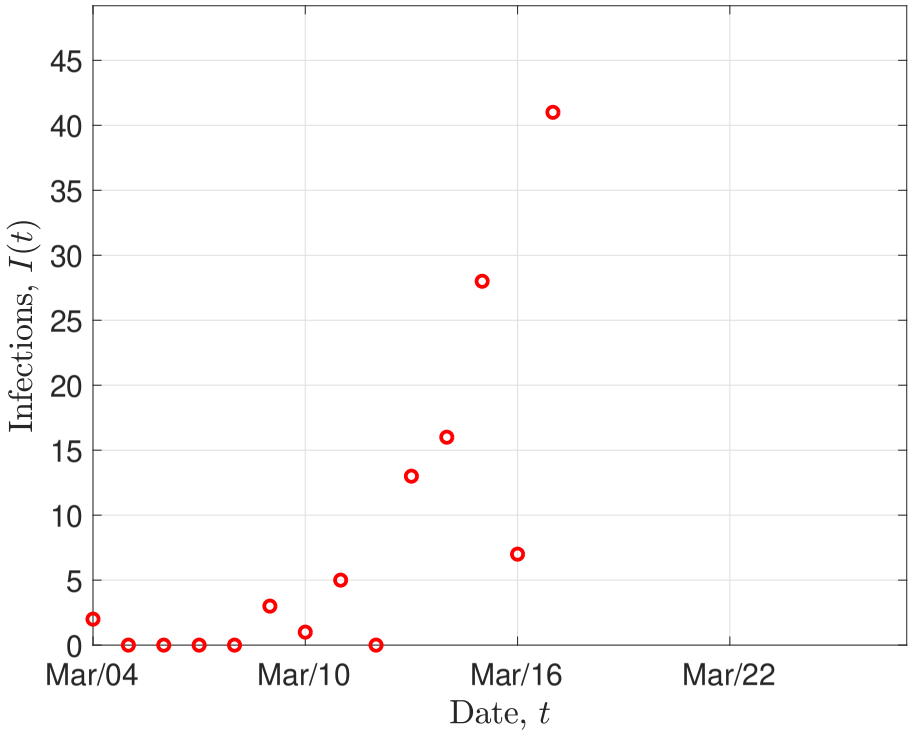
Engineering success vs. Biological correctness.

The Race To Predict Ventilator Demand

NYC



Capital District



Infection counts: very noisy dirty data.

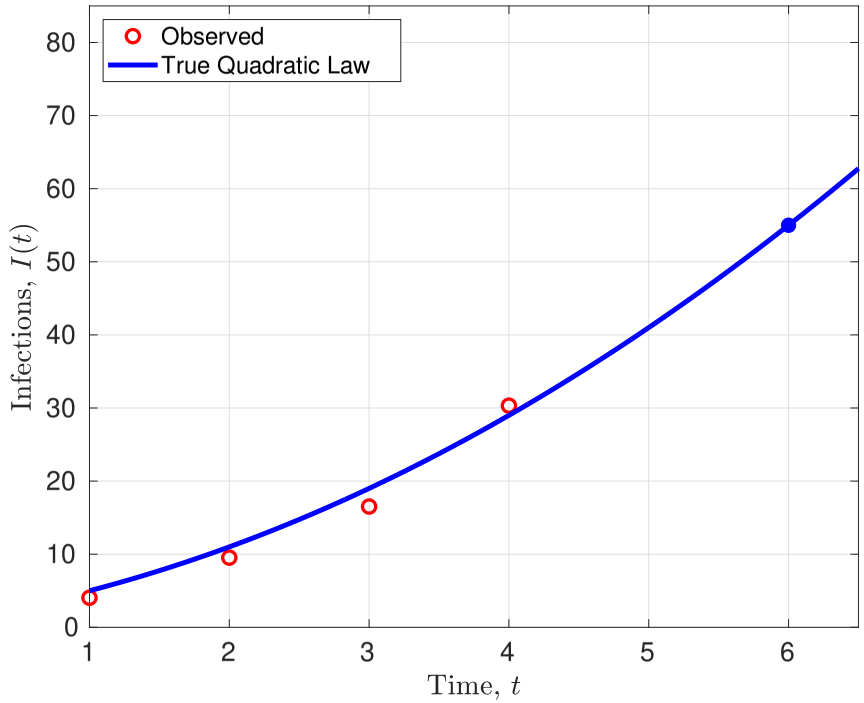
Predictions must be local: mobility patterns, density, social distancing, weather, ...

- Smaller regions: more noisy; more sparse.

A Easier Example

True "biological" law: quadratic growth.

Quadratic Fit + Extrapolate



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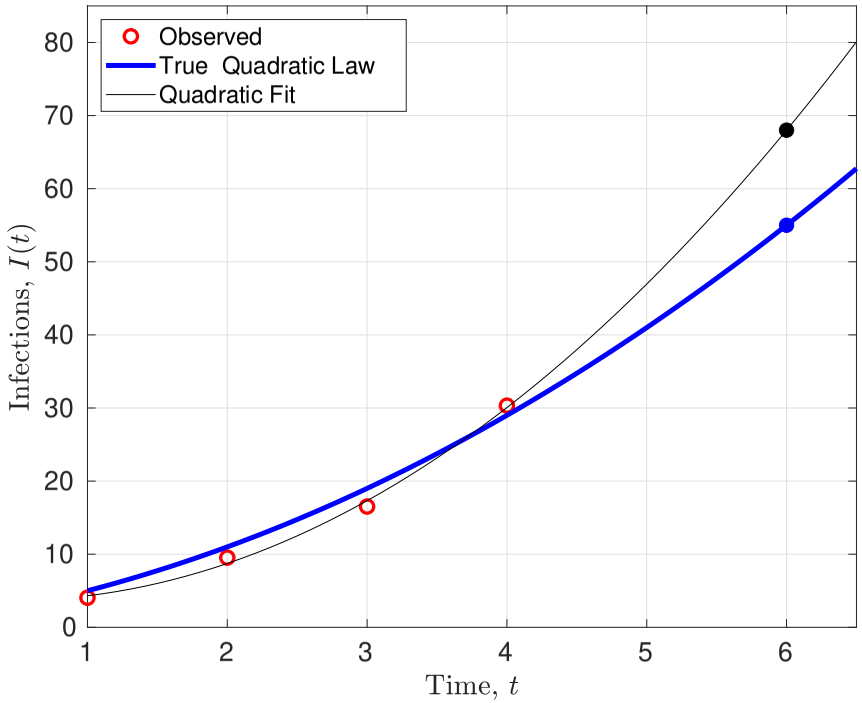

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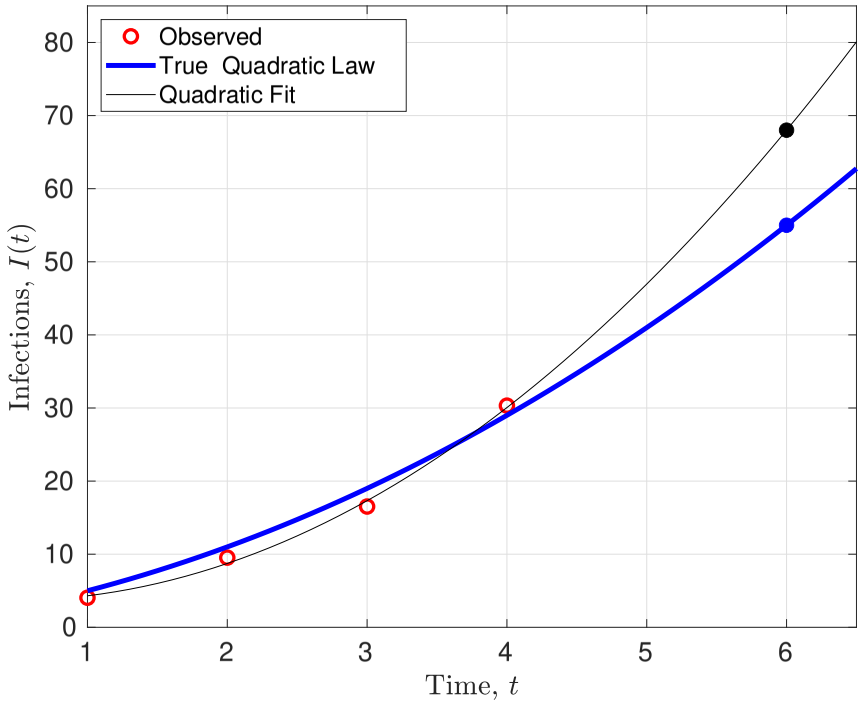
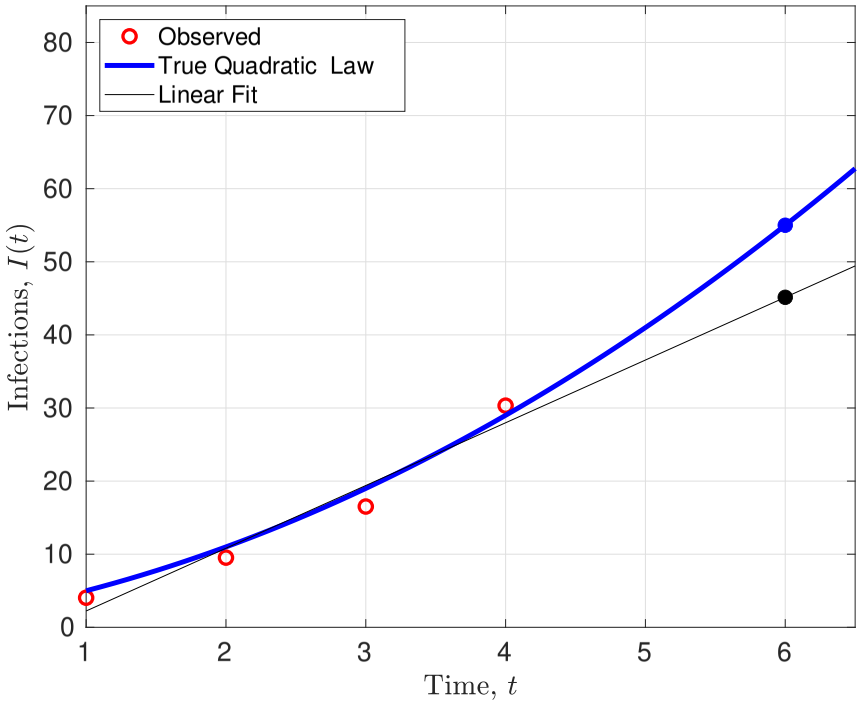


Linear Fit + Extrapolate



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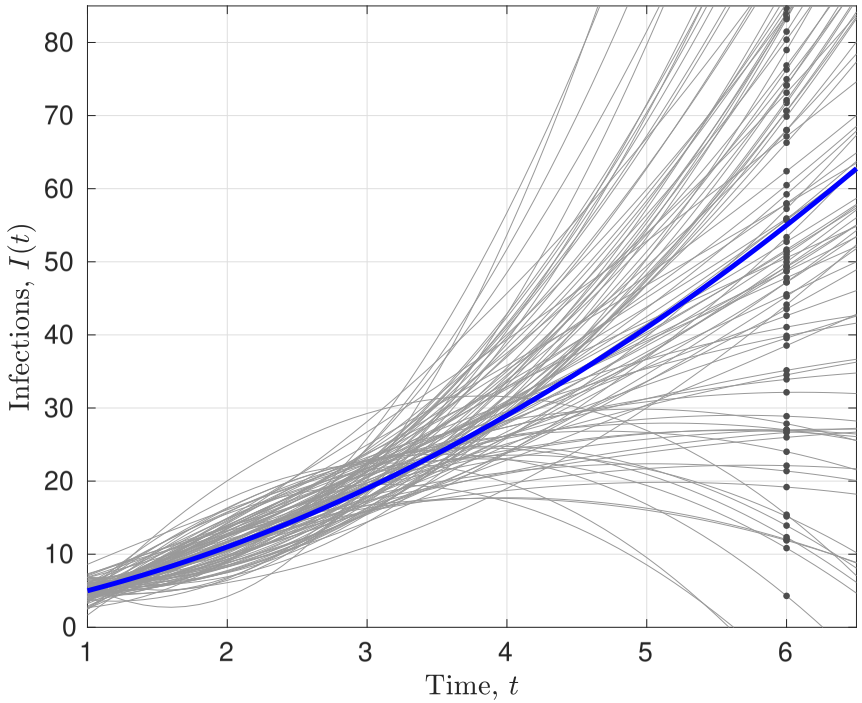
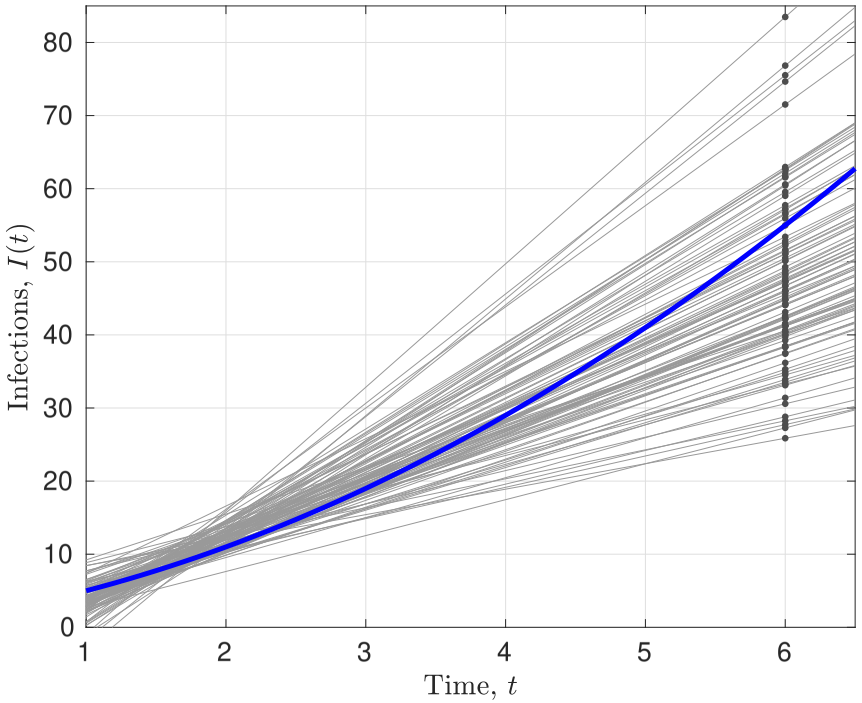


$E_{\text{out}} \approx 34$

Linear Fit + Extrapolate

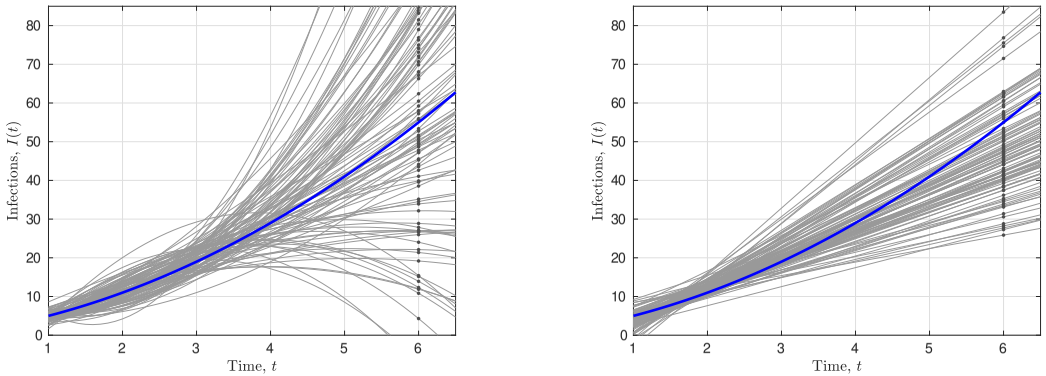


$E_{\text{out}} \approx 14$ ✓

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, ...

A Stunning Nugget From The Theory of Learning

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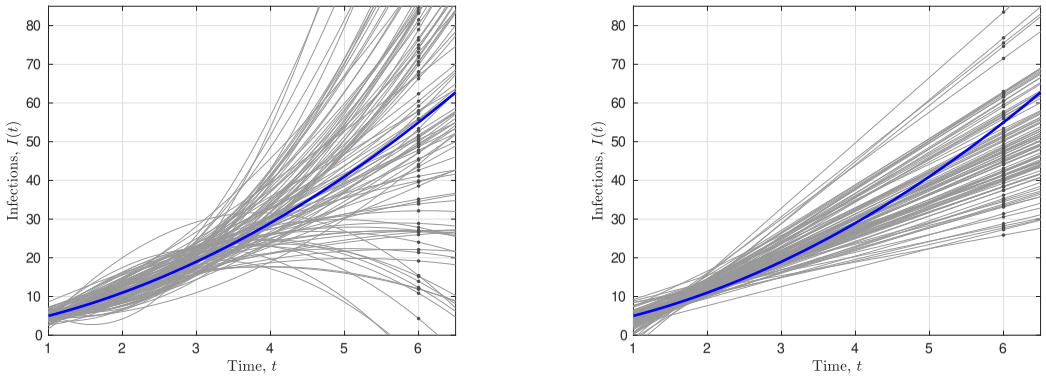
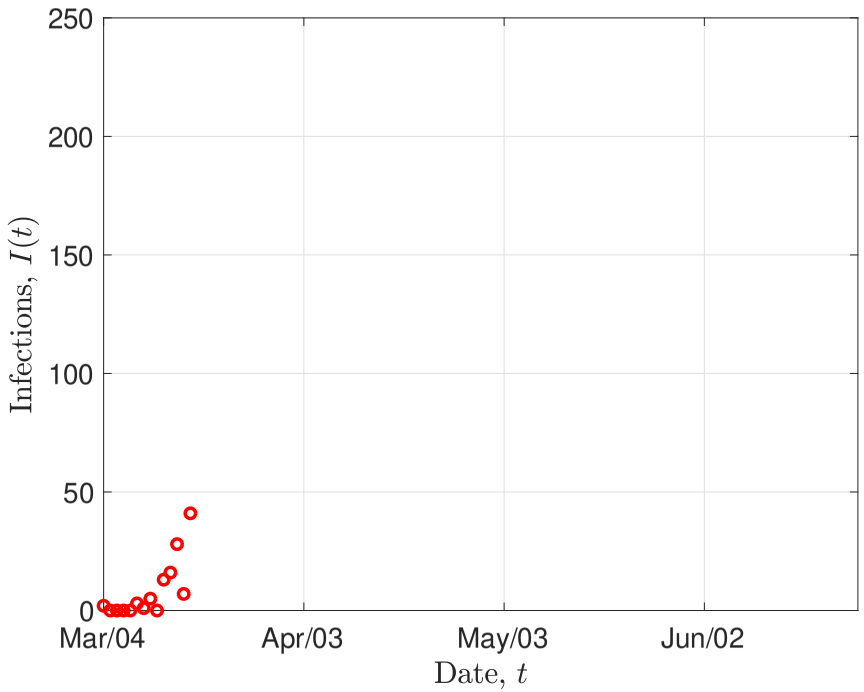


What we would like to learn versus what we *can* learn.

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



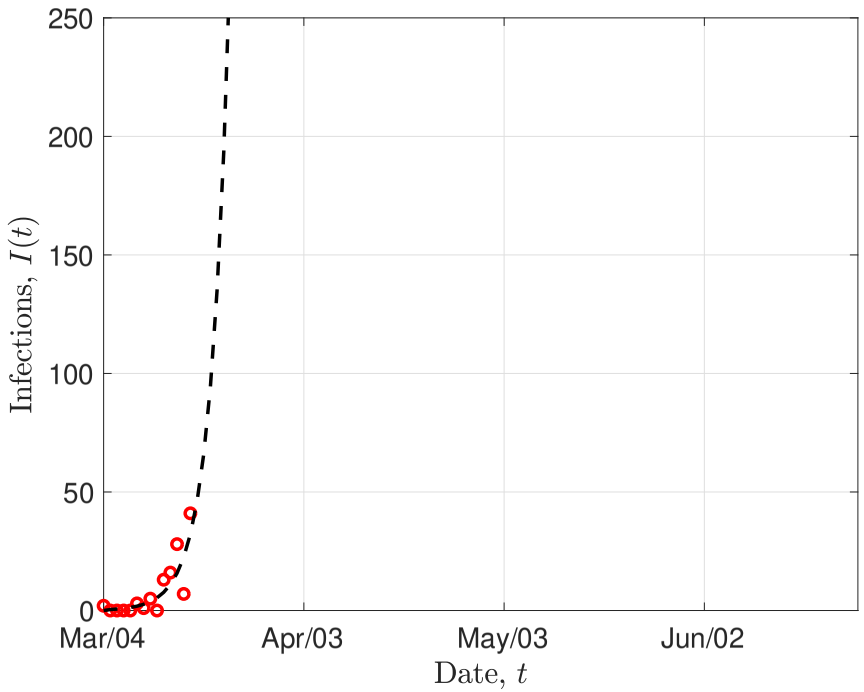
How quickly is it spreading?

How large is the pasture?

Capital District $\sim$ 1M.

- Extrapolation is hard.

Let's Predict For The Capital District



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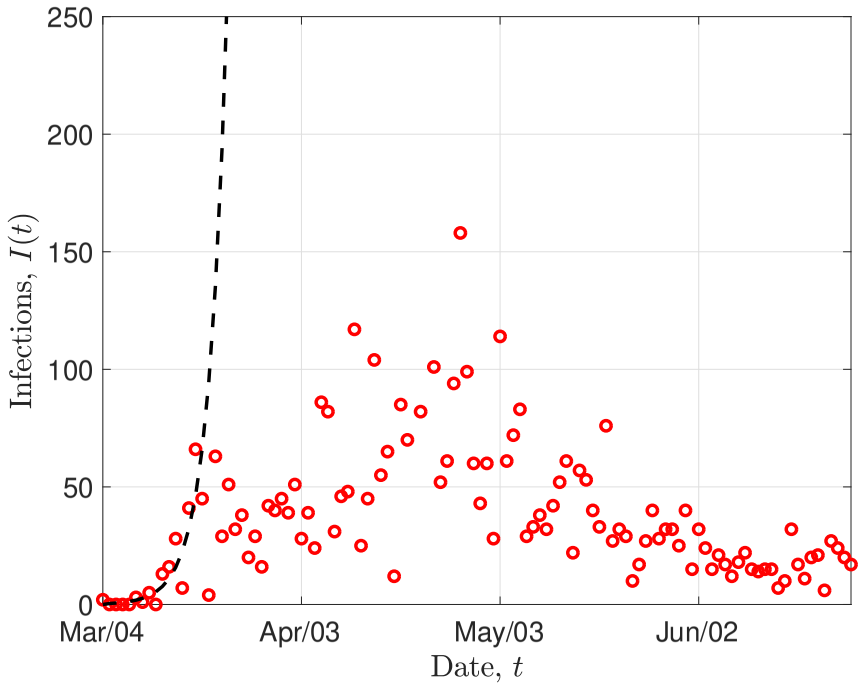

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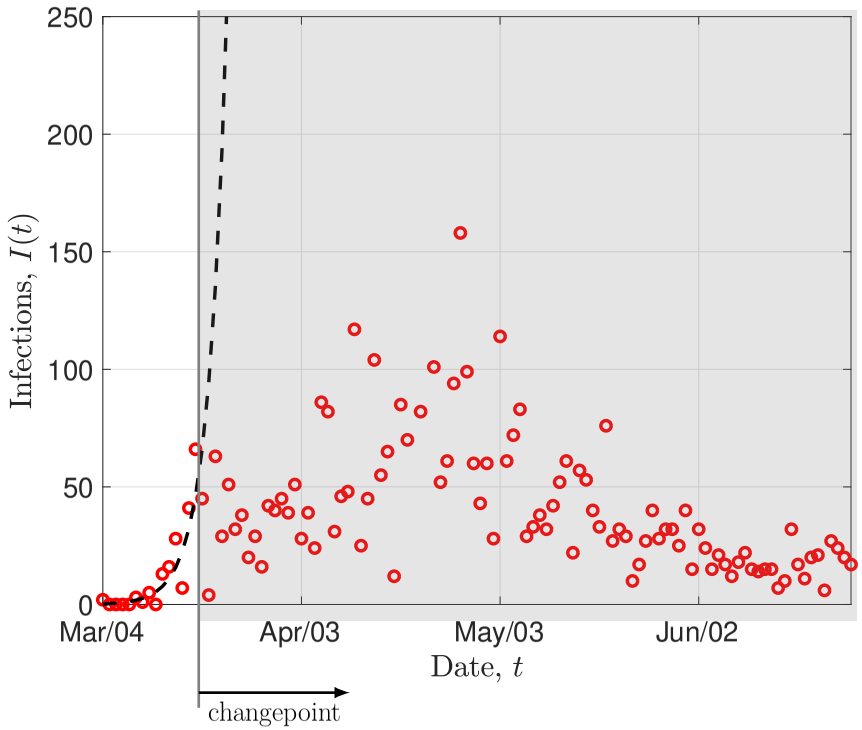
Disaster!

Let's Predict For The Capital District



How quickly is it spreading?

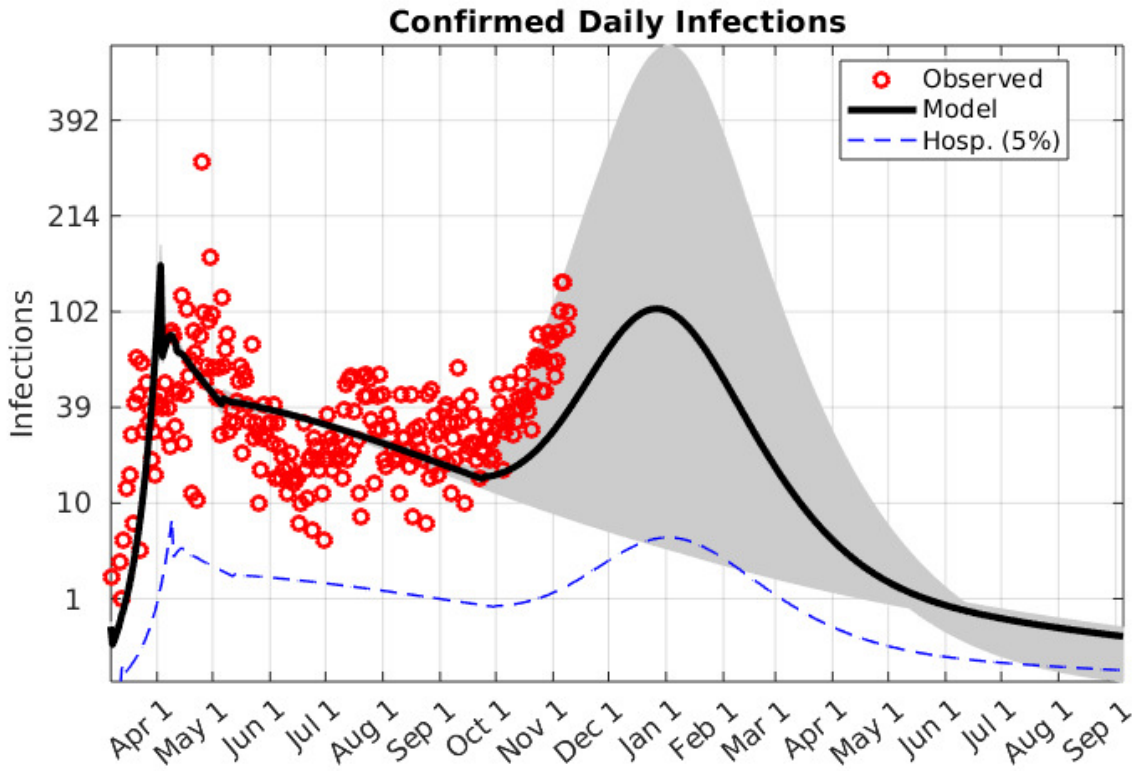
How large is the pasture?

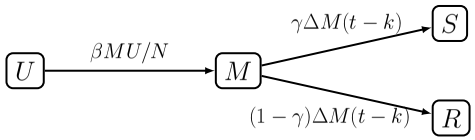
Capital District $\sim$ 1M.

- Extrapolation is hard.
- Changepoints make it impossible.

Disaster!

Keep It Simple, Really Simple. But, Adaptive



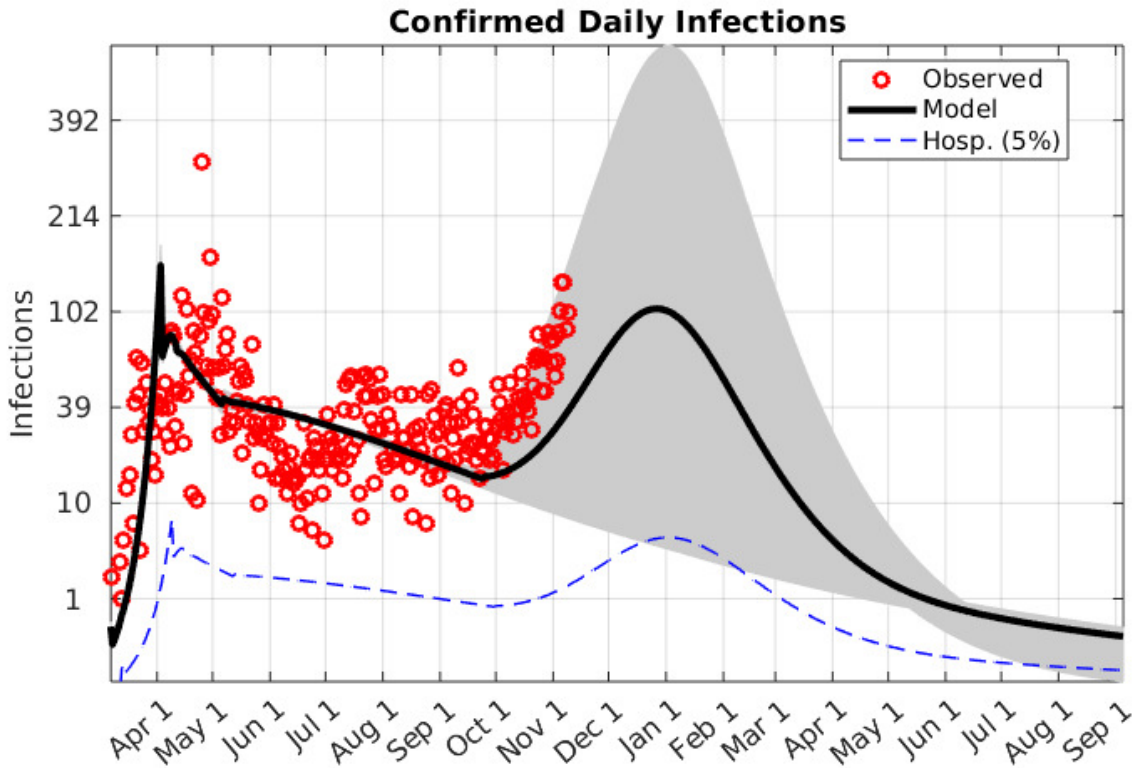


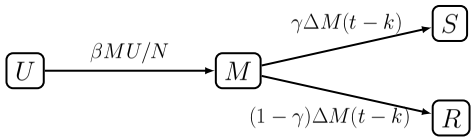
U: Uninfected.
M: Contagious.
S: Symptomatic.
R: Recovered.

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

1.
2.
3.

Keep It Simple, Really Simple. But, Adaptive





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Robust changepoints.

1. Robustly determine changepoints.
2.
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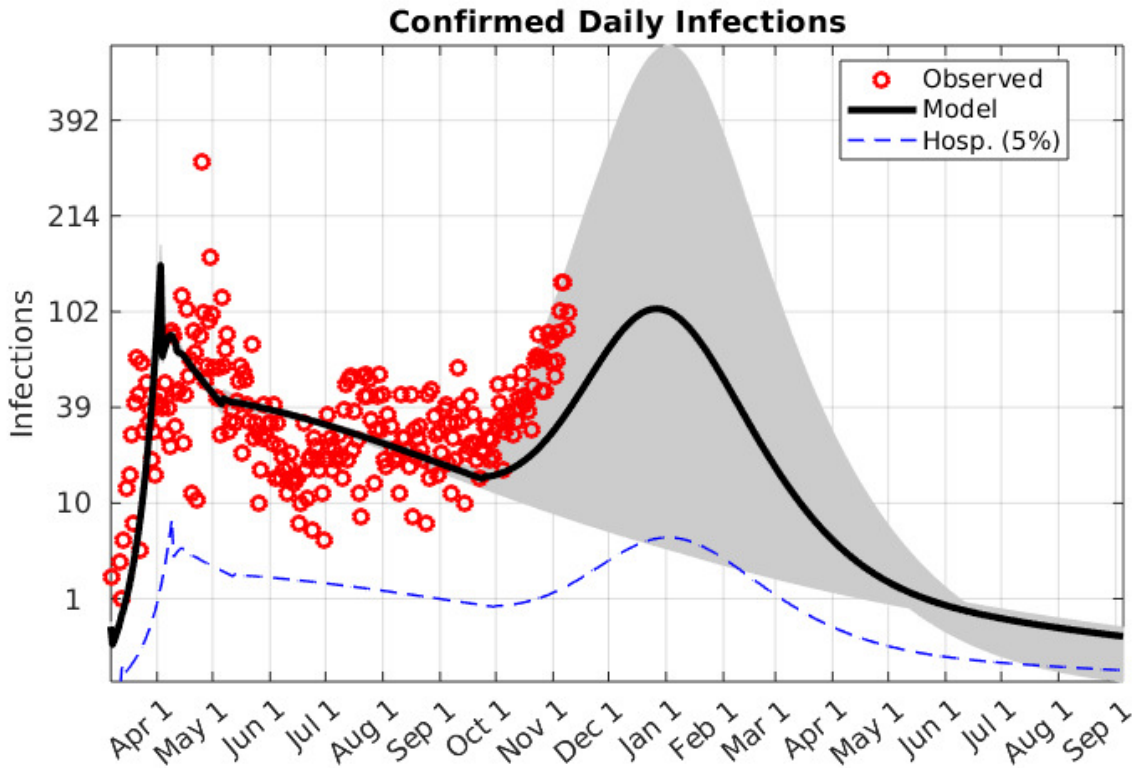

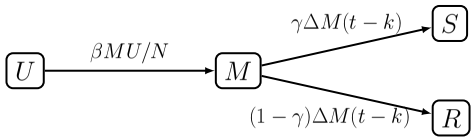

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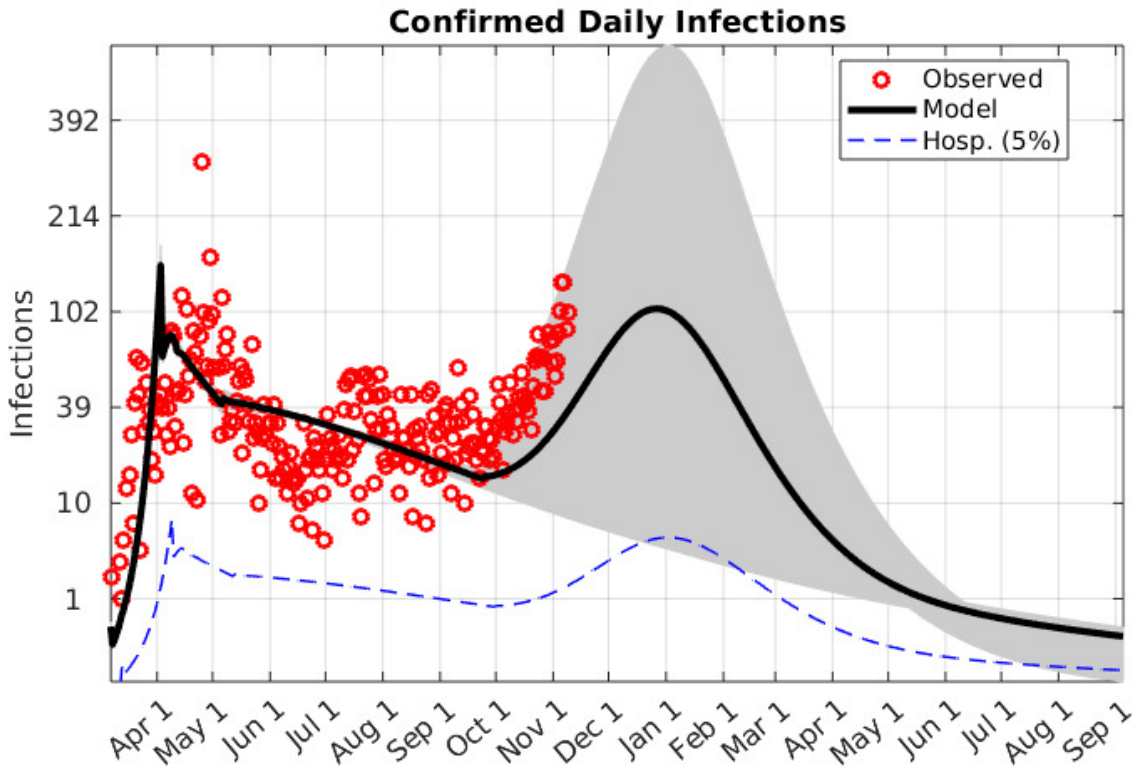
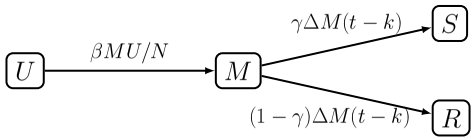
1. Robustly determine changepoints.
2. Robustly fit. Gray is uncertainty.
3.

Keep It Simple, Really Simple. But, Adaptive





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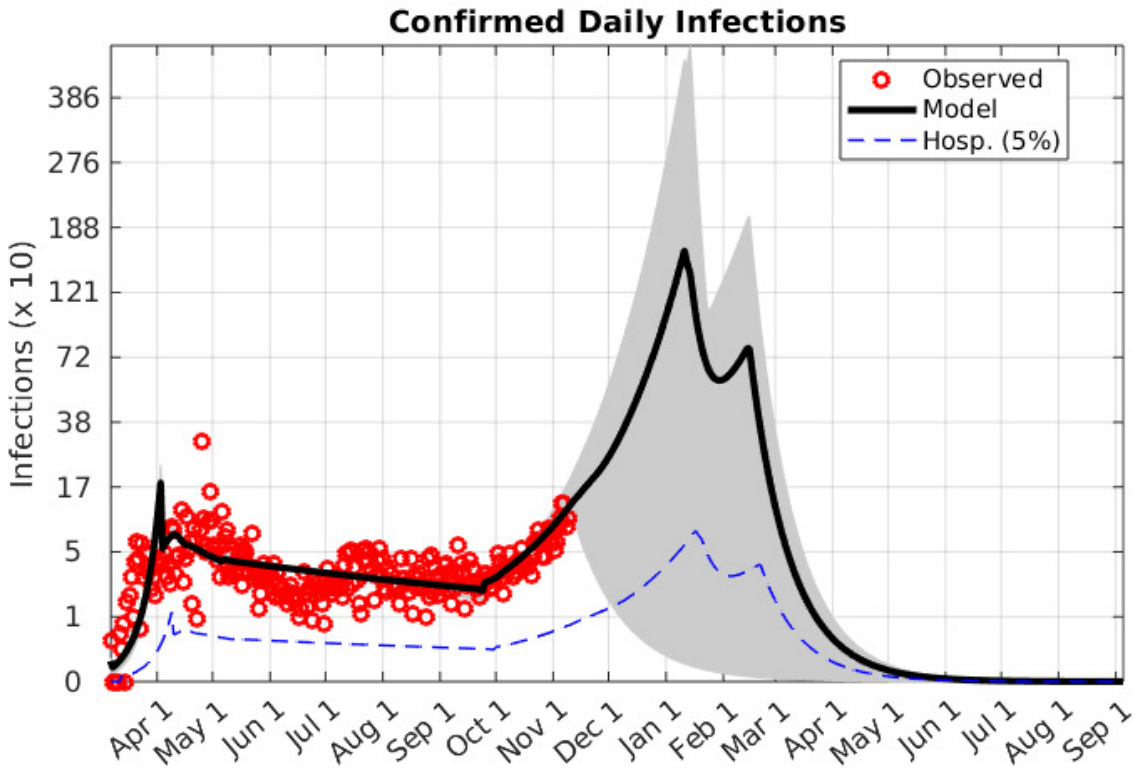
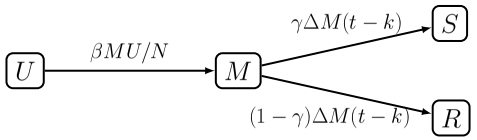
1. Robustly determine changepoints.
2. Robustly fit. Gray is uncertainty.
3. State persists across changepoints.

Keep It Simple, Really Simple. But, Adaptive





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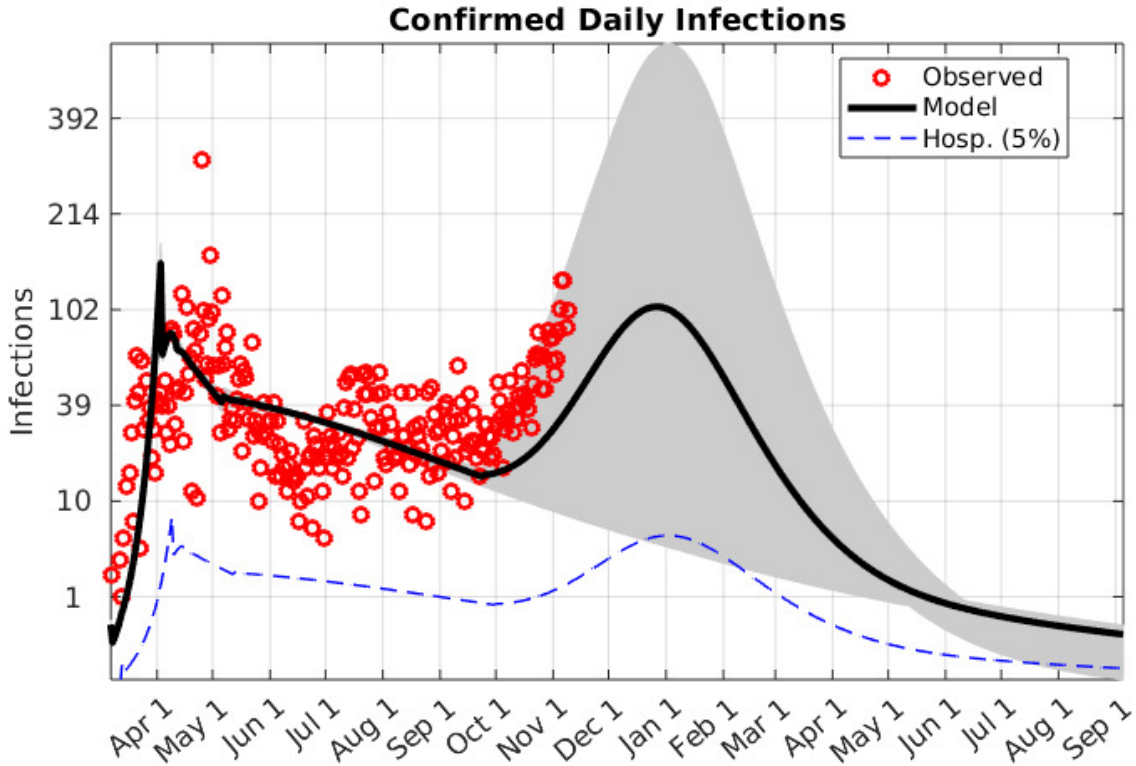
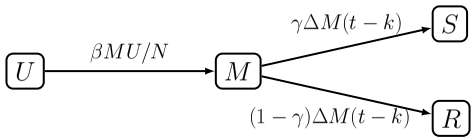
How: Even simpler analytic model pre-calibrates.

Keep It Simple, Really Simple. But, Adaptive





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Parameters:
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Robust changepoints.

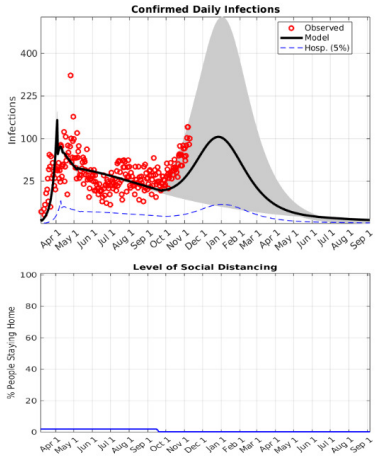
- **We get current state:**

  Infected and contagious. Immune. Social distancing.

- **Predictions assuming stabilized behavior.**

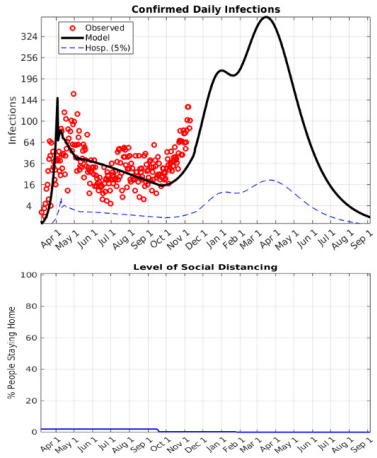
Capital District

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

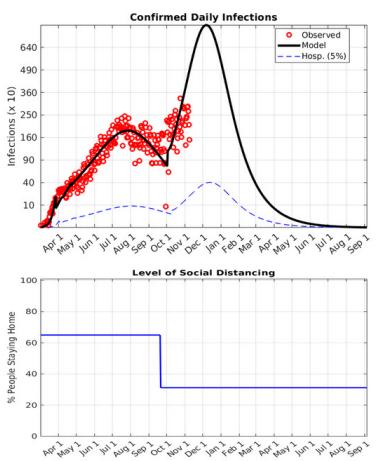
Phased Open (target 500 daily infections)



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

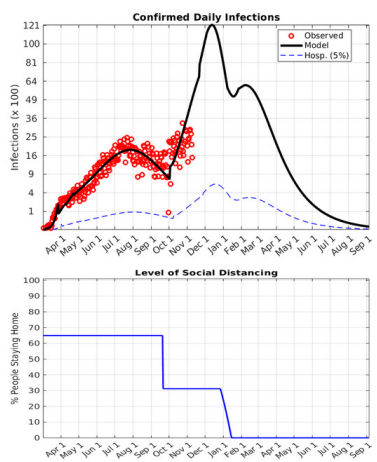
North Carolina

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)

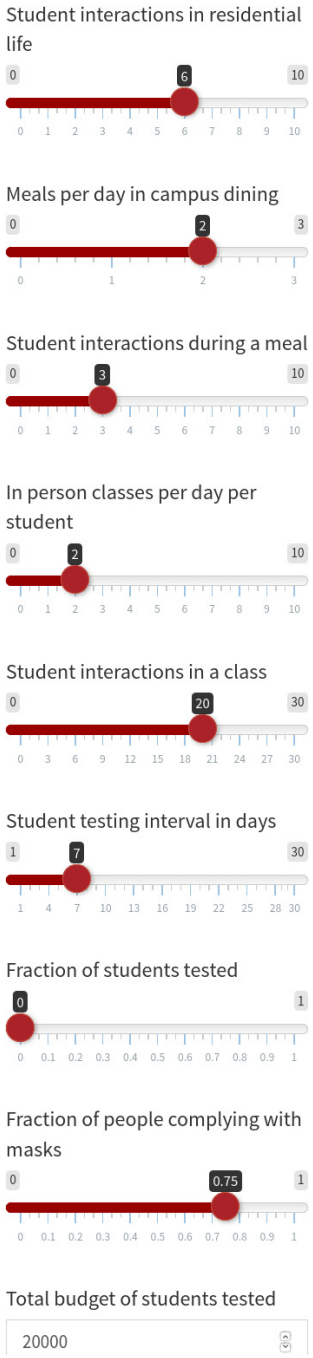


population	10,488,084
confirmed infections	294,857
total infections (model)	1,902,553
infectious (model)	3.4063%
immunity (model)	14.7339%
fatalities	4,615
fatality rate (model)	0.243%
confirmed infections, Dec 31	788,645
total infections, Dec 31	4,402,542
infectious, Dec 31	3.7023%
immunity, Dec 31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

All US Counties. All Countries.

COVID-Back-To-School

https://covidspread.idea.rpi.edu



Who's bringing covid to campus?

Ambient county infection rate?

} COVID-War-Room

Jan 19:

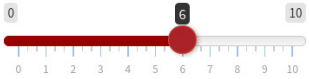
~24 cases,

~20% immunity.

COVID-Back-To-School

https://covidspread.idea.rpi.edu

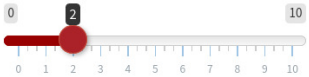
Student interactions in residential life



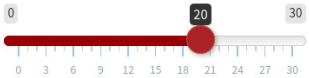
Meals per day in campus dining

Student interactions during a meal

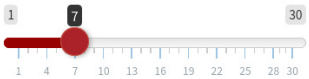
In person classes per day per student



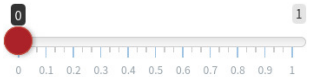
Student interactions in a class



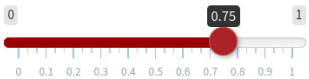
Student testing interval in days



Fraction of students tested

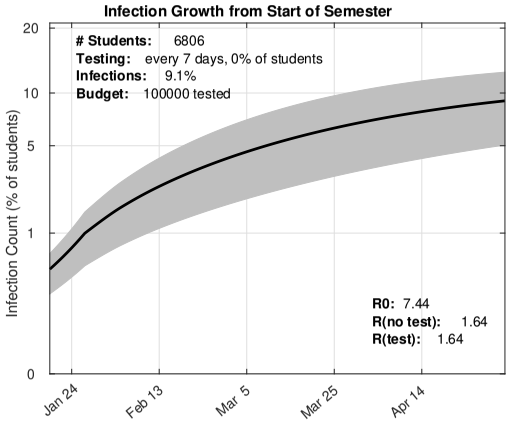


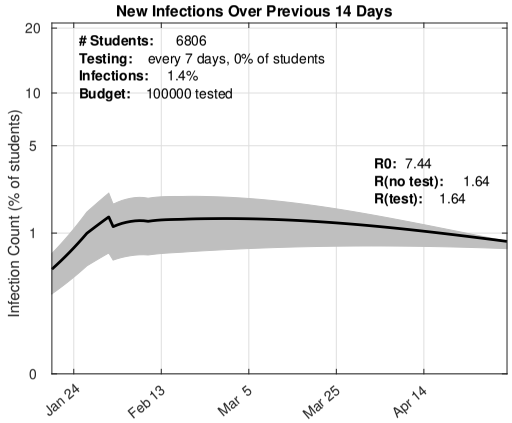
Fraction of people complying with masks



Total budget of students tested

20000





COVID-Back-To-School

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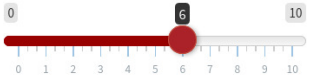
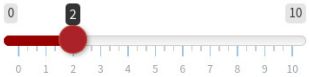
Student interactions in residential life



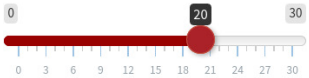
Meals per day in campus dining

Student interactions during a meal

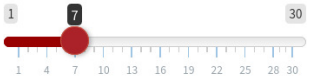
In person classes per day per student



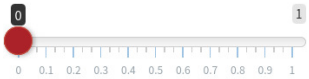
Student interactions in a class



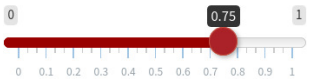
Student testing interval in days



Fraction of students tested

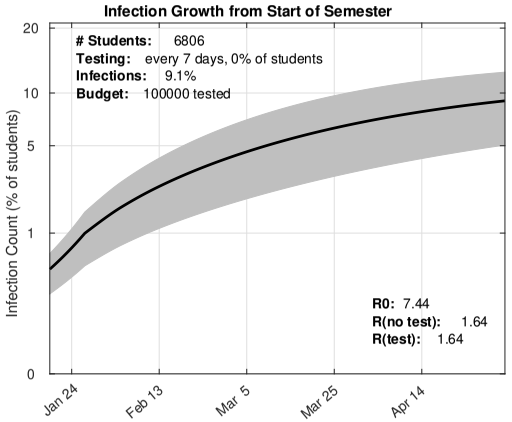


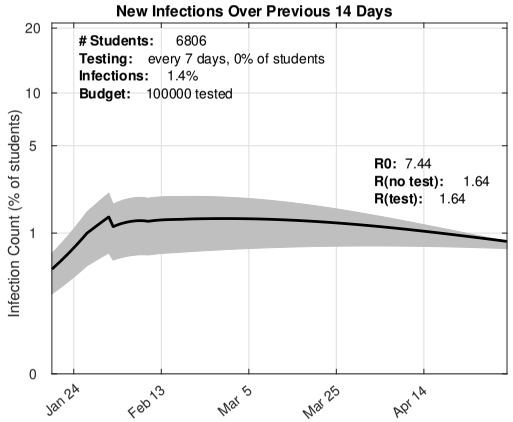
Fraction of people complying with masks

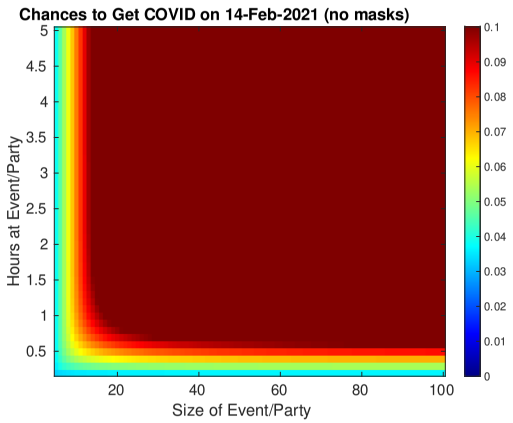


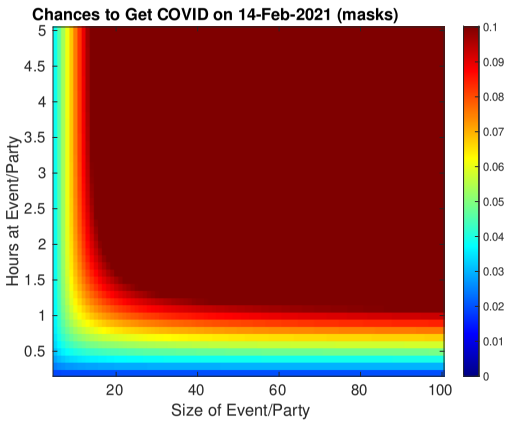
Total budget of students tested

20000









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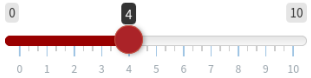
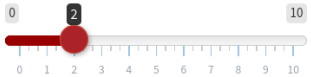
Student interactions in residential life

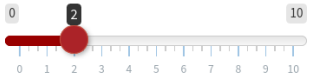


Meals per day in campus dining

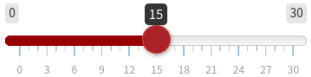
Student interactions during a meal



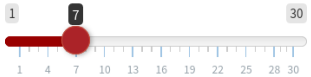
In person classes per day per student



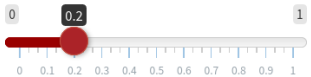
Student interactions in a class



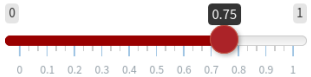
Student testing interval in days



Fraction of students tested

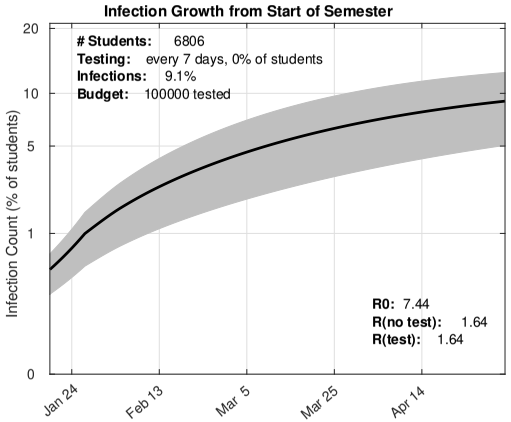


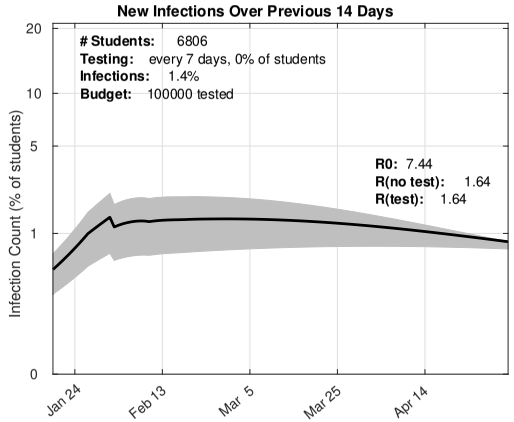
Fraction of people complying with masks

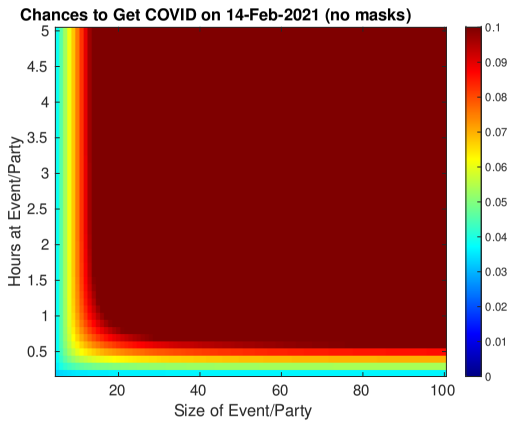


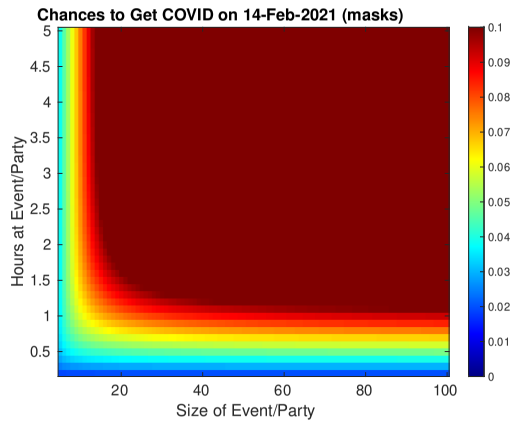
Total budget of students tested

100000









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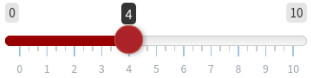
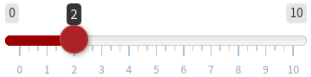
Student interactions in residential life

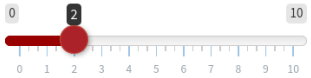


Meals per day in campus dining

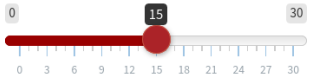
Student interactions during a meal



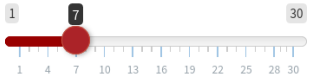
In person classes per day per student



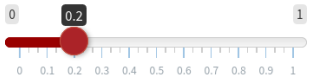
Student interactions in a class



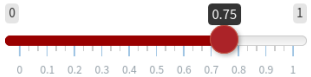
Student testing interval in days



Fraction of students tested

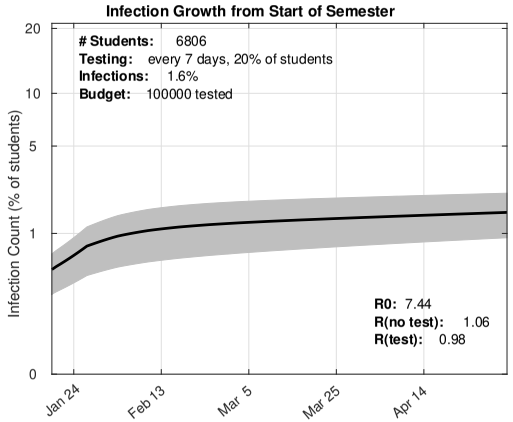


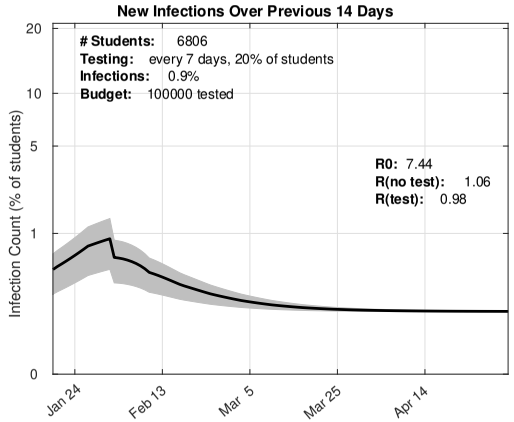
Fraction of people complying with masks

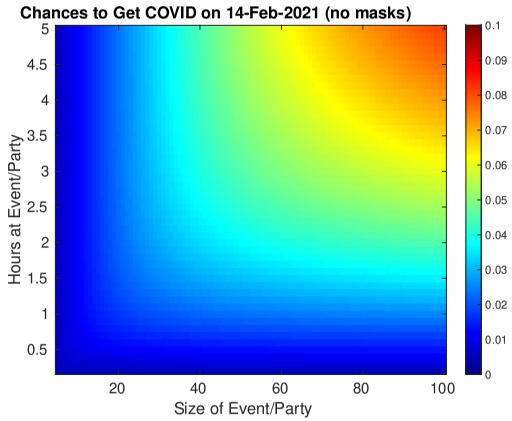


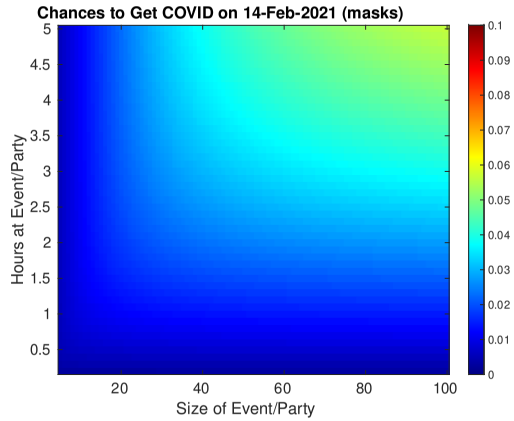
Total budget of students tested

100000









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