```
In [1]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
In [2]: | df1 = pd.read csv('Historical Product Demand.csv', parse dates=['Date'])
         df1.head()
Out[2]:
            Product_Code Warehouse Product_Category
                                                         Date Order_Demand
             Product 0993
                                        Category 028 2012-07-27
                            Whse J
                                                                        100
             Product 0979
                            Whse J
                                        Category 028 2012-01-19
                                                                        500
             Product 0979
                                        Category 028 2012-02-03
                            Whse J
                                                                        500
             Product 0979
                                        Category 028 2012-02-09
                            Whse J
                                                                        500
                                        Category 028 2012-03-02
             Product 0979
                            Whse J
                                                                        500
In [3]: df1.isnull().sum()/len(df1)*100
Out[3]: Product Code
                              0.000000
         Warehouse
                              0.000000
         Product Category
                              0.000000
         Date
                              1.071836
         Order Demand
                              0.000000
         dtype: float64
In [4]:
        df1.shape
Out[4]: (1048575, 5)
In [5]: df1.dropna(axis = 0, inplace = True)
```

```
In [6]: df1.isnull().sum()/len(df1)*100
 Out[6]: Product_Code
                              0.0
         Warehouse
                              0.0
         Product Category
                              0.0
         Date
                              0.0
         Order Demand
                              0.0
         dtype: float64
 In [7]: df1.dtypes
 Out[7]: Product Code
                                     object
         Warehouse
                                     obiect
         Product Category
                                     obiect
                              datetime64[ns]
         Date
         Order Demand
                                     object
         dtype: object
 In [8]: df1.Product Code.unique()
 Out[8]: array(['Product 0993', 'Product 0979', 'Product 1159', ...,
                 'Product 0237', 'Product 0644', 'Product 0853'], dtype=object)
 In [9]: |df1['Date'].min(), df1['Date'].max()
         #There is 6 years of data
 Out[9]: (Timestamp('2011-01-08 00:00:00'), Timestamp('2017-01-09 00:00:00'))
In [10]: #Lets start with 2012 and cap it 2016 december. Since the dates before 2012 have a lot of missing values - inspected and
         df1 = df1[(df1['Date']>='2012-01-01') & (df1['Date']<='2014-12-31')]
```

In [11]: df1

Out[11]:

	Product_Code	Warehouse	Product_Category	Date	Order_Demand
0	Product_0993	Whse_J	Category_028	2012-07-27	100
1	Product_0979	Whse_J	Category_028	2012-01-19	500
2	Product_0979	Whse_J	Category_028	2012-02-03	500
3	Product_0979	Whse_J	Category_028	2012-02-09	500
4	Product_0979	Whse_J	Category_028	2012-03-02	500
851417	Product_1723	Whse_S	Category_003	2014-12-28	1180
851424	Product_1723	Whse_S	Category_003	2014-12-15	820
852244	Product_1102	Whse_S	Category_004	2014-12-29	800
855387	Product_0158	Whse_S	Category_021	2014-12-22	600
856147	Product_2072	Whse_S	Category_009	2014-12-18	50

638337 rows × 5 columns

In [12]: df1.shape

Out[12]: (638337, 5)

```
In [13]: df1.set_index('Date', inplace = True)
df1
```

Out[13]:

	Product_Code	Warehouse	Product_Category	Order_Demand
Date				
2012-07-27	Product_0993	Whse_J	Category_028	100
2012-01-19	Product_0979	Whse_J	Category_028	500
2012-02-03	Product_0979	Whse_J	Category_028	500
2012-02-09	Product_0979	Whse_J	Category_028	500
2012-03-02	Product_0979	Whse_J	Category_028	500
2014-12-28	Product_1723	Whse_S	Category_003	1180
2014-12-15	Product_1723	Whse_S	Category_003	820
2014-12-29	Product_1102	Whse_S	Category_004	800
2014-12-22	Product_0158	Whse_S	Category_021	600
2014-12-18	Product_2072	Whse_S	Category_009	50

638337 rows × 4 columns

```
In [14]: df = df1.drop(['Warehouse', 'Product_Code', 'Product_Category'],axis = 1, inplace = True)
```

In [15]: df1.head()

Out[15]:

## Order\_Demand

Date	
2012-07-27	100
2012-01-19	500
2012-02-03	500
2012-02-09	500
2012-03-02	500

In [16]: df1.describe()

Out[16]:

	Order_Demand
count	638337
unique	2982
top	1000
frea	69449

In [17]: df1.dtypes

Out[17]: Order\_Demand object

dtype: object

```
In [18]: df1.sort_values('Date')[10:20]
```

### Out[18]:

### **Order Demand**

Date	
2012-01-02	3
2012-01-02	100
2012-01-02	5000
2012-01-02	58000
2012-01-02	500
2012-01-02	31250
2012-01-02	38000
2012-01-02	1000
2012-01-02	1000
2012-01-02	1000

```
In [19]: df1['Order_Demand'] = df1['Order_Demand'].str.replace('(', '')
df1['Order_Demand'] = df1['Order_Demand'].str.replace(')', '')
```

C:\Users\Vaishu\AppData\Local\Temp/ipykernel\_27968/3317173805.py:1: FutureWarning: The default value of regex will chan ge from True to False in a future version. In addition, single character regular expressions will \*not\* be treated as 1 iteral strings when regex=True.

```
df1['Order_Demand'] = df1['Order_Demand'].str.replace('(', '')
```

C:\Users\Vaishu\AppData\Local\Temp/ipykernel\_27968/3317173805.py:2: FutureWarning: The default value of regex will chan ge from True to False in a future version. In addition, single character regular expressions will \*not\* be treated as 1 iteral strings when regex=True.

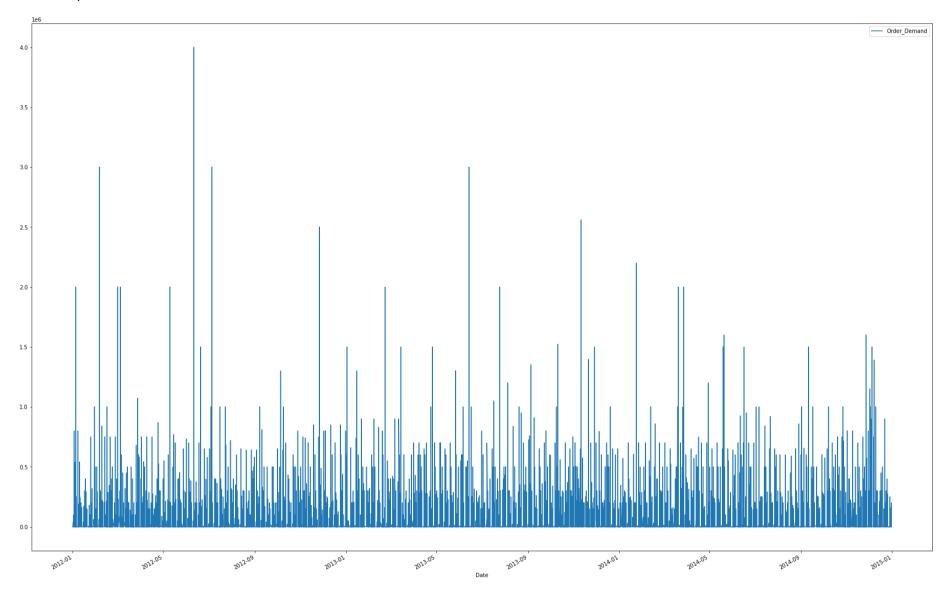
```
df1['Order_Demand'] = df1['Order_Demand'].str.replace(')', '')
```

```
In [20]: df1['Order_Demand'] = df1['Order_Demand'].astype("int64")
In [21]: df1.dtypes
Out[21]: Order_Demand int64 dtype: object
In [22]: df1.describe()
Out[22]:
Order_Demand
```

	Order_Demand
count	6.383370e+05
mean	4.753800e+03
std	2.817886e+04
min	0.000000e+00
25%	2.000000e+01
50%	3.000000e+02
75%	2.000000e+03
max	4.000000e+06

```
In [23]: plt.rcParams["figure.figsize"] = (30,20)
df1.plot()
```

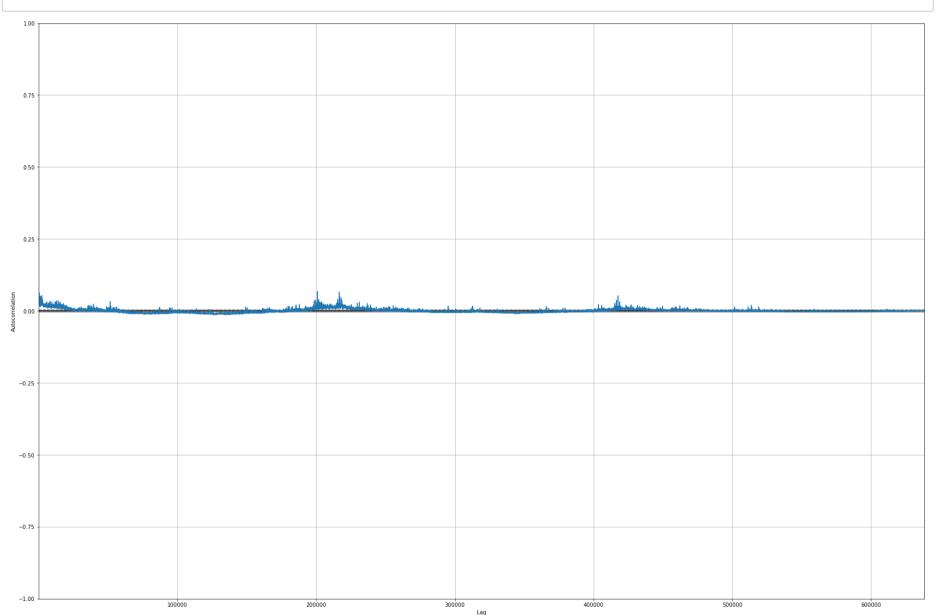
Out[23]: <AxesSubplot:xlabel='Date'>



```
"""# Ho = Its not stationary
In [30]:
         # Ha = It is stationary"""
         print('ADF Statistic: %f' % test result[0])
         print('p-value: %f' % test result[1])
         print('Critical Values:')
         for key, value in test result[4].items():
             print('\t%s: %.3f' % (key, value))
         if test result[0] < test result[4]["5%"]:</pre>
             print ("Reject Ho - Time Series is Stationary")
         else:
             print ("Failed to Reject Ho - Time Series is Non-Stationary")
         ADF Statistic: -56.864657
         p-value: 0.000000
         Critical Values:
                 1%: -3.430
                 5%: -2.862
                 10%: -2.567
         Reject Ho - Time Series is Stationary
In [28]: # As Dataset is Stationary as p-value is less than 0.5, we do not need to perform furter steps like differencing
         # If data is seasonal, then we have to perform seasonal difference i.e. shift the data by shift(12)
         # If data is not seasonal, the shift(1) is enough.
```

# **AUTO REGRESSIVE MODEL**

In [25]: from pandas.plotting import autocorrelation\_plot
 autocorrelation\_plot(df1['Order\_Demand'])
 plt.show()



```
In []: #pd.plotting.autocorrelation_plot(df1['Order_Demand'])
In [29]: from statsmodels.graphics.tsaplots import plot_acf, plot_pacf import statsmodels.api as sm

In [34]: #For Moving Average Model fig = plt.figure(figsize = (20,8)) ax1 = fig.add_subplot(211) fig = sm.graphics.tsa.plot_acf(df1['Order_Demand'], lags = 200 , ax = ax1)
Autocorrelation

Autocorrelation
```

75

125

150

175

100

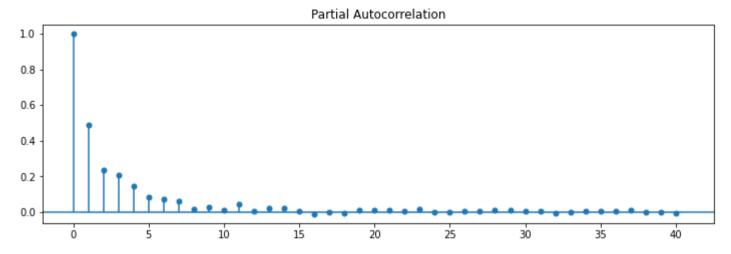
25

50

0.0

200

```
In [33]: #For Auto Regression Model
fig = plt.figure(figsize = (12,8))
ax1 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df1['Order_Demand'], lags = 40 , ax = ax1)
```



```
In [ ]: # p, d, q are important values to be considered in TSA model
# p = AR model lags
# d = Differencing
# q = MA model lags
# ARIMA model is used when data is not seasonal
# SARIMA is used for seasonal dataset.
```

```
In [ ]: # ARIMA Model

p = 8 #From pack graph of AR model(where the value reached to zero)
d = 0 #no shifts are done as data is not seasonal.
q = 0
```

```
In [40]: from statsmodels. tsa. arima_model import ARIMA
    model = ARIMA(df1['Order_Demand'], order = (0,0,1))
    model_fit = model.fit()
    model_fit.summary()
```

C:\Users\Vaishu\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:581: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.

warnings.warn('A date index has been provided, but it has no'

C:\Users\Vaishu\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:585: ValueWarning: A date index has been provided, but it is not monotonic and so will be ignored when e.g. forecasting.

warnings.warn('A date index has been provided, but it is not'

#### Out[40]:

ARMA Model Results

Dep. Variable: Order Demand No. Observations: 638337 Model: -7389402.510 ARMA(0, 1) Log Likelihood Method: css-mle S.D. of innovations 25772.991 **Date:** Fri, 15 Jul 2022 **AIC** 14778811.020 Time: 16:52:26 14778845.120 Sample: 0 **HQIC** 14778820.577

 coef
 std err
 z
 P>|z|
 [0.025
 0.975]

 const
 4753.7998
 43.752
 108.653
 0.000
 4668.047
 4839.552

 ma.L1.Order\_Demand
 0.3563
 0.001
 360.167
 0.000
 0.354
 0.358

Roots

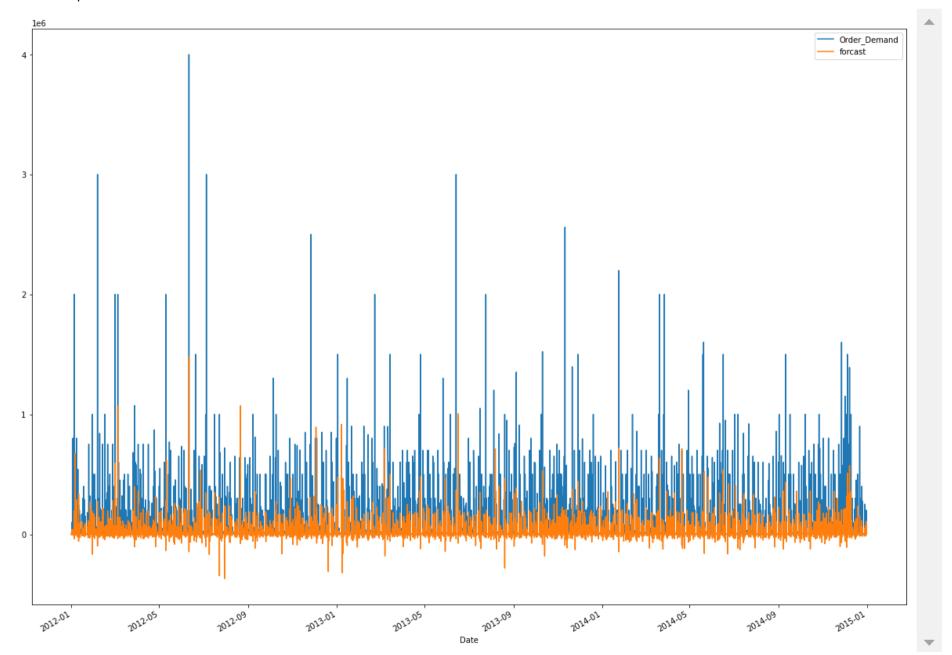
 Real
 Imaginary
 Modulus
 Frequency

 MA.1
 -2.8065
 +0.0000j
 2.8065
 0.5000

```
In [48]: df1['forcast'] = model_fit.predict()
```

```
In [57]: df1[['Order_Demand', 'forcast']].plot(figsize=(20,15))
```

Out[57]: <AxesSubplot:xlabel='Date'>



```
In [44]: from statsmodels.tsa.statespace.sarimax import SARIMAX

In [45]: model_s = sm.tsa.statespace.SARIMAX(df1['Order_Demand'], order=(0,0,1), seasonal_order=(0,0,1,12))
    result_s = model_s.fit()

C:\Users\Vaishu\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:581: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
    warnings.warn('A date index has been provided, but it has no'
    C:\Users\Vaishu\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWarning: A date index has been provided, but it is not monotonic and so will be ignored when e.g. forecasting.
    warnings.warn('A date index has been provided, but it is not'
    C:\Users\Vaishu\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:581: ValueWarning: A date index has been provided, but it has no'
    C:\Users\Vaishu\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWarning: A date index has been provided, but it has no'
    C:\Users\Vaishu\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWarning: A date index has been provided, but it is not monotonic and so will be ignored when e.g. forecasting.
    warnings.warn('A date index has been provided, but it is not'
    warnings.warn('A date index has been provided, but it is not'
    warnings.warn('A date index has been provided, but it is not'
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    warnings.warn('A date index has been provided, but it is not'
    warnings.warn('A date index has been provided, but it is not'
    warnings.warn('A date index has been provided, but i
```

In [50]: result\_s.summary()
Out[50]: SARIMAX Results

 Dep. Variable:
 Order\_Demand
 No. Observations:
 638337

 Model:
 SARIMAX(0, 0, 1)x(0, 0, 1, 12)
 Log Likelihood
 -7389317.341

 Date:
 Fri, 15 Jul 2022
 AIC
 14778640.683

 Time:
 17:05:39
 BIC
 14778674.782

 Sample:
 0
 HQIC
 14778650.239

- 638337

Covariance Type: opg

	coef	std err	Z	P> z	[0.025	0.975]
ma.L1	0.3359	6.52e-05	5150.446	0.000	0.336	0.336
ma.S.L12	0.1556	0.000	1383.575	0.000	0.155	0.156
sigma2	7.546e+08	9.65e-14	7.82e+21	0.000	7.55e+08	7.55e+08
Ljung-Box (L1) (Q): 3185.33 Jarque-Bera (JB): 241358512378.84						

 Prob(Q):
 0.00
 Prob(JB):
 0.00

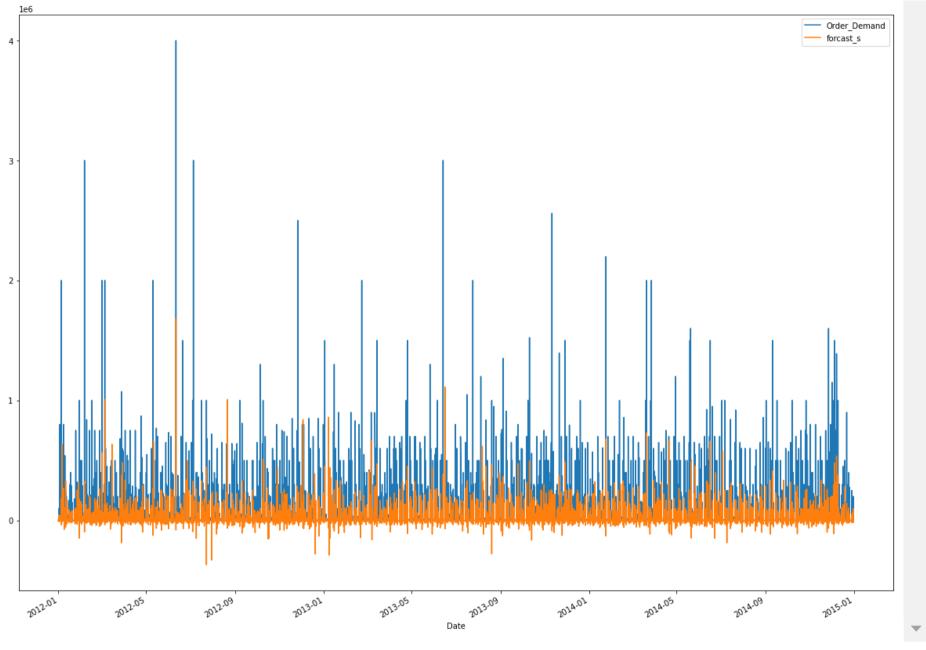
 Heteroskedasticity (H):
 0.74
 Skew:
 35.63

 Prob(H) (two-sided):
 0.00
 Kurtosis:
 3014.55

## Warnings:

- [1] Covariance matrix calculated using the outer product of gradients (complex-step).
- [2] Covariance matrix is singular or near-singular, with condition number 1.21e+34. Standard errors may be unstable.

```
In [59]: df1['forcast_s'] = result_s.predict()
    df1[['Order_Demand', 'forcast_s']].plot(figsize=(20,15))
Out[59]: <AxesSubplot:xlabel='Date'>
```



In [ ]: