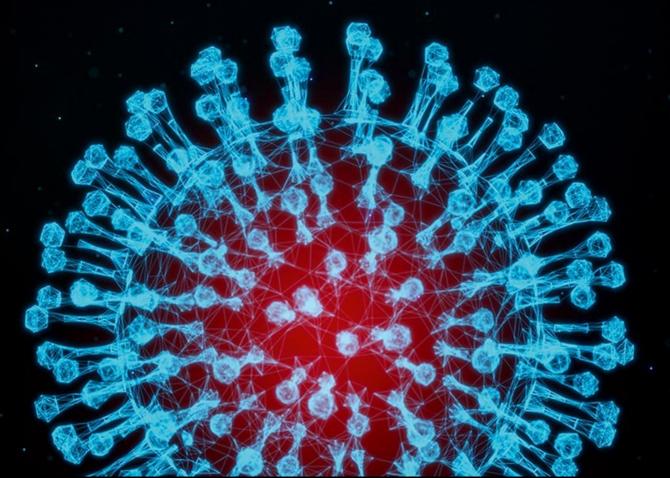
Forecasting COVID-19 cases for the next 7 days and beyond

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Intro.

- As of December 2021, > 261 million total COVID-19 cases, > 5 million total deaths were reported worldwide.
- Forecasting COVID-19 cases in the next several days/weeks/months is critical for coping with the pandemic.
- Many groups have been working on this problem using various methods.
- Less effort has been made to compare performance of different model kinds, especially when they were challenged to predict cases far ahead in the future.



Goal

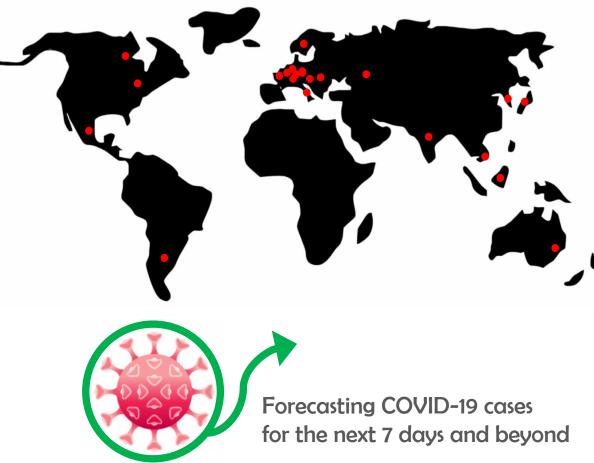
- Design and implement 4 different types of models that forecast cases in the next 7 days and further ahead into the future.
- As features, readily available data like vaccination, mobility, weather, datetime etc. should be used.
- When possible, implement the model that can generalize across diverse timevarying patterns as observed in different countries/communities.
- Compare pros/cons of the four models.



Dataset

- <u>Target</u>: COVID-19 cases in 23 countries.
- Features:

Static Categorical	Country ID (country_region_code)
Temporal Categorical	 Year (year) Month (month) Day (day) Week of year (week_of_year) Day of week (day_of_week) Holiday (holiday)
Temporal Continuous	Google Community Mobility Data Retail & Recreation (rtrc) Grocery & Pharmacy (grph) Park (prks) Transit stations (tran) Work (work) Residential (resi) Weather Data Temperature (tempC) Humidity (humidity) Cloud cover (cloudcover) Precipitation (precipMM) Vaccination (vac: the number of vaccinated people per hundred) Previous cases (cases during previous 14 days)



Models

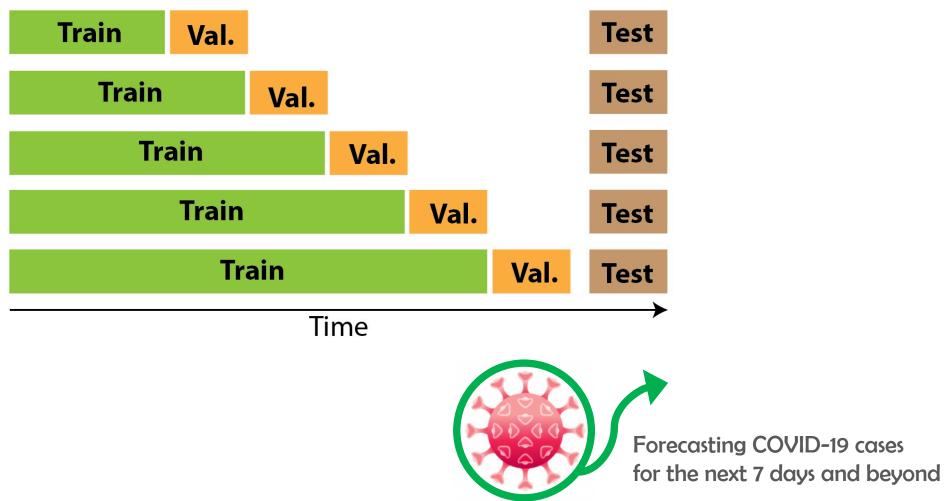
I. SARIMAX.

(Seasonal Auto-regressive Integrated Moving Average with eXogenous factors)

- II. XGBoost regressor.
- III. Multi-layer perceptron.
- IV. LSTM (Long Short-Term Memory).

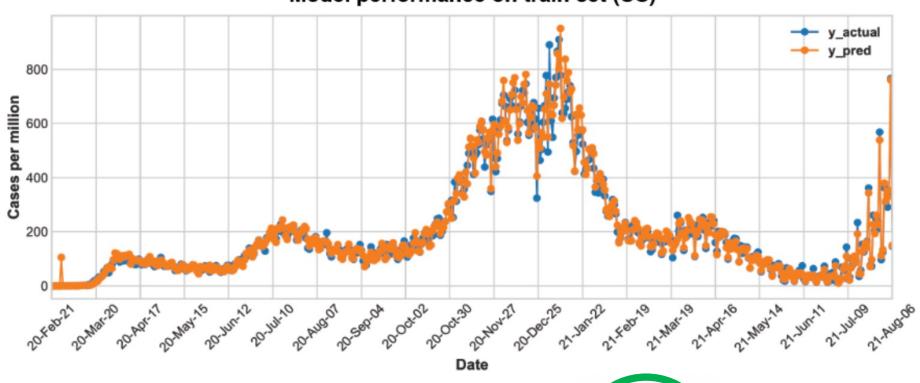


Walk forward validation



SARIMAX performance on train set

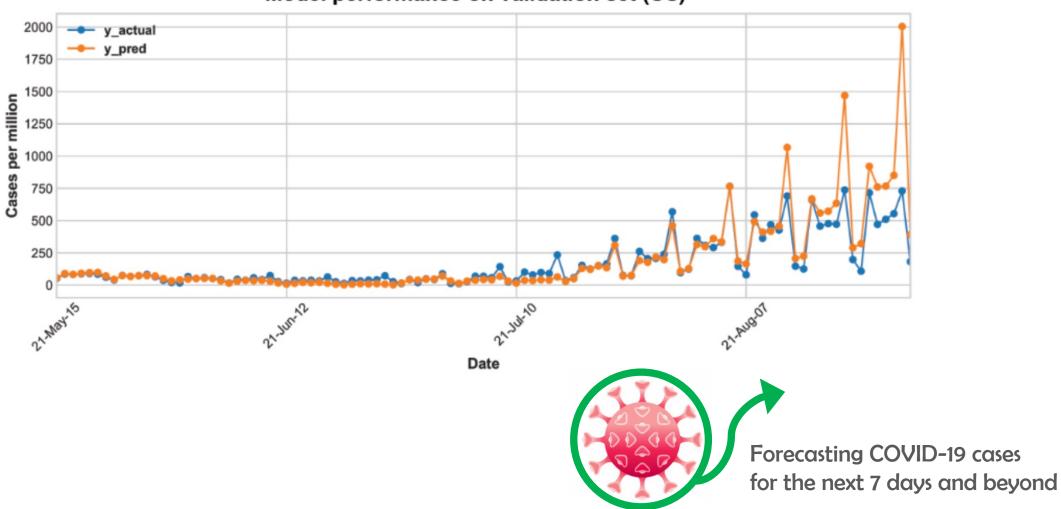
Model performance on train set (US)





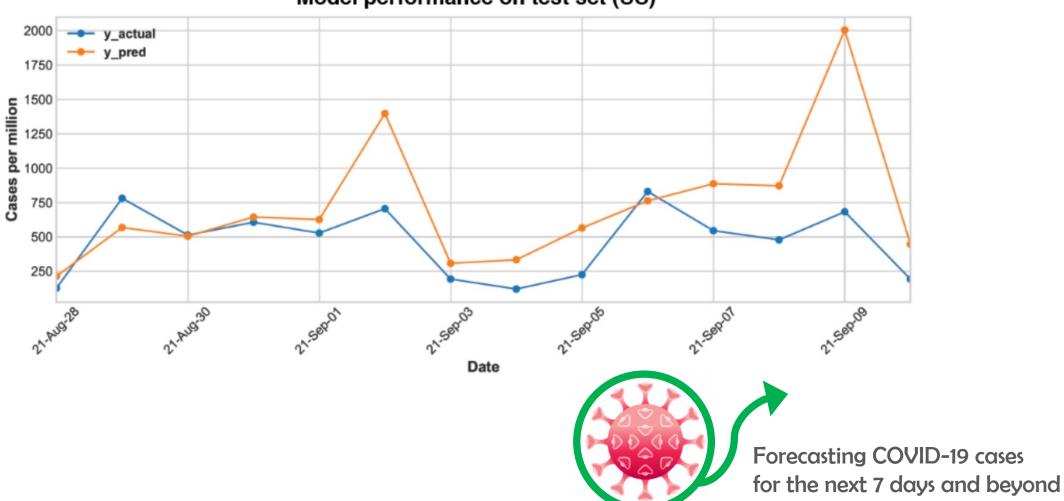
SARIMAX performance on validation set

Model performance on validation set (US)

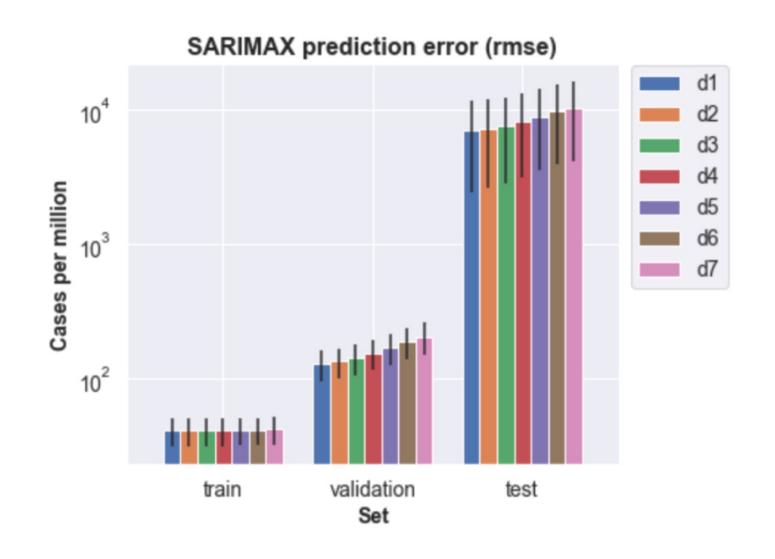


SARIMAX performance on test set

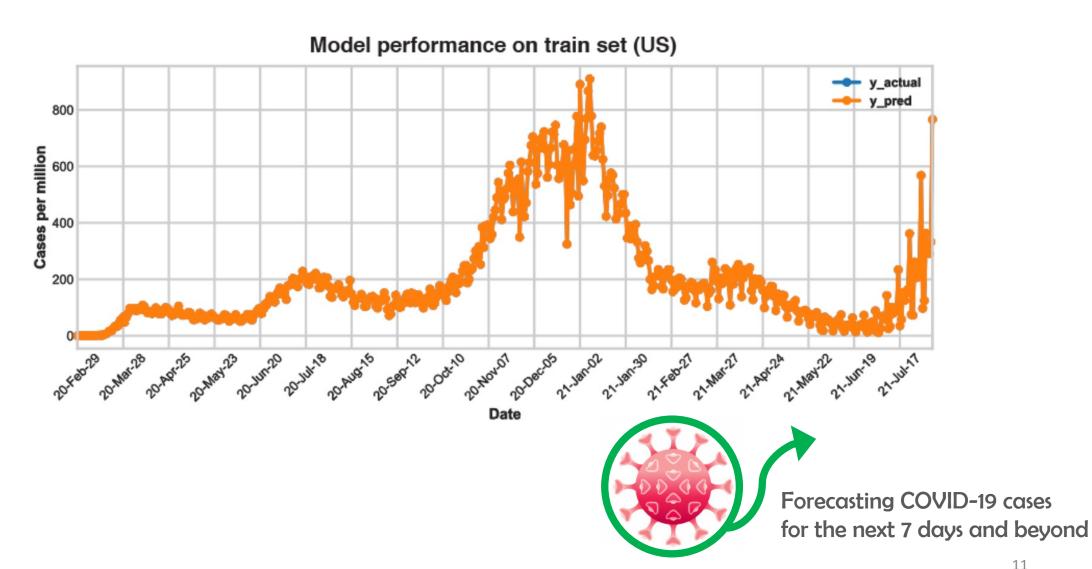
Model performance on test set (US)



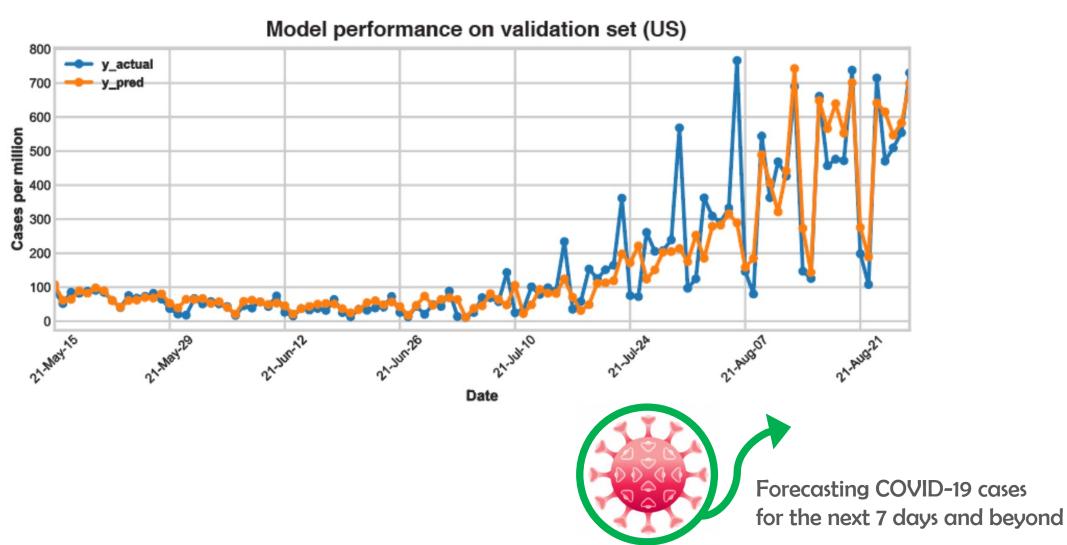
SARIMAX performance on train/validation/test sets



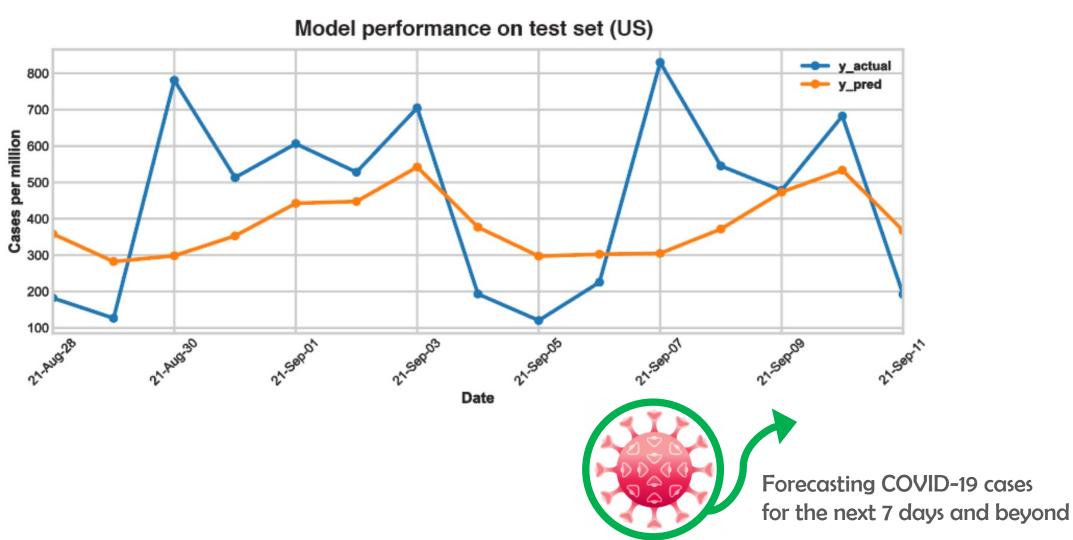
XGBoost performance on train set



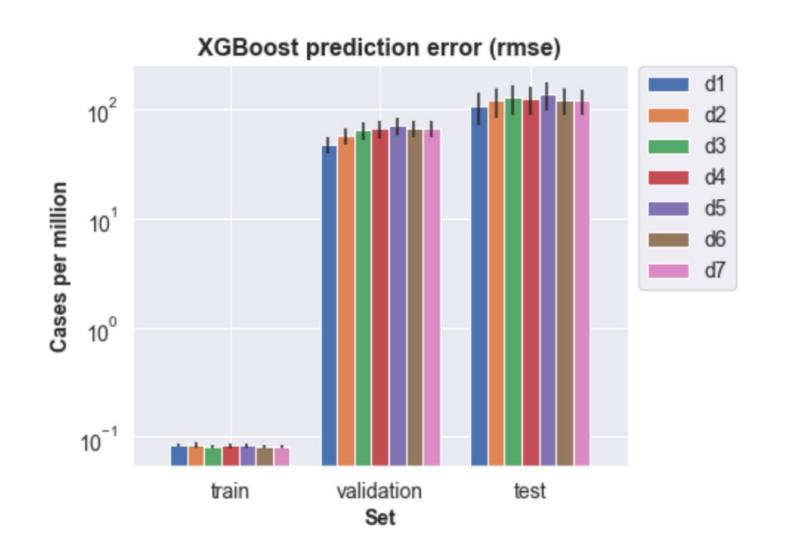
XGBoost performance on validation set



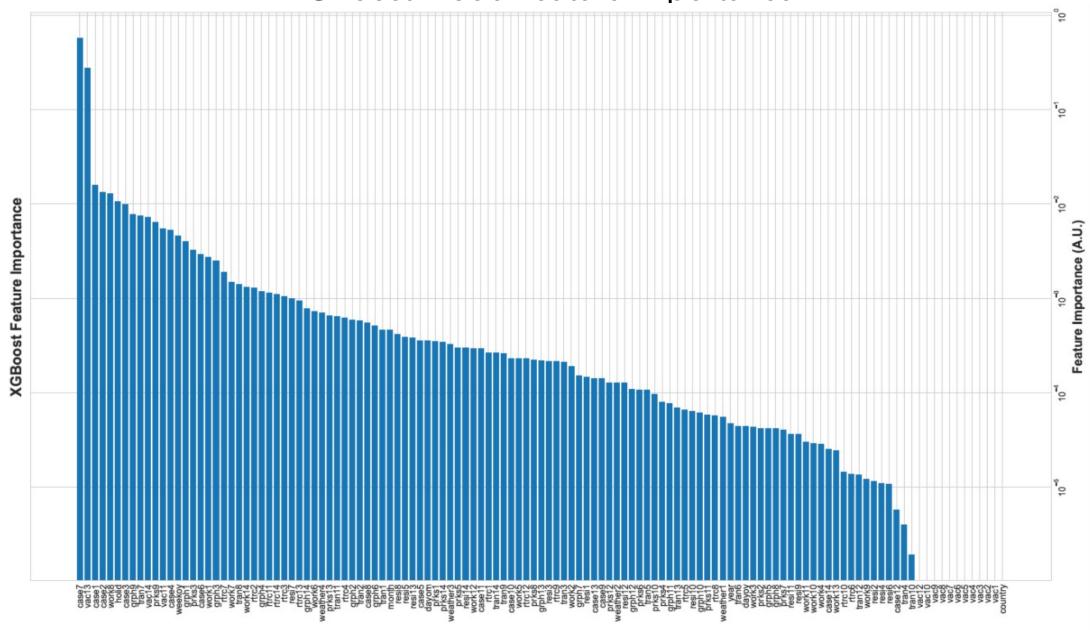
XGBoost performance on test set



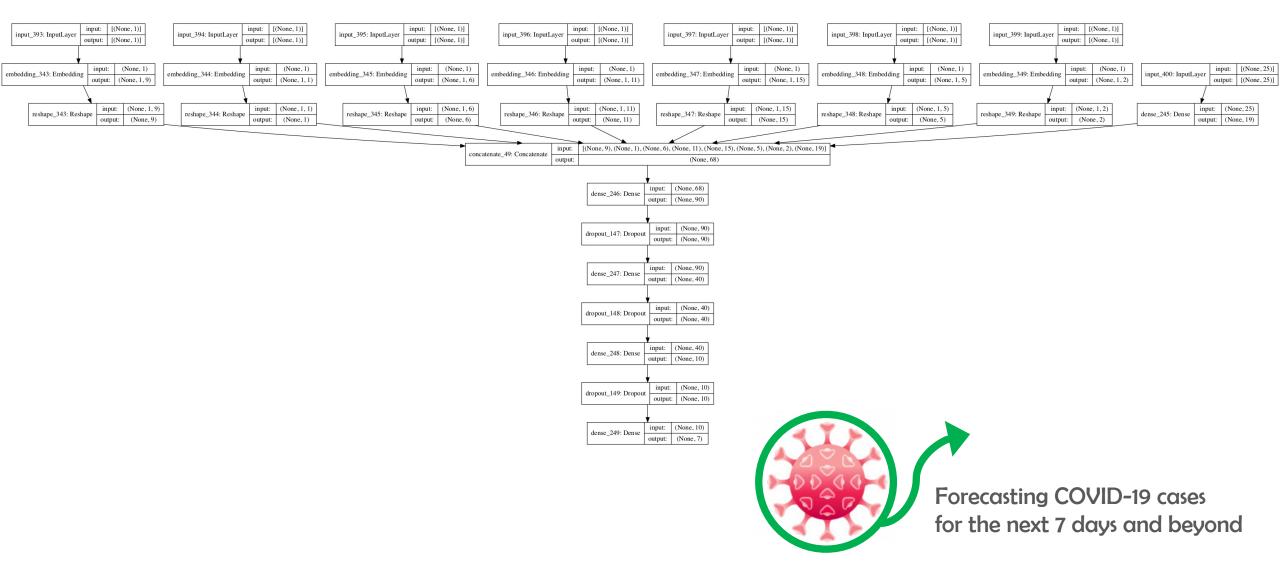
XGBoost performance on train/validation/test sets



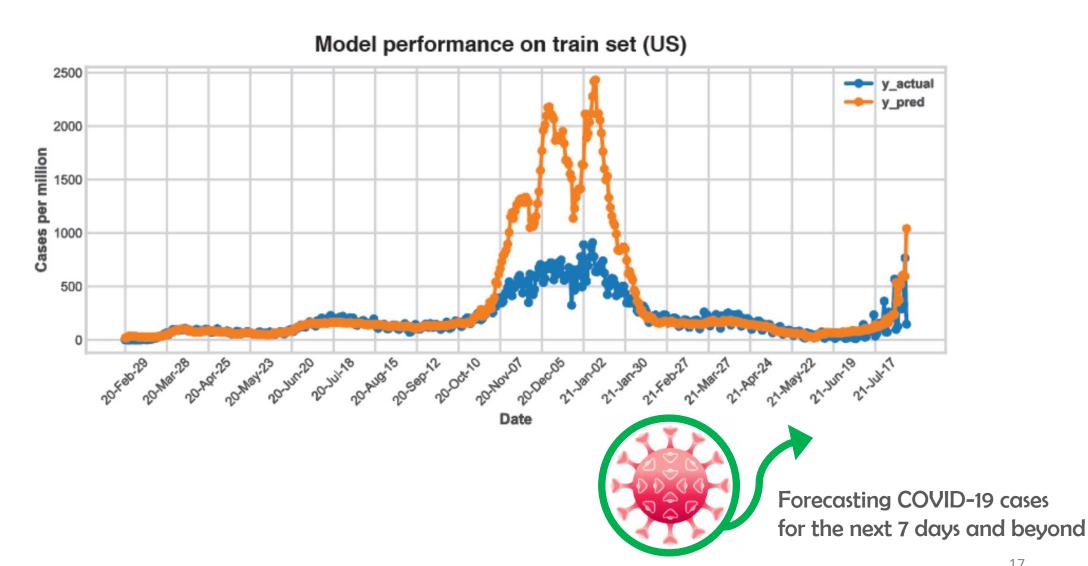
XGBoost model feature importance



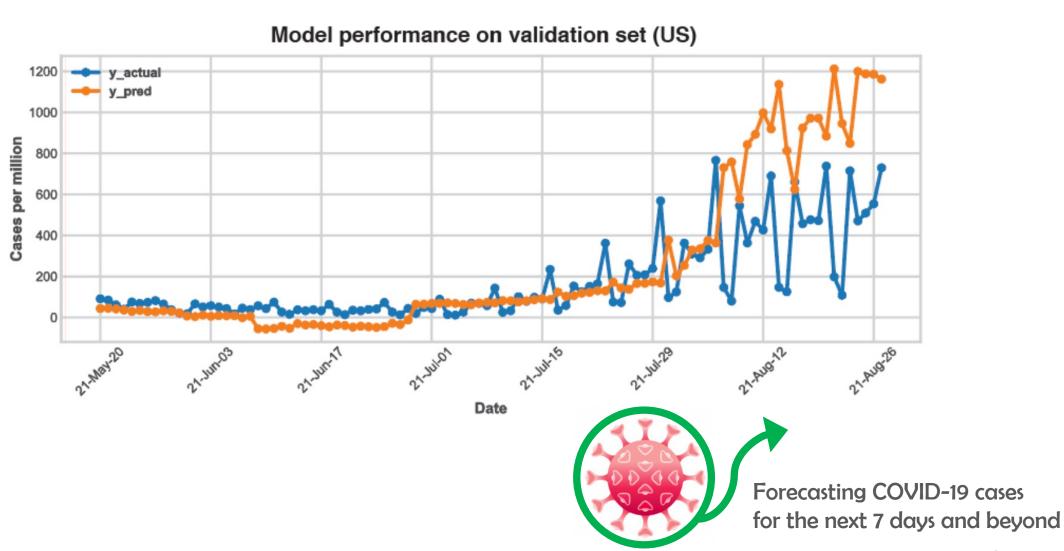
MLP model architecture with embeddings



MLP performance on train set

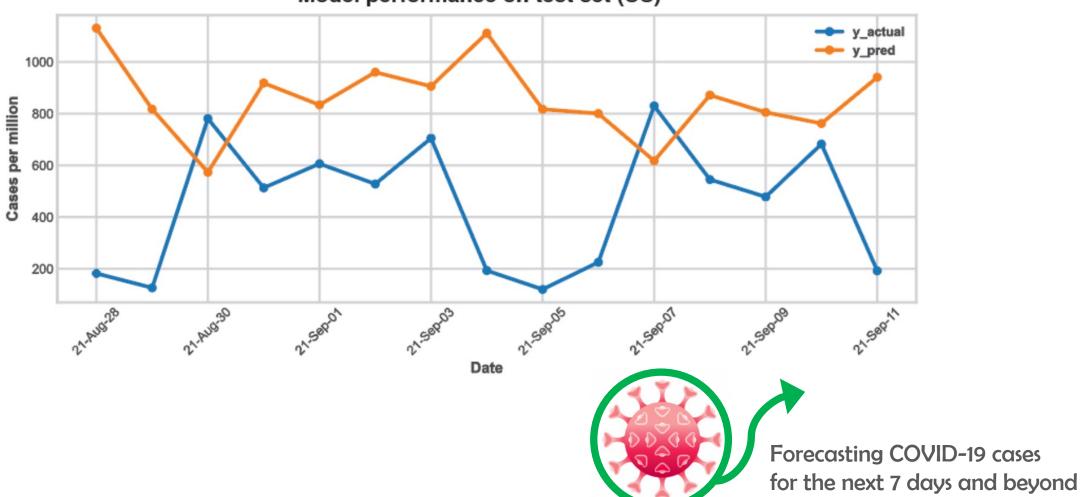


MLP performance on validation set

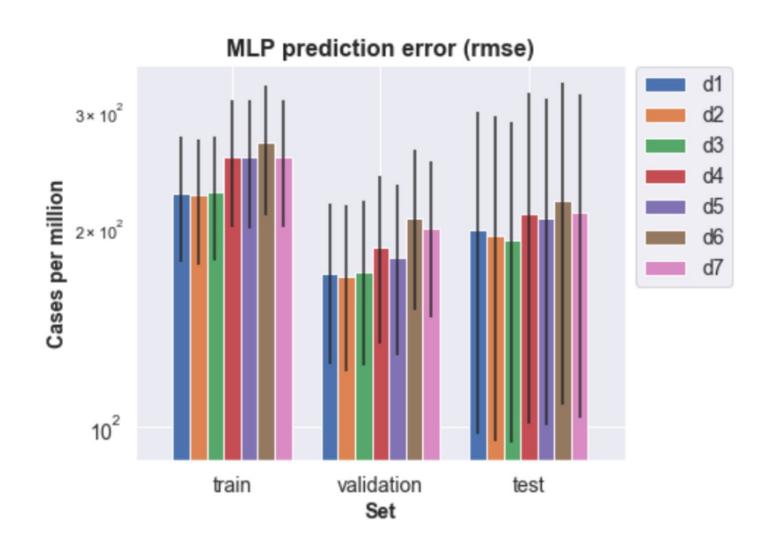


MLP performance on test set

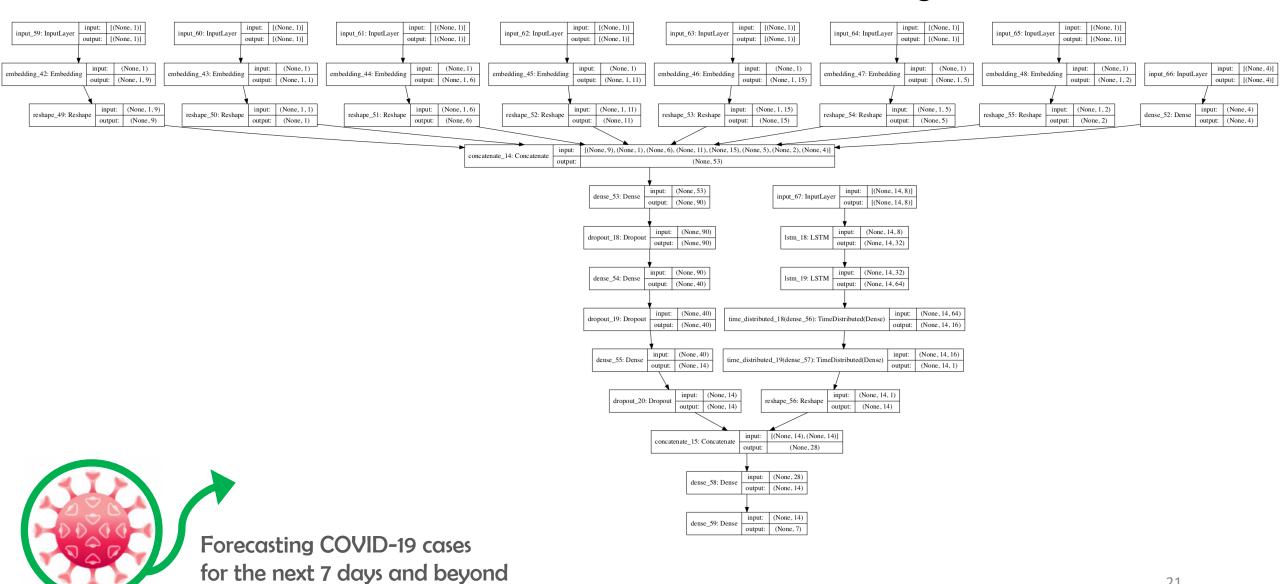




MLP performance on train/validation/test sets

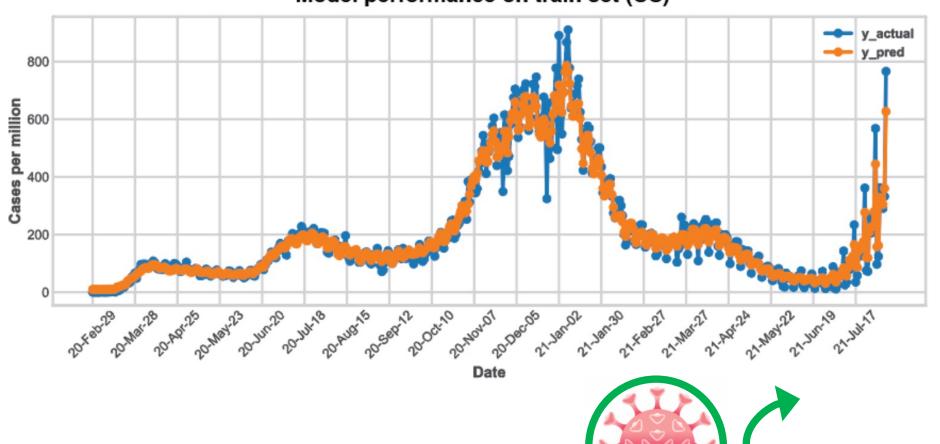


LSTM model architecture with embeddings



LSTM performance on train set

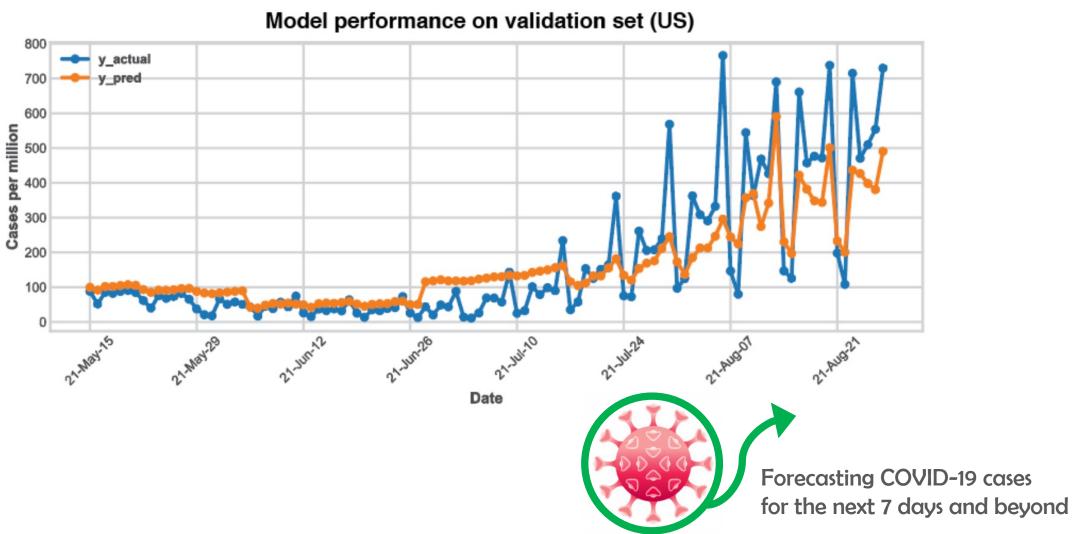
Model performance on train set (US)



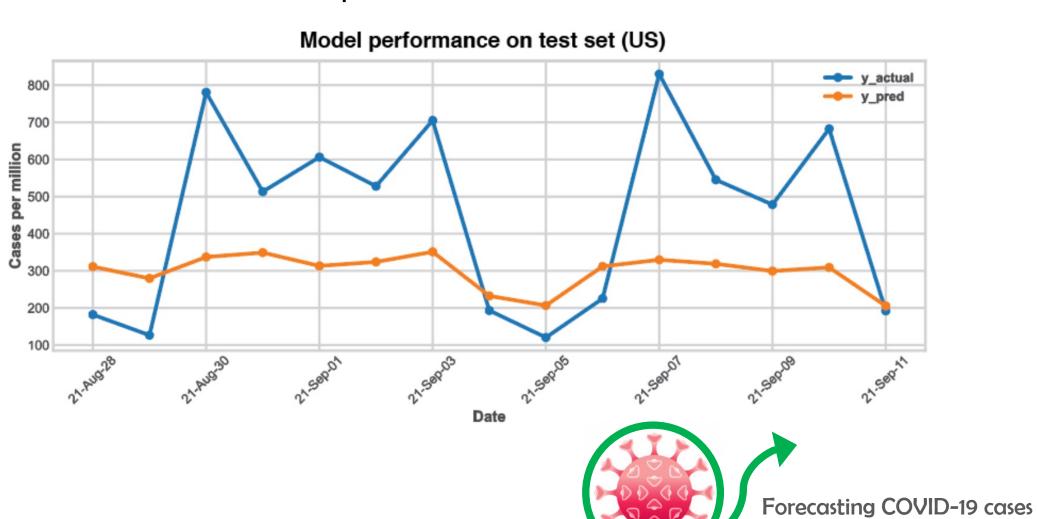
Forecasting COVID-19 cases

for the next 7 days and beyond

LSTM performance on validation set

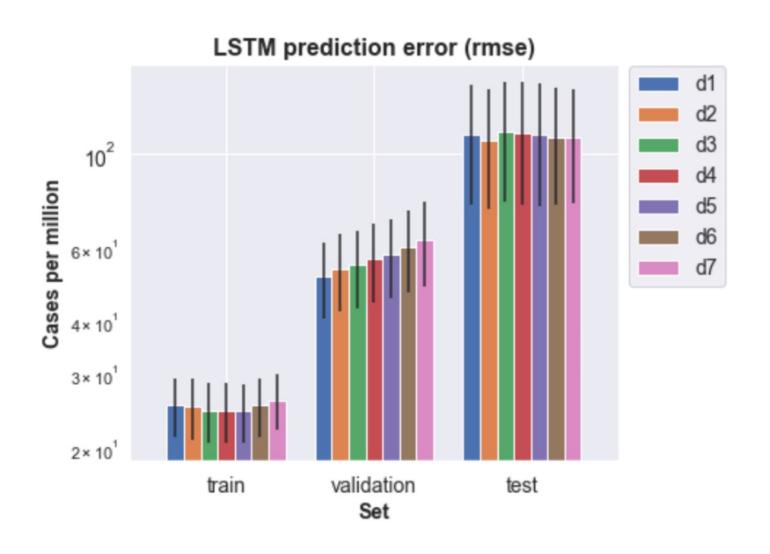


LSTM performance on test set

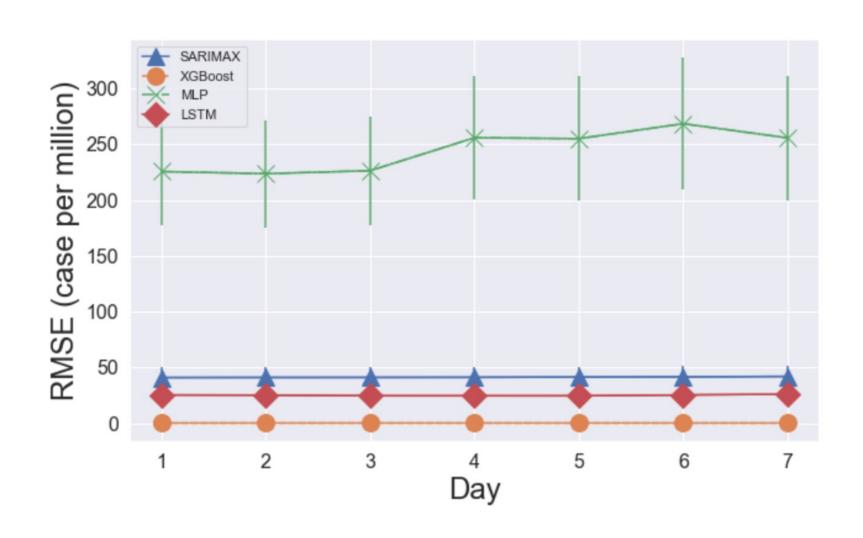


for the next 7 days and beyond

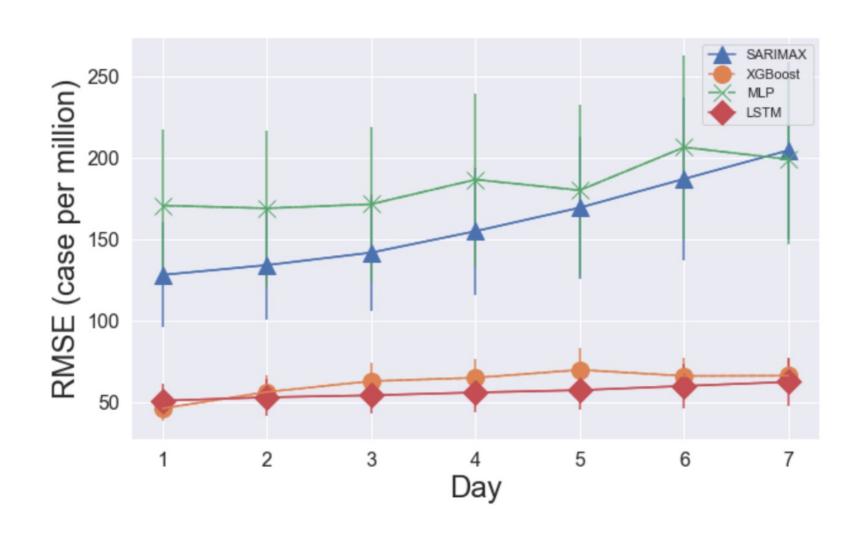
LSTM performance on train/validation/test sets



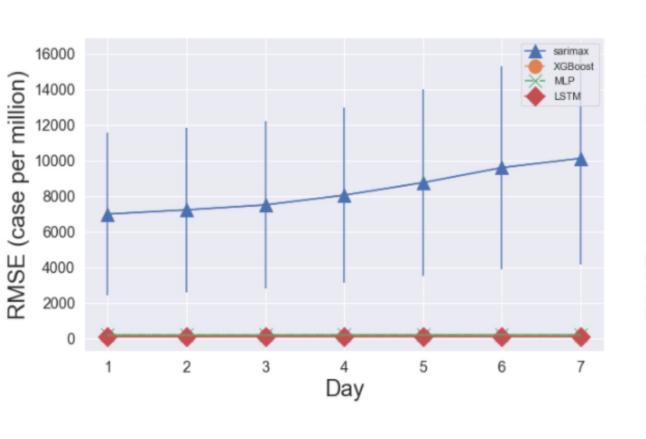
Comparing model performance on train set

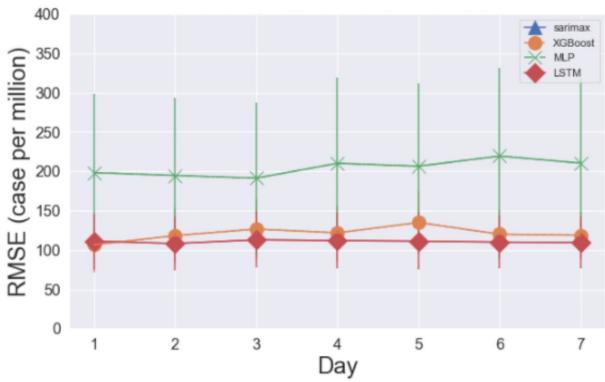


Comparing model performance on validation set



Comparing model performance on test set





Conclusion

- A traditional econometric model (SARIMAX) performed poorly when predicting far ahead (weeks or months) into the future.
- A gradient-boosting based method (XGBoost regressor) performed well even when predicting the far future.
- XGBoost was overfitted during training, meaning that with proper regularization it may perform even better.
- MLP in its current version suffered underfitting, which motivated us to try an architecture with stacked LSTM layers.
- Indeed, adding dual LSTM layers significantly improved forecasting.

