Final Code

September 16, 2020

1 COVID-19 visulization and forcasting

1.1 Goals

- Visualize the evolution of the confimed cases, deaths and recoverd cases
- Forcasting the confirmed cases, deaths and actives cases using ARIMA, prophet and LSTM

```
[1]: import plotly.offline as pyo
                                        # To work with plotly offline
     pyo.init_notebook_mode()
     import plotly.graph_objects as go # Plotly graph objects see documents for more
     #-- General packages
     import pandas as pd
     import plotly.express as px
     import matplotlib.pyplot as plt
     import numpy as np
     import seaborn as sns # To visualize data
     # To avoid plt.show()
     %matplotlib inline
     # sklearn packages
     from sklearn.impute import SimpleImputer # to replace missing values with ⊔
     →appropriate central tendencies (mean, mode, median)
     #-- Statistics model required for forcasting
     import statsmodels.api as sm
     from statsmodels.tsa.stattools import adfuller, acf, pacf,arma_order_select_ic
     from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
     from statsmodels.tsa.arima_model import ARIMA
     import warnings
     warnings.simplefilter('ignore')
```

1.2 Exploratory Data Anaylsis

- Load the required data to variables using Pandas
- Recent population data is from https://uidai.gov.in/images/state-wise-aadhaar-saturation.pdf
- \bullet Latitude and Longitude is from https://www.kaggle.com/adityarc/india-state-wise-latitudes-and-longitudes-2020
- Census and Covid cases is from https://www.kaggle.com/sudalairajkumar/covid19-in-india?select=covid_19_india.csv

```
[2]: # Data on cases upto 30th August 2020
     cases = pd.read_csv("covid_19_india.csv")
     # It contains latitude and longitude coordinates of indian states.
     lat_long = pd.read_csv("Latitude_and_Longitude_State.csv")
     # It contains the data on Area (data on population is ingnored)
     popul = pd.read_csv("population_india_census2011.csv")
     # Current population data from Adhaar data base (exact year is of 2019_
     \rightarrowpopulation)
     population_adhaar = pd.read_csv("populationData.csv") #
     # Beds available in each state
     beds = pd.read_csv("HospitalBedsIndia.csv")
     # Age group affected
     age_group = pd.read_csv("AgeGroupDetails.csv")
     # Sustainable Development Goals Index (Ranking data with score of maximum_
     →possible 100)
     # https://sdqindiaindex.niti.gov.in/#/ranking
     # SDG Index = pd.read csv("India SDG Index Rank Data.csv") # Not used
     # details of individual scores
     SDG_Index_det = pd.read_csv("India_SDG_Index_Indicator_List.csv")
     # Data on GDP or purchasing capacity of citizens statewise needed
     # Copy the data
     population = popul.copy()
```

```
[3]: # Display census data # popul
```

```
[4]: # Replace old population data with new population data in census data and □ → calculate density accordingly

# Retian columns State / Union Territory Area ( also change column name □ → without space)
```

```
population_data = pd.DataFrame()
population_data[['State/UnionTerritory','Area']] = popul[['State / Union_
→Territory','Area']]

# Convert Area into float (remove all strings from columns)
population_data['Area'] = population_data['Area'].str.replace(r"\(.*\)","")
population_data['Area'] = population_data['Area'].str.replace("km2","")
population_data['Area'] = population_data['Area'].str.replace(",","")
population_data['Area'] = population_data['Area'].astype('float')

# sort the data frame alphabetical order of states
population_data.sort_values(by= 'State/UnionTerritory',inplace = True)
population_data.reset_index(inplace=True)
population_data.drop('index',axis=1,inplace=True)
```

Adhaar population data

```
[5]: # population_adhaar
```

```
[6]: population_adhaar.rename(columns={"States":"State/UnionTerritory"},inplace=True) population_adhaar.drop(['Unnamed: 0'],axis=1,inplace=True) population_adhaar.sort_values(by= 'State/UnionTerritory',inplace=True)
```

Calculate new population density

```
[8]: # population_data
```

1.2.1 Sustainable Development Goals

- data source: https://sdgindiaindex.niti.gov.in/#/ranking 2019 data
- This is used to get information about the doctor availability, below poverty line and Health insurance

```
[9]: # Use SDG_Index_det.columns.tolist() to view all columns # SDG_Index_det.columns.tolist()
```

```
[10]: # SDG_Index_det
```

```
[11]: # Drop SNo column, drop Target and India row, ANd simplify the required column

→ names

# Also note that the many null values have '-' symbol in this SDG_Index_det ,

→ these are to be replaced with some numerical values

SDG_Index_det['Area'] = SDG_Index_det['Area'].sort_values()

SDG_Index_det.drop([0,1],inplace = True)
```

```
SDG_reduced = pd.DataFrame()
      SDG_reduced[['State/UnionTerritory','Below_poverty_line',__
       →'Health_insurance_covered', 'Doctors_nurses_available']] =
□
       →SDG_Index_det[['Area', 'Population living below National Poverty line (%)
       \hookrightarrow (Goal 1)','Households with any usual member covered by any health scheme or \sqcup
       →health insurance (%) (Goal 1)','Total physicians nurses and midwives per⊔
       →10000 population (Goal 3)']]
      SDG_reduced.reset_index(inplace=True)
      SDG_reduced.drop('index',axis=1,inplace=True)
[12]: SDG_reduced.replace({'-':np.nan},inplace=True)
      SDG reduced['Below poverty line'] = SDG reduced['Below poverty line'].
       →astype('float')
      SDG_reduced['Doctors_nurses_available'] = ___
       →SDG_reduced['Doctors_nurses_available'].astype('float')
     Imputing missing values using median of the feature values - Telangana below poverty line was
     missing so adjusted with median of the data - Doctors nurses available has missing values re-
     placed with median of the data - However Doctors nurses available may have been replaced using
     correlation with GDP and area of the state (which I will try explore later)
[13]: | # imputer = SimpleImputer(missing values=np.nan,strategy='median')
      SDG_reduced['Below_poverty_line'] = SDG_reduced['Below_poverty_line'].
       →replace({np.nan:SDG_reduced['Below_poverty_line'].median()})
      SDG_reduced['Doctors_nurses_available']=__
       →SDG reduced['Doctors_nurses_available'].replace({np.nan:
       →SDG_reduced['Below_poverty_line'].median()})
[14]: # lat_long # Print the data to see the row of Daman Diu which is 8
[15]: # Drop Daman Diu Lattitude and Longitude (consider same as Dadra and Nagaru
       \rightarrow Haveli)
      lat_long.drop(8,inplace=True) # Drop Daman Diu
      lat_long.drop('ilist',axis=1,inplace=True) # Drop 'ilist' column not needed
      lat_long.sort_values(by='State',inplace=True)
      lat_long.set_index('State',inplace=True)
      lat_long.reset_index(inplace=True)
[16]: # beds
[17]: # beds.rename(columns={"States":"State/UnionTerritory"},inplace=True)
      # beds.drop(['Hospital beds in public sector', 'Hospital beds in private_
       ⇒sector'],axis=1,inplace=True)
      # beds.sort_values(by='State/UnionTerritory',inplace=True)
```

beds.reset index(inplace=True)

```
# beds.drop('index',axis=1,inplace=True)
[18]: # age group.drop('Sno', axis=1, inplace=True)
[19]: # population_data
     Combine the SDG values with population values
[20]: population_data[['Below_poverty_line',
             'Health insurance covered', 'Doctors nurses available']] = [ ]
      →SDG_reduced[['Below_poverty_line',
             'Health_insurance_covered', 'Doctors_nurses_available']]
      population_data[['Longitude', 'Latitude']] = lat_long[['Longitude', |
       [21]: # Change name of Telangana from Telengana
      population_data['State/UnionTerritory'].replace({'Telengana':
       → 'Telangana'},inplace=True)
[22]: # population_data
     To analyze the data and visualize the time series of the confirmed cases
[23]: # Replace the name of Telangana, Daman and Diu, and remove unassinged cases
      cases['State/UnionTerritory'].replace({"Telengana" : "Telangana", __
      "Telangana***" : "Telangana"}, inplace
      →= True)
      cases['State/UnionTerritory'].replace({"Daman & Diu" : "Dadra and Nagar Haveli⊔
      ⇒and Daman and Diu",
                                                "Dadar Nagar Haveli" : "Dadra and⊔
      →Nagar Haveli and Daman and Diu"},
                                              inplace = True)
      cases = cases[(cases['State/UnionTerritory'] != 'Unassigned') &
                          (cases['State/UnionTerritory'] != 'Cases being reassigned⊔
      →to states')]
      cases['State/UnionTerritory'].unique()
[23]: array(['Kerala', 'Telangana', 'Delhi', 'Rajasthan', 'Uttar Pradesh',
             'Haryana', 'Ladakh', 'Tamil Nadu', 'Karnataka', 'Maharashtra',
             'Punjab', 'Jammu and Kashmir', 'Andhra Pradesh', 'Uttarakhand',
             'Odisha', 'Puducherry', 'West Bengal', 'Chhattisgarh',
             'Chandigarh', 'Gujarat', 'Himachal Pradesh', 'Madhya Pradesh',
             'Bihar', 'Manipur', 'Mizoram', 'Andaman and Nicobar Islands',
             'Goa', 'Assam', 'Jharkhand', 'Arunachal Pradesh', 'Tripura',
```

```
'Dadra and Nagar Haveli and Daman and Diu', 'Sikkim'], dtype=object)
[24]: # cases does not contain Lakshadeep (so drop Lakshadweep in other data)
      # Convert the datatime using pandas datetime
      cases['Date'] = pd.to_datetime(cases['Date'], dayfirst=True)
      cases.drop(['Sno', 'Time', 'ConfirmedIndianNational', __
      →'ConfirmedForeignNational'], axis = 1, inplace=True)
      cases.head()
      # cases[cases.Date == max(cases.Date)] to see the latest cases
      # drop_row_list = ['Lakshadweep']
[24]:
              Date State/UnionTerritory Cured Deaths Confirmed
      0 2020-01-30
                                 Kerala
                                             0
                                                     0
                                                                1
      1 2020-01-31
                                 Kerala
                                             0
                                                     0
                                                                1
      2 2020-02-01
                                 Kerala
                                             0
                                                     0
                                                                2
      3 2020-02-02
                                 Kerala
                                             0
                                                     0
                                                                3
      4 2020-02-03
                                 Kerala
                                                                3
[25]: | print("Starting date : ", min(cases.Date.values))
      print("Ending date : ", max(cases.Date.values))
     Starting date: 2020-01-30T00:00:00.000000000
     Ending date: 2020-08-30T00:00:00.000000000
[26]: # Dialy increment in active cases in whole nation
      daily_cases = cases.groupby('Date').sum().reset_index() # Total cases in the_
      \rightarrow nation
      daily_cases['Active'] = 1
      for val in daily_cases.index:
          if val != 0:
              daily_cases['Active'].loc[val] = daily_cases['Confirmed'].loc[val] -_

daily_cases['Cured'].loc[val-1] - daily_cases['Deaths'].loc[val-1]

      daily_cases
[26]:
                Date
                        Cured Deaths Confirmed Active
          2020-01-30
                            0
      0
                                    0
                                               1
                                                       1
      1
         2020-01-31
                            0
                                    0
                                               1
                                                       1
                                               2
                                                       2
          2020-02-01
                            0
                                    0
          2020-02-02
                            0
                                               3
                                                       3
      3
                                    0
          2020-02-03
                            0
                                    0
                                               3
                                                  771499
      209 2020-08-26 2467758
                                59449
                                         3234474
     210 2020-08-27 2523771
                                60472
                                         3310234
                                                 783027
      211 2020-08-28 2583948
                                61529
                                         3387500 803257
```

'Nagaland', 'Meghalaya',

```
212 2020-08-29 2648998 62550 3463972 818495
213 2020-08-30 2713933 63498 3542733 831185
[214 rows x 5 columns]
```

1.3 Visualise how cases are changing with Date

The total population of India is: 1371360351

```
[29]: # Percentage population infected in each state
fig = go.Figure()
for st in popul['State/UnionTerritory'].unique():
    df = popul[popul['State/UnionTerritory'] == st]
    fig.add_trace(go.Scatter(x = df['Date'], y = df['ConfirmPerc'], name = st))

fig.update_layout(title = 'Positive Cases Percentage Per Population', □
    →yaxis_title = 'Percentage (%)')
```

```
fig.show()
[30]: # Group the data on the basis of the Date and find sum to calculate cases for
      →whole nation
      popul_nation = popul.drop('ConfirmPerc', axis=1).groupby('Date').sum()
      # Total population
      popul_nation['Population'] = total_pop
      # Calculating total percentage of positive cases in whole nation
      popul_nation['TotConfirmPerc'] = (popul_nation['Confirmed']/
       →popul_nation['Population'])*100
      popul_nation
[30]:
                    Cured Deaths Confirmed Population
                                                               Density \
     Date
                                           1 1371360351
      2020-01-30
                        0
                                0
                                                            918.597200
      2020-01-31
                        0
                                0
                                           1 1371360351
                                                            918.597200
                        0
      2020-02-01
                                0
                                           2 1371360351
                                                            918.597200
                        0
      2020-02-02
                                0
                                           3 1371360351
                                                            918.597200
      2020-02-03
                        0
                                0
                                           3 1371360351
                                                            918.597200
                            59449
      2020-08-26 2467758
                                     3234474 1371360351 38590.100603
      2020-08-27
                 2523771
                            60472
                                     3310234 1371360351
                                                          38590.100603
      2020-08-28 2583948
                            61529
                                     3387500 1371360351
                                                          38590.100603
      2020-08-29
                 2648998
                            62550
                                     3463972 1371360351
                                                          38590.100603
      2020-08-30 2713933
                            63498
                                     3542733 1371360351
                                                          38590.100603
                  TotConfirmPerc
     Date
      2020-01-30
                    7.292029e-08
      2020-01-31
                   7.292029e-08
      2020-02-01
                    1.458406e-07
      2020-02-02
                    2.187609e-07
      2020-02-03
                    2.187609e-07
      2020-08-26
                    2.358588e-01
      2020-08-27
                    2.413832e-01
      2020-08-28
                    2.470175e-01
      2020-08-29
                    2.525939e-01
      2020-08-30
                    2.583371e-01
      [214 rows x 6 columns]
[31]: # Date vs Percentage cases
      fig = go.Figure()
```

```
[32]: # # To visulize the daily active cases in the country
  # daily_cases_nation = cases.groupby('Date').sum().reset_index()
  # daily_cases_nation['Active'] = 1

# for val in daily_cases_nation.index:
  # if val != 0:
  # daily_cases_nation['Active'].loc[val] = 0:
  # daily_cases_nation['Confirmed'].loc[val] - daily_cases_nation['Cured'].
  # loc[val-1] - daily_cases_nation['Deaths'].loc[val-1]

# fig = go.Figure()
  # fig.add_trace(go.Scatter(x = daily_cases_nation['Date'], y = 0)
  # daily_cases['Active'], name = 'Active Cases'))

# fig.update_layout(title = 'Daily Active Cases', xaxis_title = 'Time', 0)
  # yaxis_title = 'Count (in lakhs)')
  # fig.show()
```

```
[33]: # State wise actives versus the Date
      statewise_daily_cases = cases.sort_values(by=['State/UnionTerritory', 'Date']).
      →reset_index(drop=True)
      statewise daily cases['ActiveCases'] = 0
      for st in sorted(cases['State/UnionTerritory'].unique()):
          df = statewise_daily_cases[statewise_daily_cases['State/UnionTerritory'] ==__
       ⇔stl
          for i in df.index:
              conf = statewise_daily_cases['Confirmed'].iloc[i]
              rec = statewise_daily_cases['Cured'].iloc[i-1]
              death = statewise_daily_cases['Deaths'].iloc[i-1]
              statewise_daily_cases['ActiveCases'].iloc[i] = conf - rec - death
          statewise_daily_cases['ActiveCases'].iloc[df.index[0]] =__

→statewise_daily_cases['Confirmed'].iloc[df.index[0]]
      fig = go.Figure()
      for st in statewise_daily_cases['State/UnionTerritory'].unique():
          df = statewise_daily_cases[statewise_daily_cases['State/UnionTerritory'] ==__
       ⇔st]
          fig.add_trace(go.Scatter(x = df['Date'], y = df['ActiveCases'], name = st))
```

```
fig.update layout(title = 'Daily Active Cases', xaxis_title = 'Time', __
      →yaxis_title = 'Count (in lakhs)')
     fig.show()
[34]: # state wise daily cases with percentage active cases and confirmed cases at ____
      →each date along with poverty line etc.
     popul = popul.sort_values(by=['State/UnionTerritory', 'Date']).
      →reset_index(drop=True)
                                                ,'ConfirmPerc','Density']] =⊔
     statewise_daily_cases[['Population'
      →popul[['Population' ,'ConfirmPerc','Density']]
     statewise_daily_cases['ActivePerc'] = (statewise_daily_cases['ActiveCases']/
       [35]: statewise_daily_cases.dtypes
[35]: Date
                             datetime64[ns]
     State/UnionTerritory
                                     object
     Cured
                                      int64
     Deaths
                                      int64
     Confirmed
                                      int64
     ActiveCases
                                      int64
     Population
                                      int64
     ConfirmPerc
                                    float64
     Density
                                    float64
     ActivePerc
                                    float64
     dtype: object
[36]: popul.dtypes
[36]: Date
                             datetime64[ns]
     State/UnionTerritory
                                     object
     Cured
                                      int64
     Deaths
                                      int64
     Confirmed
                                      int64
     Population
                                      int64
     Density
                                    float64
     ConfirmPerc
                                    float64
     dtype: object
     To find the correlation between confirmed percentage cases and density, poverty, doctors avilability
[37]: dummy = statewise_daily_cases.groupby('Date')
[38]: Density_corr = []
     date = []
```

```
cases_name = 'ConfirmPerc'
for name,group in dummy:
    date.append(name)
    Density_corr.append(group[cases_name].corr(group['Density']))

[39]: correlation_time = pd.DataFrame()
```

```
[40]: correlation_time.fillna(0,inplace=True)
```

```
[41]: fig = px.line(correlation_time,x='Date',y='Density_corr',title="Correlation_
→with amount of population in each state")
fig.show()
```

Conclusion - From plot on density versus the confirmed cases percentage, it can be seen that the correlation between density and confrimed percentage cases increases, which means to say that, where there is a high popultion density there are more covid cases. - However this may not be very clear due to less testing of the individuals which creates a sampling bias towards the symptotoc patients over asymptotic patients

1.4 Forcasting using ARIMA and Prophet

correlation_time['Date'] = date

correlation_time['Density_corr'] = Density_corr

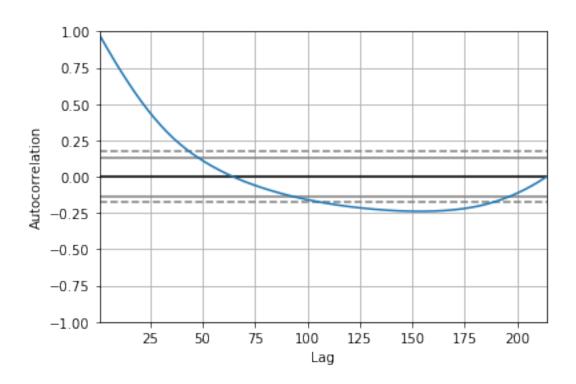
1.4.1 ARIMA model

```
[42]: from matplotlib import pyplot from pandas.plotting import autocorrelation_plot from statsmodels.tsa.arima_model import ARIMA import itertools

[43]: Confirmed_cases_country=popul_nation[['Confirmed','TotConfirmPerc']]
```

[44]: autocorrelation_plot(Confirmed_cases_country['Confirmed'])

[44]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa31f899590>



```
[45]: rolling_mean = Confirmed_cases_country.rolling(window=7,center=False).mean().

dropna()

plt.plot(rolling_mean['Confirmed'],label='Rolling mean with window 7')

plt.plot(Confirmed_cases_country['Confirmed'],label='Original series')

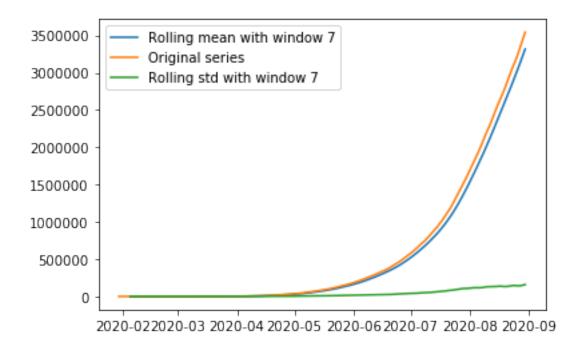
rolling_std = Confirmed_cases_country.rolling(window=7,center=False).std().

dropna()

plt.plot(rolling_std['Confirmed'],label='Rolling std with window 7')

plt.legend()
```

[45]: <matplotlib.legend.Legend at 0x7fa31f7a5250>

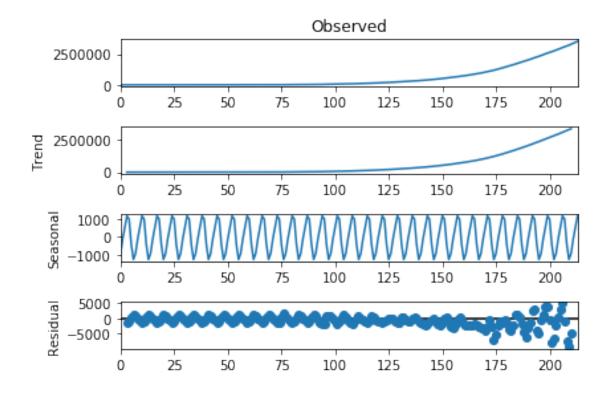


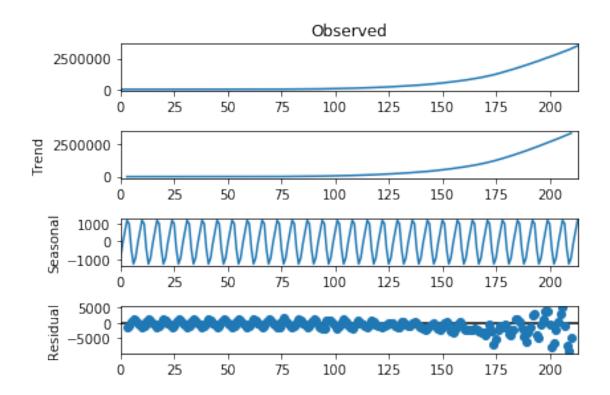
Decomposing the seasonalities - If freq is taken to be 7, we expect the time series to follow some seasonalities - There is also trend observed which is evodent since cases are increasing - Seasonality says that after every week the cases follow same pattern, may be in week days the cases are more as people go outside for jobs

```
[46]: sm.tsa.seasonal_decompose(Confirmed_cases_country['Confirmed'].values,freq=7).

→plot()
```

[46]:





To forcast the time series should be stationary so following code checks wether the series is stationary or not

```
[47]: print('Results of Dickey-Fuller Test:')

test = adfuller(Confirmed_cases_country['Confirmed'].values, autolag='AIC')

results = pd.Series(test[0:4], index=['Test Statistic','p-value','#Lags_□

→Used','Number of Observations Used'])

for i,val in test[4].items():

results['Critical Value (%s)'%i] = val

print (results)
```

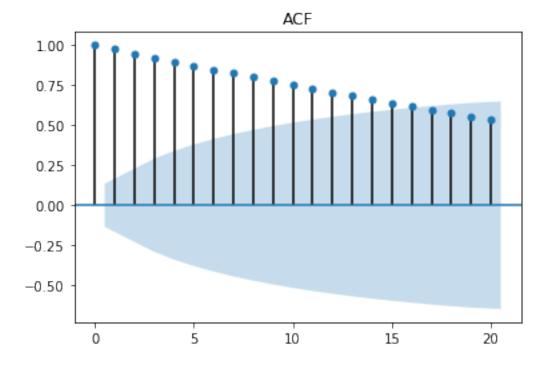
Results of Dickey-Fuller Test:

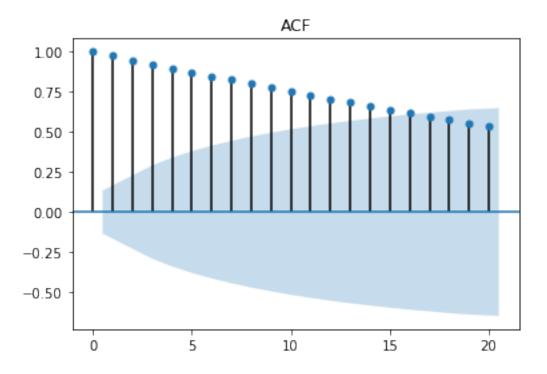
Test Statistic 1.187770
p-value 0.995900
#Lags Used 9.000000
Number of Observations Used 204.000000
Critical Value (1%) -3.462818
Critical Value (5%) -2.875815
Critical Value (10%) -2.574379
dtype: float64

Since the p-value is more than 0.05, the time series is not stationary

[48]: plot_acf(Confirmed_cases_country['Confirmed'].values,lags=20,title="ACF")

[48]:

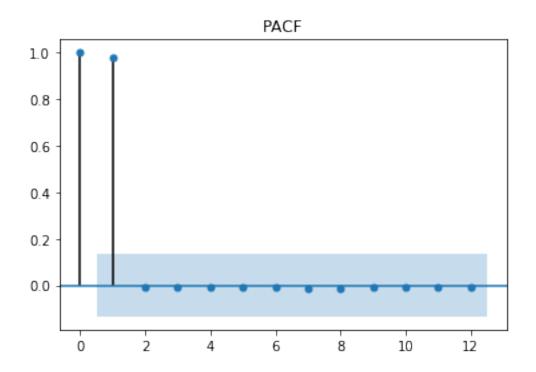


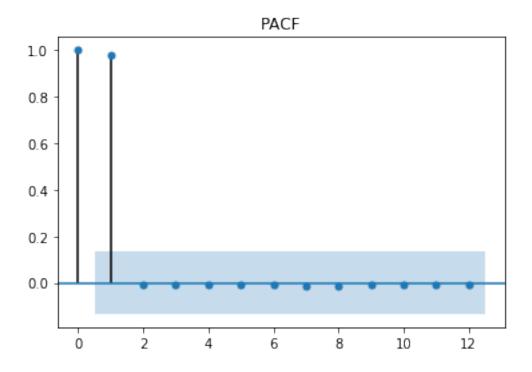


Since the ACF is decaying with lags a moving averge model upto $15\ \mathrm{lags}$ can be considered

[49]: plot_pacf(Confirmed_cases_country['Confirmed'].values,lags=12,title="PACF")

[49]:





From PACF we may have to consider lag of 1 of the auto regressive part

Create features for data frame: - As it was clear from seasonality that there

exist some repition of pattern of time series every week - Along with that feature other features such as month, week and day of week etc can be considered

```
return X
```

```
[51]: def mape(y1, y_pred):
    y1, y_pred = np.array(y1), np.array(y_pred)
    return np.mean(np.abs((y1 - y_pred) / y1)) * 100

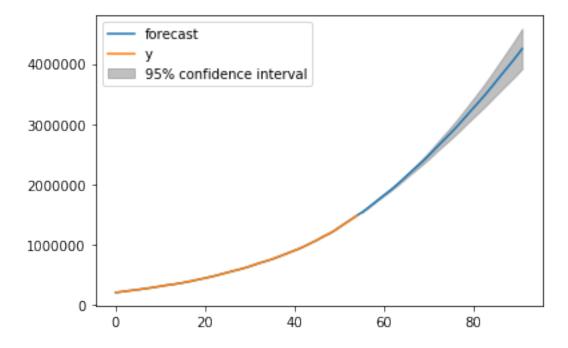
def split(ts):
    #splitting 85%/15% because of little amount of data
    size = int(len(ts) * 0.85)
    train= ts[:size]
    test = ts[size:]
    return(train,test)
```

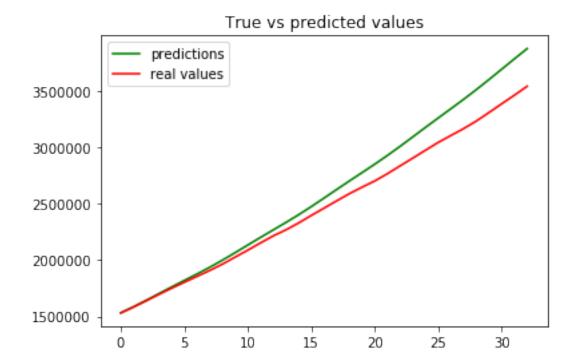
```
[52]: def split(df):
          #splitting 85%/15% because of little amount of data
          size = int(len(df) * 0.85)
          train= df[:size]
          test = df[size:]
          return(train,test)
      def arima(ts,test):
          p=range(0,15)
          d = range(0,15)
          q=range(0,15)
          a=99999
          pdq=list(itertools.product(p,d,q))
          #Determining the best parameters
          for var in pdq:
              try:
                  model = ARIMA(ts, order=var)
                  result = model.fit()
                  if (result.aic<=a) :</pre>
                      a=result.aic
                      param=var
              except:
                  continue
          #Modeling
          model = ARIMA(ts, order=param)
          result = model.fit()
          result.plot_predict(start=int(len(ts) * 0.7), end=int(len(ts) * 1.2))
          pred=result.forecast(steps=len(test))[0]
          #Plotting results
          f,ax=plt.subplots()
```

```
plt.plot(pred,c='green', label= 'predictions')
         plt.plot(test, c='red',label='real values')
         plt.legend()
         plt.title('True vs predicted values')
         #Printing the error metrics
         print(result.aic)
         print(result.summary())
         print('\nMean absolute percentage error: %f'%mape(test,pred))
         return (pred)
[53]: train_with_features , test_with_features =__
      ⇒split(Confirmed_cases_country['Confirmed'].values)
[54]:
[55]: pred=arima(train_with_features, test_with_features)
    2884.071129740485
                               ARIMA Model Results
     ______
    Dep. Variable:
                                   D2.y
                                         No. Observations:
                                                                          179
    Model:
                          ARIMA(3, 2, 8)
                                         Log Likelihood
                                                                    -1429.036
    Method:
                                css-mle
                                         S.D. of innovations
                                                                      691.307
    Date:
                        Wed, 16 Sep 2020
                                        AIC
                                                                     2884.071
                               23:37:08
    Time:
                                         BIC
                                                                     2925.507
                                         HQIC
    Sample:
                                                                     2900.873
                                                  P>|z|
                                                            Γ0.025
                    coef
                           std err
                                                                       0.9751
                           606.971
                                                  0.661
                                                          -923.101
                266.5401
                                       0.439
                                                                     1456.182
    const
                                                            2.136
    ar.L1.D2.y
                  2.1883
                             0.027
                                      81.908
                                                  0.000
                                                                        2.241
    ar.L2.D2.y
                             0.034
                                                  0.000
                                                            -2.242
                 -2.1750
                                     -64.043
                                                                       -2.108
    ar.L3.D2.y
                  0.9806
                             0.018
                                      53.067
                                                  0.000
                                                            0.944
                                                                        1.017
    ma.L1.D2.y -2.2393
                             0.086
                                     -25.905
                                                  0.000
                                                            -2.409
                                                                       -2.070
    ma.L2.D2.y
                 1.8605
                             0.198
                                      9.397
                                                  0.000
                                                            1.472
                                                                       2.249
    ma.L3.D2.y -0.0817
                             0.224
                                      -0.365
                                                  0.715
                                                            -0.520
                                                                        0.357
    ma.L4.D2.y
                                                  0.001
                 -0.7279
                             0.215
                                      -3.387
                                                            -1.149
                                                                       -0.307
    ma.L5.D2.y
                                      -1.566
                                                                        0.075
                -0.3000
                             0.192
                                                  0.117
                                                            -0.676
    ma.L6.D2.y
                 1.2788
                             0.219
                                       5.840
                                                  0.000
                                                            0.850
                                                                        1.708
    ma.L7.D2.y
                                       -4.249
                 -0.9370
                             0.221
                                                  0.000
                                                            -1.369
                                                                       -0.505
    ma.L8.D2.y
                 0.2340
                             0.099
                                        2.356
                                                  0.018
                                                            0.039
                                                                        0.429
                                      Roots
                                  Imaginary
                                                    Modulus
                                                                   Frequency
                     Real
```

AR.1	1.0079	-0.0000j	1.0079	-0.0000
AR.2	0.6051	-0.8035j	1.0059	-0.1473
AR.3	0.6051	+0.8035j	1.0059	0.1473
MA.1	-0.9604	-0.6050j	1.1351	-0.4105
MA.2	-0.9604	+0.6050j	1.1351	0.4105
MA.3	0.5145	-0.9030j	1.0393	-0.1676
MA.4	0.5145	+0.9030j	1.0393	0.1676
MA.5	1.0890	-0.6447j	1.2655	-0.0851
MA.6	1.0890	+0.6447j	1.2655	0.0851
MA.7	1.3593	-0.2647j	1.3848	-0.0306
MA.8	1.3593	+0.2647j	1.3848	0.0306

Mean absolute percentage error: 4.270643





So the model parameters which gave best prediction on the given data are (3, 2, 8), where, - 3 is the parameter for auto regressive part - 2 is the parameter for Integegrated part - 8 is for the moving average part

It has predicted that in 20 days the number of confirmed cases would double. However, note that if suddenly if lock down is announced then this model will fail to work, since it has learnt through previous history, which may not work well for sudden cannot expect the sudden cannot be suddened by the s

1.4.2 Facebooks' Prophet model

```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with yearly_seasonality=True to override this.
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
```

[60]: <fbprophet.forecaster.Prophet at 0x7fa31cba6650>

Mean absolute percentage error: 25.785738

```
[74]: future2 = model.make_future_dataframe(periods=85)

forecast_india_conf = model.predict(future2)
```

```
[75]: fig = plot_plotly(model, forecast_india_conf)
fig.update_layout(template='plotly_white')
fig.show()
```

1.4.3 Conclusion

Prophet model is predicting that the cases by october is around 4 million which around same as predicted by ARIMA.

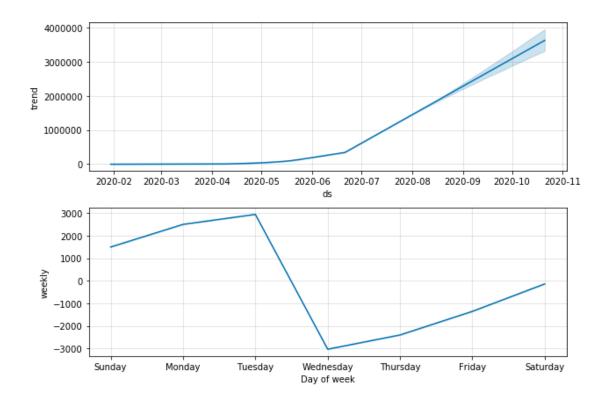
```
[76]: forecast_india_conf
```

```
trend_lower \
[76]:
                 ds
                            trend
                                    yhat_lower
                                                  yhat_upper
         2020-01-30 -2.637415e+03 -3.791495e+04 2.850014e+04 -2.637415e+03
     0
         2020-01-31 -2.554483e+03 -3.852557e+04 3.043029e+04 -2.554483e+03
     1
     2
         2020-02-01 -2.471552e+03 -3.803263e+04 3.012891e+04 -2.471552e+03
         2020-02-02 -2.388620e+03 -3.668145e+04 2.977933e+04 -2.388620e+03
     4
         2020-02-03 -2.305688e+03 -3.427198e+04 3.267913e+04 -2.305688e+03
     261 2020-10-17 3.522173e+06 3.231173e+06 3.817047e+06 3.234154e+06
     262 2020-10-18 3.549132e+06 3.256137e+06 3.855476e+06 3.256360e+06
     263 2020-10-19 3.576090e+06 3.274735e+06 3.882147e+06 3.278256e+06
     264 2020-10-20 3.603049e+06 3.296054e+06 3.929083e+06 3.299862e+06
     265 2020-10-21 3.630007e+06 3.320255e+06 3.951313e+06 3.324012e+06
```

```
additive_terms additive_terms_lower
                                                          additive terms upper
      trend_upper
0
    -2.637415e+03
                      -2402.410044
                                            -2402.410044
                                                                   -2402.410044
1
    -2.554483e+03
                      -1356.822664
                                            -1356.822664
                                                                   -1356.822664
2
    -2.471552e+03
                      -140.362462
                                             -140.362462
                                                                    -140.362462
3
    -2.388620e+03
                      1494.787003
                                             1494.787003
                                                                    1494.787003
    -2.305688e+03
4
                      2498.038062
                                             2498.038062
                                                                    2498.038062
. .
261 3.823359e+06
                      -140.362462
                                             -140.362462
                                                                    -140.362462
262
   3.855927e+06
                      1494.787003
                                             1494.787003
                                                                    1494.787003
263
    3.888865e+06
                      2498.038062
                                             2498.038062
                                                                    2498.038062
264
    3.922810e+06
                      2940.543103
                                             2940.543103
                                                                    2940.543103
                                                                   -3033.772997
265
    3.953066e+06
                      -3033.772997
                                            -3033.772997
                  weekly_lower
                                               multiplicative_terms
          weekly
                                 weekly_upper
0
    -2402.410044
                  -2402.410044
                                 -2402.410044
                                                                 0.0
1
    -1356.822664
                  -1356.822664
                                 -1356.822664
2
     -140.362462
                   -140.362462
                                  -140.362462
                                                                 0.0
3
    1494.787003
                   1494.787003
                                 1494.787003
                                                                 0.0
                                  2498.038062
     2498.038062
                   2498.038062
                                                                 0.0
. .
    -140.362462
                                  -140.362462
                                                                 0.0
261
                   -140.362462
262
    1494.787003
                   1494.787003
                                                                 0.0
                                  1494.787003
                                                                 0.0
263
    2498.038062
                   2498.038062
                                  2498.038062
264
    2940.543103
                                                                 0.0
                   2940.543103
                                  2940.543103
265 -3033.772997 -3033.772997
                                 -3033.772997
                                                                 0.0
     multiplicative_terms_lower
                                 multiplicative_terms_upper
                                                                       yhat
0
                             0.0
                                                          0.0 -5.039825e+03
1
                             0.0
                                                          0.0 -3.911306e+03
2
                             0.0
                                                          0.0 -2.611914e+03
3
                             0.0
                                                          0.0 -8.938330e+02
4
                             0.0
                                                              1.923497e+02
. .
                             0.0
                                                          0.0 3.522033e+06
261
262
                             0.0
                                                          0.0 3.550627e+06
                                                          0.0 3.578588e+06
263
                             0.0
264
                                                          0.0 3.605989e+06
                             0.0
265
                             0.0
                                                          0.0 3.626973e+06
```

[266 rows x 16 columns]

```
[77]: fig = model.plot components(forecast india conf)
```



- As expected from earlier seasonality decompositions the cases are high in week day and tend to decrease in mid week, eventually again catching at week ends.
- This is mau be due to the working days in the week days

[]: