ADS 506 Final

Project Code

John Chen

Azucena Faus

Setup

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)
```

Load/Observe Data

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

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
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
272433	560772	22720	SET OF 3 CAKE TINS PANTRY DESIGN	1	7/20/2011 16:12	10.79	NaN	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
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 = False
                                                                                 reset_inde

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 [719…

```
# 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

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:

        invoice_I2=Retail_df_NR[invoice_I].index
        Retail_df_NR=Retail_df_NR.drop(invoice_I2, axis=0)


#Retail_df_NR.shape
```

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.

# The matching item returns are found by matching CustomerID,
# Item StockCode, and Quantity inverted.

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

	InvoiceNo	StockCode	Description_x	Quantity	InvoiceDate_x	UnitPrice_x	CustomerID	Country_x	InvoiceNo_y
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


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

	Quantity	UnitPrice	CustomerID
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['Quantity'] < 1000)
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…

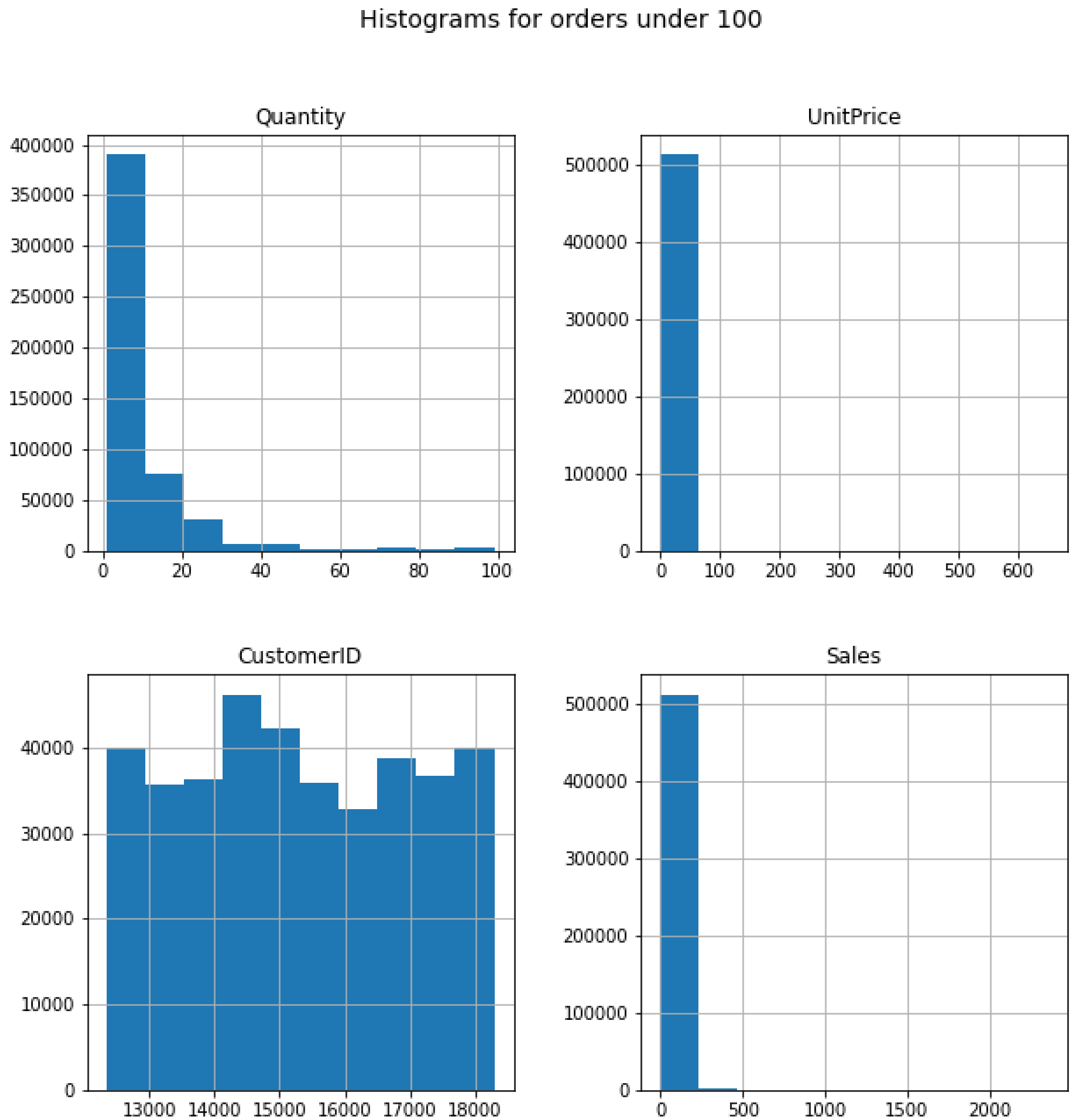
```
dfg_small_order = Retail_df_small_orders.groupby(['Description']).size().to_frame().
                                    sort_values([0], ascending = False).head(10).reset_inc
dfg_small_order.columns = ['Description', 'count']
fig = px.histogram(dfg_small_order, x='Description', y = 'count',
                  title='Top Ten Item Descriptions Purchased on Small Size orders')
fig.layout.yaxis.title.text = 'count'
fig.show()
```

In [256…

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

Out[256…

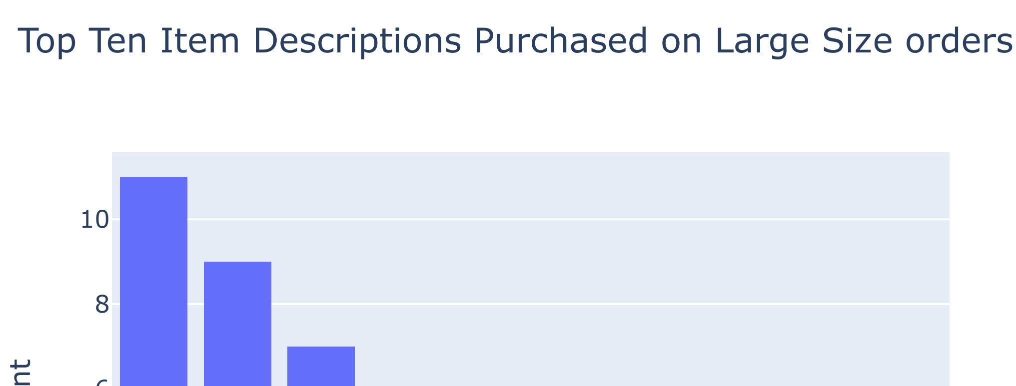
```
Text(0.5, 0.98, 'Histograms for orders under 100')
```



Large (>1000) order distributions:

In [407…

```
dfg_large_order = Retail_df_large_orders.groupby(['Description']).size().to_frame().sort_v
                                                                          ascending = False).hea
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()
```

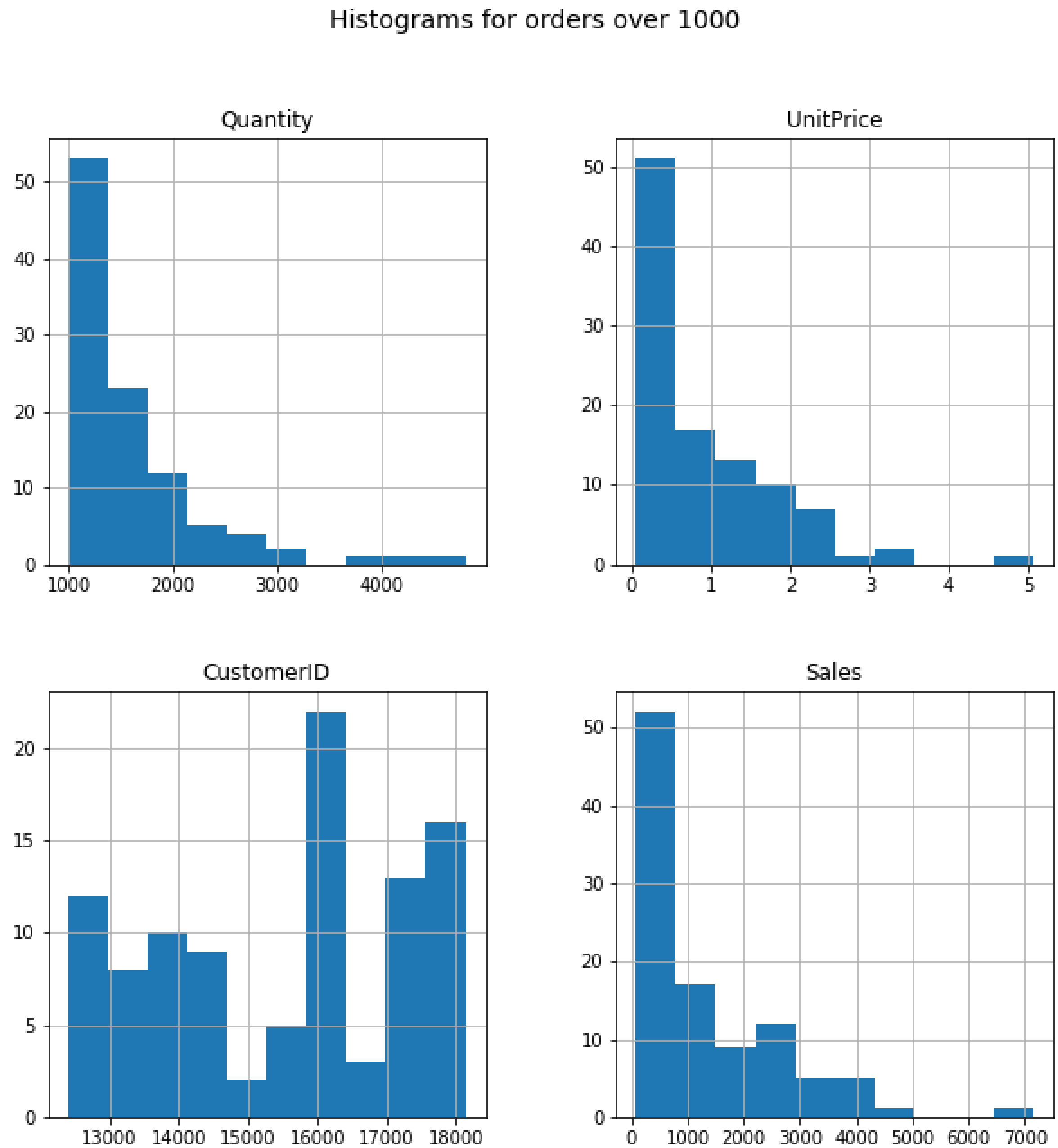


In [224…

```
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')
```



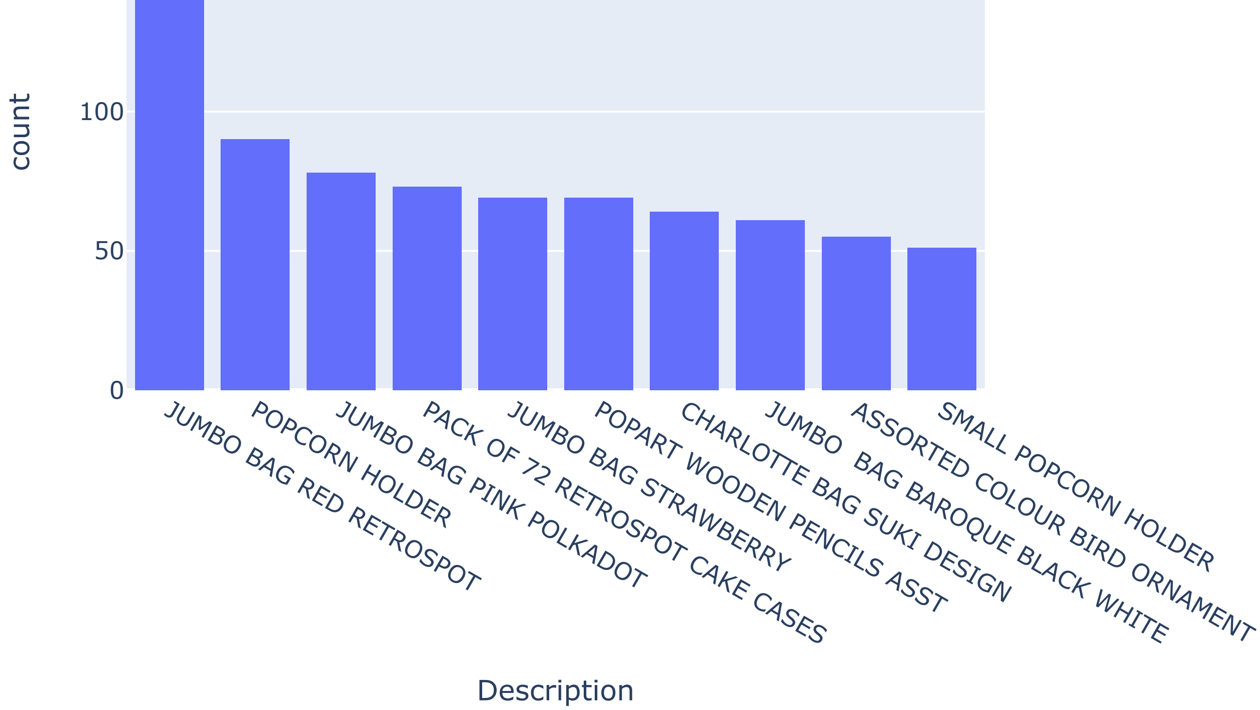
In [225…

```
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().
                                        sort_values([0], ascending = False).head(
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()
```



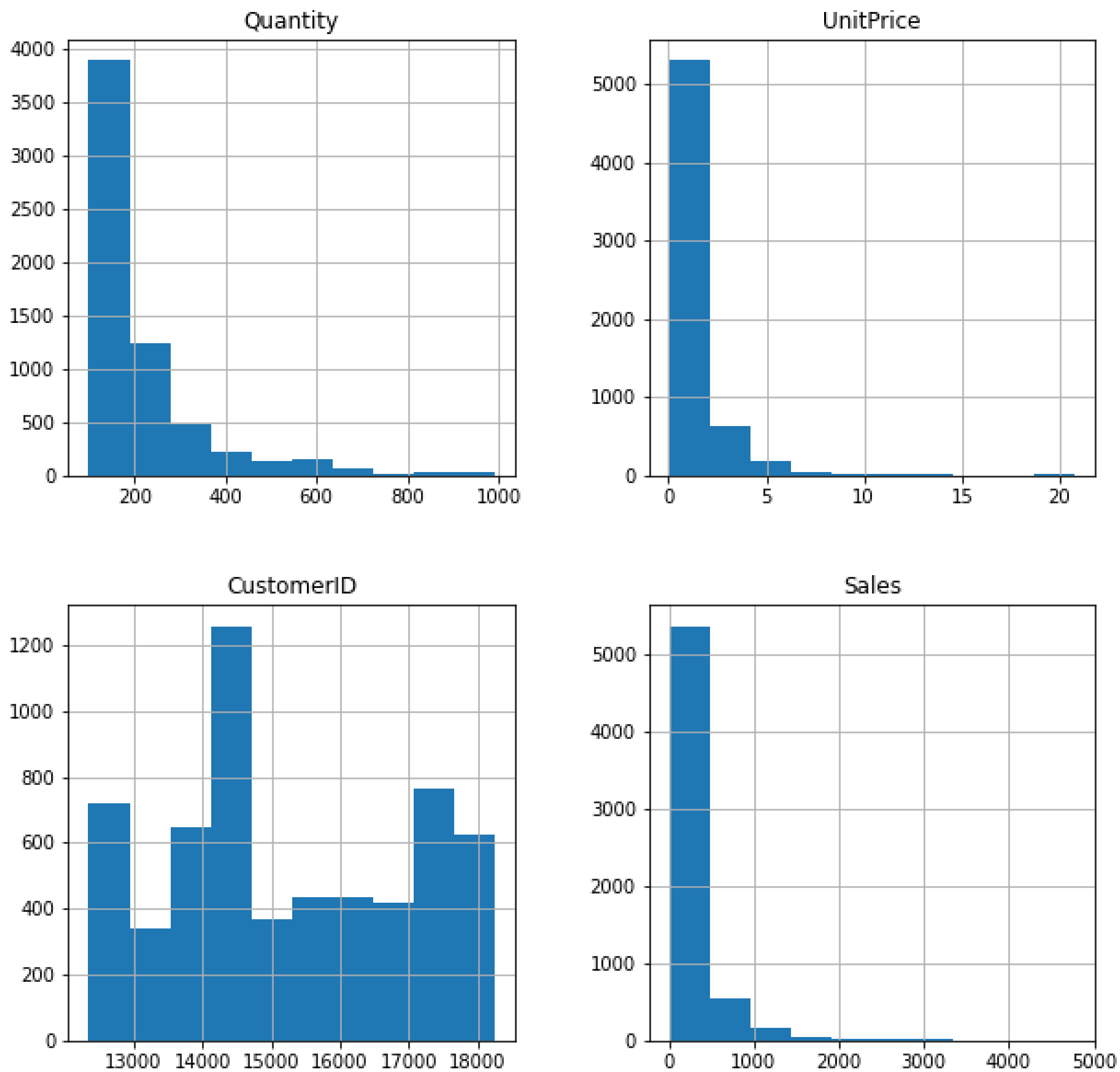
In [226…

```
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')
```

Histograms for orders over 100 but less than 1000

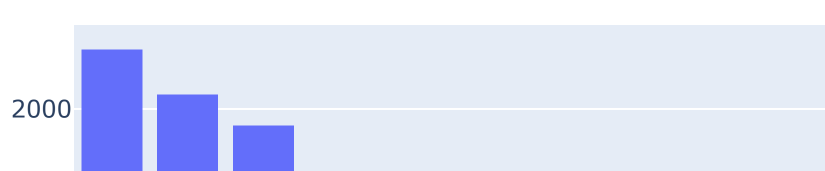


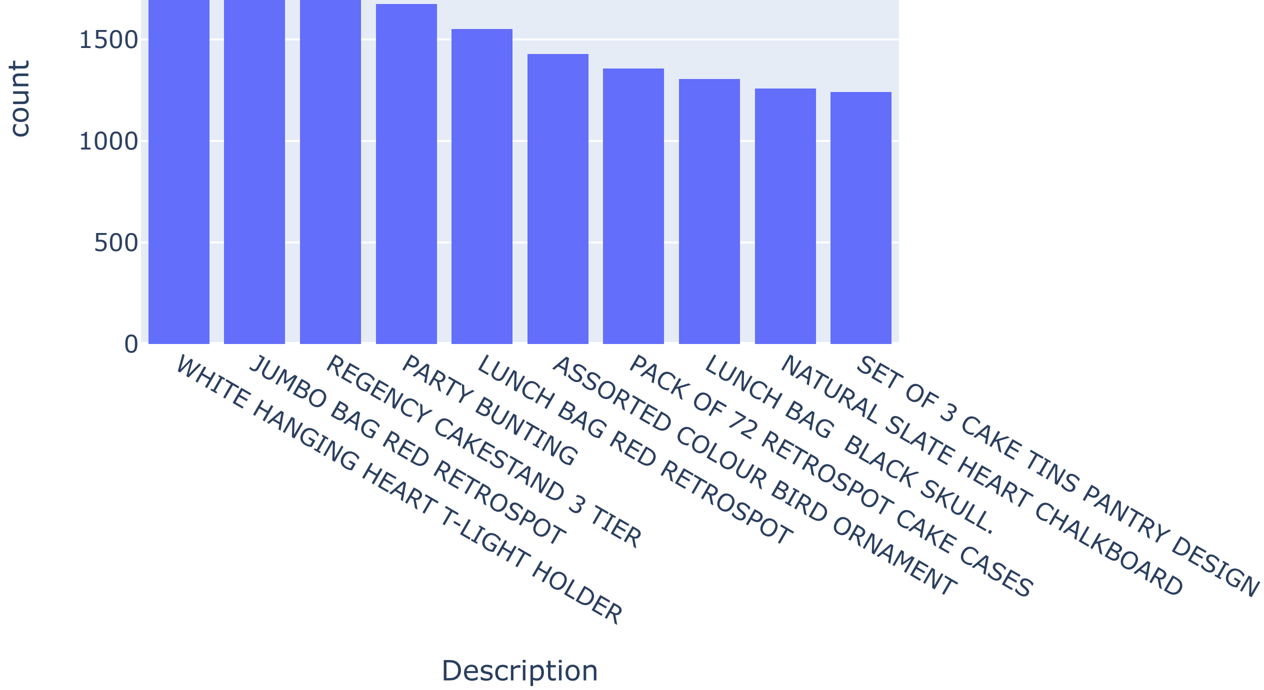
Most popular items purchased:

In [409…

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

dfg = Retail_TimeSeries_df.groupby(['Description']).size().to_frame().sort_values([0],
                                                          ascending = False).head(10).re
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()
```

Top Ten Item Descriptions Purchased on the Site





In [233…

```
MostCommonItem = Retail_TimeSeries_df[Retail_TimeSeries_df['Description'].
                                      str.contains('WHITE HANGING HEART T-LIGHT HOLDER',
                                                   na=False)]
```

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=False)]
```

In [441…

```
clock.shape
```

Out[441…

```
(7025, 9)
```

In [259…

```
clock_test = Retail_df_small_orders[Retail_df_small_orders['Description'].str.contains('CI
                                                                                       na=
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
```

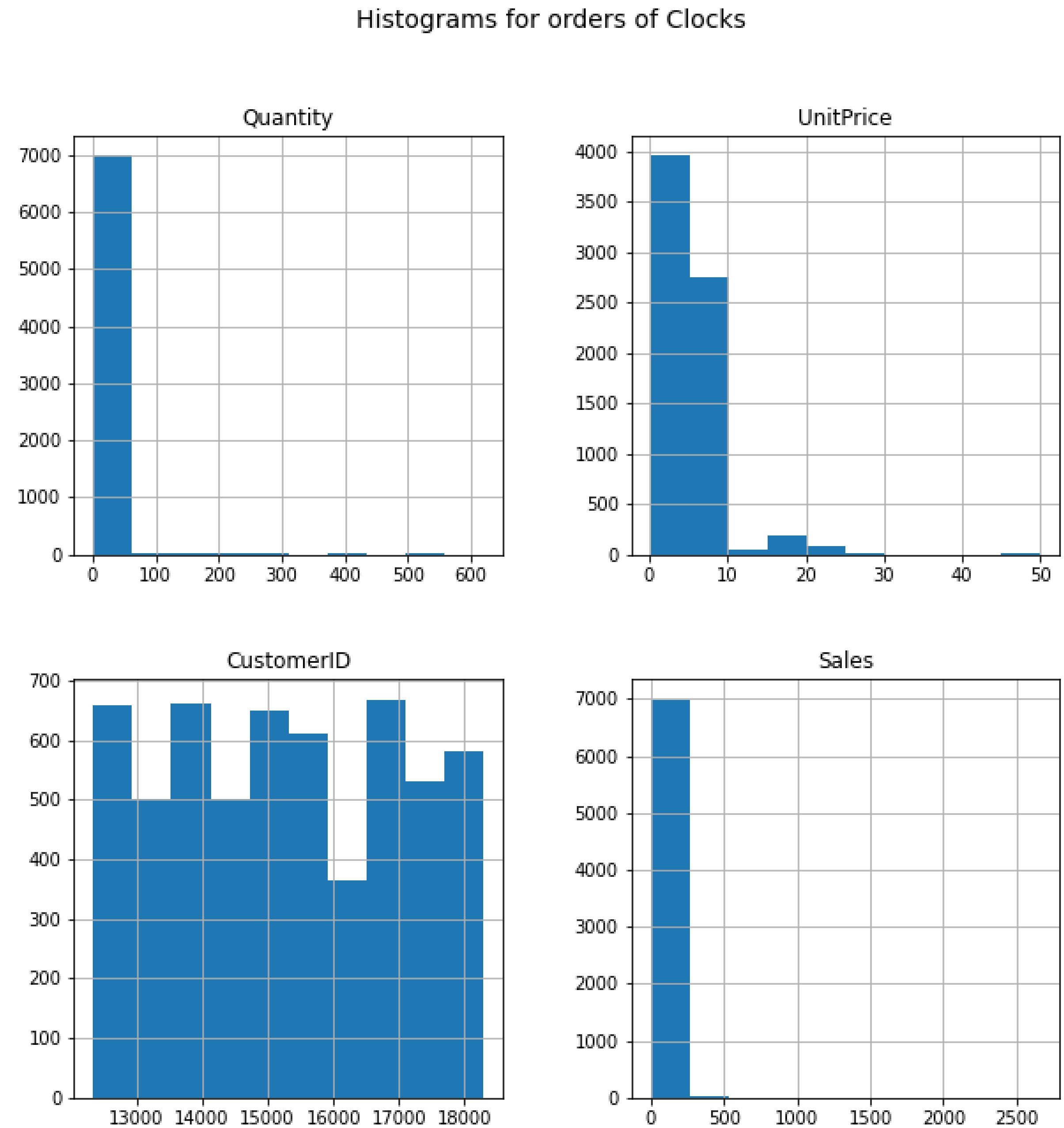
Sales from clocks alone amount to a total of 168,306 as opposed to the most popular item that amounts to 94,641 and with projected interest in clocks going up, must look at initial forecasts for this item.

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')
```



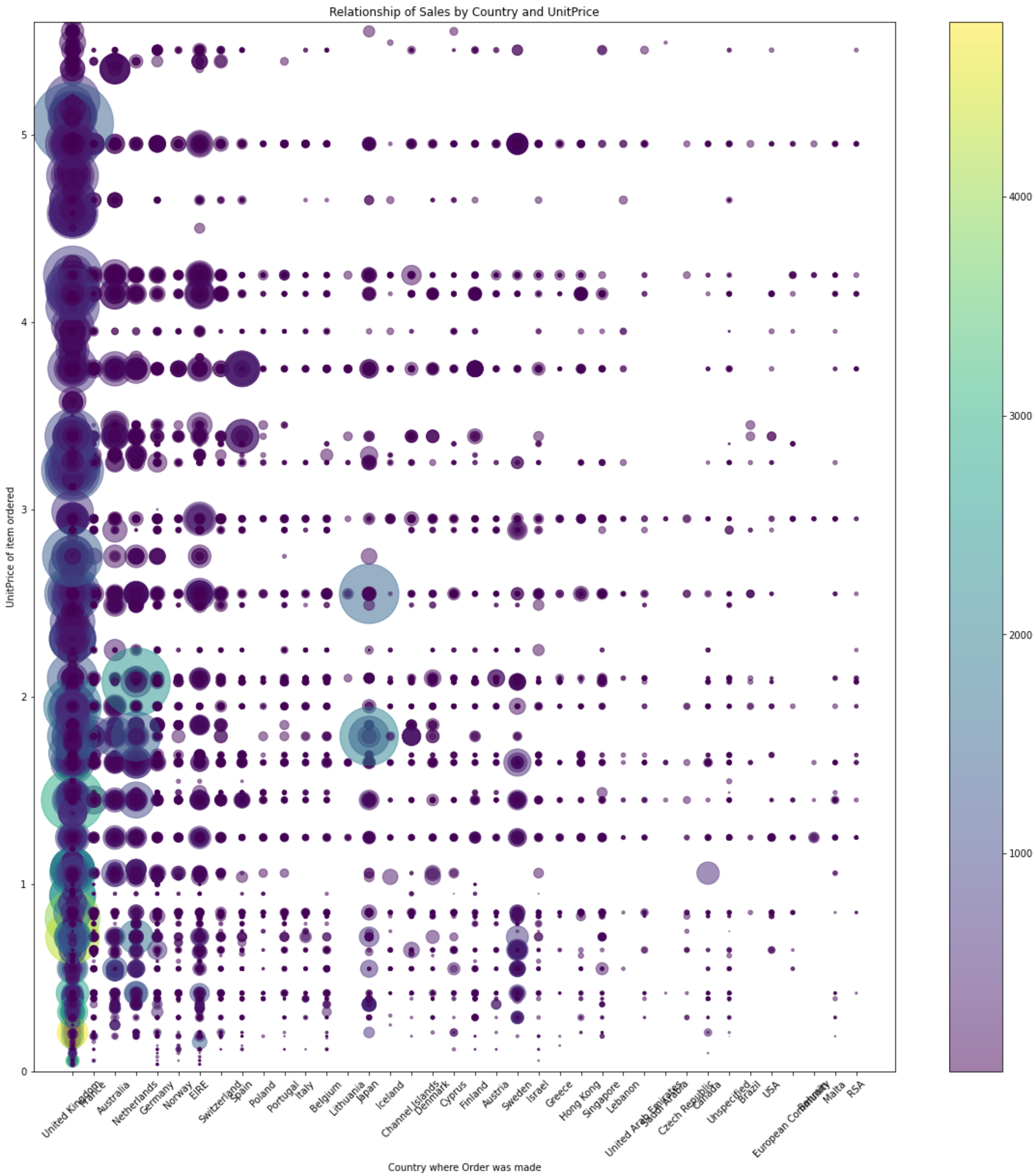
In [ ]:

```
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 ord
                      ylim=(0,5.6)))
plt.xticks(rotation=45)
plt.colorbar()
plt.show()
```

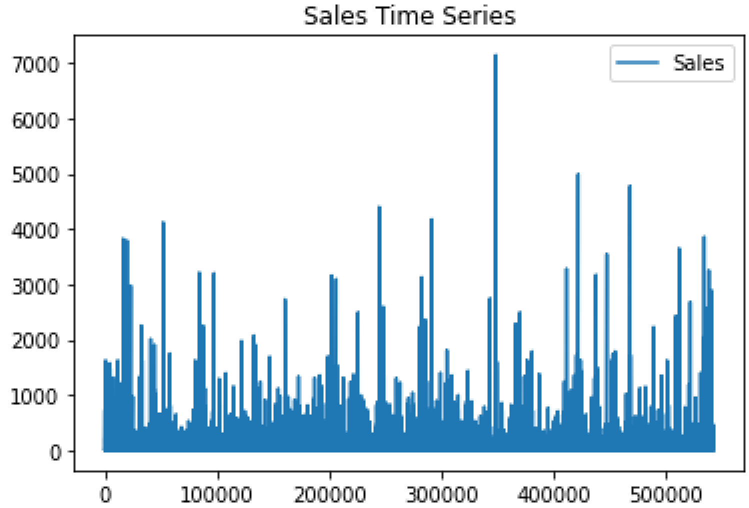


Most orders are from the UK and most are small size orders (darker purple). Large Sale values span the unit price range.

Time Series Plots

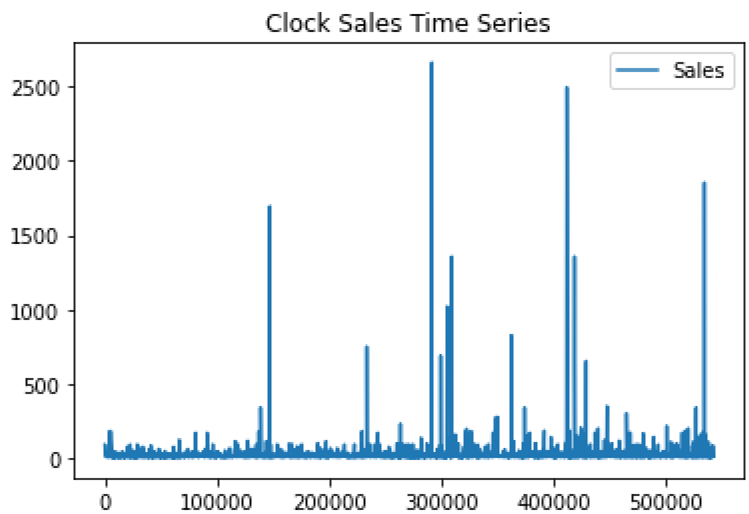
In [247…

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

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



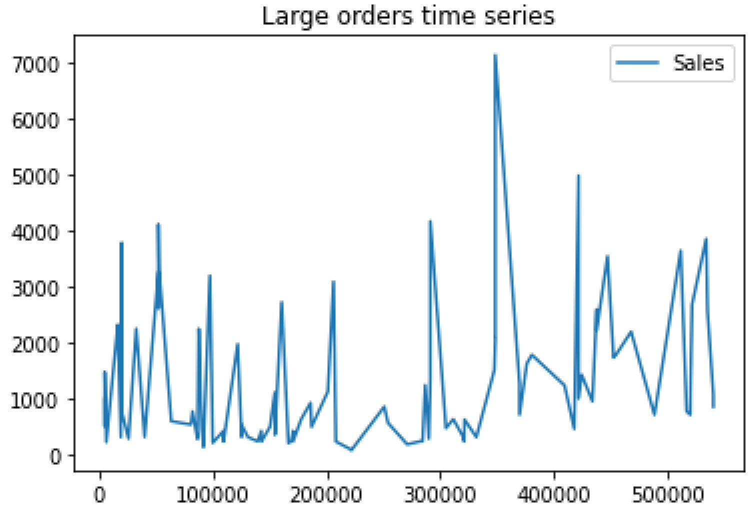
In [248…

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

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



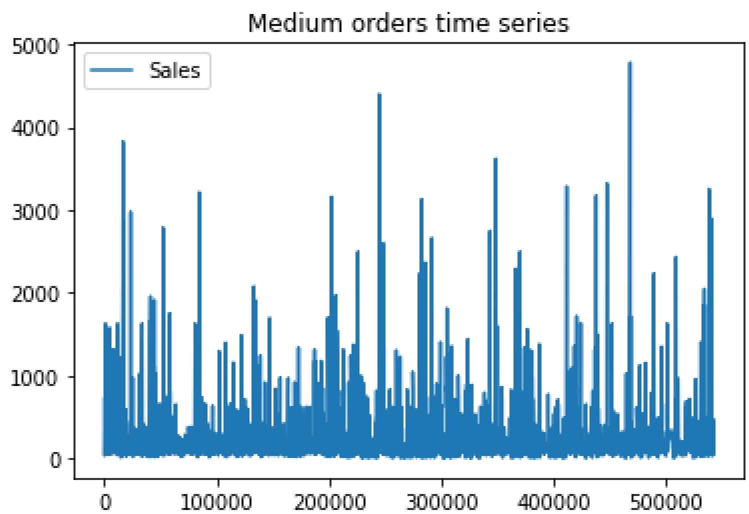
In [249…

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

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



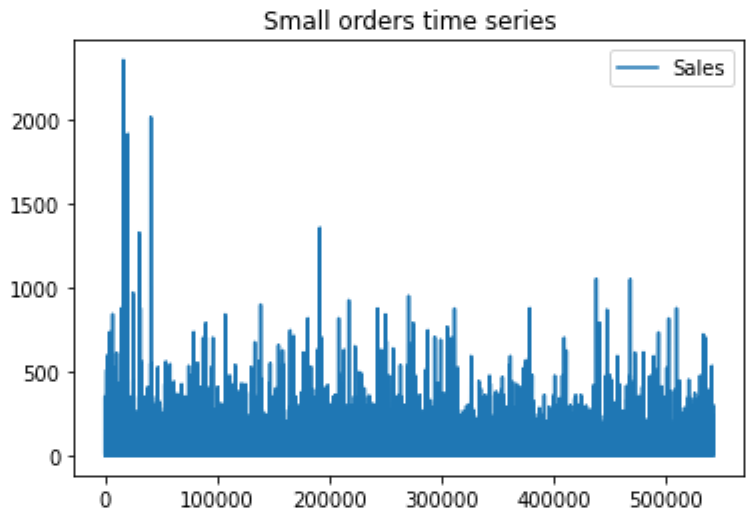
In [250…

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

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'],
                         inplace=True)

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 [411…

```
Clock_TimeSeries_date_df = read_csv('Clock_Retail_UKdata.csv', header=0, index_col=0,
                        parse_dates=True, squeeze=True)
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…

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country	Sales
InvoiceDate								
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()
```

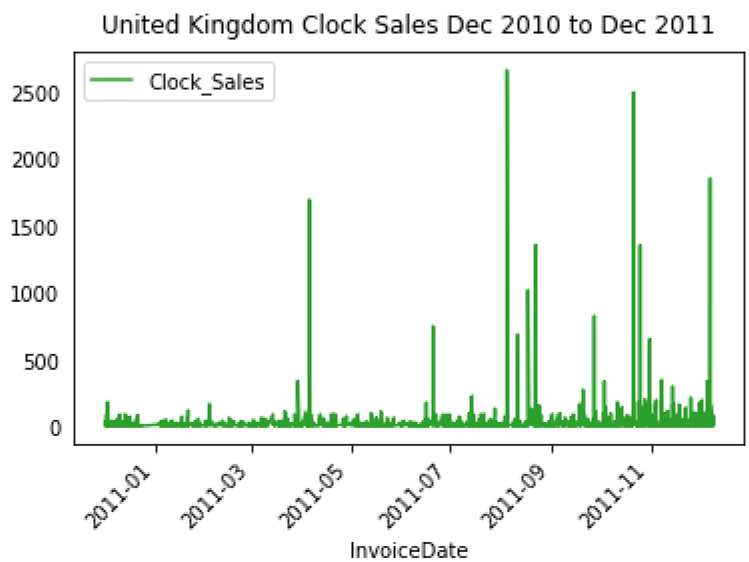
Out[426...

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country	Sales
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 [720...

```
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=(6,4))
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 432x288 with 0 Axes>



Sales per Day:

In [416...

```
UK_clock_ts.head()
```

Out[416...

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

	Sales
InvoiceDate	
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 [775…

```
UK_DailyClock_df.head(20)
```

Out[775…

	Sales
InvoiceDate	
2010-12-01	568.40
2010-12-02	747.25
2010-12-03	587.62
2010-12-05	547.25
2010-12-06	412.24
2010-12-07	504.96
2010-12-08	261.14
2010-12-09	511.44
2010-12-10	686.06
2010-12-12	167.50
2010-12-13	329.04
2010-12-14	935.50
2010-12-15	217.00
2010-12-16	342.75
2010-12-17	324.84
2010-12-19	134.25
2010-12-20	414.48
2010-12-21	542.43
2010-12-22	3.75
2010-12-23	31.49

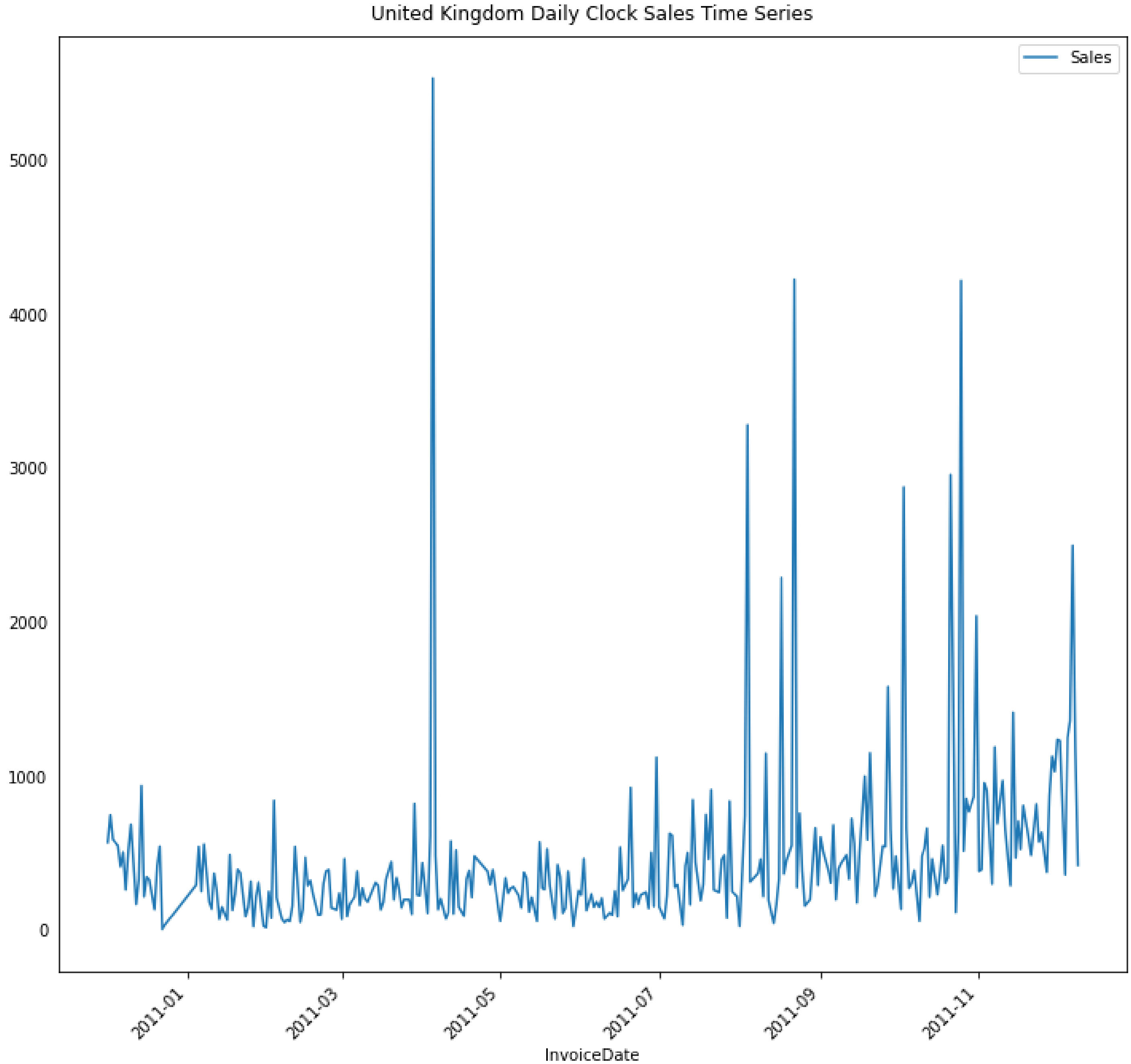
In [596…

```
UK_DailyClock_df = UK_DailyClock_df[UK_DailyClock_df['Sales'] > 1]
```

In [723…

```
plt.figure(figsize=(6,4))
UK_DailyClock_df.plot()

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

```
<Figure size 432x288 with 0 Axes>
```

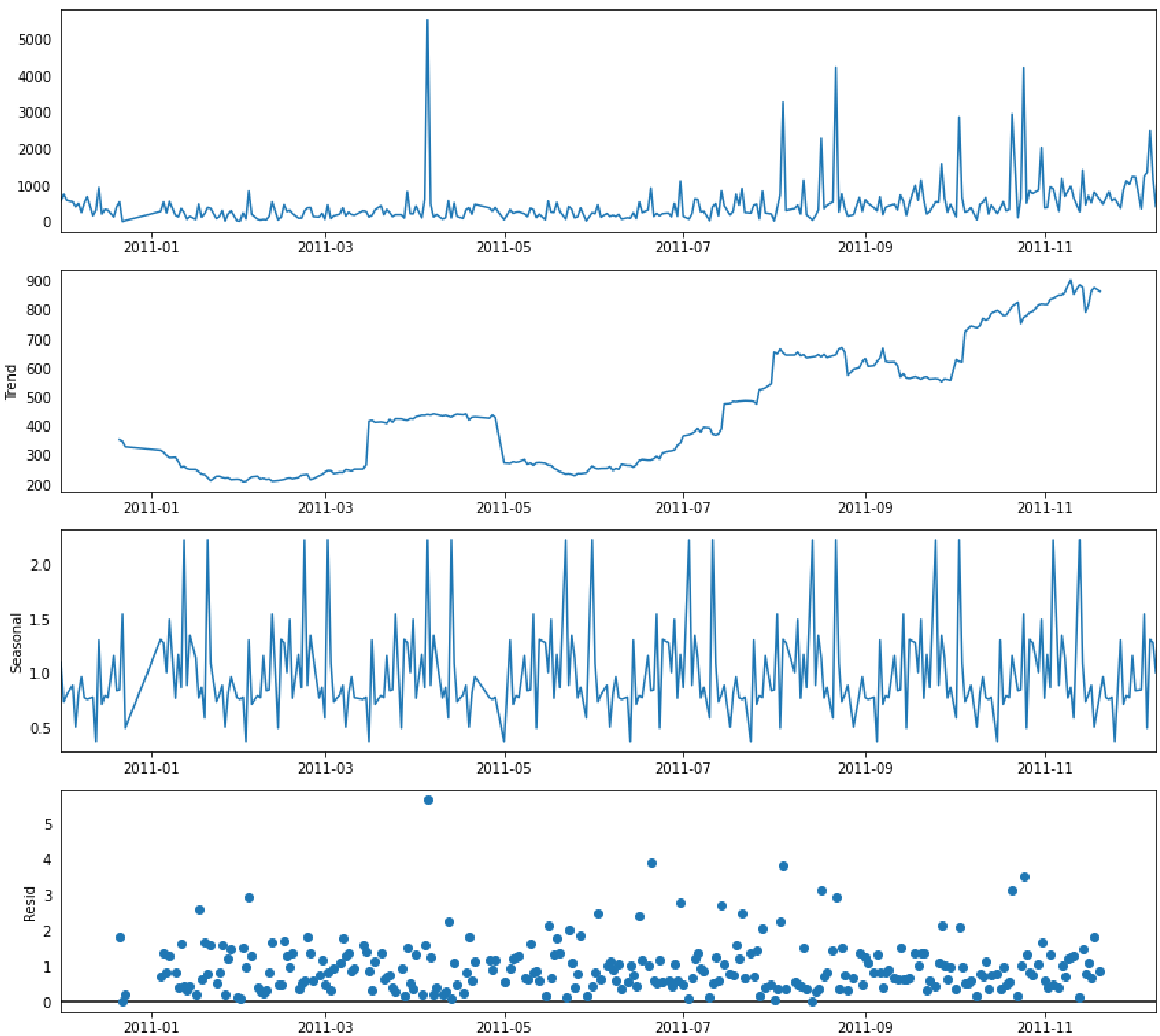


In [724…

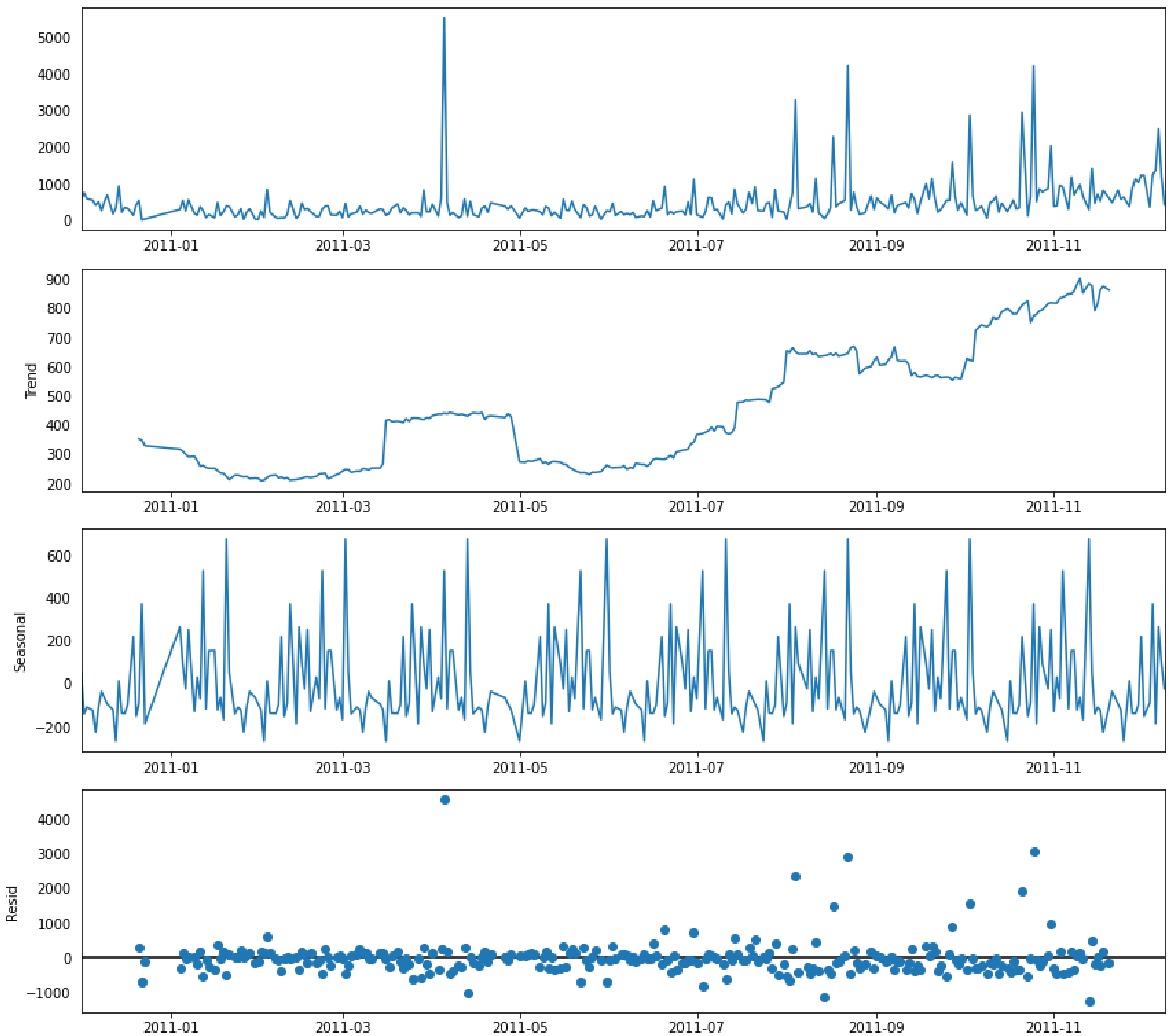
```
# Decomposition
# Decomposition of a time series can be performed by considering
# the series as an additive or multiplicative combination of the
# base level, trend, seasonal index and the residual term.

# Multiplicative Decomposition
multiplicative_decomposition = seasonal_decompose(UK_DailyClock_df, model='multiplicative'
                                                  period=35)

# Additive Decomposition
```

```
additive_decomposition = seasonal_decompose(UK_DailyClock_df, model='additive',
                                            period=35)

# Plot
plt.rcParams.update({'figure.figsize': (12,12)})
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])
```

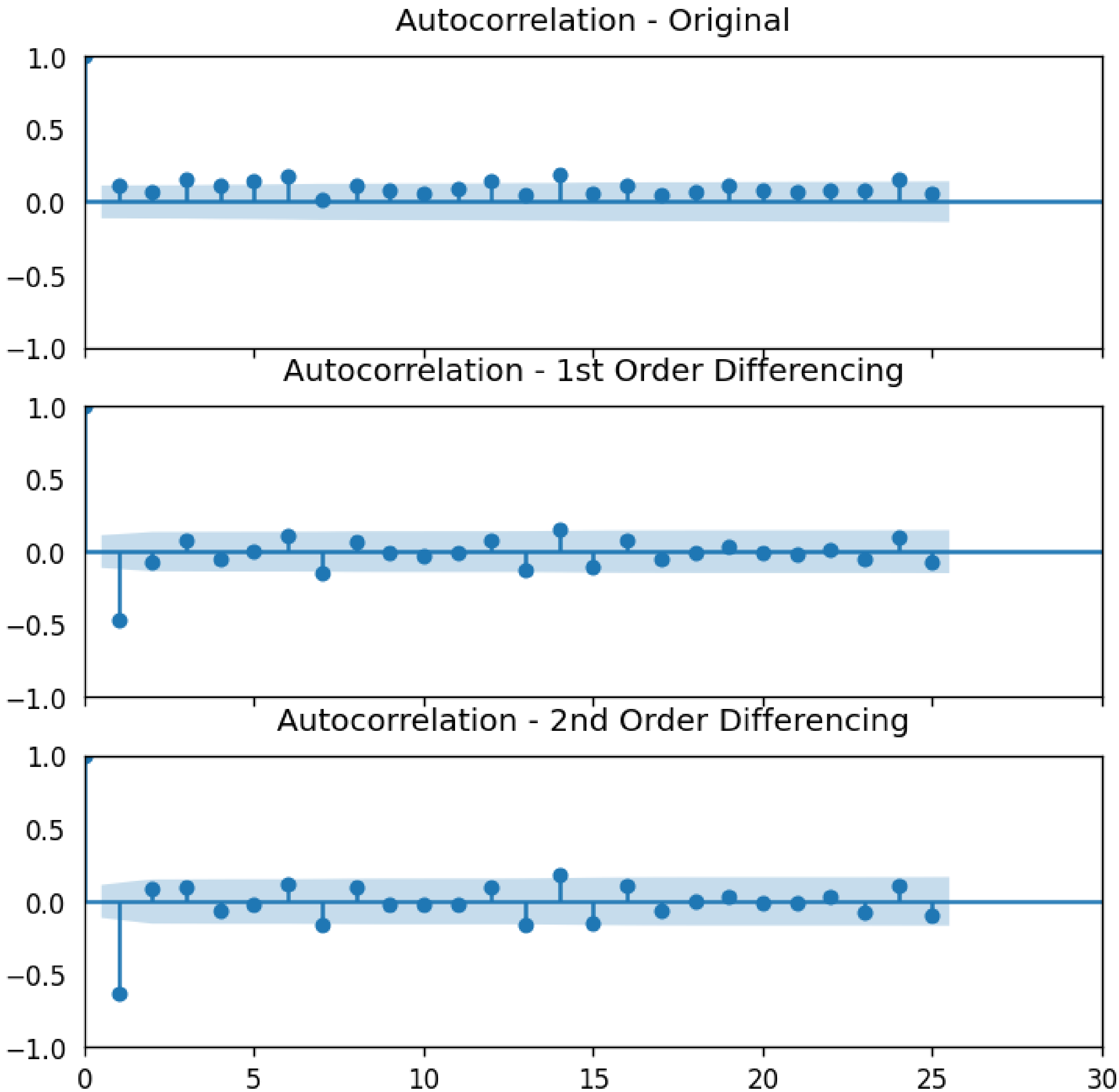
```
ADF Statistic: -4.112281
p-value: 0.000924
```

- 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

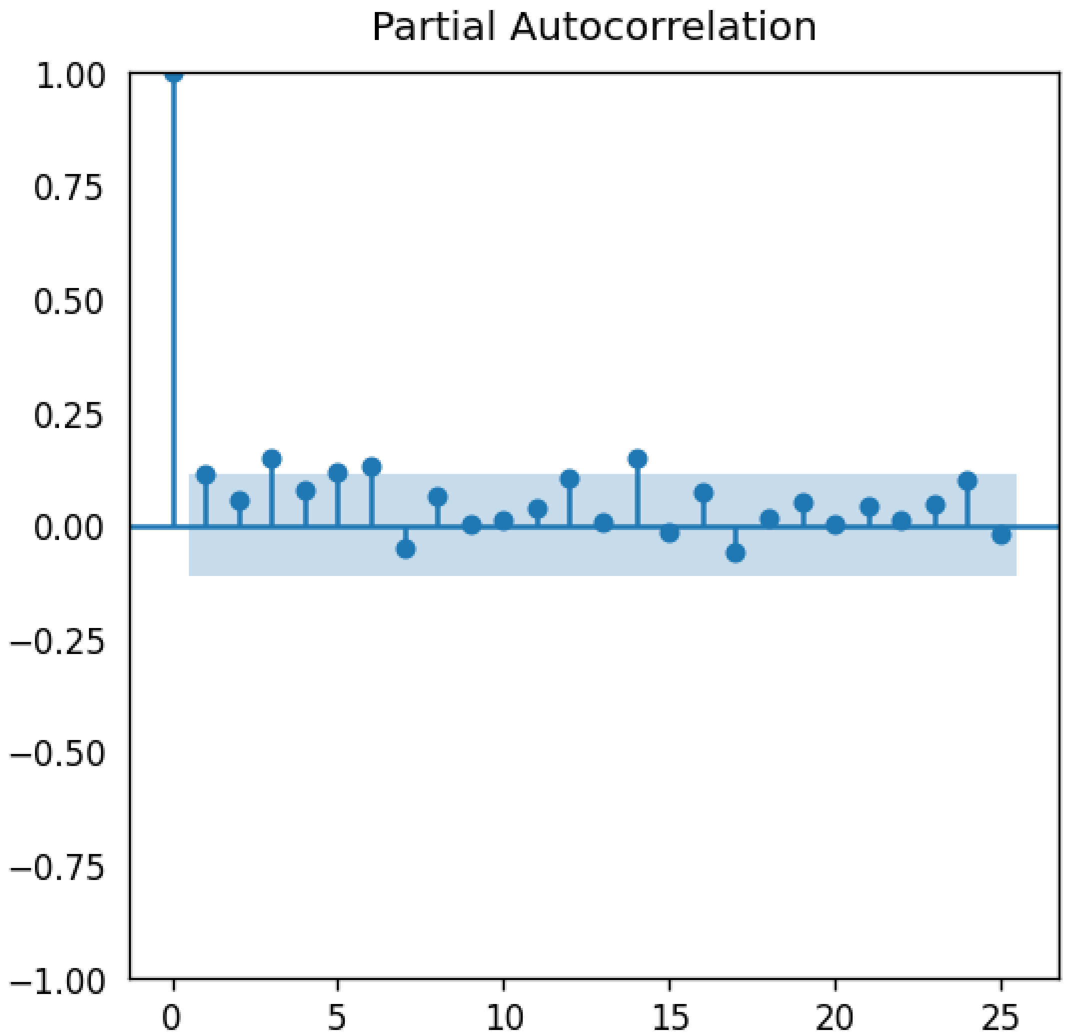
In [725…

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

# Original Series
fig, axes = plt.subplots(3, sharex=True)

plot_acf(UK_DailyClock_df, ax=axes[0])
axes[0].set_title('Autocorrelation - Original')

plot_acf(UK_DailyClock_df.diff().dropna(), ax=axes[1])
axes[1].set_title('Autocorrelation - 1st Order Differencing')

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 [727…

```
# PACF plot
plt.rcParams.update({'figure.figsize':(5,5), 'figure.dpi':120})

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

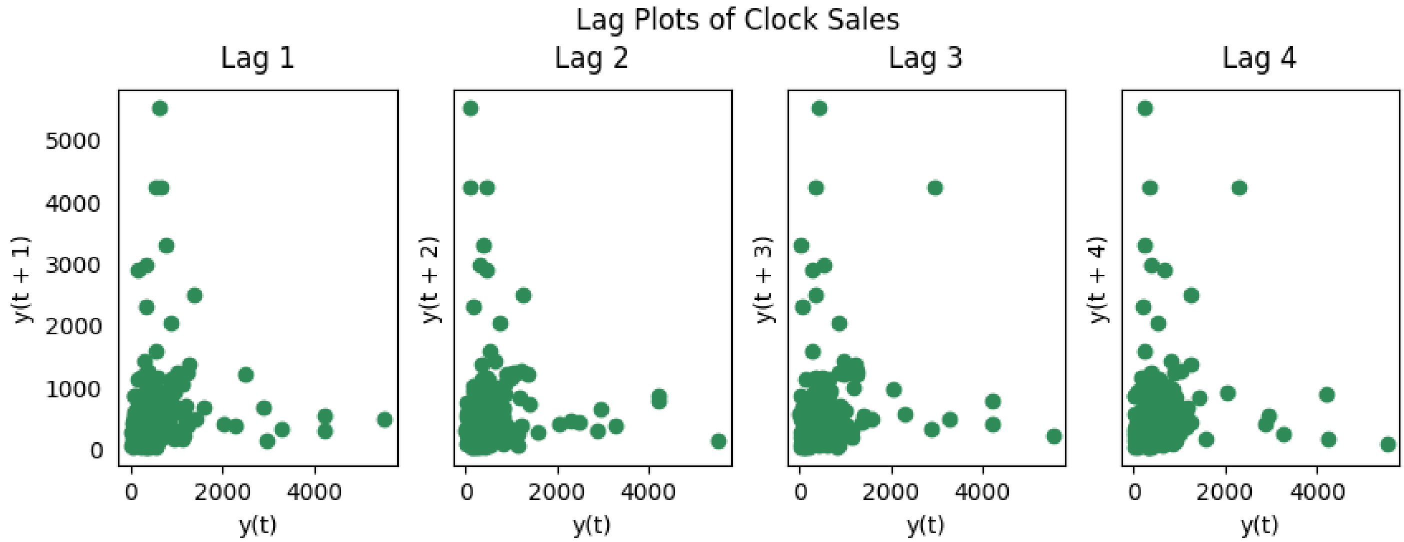


The above plot can be used to determine the order of AR model. You may note that a correlation value up to order 3 is high enough. Thus, we will train the AR model of order 3.

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

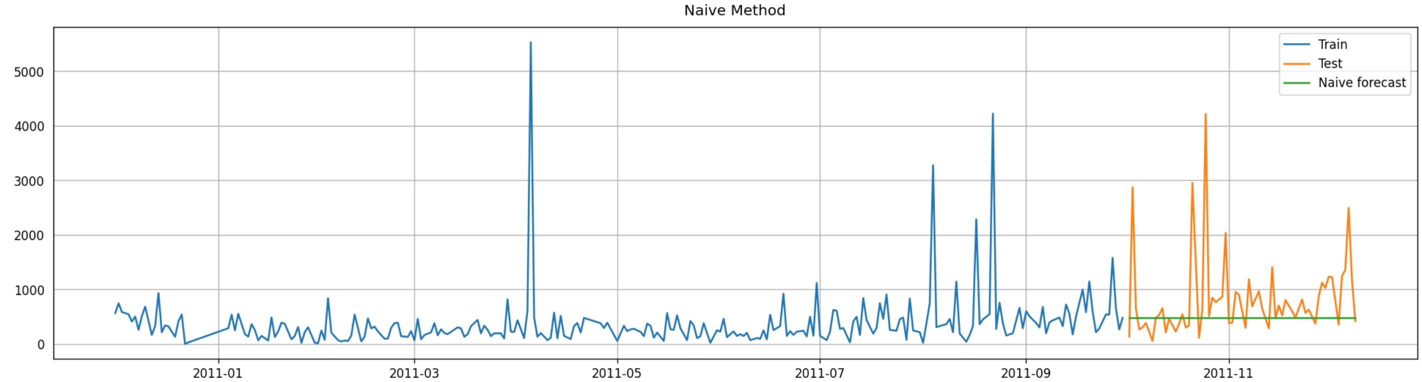
In [794…

```
# 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…

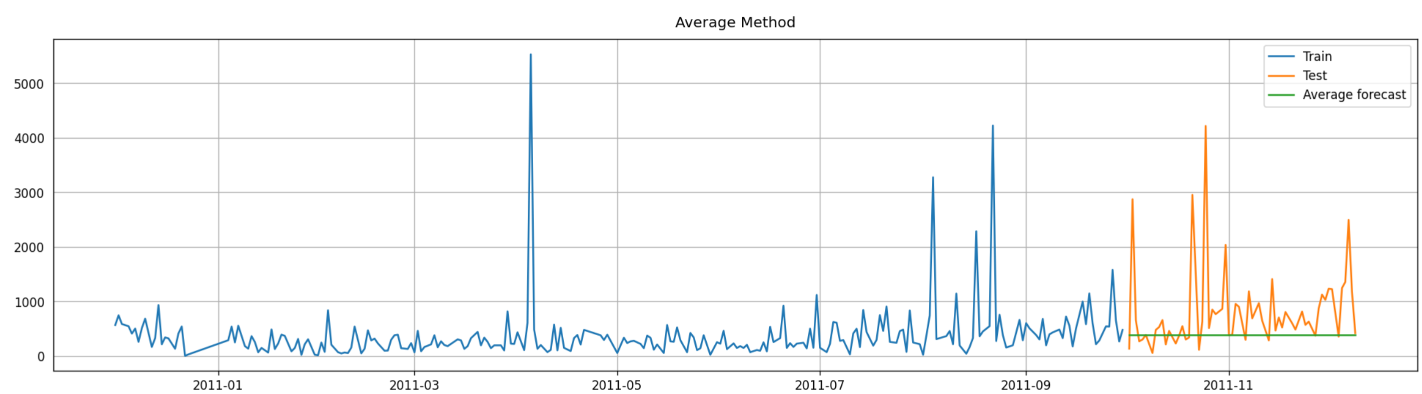
	Method	RMSE	MAPE
0	Naive method	816.73	62.92

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'])).rounc
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...

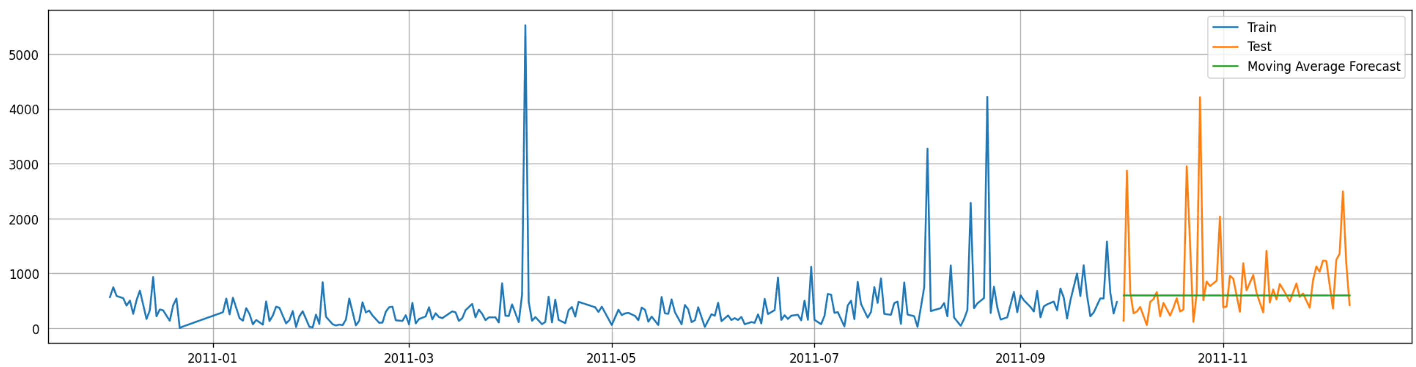
	Method	RMSE	MAPE
0	Average method	861.06	58.65

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'])).ro
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...

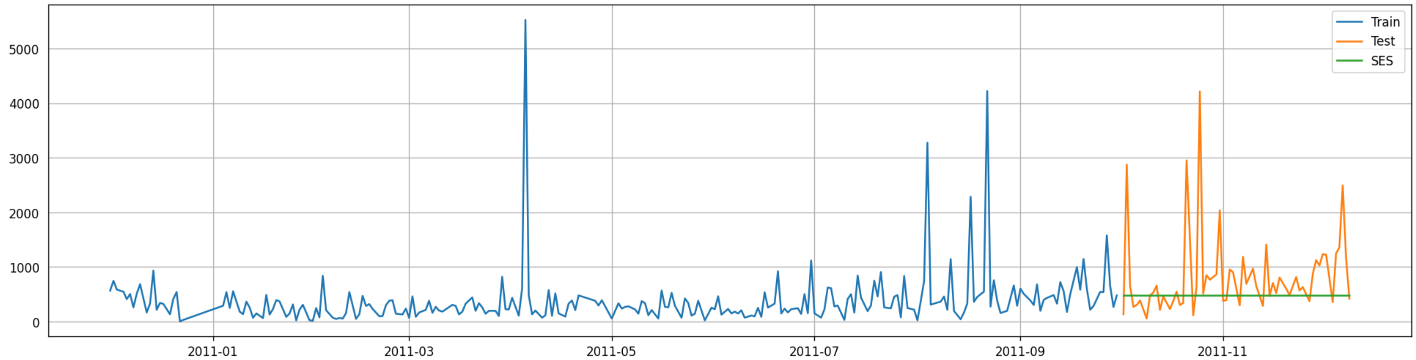
	Method	RMSE	MAPE
0	Moving Average method	771.42	74.26

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,
                                                              optimized=False)
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
                        'RMSE': [se_rmse]})
results = results[['Method', 'RMSE', 'MAPE']]
results
```

Out[700…

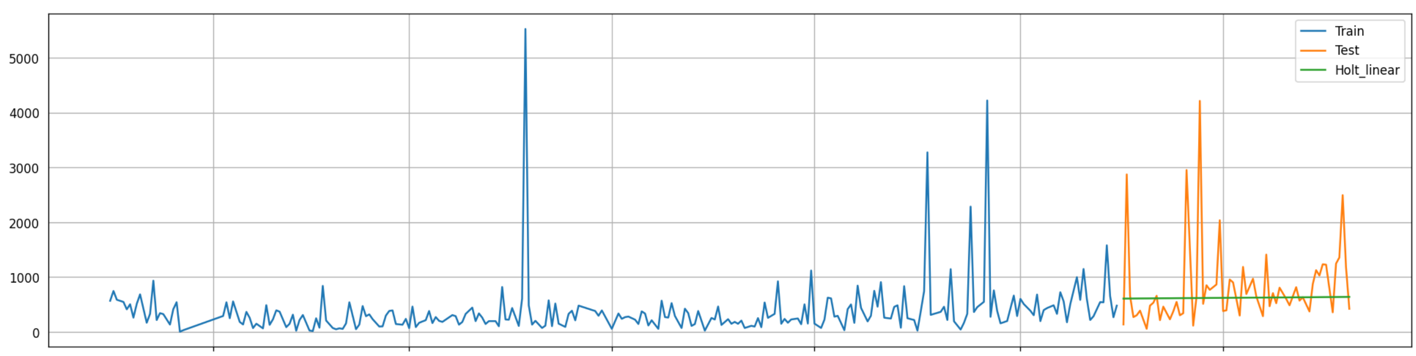
	Method	RMSE	MAPE
0	Simple Exponential Smoothing method	812.86	63.55

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 = 0.1)
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...

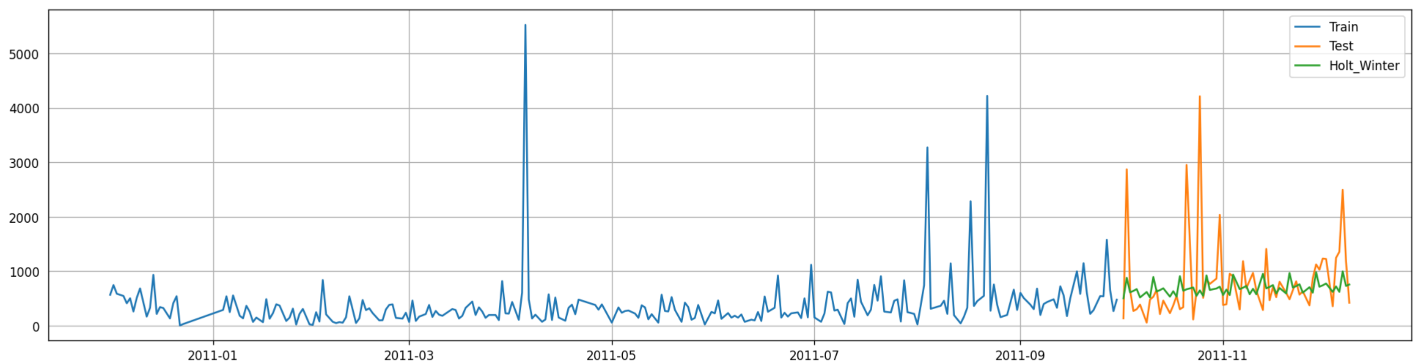
	Method	RMSE	MAPE
0	Holt Linear method	764.49	75.43

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', seasonal='add',).fit()
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...

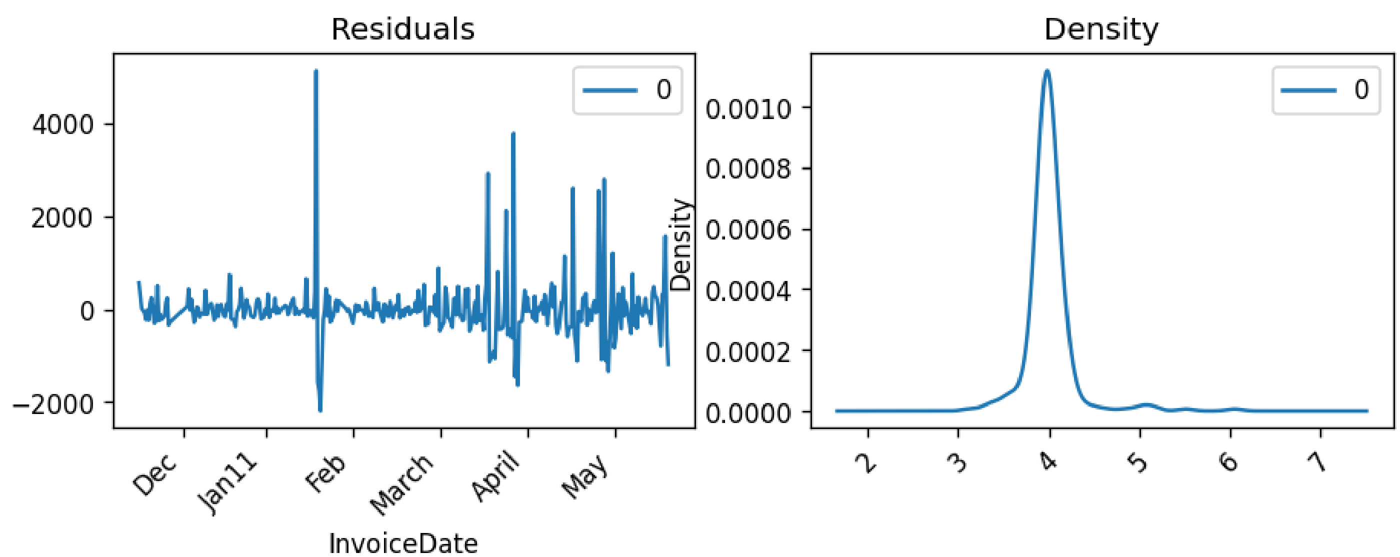
```
# Estimate by trial and error:
# that the best p would be 2 based
# on our autocorrelation plots 1 differencing
# since the signal is stationary, and q = 0
```

```
# 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…

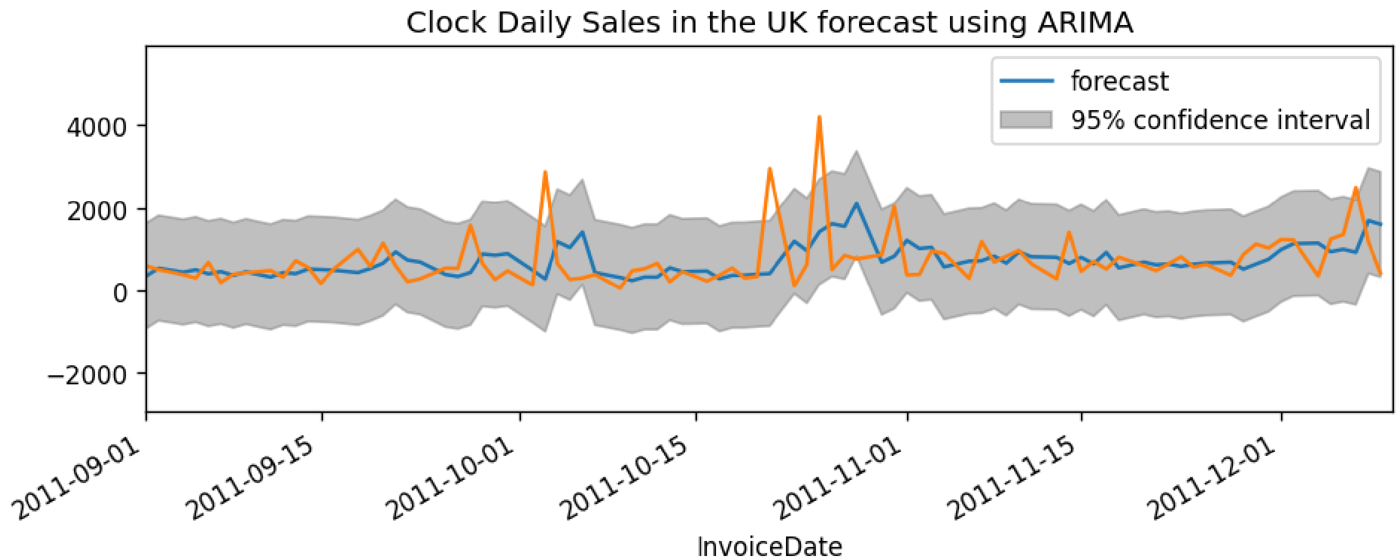
```
residuals_clks = pd.DataFrame(model_fitclks.resid)
fig, ax = plt.subplots(1,2)
residuals_clks.plot(title="Residuals", ax=ax[0])
ax[0].set_xticklabels(['Dec','Jan11','Feb','March','April','May','June',
                       'July','Aug','Sept','Oct','Nov','Dec'],rotation=45)
residuals_clks.plot(kind='kde',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

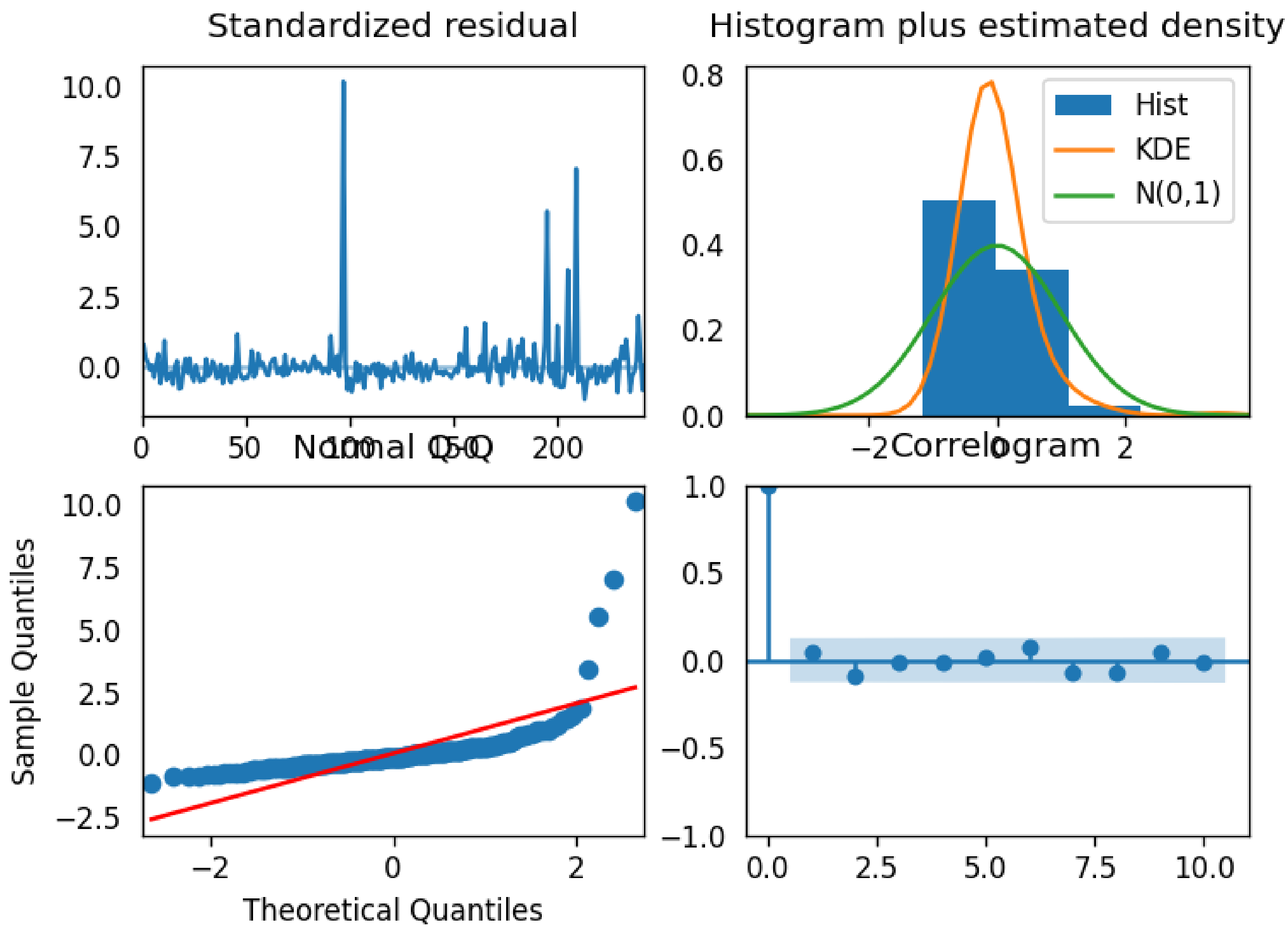
```
model_clk = auto_arima(train, start_p=1, start_q=1,
 test='adf', # use adftest to find optimal 'd'
 max_p=3, max_q=3, # maximum p and q
 m=1, # frequency of series
 d=None, # let model determine 'd'
 seasonal=False, # No Seasonality
 start_P=0,
 D=0,
 trace=True,
 error_action='ignore',
 suppress_warnings=True,
 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()
```

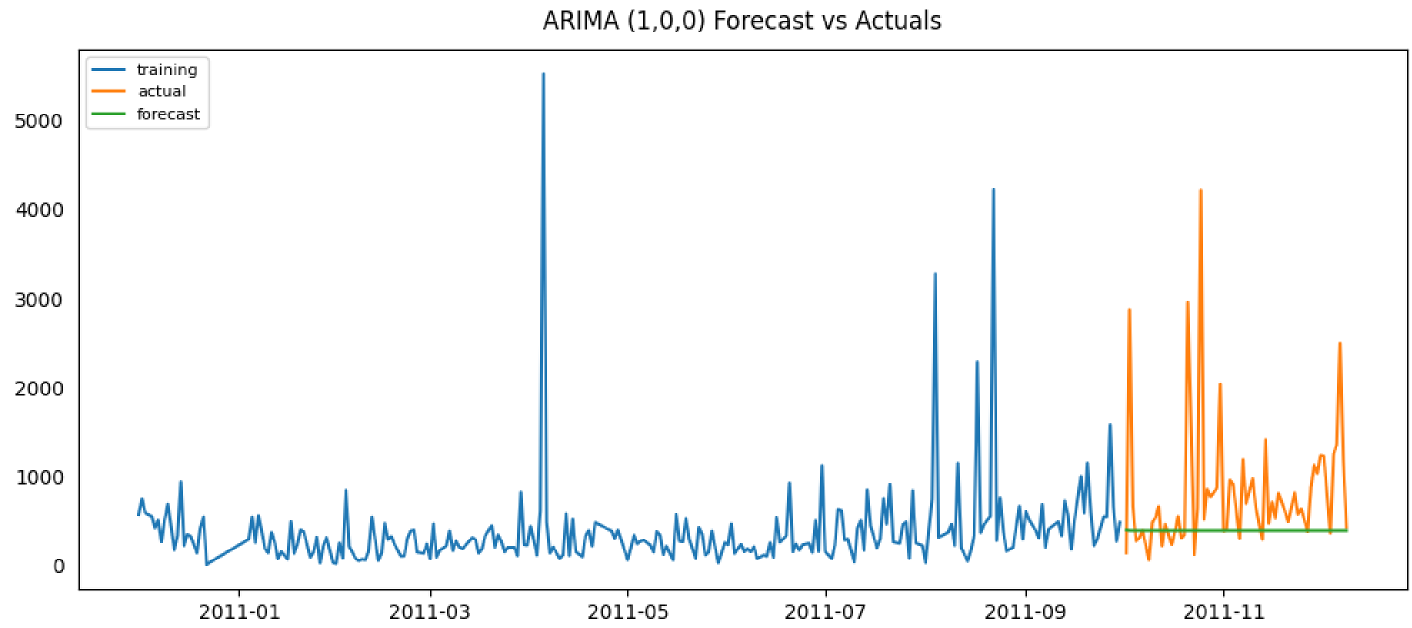


According to auto-arima, the best Arima model using auto-arima is (2,0,2)

ARIMA (1,0,0)

In [728…

```
arimaclk_model100 = ARIMA(train, order=(1, 0, 0))
fitted_arimaclk100 = arimaclk_model100.fit()
# Forecast
result_clk100=fitted_arimaclk100.forecast(60, alpha=0.05) # 95% conf
#result_clk.to_frame()
results_indexed100=pd.DataFrame(result_clk100)
results_indexed100['InvoiceDate']=test.index
results_indexed100['InvoiceDate'] = pd.to_datetime(results_indexed100['InvoiceDate'])
results_indexed100=results_indexed100.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_indexed100, label='forecast')
#plt.fill_between(lower_series.index, lower_series, upper_series,
# color='k', alpha=.15)
plt.title('ARIMA (1,0,0) 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 [729…

```
# Calculating RMSE and MAPE

arima100_rmse = np.sqrt(mean_squared_error(test['Sales'],
                                results_indexed100['predicted_mean'])).round(2)
arima100_mape = np.round(np.mean(np.abs(test['Sales'] - results_indexed100['predicted_mear

results = pd.DataFrame({'Method':['ARIMA method'], 'MAPE': [arima100_mape], 'RMSE': [arima
results = results[['Method', 'RMSE', 'MAPE']]
results
```

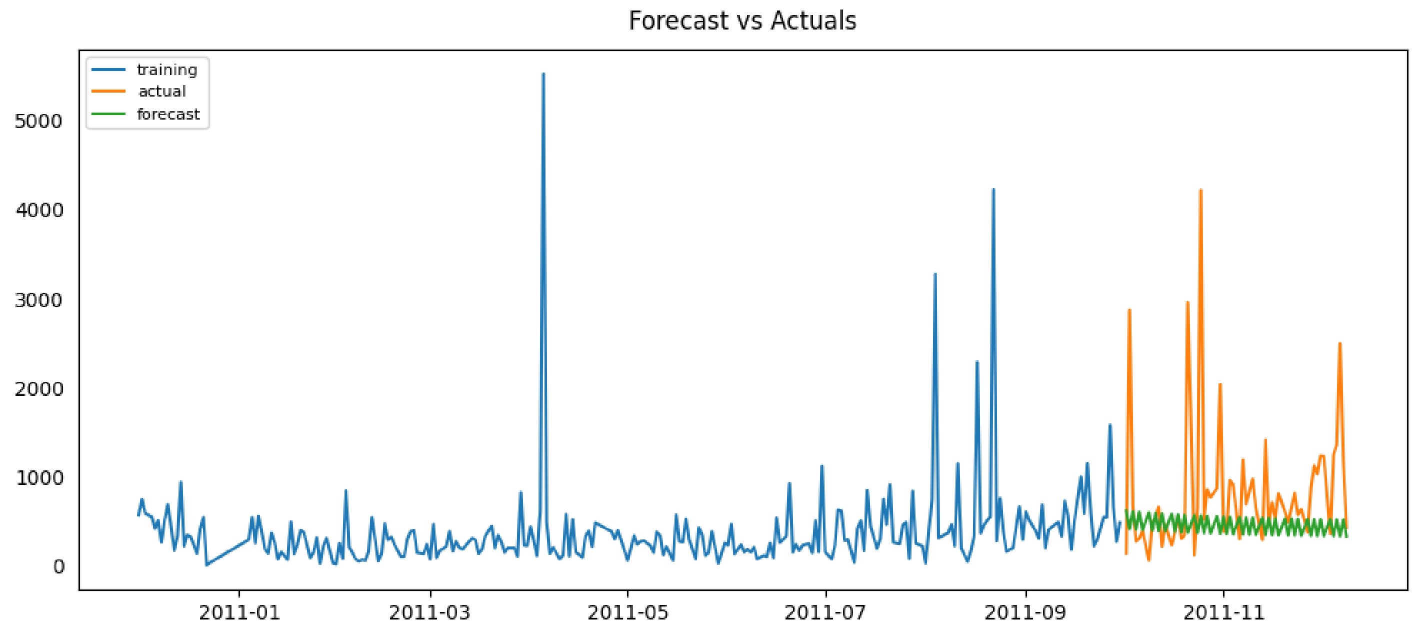
Out[729…

	Method	RMSE	MAPE
0	ARIMA method	861.07	58.74

Using auto arima Recommended model: ARIMA(2,0,2)

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'])).round(2)
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

Neural Networks (Long Short-Term Memory Network)

(Brownlee, 2016)

In [763…

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

In [783…

```
UK_DailyClock_df.shape
```

Out[783…

```
(303, 1)
```

In [784…

```
# Scale data to lie between 0 and 1:

scaler = MinMaxScaler(feature_range=(0, 1))
dataset_neural = scaler.fit_transform(UK_DailyClock_df)
```

To maintain the train/test proportions for other models which have test size of 60, our train/test proportions are 80.2/19.8

In [785…

```
# split into train and test sets
train_size = int(len(dataset_neural) * 0.802)
test_size = len(dataset_neural) - train_size
train_nn, test_nn = dataset_neural[0:train_size,:],
                    dataset_neural[train_size:len(dataset_neural),:]
```

In [787…

```
# convert an array of values and generate
# the X and y for our neural network with
# where X has lagged version of y (the current t)
# and y looks at the future:

def create_dataset(dataset, look_back=1):
 dataX, datay = [], []
 for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        dataX.append(a)
        datay.append(dataset[i + look_back, 0])
 return np.array(dataX), np.array(datay)
```

In [788…

```
# Run the above function on the already
# split train and test data so we now have
# X=t and y=t+1

look_back = 1
trainX, trainy = create_dataset(train_nn, look_back)
testX, testy = create_dataset(test_nn, look_back)
```

In [789…

```
# Data has to be reshaped to a format the neural network
# understands (samples, time steps (1), features)

trainX = np.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = np.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
```

In [ ]:

```
# create and fit the LSTM network (original attempt)
n_features_nn=1
n_steps_nn=1
model_nn = Sequential()
model_nn.add(LSTM(4, input_shape=(1, look_back)))
model_nn.add(Dense(1))
model_nn.compile(loss='mean_squared_error', optimizer='adam')
model_nn.fit(trainX, trainy, epochs=100, batch_size=1, verbose=0)
```

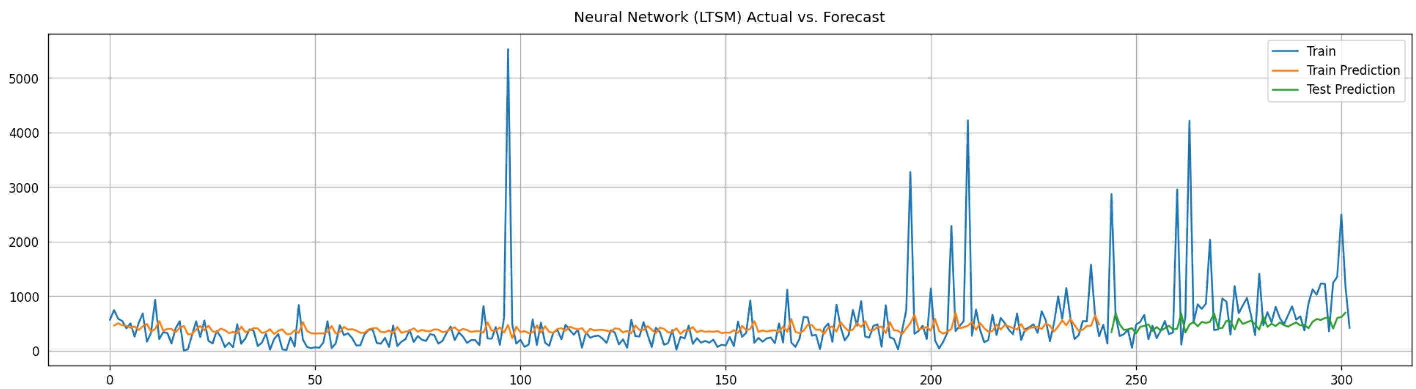
In [791…

```
# make forecast on both training and test:
trainPredict_nn = model_nn.predict(trainX)
testPredict_nn = model_nn.predict(testX)

# invert scaling done on the data:
trainPredict_nn = scaler.inverse_transform(trainPredict_nn)
trainy = scaler.inverse_transform([trainy])
testPredict_nn = scaler.inverse_transform(testPredict_nn)
testy = scaler.inverse_transform([testy])

# calculate root mean squared error
trainScore_nn = np.sqrt(mean_squared_error(trainy[0], trainPredict_nn[:,0]))
print('Train Score: %.2f RMSE' % (trainScore_nn))
testScore_nn = np.sqrt(mean_squared_error(testy[0], testPredict_nn[:,0]))
print('Test Score: %.2f RMSE' % (testScore_nn))
```

```
Train Score: 522.79 RMSE
Test Score: 830.89 RMSE
```

In [817…

```
# shift train predictions so they can plot
# in line with the original data:
trainPredictPlot_nn = np.empty_like(dataset)
trainPredictPlot_nn[:, :] = np.nan
trainPredictPlot_nn[look_back:len(trainPredict_nn)+look_back, :] = trainPredict_nn

# shift test predictions so they can plot in
# line with the original data:
testPredictPlot_nn = np.empty_like(dataset)
testPredictPlot_nn[:, :] = np.nan
testPredictPlot_nn[len(trainPredict_nn)+(look_back*2)+1:len(dataset)-1, :] = testPredict_r

# plot baseline and predictions
plt.figure(figsize=(20,5))
plt.grid()
plt.plot(scaler.inverse_transform(dataset_neural), label='Train')
plt.plot(trainPredictPlot_nn, label='Train Prediction')
plt.plot(testPredictPlot_nn, label='Test Prediction')
plt.title('Neural Network (LTSM) Actual vs. Forecast')
plt.legend(loc='best')
plt.show()
```



As impressive as Neural Nets can be, and seeing that the forecast does follow any trend however slight in the data, the performance is still lacking when compared to the Holt-Winters model, as was also the case in the Practical Time Series Forecasting example for Chapter 9 (Shmueli & Lichtendahl Jr., 2018)

Linear Regression

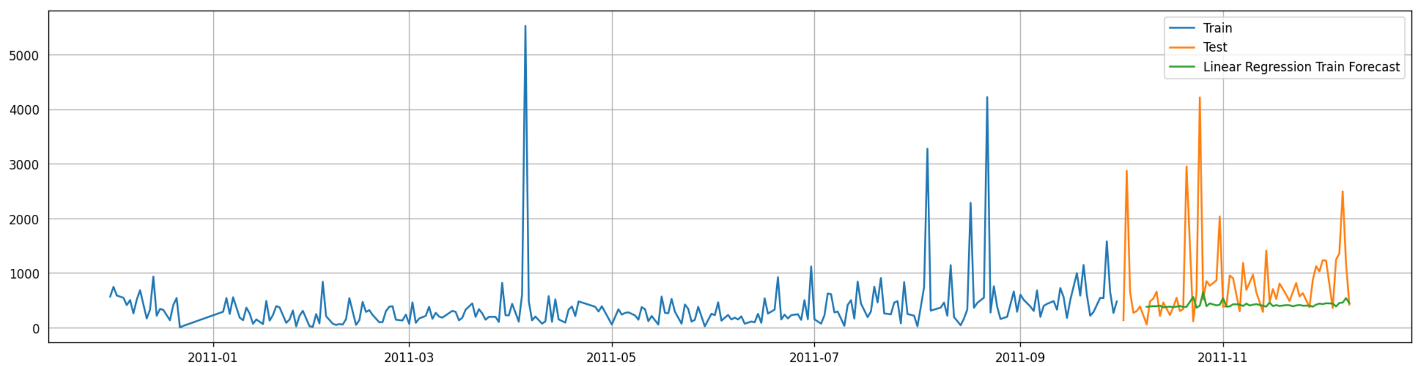
In [814…

```
# This version is not fully comparable to the other methods
# given that the regression is done on a known test data set
# with already known lags, which would normally only be
# available as forecasted lags. However, this is to demonstrate
# even with known data, the linear regression model
# does not seem to outperform many of the other
# data driven models for this series.

train_lr=train.copy()

# Adding lagged versions of data to use
# in liner regression to use as input predictors:

train_lr['Lag_1'] = train_lr['Sales'].shift(1)

# given their site may have some weak weekly trends
# and they have 6 day weeks:
train_lr['Lag_6'] = train_lr['Sales'].shift(6)
```

```python
from sklearn.linear_model import LinearRegression

X_lr = train_lr.loc[:, ['Lag_1','Lag_6']]
X_lr.dropna(inplace=True)  # drop missing values in the feature set
y_lr = train_lr.loc[:, 'Sales']  # create the target
y_lr, X_lr = y_lr.align(X, join='inner')  # drop corresponding values in target

model_lr = LinearRegression()
model_lr.fit(X_lr, y_lr)

y_pred_lr_train = pd.Series(model_lr.predict(X_lr), index=X_lr.index)

# Do the same with test data:

test_lr = test.copy()

test_lr['Lag_1'] = test_lr['Sales'].shift(1)
test_lr['Lag_6'] = test_lr['Sales'].shift(6)

X_test_lr = test_lr.loc[:, ['Lag_1','Lag_6']]
X_test_lr.dropna(inplace=True)
y_pred_lr = pd.Series(model_lr.predict(X_test_lr), index=X_test_lr.index)
```

In [798…

```python
plt.figure(figsize=(20,5))
plt.grid()
plt.plot( train_lr['Sales'], label='Train')
plt.plot(test_lr['Sales'], label='Test')
plt.plot(y_pred_lr, label='Linear Regression Train Forecast')
plt.legend(loc='best')
plt.show()
```



In [804…

```python
# Calculating RMSE and MAPE

# because output is for anything after lag of 6,
# need to onlly include data from original dataset
# that represents the last 64 samples instead of 60:

test_lr_error = test_lr.iloc[6:]
lr_rmse = np.sqrt(mean_squared_error(test_lr_error['Sales'],
                                     y_pred_lr)).round(2)
lr_mape = np.round(np.mean(np.abs(test_lr_error['Sales'] - y_pred_lr)/test_lr_error['Sales

results_lr = pd.DataFrame({'Method':['LR method'], 'MAPE': [lr_mape], 'RMSE': [lr_rmse]})
results_lr = results_lr[['Method', 'RMSE', 'MAPE']]
results_lr
```

Out[804…

	Method	RMSE	MAPE
0	LR method	826.56	60.21

In [805…

```python
# Table Results

Table = PrettyTable(["Model", "RMSE"])
Table.add_row(["Naive", n_rmse])
Table.add_row(["Simple Average", sa_rmse])
Table.add_row(["Moving Average", ma_rmse])
Table.add_row(["Simple Exponential", se_rmse])
Table.add_row(["Holt Linear", hl_rmse])
Table.add_row(["Holt Winter", hw_rmse])
Table.add_row(["ARIMA (1,0,0)", arima100_rmse])
Table.add_row(["ARIMA (2,0,2)", arima_rmse])
Table.add_row(["Linear Regression", lr_rmse])
Table.add_row(["Neural Network (LSTM)", round(testScore_nn,2)])
print("Time Series Model Performance Sorted by RMSE")
Table.sortby = "RMSE"
print(Table)
```

```
Time Series Model Performance Sorted by RMSE
+-----------------------+--------+
|         Model         |  RMSE  |
+-----------------------+--------+
|      Holt Winter      | 731.7  |
|      Holt Linear      | 764.49 |
|     Moving Average    | 771.42 |
|   Simple Exponential  | 812.86 |
|         Naive         | 816.73 |
|   Linear Regression   | 826.56 |
| Neural Network (LSTM) | 830.89 |
|     ARIMA (2,0,2)     | 851.56 |
|     Simple Average    | 861.06 |
|     ARIMA (1,0,0)     | 861.07 |
+-----------------------+--------+
```