Exploration of COVID19 Data

Due on April 30, 2020
Machine Learning Fundamentals and Applications
CS559−Spring 2020
Professor In Suk Jang

Daniel Kadyrov

Abstract

Short introduction to subject of the paper . . .

Contents

1 Introduction **1**

2 Data **1**
2.1 Data Preprocessing . . . 1
2.2 Exploration of Data . . . 3

3 Predicting COVID19 Spread through Interpolation **5**
3.1 Methodology . . . 5
3.1.1 Training and Test Data . . . 5
3.1.2 Exponential Regression . . . 5
3.1.3 Quadratic Regression . . . 5
3.1.4 Logistic Regression . . . 6
3.1.5 Accuracy . . . 6
3.2 Results . . . 7

4 Predicting the End of COVID19 **9**
4.1 Methodology . . . 9
4.2 Results . . . 10

5 Types of Mitigation and Growth Rate **12**
5.1 Methodology . . . 12
5.2 Analysis . . . 13
5.2.1 Australia . . . 13
5.2.2 Brazil . . . 14
5.2.3 China . . . 15
5.2.4 South Africa . . . 16
5.2.5 Sweden . . . 17
5.2.6 United States . . . 18
5.3 Results and Conclusion . . . 19

6 Effects of Weather Conditions **20**
6.1 Methodology . . . 20
6.2 Results . . . 21
6.2.1 New York . . . 21
6.2.2 California . . . 22
6.2.3 Michigan . . . 23
6.2.4 Louisiana . . . 24
6.3 Analysis . . . 24

7 Case Study on New York City **25**
7.1 Exploration of Data . . . 25
7.2 Correlations for Zipcode Based Data . . . 26
7.3 Predicting the End of COVID19 . . . 27
7.4 Growth Rate Mitigation . . . 28

8 Conclusion **29**

References **30**

1 Introduction

Coronavirus disease 2019, COVID-19, is an infectious disease that was first identified in December 2019 at the city of Wuhan, China and has since spread to a worldwide pandemic affecting international politics and economics, changing social interaction as governments mandate stay at home orders, and even becoming the subject of an online machine learning course project.

Even though trading restrictions and panic buying have caused a limited amount of medical supplies, like personal protective equipment and respirators, and commodities, such as food staples, cleaning products, and toilet paper, the data on COVID-19 is released and widely available to predict how this virus spreads, when it will end, study the effects of different mitigation types utilized by countries faced with the pandemic, examine if the weather affects the virus spread, and inspect how it behaves in one of the most densely populated and affected cities so far, New York City.

2 Data

COVID-19 data was made available by the John Hopkins University Center for Systems Science and Engineering. The dataset is an aggregate of sources that range from the World Health Organization, WHO, COVID Tracking Project, and the health and disease control centers of countries including China, the United States, Italy, Canada, and Taiwan. The dataset was downloaded from Kaggle.

New York City, one of the most affected cities in the United States and the world, has made the New York City Department of Health dataset available on Github. Additional data was found on New York City Open Data.

All data used for this report was accessed on April 26th 2020.

2.1 Data Preprocessing

Data was imported into Python using the `Pandas` package available through `Pip`. Column names like `ObservationDate` and `Country/Region` were renamed to `Date` and `Country`, respectively. Country names listed, such as Mainland China, UK, US, were replaced to reflect their widely used names, China, United States, and United Kingdom, respectively. The serial number column, `SNo`, was dropped.

Listing 1: Importing COVID19 dataset

```
import pandas as pd

df = pd.read_csv("../data/novel-corona-virus-2019-dataset/covid_19_data.csv",
    parse_dates=["Last Update"])
df.rename(columns={ "ObservationDate": "Date",
                    "Country/Region": "Country"}, inplace=True)

df["Country"].replace(["Mainland China"], ["China"], inplace=True)
df["Country"].replace(["US"], ["United States"], inplace=True)
df["Country"].replace(["UK"], ["United Kingdom"], inplace=True)

df = df.drop(columns="SNo")
```

Continents were added to the data through the package `Pycountry`.

Listing 2: Adding continent data

```
import pycountry_convert as pc

def get_continent(row):
    continents = {
        'NA': 'North America',
        'SA': 'South America',
        'AS': 'Asia',
        'OC': 'Oceania',
        'AF': 'Africa',
        'EU': 'Europe'
    }

    country = row["Country"]
    try:
        country_code = pc.country_name_to_country_alpha2(
            country, cn_name_format="default")
        return continents[pc.country_alpha2_to_continent_code(country_code)]
    except:
        return None

df["Continent"] = df.apply(lambda row: get_continent(row), axis=1)
```

The number of cases of COVID19 that were eradicated can be found by adding the number of recovered patients with the number of deaths.

$$N_{\text{eradicated}} = N_{\text{deaths}} + N_{\text{recovered}} \tag{1}$$

The number of active cases of COVID19 can be found by subtracting the number of eradicated cases from the number of confirmed cases.

$$N_{\text{active}} = N_{\text{confirmed}} - N_{\text{eradicated}} \tag{2}$$

Listing 3: Computed eradicated and active cases

```
df["Eradicated"] = df["Deaths"] + df["Recovered"]
df["Active"] = df["Confirmed"] - df["Eradicated"]
```

2.2 Exploration of Data

Table 1 shows the prolific spread of the virus throughout the inhabitant continents of the world.

Table 1: Spread of COVID19 by Continent

Continent	Confirmed	Deaths	Recovered	Eradicated	Active
Europe	1251929	120150	407130	527280	724649
North America	1013138	58224	125756	183980	829158
Asia	460182	16946	220668	237614	222568
South America	131250	47826	6019	53845	77405
Africa	29683	9013	1341	10354	19329
Oceania	8190	98	5375	5473	2717

Visualizing the confirmed cases over time shows how fast this virus grew in months time.

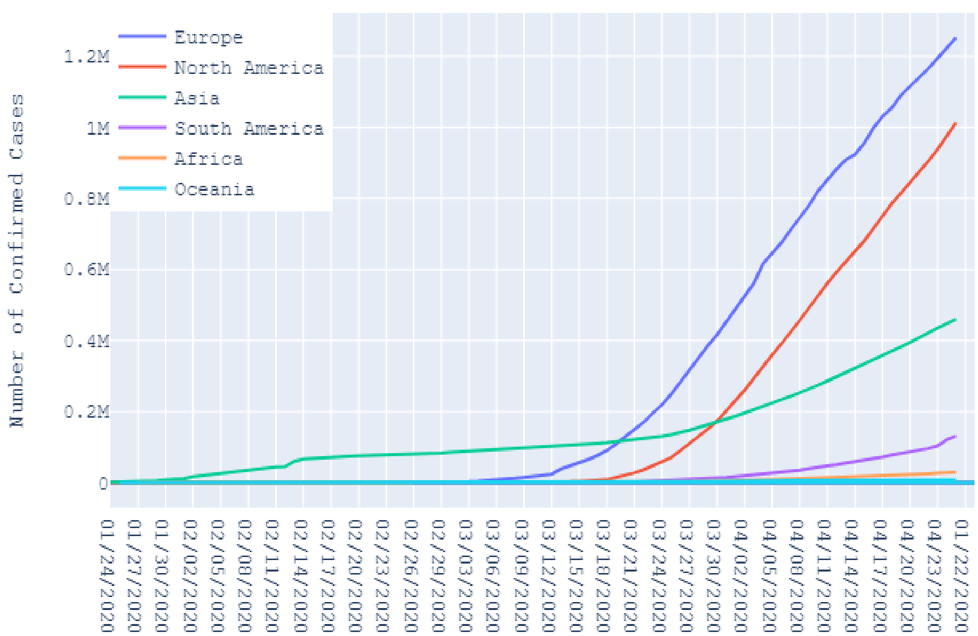


Figure 1: Spread of COVID 19 by Continent

Analyzing the top countries with confirmed cases by continent:

Table 2: Spread of COVID19 in Europe

Country	Confirmed	Deaths	Recovered	Eradicated	Active
Italy	195351	26384	63120	89504	105847
Spain	223759	22902	95708	118610	105149
Germany	156513	5877	109800	115677	40836

Table 3: Spread of COVID19 in North America

Country	Confirmed	Deaths	Recovered	Eradicated	Active
United States	938154	53755	100372	154127	784027
Canada	45493	2549	16013	18562	26931
Mexico	13842	1305	7149	8454	5388

Table 4: Spread of COVID19 in Asia

Country	Confirmed	Deaths	Recovered	Eradicated	Active
China	82827	4632	77394	82026	801
Iran	89328	5650	68193	73843	15485
Turkey	107773	2706	25582	28288	79485

Table 5: Spread of COVID19 in Africa

Country	Confirmed	Deaths	Recovered	Eradicated	Active
South Africa	4361	86	1473	1559	2802
Egypt	4319	307	1114	1421	2898
Algeria	3256	419	1479	1898	1358

Table 6: Spread of COVID19 in Oceania

Country	Confirmed	Deaths	Recovered	Eradicated	Active
Australia	6694	80	4223	4303	2391
New Zealand	1470	18	1142	1160	310
Fiji	18	0	10	10	8

3 Predicting COVID19 Spread through Interpolation

3.1 Methodology

3.1.1 Training and Test Data

Since the data provided is time dependant and the task is to build models to predict the spread of the virus, the training data was set to be all data available until March 31st, 2020 and everything after was used as test data to score the model. This split was created in Python through the following `Dataframe` manipulation:

Listing 4: Training and Test Data Split

```
x = data.loc[(data['Date'] < "04/01/2020")]["Days"]
y = data.loc[(data['Date'] < "04/01/2020")]["Confirmed"]

x2 = data.loc[(data['Date'] >= "04/01/2020")]["Days"]
y2 = data.loc[(data['Date'] >= "04/01/2020")]["Confirmed"]
```

3.1.2 Exponential Regression

An exponential model describes the growth of the virus as ever growing and unstoppable. The generic model of the exponential function is:

$$f(x, a, b, c) = ae^{b(x-c)} \tag{3}$$

This was achieved in Python using the curve fit function of the Sklearn library.

Listing 5: Exponential Model

```
from scipy.optimize import curve_fit

def exponential(x, a, b, c):
  return a*np.exp(b*(x-c))

params, corr = curve_fit(exponential, x, y, p0=[0, 0, 0])
y_pred = exponential(x2, *param)
```

3.1.3 Quadratic Regression

The quadratic model describes the growth of the virus as parabolic. The growth hits an extreme point at the vertex and symmetrically decays at the same rate. The model of the quadratic function is:

$$f(x, a, b, c) = ax^2 + bx + c \tag{4}$$

Within Python:

Listing 6: Quadratic Model

```
from scipy.optimize import curve_fit

def quadratic(x, a, b, c):
  return a*(x**2.0) + b*x + c

params, corr = curve_fit(quadratic, x, y, p0=[1, 1, 1])

y_pred = quadratic(x2, *param)
```

3.1.4 Logistic Regression

The logistic function can be appropriately used in modeling the spread of the virus because it captures the growth rate of the exponential function with the assumption that at some point, the inflection point, the rate will decrease until it reaches 1.

The logistic function formula is provided as:

$$f(x, L, k, x_0) = \frac{L}{1 + e^{-k(x-x_0)}} \tag{5}$$

where L is the curve's maximum value, or scale, k is the logistic growth rate, and x_0 is the value of the sigmoid's midpoint [1].

The logistic function requires for the data to be normalized. A scalar value is generated by assuming the last available y-value, or confirmed case number, is the highest point.

Listing 7: Logistic Model

```
from scipy.optimize import curve_fit

def logistic(x, L, k, x0):
  return L/(1+np.exp(-k*(x-x0)))

scale = y[-1]
params, corr = curve_fit(logistic, x, y/scale, p0=[1, 1, 1])

y_pred = quadratic(x2, *params) * scale
```

3.1.5 Accuracy

The accuracy of the models was determined through coefficient of determination, usually denoated as R^2. The regression score function was provied by the Sklearn metrics package. A score of 1 denotes the best possible score.

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

where

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

$$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{n=1}^{n} \epsilon_i^2$$

The accuracy score was calculated for only the predicted April data to analyze how well the models forsaw the growth of the virus in the selected country.

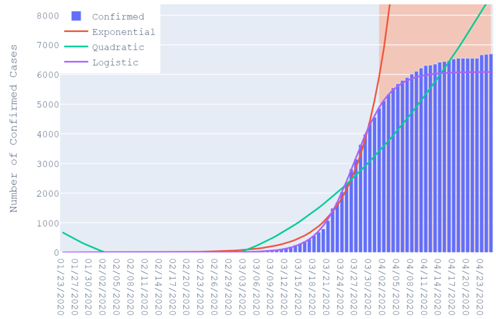
3.2 Results

Table 7 shows the accuracy results of the different regression models to predict the growth of the virus in the selected country. A score closer to the 1 indiciates that the model closer forsees how the virus spread in the month of April using the data provided in earlier months. When the exponential model predicts the growth better than the logistic model, it indiciates that the virus is spreading unmitigated. A better score in the logistic model suggests that the virus growth is tapering in the country.

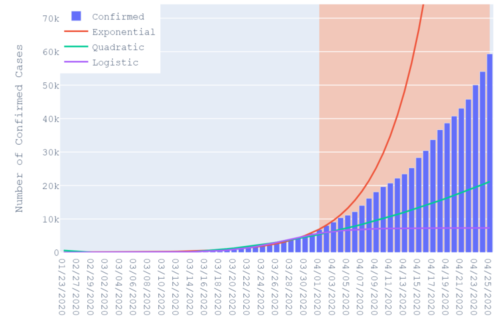
Table 7: Accuracy of COVID19 Growth Models

Country	Exponential	Quadratic	Logistic
Algeria	-300.685364	0.270597	-0.611431
Australia	-22206.120326	-4.654000	0.483841
Brazil	-41.483849	-0.409234	-1.723298
Canada	-623.689052	-2.110432	-1.267749
China	-11072.352650	-6109.919897	-6.996825
Ecuador	-45.092106	0.474223	-1.293533
Egypt	-5.323196	-0.203390	-1.830438
Fiji	-25.504067	-48.947467	-7.469834
Germany	-1429.602431	-0.291852	-1.252864
Iran	-106.636611	0.004569	0.856650
Italy	-402.243797	-0.633594	-1.250733
Mexico	-60.177645	-0.208680	-0.695200
New Zealand	-37083.631615	-6.055959	-4.194014
Peru	0.453311	-0.767787	-1.306760
South Africa	-1247.631391	-4.674649	-1.328513
Spain	-1560.444295	0.184842	-0.712448
Turkey	-9964.226390	0.808690	-1.838440
United States	-1356.526660	-2.797616	-1.677107

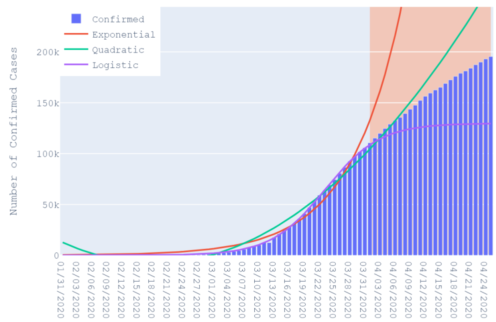
Even though R^2 accuracy is poor for all models, it demonstrates the inability to properly predict how the virus will spread especially when data is limited. It is interesting to note that the logistic model, representing the best case, and the exponential model, representing the worst case, create a boundary region for the growth. Examining the spread and models graphically per country in Figure 2 clearly shows how some countries, like Australia and Iran, have controlled the virus and reflect a logistic curve while countries like Brazil and Egypt are closer to exponential growth.



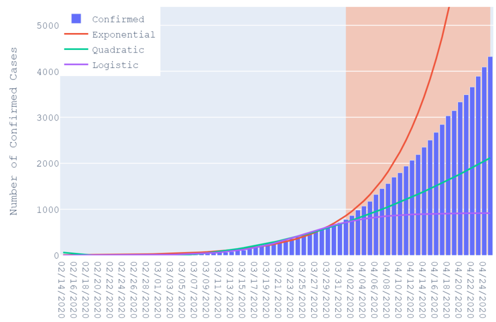
(a) Australia



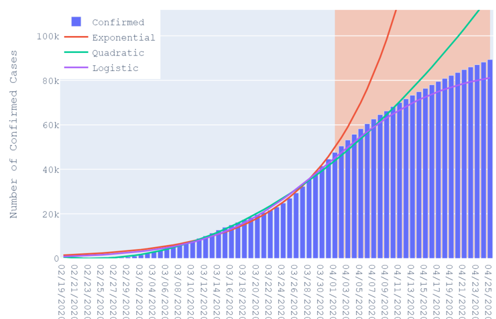
(b) Brazil



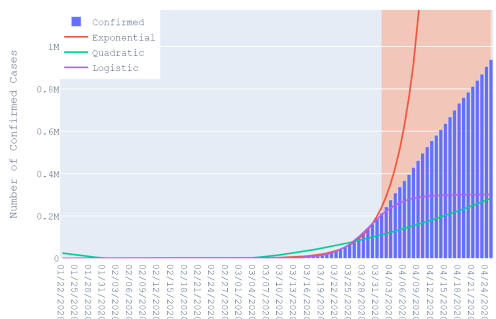
(c) Italy



(d) Egypt



(e) Iran



(f) United States

Figure 2: Modeling COVID19 Spread

4 Predicting the End of COVID19

4.1 Methodology

The logistic model detailed in the previous section captured the growth of the virus until an inflection point during which the growth rate decreases until it gets to 1, a sign that there are no new infections. The pandemic can be determined to be over when the growth rate reaches a certain threshold value which can be found with a ratio between two consecutive logistic functions.

$$t = \frac{f(x+1)}{f(x)} = \frac{\frac{L}{1+e^{-k(x+1-x_0)}}}{\frac{L}{1+e^{-k(x-x_0)}}}$$

Rearranging to solve for x, when the logistic function reaches the threshold value of t.

$$x = -\frac{1}{k}\log(\frac{1-t}{1e^{-}k-1}) + x_0 \tag{7}$$

The threshold value, t, was selected to be 1.000001 since using 1 would result in x becoming infinity. The function in Python uses the parameters found in the logistic function.

Listing 8: Predicting the Last Day

```
import numpy as np

def predict_day(params):
  threshold = 1.000001
  L, k, x0 = params
  last_day = int(round((-1/k)*np.log((1-threshold)/(threshold*np.exp(-k)-1))+x0))

  return last_day
```

All available data was used to create the logistic model and was generated for the total confirmed infections and total deaths.

4.2 Results

Table 8 shows the end date, total confirmed case, and total deaths predicted by the logistic model.

Table 8: COVID19 Country End Dates and Total Cases

Country	End Date	Total Confirmed	Total Deaths
Algeria	07/07/2020	3,484	417
Australia	05/18/2020	6,537	77
Brazil	06/26/2020	98,436	6,612
Canada	07/12/2020	54,052	3,916
China	04/25/2020	81,474	3,612
Ecuador	01/05/2021	1,583,211,969	634
Egypt	08/07/2020	6,621	393
Germany	06/15/2020	153,766	6,653
Iran	07/13/2020	93,834	5,714
Italy	07/03/2020	193,378	26,316
Mexico	07/29/2020	115,463	7,771
New Zealand	05/23/2020	1,446	20
Peru	06/29/2020	31,963	1,771
South Africa	08/26/2020	6,468	124
Spain	06/21/2020	215,326	22,369
Turkey	06/24/2020	120,058	3,258
United States	06/30/2020	995,581	65,028

Since the model only uses the data provided up to the date of the simulation, the predictions of some countries, like Ecuador, cannot be completely trusted. As of April 26th, the Institute for Health Metrics and Evaluation projects that the United States will have 67,641 deaths by August 4th [5].

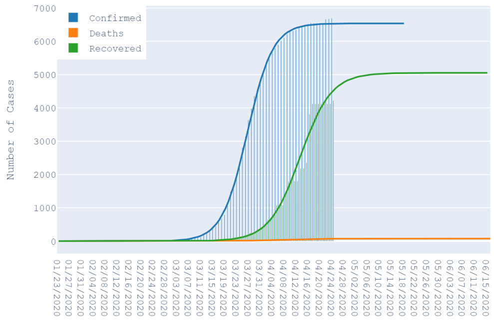
Using this model on the total world data generates the following.

Table 9: COVID19 World End Date and Total Cases

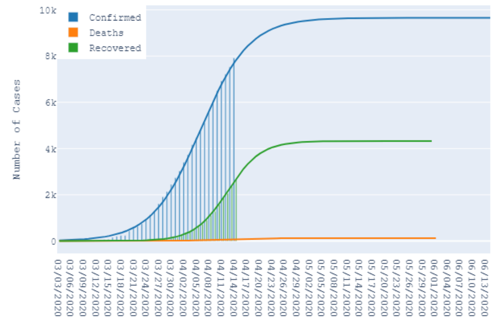
End Date	Total Confirmed	Total Deaths
07/29/2020	3,440,226	250,742

Table 10: COVID19 Continent End Date and Total Cases

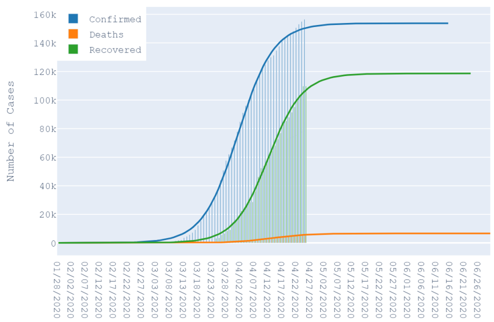
Continent	End Date	Total Confirmed	Total Deaths
Africa	06/02/2020	19432	1,103
Asia	02/17/2022	31,881,299,685	55,866
Europe	06/18/2020	106,0795	102,298
North America	06/08/2020	76,6258	36,842
Oceania	05/17/2020	7,807	119
South America	05/26/2020	98,327	3,525



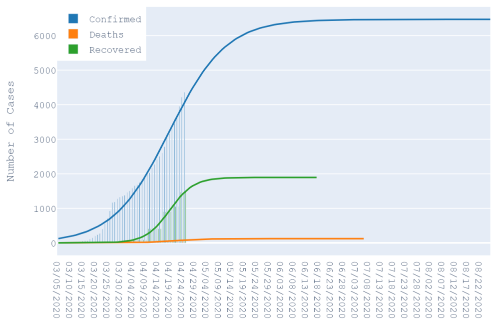
(a) Australia



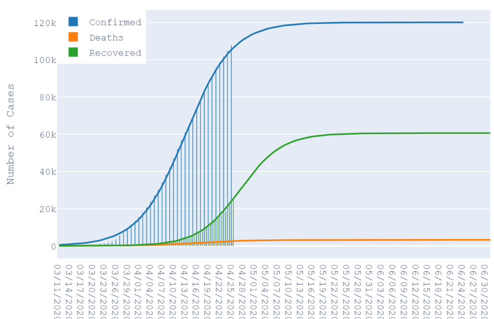
(b) Ecuador



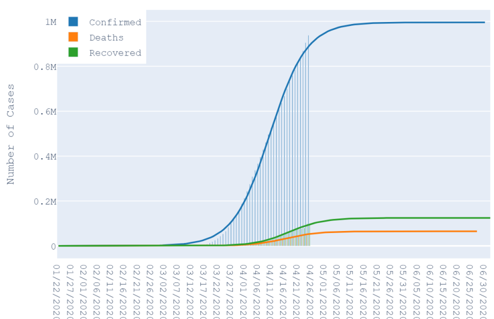
(c) Germany



(d) South Africa



(e) Turkey



(f) United States

Figure 3: Predicting the COVID19 End Date

5 Types of Mitigation and Growth Rate

5.1 Methodology

The growth rate is a metric of how fast the virus is spreading over a period of time, usually represented as a percentage. The growth rate is defined mathematically as:

$$\mathrm{GR} = \frac{x_2 - x_1}{\Delta t} \tag{8}$$

Within Python this was implemented with the following function:

Listing 9: Growth Rate Function

```
def growth_rate(data=None):
  x = []
  x.append(0)
  for i in range(data.shape[0]-1):
      next
      a = abs(data.iloc[i+1]-data.iloc[i])
      if data.iloc[i] == 0:
          v = 0.0
      else:
          v = a/data.iloc[i]
      v=v*100
      x.append(v)

  return np.array(x)

df["Growth Rate"] = growth_rate(df["Confirmed"])
```

As COVID19 spread into the confines of various countries, the governments of the respective areas reacted in different ways to mitigate the growth rate of the virus.

Using Linear Regression through the Sklearn package, the slope of the growth rate can be found to compare as a metric between different countries. The regression model was created by setting the start point as the date when the growth rate was 1% of the maximum growth rate and setting the end to be the date of the maximum growth rate.

Listing 10: Growth Rate Linear Regression

```
from sklearn.linear_model import LinearRegression

y = data.loc[(data["Growth Rate"] > 0.01*data["Growth Rate"].max())
    & (data["Growth Rate"] < data["Growth Rate"].max())
    & (data["Growth Rate"].index < data["Growth Rate"].idxmax())]["Growth Rate"]

x = y.index

regressor = LinearRegression()
regressor.fit(x.values.reshape(-1,1), y.values.reshape(-1,1))

y2 = regressor.predict(x.values.reshape(-1,1)).flatten()
```

Another metric that was examined was the length of time that it took for the country to return the growth rate to zero.

5.2 Analysis

5.2.1 Australia

Australia began its mitigation strategies by restricting flights coming in from Wuhan on January 23rd. After reporting its first coronavirus case on January 25th following with nine further cases by January 31st, Australia initiated a mandatory two week quarantine for all travelers from China. Starting March 29th, Prime Minister Scott Morrison limited public gatherings to two people and restricted movement to only essential travel. Testing was widely available and contact tracing measures were implemented to track the virus and ensure isolation measures [7].

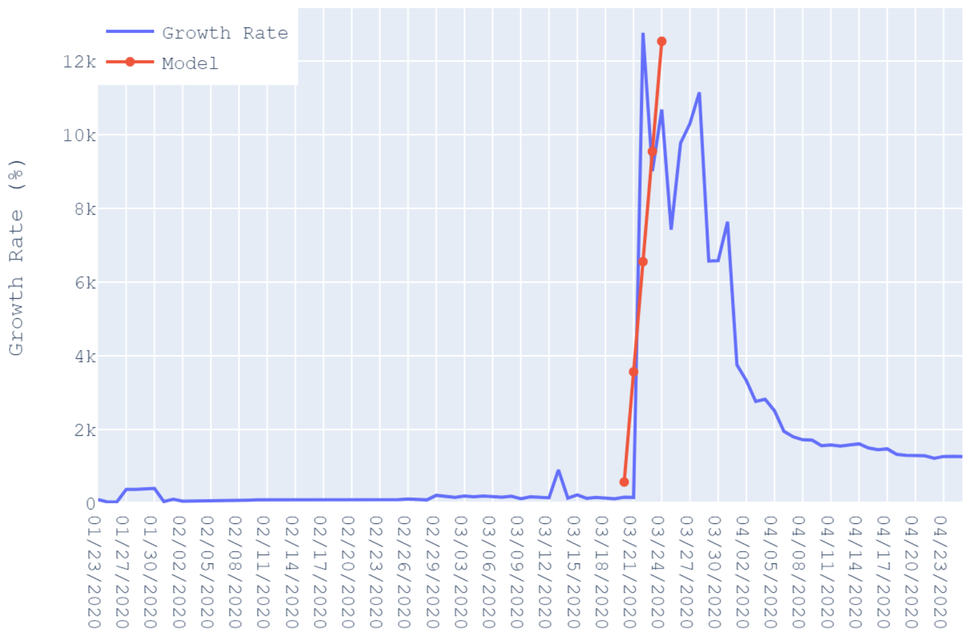


Figure 4: COVID19 Growth Rate in Australia

5.2.2 Brazil

Brazil reported its first official case of COVID19 on Feburary 25th. Even though the Brazialian Press Secretary tested positive for the virus on March 12th, Brazlian President Jair Bolsonaro continued to hold public parades for his supporters without wearing a mask. He has been heavily critized for minimizing the virus and not issueing quarantines spurring regional governments and even local gangs to step up social distancing measures. After the Minister of Health, Luiz Mandetta questioned Bolsonaro's lack of measures, the President replaced him. Brazil is the current leader for COVID19 cases in South America [3].

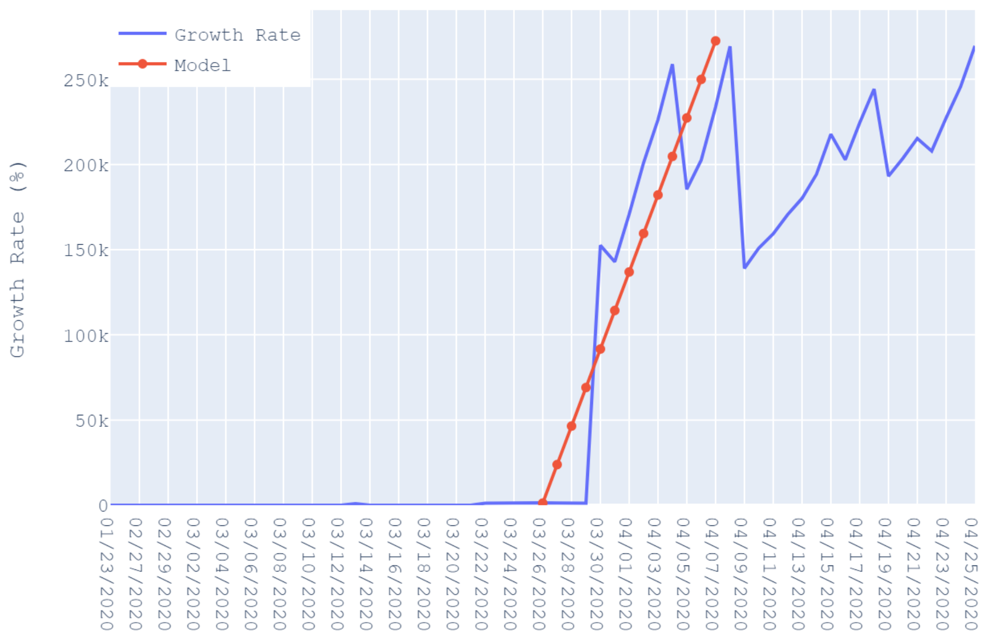


Figure 5: COVID19 Growth Rate in Brazil

5.2.3 China

Even though reports from China state that seven cases of COVID19 were documented in Wuhan on December 18th, 2019, Chinese scientists formally announced the new coronavirus on January 7th, 2020. On January 1th, China records its first death from COVID19 and by January 23rd, Wuhan is placed under quarantine followed by the rest of Hubei province. An estimated 60 million residents are placed under home lockdown. China's strategy was built around testing and isolation. While a person is tested they wait in the clinic for results. If the results are positive, they are treated in the facilities until they are free of the virus and individuals who were in contact with the person are asked to self-isolate for two weeks at home. As a result of effectively removing infectious individuals from the general population, China was the first country to lower their growth rate [4].

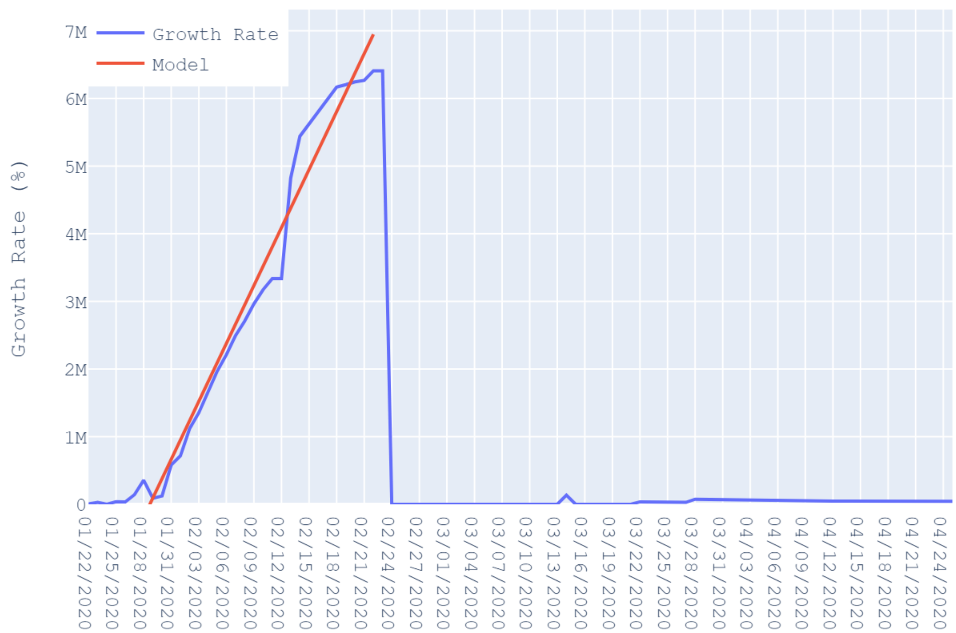


Figure 6: COVID19 Growth Rate in China

5.2.4 South Africa

The first case of COVID19 in South Africa was confirmed on March 5th. On March 15th, President Cyril Ramaphosa decalared a national state of disaster and imposed travel restrictions. Starting March 18th, President Ramaphosa closed schools and announced a 21 day lockdown with deployment of the South African National Defence Force to support it. On April 9th, the lockdown was extended until the end of the month. The enforcement of the lockdown by the police and army personnel included excessive force including incidences of beatings. A byproduct of the lockdown was a lowering of crime and domestic violence associated with an alchohol banned included in the restrictions [6].

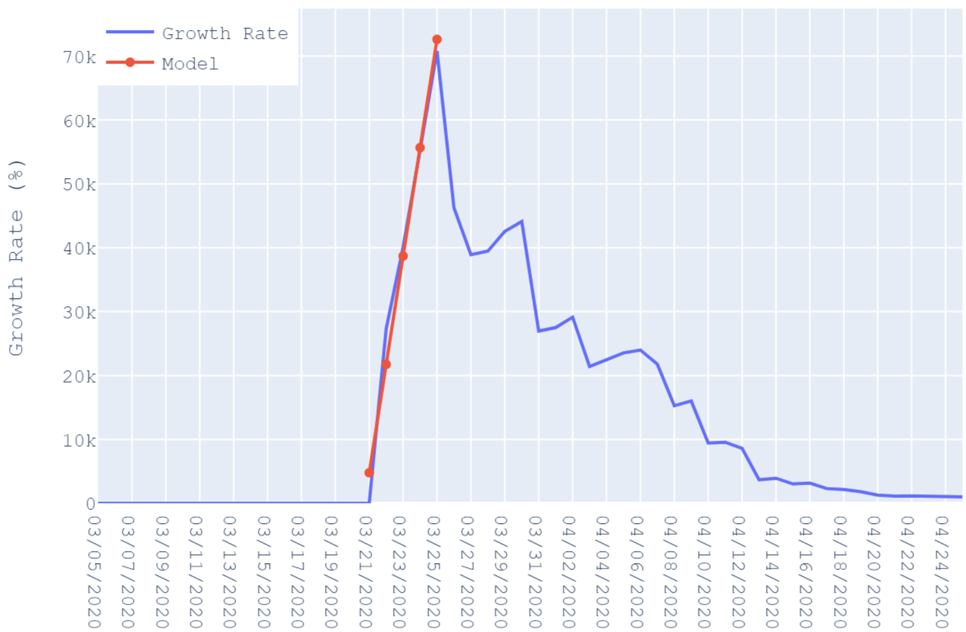


Figure 7: COVID19 Growth Rate in South Africa

5.2.5 Sweden

The first case of COVID19 in Sweden was confirmed on January 31st. Unlike most countries, especially in Europe, Sweden has not imposed any lockdown measures. Following their consitution, the Public Health Agency can only suggest measures to the government. Currently, the agency and government have only reccomended stay at home measures and social distancing but have kept schools open. The basis behind these measures are to develop a population immunity to the virus [8].

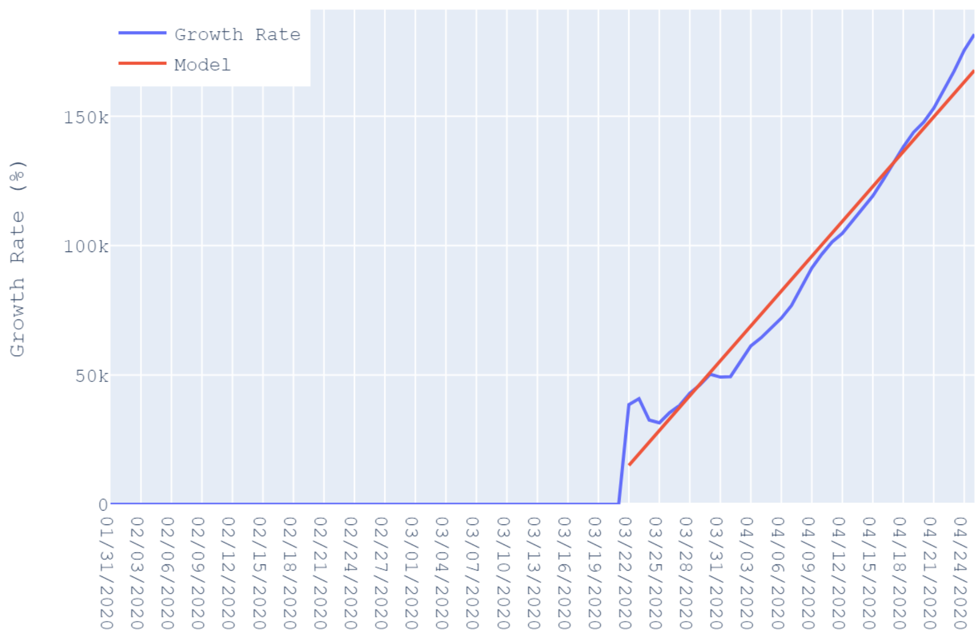


Figure 8: COVID19 Growth Rate in Sweden

5.2.6 United States

The first confirmed case of COVID19 was on January 20th in the state of Washington. A public health emergency was officially declared on January 31st by the Trump Administration following a ban on foreignors who recently traveled from China on Feburary 2nd. The United States government has faced backlash for not responding the pandemic quickly, especially with a lack of testing and providing necessary medical and protective equipment. Intially President Donald Trump minimized the virus, calling it a hoax. Most efforts on containment were intiated by states like New York and California, mostly starting by March 21st. As of April 27th, states like Georgia have began easing lockdown restrictions even as the cases of COVID19 are still climbing [9].

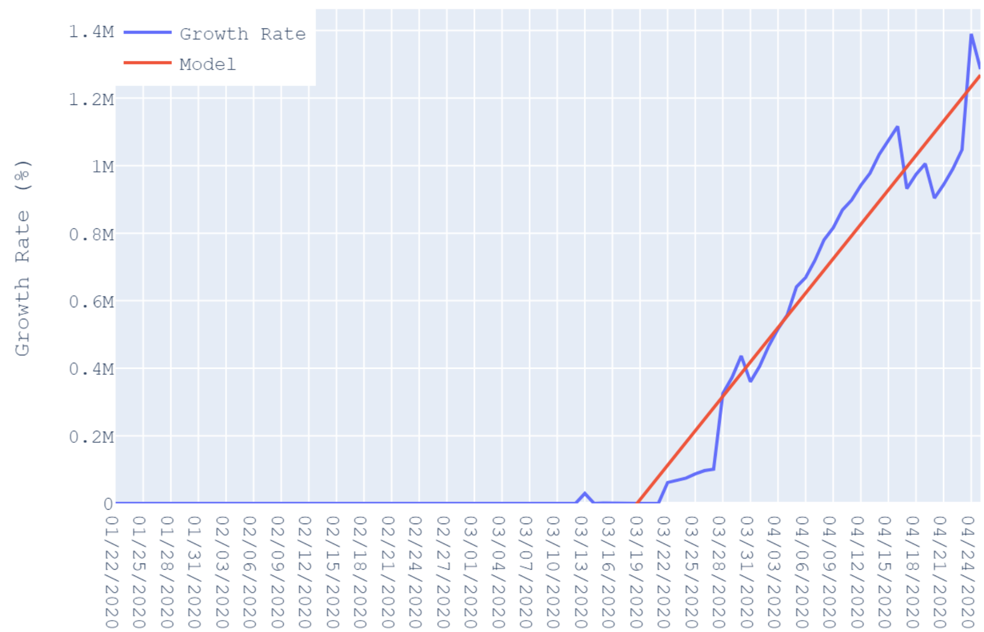


Figure 9: COVID19 Growth Rate in United States

5.3 Results and Conclusion

Table 11: COVID19 Growth Rates and Mitigation

Country	Growth Rate Slope	Start Date	End Date	Duration
Australia	2989.5	3/21/2020	Continueing	38
Brazil	22609.5	3/30/2020	Continueing	29
China	285589.4	1/27/2020	2/24/2020	28
South Africa	16959.4	3/22/2020	04/24/2020	33
Sweden	4491.7	3/22/2020	Continueing	37
United States	33966.3	3/13/2020	Continueing	46

6 Effects of Weather Conditions

6.1 Methodology

In the early days of the COVID19 spread, scientists and news establishments made assumptions that based on virus' flu like symptoms, it would subside into the spring and summer as hot temperatures arrived in the Northern hemisphere [2]. The National Oceanic and Atmospheric Administration, NOAA, provides free and widely available data on current and historic weather conditions for the United States. This data can be used to analyze a correlation between the virus spread and the weather conditions of the most affected states in different climates.

Table 12: Spread of COVID19 in United States

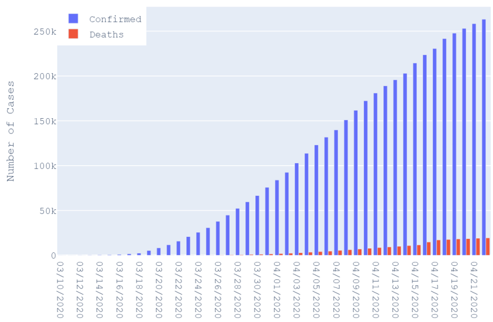
State	Confirmed	Deaths	Recovered	Eradicated	Active
New York	5255780	292667	0	292667	4963113
New Jersey	1709925	71989	2	71991	1637934
Massachusetts	718242	26601	8	26609	691633
California	673356	21472	40	21512	651844
Michigan	659639	42361	0	42361	617278
Pennsylvania	620092	19423	0	19423	600669
Illinois	591453	22091	16	22107	569346
Florida	538499	14018	0	14018	524481
Louisiana	517062	24926	0	24926	492136
Texas	376784	8581	0	8581	368203

New York, California, Michigan, and Louisiana were chosen as the states to analyze using their most affected cities as the target locations for the NOAA weather station data.

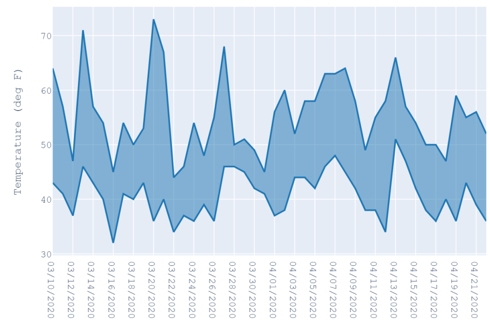
6.2 Results

6.2.1 New York

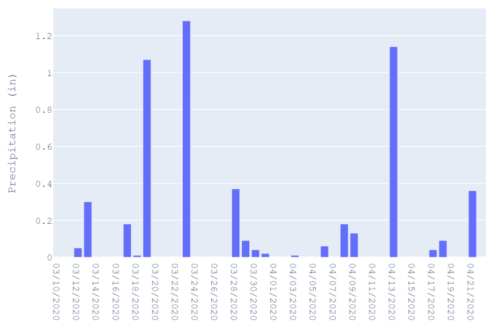
The closest correlation to COVID19 with weather data for New York is the average wind speed with about 30%.



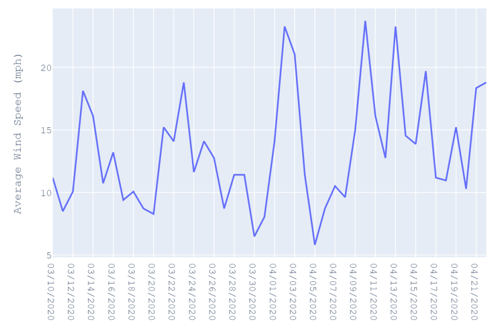
(a) COVID19 Cases



(b) New York City Temperature



(c) New York City Percipitation



(d) New York City Wind Speed

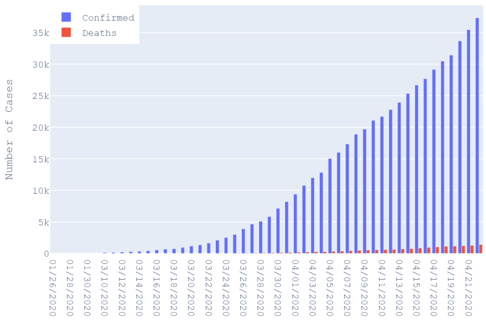
Figure 10: New York COVID19 spread and weather conditions

Table 13: Correlation between COVID19 spread and weather conditions in New York

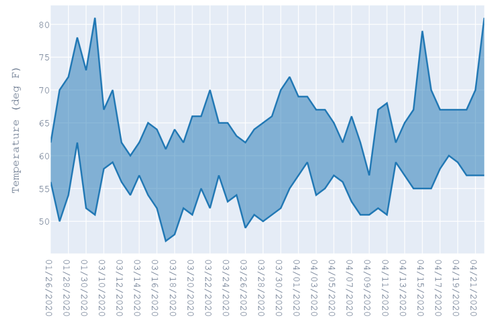
	Confirmed	Deaths	AWND	PRCP	TMAX	TMIN
Confirmed	1.000000	0.953431	0.306049	-0.067988	-0.019127	0.042965
Deaths	0.953431	1.000000	0.282089	-0.052875	-0.059731	-0.069921
AWND	0.306049	0.282089	1.000000	0.232747	-0.009109	-0.086285
PRCP	-0.067988	-0.052875	0.232747	1.000000	-0.004461	0.257297
TMAX	-0.019127	-0.059731	-0.009109	-0.004461	1.000000	0.431357
TMIN	0.042965	-0.069921	-0.086285	0.257297	0.431357	1.000000

6.2.2 California

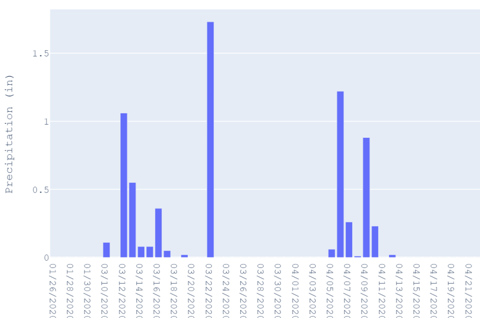
The closest correlation to COVID19 with weather data for California is the daily lower temperature with about 35%.



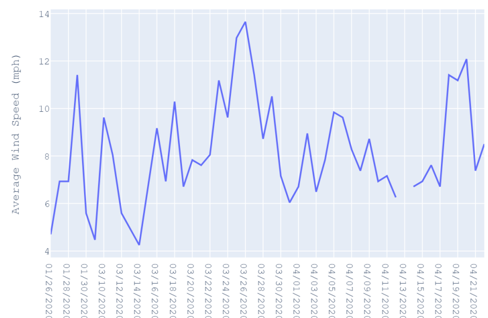
(a) California COVID19 Cases



(b) Los Angeles Temperature



(c) Los Angeles Percipitation



(d) Los Angeles Wind Speed

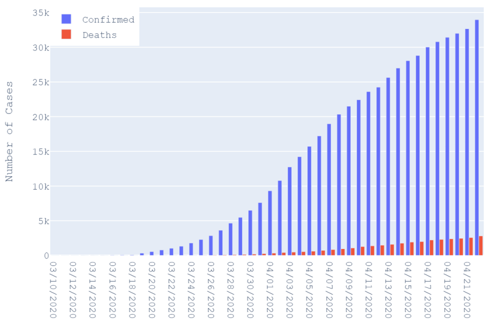
Figure 11: California COVID19 spread and weather conditions

Table 14: Correlation between COVID19 spread and weather conditions in California

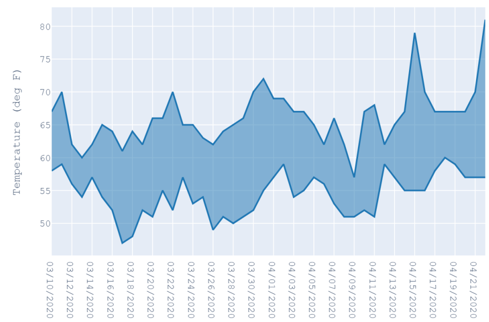
	Confirmed	Deaths	AWND	PRCP	TMAX	TMIN
Confirmed	1.000000	0.983698	0.126789	-0.110202	0.173194	0.358537
Deaths	0.983698	1.000000	0.141337	-0.130792	0.221446	0.385531
AWND	0.126789	0.141337	1.000000	-0.068453	-0.113743	0.074694
PRCP	-0.110202	-0.130792	-0.068453	1.000000	-0.241972	-0.082043
TMAX	0.173194	0.221446	-0.113743	-0.241972	1.000000	0.231867
TMIN	0.358537	0.385531	0.074694	-0.082043	0.231867	1.000000

6.2.3 Michigan

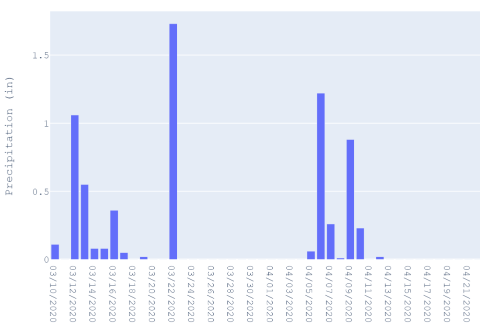
The closest correlation to COVID19 with weather data for Michigan are the daily high and low temperatures with approximately 40% and 39%, respectively.



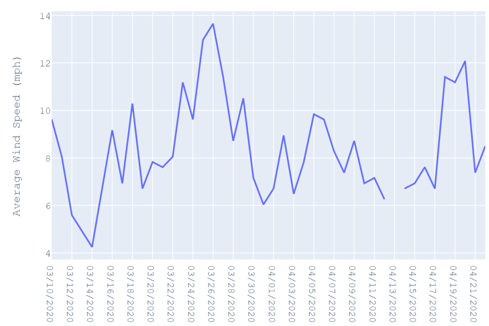
(a) Michigan COVID19 Cases



(b) Detroit Temperature



(c) Detroit Percipitation



(d) Detroit Wind Speed

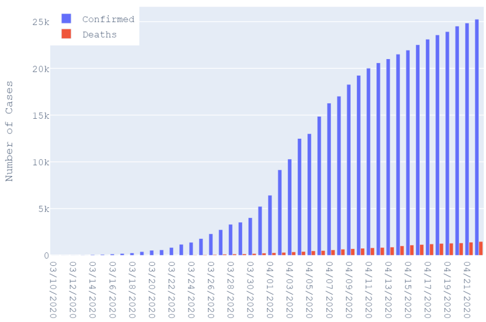
Figure 12: Michigan COVID19 spread and weather conditions

Table 15: Correlation between COVID19 spread and weather conditions in Michigan

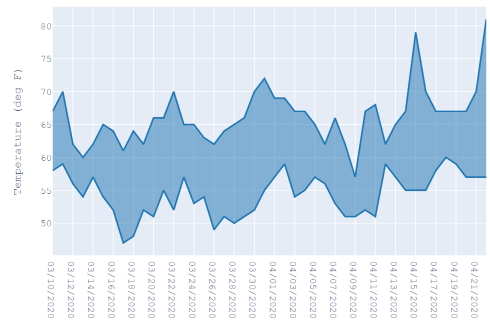
	Confirmed	Deaths	AWND	PRCP	TMAX	TMIN
Confirmed	1.000000	0.971463	0.022642	-0.157289	0.387537	0.406781
Deaths	0.971463	1.000000	0.041239	-0.180878	0.439628	0.442325
AWND	0.022642	0.041239	1.000000	-0.118884	-0.079533	-0.055577
PRCP	-0.157289	-0.180878	-0.118884	1.000000	-0.228251	-0.094460
TMAX	0.387537	0.439628	-0.079533	-0.228251	1.000000	0.317699
TMIN	0.406781	0.442325	-0.055577	-0.094460	0.317699	1.000000

6.2.4 Louisiana

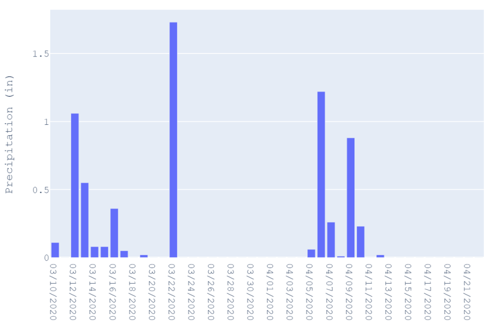
The closest correlation to COVID19 with weather data for Louisiana is the daily high and lower temperatures with approximately 35% and 40%, respectively.



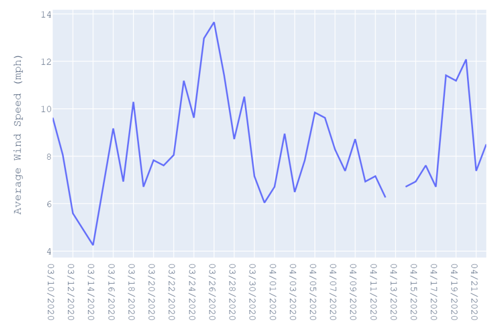
(a) Louisiana COVID19 Cases



(b) New Orleans Temperature



(c) New Orleans Percipitation



(d) New Orleans Wind Speed

Figure 13: Louisiana COVID19 spread and weather conditions

Table 16: Correlation between COVID19 spread and weather conditions in Louisiana

	Confirmed	Deaths	AWND	PRCP	TMAX	TMIN
Confirmed	1.000000	0.976245	0.012217	-0.137567	0.349143	0.391529
Deaths	0.976245	1.000000	0.041743	-0.178289	0.430731	0.427688
AWND	0.012217	0.041743	1.000000	-0.118884	-0.079533	-0.055577
PRCP	-0.137567	-0.178289	-0.118884	1.000000	-0.228251	-0.094460
TMAX	0.349143	0.430731	-0.079533	-0.228251	1.000000	0.317699
TMIN	0.391529	0.427688	-0.055577	-0.094460	0.317699	1.000000

6.3 Analysis

Based on the studies of the 4 different states listed above, a correlation between temperature and COVID19 spread cannot be made. Even though there was an approximate 40% correlation between temperature and confirmed cases, this can be attributed to the fact to seasonal change into the spring as the virus spread in these areas. This also goes against earlier thoughts that warmer temperatures would curb the virus as infact, based on the data, the virus is growing as the temperature is increasing.

7 Case Study on New York City

One of United States' most populous and high-density cities, New York City, is also the current leader for COVID19 cases and deaths. New York City has made a plethora of information about COVID19 and other city-related data available to the public. Using the tools developed in the former sections, an analysis has been performed to study the effects of the virus on New York.

7.1 Exploration of Data

Using available New York City zipcode data, a map was generated visualizing the most affected neighborhoods of New York.

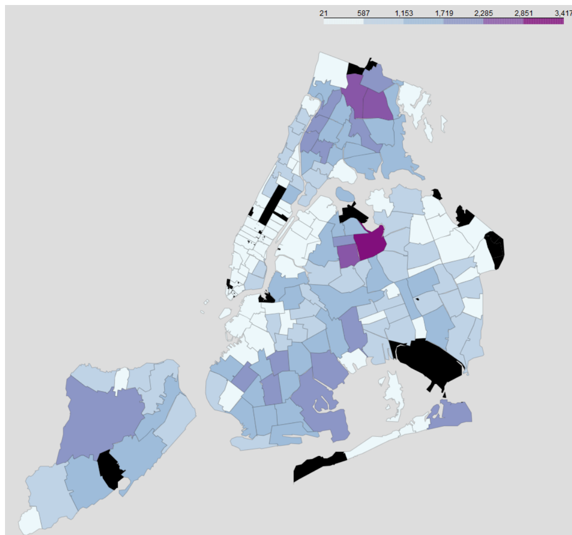


Figure 14: COVID19 New York City Zipcode Map

Analyzing the timeline of confirmed, hospitalized, and death case in New York City.

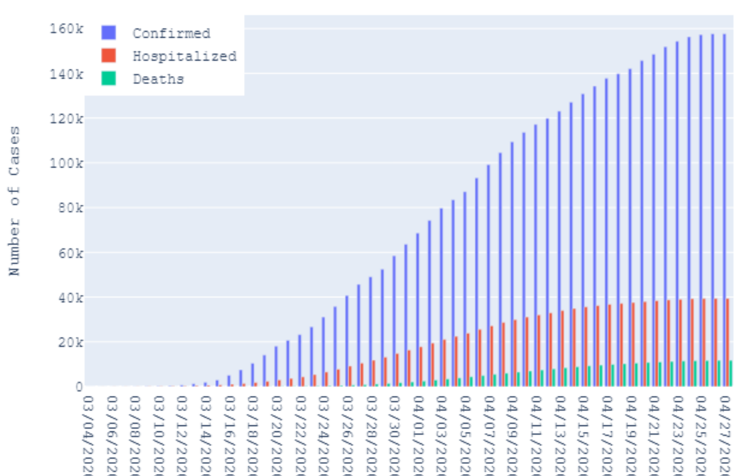


Figure 15: COVID19 Spread New York City

7.2 Correlations for Zipcode Based Data

Combining datasets on demographic data and train lines based on zipcode with the COVID19 dataset can provide insight into if any demographic or urban planning attributes correlated with the spread of COVID19 in that area.

Table 17: COVID19 Correlation in New York City

Feature	Correlation to Positive Test
Percent Female	0.381337
Percent Male	0.235687
Percent Pacific Islander	0.151903
Percent Hispanic Latino	0.359761
Percent American Indian	0.147127
Percent Asian Non Hispanic	-0.169780
Percent White Non Hispanic	0.310633
Percent Black Non Hispanic	0.257845
Percent Other Ethnicity	0.113792
Percent Ethnicity Unknown	0.057773
Percent Permanent Resident Alien	0.112616
Percent US Citizen	0.382285
Percent Other Citizen Status	0.149430
Percent Citizen Status Total	0.393533
Percent Receives Public Assistance	0.253209
Percent Public Assistance Total	0.393472
Number of Train Lines	-0.074779
Population	0.821439
Population Density	0.017639
Housing Units	0.596800
Occupied Housing Units	0.623721
Median Home Value	-0.429955
Median Household Income	-0.508028

Features such as population and amount of occupied housing units make sense for high correlation. It is interesting to note that the number of train lines in a zipcode and the median household income and home value do not show correlation with confirmed positive tests.

7.3 Predicting the End of COVID19

The end results for New York City were using the logarithmic model developed to predict the end results of the pandemic for countries of the world in earlier sections.

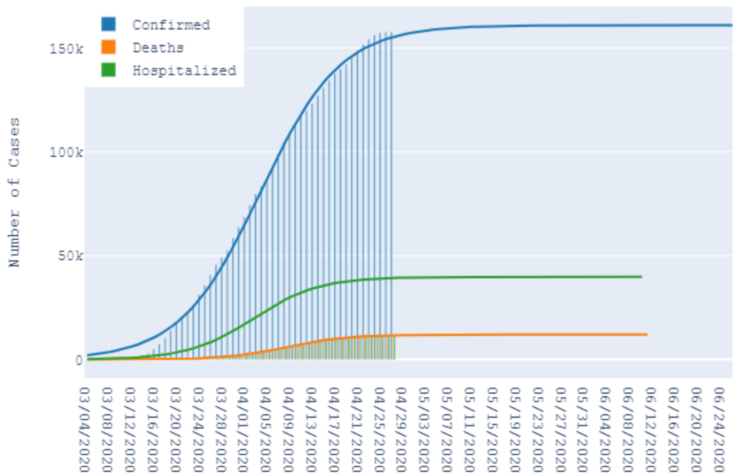


Figure 16: Modeling COVID19 Spread New York City

Table 18: Results of Modeling New York City

End Date	Total Confirmed	Total Hospitalized	Total Deaths
06/26/2020	160941	39789	12005

7.4 Growth Rate Mitigation

Calculating and visualizing the growth rate for New York shows that the city managed minimize it to zero. The first case of COVID19 was confirmed on March 1st. On March 7th, Governor Andrew Cuomo declared a state of emergency and by March 22nd announced a statewide stay in place order after several days of outcries from New York City Mayor Bill de Blasio to do so. Public schools were closed and so were non-essential businesses. Since then, New York City has been challenged with problems of high unemployment, lack of protective equipment and paramedics, testing capabilities, and overcrowding. Even with problems with social distancing for the New York City population, the city managed to lower its growth rate in almost a month.

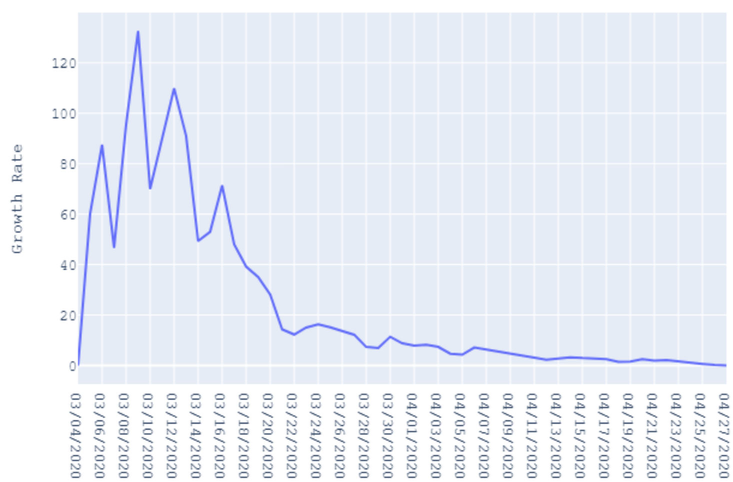


Figure 17: Modeling COVID19 Spread New York City

8 Conclusion

The Coronavirus disease 2019 has spread throughout the world quickly, effectively, and metaphorically as it demonstrated the connectivity and interdependence of all countries.

The spread of COVID-19 was estimated using different regression models. While a logistic function proved to be the better, but optimistic, predictive model, some countries faced infection amounts closer to the worse-case exponential function. Using the logistic model, the end dates and cases could be predicted. Comparing different mitigation methods between countries showed that governments that were able to control the population early on were able to lower the growth rate quickly. Analyzing New York showed that demographic information could not provide deep insight into the growth of COVID19 in affected zipcodes but that even in a densely populated city, strong government control could mitigate and lower the virus cases.

References

[1] Chris Albon. *Machine learning with Python cookbook: practical solutions from preprocessing to deep learning.* OReilly, 2018.

[2] Allison Aubrey. *Can Coronavirus Be Crushed By Warmer Weather?* Feb. 2020. URL: https://www.npr.org/sections/goatsandsoda/2020/02/12/805256402/can-coronavirus-be-crushed-by-warmer-weather.

[3] *Covid-19 in Brazil - Live blog.* URL: https://brazilian.report/coronavirus-brazil-live-blog/.

[4] Aylin Woodward Holly Secon. *A comprehensive timeline of the new coronavirus pandemic, from China's first COVID-19 case to the present.* Apr. 2020. URL: https://www.businessinsider.com/coronavirus-pandemic-timeline-history-major-events-2020-3#february-19-an-outbreak-of-the-novel-coronavirus-began-in-iran-17.

[5] *IHME: COVID-19 Projections.* URL: https://covid19.healthdata.org/united-states-of-america.

[6] Daneel Knoetze. *Police kill three people in three days of lockdown. This is normal for South Africa.* Apr. 2020. URL: https://www.groundup.org.za/article/police-kill-three-people-three-days-lockdown-normal-south-africa-data-reveals/.

[7] Rosie Perper. *Australia and New Zealand have been able to keep their number of coronavirus cases low thanks to early lockdown efforts. Experts say it's 'probably too late' for other countries to learn from them.* Apr. 2020. URL: https://www.businessinsider.com/experts-australia-new-zealand-examples-how-to-slow-coronavirus-2020-4.

[8] Maddy Savage. *Coronavirus: Has Sweden got its science right?* Apr. 2020. URL: https://www.bbc.com/news/world-europe-52395866.

[9] Live Science Staff. *Coronavirus in the US: Latest COVID-19 news and case counts.* Apr. 2020. URL: https://www.livescience.com/coronavirus-updates-united-states.html.