Importing Libraries

In [29]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
```

Importing Datasets

In [2]:
```
df1 = pd.read_excel(r'SalesAnalyticsCandidateDataset.xlsx', 'Orders',parse_dates=['
```

In [3]:
```
df2 = pd.read_excel(r'SalesAnalyticsCandidateDataset.xlsx', 'Doctors')
```

Feature Engineering in data and Data Preparing

In [5]:
```
df1.head()
```

Out[5]:

	AccountNumber	Month	Order
0	1086390	2019-11-01	0
1	1086390	2019-12-01	5
2	1079261	2019-11-01	6
3	1079261	2019-08-01	0
4	1079261	2019-12-01	10

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

Out[6]:
```
AccountNumber    0
Month            0
Order            0
dtype: int64
```

In [7]:
```
df1.describe()
```

Out[7]:

	AccountNumber	Order
count	2.205760e+05	220576.000000
mean	2.725437e+05	4.159133
std	2.029868e+05	14.209398
min	5.815400e+04	-2.000000
25%	1.316810e+05	0.000000
50%	2.113770e+05	1.000000
75%	3.875370e+05	4.000000
max	1.086390e+06	810.000000

In [8]:
```
df2.head()
```

Out[8]:

	ContactAccountNumber	ContactName	ContactProfessionalCategory	ContactCertificationDate	A
0	100297	Dr. Thad Burch	Ortho	2000-01-19	
1	1005066	Dr. Rita Cordova	GP	2018-09-26	
2	1005902	Dr. Lloyd Schneider	GP	2018-10-16	
3	100641	Dr. Paris Howe	GP	2001-12-07	
4	100688	Dr. Ernestine Harrington	GP	2001-12-07	

In [9]:
```
df2.isnull().sum()
```

Out[9]:
```
ContactAccountNumber            0
ContactName                     0
ContactProfessionalCategory     0
ContactCertificationDate      135
AvantageLevel                   0
Segment                         0
iTero_Installed                10
AccountCity                     0
AccountState                    3
InvSalesAreaLable               0
InvSalesRegionLable             0
InvSalesTerritoryLable          0
dtype: int64
```

In [10]:
```
for i in df2.columns:
    print("-"*50)
    print("|   ", i, ":" , df2[i].nunique())
print("-"*50)
```

```
--------------------------------------------------
|    ContactAccountNumber : 9681
--------------------------------------------------
|    ContactName : 9691
--------------------------------------------------
|    ContactProfessionalCategory : 4
--------------------------------------------------
|    ContactCertificationDate : 1943
--------------------------------------------------
|    AvantageLevel : 10
--------------------------------------------------
|    Segment : 5
--------------------------------------------------
|    iTero_Installed : 2
--------------------------------------------------
|    AccountCity : 2747
--------------------------------------------------
|    AccountState : 52
--------------------------------------------------
|    InvSalesAreaLable : 10
--------------------------------------------------
|    InvSalesRegionLable : 52
--------------------------------------------------
|    InvSalesTerritoryLable : 383
--------------------------------------------------
```

In [11]:
```
df2.rename(columns = {'ContactAccountNumber':'AccountNumber'}, inplace = True)
```

In [12]:
```
df3 = pd.merge(df1,df2,on ='AccountNumber',how ='left')
```

In [13]:
```
df3.head()
```

Out[13]:

	AccountNumber	Month	Order	ContactName	ContactProfessionalCategory	ContactCertificatio
0	1086390	2019-11-01	0	Dr. Branden Washington	GP	2018-
1	1086390	2019-12-01	5	Dr. Branden Washington	GP	2018-
2	1079261	2019-11-01	6	Dr. Rey Mcdowell	GP	2019-
3	1079261	2019-08-01	0	Dr. Rey Mcdowell	GP	2019-
4	1079261	2019-12-01	10	Dr. Rey Mcdowell	GP	2019-

In [14]:
```
df1.shape, df2.shape, df3.shape
```

Out[14]:
```
((220576, 3), (9691, 12), (220873, 14))
```

In [15]:
```
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 220873 entries, 0 to 220872
Data columns (total 14 columns):
 #   Column                      Non-Null Count   Dtype         
---  ------                      --------------   -----         
 0   AccountNumber               220873 non-null  int64         
 1   Month                       220873 non-null  datetime64[ns]
 2   Order                       220873 non-null  int64         
 3   ContactName                 220873 non-null  object        
 4   ContactProfessionalCategory  220873 non-null  object        
 5   ContactCertificationDate    217473 non-null  datetime64[ns]
 6   AvantageLevel               220873 non-null  object        
 7   Segment                     220873 non-null  object        
 8   iTero_Installed             220576 non-null  object        
 9   AccountCity                 220873 non-null  object        
 10  AccountState                220828 non-null  object        
 11  InvSalesAreaLable           220873 non-null  object        
 12  InvSalesRegionLable         220873 non-null  object        
 13  InvSalesTerritoryLable      220873 non-null  object        
dtypes: datetime64[ns](2), int64(2), object(10)
memory usage: 25.3+ MB
```

In [16]:
```
df3.isnull().sum()
```

Out[16]:
```
AccountNumber                    0
Month                            0
Order                            0
ContactName                      0
ContactProfessionalCategory      0
ContactCertificationDate      3400
AvantageLevel                    0
Segment                          0
iTero_Installed                297
AccountCity                      0
AccountState                    45
InvSalesAreaLable                0
InvSalesRegionLable              0
InvSalesTerritoryLable           0
dtype: int64
```

In [18]:
```
b = []
for i in df3.columns:
    if df3[i].isna().sum() > 0:
        b.append(i)
    print(i, ":" , df3[i].isna().sum(), ":", "{:.2f}%".format(df3[i].isna().sum()/l
print("="*50)
print(b)
```

```
AccountNumber : 0 : 0.00%
Month : 0 : 0.00%
Order : 0 : 0.00%
ContactName : 0 : 0.00%
ContactProfessionalCategory : 0 : 0.00%
ContactCertificationDate : 3400 : 1.54%
AvantageLevel : 0 : 0.00%
Segment : 0 : 0.00%
iTero_Installed : 297 : 0.13%
AccountCity : 0 : 0.00%
AccountState : 45 : 0.02%
InvSalesAreaLable : 0 : 0.00%
InvSalesRegionLable : 0 : 0.00%
InvSalesTerritoryLable : 0 : 0.00%
==================================================
['ContactCertificationDate', 'iTero_Installed', 'AccountState']
```

In [19]:
```
# ['ContactCertificationDate', 'iTero_Installed', 'AccountState'] contains
# null values and the null % is very low compared to the data set.
# So, we can remove the null values.
```

In [20]:
```
df3.dropna(inplace = True)
```

In [21]:
```
df3.shape
```

Out[21]:
```
(217428, 14)
```

In [22]:
```
# checking the number of unique values in our data.
```

In [25]:
```
for i in df3.columns:
    print(i, "--> ", df3[i].nunique())
```

```
AccountNumber -->  9058
Month -->  36
Order -->  267
ContactName -->  9058
ContactProfessionalCategory -->  2
ContactCertificationDate -->  1884
AvantageLevel -->  10
Segment -->  5
iTero_Installed -->  2
AccountCity -->  2658
AccountState -->  52
InvSalesAreaLable -->  8
InvSalesRegionLable -->  50
InvSalesTerritoryLable -->  380
```

In [26]:
```
# Exporting this data for analysis, charts and summary
```

In [28]:
```
df3.to_excel("output1.xlsx")
```

Seasonality and Trend Test

In [78]:
```
df1.head()
```

Out[78]:

	AccountNumber	Month	Order
0	1086390	2019-11-01	0
1	1086390	2019-12-01	5
2	1079261	2019-11-01	6
3	1079261	2019-08-01	0
4	1079261	2019-12-01	10

In [79]:
```
month_orders = df1.groupby(['Month'])['Order'].sum()
```

In [80]:
```
month_orders
```

Out[80]:
```
Month
2017-01-01    18966
2017-02-01    21078
2017-03-01    24668
2017-04-01    19266
2017-05-01    23300
2017-06-01    25638
2017-07-01    21448
2017-08-01    25727
2017-09-01    21270
2017-10-01    22169
2017-11-01    22838
2017-12-01    23616
2018-01-01    24267
2018-02-01    24095
2018-03-01    29847
2018-04-01    24275
2018-05-01    27313
2018-06-01    27259
2018-07-01    24508
2018-08-01    28915
2018-09-01    25685
2018-10-01    24392
2018-11-01    24280
2018-12-01    26067
2019-01-01    28352
2019-02-01    27711
2019-03-01    28630
2019-04-01    25319
2019-05-01    28754
2019-06-01    27983
2019-07-01    29234
2019-08-01    28797
2019-09-01    27170
2019-10-01    27560
2019-11-01    26430
2019-12-01    30578
Name: Order, dtype: int64
```

In [81]:
```
# durbin Watson Test
sm.stats.durbin_watson(month_orders)
```

Out[81]:
```
0.012448596942876814
```

In [82]:
```
# very less correlation
```

In [83]:
```
split = round(len(month_orders)/2)
```

In [84]:
```
split
```

Out[84]:
```
18
```

In [85]:
```
a1, a2 = month_orders[0:split],month_orders[split:]
```

In [86]:
```
a1.head(), a2.head()
```

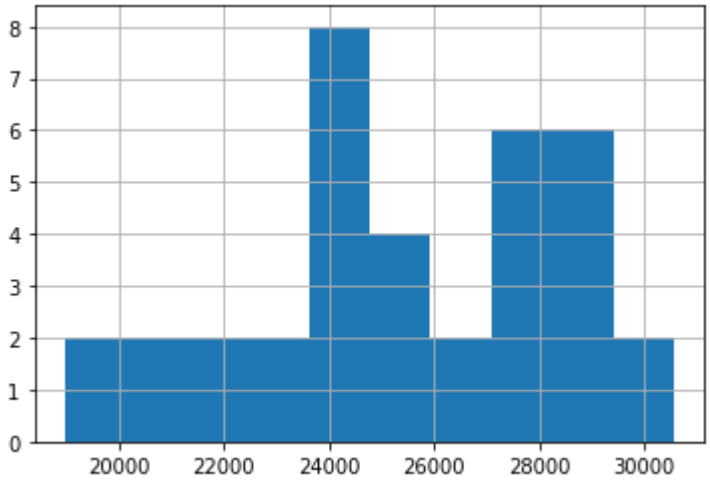
Out[86]:
```
(Month
 2017-01-01    18966
 2017-02-01    21078
 2017-03-01    24668
 2017-04-01    19266
 2017-05-01    23300
 Name: Order, dtype: int64,
 Month
 2018-07-01    24508
 2018-08-01    28915
 2018-09-01    25685
 2018-10-01    24392
 2018-11-01    24280
 Name: Order, dtype: int64)
```

In [87]:
```
mean1, mean2 = a1.mean(), a2.mean()
var1, var2 = a1.var(), a2.var()
print('mean1=%f, mean2=%f' % (mean1, mean2))
print('variance1=%f, variance2=%f' % (var1, var2))
```

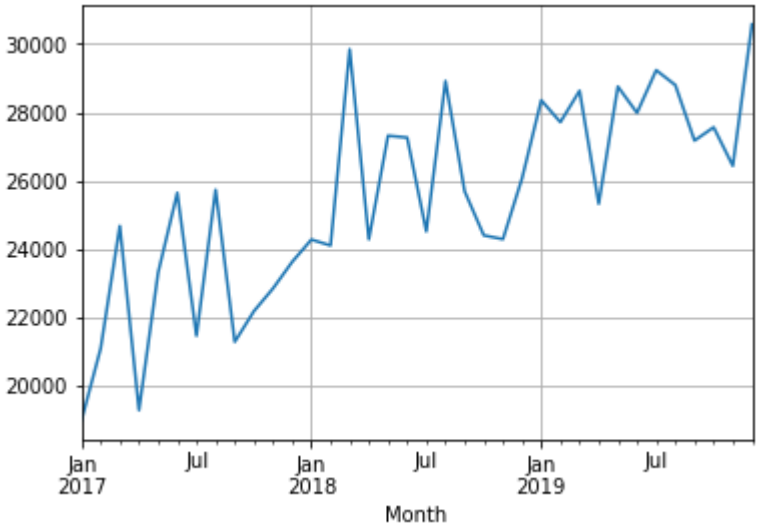
```
mean1=23724.444444, mean2=27242.500000
variance1=8016547.084967, variance2=3480405.558824
```

In [88]:
```
# as there is a large difference between the mean and variance
# hence the data is not statiory
```

In [89]:
```
month_orders.hist()
plt.show()
```



In [90]:
```
month_orders.plot()
plt.grid(True)
```



In [91]:
```
# we can clearly see the upwards trend in the data set
# Graph also depicts some SEASIONALITY trends, as we can see that:
#  - There is always a fall in total  sales at the beginning of the year.
#  - Also the sales increases in Feb and again decreases
```

In [92]:
```
month_orders = pd.DataFrame(month_orders).reset_index()
```

In [93]:
```
month_orders.head()
```

Out[93]:

	Month	Order
0	2017-01-01	18966
1	2017-02-01	21078
2	2017-03-01	24668
3	2017-04-01	19266
4	2017-05-01	23300

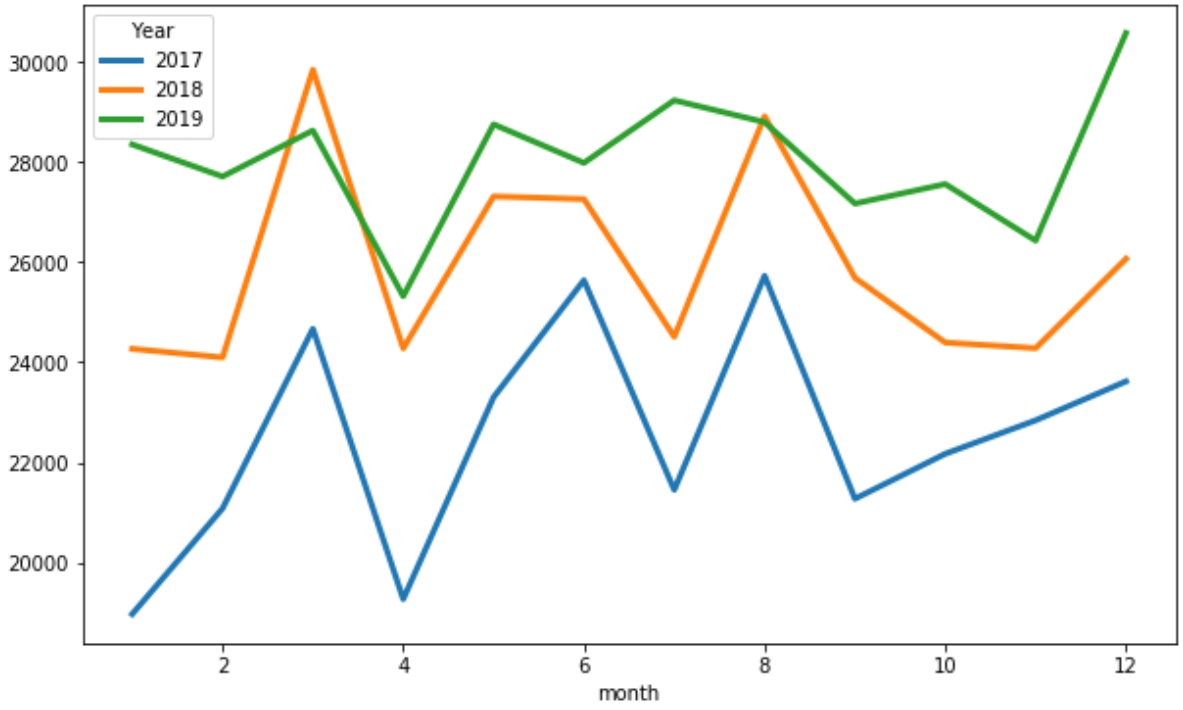
In [102…
```
season = month_orders
season['Date'] = month_orders.Month
season['Year'] = month_orders.Month.dt.year
season['month'] = month_orders.Month.dt.month
spivot = pd.pivot_table(season, index='month', columns = 'Year', values = 'Order',
```

In [103…
```
month_orders.drop(['Date', 'Year', 'month'], axis = 1, inplace = True)
month_orders.head()
```

Out[103]:

	Month	Order
0	2017-01-01	18966
1	2017-02-01	21078
2	2017-03-01	24668
3	2017-04-01	19266
4	2017-05-01	23300

In [104…
```
spivot.plot(figsize=(10,6), linewidth=3)
plt.show()
```



In [105…
```
# from the above graph its clearly visible that there is the upward trend
# as the order count kept on increasing over the year
```

In [114…
```
rolling_mean = month_orders.rolling(window = 2).mean()
rolling_std = month_orders.rolling(window = 2).std()
```

In [115…
```
month_orders.head()
```

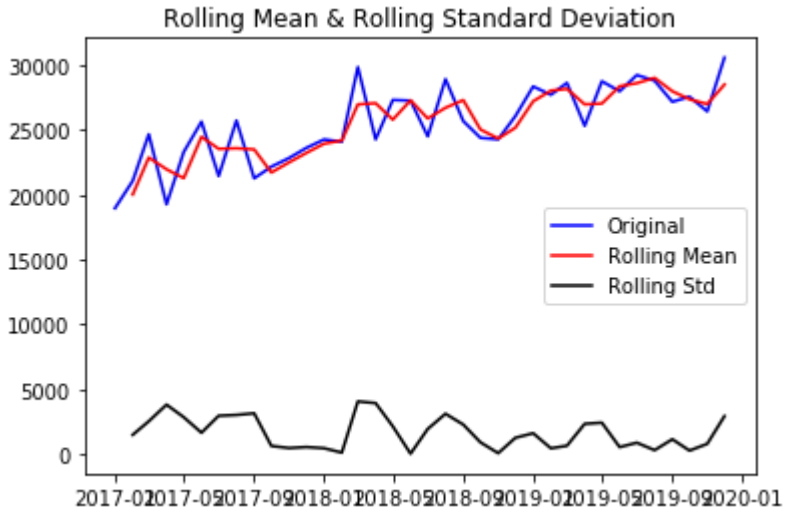
Out[115]:

Month	Order
2017-01-01	18966
2017-02-01	21078
2017-03-01	24668
2017-04-01	19266
2017-05-01	23300

In [116…
```
#month_orders = month_orders.set_index('Month')
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-116-8dfa057a1cc0> in <module>
----> 1 month_orders = month_orders.set_index('Month')

E:\New folder (2)\lib\site-packages\pandas\core\frame.py in set_index(self, keys,
drop, append, inplace, verify_integrity)
   4301
   4302         if missing:
-> 4303             raise KeyError(f"None of {missing} are in the columns")
   4304
   4305         if inplace:

KeyError: "None of ['Month'] are in the columns"
```

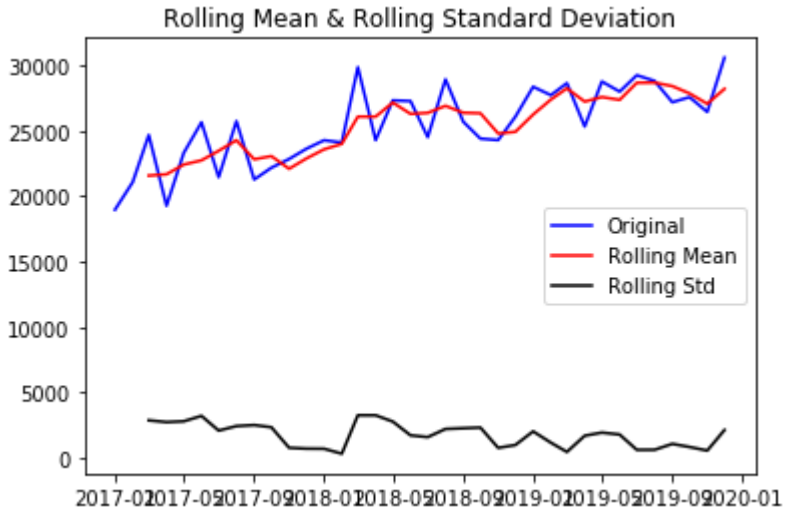
In [117…
```
plt.plot(month_orders, color = 'blue', label = 'Original')
plt.plot(rolling_mean, color = 'red', label = 'Rolling Mean')
plt.plot(rolling_std, color = 'black', label = 'Rolling Std')
plt.legend(loc = 'best')
plt.title('Rolling Mean & Rolling Standard Deviation')
plt.show()
```



In [118…
```
# rolling mean and rolling std dev smoothens our data and do bring some
# stationarity to our data
```

In [119…
```
rolling_mean2 = month_orders.rolling(window = 3).mean()
rolling_std2 = month_orders.rolling(window = 3).std()
```

In [120…
```
plt.plot(month_orders, color = 'blue', label = 'Original')
plt.plot(rolling_mean2, color = 'red', label = 'Rolling Mean')
plt.plot(rolling_std2, color = 'black', label = 'Rolling Std')
plt.legend(loc = 'best')
plt.title('Rolling Mean & Rolling Standard Deviation')
plt.show()
```



Ad fuller test for stationarity

In [121…
```
from statsmodels.tsa.stattools import adfuller
```

In [122…
```
result = adfuller(month_orders['Order'])
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
```

```
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -1.395508546974049
p-value: 0.5844274732972616
Critical Values:
        1%: -3.6996079738860943
        5%: -2.9764303469999494
        10%: -2.627601001371742
```

KPSS test

In [123…

```
from statsmodels.tsa.stattools import kpss
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(month_orders['Order'])
```

```
KPSS Statistic: 0.4610159555277874
p-value: 0.05085519158285027
num lags: 10
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
```

Converting non stationary data into Stationary data

In [124…

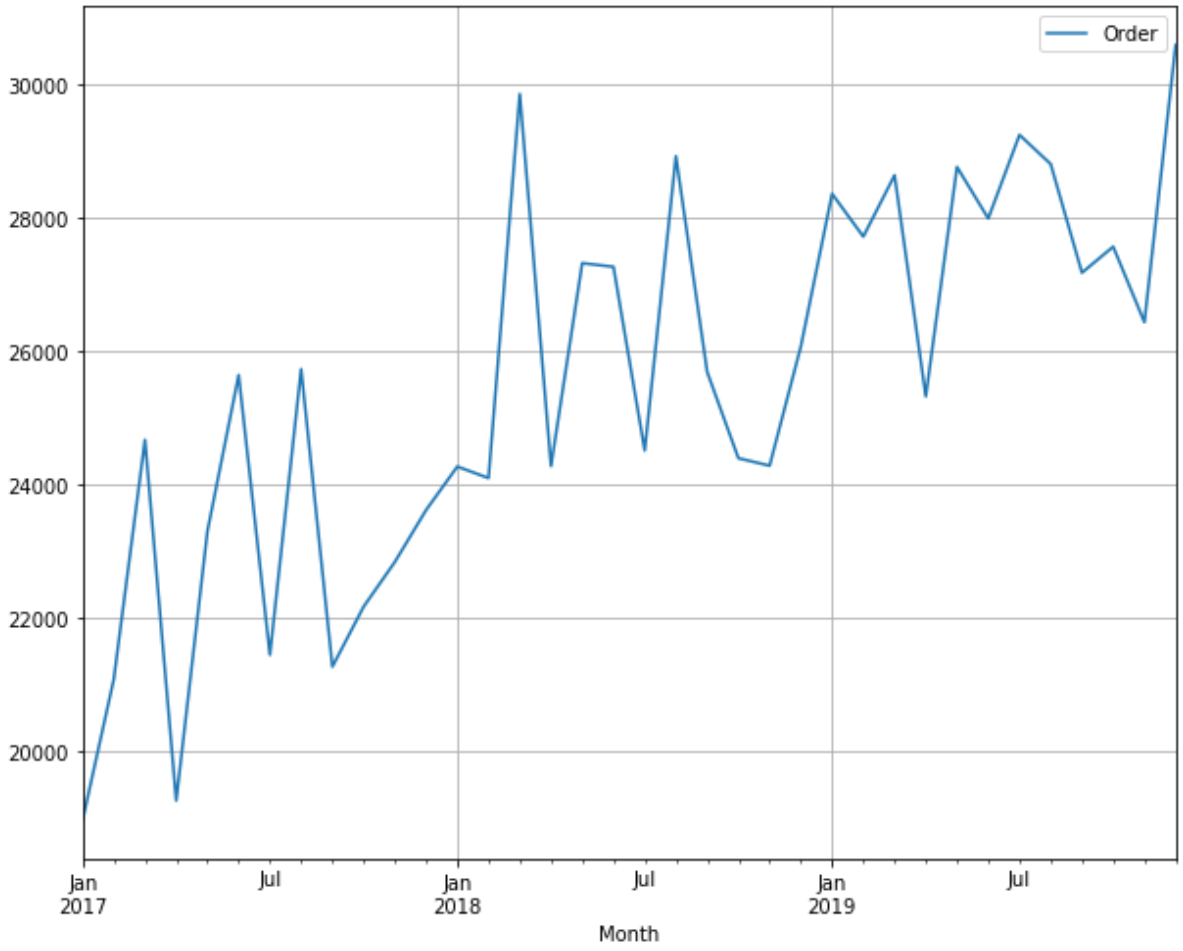
```
month_orders.head()
```

Out[124]:

Month	Order
2017-01-01	18966
2017-02-01	21078
2017-03-01	24668
2017-04-01	19266
2017-05-01	23300

In [125…

```
month_orders.plot(figsize=(10,8))
plt.grid()
plt.show()
```



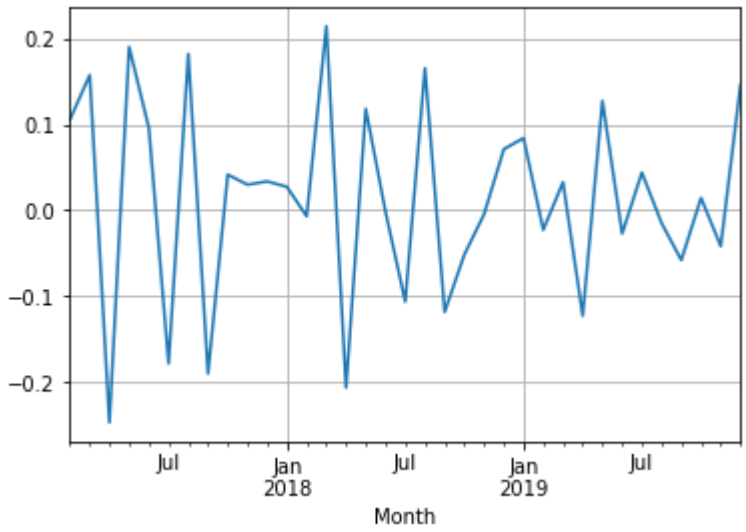
1st Shift

In [197…
```
month_orders1 = month_orders.copy()
```

In [198…
```
month_orders1.shape
```

Out[198]:
```
(36, 1)
```

In [199…
```
month_orders1['Order_lg'] = np.log(month_orders1['Order'])
month_orders1['Order_lg_df'] = month_orders1['Order_lg'] - month_orders1['Order_lg'
month_orders1['Order_lg_df'].dropna().plot()
plt.grid()
```



In [200…
```
month_orders1.head(), month_orders1.shape
```

Out[200]:
```
(            Order   Order_lg  Order_lg_df
 Month
 2017-01-01  18966   9.850403          NaN
 2017-02-01  21078   9.955985     0.105582
 2017-03-01  24668  10.113262     0.157277
 2017-04-01  19266   9.866097    -0.247165
 2017-05-01  23300  10.056209     0.190111,
 (36, 3))
```

In [201…
```
month_orders1 = month_orders1.reset_index()
month_orders1.head(), month_orders1.shape
```

Out[201]:
```
(       Month  Order   Order_lg  Order_lg_df
 0 2017-01-01  18966   9.850403          NaN
 1 2017-02-01  21078   9.955985     0.105582
 2 2017-03-01  24668  10.113262     0.157277
 3 2017-04-01  19266   9.866097    -0.247165
 4 2017-05-01  23300  10.056209     0.190111,
 (36, 4))
```

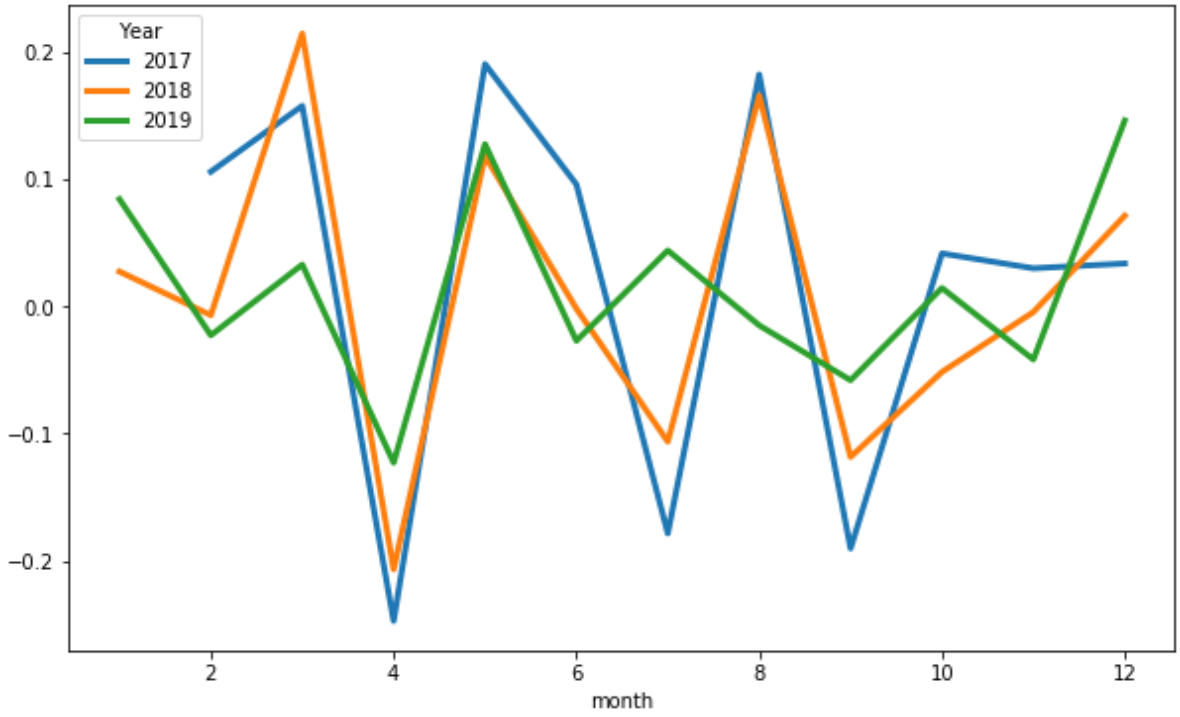
In [202…
```
season1 = month_orders1
```

In [203…
```
season1.head()
```

Out[203]:

	Month	Order	Order_lg	Order_lg_df
0	2017-01-01	18966	9.850403	NaN
1	2017-02-01	21078	9.955985	0.105582
2	2017-03-01	24668	10.113262	0.157277
3	2017-04-01	19266	9.866097	-0.247165
4	2017-05-01	23300	10.056209	0.190111

In [230…
```
season1['Date'] = month_orders1.Month
season1['Year'] = month_orders1.Month.dt.year
season1['month'] = month_orders1.Month.dt.month
season1.dropna(inplace = True)
spivot = pd.pivot_table(season1, index='month', columns = 'Year', values = 'Order_l
spivot.plot(figsize=(10,6), linewidth=3)
plt.show()
```



In [205…
```
month_orders1 = month_orders1.set_index('Month')
```

In [206…
```
month_orders1.drop(['Order','Order_lg','Date','Year','month'], axis = 1, inplace =
```

In [209…
```
month_orders1.dropna().head()
```

Out[209]:

Month	Order_lg_df
2017-02-01	0.105582
2017-03-01	0.157277
2017-04-01	-0.247165
2017-05-01	0.190111
2017-06-01	0.095622

In [212…
```
result = adfuller(month_orders1['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -3.496727206629303
p-value: 0.00807154522613824
Critical Values:
        1%: -3.6996079738860943
        5%: -2.9764303469999494
        10%: -2.627601001371742
```

In [213…
```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
```

```
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(month_orders1['Order_lg_df'].dropna())
```

```
KPSS Statistic: 0.19715527638426128
p-value: 0.1
num lags: 10
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1687: Interpolati
onWarning: p-value is greater than the indicated p-value
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

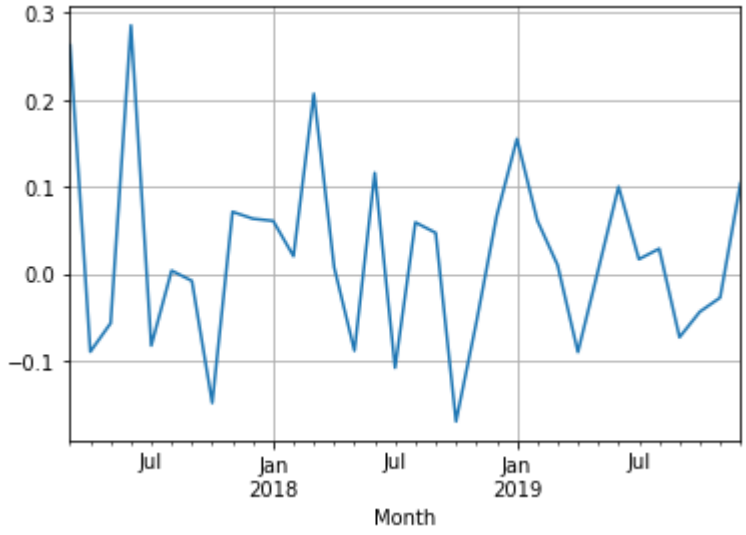
2nd Shift

In [222…
```
month_orders2 = month_orders.copy()
```

In [223…
```
month_orders2.shape
```

Out[223]:
```
(36, 1)
```

In [224…
```
month_orders2['Order_lg'] = np.log(month_orders2['Order'])
month_orders2['Order_lg_df'] = month_orders2['Order_lg'] - month_orders2['Order_lg'
month_orders2['Order_lg_df'].dropna().plot()
plt.grid()
```



In [225…
```
month_orders2 = month_orders2.reset_index()
month_orders2.head(), month_orders2.shape
```

Out[225]:
```
(       Month  Order   Order_lg  Order_lg_df
 0 2017-01-01  18966   9.850403          NaN
 1 2017-02-01  21078   9.955985          NaN
 2 2017-03-01  24668  10.113262     0.262859
 3 2017-04-01  19266   9.866097    -0.089888
 4 2017-05-01  23300  10.056209    -0.057053,
 (36, 4))
```

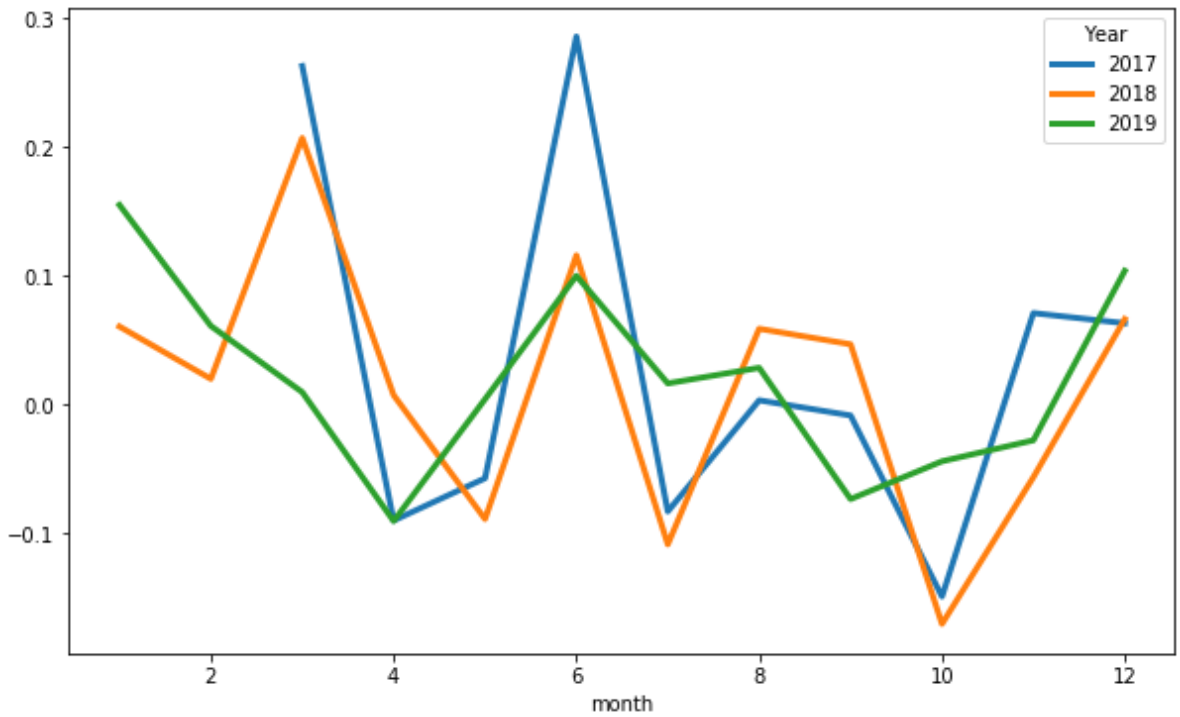
In [226…
```
season2 = month_orders2
```

In [227…
```
season2.head()
```

Out[227]:

	Month	Order	Order_lg	Order_lg_df
0	2017-01-01	18966	9.850403	NaN
1	2017-02-01	21078	9.955985	NaN
2	2017-03-01	24668	10.113262	0.262859
3	2017-04-01	19266	9.866097	-0.089888
4	2017-05-01	23300	10.056209	-0.057053

In [231…
```
season2['Date'] = month_orders2.Month
season2['Year'] = month_orders2.Month.dt.year
season2['month'] = month_orders2.Month.dt.month
season1.dropna(inplace = True)
spivot = pd.pivot_table(season2, index='month', columns = 'Year', values = 'Order_l
spivot.plot(figsize=(10,6), linewidth=3)
plt.show()
```



In [232…
```
month_orders2 = month_orders2.set_index('Month')
```

In [234…
```
month_orders2.drop(['Order','Order_lg','Date','Year','month'], axis = 1, inplace =
```

In [236…
```
month_orders2.dropna().head()
```

Out[236]:

Month	Order_lg_df
2017-03-01	0.262859
2017-04-01	-0.089888
2017-05-01	-0.057053
2017-06-01	0.285734
2017-07-01	-0.082822

In [237…

```
result = adfuller(month_orders2['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -3.1037866464157005
p-value: 0.02627422587566269
Critical Values:
        1%: -3.7377092158564813
        5%: -2.9922162731481485
        10%: -2.635746736111111
```

In [238…

```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(month_orders2['Order_lg_df'].dropna())
```

```
KPSS Statistic: 0.3580331125973205
p-value: 0.09524434801839633
num lags: 10
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

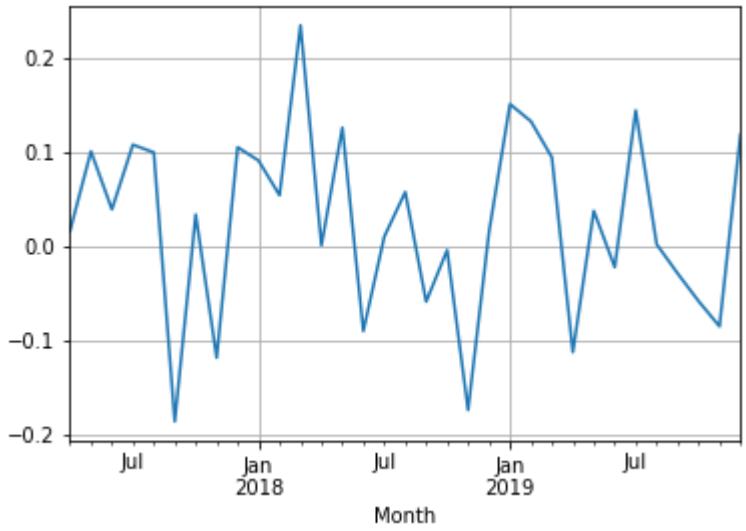
```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
```

3rd Shift

In [242…

```
month_orders3 = month_orders.copy()
month_orders3.shape
month_orders3['Order_lg'] = np.log(month_orders3['Order'])
month_orders3['Order_lg_df'] = month_orders3['Order_lg'] - month_orders3['Order_lg'
```

```
month_orders3['Order_lg_df'].dropna().plot()
plt.grid()
```

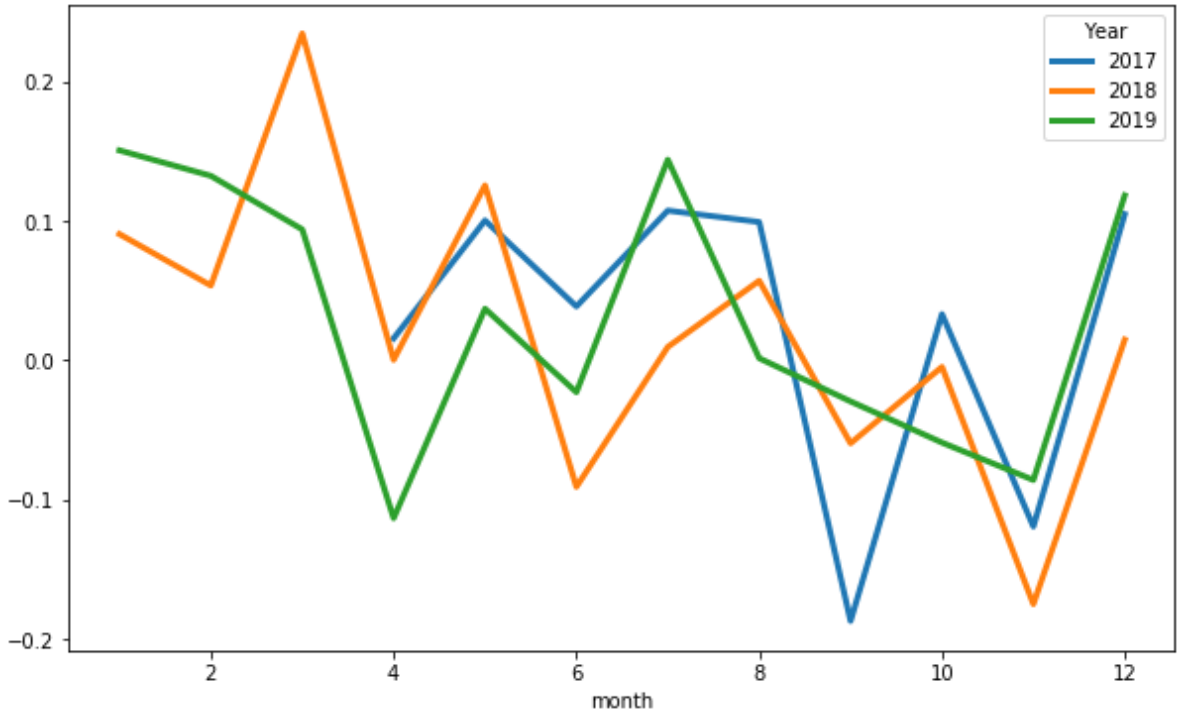


In [243…
```
month_orders3 = month_orders3.reset_index()
month_orders3.head(), month_orders3.shape
```

Out[243]:
```
(       Month  Order   Order_lg  Order_lg_df
 0 2017-01-01  18966   9.850403          NaN
 1 2017-02-01  21078   9.955985          NaN
 2 2017-03-01  24668  10.113262          NaN
 3 2017-04-01  19266   9.866097     0.015694
 4 2017-05-01  23300  10.056209     0.100224,
 (36, 4))
```

In [244…
```
season3 = month_orders3
```

In [245…
```
season3['Date'] = month_orders3.Month
season3['Year'] = month_orders3.Month.dt.year
season3['month'] = month_orders3.Month.dt.month
season3.dropna(inplace = True)
spivot = pd.pivot_table(season3, index='month', columns = 'Year', values = 'Order_l
spivot.plot(figsize=(10,6), linewidth=3)
plt.show()
```



In [246…
```
month_orders3 = month_orders3.set_index('Month')
```

In [247…
```
month_orders3.drop(['Order','Order_lg','Date','Year','month'], axis = 1, inplace =
```

In [249…
```
month_orders3.dropna().head()
```

Out[249]:

Month	Order_lg_df
2017-04-01	0.015694
2017-05-01	0.100224
2017-06-01	0.038569
2017-07-01	0.107290
2017-08-01	0.099088

In [250…
```
result = adfuller(month_orders3['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -3.4543036013111967
p-value: 0.009241222089179366
Critical Values:
        1%: -3.6996079738860943
        5%: -2.9764303469999494
        10%: -2.627601001371742
```

In [251…
```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
```

```
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(month_orders3['Order_lg_df'].dropna())
```

```
KPSS Statistic: 0.33931064641976644
p-value: 0.1
num lags: 10
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1687: Interpolati
onWarning: p-value is greater than the indicated p-value
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

In [253…

```
# I got the optimum result for stationarity at 1st shift
# so i will take 1st shift for my forecasting
```

Forecasting

In [255…

```
month_orders3 = month_orders1.dropna()
```

In [256…

```
month_orders3.head()
```

Out[256]:

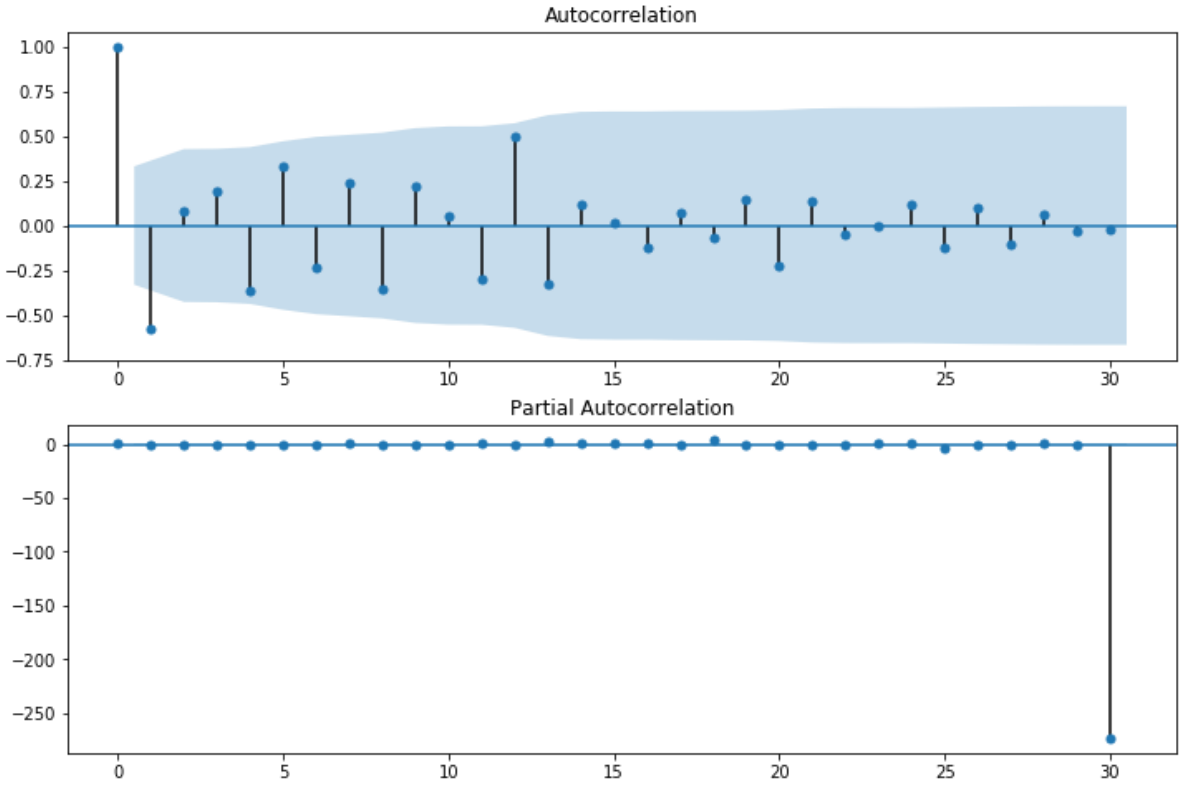
	Month	Order_lg_df
1	2017-02-01	0.105582
2	2017-03-01	0.157277
3	2017-04-01	-0.247165
4	2017-05-01	0.190111
5	2017-06-01	0.095622

finding p and q value

In [258…

```
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(month_orders3['Order_lg_df'].values.squeeze(), lags=
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(month_orders3['Order_lg_df'], lags=30, ax=ax2)
```

```
E:\New folder (2)\lib\site-packages\statsmodels\regression\linear_model.py:1406: R
untimeWarning: invalid value encountered in sqrt
  return rho, np.sqrt(sigmasq)
```



In [259…
```
# I will take p = 2 and q = 1
```

Spliting the data

In [298…
```
month_orders3 = month_orders3.set_index('Month')
```

In [299…
```
month_orders3['Order_lg_df'].dropna()
```

Out[299]:
```
Month
2017-02-01    0.105582
2017-03-01    0.157277
2017-04-01   -0.247165
2017-05-01    0.190111
2017-06-01    0.095622
2017-07-01   -0.178444
2017-08-01    0.181910
2017-09-01   -0.190243
2017-10-01    0.041397
2017-11-01    0.029731
2017-12-01    0.033499
2018-01-01    0.027193
2018-02-01   -0.007113
2018-03-01    0.214080
2018-04-01   -0.206637
2018-05-01    0.117916
2018-06-01   -0.001979
2018-07-01   -0.106384
2018-08-01    0.165361
2018-09-01   -0.118453
2018-10-01   -0.051652
2018-11-01   -0.004602
2018-12-01    0.071017
2019-01-01    0.084027
2019-02-01   -0.022868
2019-03-01    0.032626
2019-04-01   -0.122900
2019-05-01    0.127222
2019-06-01   -0.027180
2019-07-01    0.043735
2019-08-01   -0.015061
2019-09-01   -0.058158
2019-10-01    0.014252
2019-11-01   -0.041866
2019-12-01    0.145781
Name: Order_lg_df, dtype: float64
```

In [300…
```
training_data=month_orders3['Order_lg_df'].dropna()[0:28]
test_data=month_orders3['Order_lg_df'].dropna()[28:]
```

In [301…
```
training_data
```

Out[301]:
```
Month
2017-02-01    0.105582
2017-03-01    0.157277
2017-04-01   -0.247165
2017-05-01    0.190111
2017-06-01    0.095622
2017-07-01   -0.178444
2017-08-01    0.181910
2017-09-01   -0.190243
2017-10-01    0.041397
2017-11-01    0.029731
2017-12-01    0.033499
2018-01-01    0.027193
2018-02-01   -0.007113
2018-03-01    0.214080
2018-04-01   -0.206637
2018-05-01    0.117916
2018-06-01   -0.001979
2018-07-01   -0.106384
2018-08-01    0.165361
2018-09-01   -0.118453
2018-10-01   -0.051652
2018-11-01   -0.004602
2018-12-01    0.071017
2019-01-01    0.084027
2019-02-01   -0.022868
2019-03-01    0.032626
2019-04-01   -0.122900
2019-05-01    0.127222
Name: Order_lg_df, dtype: float64
```

Importing ARIMA and ARMA

In [302…
```
from statsmodels.tsa.arima_model import ARIMA, ARMA
```

ARIMA

In [303…
```
# I will take p = 2, d = 1 and q = 1
arima1= ARIMA(np.asarray(training_data),order=(2,1,1))
model1=arima1.fit()
```

In [304…
```
pred1= model1.forecast(steps=len(test_data))[0]
```

In [305…
```
from sklearn.metrics import mean_squared_error
np.sqrt(mean_squared_error(test_data,pred1)), mean_squared_error(test_data,pred1)
```

Out[305]:
```
(0.07286478635757448, 0.005309277090934973)
```

In [306…
```
# I will take p = 2, d = 1 and q = 0
arima2= ARIMA(np.asarray(training_data),order=(2,1,0))
model2=arima2.fit()
pred2= model2.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,pred2)), mean_squared_error(test_data,pred2)
```

Out[306]:
```
(0.08772959600010354, 0.007696482014341381 5)
```

In [307…
```
# I will take p = 3, d = 1 and q = 0
arima3= ARIMA(np.asarray(training_data),order=(3,1,1))
model3=arima3.fit()
pred3= model3.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,pred3)), mean_squared_error(test_data,pred3)
```

Out[307]:
```
(0.07899389839251246, 0.006240035983246584)
```

In [308…
```
# I will take p = 2, d = 2 and q = 1
arima4= ARIMA(np.asarray(training_data),order=(2,2,1))
model4=arima4.fit()
pred4= model4.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,pred4)), mean_squared_error(test_data,pred4)
```

Out[308]:
```
(0.08313177698327649, 0.006910892344397218)
```

In [309…
```
# I will take p = 3, d = 3 and q = 1
arima5= ARIMA(np.asarray(training_data),order=(3,2,1))
model5=arima5.fit()
pred5= model5.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,pred5)), mean_squared_error(test_data,pred5)
```

Out[309]:
```
(0.2613419196883266, 0.06829959898637974)
```

ARMA

In [319…
```
arma1= ARMA(training_data,order=(2,1))
m1=arma1.fit()
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\base\tsa_model.py:162: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be use
d.
  % freq, ValueWarning)
```

In [320…
```
p1= m1.forecast(steps=len(test_data))[0]
```

In [321…
```
np.sqrt(mean_squared_error(test_data,p1)), mean_squared_error(test_data,p1)
```

Out[321]:
```
(0.10102315871457569, 0.010205678596670351)
```

In [323…
```
arma2= ARMA(training_data,order=(3,1))
m2=arma2.fit()
p2= m2.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,p2)), mean_squared_error(test_data,p2)
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\base\tsa_model.py:162: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be use
d.
  % freq, ValueWarning)
```

Out[323]:
```
(0.0996511775181702, 0.00993035718075787)
```

In [325…
```
arma3= ARMA(training_data,order=(3,0))
m3=arma3.fit()
p3= m3.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,p3)), mean_squared_error(test_data,p3)
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\base\tsa_model.py:162: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be use
d.
  % freq, ValueWarning)
```

Out[325]:
```
(0.07801946320572105, 0.0060870366389088595)
```

In [326…
```
arma4= ARMA(training_data,order=(2,0))
m4=arma4.fit()
```

```
p4= m4.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,p4)), mean_squared_error(test_data,p4)
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\base\tsa_model.py:162: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be use
d.
  % freq, ValueWarning)
```

Out[326]: (0.07324962894637876, 0.0053655081407821695)

Selecting Model:

Best result is obtained from ARMA at p = 2 and q = 0 so, Model m1 is selected

Making prediction for Jan 2020, Feb 2020 and March 2020

In [327…
```
predict_Jan_Feb_Mar_2020 = m4.forecast(steps=3)[0]
```

In [328…
```
predict_Jan_Feb_Mar_2020
```

Out[328]: array([-0.02743325, -0.0181607 , 0.05752019])

In [405…
```
#function to trace back the actual order value from predicted shifted log
#value
```

In [434…
```
for i in range(3,len(month_orders3)):
    #print(i)
    prev = month_orders3['Order_lg'].iloc[i-3]
    cur_df = month_orders3['Order_lg_df'].iloc[i]
    curr = prev+cur_df
    print(round(np.exp(curr)), "->", curr)
```

```
19266.0 -> 9.86609716331757
23300.0 -> 10.056208639553791
25638.0 -> 10.15183090487208
21448.0 -> 9.973386679915794
25727.0 -> 10.155296303064102
21270.0 -> 9.965052908194282
22169.0 -> 10.006450195593953
22838.0 -> 10.036181094261593
23616.0 -> 10.0696797274002
24267.0 -> 10.096872681686062
24095.0 -> 10.089759629074432
29847.0 -> 10.30383961125747
24275.0 -> 10.097202293159526
27313.0 -> 10.215118058306537
27259.0 -> 10.21313902079189
24508.0 -> 10.106754873845546
28915.0 -> 10.272115770592318
25685.0 -> 10.153662442901368
24392.0 -> 10.10201048866809
24280.0 -> 10.097408245173435
26067.0 -> 10.168425425507316
28352.0 -> 10.252452853404808
27711.0 -> 10.22958472526072
28630.0 -> 10.262210398092162
25319.0 -> 10.13931038100741
28754.0 -> 10.266532166982538
27983.0 -> 10.239352461914338
29234.0 -> 10.283087694449238
28797.0 -> 10.268026494031647
27170.0 -> 10.209868702420394
27560.0 -> 10.224120725127595
26430.0 -> 10.182255007598334
30578.0 -> 10.32803607512056
```

In [ ]:

In [ ]:

In [ ]:

==========

Quarter Data Forecast

In [414…

```
df3.head()
```

Out[414]:

	AccountNumber	Month	Order	ContactName	ContactProfessionalCategory	ContactCertificatio
0	1086390	2019-11-01	0	Dr. Branden Washington	GP	2018-
1	1086390	2019-12-01	5	Dr. Branden Washington	GP	2018-
2	1079261	2019-11-01	6	Dr. Rey Mcdowell	GP	2019-
3	1079261	2019-08-01	0	Dr. Rey Mcdowell	GP	2019-
4	1079261	2019-12-01	10	Dr. Rey Mcdowell	GP	2019-

In [415…
```
qtr_data = df3.copy()
```

In [416…
```
qtr_data.head()
```

Out[416]:

	AccountNumber	Month	Order	ContactName	ContactProfessionalCategory	ContactCertificatio
0	1086390	2019-11-01	0	Dr. Branden Washington	GP	2018-
1	1086390	2019-12-01	5	Dr. Branden Washington	GP	2018-
2	1079261	2019-11-01	6	Dr. Rey Mcdowell	GP	2019-
3	1079261	2019-08-01	0	Dr. Rey Mcdowell	GP	2019-
4	1079261	2019-12-01	10	Dr. Rey Mcdowell	GP	2019-

In [417…
```
qtr_data['Date'] = qtr_data.Month
qtr_data['Year'] = qtr_data.Month.dt.year
qtr_data['month'] = qtr_data.Month.dt.month
```

In [418…
```
qtr_data.head()
```

Out[418]:

	AccountNumber	Month	Order	ContactName	ContactProfessionalCategory	ContactCertificatio
0	1086390	2019-11-01	0	Dr. Branden Washington	GP	2018-
1	1086390	2019-12-01	5	Dr. Branden Washington	GP	2018-
2	1079261	2019-11-01	6	Dr. Rey Mcdowell	GP	2019-
3	1079261	2019-08-01	0	Dr. Rey Mcdowell	GP	2019-
4	1079261	2019-12-01	10	Dr. Rey Mcdowell	GP	2019-

In [419…

```
conditions = [(qtr_data['month'] <= 3) & (qtr_data['Year'] == 2017),
    (qtr_data['month'] > 3) & (qtr_data['month'] <= 6) & (qtr_data['Year'] == 2017)
    (qtr_data['month'] > 6) & (qtr_data['month'] <= 9)& (qtr_data['Year'] == 2017),
    (qtr_data['month'] > 9)& (qtr_data['Year'] == 2017) ,(qtr_data['month'] <= 3)&
    (qtr_data['month'] > 3) & (qtr_data['month'] <= 6)& (qtr_data['Year'] == 2018),
    (qtr_data['month'] > 6) & (qtr_data['month'] <= 9)& (qtr_data['Year'] == 2018),
    (qtr_data['month'] > 9)& (qtr_data['Year'] == 2018) ,(qtr_data['month'] <= 3)&
    (qtr_data['month'] > 3) & (qtr_data['month'] <= 6)& (qtr_data['Year'] == 2019),
    (qtr_data['month'] > 6) & (qtr_data['month'] <= 9)& (qtr_data['Year'] == 2019),
    (qtr_data['month'] > 9)& (qtr_data['Year'] == 2019)
    ]
#values = ['Q1_2017', 'Q2_2017', 'Q3_2017', 'Q4_2017', 'Q1_2018', 'Q2_2018', 'Q3_20
values = ['01-03-2017', '01-06-2017', '01-09-2017', '01-12-2017','01-03-2018', '01-
qtr_data['Quarter'] = np.select(conditions, values)
```

In [420…

```
qtr_data.head()
```

Out[420]:

	AccountNumber	Month	Order	ContactName	ContactProfessionalCategory	ContactCertificatio
0	1086390	2019-11-01	0	Dr. Branden Washington	GP	2018-
1	1086390	2019-12-01	5	Dr. Branden Washington	GP	2018-
2	1079261	2019-11-01	6	Dr. Rey Mcdowell	GP	2019-
3	1079261	2019-08-01	0	Dr. Rey Mcdowell	GP	2019-
4	1079261	2019-12-01	10	Dr. Rey Mcdowell	GP	2019-

In [421…

```
qtr_data = pd.DataFrame(qtr_data.groupby(['Quarter'])['Order'].sum())
```

In [462…

```
qtr_data.head()
```

Out[462]:

Quarter	Order
2017-01-03	63567
2017-01-06	66889
2017-01-09	67134
2017-01-12	67274
2018-01-03	76177

In [463…
```
qtr_data.reset_index(inplace = True)
```

In [464…
```
qtr_data['Quarter'] = pd.to_datetime(qtr_data['Quarter'])
```

In [465…
```
qtr_data
```

Out[465]:

	Quarter	Order
0	2017-01-03	63567
1	2017-01-06	66889
2	2017-01-09	67134
3	2017-01-12	67274
4	2018-01-03	76177
5	2018-01-06	77147
6	2018-01-09	77390
7	2018-01-12	73262
8	2019-01-03	82943
9	2019-01-06	80103
10	2019-01-09	83333
11	2019-01-12	82640

In [466…
```
qtr_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12 entries, 0 to 11
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype         
---  ------   --------------  -----         
 0   Quarter  12 non-null     datetime64[ns]
 1   Order    12 non-null     int64         
dtypes: datetime64[ns](1), int64(1)
memory usage: 320.0 bytes
```

In [467…
```
qtr_data = qtr_data.sort_values(by = 'Quarter')
```

In [468…
```
qtr_data
```

Out[468]:

	Quarter	Order
0	2017-01-03	63567
1	2017-01-06	66889
2	2017-01-09	67134
3	2017-01-12	67274
4	2018-01-03	76177
5	2018-01-06	77147
6	2018-01-09	77390
7	2018-01-12	73262
8	2019-01-03	82943
9	2019-01-06	80103
10	2019-01-09	83333
11	2019-01-12	82640

In [469…
```
qtr_data = qtr_data.set_index('Quarter')
```

In [470…
```
from statsmodels.tsa.stattools import adfuller
```

In [471…
```
result = adfuller(qtr_data['Order'])
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -1.2125859640119503
p-value: 0.6681582497809107
Critical Values:
        1%: -4.9386902332361515
        5%: -3.477582857142857
        10%: -2.8438679591836733
```

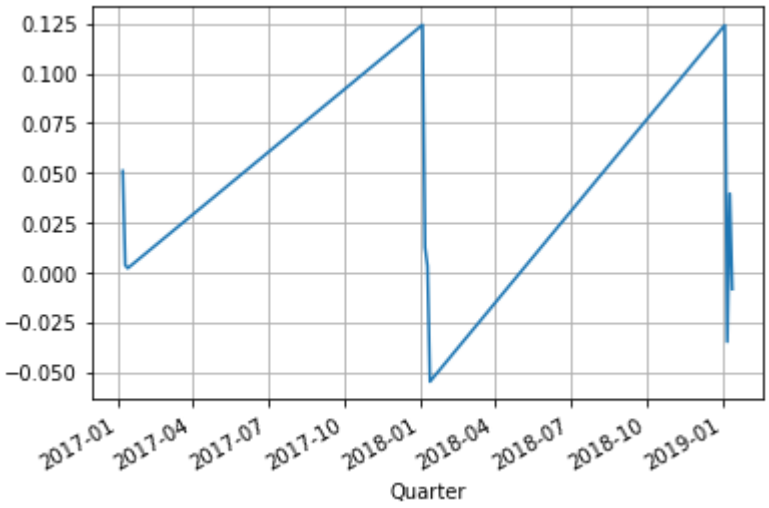
In [472…
```
from statsmodels.tsa.stattools import kpss
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(qtr_data['Order'])
```

```
KPSS Statistic: 0.39402575208821367
p-value: 0.0797302792723217
num lags: 8
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
```

In [473…

```
qtr_data1 = qtr_data.copy()
qtr_data1['Order_lg'] = np.log(qtr_data1['Order'])
qtr_data1['Order_lg_df'] = qtr_data1['Order_lg'] - qtr_data1['Order_lg'].shift(1)
qtr_data1['Order_lg_df'].dropna().plot()
plt.grid()
```



In [475…

```
qtr_data1
```

Out[475]:

Quarter	Order	Order_lg	Order_lg_df
2017-01-03	63567	11.059850	NaN
2017-01-06	66889	11.110790	0.050940
2017-01-09	67134	11.114446	0.003656
2017-01-12	67274	11.116529	0.002083
2018-01-03	76177	11.240815	0.124286
2018-01-06	77147	11.253468	0.012653
2018-01-09	77390	11.256613	0.003145
2018-01-12	73262	11.201797	-0.054816
2019-01-03	82943	11.325909	0.124112
2019-01-06	80103	11.291069	-0.034840
2019-01-09	83333	11.330600	0.039531
2019-01-12	82640	11.322249	-0.008351

In [476…

```
qtr_data1 = qtr_data1.reset_index()
qtr_data1.head(), qtr_data1.shape
```

Out[476]:
```
(     Quarter  Order   Order_lg  Order_lg_df
 0 2017-01-03  63567  11.059850          NaN
 1 2017-01-06  66889  11.110790     0.050940
 2 2017-01-09  67134  11.114446     0.003656
 3 2017-01-12  67274  11.116529     0.002083
 4 2018-01-03  76177  11.240815     0.124286,
 (12, 4))
```

In [477…
```
qtr_data1.drop(['Order','Order_lg'], axis = 1, inplace = True)
```

In [478…
```
qtr_data1.dropna().head()
```

Out[478]:

	Quarter	Order_lg_df
1	2017-01-06	0.050940
2	2017-01-09	0.003656
3	2017-01-12	0.002083
4	2018-01-03	0.124286
5	2018-01-06	0.012653

In [479…
```
result = adfuller(qtr_data1['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -1.1627422346961738
p-value: 0.689414310918847
Critical Values:
        1%: -4.9386902332361515
        5%: -3.477582857142857
        10%: -2.8438679591836733
```

In [480…
```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(qtr_data1['Order_lg_df'].dropna())
```

```
KPSS Statistic: 0.37392970705408574
p-value: 0.08839236764910097
num lags: 7
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

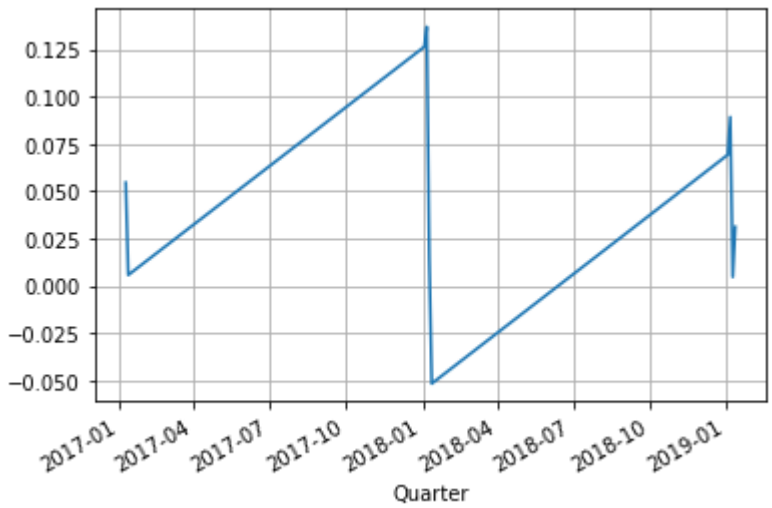
```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
```

In [481…

```
qtr_data2 = qtr_data.copy()
qtr_data2['Order_lg'] = np.log(qtr_data2['Order'])
qtr_data2['Order_lg_df'] = qtr_data2['Order_lg'] - qtr_data2['Order_lg'].shift(2)
qtr_data2['Order_lg_df'].dropna().plot()
plt.grid()
qtr_data2
```

Out[481]:

Quarter	Order	Order_lg	Order_lg_df
2017-01-03	63567	11.059850	NaN
2017-01-06	66889	11.110790	NaN
2017-01-09	67134	11.114446	0.054596
2017-01-12	67274	11.116529	0.005739
2018-01-03	76177	11.240815	0.126369
2018-01-06	77147	11.253468	0.136939
2018-01-09	77390	11.256613	0.015798
2018-01-12	73262	11.201797	-0.051671
2019-01-03	82943	11.325909	0.069296
2019-01-06	80103	11.291069	0.089271
2019-01-09	83333	11.330600	0.004691
2019-01-12	82640	11.322249	0.031181



In [482…

```
qtr_data2.drop(['Order','Order_lg'], axis = 1, inplace = True)
```

In [483…

```
qtr_data2.dropna().head()
```

Out[483]:

Quarter	Order_lg_df
2017-01-09	0.054596
2017-01-12	0.005739
2018-01-03	0.126369
2018-01-06	0.136939
2018-01-09	0.015798

In [484…

```
result = adfuller(qtr_data2['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -4.046758233714935
p-value: 0.0011845210343182015
Critical Values:
        1%: -4.6651863281249994
        5%: -3.3671868750000002
        10%: -2.802960625
```

In [485…

```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(qtr_data2['Order_lg_df'].dropna())
```

```
KPSS Statistic: 0.4012738068862438
p-value: 0.07660611772144664
num lags: 7
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
```

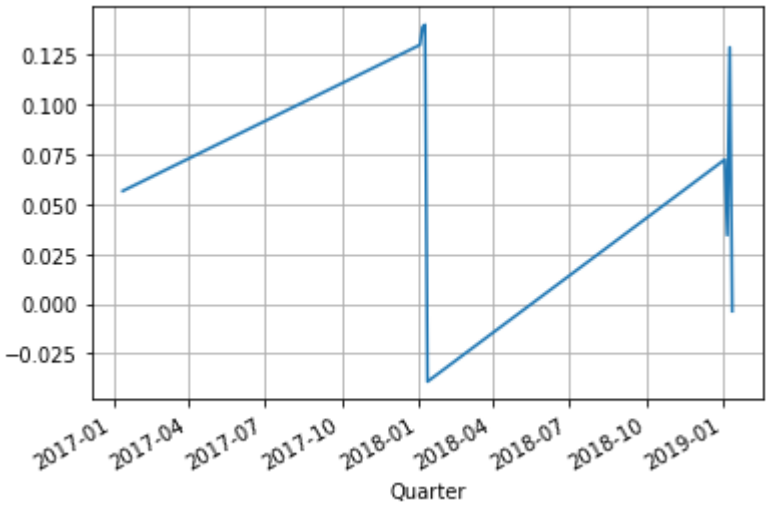
In [486…

```
qtr_data3 = qtr_data.copy()
qtr_data3['Order_lg'] = np.log(qtr_data3['Order'])
qtr_data3['Order_lg_df'] = qtr_data3['Order_lg'] - qtr_data3['Order_lg'].shift(3)
qtr_data3['Order_lg_df'].dropna().plot()
plt.grid()
qtr_data3
```

```
qtr_data3.drop(['Order','Order_lg'], axis = 1, inplace = True)
qtr_data3.dropna().head()
```

Out[486]:

Quarter	Order_lg_df
2017-01-12	0.056679
2018-01-03	0.130025
2018-01-06	0.139022
2018-01-09	0.140084
2018-01-12	-0.039018



In [487…

```
result = adfuller(qtr_data3['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -2.8040652257180105
p-value: 0.05769542177024152
Critical Values:
        1%: -4.6651863281249994
        5%: -3.3671868750000002
        10%: -2.802960625
```

In [488…

```
# Best stationarity is found at 2nd Shift
```

In [489…

```
qtr_data2
```

Out[489]:

Quarter	Order_lg_df
2017-01-03	NaN
2017-01-06	NaN
2017-01-09	0.054596
2017-01-12	0.005739
2018-01-03	0.126369
2018-01-06	0.136939
2018-01-09	0.015798
2018-01-12	-0.051671
2019-01-03	0.069296
2019-01-06	0.089271
2019-01-09	0.004691
2019-01-12	0.031181

In [492…

```
qtr = qtr_data2.dropna()
qtr.reset_index(inplace = True)
qtr
```

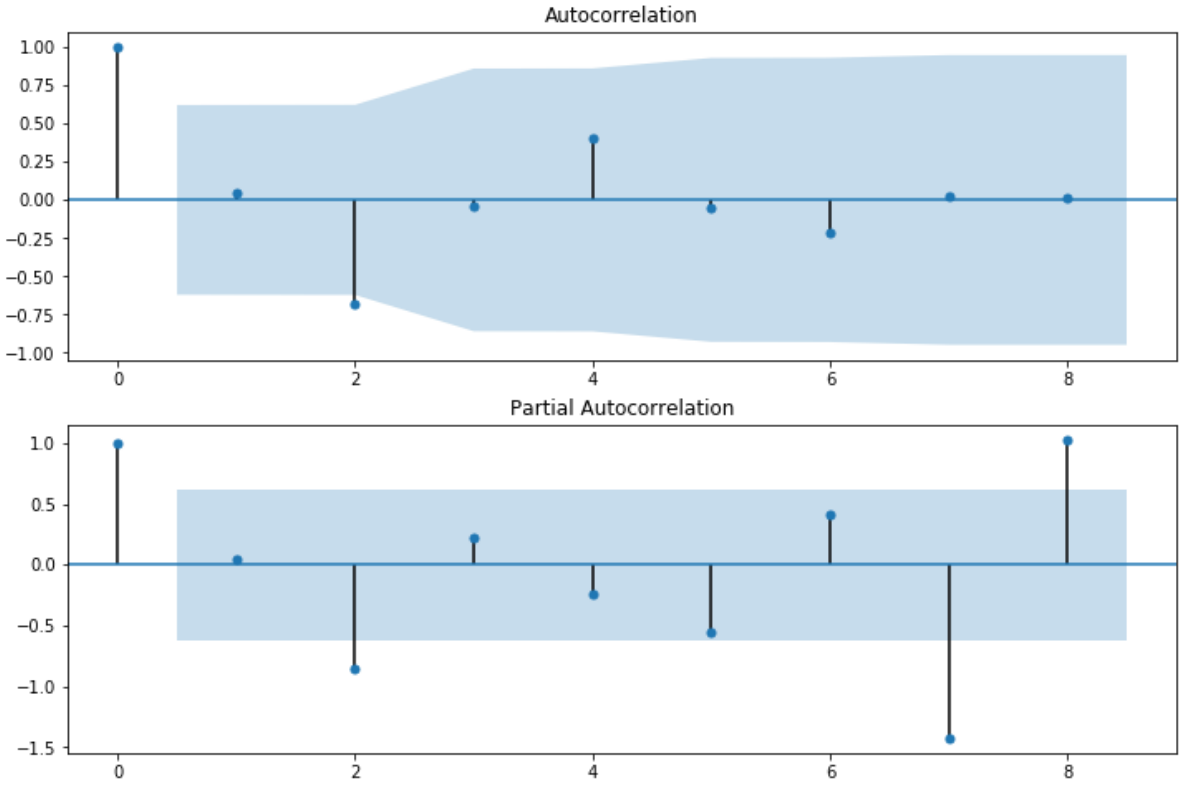
Out[492]:

	Quarter	Order_lg_df
0	2017-01-09	0.054596
1	2017-01-12	0.005739
2	2018-01-03	0.126369
3	2018-01-06	0.136939
4	2018-01-09	0.015798
5	2018-01-12	-0.051671
6	2019-01-03	0.069296
7	2019-01-06	0.089271
8	2019-01-09	0.004691
9	2019-01-12	0.031181

In [493…

```
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(qtr['Order_lg_df'].values.squeeze(), lags=8, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(qtr['Order_lg_df'], lags=8, ax=ax2)
```

```
E:\New folder (2)\lib\site-packages\statsmodels\regression\linear_model.py:1406: R
untimeWarning: invalid value encountered in sqrt
  return rho, np.sqrt(sigmasq)
```



In [494…
```
# I will take p = 1 and q = 1
```

In [495…
```
qtr, len(qtr)
```

Out[495]:
```
(     Quarter  Order_lg_df
 0 2017-01-09     0.054596
 1 2017-01-12     0.005739
 2 2018-01-03     0.126369
 3 2018-01-06     0.136939
 4 2018-01-09     0.015798
 5 2018-01-12    -0.051671
 6 2019-01-03     0.069296
 7 2019-01-06     0.089271
 8 2019-01-09     0.004691
 9 2019-01-12     0.031181,
 10)
```

In [497…
```
training_data=qtr['Order_lg_df'].dropna()[0:8]
test_data=qtr['Order_lg_df'].dropna()[8:]
```

In [498…
```
qtr
```

Out[498]:

	Quarter	Order_lg_df
0	2017-01-09	0.054596
1	2017-01-12	0.005739
2	2018-01-03	0.126369
3	2018-01-06	0.136939
4	2018-01-09	0.015798
5	2018-01-12	-0.051671
6	2019-01-03	0.069296
7	2019-01-06	0.089271
8	2019-01-09	0.004691
9	2019-01-12	0.031181

In [499…

```
x = training_data.values
x
```

Out[499]:

```
array([ 0.05459615,  0.0057393 ,  0.12636896,  0.13693886,  0.01579799,
       -0.05167064,  0.06929605,  0.08927125])
```

In [500…

```
ar1= ARIMA(x,order=(1,1,1))
```

In [501…

```
ar1.fit()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-501-cd979a9aa7ac> in <module>
----> 1 ar1.fit()

E:\New folder (2)\lib\site-packages\statsmodels\tsa\arima_model.py in fit(self, st
art_params, trend, method, transparams, solver, maxiter, full_output, disp, callba
ck, start_ar_lags, **kwargs)
   1198                                       method, transparams, solver,
   1199                                       maxiter, full_output, disp,
-> 1200                                       callback, start_ar_lags, **kwargs)
   1201         normalized_cov_params = None  # TODO: fix this?
   1202         arima_fit = ARIMAResults(self, mlefit._results.params,

E:\New folder (2)\lib\site-packages\statsmodels\tsa\arima_model.py in fit(self, st
art_params, trend, method, transparams, solver, maxiter, full_output, disp, callba
ck, start_ar_lags, **kwargs)
    984         else:  # estimate starting parameters
    985             start_params = self._fit_start_params((k_ar, k_ma, k), method,
--> 986                                                   start_ar_lags)
    987
    988         if transparams:  # transform initial parameters to ensure invertib
ility

E:\New folder (2)\lib\site-packages\statsmodels\tsa\arima_model.py in _fit_start_p
arams(self, order, method, start_ar_lags)
    575                 return -self.loglike_css(params)
    576
--> 577             start_params = self._fit_start_params_hr(order, start_ar_lags)
    578             if self.transparams:
    579                 start_params = self._invtransparams(start_params)

E:\New folder (2)\lib\site-packages\statsmodels\tsa\arima_model.py in _fit_start_p
arams_hr(self, order, start_ar_lags)
    510                     if maxlag >= nobs:
    511                         maxlag = nobs - 1
--> 512                     mod = ar_select_order(endog, maxlag, trend='n').model
    513                     armod = mod.fit()
    514                 else:

E:\New folder (2)\lib\site-packages\statsmodels\tsa\ar_model.py in ar_select_order
(endog, maxlag, ic, glob, trend, seasonal, exog, hold_back, period, missing)
   2295     full_mod = AutoReg(endog, maxlag, trend=trend, seasonal=seasonal,
   2296                        exog=exog, hold_back=hold_back, period=period,
-> 2297                        missing=missing)
   2298     nexog = full_mod.exog.shape[1] if full_mod.exog is not None else 0
   2299     y, x = full_mod._y, full_mod._x

E:\New folder (2)\lib\site-packages\statsmodels\tsa\ar_model.py in __init__(self,
endog, lags, trend, seasonal, exog, hold_back, period, missing)
    182         self._hold_back = int_like(hold_back, 'hold_back', optional=True)
    183         self._check_lags()
--> 184         self._setup_regressors()
    185         self.nobs = self._y.shape[0]
    186         self.data.xnames = self.exog_names

E:\New folder (2)\lib\site-packages\statsmodels\tsa\ar_model.py in _setup_regresso
rs(self)
    279                                 'are only {4} data points available to estima
te '
    280                                 'parameters.'.format(reg, trend, seas, lags,
--> 281                                                      nobs))
    282         self._y, self._x = y, x
    283         self._exog_names = exog_names
```

```
ValueError: The model specification cannot be estimated. The model contains 6 regr
essors (0 trend, 0 seasonal, 6 lags) but after adjustment for hold_back and creati
on of the lags, there are only 1 data points available to estimate parameters.
```

In [502…

```
arma1= ARMA(training_data,order=(1,1))
```

In [503…

```
arma1.fit(disp = 1)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-503-ded256847eec> in <module>
----> 1 arma1.fit(disp = 1)

E:\New folder (2)\lib\site-packages\statsmodels\tsa\arima_model.py in fit(self, st
art_params, trend, method, transparams, solver, maxiter, full_output, disp, callba
ck, start_ar_lags, **kwargs)
    984         else:  # estimate starting parameters
    985             start_params = self._fit_start_params((k_ar, k_ma, k), method,
--> 986                                                   start_ar_lags)
    987
    988         if transparams:  # transform initial parameters to ensure invertib
ility

E:\New folder (2)\lib\site-packages\statsmodels\tsa\arima_model.py in _fit_start_p
arams(self, order, method, start_ar_lags)
    575                 return -self.loglike_css(params)
    576
--> 577             start_params = self._fit_start_params_hr(order, start_ar_lags)
    578             if self.transparams:
    579                 start_params = self._invtransparams(start_params)

E:\New folder (2)\lib\site-packages\statsmodels\tsa\arima_model.py in _fit_start_p
arams_hr(self, order, start_ar_lags)
    510                     if maxlag >= nobs:
    511                         maxlag = nobs - 1
--> 512                     mod = ar_select_order(endog, maxlag, trend='n').model
    513                     armod = mod.fit()
    514                 else:

E:\New folder (2)\lib\site-packages\statsmodels\tsa\ar_model.py in ar_select_order
(endog, maxlag, ic, glob, trend, seasonal, exog, hold_back, period, missing)
   2295     full_mod = AutoReg(endog, maxlag, trend=trend, seasonal=seasonal,
   2296                        exog=exog, hold_back=hold_back, period=period,
-> 2297                        missing=missing)
   2298     nexog = full_mod.exog.shape[1] if full_mod.exog is not None else 0
   2299     y, x = full_mod._y, full_mod._x

E:\New folder (2)\lib\site-packages\statsmodels\tsa\ar_model.py in __init__(self,
endog, lags, trend, seasonal, exog, hold_back, period, missing)
    182         self._hold_back = int_like(hold_back, 'hold_back', optional=True)
    183         self._check_lags()
--> 184         self._setup_regressors()
    185         self.nobs = self._y.shape[0]
    186         self.data.xnames = self.exog_names

E:\New folder (2)\lib\site-packages\statsmodels\tsa\ar_model.py in _setup_regresso
rs(self)
    279                             'are only {4} data points available to estima
te '
    280                             'parameters.'.format(reg, trend, seas, lags,
--> 281                                                  nobs))
    282         self._y, self._x = y, x
    283         self._exog_names = exog_names

ValueError: The model specification cannot be estimated. The model contains 6 regr
essors (0 trend, 0 seasonal, 6 lags) but after adjustment for hold_back and creati
on of the lags, there are only 2 data points available to estimate parameters.
```

In [504…

```
qtr_data.head()
```

Out[504]:

Quarter	Order
2017-01-03	63567
2017-01-06	66889
2017-01-09	67134
2017-01-12	67274
2018-01-03	76177

==========

Account State wise prediction

In [519…
```
state_data = df3.copy()
```

In [520…
```
state_data.head()
```

Out[520]:

	AccountNumber	Month	Order	ContactName	ContactProfessionalCategory	ContactCertificatio
0	1086390	2019-11-01	0	Dr. Branden Washington	GP	2018-
1	1086390	2019-12-01	5	Dr. Branden Washington	GP	2018-
2	1079261	2019-11-01	6	Dr. Rey Mcdowell	GP	2019-
3	1079261	2019-08-01	0	Dr. Rey Mcdowell	GP	2019-
4	1079261	2019-12-01	10	Dr. Rey Mcdowell	GP	2019-

In [521…
```
state_data = state_data.groupby(['AccountState', 'Month'])['Order'].sum()
```

In [524…
```
state_data = pd.DataFrame(state_data)
```

In [525…
```
state_data
```

Out[525]:

AccountState	Month	Order
Alabama	**2017-01-01**	103
	2017-02-01	109
	2017-03-01	170
	2017-04-01	125
	2017-05-01	136
...	**...**	...
Wyoming	**2019-08-01**	5
	2019-09-01	10
	2019-10-01	12
	2019-11-01	3
	2019-12-01	13

1851 rows × 1 columns

In [528...
```
state = df3['AccountState'].unique()
state
```

Out[528]:
```
array(['California', 'Texas', 'District of Columbia', 'Florida',
       'Michigan', 'Indiana', 'Mississippi', 'Maryland', 'Washington',
       'North Carolina', 'Iowa', 'New Jersey', 'Nebraska', 'Colorado',
       'Virginia', 'Oklahoma', 'Missouri', 'Idaho', 'Georgia',
       'Massachusetts', 'Arkansas', 'Illinois', 'Hawaii', 'Kentucky',
       'New York', 'Delaware', 'South Carolina', 'Utah', 'Wisconsin',
       'Minnesota', 'Pennsylvania', 'Louisiana', 'Tennessee', 'Wyoming',
       'Alabama', 'Alaska', 'Arizona', 'Ohio', 'Connecticut', 'Oregon',
       'Nevada', 'South Dakota', 'New Mexico', 'New Hampshire', 'Montana',
       'West Virginia', 'North Dakota', 'Kansas', 'Vermont', 'Maine',
       'Rhode Island', 'ON'], dtype=object)
```

In [529...
```
df3['AccountState'].nunique()
```

Out[529]:
```
52
```

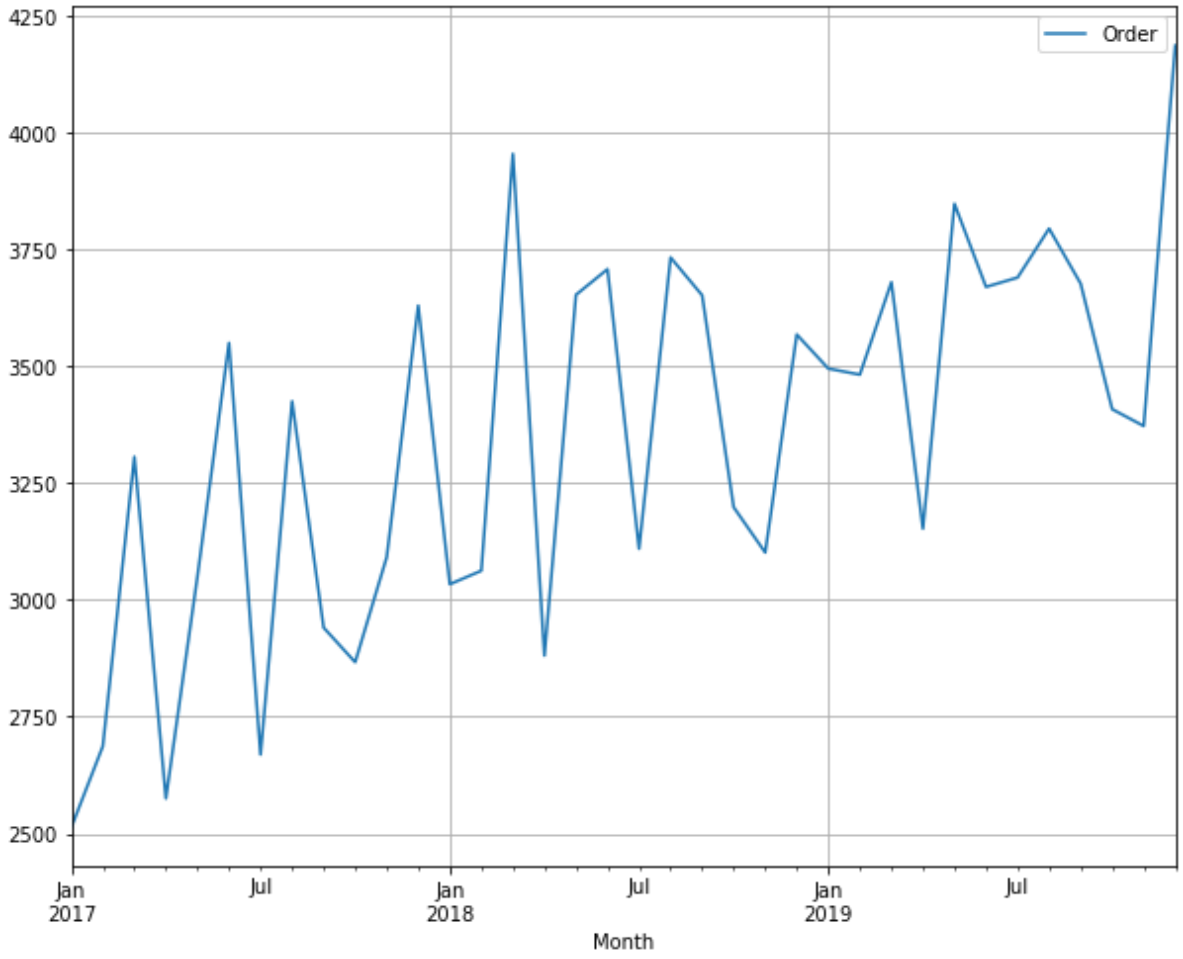
In [531...
```
state1 = state_data.loc[state[0]]
```

In [533...
```
state1.head()
```

Out[533]:

Month	Order
2017-01-01	2513
2017-02-01	2687
2017-03-01	3307
2017-04-01	2575
2017-05-01	3051

In [535…
```
state1.plot(figsize=(10,8))
plt.grid()
plt.show()
```



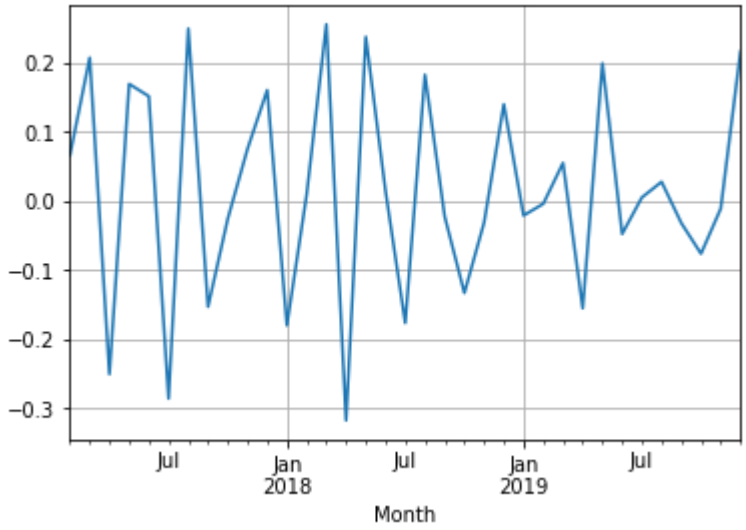
In [534…
```
sm.stats.durbin_watson(state1)
```

Out[534]:
```
array([0.02216025])
```

shift 1

In [536…
```
state11 = state1.copy()
```

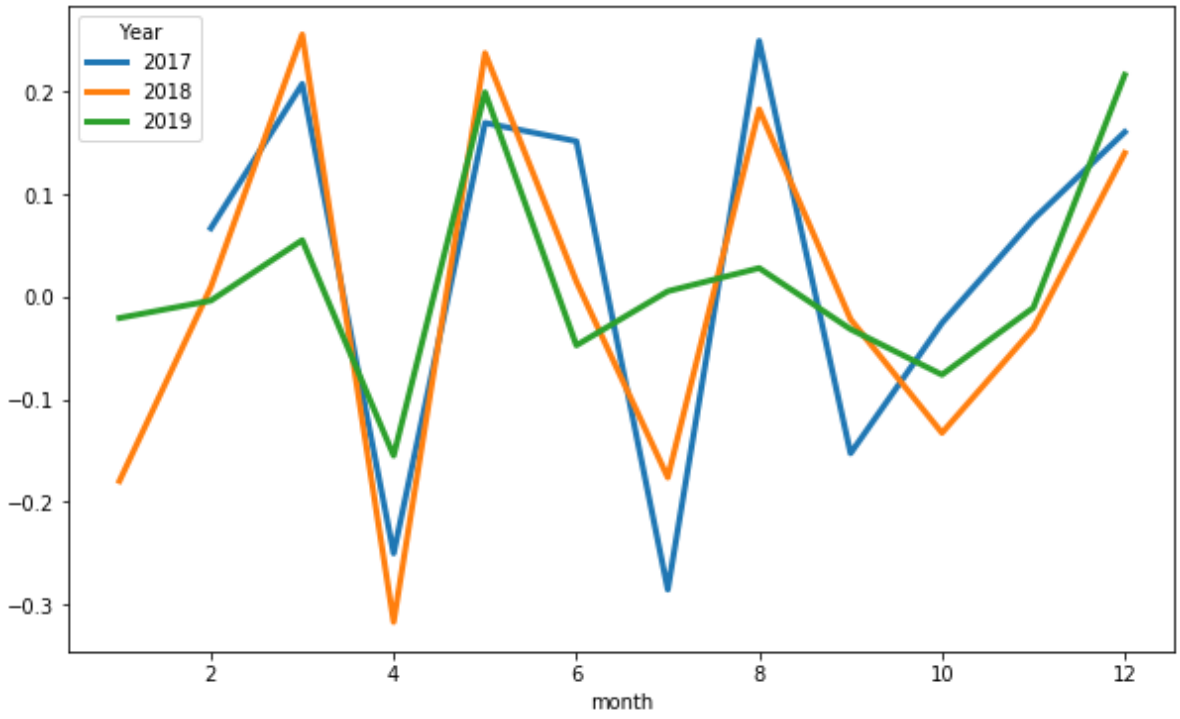
In [537…
```
state11['Order_lg'] = np.log(state11['Order'])
state11['Order_lg_df'] = state11['Order_lg'] - state11['Order_lg'].shift(1)
state11['Order_lg_df'].dropna().plot()
plt.grid()
```



In [538…
```
state11 = state11.reset_index()
state11.head(), state11.shape
```

Out[538]:
```
(       Month  Order  Order_lg  Order_lg_df
 0 2017-01-01   2513  7.829233          NaN
 1 2017-02-01   2687  7.896181     0.066948
 2 2017-03-01   3307  8.103797     0.207616
 3 2017-04-01   2575  7.853605    -0.250192
 4 2017-05-01   3051  8.023225     0.169620,
 (36, 4))
```

In [539…
```
season1 = state11
season1['Date'] = state11.Month
season1['Year'] = state11.Month.dt.year
season1['month'] = state11.Month.dt.month
season1.dropna(inplace = True)
spivot = pd.pivot_table(season1, index='month', columns = 'Year', values = 'Order_l
spivot.plot(figsize=(10,6), linewidth=3)
plt.show()
```



In [540…
```
state11 = state11.set_index('Month')
state11.drop(['Order','Order_lg','Date','Year','month'], axis = 1, inplace = True)
state11.dropna().head()
```

Out[540]:

Month	Order_lg_df
2017-02-01	0.066948
2017-03-01	0.207616
2017-04-01	-0.250192
2017-05-01	0.169620
2017-06-01	0.151760

In [541…

```
result = adfuller(state11['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -2.7547014511846672
p-value: 0.06504132904954074
Critical Values:
        1%: -3.6996079738860943
        5%: -2.9764303469999494
        10%: -2.627601001371742
```

In [542…

```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(state11['Order_lg_df'].dropna())
```

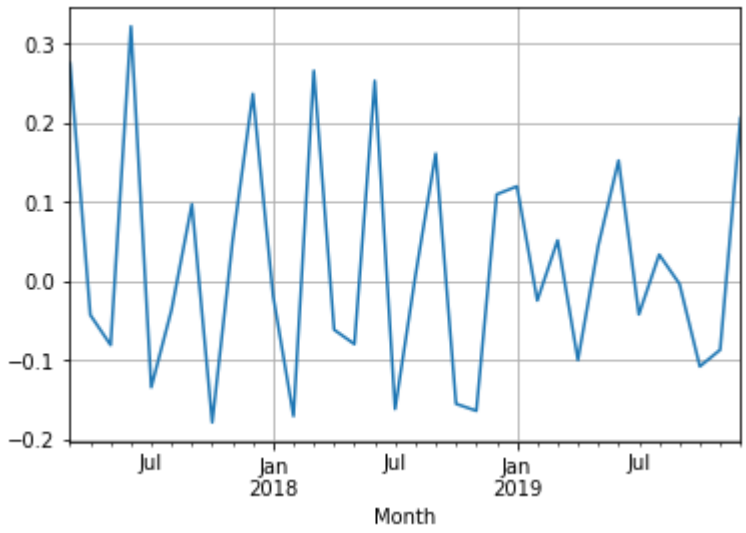
```
KPSS Statistic: 0.14922991088628848
p-value: 0.1
num lags: 10
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1687: Interpolati
onWarning: p-value is greater than the indicated p-value
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

2nd Shift

In [543…

```
state12 = state1.copy()
state12['Order_lg'] = np.log(state12['Order'])
state12['Order_lg_df'] = state12['Order_lg'] - state12['Order_lg'].shift(2)
state12['Order_lg_df'].dropna().plot()
plt.grid()
```



In [544…

```
state12
```

Out[544]:

Month	Order	Order_lg	Order_lg_df
2017-01-01	2513	7.829233	NaN
2017-02-01	2687	7.896181	NaN
2017-03-01	3307	8.103797	0.274564
2017-04-01	2575	7.853605	-0.042576
2017-05-01	3051	8.023225	-0.080572
2017-06-01	3551	8.174985	0.321380
2017-07-01	2669	7.889459	-0.133766
2017-08-01	3426	8.139149	-0.035836
2017-09-01	2941	7.986505	0.097046
2017-10-01	2867	7.961021	-0.178127
2017-11-01	3092	8.036573	0.050068
2017-12-01	3631	8.197263	0.236242
2018-01-01	3034	8.017637	-0.018936
2018-02-01	3063	8.027150	-0.170113
2018-03-01	3956	8.282989	0.265352
2018-04-01	2881	7.965893	-0.061257
2018-05-01	3654	8.203578	-0.079411
2018-06-01	3709	8.218518	0.252625
2018-07-01	3110	8.042378	-0.161200
2018-08-01	3734	8.225235	0.006718
2018-09-01	3653	8.203304	0.160926
2018-10-01	3199	8.070594	-0.154642
2018-11-01	3102	8.039802	-0.163502
2018-12-01	3569	8.180041	0.109447
2019-01-01	3496	8.159375	0.119572
2019-02-01	3483	8.155649	-0.024391
2019-03-01	3681	8.210940	0.051565
2019-04-01	3153	8.056110	-0.099540
2019-05-01	3849	8.255569	0.044629
2019-06-01	3671	8.208219	0.152110
2019-07-01	3691	8.213653	-0.041916
2019-08-01	3796	8.241703	0.033484
2019-09-01	3678	8.210124	-0.003528
2019-10-01	3409	8.134174	-0.107529
2019-11-01	3373	8.123558	-0.086567

Month	Order	Order_lg	Order_lg_df
2019-12-01	4188	8.339979	0.205804

In [546…
```
state12.drop(['Order','Order_lg'], axis = 1, inplace = True)
```

In [547…
```
state12.dropna().head()
```

Out[547]:

Month	Order_lg_df
2017-03-01	0.274564
2017-04-01	-0.042576
2017-05-01	-0.080572
2017-06-01	0.321380
2017-07-01	-0.133766

In [548…
```
result = adfuller(state12['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -2.590371148045449
p-value: 0.0950037305825912
Critical Values:
        1%: -3.7377092158564813
        5%: -2.9922162731481485
        10%: -2.635746736111111
```

In [549…
```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(state12['Order_lg_df'].dropna())
```

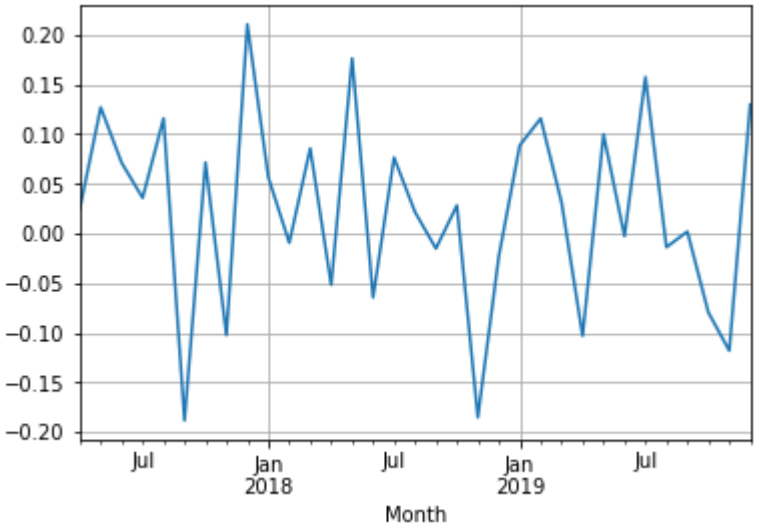
```
KPSS Statistic: 0.2556668539912943
p-value: 0.1
num lags: 10
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarni
ng: The behavior of using lags=None will change in the next release. Currently lag
s=None is the same as lags='legacy', and so a sample-size lag length is used. Afte
r the next release, the default will change to be the same as lags='auto' which us
es an automatic lag length selection method. To silence this warning, either use
'auto' or 'legacy'
  warn(msg, FutureWarning)
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1687: Interpolati
onWarning: p-value is greater than the indicated p-value
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

3rd Shift

In [551…

```
state13 = state1.copy()
state13.shape
state13['Order_lg'] = np.log(state13['Order'])
state13['Order_lg_df'] = state13['Order_lg'] - state13['Order_lg'].shift(3)
state13['Order_lg_df'].dropna().plot()
plt.grid()
```



In [553…

```
state13.head()
```

Out[553]:

Month	Order	Order_lg	Order_lg_df
2017-01-01	2513	7.829233	NaN
2017-02-01	2687	7.896181	NaN
2017-03-01	3307	8.103797	NaN
2017-04-01	2575	7.853605	0.024372
2017-05-01	3051	8.023225	0.127044

In [554…

```
state13.drop(['Order','Order_lg'], axis = 1, inplace = True)
```

In [555…

```
result = adfuller(state13['Order_lg_df'].dropna())
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -2.8287085163585854
p-value: 0.054288531051663626
Critical Values:
        1%: -3.6996079738860943
        5%: -2.9764303469999494
        10%: -2.627601001371742
```

In [556…

```
def kpss_test(series):
    statistic, p_value, n_lags, critical_values = kpss(series)
    print(f'KPSS Statistic: {statistic}')
    print(f'p-value: {p_value}')
    print(f'num lags: {n_lags}')
    print('Critial Values:')
    for key, value in critical_values.items():
        print(f'   {key} : {value}')
    print(f'Result: The series is {"not " if p_value < 0.05 else ""}stationary')

kpss_test(state13['Order_lg_df'].dropna())
```

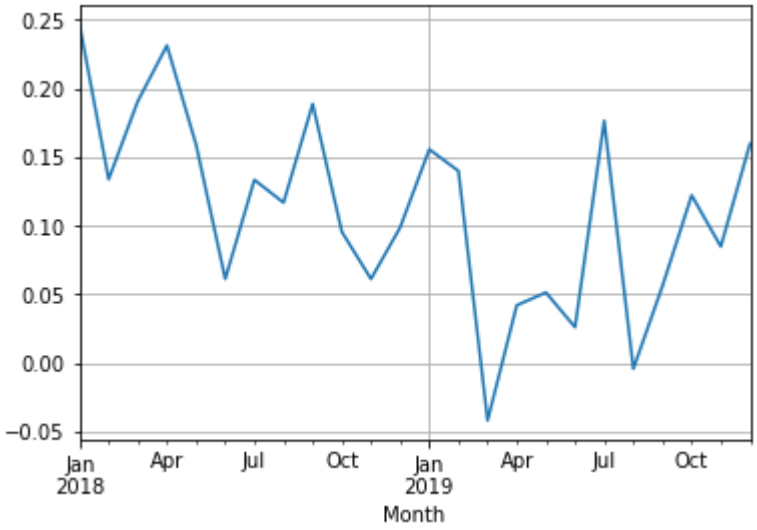
```
KPSS Statistic: 0.3297731562176494
p-value: 0.1
num lags: 10
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1661: FutureWarning: The behavior of using lags=None will change in the next release. Currently lags=None is the same as lags='legacy', and so a sample-size lag length is used. After the next release, the default will change to be the same as lags='auto' which uses an automatic lag length selection method. To silence this warning, either use 'auto' or 'legacy'
  warn(msg, FutureWarning)
E:\New folder (2)\lib\site-packages\statsmodels\tsa\stattools.py:1687: InterpolationWarning: p-value is greater than the indicated p-value
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

4th shift

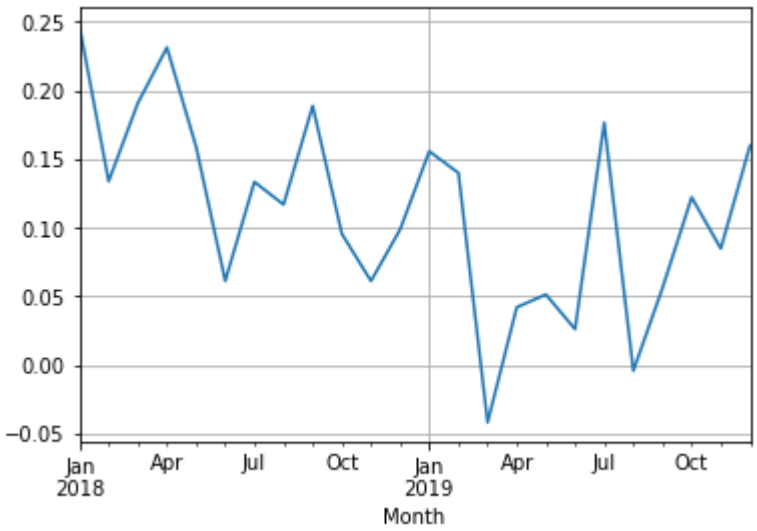
In [558…

```
state14 = month_orders.copy()
state14.shape
state14['Order_lg'] = np.log(state14['Order'])
state14['Order_lg_df'] = state14['Order_lg'] - state14['Order_lg'].shift(12)
state14['Order_lg_df'].dropna().plot()
plt.grid()
```



12th Shift

In [557…
```
state123 = month_orders.copy()
state123.shape
state123['Order_lg'] = np.log(state123['Order'])
state123['Order_lg_df'] = state123['Order_lg'] - state123['Order_lg'].shift(12)
state123['Order_lg_df'].dropna().plot()
plt.grid()
```



In [559…
```
#we are getting the best value at 1st shift, as the trend is almost removed
```

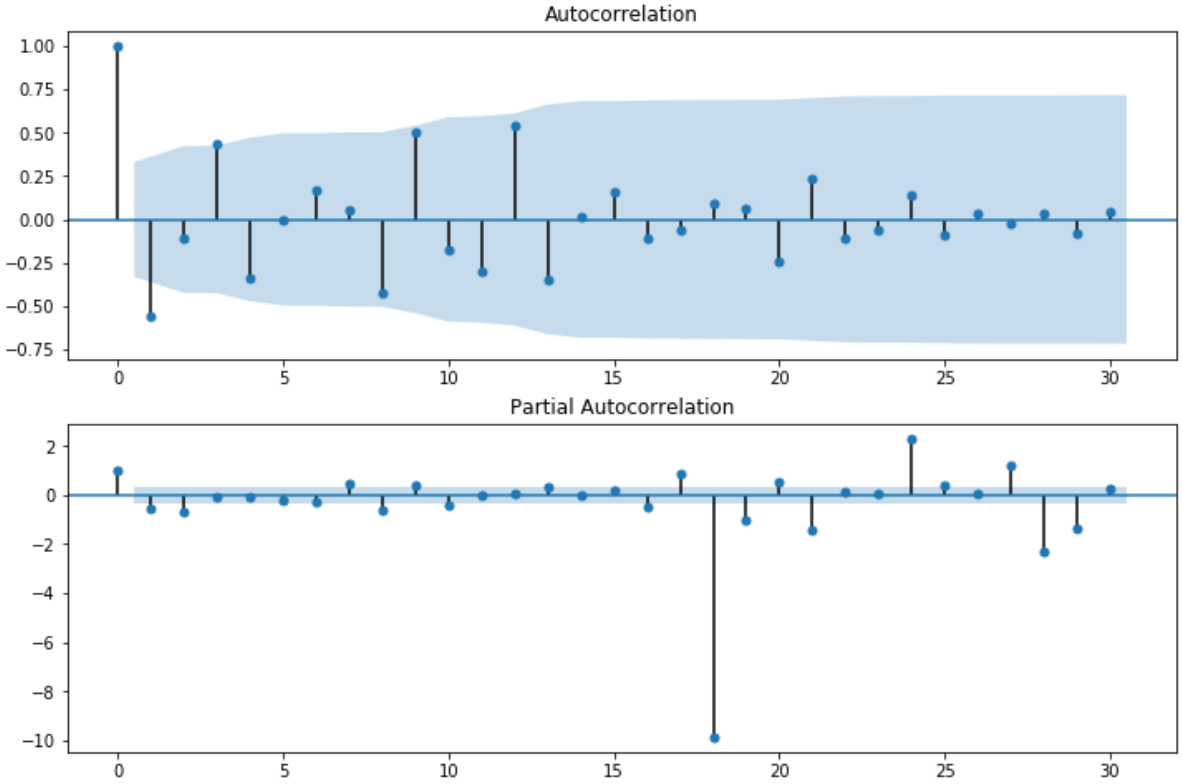
In [560…
```
state11.head()
```

Out[560]:

Month	Order_lg_df
2017-02-01	0.066948
2017-03-01	0.207616
2017-04-01	-0.250192
2017-05-01	0.169620
2017-06-01	0.151760

In [561…
```
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(state11['Order_lg_df'].values.squeeze(), lags=30, ax
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(state11['Order_lg_df'], lags=30, ax=ax2)
```

```
E:\New folder (2)\lib\site-packages\statsmodels\regression\linear_model.py:1406: R
untimeWarning: invalid value encountered in sqrt
  return rho, np.sqrt(sigmasq)
```



In [562…
```
# I will take p = 2 and q = 3
```

In [565…
```
state11.head(), len(state11)
```

Out[565]:
```
(            Order_lg_df
 Month
 2017-02-01     0.066948
 2017-03-01     0.207616
 2017-04-01    -0.250192
 2017-05-01     0.169620
 2017-06-01     0.151760,
 35)
```

In [566…
```
training_data=month_orders3['Order_lg_df'].dropna()[0:28]
test_data=month_orders3['Order_lg_df'].dropna()[28:]
```

In [567…
```
# I will take p = 2, d = 1 and q = 3
arima1= ARIMA(np.asarray(training_data),order=(2,1,1))
model1=arima1.fit()
```

In [568…
```
pred1= model1.forecast(steps=len(test_data))[0]
```

In [569…
```
np.sqrt(mean_squared_error(test_data,pred1)), mean_squared_error(test_data,pred1)
```

Out[569]:
```
(0.13591322847097378, 0.018472405673403115)
```

In [570…
```
# I will take p = 2, d = 1 and q = 2
arima2= ARIMA(np.asarray(training_data),order=(2,1,0))
model2=arima2.fit()
pred2= model2.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,pred2)), mean_squared_error(test_data,pred2)
```

Out[570]:
```
(0.11687607569154693, 0.013660017069056207)
```

In [573…
```
# I will take p = 2, d = 2 and q = 1
arima4= ARIMA(np.asarray(training_data),order=(2,2,1))
model4=arima4.fit()
pred4= model4.forecast(steps=len(test_data))[0]
np.sqrt(mean_squared_error(test_data,pred4)), mean_squared_error(test_data,pred4)
```

Out[573]:
```
(0.476373018135907, 0.22693125240791315)
```

In [586…
```
arS1= ARMA(training_data,order=(2,1))
mS1=arS1.fit()
```

```
E:\New folder (2)\lib\site-packages\statsmodels\tsa\base\tsa_model.py:162: ValueWa
rning: No frequency information was provided, so inferred frequency MS will be use
d.
  % freq, ValueWarning)
```

In [587…
```
pS1= mS1.forecast(steps=len(test_data))[0]
```

In [588…
```
np.sqrt(mean_squared_error(test_data,pS1)), mean_squared_error(test_data,pS1)
```

Out[588]:
```
(0.08620739801610451, 0.0074317154727070595)
```

Selecting the model and forcasting

In [580…
```
#Best result is obtained from ARMA at p = 2 and q = 1 so, Model m1 is selected

#Making prediction for Jan 2020, Feb 2020 and March 2020
```

In [589…
```
predict_state1_Jan_Feb_Mar_2020 = mS1.forecast(steps=3)[0]
```

In [590…
```
predict_state1_Jan_Feb_Mar_2020
```

Out[590]:
```
array([0.01476531, 0.05428729, 0.02200757])
```

In [591…
```
#Similarly we can find the result for rest of the states
```

In [592…
```
#and after the state wise forecasting we can similarly find the doctor wise
#sales
```

In [593…
```
# we can also prepare a pipeline for the same
```

In [ ]:
```
```