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DSM\_Project5.ipynb Python 3

```
[146]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pandas.tools.plotting import autocorrelation_plot
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.arima_model import ARIMA, ARMAResults
import datetime
import sys
import seaborn as sns
import statsmodels
import statsmodels.stats.diagnostic as diag
from statsmodels.tsa.stattools import adfuller
from scipy.stats.mstats import normaltest
from matplotlib.pyplot import acorr
# plt.style.use('fivethirtyeight')
import warnings
warnings.warn('ignore')
%matplotlib inline
```

C:\ProgramData\Anaconda3\lib\site-packages\ipykernel\_launcher.py:17: UserWarning: ignore

```
[2]: df = pd.read_csv('data_stocks.csv')
df.head()
```

```
[2]:
```

	DATE	SP500	NASDAQ.AAL	NASDAQ.AAPL	NASDAQ.ADBE	NASDAQ.ADI	NASDAQ.ADPR	NASDAQ.ADSK	NASDAQ.AKAM	NASDAQ.ALXN	NYSE.WYN	NYSE.XEC	NYS
0	1491226200	2363.6101	42.3300	143.6800	129.6300	82.040	102.2300	85.2200	59.760	121.52	...	84.370	119.035
1	1491226260	2364.1001	42.3600	143.7000	130.3200	82.080	102.1400	85.6500	59.840	121.48	...	84.370	119.035
2	1491226320	2362.6799	42.3100	143.6901	130.2250	82.030	102.2125	85.5100	59.795	121.93	...	84.585	119.260
3	1491226380	2364.3101	42.3700	143.6400	130.0729	82.000	102.1400	85.4872	59.620	121.44	...	84.460	119.260
4	1491226440	2364.8501	42.5378	143.6600	129.8800	82.035	102.0600	85.7001	59.620	121.60	...	84.470	119.610

5 rows × 502 columns

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```
[2]:
```

	DATE	SP500	NASDAQ.AAL	NASDAQ.AAPL	NASDAQ.ADBE	NASDAQ.ADI	NASDAQ.ADPR	NASDAQ.ADSK	NASDAQ.AKAM	NASDAQ.ALXN	NYSE.WYN	NYSE.XEC	NYS
0	1491226200	2363.6101	42.3300	143.6800	129.6300	82.040	102.2300	85.2200	59.760	121.52	...	84.370	119.035
1	1491226260	2364.1001	42.3600	143.7000	130.3200	82.080	102.1400	85.6500	59.840	121.48	...	84.370	119.035
2	1491226320	2362.6799	42.3100	143.6901	130.2250	82.030	102.2125	85.5100	59.795	121.93	...	84.585	119.260
3	1491226380	2364.3101	42.3700	143.6400	130.0729	82.000	102.1400	85.4872	59.620	121.44	...	84.460	119.260
4	1491226440	2364.8501	42.5378	143.6600	129.8800	82.035	102.0600	85.7001	59.620	121.60	...	84.470	119.610

5 rows × 502 columns

```
[3]: #Pick up the following stocks and generate forecasts accordingly
```

```
[4]: stock_features = ['NASDAQ.AAPL', 'NASDAQ.ADPR', 'NASDAQ.CBOE', 'NASDAQ.CSCO', 'NASDAQ.EBAY']
col_list = ['DATE'] + stock_features
df1 = df[col_list]
df1.head()
```

```
[4]:
```

	DATE	NASDAQ.AAPL	NASDAQ.ADPR	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	1491226200	143.6800	102.2300	81.03	33.7400	33.3975
1	1491226260	143.7000	102.1400	81.21	33.8800	33.3950

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```
[0]:
```

	DATE	NASDAQ.AAPL	NASDAQ.ADPR	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	1491226200	143.6800	102.2300	81.03	33.7400	33.3975
1	1491226260	143.7000	102.1400	81.21	33.8800	33.3950
2	1491226320	143.6901	102.2125	81.21	33.9000	33.4100
3	1491226380	143.6400	102.1400	81.13	33.8499	33.3350
4	1491226440	143.6600	102.0600	81.12	33.8400	33.4000

```
[5]: df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41266 entries, 0 to 41265
Data columns (total 6 columns):
DATE          41266 non-null int64
NASDAQ.AAPL   41266 non-null float64
NASDAQ.ADPR  41266 non-null float64
NASDAQ.CBOE   41266 non-null float64
NASDAQ.CSCO   41266 non-null float64
NASDAQ.EBAY   41266 non-null float64
dtypes: float64(5), int64(1)
memory usage: 1.9 MB
```

```
[6]: df1.isnull().sum()
```

```
[6]:
```

DATE	NASDAQ.AAPL
0	0

Screenshot of a JupyterLab session showing code execution and output.

```
[6]: DATE      0
      NASDAQ.AAPL  0
      NASDAQ.ADP   0
      NASDAQ.CBOE  0
      NASDAQ.CSCO  0
      NASDAQ.EBAY  0
      dtype: int64

[7]: df1 = df1.copy()
      df1['DATE'] = pd.to_datetime(df1['DATE'])

[8]: df1.tail()

[8]:
```

	DATE	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
41261	1970-01-01 00:00:01.504209360	164.11	106.565	100.89	32.185	36.135
41262	1970-01-01 00:00:01.504209420	164.12	106.590	100.88	32.200	36.130
41263	1970-01-01 00:00:01.504209480	164.01	106.520	100.86	32.200	36.130
41264	1970-01-01 00:00:01.504209540	163.88	106.400	100.83	32.195	36.120
41265	1970-01-01 00:00:01.504209600	163.98	106.470	100.89	32.225	36.130

```
[9]: df1.head()
```

Screenshot of a JupyterLab session showing code execution and output.

```
[9]: df1.head()

[9]:
```

	DATE	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	1970-01-01 00:00:01.491226200	143.6800	102.2300	81.03	33.7400	33.3975
1	1970-01-01 00:00:01.491226260	143.7000	102.1400	81.21	33.8800	33.3950
2	1970-01-01 00:00:01.491226320	143.6901	102.2125	81.21	33.9000	33.4100
3	1970-01-01 00:00:01.491226380	143.6400	102.1400	81.13	33.8499	33.3350
4	1970-01-01 00:00:01.491226440	143.6600	102.0600	81.12	33.8400	33.4000

```
[10]: df1 = df1.copy()
      df1['Month'] = df1['DATE'].dt.date

[11]: df1.head()

[11]:
```

	DATE	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY	Month
0	1970-01-01 00:00:01.491226200	143.6800	102.2300	81.03	33.7400	33.3975	1970-01-01
1	1970-01-01 00:00:01.491226260	143.7000	102.1400	81.21	33.8800	33.3950	1970-01-01
2	1970-01-01 00:00:01.491226320	143.6901	102.2125	81.21	33.9000	33.4100	1970-01-01
3	1970-01-01 00:00:01.491226380	143.6400	102.1400	81.13	33.8499	33.3350	1970-01-01

The screenshot shows a JupyterLab interface with a Python 3 kernel. The code cell [12] contains:

```
col_list = ['Month']+ stock_features
df2 = df1[col_list]
df2.head()
```

The resulting output cell [12] displays a DataFrame:

	Month	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	1970-01-01	143.6800	102.2300	81.03	33.7400	33.3975
1	1970-01-01	143.7000	102.1400	81.21	33.8800	33.3950
2	1970-01-01	143.6901	102.2125	81.21	33.9000	33.4100
3	1970-01-01	143.6400	102.1400	81.13	33.8499	33.3350
4	1970-01-01	143.6600	102.0600	81.12	33.8400	33.4000

Code cell [13] contains:

```
df2.isnull().sum()
```

The resulting output cell [13] displays the count of null values for each column:

Month	NASDAQ.AAPL	NASDAQ.ADP	NASDAQ.CBOE	NASDAQ.CSCO	NASDAQ.EBAY
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

The screenshot shows a JupyterLab interface with a Python 3 kernel. The code cell [14] contains:

```
df2.describe().transpose()
```

The resulting output cell [14] displays descriptive statistics for each column:

	count	mean	std	min	25%	50%	75%	max
NASDAQ.AAPL	41266.0	150.453566	6.236826	140.160	144.640	149.9450	155.065	164.51
NASDAQ.ADP	41266.0	103.480398	4.424244	95.870	101.300	102.4400	104.660	121.77
NASDAQ.CBOE	41266.0	89.325485	5.746178	80.000	84.140	89.3150	93.850	101.35
NASDAQ.CSCO	41266.0	32.139336	0.985571	30.365	31.455	31.7733	32.790	34.49
NASDAQ.EBAY	41266.0	34.794506	1.099296	31.890	34.065	34.7700	35.610	37.46

Code cell [15] contains:

```
final = df2.copy()
final['Month']=pd.to_datetime(final['Month'])
```

Code cell [16] contains:

```
#Time Series Forecasting for NASDAQ.AAPL
```

Code cell [17] contains:

```
df_AAPL = final[['Month',stock_features[0]]]
```

Screenshot of JupyterLab interface showing code execution and output.

```
[17]: df_AAPL = final[['Month',stock_features[0]]]
df_AAPL.head()

[17]:
Month    NASDAQ.AAPL
0  1970-01-01    143.6800
1  1970-01-01    143.7000
2  1970-01-01    143.6901
3  1970-01-01    143.6400
4  1970-01-01    143.6600
```

```
[18]: df_AAPL.set_index('Month',inplace=True)
df_AAPL.head()

[18]:
Month
1970-01-01    143.6800
1970-01-01    143.7000
1970-01-01    143.6901
```

Screenshot of JupyterLab interface showing code execution and output.

```
1970-01-01    143.7000
1970-01-01    143.6901
1970-01-01    143.6400
1970-01-01    143.6600
```

```
[19]: df_AAPL.index

[19]:
DatetimeIndex(['1970-01-01', '1970-01-01', '1970-01-01', '1970-01-01',
               '1970-01-01', '1970-01-01', '1970-01-01', '1970-01-01',
               '1970-01-01', '1970-01-01', '1970-01-01', '1970-01-01',
               '1970-01-01', '1970-01-01', '1970-01-01', '1970-01-01',
               '1970-01-01', '1970-01-01', '1970-01-01', '1970-01-01',
               '1970-01-01', '1970-01-01', '1970-01-01', '1970-01-01'],
              dtype='datetime64[ns]', name='Month', length=41266, freq=None)

[20]: #Summary Statistics

[21]: df_AAPL.describe().transpose()

[21]:
   count      mean      std       min     25%     50%     75%      max
NASDAQ.AAPL  41266.0  150.453566  6.236826  140.16  144.64  149.945  155.065  164.51
```

Screenshot of JupyterLab interface showing a code cell and its output.

Code cell [23]:

```
import seaborn as sns
sns.set_style('whitegrid')
df_AAPL.plot()
plt.title('Time Series Plot for NASDAQ_AAPL')
plt.show()
```

Output:

A line plot titled "Time Series Plot for NASDAQ\_AAPL". The y-axis represents price, ranging from 140 to 165. The x-axis represents time in months, from November 1967 to November 1971. The plot shows a single blue line representing the price of NASDAQ\_AAPL over time.

Screenshot of JupyterLab interface showing a code cell and its output.

Code cell [24]:

```
#Plotting Rolling Statistics and check for stationarity :
#The function will plot the moving mean or moving Standard Deviation.
#This is still visual method
#NOTE: moving mean and moving standard deviation - At any instant 't',
#we take the mean/std of the last year which in this case is 12 months
```

Code cell [25]:

```
from statsmodels.tsa.stattools import adfuller
def test_stationarity(timeseries):

    #Determining rolling statistics
    rolmean = timeseries.rolling(12).mean()
    rolstd = timeseries.rolling(12).std()
    #Plot rolling statistics:
    plt.plot(timeseries, color='blue',label='Original')
    plt.plot(rolmean, color='red', label='Rolling Mean')
    plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show()
    """
    Pass in a time series, returns ADF report
    """
    result = adfuller(timeseries)
```

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```

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Pass in a time series, returns ADF report
"""
result = adfuller(timeseries)
print('\nAugmented Dickey-Fuller Test:')
labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used']

for value,label in zip(result,labels):
    print(label+': '+str(value) )
for k,v in result[4].items():
    print('Critical {} : value {}'.format(k,v))

if result[1] <= 0.05:
    print("strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary")
else:
    print("weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary")
"""

[26]: test_stationarity(df_AAPL['NASDAQ.AAPL'])

Rolling Mean & Standard Deviation
Original Rolling Mean Rolling Std
150
125
100
75
50
25
0
1967-11 1968-05 1969-11 1969-05 1970-01 1970-11 1971-05 1971-11

```

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```

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Augmented Dickey-Fuller Test:
ADF Test Statistic : -0.9128532997926723
p-value : 0.7837101772613848
#Lags Used : 31
Number of Observations Used : 41234
Critical 1% : value -3.438508599872388
Critical 5% : value -2.8616100975579815
Critical 10% : value -2.5668073186689477
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary

[27]: """Note:
This is not stationary because :
• mean is increasing even though the std is small.
• Test stat is > critical value.
• Note: the signed values are compared and the absolute values.

1967-11 1968-05 1969-11 1969-05 1970-01 1970-11 1971-05 1971-11

```

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```
• Test stat is > critical value.  
• Note: the signed values are compared and the absolute values.  
  
MAKING THE TIME SERIES STATIONARY  
There are two major factors that make a time series non-stationary. They are:  
• Trend: non-constant mean  
• Seasonality: Variation at specific time-frames  
  
Differencing  
The first difference of a time series is the series of changes from one period to the next. We can do this easily with pandas. You can continue to take the second difference, third difference, and so on until your data is stationary.  
First Difference"""  
[27]: 'Note:\nThis is not stationary because :\nmean is increasing even though the std is small.\n\nTest stat is > critical value.\n\nNote: the signed values are compared and the absolute values.\n\nMAKING THE TIME SERIES STATIONARY\nThere are two major factors that make a time series non-stationary. They are:  
re:\n\n• Trend: non-constant mean\n• Seasonality: Variation at specific time-frames\n\nDifferencing\nThe first difference of a time series is the series of changes from one period to the next. We can do this easily with pandas. You can continue to take the second difference, third difference, and so on until your data is stationary.\n\nFirst Difference'  
[28]: df_AAPL = df_AAPL.copy()  
df_AAPL.loc[:, 'First_Difference'] = df_AAPL['NASDAQ.AAPL'] - df_AAPL['NASDAQ.AAPL'].shift(1)
```

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```
df_AAPL.loc[:, 'First_Difference'] = df_AAPL['NASDAQ.AAPL'] - df_AAPL['NASDAQ.AAPL'].shift(1)  
df_AAPL.head()  
[29]:  
NASDAQ.AAPL First_Difference  
Month  
1970-01-01 143.6800 NaN  
1970-01-01 143.7000 0.0200  
1970-01-01 143.6901 -0.0099  
1970-01-01 143.6400 -0.0501  
1970-01-01 143.6600 0.0200  
  
df_AAPL = df_AAPL.copy()  
df_AAPL.dropna(inplace=True)  
#Test Staionarity  
test_stationarity(df_AAPL['First_Difference'])
```

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```
[32]: test_stationarity(df_AAPL['First_Difference'])

Rolling Mean & Standard Deviation

1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11

Augmented Dickey-Fuller Test:
ADF Test Statistic : -35.737741483401116
p-value : 0.0
#Lags Used : 30
Number of Observations Used : 41234
Critical 1% : value -3.4305085998723857
Critical 5% : value -2.8616100075579815
Critical 10% : value -2.5668073106689477
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary
```

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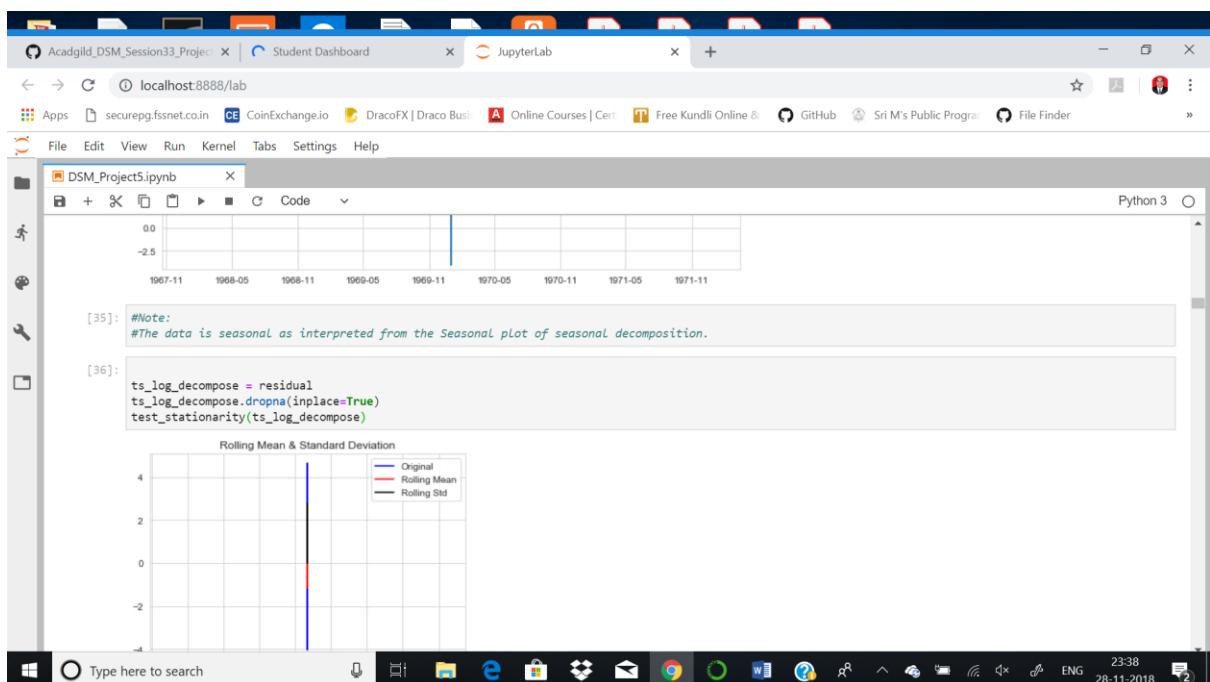
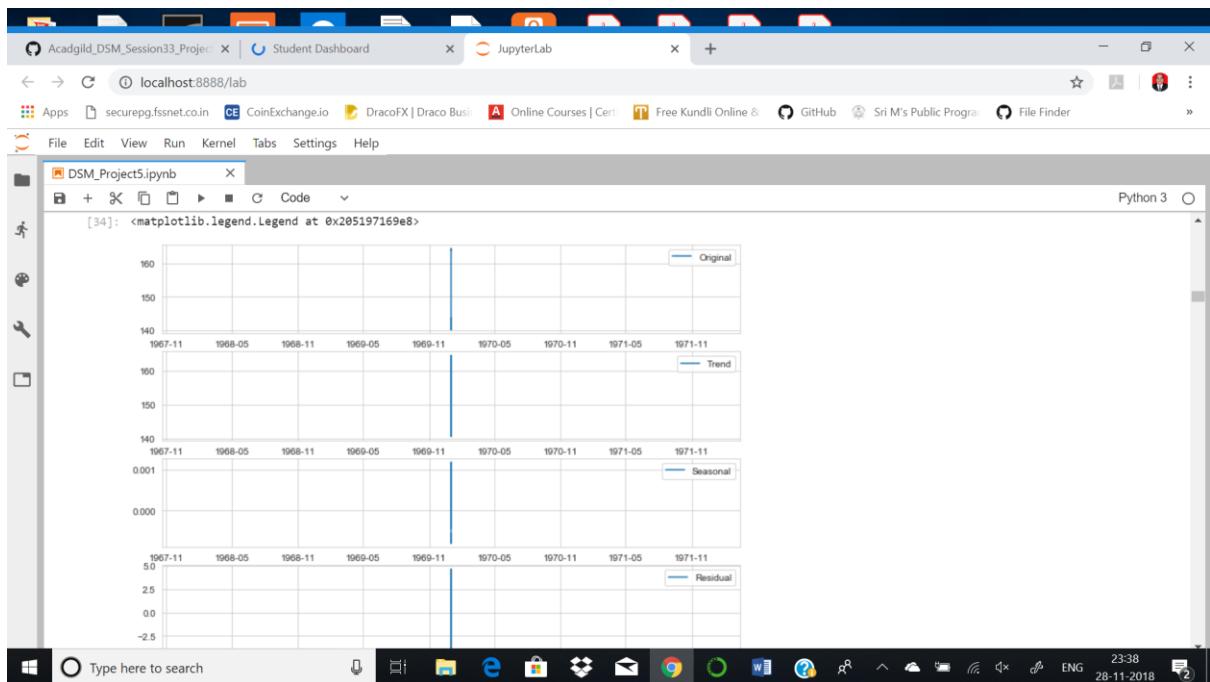
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```
[33]: #Seasonal Decomposition

from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_AAPL[['NASDAQ.AAPL']], freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_AAPL[['NASDAQ.AAPL']],label='Original')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend,label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonal')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual,label='Residual')
plt.legend(loc='best')

[34]: <matplotlib.legend.Legend at 0x205197169e8>
```

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```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
Augmented Dickey-Fuller Test:
ADF Test Statistic : -43.0434335355413
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Critical 1% : value -3.4305087423235587
Critical 5% : value -2.881618160516496
Critical 10% : value -2.566807344180027
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary
```

[37]: `"""Note :  
This is stationary because:  
  
• test statistic is lower than critical values.  
• the mean and std variations have small variations with time.  
  
Autocorrelation and Partial Autocorrelation Plots  
Autocorrelation Interpretation  
The actual interpretation and how it relates to ARIMA models can get a bit complicated, but there are some basic common methods we can use for the ARIMA model.  
If the autocorrelation plot shows positive autocorrelation at the first lag (lag-1), then it suggests to use the AR terms in relation to the lag`

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```
If the autocorrelation plot shows positive autocorrelation at the first lag (lag-1), then it suggests to use the AR terms in relation to the lag  
  
If the autocorrelation plot shows negative autocorrelation at the first lag, then it suggests using MA terms"""
```

[37]: `'Note :  
This is stationary because:  
• test statistic is lower than critical values.  
• the mean and std variations have small variations with time.  
  
Autocorrelation and Partial Autocorrelation Plots  
Autocorrelation Interpretation  
The actual interpretation and how it relates to ARIMA models can get a bit complicated, but there are some basic common methods we can use for the ARIMA model. Our main priority here is to try to figure out whether we will use the AR or MA components for the ARIMA model (or both!) as well as how many lags we should use. In general you would use either AR or MA, using both is less common.  
If the autocorrelation plot shows positive autocorrelation at the first lag (lag-1), then it suggests to use the AR terms in relation to the lag  
If the autocorrelation plot shows negative autocorrelation at the first lag, then it suggests using MA terms'''`

[38]: `from statsmodels.graphics.tsaplots import plot_acf,plot_pacf`

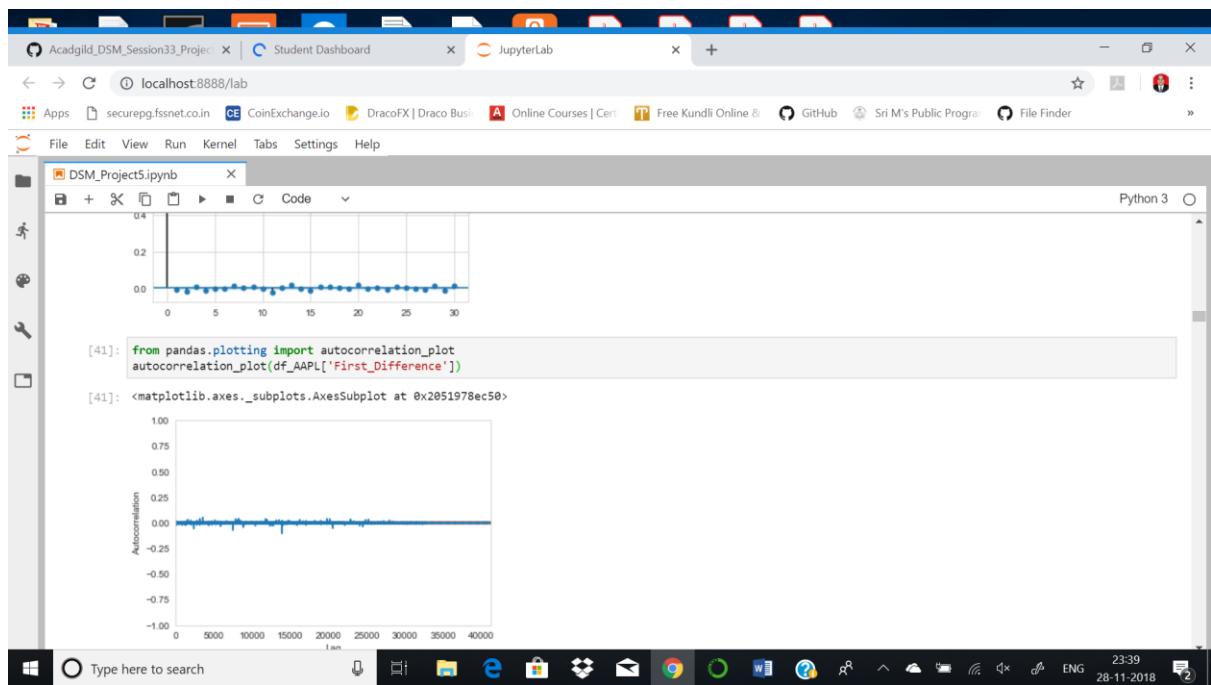
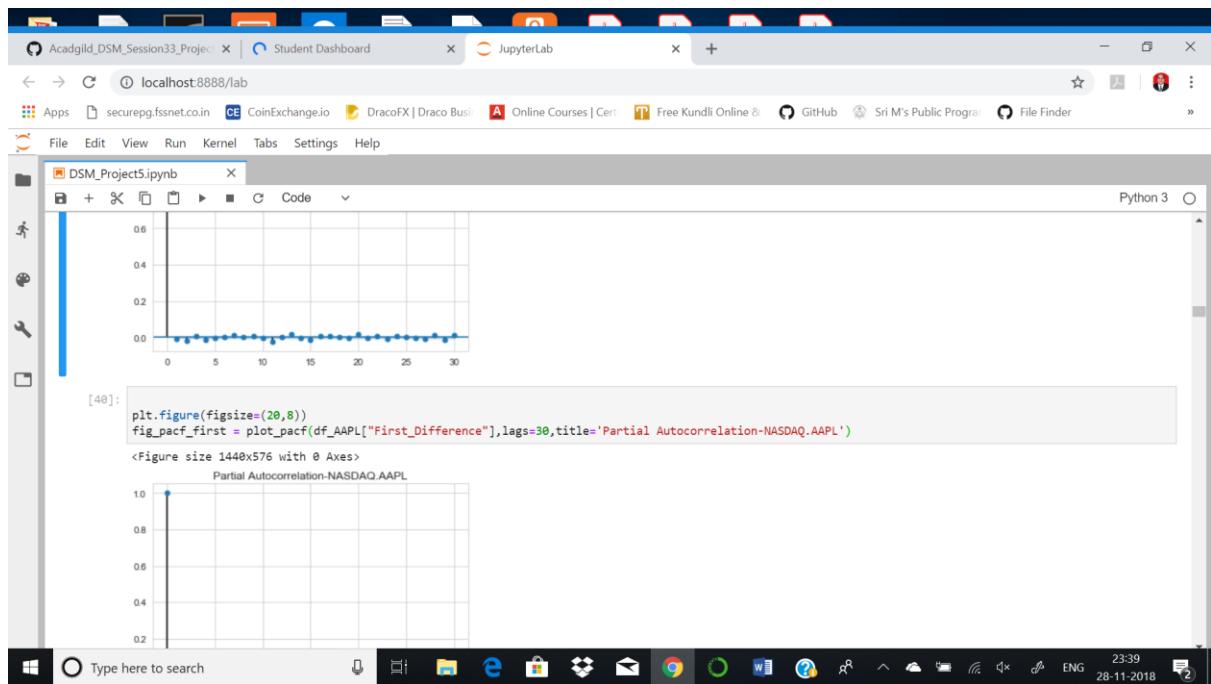
[39]: `plt.figure(figsize=(20,8))
fig_first = plot_acf(df_AAPL["First_Difference"],lags=30,title='Autocorrelation-NASDAQ.AAPL')
<Figure size 1440x576 with 0 Axes>`

Autocorrelation-NASDAQ AAPL



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```
[42]: """Forecasting a Time Series
Auto Regressive Integrated Moving Average(ARIMA) -
It is like a liner regression equation where the predictors depend on parameters (p,d,q) of the ARIMA model .

Let me explain these dependent parameters:

• p : This is the number of AR (Auto-Regressive) terms . Example - if p is 3 the predictor for y(t) will be y(t-1),y(t-2),y(t-3).

• q : This is the number of MA (Moving-Average) terms . Example - if p is 3 the predictor for y(t) will be y(t-1),y(t-2),y(t-3).

• d :This is the number of differences or the number of non-seasonal differences .

Now let's check out on how we can figure out what value of p and q to use. We use two popular plotting techniques; they are:

• Autocorrelation Function (ACF): It just measures the correlation between two consecutive (lagged version). example at lag 4, ACF will compare series at t-4 and t.

• Partial Autocorrelation Function (PACF): is used to measure the degree of association between y(t) and y(t-p)."""

[42]: 'Forecasting a Time Series\nAuto Regressive Integrated Moving Average(ARIMA)\nIt is like a liner regression equation where the predictors depend on parameters (p,d,q) of the ARIMA model .\nLet me explain these dependent parameters:\n\n• p : This is the number of AR (Auto-Regressive) terms . Example\u200a-\u200aif p is 3 the predictor for y(t) will be y(t-1),y(t-2),y(t-3).\n\n• q : This is the number of MA (Moving-Average) terms . Example\u200a-\u200aif p is 3 the predictor for y(t) will be y(t-1),y(t-2),y(t-3).\n\n• d :This is the number of differences or the number of non-seasonal differences .\n\nNow let's check out on how we can figure out what value of p and q to use. We use two popular plotting techniques; they are:\n\n• Autocorrelation Function (ACF): It just measures the correlation between two consecutive (lagged version). example at lag 4, ACF will compare series at time instance t-4 and t.\n\n• Partial Autocorrelation Function (PACF): is used to measure the degree of association between y(t) and y(t-p).'"
```

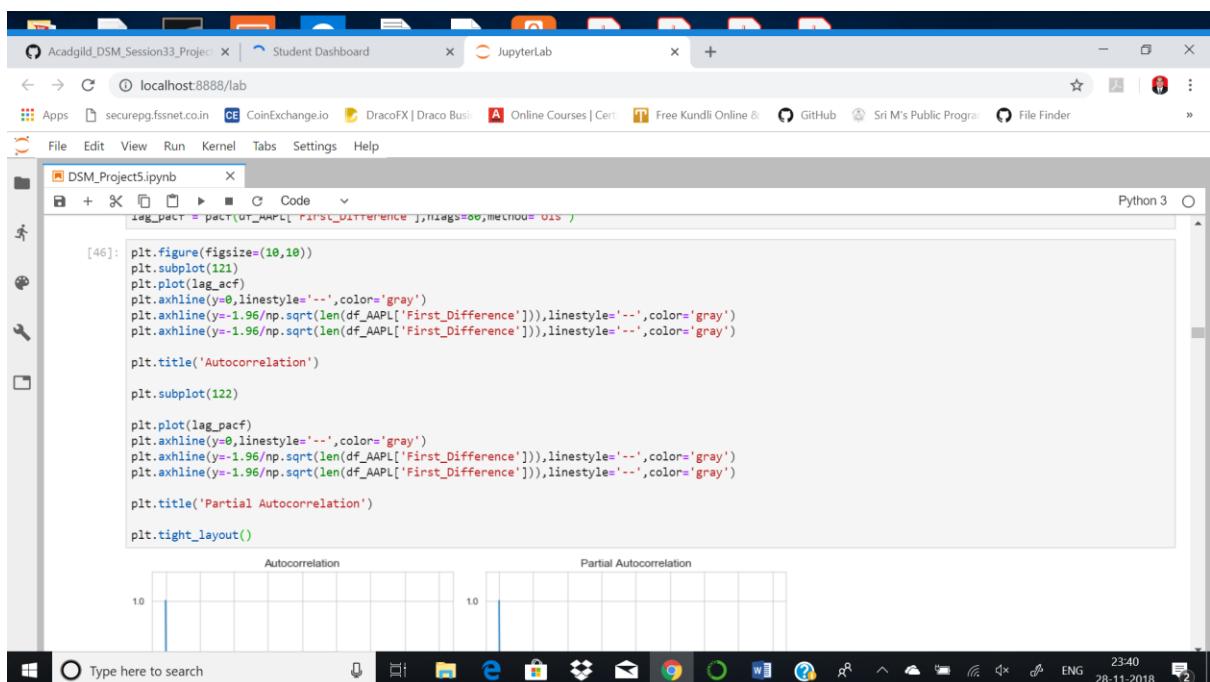
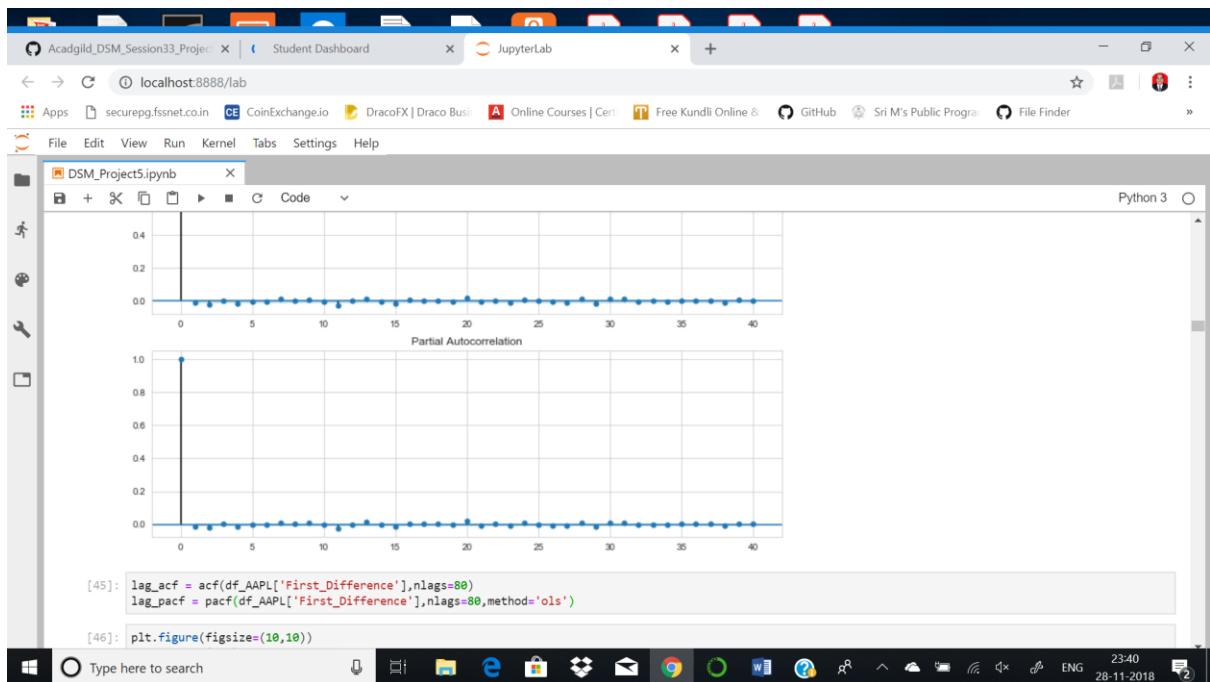
localhost:8888/lab

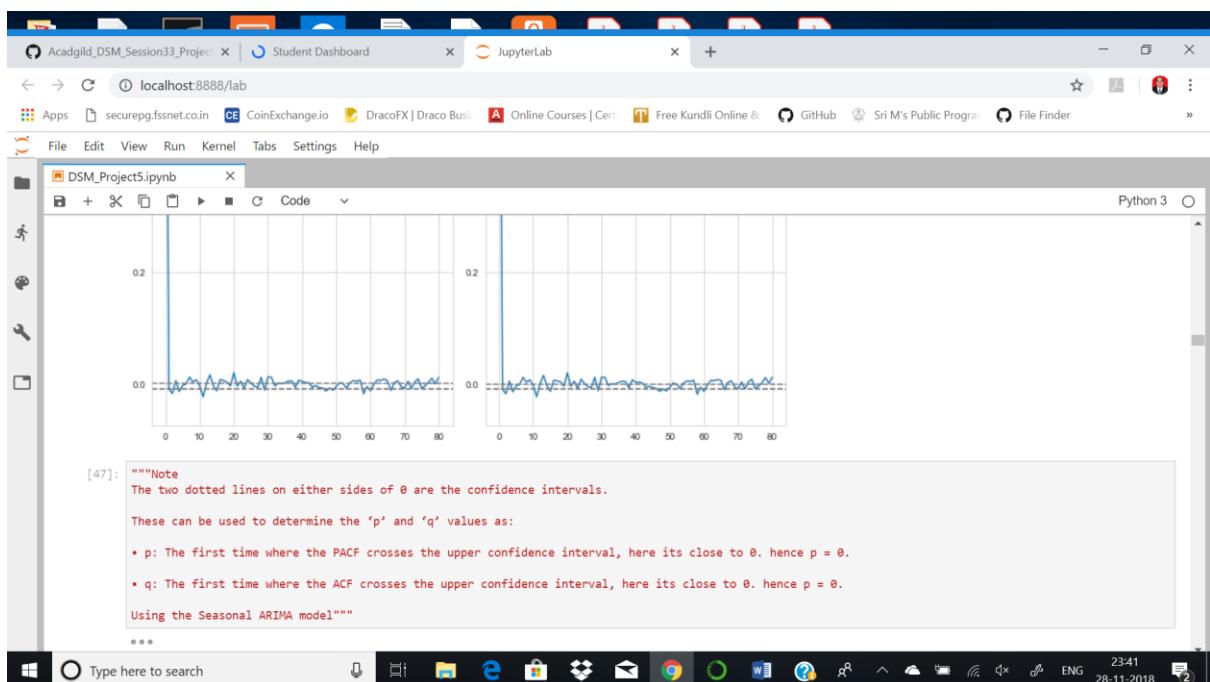
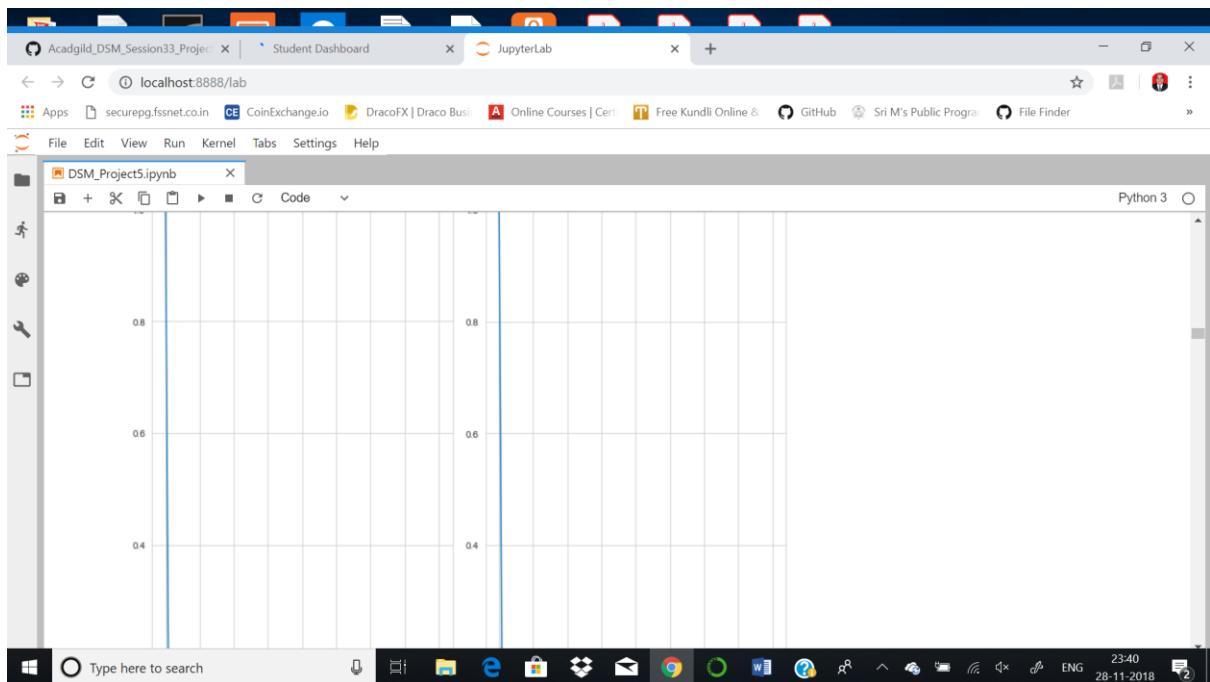
DSM\_Project5.ipynb

```
[42]: parameters (p,d,q) of the ARIMA model .
Let me explain these dependent parameters:
• p : This is the number of AR (Auto-Regressive) terms . Example\u200a-\u200aif p is 3 the predictor for y(t) will be y(t-1),y(t-2),y(t-3).
• q : This is the number of MA (Moving-Average) terms . Example\u200a-\u200aif p is 3 the predictor for y(t) will be y(t-1),y(t-2),y(t-3).
• d :This is the number of differences or the number of non-seasonal differences .
Now let's check out on how we can figure out what value of p and q to use. We use two popular plotting techniques; they are:
• Autocorrelation Function (ACF): It just measures the correlation between two consecutive (lagged version). example at lag 4, ACF will compare series at time instance t-4 and t.
• Partial Autocorrelation Function (PACF): is used to measure the degree of association between y(t) and y(t-p).'

[43]: import statsmodels.api as sm
from statsmodels.tsa.arima_model import ARIMA, ARIMAResults
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

[44]: fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_AAPL['First_Difference'].iloc[30:], lags=40, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_AAPL['First_Difference'].iloc[30:], lags=40, ax=ax2)
```





Acadgild\_DSM\_Session33\_Project x | Student Dashboard x | JupyterLab x +

localhost:8888/lab

File Edit View Run Kernel Tabs Settings Help

DSM\_Project5.ipynb x Python 3

```
Using the Seasonal ARIMA model"""
***
```

```
[48]: model= sm.tsa.statespace.SARIMAX(df_AAPL[['NASDAQ.AAPL']],order=(0,1,0),seasonal_order=(0,1,0,12))
results = model.fit()
print(results.summary())

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
Statespace Model Results
=====
Dep. Variable:      NASDAQ.AAPL  No. Observations:      41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12)  Log Likelihood:      24925.552
Date:          Wed, 28 Nov 2018  AIC:                  -49849.104
Time:            22:50:24  BIC:                  -49840.476
Sample:                 0   HQIC:                  -49846.377
                           - 41265
Covariance Type:    opg
=====
            coef  std err      z  P>|z|  [0.025  0.975]
-----
sigma2     0.0175  4.57e-06  3828.712  0.000  0.017  0.017
=====
Ljung-Box (Q):      10611.64  Jarque-Bera (JB):      3462262308.64
Prob(Q):           0.00  Prob(JB):                   0.00
Heteroskedasticity (H):      2.92  Skew:                  -2.00
Prob(H) (two-sided):      0.00  Kurtosis:                1422.26
=====
```

Type here to search

Acadgild\_DSM\_Session33\_Project x | Student Dashboard x | JupyterLab x +

localhost:8888/lab

File Edit View Run Kernel Tabs Settings Help

DSM\_Project5.ipynb x Python 3

```
Ljung-Box (Q):      10611.64  Jarque-Bera (JB):      3462262308.64
Prob(Q):           0.00  Prob(JB):                   0.00
Heteroskedasticity (H):      2.92  Skew:                  -2.00
Prob(H) (two-sided):      0.00  Kurtosis:                1422.26
=====
```

Warnings:

```
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

```
[49]: results.resid.plot()
```

```
[49]: <matplotlib.axes._subplots.AxesSubplot at 0x2052ea7fcc0>
```

The screenshot shows a Jupyter Notebook interface with the following details:

- Header:** The browser tabs include "Acadgild\_DSM\_Session33\_Project" (active), "Student Dashboard", and "JupyterLab". The address bar shows "localhost:8888/lab".
- Toolbar:** Includes icons for File, Edit, View, Run, Kernel, Tabs, Settings, Help, and Python 3.
- Code Cell [50]:** Contains the command `results.resid.plot(kind='kde')` and its output, which is a Kernal Density Estimation (KDE) plot.
- KDE Plot Output:** The plot shows a sharp peak at a density of approximately 3.0, centered around a value of 0. The x-axis is labeled "Month" and ranges from 1967-11 to 1971-11. The y-axis is labeled "Density" and ranges from 0.00 to 3.00.
- Code Cell [51]:** Contains the command `df_AAPL = df_AAPL.copy()`.

The screenshot shows a Jupyter Notebook interface with the following details:

- Header:** The browser title bar shows tabs for "Acadgild\_DSM\_Session33\_Project" (active), "Student Dashboard", and "JupyterLab". Below the tabs are navigation icons for back, forward, search, and refresh.
- Toolbar:** A standard Windows-style toolbar with icons for file operations like New, Open, Save, Print, and Exit.
- Header Bar:** Shows the URL "localhost:8888/lab" and a list of open tabs: "securepg.fssnet.co.in", "CoinExchange.io", "DracoFX | Draco Busi...", "Online Courses | Cert...", "Free Kundli Online", "GitHub", "Sri M's Public Program", and "File Finder".
- Menu Bar:** "File", "Edit", "View", "Run", "Kernel", "Tabs", "Settings", "Help".
- Code Area:** Displays Python code in cells [51] through [54].
  - [51]: 

```
df_AAPL = df_AAPL.copy()
df_AAPL['Forecast'] = results.predict()
```
  - [52]: 

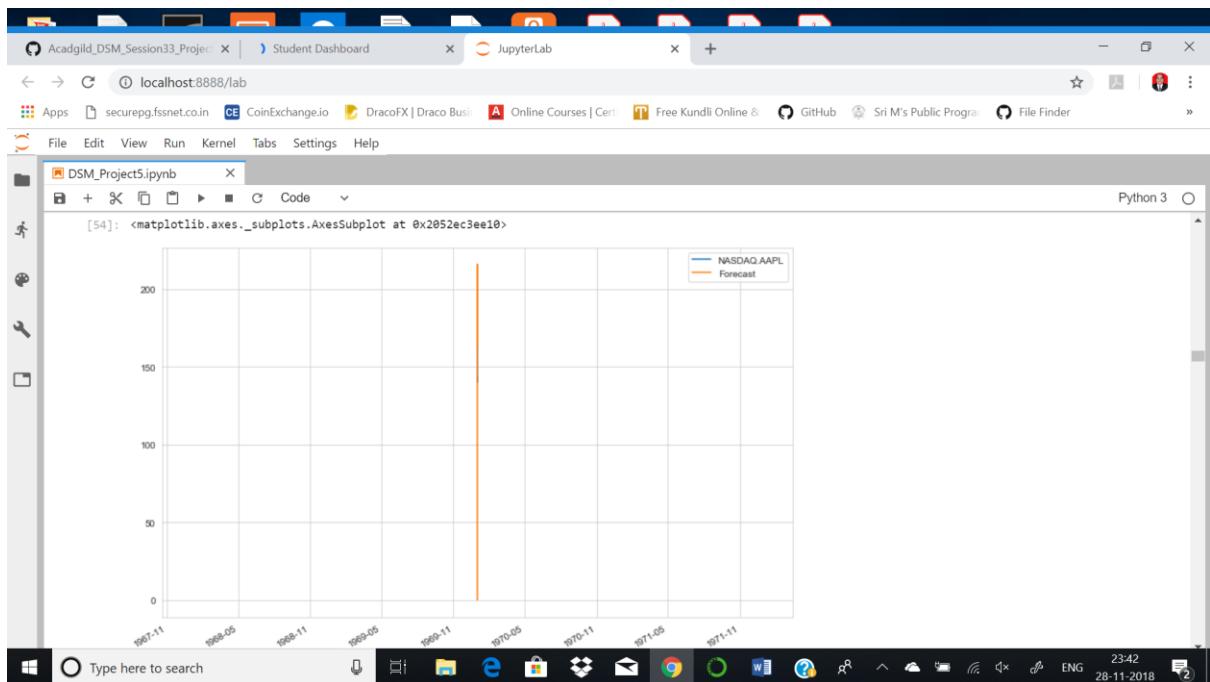
```
df_AAPL.head()
```
  - [52]: 

	NASDAQ.AAPL	First_Difference	Forecast
Month			
1970-01-01	143.7000	0.0200	0.0000
1970-01-01	143.6901	-0.0099	143.7000
1970-01-01	143.6400	-0.0501	143.6901
1970-01-01	143.6600	0.0200	143.6400
1970-01-01	143.7800	0.1200	143.6600
  - [53]: 

```
#Prediction of Future Values
```
  - [54]: 

```
df_AAPL[['NASDAQ.AAPL','Forecast']].plot(figsize=(12,8))
```
  - [54]: 

```
<matplotlib.axes._subplots.AxesSubplot at 0x2052ec3ee10>
```
- Bottom Bar:** A taskbar with icons for Start, Search, Task View, File Explorer, Edge, File Manager, File Explorer, Mail, Google Chrome, File Explorer, Word, Excel, and Powerpoint. It also shows system status icons for battery, signal, volume, and network.
- System Bar:** Shows the date and time "28-11-2018 23:41" and language "ENG".



```
[55]: results.forecast(steps=10)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
  ValueWarning)
[55]: 41265 163.960
41266 163.935
41267 163.910
41268 163.810
41269 163.940
41270 163.950
41271 163.890
41272 163.860
41273 163.870
41274 163.760
dtype: float64
[56]: results.predict(start=41264,end=41274)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
  ValueWarning)
[56]: 41264 163.930
41265 163.960
41266 163.935
41267 163.910
```

The screenshot shows a JupyterLab interface running on a Windows 10 desktop. The title bar indicates the session is titled 'Acadgild\_DSM\_Session33\_Project' and the tab is 'Student Dashboard'. The main area displays a notebook titled 'DSM\_Project5.ipynb' in Python 3. The code cell [57] contains a comment '#Accuracy of the Forecast using MSE-Mean Squared Error'. The subsequent cell [58] imports 'mean\_squared\_error, mean\_absolute\_error' from 'sklearn.metrics' and prints the Mean Squared Error and Mean Absolute Error for the 'NASDAQ.AAPL' dataset. The output shows a MSE of 0.6426408211943265 and an MAE of 0.07550728216058407. Cell [59] is a comment '#Time Series Forecasting for NASDAQ.ADP'. Cells [60] and [61] show the creation of a DataFrame 'df\_ADP' from a list of lists, with cell [61] displaying its head.

```
[57]: #Accuracy of the Forecast using MSE-Mean Squared Error
[58]: from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.AAPL -', mean_squared_error(df_AAPL['NASDAQ.AAPL'],df_AAPL['Forecast']))
print('Mean Absolute Error NASDAQ.AAPL -', mean_absolute_error(df_AAPL['NASDAQ.AAPL'],df_AAPL['Forecast']))
Mean Squared Error NASDAQ.AAPL - 0.6426408211943265
Mean Absolute Error NASDAQ.AAPL - 0.07550728216058407
[59]: #Time Series Forecasting for NASDAQ.ADP
[60]: df_ADP = final[['Month',stock_features[1]]]
[61]: df_ADP.head()
```

This screenshot shows the continuation of the JupyterLab session. The notebook 'DSM\_Project5.ipynb' is still open in Python 3. The code cell [61] shows the output of 'df\_ADP.head()' which displays the first five rows of the DataFrame. The Month column shows dates from 1970-01-01 to 1970-01-05, and the NASDAQ.ADP column shows values ranging from 102.1400 to 102.2300. The next cell, [62], runs 'df\_ADP.set\_index('Month',inplace=True)' followed by 'df\_ADP.head()'. The output shows the DataFrame indexed by 'Month' with the same data points.

```
[61]: df_ADP.head()
[61]:   Month  NASDAQ.ADP
    0  1970-01-01    102.2300
    1  1970-01-01    102.1400
    2  1970-01-01    102.2125
    3  1970-01-01    102.1400
    4  1970-01-01    102.0600
[62]: df_ADP.set_index('Month',inplace=True)
[62]: df_ADP.head()
```

Screenshot of JupyterLab interface showing a time series plot.

The code cell [64] contains:

```
#Visualize Data
df_ADP.plot()
plt.title('Time Series Plot for NASDAQ_ADP')
plt.show()
```

The resulting plot shows a single vertical blue line at approximately 102.1400 for the month of January 1970.

Screenshot of JupyterLab interface showing a time series plot and statistical test results.

The code cell [65] contains:

```
test_stationarity(df_ADP['NASDAQ.ADP'])
```

The plot shows the Rolling Mean & Standard Deviation over time, with a vertical red line indicating the mean.

The output of the Augmented Dickey-Fuller Test is:

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -1.7041735251574455
p-value : 0.42896344420670196
#Lags Used : 39
Number of Observations Used : 11326
```

localhost:8888/lab

DSM\_Project5.ipynb

```
ADF Test Statistic : -1.70427244555
p-value : 0.4289634420670196
#Lags Used : 39
Number of Observations Used : 41226
Critical 1% : value -3.4305086306509716
Critical 5% : value -2.861610111161057
Critical 10% : value -2.5668073179094897
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary
```

[66]: #MAKING THE TIME SERIES STATIONARY  
#Differencing

[67]: df\_ADP = df\_ADP.copy()  
df\_ADP['First\_Difference'] = df\_ADP['NASDAQ.ADP'] - df\_ADP['NASDAQ.ADP'].shift(1)

[68]: df\_ADP.head()

[68]:

	NASDAQ.ADP	First_Difference
Month		
1970-01-01	102.2300	NaN
1970-01-01	102.1400	-0.0900
1970-01-01	102.2125	0.0725
1970-01-01	102.1400	-0.0725
1970-01-01	102.0600	-0.0800

Type here to search

localhost:8888/lab

DSM\_Project5.ipynb

```
1970-01-01 102.1400 -0.0725
1970-01-01 102.0600 -0.0800
```

[69]: df\_ADP.dropna(inplace=True)

[70]: test\_stationarity(df\_ADP['First\_Difference'])
#Now subtract the rolling mean from the original series

Rolling Mean & Standard Deviation

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Acadgild\_DSM\_Session33\_Project x | C Student Dashboard x | JupyterLab x +

localhost:8888/lab

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DSM\_Project5.ipynb x Python 3

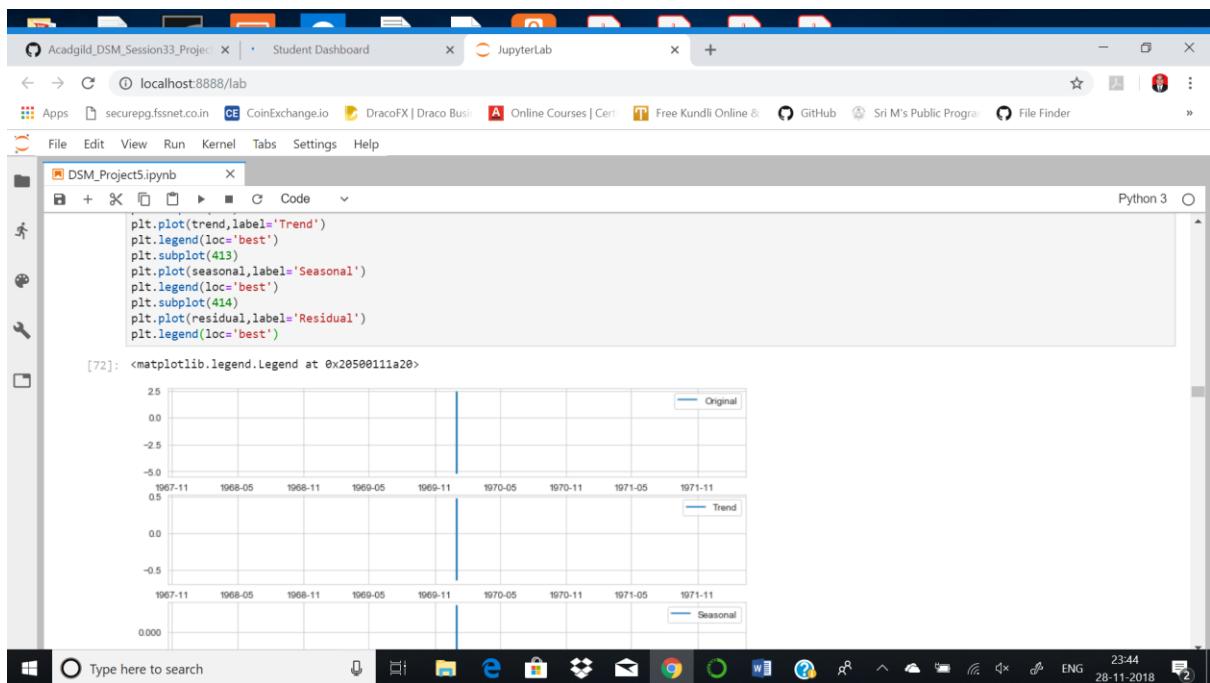
```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
```

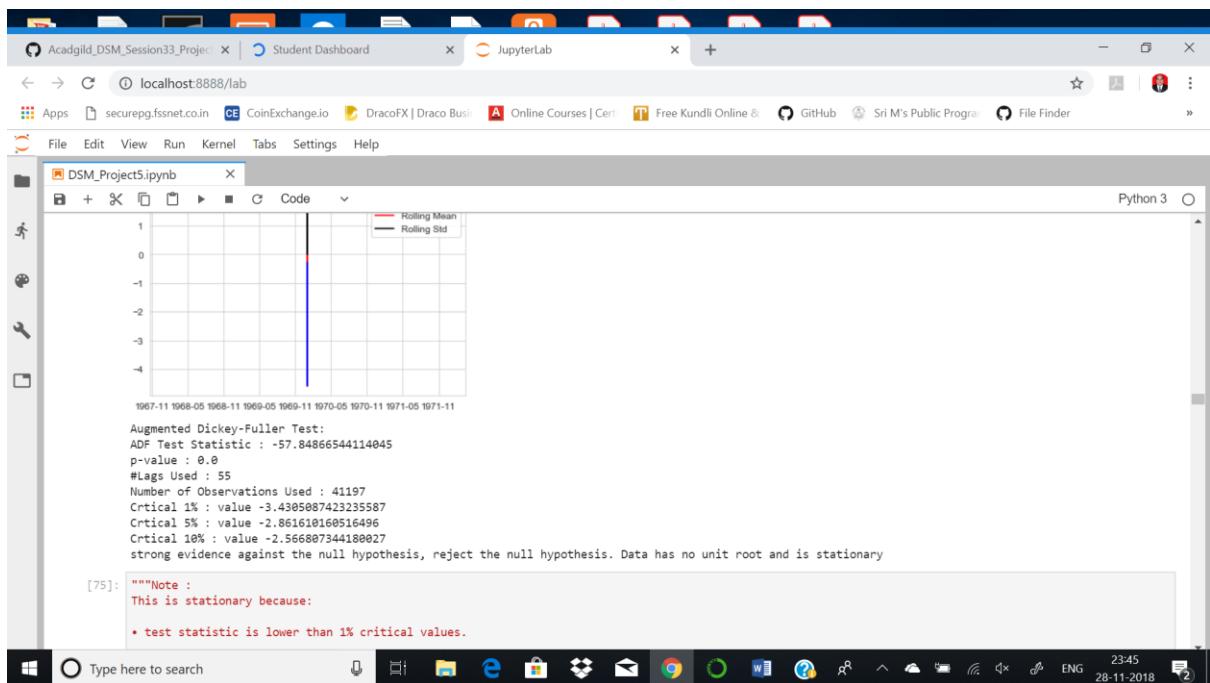
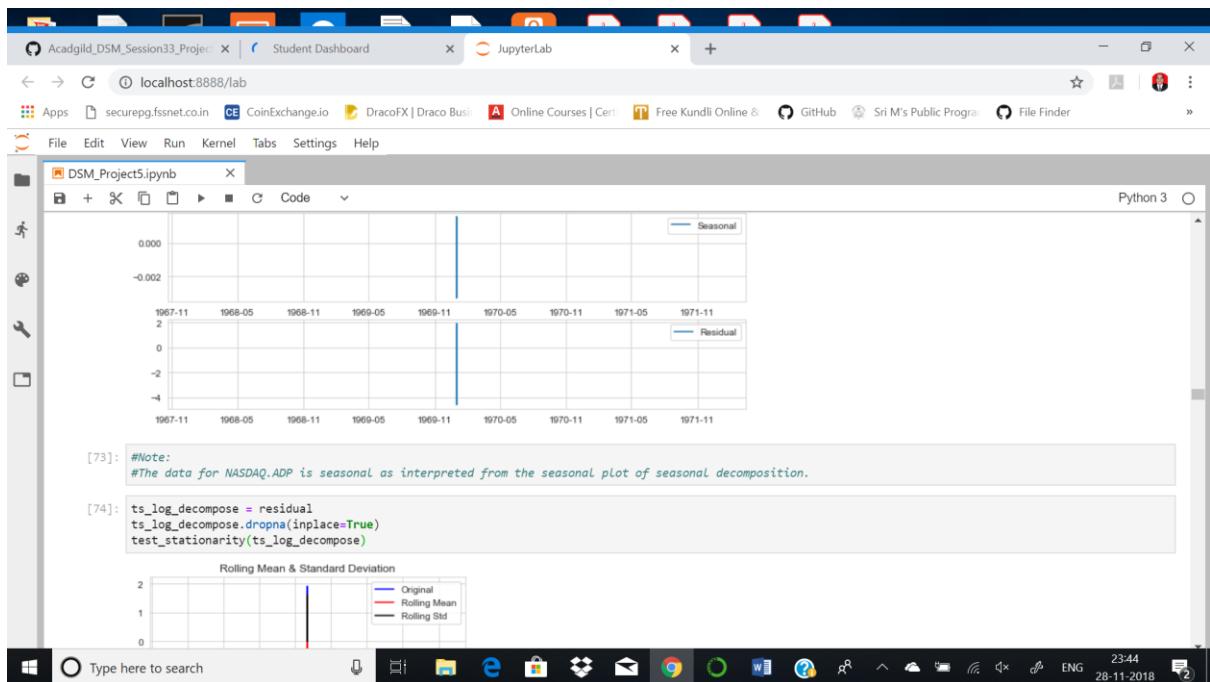
Augmented Dickey-Fuller Test:  
ADF Test Statistic : -31.055662244632277  
p-value : 0.0  
#Lags Used : 38  
Number of Observations Used : 41226  
Critical 1% : value -3.4305086306509716  
Critical 5% : value -2.861618111161057  
Critical 10% : value -2.5668073179094897  
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

[71]: #Seasonal Decomposition

[72]: from statsmodels.tsa.seasonal import seasonal\_decompose  
decomposition = seasonal\_decompose(df\_ADP['First\_Difference'], freq=12)  
trend = decomposition.trend  
seasonal = decomposition.seasonal  
residual = decomposition.resid  
plt.subplot(411)  
plt.plot(df\_ADP['First\_Difference'], label='Original')  
plt.legend(loc='best')  
plt.subplot(412)  
plt.plot(trend, label='Trend')  
plt.legend(loc='best')  
plt.subplot(413)

Type here to search





This is stationary because:

- test statistic is lower than 1% critical values.
- the mean and std variations have small variations with time

Autocorrelation and Partial Correlation plot""

```
[75]: 'Note :\\nThis is stationary because:\\n\\n• test statistic is lower than 1% critical values.\\n\\n• the mean and std variations have small variations with time\\n\\nAutocorrelation and Partial Correlation plot'
```

```
[76]: fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax2)
```

Autocorrelation

1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11

Augmented Dickey-Fuller Test:  
ADF Test Statistic : -57.84866544114045  
p-value : 0.0  
#Lags Used : 55  
Number of Observations Used : 41197  
Critical 1% : value -3.4305087423235587  
Critical 5% : value -2.861610160516496  
Critical 10% : value -2.566807344180027  
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

```
[75]: """Note :
This is stationary because:
• test statistic is lower than 1% critical values.
```

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DSM\_Project5.ipynb

```
This is stationary because:
• test statistic is lower than 1% critical values.
• the mean and std variations have small variations with time
Autocorrelation and Partial Corelation plot"""

[75]: 'Note :nThis is stationary because:n
• test statistic is lower than 1% critical values.
• the mean and std variations have small variations with time
\n\nAutocorrelation and Partial Corelation plot'

[76]: fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax2)
```

Autocorrelation

Partial Autocorrelation

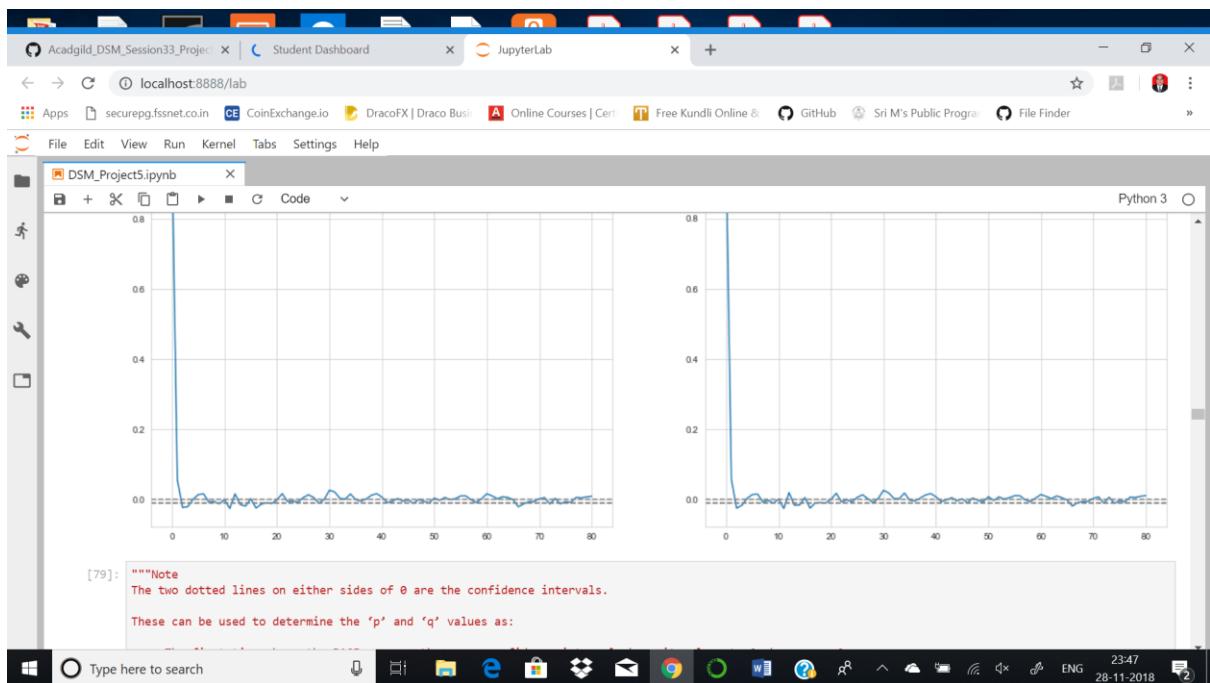
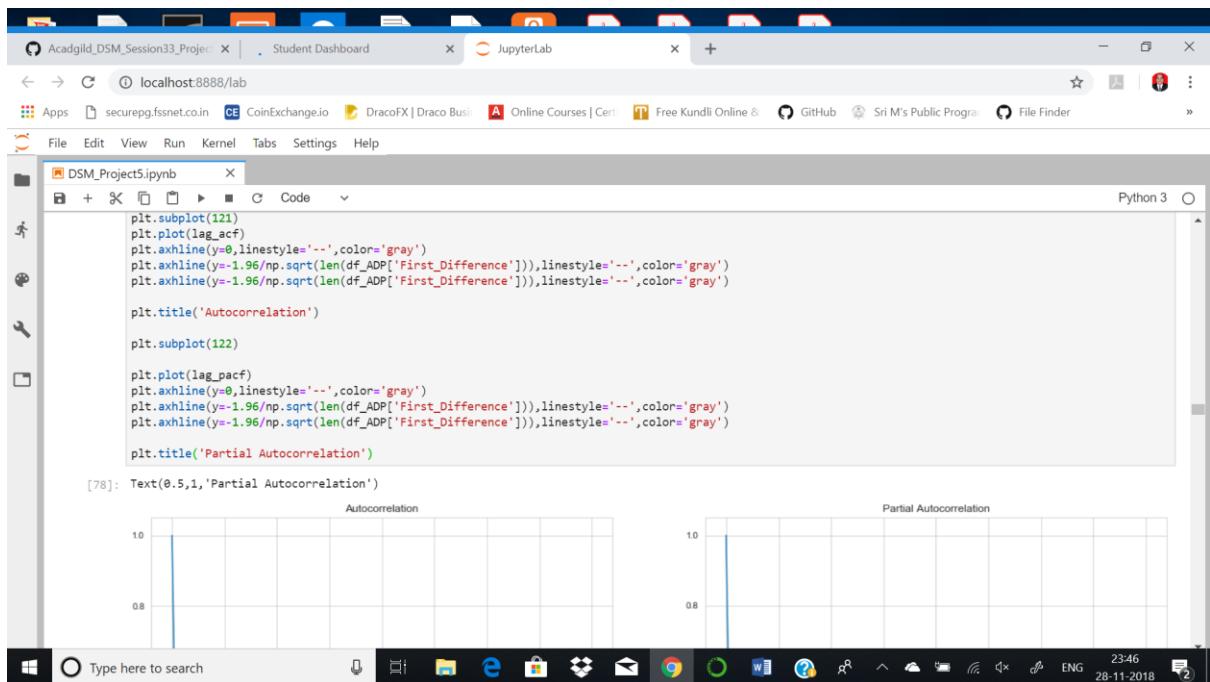
localhost:8888/lab

DSM\_Project5.ipynb

```
lag_acf = acf(df_ADP['First_Difference'], nlags=80)
lag_pacf = pacf(df_ADP['First_Difference'], nlags=80, method='ols')

plt.figure(figsize=(20,8))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0, linestyle='--', color='gray')
```

Partial Autocorrelation



Acadgild\_DSM\_Session33\_Project x | Student Dashboard x | JupyterLab x +

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DSM\_Project5.ipynb x Python 3

```
These can be used to determine the 'p' and 'q' values as:
• p: The first time where the PACF crosses the upper confidence interval, here its close to 0. hence p = 0.
• q: The first time where the ACF crosses the upper confidence interval, here its close to 0. hence p = 0.""""

[79]: 'Note\nThe two dotted lines on either sides of 0 are the confidence intervals.\n\nThese can be used to determine the 'p' and 'q' values as:\n\n• p: The first time where the PACF crosses the upper confidence interval, here its close to 0. hence p = 0.\n• q: The first time where the ACF crosses the upper confidence interval, here its close to 0. hence p = 0.'"""

[80]: model= sm.tsa.statespace.SARIMAX(df_ADP['NASDAQ.ADP'],order=(0,1,0),seasonal_order=(0,1,0,12))
results = model.fit()
print(results.summary())

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
Statespace Model Results
=====
Dep. Variable:          NASDAQ.ADP    No. Observations:      41265
Model:                  SARIMAX(0, 1, 0)x(0, 1, 0, 12) Log Likelihood       34733.913
Date:           Wed, 28 Nov 2018   AIC                  -69464.026
Time:            23:03:16         BIC                  -69455.399
Sample:                   0   HQIC                  -69461.299
                           - 41265
Covariance Type:             opg
```

Type here to search

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localhost:8888/lab

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DSM\_Project5.ipynb x Python 3

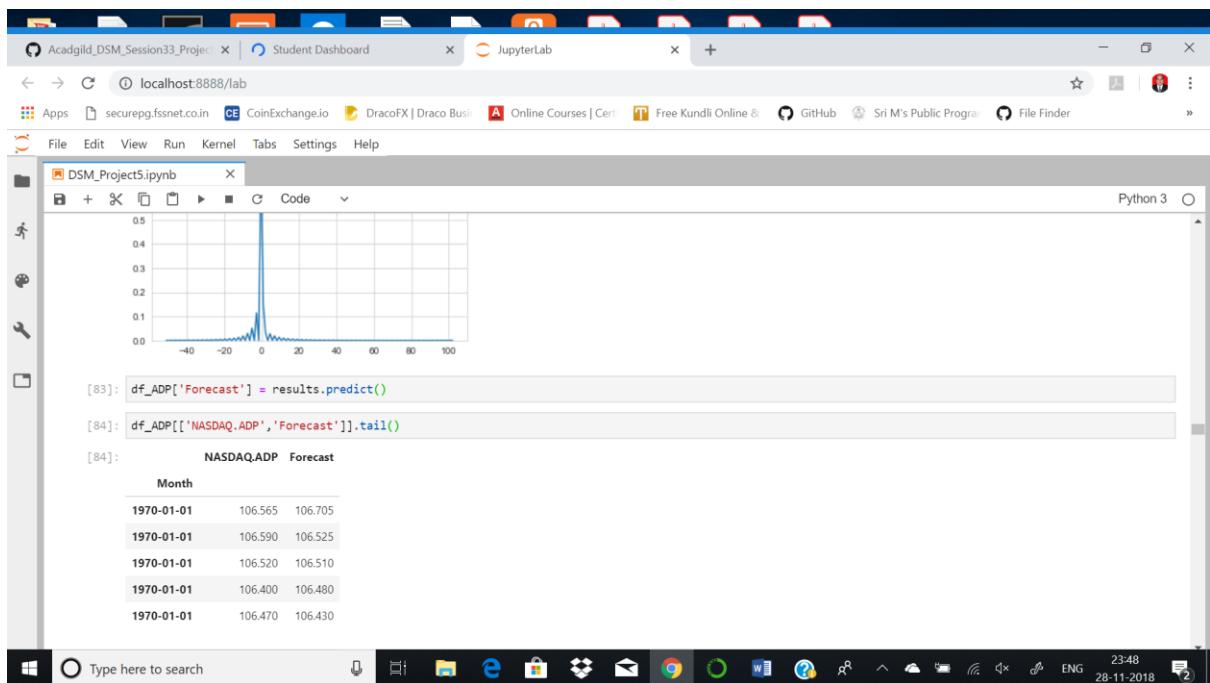
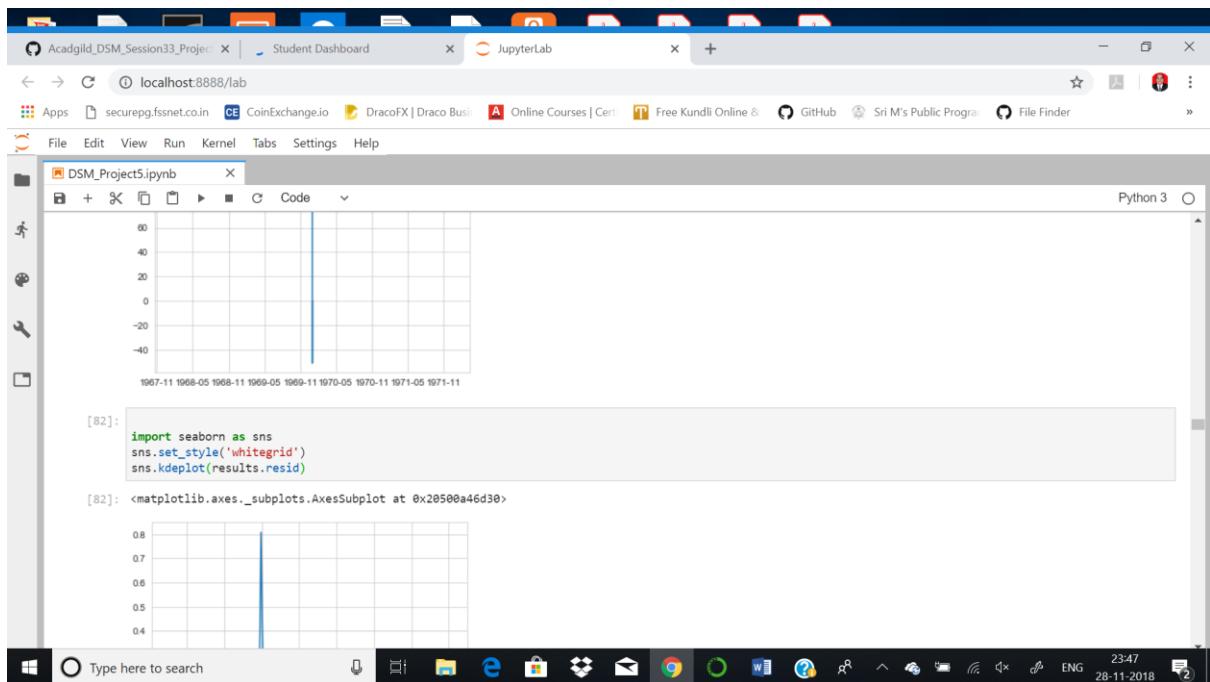
```
Sample:                      0   HQIC                  -69461.299
Covariance Type:             opg
=====
coef  std err      z  P>|z|   [0.025  0.975]
-----
sigma2  0.0109  5.34e-06  2036.759  0.000  0.011  0.011
=====
Ljung-Box (Q):           10628.96  Jarque-Bera (JB):  275266215.34
Prob(Q):                  0.00  Prob(JB):                0.00
Heteroskedasticity (H):   2.20  Skew:                  -1.59
Prob(H) (two-sided):      0.00  Kurtosis:              403.17
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[81]: plt.plot(results.resid)

[81]: []
```





The screenshot shows a JupyterLab interface running on a Windows desktop. The title bar indicates the window is titled 'JupyterLab' and the URL is 'localhost:8888/lab'. The sidebar on the left lists 'DSM\_Project5.ipynb' as the active notebook. The main area displays two code cells:

```
[85]: results.forecast(steps=10)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
ValueWarning)
[85]: 41265 106.470
41266 106.470
41267 106.440
41268 106.380
41269 106.440
41270 106.420
41271 106.450
41272 106.385
41273 106.410
41274 106.340
dtype: float64
```

```
[86]: results.predict(start=41264,end=41275)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
ValueWarning)
[86]: 41264 106.430
```

The code cells show the execution of `forecast(steps=10)` and `predict(start=41264,end=41275)`. Both executions result in `ValueWarning` messages indicating that no supported index is available, and the prediction results are given with an integer index beginning at 'start'. The output for the first cell shows a series of 10 predictions starting from index 41265. The output for the second cell shows a single prediction for index 41264.

Screenshot of a Jupyter Notebook session showing a plot and error calculations for NASDAQ ADP data.

**Code and Output:**

```

[86]: given with an integer index beginning at `start'.
ValueWarning)
[86]: 41264 106.430
41265 106.470
41266 106.470
41267 106.440
41268 106.380
41269 106.440
41270 106.420
41271 106.450
41272 106.385
41273 106.410
41274 106.340
41275 106.220
dtype: float64

[87]: df_ADp[['NASDAQ.ADP','Forecast']].plot(figsize=(20,8))
[87]: <matplotlib.axes._subplots.AxesSubplot at 0x2050054e7b8>

```

**Code and Output:**

```

[88]: from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.AAPL -', mean_squared_error(df_ADp['NASDAQ.ADP'],df_ADp['Forecast']))
print('Mean Absolute Error NASDAQ.AAPL -', mean_absolute_error(df_ADp['NASDAQ.ADP'],df_ADp['Forecast']))

Mean Squared Error NASDAQ.AAPL - 0.3267938112781698
Mean Absolute Error NASDAQ.AAPL - 0.8533967380522426

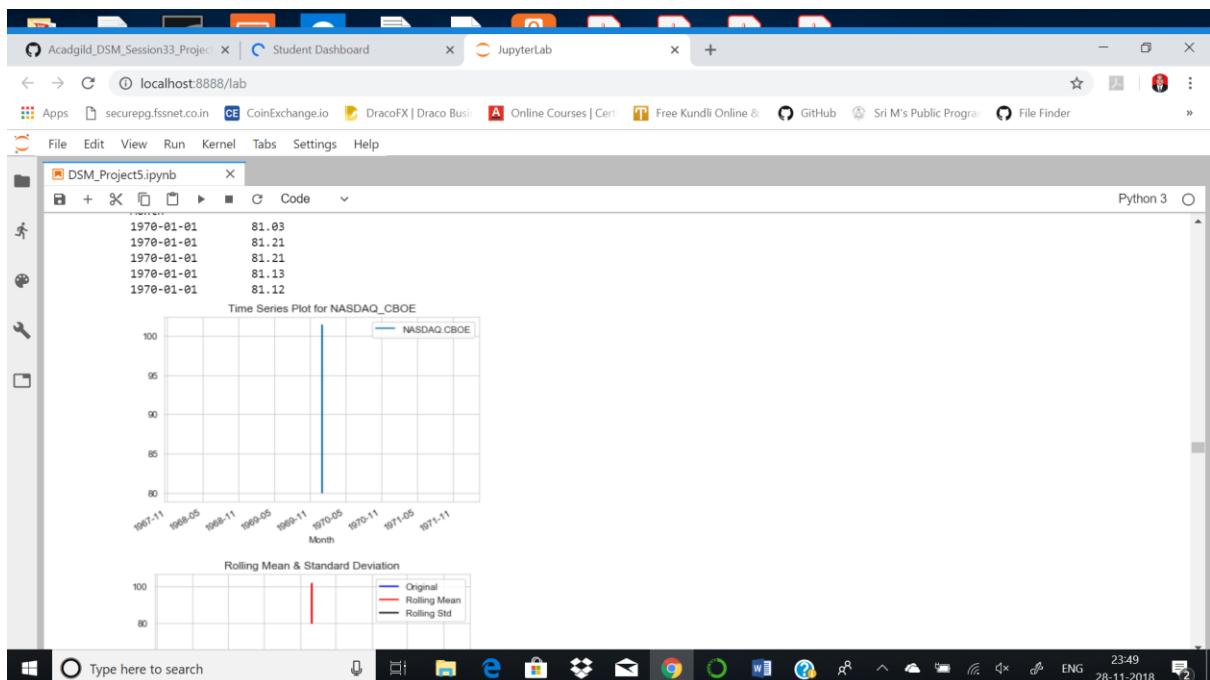
```

Acadgild\_DSM\_Session33\_Project | Student Dashboard | JupyterLab | localhost:8888/lab

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DSM\_Project5.ipynb

```
print('Mean Absolute Error NASDAQ_AAPL - ', mean_absolute_error(yt_hat['NASDAQ_AAPL'], yt_hat['forecast']))  
Mean Squared Error NASDAQ_AAPL - 0.3267938112781698  
Mean Absolute Error NASDAQ_AAPL - 0.05339673805222426  
[89]: #Times Series Forecasting for 'NASDAQ_CBOE'  
  
[90]: df_CBOE= final[['Month',stock_features[2]]]  
print(df_CBOE.head())  
df_CBOE.set_index('Month',inplace=True)  
print(df_CBOE.head())  
  
df_CBOE.plot()  
plt.title('Time Series Plot for NASDAQ_CBOE')  
plt.show()  
#test Stationarity  
test_stationarity(df_CBOE['NASDAQ_CBOE'])  
  
Month NASDAQ_CBOE  
0 1970-01-01 81.03  
1 1970-01-01 81.21  
2 1970-01-01 81.21  
3 1970-01-01 81.13  
4 1970-01-01 81.12  
NASDAQ_CBOE  
Month  
1970-01-01 81.03  
1970-01-01 81.21  
1970-01-01 81.21
```



The screenshot shows a JupyterLab interface with a plot titled "Rolling Std" and a cell containing the output of an Augmented Dickey-Fuller Test.

Augmented Dickey-Fuller Test:  
ADF Test Statistic : -0.16633930282615345  
p-value : 0.9703092030510077  
#Lags Used : 27  
Number of Observations Used : 41238  
Critical 1% : value -3.438508584487571  
Critical 5% : value -2.8616100907584228  
Critical 10% : value -2.5668073070497304  
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary

```
[91]: #MAKING THE TIME SERIES STATIONARY  
#Differencing  
[92]: df_CBOE = df_CBOE.copy()
```

The screenshot shows a JupyterLab interface with a cell containing code for differencing and printing the first difference.

```
[92]: df_CBOE = df_CBOE.copy()  
[93]: df_CBOE.head()  
[93]:  
NASDAQ.CBOE  
Month  
1970-01-01    81.03  
1970-01-01    81.21  
1970-01-01    81.21  
1970-01-01    81.13  
1970-01-01    81.12  
[94]: df_CBOE['First_Difference'] = df_CBOE['NASDAQ.CBOE'] - df_CBOE['NASDAQ.CBOE'].shift(1)  
df_CBOE.head()  
[94]:  
NASDAQ.CBOE  First_Difference  
Month  
1970-01-01    81.03    NaN
```

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Month

1970-01-01	81.03	NaN
1970-01-01	81.21	0.18
1970-01-01	81.21	0.00
1970-01-01	81.13	-0.08
1970-01-01	81.12	-0.01

```
[95]: df_CBOE.dropna(inplace=True)
```

```
[96]: #Test Seasonality
```

```
[97]: test_stationarity(df_CBOE['First_Difference'])
```

Rolling Mean & Standard Deviation

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Acadgild\_DSM\_Session33\_Project | Student Dashboard | JupyterLab

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DSM\_Project5.ipynb

```
[95]:
```

```
[96]:
```

```
[97]:
```

```
[98]: #Seasonal Decomposition
```

```
[98]: from statsmodels.tsa.seasonal import seasonal_decompose
```

```
[98]: plt.figure(figsize=(11,8))
```

```
[98]: decomposition = seasonal_decompose(df_CBOE['NASDAQ.CBOE'], freq=12)
```

```
[98]: trend = decomposition.trend
```

```
[98]: seasonal = decomposition.seasonal
```

```
[98]: residual = decomposition.resid
```

```
[98]: plt.subplot(411)
```

```
[98]: plt.plot(df_CBOE['NASDAQ.CBOE'], label='Original')
```

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Acadgild\_DSM\_Session33\_Project x | Student Dashboard x JupyterLab x +

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DSM\_Project5.ipynb x Python 3

```
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_CBOE['NASDAQ.CBOE'],label='Original')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend,label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonal')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual,label='Residual')
plt.legend(loc='best')
```

[98]: <matplotlib.legend.Legend at 0x205193fbe10>

The figure consists of four vertically stacked subplots. The first subplot shows the 'Original' time series from November 1967 to November 1971. The second subplot shows the 'Trend' component. The third subplot shows the 'Seasonal' component. The fourth subplot shows the 'Residual' component. All plots share a common x-axis representing time from November 1967 to November 1971.

Acadgild\_DSM\_Session33\_Project x | Student Dashboard x JupyterLab x +

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DSM\_Project5.ipynb x Python 3

```
plt.figure(figsize=(20,8))
fig_acf = plot_acf(df_AAPL["First_Difference"],lags=30,title='Autocorrelation-NASDAQ.AAPL')
```

<Figure size 1440x576 with 0 Axes>

Autocorrelation-NASDAQ AAPL

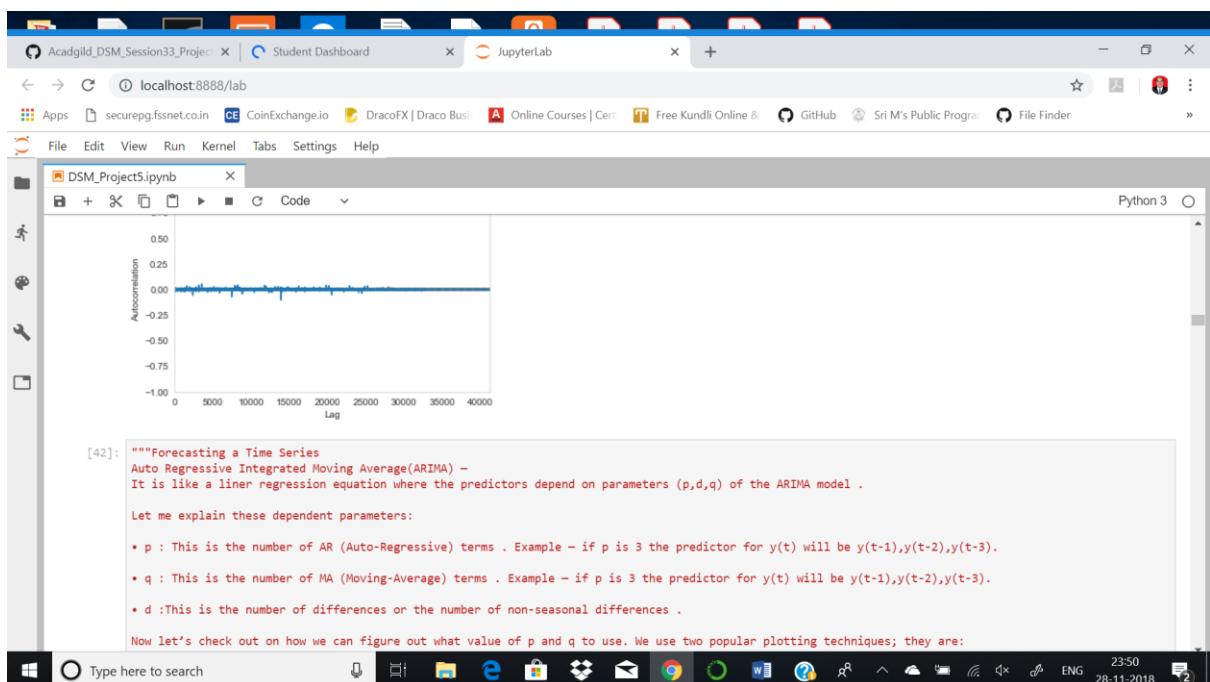
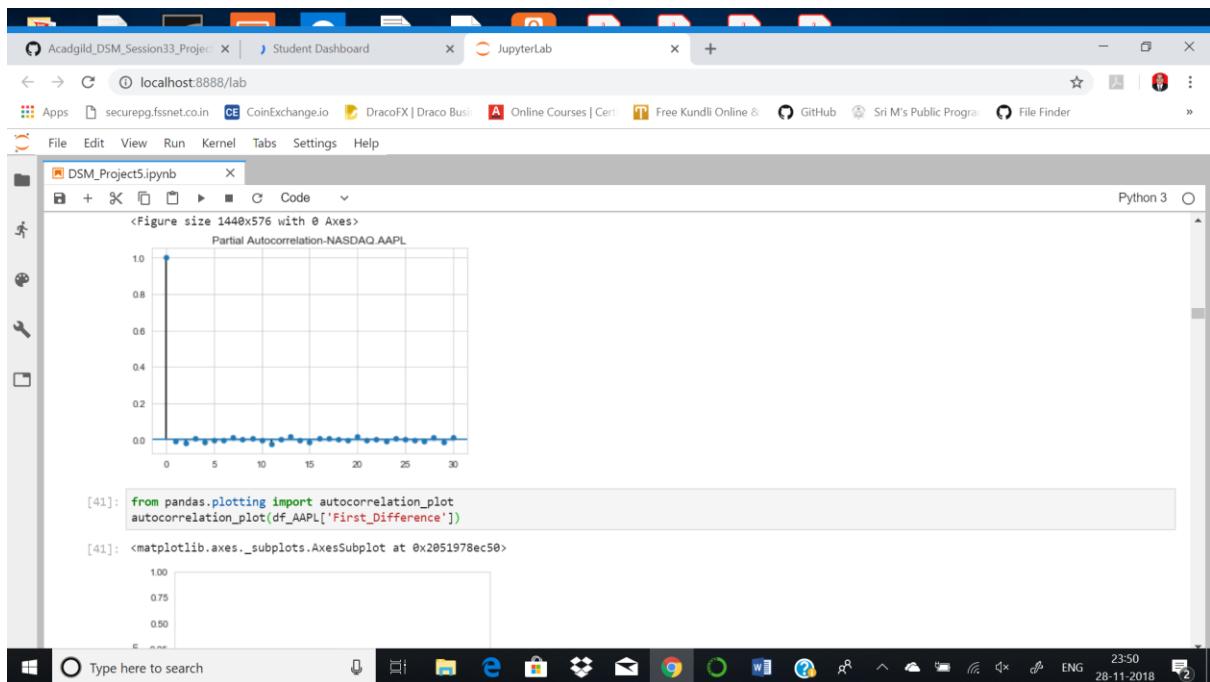
This is an autocorrelation function (ACF) plot titled 'Autocorrelation-NASDAQ AAPL'. It shows the autocorrelation values for the first difference of the NASDAQ AAPL dataset over 30 lags. The y-axis ranges from 0.0 to 1.0, and the x-axis ranges from 0 to 30. The autocorrelation value at lag 0 is approximately 1.0, while all other lags are near zero.

```
plt.figure(figsize=(20,8))
fig_pacf_first = plot_pacf(df_AAPL["First_Difference"],lags=30,title='Partial Autocorrelation-NASDAQ.AAPL')
```

<Figure size 1440x576 with 0 Axes>

Partial Autocorrelation-NASDAQ AAPL

This is a partial autocorrelation function (PACF) plot titled 'Partial Autocorrelation-NASDAQ AAPL'. It shows the partial autocorrelation values for the first difference of the NASDAQ AAPL dataset over 30 lags. The y-axis ranges from 0.0 to 1.0, and the x-axis ranges from 0 to 30. The partial autocorrelation value at lag 0 is approximately 1.0, while all other lags are near zero.

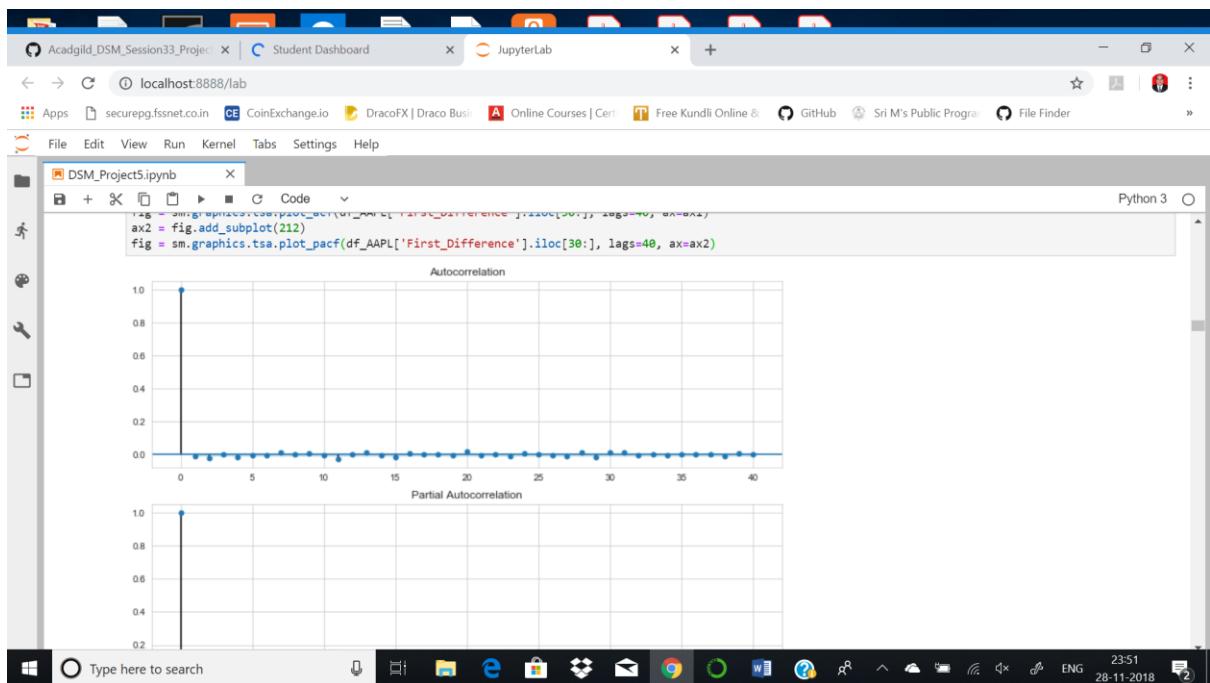


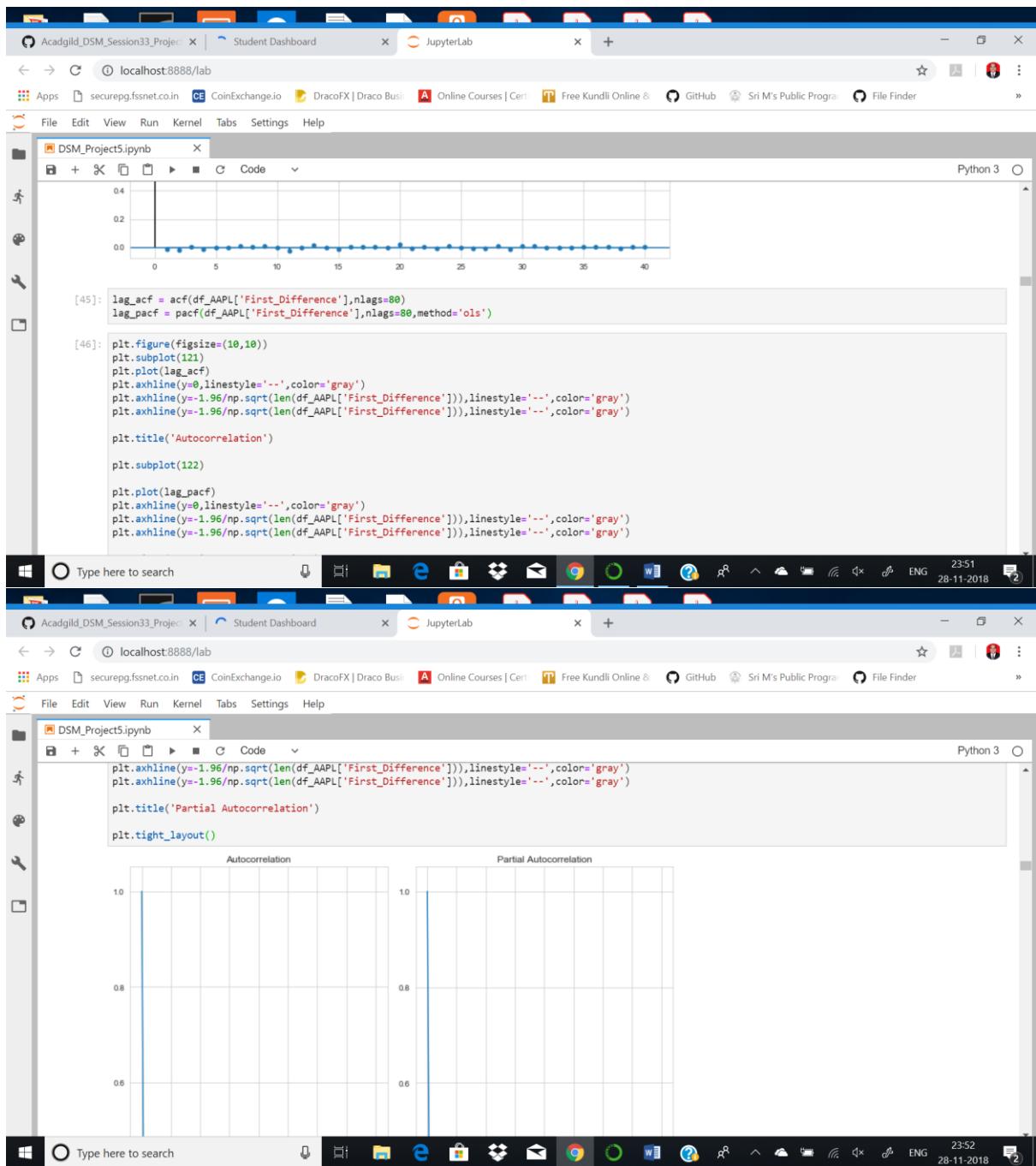
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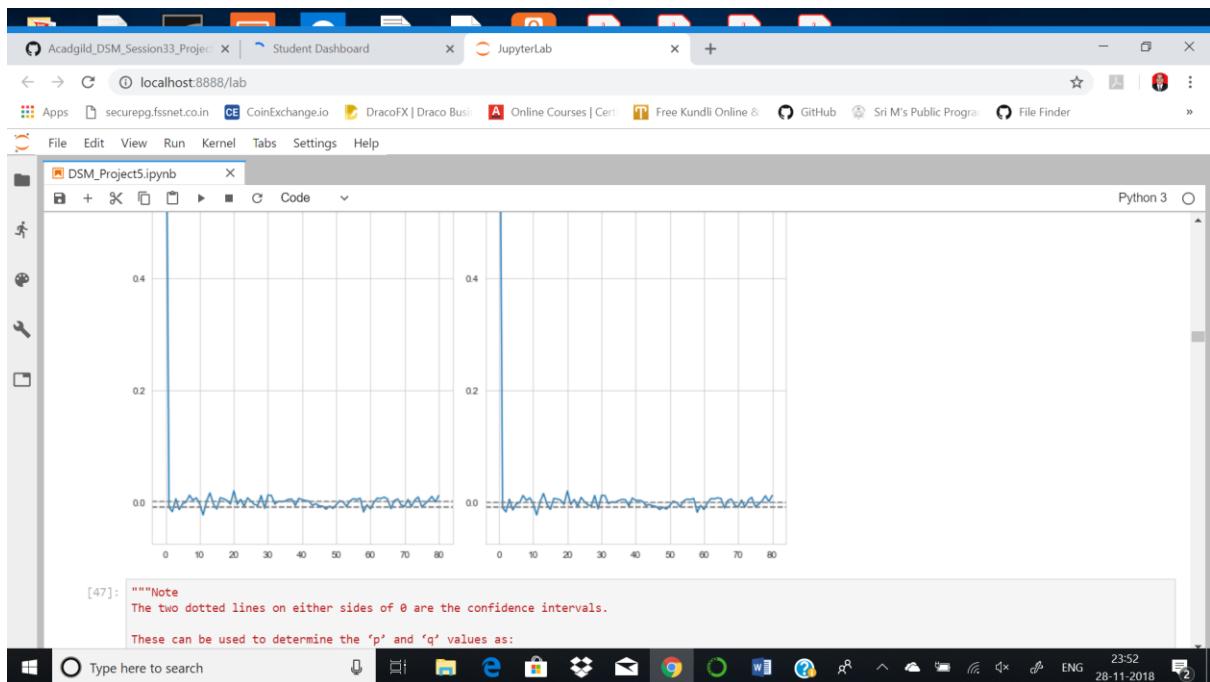
DSM\_Project5.ipynb

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```
[42]: • d :This is the number of differences or the number of non-seasonal differences .  
Now let's check out on how we can figure out what value of p and q to use. We use two popular plotting techniques; they are:  
• Autocorrelation Function (ACF): It just measures the correlation between two consecutive (lagged version). example at lag 4, ACF will compare series at t  
• Partial Autocorrelation Function (PACF): is used to measure the degree of association between  $y(t)$  and  $y(t-p)$ .  
[42]: 'Forecasting a Time Series\nAuto Regressive Integrated Moving Average(ARIMA)\nIt is like a liner regression equation where the predictors depend on parameters (p,d,q) of the ARIMA model .\nlet me explain these dependent parameters:\n p : This is the number of AR (Auto-Regressive) terms . Example\n p is 3 the predictor for  $y(t)$  will be  $y(t-1),y(t-2),y(t-3)$ .  
q : This is the number of MA (Moving-Average) terms . Example\nif p is 3 the predictor for  $y(t)$  will be  $y(t-1),y(t-2),y(t-3)$ .  
d :This is the number of differences or the number of non-seasonal differences .\nNow let's check out on how we can figure out what value of p and q to use. We use two popular plotting techniques; they are:\nAutocorrelation Function (ACF): It just measures the correlation between two consecutive (lagged version). example at lag 4, ACF will compare series at time instance t1-t2 with series at instance t1-4..t2-4.  
Partial Autocorrelation Function (PACF): is used to measure the degree of association between  $y(t)$  and  $y(t-p)$ .'  
[43]: import statsmodels.api as sm  
from statsmodels.tsa.arima_model import ARIMA, ARIMAResults  
from statsmodels.tsa.stattools import acf, pacf  
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf  
[44]: fig = plt.figure(figsize=(12,8))  
ax1 = fig.add_subplot(211)  
fig = sm.graphics.tsa.plot_acf(df_AAPL['First_Difference'].iloc[30:], lags=40, ax=ax1)  
ax2 = fig.add_subplot(212)  
fig = sm.graphics.tsa.plot_pacf(df_AAPL['First_Difference'].iloc[30:], lags=40, ax=ax2)
```







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```
[48]: model = sm.tsa.statespace.SARIMAX(df_AAPL[['NASDAQ.AAPL']],order=(0,1,0),seasonal_order=(0,1,0,12))
results = model.fit()
print(results.summary())

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
Statespace Model Results
=====
Dep. Variable:          NASDAQ.AAPL    No. Observations:      41265
Model:                 SARIMAX(0, 1, 0)x(0, 1, 0, 12) Log Likelihood       24925.552
Date:                  Wed, 28 Nov 2018   AIC                  -49849.104
Time:                      22:58:24     BIC                  -49848.476
Sample:                   0 - 41265   HQIC                  -49846.377
Covariance Type:             opg
=====
            coef    std err      z   P>|z|      [0.025      0.975]
-----
sigma2     0.0175  4.57e-06  3828.712      0.000      0.017      0.017
=====
Ljung-Box (Q):        10611.64  Jarque-Bera (JB):      3462262308.64
Prob(Q):           0.00  Prob(JB):                0.00
Heteroskedasticity (H):      2.92  Skew:                  -2.00
Prob(H) (two-sided):      0.00  Kurtosis:              1422.26
=====
```

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```
[49]: results.resid.plot()

[49]: <matplotlib.axes._subplots.AxesSubplot at 0x2052ea7fcc>
```

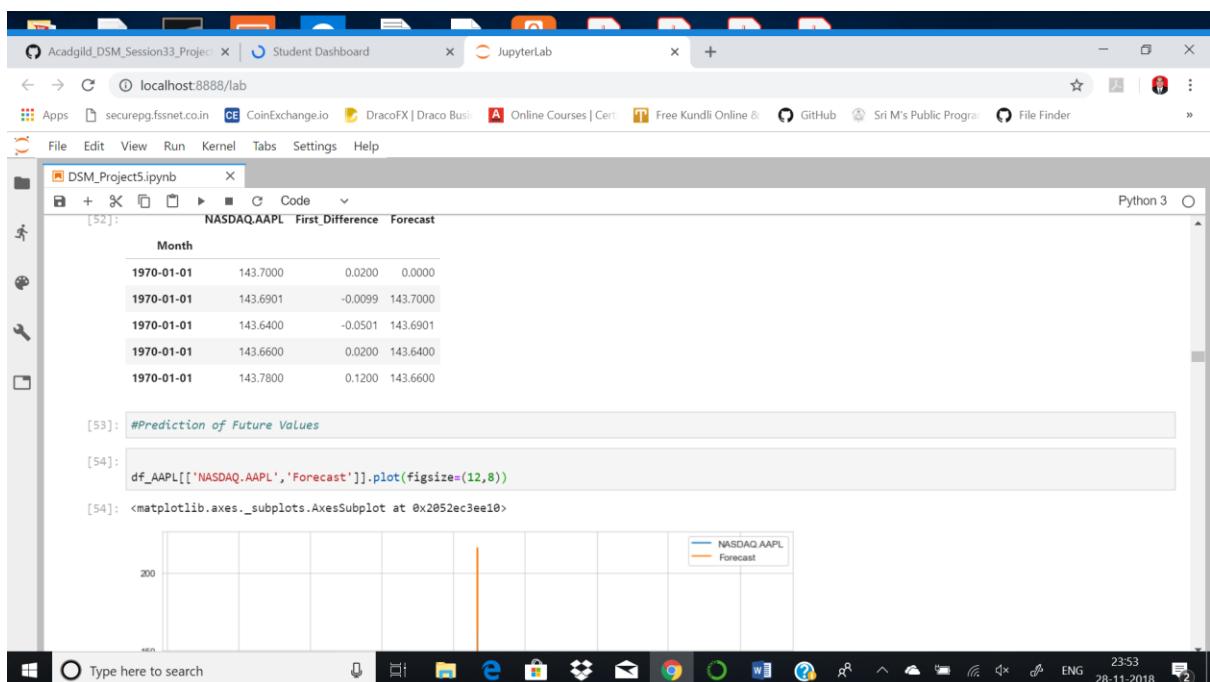
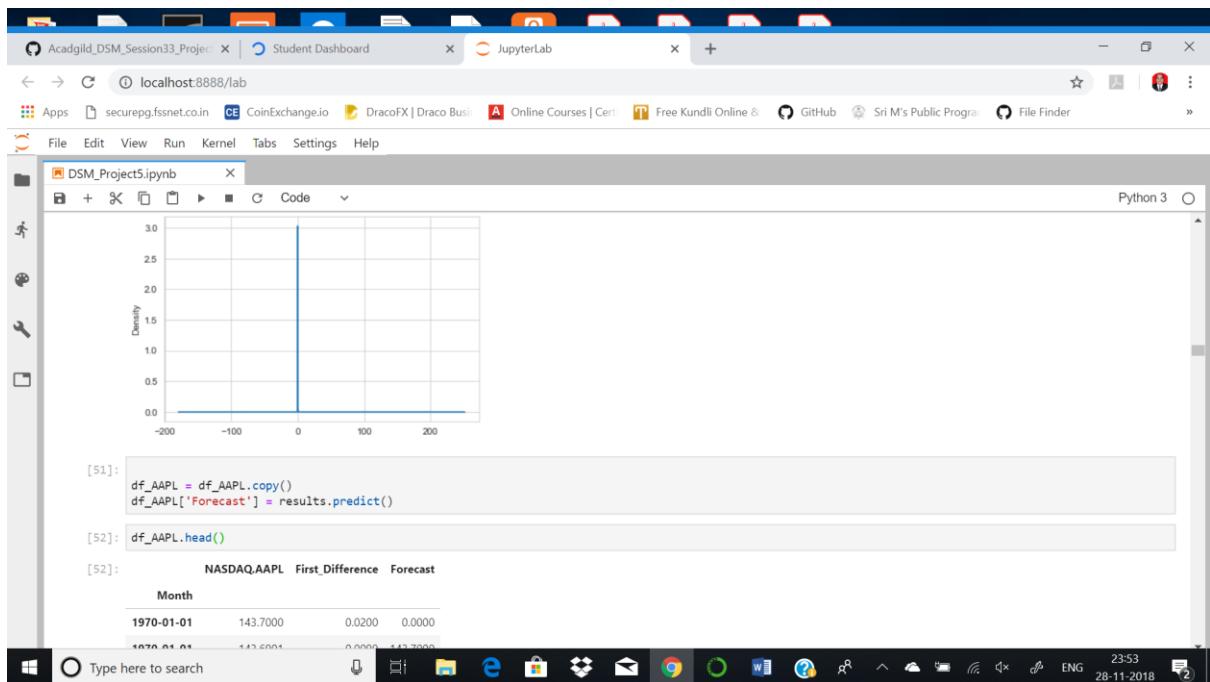
Warnings:

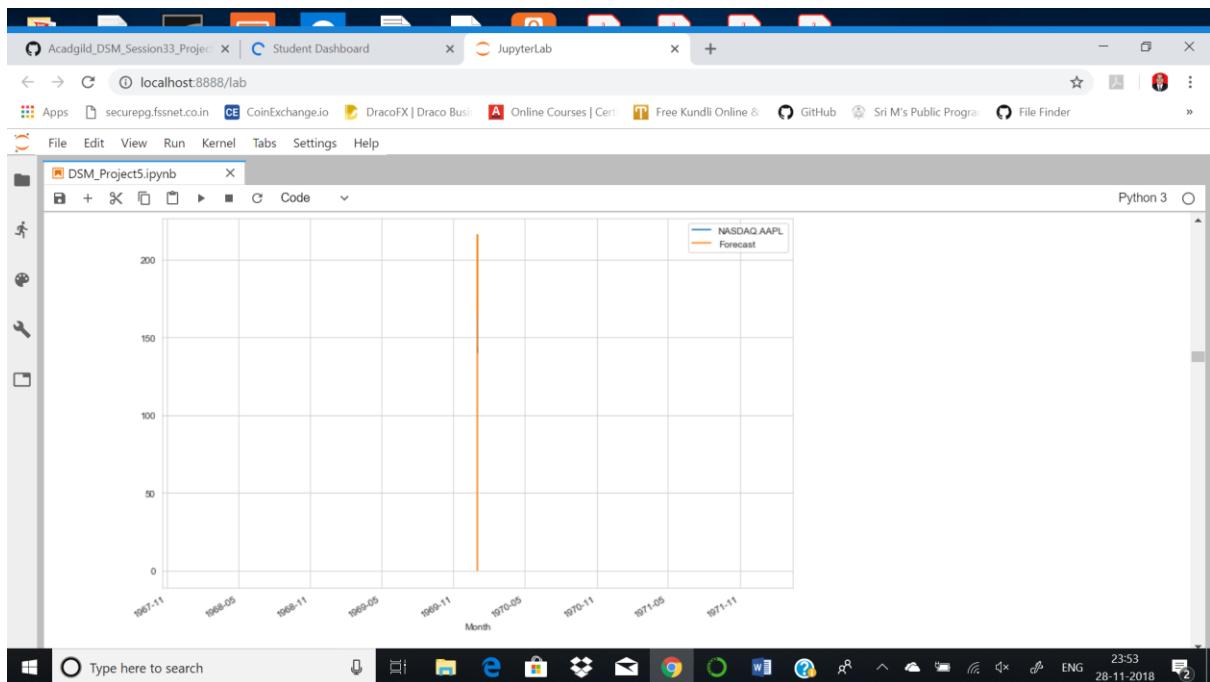
- [1] Covariance matrix calculated using the outer product of gradients (complex-step).

```
[49]: results.resid.plot(kind='kde')

[50]: <matplotlib.axes._subplots.AxesSubplot at 0x205192cdb00>
```

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```

results.forecast(steps=10)

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at `start`.
  ValueWarning)
[55]: 41265 163.960
41266 163.935
41267 163.910
41268 163.810
41269 163.940
41270 163.950
41271 163.890
41272 163.860
41273 163.870
41274 163.760
dtype: float64

[56]: results.predict(start=41264,end=41274)

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at `start`.
  ValueWarning)
[56]: 41264 163.990
41265 163.960
41266 163.935
41267 163.910
41268 163.810

```

```
41271 163.890
41272 163.860
41273 163.870
41274 163.760
dtype: float64
```

```
[57]: #Accuracy of the Forecast using MSE-Mean Squared Error

[58]: from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.AAPL - ', mean_squared_error(df_AAPL['NASDAQ.AAPL'],df_AAPL['Forecast']))
print('Mean Absolute Error NASDAQ.AAPL - ', mean_absolute_error(df_AAPL['NASDAQ.AAPL'],df_AAPL['Forecast']))

Mean Squared Error NASDAQ.AAPL - 0.6426408211943265
Mean Absolute Error NASDAQ.AAPL - 0.07550728216058407
```

```
[59]: #Time Series Forecasting for NASDAQ.ADP
```

```
[60]: df_ADP = final[['Month',stock_features[1]]]
```

```
[61]: df_ADP.head()
```

```
[61]:   Month  NASDAQ.ADP
0  1970-01-01    102.2300
1  1970-01-01    102.1400
2  1970-01-01    102.2125
```

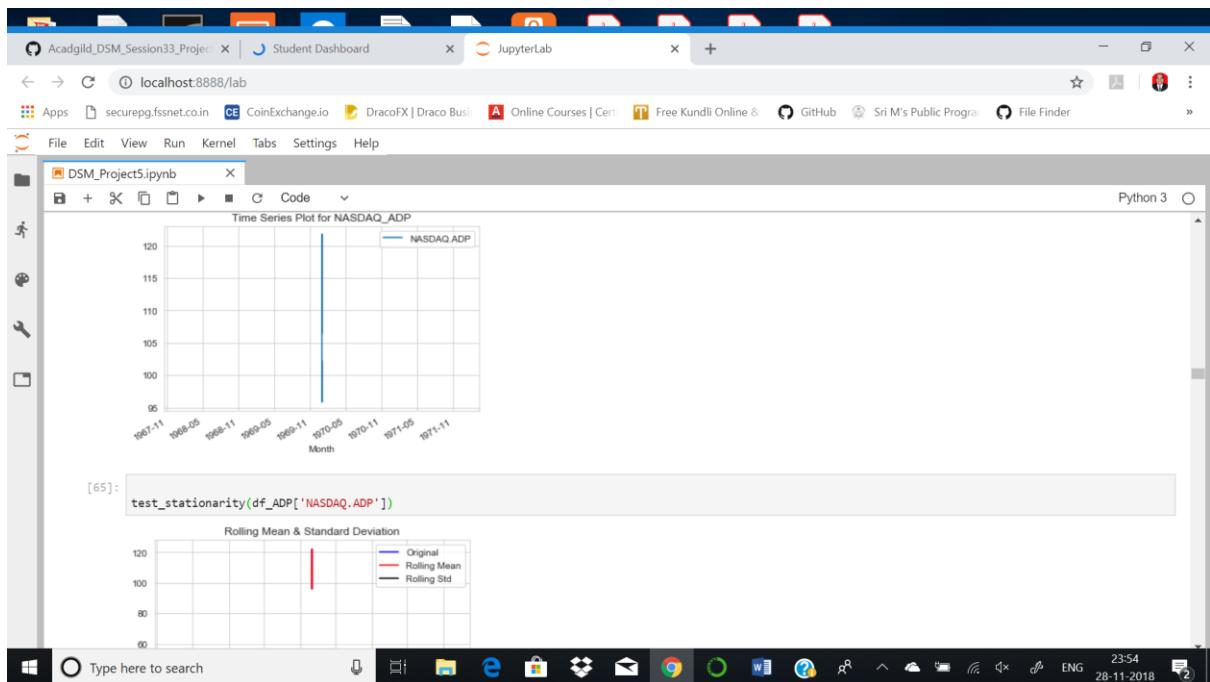
```
3 1970-01-01    102.1400
4 1970-01-01    102.0600
```

```
[62]: df_ADP.set_index('Month',inplace=True)
df_ADP.head()
```

```
[62]:   NASDAQ.ADP
      Month
1970-01-01    102.2300
1970-01-01    102.1400
1970-01-01    102.2125
1970-01-01    102.1400
1970-01-01    102.0600
```

```
[63]: #Visualize Data
```

```
[64]: df_ADP.plot()
plt.title('Time Series Plot for NASDAQ_ADP')
plt.show()
```



The screenshot shows a Jupyter Notebook interface with the following elements:

- Title Bar:** Shows tabs for "Acadgild\_DSM\_Session33\_Project", "Student Dashboard", and "JupyterLab".
- Toolbar:** Includes File, Edit, View, Run, Kernel, Tabs, Settings, Help.
- Code Cell:** Displays the code: `[66]: #MAKING THE TIME SERIES STATIONARY  
#Differencing`, `[67]: df_ADP = df_ADP.copy()  
df_ADP['First_Difference'] = df_ADP['NASDAQ.ADP'] - df_ADP['NASDAQ.ADP'].shift(1)`, and `[68]: df_ADP.head()`.
- Output:** A large block of text output from the "Augmented Dickey-Fuller Test" command, including statistical values and critical levels.
- System Tray:** Shows the date and time as 28-11-2018 23:54.

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```
[68]: df_ADP.head()
[68]: NASDAQ.ADP First_Difference
Month
1970-01-01    102.2300    NaN
1970-01-01    102.1400   -0.0900
1970-01-01    102.2125   0.0725
1970-01-01    102.1400   -0.0725
1970-01-01    102.0600   -0.0800

[69]: df_ADP.dropna(inplace=True)
[70]: test_stationarity(df_ADP['First_Difference'])
#Now subtract the rolling mean from the original series
```

Rolling Mean & Standard Deviation

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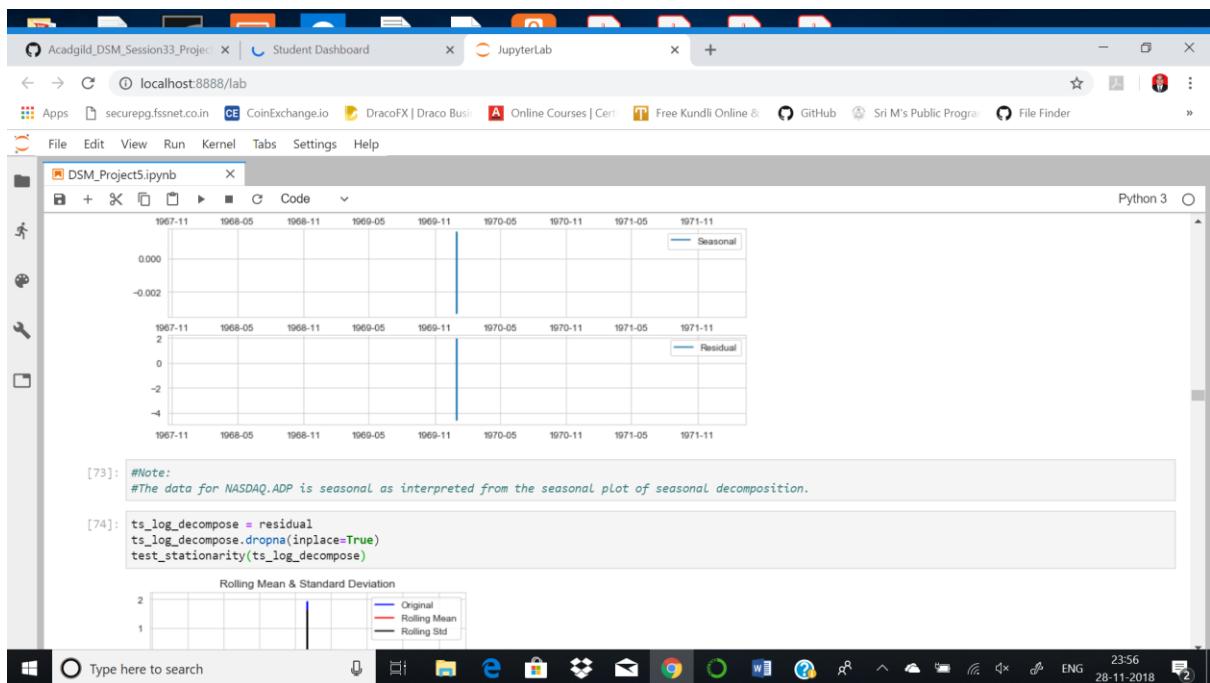
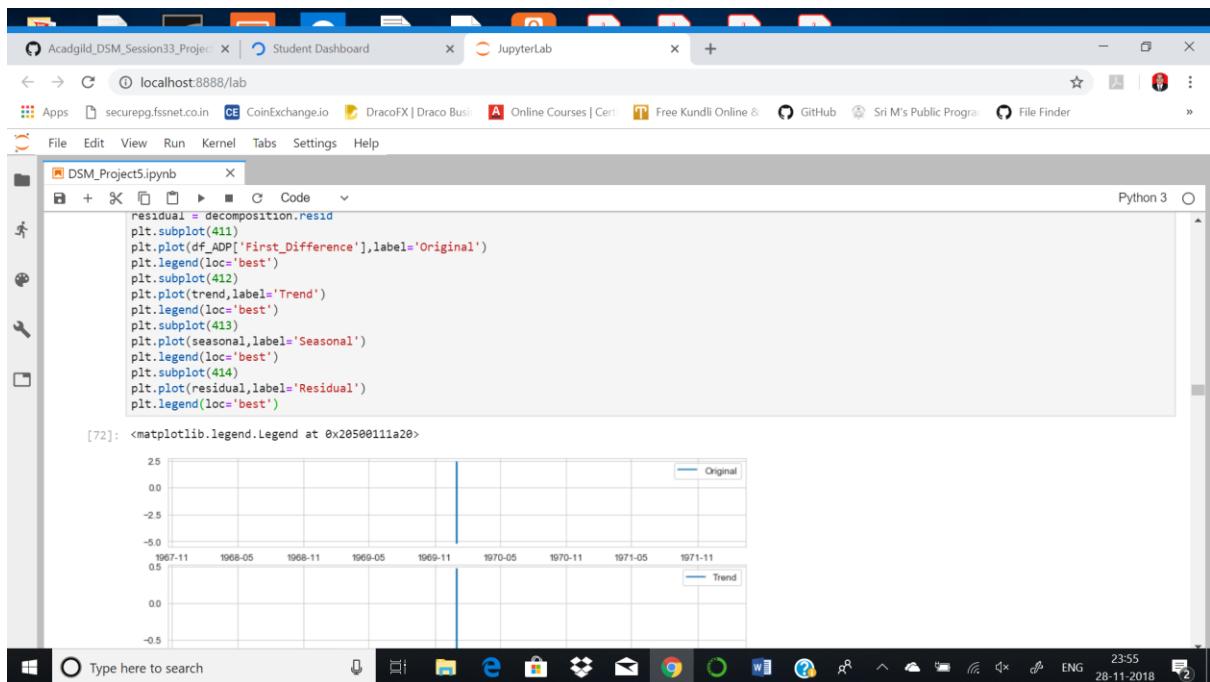
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```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -31.055662244632277
p-value : 0.0
#Lags Used : 38
Number of Observations Used : 41226
Critical 1% : value -3.4305066306509716
Critical 5% : value -2.861618111161057
Critical 10% : value -2.5668073179094897
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

[71]: #Seasonal Decomposition
[72]: from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_ADP['First_Difference'], freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
```

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DSM\_Project5.ipynb

**Rolling Mean & Standard Deviation**

Augmented Dickey-Fuller Test:  
ADF Test Statistic : -57.84866544114045  
p-value : 0.0  
#Lags Used : 55  
Number of Observations Used : 41197  
Critical 1% : value -3.4305087423235587  
Critical 5% : value -2.861610160516496  
Critical 10% : value -2.566807344180027  
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

```
[75]: """Note :
This is stationary because:
```

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DSM\_Project5.ipynb

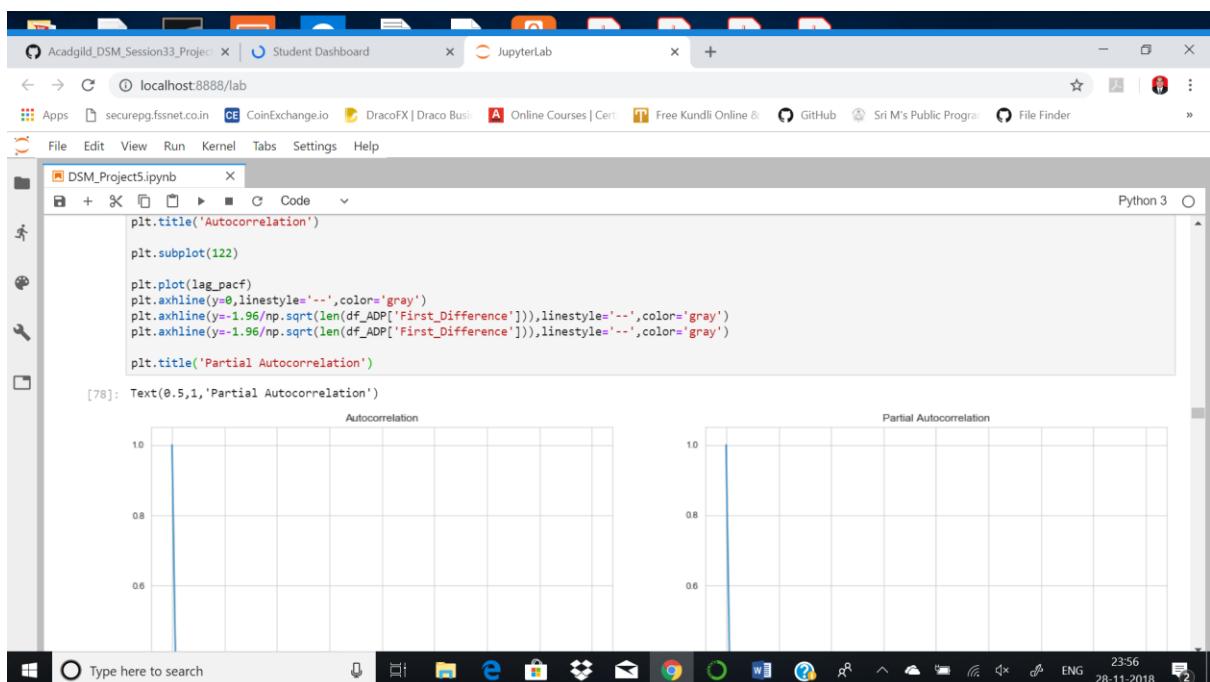
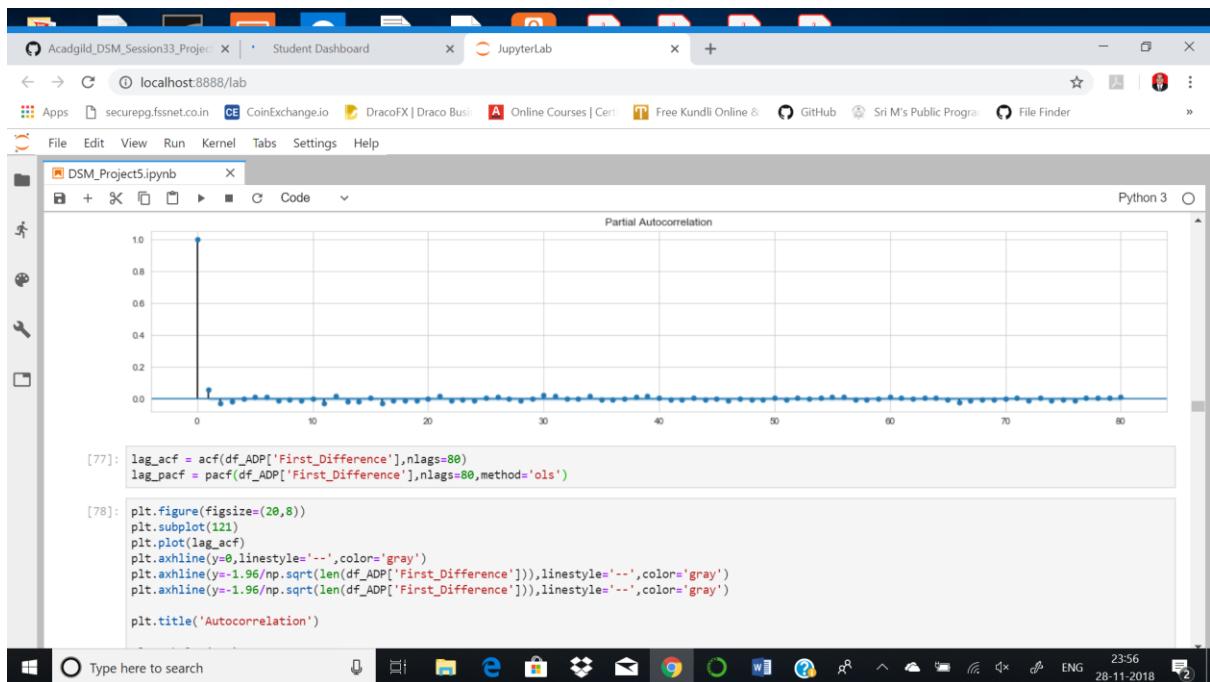
• the mean and std variations have small variations with time  
Autocorrelation and Partial Correlation plot"""

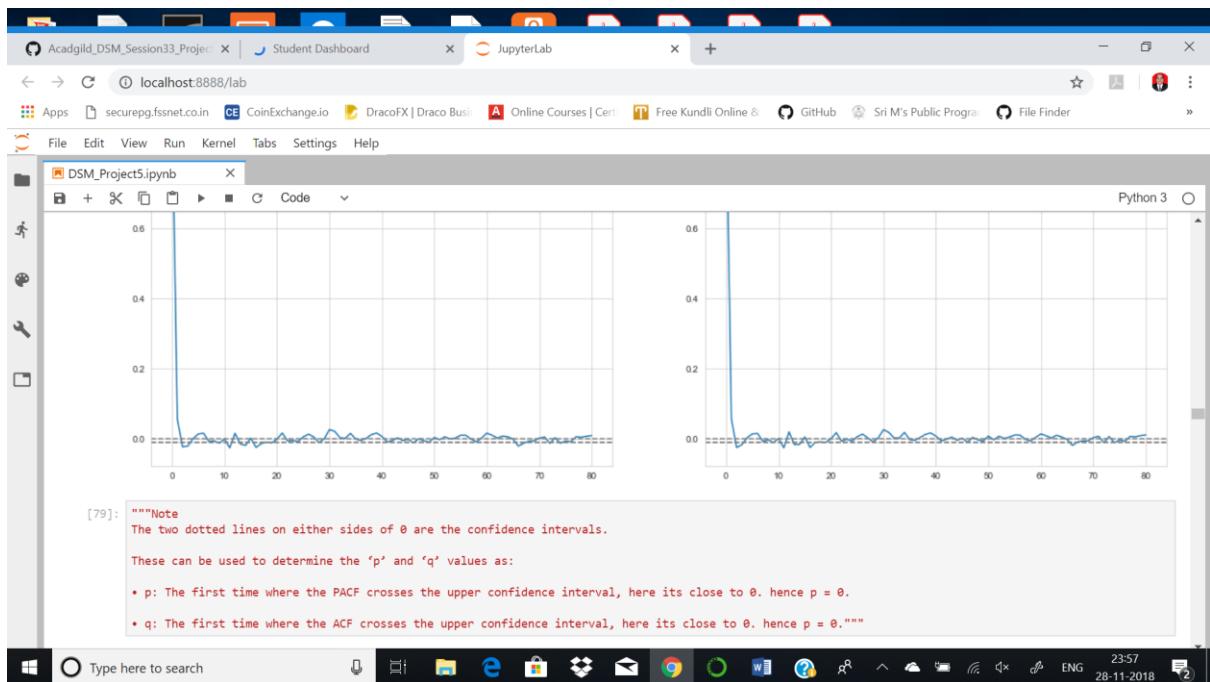
```
[75]: 'Note :\nThis is stationary because:\n\n• test statistic is lower than 1% critical values.\n\n• the mean and std variations have small variations with time\n\n\nAutocorrelation and Partial Correlation plot'

[76]: fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_ADP['First_Difference'].iloc[38:], lags=80, ax=ax2)
```

Autocorrelation

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The screenshot shows a JupyterLab interface with a code cell containing SARIMAX model code. A red warning message is displayed above the output:

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  'ignored when e.g. forecasting.', ValueWarning)
```

The output shows the Statespace Model Results:

```
=====
Dep. Variable:      NASDAQ.ADP  No. Observations:      41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12)  Log Likelihood:     34733.013
Date:           Wed, 28 Nov 2018  AIC:                  -69464.026
Time:            23:03:16   BIC:                  -69455.399
Sample:          0 - 41265   HQIC:                  -69461.299
Covariance Type: opg
=====
            coef    std err      z   P>|z|      [0.025      0.975]
-----
sigma2    0.0109  5.34e-06  2036.759    0.000      0.011      0.011
Ljung-Box (Q):        10628.96  Jarque-Bera (JB):    275266215.34
Prob(Q):            0.00  Prob(JB):                0.00
Heteroskedasticity (H):    2.20  Skew:                 -1.59
Prob(H) (two-sided):    0.00  Kurtosis:              403.17
=====
```

Screenshot of JupyterLab interface showing a notebook named 'DSM\_Project5.ipynb'.

Code in cell [81]:

```
plt.plot(results.resid)
```

Output of cell [81]:

Code in cell [82]:

```
import seaborn as sns
sns.set_style('whitegrid')
sns.kdeplot(results.resid)
```

Screenshot of JupyterLab interface showing a notebook named 'DSM\_Project5.ipynb'.

Code in cell [82]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20500a46d30>
```

Output of cell [82]:

Code in cell [83]:

```
df_ADP['Forecast'] = results.predict()
```

Code in cell [84]:

```
df_ADP[['NASDAQ.ADP','Forecast']].tail()
```

Output of cell [84]:

Month	NASDAQ.ADP	Forecast
1970-01-01	106.565	106.705

Acadgild\_DSM\_Session33\_Project x | Student Dashboard x | JupyterLab x +

localhost:8888/lab

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DSM\_Project5.ipynb x Python 3

```
[85]: results.forecast(steps=10)

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
ValueWarning)
[85]: 41265 106.470
41266 106.470
41267 106.440
41268 106.380
41269 106.440
41270 106.420
41271 106.450
41272 106.385
41273 106.410
41274 106.340
dtype: float64
```

Type here to search 23:57 28-11-2018

Acadgild\_DSM\_Session33\_Project x | Student Dashboard x | JupyterLab x +

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DSM\_Project5.ipynb x Python 3

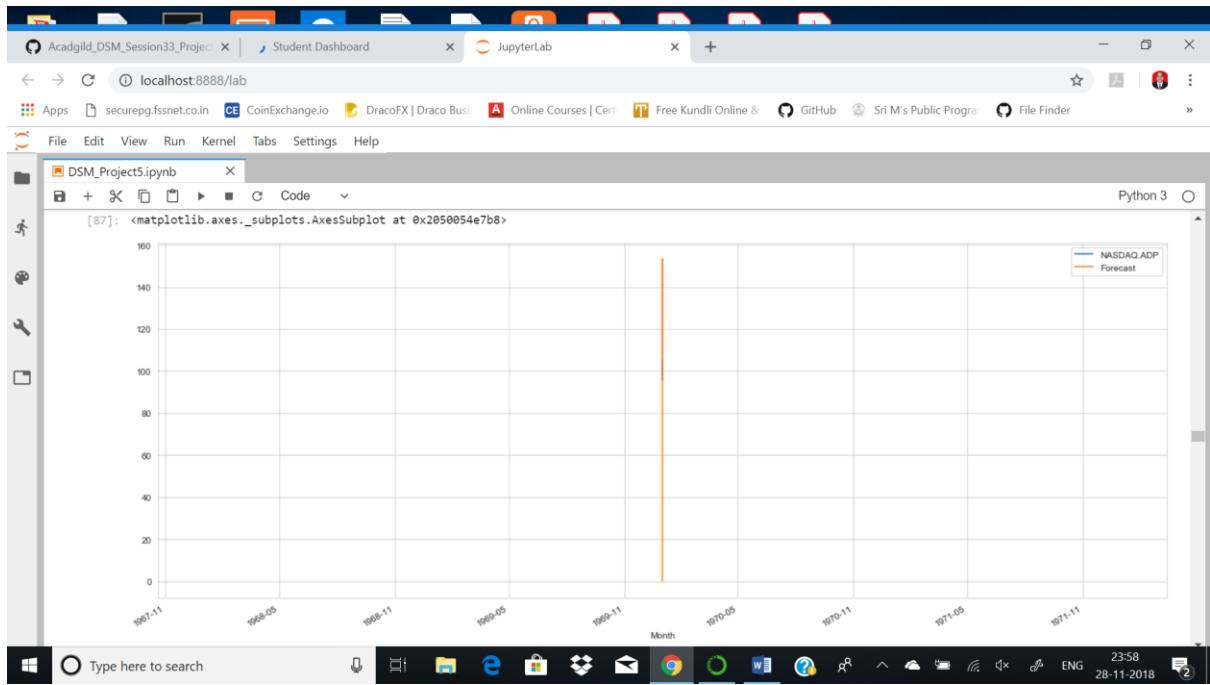
```
[86]: results.predict(start=41264,end=41275)

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
ValueWarning)
[86]: 41264 106.430
41265 106.470
41266 106.470
41267 106.440
41268 106.380
41269 106.440
41270 106.420
41271 106.450
41272 106.385
41273 106.410
41274 106.340
41275 106.220
dtype: float64
```

```
[87]: df_ADP[['NASDAQ.ADP','Forecast']].plot(figsize=(20,8))

[87]: <matplotlib.axes._subplots.AxesSubplot at 0x2050054e7b8>
```

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```
[88]: from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.AAPL -', mean_squared_error(df_ADP['NASDAQ.ADP'],df_ADP['Forecast']))
print('Mean Absolute Error NASDAQ.AAPL -', mean_absolute_error(df_ADP['NASDAQ.ADP'],df_ADP['Forecast']))

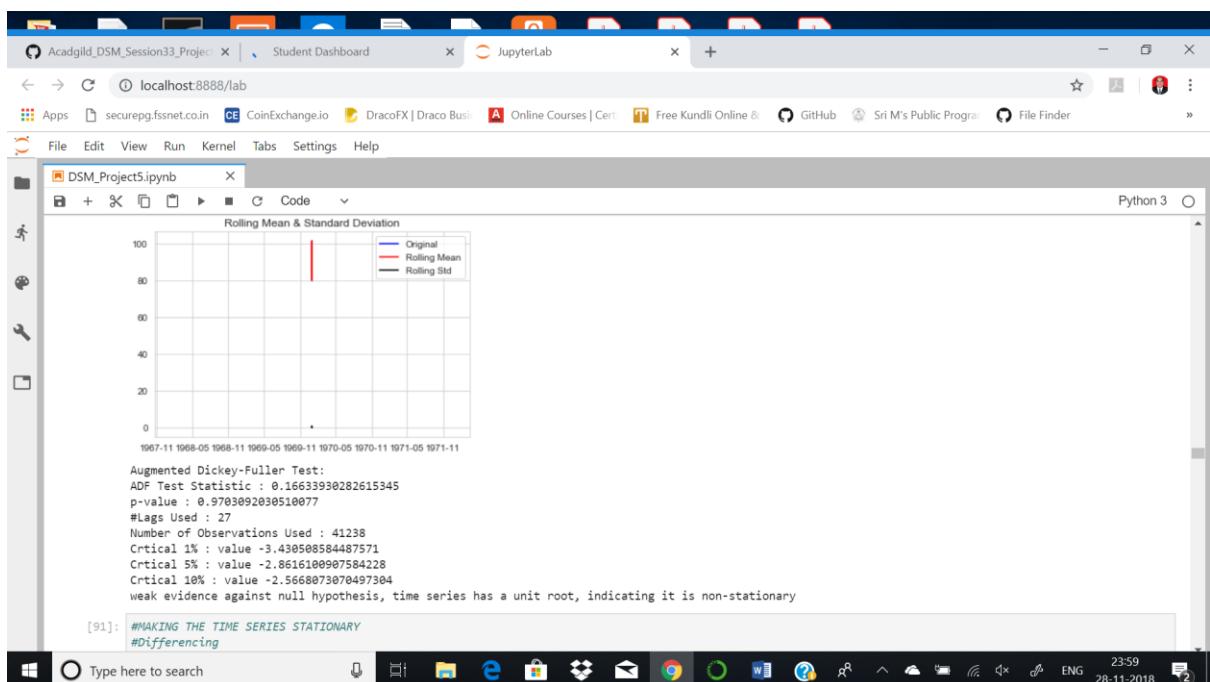
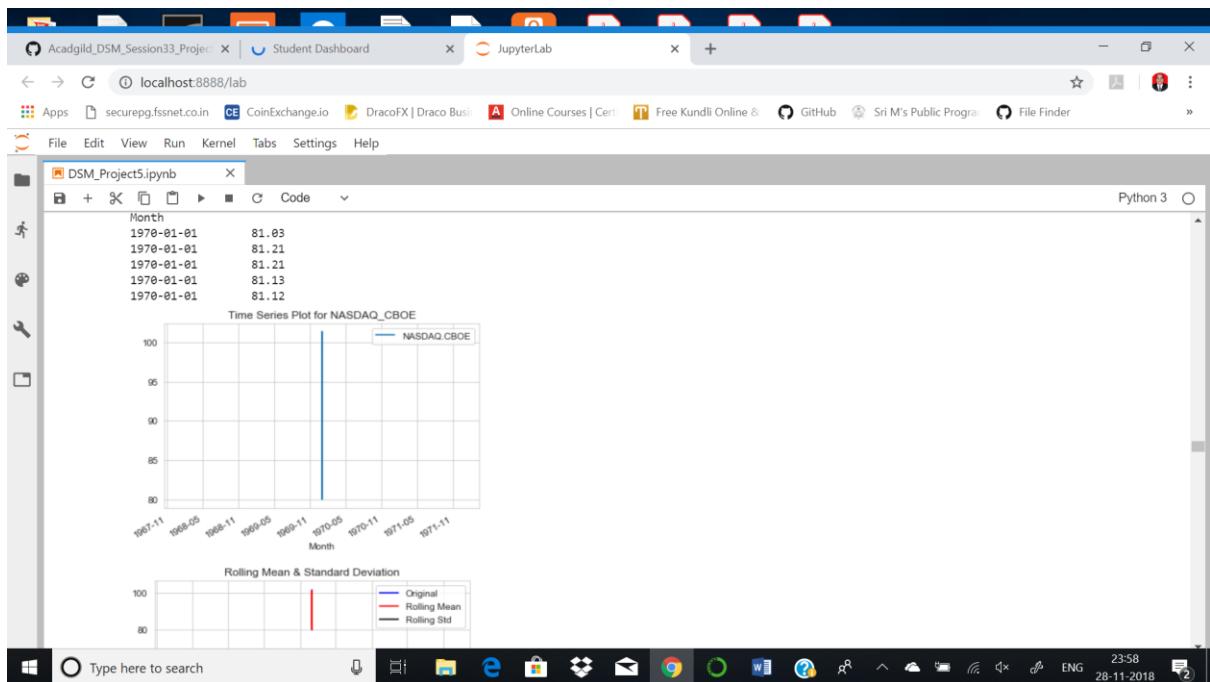
Mean Squared Error NASDAQ.AAPL - 0.3267938112781698
Mean Absolute Error NASDAQ.AAPL - 0.05339673805222426

[89]: #Time Series Forecasting for 'NASDAQ.CBOE'

[90]: df_CBOE= final[['Month',stock_features[2]]]
print(df_CBOE.head())
df_CBOE.set_index('Month',inplace=True)
print(df_CBOE.head())

df_CBOE.plot()
plt.title('Time Series Plot for NASDAQ.CBOE')
plt.show()
#test Stationarity
test_stationarity(df_CBOE['NASDAQ.CBOE'])

      Month    NASDAQ.CBOE
0 1970-01-01     81.03
1 1970-01-01     81.21
2 1970-01-01     81.21
3 1970-01-01     81.13
4 1970-01-01     81.12
   NASDAQ.CBOE
Month
```



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```
[92]: df_CBOE = df_CBOE.copy()
[93]: df_CBOE.head()
[93]: NASDAQ,CBOE
Month
1970-01-01    81.03
1970-01-01    81.21
1970-01-01    81.21
1970-01-01    81.13
1970-01-01    81.12
```

```
[94]: df_CBOE['First_Difference'] = df_CBOE['NASDAQ,CBOE'] - df_CBOE['NASDAQ,CBOE'].shift(1)
df_CBOE.head()
[94]: NASDAQ,CBOE  First_Difference
Month
1970-01-01    81.03      NaN
1970-01-01      NaN      NaN
```

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```
1970-01-01    81.21    0.00
1970-01-01    81.13   -0.08
1970-01-01    81.12   -0.01
```

```
[95]: df_CBOE.dropna(inplace=True)
[96]: #Test Seasonality
[97]: test_stationarity(df_CBOE['First_Difference'])

Rolling Mean & Standard Deviation
```

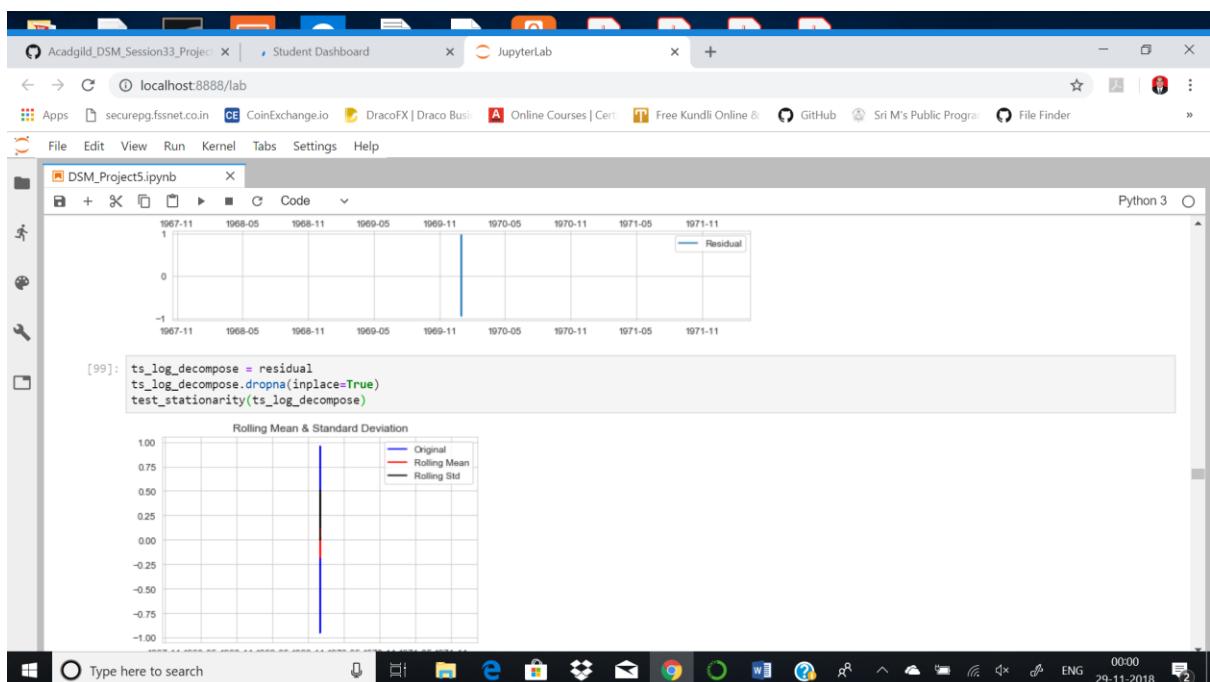
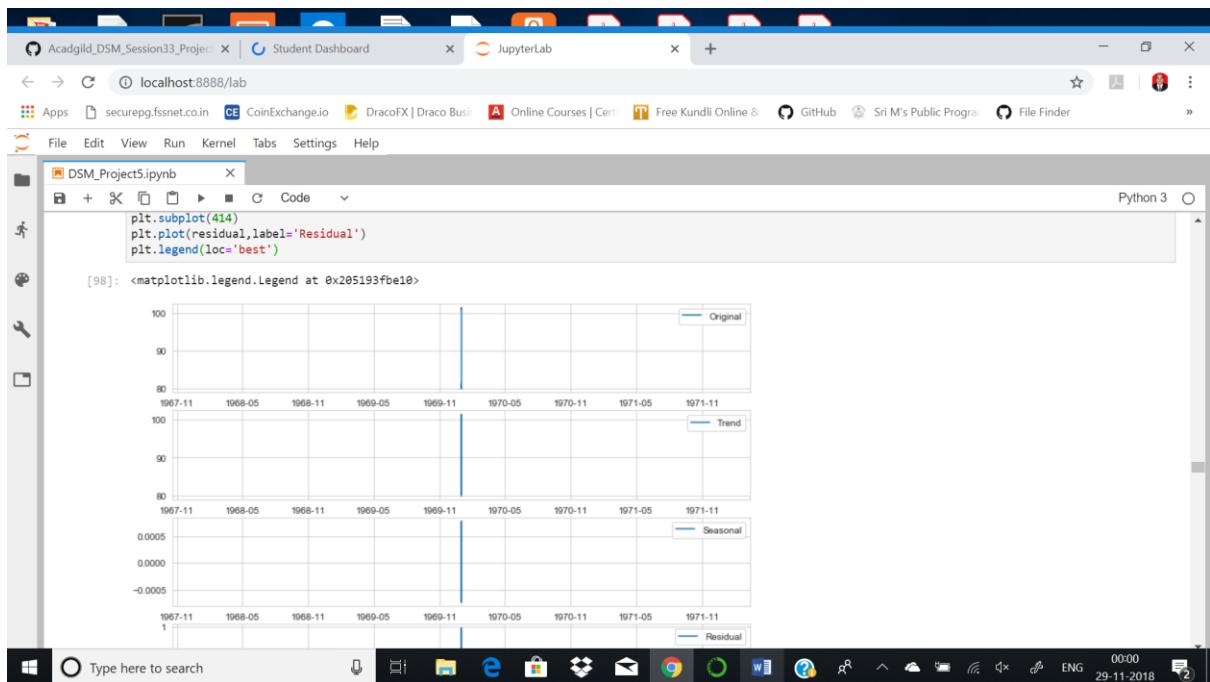
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```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
Augmented Dickey-Fuller Test:
ADF Test Statistic : -41.64209364543141
p-value : 0.0
#Lags Used : 26
Number of Observations Used : 41238
Critical 1% : value -3.430508584487571
Critical 5% : value -2.8616100907584228
Critical 10% : value -2.5668073070497304
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

[98]: #Seasonal Decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_CBOE['NASDAQ.CBOE'], freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_CBOE['NASDAQ.CBOE'],label='Original')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend,label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonal')
plt.legend(loc='best')
```

```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
Augmented Dickey-Fuller Test:
ADF Test Statistic : -41.64209364543141
p-value : 0.0
#Lags Used : 26
Number of Observations Used : 41238
Critical 1% : value -3.430508584487571
Critical 5% : value -2.8616100907584228
Critical 10% : value -2.5668073070497304
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

[98]: #Seasonal Decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_CBOE['NASDAQ.CBOE'], freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
plt.subplot(411)
plt.plot(df_CBOE['NASDAQ.CBOE'],label='Original')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend,label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonal')
plt.legend(loc='best')
```

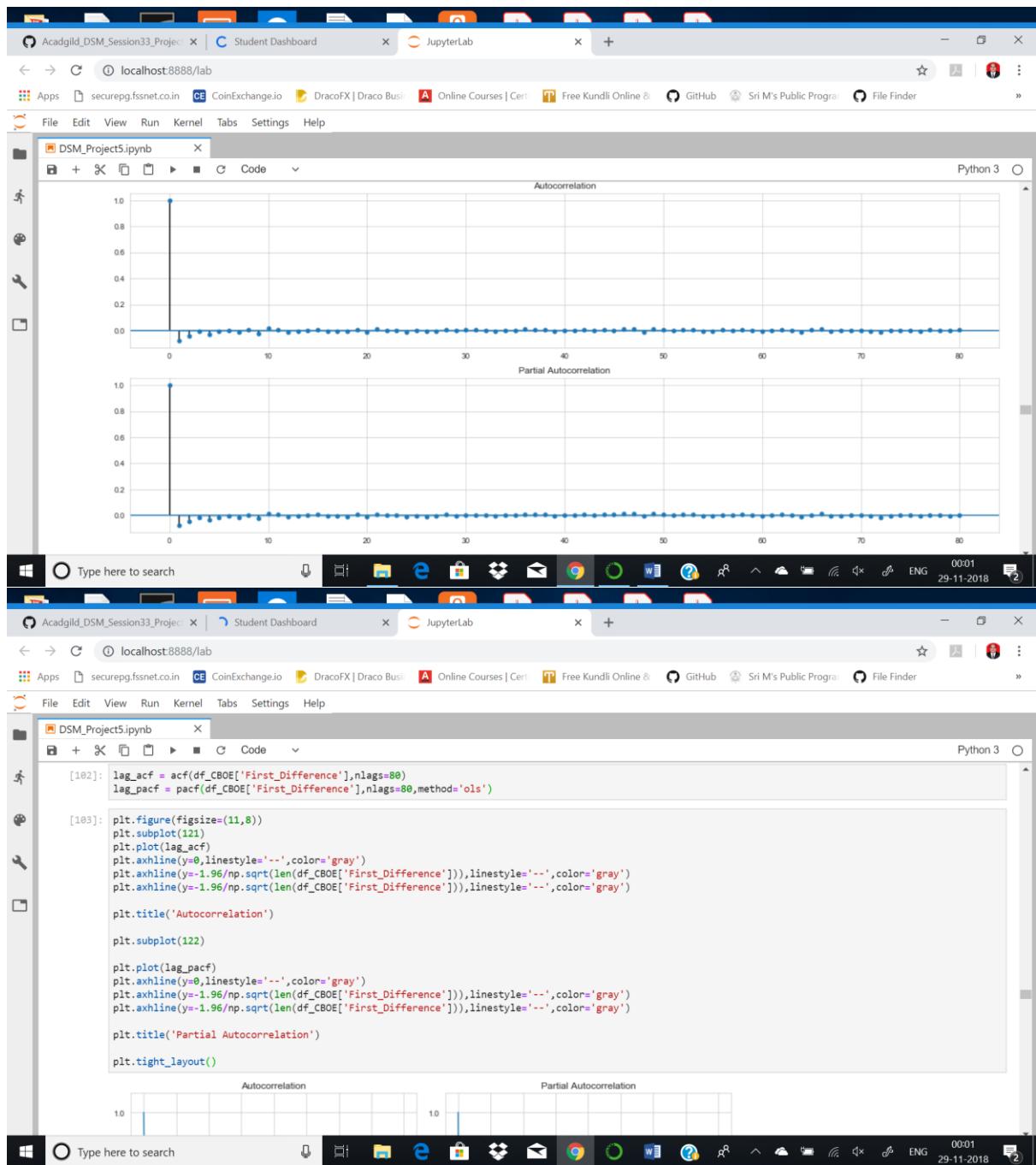


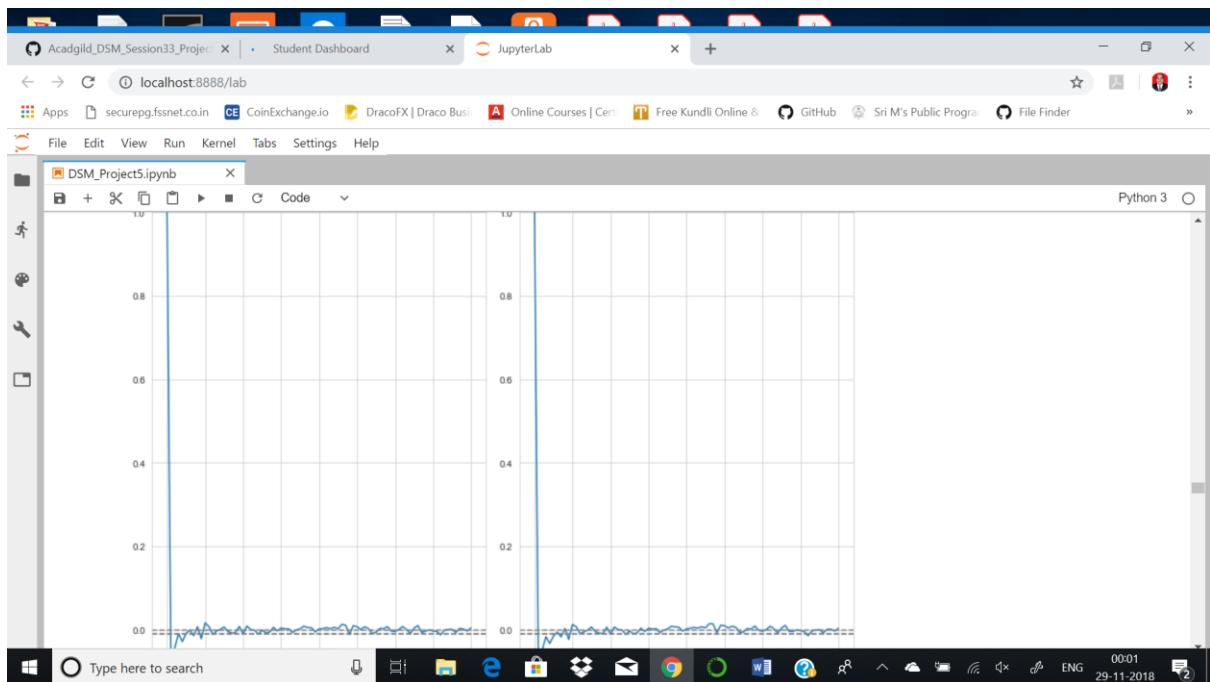
```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
Augmented Dickey-Fuller Test:
ADF Test Statistic : -46.216720532157176
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Critical 1% : value -3.4305087423235587
Critical 5% : value -2.861618160516496
Critical 10% : value -2.566807344180027
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

[100]: """Note :
This is stationary because:
• test statistic is lower than 1% critical values.
• the mean and std variations have small variations with time
Autocorrelation and Partial Corelation plot"""

[100]: 'Note :\nThis is stationary because:\n\n• test statistic is lower than 1% critical values.\n\n• the mean and std variations have small variations with time\n\nAutocorrelation and Partial Corelation plot'

[101]: fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_CBOE['First_Difference'].iloc[26:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
```





```

[104]: """Note
The two dotted lines on either sides of 0 are the confidence intervals.

These can be used to determine the 'p' and 'q' values as:

• p: The first time where the PACF crosses the upper confidence interval, here its close to 0. hence p = 0.

• q: The first time where the ACF crosses the upper confidence interval, here its close to 0. hence p = 0."""

[104]: 'Note\nThe two dotted lines on either sides of 0 are the confidence intervals.\n\nThese can be used to determine the "p" and "q" values as:\n\n• p: The first time where the PACF crosses the upper confidence interval, here its close to 0. hence p = 0.\n• q: The first time where the ACF crosses the upper confidence interval, here its close to 0. hence p = 0.'

[105]: # fit model
model = sm.tsa.statespace.SARIMAX(df_CBOE[['NASDAQ.CBOE']], order=(0,1,0), seasonal_order=(0,1,0,12))
results = model.fit()
print(results.summary())
print(results.forecast())
df_CBOE[['Forecast']] = results.predict()
df_CBOE[['NASDAQ.CBOE','Forecast']].plot(figsize=(20,8))
plt.show()

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  'ignored when e.g. forecasting.', ValueWarning)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check message for details

```

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DSM\_Project5.ipynb

Statespace Model Results

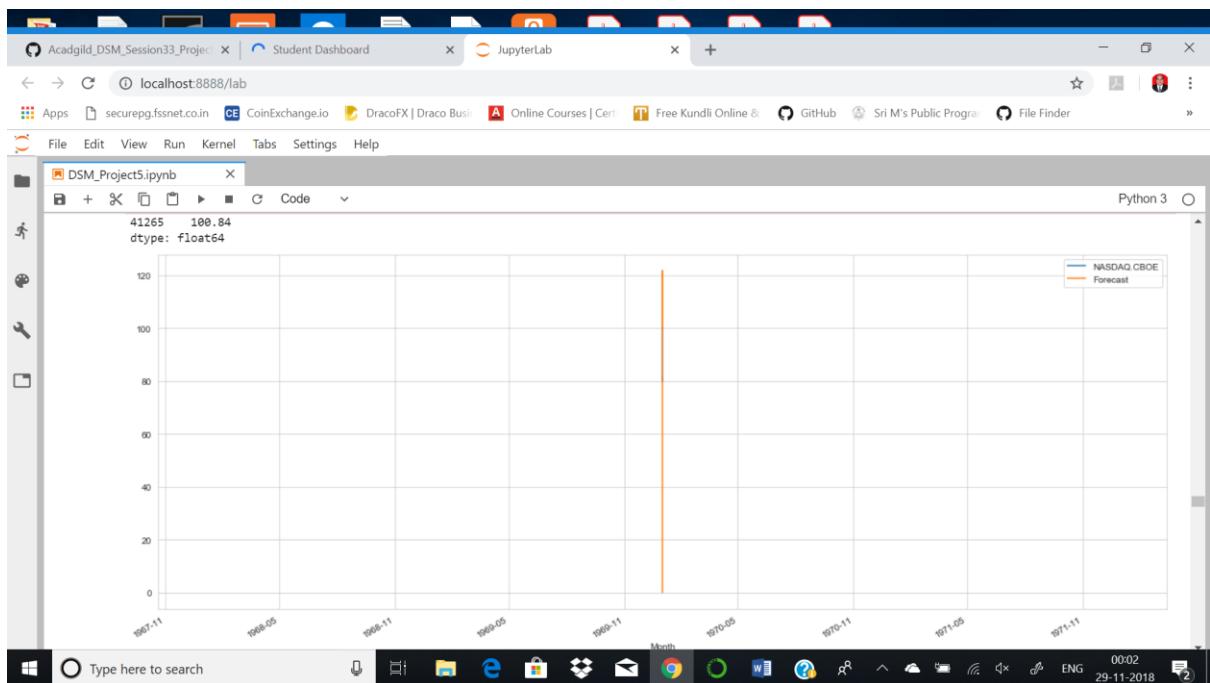
```
=====
Dep. Variable:      NASDAQ.CBOE    No. Observations:      41265
Model:             SARIMAX(0, 1, 0)x(0, 1, 0, 12) Log Likelihood:   -53414.092
Date:          Wed, 28 Nov 2018   AIC:                  -106826.184
Time:              23:13:58     BIC:                  -106817.557
Sample:           0 - 41265    HQIC:                 -106823.457
Covariance Type: opg
=====
            coef  std err      z   P>|z|      [0.025  0.975]
-----
sigma2     0.0044  5.33e-06  824.305  0.000      0.004
=====
Ljung-Box (Q):    11084.06  Jarque-Bera (JB):    7011759.88
Prob(Q):        0.00  Prob(JB):        0.00
Heteroskedasticity (H):  0.94  Skew:        -0.46
Prob(H) (two-sided):  0.00  Kurtosis:      66.86
=====
```

Warnings:

```
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:53: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.  
ValueWarning

```
41265  100.84
dtype: float64
```



```
[106]: results.forecast(steps=10)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
ValueWarning)
[106]: 41265 100.8400
41266 100.8900
41267 100.9100
41268 100.8700
41269 100.8800
41270 100.8700
41271 100.8799
41272 100.8800
41273 100.8700
41274 100.8500
dtype: float64

[107]: results.predict(start=41264,end=41273)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
ValueWarning)
[107]: 41264 100.8200
41265 100.8400
41266 100.8900
41267 100.9100
41268 100.8700
41269 100.8800
41270 100.8700
41271 100.8799
41272 100.8800
41273 100.8700
dtype: float64
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
ValueWarning)
[107]: 41264 100.8200
41265 100.8400
41266 100.8900
41267 100.9100
41268 100.8700
41269 100.8800
41270 100.8700
41271 100.8799
41272 100.8800
41273 100.8700
dtype: float64

[108]: from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.CBOE -', mean_squared_error(df_CBOE['NASDAQ.CBOE'],df_CBOE['Forecast']))
print('Mean Absolute Error NASDAQ.CBOE -', mean_absolute_error(df_CBOE['NASDAQ.CBOE'],df_CBOE['Forecast']))

Mean Squared Error NASDAQ.CBOE - 0.20399400190806427
Mean Absolute Error NASDAQ.CBOE - 0.043566305307009154

[112]: #Time Series Forecasting for 'NASDAQ.CSCO'

[113]: df_CSCO = final[['Month',stock_features[3]]]
print(df_CSCO.head())
df_CSCO.set_index('Month',inplace=True)
```

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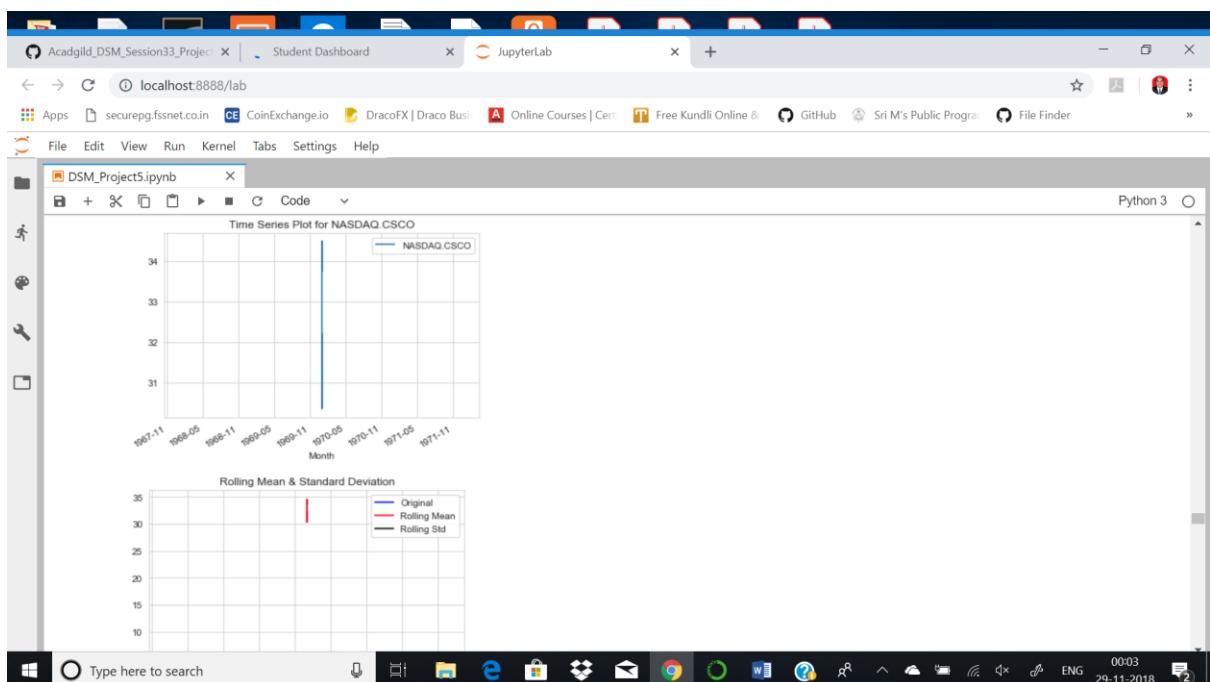
File Edit View Run Kernel Tabs Settings Help Python 3

```
[113]: df_CSCO = final[['Month',stock_features[3]]]
print(df_CSCO.head())
df_CSCO.set_index('Month',inplace=True)
print(df_CSCO.head())
df_CSCO.plot()
plt.title("Time Series Plot for NASDAQ.CSCO")
plt.show()
#Test Stationarity
test_stationarity(df_CSCO['NASDAQ.CSCO'])

Month NASDAQ.CSCO
0 1970-01-01 33.7400
1 1970-01-01 33.8800
2 1970-01-01 33.9000
3 1970-01-01 33.8499
4 1970-01-01 33.8400
NASDAQ.CSCO
Month
1970-01-01 33.7400
1970-01-01 33.8800
1970-01-01 33.9000
1970-01-01 33.8499
1970-01-01 33.8400
```

Time Series Plot for NASDAQ.CSCO

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DSM\_Project5.ipynb

```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
Augmented Dickey-Fuller Test:
ADF Test Statistic : -2.395554610889459
p-value : 0.14299501995164532
#Lags Used : 47
Number of Observations Used : 41218
Critical 1% : value -3.430508661441506
Critical 5% : value -2.8616181247694137
Critical 10% : value -2.566807325152842
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary
```

```
[114]: #MAKING TIME SERIES STATIONARY
#Differencing
```

```
[115]: df_CSCO = df_CSCO.copy()
df_CSCO['First_Difference'] = df_CSCO['NASDAQ.CSCO'] - df_CSCO['NASDAQ.CSCO'].shift(1)
df_CSCO.dropna(inplace=True)
test_stationarity(df_CSCO['First_Difference'])
```

Rolling Mean & Standard Deviation

Type here to search

localhost:8888/lab

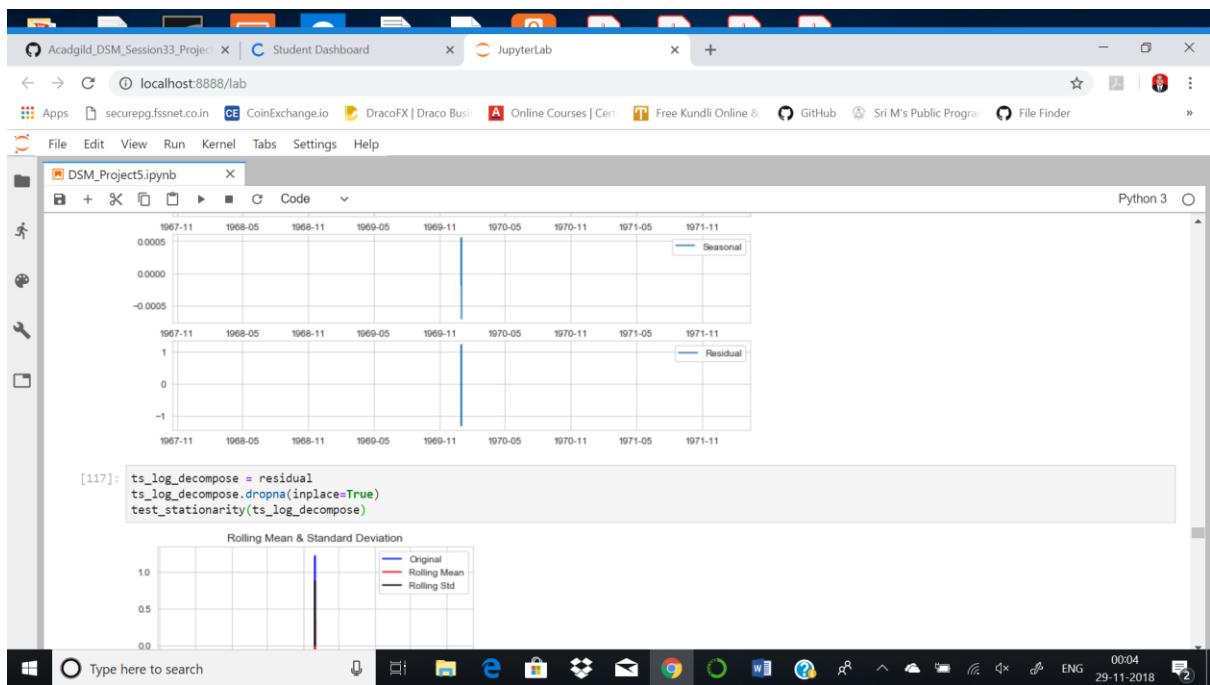
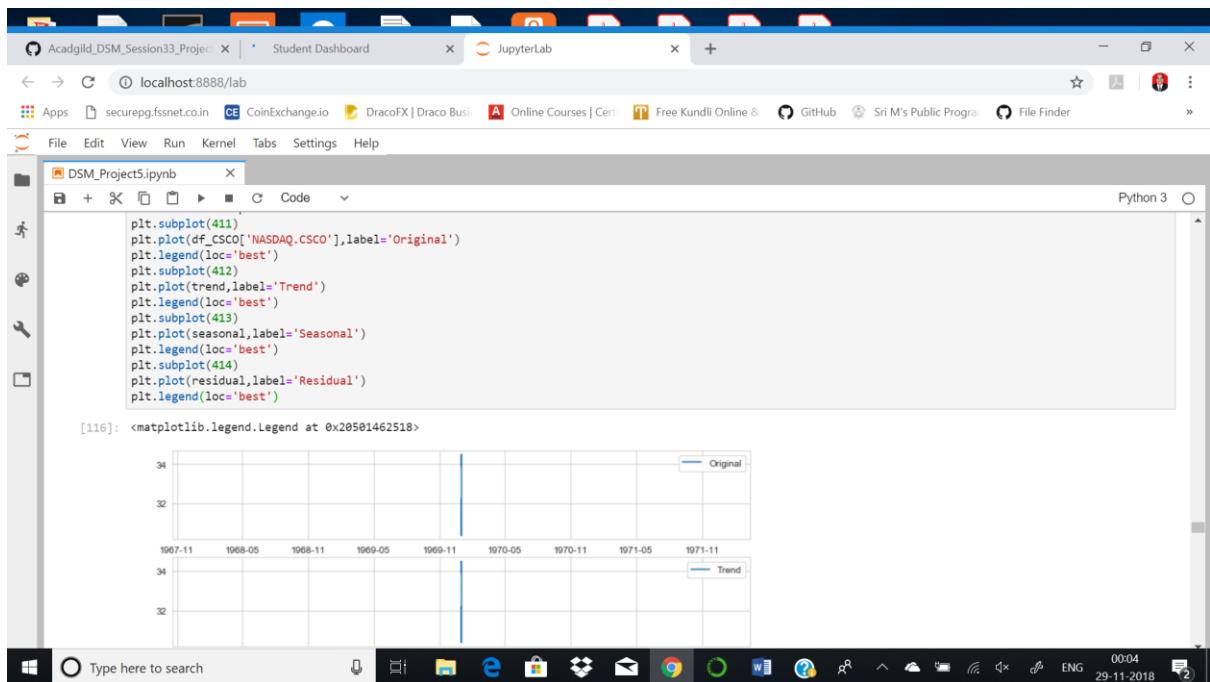
File Edit View Run Kernel Tabs Settings Help

DSM\_Project5.ipynb

```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
Augmented Dickey-Fuller Test:
ADF Test Statistic : -30.356682532566747
p-value : 0.0
#Lags Used : 46
Number of Observations Used : 41218
Critical 1% : value -3.430508661441506
Critical 5% : value -2.8616181247694137
Critical 10% : value -2.566807325152842
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary
```

```
[116]: #Seasonal Decomposition
from statsmodels.tsa.seasonal import seasonal_decompose
plt.figure(figsize=(11,8))
decomposition = seasonal_decompose(df_CSCO['NASDAQ.CSCO'], freq=12)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid
```

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Screenshot of JupyterLab interface showing a notebook named 'DSM\_Project5.ipynb'.

The code cell [118] contains the following text:

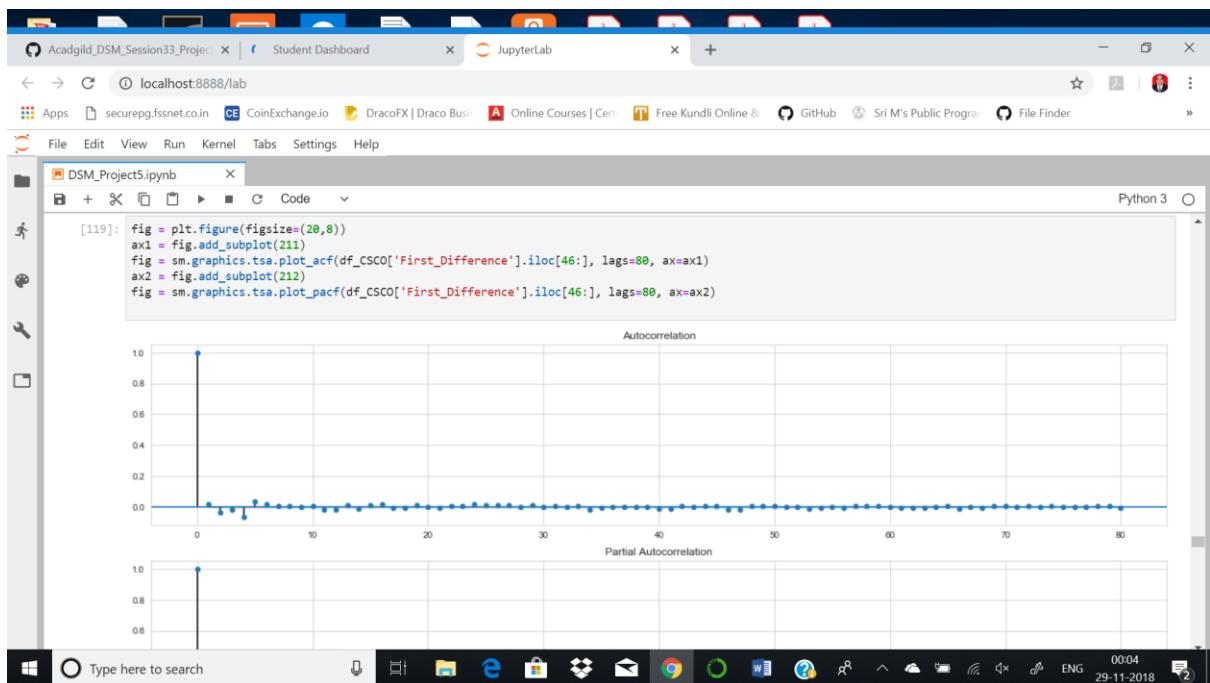
```
Augmented Dickey-Fuller Test:  
ADF Test Statistic : -43.94517780543558  
p-value : 0.0  
#Lags Used : 55  
Number of Observations Used : 41197  
Critical 1% : value -3.4305087423235587  
Critical 5% : value -2.861610160516496  
Critical 10% : value -2.566887344180027  
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary
```

The output cell [118] shows the results of the ADF test and a note explaining stationarity:

```
[118]: """Note :  
This is stationary because:  
• test statistic is lower than critical values.  
• the mean and std variations have small variations with time  
Auto Corealction and Partial Autocorelation Plots"""
```

The output cell [118] also includes a note about autocorrelation and partial autocorrelation plots:

```
[118]: 'Note :\\nThis is stationary because:\\n\\n• test statistic is lower than critical values.\\n\\n• the mean and std variations have small variations with time\\n\\nAuto Corealction and Partial Autocorelation Plots'
```



Screenshot of JupyterLab interface showing code execution and plots.

Code executed:

```
[120]: lag_acf = acf(df_CSCO['First_Difference'], nlags=80)
lag_pacf = pacf(df_CSCO['First_Difference'], nlags=80, method='ols')

[121]: plt.figure(figsize=(20,8))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0, linestyle='--', color='gray')
plt.axhline(y=1.96/np.sqrt(len(df_CSCO['First_Difference'])), linestyle='--', color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_CSCO['First_Difference'])), linestyle='--', color='gray')

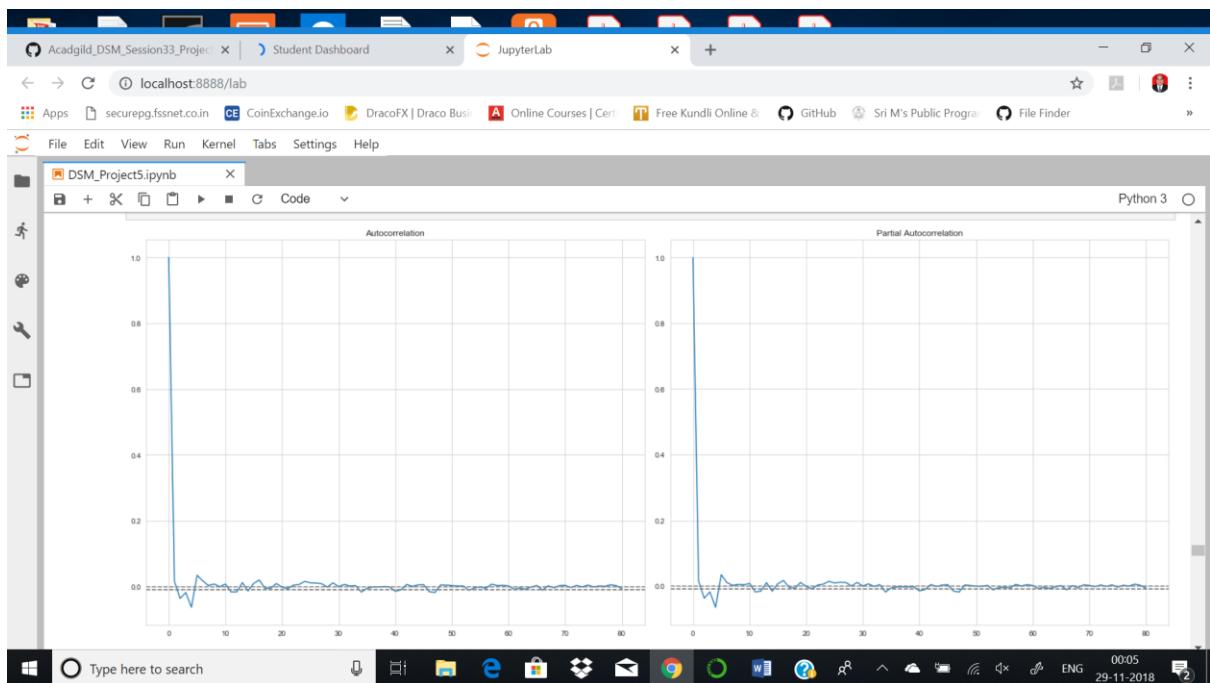
plt.title('Autocorrelation')

plt.subplot(122)

plt.plot(lag_pacf)
plt.axhline(y=0, linestyle='--', color='gray')
plt.axhline(y=1.96/np.sqrt(len(df_CSCO['First_Difference'])), linestyle='--', color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_CSCO['First_Difference'])), linestyle='--', color='gray')

plt.title('Partial Autocorrelation')

plt.tight_layout()
```



Acadgild\_DSM\_Session33\_Project | Student Dashboard | JupyterLab

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DSM\_Project5.ipynb

```
[122]: """Note  
The two dotted lines on either sides of 0 are the confidence intervals.  
  
These can be used to determine the 'p' and 'q' values as:  
  
• p: The first time where the PACF crosses the upper confidence interval, here its close to 0. hence p = 0.  
  
• q: The first time where the ACF crosses the upper confidence interval, here its close to 0. hence p = 0.***  
  
[123]: 'Note\nThe two dotted lines on either sides of 0 are the confidence intervals.\nThese can be used to determine the 'p' and 'q' values as:\n\n• p: The first time where the PACF crosses the upper confidence interval, here its close to 0. hence p = 0.\n• q: The first time where the ACF crosses the upper confidence interval, here its close to 0. hence p = 0.'  
  
# fit model  
model= sm.tsa.statespace.SARIMAX(df_CSCO[['NASDAQ.CSCO']],order=(0,1,0),seasonal_order=(0,1,0,12))  
results = model.fit()  
print(results.summary())  
df_CSCO[['Forecast']] = results.predict()  
df_CSCO[['NASDAQ.CSCO','Forecast']].plot(figsize=(20,8))  
plt.show()  
  
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.  
' ignored when e.g. forecasting.', ValueWarning)  
Statespace Model Results  
=====
```

Type here to search

Acadgild\_DSM\_Session33\_Project | Student Dashboard | JupyterLab

localhost:8888/lab

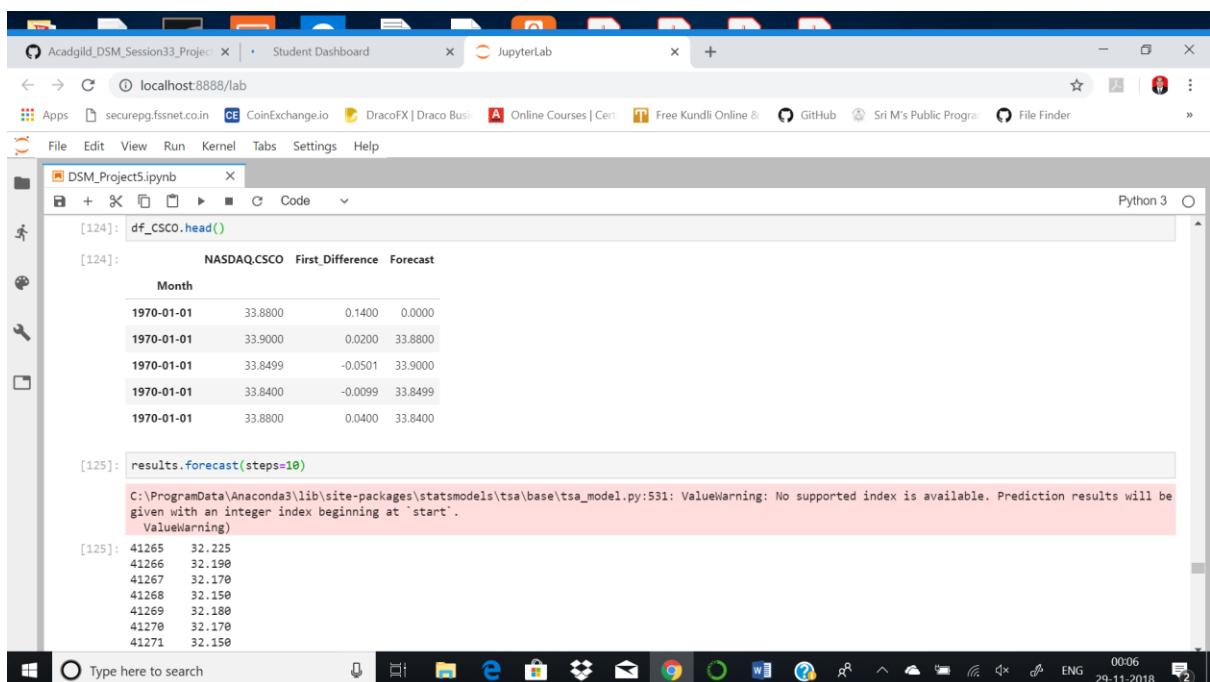
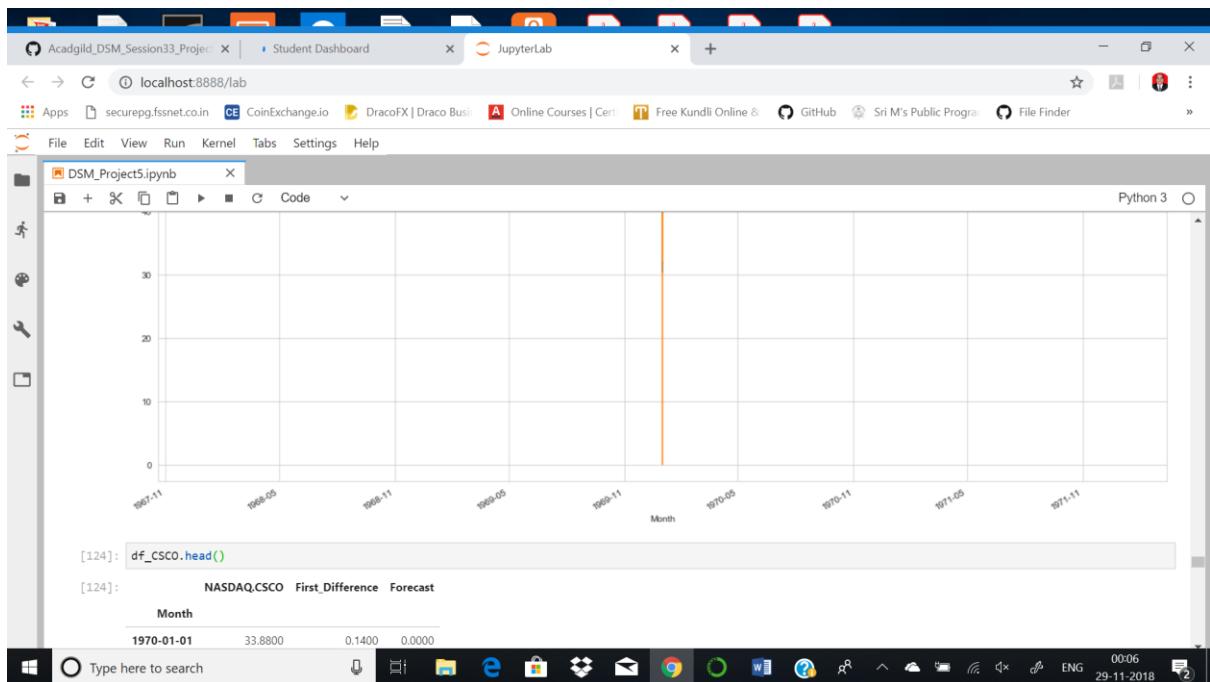
File Edit View Run Kernel Tabs Settings Help

DSM\_Project5.ipynb

```
=====  
Dep. Variable: NASDAQ.CSCO No. Observations: 41265  
Model: SARIMAX(0, 1, 0)x(0, 1, 0, 12) Log Likelihood: 85502.595  
Date: Wed, 28 Nov 2018 AIC: -171003.198  
Time: 23:21:10 BIC: -170994.563  
Sample: 0 HQIC: -171000.463  
- 41265  
Covariance Type: opg  
=====  
coef std err z P>|z| [0.025 0.975]  
-----  
sigma2 0.0009 1.54e-07 6012.819 0.000 0.001 0.001  
=====  
Ljung-Box (Q): 11736.64 Jarque-Bera (JB): 21073382447.00  
Prob(Q): 0.00 Prob(JB): 0.00  
Heteroskedasticity (H): 0.30 Skew: 2.67  
Prob(H) (two-sided): 0.00 Kurtosis: 3504.46  
=====  
Warnings:  
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```



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Screenshot of JupyterLab interface showing code execution and error handling.

```
41271    32.150
41272    32.165
41273    32.180
41274    32.180
dtype: float64
```

```
[126]: results.predict(start=41264,end=41275)

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:531: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at 'start'.
  ValueWarning)
```

```
[126]: 41264    32.195
41265    32.225
41266    32.190
41267    32.170
41268    32.150
41269    32.180
41270    32.170
41271    32.150
41272    32.165
41273    32.180
41274    32.180
41275    32.175
dtype: float64
```

```
[127]: from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.CSCO -', mean_squared_error(df_CSCO['NASDAQ.CSCO'],df_CSCO['Forecast']))
print('Mean Absolute Error NASDAQ.CSCO -', mean_absolute_error(df_CSCO['NASDAQ.CSCO'],df_CSCO['Forecast']))
```

Screenshot of JupyterLab interface showing time series forecasting and stationarity analysis.

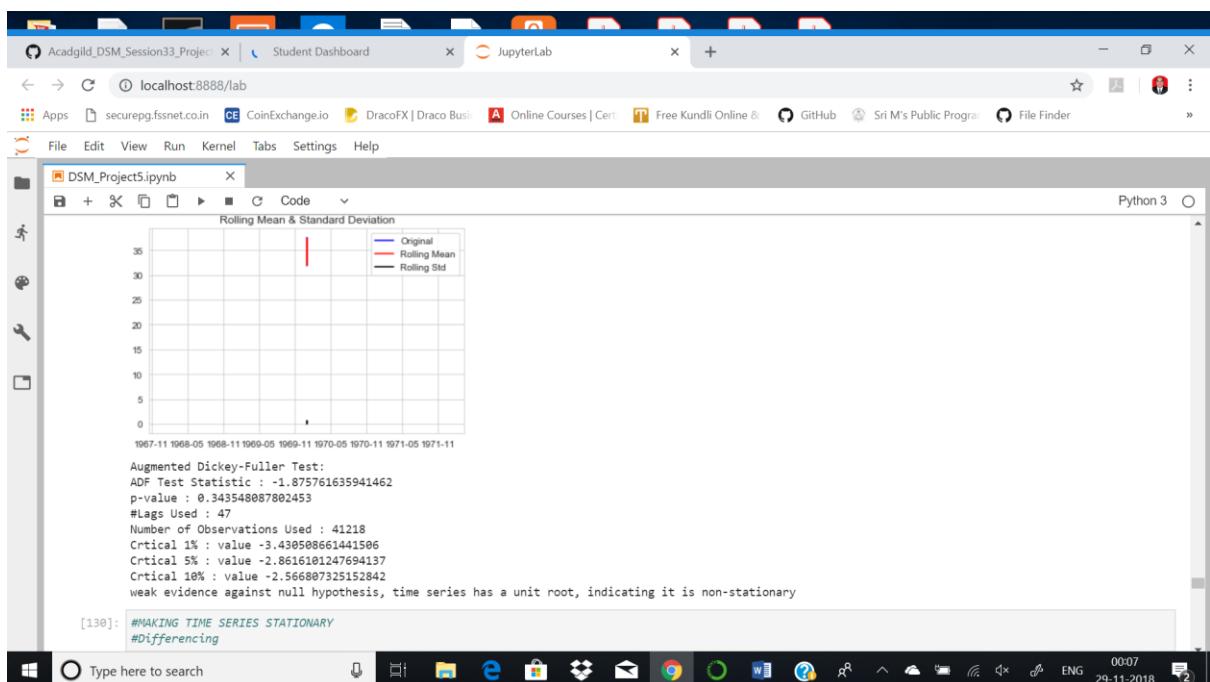
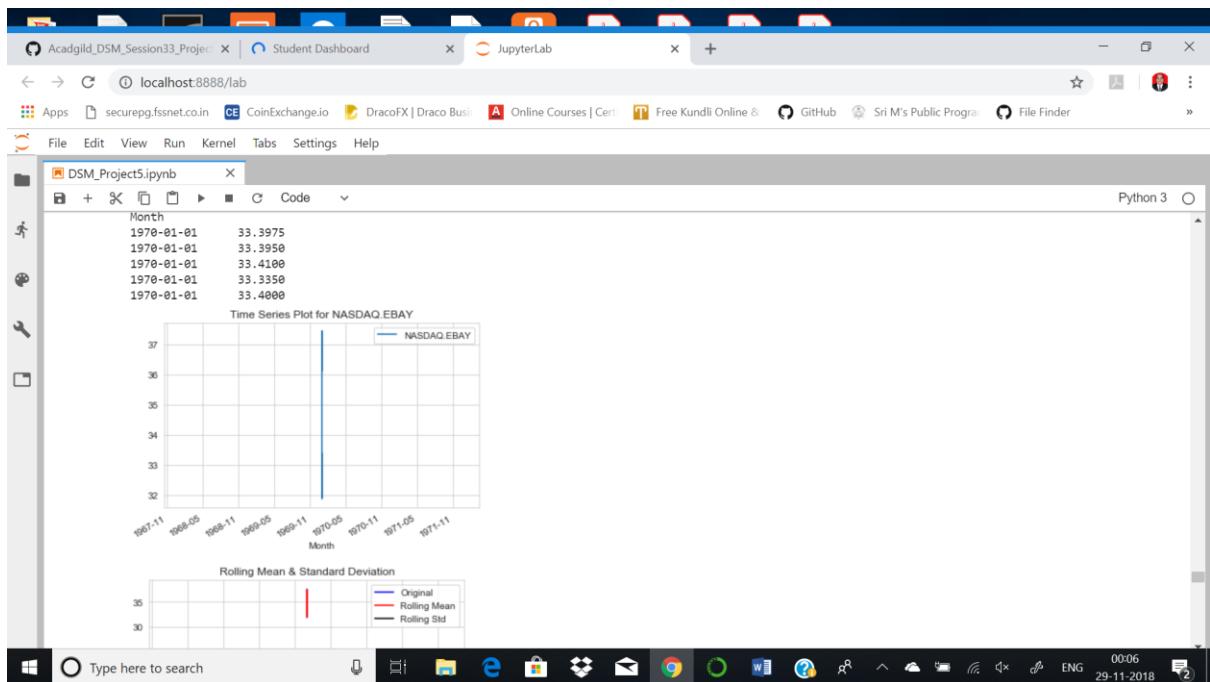
```
[127]: from sklearn.metrics import mean_squared_error,mean_absolute_error
print('Mean Squared Error NASDAQ.CSCO -', mean_squared_error(df_CSCO['NASDAQ.CSCO'],df_CSCO['Forecast']))
print('Mean Absolute Error NASDAQ.CSCO -', mean_absolute_error(df_CSCO['NASDAQ.CSCO'],df_CSCO['Forecast']))

Mean Squared Error NASDAQ.CSCO - 0.03569378449696079
Mean Absolute Error NASDAQ.CSCO - 0.015775407730929027
```

```
[128]: #Time Series Forecasting for NASDAQ.EBAY
```

```
[129]: df_EBAY = final[['Month',stock_features[4]]]
print(df_EBAY.head())
df_EBAY.set_index('Month',inplace=True)
print(df_EBAY.head())
df_EBAY.plot()
plt.title("Time Series Plot for NASDAQ.EBAY")
plt.show()
#Test Stationarity
test_stationarity(df_EBAY['NASDAQ.EBAY'])

      Month  NASDAQ.EBAY
0 1970-01-01    33.3975
1 1970-01-01    33.3950
2 1970-01-01    33.4100
3 1970-01-01    33.3350
4 1970-01-01    33.4000
      Month  NASDAQ.EBAY
1970-01-01    33.3975
```



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```
[130]: #MAKING TIME SERIES STATIONARY  
#Differencing
```

```
[131]: df_EBAY = df_EBAY.copy()  
df_EBAY['First_Difference'] = df_EBAY['NASDAQ.EBAY'] - df_EBAY['NASDAQ.EBAY'].shift(1)  
df_EBAY.dropna(inplace=True)  
#test Stationarity  
test_stationarity(df_EBAY['NASDAQ.EBAY'])
```

Rolling Mean & Standard Deviation

```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11  
Augmented Dickey-Fuller Test:  
ADF Test Statistic : -1.8639133106583694
```

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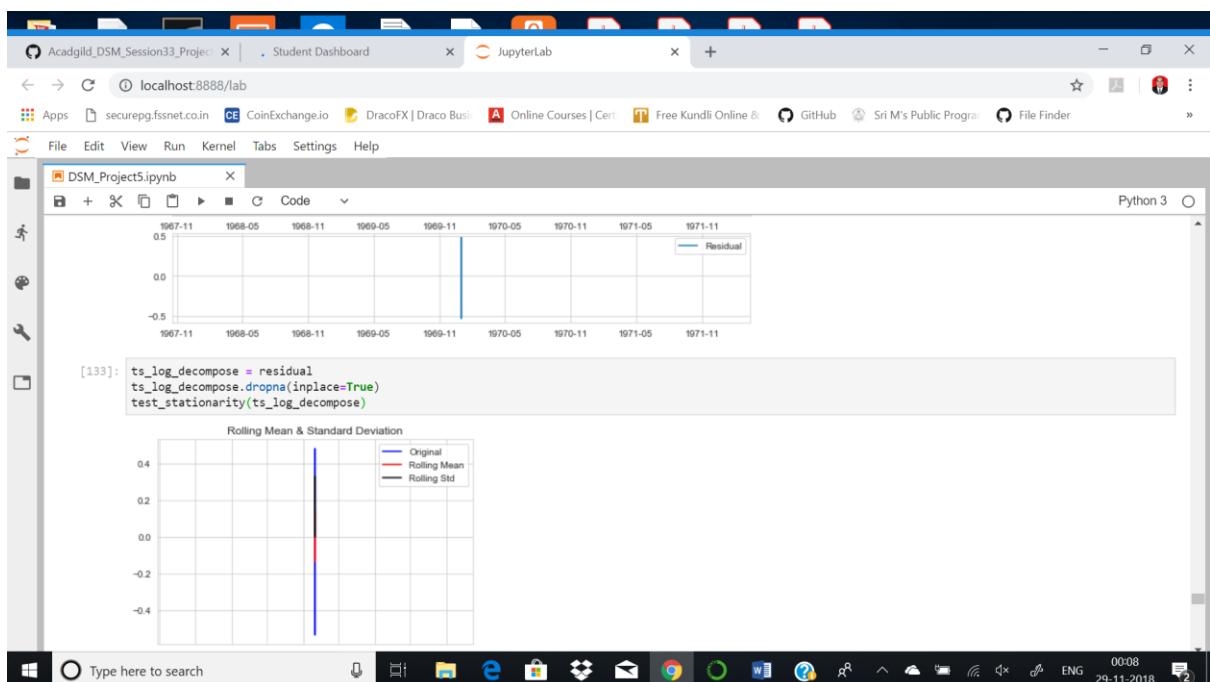
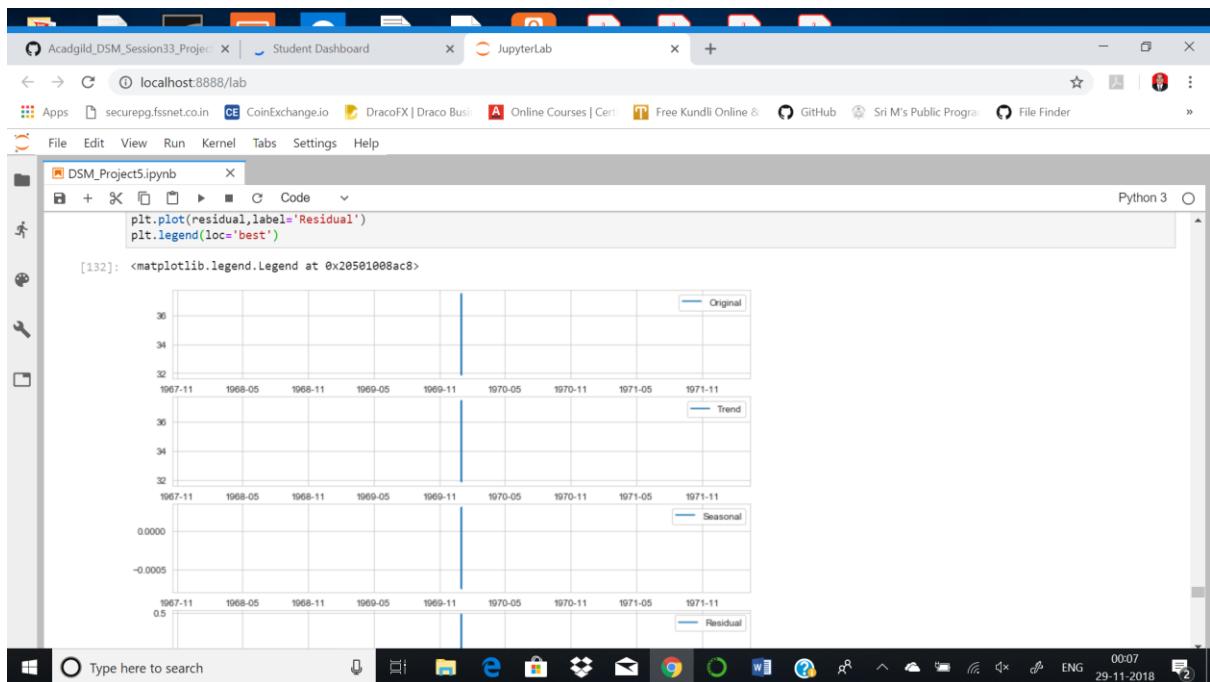
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```
Augmented Dickey-Fuller Test:  
ADF Test Statistic : -1.8639133106583694  
p-value : 0.3492231149987619  
#Lags Used : 47  
Number of Observations Used : 41217  
Critical 1% : value : -3.4305086652911636  
Critical 5% : value : -2.8616101264708296  
Critical 10% : value : -2.5668073260584587  
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary
```

```
[132]: #Seasonal Decomposition  
from statsmodels.tsa.seasonal import seasonal_decompose  
plt.figure(figsize=(11,8))  
decomposition = seasonal_decompose(df_EBAY['NASDAQ.EBAY'], freq=12)  
trend = decomposition.trend  
seasonal = decomposition.seasonal  
residual = decomposition.resid  
plt.subplot(411)  
plt.plot(df_EBAY['NASDAQ.EBAY'], label='Original')  
plt.legend(loc='best')  
plt.subplot(412)  
plt.plot(trend, label='Trend')  
plt.legend(loc='best')  
plt.subplot(413)  
plt.plot(seasonal, label='Seasonal')  
plt.legend(loc='best')  
plt.subplot(414)  
plt.plot(residual, label='Residual')
```

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```
1967-11 1968-05 1968-11 1969-05 1969-11 1970-05 1970-11 1971-05 1971-11
Augmented Dickey-Fuller Test:
ADF Test Statistic : -44.88049175892094
p-value : 0.0
#Lags Used : 55
Number of Observations Used : 41197
Critical 1% : value -3.4305087423235587
Critical 5% : value -2.861618160516496
Critical 10% : value -2.566887344180027
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationary

[134]: """Note :
This is stationary because:

• test statistic is lower than critical values.

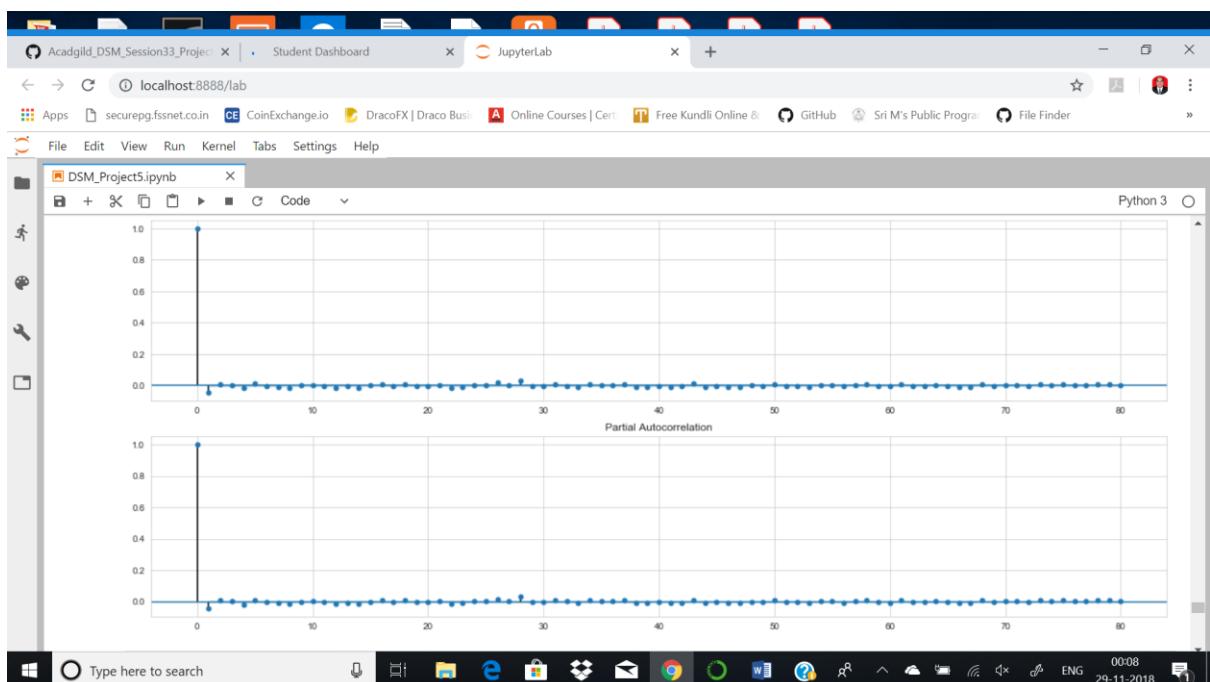
• the mean and std variations have small variations with time"""

[134]: 'Note :\nThis is stationary because:\n\n• test statistic is lower than critical values.\n\n• the mean and std variations have small variations with time'

[135]: #Autocorealtion plot and Partial Autocorelation plots

[136]: fig = plt.figure(figsize=(20,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(df_EBAY['First_Difference'].iloc[47:], lags=80, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(df_EBAY['First_Difference'].iloc[47:], lags=80, ax=ax2)
```

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Screenshot of a JupyterLab session on a Windows 10 desktop. The code cell contains Python code for generating Autocorrelation and Partial Autocorrelation plots.

```
[137]: lag_acf = acf(df_EBAY['First_Difference'], nlags=80)
lag_pacf = pacf(df_EBAY['First_Difference'], nlags=80, method='ols')

[138]: plt.figure(figsize=(20,8))
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0, linestyle='--', color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_EBAY['First_Difference'])), linestyle='--', color='gray')
plt.axhline(y=1.96/np.sqrt(len(df_EBAY['First_Difference'])), linestyle='--', color='gray')

plt.title('Autocorrelation')

plt.subplot(122)

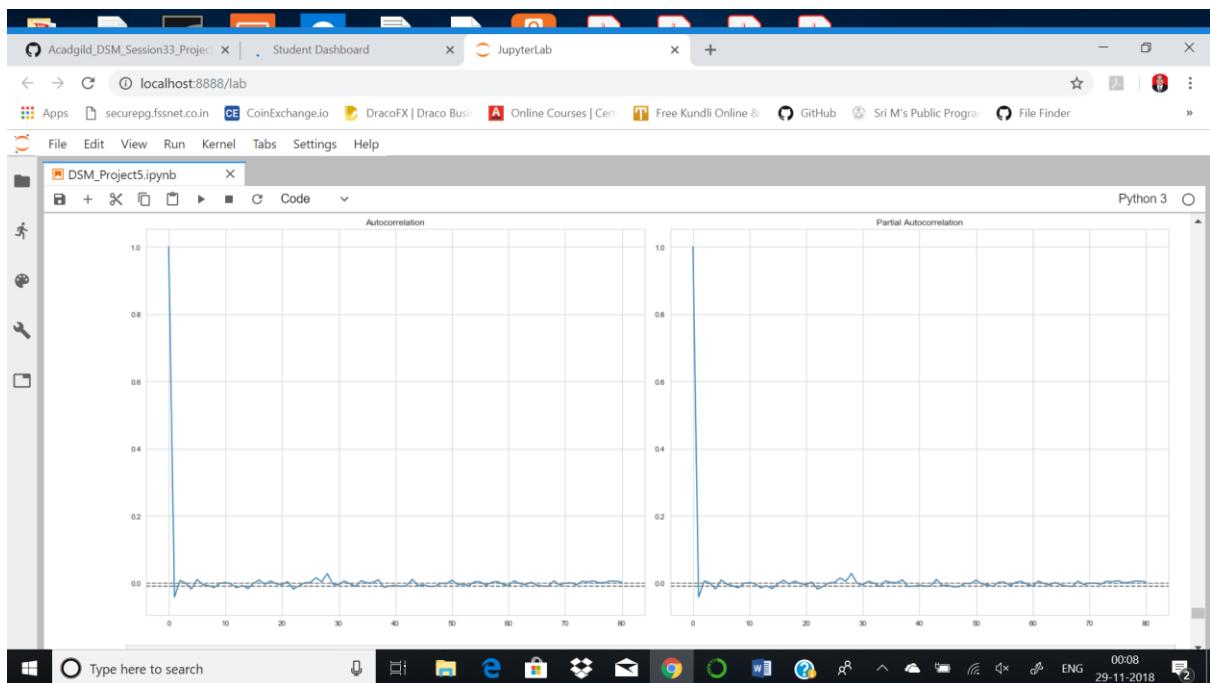
plt.plot(lag_pacf)
plt.axhline(y=0, linestyle='--', color='gray')
plt.axhline(y=-1.96/np.sqrt(len(df_EBAY['First_Difference'])), linestyle='--', color='gray')
plt.axhline(y=1.96/np.sqrt(len(df_EBAY['First_Difference'])), linestyle='--', color='gray')

plt.title('Partial Autocorrelation')

plt.tight_layout()
```



The figure consists of two side-by-side line plots. The left plot, titled 'Autocorrelation', shows a sharp peak at lag 0 (value ~1.0) and a smaller peak at lag 1 (~0.1). The right plot, titled 'Partial Autocorrelation', also shows a sharp peak at lag 0 (~1.0) and a smaller peak at lag 1 (~0.1). Both plots include horizontal dashed lines at y=0, y=-1.96/np.sqrt(len(df\_EBAY['First\_Difference'])) (approx -0.02), and y=1.96/np.sqrt(len(df\_EBAY['First\_Difference'])) (approx 0.02), representing the 95% confidence interval bounds.



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DSM\_Project5.ipynb

```
[139]: """Note  
The two dotted lines on either sides of 0 are the confidence intervals.  
  
These can be used to determine the 'p' and 'q' values as:  
  
• p: The first time where the PACF crosses the upper confidence interval, here its close to 0. hence p = 0.  
• q: The first time where the ACF crosses the upper confidence interval, here its close to 0. hence p = 0.***  
***  
[140]: # fit model  
model= sm.tsa.statespace.SARIMAX(df_EBAY[['NASDAQ.EBAY']],order=(0,1,0),seasonal_order=(0,1,0,12))  
results = model.fit()  
print(results.summary())  
df_EBAY[['Forecast']] = results.predict()  
df_EBAY[['NASDAQ.EBAY','Forecast']].plot(figsize=(20,8))  
plt.show()
```

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.  
' ignored when e.g. forecasting.', ValueWarning)

Statespace Model Results

```
=====
```

Dep. Variable:	NASDAQ.EBAY	No. Observations:	41265
Model:	SARIMAX(0, 1, 0)x(0, 1, 0, 12)	Log Likelihood:	82104.712
Date:	Wed, 28 Nov 2018	AIC:	-164207.425
Time:	23:28:45	BIC:	-164198.797
Sample:	0 - 41265	HQIC:	-164204.698

Covariance Type: opg

```
=====
```

coef	std err	z	P> z	[0.025	0.975]
sigma2	0.0011	9.43e-07	1158.841	0.000	0.001

```
=====
```

Ljung-Box (Q):	10939.63	Jarque-Bera (JB):	28223015.54
Prob(Q):	0.00	Prob(JB):	0.00
Heteroskedasticity (H):	1.21	Skew:	0.35
Prob(H) (two-sided):	0.00	Kurtosis:	131.14

```
=====
```

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

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```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:225: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.  
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```

Statespace Model Results

```
=====
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=====
```

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```
=====
```

Ljung-Box (Q):	10939.63	Jarque-Bera (JB):	28223015.54
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```
=====
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```
Ljung-Box (Q): 10939.63 Jarque-Bera (JB): 28223015.54
Prob(Q): 0.00 Prob(JB): 0.00
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Prob(H) (two-sided): 0.00 Kurtosis: 131.14
```

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

NASDAQ EBAY  
Forecast

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NASDAQ EBAY Forecast

```
[141]: df_EBAY.head()
```

	NASDAQ.EBAY	First_Difference	Forecast
Month			
1970-01-01	33.395	-0.0025	0.000
1970-01-01	33.410	0.0150	33.395
1970-01-01	33.335	-0.0750	33.410
1970-01-01	33.400	0.0650	33.335
1970-01-01	33.430	0.0300	33.400

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The screenshot shows a JupyterLab interface running on a Windows desktop. The code cell [142] imports `mean\_squared\_error` and `mean\_absolute\_error` from `sklearn.metrics` and prints the Mean Squared Error and Mean Absolute Error for the 'NASDAQ.EBAY' dataset. The results are:

```
Mean Squared Error NASDAQ.EBAY - 0.034835678936282845  
Mean Absolute Error NASDAQ.EBAY - 0.02168803346794987
```

The code cell [143] runs `results.forecast(steps=10)` and prints the forecasted values for steps 41265 to 41274. The output is:

```
41265 36.090  
41266 36.030  
41267 36.030  
41268 36.020  
41269 36.020  
41270 36.025  
41271 36.020  
41272 36.025  
41273 36.020  
41274 36.020  
dtype: float64
```

The code cell [144] runs `results.predict(start=41265,end=41275)` and prints the predicted values for the same range. The output is identical to the forecasted values.

This screenshot shows the continuation of the JupyterLab session. The code cell [144] is identical to the one above, printing forecasted values for steps 41265 to 41274.

The code cell [145] contains a multi-line string:

```
"""CONCLUSION :  
The predicted stock prices values have been stored in the Forecast Columns of the each stock entity dataframe"""  
CONCLUSION :  
The predicted stock prices values have been stored in the Forecast Columns of the each stock entity dataframe'
```