COVID-19 Case Forecast Model Evaluation

Between Specific Model Types

Agenda

INTRODUCTION

Hypothesis & what does this project entail

METHODS

• Step by Step details

RESULTS

• What outputs were produced

DISCUSSION

• What did I find

Introduction

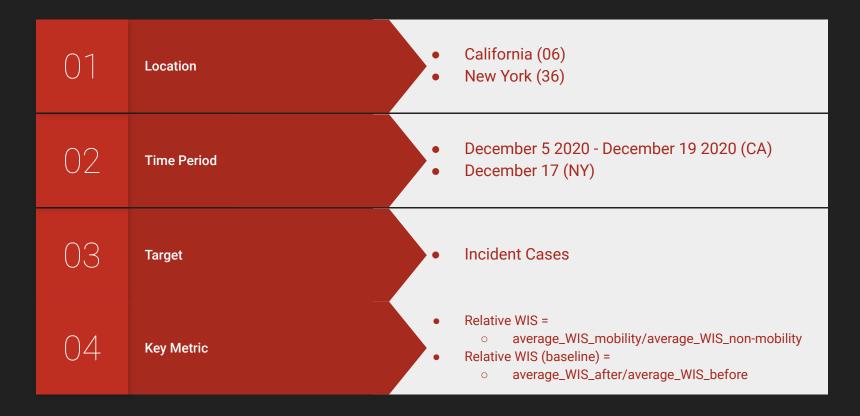
Hypothesis:

 When there is a sudden change in population mobility patterns, forecasts from models that include mobility data will be more accurate than those from models that do not include such data

Methods

Determined the Inclusion Created a Table of Model **Evaluation Graphs &** Characteristics Criteria Charts Looked for models that Truth data • Location included mobility data Time Period **Forecasts** Determined what data Target WIS each model used Confirm all model Relative WIS Determined the model information for selected models type

Inclusion Criteria



Models and Model Characteristics

Model	Case Data	Model Type	Social Distancing Assumptions?	Mobility Data?	Notes
COVIDhub- baseline	JHU CSSE	Median prediction at	no	no	Notes
LANL- GrowthRate	JHU CSSE	all future horizons Statistical dynamical	no	no	
COVIDhub- ensemble		growth model Unweighted average or median of	no	no	
RobertWalraven	- JHU CSSE	submitted forecasts SEIR model	no	no	
_ESG IowaStateLW- STEM	NYT, Johns Hopkins, Covid Tracking	Nonparametric space-time disease transmission	no	yes	
	Project, USA Facts	model			
UVA- Ensemble	CDC	AR, ISTM, SEIR model	no	yes (Baidu)	
JHU_CSSE- DECOM	JHU CSSE	Empirical machine <u>learning model</u>	no	yes (SafeGraph)	

How were these models selected?



Case Forecast

Determined which models submitted case forecasts

Mobility Data?

Separated models with and without mobility data

Time Period

Narrowed down models that were submitting during selected time

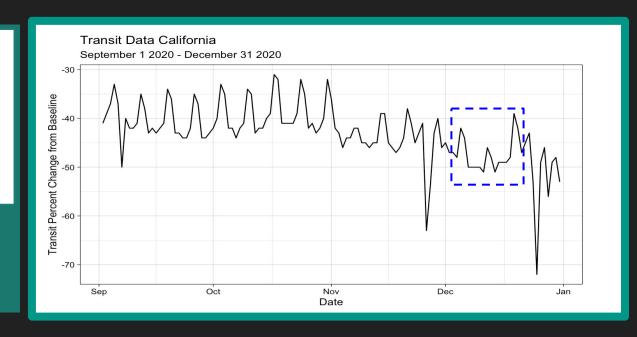
CALIFORNIA

Time Period Selection

California

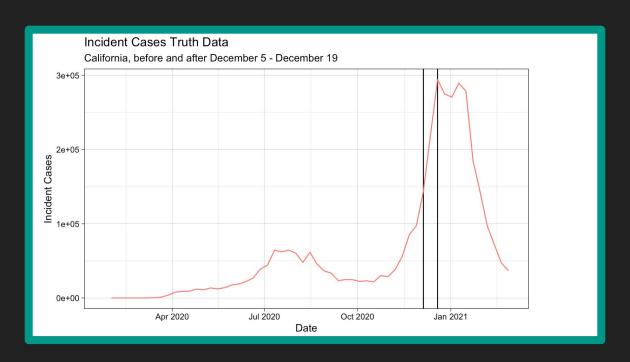
<u>Date:</u> December 5 2020 -December 19 2020

• Transit Mobility Change



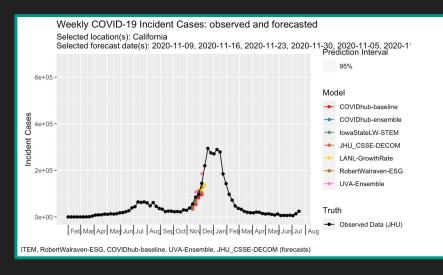
Baseline: median transit mobility value from January 3 - February 6 2020

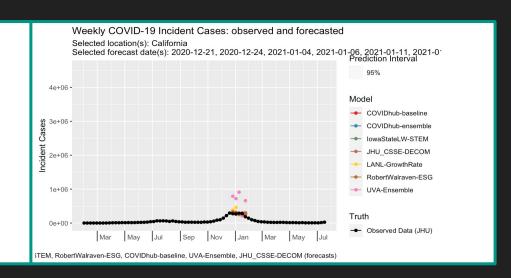
California Truth Data



- Cases increasing before
- Cases decreased after
- Cases increased in between

Forecasts



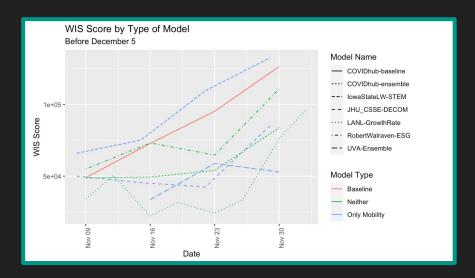


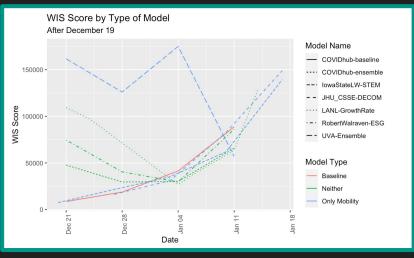
Forecasts 1 month before

Forecasts 1 month after

 Some forecasts seem very off, but this visual is not extremely clear

WIS by Model and Type





- Looked at WIS 1 month before and 1 month after
- Mobility models got worse after
- Models without mobility data had consistent WIS

model <chr></chr>	location <chr></chr>	wis_before <dbl></dbl>
COVIDhub-baseline	06	85913.46
COVIDhub-ensemble	06	58995.78
IlowaStateLW-STEM	06	95910.37
JHU_CSSE-DECOM	06	55792.20
LANL-GrowthRate	06	46102.31
RobertWalraven-ESG	06	75945.70
UVA–Ensemble	06	48449.70
model <chr></chr>	location <chr></chr>	wis_after <dbl></dbl>

model <chr></chr>	location <chr></chr>	wis_after <dbl></dbl>
COVIDhub-baseline	06	39404.23
COVIDhub-ensemble	06	43353.52
¡lowaStateLW-STEM	-06	¯ 53 Ī 10.55 ¯
JHU_CSSE-DECOM	06	69761.35
LANL-GrowthRate	06	77374.51
RobertWalraven-ESG	06	57724.02
UVA-Ensemble	06	129886.03

- lowa got better but JHU and UVA got worse
- Non-Mobility models got better with the exception of LANL

wis_before_mob <dbl></dbl>	wis_before_neither <dbl></dbl>
73204.09	52853.59
wis_after_mob <dbl></dbl>	wis_after_neither <dbl></dbl>
93314.89	59625.27

- Average WIS for mobility got much worse
- Average WIS for no mobility got slightly worse



relwis_baseline <dbl>
0.4586502

- Relative WIS increased meaning mobility WIS increased
- Baseline performed well

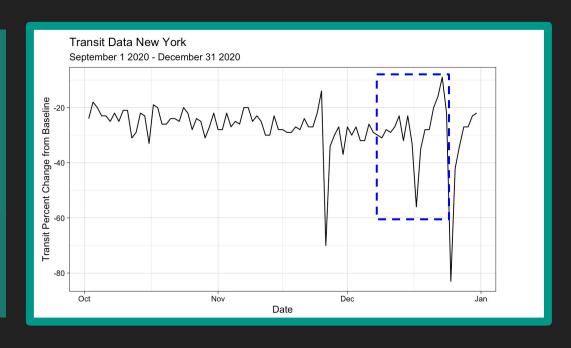
NEW YORK

Time Period Selection

New York

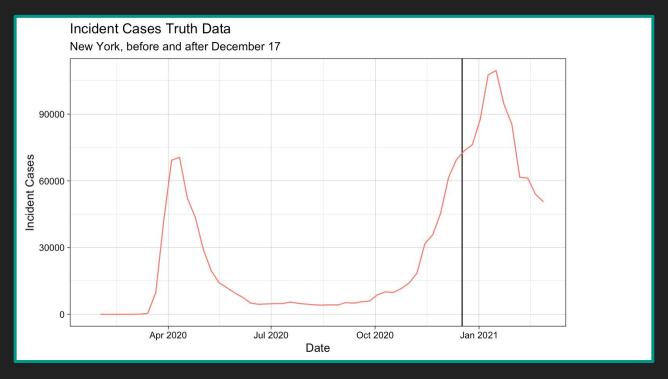
Date: December 17 2020

• Transit Mobility Change



Baseline: median transit mobility value from January 3 - February 6 2020

New York Truth Data



Cases were increasing before and after

wis_before_mob	wis_before_neither
<dbl></dbl>	<dbl></dbl>
11882.57	8234.446
wis_after_mob	wis_after_neither
<dbl></dbl>	<dbl></dbl>
19604.35	20117.89

- Average WIS for mobility got slightly worse
- Average WIS for no mobility got much worse



relwis_baseline <dbl>
0.8990317

- Relative WIS decreased meaning mobility WIS decreased and performed better than non-mobility
- Baseline performed well

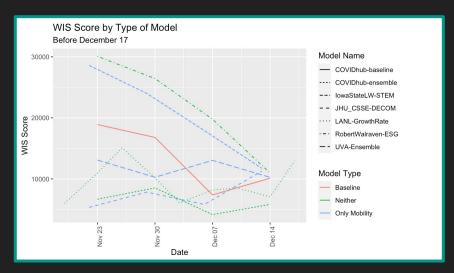
Discussion

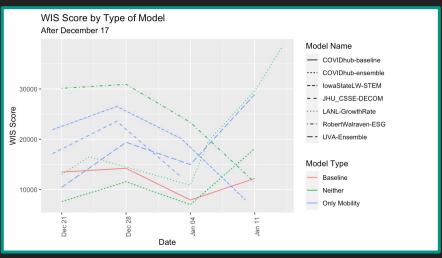
- If models with mobility data performed better, we would have expected the relative WIS after to be less than 1
- In California: the relative WIS after was greater than 1 and greater than the relative WIS before
- In New York: the relative WIS after was less than 1
- Models with mobility data did not perform better than models without mobility data for California, but they did perform better for New York
- 2 Options:
 - Conclude that models with mobility are not more or less likely to perform better
 - OR
 - We need to look into more states and dates to see what the variations are

Appendix

More slides for New York

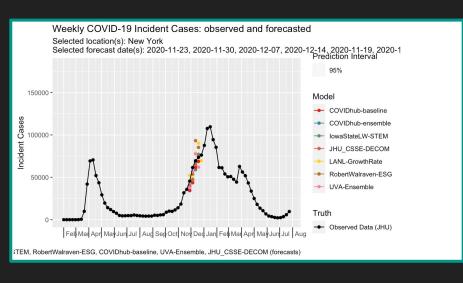
WIS by Model and Type

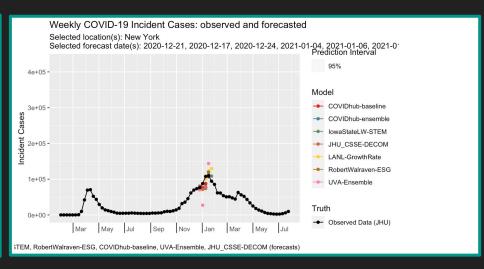




- Looked at WIS 1 month before and 1 month after
- Mobility models got a little better after
 - o Below 30000
- Models without mobility data also got a little better
 - LANL got much worse

Forecasts





Forecasts 1 month before

Forecasts 1 month after

 Still relatively close forecasts with a few being off

model <chr></chr>	location <chr></chr>	wis_before <dbl></dbl>
COVIDhub-baseline	36	13295.667
COVIDhub-ensemble	36	6288.092
IowaStateLW-STEM	36	20559.537
JHU_CSSE-DECOM	36	7566.242
LANL-GrowthRate	36	9448.235
RobertWalraven-ESG	36	21813.464
UVA-Ensemble	36	11660.976

model <chr></chr>	location <chr></chr>	wis_after <dbl></dbl>
COVIDhub-baseline	36	11953.23
COVIDhub-ensemble	36	11072.20
lowaStateLW-STEM	36	19125.26
JHU_CSSE-DECOM	36	17735.72
LANL-GrowthRate	36	21364.05
_RobertWalraven-ESG	_36	_23961.83
UVA-Ensemble	36	18426.98

- lowa got better but JHU and UVA got worse
- All the non-mobility models got worse