ADS Final Project

Preliminary EDA

In [716…

```
%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 datetime
from dateutil.parser import parse
import statsmodels.api as sm
#import statsmodels.formula.api as smf
from sklearn.metrics import accuracy_score
import plotly.express as px
import plotly.io as pio
from pandas import read_csv
import datetime
from numpy import log
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_predict
from statsmodels.tsa.stattools import acf
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.metrics import mean_squared_error
from dateutil.parser import parse
from statsmodels.tsa.api import ExponentialSmoothing, SimpleExpSmoothing, Holt
from pandas.plotting import autocorrelation_plot
from pmdarima.arima import auto_arima
from statsmodels.tsa.seasonal import seasonal_decompose
from dateutil.parser import parse
from sklearn.model_selection import ParameterGrid
from sklearn.metrics import r2_score, mean_absolute_error
from prettytable import PrettyTable
import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [3]:

```
Retail_df = pd.read_csv('Online_Retail.csv')
Retail_df.sample(5)
```

Out[3]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
71850	542216	22983	CARD BILLBOARD FONT	12	1/26/2011 12:29	0.42	14911.0	EIRE
187279	552958	21174	POTTERING IN THE SHED METAL SIGN	12	5/12/2011 12:49	2.08	15498.0	United Kingdom
159144	550326	21212	PACK OF 72 RETROSPOT CAKE CASES	1	4/17/2011 13:05	0.55	14532.0	United Kingdom
249707	558906	82483	WOOD 2 DRAWER CABINET WHITE FINISH	2	7/4/2011 16:35	6.95	15555.0	United Kingdom

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
272433	560772	22720	SET OF 3 CAKE TINS PANTRY DESIGN	1	7/20/2011 16:12	10.79	NaN	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
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

In [39]:

```
Retail_df.shape
```

Out[39]:

```
(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

	Quantity	UnitPrice	CustomerID
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

Data Cleaning

Check for nulls

In [103…

```
Retail_noNA = Retail_df.dropna()
```

In [406…

```
pio.renderers.default='notebook'

dfg = Retail_noNA.groupby(['Description']).size().to_frame().sort_values([0], ascending =
dfg.columns = ['Description', 'count']
fig = px.histogram(dfg, x='Description', y = 'count',
                   title='Top Ten Item Descriptions Purchased on the Site')
fig.layout.yaxis.title.text = 'count'
fig.show()
```

missing values are not related to the forecast problem variables being used:

In [101…

```
Retail_df.isnull().values.any()
```

Out[101… True

In [102…

```
Retail_df.isnull().sum()
```

Out[102…

```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

Remove transactions that have to do with returns:

In [197…

```
# Remove transactions that were later returned with a negative
# quantity, so find the negative quantities, then
# the matching purchase for that return and remove both records
# from the data

# But first, make a copy of the dataframe to be modified:
Retail_df_NR = Retail_df.copy()

outlier_rows = Retail_df_NR['Quantity']< 0
outlier=Retail_df_NR[outlier_rows]
outlier

outlierI=outlier.copy()
# find records with negative of the negative quantity (positive)
outlierI['Quantity'] = -outlier['Quantity']

# Combine the data for invoice numbers for purchases that match
# Return invoices with negative quantity values:
commondf=pd.merge(Retail_df_NR,outlierI, on=['StockCode','CustomerID','Quantity'])
commondf = commondf.rename(columns={'InvoiceNo_x': 'InvoiceNo'})

vector_invoices=commondf['InvoiceNo']
b=commondf.iloc[:,0].values
c=commondf.iloc[:,1].values

# initialize invoice_I2
#invoice_I2=[]

for i in range(0,len(b)):
    invoice_I = (Retail_df_NR['InvoiceNo'] == b[i]) & (Retail_df_NR['StockCode'] == c[i])
    if Retail_df_NR[invoice_I].empty:
        print('')
    else:
        #returned_records=Retail_df[matching_row]
        #Retail_df = Retail_df.drop(index=invoice_I)
        invoice_I2=Retail_df_NR[invoice_I].index
        Retail_df_NR=Retail_df_NR.drop(invoice_I2, axis=0)


Retail_df_NR.shape
```

Out[197…

```
(532960, 8)
```

Matrix Generated that combines the original transaction with it's Return counterpart:

In [201…

```
# This was used to remove all the transactions
# that were actually refunded so as to not include false
# sales in our forecast:

commondf.head()
```

Out[201…

	InvoiceNo	StockCode	Description_x	Quantity	InvoiceDate_x	UnitPrice_x	CustomerID	Country_x	InvoiceNo_y
0	536366	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 8:28	1.85	17850.0	United Kingdom	C543611
1	536372	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 9:01	1.85	17850.0	United Kingdom	C543611
2	536377	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 9:34	1.85	17850.0	United Kingdom	C543611
3	536399	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 10:52	1.85	17850.0	United Kingdom	C543611
4	536407	22632	HAND WARMER RED POLKA DOT	6	12/1/2010 11:34	1.85	17850.0	United Kingdom	C543611

In [199…

```
# new size of the retail data:
Retail_df_NR.shape
```

Out[199…

```
(532960, 8)
```

In [200…

```
# Since the for loop to get rid of
# returns lasted too long, saved the data
# for future reference on modeling etc:

Retail_df_NR.to_csv('Retail_NoReturn_Transactions.csv')
```

In [ ]:

```
p=sns.jointplot(x='vote_average',y='vote_count', data=Retail_df)
p.fig.suptitle("Relationship between Vote_Average and Vote_Count in Movie MetaData")
```

Remove Irrelevant and Unrealistic Records:

These have to do with fees, postage, and adjusted debt/credit transactions, not retail orders

In [202…

```
# Remove rows with negative quantities - these were used during adjustments
unreal_rows1 = Retail_df_NR[Retail_df_NR['Quantity'] <= 0].index
#unreal_rows2 = Retail_df[Retail_df['Price'] <= 0].index

Retail_df_pre = Retail_df_NR.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)
```

Data after removing both returns and irrelevant transactions that have nothing to do with sales:

In [203…

```
Retail_df_pre4.describe()
```

Out[203…

	Quantity	UnitPrice	CustomerID
count	519966.000000	519966.000000	391016.000000
mean	10.171529	3.235760	15300.029428
std	36.451073	4.165506	1709.264898
min	1.000000	0.001000	12347.000000
25%	1.000000	1.250000	13971.000000
50%	3.000000	2.080000	15159.000000
75%	11.000000	4.130000	16800.000000
max	4800.000000	649.500000	18287.000000

In [204…

```
Retail_df_pre4.shape
```

Out[204…

```
(519966, 8)
```

In [243…

```
Retail_TimeSeries_df=Retail_df_pre4.copy()
```

In [244…

```
Retail_TimeSeries_df.isna().sum()
```

Out[244…

```
InvoiceNo           0
StockCode           0
Description         0
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     128950
Country             0
dtype: int64
```

Feature engineering SalesTotal:

In [245…

```
Retail_TimeSeries_df['Sales'] = (Retail_TimeSeries_df['Quantity'] * Retail_TimeSeries_df['
```

Exploratory Data Analysis

Observe time series and distributions based on size of orders

In [253…

```
rows_small_orders = (Retail_TimeSeries_df['Quantity'] < 100)
Retail_df_small_orders = Retail_TimeSeries_df[rows_small_orders]
Retail_df_small_orders.shape
```

Out[253…

```
(513663, 9)
```

In [221…

```
rows_medlarge_orders = (Retail_TimeSeries_df['Quantity'] >= 100) & (Retail_TimeSeries_df['
Retail_df_medlarge_orders = Retail_TimeSeries_df[rows_medlarge_orders]
Retail_df_medlarge_orders.shape
```

Out[221…

```
(6201, 9)
```

In [222…

```
rows_large_orders = Retail_TimeSeries_df['Quantity'] >= 1000
Retail_df_large_orders = Retail_TimeSeries_df[rows_large_orders]
```

In [223…

```
Retail_df_large_orders.shape
```

Out[223…

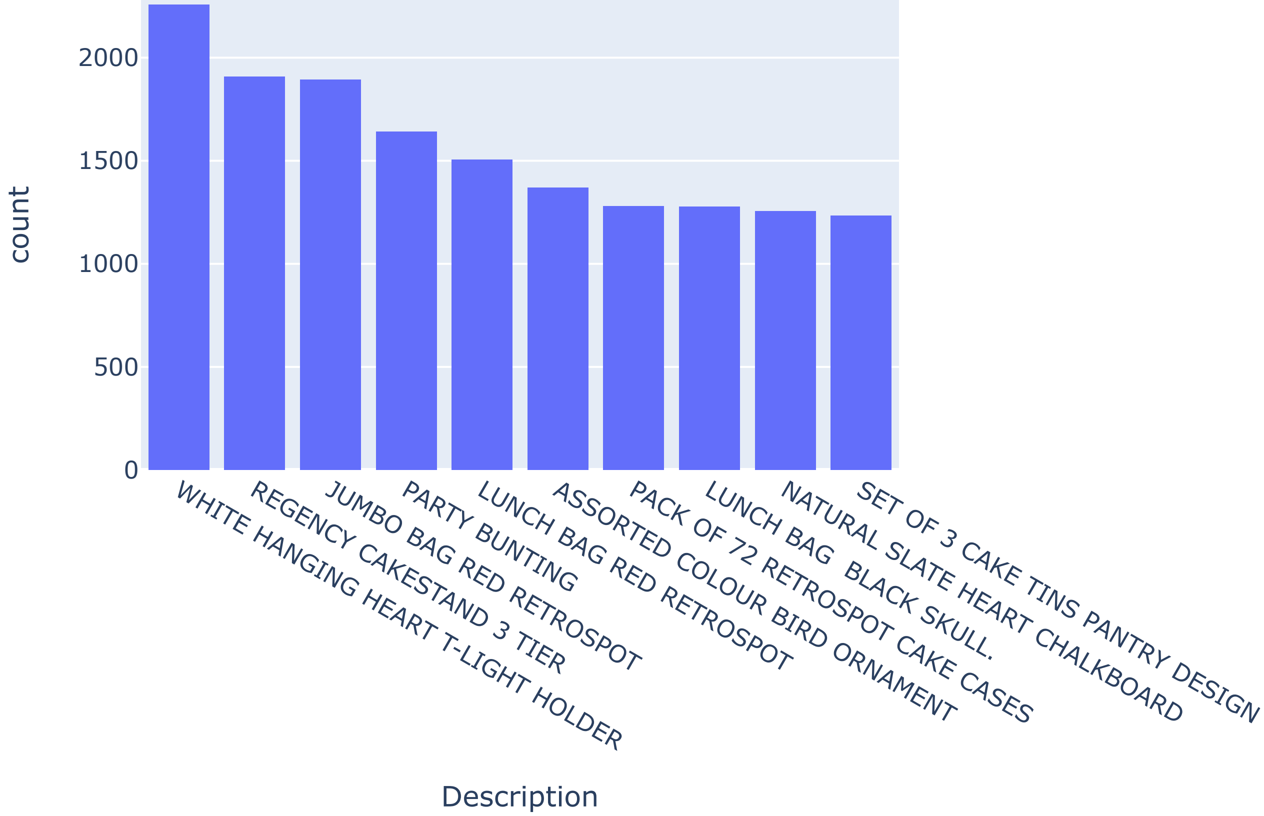
```
(102, 9)
```

Small order distributions (under 100 units)

In [405…

```
dfg_small_order = Retail_df_small_orders.groupby(['Description']).size().to_frame().sort_v
dfg_small_order.columns = ['Description', 'count']
fig = px.histogram(dfg_small_order, x='Description', y = 'count',
                   title='Top Ten Item Descriptions Purchased on Small Size orders')
fig.layout.yaxis.title.text = 'count'
fig.show()
```

Top Ten Item Descriptions Purchased on Small Size orders

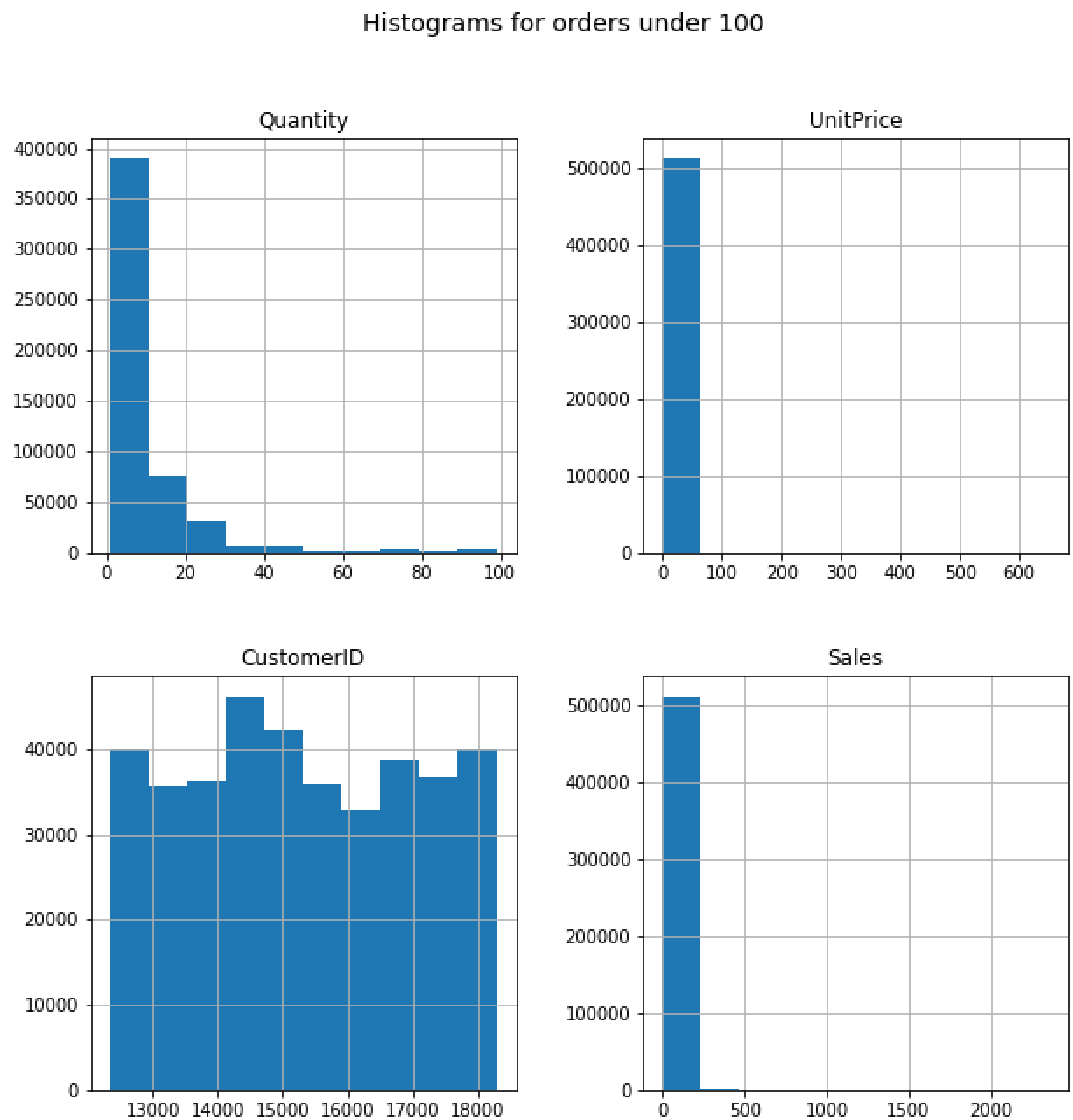


In [256…

```
Retail_df_small_orders.hist(figsize=[10,10])
plt.suptitle("Histograms for orders under 100", fontsize=14)
```

Out[256…

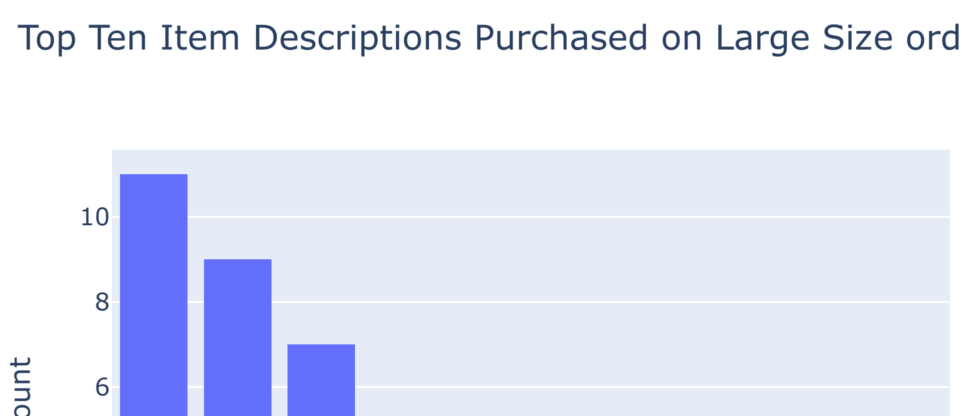
```
Text(0.5, 0.98, 'Histograms for orders under 100')
```



Large (>1000) order distributions:

In [407…

```
dfg_large_order = Retail_df_large_orders.groupby(['Description']).size().to_frame().sort_v
dfg_large_order.columns = ['Description', 'count']
fig = px.histogram(dfg_large_order, x='Description', y = 'count',
                   title='Top Ten Item Descriptions Purchased on Large Size orders')
fig.layout.yaxis.title.text = 'count'
fig.show()
```

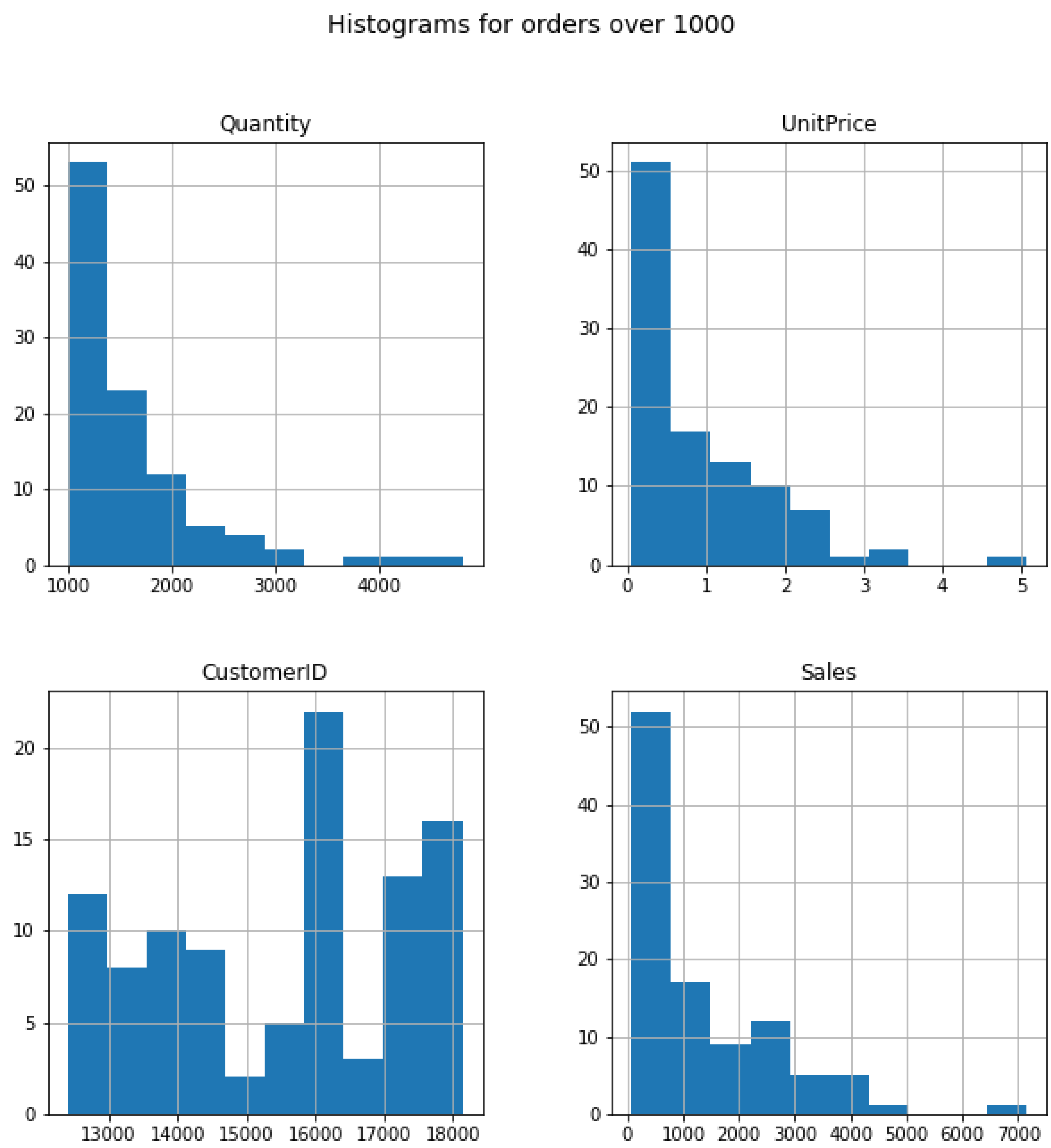


In [224…

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

Out[224…

```
Text(0.5, 0.98, 'Histograms for orders over 1000')
```



In [225…

```
Retail_df_large_orders.to_csv('Retail_df_large_orders.csv')
```

Medium (100-1000 units) order Distributions:

In [408…

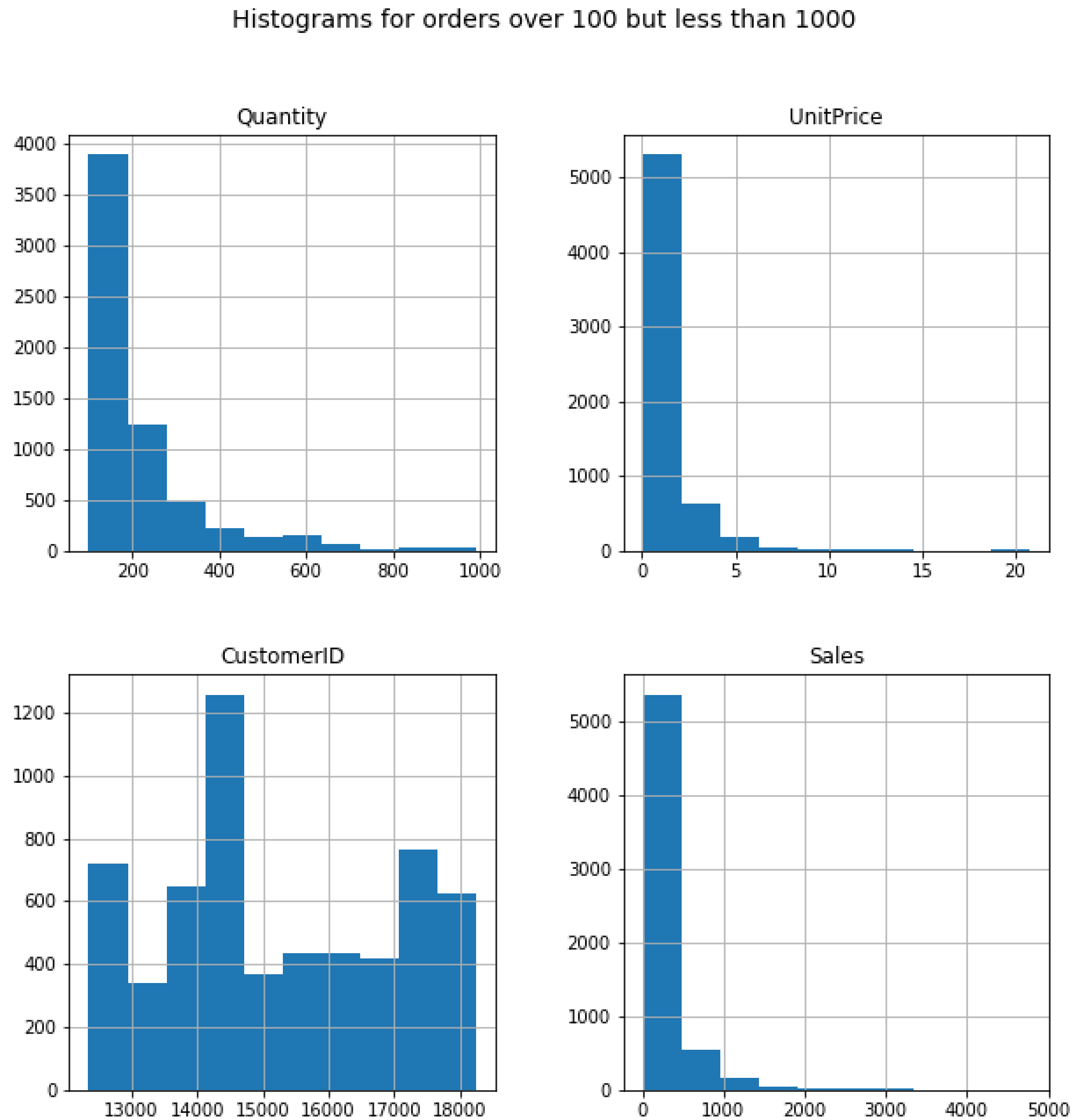
```
dfg_medium_order = Retail_df_medlarge_orders.groupby(['Description']).size().to_frame().sc
dfg_medium_order.columns = ['Description', 'count']
fig = px.histogram(dfg_medium_order, x='Description', y = 'count',
                   title='Top Ten Item Descriptions Purchased on Medium Size orders')
fig.layout.yaxis.title.text = 'count'
fig.show()
```

In [226…

```
Retail_df_medlarge_orders.hist(figsize=[10,10])
plt.suptitle("Histograms for orders over 100 but less than 1000", fontsize=14)
```

Out[226…

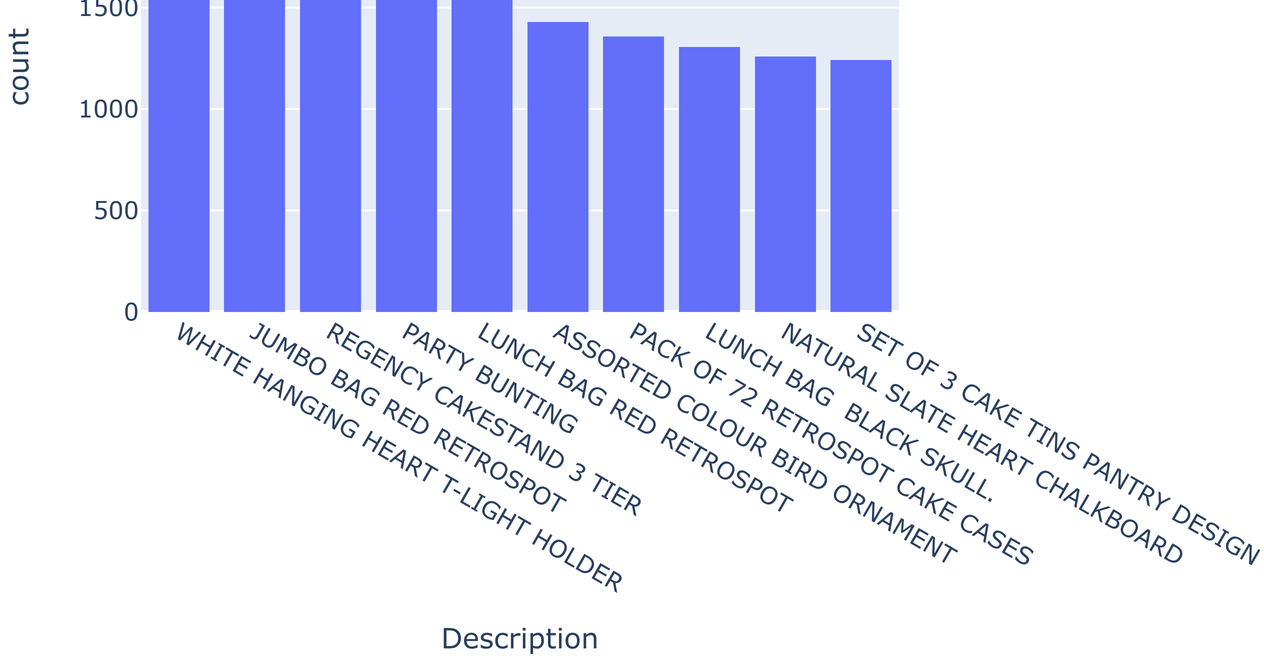
```
Text(0.5, 0.98, 'Histograms for orders over 100 but less than 1000')
```



Most popular items purchased:

In [409…

```
pio.renderers.default='notebook'

dfg = Retail_TimeSeries_df.groupby(['Description']).size().to_frame().sort_values([0], asc
dfg.columns = ['Description', 'count']
fig = px.histogram(dfg, x='Description', y = 'count',
                   title='Top Ten Item Descriptions Purchased on the Site')
fig.layout.yaxis.title.text = 'count'
fig.show()
```



In [233…

```
MostCommonItem = Retail_TimeSeries_df[Retail_TimeSeries_df['Description'].str.contains('WH
                                                                                      na=
```

In [234…

```
MostCommonItem.shape
```

Out[234…

```
(2293, 9)
```

In [236…

```
MostCommonItem.describe()
```

Out[236…

	Quantity	UnitPrice	CustomerID	Sales
count	2293.000000	2293.000000	1998.000000	2293.000000
mean	14.501526	3.221029	15558.954454	41.273973
std	43.009513	0.995402	1618.141817	129.383443
min	1.000000	2.550000	12370.000000	2.950000
25%	3.000000	2.950000	14221.000000	8.850000
50%	6.000000	2.950000	15584.000000	17.700000
75%	12.000000	2.950000	16931.000000	35.400000
max	1010.000000	6.770000	18283.000000	3272.400000

In [238…

```
MostCommonItem.Sales.sum()
```

Out[238…

```
94641.22
```

Particular item order Distributions: Clocks

In [227…

```
clock = Retail_TimeSeries_df[Retail_TimeSeries_df['Description'].str.contains('CLOCK', na=
```

In [441…

```
clock.shape
```

Out[441…

```
(7025, 9)
```

In [259…

```
clock_test = Retail_df_small_orders[Retail_df_small_orders['Description'].str.contains('Cl
clock_test.shape
```

Out[259…

```
(6990, 9)
```

Most clock sales come from small orders with some coming from medium sized orders

In [219…

```
clock.shape
```

Out[219…

```
(7025, 8)
```

In [237…

```
clock.describe()
```

Out[237…

	Quantity	UnitPrice	CustomerID	Sales
count	7025.000000	7025.000000	5726.000000	7025.000000
mean	5.303203	6.096231	15250.322040	23.958272
std	18.973171	3.737963	1739.507654	76.379316
min	1.000000	0.190000	12347.000000	0.190000
25%	1.000000	3.750000	13767.000000	8.290000
50%	2.000000	3.750000	15178.000000	15.000000
75%	4.000000	8.500000	16729.000000	19.900000
max	620.000000	49.960000	18280.000000	2662.200000

In [239…

```
clock.Sales.sum()
```

Out[239…

```
168306.86000000002
```

Sales from clocks alone amount to a total of 168,306 as opposed to the most popular item that amounts to 94,641 and with projected interest in clocks going up, must look at initial forecasts for this item.

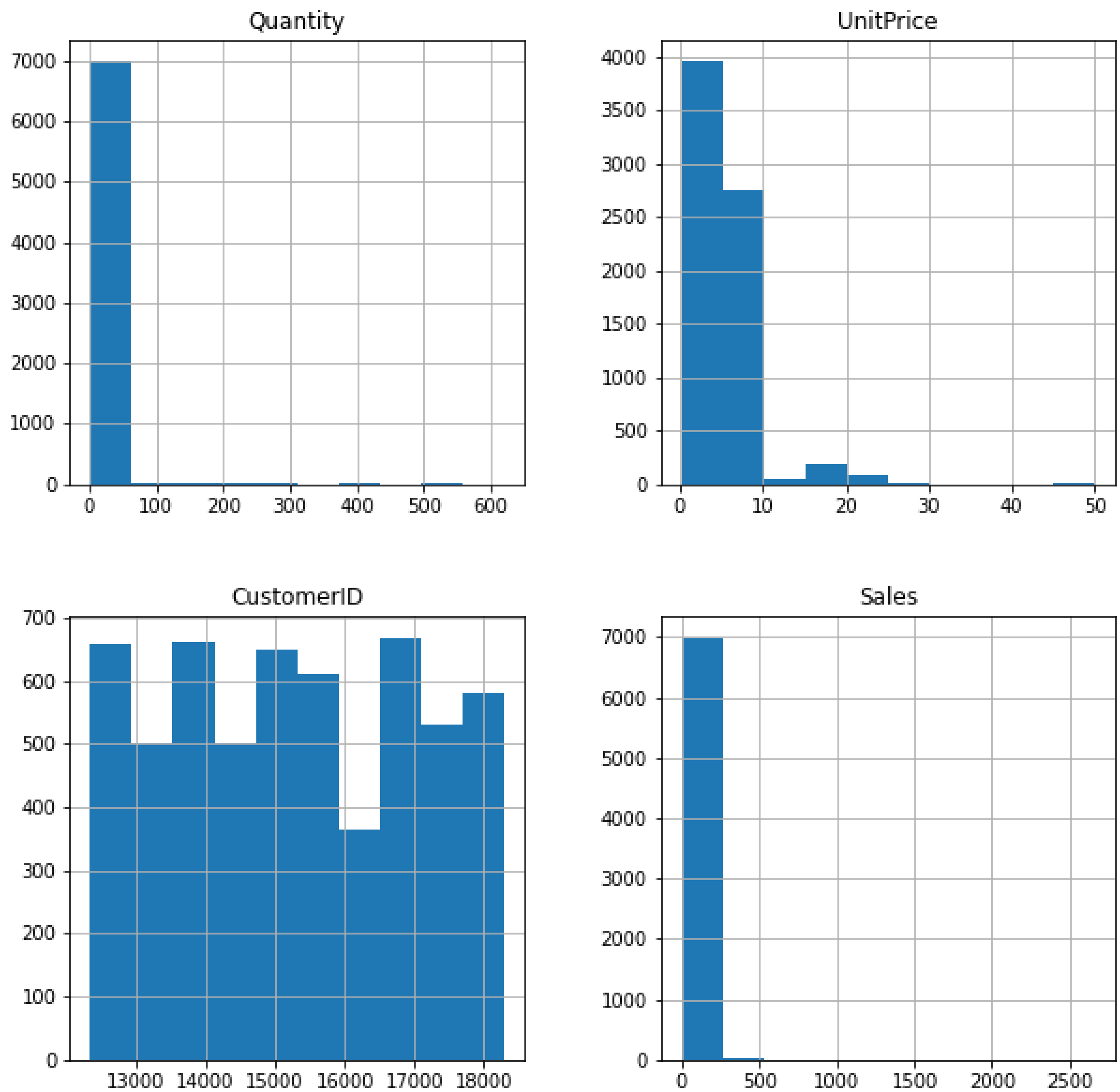
In [228…

```
clock.hist(figsize=[10,10])
plt.suptitle("Histograms for orders of Clocks", fontsize=14)
```

Out[228…

```
Text(0.5, 0.98, 'Histograms for orders of Clocks')
```

Histograms for orders of Clocks



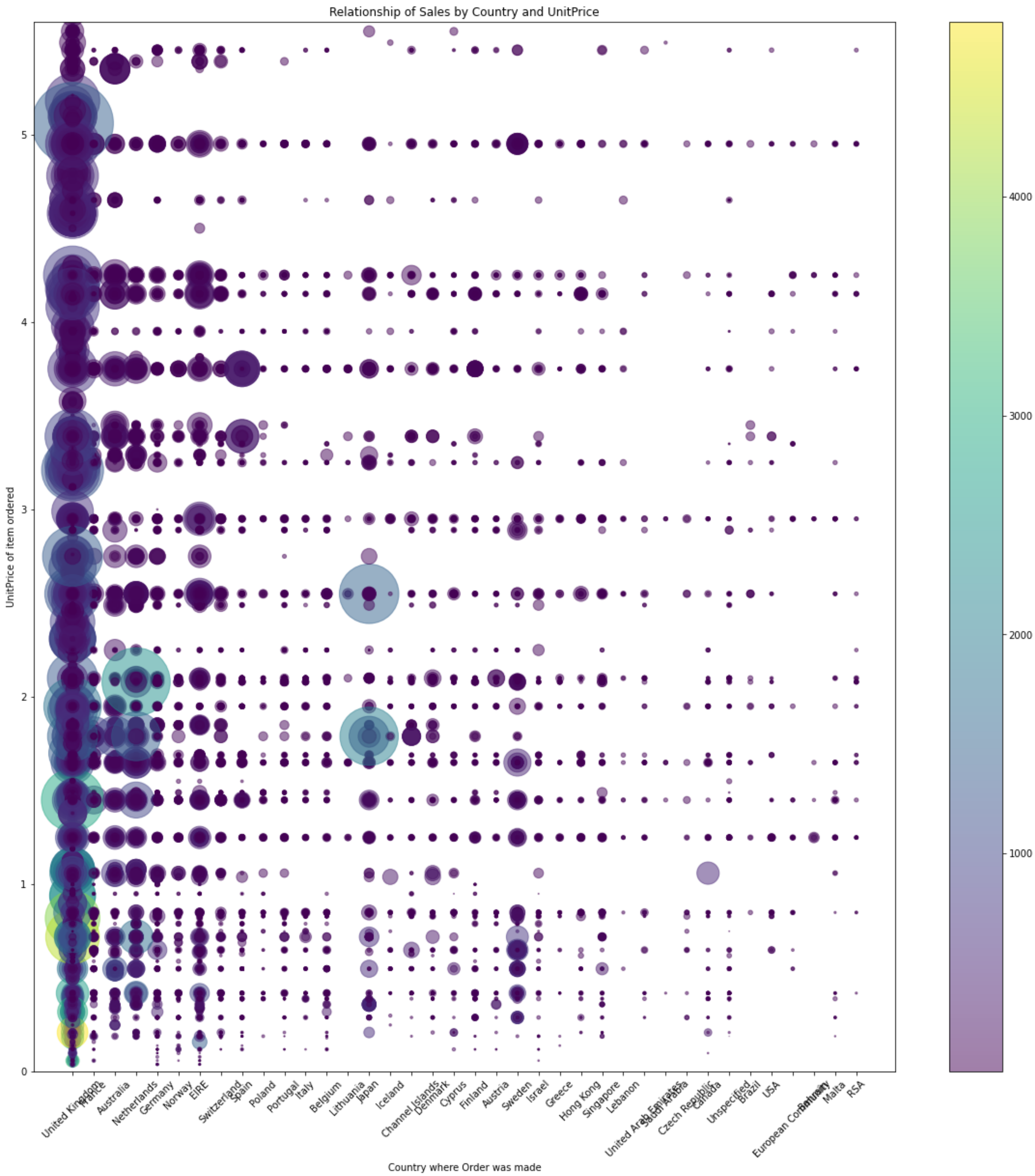
In [ ]:

```
clock['Clock_Purchase'] = 1
```

Relationship between Sales and other variables

In [264…

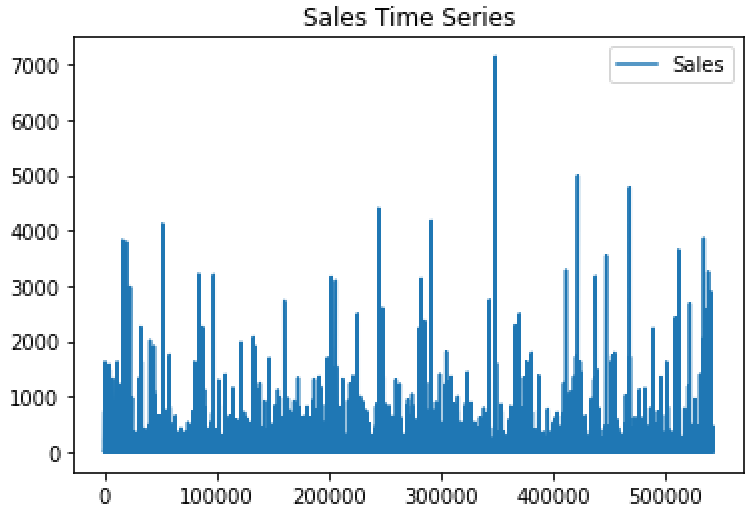
```
plt.figure(figsize=(20,20))
plt.scatter(Retail_TimeSeries_df['Country'], Retail_TimeSeries_df['UnitPrice'],
            s=Retail_TimeSeries_df['Sales'], c=Retail_TimeSeries_df['Quantity'], alpha=0.5
           )
plt.gca().update(dict(title='Relationship of Sales by Country and UnitPrice',
                      xlabel='Country where Order was made', ylabel='UnitPrice of item orc
plt.xticks(rotation=45)
plt.colorbar()
plt.show()
```



Time Series Plots

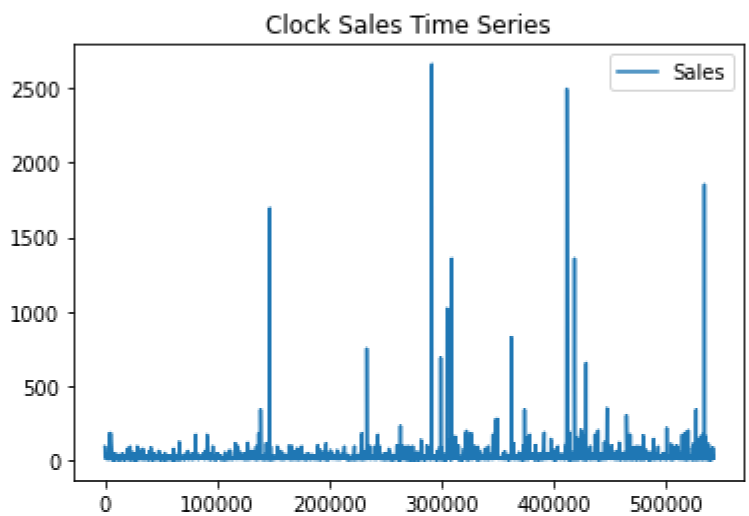
In [247…

```
Retail_SalesOnly = Retail_TimeSeries_df.copy()
Retail_SalesOnly.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity'],inplace=

Retail_Sales.plot()
plt.title('Sales Time Series')
plt.show()
```



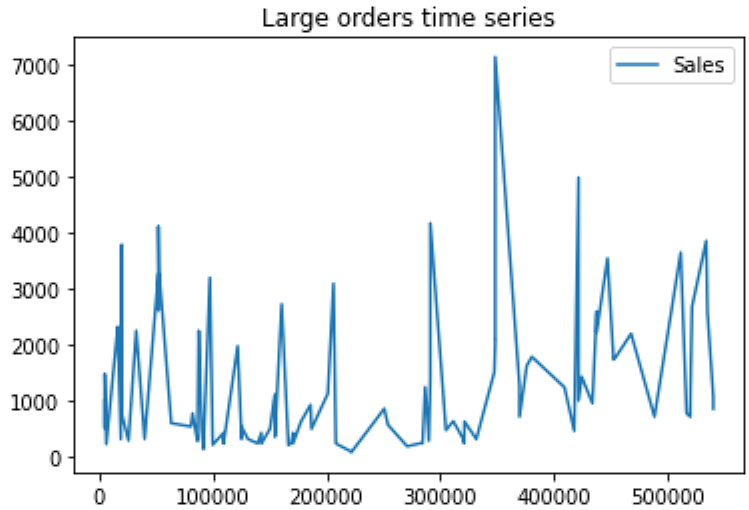
In [248…

```
Clock_SalesOnly = clock.copy()
Clock_SalesOnly.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity'],inplace=Tr

Clock_SalesOnly.plot()
plt.title('Clock Sales Time Series')
plt.show()
```



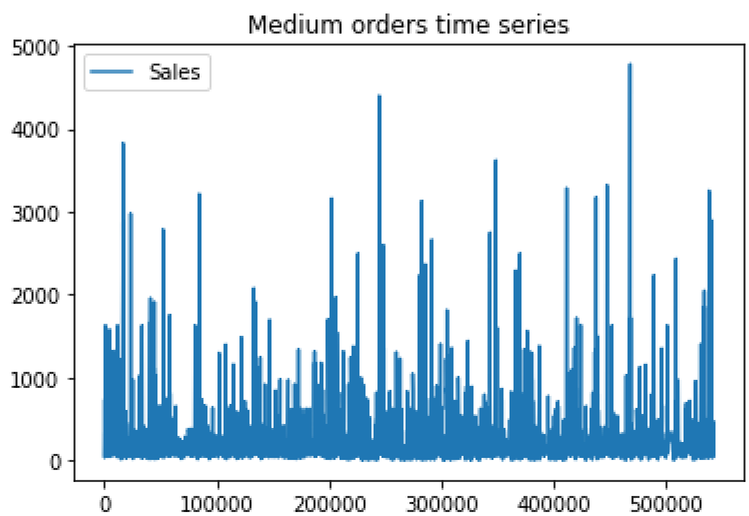
In [249…

```
series_time_retail = read_csv('Retail_df_large_orders.csv', header=0, index_col=0, parse_c
series_time_retail.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity'],inplace

series_time_retail.plot()
plt.title('Large orders time series')
plt.show()
```



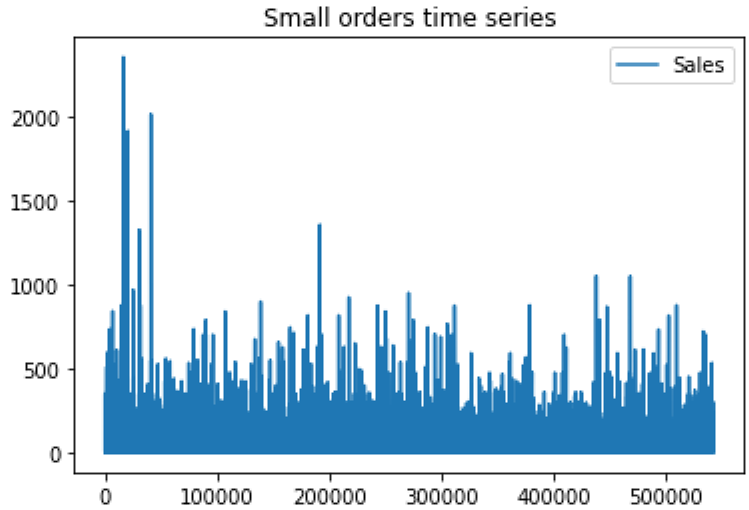
In [250…

```
series_time_retail2 = Retail_df_medlarge_orders.copy()
series_time_retail2.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity'],inplac

series_time_retail2.plot()
plt.title('Medium orders time series')
plt.show()
```



In [260…

```
series_time_retail3 = Retail_df_small_orders.copy()
series_time_retail3.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity'],inplac

series_time_retail3.plot()
plt.title('Small orders time series')
plt.show()
```



- Most orders originate from the UK, which is where the company is based
- Most sales are small quantities (purple color)

Clock Modeling Pre-Processing Sales Data Set:

Time series by Date:

In [410…

```
clock.to_csv('Clock_Retail_UKdata.csv')
```

In [308…

```
#Retail_TimeSeries_test_df = read_csv('Retail_DataClean_beforeDate.csv', header=0, index_c
#Retail_TimeSeries_daily_df = Retail_TimeSeries_test_df.resample('D', on='InvoiceDate').Sa
#Retail_TimeSeries_daily_df=Retail_TimeSeries_daily_df.set_index('InvoiceDate')
```

In [411…

```
Clock_TimeSeries_date_df = read_csv('Clock_Retail_UKdata.csv', header=0, index_col=0, pars
Clock_TimeSeries_date_df['InvoiceDate'] = pd.to_datetime(Clock_TimeSeries_date_df['Invoice

Clock_TimeSeries_date_df=Clock_TimeSeries_date_df.set_index('InvoiceDate')
```

In [412…

```
Clock_TimeSeries_date_df.head()
```

Out[412…

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country	Sales
2010-12-01 08:45:00	536370	22728	ALARM CLOCK BAKELIKE PINK	24	3.75	12583.0	France	90.0
2010-12-01 08:45:00	536370	22727	ALARM CLOCK BAKELIKE RED	24	3.75	12583.0	France	90.0
2010-12-01 08:45:00	536370	22726	ALARM CLOCK BAKELIKE GREEN	12	3.75	12583.0	France	45.0
2010-12-01 09:45:00	536382	22726	ALARM CLOCK BAKELIKE GREEN	4	3.75	16098.0	United Kingdom	15.0
2010-12-01 10:03:00	536389	22193	RED DINER WALL CLOCK	2	8.50	12431.0	Australia	17.0

Focus only on UK sales:

In [413…

```
Clock_TimeSeries_date_df = Clock_TimeSeries_date_df[Clock_TimeSeries_date_df['Country'].st
```

In [426…

```
Clock_TimeSeries_date_df.head()
```

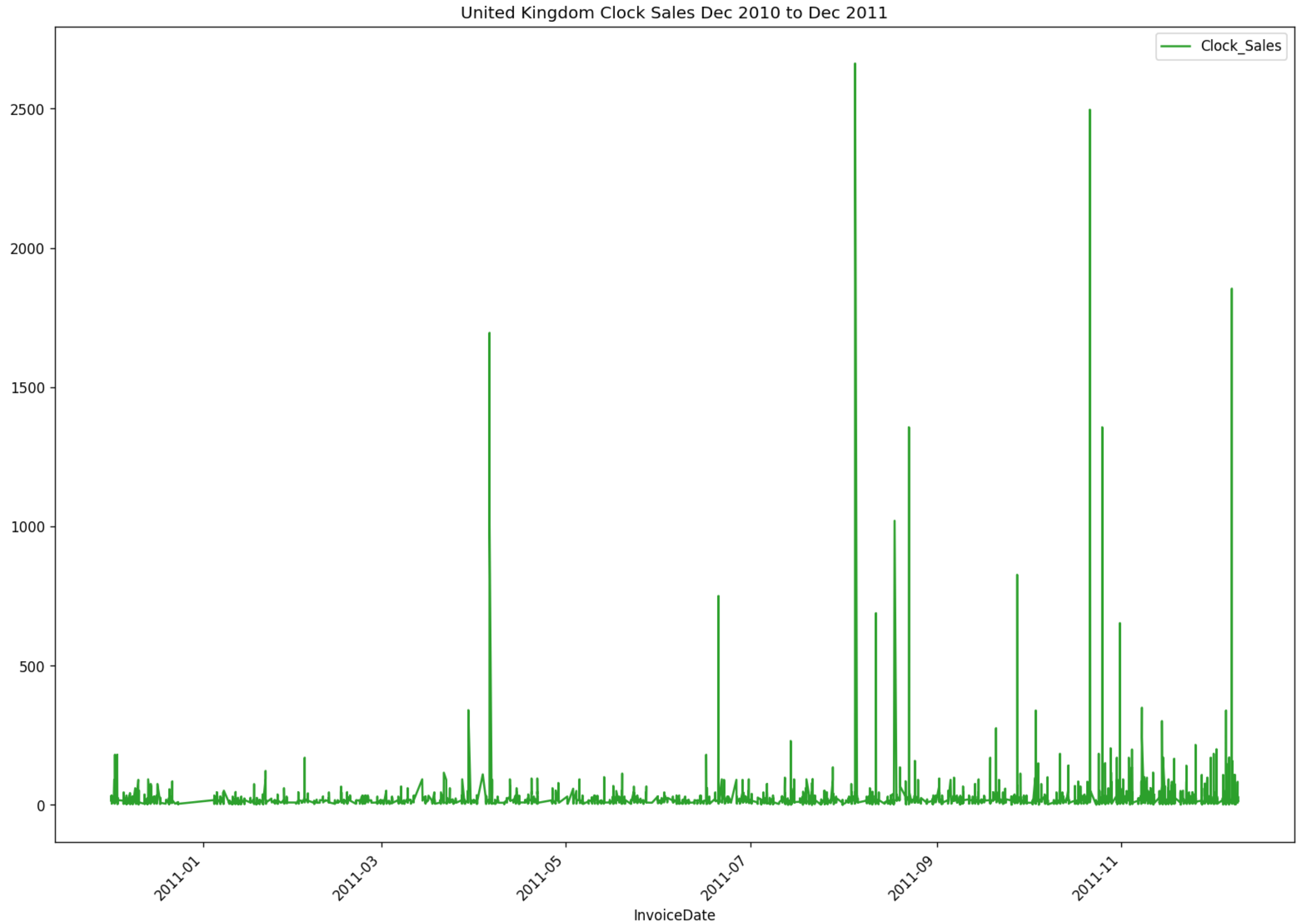
Out[426…

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country	Sales
InvoiceDate								
2010-12-01 09:45:00	536382	22726	ALARM CLOCK BAKELIKE GREEN	4	3.75	16098.0	United Kingdom	15.0
2010-12-01 10:47:00	536395	22730	ALARM CLOCK BAKELIKE IVORY	4	3.75	13767.0	United Kingdom	15.0
2010-12-01 10:47:00	536395	22727	ALARM CLOCK BAKELIKE RED	8	3.75	13767.0	United Kingdom	30.0
2010-12-01 10:47:00	536395	22729	ALARM CLOCK BAKELIKE ORANGE	8	3.75	13767.0	United Kingdom	30.0
2010-12-01 10:47:00	536395	22726	ALARM CLOCK BAKELIKE GREEN	8	3.75	13767.0	United Kingdom	30.0

In [478…

```
UK_clock_ts = Clock_TimeSeries_date_df.copy()
UK_clock_ts.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity',
                          'StockCode','Description','Country'],inplace=True)
plt.figure(figsize=(10,4))
UK_clock_ts.plot(color='tab:green')
plt.title('United Kingdom Clock Sales Dec 2010 to Dec 2011')
plt.xticks(rotation=45)
plt.legend(['Clock_Sales'])
plt.show()
```

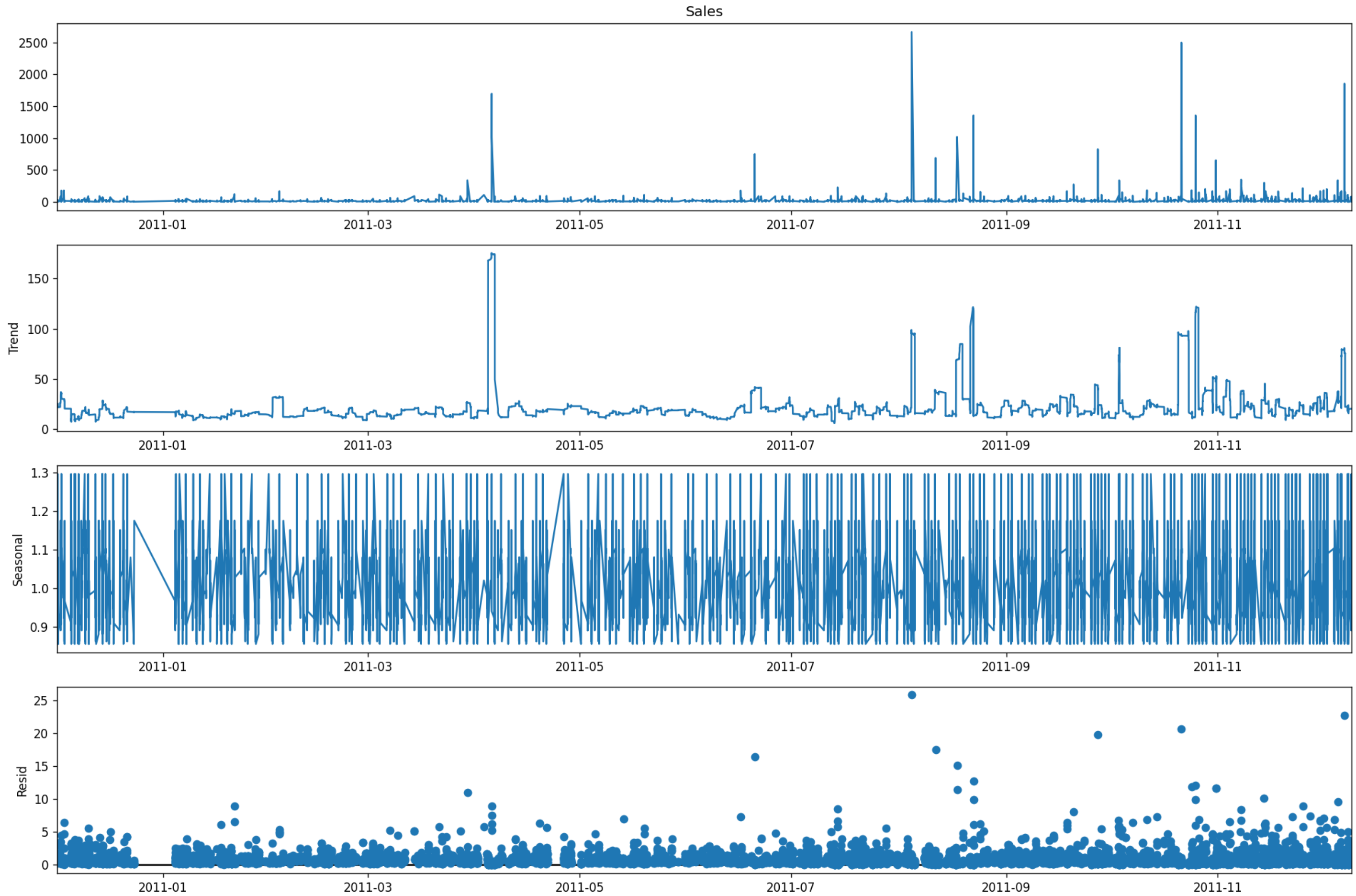
```
<Figure size 1200x480 with 0 Axes>
```



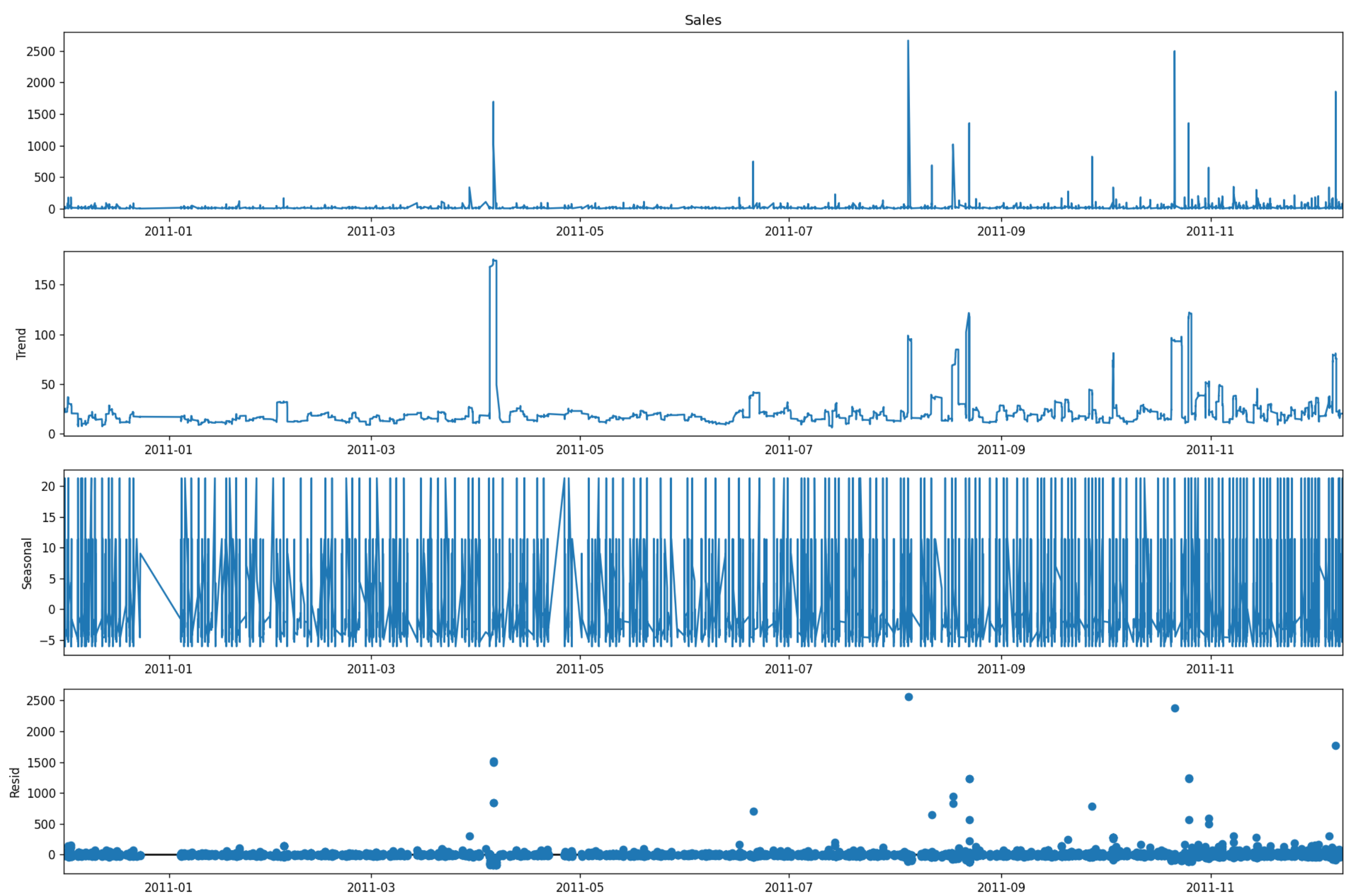
In [479…

```
# Decomposition
# Decomposition of a time series can be performed by considering the series as an additive

# Multiplicative Decomposition
multiplicative_decomposition = seasonal_decompose(Clock_TimeSeries_date_df['Sales'], model

# Additive Decomposition
additive_decomposition = seasonal_decompose(Clock_TimeSeries_date_df['Sales'], model='addi

# Plot
plt.rcParams.update({'figure.figsize': (16,12)})
multiplicative_decomposition.plot().suptitle('Multiplicative Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

additive_decomposition.plot().suptitle('Additive Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

plt.show()
```

Multiplicative Decomposition



Additive Decomposition



Sales per Day:

In [416…
```
UK_clock_ts.head()
```

Out[416…

	Sales
InvoiceDate	
2010-12-01 09:45:00	15.0
2010-12-01 10:47:00	15.0
2010-12-01 10:47:00	30.0
2010-12-01 10:47:00	30.0
2010-12-01 10:47:00	30.0

In [417…
```
UK_clock_ts.shape
```

Out[417…
```
(6281, 1)
```

Clock Dataset with only Daily Sales and Date Index:

In [418…
```
UK_DailyClock_ts = UK_clock_ts.iloc[:,0].resample('d').sum()
```

In [443…
```
UK_DailyClock_df=pd.DataFrame(UK_DailyClock_ts)
```

In [444…
```
UK_DailyClock_df.head()
```

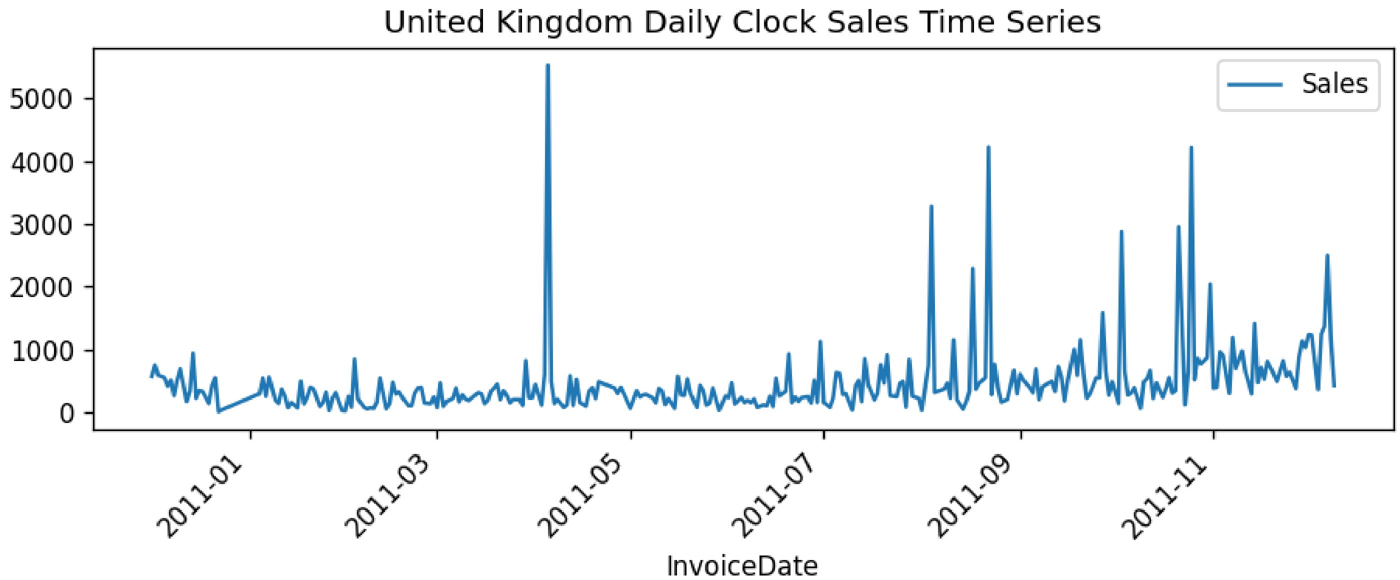
Out[444…

	Sales
InvoiceDate	
2010-12-01	568.40
2010-12-02	747.25
2010-12-03	587.62
2010-12-04	0.00
2010-12-05	547.25

In [596…
```
UK_DailyClock_df = UK_DailyClock_df[UK_DailyClock_df['Sales'] > 1]
```

In [597…
```
plt.figure(figsize=(7,4))
UK_DailyClock_df.plot()

plt.title('United Kingdom Daily Clock Sales Time Series')
plt.xticks(rotation=45)
plt.show()
```

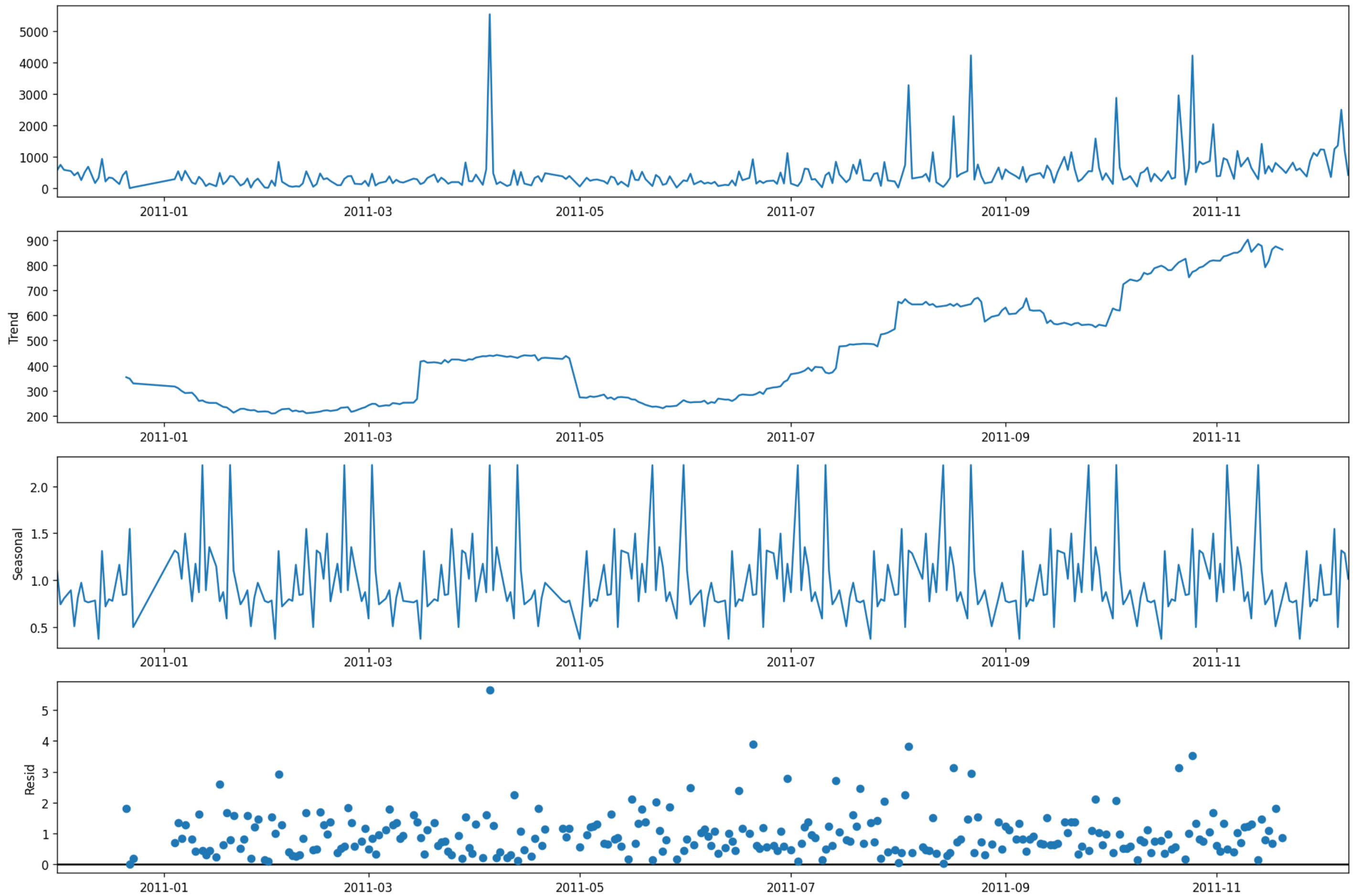
```
<Figure size 840x480 with 0 Axes>
```



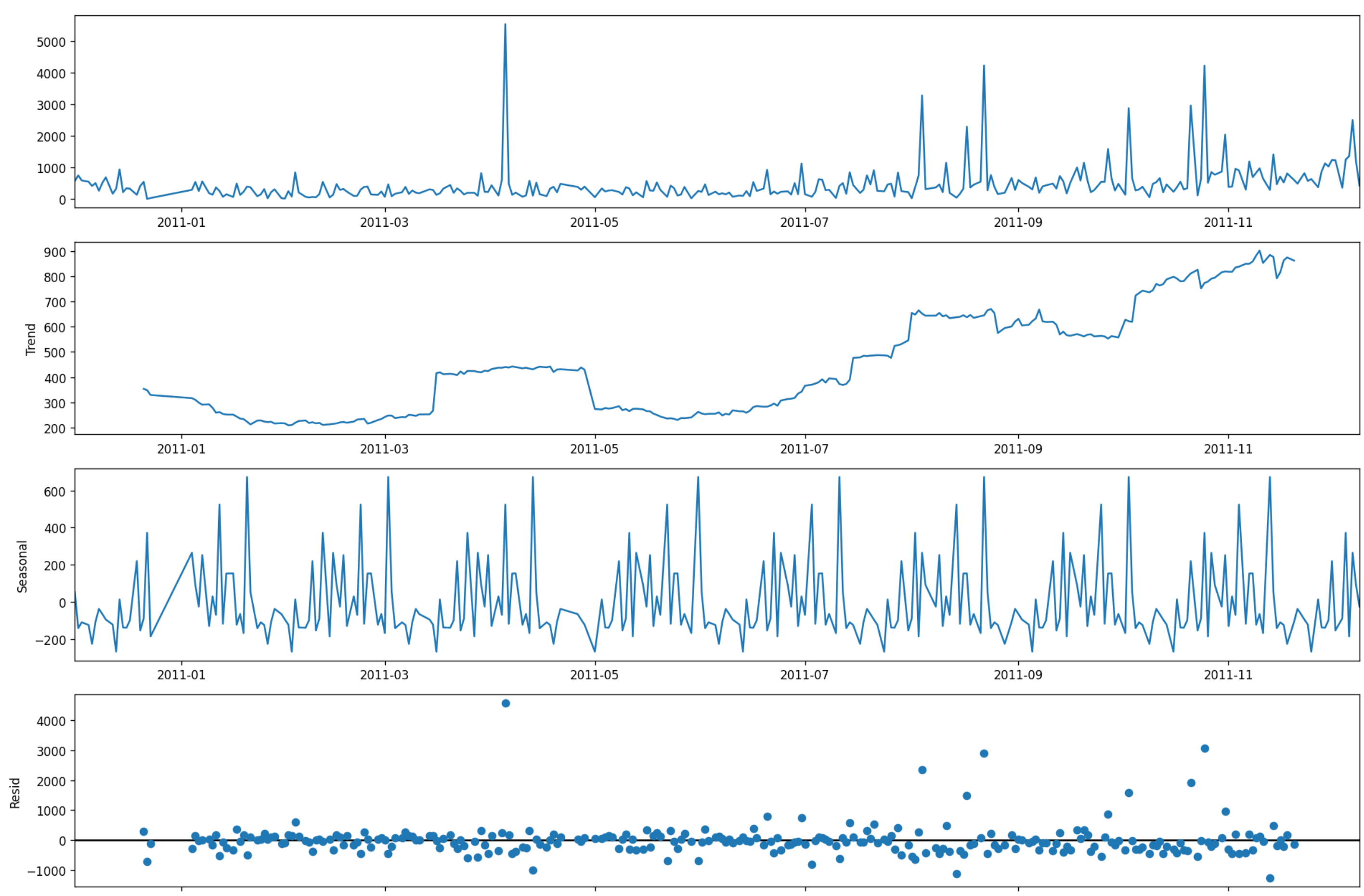
In [598…

```
# Decomposition
# Decomposition of a time series can be performed by considering the series as an additive

# Multiplicative Decomposition
multiplicative_decomposition = seasonal_decompose(UK_DailyClock_df, model='multiplicative'

# Additive Decomposition
additive_decomposition = seasonal_decompose(UK_DailyClock_df, model='additive', period=35)

# Plot
plt.rcParams.update({'figure.figsize': (16,12)})
multiplicative_decomposition.plot().suptitle('Multiplicative Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

additive_decomposition.plot().suptitle('Additive Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

plt.show()
```

Multiplicative Decomposition



Additive Decomposition



If we look at the residuals of the additive decomposition closely, it has some pattern left over.

The multiplicative decomposition, looks quite random which is good. So ideally, multiplicative decomposition should be preferred for this particular series.

Stationarity and Correlation Tests on Time Series:

In [599…

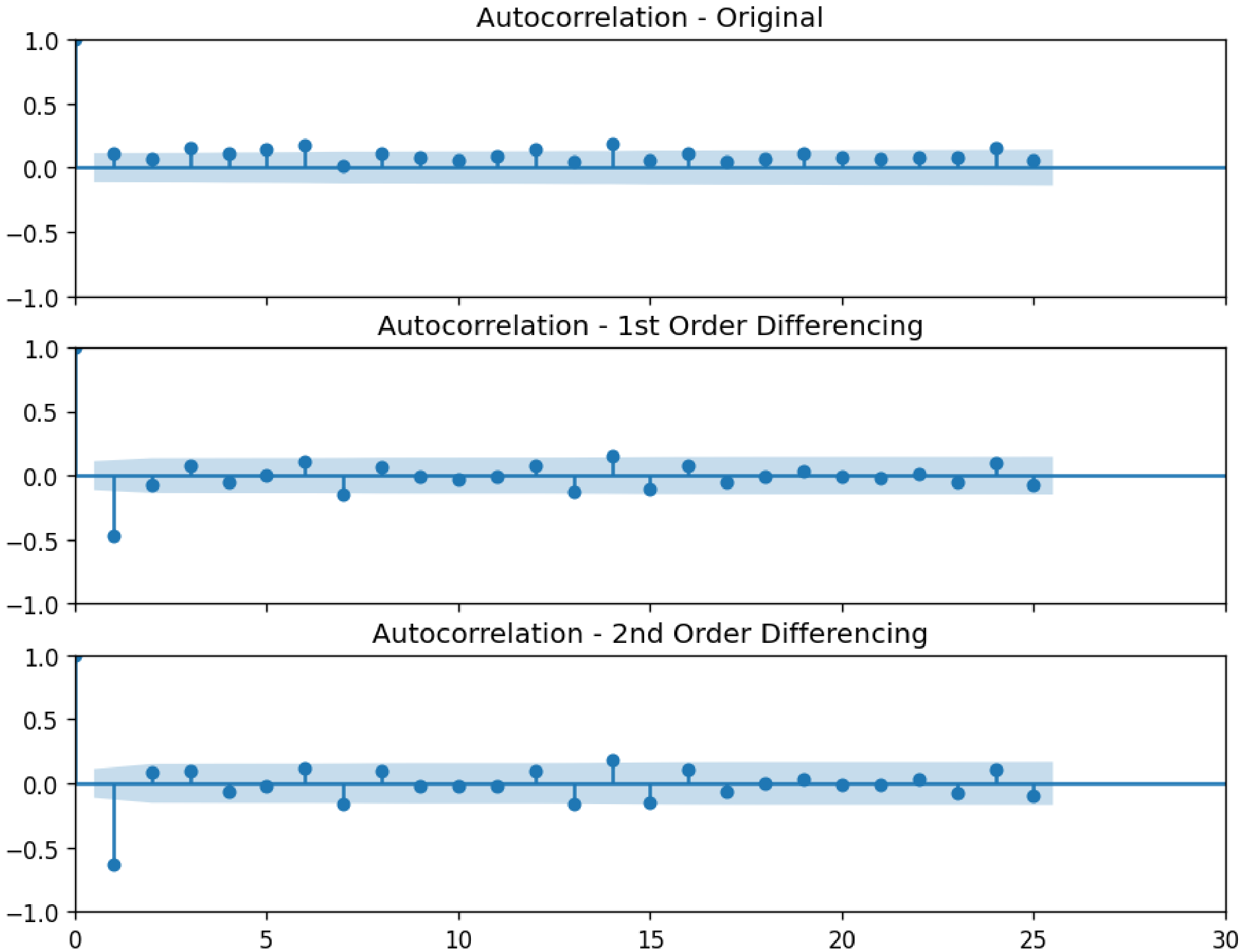
```
# Check for stationarity and if the signal is a random walk:

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

```
ADF Statistic: -4.112281
p-value: 0.000924
```

- Null Hypothesis: series is non-stationary
- Alternate Hypothesis: series is stationary
  - p-value is < 0.05 so we can reject the null hypothesis.
  - Therefore, the series is stationary

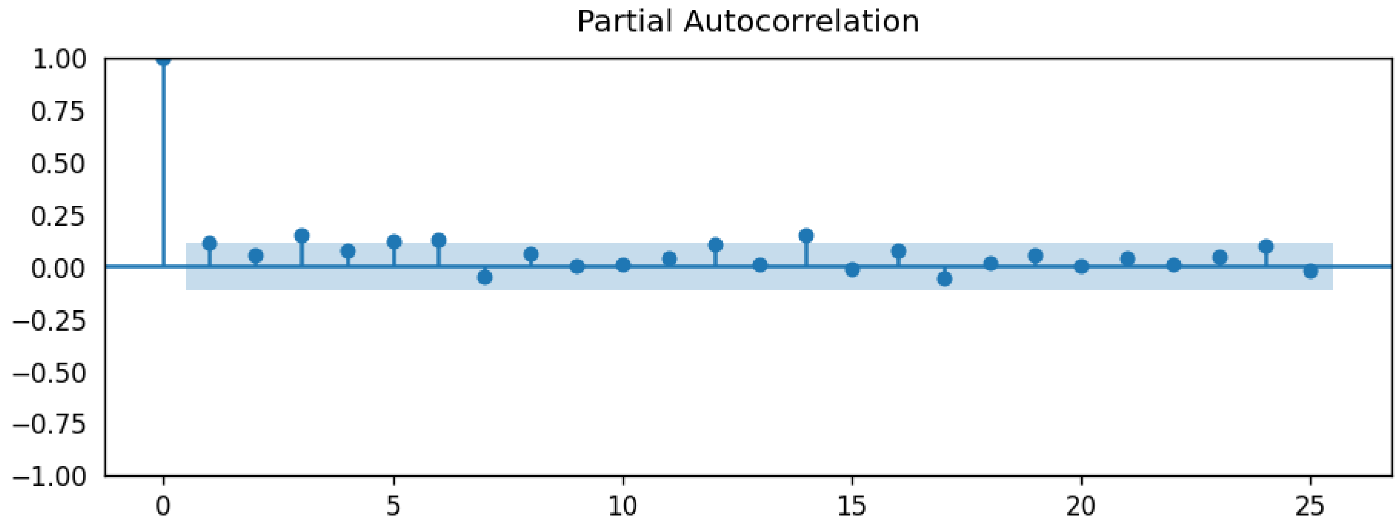
In [601…

```
plt.rcParams.update({'figure.figsize':(9,7), 'figure.dpi':120})
# Import data

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


plot_acf(UK_DailyClock_df, ax=axes[0])
axes[0].set_title('Autocorrelation - Original')
# 1st Differencing
#axes[1, 0].plot(UK_DailyClock_ts.diff()); axes[1, 0].set_title('1st Order Differencing')
plot_acf(UK_DailyClock_df.diff().dropna(), ax=axes[1])
axes[1].set_title('Autocorrelation - 1st Order Differencing')

# 2nd Differencing
#axes[2, 0].plot(UK_DailyClock_ts.diff().diff()); axes[2, 0].set_title('2nd Order Differe
plot_acf(UK_DailyClock_df.diff().diff().dropna(), ax=axes[2])
axes[2].set_title('Autocorrelation - 2nd Order Differencing')

plt.xlim([0, 30])
plt.show()
```



In [686…

```
# PACF plot of 1st differenced series
#plt.rcParams.update({'figure.figsize':(9,3), 'figure.dpi':120})
#fig, axes = plt.subplots(1, sharex=True)
##axes[0].plot(UK_DailyClock_ts.diff()); axes[0].set_title('1st Differencing')
##axes[0].set(ylim=(0,8))
#plot_pacf(UK_DailyClock_df.dropna(), lags=5, ax=axes)
#plt.xlim([0, 6])
#plt.xticks(rotation=45)

pacf = plot_pacf(UK_DailyClock_df['Sales'], lags=25)
plt.title('Partial Autocorrelation')
plt.show()
```

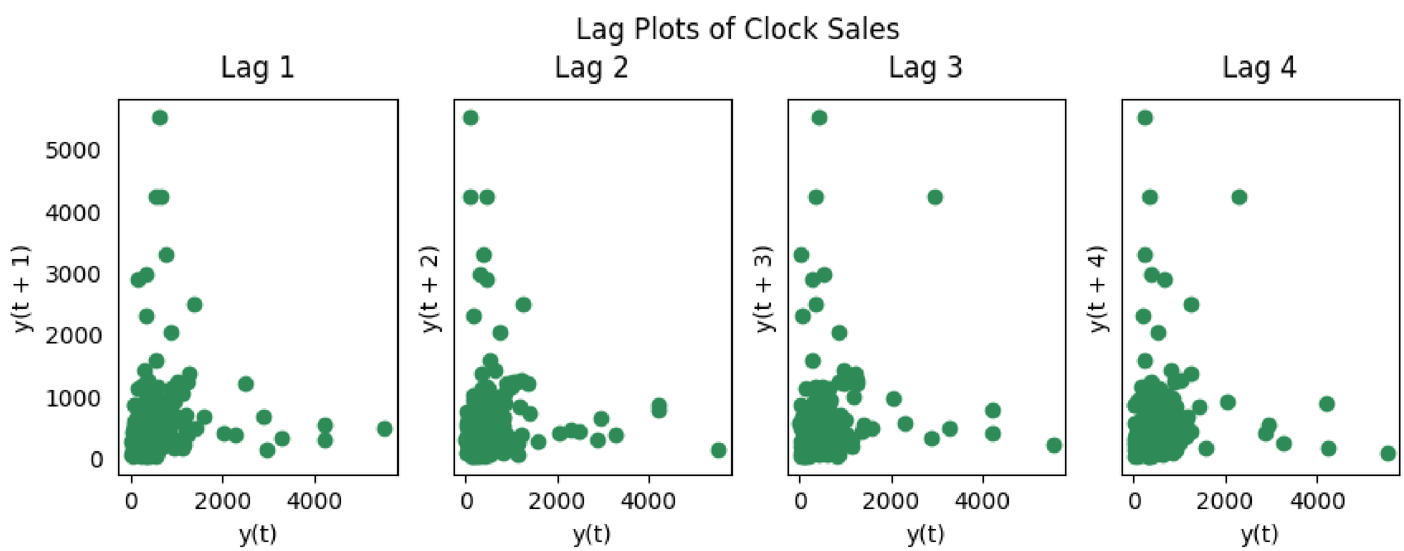


The above plot can be used to determine the order of AR model. You may note that a correlation value up to order 3 is high enough. Thus, we will train the AR model of order 3.

If partial autocorrelation values are close to 0, then values between observations and lagged observations are not correlated with one another. Inversely, partial autocorrelations with values close to 1 or -1 indicate that there exists strong positive or negative correlations between the lagged observations of the time series.

In [684…

```
# Lag Plots

from pandas.plotting import lag_plot
plt.rcParams.update({'ytick.left' : False, 'axes.titlepad':10})

# Plot
fig, axes = plt.subplots(1, 4, figsize=(10,3), sharex=True, sharey=True, dpi=100)
for i, ax in enumerate(axes.flatten()[:4]):
    lag_plot(UK_DailyClock_df['Sales'], lag=i+1, ax=ax, c='seagreen')
    ax.set_title('Lag ' + str(i+1))

fig.suptitle('Lag Plots of Clock Sales', y=1.05)
plt.show()
```



A Lag plot is a scatter plot of a time series against a lag of itself. It is normally used to check for autocorrelation. If there is any pattern existing in the series, the series is autocorrelated. If there is no such pattern, the series is likely to be random white noise.

Naive Forecast Method

In [687…

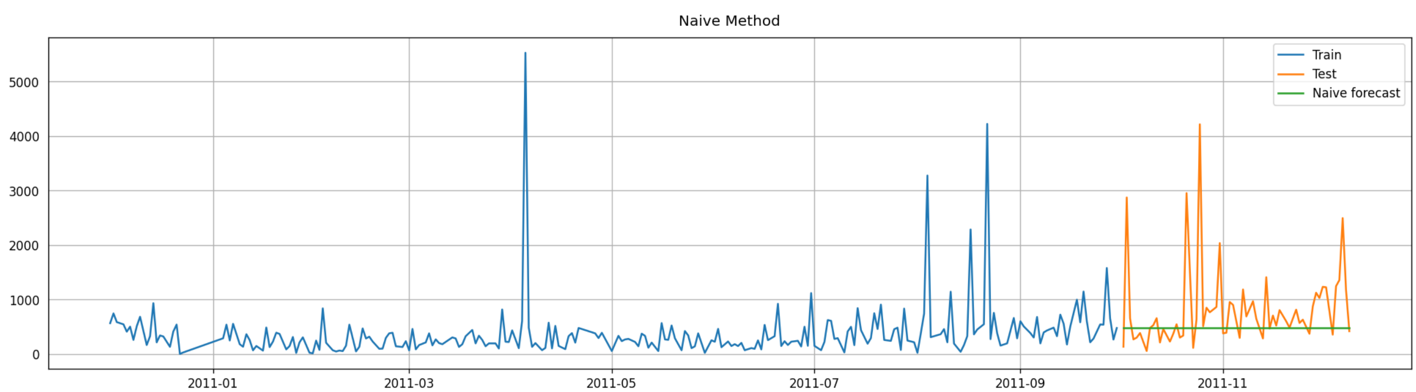
```
# Split Train / Test

train_length = 243
train = UK_DailyClock_df[0:train_length]
test = UK_DailyClock_df[train_length:]
print(len(train))
print('')
print(len(test))
```

243

60

In [689…

```
# Naive Forecast

naive = test.copy()
naive['naive_forecast'] = train['Sales'][train_length-1]

plt.figure(figsize=(20,5))
plt.grid()
plt.plot(train['Sales'], label='Train')
plt.plot(test['Sales'], label='Test')
plt.plot(naive['naive_forecast'], label='Naive forecast')
plt.legend(loc='best')
plt.title('Naive Method')
plt.show()
```



In [691…

```
n_rmse = np.sqrt(mean_squared_error(test['Sales'], naive['naive_forecast'])).round(2)
n_mape = np.round(np.mean(np.abs(test['Sales']-naive['naive_forecast'])/test['Sales'])*10(

results = pd.DataFrame({'Method':['Naive method'], 'MAPE': [n_mape], 'RMSE': [n_rmse]})
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[691…

	Method	RMSE	MAPE
0	Naive method	816.73	62.92

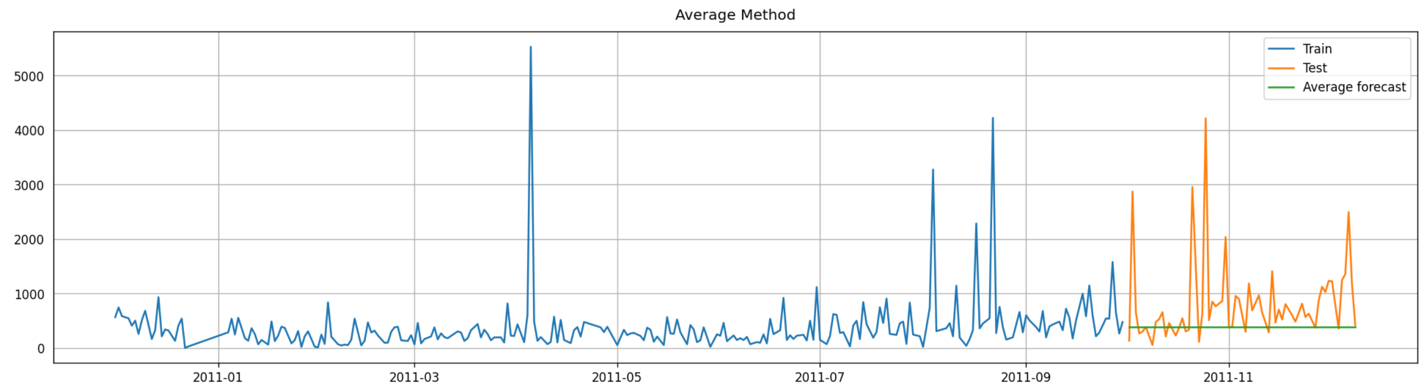
Per the graph naive method is not suitable for data with high variability

Simple Average

In [692…

```
simple_average = test.copy()
simple_average['avg_forecast'] = train['Sales'].mean()

plt.figure(figsize=(20,5))
plt.grid()
```

```
plt.plot(train['Sales'], label='Train')
plt.plot(test['Sales'], label='Test')
plt.plot(simple_average['avg_forecast'], label='Average forecast')
plt.legend(loc='best')
plt.title('Average Method')
plt.show()
```



In [694…

```
sa_rmse = np.sqrt(mean_squared_error(test['Sales'], simple_average['avg_forecast'])).round
sa_mape = np.round(np.mean(np.abs(test['Sales']-simple_average['avg_forecast'])/test['Sale

results = pd.DataFrame({'Method':['Average method'], 'MAPE': [sa_mape], 'RMSE': [sa_rmse]}
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[694…

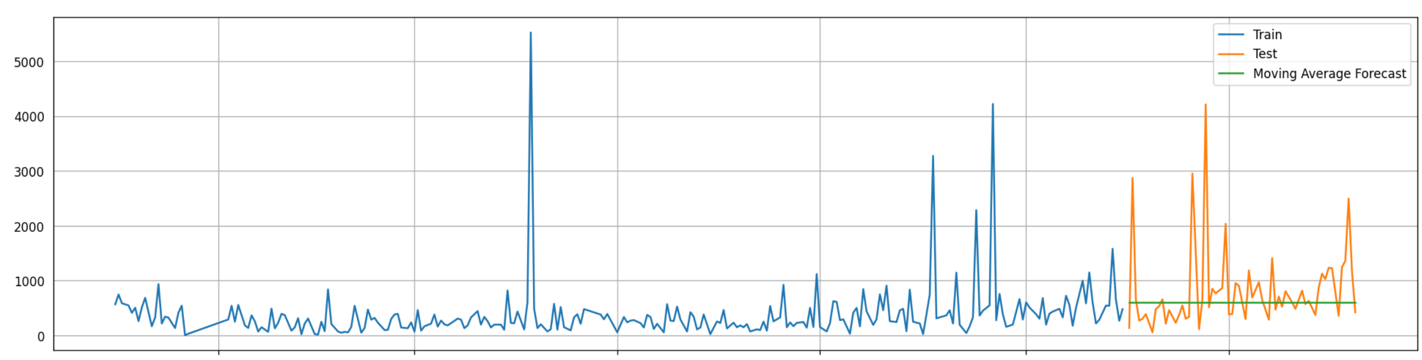
	Method	RMSE	MAPE
0	Average method	861.06	58.65

This model did improve our score, it seems the average of our data is pretty consistent.

Moving Average

In [695…

```
moving_avg = test.copy()
moving_avg['moving_avg_forecast'] = train['Sales'].rolling(60).mean().iloc[-1]

plt.figure(figsize=(20,5))
plt.grid()
plt.plot(train['Sales'], label='Train')
plt.plot(test['Sales'], label='Test')
plt.plot(moving_avg['moving_avg_forecast'], label='Moving Average Forecast')
plt.legend(loc='best')
plt.show()
```



In [697…

```
ma_rmse = np.sqrt(mean_squared_error(test['Sales'], moving_avg['moving_avg_forecast'])).rc
ma_mape = np.round(np.mean(np.abs(test['Sales']-moving_avg['moving_avg_forecast'])/test['S
```

```
results = pd.DataFrame({'Method':['Moving Average method'], 'MAPE': [ma_mape], 'RMSE': [ma
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[697…

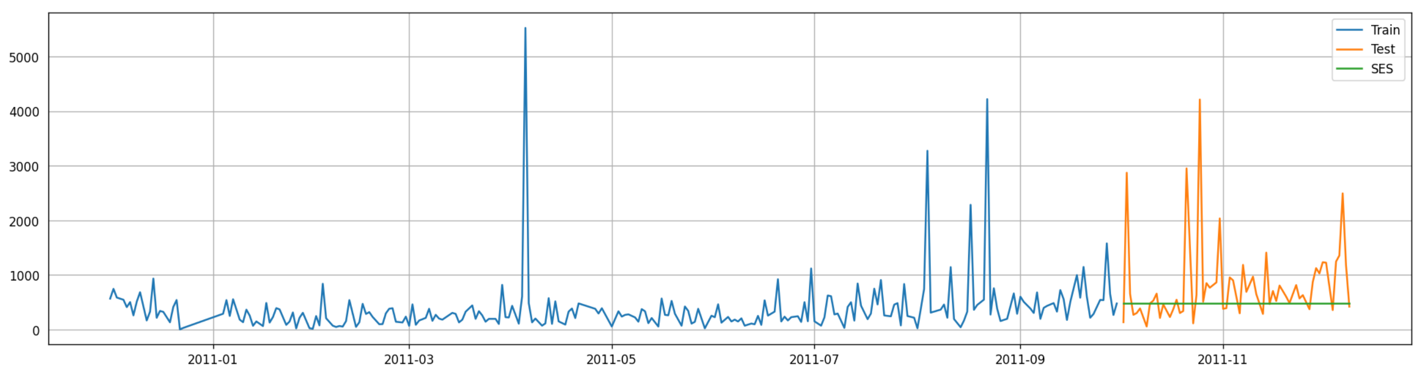
	Method	RMSE	MAPE
0	Moving Average method	771.42	74.26

Interestingly enough this model did not improve our results after choosing the last 60 days. We could adjust the window and see if that improves our results.

Simple Exponential Smoothing

In [698…

```
ses = test.copy()
ses_fit = SimpleExpSmoothing(np.asarray(train['Sales'])).fit(smoothing_level=0.6,optimizec
ses['SES'] = ses_fit.forecast(len(test))

plt.figure(figsize=(20,5))
plt.grid()
plt.plot(train['Sales'], label='Train')
plt.plot(test['Sales'], label='Test')
plt.plot(ses['SES'], label='SES')
plt.legend(loc='best')
plt.show()
```



In [700…

```
se_rmse = np.sqrt(mean_squared_error(test['Sales'], ses['SES'])).round(2)
se_mape = np.round(np.mean(np.abs(test['Sales']-ses['SES'])/test['Sales'])*100,2)

results = pd.DataFrame({'Method':['Simple Exponential Smoothing method'], 'MAPE': [se_mape
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[700…

	Method	RMSE	MAPE
0	Simple Exponential Smoothing method	812.86	63.55

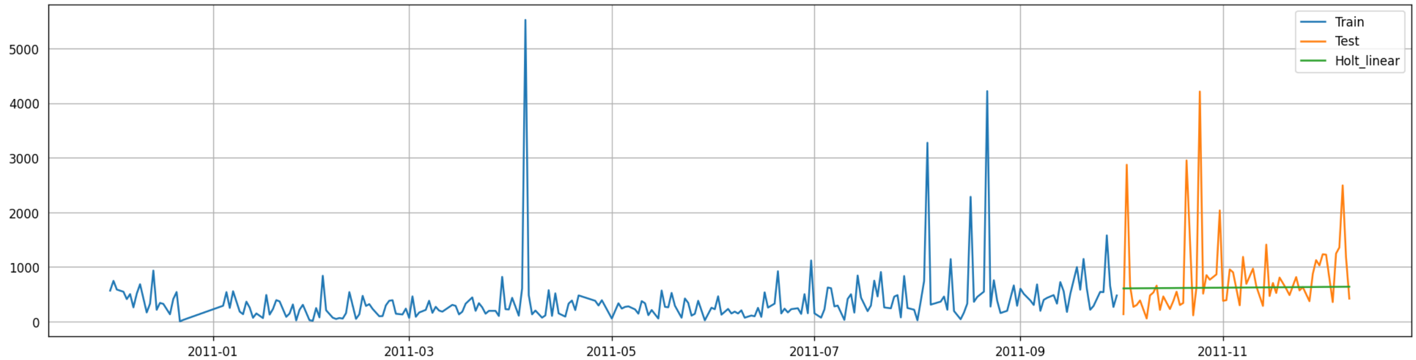
So far the second best model after simple average. We can tune to alpha from 0.6 to another number to see if it helps improve the model.

Holt Linear Method (double exponential smoothing)

In [701…

```
holt = test.copy()
holt_fit = Holt(np.asarray(train['Sales'])).fit(smoothing_level = 0.3, smoothing_slope = (
holt['Holt_linear'] = holt_fit.forecast(len(test))

plt.figure(figsize=(20,5))
```

```
plt.grid()
plt.plot(train['Sales'], label='Train')
plt.plot(test['Sales'], label='Test')
plt.plot(holt['Holt_linear'], label='Holt_linear')
plt.legend(loc='best')
plt.show()
```



In [702…

```
hl_rmse = np.sqrt(mean_squared_error(test['Sales'], holt['Holt_linear'])).round(2)
hl_mape = np.round(np.mean(np.abs(test['Sales']-holt['Holt_linear'])/test['Sales'])*100,2)

results = pd.DataFrame({'Method':['Holt Linear method'], 'MAPE': [hl_mape], 'RMSE': [hl_rr
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[702…

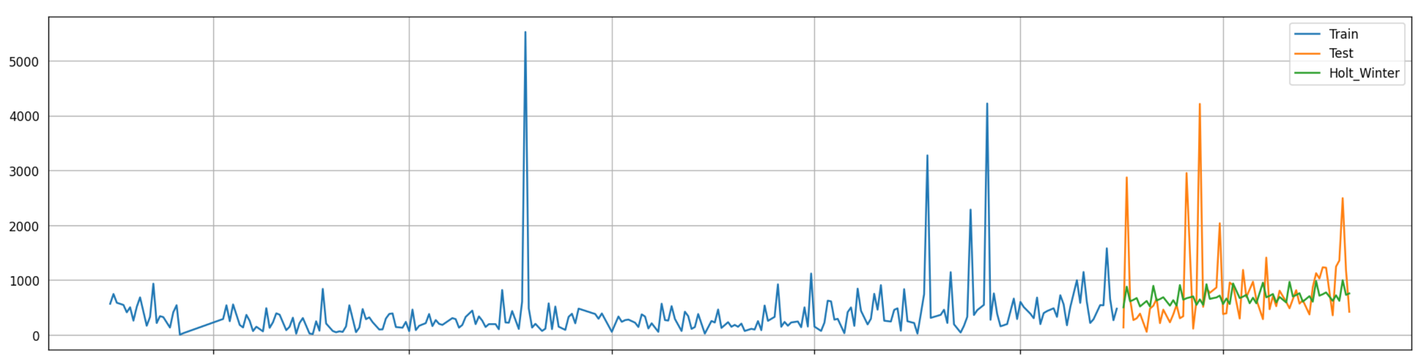
	Method	RMSE	MAPE
0	Holt Linear method	764.49	75.43

Results were not very good on the first run, model can be tuned to see if there's improvement

Holt Winters Method

In [703…

```
hw = test.copy()
hw_fit = ExponentialSmoothing(np.asarray(train['Sales']) ,seasonal_periods=7 ,trend='add',
hw['Holt_Winter'] = hw_fit.forecast(len(test))

plt.figure(figsize=(20,5))
plt.grid()
plt.plot( train['Sales'], label='Train')
plt.plot(test['Sales'], label='Test')
plt.plot(hw['Holt_Winter'], label='Holt_Winter')
plt.legend(loc='best')
plt.show()
```



In [705…

```
hw_rmse = np.sqrt(mean_squared_error(test['Sales'], hw['Holt_Winter'])).round(2)
```

```
hw_mape = np.round(np.mean(np.abs(test['Sales']-hw['Holt_Winter'])/test['Sales'])*100,2)

results = pd.DataFrame({'Method':['Holt Winters method'], 'MAPE': [hw_mape], 'RMSE': [hw_r
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[705…

	Method	RMSE	MAPE
0	Holt Winters method	731.7	79.48

Acheived better results with RMSE and the signal forecast seems to follow the general shape of the actual validation data.

ARIMA

First on entire dataset:

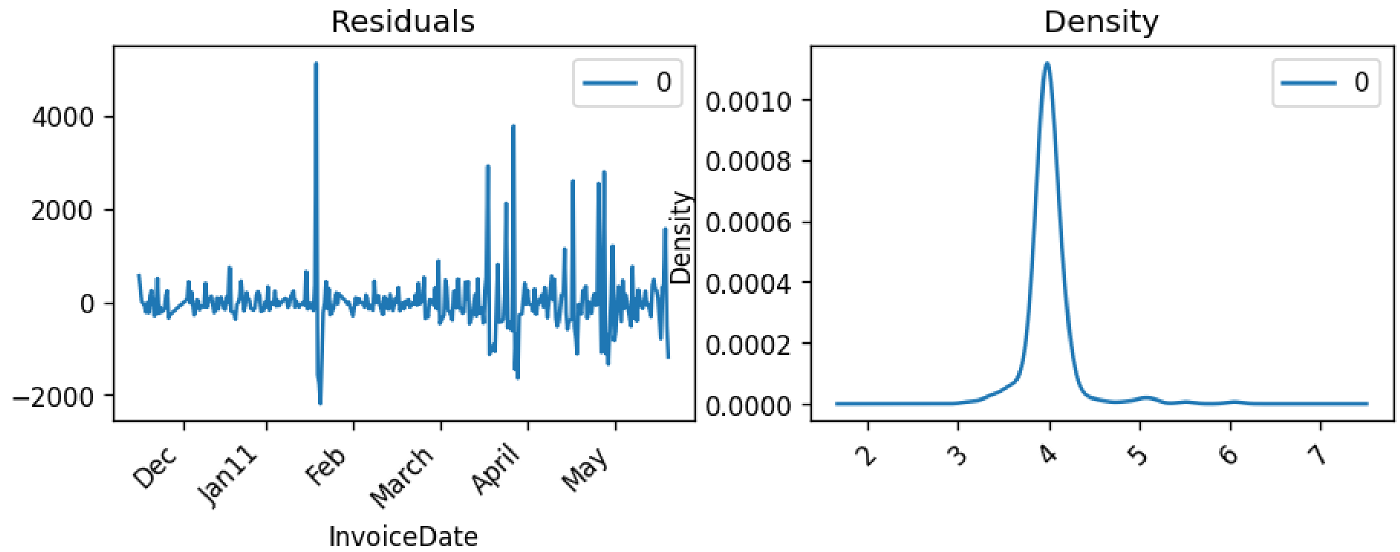
In [639…

```
# Estimate by trial and error:
# that the best p would be 2 based
# on our autocorrelation plots 1 differencing
# since the signal is stationary, and q = 0
# based on partial autocorrelation plots:

modelclks = ARIMA(UK_DailyClock_df, order=(2,1,0))
model_fitclks = modelclks.fit()
print(model_fitclks.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  Sales   No. Observations:                  303
Model:                 ARIMA(2, 1, 0)   Log Likelihood               -2383.720
Date:                Fri, 02 Dec 2022   AIC                           4773.439
Time:                        12:01:08   BIC                           4784.571
Sample:                             0   HQIC                          4777.893
                                - 303
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6678      0.029    -22.982      0.000      -0.725      -0.611
ar.L2         -0.4002      0.023    -17.258      0.000      -0.446      -0.355
sigma2      4.221e+05   1.06e+04     39.799      0.000    4.01e+05    4.43e+05
===================================================================================
Ljung-Box (L1) (Q):                   3.02   Jarque-Bera (JB):              5328.56
Prob(Q):                              0.08   Prob(JB):                         0.00
Heteroskedasticity (H):               1.66   Skew:                             2.98
Prob(H) (two-sided):                  0.01   Kurtosis:                        22.69
===================================================================================

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

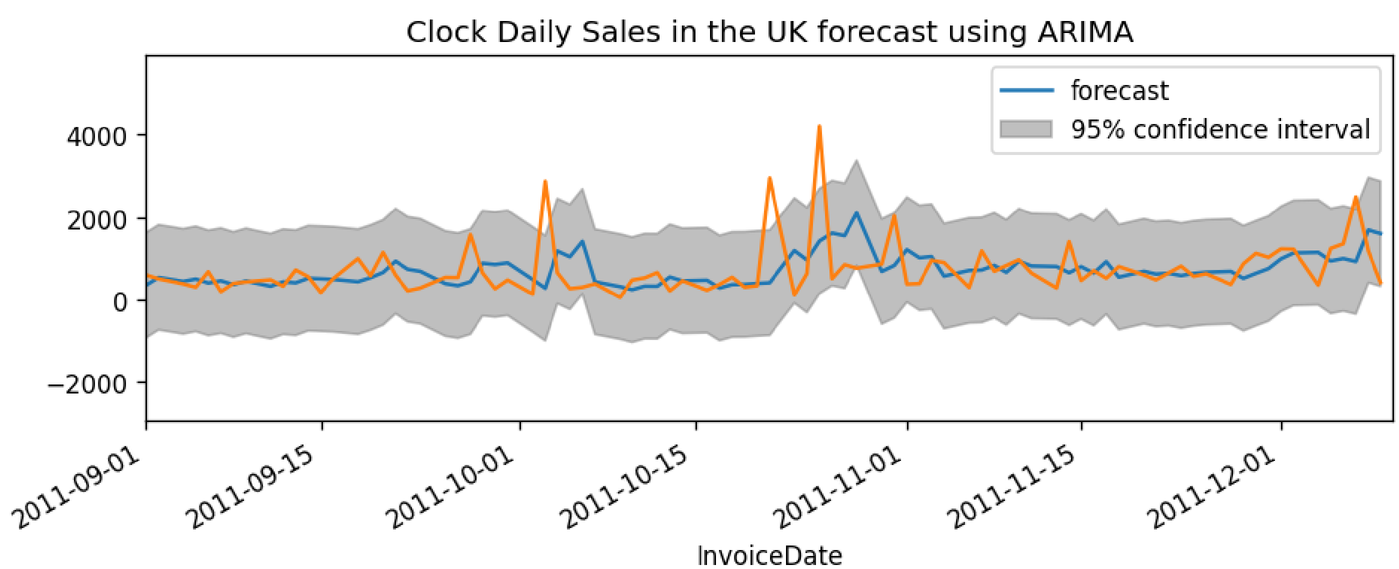
In [640…

```
residuals_clks = pd.DataFrame(model_fitclks.resid)
fig, ax = plt.subplots(1,2)
residuals_clks.plot(title="Residuals", ax=ax[0])
ax[0].set_xticklabels(['Dec','Jan11','Feb','March','April','May','June',
                       'July','Aug','Sept','Oct','Nov','Dec'],rotation=45)
residuals_clks.plot(kind='kde', title='Density', ax=ax[1])
ax[1].set_xticklabels([1,2,3,4,5,6,7,8],rotation=45)

plt.show()
```



In [641…

```
# Actual vs Fitted
plot_predict(model_fitclks)
plt.plot(UK_DailyClock_df)
plt.title('Clock Daily Sales in the UK forecast using ARIMA')
plt.xlim([pd.Timestamp('2011-09-01'), pd.Timestamp('2011-12-10')])
plt.show()
```



ARIMA model appears to be a version of a somewhat delayed and smaller version of the data. The true test is performance on validation.

Validation of the ARIMA model:

In [608…

```
UK_DailyClock_df.shape
```

Out[608…

```
(303, 1)
```

In [642…

```
# Create Training and Test
# Forecast first 9 days of December:
train_clk = UK_DailyClock_df.Sales[:'2011-11-30']
test_clk = UK_DailyClock_df.Sales['2011-12-01':]
```

Attempt Auto Arima for better parameters:

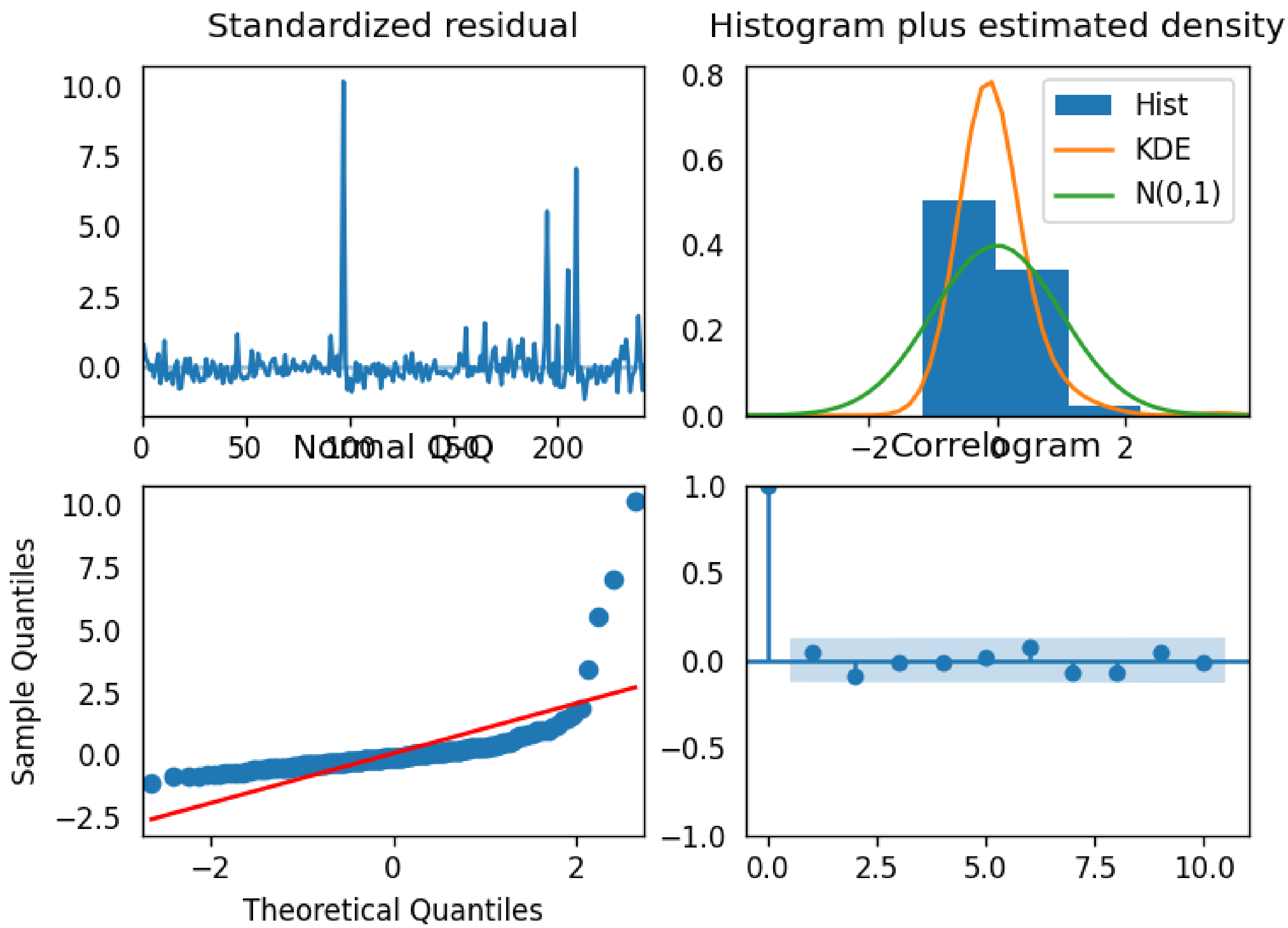
In [706…

```
model_clk = auto_arima(train, 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_clk.summary())
```

```
Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,0,0)[0]             : AIC=3740.053, Time=0.16 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=3841.810, Time=0.00 sec
 ARIMA(1,0,0)(0,0,0)[0]             : AIC=3802.624, Time=0.02 sec
 ARIMA(0,0,1)(0,0,0)[0]             : AIC=3816.718, Time=0.02 sec
 ARIMA(2,0,1)(0,0,0)[0]             : AIC=3741.935, Time=0.34 sec
 ARIMA(1,0,2)(0,0,0)[0]             : AIC=3741.923, Time=0.30 sec
 ARIMA(0,0,2)(0,0,0)[0]             : AIC=3806.975, Time=0.08 sec
 ARIMA(2,0,0)(0,0,0)[0]             : AIC=3790.880, Time=0.03 sec
 ARIMA(2,0,2)(0,0,0)[0]             : AIC=3739.021, Time=0.31 sec
 ARIMA(3,0,2)(0,0,0)[0]             : AIC=inf, Time=0.36 sec
 ARIMA(2,0,3)(0,0,0)[0]             : AIC=inf, Time=0.47 sec
 ARIMA(1,0,3)(0,0,0)[0]             : AIC=3743.504, Time=0.31 sec
 ARIMA(3,0,1)(0,0,0)[0]             : AIC=3743.447, Time=0.36 sec
 ARIMA(3,0,3)(0,0,0)[0]             : AIC=3743.269, Time=0.41 sec
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=3740.057, Time=0.33 sec

Best model:  ARIMA(2,0,2)(0,0,0)[0]
Total fit time: 3.517 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  243
Model:               SARIMAX(2, 0, 2)   Log Likelihood               -1864.510
Date:                Fri, 02 Dec 2022   AIC                           3739.021
Time:                        13:02:21   BIC                           3756.486
Sample:                             0   HQIC                          3746.055
                                - 243
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0005      0.030      0.015      0.988      -0.058       0.059
ar.L2          0.9973      0.028     35.580      0.000       0.942       1.052
ma.L1          0.0324      0.096      0.339      0.735      -0.155       0.220
ma.L2         -0.9472      0.055    -17.126      0.000      -1.056      -0.839
sigma2      2.668e+05   1.25e+04     21.276      0.000    2.42e+05    2.91e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.60   Jarque-Bera (JB):             31614.46
Prob(Q):                              0.44   Prob(JB):                         0.00
Heteroskedasticity (H):              10.09   Skew:                             6.54
Prob(H) (two-sided):                  0.00   Kurtosis:                        57.33
===================================================================================

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

In [707…

```
model_clk.plot_diagnostics(figsize=(7,5))
plt.show()
```

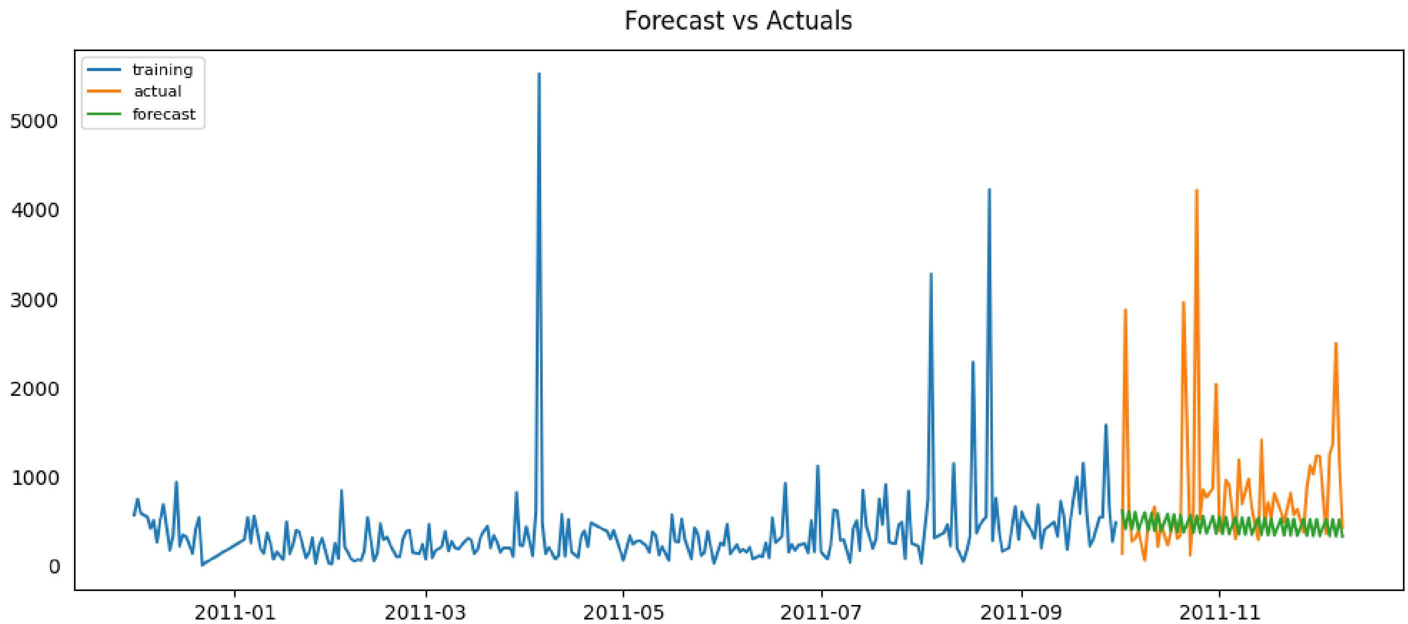


According to auto-arima, the best Arima model using auto-arima is (2,0,2)

Using auto arima Recommended model:

In [713…

```
arimaclk_model = ARIMA(train, order=(2, 0, 2))
fitted_arimaclk = arimaclk_model.fit()
# Forecast
result_clk=fitted_arimaclk.forecast(60, alpha=0.05) # 95% conf
#result_clk.to_frame()
results_indexed=pd.DataFrame(result_clk)
results_indexed['InvoiceDate']=test.index
results_indexed['InvoiceDate'] = pd.to_datetime(results_indexed['InvoiceDate'])
results_indexed=results_indexed.set_index('InvoiceDate')
## 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(results_indexed, 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.xlim([pd.Timestamp('2011-10-01'), pd.Timestamp('2011-12-10')])
plt.show()
```



In [715…

```
# Calculating RMSE and MAPE

arima_rmse = np.sqrt(mean_squared_error(test['Sales'], results_indexed['predicted_mean']))
arima_mape = np.round(np.mean(np.abs(test['Sales'] - results_indexed['predicted_mean'])/te

results = pd.DataFrame({'Method':['ARIMA method'], 'MAPE': [arima_mape], 'RMSE': [arima_rm
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[715…

	Method	RMSE	MAPE
0	ARIMA method	851.56	75.39

In [718…

```
# Table Results

Table = PrettyTable(["Model","MAPE", "RMSE"])
Table.add_row(["Naive", n_mape, n_rmse])
Table.add_row(["Simple Average", sa_mape, sa_rmse])
Table.add_row(["Moving Average", ma_mape, ma_rmse])
Table.add_row(["Simple Exponential", se_mape, se_rmse])
Table.add_row(["Holt Linear", hl_mape, hl_rmse])
Table.add_row(["Holt Winter", hw_mape, hw_rmse])
Table.add_row(["ARIMA", arima_mape, arima_rmse])
print("Time Series Model Performance Sorted by MAPE")
Table.sortby = "RMSE"
print(Table)
```

```
Time Series Model Performance Sorted by MAPE
+--------------------+-------+--------+
|       Model        |  MAPE |  RMSE  |
+--------------------+-------+--------+
|    Holt Winter     | 79.48 | 731.7  |
|    Holt Linear     | 75.43 | 764.49 |
|   Moving Average   | 74.26 | 771.42 |
| Simple Exponential | 63.55 | 812.86 |
|       Naive        | 62.92 | 816.73 |
|       ARIMA        | 75.39 | 851.56 |
|   Simple Average   | 58.65 | 861.06 |
+--------------------+-------+--------+
```

Extra: Full Clean Retail Data Set:

Time series by Date:

In [265…

```
Retail_TimeSeries_df.to_csv('Retail_DataClean_beforeDate.csv')
```

In [308…

```
#Retail_TimeSeries_test_df = read_csv('Retail_DataClean_beforeDate.csv', header=0, index_c
#Retail_TimeSeries_daily_df = Retail_TimeSeries_test_df.resample('D', on='InvoiceDate').Sa
#Retail_TimeSeries_daily_df=Retail_TimeSeries_daily_df.set_index('InvoiceDate')
```

In [329…

```
Retail_TimeSeries_date_df = read_csv('Retail_DataClean_beforeDate.csv', header=0, index_co
Retail_TimeSeries_date_df['InvoiceDate'] = pd.to_datetime(Retail_TimeSeries_date_df['Invoi

Retail_TimeSeries_date_df=Retail_TimeSeries_date_df.set_index('InvoiceDate')
```

In [332…

```
Retail_TimeSeries_date_df.head()
```

Out[332…

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country	Sales
InvoiceDate								
2010-12-01 08:26:00	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2.55	17850.0	United Kingdom	15.30
2010-12-01 08:26:00	536365	71053	WHITE METAL LANTERN	6	3.39	17850.0	United Kingdom	20.34
2010-12-01 08:26:00	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2.75	17850.0	United Kingdom	22.00
2010-12-01 08:26:00	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	3.39	17850.0	United Kingdom	20.34
2010-12-01 08:26:00	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	3.39	17850.0	United Kingdom	20.34

Focus only on UK sales:

In [333…

```
Retail_TimeSeries_dateUK_df = Retail_TimeSeries_date_df[Retail_TimeSeries_date_df['Country
```

In [292…

```
#Retail_TimeSeries_dateUK_df=Retail_TimeSeries_dateUK_df.set_index('InvoiceDate')
```

In [334…

```
Retail_TimeSeries_dateUK_df.head()
```

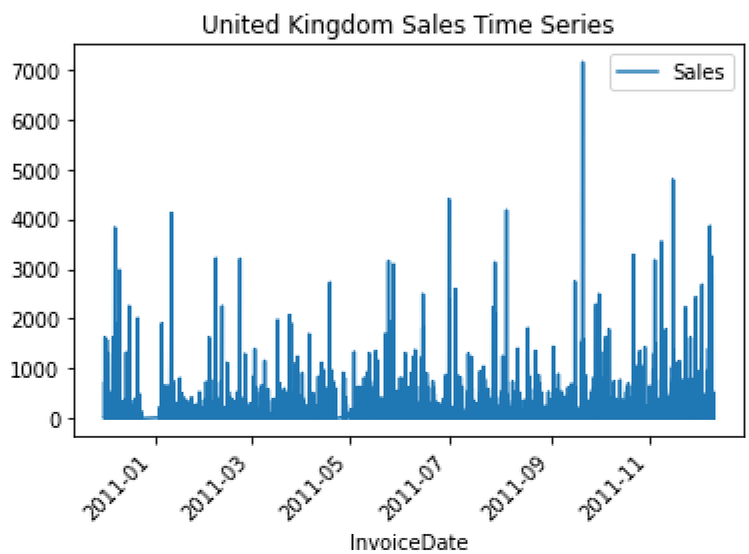
Out[334…

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country	Sales
InvoiceDate								
2010-12-01 08:26:00	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2.55	17850.0	United Kingdom	15.30
2010-12-01 08:26:00	536365	71053	WHITE METAL LANTERN	6	3.39	17850.0	United Kingdom	20.34

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country	Sales
InvoiceDate								
2010-12-01 08:26:00	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2.75	17850.0	United Kingdom	22.00
2010-12-01 08:26:00	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	3.39	17850.0	United Kingdom	20.34
2010-12-01 08:26:00	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	3.39	17850.0	United Kingdom	20.34

In [335…

```
UK_Sales_ts = Retail_TimeSeries_dateUK_df.copy()
UK_Sales_ts.drop(columns=['InvoiceNo', 'CustomerID','UnitPrice','Quantity',
                         'StockCode','Description','Country'],inplace=True)

UK_Sales_ts.plot()
plt.title('United Kingdom Sales Time Series')
plt.xticks(rotation=45)
plt.show()
```



Sales per Day:

In [336…

```
UK_Sales_ts.head()
```

Out[336…

	Sales
InvoiceDate	
2010-12-01 08:26:00	15.30
2010-12-01 08:26:00	20.34
2010-12-01 08:26:00	22.00
2010-12-01 08:26:00	20.34
2010-12-01 08:26:00	20.34

In [337…

```
UK_Sales_ts.shape
```

Out[337…

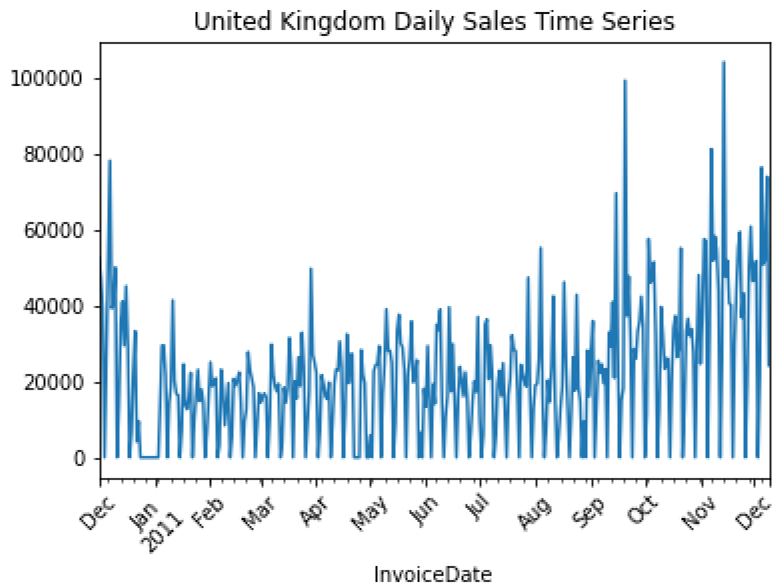
```
(477092, 1)
```

In [338…

```
UK_DailySales_ts = UK_Sales_ts.iloc[:,0].resample('d').sum()
```

In [340…

```
UK_DailySales_ts.plot()
plt.title('United Kingdom Daily Sales Time Series')
plt.xticks(rotation=45)
plt.show()
```



Module 4 ARIMA approach:

In [341…

```
# Check for stationarity and if the signal is a random walk:

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

```
ADF Statistic: -2.046738
p-value: 0.266463
```

- Null Hypothesis: series is non-stationary
- Alternate Hypothesis: series is stationary
  - p-value is > 0.05 so we cannot reject the null hypothesis.
  - Therefore, the series is non-stationary (has seasonality/trend)

In [348…

```
UK_DailySales_ts=pd.DataFrame(UK_DailySales_ts)

values_dailyUKsales=pd.DataFrame(UK_DailySales_ts.Sales.values)
```

In [349…

```
UK_DailySales_ts.head()
```

Out[349…

	Sales
InvoiceDate	

	Sales
InvoiceDate	
2010-12-01	52666.96
2010-12-02	47159.23
2010-12-03	39020.87
2010-12-04	0.00
2010-12-05	25460.31

In [350…

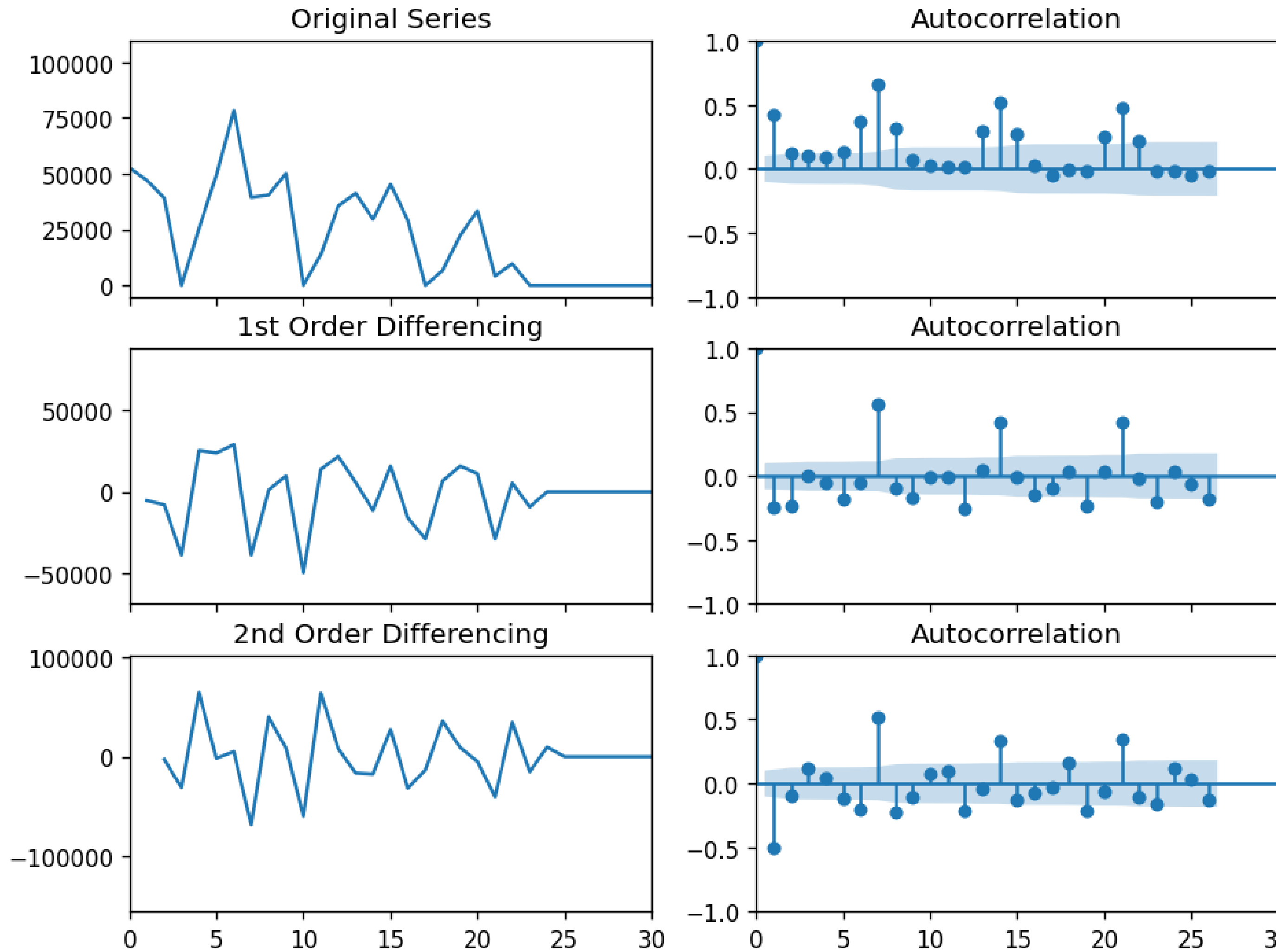
```
values_dailyUKsales.head()
```

Out[350…

	0
0	52666.96
1	47159.23
2	39020.87
3	0.00
4	25460.31

In [353…

```
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_dailyUKsales); axes[0, 0].set_title('Original Series')


plot_acf(UK_DailySales_ts, ax=axes[0, 1])
# 1st Differencing
axes[1, 0].plot(values_dailyUKsales.diff()); axes[1, 0].set_title('1st Order Differencing'
plot_acf(values_dailyUKsales.diff().dropna(), ax=axes[1, 1])
# 2nd Differencing
axes[2, 0].plot(values_dailyUKsales.diff().diff()); axes[2, 0].set_title('2nd Order Differe
plot_acf(values_dailyUKsales.diff().diff().dropna(), ax=axes[2, 1])
plt.xlim([0, 30])
plt.show()
```



DIfferencing first order is enough to reach stationarity

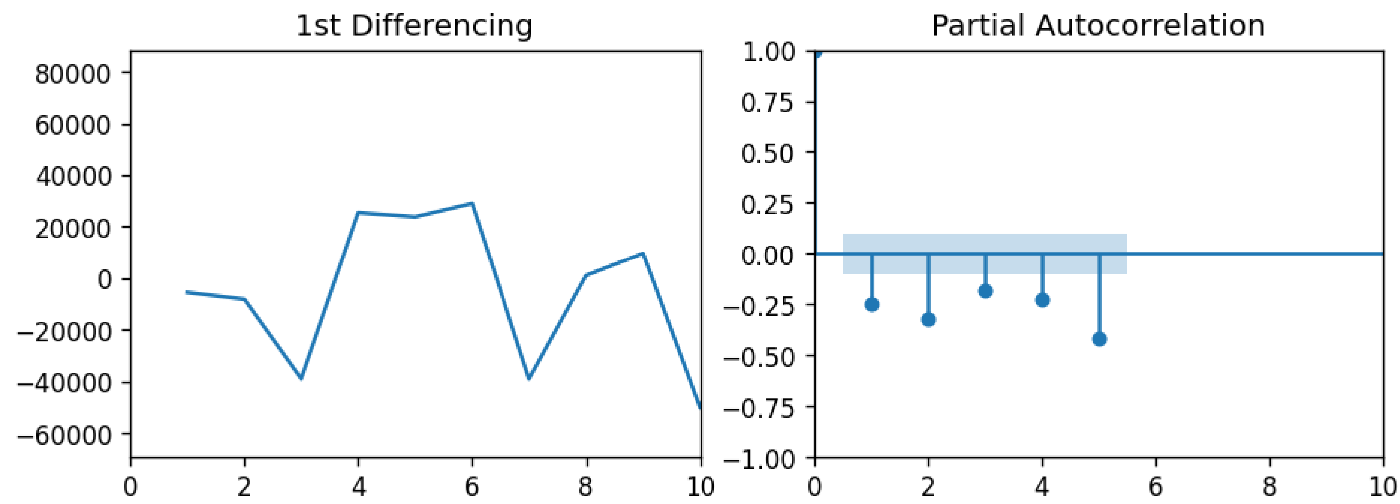
In [356…

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

```
ADF Statistic: -7.732066
p-value: 0.000000
```

In [358…

```
# 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_dailyUKsales.diff()); axes[0].set_title('1st Differencing')
axes[1].set(ylim=(0,5))
plot_pacf(values_dailyUKsales.diff().dropna(), lags=5, ax=axes[1])
plt.xlim([0, 10])
plt.show()
```



In [361…

```python
# Test for random walk :

# 1,0,0 ARIMA Model
model = ARIMA(values_dailyUKsales, order=(1,0,0))
model_fit = model.fit()
print(model_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      0   No. Observations:                  374
Model:                 ARIMA(1, 0, 0)   Log Likelihood               -4144.816
Date:                Thu, 01 Dec 2022   AIC                           8295.632
Time:                        15:16:09   BIC                           8307.405
Sample:                             0   HQIC                          8300.307
                                - 374
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       2.197e+04   1474.528     14.901      0.000    1.91e+04    2.49e+04
ar.L1          0.4205      0.051      8.211      0.000       0.320       0.521
sigma2      2.459e+08      0.086   2.86e+09      0.000    2.46e+08    2.46e+08
===================================================================================
Ljung-Box (L1) (Q):                   0.20   Jarque-Bera (JB):               240.11
Prob(Q):                              0.66   Prob(JB):                         0.00
Heteroskedasticity (H):               2.77   Skew:                             0.93
Prob(H) (two-sided):                  0.00   Kurtosis:                         6.45
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 9.08e+24. Standa
rd errors may be unstable.
```

Since the coefficient for the AR(1) model is not even near 1, then this signal is not a random walk (we already knew that just upon observation though)

In [371…

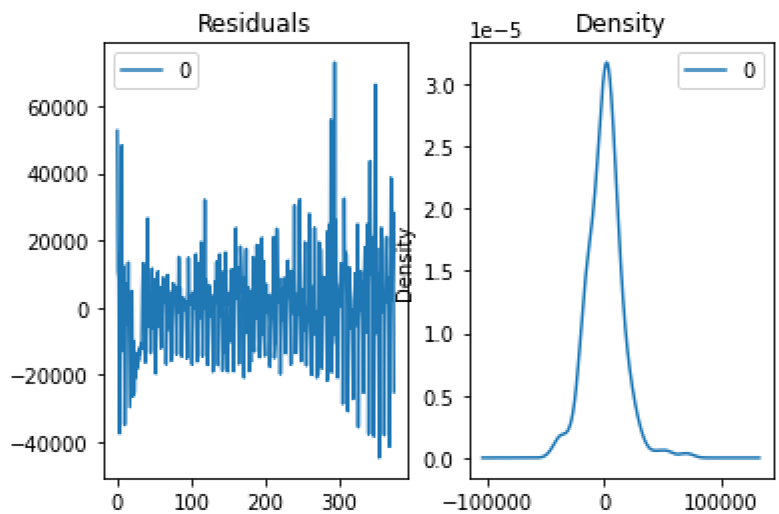
```python
# 2,1,2 ARIMA Model
model_dailysales = ARIMA(values_dailyUKsales, order=(2,1,2))
model_fit_dailysales = model_dailysales.fit()
print(model_fit_dailysales.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      0   No. Observations:                  374
Model:                 ARIMA(2, 1, 2)   Log Likelihood               -4120.861
```

```
Date:                     Thu, 01 Dec 2022   AIC                           8251.723
Time:                             15:22:13   BIC                           8271.331
Sample:                                  0   HQIC                          8259.509
                                     - 374
Covariance Type:                       opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.5584      0.073     -7.670      0.000      -0.701      -0.416
ar.L2          0.1167      0.046      2.525      0.012       0.026       0.207
ma.L1         -0.0757      0.043     -1.768      0.077      -0.160       0.008
ma.L2         -0.8264      0.040    -20.482      0.000      -0.905      -0.747
sigma2      1.695e+08   2.13e-10   7.94e+17      0.000     1.7e+08     1.7e+08
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):               141.27
Prob(Q):                              0.92   Prob(JB):                         0.00
Heteroskedasticity (H):               2.50   Skew:                             0.51
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.84
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.31e+33. Standa
rd errors may be unstable.
```

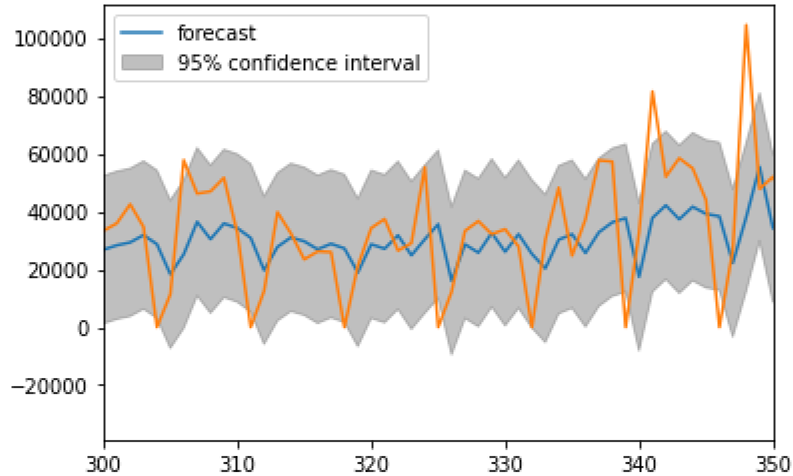
In [372…

```python
residuals = pd.DataFrame(model_fit_dailysales.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 [373…

```python
# Actual vs Fitted
plot_predict(model_fit_dailysales)
plt.plot(values_dailyUKsales)
plt.xlim([300,350])
plt.show()
```



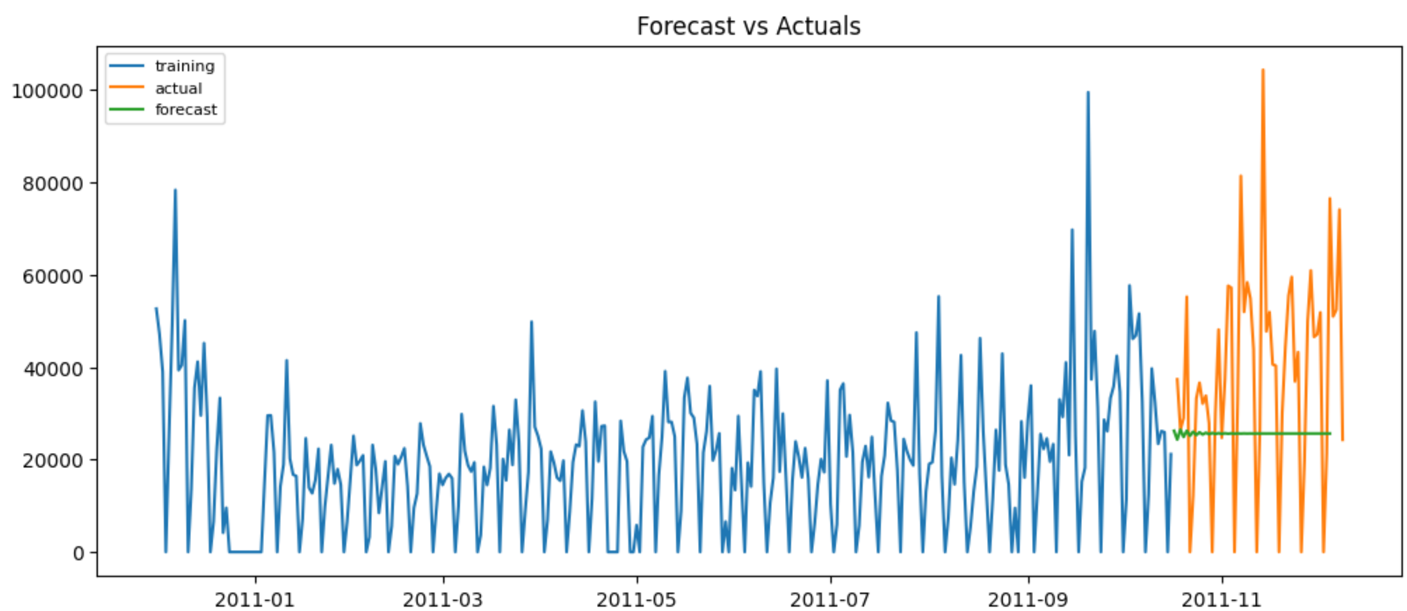
validating the ARIMA model:

In [394…

```
# Create Training and Test
train = UK_DailySales_ts.Sales[:320]
test = UK_DailySales_ts.Sales[321:]
```

In [395…

```
arima212_model = ARIMA(train, order=(2, 1, 2))
fitted_arima212 = arima212_model.fit()
# Forecast
result=fitted_arima212.get_forecast(50, 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(result.predicted_mean, 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 [402…

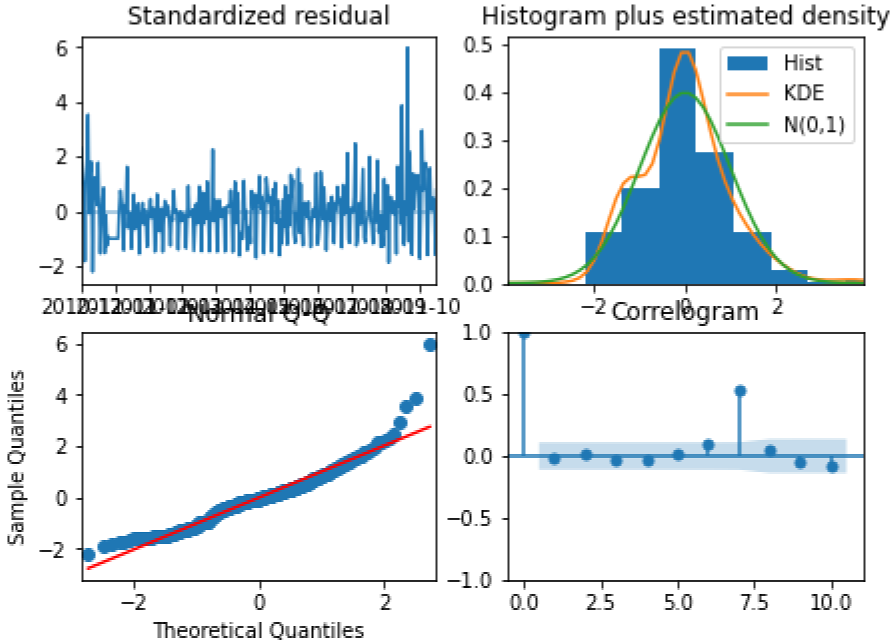
```
model = auto_arima(train, start_p=1, start_q=1,
```

```
    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=True, # No Seasonality
    start_P=0,
    D=0,
    trace=True,
    error_action='ignore',
    suppress_warnings=True,
    stepwise=True)
print(model.summary())
```

```
Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=7004.784, Time=0.18 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=7049.806, Time=0.04 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=7004.767, Time=0.08 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=7006.440, Time=0.11 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=7367.236, Time=0.03 sec
 ARIMA(2,0,0)(0,0,0)[0] intercept   : AIC=7003.645, Time=0.16 sec
 ARIMA(3,0,0)(0,0,0)[0] intercept   : AIC=7004.908, Time=0.24 sec
 ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=7005.869, Time=0.35 sec
 ARIMA(3,0,1)(0,0,0)[0] intercept   : AIC=7006.937, Time=0.49 sec
 ARIMA(2,0,0)(0,0,0)[0]             : AIC=7079.779, Time=0.13 sec

Best model:  ARIMA(2,0,0)(0,0,0)[0] intercept
Total fit time: 1.883 seconds
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  320
Model:               SARIMAX(2, 0, 0)   Log Likelihood               -3497.822
Date:                Thu, 01 Dec 2022   AIC                           7003.645
Time:                        17:58:20   BIC                           7018.718
Sample:                    12-01-2010   HQIC                          7009.664
                         - 10-16-2011
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept   1.329e+04   1524.670      8.717      0.000    1.03e+04    1.63e+04
ar.L1          0.4078      0.060      6.755      0.000       0.289       0.526
ar.L2         -0.1002      0.048     -2.077      0.038      -0.195      -0.006
sigma2      1.799e+08      0.080   2.26e+09      0.000     1.8e+08     1.8e+08
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):               276.03
Prob(Q):                              0.89   Prob(JB):                         0.00
Heteroskedasticity (H):               1.70   Skew:                             1.06
Prob(H) (two-sided):                  0.01   Kurtosis:                         7.03
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 7.12e+24. Standa
rd errors may be unstable.
```

In [403…

```
model.plot_diagnostics(figsize=(7,5))
plt.show()
```


Standardized residual
Histogram plus estimated density
Hist
KDE
N(0,1)
Normal Q-Q
Sample Quantiles
Theoretical Quantiles
Correlogram