Vamshikrishna_Narmula_PROJECT-4(Time Series)

In [1]:

```
#importing required libraries
import numpy as np #mathematical operations
import pandas as pd # To operate the dataframes
import matplotlib.pyplot as plt # To visualize
import seaborn as sb #To visualize

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
dataset = pd.read_excel('DS3_C6_S4_TimeSeries_Sales_Data_Project.xls',parse_dates=True)
dataset.head()
```

Out[2]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	Cit
0	1	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderso
1	2	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderso
2	3	CA-2016-138688	2016-06-12	2016-06-16	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	Lo Angele
3	4	US-2015-108966	2015-10-11	2015-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fo Lauderdal
4	5	US-2015-108966	2015-10-11	2015-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fo Lauderdal

5 rows × 21 columns

In [3]:

```
#structure
dataset.shape
```

Out[3]:

```
(9994, 21)
```

In [4]:

```
#dataset for the category of furniture
df = dataset[dataset.Category == 'Furniture']
df.head()
```

Out[4]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	C
0	1	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henders
1	2	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henders
3	4	US-2015-108966	2015-10-11	2015-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	F Lauderd
5	6	CA-2014-115812	2014-06-09	2014-06-14	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	L Angel
10	11	CA-2014-115812	2014-06-09	2014-06-14	Standard Class	BH-11710	Brosina Hoffman	Consumer	United States	L Angel

5 rows × 21 columns

In [5]:

```
df.shape
```

Out[5]:

```
(2121, 21)
```

In [6]:

```
#datatypes
df.dtypes
```

Out[6]:

```
Row ID                     int64
Order ID                  object
Order Date        datetime64[ns]
Ship Date         datetime64[ns]
Ship Mode                 object
Customer ID               object
Customer Name             object
Segment                   object
Country                   object
City                      object
State                     object
Postal Code                int64
Region                    object
Product ID                object
Category                  object
Sub-Category              object
Product Name              object
Sales                    float64
Quantity                   int64
Discount                 float64
Profit                   float64
dtype: object
```

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
Row ID           0
Order ID         0
Order Date       0
Ship Date        0
Ship Mode        0
Customer ID      0
Customer Name    0
Segment          0
Country          0
City             0
State            0
Postal Code      0
Region           0
Product ID       0
Category         0
Sub-Category     0
Product Name     0
Sales            0
Quantity         0
Discount         0
Profit           0
dtype: int64
```

* No null values in the dataset

In [8]:

```
for i in df:
    v=df[i].value_counts()
    print(v)
```

...

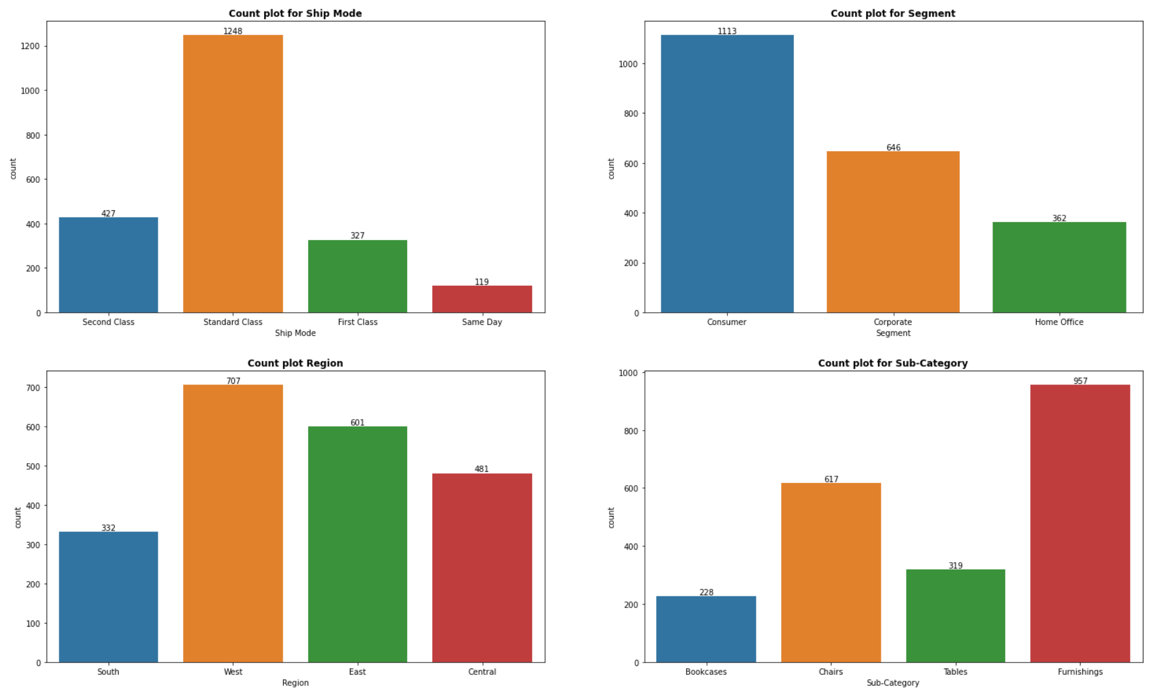
    * No special characters in the given dataset.

Data Visualization - EDA

1.UNIVARIATE ANALYSIS

In [9]:

```
#Countplots for categorical features 'Ship Mode', 'Segment', 'Region', 'Sub-category'
plt.subplots(2,2,figsize=(25,15))

plt.subplot(221)
ax = sb.countplot(data=df,x='Ship Mode')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Count plot for Ship Mode',fontweight='bold')

plt.subplot(222)
ax1 = sb.countplot(data=df,x='Segment')
for container in ax1.containers:
    ax1.bar_label(container)
plt.title('Count plot for Segment',fontweight='bold')

plt.subplot(223)
ax3 = sb.countplot(data=df,x='Region')
for container in ax3.containers:
    ax3.bar_label(container)
plt.title('Count plot Region',fontweight='bold')

plt.subplot(224)
ax4 = sb.countplot(data=df,x='Sub-Category')
for container in ax4.containers:
    ax4.bar_label(container)
plt.title('Count plot for Sub-Category',fontweight='bold')

plt.show()
```



Interpretation:-

In the Sales of Furniture

```
* The mostly used Ship mode is 'Standard Class' followed by 'Second class'.
* The highest segment the sales of furniture belongs to 'Consumer Segment'.
* The most products of furniture are sold in the 'West region'.
* The subcategory 'Furnishings' are mostly sold followed by 'Chairs'.
```

In [10]:

```
#min age
df['Sales'].min()
```

Out[10]:

```
1.8920000000000003
```

In [11]:

```
#max age
df['Sales'].max()
```

Out[11]:

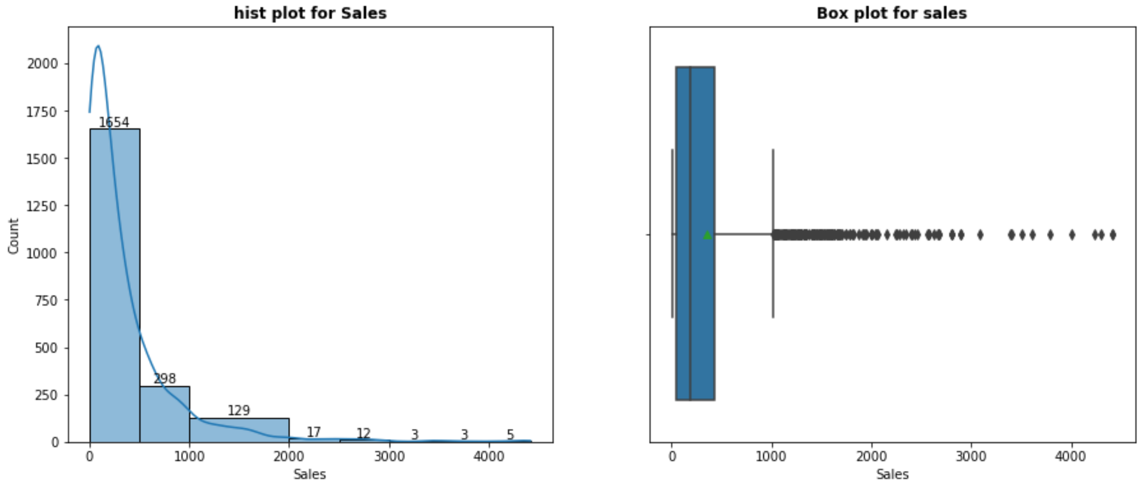
```
4416.174
```

In [12]:

```
#creating bins for sales
b1 = [1,500,1000,1500,2000,2500,3000,3500,4000,4420]
```

In [13]:

```
#Histplot for sales
plt.subplots(1,2,figsize=(15,6))

plt.subplot(121)
ax5 = sb.histplot(data=df['Sales'],bins=b1,kde=True)
for container in ax5.containers:
    ax5.bar_label(container)
plt.title('hist plot for Sales',fontweight='bold')

#boxplot for the feature sales
plt.subplot(122)
sb.boxplot(data=df, x='Sales', showmeans=True)
plt.title('Box plot for sales',fontweight='bold')
plt.show()
```



Interpretation:-

    * The Sales are not distributed normally from the box plot we can see thei
    r are more outliers.
    * The mean is greater than median data is right skewed and the data is mos
    tly towards the left.

In [14]:

```
#min profit
df['Profit'].min()
```

Out[14]:

-1862.3124000000003

In [15]:

```
#min profit
df['Profit'].max()
```

Out[15]:

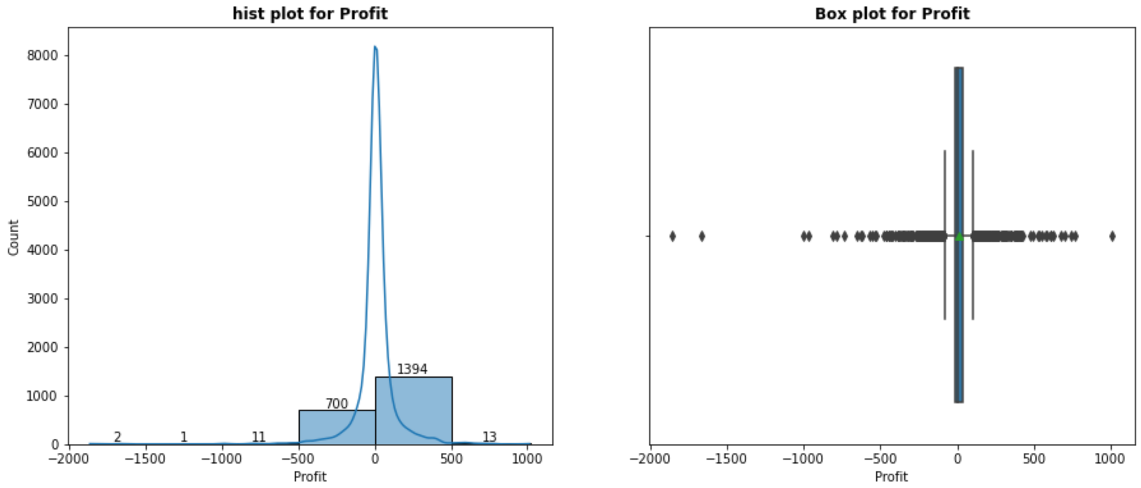
1013.1270000000001

In [16]:

```
#creating bins for profit
b2 = [-1865,-1500,-1000,-500,0,500,1020]
```

In [17]:

```
#Histplot for profit
plt.subplots(1,2,figsize=(15,6))

plt.subplot(121)
ax5 = sb.histplot(data=df['Profit'],bins=b2,kde=True)
for container in ax5.containers:
    ax5.bar_label(container)
plt.title('hist plot for Profit',fontweight='bold')

#boxplot for the feature profit
plt.subplot(122)
sb.boxplot(data=df, x='Profit', showmeans=True)
plt.title('Box plot for Profit',fontweight='bold')
plt.show()
```



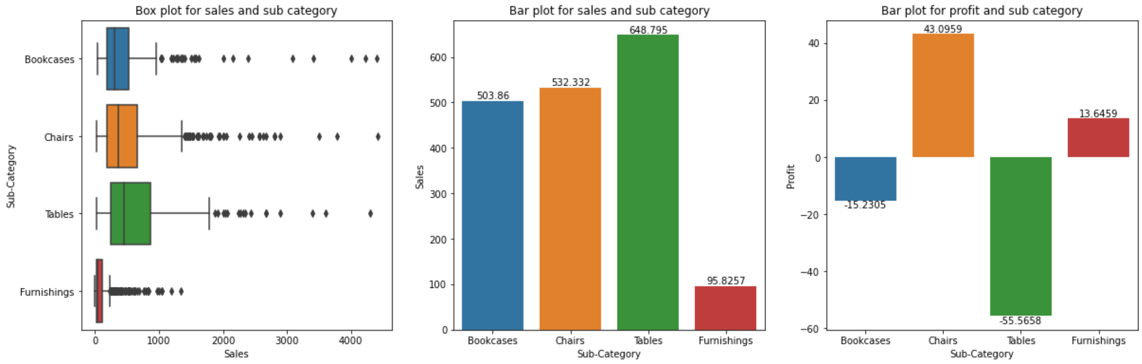
Interpretation:-

    * The profits are not distributed normally from the box plot we can see th
eir are more outliers.
    * The mean is less than median data is left skewed and the data is mostly
towards the right.

2.BIVARIATE ANALYSIS

In [18]:

```
#Plot for the features sales and Sub-category
plt.subplots(1,3,figsize=(20,6))

plt.subplot(131)
sb.boxplot(data=df, x='Sales', y='Sub-Category')
plt.title('Box plot for sales and sub category')

plt.subplot(132)
ax=sb.barplot(data=df, y='Sales', x='Sub-Category',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for sales and sub category')

plt.subplot(133)
ax=sb.barplot(data=df, y='Profit', x='Sub-Category',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for profit and sub category')
plt.show()
```

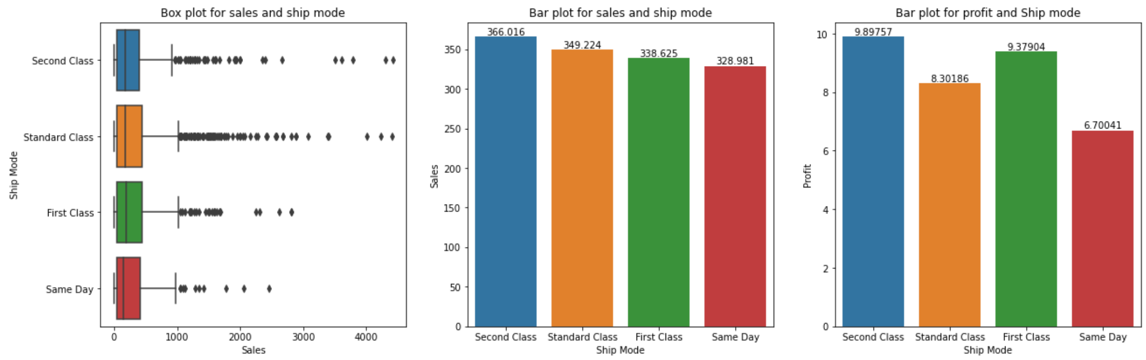


Interpretation:- For sub-Category

```
    * The Sales of 'Tables' are highest compared to others but these products a
re not profitable they are in losses.
    * The Sales of 'Chairs' are second highest and the 'profits' are highest co
mpared to other sub category products.
    * The Sales of 'Bookcases' are third highest but not profitable they are in
losses.
    * The Sales of 'furnishings' are least but these sub category products are
profitable.
```

In [19]:

```python
#Plot for the features sales and Ship Mode
plt.subplots(1,3,figsize=(20,6))

plt.subplot(131)
sb.boxplot(data=df, x='Sales', y='Ship Mode')
plt.title('Box plot for sales and ship mode')

plt.subplot(132)
ax=sb.barplot(data=df, y='Sales', x='Ship Mode',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for sales and ship mode')

plt.subplot(133)
ax=sb.barplot(data=df, y='Profit', x='Ship Mode',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for profit and Ship mode')
plt.show()
```

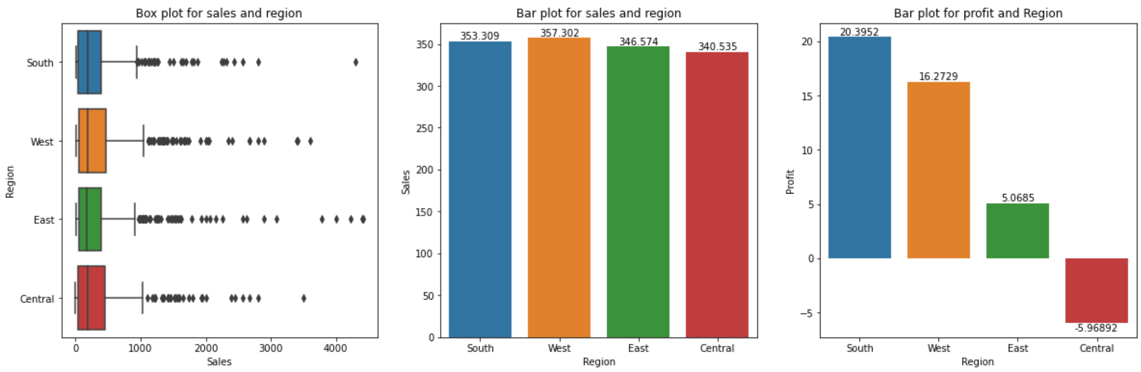


Interpretation:- For Ship Mode

* The Sales and the profits of the 'Second Class' ship mode are highest compared to other ship modes.
* The Sales 'Standard Class' are second highest and the 'profits' are more compared to 'Same day' ship mode.
* The Sales of 'First Class' are third highest but the profits are more than 'Standard class' and less than 'Second Class'.
* The Sales and profits of 'Same Day' ship mode are least.

In [20]:

```python
#Plot for the features sales and Region
plt.subplots(1,3,figsize=(20,6))

plt.subplot(131)
sb.boxplot(data=df, x='Sales', y='Region')
plt.title('Box plot for sales and region')

plt.subplot(132)
ax=sb.barplot(data=df, y='Sales', x='Region',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for sales and region')

plt.subplot(133)
ax=sb.barplot(data=df, y='Profit', x='Region',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for profit and Region')
plt.show()
```

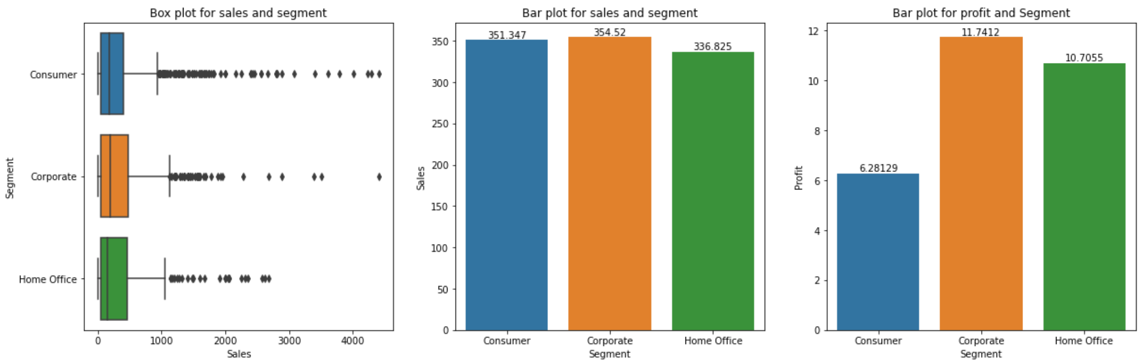


Interpretation:- For region

* The Sales are Highest in the 'West Region' but the profits are less compared to 'South region'.
* The Sales in 'South Region' are second highest and the 'profits' are highest compared to other regions.
* The Sales in 'East Region' are third highest but profits are less than South and West regions.
* The Sales in 'Central Region' are least and in these region products are not profitable.

In [21]:

```python
#Plot for the features sales and segment
plt.subplots(1,3,figsize=(20,6))

plt.subplot(131)
sb.boxplot(data=df, x='Sales', y='Segment')
plt.title('Box plot for sales and segment')

plt.subplot(132)
ax=sb.barplot(data=df, y='Sales', x='Segment',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for sales and segment')

plt.subplot(133)
ax=sb.barplot(data=df, y='Profit', x='Segment',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for profit and Segment')
plt.show()
```



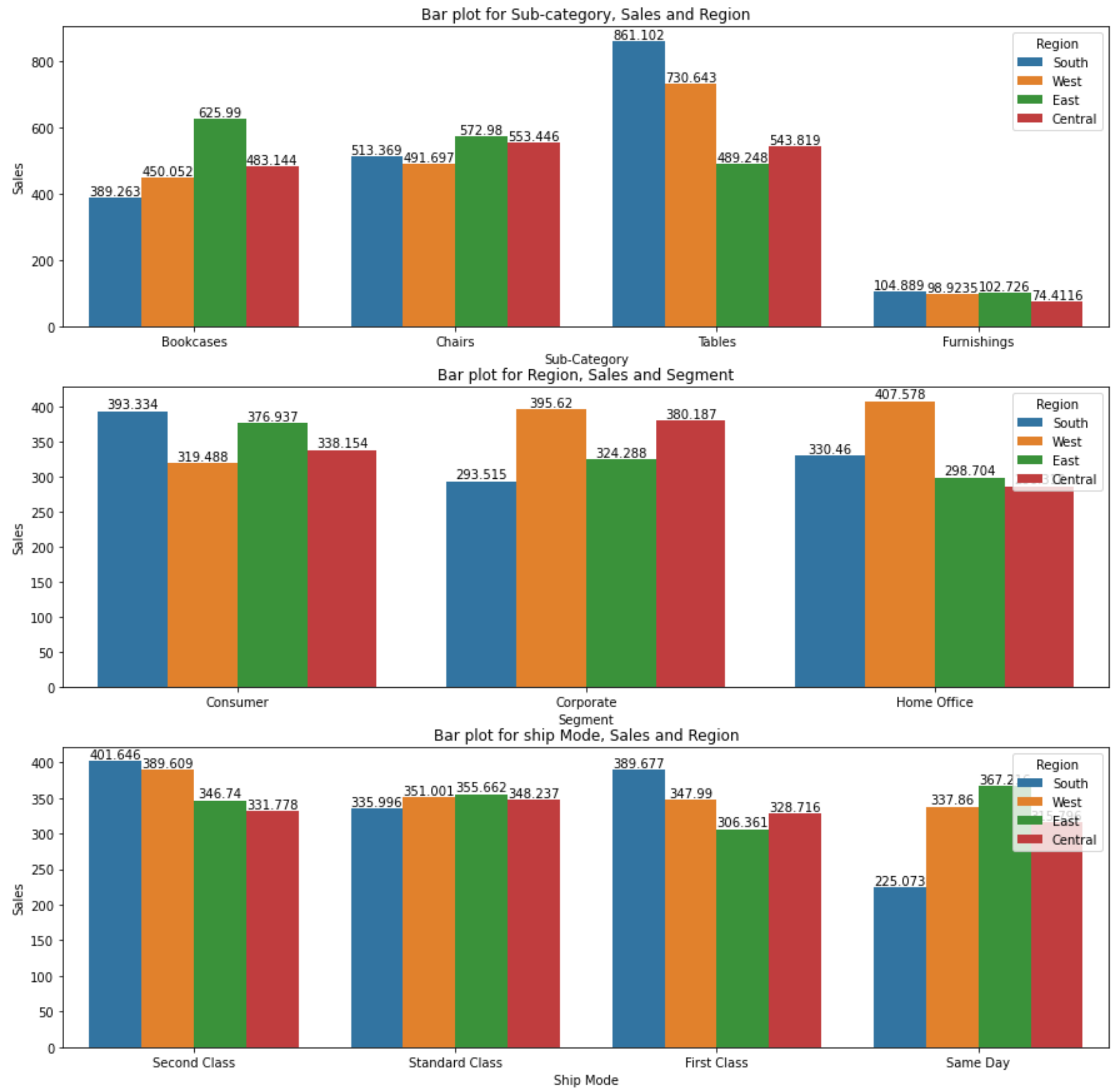
Interpretation:- For Segment

```
    * The Sales and profits are highest in 'Corporate Segment' compared to othe
r segments.
    * In 'Consumer Segment' the Sales are second highest but the profits are le
ast compared to other segments.
    * The Sales are least in 'Home Office' but the profits are more compared to
'Consumer Segment' and
    less compared to 'Corporate segment'.
```

3.MULTIVARIATE ANALYSIS

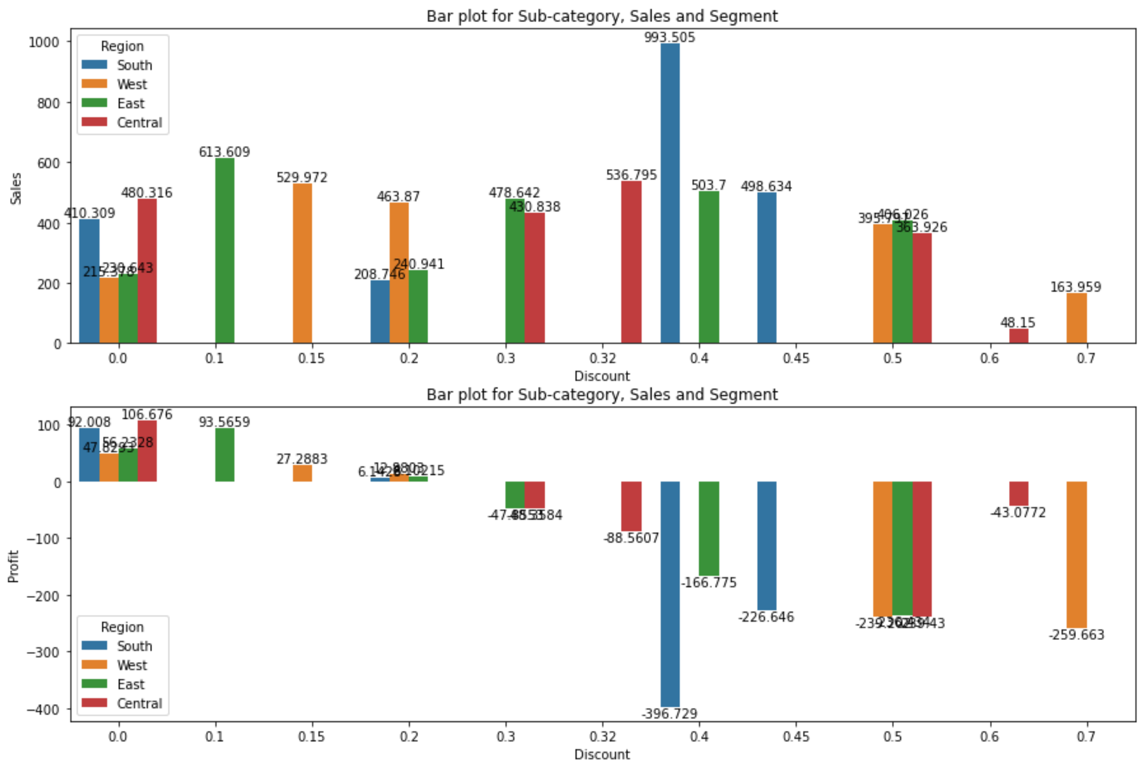
In [22]:

```
plt.subplots(3,1,figsize=(15,15))

plt.subplot(311)
ax=sb.barplot(data=df, x='Sub-Category', y='Sales',hue='Region',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for Sub-category, Sales and Region')

plt.subplot(312)
ax=sb.barplot(data=df, x='Segment', y='Sales',hue='Region',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for Region, Sales and Segment')

plt.subplot(313)
ax=sb.barplot(data=df, x='Ship Mode', y='Sales',hue='Region',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for ship Mode, Sales and Region')
plt.show()
```



In [23]:

```
plt.subplots(2,2,figsize=(15,10))

plt.subplot(211)
ax=sb.barplot(data=df, x='Discount', y='Sales',hue='Region',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for Sub-category, Sales and Segment')

plt.subplot(212)
ax=sb.barplot(data=df, x='Discount', y='Profit',hue='Region',ci=None)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Bar plot for Sub-category, Sales and Segment')

plt.show()
```

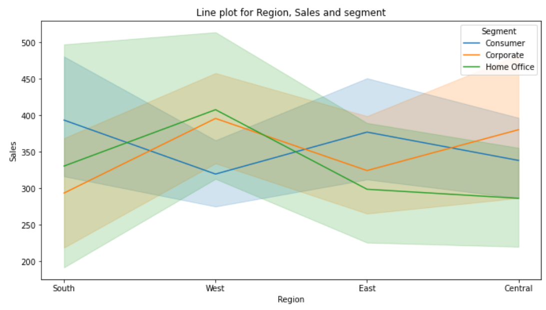


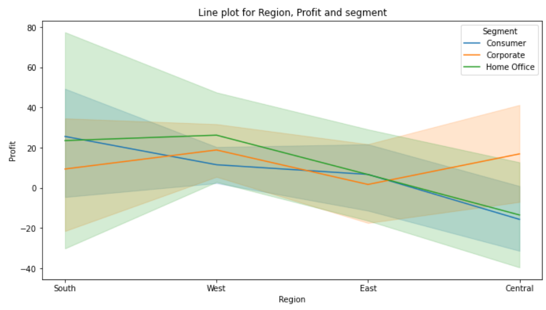
Interpretation:-

    * There are losses for the products if the discount is more than 0.2 in al
  l the regions.

In [24]:

```
plt.subplots(1,2,figsize=(25,6))

plt.subplot(121)
sb.lineplot(data=df,x='Region',y='Sales',hue='Segment')
plt.title('Line plot for Region, Sales and segment')

plt.subplot(122)
sb.lineplot(data=df,x='Region',y='Profit',hue='Segment')
plt.title('Line plot for Region, Profit and segment')
plt.show()
```





Interpretation:-

```
  * For 'Home Office Segment' the Sales and profits are highest in the 'West Re
gion' and least in 'Central region'.
  * For 'Corporate Segment' the Sales are highest in 'West region' and least in
'South region' and profits are
  highest in 'Central region' and least in 'East region'.
  * For 'Consumer Segment' the Sales are highest in 'south region' and least in
'West region' and profits are
  highest in 'South region' and least in 'Central region'.
```

Data Preprocessing

In [25]:

```
#df1 = df.groupby('Order Date')['Sales'].sum().reset_index()
```

In [26]:

```
df1 = df[['Order Date','Sales']]
```

In [27]:

```
# setting the index as Order Date
df1 = df1.set_index('Order Date')
df1.head(3)
```

Out[27]:

	Sales
Order Date	
2016-11-08	261.9600
2016-11-08	731.9400
2015-10-11	957.5775

In [28]:

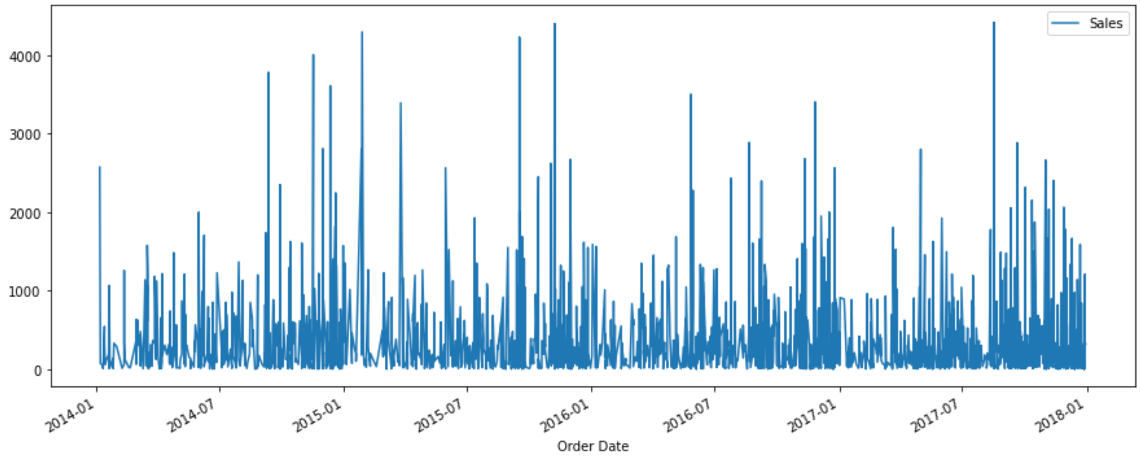
```
# separting the required features to another datset d
d = df1[['Sales']]
d.head(3)
```

Out[28]:

	Sales
Order Date	
2016-11-08	261.9600
2016-11-08	731.9400
2015-10-11	957.5775

In [29]:

```
#plotting the sales with orderdate
d.plot(figsize=(15,6))
plt.show()
```



In [30]:

```
#resampling the data to weekly data using the mean function
df2 = df1.resample('W').mean()
df2.head()
```

Out[30]:

Order Date	Sales
2014-01-12	678.107000
2014-01-19	250.094600
2014-01-26	183.995333
2014-02-02	311.833000
2014-02-09	14.560000

In [31]:

```
#check for structure after resampling
df2.shape
```

Out[31]:

```
(208, 1)
```

In [32]:

```
#check for null values
df2.isnull().sum()
```

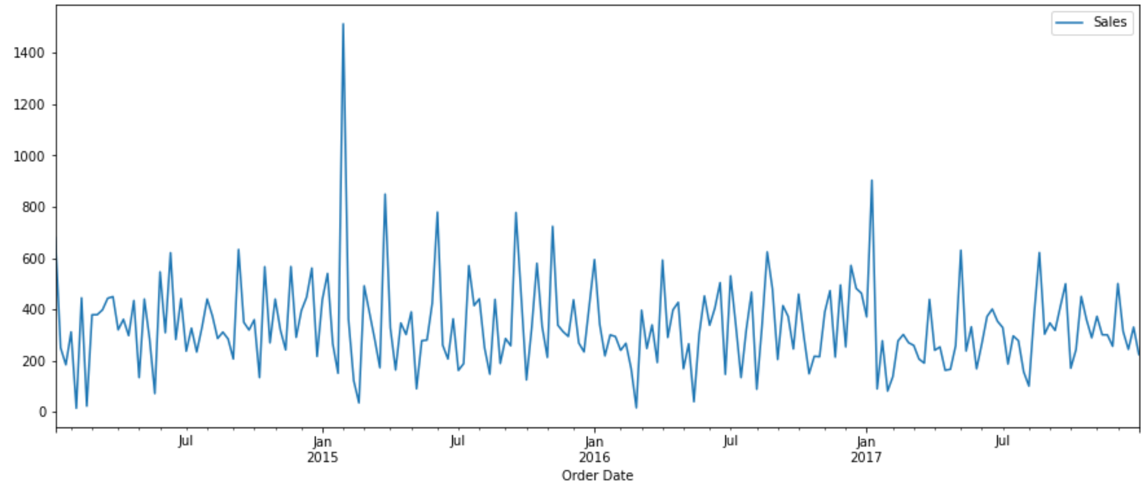
Out[32]:

```
Sales    0
dtype: int64
```

* No null values after resampling the data to weekly data

In [33]:

```
#plotting the sales with orderdate after resampling to weekly data
df2.plot(figsize=(15,6))
plt.show()
```



In [34]:

```
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [35]:

```
decomp1 = seasonal_decompose(df2,period=7)
```

In [36]:

```
d_trend = decomp1.trend
d_seasonal = decomp1.seasonal
d_residual = decomp1.resid
```

In [37]:

```python
#plots for seasonal components
plt.subplots(4,1,figsize=(30,28))

plt.subplot(411)
plt.plot(df2['Sales'],label='Actual data')
plt.title('Actual Data',fontweight='bold',size=20)
plt.legend(loc='best')

plt.subplot(412)
plt.plot(d_trend,color='r',label='Trend')
plt.title('Trend',fontweight='bold',size=20)
plt.legend(loc='best')

plt.subplot(413)
plt.plot(d_seasonal,color='b',label='Seasonality')
plt.title('Seasonality',fontweight='bold',size=20)
plt.legend(loc='best')

plt.subplot(414)
plt.plot(d_residual,color='g',label='Residual')
plt.title('Residual',fontweight='bold',size=20)
plt.legend(loc='best')
plt.show()
```

Interpretation:-

```
        * From the graph-1 we can see the actual data in which trend,seasonality
 and noise are present.
        * From graph-2 we can see the upward trend.
        * From graph-3 we can see the Seasonality present in the data.
        * from graph-4 we can see the presence of noise in the data.
```

In [38]:

```
#moving average

lags = [3,6,9,12]
moving_av = []
for i in lags:
    moving_avg = df2.rolling(window=i).mean()
    moving_av.append(moving_avg)
```

In [39]:

```
#creating a dataframe for assigning the actual data and moving averages
df3 = pd.DataFrame()

df3['Actual_data'] = df2
df3['Moving_average3'] = moving_av[0]
df3['Moving_average6'] = moving_av[1]
df3['Moving_average9'] = moving_av[2]
df3['Moving_average12'] = moving_av[3]
```

In [40]:

```
df3.head()
```

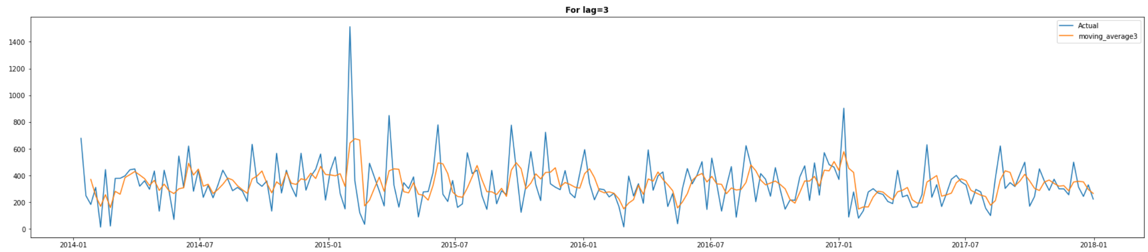
Out[40]:

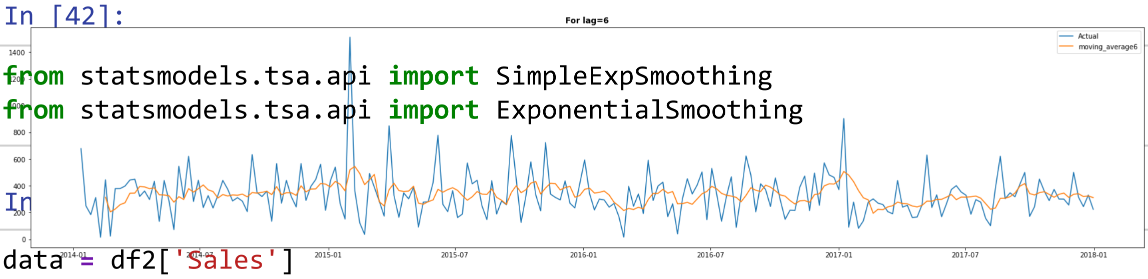
	Actual_data	Moving_average3	Moving_average6	Moving_average9	Moving_average12
Order Date					
2014-01-12	678.107000	NaN	NaN	NaN	NaN
2014-01-19	250.094600	NaN	NaN	NaN	NaN
2014-01-26	183.995333	370.732311	NaN	NaN	NaN
2014-02-02	311.833000	248.640978	NaN	NaN	NaN
2014-02-09	14.560000	170.129444	NaN	NaN	NaN

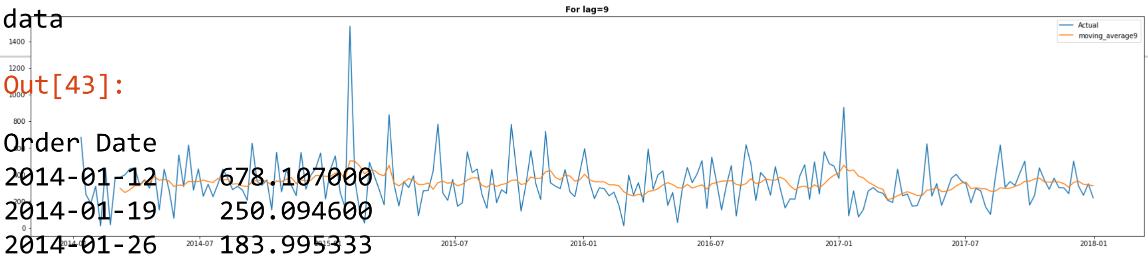
In [41]:

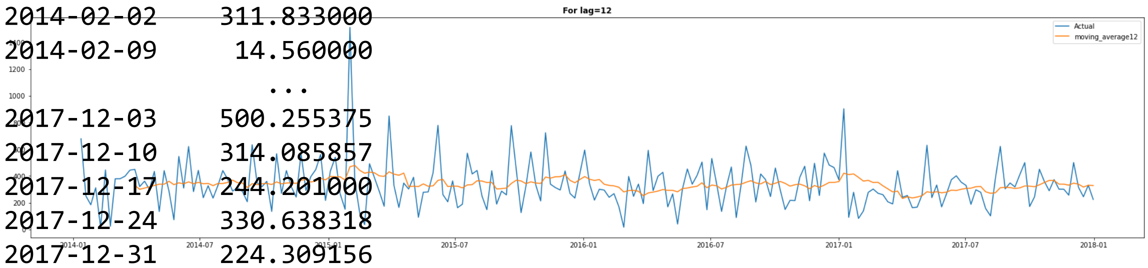
```
#plotting for actual and different lags
plt.figure(figsize=(15,6))
fig,ax=plt.subplots(4,1,figsize=(30,28))

plt.subplot(411)
plt.plot(df3['Actual_data'],label='Actual')
plt.plot(df3['Moving_average3'],label='moving_average3')
plt.title('For lag=3',fontweight='bold', size=12)
plt.legend(loc='best')


plt.subplot(412)
plt.plot(df3['Actual_data'],label='Actual')
plt.plot(df3['Moving_average6'],label='moving_average6')
plt.title('For lag=6',fontweight='bold', size=12)
plt.legend(loc='best')


plt.subplot(413)
plt.plot(df3['Actual_data'],label='Actual')
plt.plot(df3['Moving_average9'],label='moving_average9')
plt.title('For lag=9',fontweight='bold', size=12)
plt.legend(loc='best')


plt.subplot(414)
plt.plot(df3['Actual_data'],label='Actual')
plt.plot(df3['Moving_average12'],label='moving_average12')
plt.title('For lag=12',fontweight='bold', size=12)
plt.legend(loc='best')

plt.show()
```

```
<Figure size 1080x432 with 0 Axes>
```









In [42]:

```
from statsmodels.tsa.api import SimpleExpSmoothing
from statsmodels.tsa.api import ExponentialSmoothing
```

In [43]:

```
data = df2['Sales']
data
```

Out[43]:

```
Order Date
2014-01-12    678.107000
2014-01-19    250.094600
2014-01-26    183.995333
2014-02-02    311.833000
2014-02-09     14.560000
                 ...
2017-12-03    500.255375
2017-12-10    314.085857
2017-12-17    244.201000
2017-12-24    330.638318
2017-12-31    224.309156
Freq: W-SUN, Name: Sales, Length: 208, dtype: float64
```

In [44]:

```
def simplesmoothening(data,alpha):
    model=SimpleExpSmoothing(data).fit(smoothing_level=alpha)
    fcast = model.fittedvalues
    d1=pd.DataFrame({'Actual':data,'Forecast':fcast})
    return(model,d1)
```

In [45]:

```
#smoothening parameter ---> alpha
alphas = [0.0,0.2,0.4,0.6,0.8]
d_simple_exp = {}  #stores forecasted values for a given alpha
models = []
```

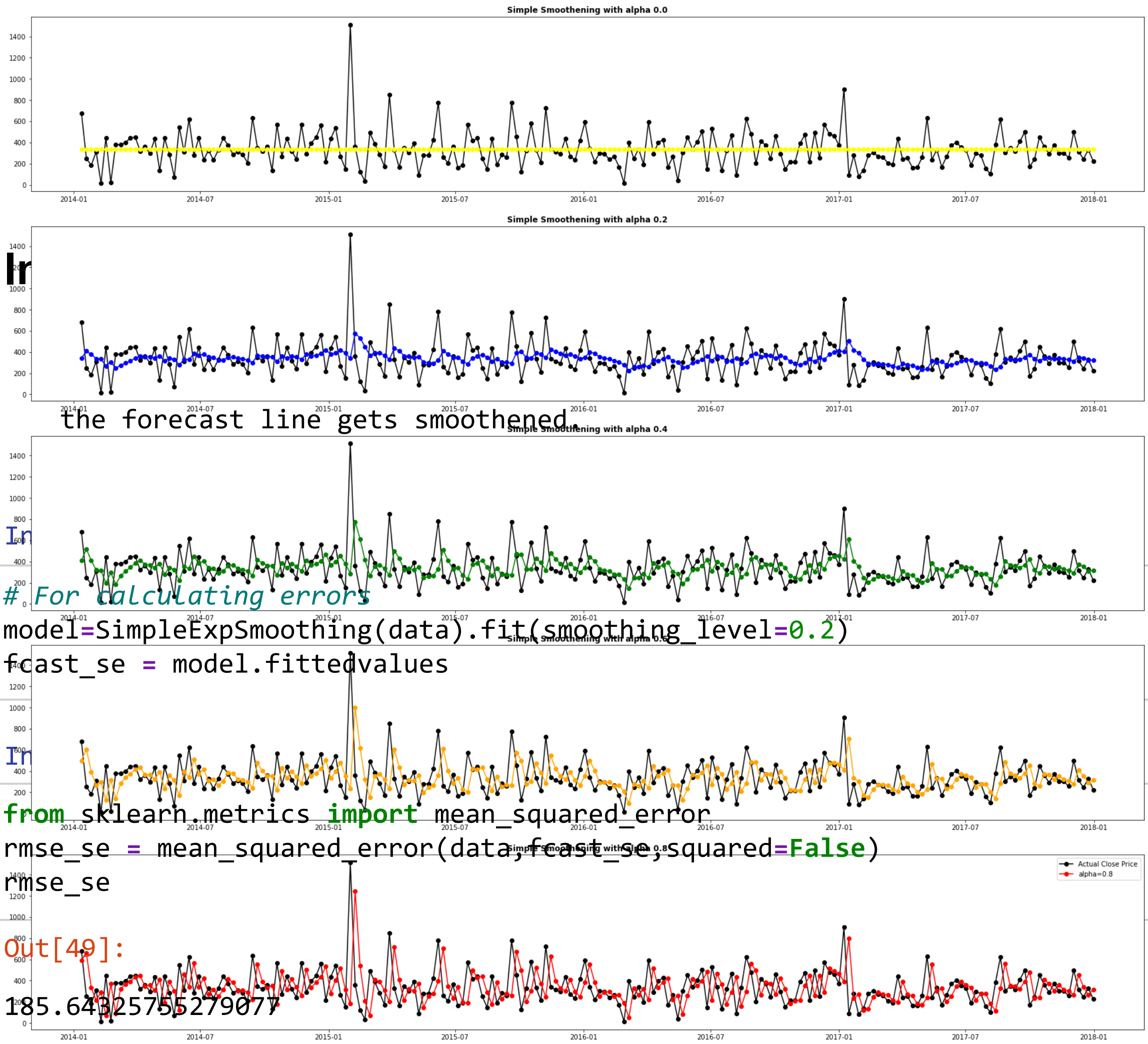
In [46]:

```
for a in alphas:
    m,d = simplesmoothening(df2['Sales'],a)
    d_simple_exp[a]=d.Forecast
    models.append(m)
```

In [47]:

```
plt.figure(figsize=(15,6))
fig,ax=plt.subplots(5,1,figsize=(30,28))

plt.subplot(511)
plt.plot(data, marker='o', color='black',label='Actual Close Price')
plt.plot(d_simple_exp.get(0.0), marker='o', color='yellow',label='alpha=0.0')
plt.title('Simple Smoothening with alpha 0.0',fontweight='bold', size=12)

plt.subplot(512)
plt.plot(data, marker='o', color='black',label='Actual Close Price')
plt.plot(d_simple_exp.get(0.2), marker='o', color='blue',label='alpha=0.2')
plt.title('Simple Smoothening with alpha 0.2',fontweight='bold', size=12)

plt.subplot(513)
plt.plot(data, marker='o', color='black',label='Actual Close Price')
plt.plot(d_simple_exp.get(0.4), marker='o', color='green',label='alpha=0.4')
plt.title('Simple Smoothening with alpha 0.4',fontweight='bold', size=12)

plt.subplot(514)
plt.plot(data, marker='o', color='black',label='Actual Close Price')
plt.plot(d_simple_exp.get(0.6), marker='o', color='orange',label='alpha=0.6')
plt.title('Simple Smoothening with alpha 0.6',fontweight='bold', size=12)

plt.subplot(515)
plt.plot(data, marker='o', color='black',label='Actual Close Price')
plt.plot(d_simple_exp.get(0.8), marker='o', color='red',label='alpha=0.8')
plt.title('Simple Smoothening with alpha 0.8',fontweight='bold', size=12)


plt.legend(loc='best')
plt.show()
```

```
<Figure size 1080x432 with 0 Axes>
```



In

value of

the forecast line gets smoothened.

```
# For calculating errors
model=SimpleExpSmoothing(data).fit(smoothing_level=0.2)
fcast_se = model.fittedvalues
```

```
from sklearn.metrics import mean_squared_error
rmse_se = mean_squared_error(data,fcast_se,squared=False)
rmse_se
```

Out[49]:

185.64325755279077

2.Double Exponential

In [50]:

```
# Double exponential Smoothing
alpha = 0.2; beta = 0.35
```

In [51]:

```
model1 = ExponentialSmoothing(data,trend='Additive').fit(smoothing_level=alpha, smoothin
```

In [52]:

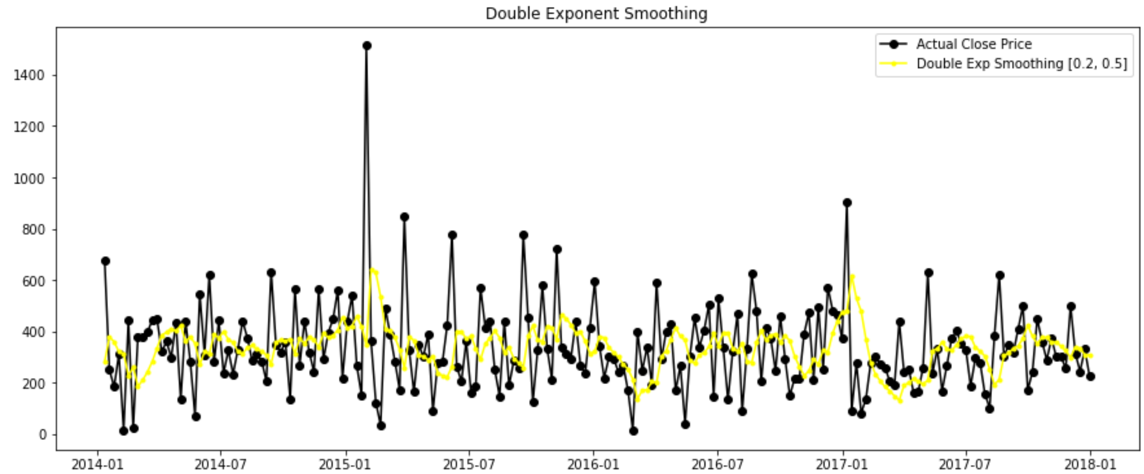
```
# forecast
fcast_de = model1.fittedvalues
```

In [53]:

```
#plot the original and smoothened data

plt.figure(figsize=(15,6))
plt.plot(data,marker='o',color='black',label='Actual Close Price')
plt.plot(fcast_de, marker='.',color='yellow',label='Double Exp Smoothing [0.2, 0.5]')
plt.legend()
plt.title('Double Exponent Smoothing')
```

Out[53]:

```
Text(0.5, 1.0, 'Double Exponent Smoothing')
```



In [54]:

```
rmse_de = mean_squared_error(data,fcast_de,squared=False)
rmse_de
```

Out[54]:

```
199.59717558410682
```

3.Triple Exponential Smoothening

In [55]:

```
## Triple Exponential Smoothing (tes)
alpha = 0.2; beta = 0.35; gama =0.5
```

In [56]:

```
model_tes = ExponentialSmoothing(data, trend='additive', seasonal='additive',seasonal_pe
```

In [57]:

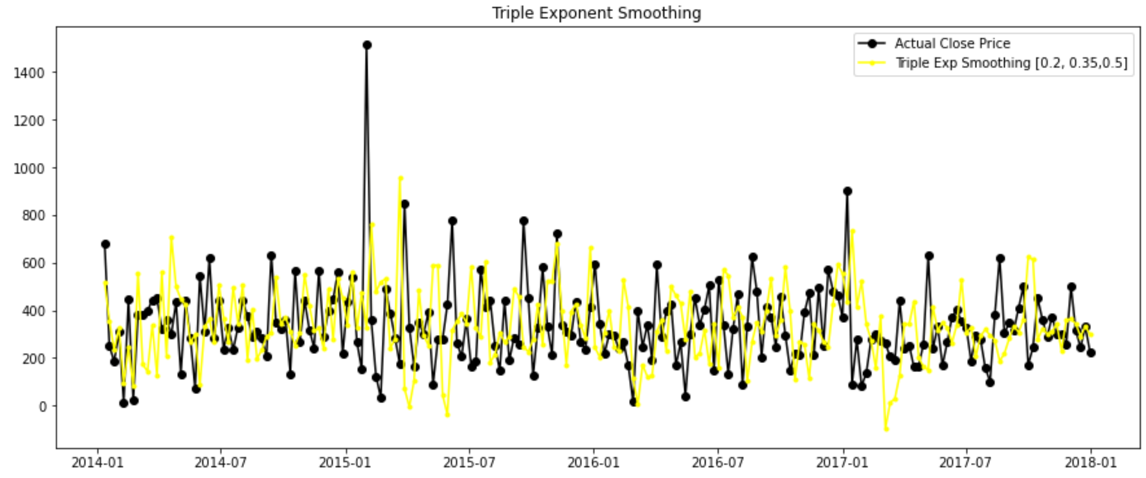
```
#forecast
fcast_tes=model_tes.fittedvalues
fcast_tes
```

Out[57]:

```
Order Date
2014-01-12    517.665264
2014-01-19    354.047161
2014-01-26    233.476021
2014-02-02    327.930311
2014-02-09     92.164554
                 ...
2017-12-03    362.440579
2017-12-10    343.507612
2017-12-17    289.756530
2017-12-24    332.078639
2017-12-31    299.243832
Freq: W-SUN, Length: 208, dtype: float64
```

In [58]:

```
#plot
plt.figure(figsize=(15,6))
plt.plot(data,marker='o',color='black',label='Actual Close Price')
plt.plot(fcast_tes, marker='.',color='yellow',label='Triple Exp Smoothing [0.2, 0.35,0.5

plt.legend()
plt.title('Triple Exponent Smoothing')
plt.show()
```



In [59]:

```
rmse_tes = mean_squared_error(data,fcast_tes,squared=False)
rmse_tes
```

Out[59]:

```
238.8665504103795
```

Checking for stationarity

In [60]:

```
# Checking for stationarity
from statsmodels.tsa.stattools import adfuller
def checkstationarity(data):
    pvalue = adfuller(data)[1]
    print(pvalue)

    if pvalue < 0.05:
        ret = 'Data is Stationary. Proceed to model building'
    else:
        ret = 'Data is not stationary. Make data stationary and proceed to model buildin

    return(ret)
```

In [61]:

```
checkstationarity(df2)
```

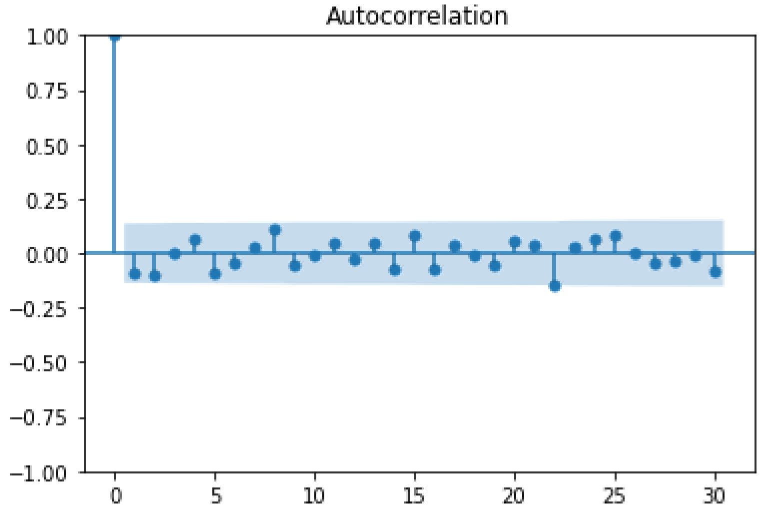
8.124101346205066e-22

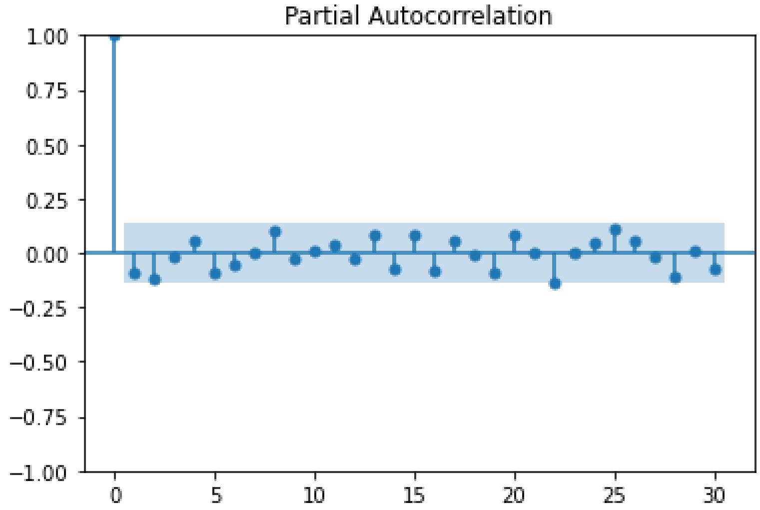
Out[61]:

'Data is Stationary. Proceed to model building'

In [62]:

```
# plotting acf and pacf
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf

plot_acf(df2,lags=30)
plot_pacf(df2,lags=30)
plt.show()
```





In [63]:

```
p=3;q=4
```

In [64]:

```
#splitting the data
num = int(0.7*len(df2))

train = df2.iloc[:num]
test = df2.iloc[num:]

train.shape,test.shape
```

Out[64]:

```
((145, 1), (63, 1))
```

In [65]:

```
#checking for best p,d and q values by building arima model
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error

def arima_model(data):
    list1 = []
    for p in range(2):
        for q in range(2):
            list1.append((p,0,q))

    model = []
    for i in list1:
        m=ARIMA(train,order=i).fit()
        model.append(m)

    aic=[]
    bic=[]
    for j in model[0:]:
        aic.append(j.aic)
        bic.append(j.bic)

    forecast = []
    for v in model:
        f=v.predict(0,len(test)-1)
        forecast.append(f)

    RMSE=[]
    for a in forecast[0:]:
        rmse = mean_squared_error(test,a,squared=False)
        RMSE.append(round(rmse,3))



    v1 = pd.DataFrame({'model':model,'p,d,q':list1,'RMSE':RMSE,'AIC':aic,'BIC':bic})


    return(v1)
```

In [66]:

```
dff = arima_model(train)
dff
```

Out[66]:

	model	p,d,q	RMSE	AIC	BIC
0	<statsmodels.tsa.arima.model.ARIMAResultsWrapp...	(0, 0, 0)	145.265	1928.240281	1934.193749
1	<statsmodels.tsa.arima.model.ARIMAResultsWrapp...	(0, 0, 1)	143.753	1925.947630	1934.877831
2	<statsmodels.tsa.arima.model.ARIMAResultsWrapp...	(1, 0, 0)	142.874	1927.436320	1936.366522
3	<statsmodels.tsa.arima.model.ARIMAResultsWrapp...	(1, 0, 1)	143.134	1925.390514	1937.297449

In [67]:

```
dff['RMSE'].min()
```

Out[67]:

142.874

In [68]:

```
dff[dff.RMSE == dff['RMSE'].min()]
```

Out[68]:

	model	p,d,q	RMSE	AIC	BIC
2	<statsmodels.tsa.arima.model.ARIMAResultsWrapp...	(1, 0, 0)	142.874	1927.43632	1936.366522

In [69]:

```
from pmdarima.arima import auto_arima
```

In [70]:

```
stepwise_fit = auto_arima(df2['Sales'],start_p=0,max_p=3,start_q=0,max_q=4,trace=True,se
```

```
Performing stepwise search to minimize aic
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=2738.479, Time=0.02 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=2738.566, Time=0.05 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=2738.023, Time=0.06 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=3061.955, Time=0.01 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=2741.195, Time=0.09 sec
 ARIMA(0,0,2)(0,0,0)[0] intercept   : AIC=2737.954, Time=0.08 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=2740.230, Time=0.10 sec
 ARIMA(0,0,3)(0,0,0)[0] intercept   : AIC=2739.946, Time=0.13 sec
 ARIMA(1,0,3)(0,0,0)[0] intercept   : AIC=2741.794, Time=0.07 sec
 ARIMA(0,0,2)(0,0,0)[0]             : AIC=2934.784, Time=0.07 sec

Best model:  ARIMA(0,0,2)(0,0,0)[0] intercept
Total fit time: 0.715 seconds
```

Model Building

1.ARMA MODEL

In [71]:

```
def arima_func(data,p,d,q):

    m1 = ARIMA(data,order=(p,d,q)).fit()
    predictions = m1.predict(len(train),len(train)+len(test)-1)

    return m1.summary(),predictions
```

In [72]:

```
summary_arma, pred_arma = arima_func(train,1,0,0)
```

In [73]:

```
summary_arma
```

Out[73]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	145
Model:	ARIMA(1, 0, 0)	**Log Likelihood**	-960.718
Date:	Sun, 13 Nov 2022	**AIC**	1927.436
Time:	09:26:28	**BIC**	1936.367
Sample:	01-12-2014	**HQIC**	1931.065
	- 10-16-2016		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	345.0579	16.196	21.305	0.000	313.315	376.801
ar.L1	-0.1400	0.106	-1.327	0.184	-0.347	0.067
sigma2	3.33e+04	2189.840	15.207	0.000	2.9e+04	3.76e+04

Ljung-Box (L1) (Q):	0.08	**Jarque-Bera (JB):**	613.16
Prob(Q):	0.78	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.04	**Skew:**	1.86
Prob(H) (two-sided):	0.89	**Kurtosis:**	12.36

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

In [74]:

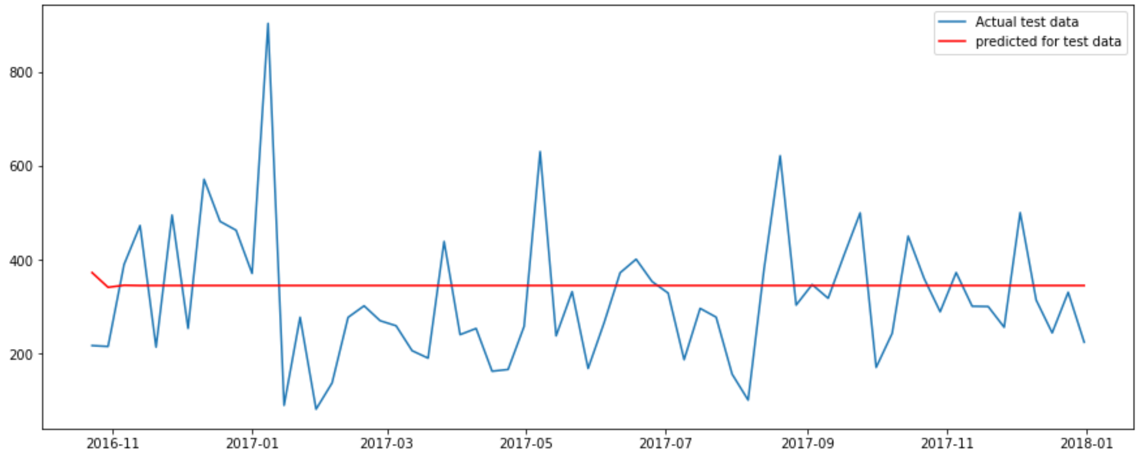
```
pred_arma
```

Out[74]:

```
2016-10-23    372.539911
2016-10-30    341.209339
2016-11-06    345.596891
2016-11-13    344.982456
2016-11-20    345.068501
                 ...
2017-12-03    345.057932
2017-12-10    345.057932
2017-12-17    345.057932
2017-12-24    345.057932
2017-12-31    345.057932
Freq: W-SUN, Name: predicted_mean, Length: 63, dtype: float64
```

In [75]:

```
plt.figure(figsize=(15,6))

plt.plot(test['Sales'],label='Actual test data')
plt.plot(pred_arma,'r',label='predicted for test data')
plt.legend(loc='best')
plt.show()
```



In [76]:

```
#forecasting for next 1year
model1 = ARIMA(train,order=(1,0,0)).fit()

fcast_arma = model1.predict(len(df2),len(df2)+52,type='levels')
```

In [77]:

```
import statsmodels.api as sm
pvalue = sm.stats.acorr_ljungbox(model1.resid,lags=[1],return_df=True)['lb_pvalue'].valu
```

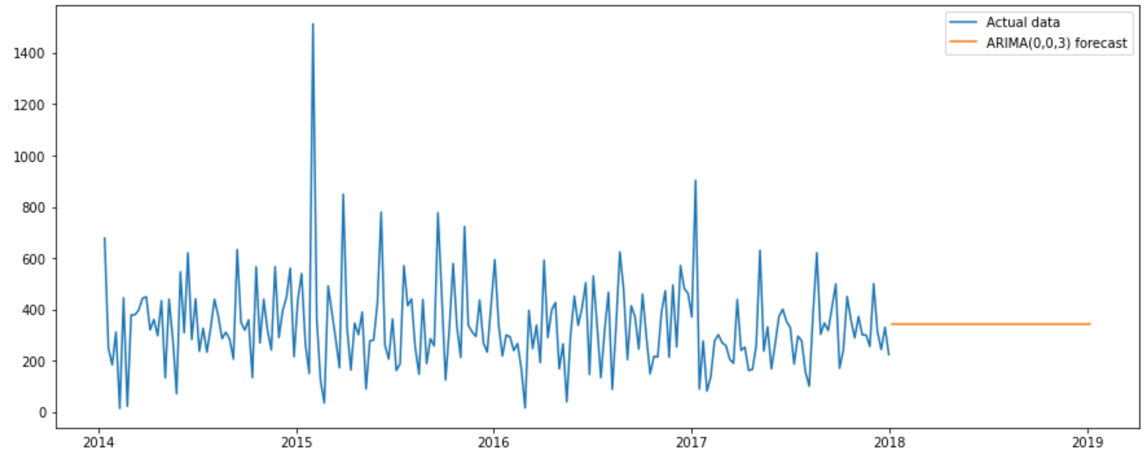
In [78]:

```
if pvalue <0.05:
    print('not good')
else:
    print('good')
```

good

In [79]:

```
plt.figure(figsize=(15,6))

plt.plot(df2.Sales,label='Actual data')
plt.plot(fcast_arma,label='ARIMA(0,0,3) forecast')
plt.legend(loc='best')
plt.show()
```



In [80]:

```
AIC_ARMA = 2234.074
BIC_ARMA = 2248.958
```

In [81]:

```
AIC_ARMA = model1.aic
BIC_ARMA = model1.bic
AIC_ARMA,BIC_ARMA
```

Out[81]:

```
(1927.4363203564249, 1936.3665215836866)
```

In [82]:

```
# Evaluation of data
from sklearn.metrics import mean_squared_error

mse_arma = mean_squared_error(test.Sales,pred_arma)
rmse_arma = mean_squared_error(test.Sales,pred_arma,squared=False)

print(mse_arma)
print(rmse_arma)
```

```
21205.460409117564
145.62094770024527
```

2.SARIMA MODEL

In [83]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [116]:

```
model2 = SARIMAX(train,order=(1,0,0),seasonal_order=(1,0,0,7)).fit()
```

In [117]:

```
import statsmodels.api as sm
pvalue = sm.stats.acorr_ljungbox(model2.resid,lags=[1],return_df=True)['lb_pvalue'].valu
```

In [118]:

```
if pvalue <0.05:
    print('not good')
else:
    print('good')
```

```
good
```

In [119]:

```
model2.summary()
```

Out[119]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	145
Model:	SARIMAX(1, 0, 0)x(1, 0, 0, 7)	**Log Likelihood**	-1000.187
Date:	Sun, 13 Nov 2022	**AIC**	2006.373
Time:	09:27:40	**BIC**	2015.303
Sample:	01-12-2014	**HQIC**	2010.002
	- 10-16-2016		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.0567	0.084	-0.676	0.499	-0.221	0.108
ar.S.L7	0.8113	0.029	27.585	0.000	0.754	0.869
sigma2	5.45e+04	3804.729	14.324	0.000	4.7e+04	6.2e+04

Ljung-Box (L1) (Q):	2.03	**Jarque-Bera (JB):**	264.94
Prob(Q):	0.15	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.09	**Skew:**	-0.12
Prob(H) (two-sided):	0.77	**Kurtosis:**	9.62

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

In [120]:

```
AIC_SARIMA=model2.aic
BIC_SARIMA=model2.bic
AIC_SARIMA,BIC_SARIMA
```

Out[120]:

```
(2006.3731819315196, 2015.3033831587813)
```

In [121]:

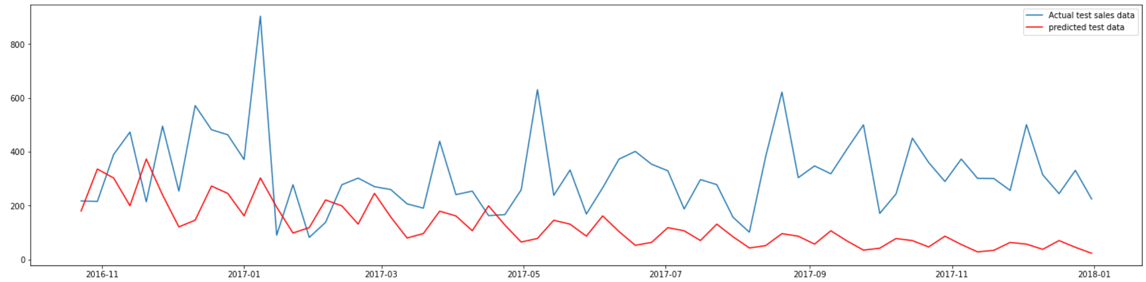
```
pred_sarima = model2.predict(test.index[0],test.index[-1])
pred_sarima
```

Out[121]:

```
2016-10-23    179.521190
2016-10-30    335.478820
2016-11-06    302.011277
2016-11-13    199.268246
2016-11-20    372.706062
                 ...
2017-12-03     56.660778
2017-12-10     37.385008
2017-12-17     69.923931
2017-12-24     44.852799
2017-12-31     22.649755
Freq: W-SUN, Name: predicted_mean, Length: 63, dtype: float64
```

In [122]:

```
plt.figure(figsize=(25,6))

plt.plot(test.Sales,label='Actual test sales data')
plt.plot(pred_sarima,'r',label='predicted test data')
plt.legend(loc='best')
plt.show()
```



In [123]:

```
#Evalution

mse_sarima = mean_squared_error(test.Sales,pred_sarima)
rmse_sarima = mean_squared_error(test.Sales,pred_sarima,squared=False)

print(mse_sarima)
print(rmse_sarima)
```

```
61245.18192010673
247.47763923253092
```

In [124]:

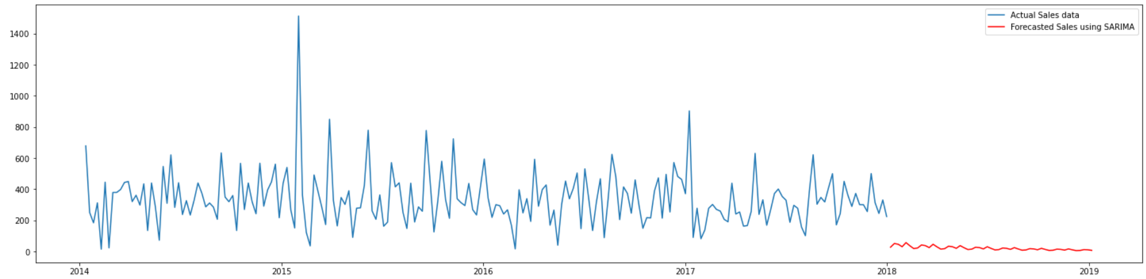
```
fcast_sarima = model2.predict(len(df2),len(df2)+52,type='levels')
fcast_sarima
```

Out[124]:

```
2018-01-07    27.323260
2018-01-14    51.060129
2018-01-21    45.966344
2018-01-28    30.328777
2018-02-04    56.726143
2018-02-11    36.387061
2018-02-18    18.374729
2018-02-25    22.166133
2018-03-04    41.422788
2018-03-11    37.290429
2018-03-18    24.604374
2018-03-25    46.019371
2018-04-01    29.519187
2018-04-08    14.906592
2018-04-15    17.982388
2018-04-22    33.604447
2018-04-29    30.252050
2018-05-06    19.960423
2018-05-13    37.333448
2018-05-20    23.947590
2018-05-27    12.093048
2018-06-03    14.588303
2018-06-10    27.261778
2018-06-17    24.542128
2018-06-24    16.192994
2018-07-01    30.286949
2018-07-08    19.427604
2018-07-15     9.810546
2018-07-22    11.834835
2018-07-29    22.116255
2018-08-05    19.909926
2018-08-12    13.136649
2018-08-19    24.570441
2018-08-26    15.760742
2018-09-02     7.958856
2018-09-09     9.601070
2018-09-16    17.941924
2018-09-23    16.152028
2018-09-30    10.657173
2018-10-07    19.932894
2018-10-14    12.785982
2018-10-21     6.456662
2018-10-28     7.788917
2018-11-04    14.555477
2018-11-11    13.103415
2018-11-18     8.645685
2018-11-25    16.170662
2018-12-02    10.372693
2018-12-09     5.238000
2018-12-16     6.318798
2018-12-23    11.808204
2018-12-30    10.630212
2019-01-06     7.013856
Freq: W-SUN, Name: predicted_mean, dtype: float64
```

In [125]:

```
plt.figure(figsize=(25,6))

plt.plot(df2.Sales,label = 'Actual Sales data')
plt.plot(fcast_sarima,'r',label='Forecasted Sales using SARIMA')
plt.legend(loc='best')
plt.show()
```



SARIMAX

In [94]:

```
df6 = df[['Order Date','Sales','Quantity','Profit','Discount']]
df6.shape
```

Out[94]:

```
(2121, 5)
```

In [95]:

```
df6.head()
```

Out[95]:

	Order Date	Sales	Quantity	Profit	Discount
0	2016-11-08	261.9600	2	41.9136	0.00
1	2016-11-08	731.9400	3	219.5820	0.00
3	2015-10-11	957.5775	5	-383.0310	0.45
5	2014-06-09	48.8600	7	14.1694	0.00
10	2014-06-09	1706.1840	9	85.3092	0.20

In [96]:

```
df6.dtypes
```

Out[96]:

```
Order Date    datetime64[ns]
Sales                float64
Quantity               int64
Profit               float64
Discount             float64
dtype: object
```

In [97]:

```
# setting the index as Order Date
df6_1 = df6.set_index('Order Date')
df6_1.head(3)
```

Out[97]:

	Sales	Quantity	Profit	Discount
Order Date				
2016-11-08	261.9600	2	41.9136	0.00
2016-11-08	731.9400	3	219.5820	0.00
2015-10-11	957.5775	5	-383.0310	0.45

In [98]:

```
df6_1 = df6_1.resample('W').mean()
```

In [99]:

```
df6_1.head()
```

Out[99]:

	Sales	Quantity	Profit	Discount
Order Date				
2014-01-12	678.107000	3.750000	179.268750	0.150000
2014-01-19	250.094600	4.800000	-50.800880	0.310000
2014-01-26	183.995333	2.888889	39.514033	0.022222
2014-02-02	311.833000	2.500000	-6.615200	0.175000
2014-02-09	14.560000	2.000000	5.532800	0.000000

In [100]:

```
# hexogeneous variables to forecast 'var'
num1 = int(0.7*len(df6_1))
train1 = df6_1.iloc[:num1]
test1 = df6_1.iloc[num1:]
```

In [101]:

```
exog_train = train1[['Quantity','Profit','Discount']]
exog_test = test1[['Quantity','Profit','Discount']]
```

In [126]:

```
model3 = SARIMAX(train1.Sales,order=(1,0,0),seasonal_order=(1,0,0,7),exog=exog_train).fi
```

In [127]:

```
model3.summary()
```

Out[127]:

SARIMAX Results

Dep. Variable:	Sales	**No. Observations:**	145
Model:	SARIMAX(1, 0, 0)x(1, 0, 0, 7)	**Log Likelihood**	-946.954
Date:	Sun, 13 Nov 2022	**AIC**	1905.908
Time:	09:28:21	**BIC**	1923.769
Sample:	01-12-2014	**HQIC**	1913.166
	- 10-16-2016		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
Quantity	94.0363	6.843	13.742	0.000	80.624	107.449
Profit	-0.3630	0.112	-3.236	0.001	-0.583	-0.143
Discount	-117.0601	159.757	-0.733	0.464	-430.177	196.057
ar.L1	-0.0869	0.104	-0.833	0.405	-0.291	0.118
ar.S.L7	0.1543	0.096	1.603	0.109	-0.034	0.343
sigma2	2.725e+04	2796.036	9.745	0.000	2.18e+04	3.27e+04

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	89.03
Prob(Q):	0.94	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.87	**Skew:**	0.90
Prob(H) (two-sided):	0.63	**Kurtosis:**	6.39

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

In [128]:

```
import statsmodels.api as sm
pvalue = sm.stats.acorr_ljungbox(model3.resid,lags=[1],return_df=True)['lb_pvalue'].valu
```

In [129]:

```
if pvalue <0.05:
    print('not good')
else:
    print('good')
```

good

In [130]:

```
AIC_SARIMAX = model3.aic
BIC_SARIMAX = model3.bic
```

In [131]:

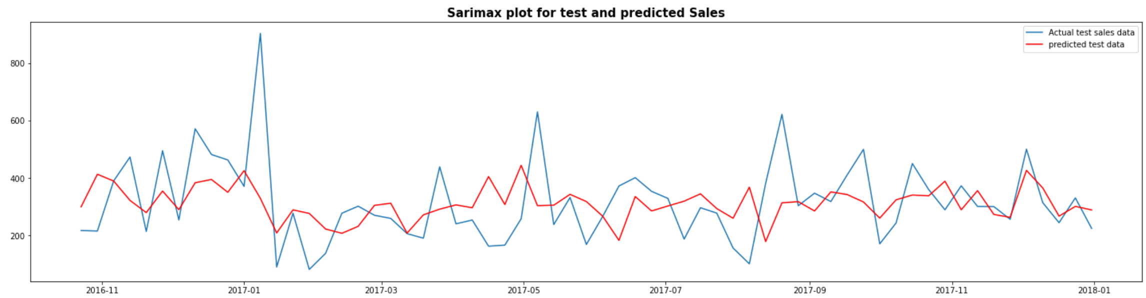
```
#forecasted values for test data
pred_sarimax = model3.forecast(len(test1.Sales),exog = exog_test)
pred_sarimax
```

Out[131]:

```
2016-10-23    299.438472
2016-10-30    412.918152
2016-11-06    389.353769
2016-11-13    322.043197
2016-11-20    279.343735
                 ...
2017-12-03    426.384747
2017-12-10    365.268442
2017-12-17    267.132380
2017-12-24    301.021079
2017-12-31    288.703329
Freq: W-SUN, Name: predicted_mean, Length: 63, dtype: float64
```

In [132]:

```
plt.figure(figsize=(25,6))

plt.plot(test1.Sales,label='Actual test sales data')
plt.plot(pred_sarimax,'r',label='predicted test data')
plt.legend(loc='best')
plt.title('Sarimax plot for test and predicted Sales',fontweight='bold',size=15)
plt.show()
```



In [133]:

```
#Evalution

mse_sarimax = mean_squared_error(test1.Sales,pred_sarimax)
rmse_sarimax = mean_squared_error(test1.Sales,pred_sarimax,squared=False)

print(mse_sarimax)
print(rmse_sarimax)
```

```
19444.599131388713
139.44389241335998
```

In [134]:

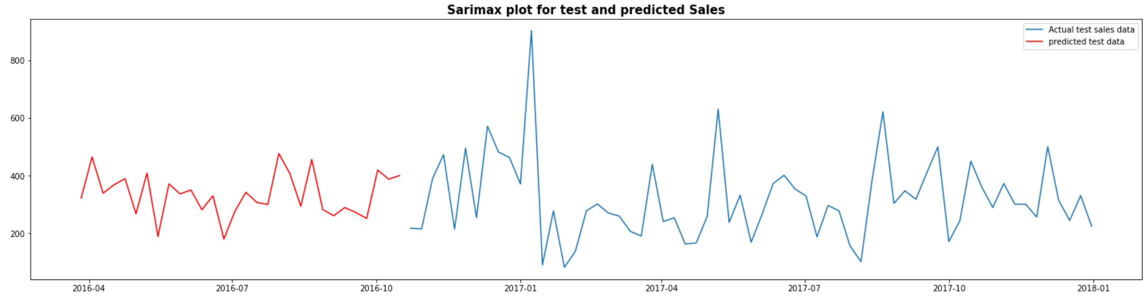
```
pred_sarimax1 =  model3.predict(len(test1.Sales)+52,exog = len(exog_test)+52)
pred_sarimax1
```

Out[134]:

```
Order Date
2016-03-27    321.529766
2016-04-03    464.606224
2016-04-10    338.815607
2016-04-17    368.209376
2016-04-24    389.367433
2016-05-01    267.564042
2016-05-08    408.820108
2016-05-15    188.868690
2016-05-22    371.321501
2016-05-29    336.475394
2016-06-05    350.011315
2016-06-12    281.358370
2016-06-19    329.922249
2016-06-26    179.927196
2016-07-03    275.912519
2016-07-10    342.088899
2016-07-17    306.861284
2016-07-24    299.994784
2016-07-31    476.446618
2016-08-07    407.710703
2016-08-14    293.632705
2016-08-21    456.000792
2016-08-28    282.189891
2016-09-04    260.742103
2016-09-11    288.956337
2016-09-18    272.554999
2016-09-25    251.021424
2016-10-02    419.380678
2016-10-09    387.480718
2016-10-16    400.144625
Freq: W-SUN, Name: predicted_mean, dtype: float64
```

In [135]:

```
plt.figure(figsize=(25,6))

plt.plot(test1.Sales,label='Actual test sales data')
plt.plot(pred_sarimax1,'r',label='predicted test data')
plt.legend(loc='best')
plt.title('Sarimax plot for test and predicted Sales',fontweight='bold',size=15)
plt.show()
```



In [136]:

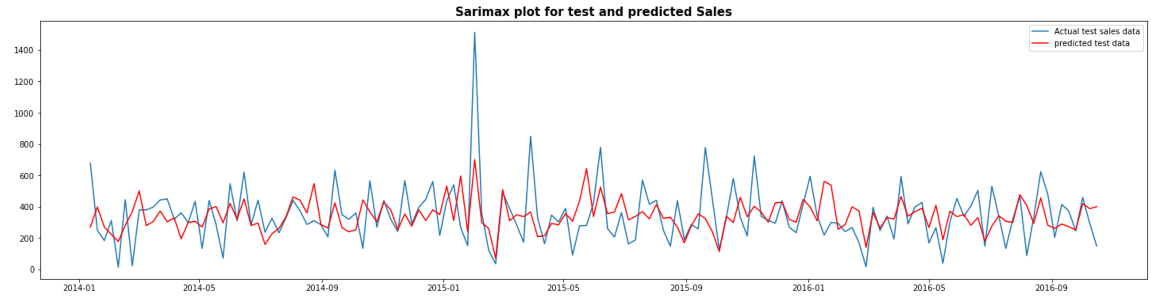
```
#Forecast  (fv = forecasted values)

sarimax_fv = model3.fittedvalues
sarimax_fv
```

Out[136]:

```
Order Date
2014-01-12    270.002647
2014-01-19    398.060506
2014-01-26    270.656315
2014-02-02    223.156112
2014-02-09    177.782430
                 ...
2016-09-18    272.554999
2016-09-25    251.021424
2016-10-02    419.380678
2016-10-09    387.480718
2016-10-16    400.144625
Freq: W-SUN, Length: 145, dtype: float64
```

In [137]:

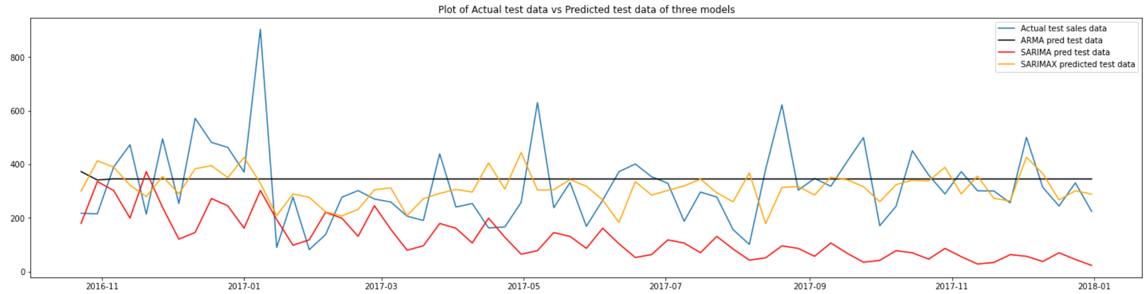
```
plt.figure(figsize=(25,6))

plt.plot(train1.Sales,label='Actual test sales data')
plt.plot(sarimax_fv,'r',label='predicted test data')
plt.legend(loc='best')
plt.title('Sarimax plot for test and predicted Sales',fontweight='bold',size=15)
plt.show()
```



Final plot for all models:-

In [138]:

```
plt.figure(figsize=(25,6))

plt.plot(test.Sales,label='Actual test sales data')
plt.plot(pred_arma,'black',label='ARMA pred test data')
plt.plot(pred_sarima,'r',label='SARIMA pred test data')
plt.plot(pred_sarimax,'orange',label='SARIMAX predicted test data')
plt.title('Plot of Actual test data vs Predicted test data of three models')
plt.legend(loc='best')
plt.show()
```



In [115]:

```
v1 = pd.DataFrame({'ARMA':[AIC_ARMA,BIC_ARMA,mse_arma,rmse_arma],'SARIMA':[AIC_SARIMA,BI
                  'SARIMAX':[AIC_SARIMAX,BIC_SARIMAX,mse_sarimax,rmse_sarimax]})
v1.index = ['AIC','BIC','MSE','RMSE']
v1
```

Out[115]:

	ARMA	SARIMA	SARIMAX
AIC	1927.436320	2029.511347	1907.403437
BIC	1936.366522	2038.441548	1925.263839
MSE	21205.460409	103544.003482	19112.557486
RMSE	145.620948	321.782541	138.248174

Interpretations:-

```
    * The best model for predictions is 'SARIMAX' with less AIC,BIC and RMSE val
ues.
    * By Sarimax model the  Predicted values are also nearer to the actual test
values.
```

In [ ]: