Preface

In this notebook, I will try to use the COVID-19 data from OWID in order to get a feel for doing basic data visualization and analysis

The main goals I have for this project are:

1. Learn about and gain experience using Python for basic data visualization and analysis
2. Gain some experience using machine learning algorithms to make predictive models
3. Try to parse through chunks of data and find relationships that may not be so obvious or apparent at first glance

Because I am going in to this project without a particular problem to be solved, I will start it off by attempting what I would consider relatively simple tasks (making basic relational plots and doing simple analysis based on them) then work my way up towards more advanced tasks.

Progress Updates

- 12/2/2020 through 12/16: Started working on project; Analysis 1: made basic visualizations of normalized case and death rates in the US; Analysis 2: looked at stringency index values and their correlation with case and death rates; made preliminary plots for Analysis 3 which will be for making more comparisons between multiple countries
- 12/28/2020 through 1/10/2021: Added Analysis 4; Predicted US Case numbers over time by making multiple predictive models using the sklearn library for Python; models were compared using different metrics to test error scores and determine model accuracy

Analysis 1: Looking at Case and Death values in the US

The first thing I want to do is make a few basic plots for COVID metrics for the US.

In [88]:
```
# import pandas and numpy to work on data given
import warnings
warnings.simplefilter('ignore')
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import numpy as np
import pandas as pd
import seaborn as sns
```

In [89]:
```
# download and save data that is uploaded daily
import urllib.request

url = 'https://covid.ourworldindata.org/data/owid-covid-data.json'
urllib.request.urlretrieve(url, 'owid-covid-data.json')
```

```
# read json of downloaded data
```

In [90]:
```
data = pd.read_json('owid-covid-data.json', orient='values').transpose()
```

In [91]:
```
# take a look at the data
data.head()
```

Out[91]:

	continent	location	population	population_density	median_age	aged_65_older	aged_70_old
AFG	Asia	Afghanistan	3.89283e+07	54.422	18.6	2.581	1.3:
ALB	Europe	Albania	2.8778e+06	104.871	38	13.188	8.6
DZA	Africa	Algeria	4.3851e+07	17.348	29.1	6.211	3.8!
AND	Europe	Andorra	77265	163.755	NaN	NaN	Na
AGO	Africa	Angola	3.28663e+07	23.89	16.8	2.405	1.3

In [92]:
```
data.describe()
```

Out[92]:

	continent	location	population	population_density	median_age	aged_65_older	aged_70_older
count	190	191	191.0	187.000	182.0	180.000	181.000
unique	6	191	191.0	187.000	130.0	179.000	177.000
top	Africa	Qatar	32971846.0	255.573	32.4	6.933	1.726
freq	54	1	1.0	1.000	4.0	2.000	2.000

In [93]:
```
# extract data for US data
usa_data = pd.DataFrame.from_dict(data.loc['USA','data'])
usa_data.replace(np.nan, 0, inplace=True)
```

In [94]:
```
usa_data.head()
```

Out[94]:

	date	total_cases	total_cases_per_million	stringency_index	new_cases	new_cases_per_million	new_c
0	2020-01-22	1.0	0.003	0.0	0.0	0.000	
1	2020-01-23	1.0	0.003	0.0	0.0	0.000	
2	2020-01-24	2.0	0.006	0.0	1.0	0.003	
3	2020-01-25	2.0	0.006	0.0	0.0	0.000	
4	2020-01-26	5.0	0.015	0.0	3.0	0.009	

5 rows × 36 columns

In [95]:

```
usa_data.drop(usa_data.tail(1).index,inplace=True)
```

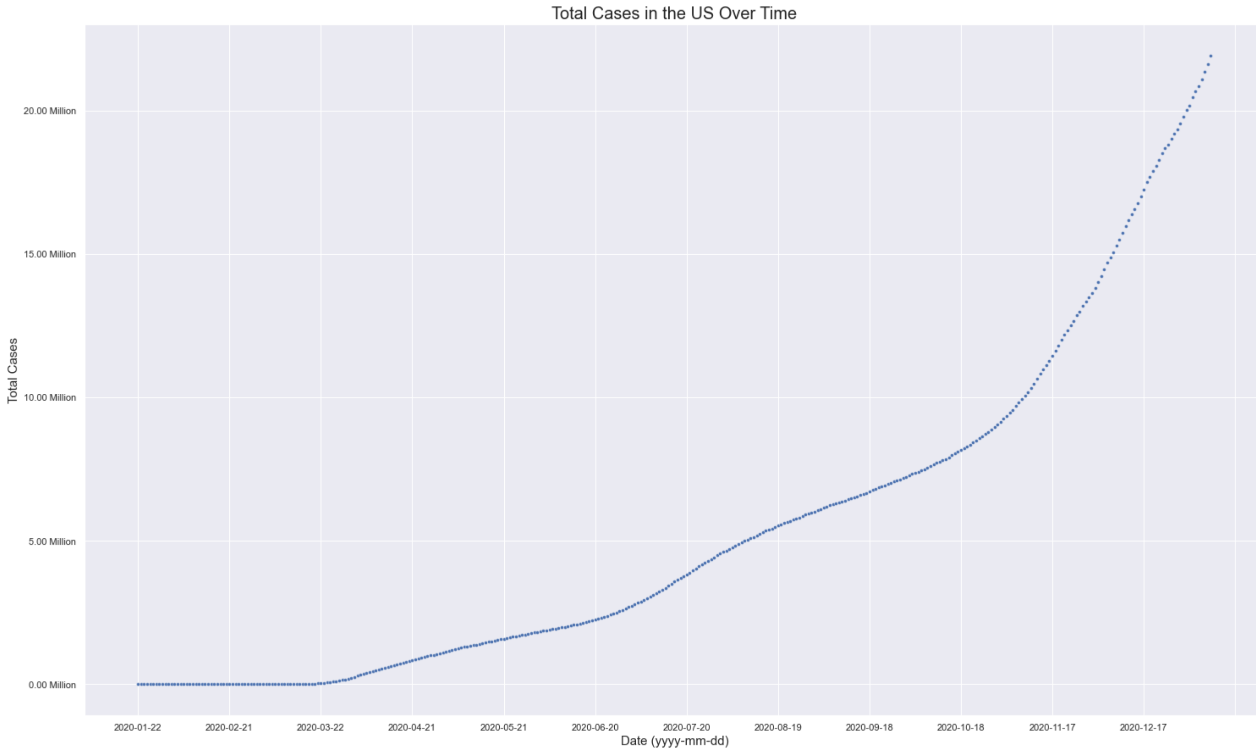
When looking at data over time for the US, the main metrics that I'd like to plot include total cases, total deaths, daily cases, and daily deaths.

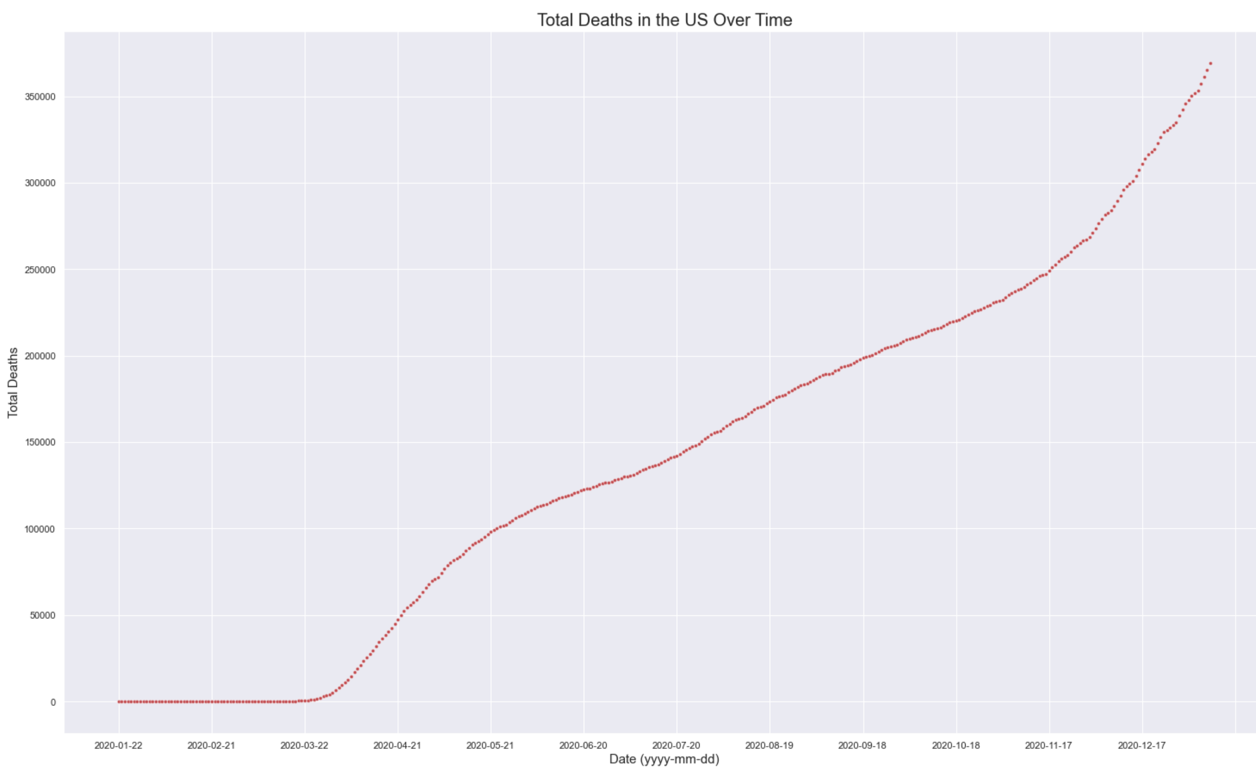
In [96]:

```
# plot total cases over time
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', s=15)
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Total Cases in the US Over Time',size=20)
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

# plot total deaths over time
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_deaths', s=15, color='r')
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.set_title('Total Deaths in the US Over Time', size=20)
ax.set_ylabel('Total Deaths', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)
```

Out[96]:

```
Text(0.5, 0, 'Date (yyyy-mm-dd)')
```



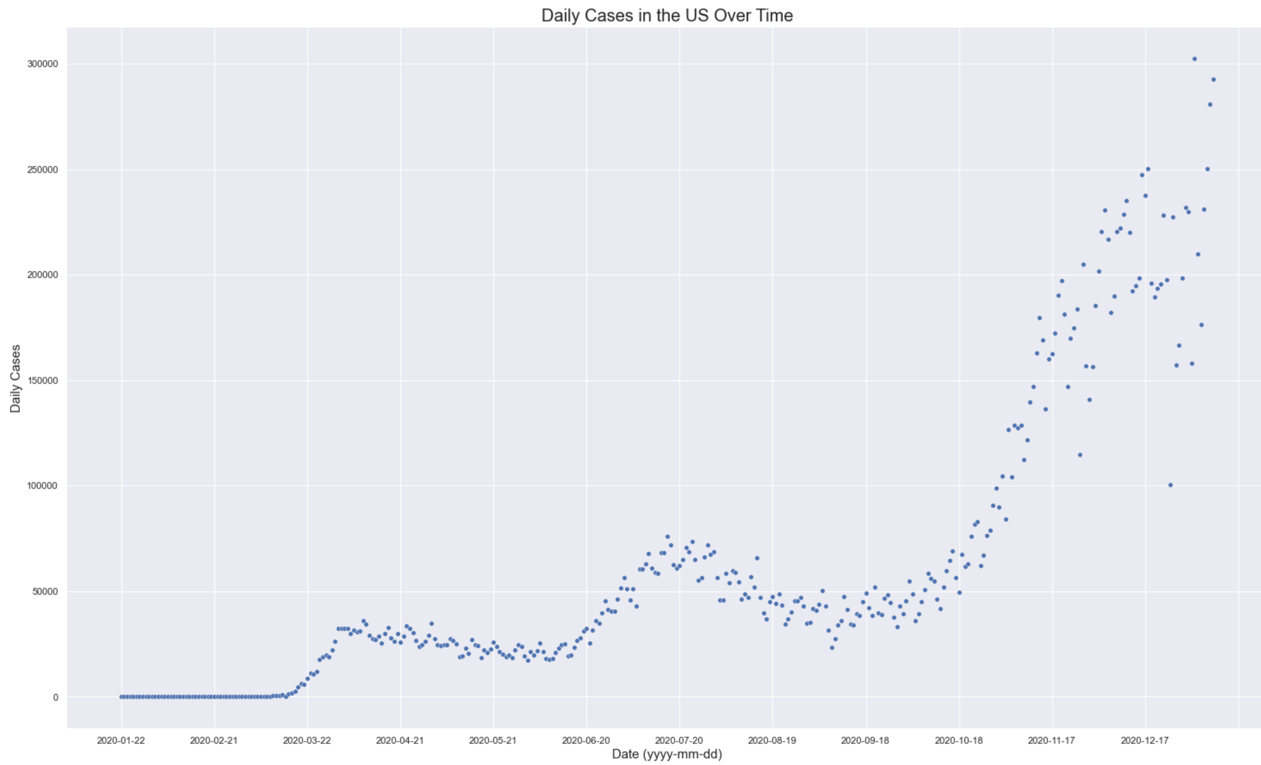


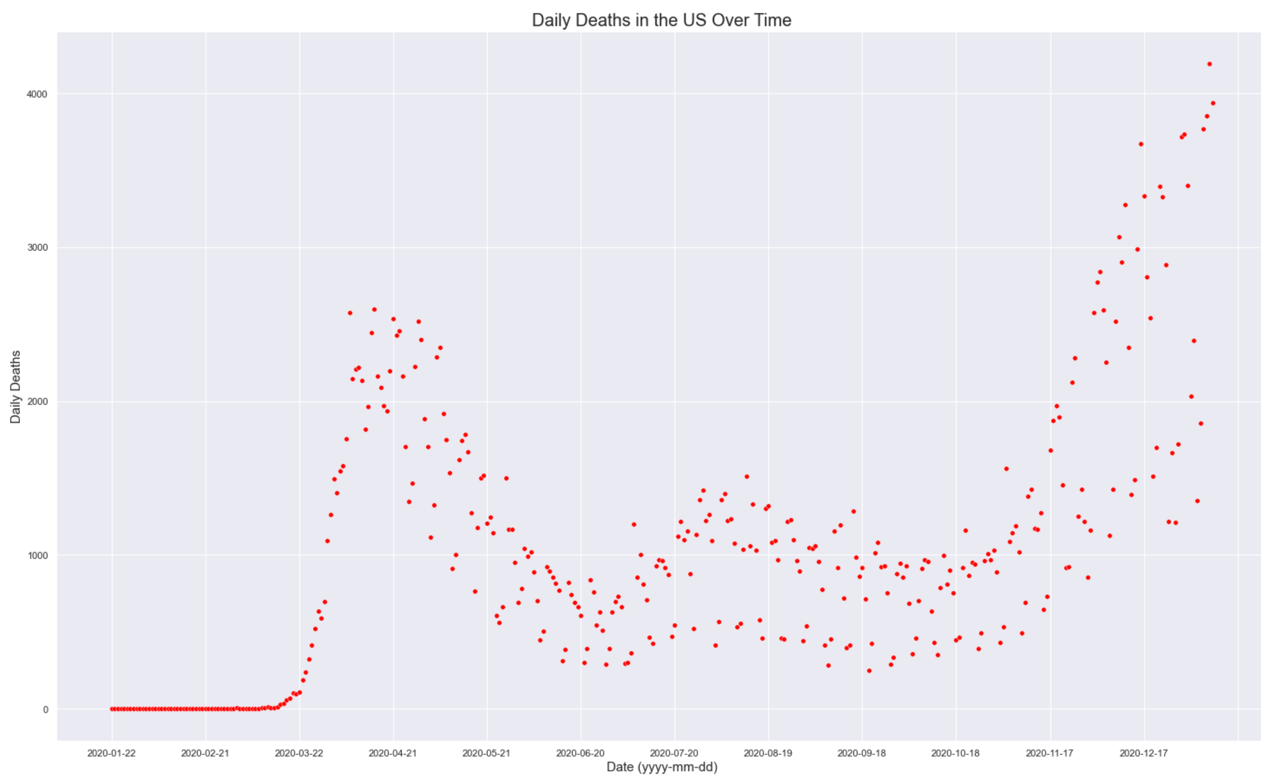
Looking at the plots, we see that total cases is exponentially increasing for the most part while the rate of total deaths varies. To take a further look, I'll plot the daily cases and deaths over time.

In [97]:
```
# plot new daily cases over time
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='new_cases', s=30)
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.set_title('Daily Cases in the US Over Time', size=20)
ax.set_ylabel('Daily Cases', size=15)
```

```
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

# plot new daily deaths over time
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='new_deaths', s=30, color='red')
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.set_title('Daily Deaths in the US Over Time', size=20)
ax.set_ylabel('Daily Deaths', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)
```

Out[97]: Text(0.5, 0, 'Date (yyyy-mm-dd)')





When looking at the daily cases and deaths, we see that both the rates of cases and deaths have spikes where they increase significantly and the most recent trends show a trend of increasing exponentially. Both metrics similar shapes with spikes occuring in the same time periods.

There are a few questions/talking points that these plots bring up:

1. Are there specific explanations for the spikes in daily cases and deaths that occur in April and July? Why are case/death rates spiking rather than constantly increasing?
2. Is there a particular reason as to why death rates were especially bad during the initial outbreak period in March/April?

To answer these, I need to look up some resources and articles regarding COVID.

Question 1

The first question can most likely be explained by national and state policies made in response to the pandemic (lockdowns, social distancing reopening, etc.). The USA Today Coronavirus Timeline shows key events regarding COVID and its unfolding over the past year. In addition, Wikipedia has a timeline page for events and responses related to COVID-19 across the world.

When trying to find any relations between particular events and daily case/death spikes, it's important to note that COVID-19 is generally accepted to have an incubation period of up to 14 days, so any events that occur up to and around 14 days prior to a spike may be a relevant cause/factor of the spike.

The first spike in daily cases and deaths occurs around early April. COVID-19 was officially declared a national emergency on March 13. Soon after, states began enforcing policies such as masks mandates, social distancing, and stay-at-home orders in order to curb infection rates. A lot of these policies began rolling out during the latter half of April. As a result, we can assume that the first 15-20 days of March saw a large amount of transmission as most people carried on with gatherings and going out without any restrictions. By the time restrictions began being enforced, a large amount of people were already infected, which is proven by the spike in daily case rate seen in early April. For the next 2 months until mid-June, the effects of COVID response policies can be seen with decreasing daily deaths and almost constant cases (something that would be expected to decrease with stricter restriction policies).

Then what about the spike in late June/early July? Throughout most of April and June, states began gradually relaxing restrictions and allowing businesses to reopen, thus leading to the increasing daily cases and deaths from mid-June to late-July. Around mid-July to early-July, states began reinstating business and gathering restrictions once it became apparent that cases were rising again and a second wave of infection was likely. Similar to the first spike, the daily cases and deaths saw a decrease in numbers, but after roughly two months these metrics began to rise again, and we are now at a point where they are at an all-time high. Recently, only a handful of states have returned to having stay-at-home orders/advisories. With this in mind, it is likely that numbers will continue to grow significantly until the recently developed COVID vaccines begin mass distribution.

Question 2

An important trend that can be seen from the plots is that overall death rates from COVID infections were decreasing over time. Despite daily cases increasing almost constantly since March, daily deaths
were the worst during the initial outbreak phase in March and have only recently exceeded those levels once again (with corresponding daily case counts being roughly 7 times larger than March counts). Both articles and academic studies can be found online with some explanations.

Some of the key reasons mentioned in the sources found are:

1. A shift towards younger people, who have less risk factors, getting infected compared to March when older adults saw higher infection numbers.
2. Better clinical experience/more standardized approach to handling COVID patients
3. Improvements to both pharmacologic and non-pharmacologic treatments
4. Earlier intervention
5. Lower viral load due to mask wearing, social distancing, community awareness, etc.

Analysis 2: Looking at Stringency Index in the US

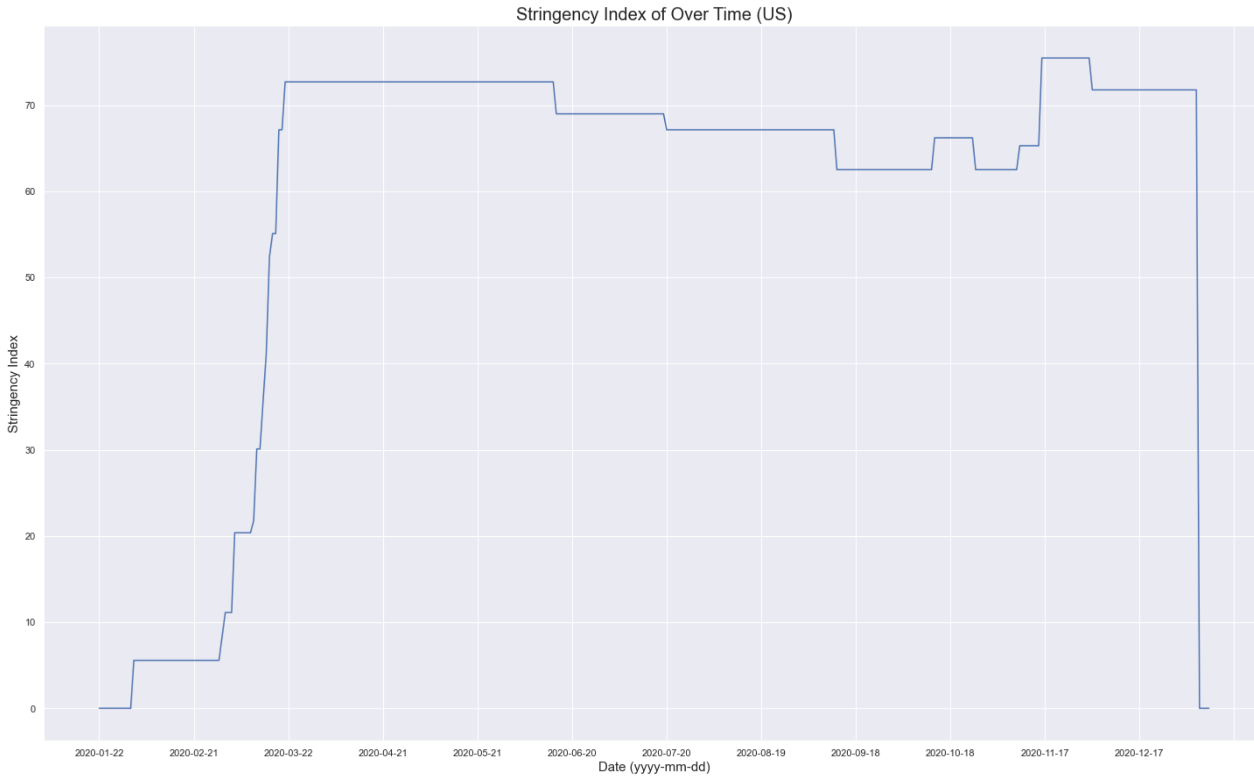
Another metric that I am interested in analyzing is the strigency index. According to the OWID COVID-19 data codebook, the stringency index is a numerical composite measure based on government response indicators such as school closures, travel bans, workplace closures, etc. In general, the severity of impact that a disease has in a pandemic scenario is dependent on many factors, but one major factor is the response a government has in enforcing rules and policies to deal with the pandemic. By comparing stringency index values with daily case and death numbers, I believe I can get some insight on the way the US government responded to the COVID-19 pandemic.

In [98]:

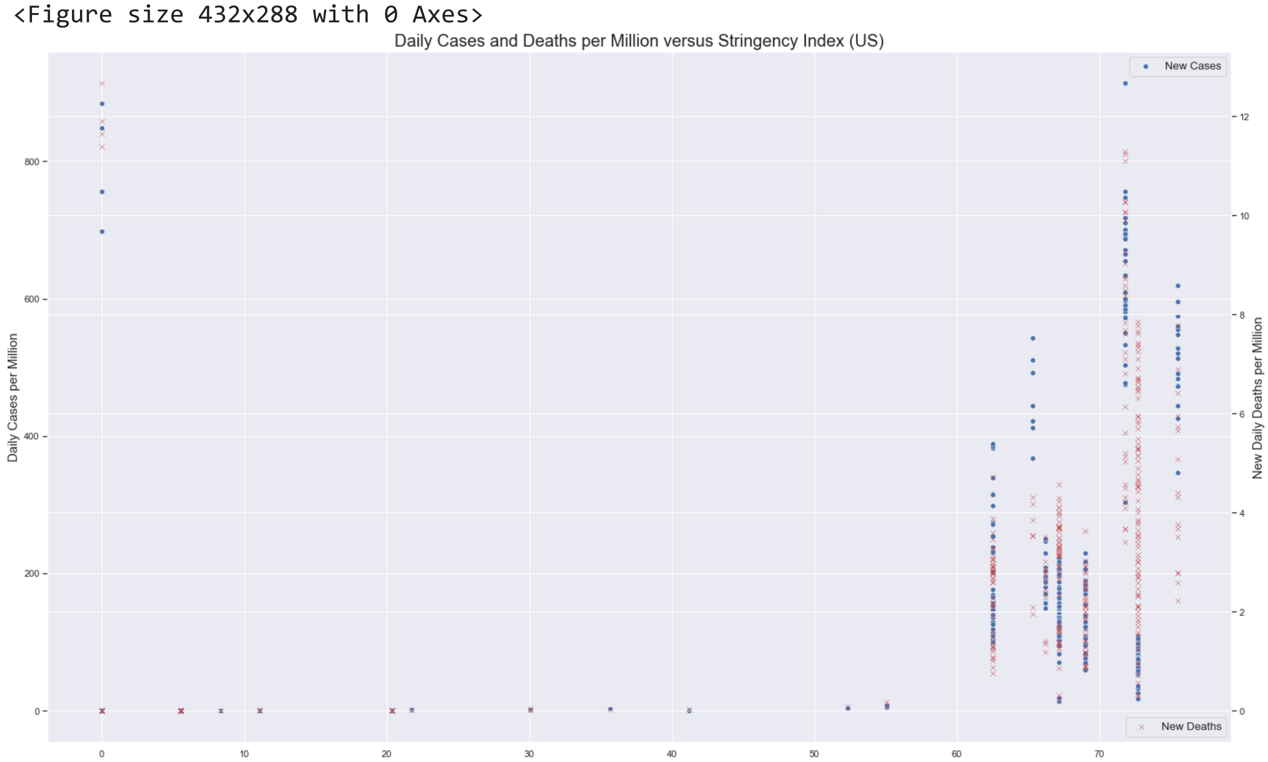
```
# plot stringency index over time
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.lineplot(data=usa_data, x='date',y='stringency_index')
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.set_title('Stringency Index of Over Time (US)',size=20)
ax.set_ylabel('Stringency Index', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

# plot new daily cases and deaths versus stringency index
plt.figure()
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='stringency_index',y='new_cases_per_million', s=3
ax.xaxis.set_major_locator(ticker.MultipleLocator(10))
ax.set_title('Daily Cases and Deaths per Million versus Stringency Index (US)',size=20)
ax.set_ylabel('Daily Cases per Million', size=15)
ax.set_xlabel('Stringency Index', size=15)
ax2 = ax.twinx()
sns.scatterplot(data=usa_data, x='stringency_index',y='new_deaths_per_million', s=35, a
ax2.set_ylabel('New Daily Deaths per Million', size=15)
```

```
ax.legend(['New Cases'], prop={'size': 13})
ax2.legend(['New Deaths'], loc=4, prop={'size': 13})
```

Out[98]: <matplotlib.legend.Legend at 0x19c84527d60>



<Figure size 432x288 with 0 Axes>



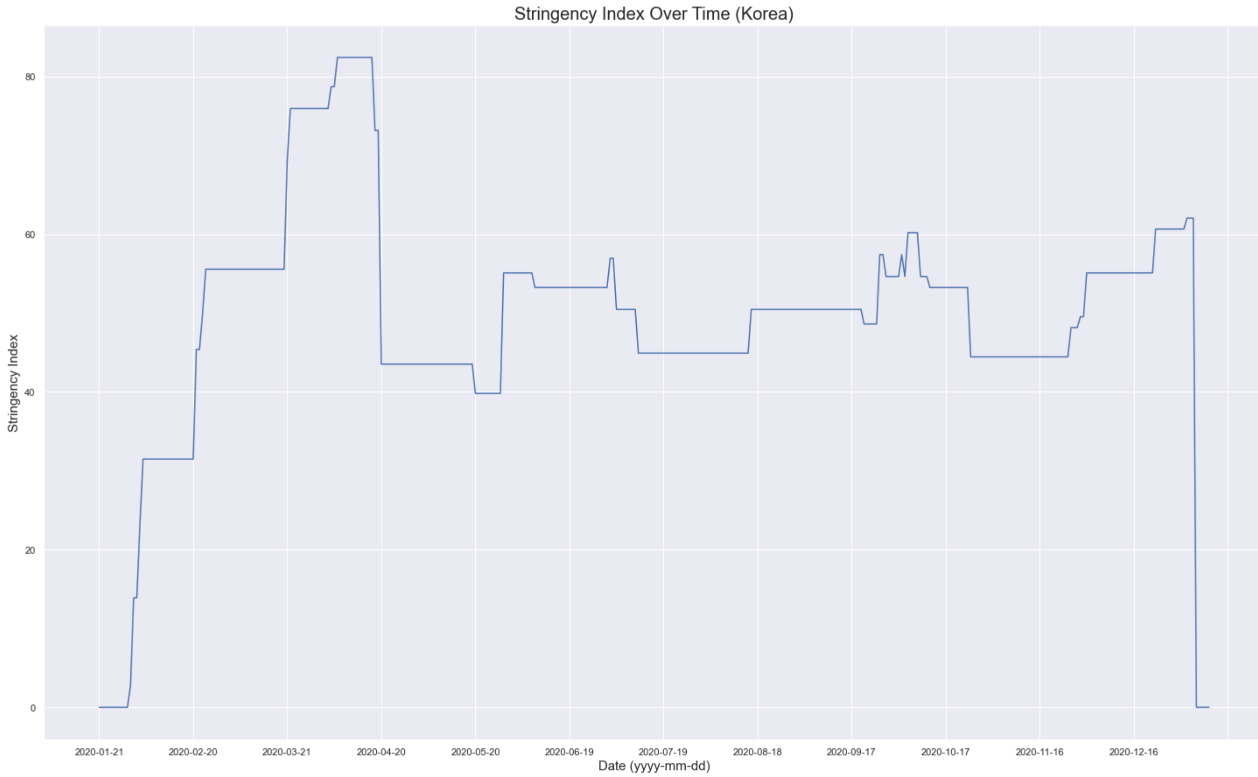
Note: high case and death values occuring at x=0 are due to missing values in the dataset. It seems that stringency indexes from some countries are no longer being monitored sadly

Here we see the change in stringency index over time and the number of daily cases and deaths in the US plotted versus corresponding stringency index values from the dates the values were taken from. From the first plot, the main trend I notice, is that starting from the end of March, around the time the outbreak started spreading in the US significantly, the stringency index jumps to over 60 and has stayed so since then. in the second plot, The main trend I notice is that the relatively high values of daily cases and deaths only occur at high stringency values (above 60 in this case).

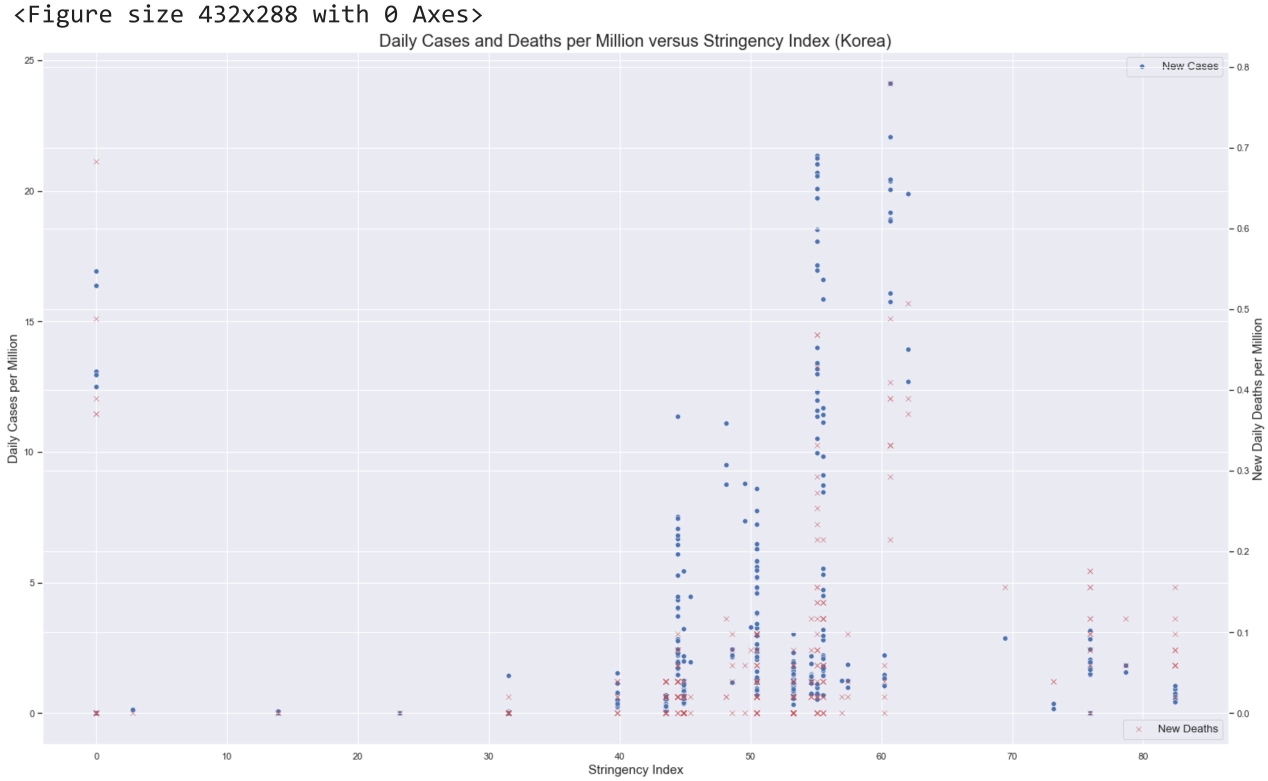
To get a little more insight, I'll make the same graph for a different country for comparison. In this case, I'll be using numbers from Korea. Korea is regarded as having the best handling of early COVID-19 pandemic transmission among wealthy nations, and I think it will be interesting to see if there are any significant stringency index trend differences between the US and Korea beyond the magnitude of normalized deaths/cases.

In [99]:
```
# extract data for Korea data
kor_data = pd.DataFrame.from_dict(data.loc['KOR','data'])
kor_data.replace(np.nan, 0, inplace=True)

# plot stringency index over time
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.lineplot(data=kor_data, x='date',y='stringency_index')
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.set_title('Stringency Index Over Time (Korea)',size=20)
ax.set_ylabel('Stringency Index', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

# plot new daily cases and deaths versus stringency index
plt.figure()
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=kor_data, x='stringency_index',y='new_cases_per_million', s=3
ax.xaxis.set_major_locator(ticker.MultipleLocator(10))
ax.set_title('Daily Cases and Deaths per Million versus Stringency Index (Korea)',size=
ax.set_ylabel('Daily Cases per Million', size=15)
ax.set_xlabel('Stringency Index', size=15)
ax2 = ax.twinx()
sns.scatterplot(data=kor_data, x='stringency_index',y='new_deaths_per_million', s=35, a
ax2.set_ylabel('New Daily Deaths per Million', size=15)
ax.legend(['New Cases'], prop={'size': 13})
ax2.legend(['New Deaths'], loc=4, prop={'size': 13})
```

Out[99]:
```
<matplotlib.legend.Legend at 0x19d013284f0>
```



<Figure size 432x288 with 0 Axes>



Note: high case and death values occuring at x=0 are due to missing values in the dataset

When comparing the plots for Korea to the plots for the US, there are a few noticeable differences:

1. The stringency index of Korea began increasing in early-February, much earlier than the US. Reasons for this may include:
   - Earlier virus outbreak due to proximity to China and frequency of travel between the two countries

- A more preemptive/preventative approach to handling the pandemic
- A more aggressive approach to handling the pandemic

2. Korea showed more of a spike in stringency during initial outbreak then soon dropped and stayed within the range of 40 to 60. Only recently did the stringency value go back to over 60. Reasons for this may include:
   - A more effective general pandemic response approach allowing for restrictions to be relaxed after the inital outbreak was contained
   - The stringency index does not fully cover the 'strictness' of policies enforced and the contexts surrounding them, thus leading to either inflated or deflated index values
3. Because Korea has stayed within the 40 to 60 index range for most of the year, most of the case and death values occured in that range. Korea experienced a higher maximum stringency index than the US, but the highest normalized case and death rates occured around an index value of 60 (in the US, the highest rates occured near its maximum index value at a little over 70.

In terms of the amount of daily cases and deaths per million, Korea experienced much lower numbers accross the board during comparable timeframes.

Analysis 3: Global Values

As of now, I've only made the following plots to test how they would look. As for which countries I'd like to compare for analysis, I haven't decided yet

In [100…

```
# compile metrics over time for various countries

cot = pd.DataFrame() # cases per million over time
dot = pd.DataFrame() # deaths per million over time
for i, row in data.iterrows():
    country_data = pd.DataFrame.from_dict(data.loc[i,'data'])
    country_data.replace(np.nan, 0, inplace=True)
    for j, row2 in country_data.iterrows():
        date = row2['date']
        row2
        try:
            cot.loc[date, i] = row2['new_cases_per_million']
        except:
            cot.loc[date, i] = 'no_data'
        try:
            dot.loc[date, i] = row2['new_deaths_per_million']
        except:
            dot.loc[date, i] = 'no_data'
```

In [101…

```
# Some countries have inconsistencies with extra rows of null values
cot.drop(cot.tail(55).index,inplace=True)
dot.drop(dot.tail(55).index,inplace=True)
```

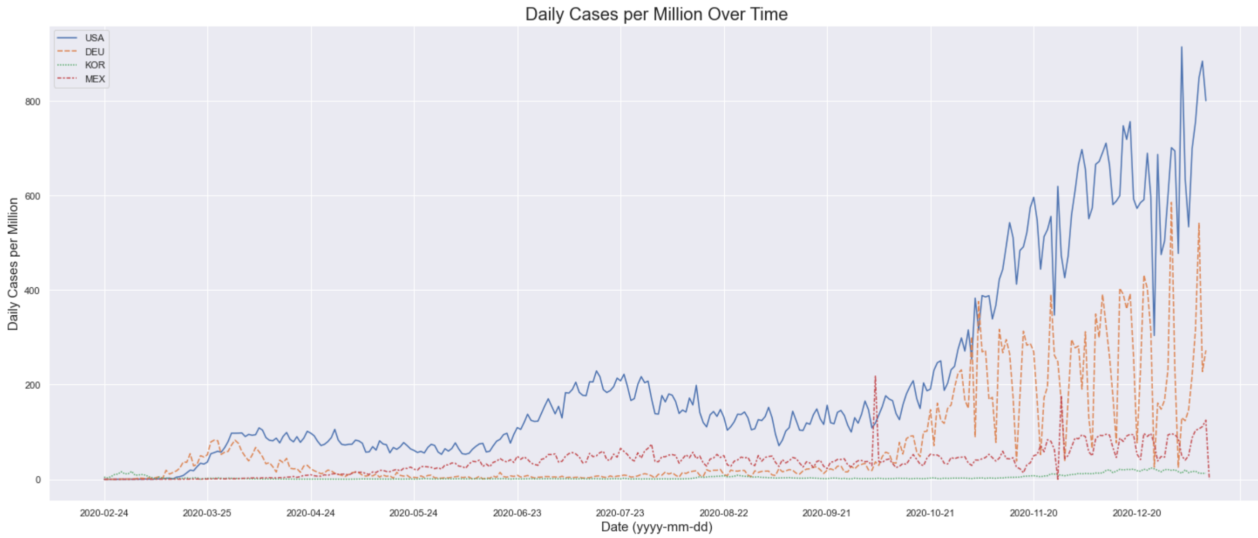
In [102…

```
# plot total deaths per million of USA, Germany, and Korea
cot_data = cot.loc[:, ['USA','DEU','KOR','MEX']]
fig, ax = plt.subplots(figsize=(25,10))
sns.set_theme()
```

```
ax = sns.lineplot(data=cot_data)
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.set_title('Daily Cases per Million Over Time', size=20)
ax.set_ylabel('Daily Cases per Million', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)
```

Out[102…

```
Text(0.5, 0, 'Date (yyyy-mm-dd)')
```

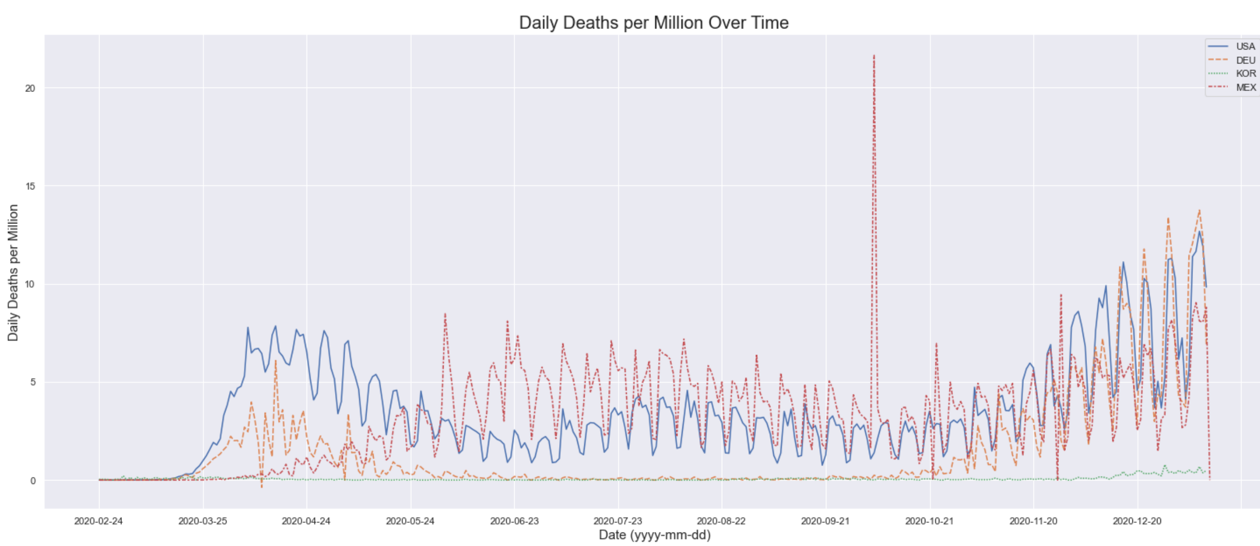


In [103…

```
# plot total deaths per million of USA, Germany, and Korea
dot_data = dot.loc[:, ['USA','DEU','KOR','MEX']]
fig, ax = plt.subplots(figsize=(25,10))
sns.set_theme()
ax = sns.lineplot(data=dot_data)
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.set_title('Daily Deaths per Million Over Time', size=20)
ax.set_ylabel('Daily Deaths per Million', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)
```

Out[103…

```
Text(0.5, 0, 'Date (yyyy-mm-dd)')
```



Analysis 4: Predicting US Case Numbers

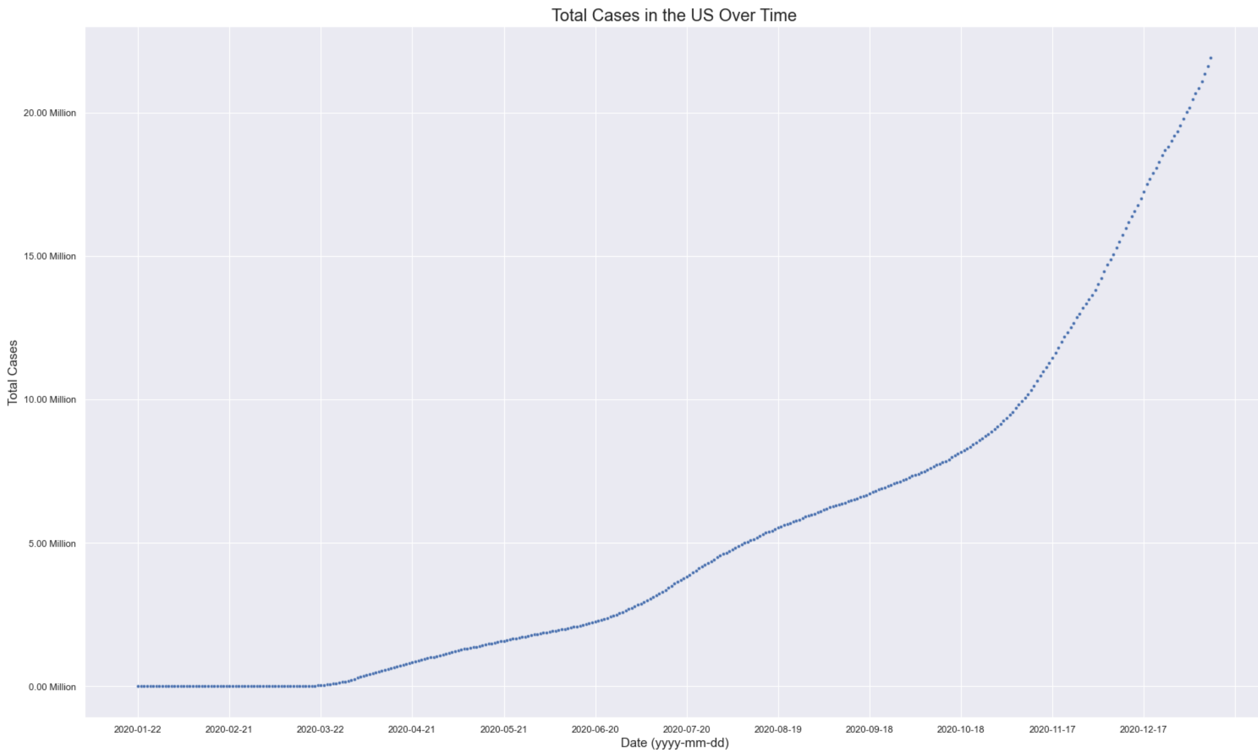
Now I'll try to make a few predictive models of COVID cases in the US

In [104…

```
# Plot US case data
# plot total cases over time
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', s=15)
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Total Cases in the US Over Time',size=20)
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)
```

Out[104…

```
Text(0.5, 0, 'Date (yyyy-mm-dd)')
```



Visually speaking, it seems like total cases are increasing at an exponential rate. I will try a few different regression models to see what may work. The types of linear models I plan to use are a regular polynomial regression, a Ridge regression, and a Lasso regression. From my basic understnding, each of these three are variations of linear regression. The main difference between the three is the cost function they use to determine the best fitting model. Standard regression uses only the sum of the squares of the residual errors found between the model and test data. This causes standard regression to be the most prone to overfitting since the model will try to make a fit purely based on how close it is to the original test data. Ridge and Lasso regression add an additional element to the cost function on top of the square residual error. This additional element is based on the slope coefficients of the model (Ridge regression is based on the square of the coefficient sum while Lasso is based on the absolute value). The addition of this element makes the model find a balance between fitting for residual error and fitting to avoid being too steep so that the cost function when testing non-training data is also minimized.

I'll start with a polynomial regression.

In [105…

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

# split up dataset into testing and training groups, cut off the first~ 50 days where c
index = np.reshape(usa_data.index, (-1, 1))
t_cases = np.array(usa_data['total_cases'])
x_train, x_test, y_train, y_test = train_test_split(index[40:,:], t_cases[40:], test_si

# make polynomial regression models with varying degrees and evaluate performance
degrees = np.arange(2,10)
r2 = []
rmse = []
for i in degrees:
    poly = PolynomialFeatures(degree=i)
    x_train_poly = poly.fit_transform(x_train)
    x_test_poly = poly.fit_transform(x_test)

    # make linear regression model
    clf = LinearRegression()
    clf.fit(x_train_poly, y_train)
    y_predict = clf.predict(x_test_poly)
    r2.append(r2_score(y_test, clf.predict(x_test_poly)))
    rmse.append(mean_squared_error(y_test, clf.predict(x_test_poly), squared=False))
print(r2)
print(rmse)
```

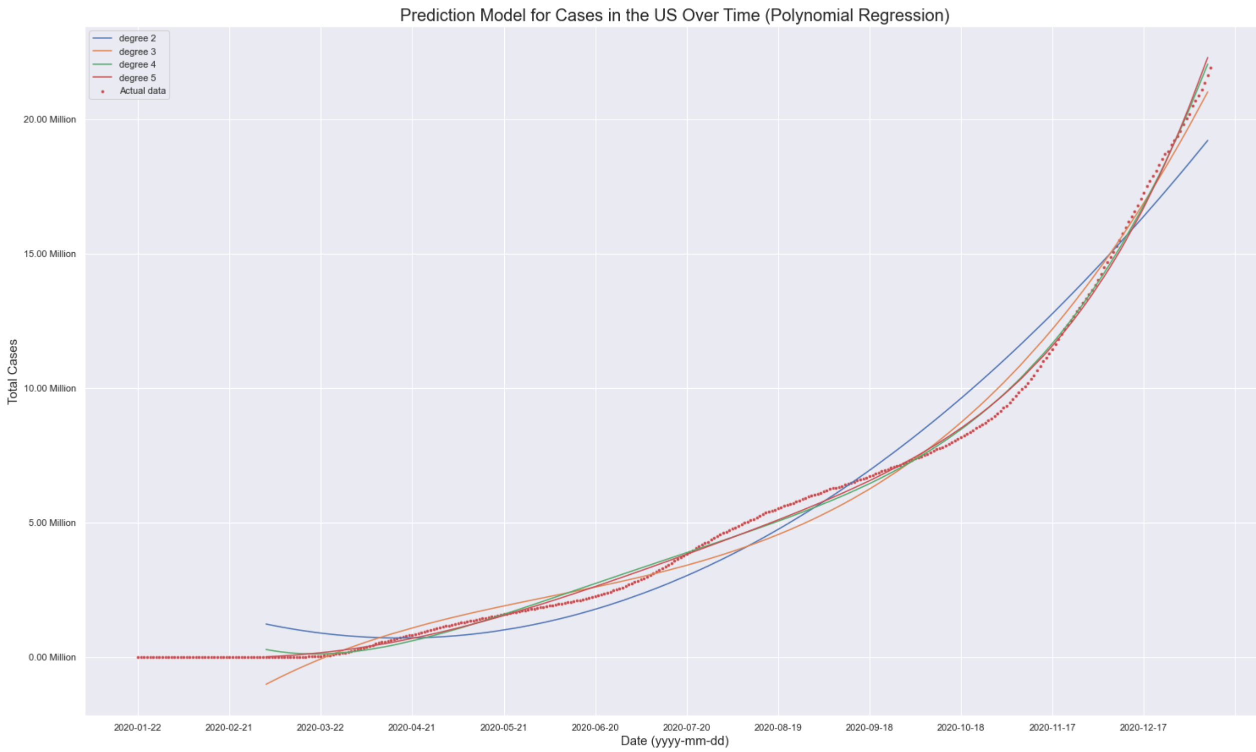
```
[0.9698794377743662, 0.9879800970976723, 0.9965681452788699, 0.9971181954491174, 0.99798
88922663472, 0.9990690067523317, 0.9984640190111228, 0.9985965738569584]
[909110.7875061503, 574295.9502713352, 306866.67066674464, 281201.4368888294, 234910.777
41801468, 159830.08840026878, 205294.91591211382, 196236.6201450782]
```

In the cell above, I made multiple polynomial regression fits to the total case data with degree ranging from 2 to 10. As expected, higher degree models showed less error, but also are likely to be overfitted, so I'll take a visual look.

In [106…

```
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=15)

ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Model for Cases in the US Over Time (Polynomial Regression)',s
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

test_degrees=[2,3,4,5]

for i in test_degrees:
    poly = PolynomialFeatures(degree=i)
    x_train_poly = poly.fit_transform(x_train)
    x_test_poly = poly.fit_transform(x_test)

    # make linear regression model
    clf = LinearRegression()
    clf.fit(x_train_poly, y_train)
    y_predict = clf.predict(x_test_poly)
    ax = sns.lineplot(x=np.ndarray.flatten(x_test), y=np.array(y_predict))
ax.legend(['degree 2', 'degree 3','degree 4','degree 5','Actual data'])
```

Out[106… <matplotlib.legend.Legend at 0x19c83dd42e0>

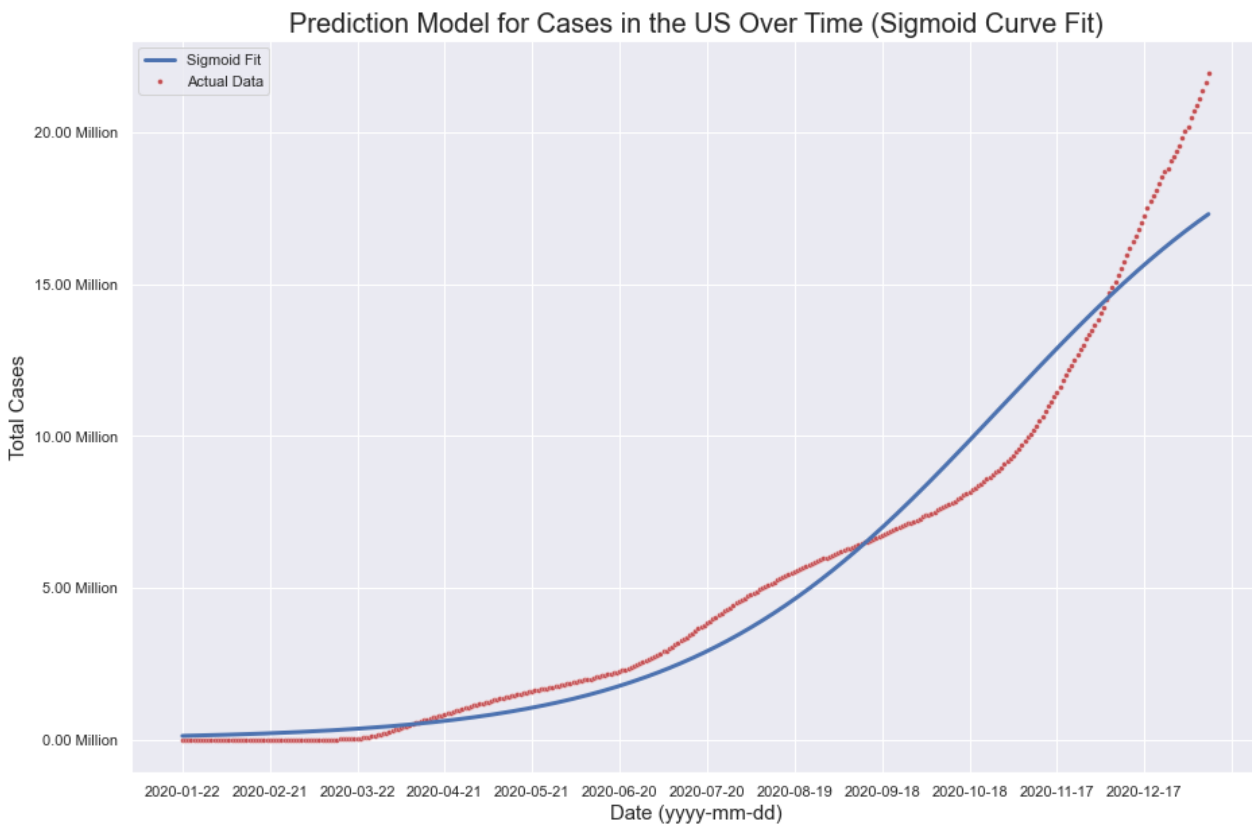


The plot above shows the results of three regression models of degree 2 through 5. We see a noticeable improvement as we increase the degree of the polynomial fit. Data from the first 40 days of data collection were trimmed off in order to get fit that is more fitting for the portion of data where cases are rising. Further analysis on the polynomial regression could be made through more quantitative and qualitative comparisons betweeen varying degrees of polynomial fits, but for now, I will move on to trying out other types of models to see how they stack up and use the polynomial fit of degree 4 as the reference for comparison.

In [107…
```
# Make a sigmoid fit for the data
from sklearn.preprocessing import MinMaxScaler
from scipy.optimize import curve_fit

# define sigmoid function
def sigmoid(x, Beta_1, Beta_2):
     y = 1 / (1 + np.exp(-Beta_1*(x-Beta_2)))
     return y

# get data to be used for curve fitting
x_data = np.reshape(usa_data.index, (-1, 1))
y_data = usa_data['total_cases']

# normalize and reformat data
xdata =x_data/max(x_data)
ydata =y_data/max(y_data)
xdata = xdata.flatten().transpose()

# make curve fit to get function parameters
popt, pcov = curve_fit(sigmoid, xdata, ydata)

#print the parameters
print(" beta_1 = %f, beta_2 = %f" % (popt[0], popt[1]))
```

```
# plot the curve fit over the actual data
fig, ax = plt.subplots(figsize=(15,10))
x = x_data/max(x_data)
y = sigmoid(x, *popt)*max(y_data)
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=15)
plt.plot(x_data,y, linewidth=3.0, label='fit')
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Model for Cases in the US Over Time (Sigmoid Curve Fit)',size=
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)
ax.legend([ 'Sigmoid Fit', 'Actual Data'])

print(r2_score(y_data, y))
print(mean_squared_error(y_data, y, squared=False))
```

```
 beta_1 = 6.541965, beta_2 = 0.798337
0.9597281343511536
1131827.6552004253
```



Above is a simple sigmoid curve fit to the data. Compared to the previous polynomial regression, the curve has more error. In hindsight, a sigmoid fit would not have been ideal for a predictive model that assumes continuous growth anyways, since the model would eventually plateau after a certain point (which could be used to make a more realistic model, but that cannot be predicted easily). Regardless, this was still good practice for simple curve fitting and modeling.

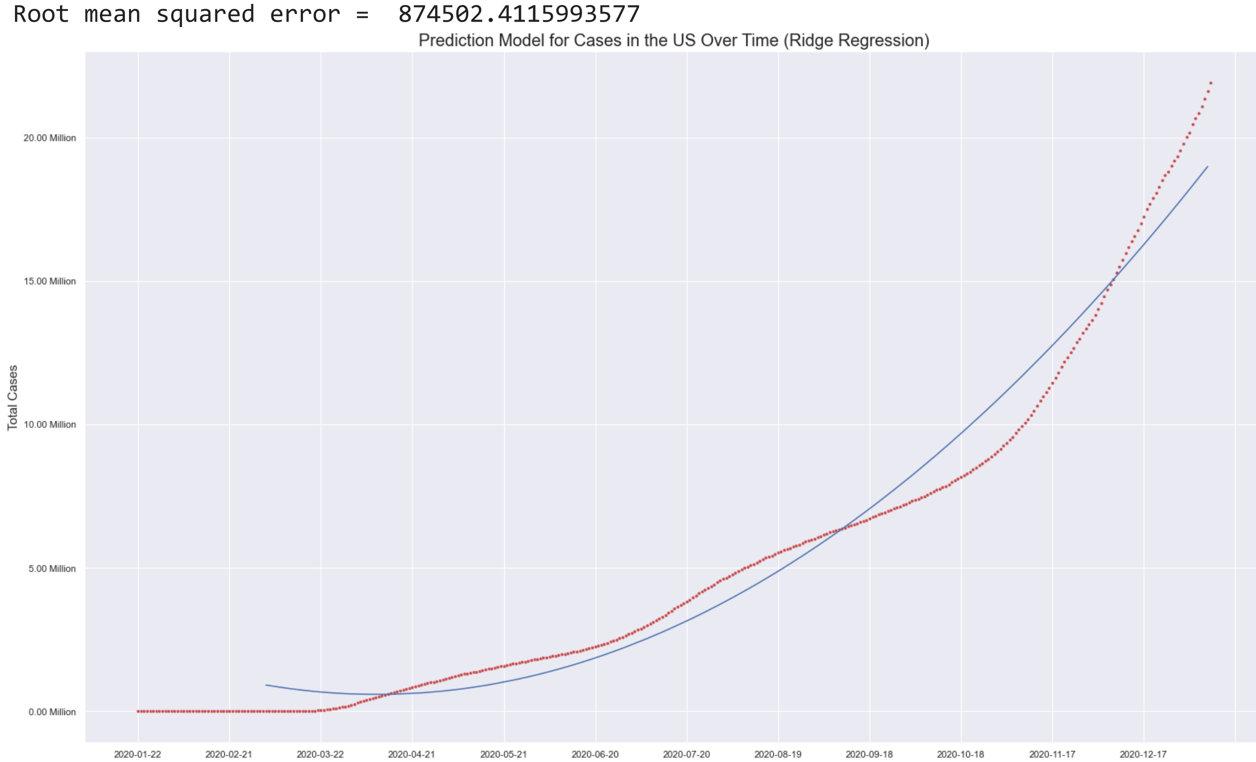
Next I'll try to use a Ridge Regression model to make a predictive model.

In [108…

```
# Ridge regression fit for the data
from sklearn.linear_model import Ridge

# set ridge alpha value to 0.1
```

```
RidgeModel=Ridge(alpha=10000)

# do 2nd degree polynomial for first test
poly = PolynomialFeatures(degree=2)

# use the same train/test split values from the polynomial regression
x_train_poly = poly.fit_transform(x_train)
x_test_poly = poly.fit_transform(x_test)

# make linear regression model
RidgeModel.fit(x_train_poly, y_train)
y_predict = RidgeModel.predict(x_test_poly)

fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()

ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=15)

ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Model for Cases in the US Over Time (Ridge Regression)',size=2
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

ax = sns.lineplot(x=np.ndarray.flatten(x_test), y=np.array(y_predict))

print('R2 score = ', r2_score(y_test, y_predict))
print('Root mean squared error = ', mean_squared_error(y_test, y_predict, squared=False
```

```
R2 score =  0.9721290690888078
Root mean squared error =  874502.4115993577
```



Not bad. However, the Ridge regression model is affected by both its alpha value and the degree of the polynomial, so I'll change those values to check model error. First, I'll start off with finding the best alpha value using GridSearchCV

In [109…

```
# use gridsearch to do ridge regression with multiple alpha values
```

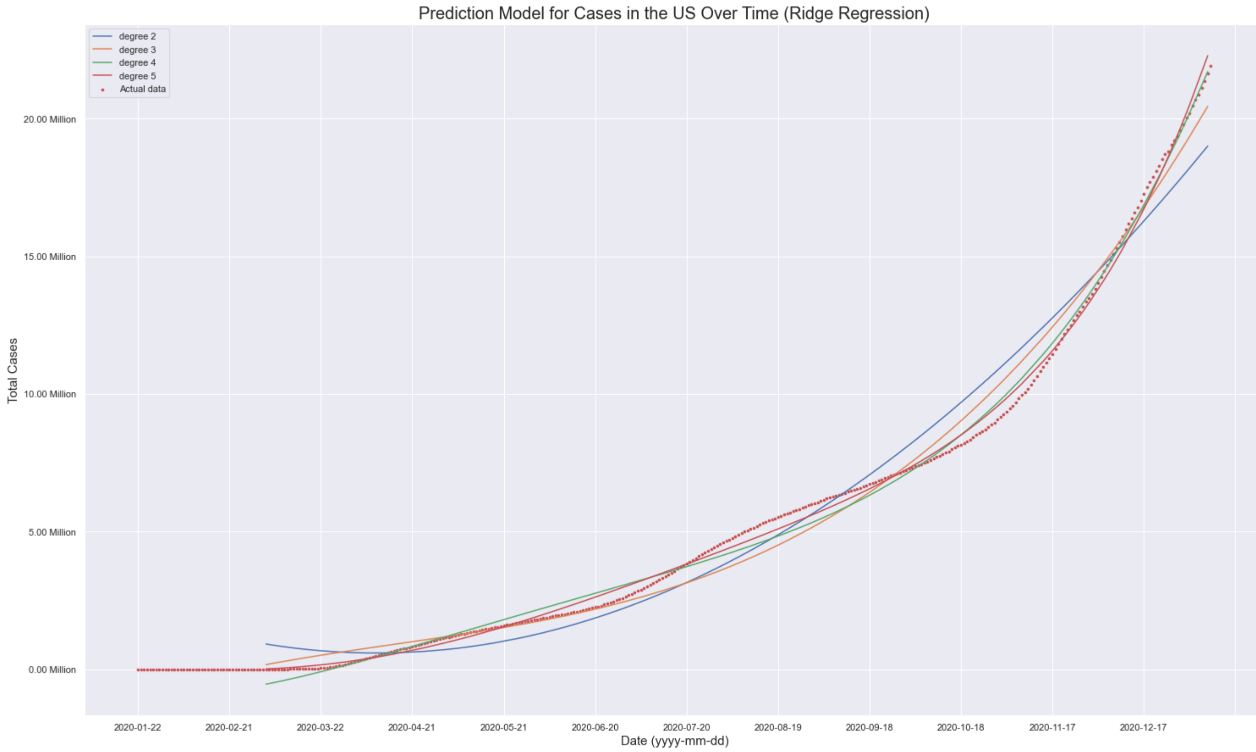
```
from sklearn.model_selection import GridSearchCV

# set alpha parameters to be tested
parameters= [{'alpha': [0.001,0.1,1, 10, 100, 1000, 10000, 100000, 100000]}]

Grid = GridSearchCV(Ridge(), parameters,cv=4)
Grid.fit(x_train, y_train)

Grid.best_estimator_
```

Out[109… Ridge(alpha=1000)

In [110…

```
# best alpha value was found to be 10000 from gridsearch, so now we iterate through pol

fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=15)

ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Model for Cases in the US Over Time (Ridge Regression)',size=2
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

test_degrees=[2,3,4,5]

r2 = []
rmse = []
for i in test_degrees:
    poly = PolynomialFeatures(degree=i)
    x_train_poly = poly.fit_transform(x_train)
    x_test_poly = poly.fit_transform(x_test)

    # make linear regression model
    RidgeModel = Ridge(alpha = 10000)
    RidgeModel.fit(x_train_poly, y_train)
    y_predict = RidgeModel.predict(x_test_poly)
    ax = sns.lineplot(x=np.ndarray.flatten(x_test), y=np.array(y_predict))

    # get error
    r2.append(r2_score(y_test, RidgeModel.predict(x_test_poly)))
    rmse.append(mean_squared_error(y_test, RidgeModel.predict(x_test_poly), squared=Fal
ax.legend(['degree 2', 'degree 3','degree 4', 'degree 5','Actual data'])

print('R squared error with ascending degree:', r2)
print('Root mean squared error with ascending degree:',rmse)
```

```
R squared error with ascending degree: [0.9721290690888078, 0.984805182788481, 0.9941800
864365683, 0.9971166263731286]
Root mean squared error with ascending degree: [874502.4115993577, 645703.3121138507, 39
9616.619286826, 281277.98031358566]
```

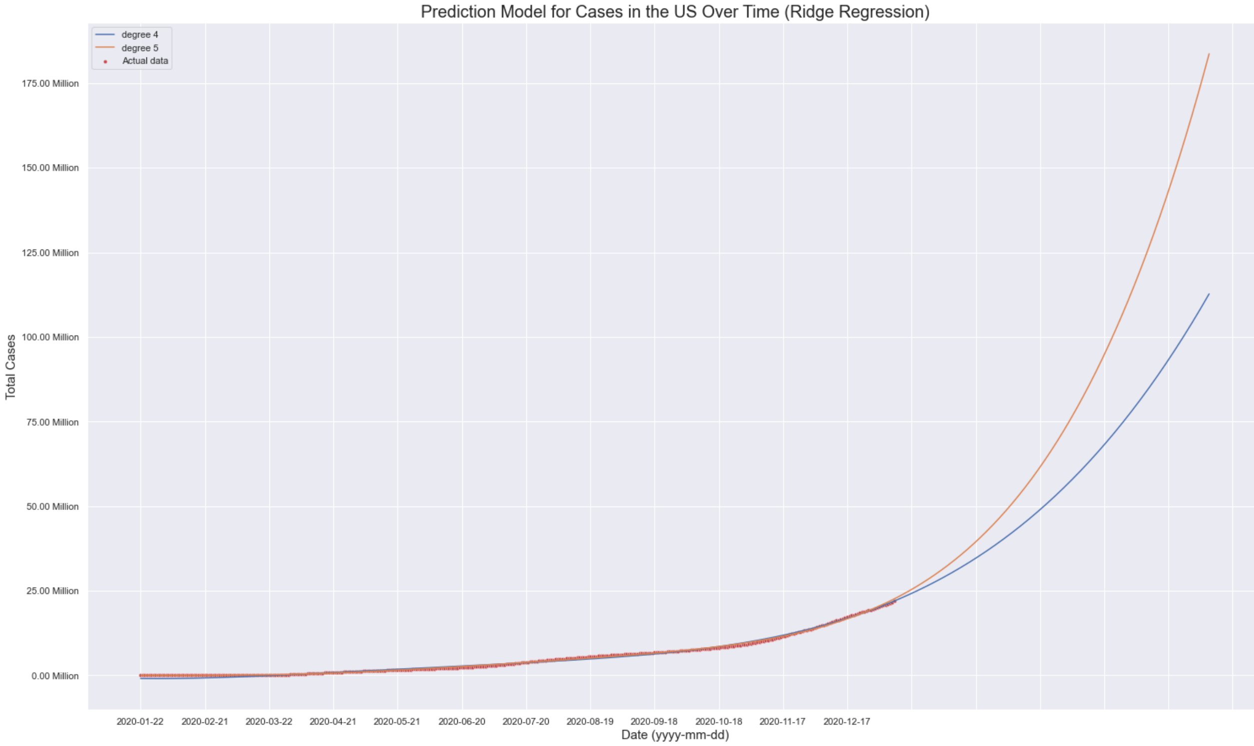


Above are the Ridge prediction models for an alpha value of 10000 from degrees 2 through 5. As expected, predection models with higher degrees showed less error. Starting from degree 4, noticeable diminishing returns on error improvement were seen. Between the degree 4 and degree 5 model, it's hard to say which one would be a better predictive model. I'll make an expanded plot to show the trajectories of the models beyond the present.

In [111…

```
# visualize long-term prediction
predict_x = np.reshape(np.arange(500), (-1, 1))

predict_degrees=[4,5]

fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=20)

ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Model for Cases in the US Over Time (Ridge Regression)',size=2
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

for i in predict_degrees:
    poly = PolynomialFeatures(degree=i)
    x_train_poly = poly.fit_transform(x_train)
    x_predict_poly = poly.fit_transform(predict_x)

    # make linear regression model
    RidgeModel = Ridge(alpha = 10000)
    RidgeModel.fit(x_train_poly, y_train)
    predict = RidgeModel.predict(x_predict_poly)
    ax = sns.lineplot(x=np.ndarray.flatten(predict_x), y=np.array(predict))

ax.legend(['degree 4', 'degree 5','Actual data'])
```

Out[111… <matplotlib.legend.Legend at 0x19d00f14f70>



When looking at the trajectories of the two models, the model using a degree of 4 seems like a more reasonable prediction of total case numbers (based on the trend up to now). However, the model using a degree of 5 could also be entirely possible under the case that more aggressive variants of COVID-19 appear and pandemic restrictions are lifted (or less people follow them). For final comparison with other models, I will use the model with degree 4.

Lastly, it's time to try a lasso regression model.

In [112…

```
from sklearn.linear_model import Lasso

# set alpha parameters to be tested
parameters= [{'alpha': [0.001,0.1,1, 10, 100, 1000, 10000, 100000, 100000]}]

lasso = Lasso()

Grid = GridSearchCV(lasso, parameters,cv=4)
Grid.fit(x_train, y_train)

Grid.best_estimator_
```

Out[112…

```
Lasso(alpha=100000)
```

In [113…

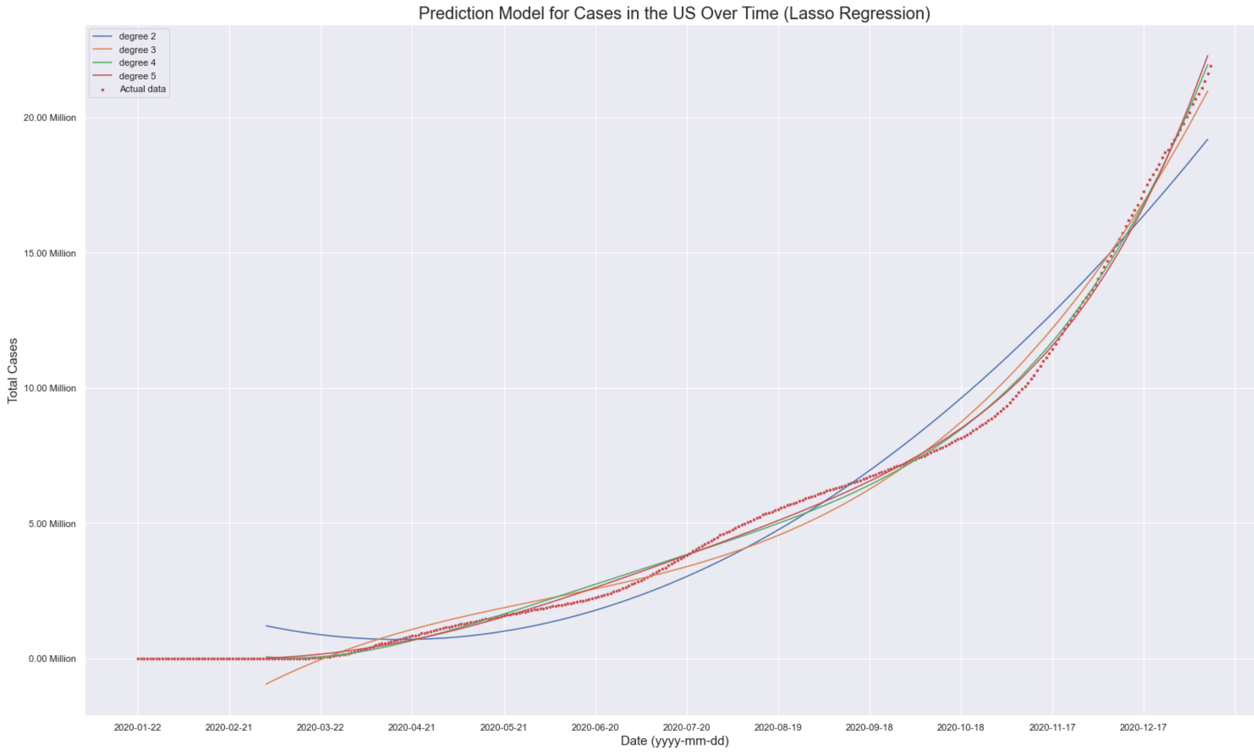
```
# best alpha value was found to be 10000 from gridsearch, so now we iterate through pol

fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=15)

ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Model for Cases in the US Over Time (Lasso Regression)',size=2
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)
```

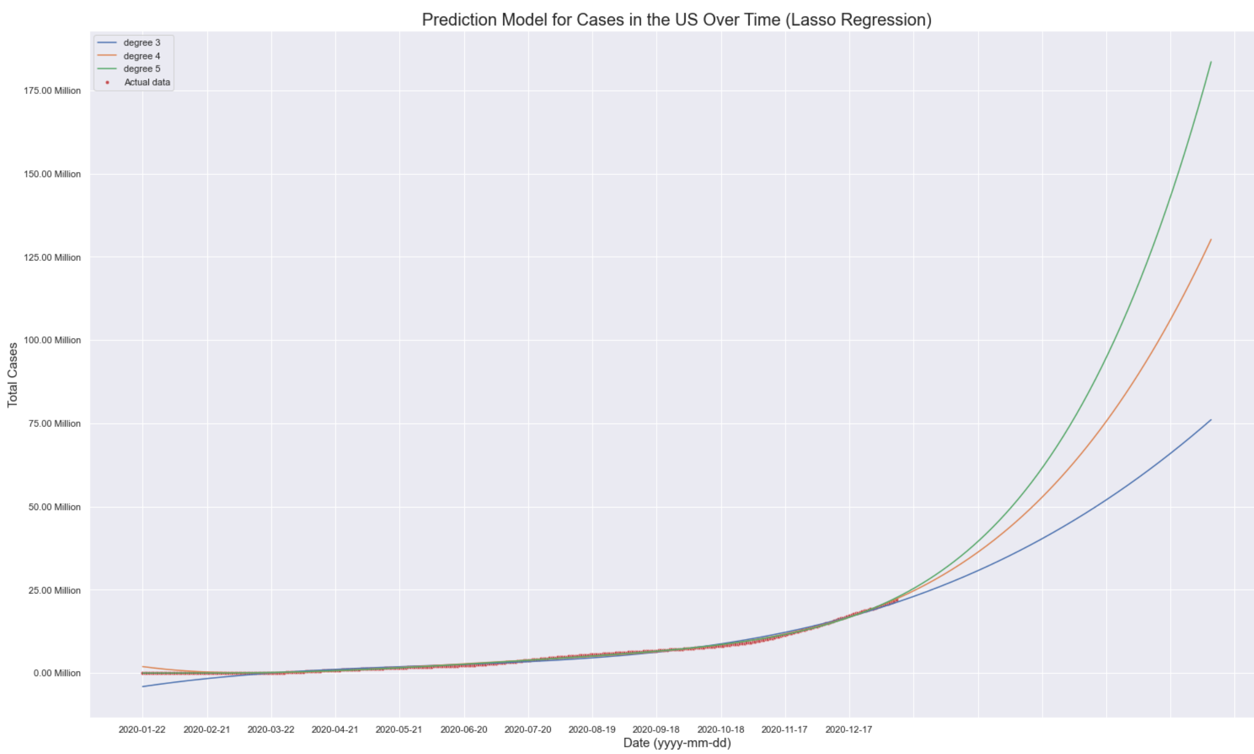
```
test_degrees=[2,3,4,5]

r2 = []
rmse = []
for i in test_degrees:
    poly = PolynomialFeatures(degree=i)
    x_train_poly = poly.fit_transform(x_train)
    x_test_poly = poly.fit_transform(x_test)

    # make linear regression model, max iterations must be 10000000 for solution to con
    LassoModel = Lasso(alpha = 100000,tol=.0001,max_iter=10000000)
    LassoModel.fit(x_train_poly, y_train)
    y_predict = LassoModel.predict(x_test_poly)
    ax = sns.lineplot(x=np.ndarray.flatten(x_test), y=np.array(y_predict))

    # get error
    r2.append(r2_score(y_test, LassoModel.predict(x_test_poly)))
    rmse.append(mean_squared_error(y_test, LassoModel.predict(x_test_poly), squared=Fal
ax.legend(['degree 2', 'degree 3','degree 4', 'degree 5','Actual data'])

print('R squared error with ascending degree:', r2)
print('Mean squared error with ascending degree:',rmse)

# visualize long-term prediction
predict_x = np.reshape(np.arange(500), (-1, 1))

predict_degrees=[3,4,5]

fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=20)

ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Model for Cases in the US Over Time (Lasso Regression)',size=2
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

for i in predict_degrees:
    poly = PolynomialFeatures(degree=i)
    x_train_poly = poly.fit_transform(x_train)
    x_predict_poly = poly.fit_transform(predict_x)

    # make linear regression model
    LassoModel = Lasso(alpha = 100000,tol=.0001,max_iter=10000000)
    LassoModel.fit(x_train_poly, y_train)
    predict = LassoModel.predict(x_predict_poly)
    ax = sns.lineplot(x=np.ndarray.flatten(predict_x), y=np.array(predict))

ax.legend(['degree 3', 'degree 4', 'degree 5','Actual data'])
```

```
R squared error with ascending degree: [0.9700303542322167, 0.9880941690716613, 0.996306
2572390097, 0.9971159689547718]
Mean squared error with ascending degree: [906830.4172461822, 571564.3456815045, 318360.
07448658964, 281310.0446230223]
```

Out[113…

```
<matplotlib.legend.Legend at 0x19d0176b7f0>
```





Above are the Lasso prediction models for an alpha value of 10000 from degrees 2 through 5. When comparing the error scores and future trajectories of the Lasso model using degrees 3, 4 , and 5, the model with degree 4 is most in-line with the other models that were selected for final comparison.

Now I'll compare the different regression models.

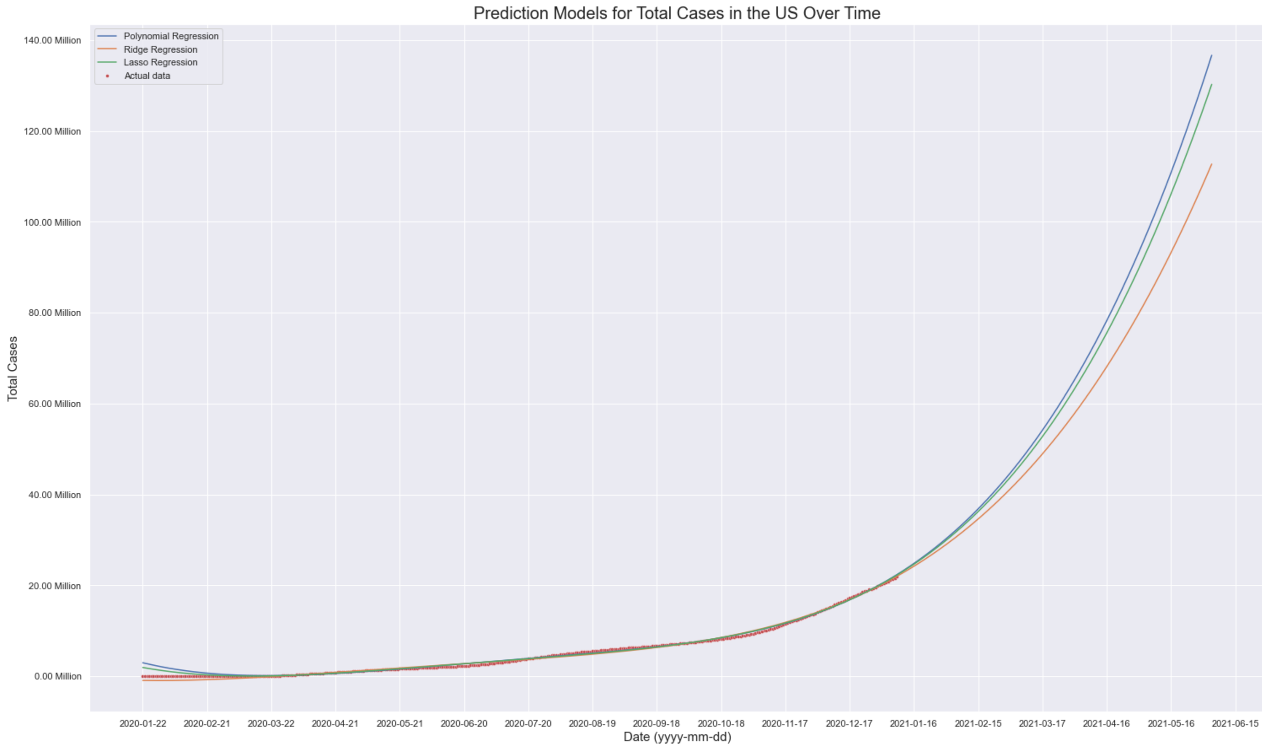
In [114…

```
fig, ax = plt.subplots(figsize=(25,15))
sns.set_theme()
ax = sns.scatterplot(data=usa_data, x='date',y='total_cases', color='r', s=15)
```

```
ax.xaxis.set_major_locator(ticker.MultipleLocator(30))
ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda y, pos: '{:,.2f}'.format(y/100
ax.set_title('Prediction Models for Total Cases in the US Over Time',size=20)
ax.set_ylabel('Total Cases', size=15)
ax.set_xlabel('Date (yyyy-mm-dd)', size=15)

poly = PolynomialFeatures(4)

# poly regression
x_train_poly = poly.fit_transform(x_train)
x_predict_poly = poly.fit_transform(predict_x)
clf = LinearRegression()
clf.fit(x_train_poly, y_train)
predict = clf.predict(x_predict_poly)
ax = sns.lineplot(x=np.ndarray.flatten(predict_x), y=np.array(predict))

# Ridge regression
x_train_poly = poly.fit_transform(x_train)
x_predict_poly = poly.fit_transform(predict_x)
RidgeModel = Ridge(alpha = 10000)
RidgeModel.fit(x_train_poly, y_train)
predict = RidgeModel.predict(x_predict_poly)
ax = sns.lineplot(x=np.ndarray.flatten(predict_x), y=np.array(predict))

# Lasso regression
x_train_poly = poly.fit_transform(x_train)
x_predict_poly = poly.fit_transform(predict_x)
LassoModel = Lasso(alpha = 100000,tol=.0001,max_iter=10000000)
LassoModel.fit(x_train_poly, y_train)
predict = LassoModel.predict(x_predict_poly)
ax = sns.lineplot(x=np.ndarray.flatten(predict_x), y=np.array(predict))

ax.legend(['Polynomial Regression', 'Ridge Regression', 'Lasso Regression','Actual data

dates = pd.date_range(start='12/23/2019', end='6/30/2021')
dates = dates.date
dates = np.array(dates)
ax.set_xticklabels(dates[0::30])
```

Out[114…

```
[Text(-30.0, 0, '2019-12-23'),
 Text(0.0, 0, '2020-01-22'),
 Text(30.0, 0, '2020-02-21'),
 Text(60.0, 0, '2020-03-22'),
 Text(90.0, 0, '2020-04-21'),
 Text(120.0, 0, '2020-05-21'),
 Text(150.0, 0, '2020-06-20'),
 Text(180.0, 0, '2020-07-20'),
 Text(210.0, 0, '2020-08-19'),
 Text(240.0, 0, '2020-09-18'),
 Text(270.0, 0, '2020-10-18'),
 Text(300.0, 0, '2020-11-17'),
 Text(330.0, 0, '2020-12-17'),
 Text(360.0, 0, '2021-01-16'),
 Text(390.0, 0, '2021-02-15'),
 Text(420.0, 0, '2021-03-17'),
 Text(450.0, 0, '2021-04-16'),
 Text(480.0, 0, '2021-05-16'),
 Text(510.0, 0, '2021-06-15'),
 Text(540.0, 0, '')]
```



Above we see the three different models and their predictive trajectories. Each of the models had the following error scores:

Model	R Squared Error	Root Mean Squared Error
Polynomial	0.9966	306867
Ridge	0.9942	399617
Lasso	0.9963	318360

If we were to decide the best model solely on error scores, then the standard polynomial regression is the best model. However, like I mentioned near the start of this section, standard regression is most prone to overfitting, and good error scores may be an indicator of overfitting rather than being a good model. In terms of case numbers themselves, the regular regression and Lasso model showed similar values for long term growth while the Ridge model showed slightly lower values. Of the three models, I would say that the Ridge model actually does the best job at following the data trends from start to finish, but all three do a reasonable job of modeling case number trajectories.

Self-Critiques

- Since this is my first time attempting to use machine learning libraries, there are still a lot of techniques/optimizations that I am not familiar with that probably could have been used to make better predictive models
- Making an accurate model for something like pandemic cases is difficult as there are many unpredictable factors that can affect it (government-imposed restrictions, public opinion of the virus, improvements in preemptive medicine and prevention measures, virus mutations, vaccine development, etc.), and I am not sure how to approach making a model that accounts for all of these factors

Ultimately, this became more of an exercise in learning and using some of the machine learning options available to Python and getting a feel for the overall process of making a predictive model, regardless of how accurate the final model may have been.

Next Steps

- Provide some more analysis in Analysis 2 to evaluate US stringency effectiveness and how it differs from Korea
- Continue with plotting, comparing, and analyzing COVID metrics between multiple countries around the world to get an idea of similarities and differences between them

In [ ]:

```

```