COVID19 EDA - Trends and Outbreak Prediction of Spread in USA

Project Title : COVID19 EDA - Trends and Outbreak Prediction of Spread in USA

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Course Name : DSC530-T302 Data Exploration and Analysis

Project Goal : Develop COVID19 Data Tracker Tool with Key Performance Indicators (KPI), Trends, Geographic and Various visualizations, Prediction of CoronaVirus in the USA by using COVID19 Datasets and Python Programming Language.

Project Purpose : By using the COVID19 Data Tracker , end users can see the current spread and future forecast details across the country along with various entities like Ethnicity, Geographic , Income Etc. Also COVID19 Data Tracker, will alert the end users with trends on Daily and Monthly Changes.

Research Questions :

1. Daily Confirmed, new Confirmed and Death cases Analysis by Country, State, County
2. Predict the Corona Cases and Death
3. State Level Counts of Corona virus, Comparison between States
4. Calculate Recovery and Death Rates, Deaths per 100k
5. Number of Corona Cases comparison : Positive vs Negative
6. Testing Count Details by Country, State, County
7. Count of patients : Infected by Virus and Deaths

Introduction:

As of today, Corona cases in USA as below.

1. Number of Cases - 11.8 M
2. Number of Deaths - 252K

The Analyses of current and future Spread is very important step in facing this pandemic situation. This Analysis will help Government/Local bodies plan for the next steps.

Project Approaches:

I am going to follow the below 4 steps in the Project. (Shown in below diagram below References)

1. Data Exploration
2. Data Cleaning and Preparation
3. Exploratory Data Analysis

```
 Confirmed vs Deaths Count Analysis - Scatter Plot
 US Death vs Death Rate Percentage
 PMF (Probability Mass function) - Death Rate Analysis by using Hist
ogram
 CDF (Cumulative distribution function) - Confirmed Cases, Death Ana
lysis
 Normal Probability - Mean, Standard Deviation Analysis
 PDF (probability density function) - Death Analysis with P-Values
 Correlation Verification - Confirmed Cases Vs Death Counts
 Confirmed vs Death cases with the Fitted line - Slope
 Hypothesis Test
 Linear Regression - Death vs Cases ( ordinary least squares )
 Logistic Regression Analysis of Death Rate with Confirmed, Death Ca
ses
 Forecast using ARIMA Model
 Prediction of Confirmed Cases - ARIMA Model - Time Series Forecasti
ng
```

4. Conclusion
5. References

Datasets from NY Times and CDC Goverment website

https://aws.amazon.com/marketplace/pp/prodview-jmb464qw2yg74 (https://aws.amazon.com/marketplace/pp/prodview-jmb464qw2yg74)

https://www.cdc.gov/nchs/covid19/covid-19-mortality-data-files.htm (https://www.cdc.gov/nchs/covid19/covid-19-mortality-data-files.htm)

Exploratory Data Analysis

1. Importing Python Packages and Libraries

In [559]:

```
# All Required Python Packages and Libraries - Import
import pandas as pd
import numpy as np
import seaborn as sns
from scipy.integrate import odeint
import scipy.stats as sp
import matplotlib.pyplot as plt
%matplotlib inline
import math
import bokeh

from urllib.request import urlopen
import json

from dateutil import parser
from bokeh.layouts import gridplot
from bokeh.plotting import figure, show, output_file
from bokeh.layouts import row, column
from bokeh.resources import INLINE
from bokeh.io import output_notebook
from bokeh.models import Span
import warnings
warnings.filterwarnings("ignore")
output_notebook(resources=INLINE)

from __future__ import print_function, division
%matplotlib inline
import thinkstats2
import thinkplot

import statsmodels.formula.api as smf

#pip install pmdarima
# Import the library
from pmdarima import auto_arima
import datetime

from statsmodels.tsa.seasonal import seasonal_decompose

# Load specific evaluation tools
from sklearn.metrics import mean_squared_error
from statsmodels.tools.eval_measures import rmse

```

(https://bokeh.org) Loading BokehJS ...

2. Loading the data from Source file to Dataframe - Meta Data Verification

In [547]:

```
# Dataset preparation
# Downloaded the data files (.csv) from NY times Github location

# Data US Country Level
USCountry_DF = pd.read_csv('C:/Users/ragun/Documents/GitHub/dsc520-master

# Data US States Level
USStates_DF = pd.read_csv('C:/Users/ragun/Documents/GitHub/dsc520-master/

# Data US Counties Level
USCounties_DF = pd.read_csv('C:/Users/ragun/Documents/GitHub/dsc520-maste

# Data World Level
World_DF = pd.read_csv('C:/Users/ragun/Documents/GitHub/dsc520-master/DS

```

In [518]:

```
##### Converts dates to a specific format
# Removing the data with NA data
USCountry_DF.cases.dropna()
USStates_DF.deaths.dropna()

# Removing the data with NA data
USStates_DF.state.dropna()
USStates_DF.date.dropna()
USStates_DF.cases.dropna()
USStates_DF.deaths.dropna()

print(" *****************************************************************
USCountry_DF.info()
print("Size/Shape of the Country Level dataset: ",USCountry_DF.shape)
print("Size/Shape of the State Level dataset: ",USStates_DF.shape)
print("Size/Shape of the Counties Level dataset: ",USCounties_DF.shape)
print(" *****************************************************************
print("Checking for null values:\n",USCountry_DF.isnull().sum())
print("Checking Data-type of each column: Country Level \n",USCountry_DF
print(" *****************************************************************
print("Checking Data-type of each column: State Level \n",USStates_DF.dt
print(" *****************************************************************
USStates_DF.info()
#Dropping column as SNo is of no use, and "Country" contains too many mi
#USCountry_DF.drop(["SNo"],1,inplace=True)
print(" *****************************************************************
USCounties_DF.info()
```

```
 ************************************************************************
****************
<class 'pandas.core.frame.DataFrame'>
Index: 303 entries, 2020-11-18 to 2020-01-21
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   cases      303 non-null    int64  
 1   deaths     303 non-null    int64  
 2   fips       303 non-null    int64  
 3   DeathRate  303 non-null    float64
dtypes: float64(1), int64(3)
memory usage: 21.8+ KB
Size/Shape of the Country Level dataset:  (303, 4)
Size/Shape of the State Level dataset:  (14369, 5)
Size/Shape of the Counties Level dataset:  (745255, 6)
 ************************************************************************
****************
Checking for null values:
 cases        0
deaths       0
fips         0
DeathRate    0
dtype: int64
Checking Data-type of each column: Country Level 
 cases          int64
deaths         int64
fips           int64
```

```
DeathRate    float64
dtype: object
 *********************************************************************
****************
Checking Data-type of each column: State Level
 date      object
state     object
fips       int64
cases      int64
deaths     int64
dtype: object
 *********************************************************************
****************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14369 entries, 0 to 14368
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   date    14369 non-null  object
 1   state   14369 non-null  object
 2   fips    14369 non-null  int64 
 3   cases   14369 non-null  int64 
 4   deaths  14369 non-null  int64 
dtypes: int64(3), object(2)
memory usage: 561.4+ KB
 *********************************************************************
****************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 745255 entries, 0 to 745254
Data columns (total 6 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   date    745255 non-null  object 
 1   county  745255 non-null  object 
 2   state   745255 non-null  object 
 3   fips    738157 non-null  float64
 4   cases   745255 non-null  int64  
 5   deaths  745255 non-null  int64  
dtypes: float64(1), int64(2), object(3)
memory usage: 34.1+ MB
```

In [519]:

```
USStates_DF.head(20)
```

Out[519]:

	date	state	fips	cases	deaths
0	2020-01-21	Washington	53	1	0
1	2020-01-22	Washington	53	1	0
2	2020-01-23	Washington	53	1	0
3	2020-01-24	Illinois	17	1	0
4	2020-01-24	Washington	53	1	0
5	2020-01-25	California	6	1	0
6	2020-01-25	Illinois	17	1	0
7	2020-01-25	Washington	53	1	0
8	2020-01-26	Arizona	4	1	0
9	2020-01-26	California	6	2	0
10	2020-01-26	Illinois	17	1	0
11	2020-01-26	Washington	53	1	0
12	2020-01-27	Arizona	4	1	0
13	2020-01-27	California	6	2	0
14	2020-01-27	Illinois	17	1	0
15	2020-01-27	Washington	53	1	0
16	2020-01-28	Arizona	4	1	0
17	2020-01-28	California	6	2	0
18	2020-01-28	Illinois	17	1	0
19	2020-01-28	Washington	53	1	0

3. Summary Report - Confirmed Cases, Death Count at Date Level

```
        Created new column called Death Rate by considering death / Case
s
```

In [505]:

```
# Summary Dataset Based on the Date - Group by

#pivot - rows into columns based on date
USCountry_DF = pd.pivot_table(USStates_DF, values=['cases','deaths','fip

# death Rate calculation
USCountry_DF['DeathRate'] = round(USCountry_DF['deaths'] /USCountry_DF['

# Summary Report based on the Confirmed Cases count order along colors t
USCountry_DF = USCountry_DF.sort_values(by='cases', ascending= False)
USCountry_DF.style.background_gradient(cmap='YlOrRd')
```

Out[505]:

date	cases	deaths	fips	DeathRate
2020-11-18	11613875	250409	1762	0.020000
2020-11-17	11441484	248486	1762	0.020000
2020-11-16	11279747	246879	1762	0.020000
2020-11-15	11113482	246083	1762	0.020000
2020-11-14	10978295	245460	1762	0.020000
2020-11-13	10819174	244250	1762	0.020000
2020-11-12	10637603	242861	1762	0.020000
2020-11-11	10474163	241689	1762	0.020000
2020-11-10	10331303	240258	1762	0.020000
2020-11-09	10191549	238793	1762	0.020000
2020-11-08	10061162	238048	1762	0.020000
2020-11-07	9957746	237584	1762	0.020000
2020-11-06	9831814	236577	1762	0.020000
2020-11-05	9698960	235331	1762	0.020000
2020-11-04	9577421	234223	1762	0.020000
2020-11-03	9469493	232607	1762	0.020000
2020-11-02	9376874	231477	1762	0.020000
2020-11-01	9283188	230937	1762	0.020000
2020-10-31	9208952	230510	1762	0.030000
2020-10-30	9124654	229672	1762	0.030000
2020-10-29	9024852	228701	1762	0.030000
2020-10-28	8934082	227697	1762	0.030000
2020-10-27	8852180	226681	1762	0.030000
2020-10-26	8777727	225698	1762	0.030000
2020-10-25	8703284	225160	1762	0.030000
2020-10-24	8643572	224821	1762	0.030000
2020-10-23	8564816	223948	1762	0.030000

The above table shows the Confirmed cases and Death count at each date Level. On March 3rd,2020, we have seen the death rate is 8%. The above chart explains the Confirmed Cases, Death on each day. I have derived new variable called Death Rate which explains the percentage of death on that day when compared to Confirmed Cases. On Feb 29,2020, we have seen first death recorded, hence the rate begins from that day.

4. US COVID Active Cases Graph

In [72]:

```
# Daily Case Count Graph
dailycases=USCountry_DF.groupby(["date"]).agg({"cases":'sum',"deaths":'su
DailyCaseCount=px.bar(x=dailycases.index,y=dailycases["cases"]-dailycase
DailyCaseCount.update_layout(title="US COVID Active Cases Graph",
                    xaxis_title="Date",yaxis_title="Number of Cases",)
DailyCaseCount.show()
```

The above Chart shows that each day how the Corona cases confirmed. We can see that it's gradually increasing and as of November 18, the confirmed cases reached to 11 Million positive cases.

5. Confirmed & Deaths Count Analysis - Through Animation at State and Date Level

In this Chart is automated to play the video of Confirmed & Deaths Count Analysis at Date and State level.

In [520]:

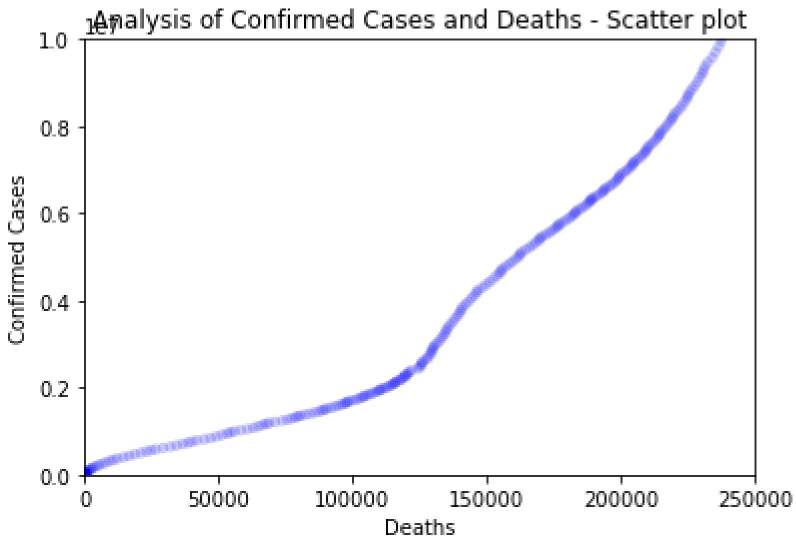
```


USDataframe = USStates_DF.groupby(["state", "date"])["cases", "deaths"].:

plotUSDF = px.scatter(USDataframe, x="cases", y="deaths", animation_fram(
           size="cases", color="state", hover_name="state",
           log_x=False, size_max=55, range_x=[0,550000], range_y=[-20,10(

layout = go.Layout(
    title=go.layout.Title(
        text="Confirmed & Deaths in US states- Date",
        x=0.5
    ),
    font=dict(size=14),
    xaxis_title = "Total number of confirmed cases",
    yaxis_title = "Total number of death cases"
)

plotUSDF.update_layout(layout)

plotUSDF.show()
```

When I choose the Date 2020-09-19, we can see that New York State shows that 453747 as confirmed Cases. Death count as 32.67 K.

6. Confirmed vs Deaths Count Analysis - Scatter Plot

In [271]:

```
thinkplot.Scatter(USCountry_DF["deaths"], USCountry_DF["cases"])
thinkplot.Config(xlabel='Deaths',
                 ylabel='Confirmed Cases',
                 axis=[0, 250000,0,10000000], title= "Analysis of Confir
            )
```



The above Chart shows that each day how the Corona cases confirmed and Deaths happened in each state.

7. US Death vs Death Rate Percentage

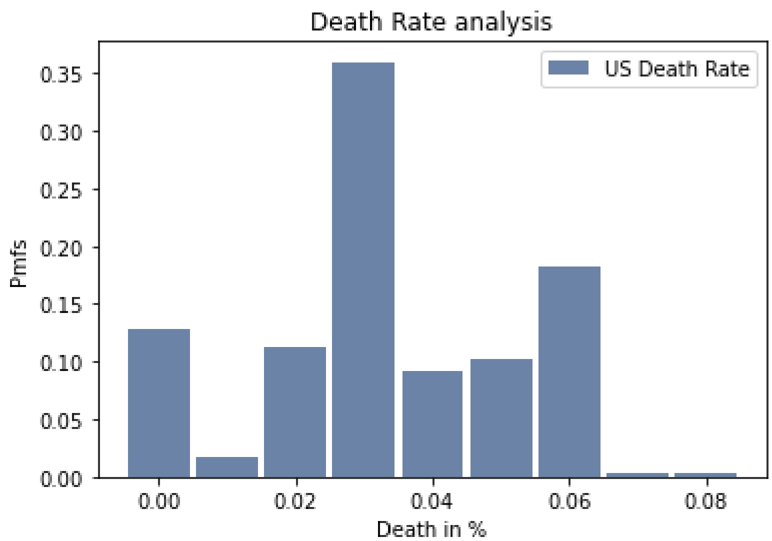
In [194]:

```
deathrate=px.bar(x=USCountry_DF.index,y=USCountry_DF["Death Rate"])
deathrate.update_layout(title="US Death Rate Analysis",
                  xaxis_title="Date",yaxis_title="Death Rate in %",)
deathrate.show()

```

8. PMF (Probability Mass function) - Death Rate Analysis by using Histogram

In [214]:

```
# Probability Mass Functions (PMF)
US_DeathRate=USCountry_DF["Death Rate"]

pmf = thinkstats2.Pmf(US_DeathRate, label='US Death Rate')

thinkplot.Hist(pmf)
thinkplot.Config(xlabel='Death in %', ylabel='Pmfs',title= "Death Rate ar
```



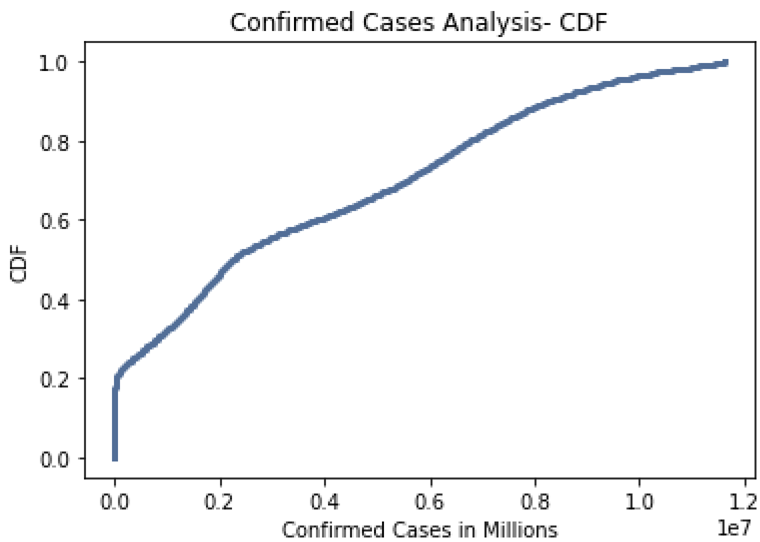
The Above Histogram shows that how death rates hapepend over the period of time

This diagram shows that death rate is decreaing from August. The more death rate is 0.08% and the death rate was stayed 100 days on 0.03%.

9. CDF (Cumulative distribution function) - Confirmed Cases, Death Analysis

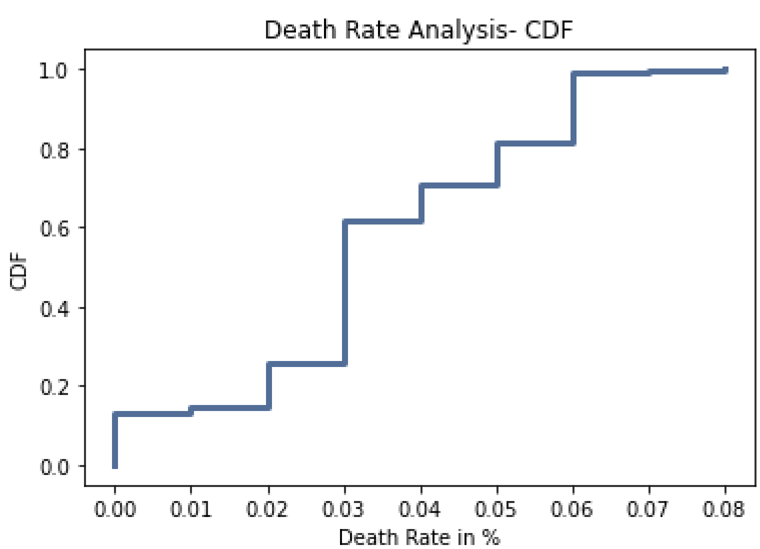
In [226]:

```
#  Cumulative Distribution Functions (CDF)
US_ConfirmedCases=USCountry_DF["cases"]

cdf_ConfirmedCases = thinkstats2.Cdf(US_ConfirmedCases)
thinkplot.Cdf(cdf_ConfirmedCases)
thinkplot.Config(xlabel='Confirmed Cases in Millions',
                 ylabel='CDF',title= "Confirmed Cases Analysis- CDF")

```



In [225]:

```
cdf_deathRate = thinkstats2.Cdf(US_DeathRate)
thinkplot.Cdf(cdf_deathRate)
thinkplot.Config(xlabel='Death Rate in %',
                 ylabel='CDF',title= "Death Rate Analysis- CDF")

```



Cumulative Distribution Functions (CDF), we can see that 0.08% as peak and that consider as 1 or 100%,

10. Normal Probability - Mean, Standard Deviation Analysis

In [237]:

```
mean, std = US_ConfirmedCases.mean(), US_ConfirmedCases.std()
print(" Here are the mean and standard deviation of Variables in the Stat
mean, std
```

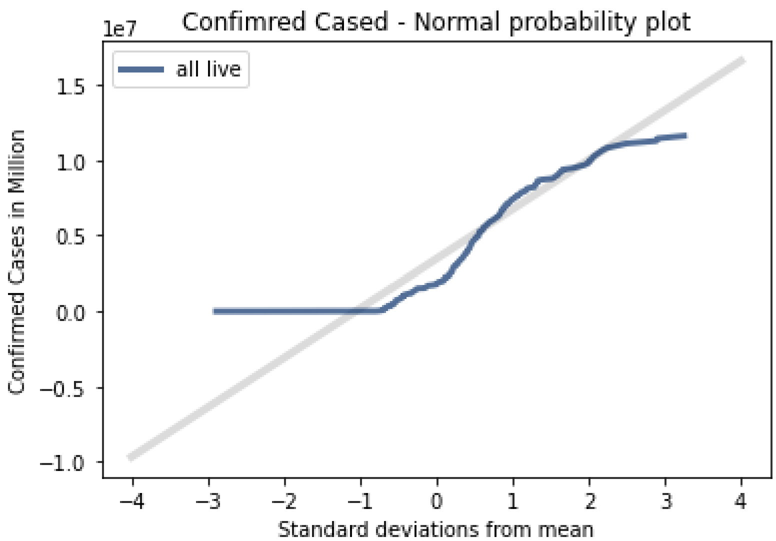
```
 Here are the mean and standard deviation of Variables in the State Datas
et
```

Out[237]:

```
(3460469.207920792, 3281429.5018072585)
```

In [238]:

```
xs = [-4, 4]
fxs, fys = thinkstats2.FitLine(xs, mean, std)
thinkplot.Plot(fxs, fys, linewidth=4, color='0.8')

xs, ys = thinkstats2.NormalProbability(US_ConfirmedCases)
thinkplot.Plot(xs, ys, label='all live')

thinkplot.Config(title='Confimred Cases - Normal probability plot',
                 xlabel='Standard deviations from mean',
                 ylabel='Confirmed Cases in Million')
```



The Above curve shows that not normal distribution since the pdf object shows.

Mean of Datset - US State Level : Confirmed Cases - 72971.13 and Number of deaths - 2348.70

Standard Deviation of Datset - US State Level : Confirmed Cases - 135907.74 and Number of deaths - 4823.27

In [239]:

```
mean, std = USStates_DF.mean(), USStates_DF.std()
print(" Here are the mean and standard deviation of Variables in the Stat
mean, std
```

```
 Here are the mean and standard deviation of Variables in the State Dataset
```

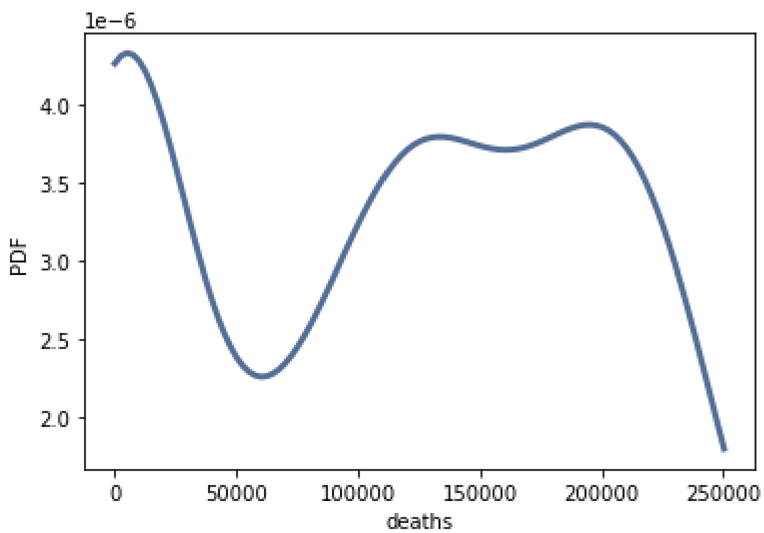
Out[239]:

```
(fips          31.882038
 cases      72971.130211
 deaths      2348.709444
 dtype: float64,
 fips           18.624818
 cases      135907.744139
 deaths       4823.272479
 dtype: float64)
```

11. PDF (probability density function) - Death Analyis

In [305]:

```
US_deaths=USCountry_DF["deaths"]

US_death = US_deaths.dropna()
pdf = thinkstats2.EstimatedPdf(US_death)
thinkplot.Pdf(pdf, label='deaths')
thinkplot.Config(xlabel='deaths', ylabel='PDF')

```



In [254]:

```
pdf = thinkstats2.NormalPdf(mean, std)
pdf.Density(mean + std)

```

Out[254]:

```
array([1.29918438e-02, 1.78040424e-06, 5.01673346e-05])
```

In [255]:
```
y=np.array(USStates_DF['cases'].dropna().values, dtype=float)
x=np.array(pd.to_datetime(USStates_DF['date'].dropna()).index.values, dty
slope, intercept, r_value, p_value, std_err =sp.linregress(x,y)
xf = np.linspace(min(x),max(x),100)
xf1 = xf.copy()
xf1 = pd.to_datetime(xf1)
yf = (slope*xf)+intercept
print('r = ', r_value, '\n', 'p = ', p_value, '\n', 's = ', std_err)


```

```
r =  0.4197291503333768
 p =  0.0
 s =  0.24810084952424205
```

P values come as 0.0 for the dataset which shows that this dataset is statistically significant

(I will verify this by using Hypothesis testing too)

12. Correlation Verfication - Confirmed Cases Vs Death Counts

In [521]:
```
np.corrcoef(US_ConfirmedCases, US_deaths)
```

Out[521]:
```
array([[1.       , 0.9569576],
       [0.9569576, 1.       ]])
```

The correlation coefficient matrix on the diagonal with 1 and 0.95 as self correlation.

13. Confirmed vs Death cases with the Fitted line - Slope

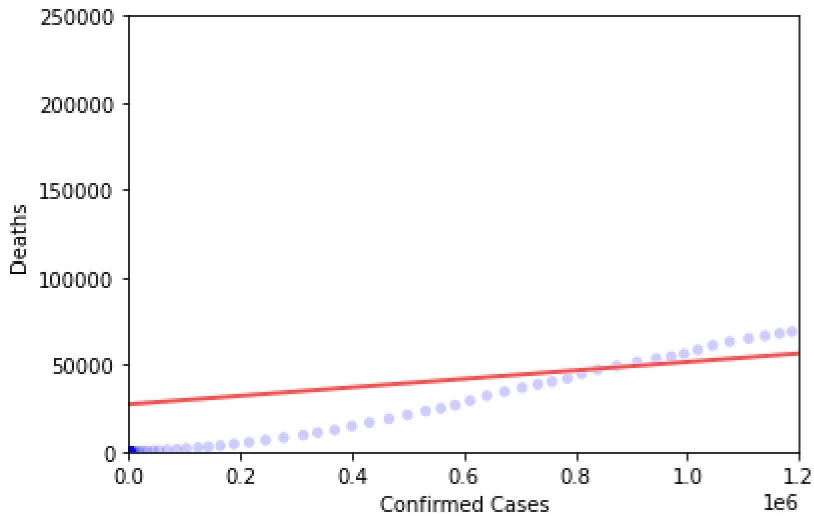
In [285]:
```
from thinkstats2 import Mean, MeanVar, Var, Std, Cov

def LeastSquares(xs, ys):
    meanx, varx = MeanVar(xs)
    meany = Mean(ys)

    slope = Cov(xs, ys, meanx, meany) / varx
    inter = meany - slope * meanx

    return inter, slope

def FitLine(xs, inter, slope):
    fit_xs = np.sort(xs)
    fit_ys = inter + slope * fit_xs
    return fit_xs, fit_ys
```

In [286]:

```
inter, slope = LeastSquares(US_ConfirmedCases, US_deaths)
fit_xs, fit_ys = FitLine(US_ConfirmedCases, inter, slope)
```

In [304]:

```
thinkplot.Scatter(US_ConfirmedCases, US_deaths, color='blue')
thinkplot.Plot(fit_xs, fit_ys, color='white', linewidth=3)
thinkplot.Plot(fit_xs, fit_ys, color='red', linewidth=2)
thinkplot.Config(xlabel="Confirmed Cases",
                 ylabel='Deaths',
                 axis=[0, 1200000, 0, 250000],
                 legend=False)
```



The Above graph shows the scatterplot of the confirmed vs death cases with the fitted line

14. HypothesisTest

In [309]:

```
class SlopeTest(thinkstats2.HypothesisTest):

    def TestStatistic(self, data):
        ages, weights = data
        _, slope = thinkstats2.LeastSquares(ages, weights)
        return slope

    def MakeModel(self):
        _, weights = self.data
        self.ybar = weights.mean()
        self.res = weights - self.ybar

    def RunModel(self):
        ages, _ = self.data
        weights = self.ybar + np.random.permutation(self.res)
        return ages, weights
```

In [310]:

```python
ht = SlopeTest((US_ConfirmedCases, US_deaths))
pvalue = ht.PValue()
pvalue
```

Out[310]: 0.0

This is reflecting our previous analysis at State Level data too. pvalue came as 0.0. Hence there is significant relation betwen cases confirmed with Death cases. (I want to verify this eventhough we know this has significance)

15 . Linear Regression - Death vs Cases (ordinary least squares)

In [327]:

```python
# ordinary least squares.
model = smf.ols('deaths ~ cases', data=USCountry_DF)
results = model.fit()
results.summary()
```

Out[327]:

OLS Regression Results

Dep. Variable:	deaths	**R-squared:**	0.916
Model:	OLS	**Adj. R-squared:**	0.915
Method:	Least Squares	**F-statistic:**	3272.
Date:	Sat, 21 Nov 2020	**Prob (F-statistic):**	9.24e-164
Time:	11:59:58	**Log-Likelihood:**	-3488.0
No. Observations:	303	**AIC:**	6980.
Df Residuals:	301	**BIC:**	6987.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.722e+04	2025.927	13.436	0.000	2.32e+04	3.12e+04
cases	0.0243	0.000	57.205	0.000	0.023	0.025

Omnibus:	113.160	**Durbin-Watson:**	0.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	16.715
Skew:	-0.090	**Prob(JB):**	0.000235
Kurtosis:	1.864	**Cond. No.**	6.93e+06

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.93e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

By using ordinary least squares model, R-squared Value from the model is 0.916 (91.6%) which shows that almost every confimred Cases can be explained by movements since 91.6% coefficient of determination.

16. Logistic Regression Analysis of Death Rate with Confirmed, Death Cases

In [352]:

```
formula='DeathRate ~ cases + deaths'
model = sm.Logit.from_formula(formula, USCountry_DF).fit()
print(model.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.043430
         Iterations 8
                           Logit Regression Results
==========================================================================
=====
Dep. Variable:              DeathRate   No. Observations:
303
Model:                          Logit   Df Residuals:
300
Method:                           MLE   Df Model:
2
Date:                Sat, 21 Nov 2020   Pseudo R-squ.:
inf
Time:                        12:17:18   Log-Likelihood:                 -1
3.159
converged:                       True   LL-Null:
0.0000
Covariance Type:            nonrobust   LLR p-value:
1.000
==========================================================================
=====
                 coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------
-----
Intercept     -3.8923      0.735     -5.299      0.000      -5.332      -
2.453
cases      -4.392e-07   3.56e-07     -1.233      0.218   -1.14e-06     2.5
9e-07
deaths      1.763e-05   1.41e-05      1.249      0.212      -1e-05     4.5
3e-05
==========================================================================
=====
```

In [353]:
```python
t = model.pred_table()
print(t)
print("Accuracy:",np.diag(t).sum()/t.sum())
```

```
[[303.   0.]
 [  0.   0.]]
Accuracy: 1.0
```

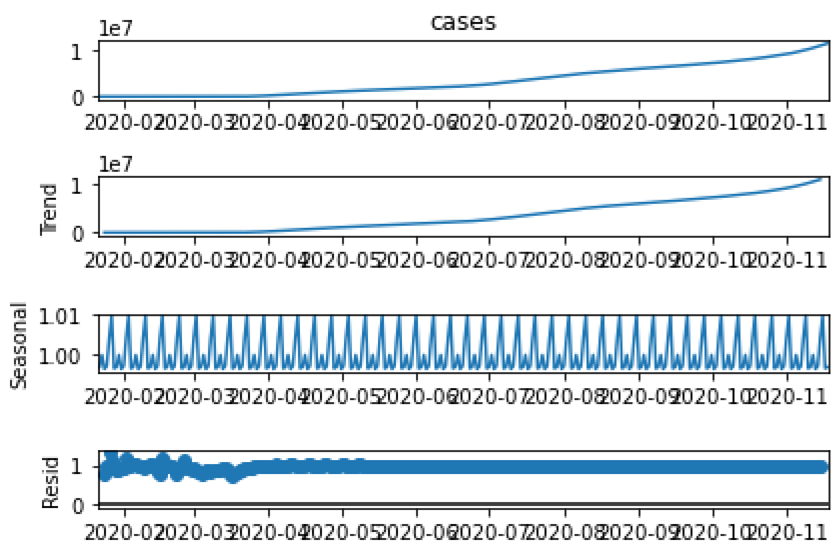
By using Logistice Regression for death Rate, Accuracy of logistic regression for this data set is 1 which is 100%.

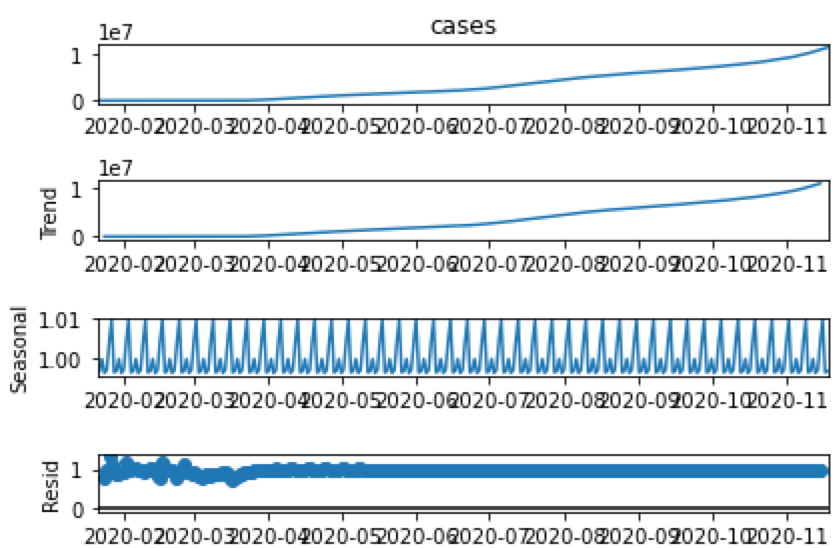
ETS (Error, Trend, and Seasonality) - of US Country Dataset:

In [442]:
```python
result = seasonal_decompose(USCountry_DF['cases'],
                            model ='multiplicative')
```

In [446]:
```python
result.plot()
```

Out[446]:





16. Forecast using ARIMA Model

In [448]:

```
# Ignore harmless warnings
import warnings
warnings.filterwarnings("ignore")

# Fit auto_arima function to US Country dataset
stepwise_fit = auto_arima(USCountry_DF['cases'], start_p = 1, start_q = 
                          max_p = 3, max_q = 3, m = 12,
                          start_P = 0, seasonal = True,
                          d = None, D = 1, trace = True,
                          error_action ='ignore',
                          suppress_warnings = True,
                          stepwise = True)

# show the the summaary of ARIMA output
stepwise_fit.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(1,2,1)(0,1,1)[12]             : AIC=inf, Time=1.29 sec
 ARIMA(0,2,0)(0,1,0)[12]             : AIC=6139.389, Time=0.02 sec
 ARIMA(1,2,0)(1,1,0)[12]             : AIC=6060.433, Time=0.28 sec
 ARIMA(0,2,1)(0,1,1)[12]             : AIC=inf, Time=0.64 sec
 ARIMA(1,2,0)(0,1,0)[12]             : AIC=6140.318, Time=0.04 sec
 ARIMA(1,2,0)(2,1,0)[12]             : AIC=6027.930, Time=0.70 sec
 ARIMA(1,2,0)(2,1,1)[12]             : AIC=5943.243, Time=3.69 sec
 ARIMA(1,2,0)(1,1,1)[12]             : AIC=6010.583, Time=0.37 sec
 ARIMA(1,2,0)(2,1,2)[12]             : AIC=inf, Time=5.94 sec
 ARIMA(1,2,0)(1,1,2)[12]             : AIC=6009.906, Time=1.76 sec
 ARIMA(0,2,0)(2,1,1)[12]             : AIC=5951.583, Time=3.71 sec
 ARIMA(2,2,0)(2,1,1)[12]             : AIC=5973.670, Time=1.98 sec
 ARIMA(1,2,1)(2,1,1)[12]             : AIC=5938.064, Time=5.62 sec
 ARIMA(1,2,1)(1,1,1)[12]             : AIC=6008.608, Time=0.78 sec
 ARIMA(1,2,1)(2,1,0)[12]             : AIC=6020.481, Time=3.61 sec
 ARIMA(1,2,1)(2,1,2)[12]             : AIC=6010.463, Time=4.57 sec
 ARIMA(1,2,1)(1,1,0)[12]             : AIC=inf, Time=1.97 sec
 ARIMA(1,2,1)(1,1,2)[12]             : AIC=inf, Time=11.03 sec
 ARIMA(0,2,1)(2,1,1)[12]             : AIC=6007.477, Time=2.76 sec
 ARIMA(2,2,1)(2,1,1)[12]             : AIC=5975.655, Time=4.67 sec
 ARIMA(1,2,2)(2,1,1)[12]             : AIC=5959.684, Time=4.49 sec
 ARIMA(0,2,2)(2,1,1)[12]             : AIC=5960.338, Time=3.43 sec
 ARIMA(2,2,2)(2,1,1)[12]             : AIC=5961.048, Time=5.58 sec
 ARIMA(1,2,1)(2,1,1)[12] intercept   : AIC=6008.162, Time=2.48 sec

Best model:  ARIMA(1,2,1)(2,1,1)[12]
Total fit time: 71.463 seconds
```

Out[448]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	303
Model:	SARIMAX(1, 2, 1)x(2, 1, 1, 12)	**Log Likelihood**	-2963.032
Date:	Sat, 21 Nov 2020	**AIC**	5938.064
Time:	13:26:31	**BIC**	5960.062
Sample:	0	**HQIC**	5946.878
	- 303		

Covariance Type: opg

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.2669	0.143	1.861	0.063	-0.014	0.548
ma.L1	-0.5200	0.116	-4.490	0.000	-0.747	-0.293
ar.S.L12	-0.2926	0.067	-4.344	0.000	-0.425	-0.161
ar.S.L24	-0.2575	0.089	-2.898	0.004	-0.432	-0.083
ma.S.L12	-0.8583	0.045	-18.979	0.000	-0.947	-0.770
sigma2	4.465e+07	1.76e-09	2.53e+16	0.000	4.47e+07	4.47e+07

Ljung-Box (Q):	401.01	**Jarque-Bera (JB):**	165.63
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	18.81	**Skew:**	0.55
Prob(H) (two-sided):	0.00	**Kurtosis:**	6.54

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.64e+32. Standard errors may be unstable.

17. Comparision of Prediction vs Actual

In [499]:

```
split_date = "2020-06-01"
df_train = df.loc[: split_date].copy()
df_test = df.loc[split_date :].copy()

```

In [536]:

```
# Fit a SARIMAX(0, 1, 1)x(2, 1, 1, 12) on the training set
from statsmodels.tsa.statespace.sarimax import SARIMAX

model = SARIMAX(df_train['cases'],
                order = (0, 1, 1),
                seasonal_order =(2, 1, 1, 12))

SARIMAX_Result = model.fit()
SARIMAX_Result.summary()
```

Out[536]:

SARIMAX Results

Dep. Variable:	cases	**No. Observations:**	133
Model:	SARIMAX(0, 1, 1)x(2, 1, 1, 12)	**Log Likelihood**	-890.329
Date:	Sat, 21 Nov 2020	**AIC**	1790.658
Time:	16:11:09	**BIC**	1804.595
Sample:	01-21-2020	**HQIC**	1796.318
	- 06-01-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ma.L1	0.9555	0.042	22.911	0.000	0.874	1.037
ar.S.L12	0.8213	0.070	11.762	0.000	0.684	0.958
ar.S.L24	-0.0516	0.086	-0.598	0.550	-0.221	0.117
ma.S.L12	-0.9975	0.118	-8.474	0.000	-1.228	-0.767
sigma2	1.471e+05	8.26e-07	1.78e+11	0.000	1.47e+05	1.47e+05

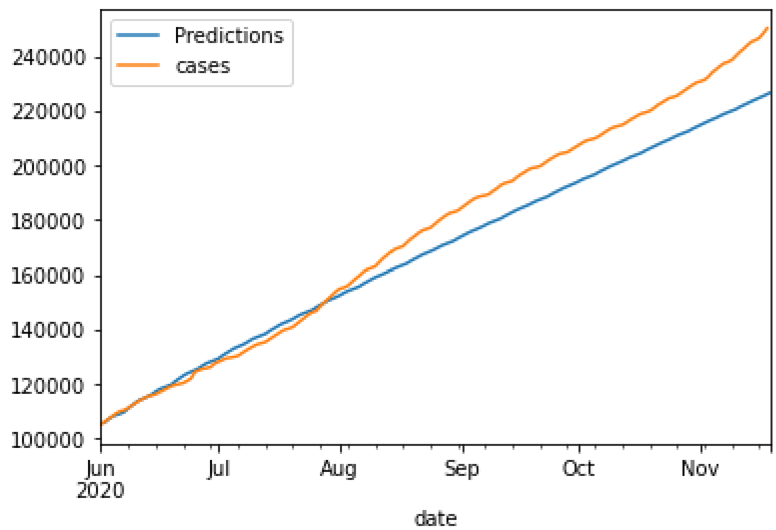
Ljung-Box (Q):	320.82	**Jarque-Bera (JB):**	17.62
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	141213.01	**Skew:**	-0.21
Prob(H) (two-sided):	0.00	**Kurtosis:**	4.83

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.19e+26. Standard errors may be unstable.

In [550]:

```
start = len(df_train)
end = len(df_train) + len(df_test) - 1

# Predictions for one-year against the test set
predictions = SARIMAX_Result.predict(start, end,
                              typ = 'levels').rename("Predictions")

# plot predictions and actual values
predictions.plot(legend = True)
df_test['cases'].plot(legend = True)
```

Out[550]: <matplotlib.axes._subplots.AxesSubplot at 0x143ac388d90>



The prediction count was 220 k but the real death count was 250K. Actually I have considered my training dataset up to Jun 1,2020. Based on that, we have seen the prediction was 220K but reality was little different since we have seen more deaths in July, Aug, Sept.

In [532]:

```

# Calculate root mean squared error
rmse(df_test["cases"], predictions)

# Calculate mean squared error
mean_squared_error(df_test["cases"], predictions)
```

Out[532]: 104651880.91971856

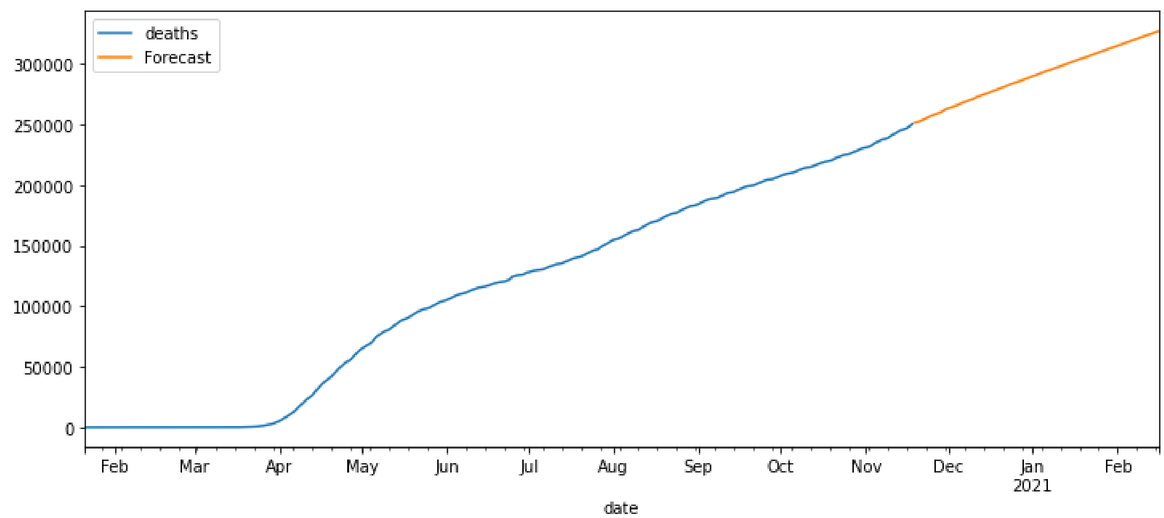
18 . Prediction of Confirmed Cases - ARIMA Model - Time Series

Forecasting

In [557]:

```
model = model = SARIMAX(USCountry_DF['deaths'],
                        order = (0, 1, 1),
                        seasonal_order =(2, 1, 1, 12))
result = model.fit()

# Forecast for the next 3 months
forecast = result.predict(start = len(USCountry_DF),
                          end = (len(USCountry_DF)-1) + 6 * 15,
                          typ = 'levels').rename('Forecast')

# death count
USCountry_DF['deaths'].plot(figsize = (12, 5), legend = True)
forecast.plot(legend = True)
```

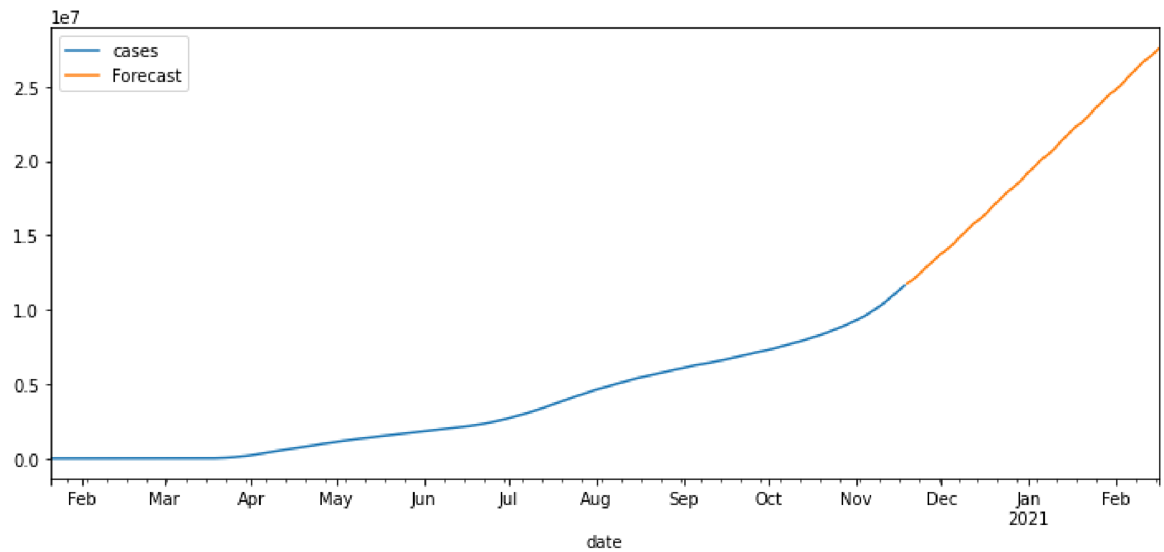
Out[557]: <matplotlib.axes._subplots.AxesSubplot at 0x143b48459a0>



In [556]:

```
model = model = SARIMAX(USCountry_DF['cases'],
                        order = (0, 1, 1),
                        seasonal_order =(2, 1, 1, 12))
result = model.fit()

# Forecast for the next 6 months
forecast = result.predict(start = len(USCountry_DF),
                          end = (len(USCountry_DF)-1) + 6 * 15,
                          typ = 'levels').rename('Forecast')

# Plot the forecast values
USCountry_DF['cases'].plot(figsize = (12, 5), legend = True)
forecast.plot(legend = True)
```

Out[556]: <matplotlib.axes._subplots.AxesSubplot at 0x143ab659f70>



As part of the above prediction shows that by next year January, the death count may reach to around 290 K.

Conclusion

As part of this project, I have analyzed various techniques to perform the EDA of COVID19 Trends and Outbreak Prediction of Spread in USA.

The below are the outcomes of my EDA

1. Calculated DeathRate Ratio - From Feb 29,2020 to Nov 18,2020, overall Death Count is 250K. Initially Death Ratio was increased and it started gradually decreasing from July,2020
2. Number of Death : Number of deaths is increasing day by day (as of Nov 18)
3. Confirmed Cases : Number of positive Count is increasing day by day (as of Nov 18) - 11.61 M
4. State Level Cases : Created Animation plot for State Level counts on daily basis. (Both Confirmed and Death count) observed NY State count had highest counts.
5. Based on the Data as of Nov 18,2020, The prediction of Death count on January 31,2021 is 280K (If the same situation continuous, the count may reach more than 300K in Feb 2021)

6. Based on the Data as of Nov 18,2020, The prediction of Confirmed Cases count on January 31,2021 is 18 Million (If the same situation continuous, the count may reach more than 22 Million in Feb 2021)

The below are various techniques I used in this project to perform the Detailed EDA of COVID19 Trends and Outbreak Prediction of Spread in USA

As of November 21,2020, We are hearing that vaccination is going to provided to people and I hope this will help to stop the COVID Spread and deaths.

My sincere Thanks to Professor Dr.Shankar Parajulee for all his guidance and support on this semester which helped me to perfume this detailed analysis of COVID Spread in USA.

References:

1. We’re Sharing Coronavirus Case Data for Every U.S. County by NY Times

    `https://www.nytimes.com/article/coronavirus-county-data-us.html`

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    `https://covid.cdc.gov/covid-data-tracker/?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fcases- update s%2Fcases-in-us.html#cases_casesinlast7days`

3. Analyze NY Times Covid-19 Dataset, Medium

    `https://towardsdatascience.com/analyze-ny-times-covid-19-dataset-86c802164210`

4. HOW TO USE DATA ANALYSIS FOR MACHINE LEARNING by Sharp Sight

    `https://www.sharpsightlabs.com/blog/data-analysis-machine-learning-example-1/`

5. Python | ARIMA Model for Time Series Forecasting by geeksforgeeks

    `https://www.geeksforgeeks.org/python-arima-model-for-time-series-forecasting/`

6. Modeling COVID-19 epidemic with Python Medium

    `https://towardsdatascience.com/modeling-covid-19-epidemic-with-python-bed21b8f6baf`

In [ ]:

```
 
```