Project - COVID-19 New Jersey Trends & Impact on RideSharing Platform

In [48]:
```
import pandas as pd
# import the seaborn module
import seaborn as sns
import matplotlib.pyplot as plt
import datetime  as dt
import numpy as np
from matplotlib.ticker import PercentFormatter
import os
import missingno as msno # visualize the distribution of NaN values
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
import plotly
from datetime import datetime
import dexplot as dxp
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.express as px

# import plotly.graph_objects
# from plotly.subplots import make_subplots
```

COVID-19 Dataset --> We have taken New Jersey covid19 data

source --> https://covidtracking.com/api/v1/states/daily.csv (https://covidtracking.com/api/v1/states/daily.csv)

X Dataset --> We are trying to observe the impact of COVID-19 on the stock prices of major Ridesharing Players (Uber + Lyft)

Source --> https://finance.yahoo.com/quote/UBER/history?p=UBER (https://finance.yahoo.com/quote/UBER/history?p=UBER)

https://finance.yahoo.com/quote/LYFT/history?p=LYFT (https://finance.yahoo.com/quote/LYFT/history?p=LYFT)

Project Git Repository --> https://github.com/marif1901/COVID19_NJ_ImpactAnalysis (https://github.com/marif1901/COVID19_NJ_ImpactAnalysis)

Part 1: Data Pre Processing (10%)

In [2]:
```
cov_url= 'https://raw.githubusercontent.com/marif1901/COVID19_NJ_ImpactAnalysis/master/COVID19_Data_NJ.csv'
x_uber_url= "https://raw.githubusercontent.com/marif1901/COVID19_NJ_ImpactAnalysis/master/UBER_1Y.csv"
x_lyft_url= "https://raw.githubusercontent.com/marif1901/COVID19_NJ_ImpactAnalysis/master/LYFT_1Y.csv"
```

Reading Datasets

In [3]:
```
covid = pd.read_csv(cov_url,sep=',')# use sep="," for coma separation.
xuber = pd.read_csv(x_uber_url,sep=',')
xlyft = pd.read_csv(x_lyft_url,sep=',')
print(covid.columns)
print(xuber.columns)
print(xlyft.columns)
```

```
Index(['date', 'state', 'positive', 'negative', 'pending',
       'hospitalizedCurrently', 'hospitalizedCumulative', 'inIcuCurrently',
       'inIcuCumulative', 'onVentilatorCurrently', 'onVentilatorCumulative',
       'recovered', 'hash', 'dateChecked', 'death', 'hospitalized', 'total',
       'totalTestResults', 'posNeg', 'fips', 'deathIncrease',
       'hospitalizedIncrease', 'negativeIncrease', 'positiveIncrease',
       'totalTestResultsIncrease', 'dailypositvecases', 'dailynegativecases',
       'dailytestingdone', 'dailydeath'],
      dtype='object')
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume'], dtype='object')
```

Preprocessing on COVID Data

In [4]:
```
covid_cols= ['date','dailypositvecases','dailynegativecases','dailydeath','dailytestingdone',
             'positiveIncrease','negativeIncrease', 'deathIncrease','totalTestResultsIncrease',
            'positive', 'negative', 'death','totalTestResults']
covid_sel= covid[covid_cols].copy()

covid_cols= ['date','dailypositvecases','dailynegativecases','dailydeath','dailytestingdone',
             'positiveIncrease','negativeIncrease', 'deathIncrease','totalTestResultsIncrease',
            'cumpositive', 'cumnegative', 'cumdeath','cumtotalTestResults']

covid_sel.columns=  covid_cols
```

Dropping rows where data is NA

In [5]:
```
sum(pd.isna(covid_sel['date']))
index = covid_sel[pd.isna(covid_sel['date'])].index
covid_sel.drop(index , inplace=True)
```

Converting date to proper %Y%m%d format

In [6]:
```
covid_sel['date']= covid_sel['date'].astype(str)
covid_sel['date'] = pd.to_datetime(covid_sel['date'], format='%Y%m%d').dt.strftime("%Y-%m-%d");
```

In [7]:
```
int_col= ['dailypositvecases','dailynegativecases','dailydeath','dailytestingdone',
             'positiveIncrease','negativeIncrease', 'deathIncrease','totalTestResultsIncrease',
            'cumpositive', 'cumnegative', 'cumdeath','cumtotalTestResults']
covid_sel[int_col] = covid_sel[int_col].convert_objects(convert_numeric=True)
covid_sel.head()
```

Out[7]:

	date	dailypositvecases	dailynegativecases	dailydeath	dailytestingdone	positiveIncrease	negativeIncrease	deathIncrease	totalTestResultsIncrease	cumpositive	cumnegative	cumdeath	cumtotalTestResults
0	2020-04-26	3515	5943	75	9458	3515	5943	75	9458	109038	114106	5938	223144
1	2020-04-25	3327	4397	246	7724	3327	4397	246	7724	105523	108163	5863	213686
2	2020-04-24	2207	3607	249	5814	2207	3607	249	5814	102196	103766	5617	205962
3	2020-04-23	4124	4365	305	8489	4124	4365	305	8489	99989	100159	5368	200148
4	2020-04-22	3478	3355	310	6833	3478	3355	310	6833	95865	95794	5063	191659

In [8]:
```
print('Min Date observed for COVID : ' + str(covid_sel['date'].min()))
print('Max Date observed for COVID: ' + str(covid_sel['date'].max()))
```

```
Min Date observed for COVID : 2020-03-05
Max Date observed for COVID: 2020-04-26
```

Preprocessing on X Data

In [9]:
```
x_cols= ['Date','Close','Volume']

xuber_sel= xuber[x_cols].copy()
xlyft_sel= xlyft[x_cols].copy()

x_cols= ['date','UberClosingPrice','UberVolume']
xuber_sel.columns= x_cols

x_cols= ['date','LyftClosingPrice','LyftVolume']
xlyft_sel.columns=x_cols
```

In [10]:
```
xuber_sel.date= pd.to_datetime(xuber_sel['date']).dt.strftime('%Y-%m-%d')
xlyft_sel.date=pd.to_datetime(xlyft_sel['date']).dt.strftime('%Y-%m-%d')
```

In [12]:
```
x_sel= pd.merge(xuber_sel, xlyft_sel,on='date')
print('\033[1m' + 'Min Date observed for X : ' + str(x_sel['date'].min()))
print('\033[1m' + 'Max Date observed for X: ' + str(x_sel['date'].max()))
```

Min Date observed for X : 2019-05-10
Max Date observed for X: 2020-04-24

In [13]:
```
x_sel.head()
```

Out[13]:

	date	UberClosingPrice	UberVolume	LyftClosingPrice	LyftVolume
0	2019-05-10	41.570000	186322500	51.090000	23111200
1	2019-05-13	37.099998	79442400	48.150002	10007400
2	2019-05-14	39.959999	46661100	50.520000	7007400
3	2019-05-15	41.290001	36086100	54.040001	7909300
4	2019-05-16	43.000000	38115500	55.599998	7101700

Merging COVID data with X Data for Analysing impact in the same time frame

In [15]:
```
comb_df= covid_sel.merge(x_sel, how='inner', on='date')
comb_df=comb_df.drop_duplicates()
print('\033[1m' + 'Min Date observed for comb_df : ' + str(comb_df['date'].min()))
print('\033[1m' + 'Max Date observed for comb_df: ' + str(comb_df['date'].max()))
```

Min Date observed for comb_df : 2020-03-05
Max Date observed for comb_df: 2020-04-24

Filtering 4 weeks timeframe for Analysis

In [16]:
```

st_dt= pd.to_datetime('2020-03-23').strftime('%Y-%m-%d')
print(st_dt)
end_dt= pd.to_datetime('2020-04-19').strftime('%Y-%m-%d')
print(end_dt)

comb_df = comb_df[ (comb_df['date']>=st_dt) & (comb_df['date']<=end_dt)]

print('\033[1m' + 'Min Date observed for comb_df : ' + str(comb_df['date'].min()))
print('\033[1m' + 'Max Date observed for comb_df: ' + str(comb_df['date'].max()))

comb_df.head()
```

```
2020-03-23
2020-04-19
```
Min Date observed for comb_df : 2020-03-23
Max Date observed for comb_df: 2020-04-17

Out[16]:

	date	dailypositvecases	dailynegativecases	dailydeath	dailytestingdone	positiveIncrease	negativeIncrease	deathIncrease	totalTestResultsIncrease	cumpositive	cumnegative	cumdeath	cumtotalTestResults	UberClosingP
5	2020-04-17	3150	2469	322	5619	3150	2469	322	5619	78467	78982	3840	157449	28.00(
6	2020-04-16	4287	3522	362	7809	4287	3522	362	7809	75317	76513	3518	151830	27.03(
7	2020-04-15	2206	2041	351	4247	2206	2041	351	4247	71030	72991	3156	144021	27.41(
8	2020-04-14	4240	6065	362	10305	4240	6065	362	10305	68824	70950	2805	139774	27.75(
9	2020-04-13	2734	0	93	2734	2734	0	93	2734	64584	64885	2443	129469	27.99(

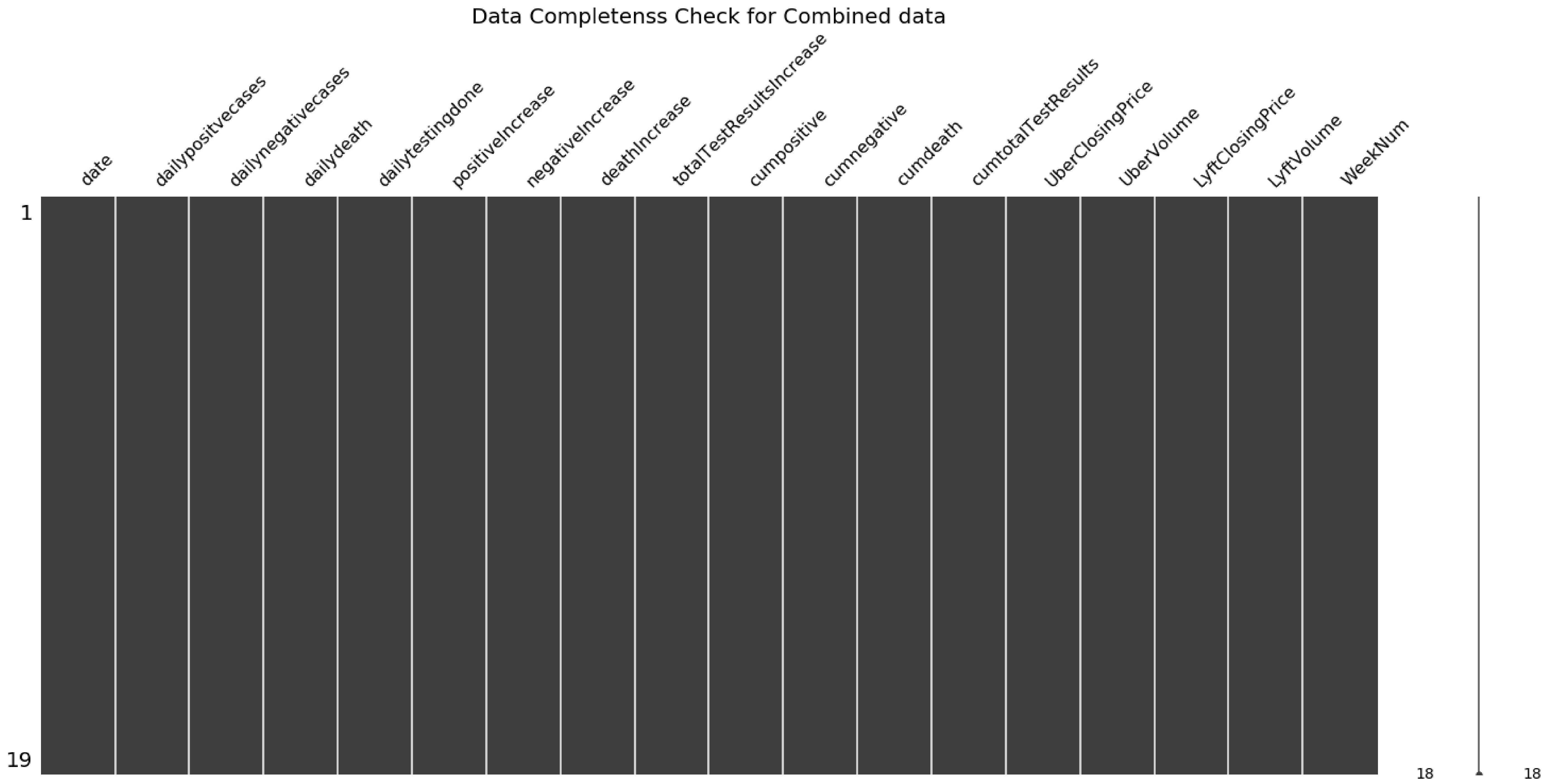
Assigning Week Number

In [17]:
```
comb_df['WeekNum'] = ((pd.to_datetime(comb_df['date']) - pd.to_datetime(st_dt)).dt.days)//7 +1
# weeklycount=comb_df['WeekNum'].value_counts()
# weeklycount
```

Checking Nullity and Data Completeness

In [20]:
```
msno.matrix(comb_df)
plt.title('Data Completenss Check for Combined data', size = 20)
```

Out[20]:
```
Text(0.5, 1.0, 'Data Completenss Check for Combined data')
```



No Nullity found above

comb_df is the master data set that is preserved through out the exercise for analysis

In [21]:
```
comb_df= comb_df.sort_values(by="date")
```

Part 2: General Trends in Covid + X Data (10%)

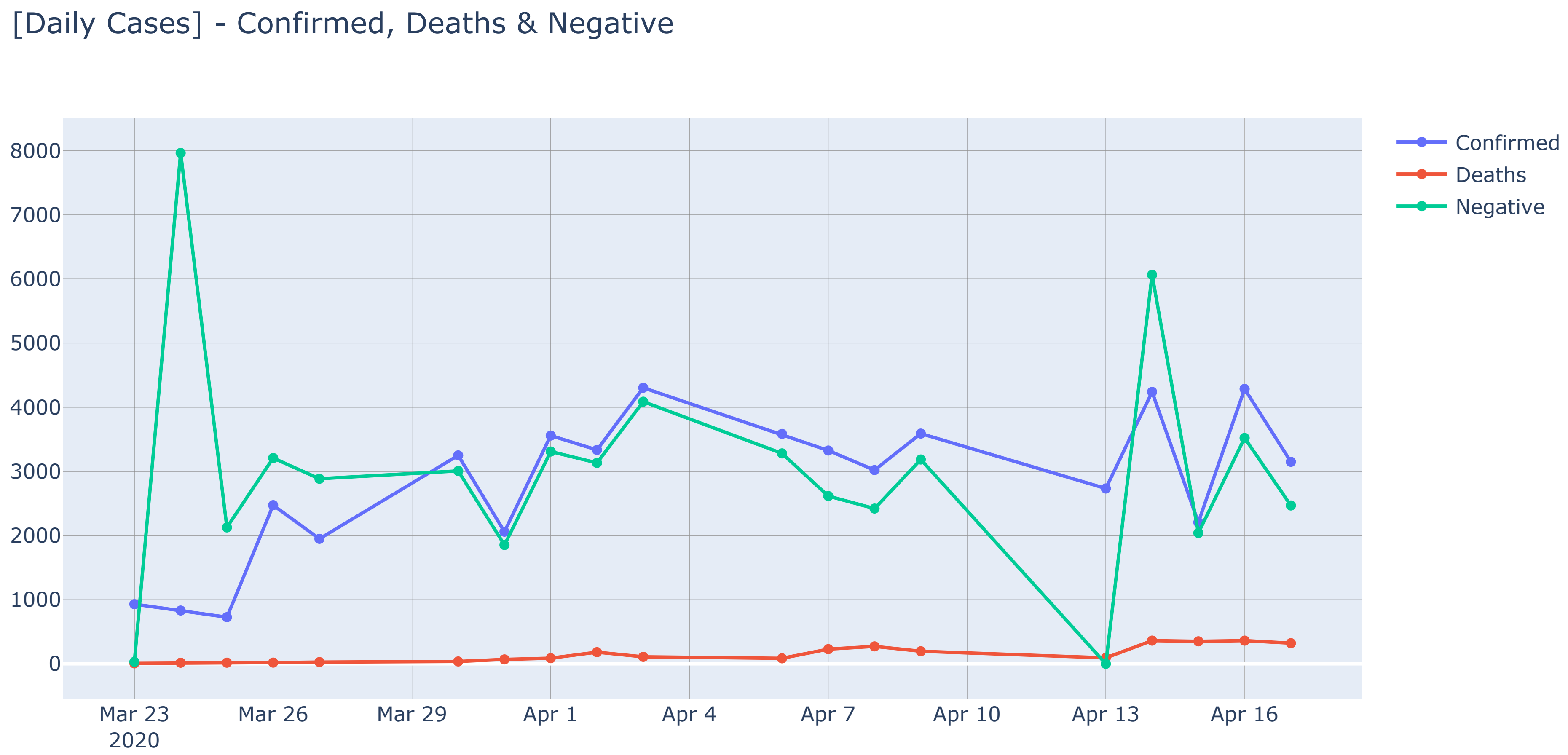
PDF and CDF of COVID 19 Growth

In [26]:
```
comb_df.head(3)
```

Out[26]:

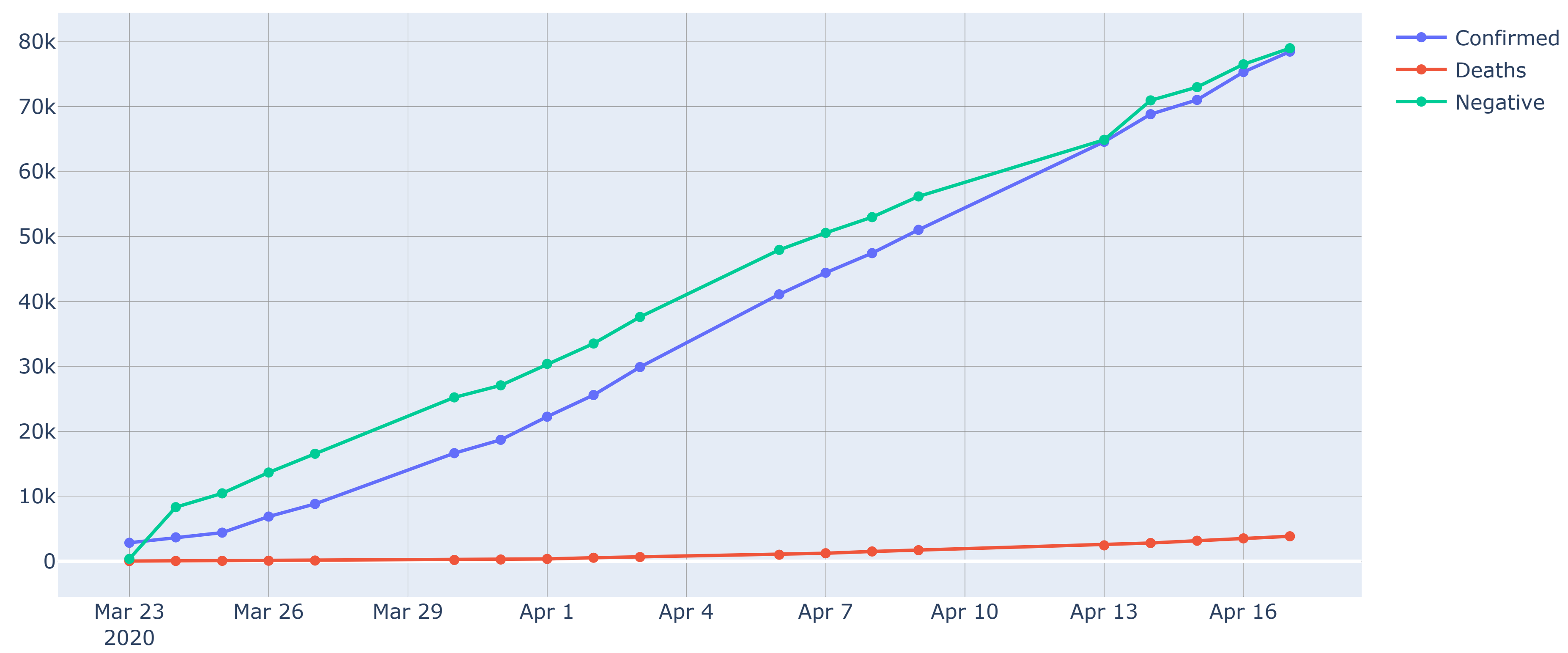
	date	dailypositvecases	dailynegativecases	dailydeath	dailytestingdone	positiveIncrease	negativeIncrease	deathIncrease	totalTestResultsIncrease	cumpositive	cumnegative	cumdeath	cumtotalTestResults	UberClosing
23	2020-03-23	930	32	7	962	930	32	7	962	2844	359	27	3203	22.4(
22	2020-03-24	831	7966	17	8797	831	7966	17	8797	3675	8325	44	12000	26.3ε
21	2020-03-25	727	2127	18	2854	727	2127	18	2854	4402	10452	62	14854	26.1(

In [97]:
```
fig = go.Figure()
fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['dailypositvecases'],
                         mode='lines+markers', name='Confirmed'))
fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['dailydeath'],
                         mode='lines+markers', name='Deaths'))
fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['dailynegativecases'],
                         mode='lines+markers', name='Negative'))

fig.update_layout(
        xaxis_title="",
        yaxis_title="",
        title = '[Daily Cases] - Confirmed, Deaths & Negative'
        #yaxis_type="log"
    )
fig.show()
```

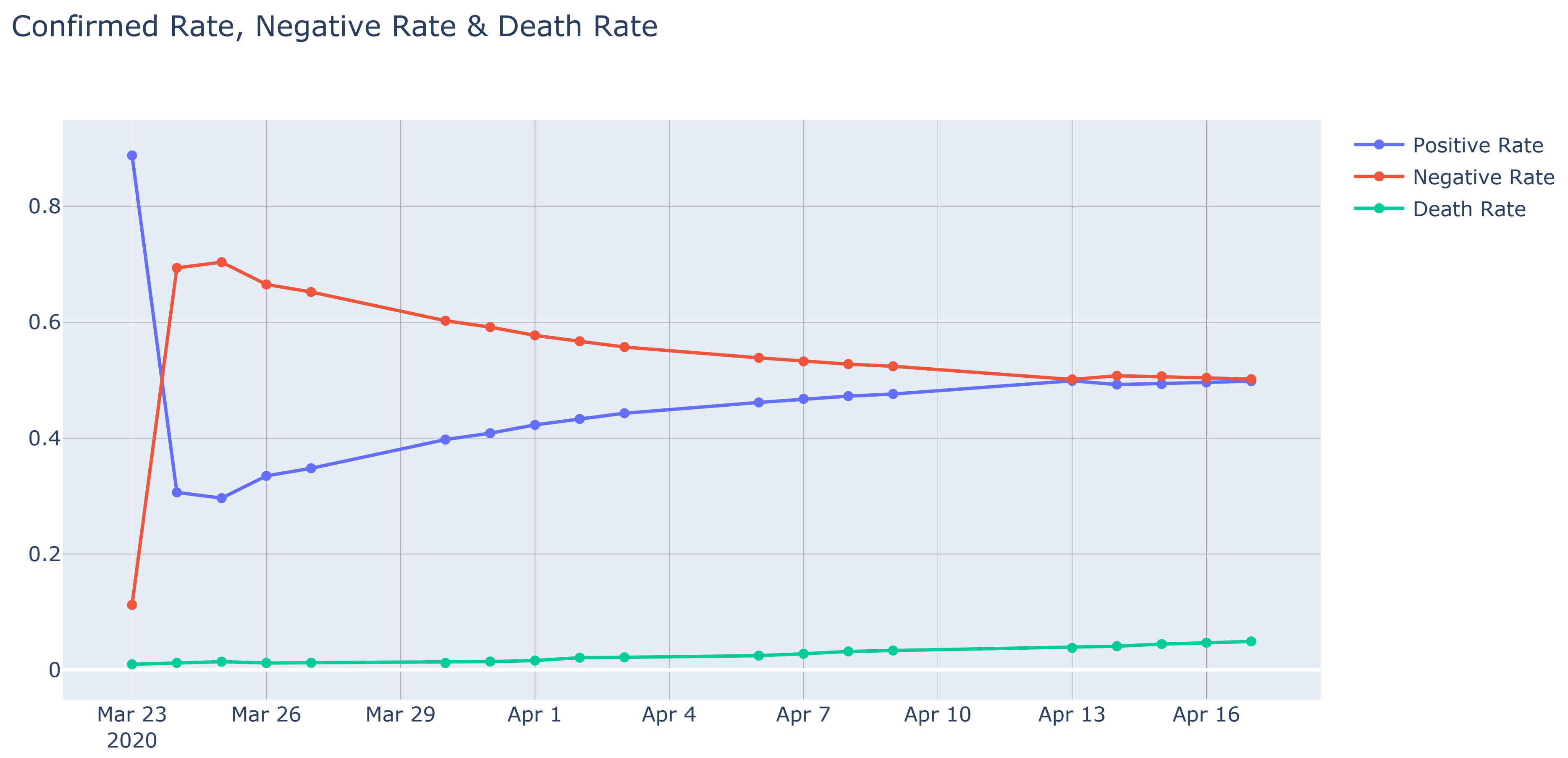


In [98]:
```
fig = go.Figure()
fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['cumpositive'],
                         mode='lines+markers', name='Confirmed'))
fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['cumdeath'],
                         mode='lines+markers', name='Deaths'))
fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['cumnegative'],
                         mode='lines+markers', name='Negative'))

fig.update_layout(
        xaxis_title="",
        yaxis_title="",
        title = 'Cumulative -> Confirmed, Deaths & Negative Results'
#         title = 'CDF [Log Scale]-> Confirmed, Deaths & Negative Results',
        #yaxis_type="log"
    )
fig.show()
```

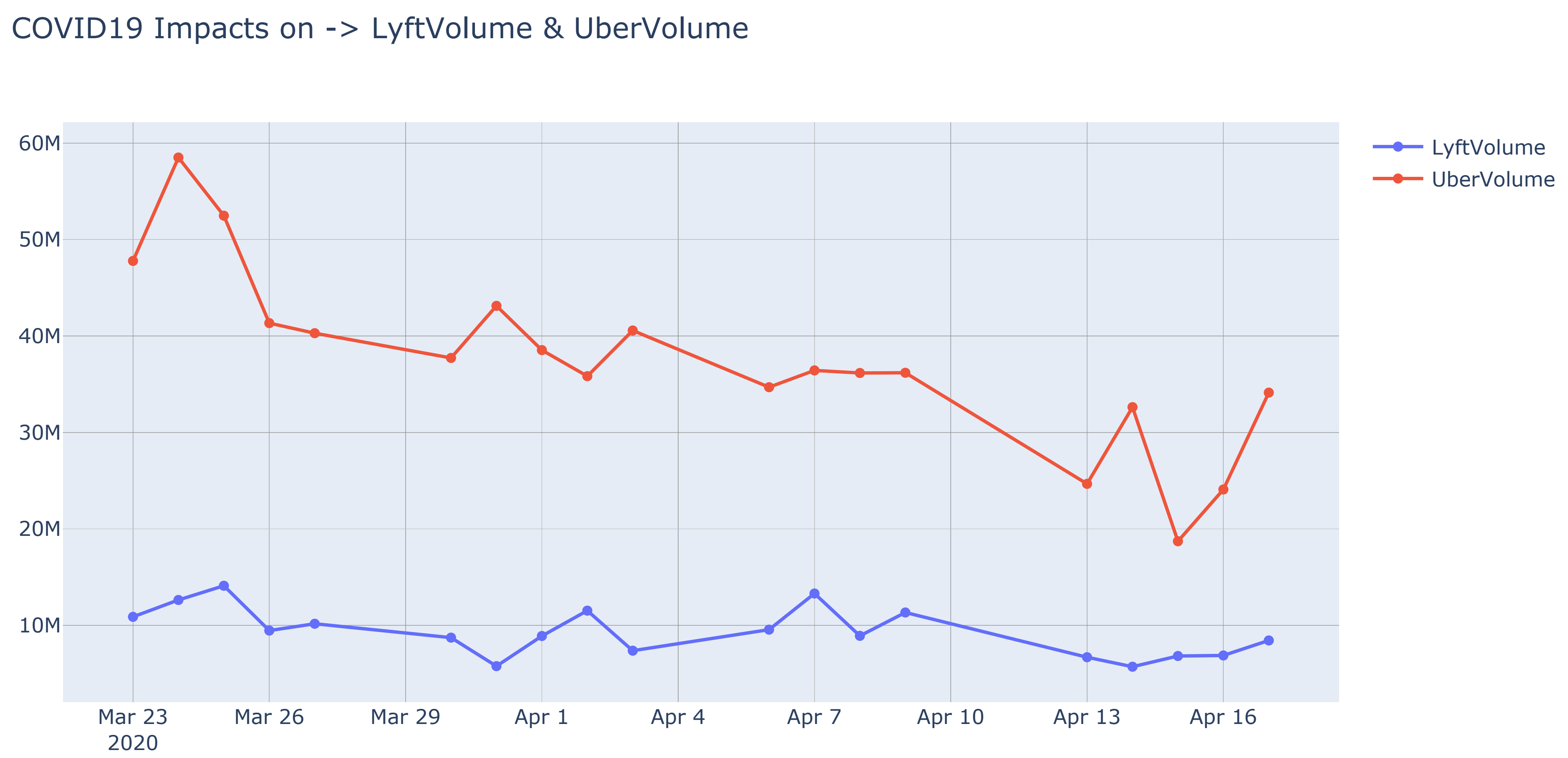
Cumulative -> Confirmed, Deaths & Negative Results



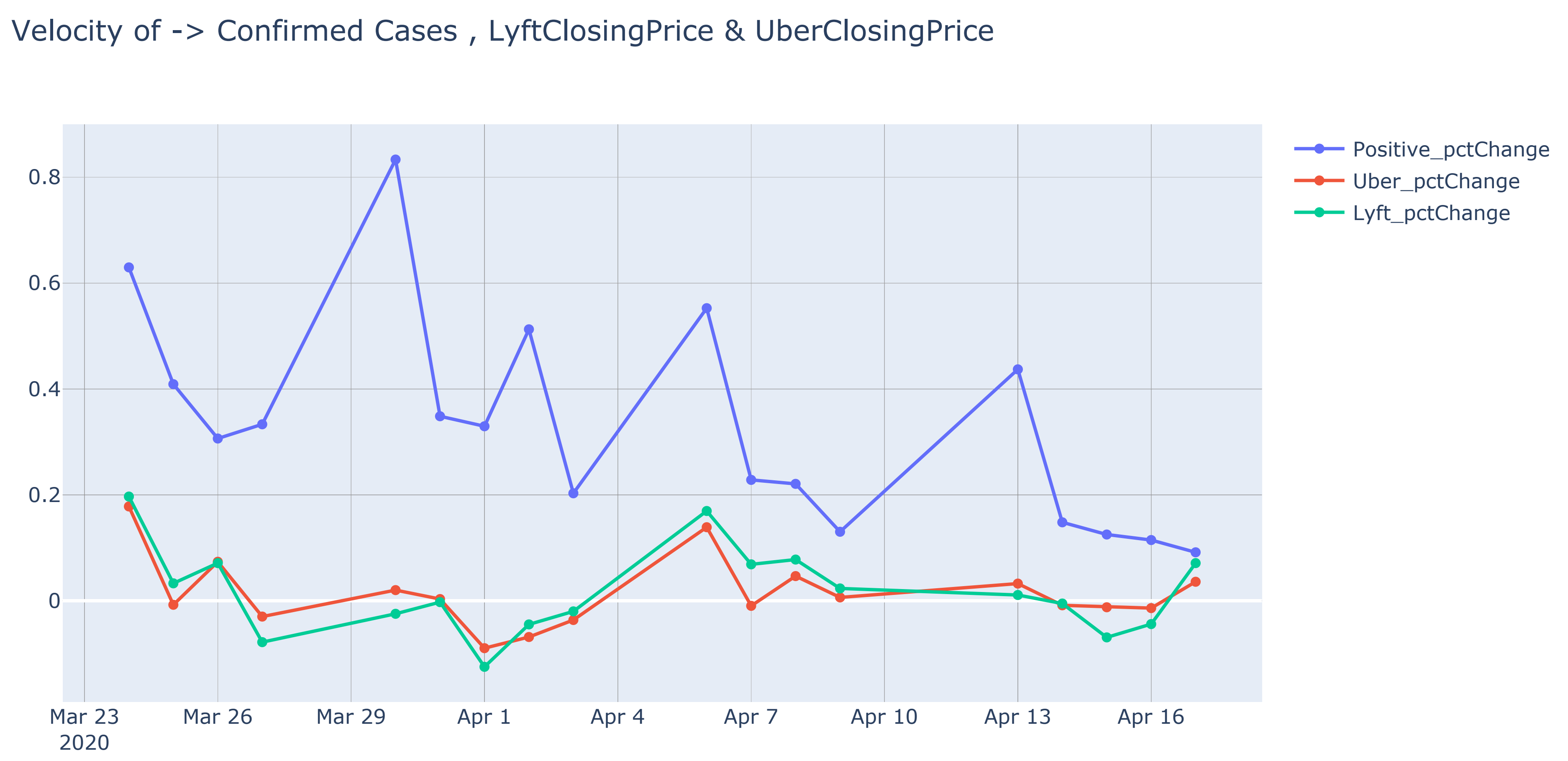
In [111]:
```
df_t= comb_df.copy()
df_t['Positive Rate'] = df_t['cumpositive']/df_t['cumtotalTestResults']
df_t['Negative Rate'] = df_t['cumnegative']/df_t['cumtotalTestResults']

df_t['Death Rate'] = df_t['cumdeath']/df_t['cumpositive']



fig = go.Figure()
fig.add_trace(go.Scatter(x=df_t['date'], y=df_t['Positive Rate'],
                         mode='lines+markers', name='Positive Rate'))
fig.add_trace(go.Scatter(x=df_t['date'], y=df_t['Negative Rate'],
                         mode='lines+markers', name='Negative Rate'))
fig.add_trace(go.Scatter(x=df_t['date'], y=df_t['Death Rate'],
                         mode='lines+markers', name='Death Rate'))
fig.update_layout(
        xaxis_title="",
        yaxis_title="",
        title = 'Confirmed Rate, Negative Rate & Death Rate'
#         yaxis_type="log"
    )
fig.show()
```



In [104]:
```
fig = go.Figure()

fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['LyftVolume'],
                         mode='lines+markers', name='LyftVolume'))

fig.add_trace(go.Scatter(x=comb_df['date'], y=comb_df['UberVolume'],
                         mode='lines+markers', name='UberVolume'))

fig.update_layout(
        xaxis_title="",
        yaxis_title="",
        title = 'COVID19 Impacts on -> LyftVolume & UberVolume'
#         title = 'CDF [Log Scale]-> Confirmed, Deaths & Negative Results',
#         yaxis_type="log"
    )
fig.show()
```



In [146]:
```
df_temp= comb_df.copy()
df_temp['Uber_pctChange'] = df_temp['UberClosingPrice'].pct_change(periods=1)
df_temp['Lyft_pctChange'] = df_temp['LyftClosingPrice'].pct_change(periods=1)
df_temp['Positive_pctChange'] = df_temp['cumdeath'].pct_change(periods=1)
df_temp = df_temp.iloc[1:]
# df_temp.head()


fig = go.Figure()
fig.add_trace(go.Scatter(x=df_temp['date'], y=df_temp['Positive_pctChange'],
                         mode='lines+markers', name='Positive_pctChange'))

fig.add_trace(go.Scatter(x=df_temp['date'], y=df_temp['Uber_pctChange'],
                         mode='lines+markers', name='Uber_pctChange'))

fig.add_trace(go.Scatter(x=df_temp['date'], y=df_temp['Lyft_pctChange'],
                         mode='lines+markers', name='Lyft_pctChange'))

fig.update_layout(
        xaxis_title="",
        yaxis_title="",
        title = 'Velocity of -> Confirmed Cases , LyftClosingPrice & UberClosingPrice'
#          title = 'CDF [Log Scale]-> Confirmed, Deaths & Negative Results',
#          yaxis_type="log"
    )
fig.show()
```



Inference from above graph: As the velocity in the Positive Cases increases we see that velocity in the Uber Lyft Price decreases and when the velocity of confirm cases decreases then velocity in the Stock

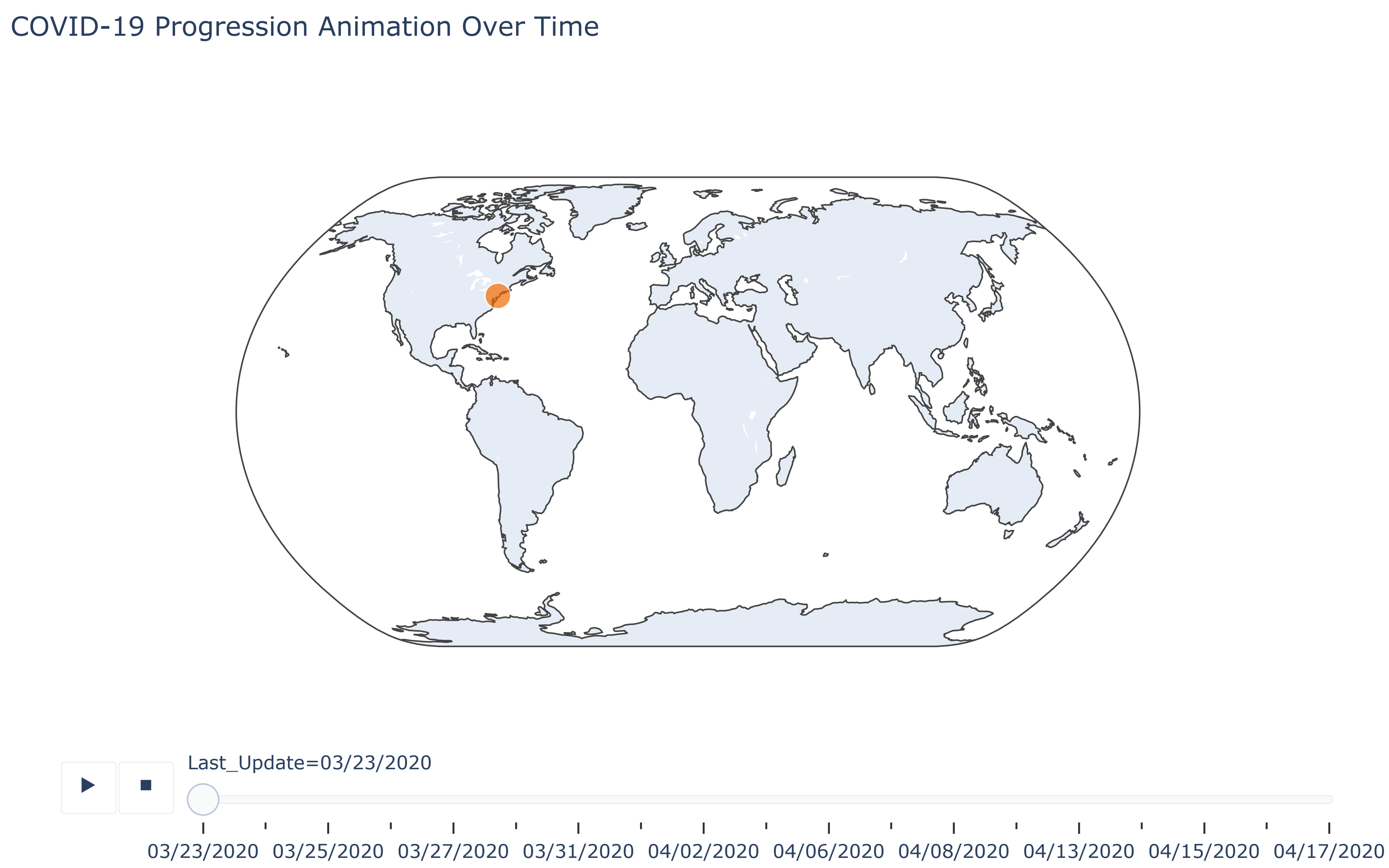
Prices of Uber Lyft Increases

In [83]:
```
df_temp=comb_df.copy()
df_temp['Country_Region']= 'NJ'
df_temp['Lat']= 39.833851
df_temp['Long']= -74.871826

df_temp = df_temp.groupby(['date', 'Country_Region','Lat','Long'])['cumpositive', 'cumdeath'].max().reset_index()
df_temp["date"] = pd.to_datetime(df_temp["date"]).dt.strftime('%m/%d/%Y')
df_temp.columns=['Last_Update','Country_Region','Lat','Long','Confirmed','Deaths']
df_temp['Confirmed'].fillna(0, inplace=True)
df_temp.sort_values('Confirmed', ascending=False).head()
```

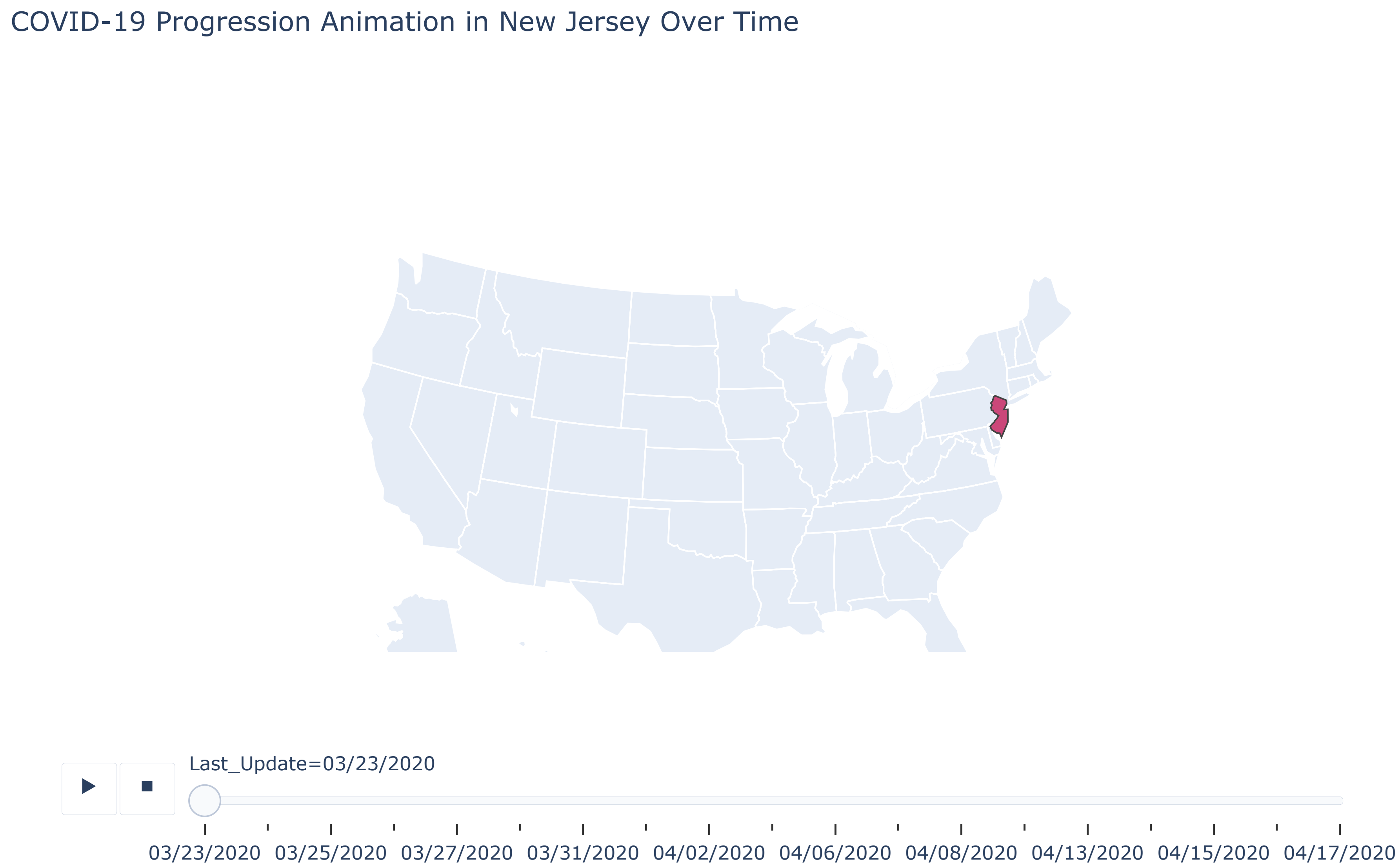
Out[83]:

	Last_Update	Country_Region	Lat	Long	Confirmed	Deaths
18	04/17/2020	NJ	39.833851	-74.871826	78467	3840
17	04/16/2020	NJ	39.833851	-74.871826	75317	3518
16	04/15/2020	NJ	39.833851	-74.871826	71030	3156
15	04/14/2020	NJ	39.833851	-74.871826	68824	2805
14	04/13/2020	NJ	39.833851	-74.871826	64584	2443

In [84]:
```
fig = px.scatter_geo(df_temp,
                     #locations="Country_Region",
                     locationmode='country names',
                     lat='Lat', lon='Long',
                     #hover_name="Country_Region",
                     hover_data=["Confirmed", "Deaths"], animation_frame="Last_Update",
                     color=np.log10(df_temp["Confirmed"]+1)-1, size=np.power(df_temp["Confirmed"]+1, 0.3)-1,
                     range_color= [0, max(np.log10(df_temp["Confirmed"]+1))],
                     title="COVID-19 Progression Animation Over Time",
                     color_continuous_scale=px.colors.sequential.Plasma,
                     projection="natural earth"
                    )
fig.update_coloraxes(colorscale="hot")
fig.update(layout_coloraxis_showscale=False)
#fig.update_coloraxes(colorbar_title="Color (Confirmed Cases Log Scale)")
fig.show()
```



In [86]:
```
fig = px.choropleth(df_temp,
                    locations="Country_Region",
                    locationmode="USA-states",
                    #lat='Lat', lon='Long',
                    hover_name="Country_Region",
                    hover_data=["Confirmed", "Deaths"], animation_frame="Last_Update",
                    color=np.log10(df_temp["Confirmed"]),

                    title="COVID-19 Progression Animation in New Jersey Over Time",
                    color_continuous_scale=px.colors.sequential.Plasma,
                    scope="usa",
                   )
fig.update(layout_coloraxis_showscale=False)
fig.show()
```



Part 3: Required Inferences (50%)

3.1 Predicting the COVID19 fatality & #cases over next one week

```
Use your COVID19 dataset to predict the COVID19 fatality and #cases for the next one week. Use the following four prediction techniques: (i) AR(3), (ii) AR(5), (iii) EWMA with alpha = 0.5, and (iv) EWMA with alpha = 0.8. Make sure that your dataset allows you to verify the one week prediction. For example, use the first three weeks of data to predict the fourth week, and report the accuracy of your predictions using the actual fourth week data. Use metrics learned in class (MAPE as a % and MSE) to report accuracy numbers.
```

3.1.1 AR(3)

In [ ]:

In [ ]:

In [ ]:

3.1.2 AR(5)

In [ ]:

In [ ]:

In [ ]:

3.1.3 EWMA with alpha = 0.5

In [ ]:

In [ ]:

In [ ]:

3.1.4 EWMA with alpha = 0.8

In [ ]:

In [ ]:

In [ ]:

In [ ]:

3.2 Apply the Wald's test, Z-test, and t-test to check whether the mean of COVID19 deaths and #cases are different from the first week to the last week

```
Apply the Wald's test, Z-test, and t-test (assume all are applicable) to check whether the mean of COVID19 deaths and #cases are different from the first week to the last week in your dataset. Use MLE for Wald's test as the estimator. Note, you have to report results for deaths and #cases separately, so think of this as two inferences. After running the test and reporting the numbers, check and comment on whether the tests are applicable or not. First use one-sample tests by computing the mean of the first week data and using that as guess for last week data. Then, repeat with a two-sample version of Wald and t-tests. For t-test, use both paired and unpaired tests. Use alpha value of 0.05 for all. For t-test, the threshold to check against is tn-1, alpha/2 for two-tailed and tn-1, alpha for one-tailed, where n is the number of data points. You can find these values in online t tables, similar to z tables.
```

3.2.1 Use MLE for Wald's test as the estimator

In [ ]:

In [ ]:

In [ ]:

3.2.2 Two-sample version of Wald and t-tests

In [ ]:

In [ ]:

In [ ]:

3.2.3 Z-test

In [ ]:

In [ ]:

In [ ]:

3.3 Equality of distributions (distribution of first week and last week), using K-S test and Permutation test

```
Repeat inference 2 above but for equality of distributions (distribution of first week and last week), using K-S test and Permutation test. For the K-S test, use
both 1-sample and 2-sample tests. For the 1-sample test, try Poisson, Geometric, and Binomial. To obtain parameters of these distributions to check against in 1-
sample KS, use MME on first week's data to obtain parameters of the distribution, and then check whether the last week's data has the distribution with the obtained
MME parameters. Use a threshold of 0.05 for both K-S test and Permutation test.
```

3.3.1 K-S Test

In [ ]:

In [ ]:

In [ ]:

3.3.2 Permutation Test

In [ ]:

In [ ]:

In [ ]:

3.4 Pearson correlation for #deaths and Stock Prices, #cases and Stock Prices

```
Report the Pearson correlation value for #deaths and your X dataset, and also for #cases and your X dataset over one month of data. Use the most relevant column in X
to compare against the covid numbers.
```

In [129]:

```python
import math
def p_coeff(a,b):

    ab_n1 = 0
    ab_d1 = 0
    ab_d2 = 0

    mean_a = sum(a)/len(a)
    mean_b = sum(b)/len(b)
    for i, j in zip(a,b):
        ab_n1 += (i- mean_a) * (j- mean_b)
        ab_d1 += (i- mean_a) * (i- mean_a)
        ab_d2 += (j- mean_b) * (j- mean_b)
    ab = ab_n1 / (math.sqrt(ab_d1) * math.sqrt(ab_d2))
    return ab
```

3.4.1 Pearson correlation for #deaths and Stock Price

In [130]:

```python
corr= p_coeff(comb_df['cumdeath'], comb_df['UberVolume'])
print('\033[1m' + 'Pearsons correlation of #deaths and Stock Price of Uber: %.3f' % corr)

corr = p_coeff(comb_df['cumdeath'], comb_df['LyftVolume'])
print('\033[1m' + 'Pearsons correlation of #deaths and Stock Price of Lyft: %.3f' % corr)
```

```
Pearsons correlation of #deaths and Stock Price of Uber: -0.769
Pearsons correlation of #deaths and Stock Price of Lyft: -0.502
```

Inference: We can observe a high negative linear correlation between stock prices of Uber/Lyft v/s the Deaths, this means that increase in #deaths day on day has adversely affected ride sharing company with less people moving out

3.4.2 Pearson correlation for #cases and Stock Price

In [131]:

```python
corr= p_coeff(comb_df['cumpositive'], comb_df['UberVolume'])
print('\033[1m' + 'Pearsons correlation of #Confirmed Cases and Stock Price of Uber: %.3f' % corr)

corr= p_coeff(comb_df['cumpositive'], comb_df['LyftVolume'])
print('\033[1m' + 'Pearsons correlation of #Confirmed Cases and Stock Price of Lyft: %.3f' % corr)
```

```
Pearsons correlation of #Confirmed Cases and Stock Price of Uber: -0.829
Pearsons correlation of #Confirmed Cases and Stock Price of Lyft: -0.524
```

Inference: We can observe a high negative linear correlation between stock prices of Uber/Lyft v/s the #Confirm cases, this means that increase in #Confim cases day on day has brought the city to a halt and ride sharing company stocks are going down as less and less people are moving out

In [ ]:

3.5 Posterior Distributions for daily deaths parameter estimator

```
Assume the daily deaths are Poisson distributed with parameter lambda. Assume an Exponential prior on lambda. Use first week's data to obtain the posterior for lambda via Bayesian inference. Now, use second week's data to obtain the new posterior, using prior as posterior after week 1. Repeat till the end of week 4. Plot all posterior distributions on one graph. Report the MAP for all posteriors.
```

3.5.1 First week to Second week

In [ ]:

In [ ]:

In [ ]:

3.5.2 Second week to third week

In [ ]:

In [ ]:

In [ ]:

3.5.3 Third week to fourth week

In [ ]:

In [ ]:

In [ ]:

In [ ]:

3.5.4 Plot all posterior distributions on one graph

In [ ]:

In [ ]:

In [ ]:

3.5.5 Report the MAP for all posteriors

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Part 4: Creative Inferences (30%)

```
Propose three new inferences for your dataset and solve them using tools learned in class. You will be graded on creativity/practicality of your inferences. For each
inference you propose, provide a paragraph of text to explain why this inference is practical and useful. Also comment on the results of your inference, as
appropriate. See “Sample inferences section below for ideas. Only use tools/tests learned in class. This will be 30% of the project grade.
```

Hypothesis1: Due to COVID outbreak Stock prices of Uber+Lyft decreased significantly

In [ ]:

In [ ]:

In [ ]:

Inference1: Below are the inference for H1

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Hypothesis2: Due to Uber Lyft being functional Covid Spread Quickly and once they were shut spread went down, pre v/s post lockdown impact on spread

In [ ]:

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In [ ]:

In [ ]:

Inference2: Below are the inference for H2

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Inference3: linear regression to find the impact on Stock Prices of Uber +Lyft because of the severity of covid19 duration

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: