ADS Final Project

Preliminary EDA

In [3]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pylab as plt
import seaborn as sns
import dmba
from pathlib import Path

import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn.metrics import accuracy_score


import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [4]:
```
Retail_df = pd.read_csv('Online_Retail.csv')
Retail_df.sample(5)
```

Out[4]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
304889	563614	23328	SET 6 SCHOOL MILK BOTTLES IN CRATE	240	8/18/2011 8:51	3.39	12415.0	Australia
232914	557389	21314	SMALL GLASS HEART TRINKET POT	1	6/20/2011 11:03	2.10	15921.0	United Kingdom
515973	579832	21181	PLEASE ONE PERSON METAL SIGN	12	11/30/2011 15:58	2.10	17434.0	United Kingdom
458137	575760	23581	JUMBO BAG PAISLEY PARK	14	11/11/2011 10:50	2.08	15965.0	United Kingdom
209283	555201	22128	PARTY CONES CANDY ASSORTED	12	6/1/2011 12:10	1.25	16969.0	United Kingdom

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

Out[13]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

In [3]:
```
Retail_df.shape
```

Out[3]:
```
(541909, 8)
```

In [4]:
```
Retail_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   InvoiceNo    541909 non-null  object 
 1   StockCode    541909 non-null  object 
 2   Description  540455 non-null  object 
 3   Quantity     541909 non-null  int64  
 4   InvoiceDate  541909 non-null  object 
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object 
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

In [6]:
```
Retail_df.describe()
```

Out[6]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

Maximum and minimum unit price/quantity is extreme there is probably a corrupt record

In [24]:
```
# look for the outlier record:
outlier_rows = Retail_df['Quantity']== -80995
outlier=Retail_df[outlier_rows]
outlier

outlier_rows2 = Retail_df['Quantity']== 80995
outlier2=Retail_df[outlier_rows2]

outlier_rows3 = Retail_df['UnitPrice']== 38970
outlier3=Retail_df[outlier_rows3]
```

```
outlier_rows4 = Retail_df['UnitPrice']== -11062.06
outlier4=Retail_df[outlier_rows4]
```

In [25]:
```
outlier4
```

Out[25]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
299983	A563186	B	Adjust bad debt	1	8/12/2011 14:51	-11062.06	NaN	United Kingdom
299984	A563187	B	Adjust bad debt	1	8/12/2011 14:52	-11062.06	NaN	United Kingdom

---

Temporary Removal of Large Orders to View Common Orders Made Distributions

In [61]:
```
Retail_clean = Retail_df[Retail_df['UnitPrice'].between(Retail_df['UnitPrice'].quantile(.2
                                                        Retail_df['UnitPrice'].qua
```

In [62]:
```
Retail_clean_df = Retail_clean[Retail_clean['Quantity'].between(Retail_clean['Quantity'].q
                                                               Retail_clean['Quantity'].quantile(.
```

In [64]:
```
Retail_clean_df.shape
```

Out[64]:
```
(223391, 8)
```

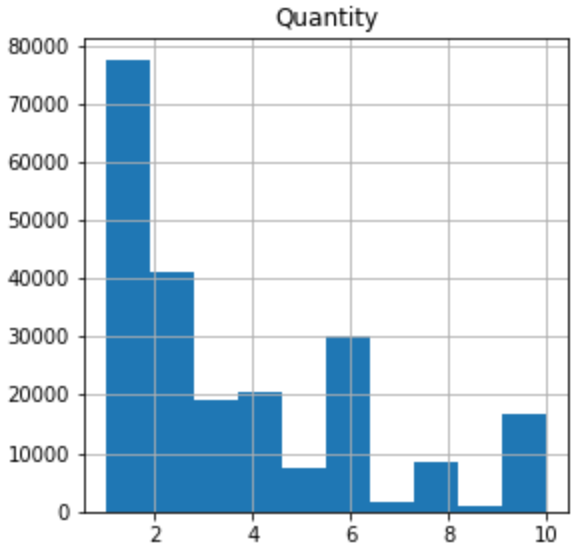
In [56]:
```
Retail_clean_df.describe()
```

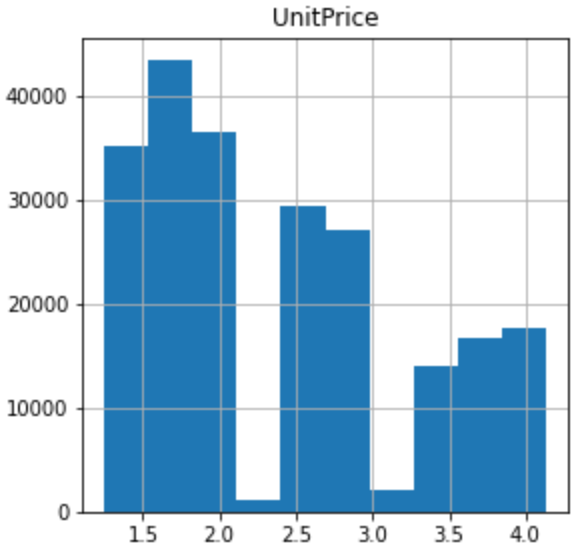
Out[56]:

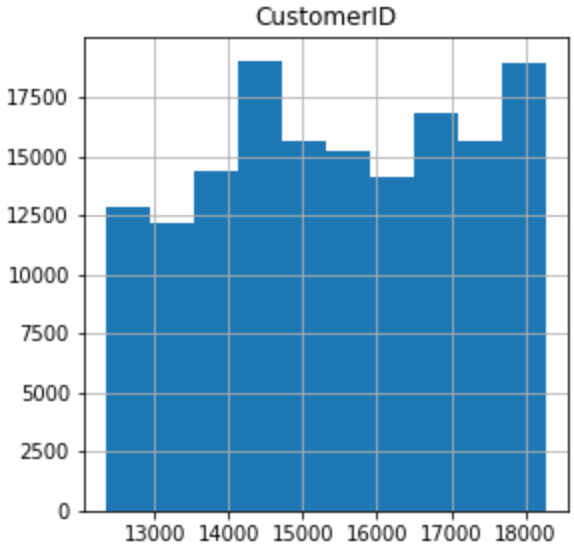
	Quantity	UnitPrice	CustomerID
count	220165.000000	220165.000000	152771.000000
mean	3.439811	2.900183	15406.978857
std	2.706716	1.042228	1692.378366
min	1.000000	1.630000	12347.000000
25%	1.000000	2.080000	14096.000000
50%	2.000000	2.550000	15358.000000
75%	6.000000	3.750000	16907.000000
max	10.000000	4.950000	18287.000000

In [65]:
```
Retail_clean_df.hist(figsize=[10,10])
```

Out[65]:
```
array([[<AxesSubplot:title={'center':'Quantity'}>,
        <AxesSubplot:title={'center':'UnitPrice'}>],
       [<AxesSubplot:title={'center':'CustomerID'}>, <AxesSubplot:>]],
      dtype=object)
```







Remove Irrelevant and Unrealistic Records:

In [5]:

```
unreal_rows1 = Retail_df[Retail_df['Quantity'] <= 0].index
#unreal_rows2 = Retail_df[Retail_df['Price'] <= 0].index

Retail_df_pre = Retail_df.drop(index=unreal_rows1)
unreal_rows2 = Retail_df_pre[Retail_df_pre['UnitPrice'] <= 0].index

Retail_df_pre2 = Retail_df_pre.drop(index=unreal_rows2)
unreal_rows3 = Retail_df_pre2[Retail_df_pre2['Quantity'] >= 80000].index

Retail_df_pre3 = Retail_df_pre2.drop(index=unreal_rows3)
unreal_rows4 = Retail_df_pre3[(Retail_df_pre3['StockCode'] == 'AMAZONFEE') |
                              (Retail_df_pre3['StockCode'] == 'DOT') |
                              (Retail_df_pre3['StockCode'] == 'M') |
                              (Retail_df_pre3['StockCode'] == 'B') |
                              (Retail_df_pre3['StockCode'] == 'POST')].index

Retail_df_pre4 = Retail_df_pre3.drop(index=unreal_rows4)
```

In [6]:

```
unreal_rows4 = Retail_df_pre4['Quantity'] >= 1000
Retail_df_pre4[unreal_rows4]
```

Out[6]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
4850	536809	84950	ASSORTED COLOUR T-LIGHT HOLDER	1824	12/2/2010 16:48	0.55	15299.0	United Kingdom
4945	536830	84077	WORLD WAR 2 GLIDERS ASSTD DESIGNS	2880	12/2/2010 17:38	0.18	16754.0	United Kingdom
4946	536830	21915	RED HARMONICA IN BOX	1400	12/2/2010 17:38	1.06	16754.0	United Kingdom
6365	536890	17084R	ASSORTED INCENSE PACK	1440	12/3/2010 11:48	0.16	14156.0	EIRE
16435	537659	22189	CREAM HEART CARD HOLDER	1008	12/7/2010 16:43	2.31	18102.0	United Kingdom
...	...	...	...	...	...	...	...	...
521375	580363	23582	VINTAGE DOILY JUMBO BAG RED	1500	12/2/2011 16:32	1.79	13868.0	United Kingdom
533812	581115	22413	METAL SIGN TAKE IT OR LEAVE IT	1404	12/7/2011 12:20	2.75	15195.0	United Kingdom
534952	581175	23084	RABBIT NIGHT LIGHT	1440	12/7/2011 15:16	1.79	14646.0	Netherlands
540070	581458	22197	POPCORN HOLDER	1500	12/8/2011 18:45	0.72	17949.0	United Kingdom
540071	581459	22197	POPCORN HOLDER	1200	12/8/2011 18:46	0.72	17949.0	United Kingdom

114 rows × 8 columns

In [27]:
```
Retail_df_hist.describe()
```

Out[27]:

	Quantity	UnitPrice	CustomerID
count	527944.000000	527944.000000	396481.000000
mean	10.270070	3.276816	15301.442505
std	37.727013	4.267975	1709.759660
min	1.000000	0.001000	12347.000000
25%	1.000000	1.250000	13975.000000
50%	3.000000	2.080000	15159.000000
75%	11.000000	4.130000	16801.000000
max	4800.000000	295.000000	18287.000000

In [97]:
```
Retail_df_pre4.shape
```

Out[97]:
```
(527947, 8)
```

In [100…
```
Retail_TimeSeries_df=Retail_df_pre4.copy()
```

In [16]:
```
finding_row = Retail_df_pre4['Quantity'] == 74215
```

In [17]:
```
Retail_df_pre4[finding_row]
```

Out[17]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
61619	541431	23166	MEDIUM CERAMIC TOP STORAGE JAR	74215	1/18/2011 10:01	1.04	12346.0	United Kingdom

In [20]:
```
finding_row2 = Retail_df_pre4['UnitPrice'] == 649.5
```

In [21]:
```
Retail_df_pre4[finding_row2]
```

Out[21]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
222680	556444	22502	PICNIC BASKET WICKER 60 PIECES	60	6/10/2011 15:28	649.5	15098.0	United Kingdom
222682	556446	22502	PICNIC BASKET WICKER 60 PIECES	1	6/10/2011 15:33	649.5	15098.0	United Kingdom

In [41]:
```
Retail_df_hist = Retail_df_pre4.drop(index=61619)
#Retail_df_large_orders = Retail_df_pre4.drop(index=rows_small_orders)
```

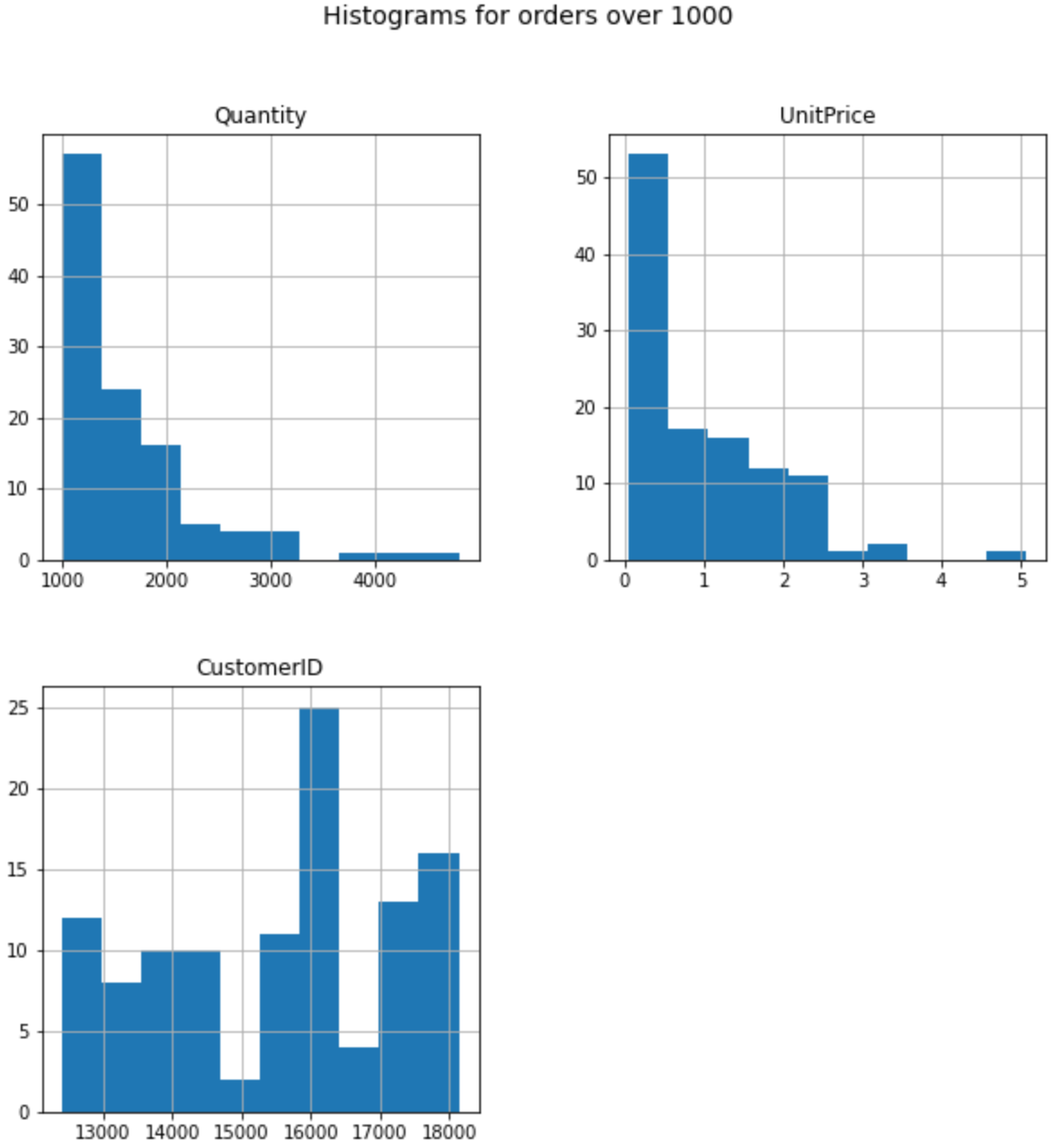
In [125…
```
rows_medlarge_orders = Retail_df_hist['Quantity'] >= 100
Retail_df_medlarge_orders = Retail_df_hist[rows_medlarge_orders]
Retail_df_medlarge_orders.shape
```

Out[125…
```
(6647, 8)
```

In [42]:
```
rows_large_orders = Retail_df_hist['Quantity'] >= 1000
Retail_df_large_orders = Retail_df_hist[rows_large_orders]
```

In [50]:
```
Retail_df_large_orders.hist(figsize=[10,10])
plt.suptitle("Histograms for orders over 1000", fontsize=14)
```

Out[50]:
```
Text(0.5, 0.98, 'Histograms for orders over 1000')
```

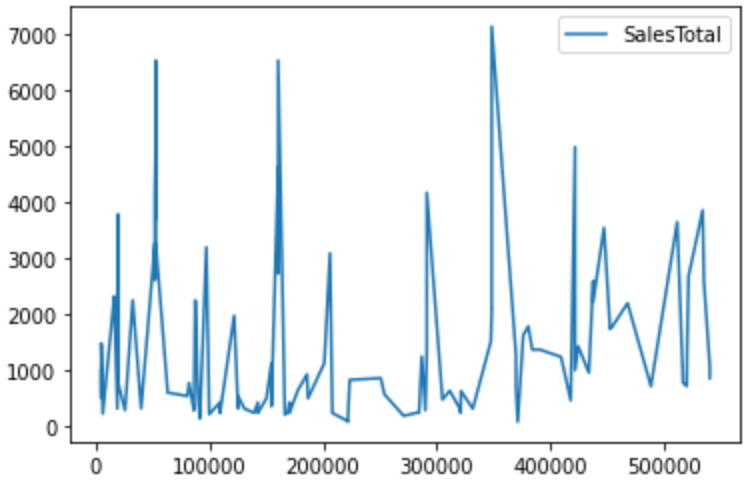


In [51]:
```
Retail_df_large_orders.to_csv('Retail_df_large_orders.csv')
```

In [124…
```
Retail_df_large_orders.shape
```

Out[124…
```
(113, 8)
```

In [127…
```
from pandas import read_csv
series_time_retail = read_csv('Retail_df_large_orders.csv', header=0, index_col=0, parse_c
series_time_retail['SalesTotal']=series_time_retail['Quantity']*series_time_retail['UnitPr
series_time_retail.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity'],inplace

series_time_retail.plot()
plt.show()
```



In [80]:
```
series_time_retail.tail(20)
```

Out[80]:

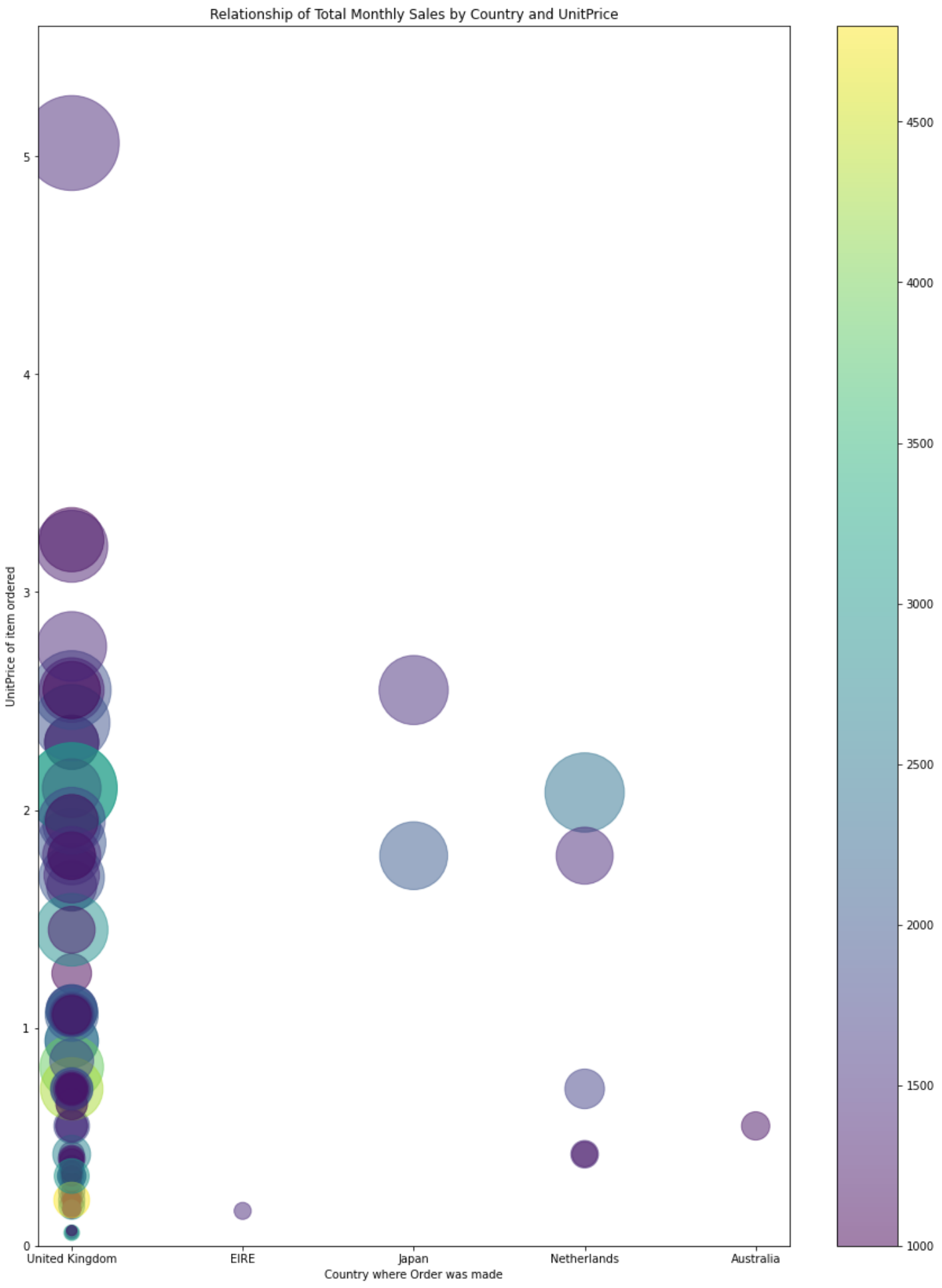
InvoiceDate	StockCode	Description	InvoiceDate	Country	SalesTotal
2011-10-27 12:11:00	23084	RABBIT NIGHT LIGHT	10/27/2011 12:11	Netherlands	4992.00
2011-10-27 12:26:00	84077	WORLD WAR 2 GLIDERS ASSTD DESIGNS	10/27/2011 12:26	United Kingdom	1008.00
2011-10-28 12:32:00	22197	POPCORN HOLDER	10/28/2011 12:32	United Kingdom	1434.24
2011-11-02 11:24:00	16014	SMALL CHINESE STYLE SCISSOR	11/2/2011 11:24	United Kingdom	960.00
2011-11-03 15:47:00	22086	PAPER CHAIN KIT 50'S CHRISTMAS	11/3/2011 15:47	United Kingdom	2601.00
2011-11-03 15:47:00	21915	RED HARMONICA IN BOX	11/3/2011 15:47	United Kingdom	2226.00
2011-11-07 17:42:00	22197	POPCORN HOLDER	11/7/2011 17:42	United Kingdom	3549.00
2011-11-09 13:56:00	84879	ASSORTED COLOUR BIRD ORNAMENT	11/9/2011 13:56	United Kingdom	1740.00
2011-11-10 11:55:00	85099B	JUMBO BAG RED RETROSPOT	11/10/2011 11:55	United Kingdom	1790.00
2011-11-14 17:55:00	22197	POPCORN HOLDER	11/14/2011 17:55	United Kingdom	2203.50
2011-11-22 08:44:00	22197	POPCORN HOLDER	11/22/2011 8:44	United Kingdom	720.00
2011-11-29 15:52:00	23084	RABBIT NIGHT LIGHT	11/29/2011 15:52	Japan	3651.60
2011-12-01 10:07:00	21787	RAIN PONCHO RETROSPOT	12/1/2011 10:07	United Kingdom	780.00
2011-12-02 11:39:00	22197	POPCORN HOLDER	12/2/2011 11:39	United Kingdom	720.00
2011-12-02 12:19:00	21915	RED HARMONICA IN BOX	12/2/2011 12:19	United Kingdom	1187.20

InvoiceDate	StockCode	Description	InvoiceDate	Country	SalesTotal
2011-12-02 16:32:00	23582	VINTAGE DOILY JUMBO BAG RED	12/2/2011 16:32	United Kingdom	2685.00
2011-12-07 12:20:00	22413	METAL SIGN TAKE IT OR LEAVE IT	12/7/2011 12:20	United Kingdom	3861.00
2011-12-07 15:16:00	23084	RABBIT NIGHT LIGHT	12/7/2011 15:16	Netherlands	2577.60
2011-12-08 18:45:00	22197	POPCORN HOLDER	12/8/2011 18:45	United Kingdom	1080.00
2011-12-08 18:46:00	22197	POPCORN HOLDER	12/8/2011 18:46	United Kingdom	864.00

Observe relationship between sales and unit price - are there more sales if the price is low or vice versa?

In [86]:
```
series_time_retail2 = read_csv('Retail_df_large_orders.csv', header=0, index_col=0, parse_
series_time_retail2['SalesTotal']=series_time_retail2['Quantity']*series_time_retail2['Uni
```

In [123…
```
plt.figure(figsize=(15,20))
plt.scatter(series_time_retail2['Country'], series_time_retail2['UnitPrice'],
            s=series_time_retail2['SalesTotal'], c=series_time_retail2['Quantity'], alpha=
#           ,main='Scatter Plot Relationship of Total Monthly Sales by Country and UnitPri
           )
#plt.title('Relationship of Total Monthly Sales by Country and UnitPrice')
plt.gca().update(dict(title='Relationship of Total Monthly Sales by Country and UnitPrice'
                      xlabel='Country where Order was made', ylabel='UnitPrice of item orc
plt.colorbar()
plt.show()
```



- Most orders have a unit price below 3.5
- Most orders originate from the UK, which is where the company is based

- Quantity lies in a certain range for most orders (purple/blue) with just a few yellow/green from UK
- Total Sales are small for EIRE and larger sales come from the higher priced items

Plot monthly orders with a different line color for each country:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Parse the InvoiceDate column

In [62]:
```
import datetime
from dateutil.parser import parse
#datetime.datetime.strptime('Mon Feb 15 2010', '%a %b %d %Y').strftime('%d/%m/%Y')
#'15/02/2010'
```

In [239…
```
series_time_retail33 = read_csv('Retail_df_large_orders.csv', header=0, index_col=0, parse
series_time_retail33['SalesTotal']=series_time_retail33['Quantity']*series_time_retail33['
```

In [263…
```
series_time_retail3
```

Out[263…

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	SalesTo
2010-12-02 16:48:00	536809	84950	ASSORTED COLOUR T-LIGHT HOLDER	1824	12/2/2010 16:48	0.55	15299.0	United Kingdom	1003
2010-12-02 17:38:00	536830	84077	WORLD WAR 2 GLIDERS ASSTD DESIGNS	2880	12/2/2010 17:38	0.18	16754.0	United Kingdom	518
2010-12-02 17:38:00	536830	21915	RED HARMONICA IN BOX	1400	12/2/2010 17:38	1.06	16754.0	United Kingdom	1484
2010-12-03 11:48:00	536890	17084R	ASSORTED INCENSE PACK	1440	12/3/2010 11:48	0.16	14156.0	EIRE	230
2010-12-07 16:43:00	537659	22189	CREAM HEART CARD HOLDER	1008	12/7/2010 16:43	2.31	18102.0	United Kingdom	2328
…	…	…	…	…	…	…	…	…	
2011-12-02 16:32:00	580363	23582	VINTAGE DOILY JUMBO BAG RED	1500	12/2/2011 16:32	1.79	13868.0	United Kingdom	2685

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	SalesTo
2011-12-07 12:20:00	581115	22413	METAL SIGN TAKE IT OR LEAVE IT	1404	12/7/2011 12:20	2.75	15195.0	United Kingdom	3861
2011-12-07 15:16:00	581175	23084	RABBIT NIGHT LIGHT	1440	12/7/2011 15:16	1.79	14646.0	Netherlands	2577
2011-12-08 18:45:00	581458	22197	POPCORN HOLDER	1500	12/8/2011 18:45	0.72	17949.0	United Kingdom	1080
2011-12-08 18:46:00	581459	22197	POPCORN HOLDER	1200	12/8/2011 18:46	0.72	17949.0	United Kingdom	864

113 rows × 9 columns

In [265…

```
#series_time_retail3['InvoiceDate']=series_time_retail3['InvoiceDate'].astype('string')
series_time_retail33.index = pd.to_datetime(series_time_retail33['InvoiceDate'],format='%r
##series_monthly_time_retail = series_time_retail.groupby(by=[series_time_retail.index.mor
series_monthly_time_retail3 = series_time_retail3.groupby(by=[series_time_retail33.index.y
#series_monthly_time_retail3 = series_time_retail33.groupby(series_time_retail33.index.yea
```

In [266…

```
series_monthly_time_retail3
```

Out[266…

InvoiceDate	InvoiceDate	InvoiceNo	Quantity	UnitPrice	CustomerID	SalesTotal
2010	**12**	6453640	18866	11.35	189837.0	15647.82
2011	**1**	4326900	13434	17.85	129992.0	29091.82
	2	5981955	20094	4.91	180134.0	9600.84
	3	3827994	9448	3.21	106261.0	4082.72
	4	7701703	20392	11.75	221867.0	21321.08
	5	3322127	12702	2.78	91456.0	6547.42
	6	1669018	4315	0.68	44326.0	1013.25
	7	3364285	10146	1.69	82468.0	2365.56
	8	3942020	10988	4.77	108080.0	8546.32
	9	6238890	16186	13.67	175381.0	20509.80
	10	6283263	19748	10.22	168618.0	16774.08
	11	5182114	14310	13.58	109638.0	19441.10
	12	4645919	10364	10.20	126790.0	13754.80

In [231…

```
series_monthly_time_retail3
```

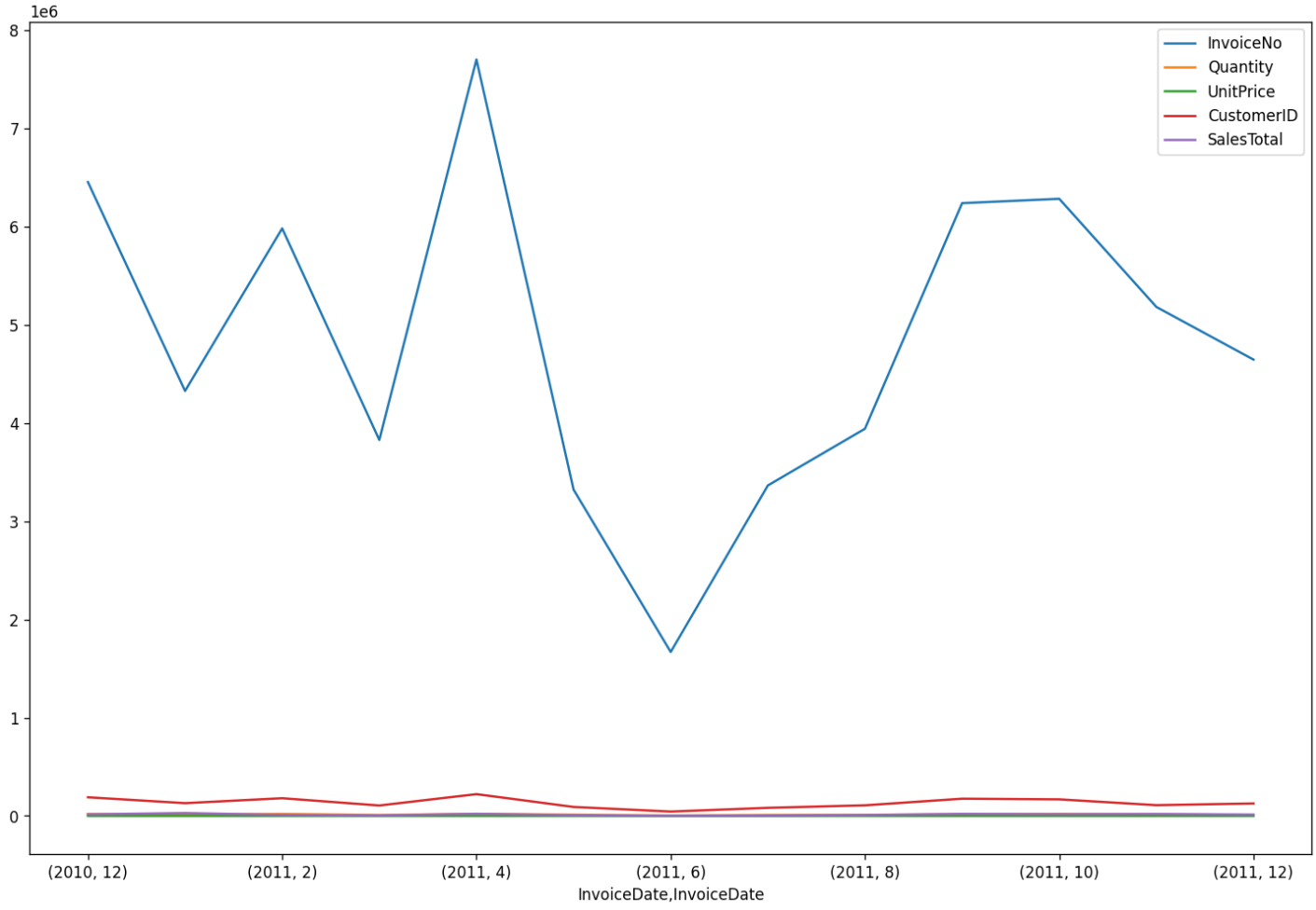
Out[231…

InvoiceDate	InvoiceDate	InvoiceNo	Quantity	UnitPrice	CustomerID	SalesTotal
2010	**12**	6453640	18866	11.35	189837.0	15647.82

InvoiceDate	InvoiceDate	InvoiceNo	Quantity	UnitPrice	CustomerID	SalesTotal
2011	**1**	4326900	13434	17.85	129992.0	29091.82
	2	5981955	20094	4.91	180134.0	9600.84
	3	3827994	9448	3.21	106261.0	4082.72
	4	7701703	20392	11.75	221867.0	21321.08
	5	3322127	12702	2.78	91456.0	6547.42
	6	1669018	4315	0.68	44326.0	1013.25
	7	3364285	10146	1.69	82468.0	2365.56
	8	3942020	10988	4.77	108080.0	8546.32
	9	6238890	16186	13.67	175381.0	20509.80
	10	6283263	19748	10.22	168618.0	16774.08
	11	5182114	14310	13.58	109638.0	19441.10
	12	4645919	10364	10.20	126790.0	13754.80

In [268…

```
series_monthly_time_retail3.plot(figsize=(15,10))
plt.show()
```



Examples from readings:

Module 4 ARIMA approach:

In [293…
```
from numpy import log
from statsmodels.tsa.stattools import adfuller

result = adfuller(values_sales.dropna())
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
```

```
ADF Statistic: -2.308185
p-value: 0.169342
```

Null Hypothesis: series is non-stationary p-value is > 0.05 so we cannot reject the null hypothesis.

Therefore, the series is non-stationary.

In [281…
```
values_sales=DataFrame(series_monthly_time_retail3.SalesTotal.values)
```

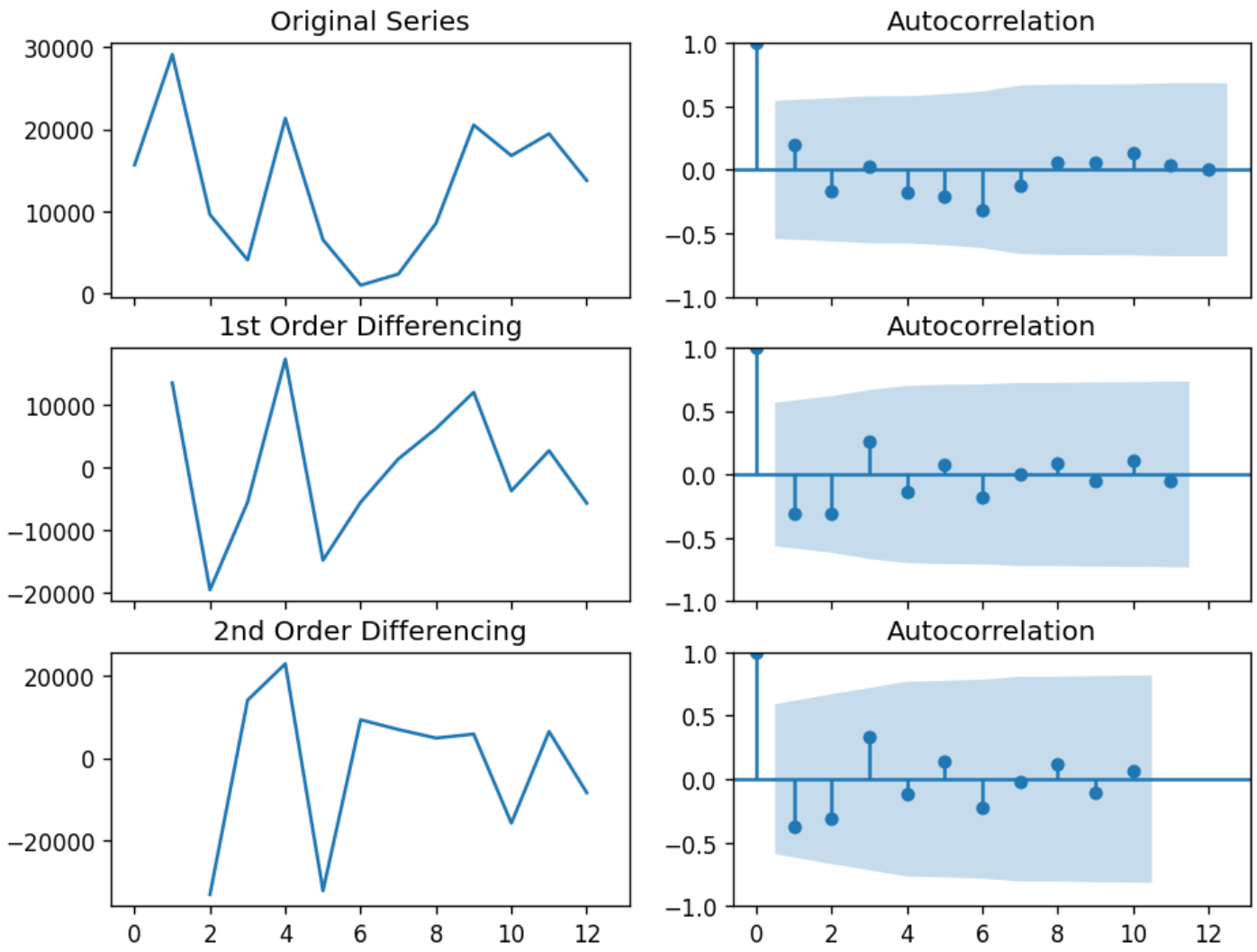
In [290…
```
values_sales
```

Out[290…

	0
0	15647.82
1	29091.82
2	9600.84
3	4082.72
4	21321.08
5	6547.42
6	1013.25
7	2365.56
8	8546.32
9	20509.80
10	16774.08
11	19441.10
12	13754.80

In [289…
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plt.rcParams.update({'figure.figsize':(9,7), 'figure.dpi':120})
# Import data

# Original Series
fig, axes = plt.subplots(3, 2, sharex=True)
axes[0, 0].plot(values_sales); axes[0, 0].set_title('Original Series')


plot_acf(values_sales, ax=axes[0, 1])
# 1st Differencing
axes[1, 0].plot(values_sales.diff()); axes[1, 0].set_title('1st Order Differencing')
plot_acf(values_sales.diff().dropna(), ax=axes[1, 1])
# 2nd Differencing
axes[2, 0].plot(values_sales.diff().diff()); axes[2, 0].set_title('2nd Order Differencing'
```

```
plot_acf(values_sales.diff().diff().dropna(), ax=axes[2, 1])
plt.show()
```



DIfferencing first order is enough to reach stationarity

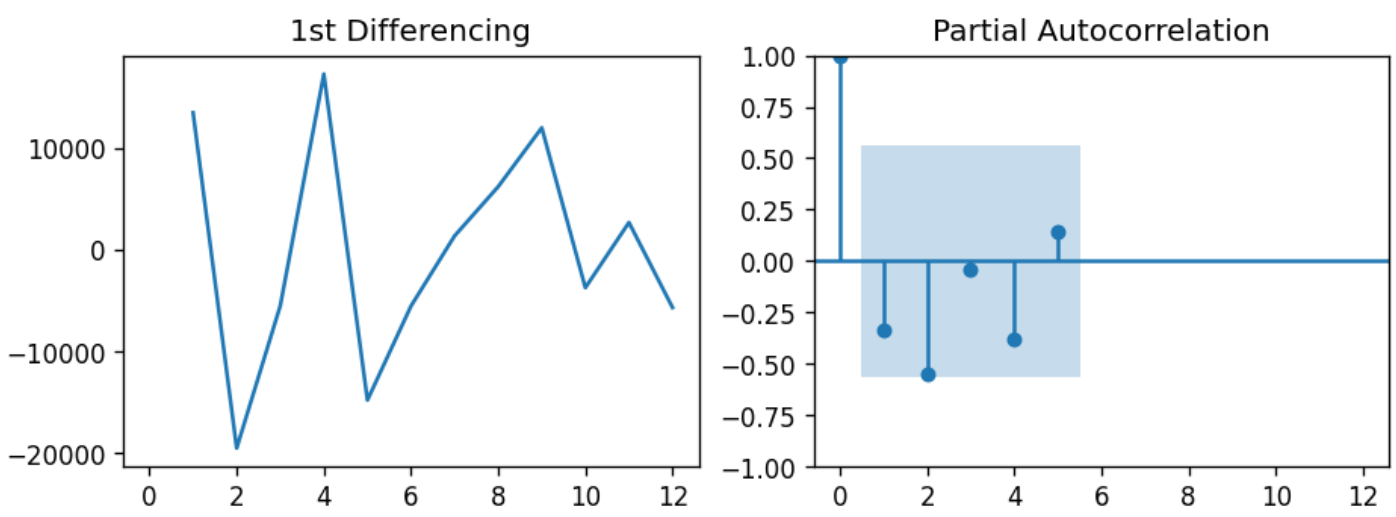
In [294…

```
result = adfuller(values_sales.diff().dropna())
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
```

```
ADF Statistic: -4.442813
p-value: 0.000249
```

In [298…

```
# PACF plot of 1st differenced series
plt.rcParams.update({'figure.figsize':(9,3), 'figure.dpi':120})
fig, axes = plt.subplots(1, 2, sharex=True)
axes[0].plot(values_sales.diff()); axes[0].set_title('1st Differencing')
axes[1].set(ylim=(0,5))
plot_pacf(values_sales.diff().dropna(), lags=5, ax=axes[1])
plt.show()
```



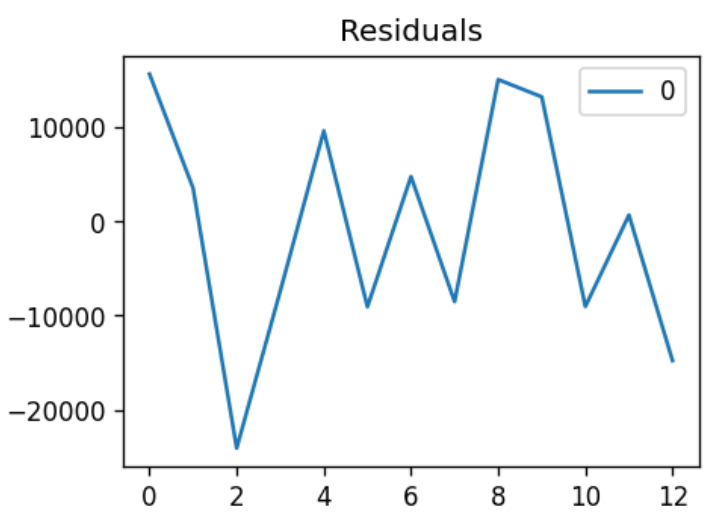
In [364…

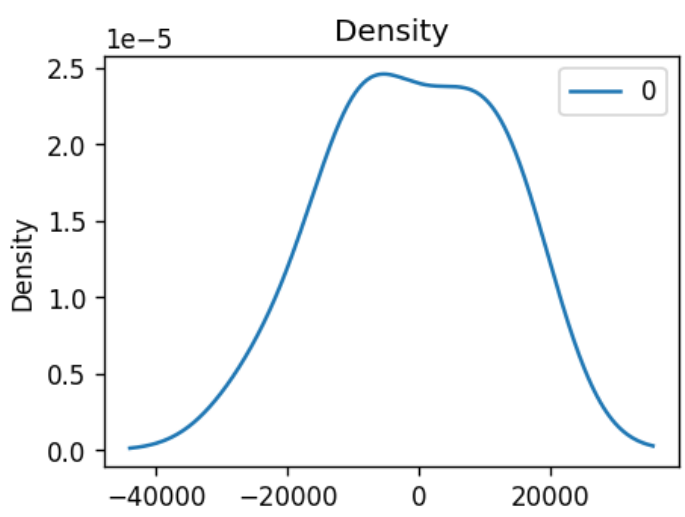
```
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_predict
# 1,1,2 ARIMA Model
model = ARIMA(values_sales, order=(2,2,0))
model_fit = model.fit()
print(model_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      0   No. Observations:                   13
Model:                 ARIMA(2, 2, 0)   Log Likelihood                -119.392
Date:                Fri, 18 Nov 2022   AIC                            244.785
Time:                        14:51:13   BIC                            245.978
Sample:                             0   HQIC                           244.032
                                  - 13
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6059      0.250     -2.425      0.015      -1.096      -0.116
ar.L2         -0.6559      0.161     -4.078      0.000      -0.971      -0.341
sigma2      1.02e+08   2.45e-10   4.17e+17      0.000    1.02e+08    1.02e+08
===================================================================================
Ljung-Box (L1) (Q):                   0.08   Jarque-Bera (JB):                 0.46
Prob(Q):                              0.78   Prob(JB):                         0.80
Heteroskedasticity (H):               0.59   Skew:                            -0.02
Prob(H) (two-sided):                  0.62   Kurtosis:                         2.00
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 7.2e+33. Standar
d errors may be unstable.
```

In [365…

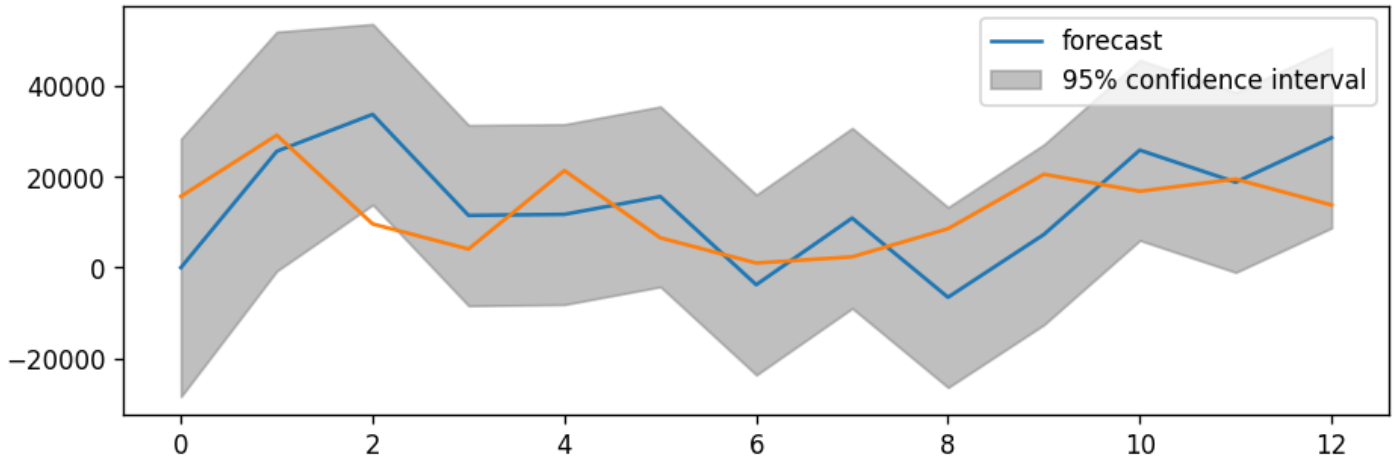
```
residuals = pd.DataFrame(model_fit.resid)
fig, ax = plt.subplots(1,2)
residuals.plot(title="Residuals", ax=ax[0])
residuals.plot(kind='kde', title='Density', ax=ax[1])
plt.show()
```





In [366…

```
# Actual vs Fitted
plot_predict(model_fit)
plt.plot(values_sales)
plt.show()
```



validating the ARIMA model:

In [ ]:

```
from statsmodels.tsa.stattools import acf
# Create Training and Test
train = df.value[:85]
test = df.value[85:]
```

In [ ]:

```
model = ARIMA(train, order=(1, 1, 1))
fitted = model.fit(disp=-1)
# Forecast
fc, se, conf = fitted.forecast(15, alpha=0.05) # 95% conf
# Make as pandas series
fc_series = pd.Series(fc, index=test.index)
lower_series = pd.Series(conf[:, 0], index=test.index)
upper_series = pd.Series(conf[:, 1], index=test.index)
# Plot
plt.figure(figsize=(12,5), dpi=100)
plt.plot(train, label='training')
plt.plot(test, label='actual')
plt.plot(fc_series, label='forecast')
plt.fill_between(lower_series.index, lower_series, upper_series,
 color='k', alpha=.15)
plt.title('Forecast vs Actuals')
```

```
plt.legend(loc='upper left', fontsize=8)
plt.show()
```

In [ ]:
```
model = pm.auto_arima(df.value, start_p=1, start_q=1,
 test='adf', # use adftest to find optimal 'd'
 max_p=3, max_q=3, # maximum p and q
 m=1, # frequency of series
 d=None, # let model determine 'd'
 seasonal=False, # No Seasonality
 start_P=0,
 D=0,
 trace=True,
 error_action='ignore',
 suppress_warnings=True,
 stepwise=True)
print(model.summary())
```

In [ ]:
```
model.plot_diagnostics(figsize=(7,5))
plt.show()
```

In [ ]:
```
# Forecast
n_periods = 24
fc, confint = model.predict(n_periods=n_periods, return_conf_int=True)
index_of_fc = np.arange(len(df.value), len(df.value)+n_periods)
# make series for plotting purpose
fc_series = pd.Series(fc, index=index_of_fc)
lower_series = pd.Series(confint[:, 0], index=index_of_fc)
upper_series = pd.Series(confint[:, 1], index=index_of_fc)
# Plot
plt.plot(df.value)
plt.plot(fc_series, color='darkgreen')
plt.fill_between(lower_series.index,
 lower_series,
 upper_series,
 color='k', alpha=.15)
plt.title("Final Forecast of WWW Usage")
plt.show()
```

SARIMA

In [ ]:
```
fig, axes = plt.subplots(2, 1, figsize=(10,5), dpi=100, sharex=True)
# Usual Differencing
axes[0].plot(data[:], label='Original Series')
axes[0].plot(data[:].diff(1), label='Usual Differencing')
axes[0].set_title('Usual Differencing')
axes[0].legend(loc='upper left', fontsize=10)
# Seasinal Dei
axes[1].plot(data[:], label='Original Series')
axes[1].plot(data[:].diff(12), label='Seasonal Differencing', color='green')
axes[1].set_title('Seasonal Differencing')
plt.legend(loc='upper left', fontsize=10)
plt.suptitle('a10 - Drug Sales', fontsize=16)
plt.show()
```

In [ ]:
```
# !pip3 install pyramid-arima
import pmdarima as pm
# Seasonal - fit stepwise auto-ARIMA
smodel = pm.auto_arima(data, start_p=1, start_q=1,
 test='adf',
```

```
 max_p=3, max_q=3, m=12,
 start_P=0, seasonal=True,
 d=None, D=1, trace=True,
 error_action='ignore',
 suppress_warnings=True,
 stepwise=True)
smodel.summary()
```

In [ ]:

```
# Forecast
n_periods = 24
fitted, confint = smodel.predict(n_periods=n_periods, return_conf_int=True)
index_of_fc = pd.date_range(data.index[-1], periods = n_periods, freq='MS')
# make series for plotting purpose
fitted_series = pd.Series(fitted, index=index_of_fc)
lower_series = pd.Series(confint[:, 0], index=index_of_fc)
upper_series = pd.Series(confint[:, 1], index=index_of_fc)
# Plot
plt.plot(data)
plt.plot(fitted_series, color='darkgreen')
plt.fill_between(lower_series.index,
 lower_series,
 upper_series,
 color='k', alpha=.15)
plt.title("SARIMA - Final Forecast of a10 - Drug Sales")
plt.show()
```

SARIMAX

In [ ]:

```
# Compute Seasonal Index
from statsmodels.tsa.seasonal import seasonal_decompose
from dateutil.parser import parse
# multiplicative seasonal component
result_mul = seasonal_decompose(data['value'][-36:], # 3 years
 model='multiplicative',
 extrapolate_trend='freq')
seasonal_index = result_mul.seasonal[-12:].to_frame()
seasonal_index['month'] = pd.to_datetime(seasonal_index.index).month
# merge with the base data
data['month'] = data.index.month
df = pd.merge(data, seasonal_index, how='left', on='month')
df.columns = ['value', 'month', 'seasonal_index']
df.index = data.index # reassign the index.
```

In [ ]:

```
import pmdarima as pm
# SARIMAX Model
sxmodel = pm.auto_arima(df[['value']], exogenous=df[['seasonal_index']],
 start_p=1, start_q=1,
 test='adf',
 max_p=3, max_q=3, m=12,
 start_P=0, seasonal=True,
 d=None, D=1, trace=True,
 error_action='ignore',
 suppress_warnings=True,
 stepwise=True)
sxmodel.summary()
```

In [ ]:

```
# Forecast
n_periods = 24
fitted, confint = sxmodel.predict(n_periods=n_periods,
 exogenous=np.tile(seasonal_index.value, 2).reshape(-1,1),
```

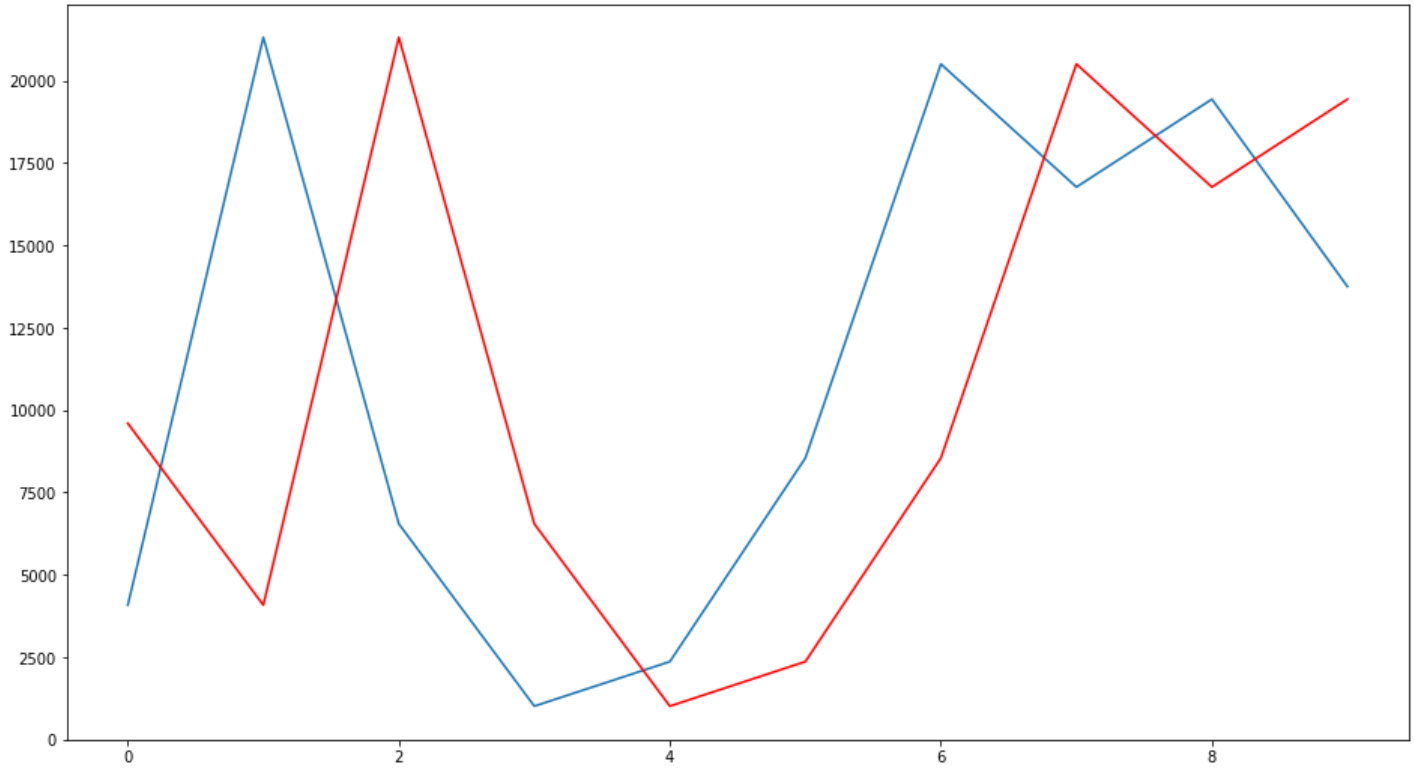
```
 return_conf_int=True)
index_of_fc = pd.date_range(data.index[-1], periods = n_periods, freq='MS')
# make series for plotting purpose
fitted_series = pd.Series(fitted, index=index_of_fc)
lower_series = pd.Series(confint[:, 0], index=index_of_fc)
upper_series = pd.Series(confint[:, 1], index=index_of_fc)
# Plot
plt.plot(data['value'])
plt.plot(fitted_series, color='darkgreen')
plt.fill_between(lower_series.index,
 lower_series,
 upper_series,
 color='k', alpha=.15)
plt.title("SARIMAX Forecast of a10 - Drug Sales")
plt.show()
```

In [ ]:

In [176…

```
from pandas import DataFrame
from pandas import concat
from matplotlib import pyplot
from sklearn.metrics import mean_squared_error

# create lagged dataset
values = DataFrame(series_monthly_time_retail.SalesTotal)
dataframe = concat([values.shift(1), values], axis=1)
dataframe.columns = ['t-1', 't+1']

# split into train and test sets
X2 = dataframe.values
train, test = X2[1:len(X2)-10], X2[len(X2)-10:]
train_X, train_y = train[:,0], train[:,1]
test_X, test_y = test[:,0], test[:,1]

# persistence model
def model_persistence(x):
    return x

# walk-forward validation
predictions = list()
for x in test_X:
    yhat = model_persistence(x)
    predictions.append(yhat)

test_score = mean_squared_error(test_y, predictions)
print('Test MSE: %.3f' % test_score)
# plot predictions vs expected
plt.plot(test_y)
plt.plot(predictions, color='red')
plt.show()
```

```
Test MSE: 81305676.872
```



In [250…

```
series_monthly_time_retail

series_time_retail.index = pd.to_datetime(series_time_retail['InvoiceDate'],format='%m/%d/
#series_monthly_time_retail = series_time_retail.groupby(by=[series_time_retail.index.mont
series_monthly_time_retail = series_time_retail.groupby(by=[series_time_retail.index.year,
```

In [253…

```
series_monthly_time_retail
```

Out[253…

		SalesTotal
InvoiceDate	**InvoiceDate**	
2010	**12**	15647.82
2011	**1**	29091.82
	2	9600.84
	3	4082.72
	4	21321.08
	5	6547.42
	6	1013.25
	7	2365.56
	8	8546.32
	9	20509.80
	10	16774.08
	11	19441.10
	12	13754.80

In [254…

```
series_monthly_time_retail.columns = series_monthly_time_retail.columns.to_flat_index()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_11348/1697183643.py in <module>
----> 1 series_monthly_time_retail.InvoiceDate = series_monthly_time_retail.InvoiceDate.to
_flat_index()

~\anaconda3\envs\humans\lib\site-packages\pandas\core\generic.py in __getattr__(self, nam
e)
   5573         ):
   5574             return self[name]
-> 5575         return object.__getattribute__(self, name)
   5576
   5577     def __setattr__(self, name: str, value) -> None:

AttributeError: 'DataFrame' object has no attribute 'InvoiceDate'
```

In [212…

```
from statsmodels.tsa.ar_model import AutoReg
from math import sqrt

# split dataset
X3 = series_monthly_time_retail.SalesTotal
train3, test3 = X3[0:len(X3)-3], X3[len(X3)-3:]

# train autoregression
model3 = AutoReg(train3, lags=3)
model_fit3 = model3.fit()
print('Coefficients: %s' % model_fit3.params)
```

```
Coefficients: const            10815.757760
SalesTotal.L1      0.012140
SalesTotal.L2     -0.372338
SalesTotal.L3      0.178548
dtype: float64
C:\Users\Susy\anaconda3\envs\humans\lib\site-packages\statsmodels\tsa\base\tsa_model.py:59
0: ValueWarning: An unsupported index was provided and will be ignored when e.g. forecasti
ng.
  warnings.warn('An unsupported index was provided and will be'
```

In [213…

```
# make predictions
predictions3 = model_fit3.predict(start=len(train3), end=len(train3)+len(test3)-1, dynamic
```

```
C:\Users\Susy\anaconda3\envs\humans\lib\site-packages\statsmodels\tsa\base\tsa_model.py:39
0: ValueWarning: No supported index is available. Prediction results will be given with an
integer index beginning at `start`.
  warnings.warn('No supported index is available.'
```

In [220…

```
train3
```

Out[220…

```
InvoiceDate  InvoiceDate
2010         12             15647.82
2011         1              29091.82
             2               9600.84
             3               4082.72
             4              21321.08
             5               6547.42
             6               1013.25
             7               2365.56
             8               8546.32
             9              20509.80
Name: SalesTotal, dtype: float64
```

In [219…

```
test3
```

Out[219…

```
InvoiceDate  InvoiceDate
2011         10             16774.08
             11             19441.10
             12             13754.80
Name: SalesTotal, dtype: float64
```

In [217…

```
predictions3[10]
```

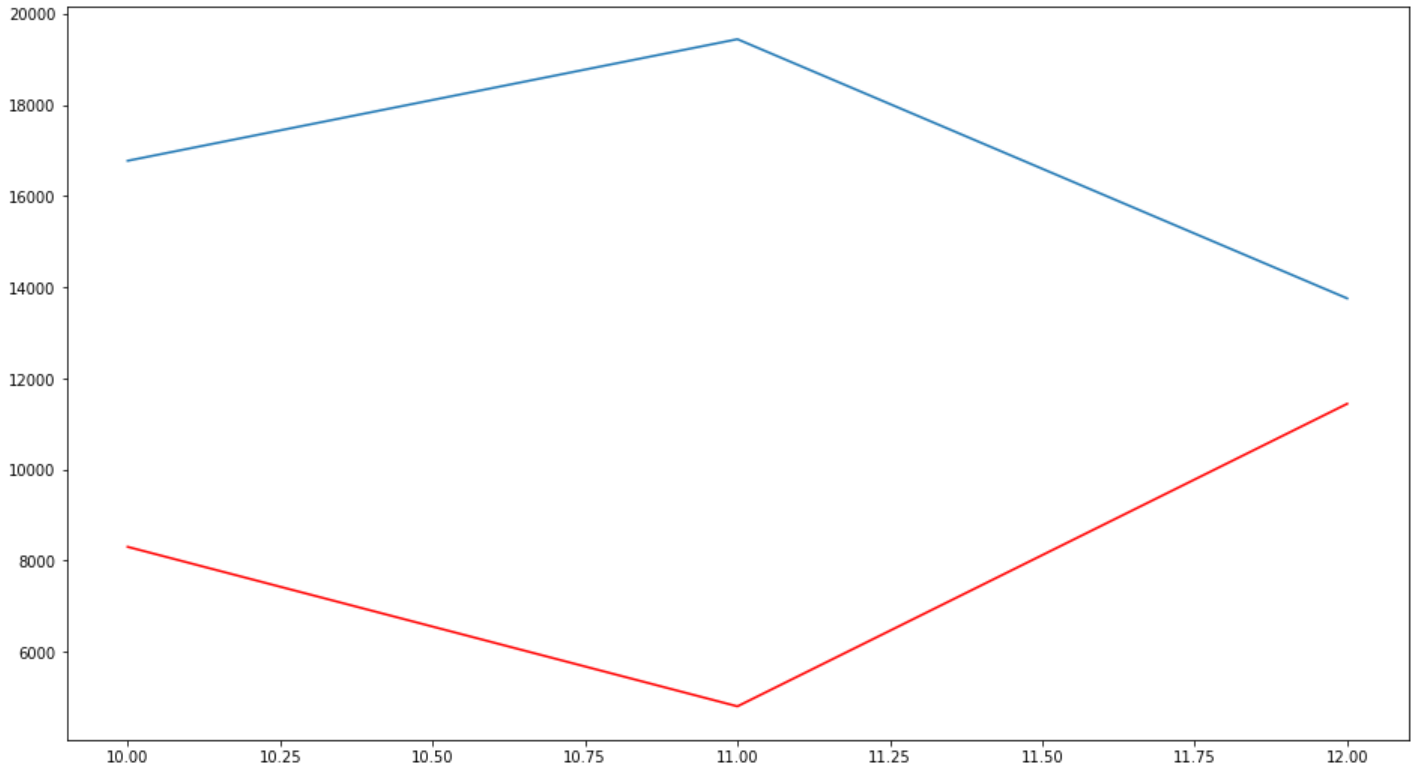
Out[217…

```
8304.99902023769
```

In [222…

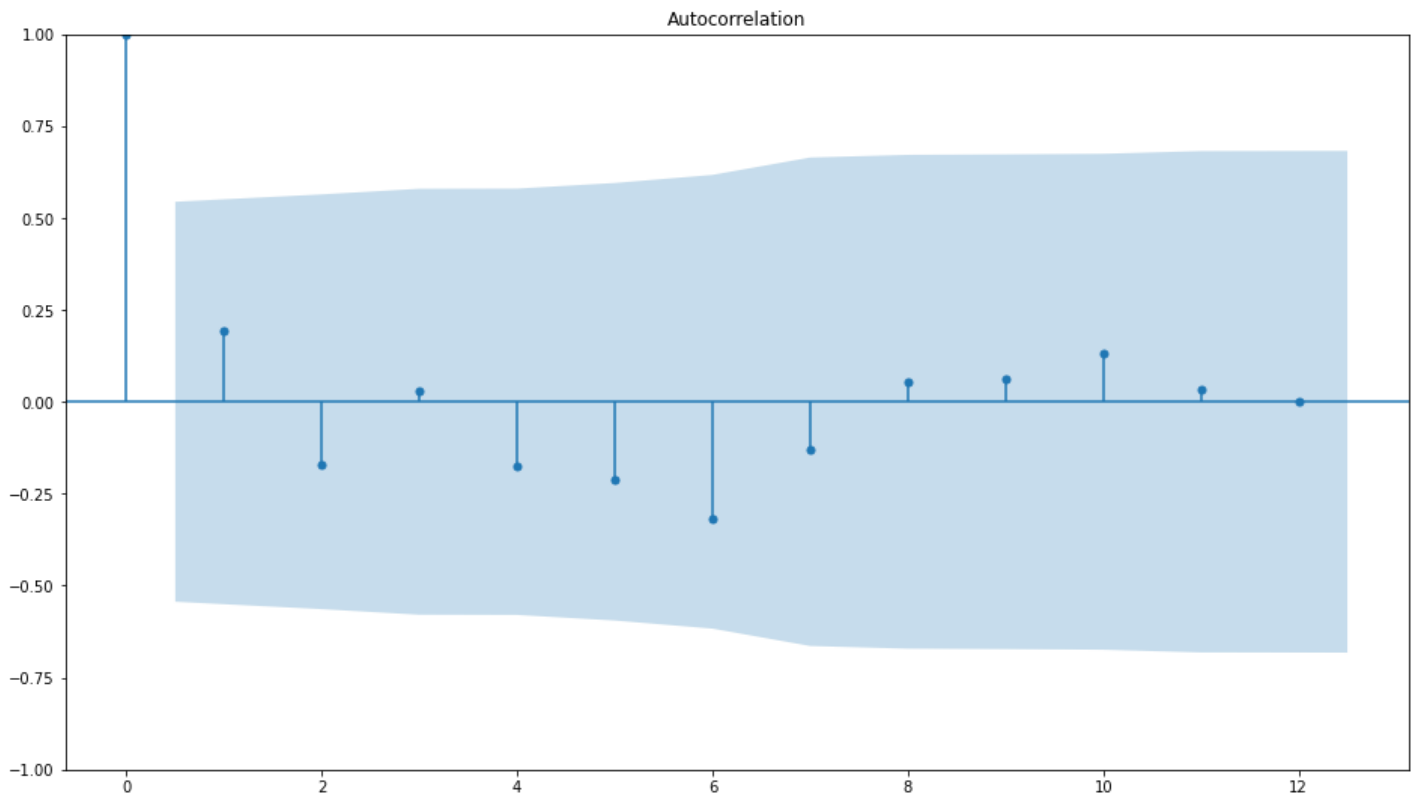
```
for i3 in [10,11,12]:
    print('predicted=%f, expected=%f' % (predictions3[i3], test3[2011][i3]))
rmse3 = sqrt(mean_squared_error(test3, predictions3))
print('Test RMSE: %.3f' % rmse3)

# plot results
plt.plot(test3[2011])
plt.plot(predictions3, color='red')
plt.show()
```

```
predicted=8304.999020, expected=16774.080000
predicted=4805.927297, expected=19441.100000
predicted=11443.809491, expected=13754.800000
Test RMSE: 9853.160
```



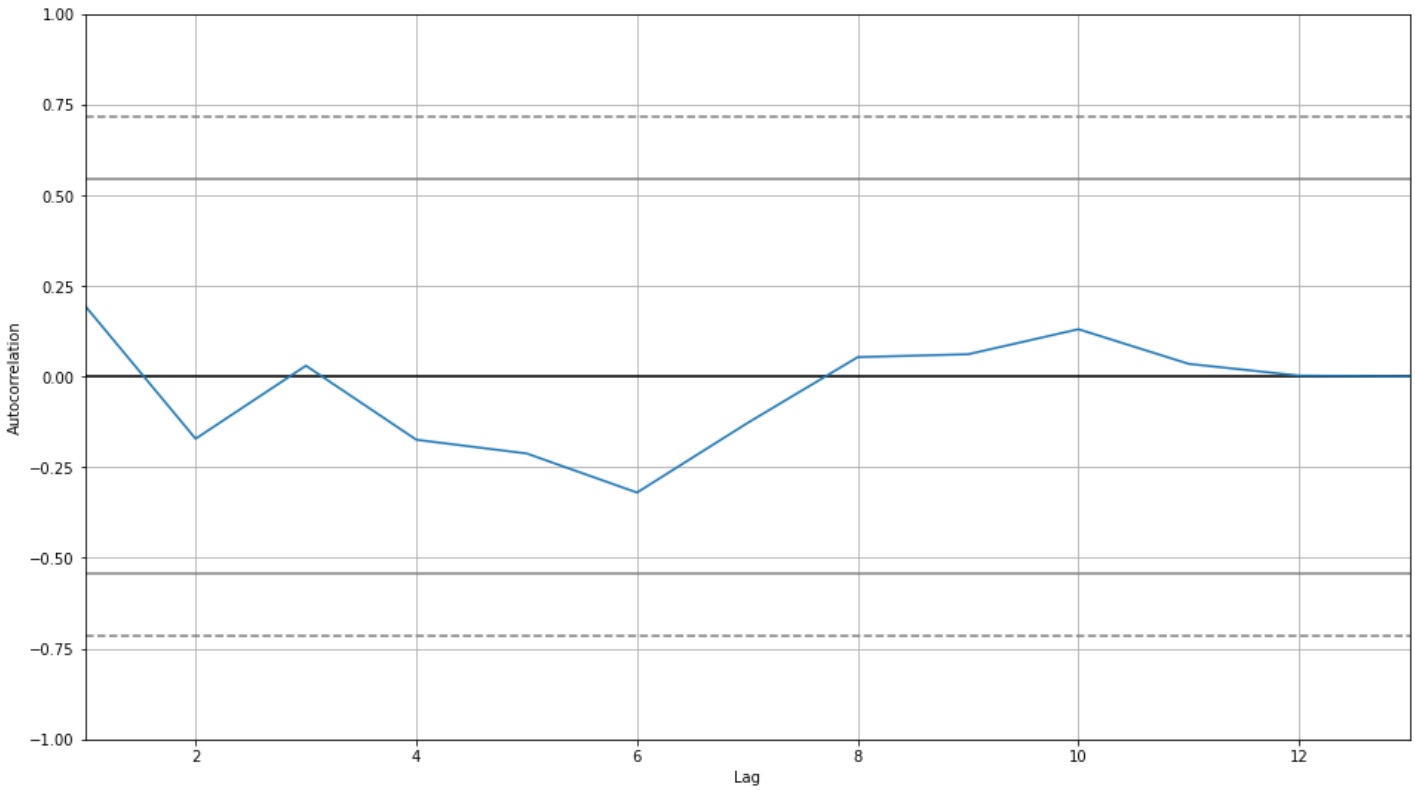
In [174…

```
from statsmodels.graphics.tsaplots import plot_acf
plot_acf(series_monthly_time_retail, lags=12)
plt.show()
```



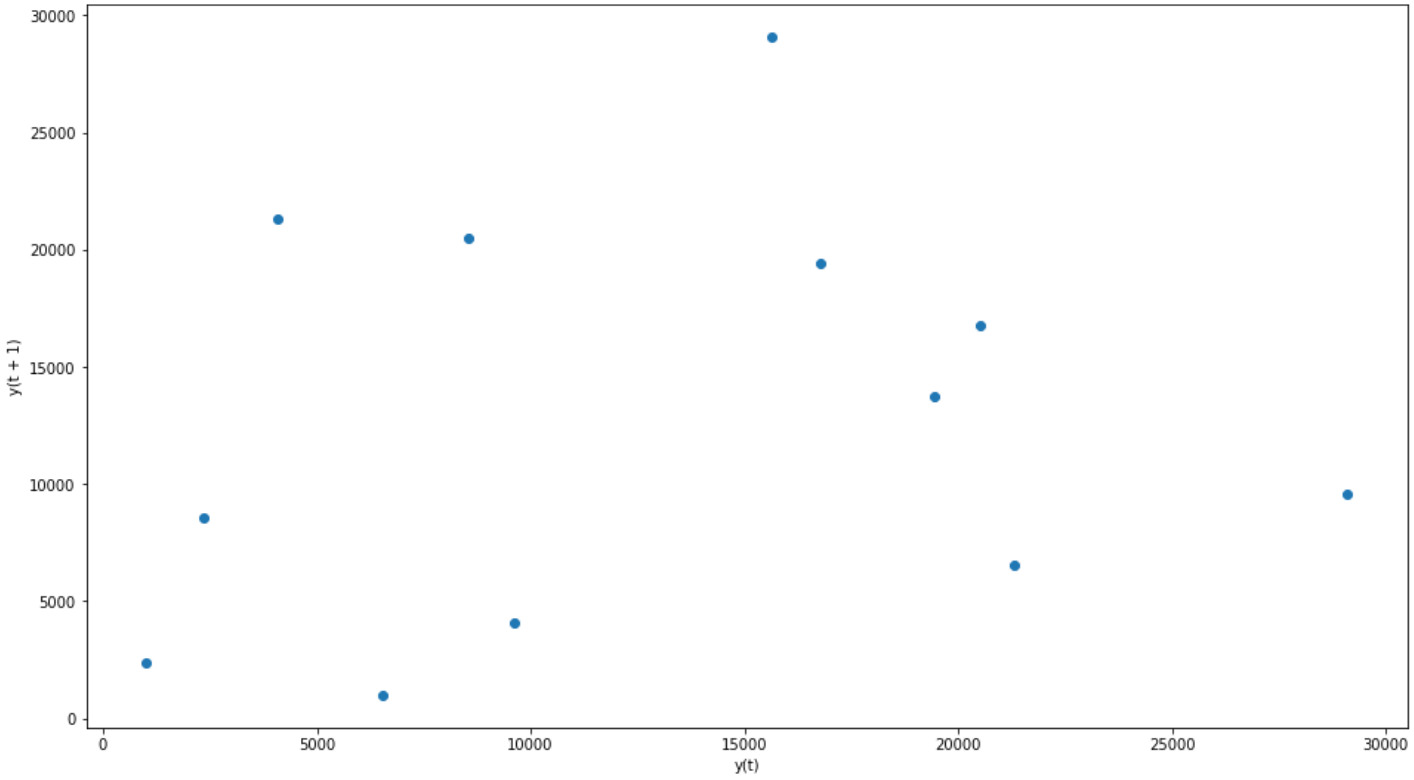
In [172…

```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(series_monthly_time_retail)
plt.show()
```



In [170…

```
from pandas.plotting import lag_plot
lag_plot(series_monthly_time_retail)
plt.show()
```



In [143…

```
from sklearn.model_selection import ParameterGrid

from statsmodels.tsa.api import SimpleExpSmoothing
from statsmodels.tsa.api import Holt
from statsmodels.tsa.api import ExponentialSmoothing
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

In [128…

```
series_monthly_time_retail.shape
```

Out[128…

```
(13, 1)
```

In [167…

```
series_monthly_time_retail.head()
```

Out[167…

		SalesTotal
InvoiceDate	**InvoiceDate**	
2010	**12**	15647.82
2011	**1**	29091.82
	2	9600.84
	3	4082.72
	4	21321.08

In [168…

```
ts = series_monthly_time_retail.set_index(['InvoiceDate']['InvoiceDate'])
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_11348/3358868900.py in <module>
----> 1 ts = series_monthly_time_retail.set_index(['InvoiceDate']['InvoiceDate'])

TypeError: list indices must be integers or slices, not str
```

In [137…

```
X = series_monthly_time_retail['SalesTotal']

trainX = X.iloc[-12:]
testX = X.iloc[:-12]
```

In [138…

```
testX
```

Out[138…

```
InvoiceDate  InvoiceDate
2010         12             15647.82
Name: SalesTotal, dtype: float64
```

In [131…

```
def mean_absolute_percentage_error_func(y_true, y_pred):
    '''
    Calculate the mean absolute percentage error as a metric for evaluation

    Args:
        y_true (float64): Y values for the dependent variable (test part), numpy array of
        y_pred (float64): Predicted values for the dependen variable (test parrt), numpy a

    Returns:
        Mean absolute percentage error
    '''
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

In [147…

```
def timeseries_evaluation_metrics_func(y_true, y_pred):
    '''
    Calculate the following evaluation metrics:
        - MSE
        - MAE
        - RMSE
        - MAPE
        - R²

    Args:
        y_true (float64): Y values for the dependent variable (test part), numpy array of
        y_pred (float64): Predicted values for the dependen variable (test parrt), numpy a

    Returns:
        MSE, MAE, RMSE, MAPE and R²
    '''
    print('Evaluation metric results: ')
    print(f'MSE is : {mean_squared_error(y_true, y_pred)}')
    print(f'MAE is : {mean_absolute_error(y_true, y_pred)}')
    print(f'RMSE is : {np.sqrt(mean_squared_error(y_true, y_pred))}')
    print(f'MAPE is : {mean_absolute_percentage_error_func(y_true, y_pred)}')
    print(f'R2 is : {r2_score(y_true, y_pred)}',end='\n\n')
#
# 4 Simple Exponential Smoothing
# Simple Exponential Smoothing is one of the minimal models of the exponential smoothing a

# Assume that a time series has the following:

# Level
# No trends
# No seasonality
# Noise
# 4.1 Searching for best parameters for SES
# In the Simple Exponential Smoothing function we have the following parameter that we ca
```

```
#smooting_level(float, optional)
# To find out which value fits best for this we perform a for-loop.
```

In [148…

```
resu = []
temp_df = pd.DataFrame()
for i in [0 , 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90,1]:
    print(f'Fitting for smoothing level= {i}')
    fit_v = SimpleExpSmoothing(np.asarray(trainX)).fit(i)
    fcst_pred_v= fit_v.forecast(len(testX))
    timeseries_evaluation_metrics_func(testX, fcst_pred_v)
```

```
Fitting for smoothing level= 0
Evaluation metric results:
MSE is : 8373769.350719552
MAE is : 2893.746594074808
RMSE is : 2893.746594074808
MAPE is : 18.492969589852184
R2 is : nan

Fitting for smoothing level= 0.1
Evaluation metric results:
MSE is : 6778796.182967856
MAE is : 2603.6121414234985
RMSE is : 2603.6121414234985
MAPE is : 16.638817045591644
R2 is : nan

Fitting for smoothing level= 0.2
Evaluation metric results:
MSE is : 3500559.276786317
MAE is : 1870.9781604247328
RMSE is : 1870.9781604247328
MAPE is : 11.95679756301346
R2 is : nan

Fitting for smoothing level= 0.3
Evaluation metric results:
MSE is : 1092876.586953291
MAE is : 1045.4073784670218
RMSE is : 1045.4073784670218
MAPE is : 6.680849974418301
R2 is : nan

Fitting for smoothing level= 0.4
Evaluation metric results:
MSE is : 177348.24519251936
MAE is : 421.1273503259072
RMSE is : 421.1273503259072
MAPE is : 2.691284474935852
R2 is : nan

Fitting for smoothing level= 0.5
Evaluation metric results:
MSE is : 17398.786579238436
MAE is : 131.90446004301157
RMSE is : 131.90446004301157
MAPE is : 0.8429574218198547
R2 is : nan

Fitting for smoothing level= 0.6
Evaluation metric results:
MSE is : 27469.686443698225
MAE is : 165.73981550520148
RMSE is : 165.73981550520148
```

```
MAPE is : 1.0591878964942176
R2 is : nan

Fitting for smoothing level= 0.7
Evaluation metric results:
MSE is : 191233.38004704332
MAE is : 437.3023897111052
RMSE is : 437.3023897111052
MAPE is : 2.794653758230253
R2 is : nan

Fitting for smoothing level= 0.8
Evaluation metric results:
MSE is : 728735.7700391035
MAE is : 853.6602193139279
RMSE is : 853.6602193139279
MAPE is : 5.455457816577184
R2 is : nan

Fitting for smoothing level= 0.9
Evaluation metric results:
MSE is : 1818676.9258047538
MAE is : 1348.5833032500268
RMSE is : 1348.5833032500268
MAPE is : 8.618346218514954
R2 is : nan

Fitting for smoothing level= 1
Evaluation metric results:
MSE is : 3583524.720400002
MAE is : 1893.0200000000004
RMSE is : 1893.0200000000004
MAPE is : 12.097659610092656
R2 is : nan
```

ideal smoothing value is 0.5

In [149…

```
resu = []
temp_df = pd.DataFrame()
for i in [0 , 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90,1]:
    fit_v = SimpleExpSmoothing(np.asarray(trainX)).fit(i)
    fcst_pred_v= fit_v.forecast(len(testX))
    rmse = np.sqrt(mean_squared_error(testX, fcst_pred_v))
    df3 = {'smoothing parameter':i, 'RMSE': rmse}
    temp_df = temp_df.append(df3, ignore_index=True)
```

In [150…

```
SES = SimpleExpSmoothing(np.asarray(trainX))
fit_SES = SES.fit(smoothing_level = .5, optimized=False)

fcst_gs_pred = fit_SES.forecast(len(testX))
timeseries_evaluation_metrics_func(testX, fcst_gs_pred)
```

```
Evaluation metric results:
MSE is : 16763.40894975929
MAE is : 129.4735839843761
RMSE is : 129.4735839843761
MAPE is : 0.8274225034821215
R2 is : nan
```

In [151…

```
SES = SimpleExpSmoothing(np.asarray(trainX))
fit_SES_auto = SES.fit(optimized= True, use_brute = True)
```

```
fcst_auto_pred = fit_SES_auto.forecast(len(testX))
timeseries_evaluation_metrics_func(testX, fcst_auto_pred)
```

```
Evaluation metric results:
MSE is : 523240.73315811984
MAE is : 723.3538091128848
RMSE is : 723.3538091128848
MAPE is : 4.6227129984424975
R2 is : nan

C:\Users\Susy\anaconda3\envs\humans\lib\site-packages\statsmodels\tsa\holtwinters\model.p
y:915: ConvergenceWarning: Optimization failed to converge. Check mle_retvals.
  warnings.warn(
```

In [152…

```
fit_SES_auto.summary()
```

Out[152…

SimpleExpSmoothing Model Results

Dep. Variable:	endog	**No. Observations:**	12
Model:	SimpleExpSmoothing	**SSE**	1127447894.794
Optimized:	True	**AIC**	224.300
Trend:	None	**BIC**	225.270
Seasonal:	None	**AICC**	230.014
Seasonal Periods:	None	**Date:**	Thu, 17 Nov 2022
Box-Cox:	False	**Time:**	17:21:39
Box-Cox Coeff.:	None		

	coeff	code	optimized
smoothing_level	0.7711770	alpha	True
initial_level	26288.337	l.0	True

In [153…

```
fit_SES.summary()
```

Out[153…

SimpleExpSmoothing Model Results

Dep. Variable:	endog	**No. Observations:**	12
Model:	SimpleExpSmoothing	**SSE**	1188523101.010
Optimized:	False	**AIC**	224.933
Trend:	None	**BIC**	225.903
Seasonal:	None	**AICC**	230.647
Seasonal Periods:	None	**Date:**	Thu, 17 Nov 2022
Box-Cox:	False	**Time:**	17:22:07
Box-Cox Coeff.:	None		

	coeff	code	optimized
smoothing_level	0.5000000	alpha	False
initial_level	29091.820	l.0	False

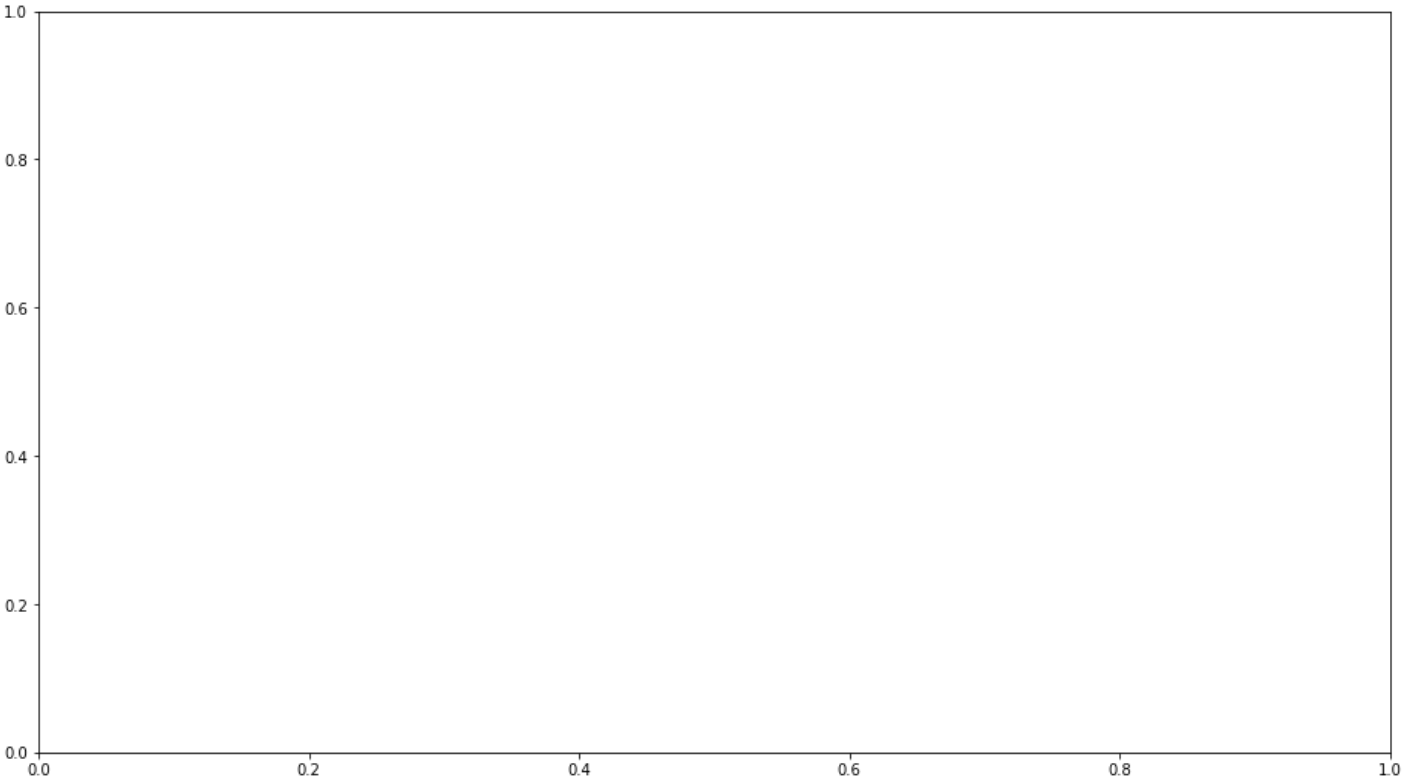
In [154…
```
df_fcst_gs_pred = pd.DataFrame(fcst_gs_pred, columns=['Close_grid_Search'])
df_fcst_gs_pred["new_index"] = range(len(trainX), len(X))
df_fcst_gs_pred = df_fcst_gs_pred.set_index("new_index")
```

In [155…
```
df_fcst_auto_pred = pd.DataFrame(fcst_auto_pred, columns=['Close_auto_search'])
df_fcst_auto_pred["new_index"] = range(len(trainX), len(X))
df_fcst_auto_pred = df_fcst_auto_pred.set_index("new_index")
```

In [163…
```
plt.plot(trainX)
plt.plot(testX)
plt.plot(df_fcst_gs_pred)
plt.plot(df_fcst_auto_pred)
plt.legend(['train', 'test', 'SES with custom grid search','SES with optimizer'])
plt.show()
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
TypeError: float() argument must be a string or a number, not 'tuple'

The above exception was the direct cause of the following exception:

ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_11348/1886055119.py in <module>
----> 1 plt.plot(trainX)
      2 plt.plot(testX)
      3 plt.plot(df_fcst_gs_pred)
      4 plt.plot(df_fcst_auto_pred)
      5 plt.legend(['train', 'test', 'SES with custom grid search','SES with optimizer'])

~\anaconda3\envs\humans\lib\site-packages\matplotlib\pyplot.py in plot(scalex, scaley, dat
a, *args, **kwargs)
   2755 @_copy_docstring_and_deprecators(Axes.plot)
   2756 def plot(*args, scalex=True, scaley=True, data=None, **kwargs):
-> 2757     return gca().plot(
   2758         *args, scalex=scalex, scaley=scaley,
   2759         **({"data": data} if data is not None else {}), **kwargs)

~\anaconda3\envs\humans\lib\site-packages\matplotlib\axes\_axes.py in plot(self, scalex, s
caley, data, *args, **kwargs)
   1632         lines = [*self._get_lines(*args, data=data, **kwargs)]
   1633         for line in lines:
-> 1634             self.add_line(line)
   1635         self._request_autoscale_view(scalex=scalex, scaley=scaley)
   1636         return lines

~\anaconda3\envs\humans\lib\site-packages\matplotlib\axes\_base.py in add_line(self, line)
   2281             line.set_clip_path(self.patch)
   2282
-> 2283         self._update_line_limits(line)
   2284         if not line.get_label():
   2285             line.set_label(f'_child{len(self._children)}')

~\anaconda3\envs\humans\lib\site-packages\matplotlib\axes\_base.py in _update_line_limits
(self, line)
   2304         Figures out the data limit of the given line, updating self.dataLim.
   2305         """
-> 2306         path = line.get_path()
   2307         if path.vertices.size == 0:
   2308             return

~\anaconda3\envs\humans\lib\site-packages\matplotlib\lines.py in get_path(self)
    997         """Return the `~matplotlib.path.Path` associated with this line."""
```

```
    998         if self._invalidy or self._invalidx:
--> 999             self.recache()
   1000         return self._path
   1001

~\anaconda3\envs\humans\lib\site-packages\matplotlib\lines.py in recache(self, always)
    650         if always or self._invalidx:
    651             xconv = self.convert_xunits(self._xorig)
--> 652             x = _to_unmasked_float_array(xconv).ravel()
    653         else:
    654             x = self._x

~\anaconda3\envs\humans\lib\site-packages\matplotlib\cbook\__init__.py in _to_unmasked_flo
at_array(x)
   1296         return np.ma.asarray(x, float).filled(np.nan)
   1297     else:
-> 1298         return np.asarray(x, float)
   1299
   1300

ValueError: setting an array element with a sequence.
```



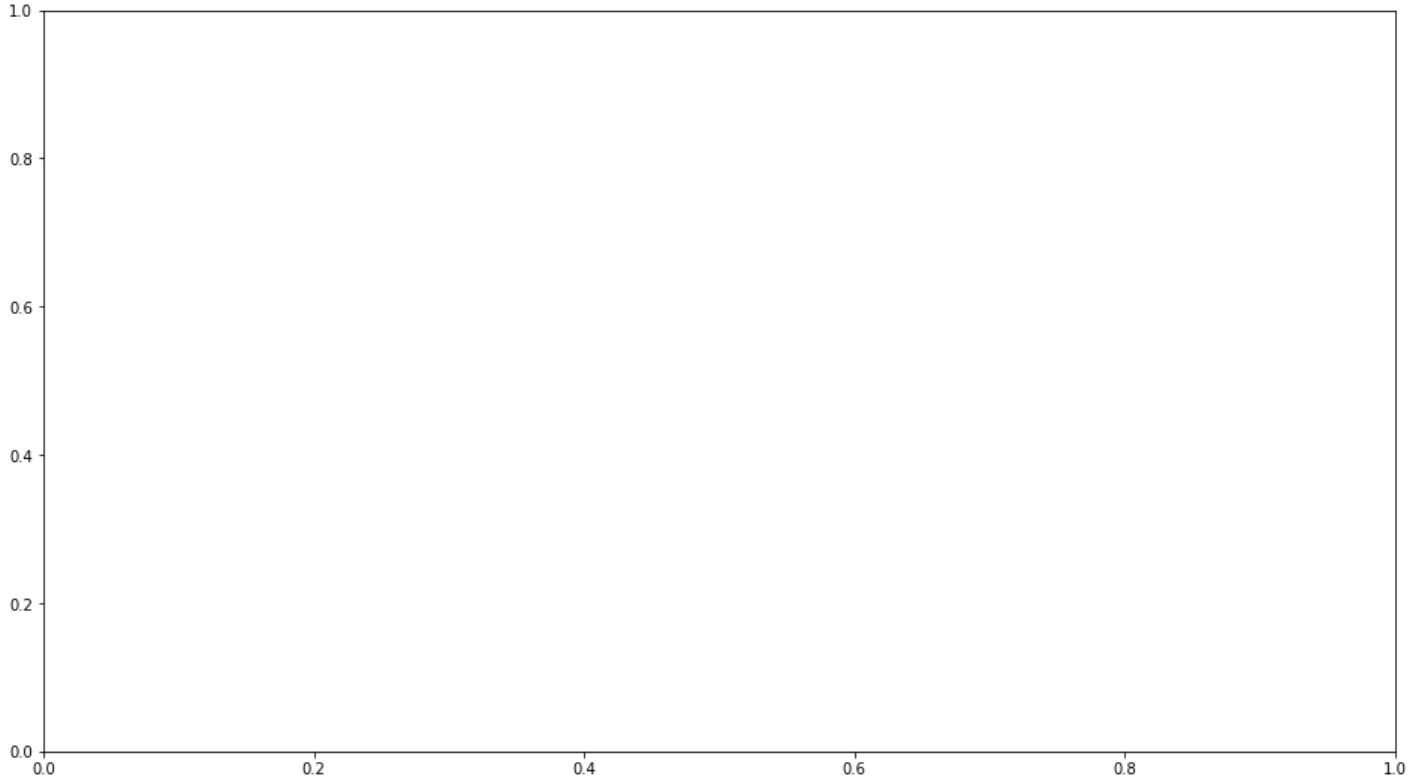
In [ ]:

In [164…

```
#plt.rcParams["figure.figsize"] = [16,9]
plt.plot(trainX)
#plt.plot(testX)
#plt.plot(df_fcst_gs_pred)
#plt.plot(df_fcst_auto_pred)
#plt.legend(['train', 'test', 'SES with custom grid search','SES with optimizer'])
#plt.show()
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
TypeError: float() argument must be a string or a number, not 'tuple'

The above exception was the direct cause of the following exception:
```

```
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_11348/3675644388.py in <module>
      1 #plt.rcParams["figure.figsize"] = [16,9]
----> 2 plt.plot(trainX)
      3 #plt.plot(testX)
      4 #plt.plot(df_fcst_gs_pred)
      5 #plt.plot(df_fcst_auto_pred)

~\anaconda3\envs\humans\lib\site-packages\matplotlib\pyplot.py in plot(scalex, scaley, dat
a, *args, **kwargs)
   2755 @_copy_docstring_and_deprecators(Axes.plot)
   2756 def plot(*args, scalex=True, scaley=True, data=None, **kwargs):
-> 2757     return gca().plot(
   2758         *args, scalex=scalex, scaley=scaley,
   2759         **({"data": data} if data is not None else {}), **kwargs)

~\anaconda3\envs\humans\lib\site-packages\matplotlib\axes\_axes.py in plot(self, scalex, s
caley, data, *args, **kwargs)
   1632         lines = [*self._get_lines(*args, data=data, **kwargs)]
   1633         for line in lines:
-> 1634             self.add_line(line)
   1635         self._request_autoscale_view(scalex=scalex, scaley=scaley)
   1636         return lines

~\anaconda3\envs\humans\lib\site-packages\matplotlib\axes\_base.py in add_line(self, line)
   2281             line.set_clip_path(self.patch)
   2282
-> 2283         self._update_line_limits(line)
   2284         if not line.get_label():
   2285             line.set_label(f'_child{len(self._children)}')

~\anaconda3\envs\humans\lib\site-packages\matplotlib\axes\_base.py in _update_line_limits
(self, line)
   2304         Figures out the data limit of the given line, updating self.dataLim.
   2305         """
-> 2306         path = line.get_path()
   2307         if path.vertices.size == 0:
   2308             return

~\anaconda3\envs\humans\lib\site-packages\matplotlib\lines.py in get_path(self)
    997         """Return the `~matplotlib.path.Path` associated with this line."""
    998         if self._invalidy or self._invalidx:
--> 999             self.recache()
   1000         return self._path
   1001

~\anaconda3\envs\humans\lib\site-packages\matplotlib\lines.py in recache(self, always)
    650         if always or self._invalidx:
    651             xconv = self.convert_xunits(self._xorig)
--> 652             x = _to_unmasked_float_array(xconv).ravel()
    653         else:
    654             x = self._x

~\anaconda3\envs\humans\lib\site-packages\matplotlib\cbook\__init__.py in _to_unmasked_flo
at_array(x)
   1296         return np.ma.asarray(x, float).filled(np.nan)
   1297     else:
-> 1298         return np.asarray(x, float)
   1299
   1300

ValueError: setting an array element with a sequence.
```



Double Exponential Smoothing:

In [ ]:
```
param_grid_DES = {'smoothing_level': [0.10, 0.20,.30,.40,.50,.60,.70,.80,.90],
                  'smoothing_slope':[0.10, 0.20,.30,.40,.50,.60,.70,.80,.90],
                  'damping_slope': [0.10, 0.20,.30,.40,.50,.60,.70,.80,.90],
                  'damped': [True, False]}
pg_DES = list(ParameterGrid(param_grid_DES))
```

In [ ]:
```
df_results_DES = pd.DataFrame(columns=['smoothing_level', 'smoothing_slope', 'damping_slop

for a,b in enumerate(pg_DES):
    smoothing_level = b.get('smoothing_level')
    smoothing_slope = b.get('smoothing_slope')
    damping_slope = b.get('damping_slope')
    damped = b.get('damped')

    fit_Holt = Holt(trainX, damped=damped).fit(smoothing_level=smoothing_level, smoothing_
    fcst_gs_pred_Holt = fit_Holt.forecast(len(testX))

    df_pred = pd.DataFrame(fcst_gs_pred_Holt, columns=['Forecasted_result'])
    RMSE = np.sqrt(metrics.mean_squared_error(testX, df_pred.Forecasted_result))
    r2 = metrics.r2_score(testX, df_pred.Forecasted_result)

    df_results_DES = df_results_DES.append({'smoothing_level':smoothing_level, 'smoothing_
```

In [ ]:
```
df_results_DES.sort_values(by=['RMSE','R²']).head(10)
```

In [ ]:
```
df_results_DES.to_csv('df_results_DES.csv')
```

In [ ]:
```
best_values_DES = df_results_DES.sort_values(by=['RMSE','R²']).head(1)
best_values_DES
```

In [ ]:

```
smoothing_level_value_DES = best_values_DES['smoothing_level'].iloc[0]
smoothing_slope_value_DES = best_values_DES['smoothing_slope'].iloc[0]
damping_slope_value_DES = best_values_DES['damping_slope'].iloc[0]
damped_setting_DES = best_values_DES['damped'].iloc[0]

print("smoothing_level_value_DES: ", smoothing_level_value_DES)
print("smoothing_slope_value_DES: ", smoothing_slope_value_DES)
print("damping_slope_value_DES: ", damping_slope_value_DES)
print("damped_setting_DES: ", damped_setting_DES)
```

In [ ]:

```
DES = Holt(trainX,damped=damped_setting_DES)
fit_Holt = DES.fit(smoothing_level=smoothing_level_value_DES, smoothing_slope=smoothing_sl
                   damping_slope=damping_slope_value_DES ,optimized=False)

fcst_gs_pred_Holt = fit_Holt.forecast(len(testX))
timeseries_evaluation_metrics_func(testX, fcst_gs_pred_Holt)
```

In [ ]:

```
DES = Holt(trainX)
fit_Holt_auto = DES.fit(optimized= True, use_brute = True)

fcst_auto_pred_Holt = fit_Holt_auto.forecast(len(testX))
timeseries_evaluation_metrics_func(testX, fcst_auto_pred_Holt)
```

In [ ]:

```
fit_Holt_auto.summary()
```

In [ ]:

```
plt.rcParams["figure.figsize"] = [16,9]
plt.plot(trainX, label='Train')
plt.plot(testX, label='Test')
plt.plot(fcst_gs_pred_Holt, label='Double Exponential Smoothing with custom grid search')
plt.plot(fcst_auto_pred_Holt, label='Double Exponential Smoothing using optimized=True')
plt.legend(loc='best')
plt.show()
```

Triple Exponential Smoothing:

In [ ]:

```
param_grid_TES = {'trend': ['add', 'mul'], 'seasonal' :['add', 'mul'],
                  'seasonal_periods':[3,6,12],
                  'smoothing_level': [.20, .40, .60, .80],  # extended search grid: [.10,
                  'smoothing_slope':[.20, .40, .60, .80],   # extended search grid: [.10,
                  'damping_slope': [.20, .40, .60, .80],    # extended search grid: [.10,
                  'damped' : [True, False], 'use_boxcox':[True, False],
                  'remove_bias':[True, False],'use_basinhopping':[True, False]}
pg_TES = list(ParameterGrid(param_grid_TES))
```

In [ ]:

```
df_results_TES = pd.DataFrame(columns=['trend','seasonal_periods','smoothing_level', 'smoo
                                       'damping_slope','damped','use_boxcox','remove_bias
                                       'use_basinhopping','RMSE','R²'])

for a,b in enumerate(pg_TES):
    trend = b.get('trend')
    smoothing_level = b.get('smoothing_level')
    seasonal_periods = b.get('seasonal_periods')
    smoothing_level = b.get('smoothing_level')
    smoothing_slope = b.get('smoothing_slope')
    damping_slope = b.get('damping_slope')
    damped = b.get('damped')
    use_boxcox = b.get('use_boxcox')
```

```
    remove_bias = b.get('remove_bias')
    use_basinhopping = b.get('use_basinhopping')

    fit_ES = ExponentialSmoothing(trainX, trend=trend, damped=damped, seasonal_periods=sea
                                  smoothing_slope=smoothing_slope, damping_slope=damping_s
    fcst_gs_pred_ES = fit_ES.forecast(len(testX))

    df_pred = pd.DataFrame(fcst_gs_pred_ES, columns=['Forecasted_result'])
    RMSE = np.sqrt(metrics.mean_squared_error(testX, df_pred.Forecasted_result))
    r2 = metrics.r2_score(testX, df_pred.Forecasted_result)

    df_results_TES = df_results_TES.append({'trend':trend, 'seasonal_periods':seasonal_per
                                            'smoothing_slope':smoothing_slope, 'damping_sl
                                            'use_boxcox':use_boxcox, 'remove_bias':remove_
                                            ignore_index=True)
```

In [ ]:
```
df_results_TES.sort_values(by=['RMSE','R²']).head(10)
```

In [ ]:
```
df_results_TES.to_csv('df_results_TES.csv')
```

In [ ]:
```
best_values_TES = df_results_TES.sort_values(by=['RMSE','R²']).head(1)
best_values_TES
```

In [ ]:
```
trend_setting_TES = best_values_TES['trend'].iloc[0]
damped_setting_TES = best_values_TES['damped'].iloc[0]
seasonal_periods_values_TES = best_values_TES['seasonal_periods'].iloc[0]
smoothing_level_values_TES = best_values_TES['smoothing_level'].iloc[0]
smoothing_slope_values_TES = best_values_TES['smoothing_slope'].iloc[0]
damping_slope_values_TES = best_values_TES['damping_slope'].iloc[0]
use_boxcox_setting_TES = best_values_TES['use_boxcox'].iloc[0]
remove_bias_setting_TES = best_values_TES['remove_bias'].iloc[0]
use_basinhopping_setting_TES = best_values_TES['use_basinhopping'].iloc[0]

rend_setting_TES: ", trend_setting_TES)
print("damped_setting_TES: ", damped_setting_TES)
print("seasonal_periods_values_TES: ", seasonal_periods_values_TES)
print("smoothing_level_values_TES: ", smoothing_level_values_TES)
print("smoothing_slope_values_TES: ", smoothing_slope_values_TES)
print("damping_slope_values_TES: ", damping_slope_values_TES)
print("use_boxcox_setting_TES: ", use_boxcox_setting_TES)
print("remove_bias_setting_TES: ", remove_bias_setting_TES)
print("use_basinhopping_setting_TES: ", use_basinhopping_setting_TES)
```

In [ ]:
```
TES = ExponentialSmoothing(trainX, trend=trend_setting_TES, damped=damped_setting_TES,
                           seasonal_periods=seasonal_periods_values_TES)
fit_ES = TES.fit(smoothing_level=smoothing_level_values_TES, smoothing_slope=smoothing_slo
                 damping_slope=damping_slope_values_TES, use_boxcox=use_boxcox_setting_TES
                 remove_bias=remove_bias_setting_TES, optimized=False)

fcst_gs_pred_ES = fit_ES.forecast(len(testX))
timeseries_evaluation_metrics_func(testX, fcst_gs_pred_ES)
```

In [ ]:
```
TES = ExponentialSmoothing(trainX)
fit_ES_auto = TES.fit(optimized= True, use_brute = True)

fcst_auto_pred_ES = fit_ES_auto.forecast(len(testX))
timeseries_evaluation_metrics_func(testX, fcst_auto_pred_ES)
```

In [ ]:
```
fit_ES_auto.summary()
```

In [ ]:
```
plt.rcParams["figure.figsize"] = [16,9]
plt.plot(trainX, label='Train')
plt.plot(testX, label='Test')
plt.plot(fcst_gs_pred_ES, label='Triple Exponential Smoothing with custom grid search')
plt.plot(fcst_auto_pred_ES, label='Triple Exponential Smoothing using optimized=True')
plt.legend(loc='best')
plt.show()
```

hyper-parameter tuning on a time series

In [ ]:
```
lasso_regression = Lasso()
parameters = {'alpha':[10**-5, 10**-4, 10**-3, 10**-2, 0.1, 1, 10, 10**2, 10**3, 10**4, 10
tscv = TimeSeriesSplit(n_splits=3)
clf = GridSearchCV(lasso_regression, parameters, cv=tscv, scoring='neg_mean_squared_error'
clf.fit(X_train_select, np.log1p(y_train))

results = pd.DataFrame.from_dict(clf.cv_results_)
```

In [ ]:
```
xgb_reg=xgb.XGBRegressor()

prams={
    'learning_rate':[0.03,0.05,0.1],
    'n_estimators':[500,2000,4000],
    'max_depth':[5,7,10],
    'colsample_bytree':[0.1,0.3,0.5,1],
    'subsample':[0.1,0.3,0.5,1]
}
tscv = TimeSeriesSplit(n_splits=3)
random_clf=RandomizedSearchCV(xgb_reg, param_distributions=prams,verbose=1,
                              n_jobs=3, cv = tscv, n_iter=10)
random_clf.fit(X_train_select, np.log1p(y_train))
```

In [ ]:
```
params = {"objective": "reg:squarederror",
          "eta": 0.05,
          "max_depth": 10,
          "subsample": 0.5,
          "colsample_bytree": 0.3,
          "silent": 1,
          "seed": 10
          }
num_boost_round = 3000

dtrain = xgb.DMatrix(X_train_select, np.log1p(y_train))
dvalid = xgb.DMatrix(X_valid_select, np.log1p(y_valid))
watchlist = [(dtrain, 'train'), (dvalid, 'eval')]

#training the model
model = xgb.train(params, dtrain, num_boost_round, evals=watchlist,
                  early_stopping_rounds= 50, feval=rmspe_xg_log, verbose_eval=True)

#prediction
dtest = xgb.DMatrix(X_test_select)
y_test = model.predict(dtest)
```

is time series stationary?

In [ ]:
```
# Import adfuller
from statsmodels.tsa.stattools import adfuller

result = adfuller(data.Close)
print('ADF Test Statistic: %.2f' % result[0])
print('5%% Critical Value: %.2f' % result[4]['5%'])
print('p-value: %.2f' % result[1])
```

Implementing Differencing to transform non-stationary to stationary

In [ ]:
```
# Change for (t)th day is Close for (t)th day minus Close for (t-1)th day.
data['Difference'] = data['Close'].diff()

# Plot the Change
plt.figure(figsize=(10, 7))
plt.plot(data['Difference'])
plt.title('First Order Differenced Series', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Difference', fontsize=12)
plt.show()
```

In [ ]:
```

```

In [ ]:
```

```