COVID-19 **CHINA'S PROJECTIONS**

By: Peng Zhang, Brenda Mas & Mohu Sah

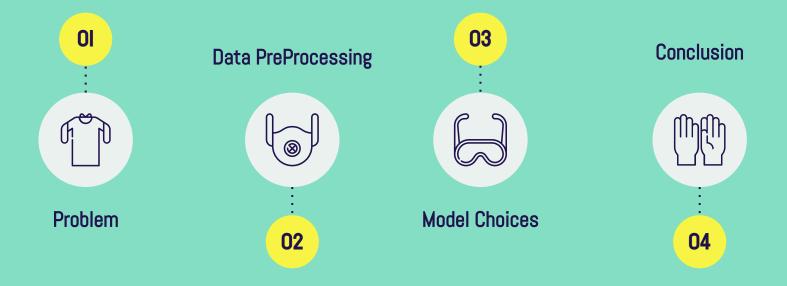


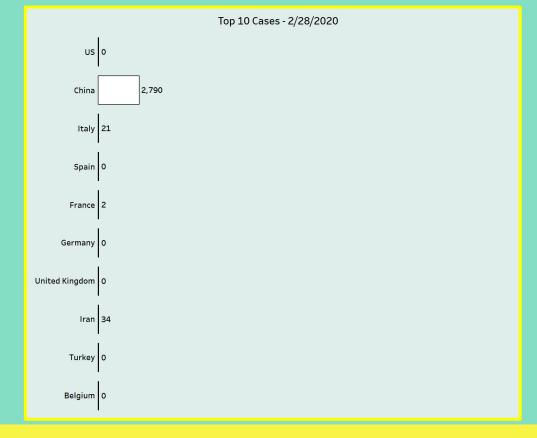




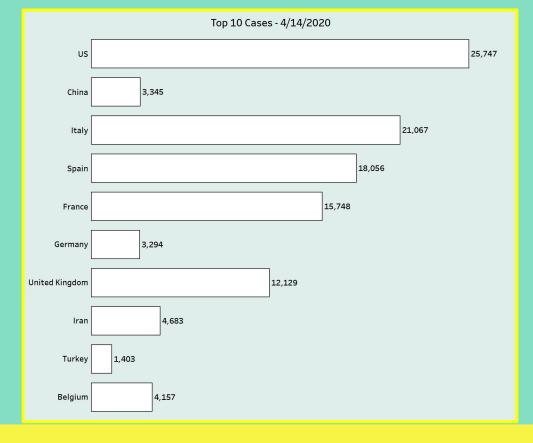


AGENDA





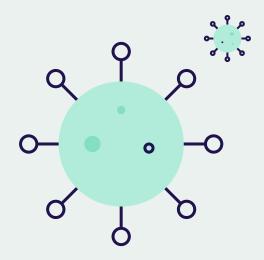
WORLD CASES ON FEB 28



WORLD CASES ON MAR 28

QUESTION

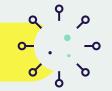
Is China Under Reporting Their Cases?



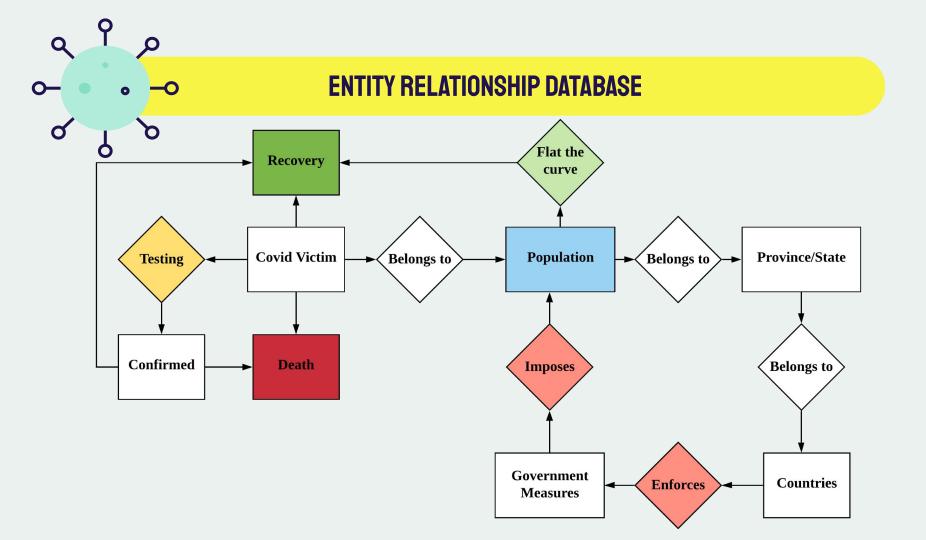


LITERATURE REVIEW

Are China's COVID Statistics Reliable?



- Autocratic & Dictatorship Government in the past have inflated their statistics General line of reasoning
- Governance system rewards positive news
- Efforts to downplay the impact of novel Coronavirus
- China's COVID numbers are likely much higher as previously stated
- A drop in mobile phone & landline usage witnessed in China during the time of quarantine. One would rather expect an increase in mobile usage.
- Mortality Rate in Italy 9%, suggests numbers to be misrepresented



FEATURE SELECTION



Entity



Stringent Index



Density

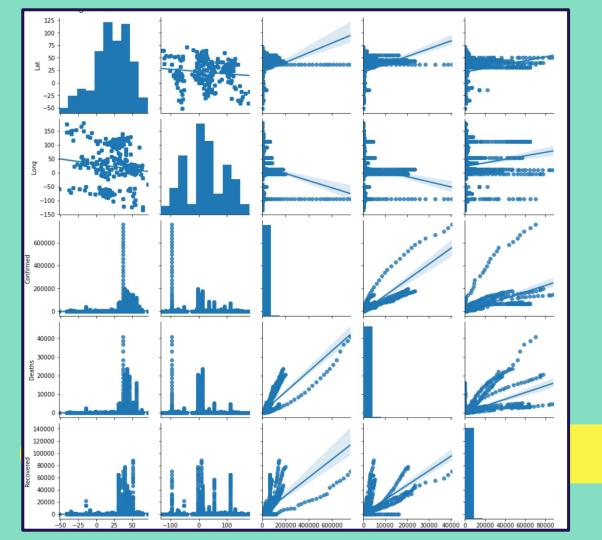


Age Group

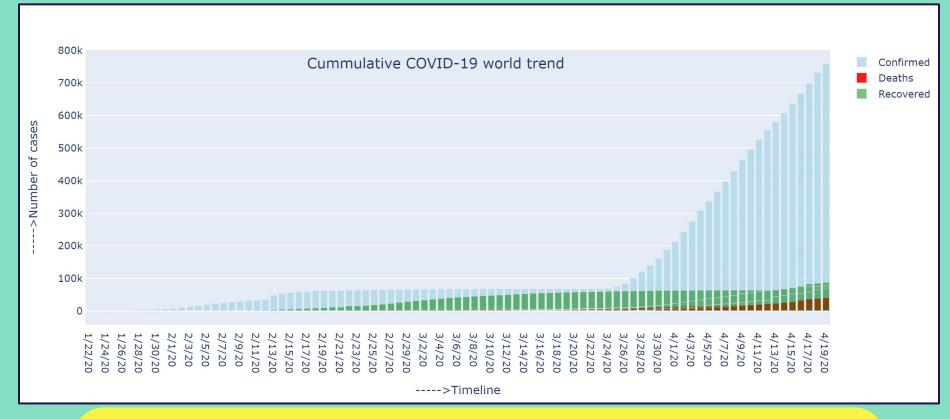


02.

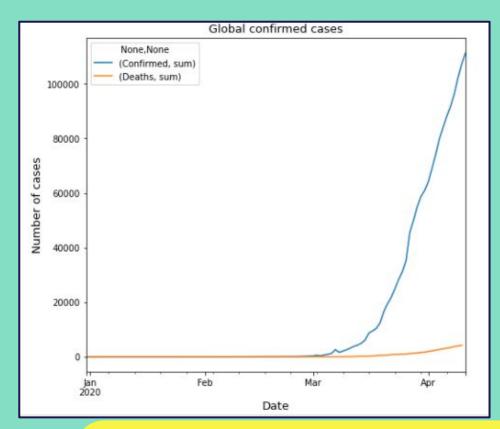
DATA PRE-PROCESSING

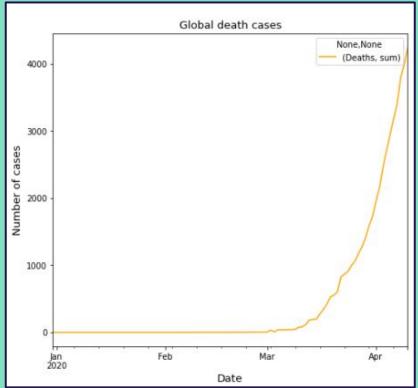


PAIRPLOTS



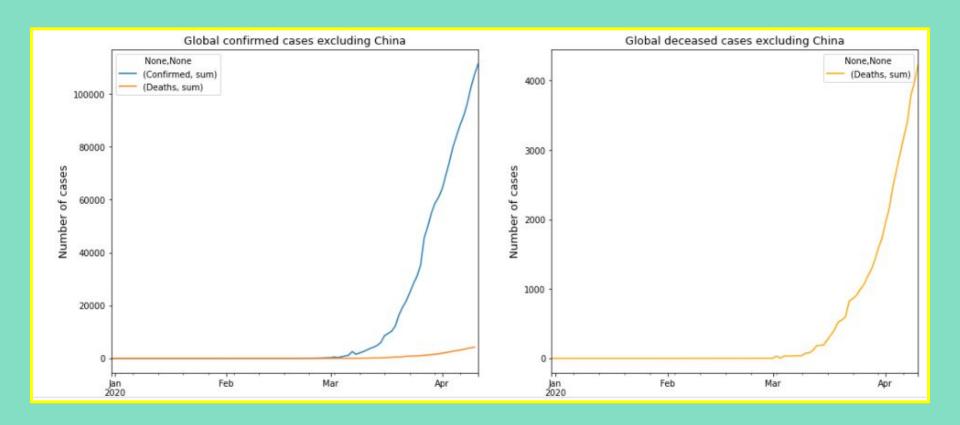
INCREMENTAL COVID-19 TREND



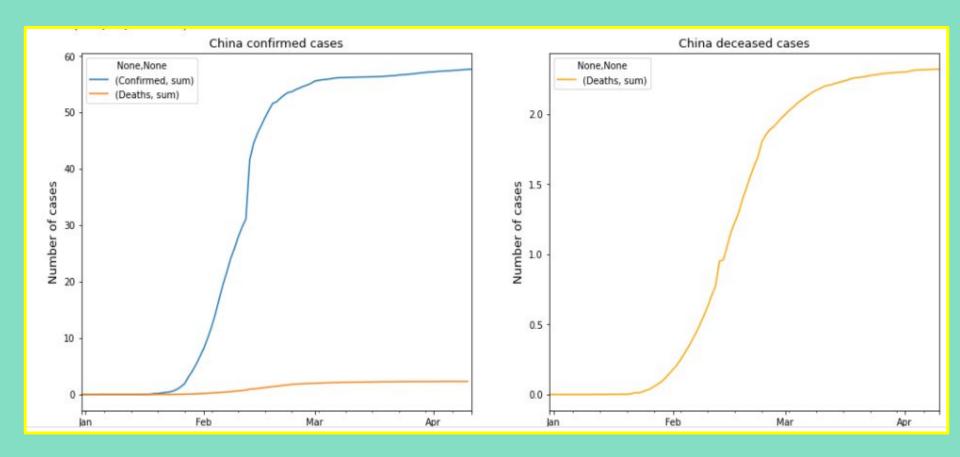


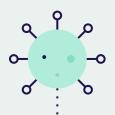
GLOBAL TREND

TRENDS OF THE WORLD WITHOUT CHINA



COVID 19 SITUATION IN CHINA





METHODOLOGY

- Clean & Merge datasets
- Population: Median age, population density & urban population
- Stringency (Government imposed measures):
 Lockdown, investment in healthcare, tracing, International support

POPULATION & STRINGENCY DATA

Country (or dependency)	med_age	urban_pop	density	land_area	world_share
China	38	61 %	153	9388211	18.47 %
India	28	35 %	464	2973190	17.70 %
United States	38	83 %	36	9147420	4.25 %
Indonesia	30	56 %	151	1811570	3.51 %
Pakistan	23	35 %	287	770880	2.83 %

H3_Contact tracing	E4_International support	investment in healthcare	H5_Investment in vaccines	H2_Testing policy	H3_Contact tracing.1	E1_Income support	StringencyIndex
1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0
1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0
1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0
1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0
1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0

STANDARDIZE DATA OVER WEEKS

- Standardized (Population & Time): Daily new cases per week, per million
- To compare apples-to-apples
- Every country's Day 1: When infection started

		Confirmed	Daily	Deaths	med_age	density	H3_Contact tracing
Entity	Week NUM						
Afghanistan	1	0.025688	0.026	0.000000	18.0	60.0	1.0
	2	0.565141	0.539	0.000000	18.0	60.0	1.0
	3	1.926617	1.361	0.025688	18.0	60.0	1.0
	4	4.932139	3.006	0.102753	18.0	60.0	1.0
	5	10.866119	5.935	0.359635	18.0	60.0	1.0

AGGREGATE BY COUNTRY

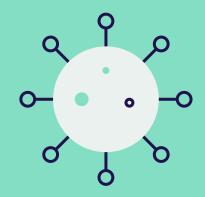
- Aggregate data per country
- One row per country

	Confirmed	Daily	Deaths	med_age	density	H3_Contact tracing	E4_International support
Entity							
Afghanistan	13.383565	2.230667	0.385323	18.0	60.0	1.0	0.0
Africa	9.661359	1.073667	0.469939	0.0	0.0	NaN	NaN
Albania	144.554868	28.910400	7.992216	36.0	105.0	1.0	0.0
Algeria	40.158680	6.693500	5.359052	29.0	18.0	0.0	0.0
Andorra	7778.424901	1555.684400	323.561768	0.0	164.0	1.0	0.0

DATA CLEANING

- Remove null values
- Remove arbitrary country names like Africa, World, Oceania
- Date ready for feature modelling

Confirmed	Daily	Deaths	med_age	density	H3_Contact tracing	E4_International support
13.383565	2.230667	0.385323	18.0	60.0	1.0	0.0
144.554868	28.910400	7.992216	36.0	105.0	1.0	0.0
40.158680	6.693500	5.359052	29.0	18.0	0.0	0.0
7778.424901	1555.684400	323.561768	0.0	164.0	1.0	0.0
0.578100	0.192333	0.060853	17.0	26.0	0.0	0.0
	13.383565 144.554868 40.158680 7778.424901	13.383565 2.230667 144.554868 28.910400 40.158680 6.693500 7778.424901 1555.684400	13.383565 2.230667 0.385323 144.554868 28.910400 7.992216 40.158680 6.693500 5.359052 7778.424901 1555.684400 323.561768	13.383565 2.230667 0.385323 18.0 144.554868 28.910400 7.992216 36.0 40.158680 6.693500 5.359052 29.0 7778.424901 1555.684400 323.561768 0.0	13.383565 2.230667 0.385323 18.0 60.0 144.554868 28.910400 7.992216 36.0 105.0 40.158680 6.693500 5.359052 29.0 18.0 7778.424901 1555.684400 323.561768 0.0 164.0	Confirmed Daily Deaths med_age density —tracing 13.383565 2.230667 0.385323 18.0 60.0 1.0 144.554868 28.910400 7.992216 36.0 105.0 1.0 40.158680 6.693500 5.359052 29.0 18.0 0.0 7778.424901 1555.684400 323.561768 0.0 164.0 1.0



03.



MODEL CHOICES



CHOICES

OI. CLUSTERING

02. SMOTE

Deal with Imbalanced Data

03. REGRESSION

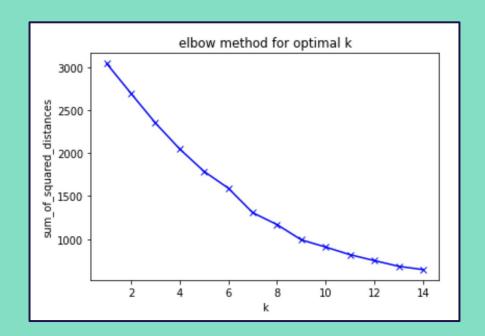
For Feature Selection

03. RANDOM FOREST

Determine Trend

04. LSTM

Determine Variation



K-MEANS CLUSTERING

Unsupervised learning

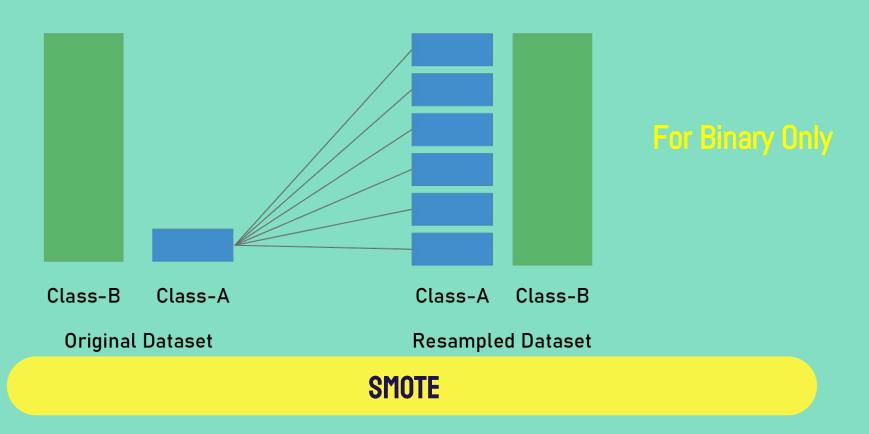
Only numerical input

Drop the country column

OPTIMAL # OF CLUSTERS: 7

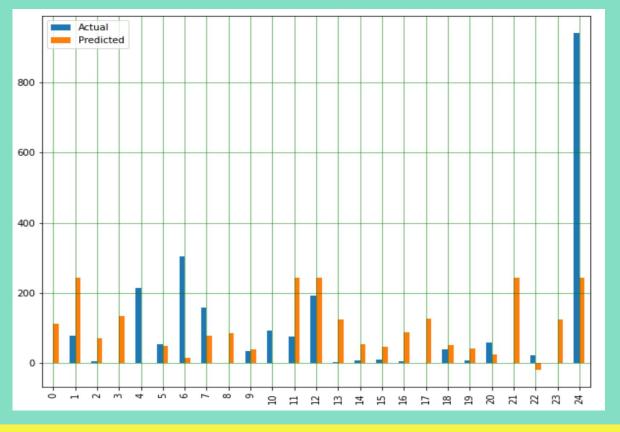
Silhouette Coefficient: 0.2825; Calinski Harabasz Score: 42.37

Over Sampling



```
OLS Regression Results
Dep. Variable:
                          Daily R-squared (uncentered):
                                                                    0.076
                                Adj. R-squared (uncentered): 0.028
Model:
Method:
                Least Squares
                                F-statistic:
                                                                   1.577
              Fri, 08 May 2020
                                Prob (F-statistic):
                                                                9.147
Date:
                                Log-Likelihood:
                                                                  -1015.6
Time:
                        00:41:38
No Observations:
                            142
                                AIC:
                                                                    2045.
Df Residuals:
                                 BIC:
                           135
                                                                    2066.
Df Model:
Covariance Type:
                     nonrobust
                                                               P>|t|
                                    coef
                                           std err
                                                                        [0.025
                                                                                  0.975]
                                 0.0786 1.446 0.054 0.957 -2.781 2.938
med age
                              0.0201 0.011 1.768 0.079 -0.002 0.043 -13.6201 42.493 -0.321 0.749 -97.658 70.418
density
H3 Contact tracing
E4_International support -6.605e-06 2.56e-05 -0.258 0.796 -5.72e-05 4.39e-05
H4 Emergency investment in healthcare 7.846e-09 1.62e-07 0.048 0.961 -3.13e-07 3.28e-07
H5 Investment in vaccines
                        -5.608e-06 5.59e-05 -0.100 0.920
                                                                     -0.000
                                                                                   0.000
H2 Testing policy
                            56.0657 34.407 1.629 0.106 -11.981 124.113
                           -1.062e-12 4.09e-12 -0.260 0.795 -9.15e-12 7.03e-12
E1 Income support
Omnibus:
                         185.312 Durbin-Watson:
                                                             2.017
```

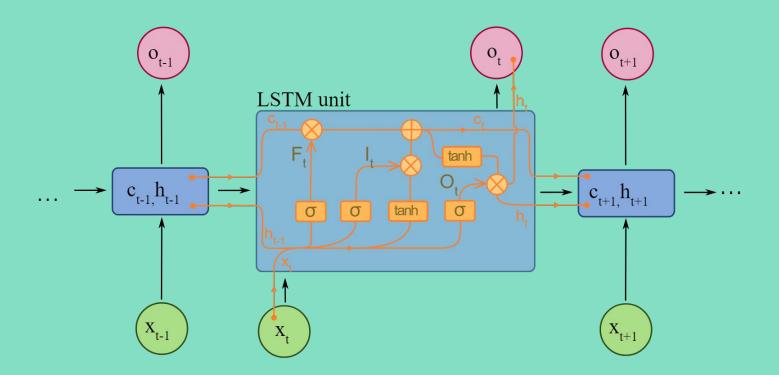
REGRESSION



ACTUAL

```
Mean Absolute Error (MAE): 91.5225513570864
Mean Squared Error (MSE): 32004.957400494695
Root Mean Squared Error (RMSE): 178.89929401899465
Mean Absolute Percentage Error (MAPE): 24.22
Accuracy: 75.78
```

RANDOM FOREST REGRESSOR



LSTM NEURAL NETWORK

- LSTM = Long Short Term Memory
- RNN (Recurrent Neural Network) that overcome technical problems
- RNNs fail to learn in the presence of time lags
- LSTM are better for time window-based feedforward networks
- Recall patterns that are very far into the past (or future)
- Resistant to noise (i.e. fluctuations in inputs that are random/irrelevant to predicting correct output)
- Parameters are trainable (in reasonable time)
- LSTM used for: handwriting recognition & generation, language modeling & translation, acoustic modeling of speech, analysis of audio, and video data

WHY LSTM?

Italy

- ★ Use Italy as Comparable
- ★ Predict Italy from May 1 to May 9
- ★ Compare Predicted to Actual
- ★ Good predictor?

Yes = Use to Predict China

No = Seek Other Method

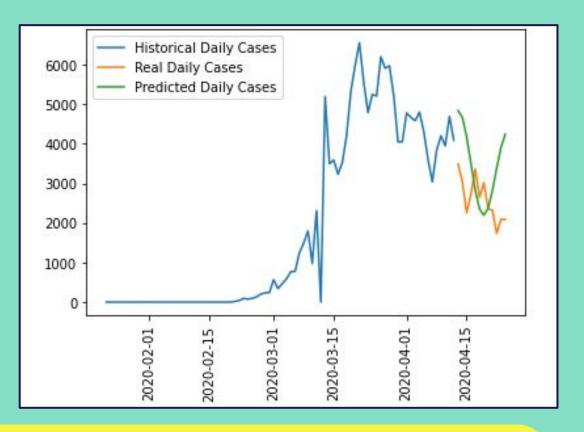


METHODOLOGY

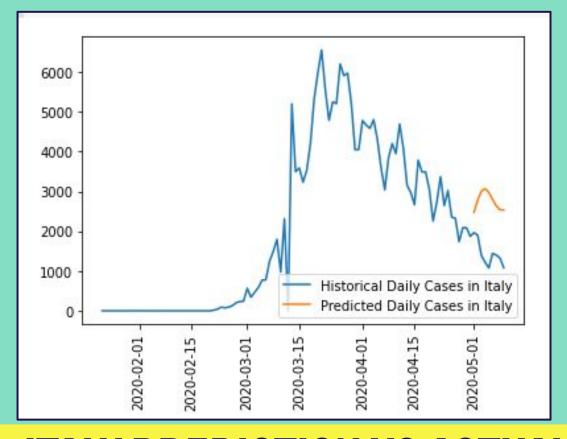
Training



GOOD PREDICTOR



ITALY PREDICTION

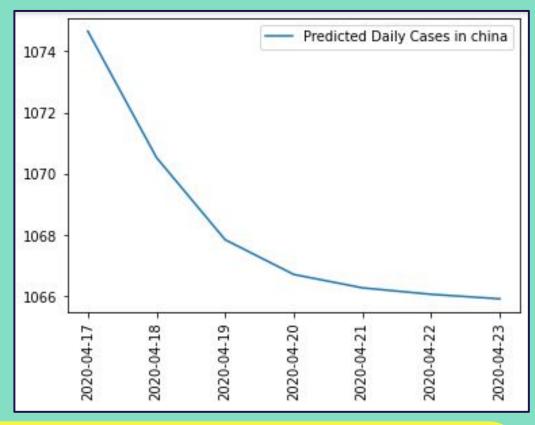


ITALY PREDICTION VS ACTUAL



Apply LSTM

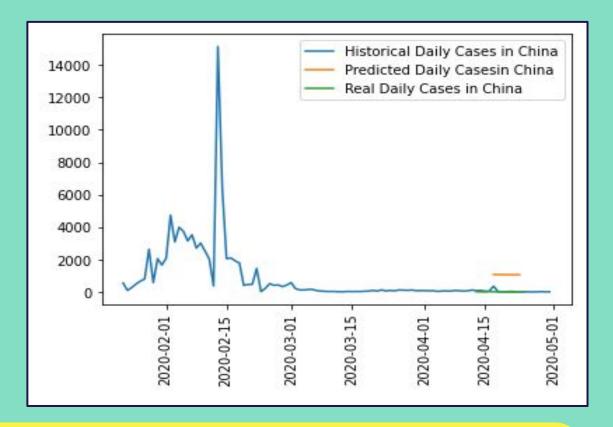
Using China's Data



CHINA PREDICTION DAILY

RESULTS: Inconclusive

Leveling off
Consistent w/Italy



CHINA PREDICTION

O4. CONCLUSION



SUMMARY

OI

Figures Suspiciously Low

CHINA

04

SMOTE

Oversampling for Imbalanced Data when Variable is Binary

02

FEATURES

Government Stringency Standardized: Population & Time

05

RANDOM FOREST

Features Don't Correlate Accuracy: 75.78 03

CLUSTERING

7 Clusters Optimal

06

LSTM (Good Predictor)

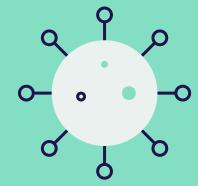
Italy as Sample China Results: Inconclusive

REFERENCES

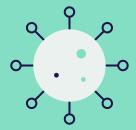
- https://thediplomat.com/2020/03/can-chinas-covid-19-statistics-be-trusted/
- https://www.theguardian.com/world/2020/apr/09/the-cluster-effect-how-social-gatherings-were-rocket-fuel-for-coronavirus
- https://arxiv.org/pdf/2002.12298.pdf
- https://towardsdatascience.com/machine-learning-methods-to-aid-in-coronavirus-response-70df8bfc7861
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- https://www.bbc.com/news/world-52103747
- https://www.google.com/covid19/mobility/https://ourworldindata.org/coronavirus-data
- https://data.worldbank.org/indicator/sp.pop.totl
- https://www.kaggle.com/imdevskp/corona-virus-report
- https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19_time_series
- https://www.bsg.ox.ac.uk/research/research-projects/oxford-covid-19-government-response-tracker
 https://www.bbc.com/news/world-52103747
- http://weekly.chinacdc.cn/news/TrackingtheEpidemic.htm
- https://www.curiousily.com/posts/time-series-forecasting-with-lstm-for-daily-coronavirus-cases/
- https://towardsdatascience.com/machine-learning-algorithms-part-9-k-means-example-in-python-f2ad05ed5203
- https://blog.statsbot.co/time-series-prediction-using-recurrent-neural-networks-lstms-807fa6ca7f

Visualizations:





THANKS!



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