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TEXAS

The University of Texas at Austin

# HPC for epidemic modeling with limited data: COVID-19 Case Studies

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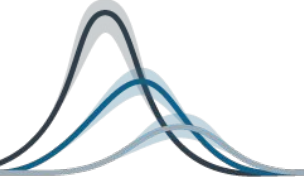
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ECSS Symposium | March 16, 2021

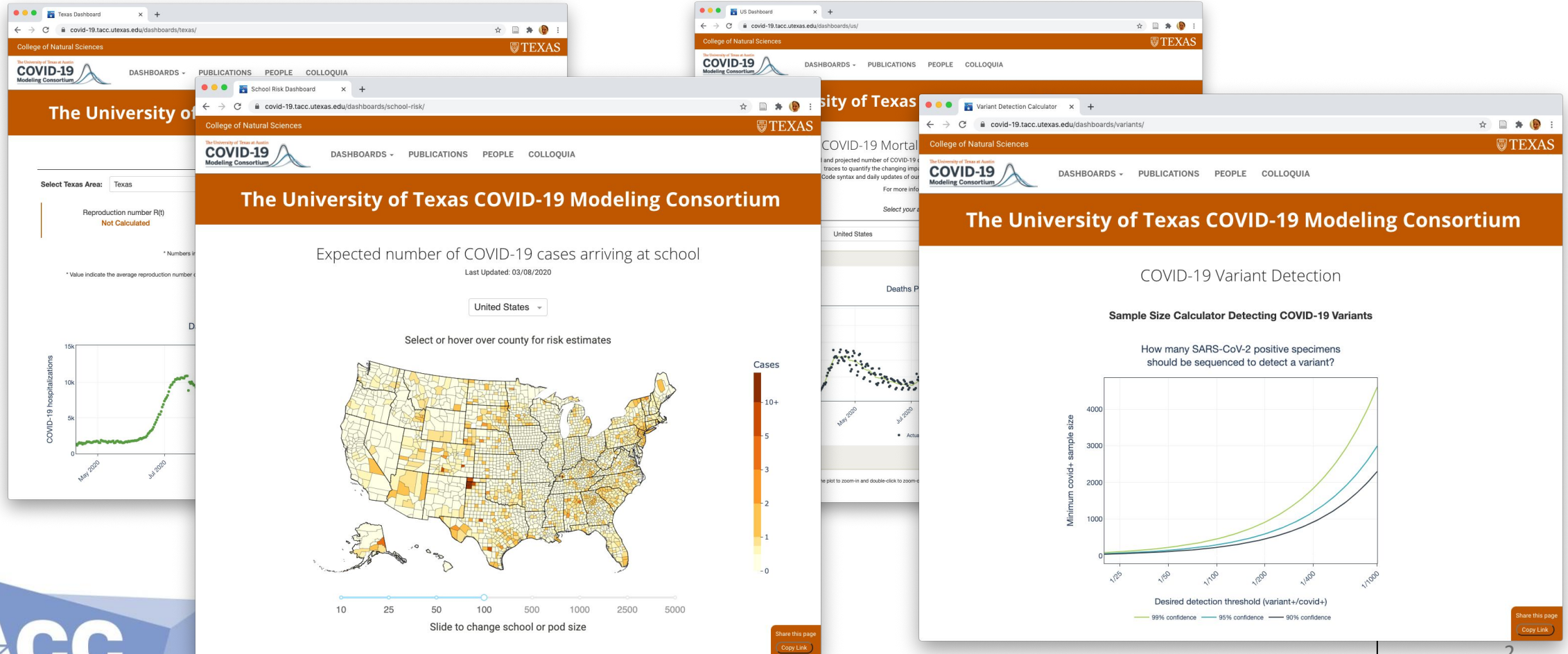
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# COVID-19 Modeling Consortium



# Situational awareness models

public facing dashboards at <https://covid-19.tacc.utexas.edu/>



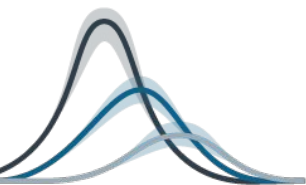
# Conclusions after 1 year of COVID-19

- Small amounts of data can provide crucial insights when used carefully
- Public health data collection, aggregation and dissemination have changed dramatically in the last 12 months (but need more investment)
- HPC and HPC Centers support fast iteration and short turn-around on research and production models

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# COVID-19

Modeling Consortium



# TEXAS

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<https://covid-19.tacc.utexas.edu/>

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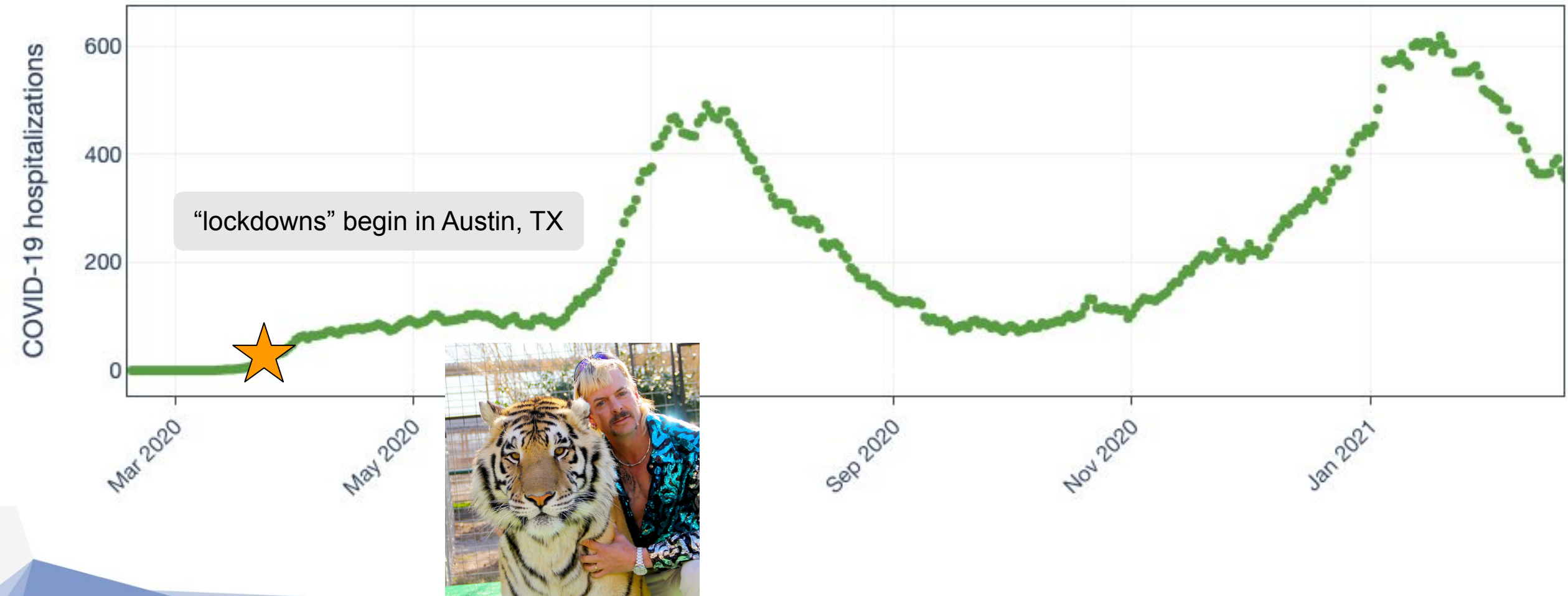
## Consortium Affiliates

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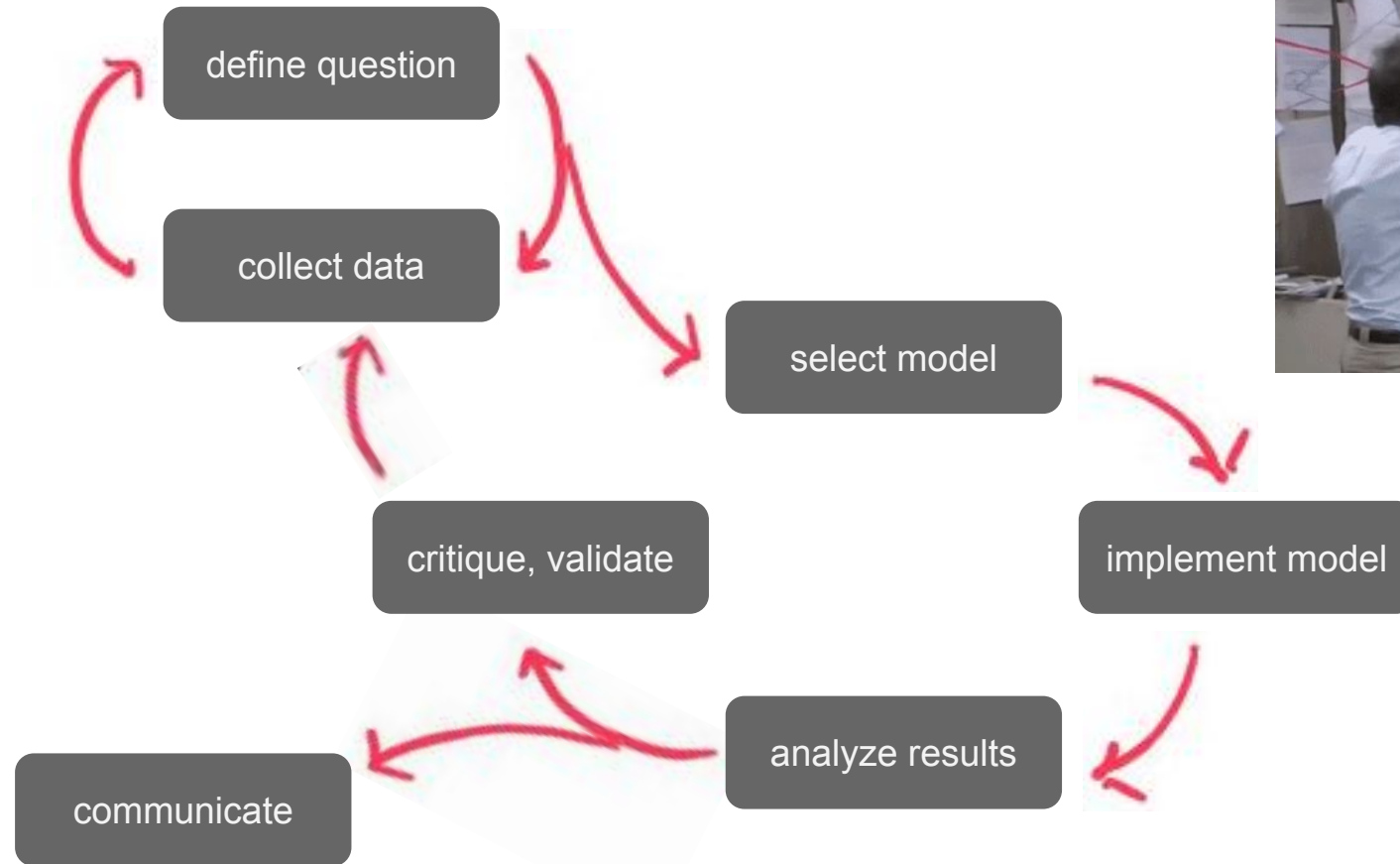
# TACC

# Modeling the first wave

## Daily COVID-19 Hospitalizations in the Austin-Round Rock MSA



# Modeling the first wave: model life cycle





**Dr. Anne Marie Darling** @amdar1ing · Mar 11, 2020

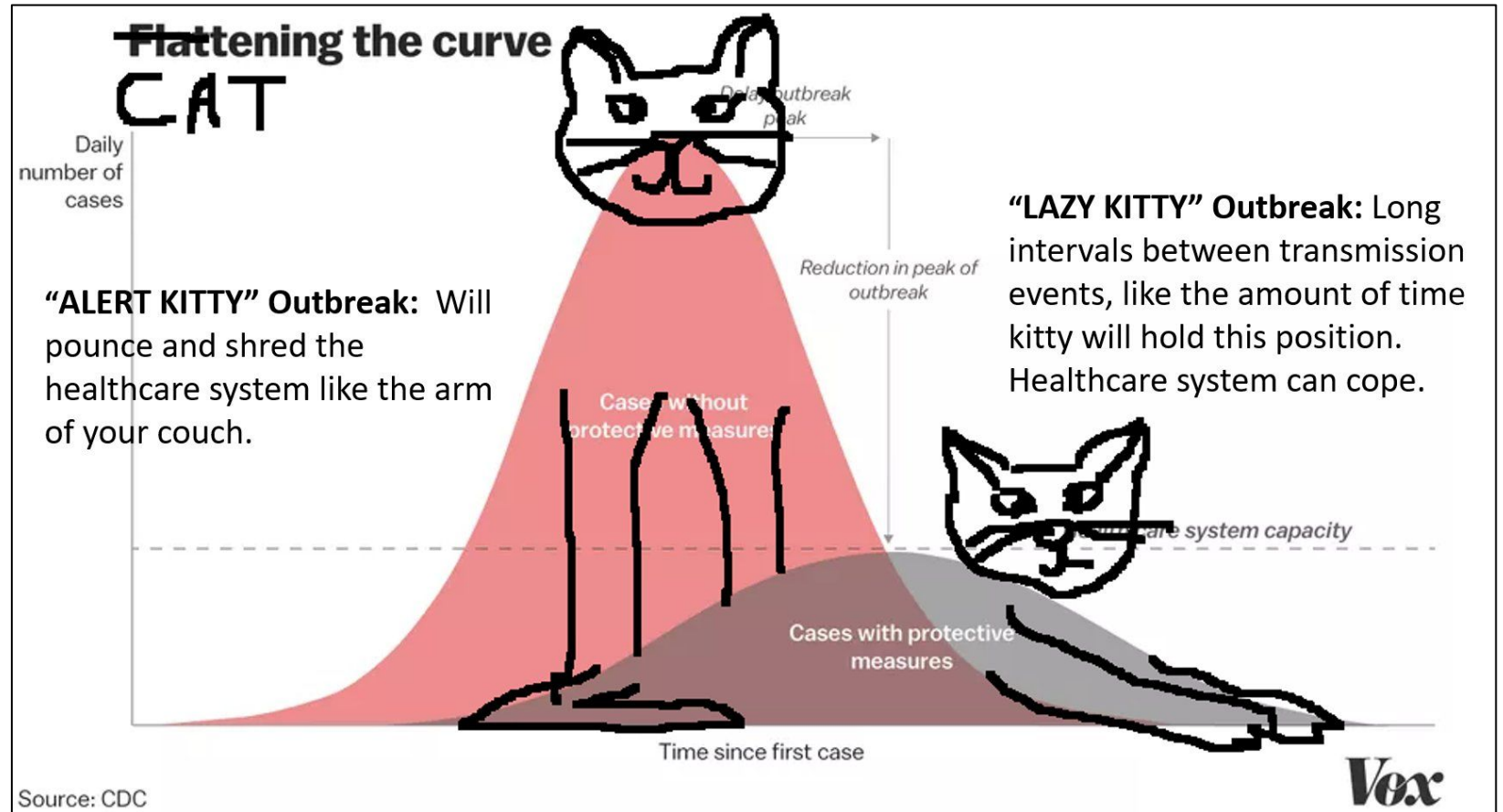
Lots of science-y folks are posting this graph. But if there is one thing I have learned from being on the internet, it is this:

Data/graphs: Not compelling to many.

Kitties: Compelling to many.

So I present: [#Catteningthecurve](#).

[#scicomm](#) [#epitwitter](#)



# Are we flat yet? (How bad will this get?)

## *Healthcare demand projections*



Many groups with shared goal:



*Imperial College COVID-19 Response Team*

JOHNS HOPKINS  
UNIVERSITY & MEDICINE

**CORONAVIRUS  
RESOURCE CENTER**



# Are we flat yet? (How bad will this get?)

## *Healthcare demand projections*



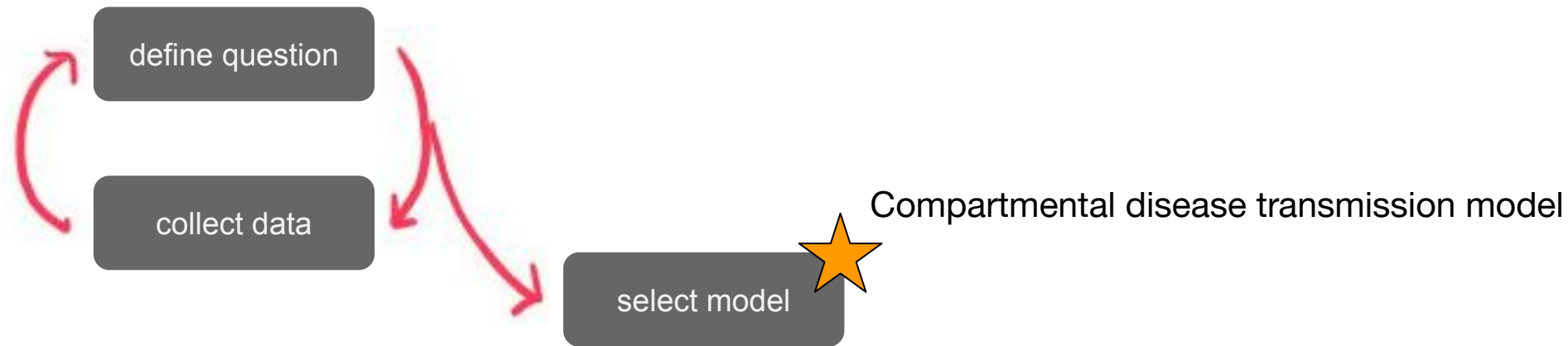
**Rate parameters** are informed by observations from clinical literature and define time course of infection.

**Age-structured contact patterns** are drawn from journal studies and informed by local demographics.

**Risk** of severe outcome and mortality informed by comorbidities data.

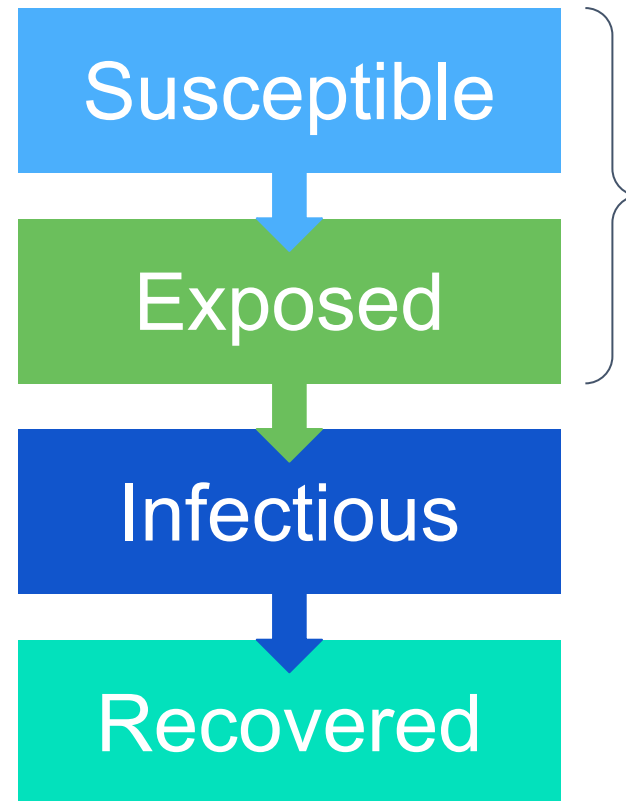
# Are we flat yet? (How bad will this get?)

## *Healthcare demand projections*



# Compartmental disease transmission models

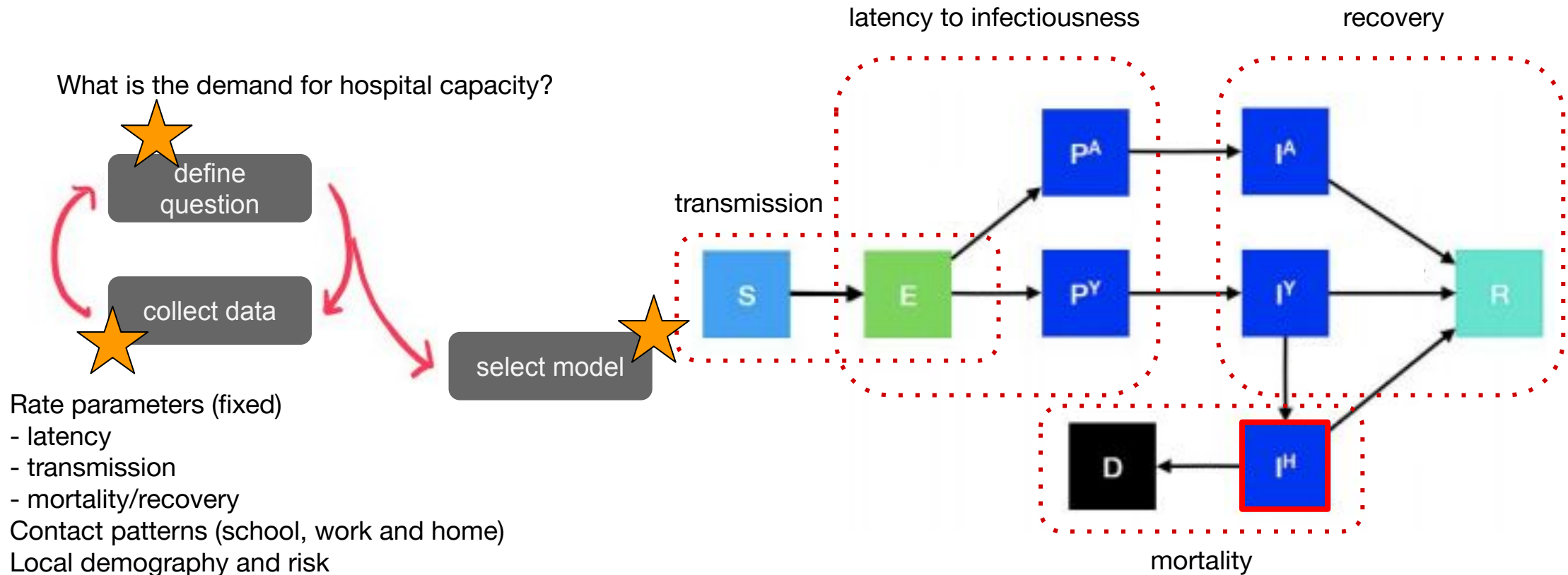
System of equations to track the population in each compartment through time



$$\frac{dS}{dt} = \frac{SI}{N} \beta$$

where  $\beta$  is the per capita per contact probability of transmission from an infected person to a susceptible person

# Healthcare demand projections



# March 26, 2020 Healthcare demand projections

critique,  
validate

communicate

analyze  
results

No social distancing

close schools

50% reduction

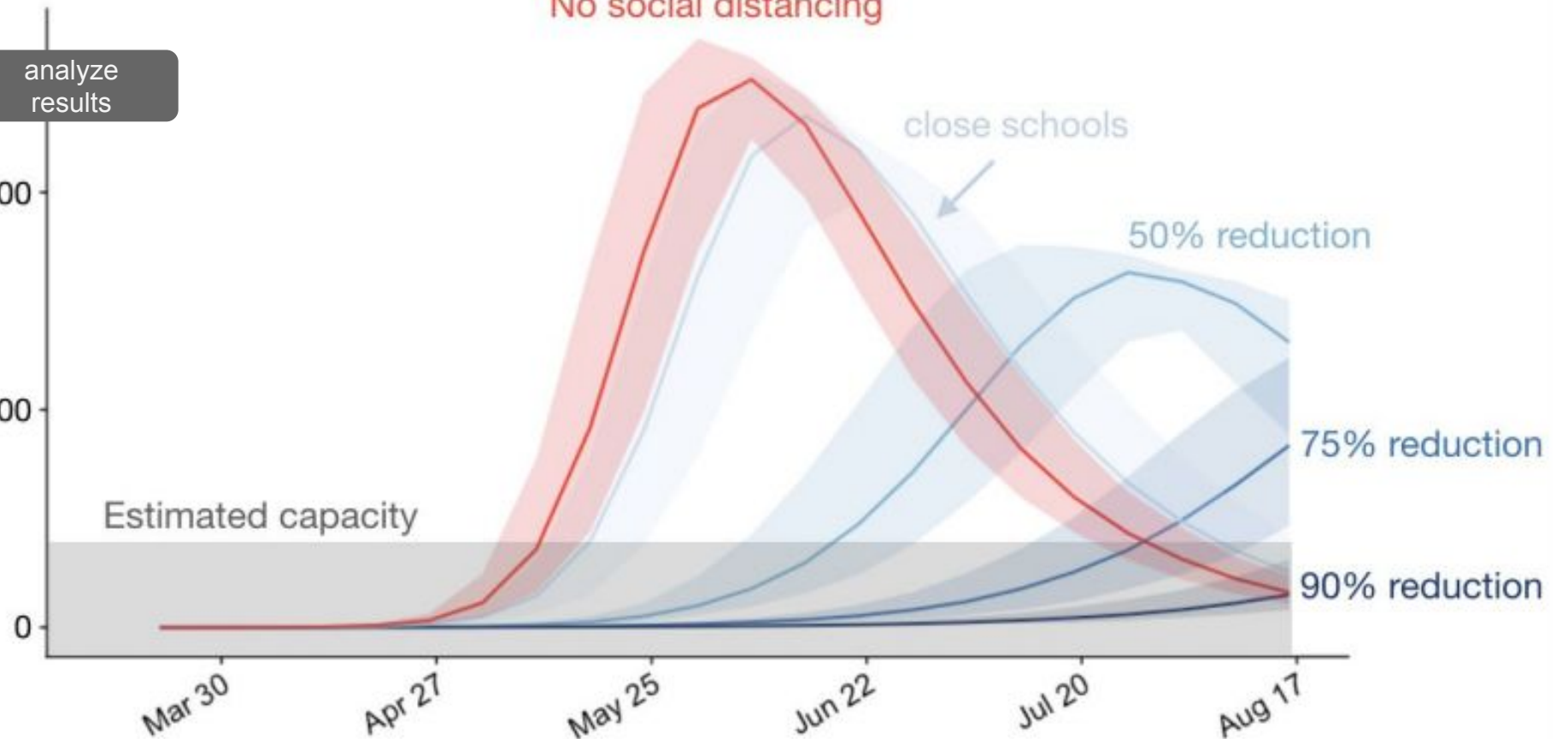
75% reduction

90% reduction

Hospitalizations

Estimated capacity

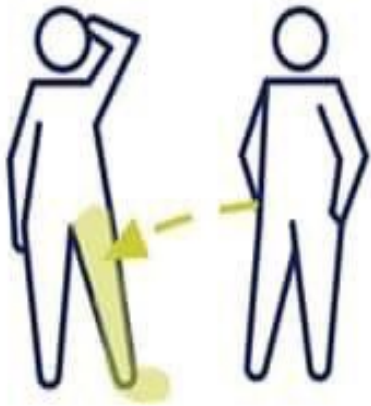
$$\frac{dS}{dt} = \frac{SI}{N}\beta$$



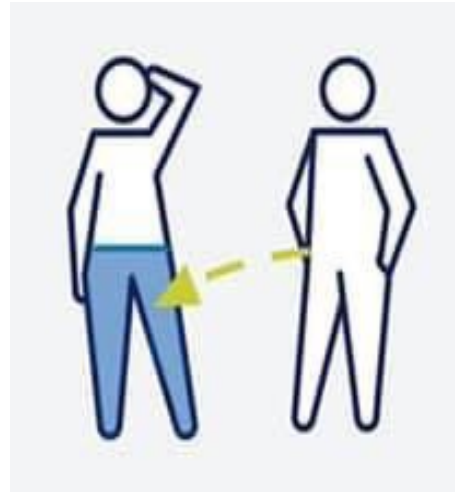
# Behavior impacts transmission probability

critique,  
validate

analyze  
results



high transmission

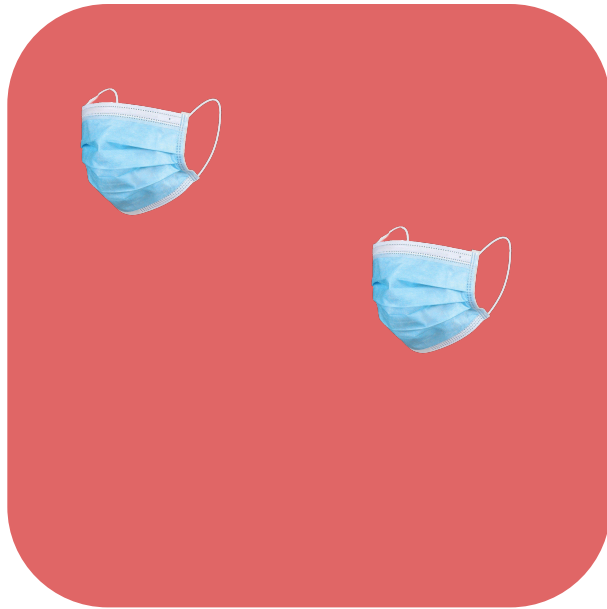


medium  
transmission



low  
transmission

# Behavioral norms (and intervention policies) have evolved over time



high  $\beta$



medium  $\beta$

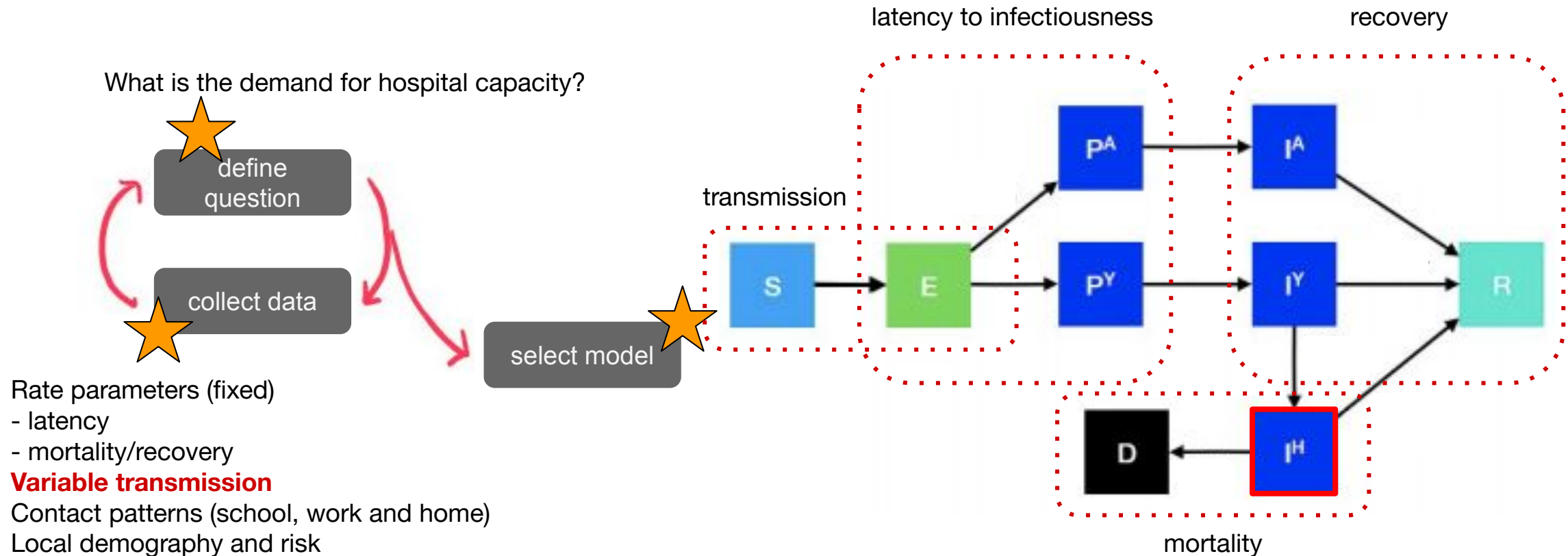


low  $\beta$



time

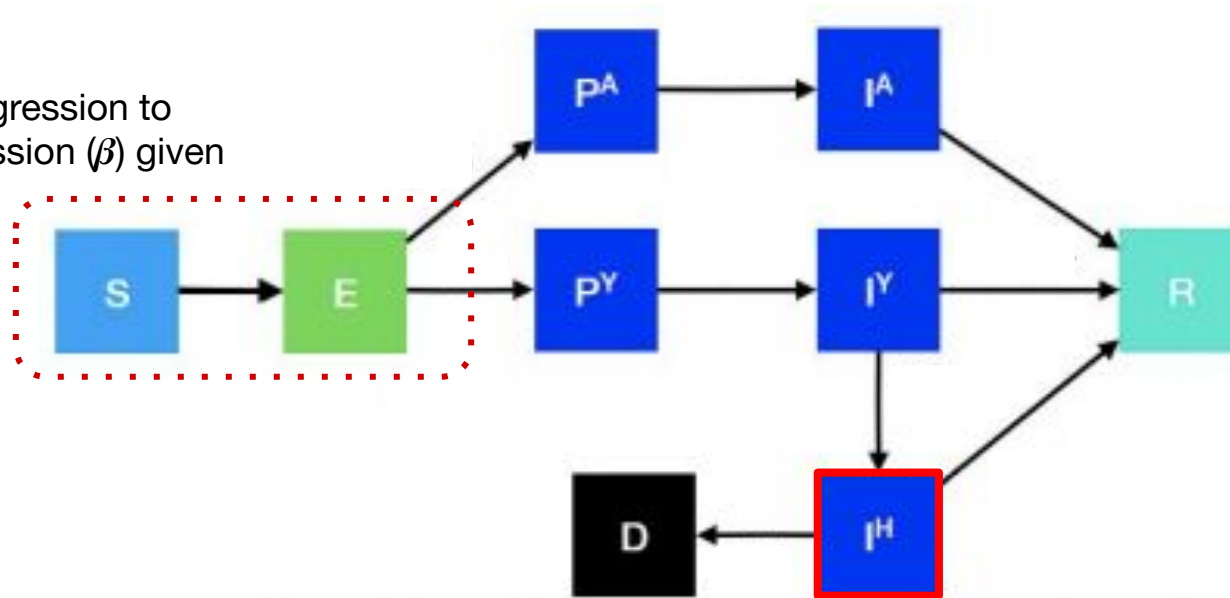
# Update model and data



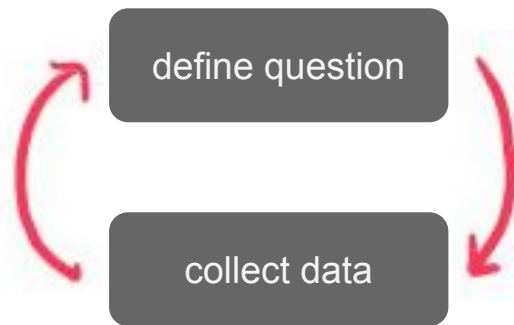
# Estimating transmission probability, $\beta$

What transmission probability would produce the observed hospitalizations?

Least squares regression to estimate transmission ( $\beta$ ) given hospitalizations



# Estimating $\beta$ as a function of available data



Possible Questions (what will happen?)	Informative Data (what has happened?)
How many infections do we expect?	How many cases have been reported? <ul style="list-style-type: none"><li>• Are suspected cases being tested?</li><li>• Do testing policies bias case reports?</li></ul>
How many hospitalizations do we expect?	How many have been hospitalized with COVID-19?
How many deaths do we expect?	How many deaths have been attributed to COVID-19?

# Stepwise transmission probability estimation

1. Estimate baseline transmission probability for a time period with
  - known hospital census (“heads in beds”)
  - no intervention policies
2. Estimate transmission reduction for subsequent time period with
  - known hospital census
  - constant(ish) intervention policy

# Hospitalizations as a new, key metric in pandemic surveillance

- Reliable but lagged
  - only true COVID-19 cases are reported
  - it takes on approx. 7 days between infection and hospitalization
- Incomplete but actionable
  - many COVID-19 cases do not produce severe infection
  - no standardized reporting infrastructure for hospitalizations
  - hospital demand projections inform resource allocation and planning
- Proxy for **severe** SARS-CoV-2 infection

# Update model and data

What is the demand for hospital capacity?



Rate parameters (fixed)

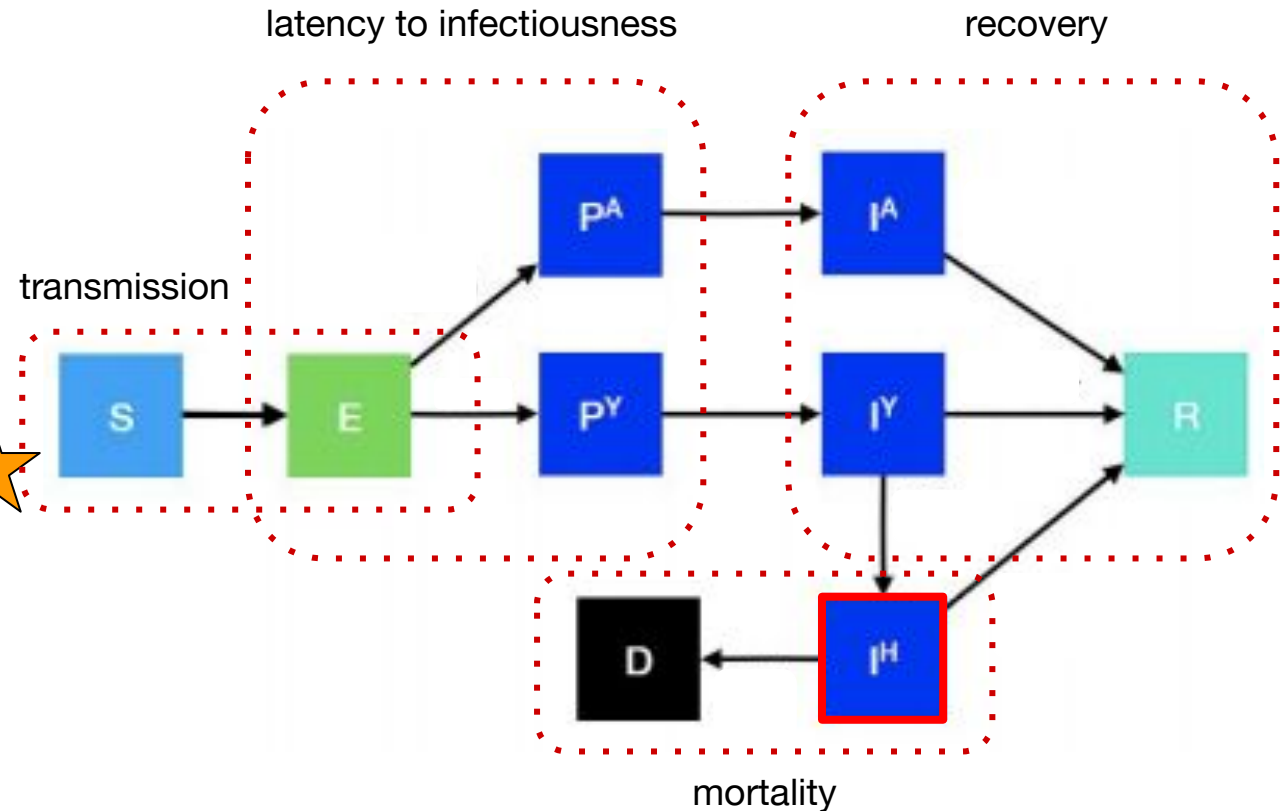
- latency
- mortality/recovery

**Variable transmission**

Contact patterns (school, work and home)

Local demography and risk

**Hospital census**

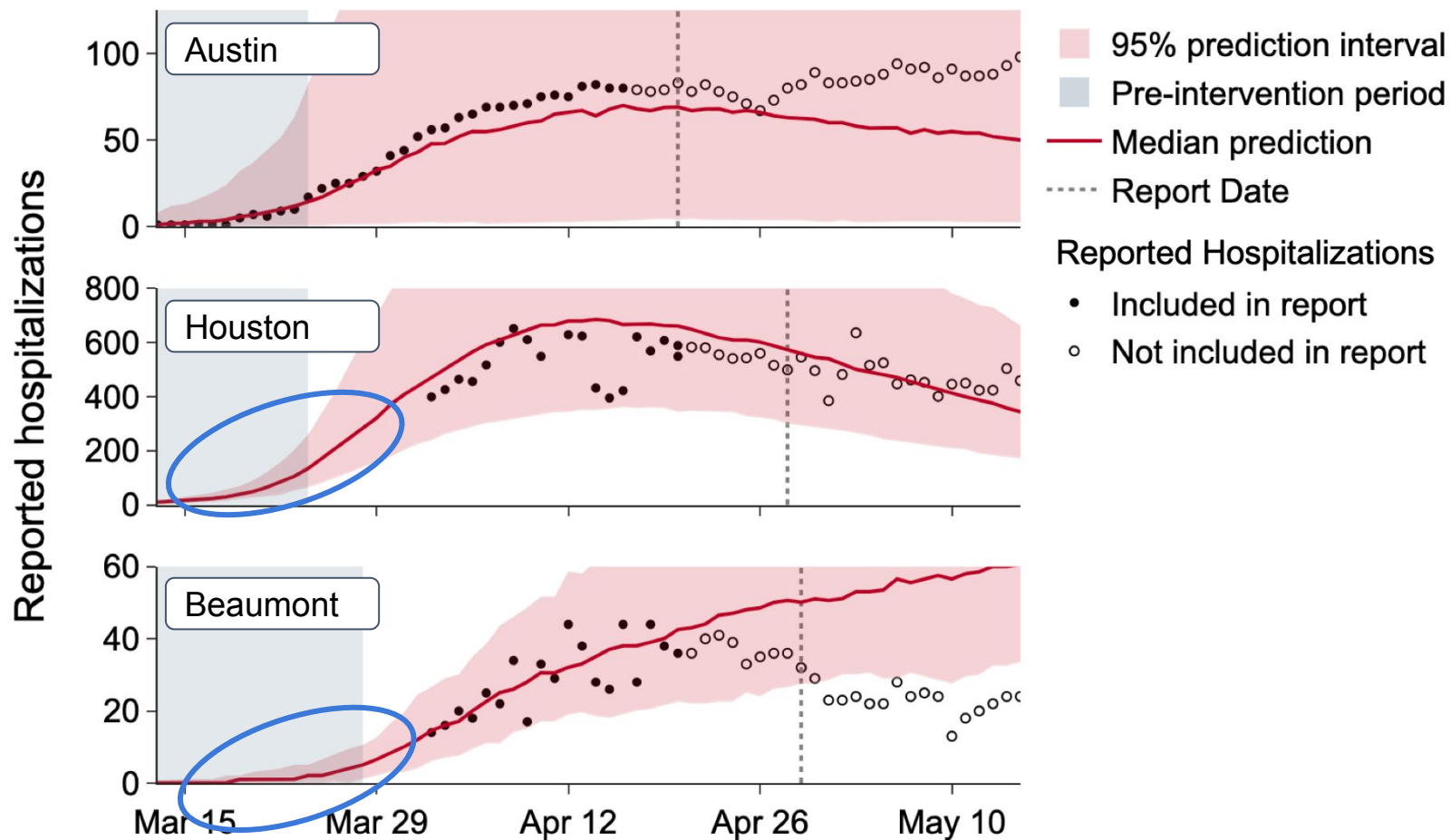


# Stepwise transmission probability estimation

Daily COVID-19 Hospitalizations in the Austin-Round Rock MSA



# April 20, 2020 Healthcare demand projections



# Impact of HPC on projection turn-around

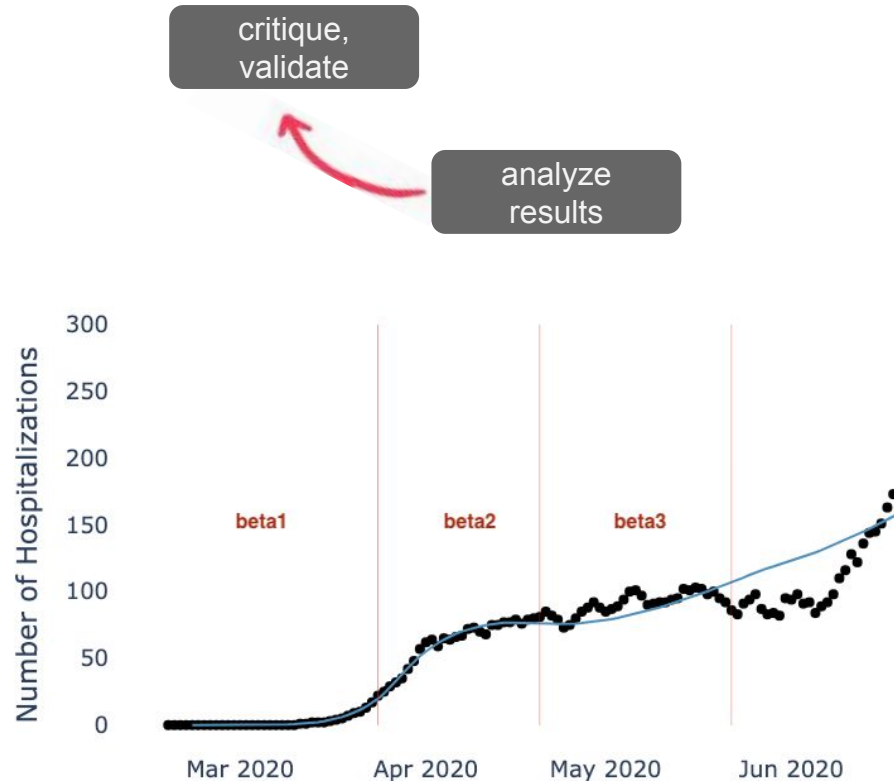
**TABLE 1.** Model run types and wall clock times.

Run type	N runs	Single core wall clock time (s) <sup>a</sup>	Single node wall clock time (s) <sup>b</sup>
Deterministic fitting	30	189	189
Stochastic	2100	6.31	240
Hybrid	4300	12.6	968
Total	6330	208	1397

<sup>a</sup>Average single core wall clock time on Frontera Intel Xeon Platinum 8280 from 10 benchmark runs.

<sup>b</sup>Average wall clock time multiplied by the number of 56 core Intel Xeon Platinum 8280 nodes required for the run volume specified.

# The problem with stepwise transmission



<https://www.texastribune.org/2020/07/31/coronavirus-timeline-texas/>

March 6, 2020 6 confirmed cases

**Austin officials cancel SXSW**

March 13, 2020 50 confirmed cases

**Governor declares statewide emergency**

March 31, 2020 3,266 confirmed cases

**Governor tells Texans to stay home, closes schools until May 4**

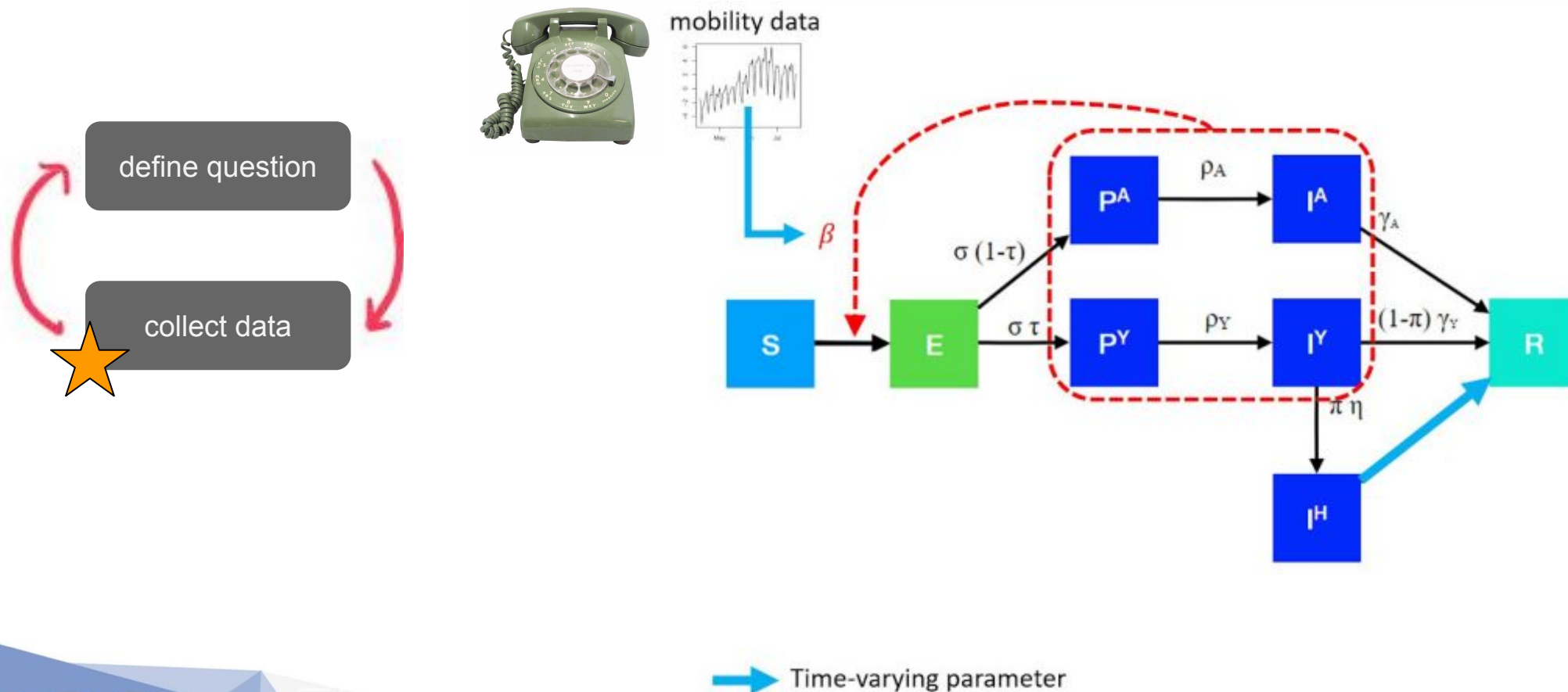
April 3, 2020 5,330 confirmed cases

**CDC recommends cloth face coverings**

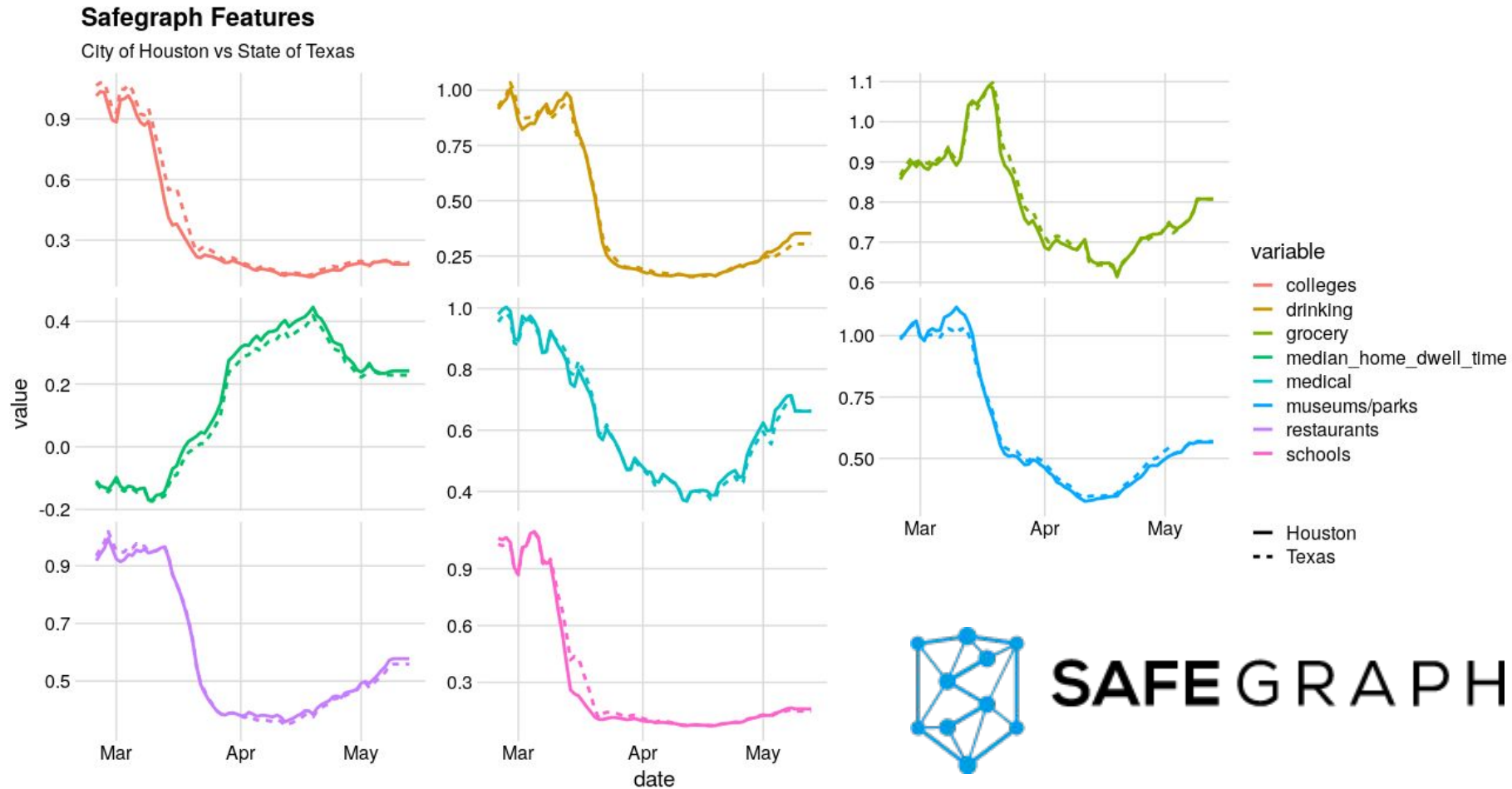
May 1, 2020 29,229 confirmed cases

**Several businesses reopen**

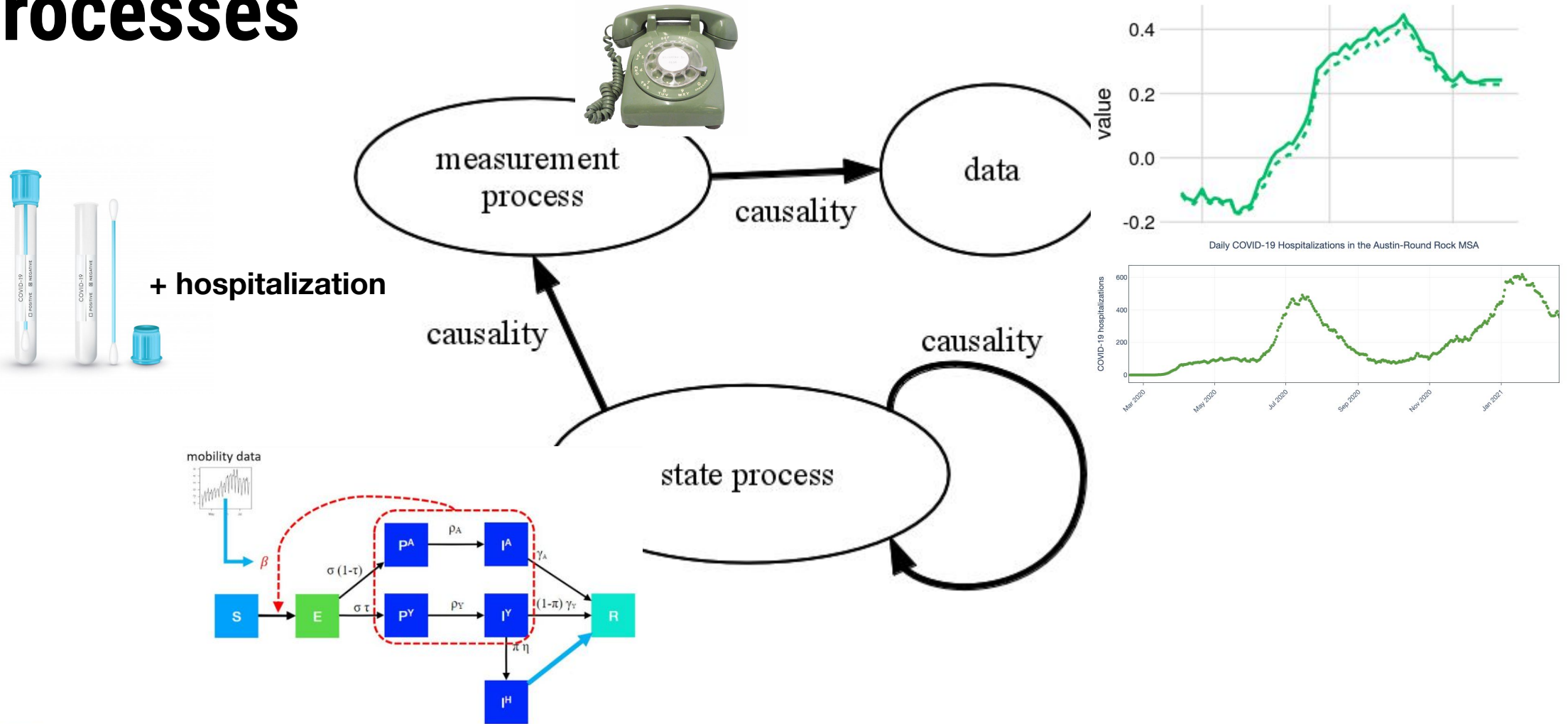
# Cell phone mobility data as a proxy for behavior



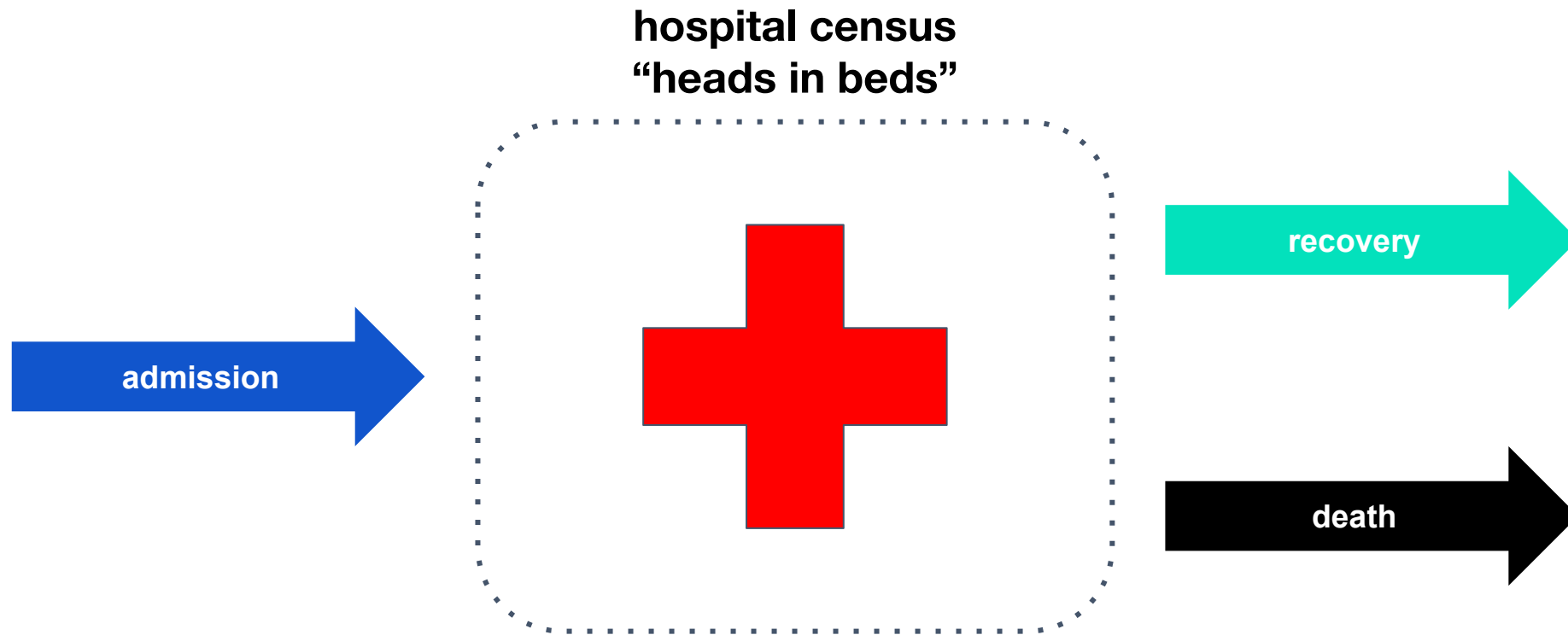
# Cell phone mobility data as a proxy for behavior



# Regression using partially observed Markov processes

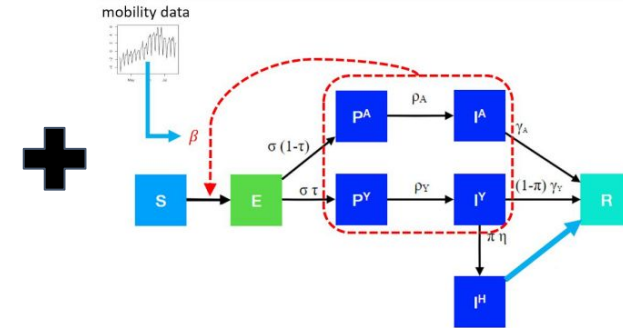
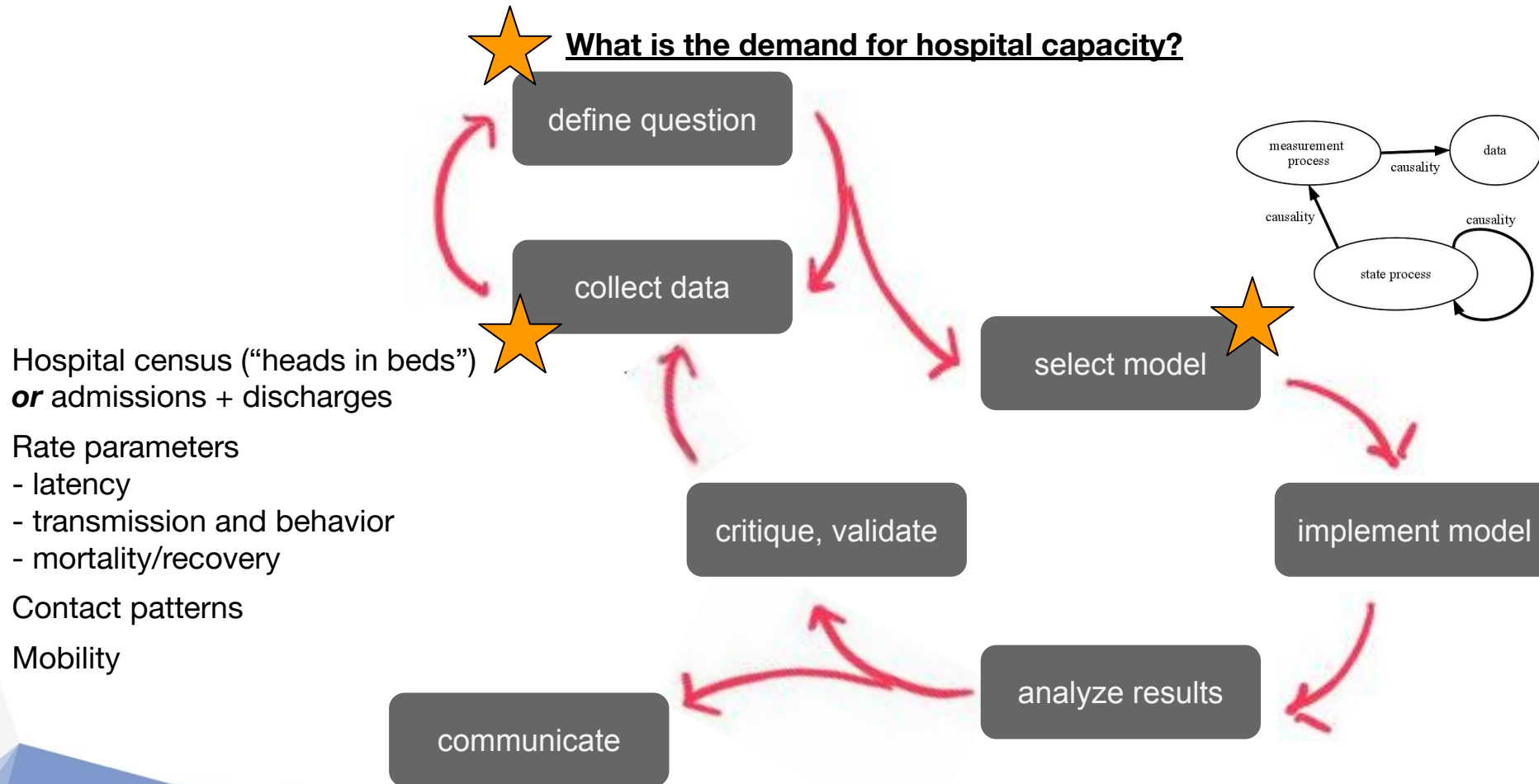


# Hospital census vs admits and discharges



First choice: hospital admission data ("line list" data)  
Second choice: hospital census data

# Revisiting the model life cycle



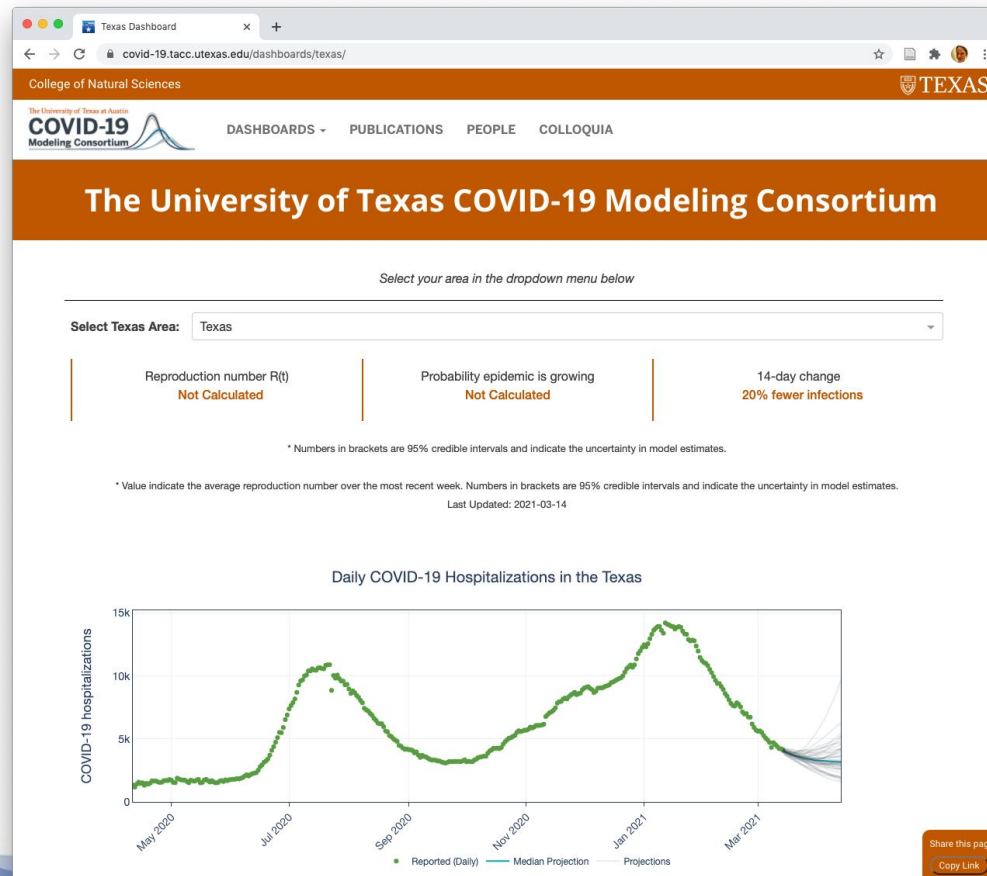
# Implementation

- Combination of R and Python
  - partially observed Markov processes in `pomp` R package
  - python utilities for processing mobility data, dashboard visualizations
- Trivially parallel simulations
- Modeling a single locality takes approximately 4 hours (minimal optimization - room for automation and improvement)

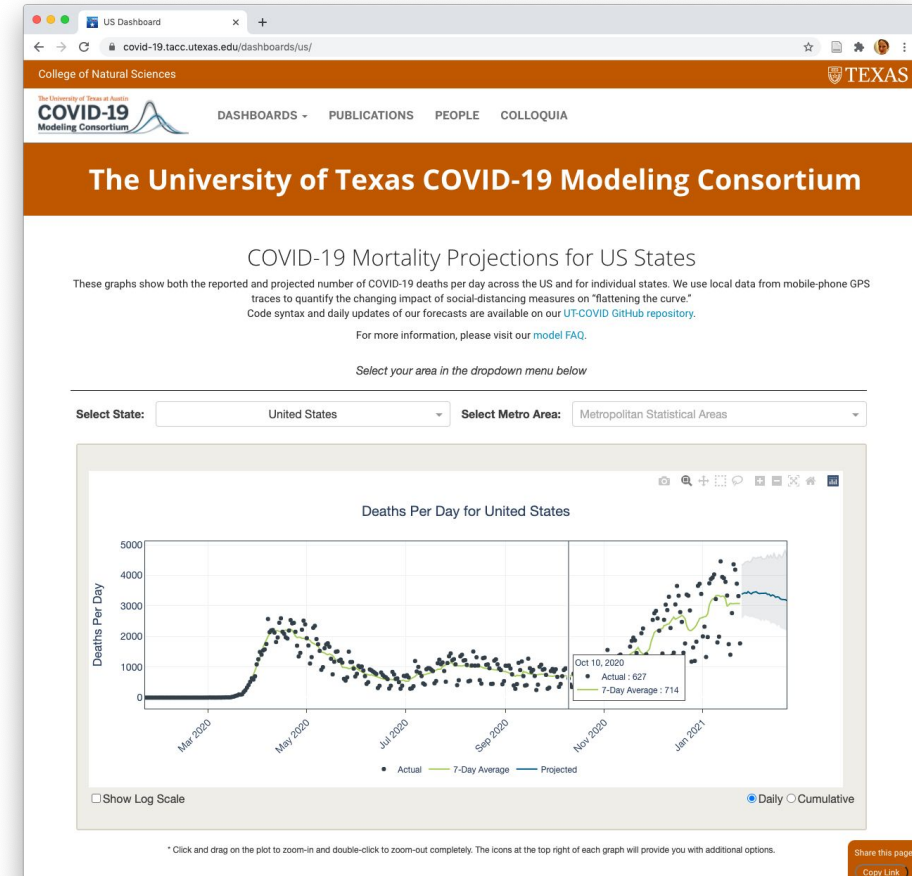


# Projection dashboards

## Healthcare demands in Texas



## Mortality across the United States



# Beyond “flattening the curve”

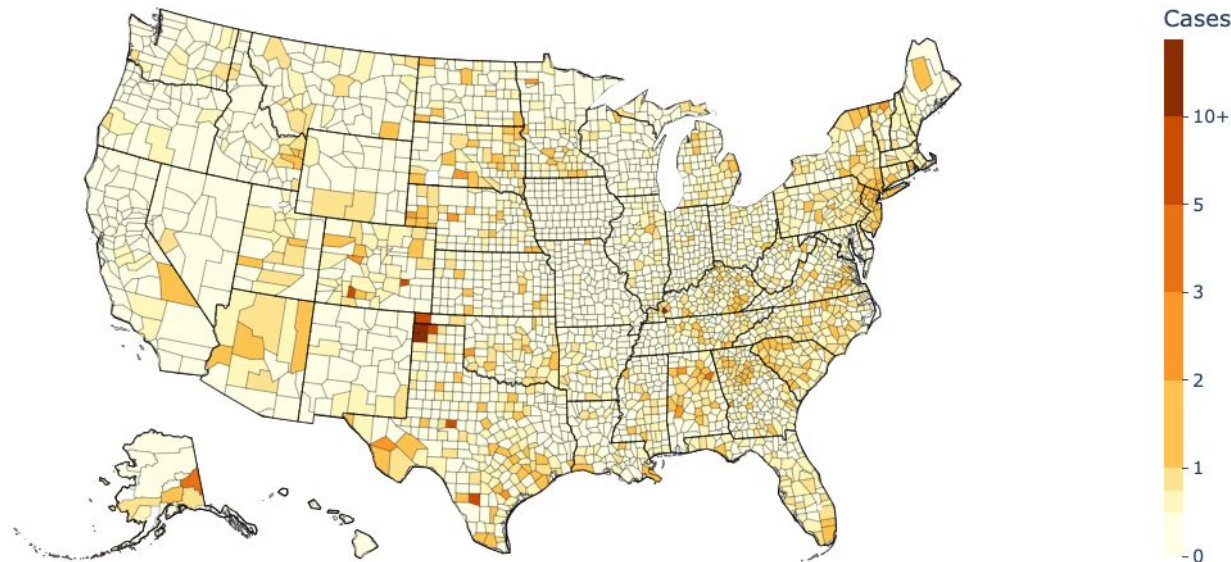
# School reopening - introduction risk

Expected number of COVID-19 cases arriving at school

Last Updated: 03/08/2020

United States ▾

Select or hover over county for risk estimates

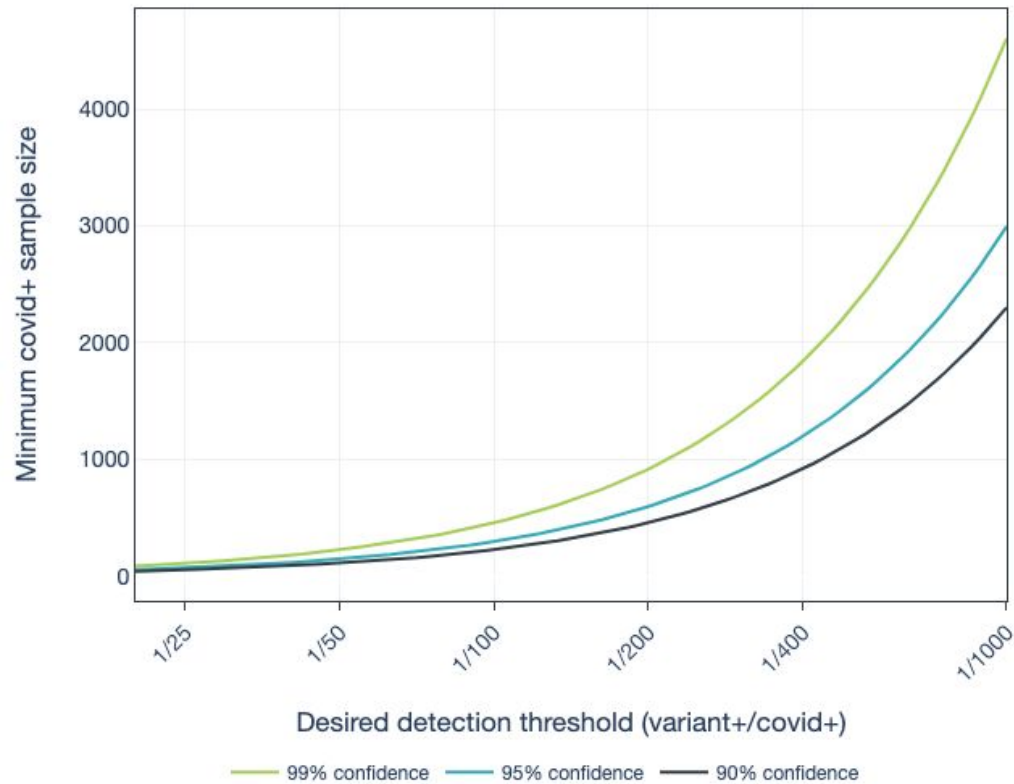


10 25 50 100 500 1000 2500 5000

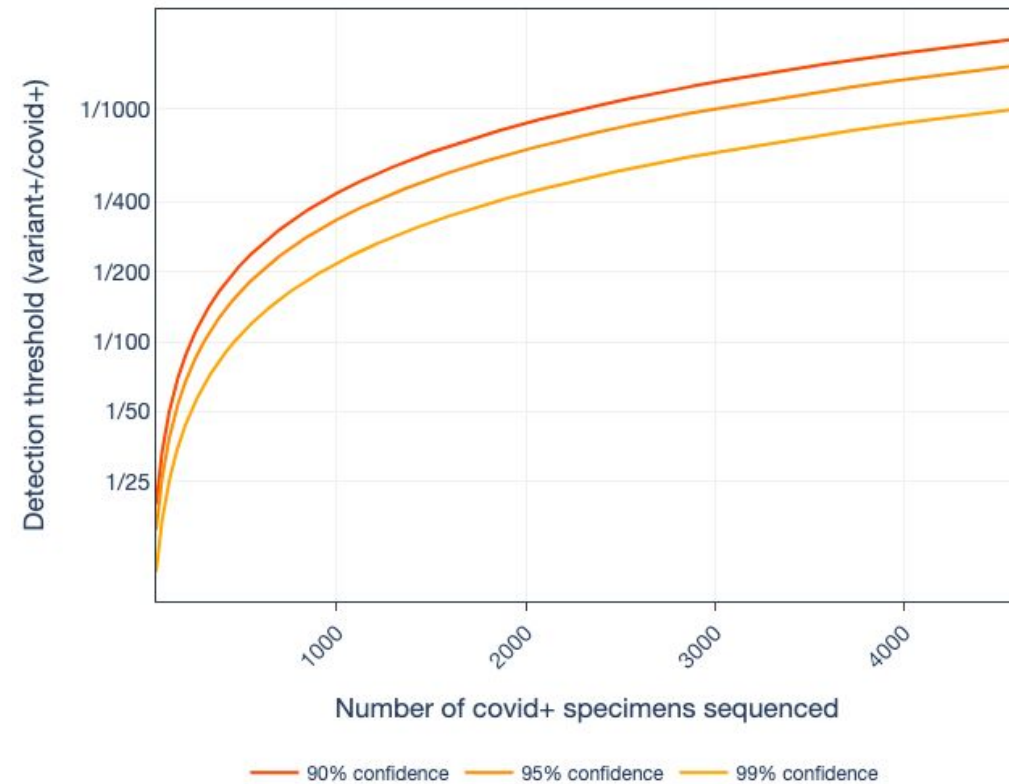
Slide to change school or pod size

# Variant detection

How many SARS-CoV-2 positive specimens should be sequenced to detect a variant?

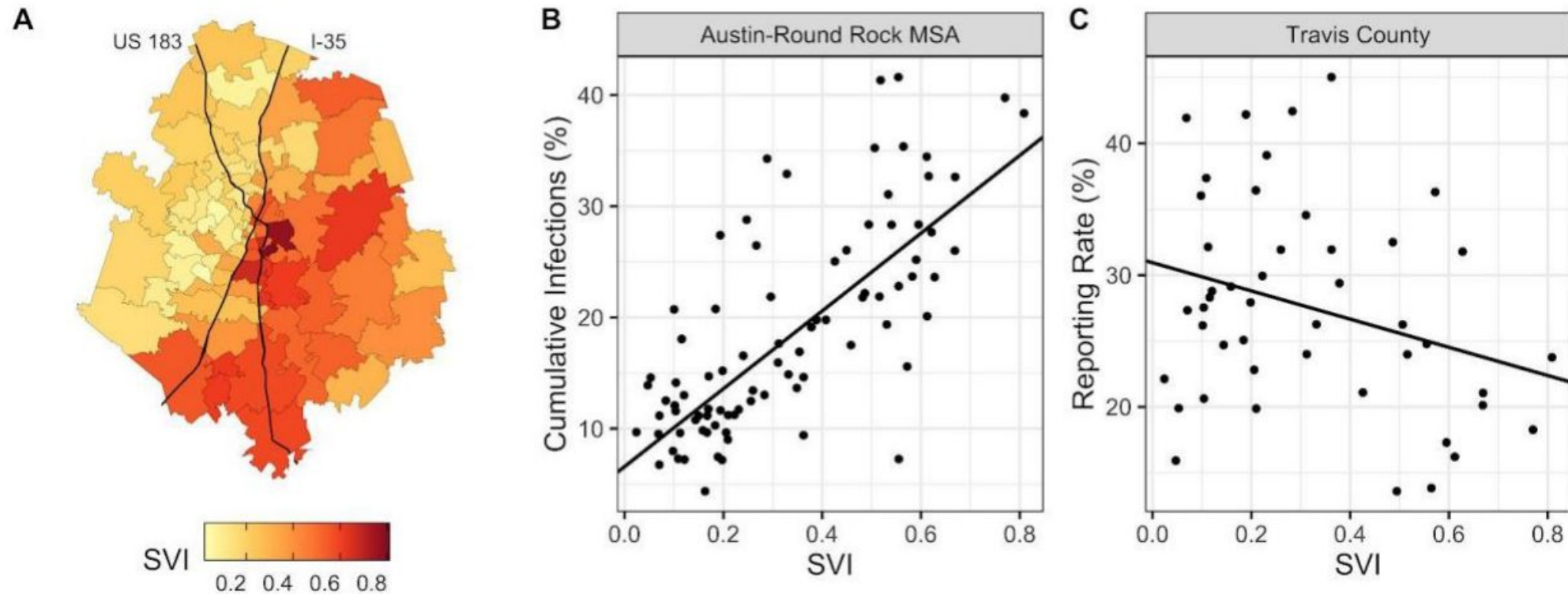


How early can an emerging variant be detected with a given sample size?



# Heterogeneous vulnerability and burden

Social Vulnerability Index (SVI) predicts vulnerability and infection burden



# Conclusions after 1 year of COVID-19

- **Hospital census or admissions data are critical.**
  - Small amounts of data can provide crucial insights when used carefully
  - Public health data collection, aggregation and dissemination have changed dramatically in the last 12 months (but need more investment)
- **Fast model development allowed the consortium to expand research capacity.**
  - HPC and HPC Centers support fast iteration and short turn-around on research and production models

# Contact

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