

# SIR implementation in a mobility network

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June 2020



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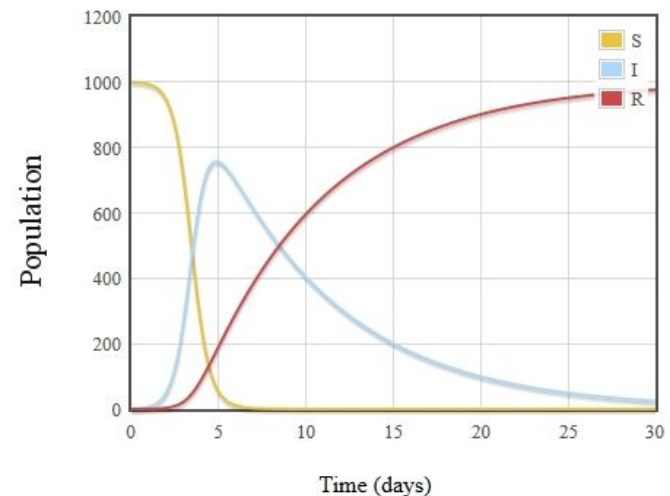
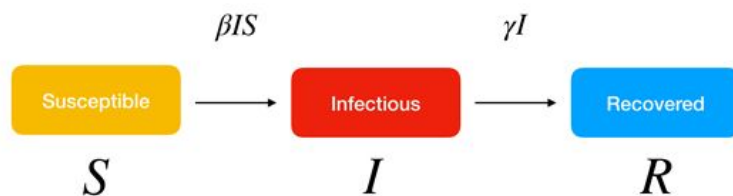
# SIR Model

## Three compartments

- Susceptible, infectious, recovered
- Interaction parameters  $\beta$ ,  $\gamma$

## Every US State is own compartment model

- No mobility between states included (yet)
- Parameters initially unknown, but bounds are given; fitting is optimisation problem
- Dynamics change with every wave: adaptive parameters



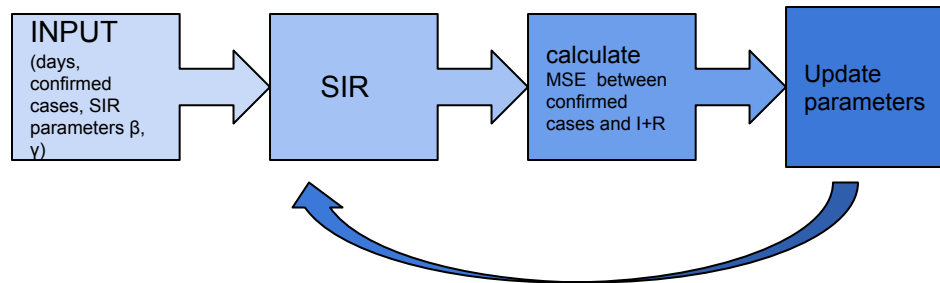
# Implementation:

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Code based on

<https://github.com/cidacslab/Mathematical-and-Statistical-Modeling-of-COVID19-in-Brazil/blob/master/main/modelos.py>

## Pipeline



Preparing the data:

- Group by state total number of confirmed cases.
- Create an array per state of number of confirmed cases.
- Create a dictionary with key=state name and value=Population size.
- Initialize SIR object for each state, with their respective population size.

# Optimization

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## Powell method vs. L-BFGS-B method

Needed to check:

- Sensitivity of initial parameters
- Local minima

We observed that:

- Minima obtained with Powell method were more consistent.
- Values obtained with L-BFGS-B tended to go to the boundaries.
- Comparing both methods, Powell gave generally lower errors.



## Second approach: Nonhomogeneous $\beta$

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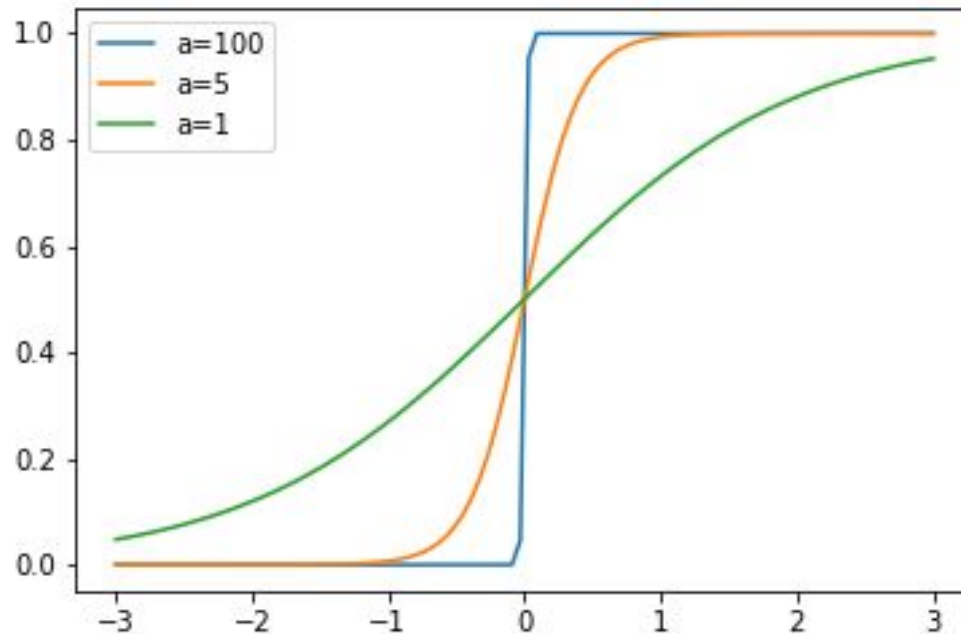
Assuming a constant  $\beta$  might not be the best way to model the dynamics.

We used a “discrete time varying” beta instead, of the form

$$\beta(t) = \beta_1 f(t^* - t) + \beta_2 f(t - t^*)$$

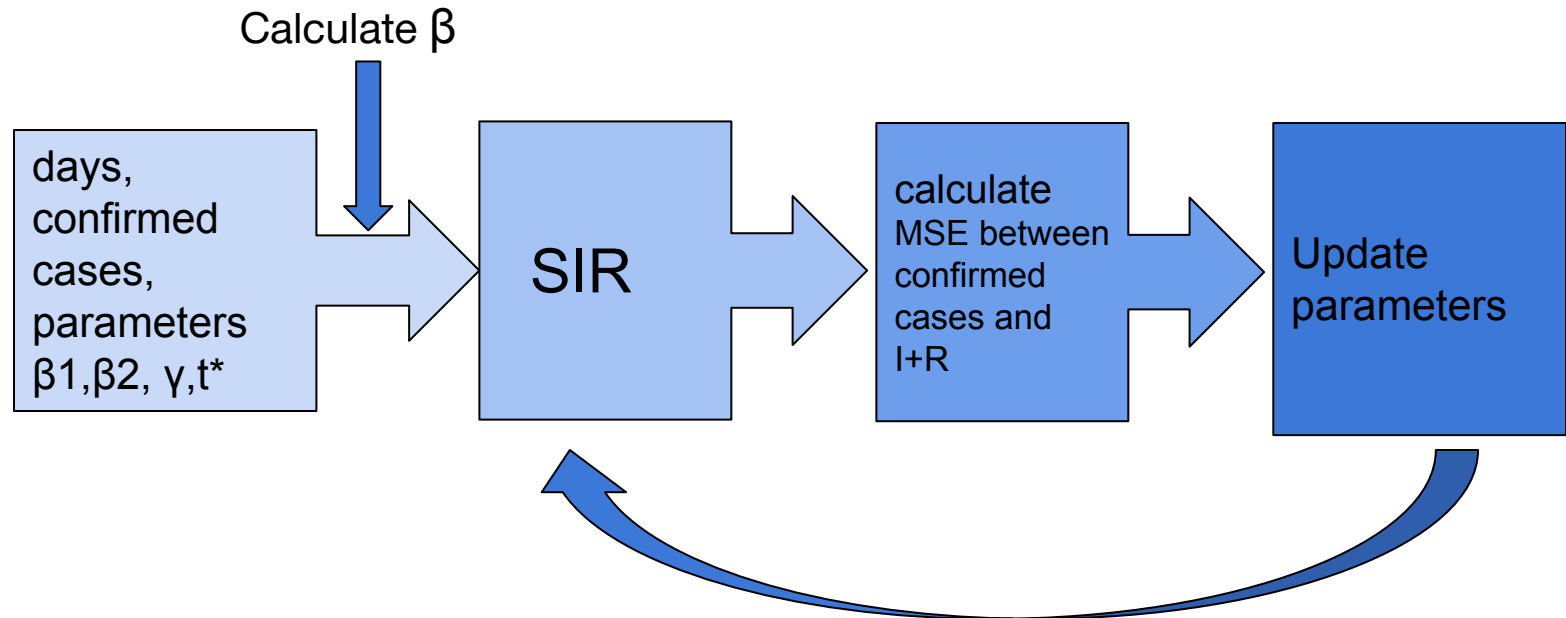
where

$$f(t) = \frac{1}{1+e^{-at}}$$

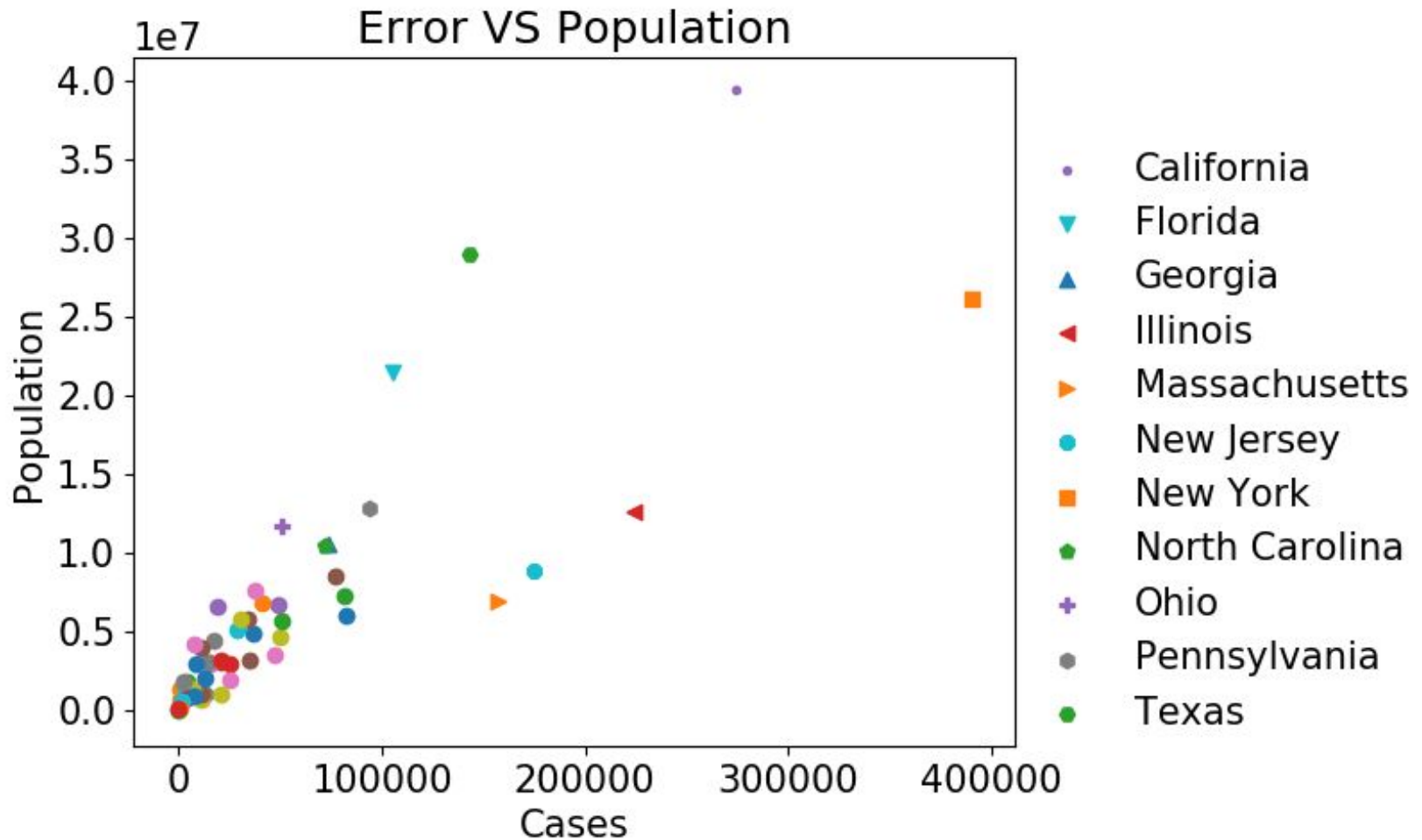


# Fitting pipeline

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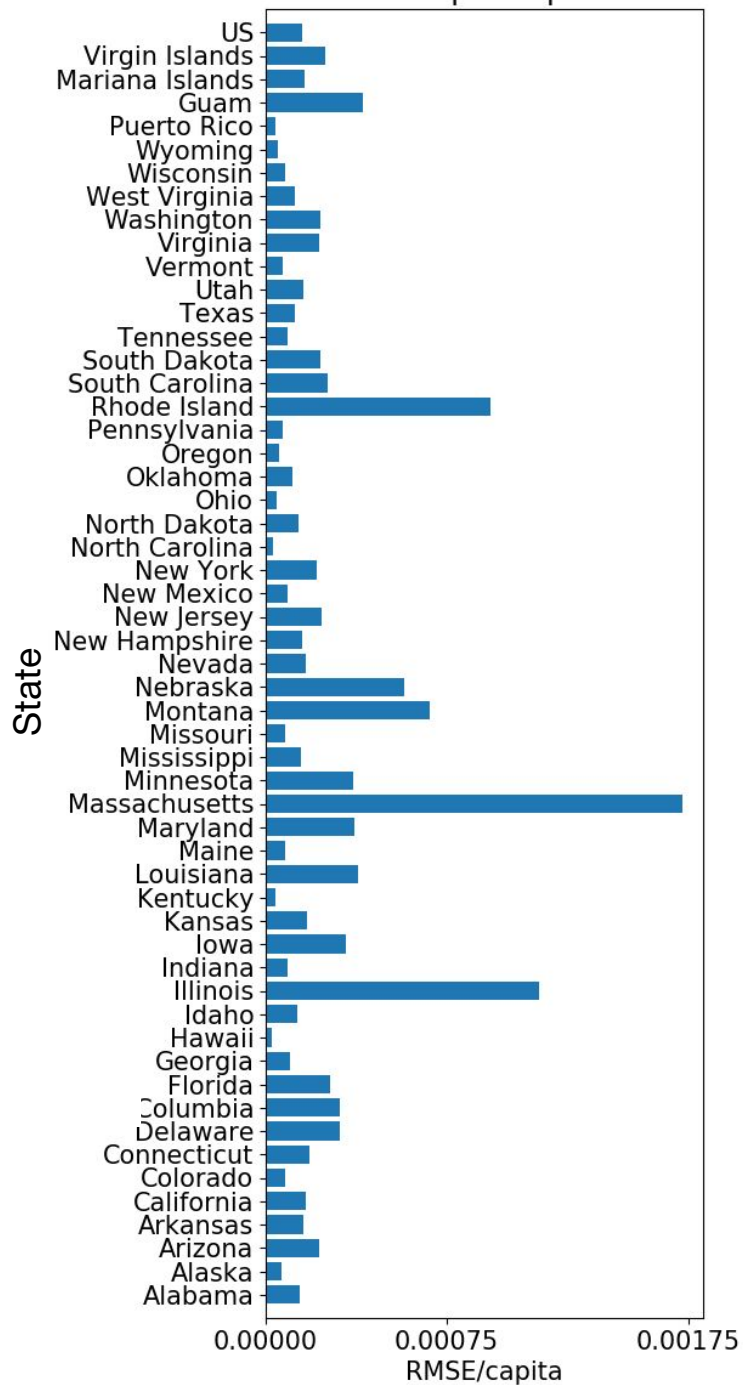


# Cases distribution

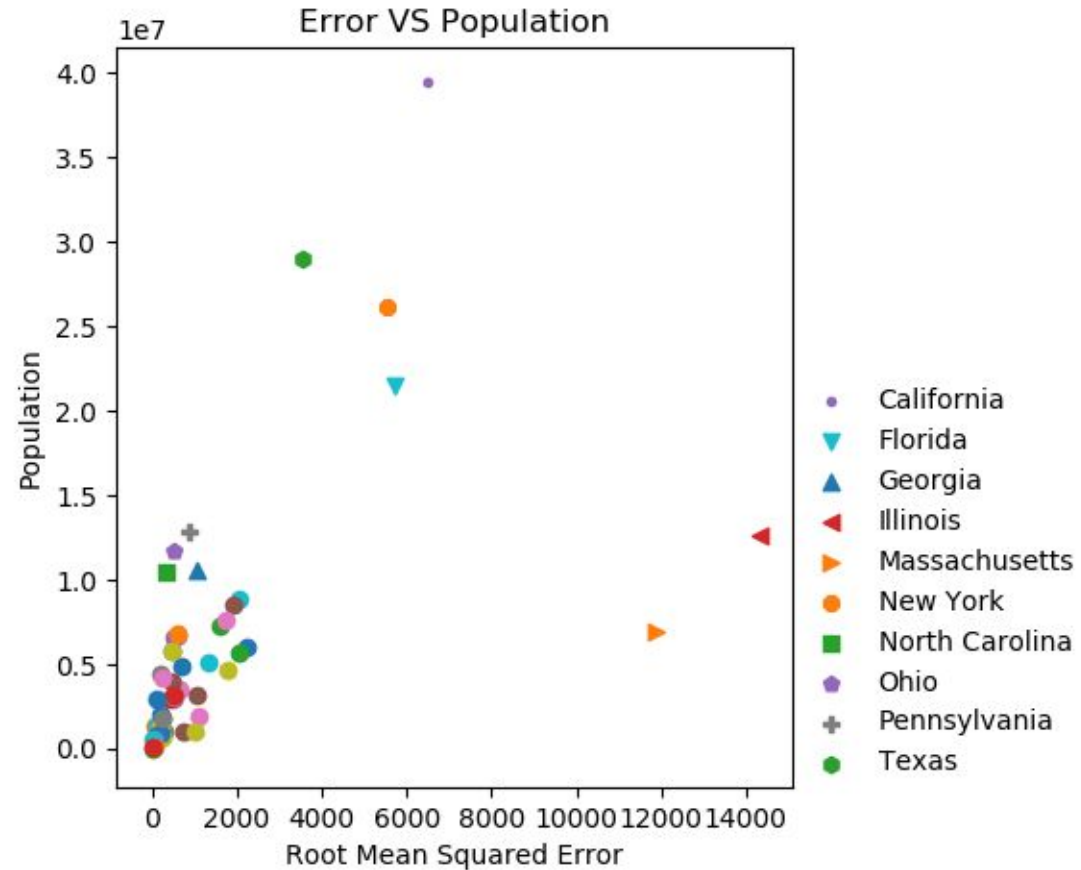




Error per capita



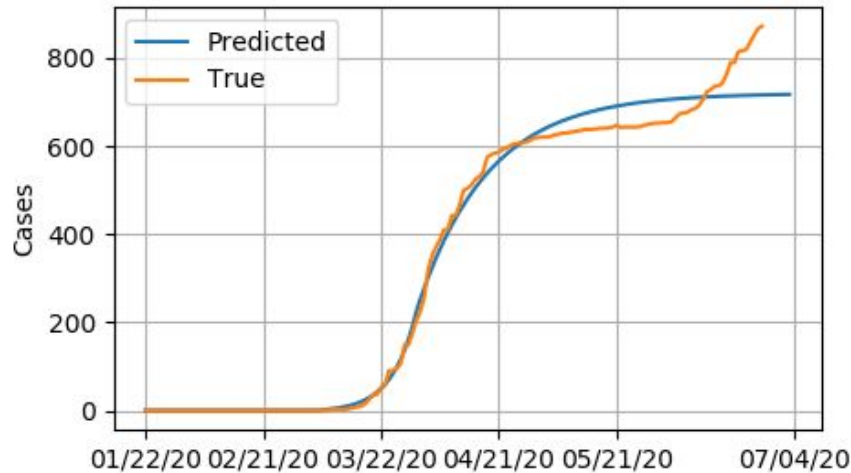
## Results by state



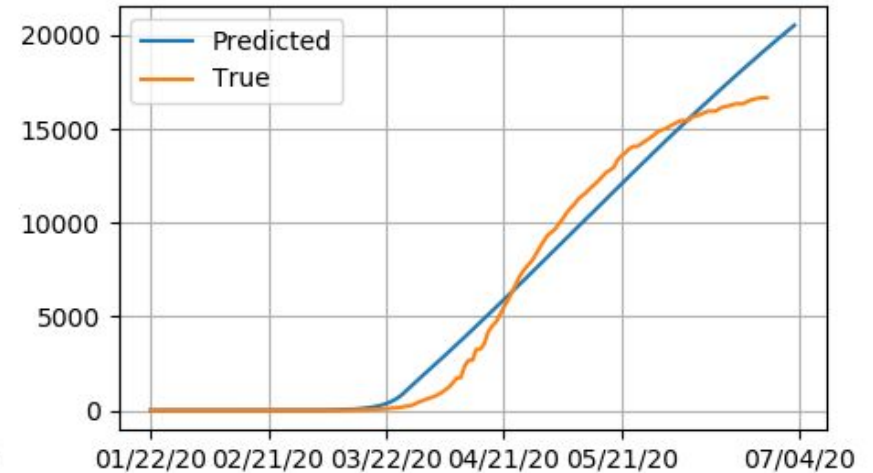
# Results by state

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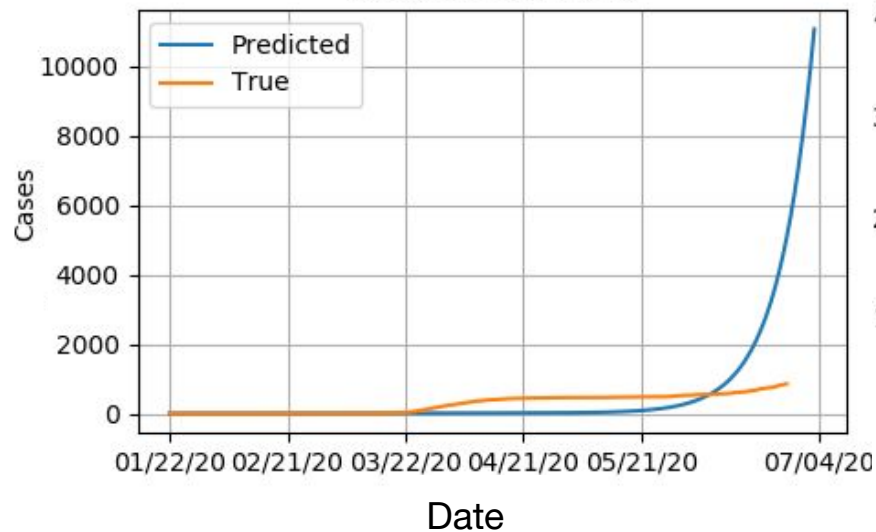
Cases for Hawaii



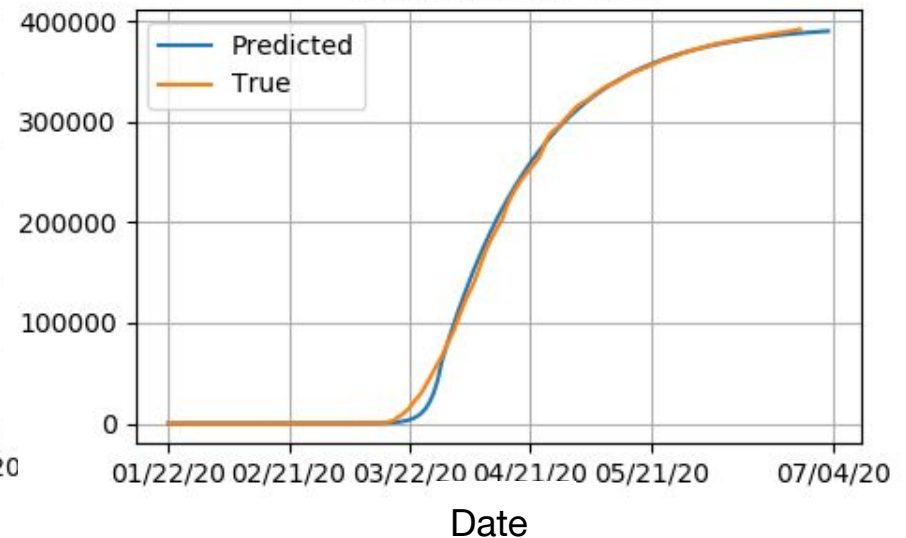
Cases for Rhode Island



Cases for Montana

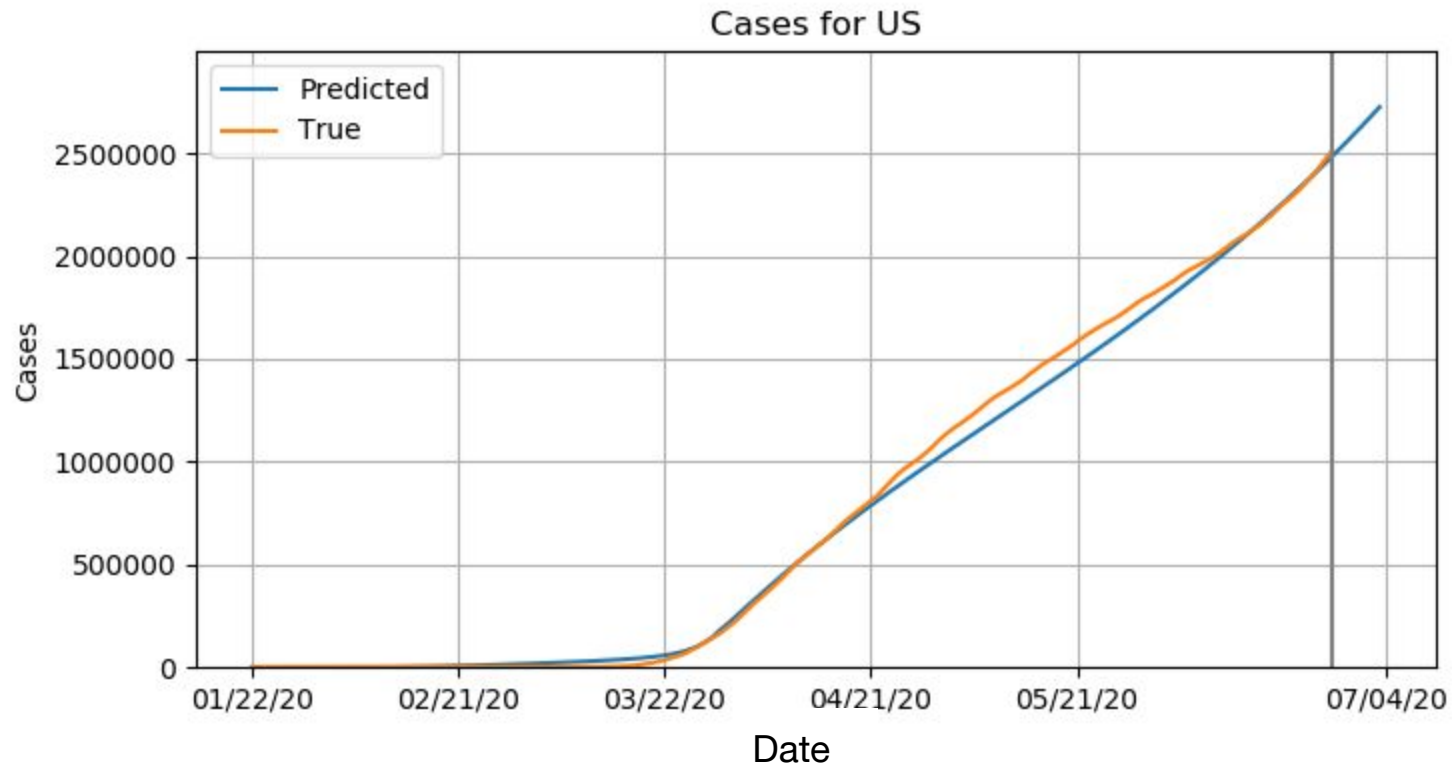


Cases for New York



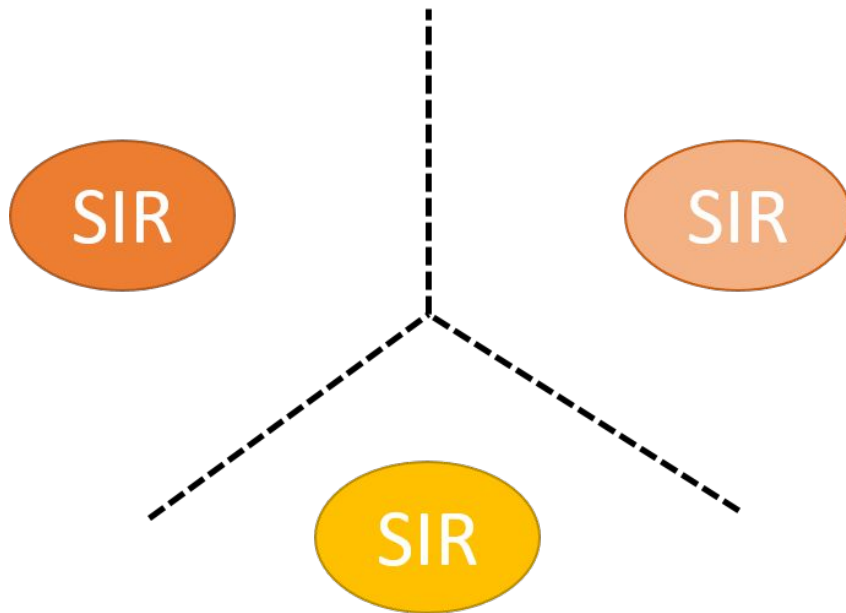
# National results

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## Further work: Mobility dependencies

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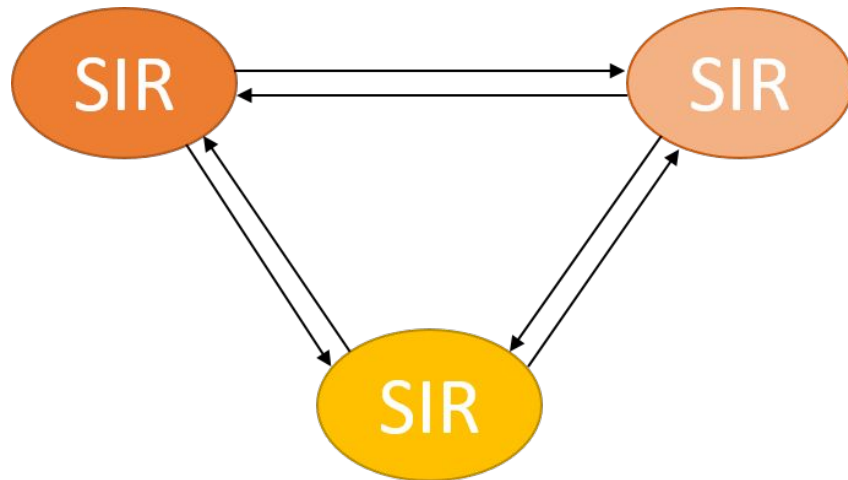
How to include mobility data ?

$$\beta_{m_i} = \frac{1}{\alpha} \sum_{j \neq i} m_{ji} \frac{I_j}{Pop_j}$$

where  $m_{ji}$  is the number of passenger from  $j$  to  $i$ .

## Further work: Mobility dependencies

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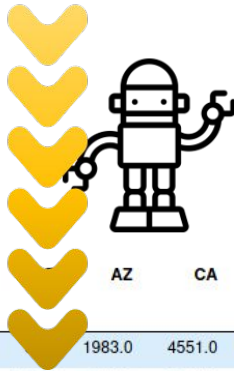
We then need to combine the betas:

$$\beta_i = \theta \beta_{0_i} + (1 - \theta) \beta_{m_i}$$

**2 general parameters to optimize:**

**$\alpha$  and  $\theta$**

# Further work: Getting mobility data



DEST_STATE_ABR	AK	AL	AZ	CA	CO	CT	FL	GA	HI	...
Abb										
AK	23662.0	106.0	1983.0	4551.0	1090.0	20.0	1517.0	458.0	3124.0	...
AL	122.0	42.0	284.0	1400.0	4865.0	2550.0	340.0	8107.0	925.0	337.0
AR	75.0	274.0	0.0	1057.0	4043.0	1393.0	145.0	5185.0	2152.0	255.0
AZ	2026.0	1374.0	1030.0	436.0	78713.0	26445.0	1585.0	20189.0	7583.0	5395.0
CA	4852.0	4848.0	4102.0	77403.0	406497.0	73748.0	4782.0	88940.0	36153.0	66707.0
CO	1161.0	2676.0	1463.0	26581.0	74921.0	2373.0	1618.0	49143.0	14010.0	5778.0
CT	19.0	352.0	168.0	1606.0	4735.0	1549.0	0.0	28343.0	2936.0	243.0
FL	1627.0	8283.0	5157.0	20160.0	90002.0	47857.0	28126.0	35519.0	63993.0	3396.0
GA	499.0	969.0	2125.0	7616.0	36208.0	13997.0	3053.0	64664.0	1737.0	1793.0
HI	3280.0	360.0	268.0	5350.0	67129.0	5693.0	254.0	3474.0	1766.0	106325.0

- We have coded a bot that gather the needed data and combine it to mobility matrix.
  - A script linking the matrix rows to the corresponding state in the code has been done.
- The global optimization has not been implemented.



# Conclusion

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- A model of independent SIRs has been implemented with automatic data cleaning.
- A dual beta model has been done to take time dependency into account.
- An alternative model to take mobility data into account has been proposed including data acquisition.

## What we have learned:

- An understanding of pandemic modeling including its difficulties.
- Good practice for further projects on modeling and prediction.

