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Time Series Forecasting

In [1]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
import requests
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
url = "http://archive.ics.uci.edu/ml/machine-learning-databases/00352/Online%20R
resp = requests.get(url)
with open('test.xlsx','wb') as output:
    output.write(resp.content)
```

In [4]:
```
df=pd.read_excel('test.xlsx')
```

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

Out[5]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

In [6]:
```
# The dataframe contains 541,909 observations and 8 features. There are missing
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  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

In [7]:
```
#Let's shift InvoiceDate as our index and convert County column to a categorical
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate']).dt.date
```

In [8]:
```
df1=df.set_index('InvoiceDate')
```

In [9]:
```
df1['Country']=df1['Country'].astype('category')
df1['Country'].value_counts().head(10)
```

Out[9]:
```
United Kingdom    495478
Germany             9495
France              8557
EIRE                8196
Spain               2533
Netherlands         2371
Belgium             2069
Switzerland         2002
Portugal            1519
Australia           1259
Name: Country, dtype: int64
```

In [10]:
```
df1['InvoiceNo']=df1['InvoiceNo'].astype(str)
```

In [11]:
```
# It is evident that there are missing values in CustomerID field.
# Also, this dataset may need to be adjusted for non-positive observations of Un
df1.describe()
```

Out[11]:

	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

In [12]:
```
df1.head()
```

Out[12]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country

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

In [13]:

```
df1.tail()
```

Out[13]:

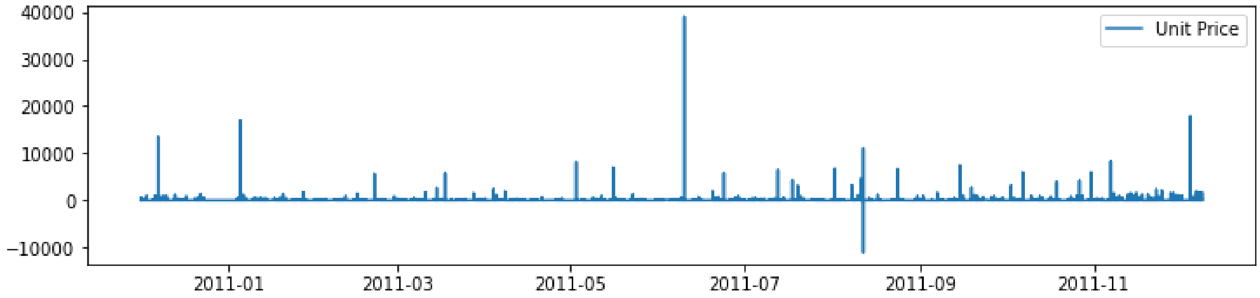
	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country
InvoiceDate							
2011-12-09	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	0.85	12680.0	France
2011-12-09	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2.10	12680.0	France
2011-12-09	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	4.15	12680.0	France
2011-12-09	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	4.15	12680.0	France
2011-12-09	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	4.95	12680.0	France

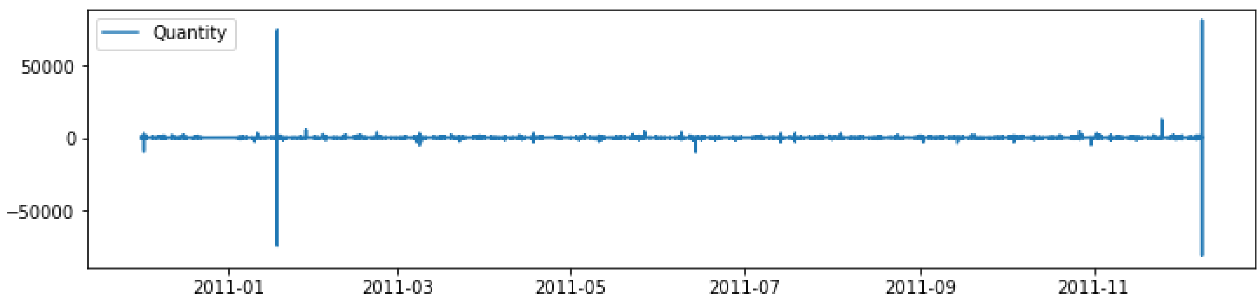
In [14]:

```
# Plot UnitPrice and Quantity
fig, ax =plt.subplots(2, figsize=(12,6))
ax[0].plot(df1['UnitPrice'], label = 'Unit Price')
ax[0].legend()
ax[1].plot(df1['Quantity'], label = 'Quantity')
ax[1].legend()
#In the second graph, there are two symmetrical spikes, which needs to be furthe
```

Out[14]:

```
<matplotlib.legend.Legend at 0x7fa43d380190>
```





In [15]:
```
# Check how many records have zero or less unit price
len(df1[df1.UnitPrice<=0])
```

Out[15]: 2517

In [16]:
```
df1[df1.UnitPrice<=0].Description.isna().sum()
```

Out[16]: 1454

In [17]:
```
df1[df1.UnitPrice<=0].Description.value_counts()
```

Out[17]:
```
check                                   159
?                                        47
damages                                  45
damaged                                  43
found                                    25
                                       ...
HEART OF WICKER LARGE                     1
?sold as sets?                            1
CERAMIC HEART FAIRY CAKE MONEY BANK       1
MINI CAKE STAND  HANGING STRAWBERY        1
WATERING CAN PINK BUNNY                   1
Name: Description, Length: 377, dtype: int64
```

In [18]:
```
# Remove it from the dataset
df1=df1[df1.UnitPrice>0]
df1.head()
```

Out[18]:

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

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

In [19]:

```
# Verify what negative quantities are attributed to:
neg=df1[df1.Quantity<0].sort_values(by='Quantity')
neg.head(5)
#It is evident that two spikes are the cancelled invoices 581484 and 23166.
```

Out[19]:

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country
2011-12-09	C581484	23843	PAPER CRAFT , LITTLE BIRDIE	-80995	2.08	16446.0	United Kingdom
2011-01-18	C541433	23166	MEDIUM CERAMIC TOP STORAGE JAR	-74215	1.04	12346.0	United Kingdom
2010-12-02	C536757	84347	ROTATING SILVER ANGELS T-LIGHT HLDR	-9360	0.03	15838.0	United Kingdom
2011-04-18	C550456	21108	FAIRY CAKE FLANNEL ASSORTED COLOUR	-3114	2.10	15749.0	United Kingdom
2011-04-18	C550456	21175	GIN + TONIC DIET METAL SIGN	-2000	1.85	15749.0	United Kingdom

In [20]:

```
#Since top 5 represent 61% of cancellation quantity, let's look at the top 5 rec
neg.head(5).Quantity.sum()/neg.Quantity.sum()
```

Out[20]:

```
0.6113108576451685
```

In [21]:

```
# Inspect the records
[df1[df1.StockCode==x].sort_values(by='Quantity') for x in neg.head(5).StockCode
```

Out[21]:

```
[             InvoiceNo StockCode                   Description  Quantity  \
 InvoiceDate
 2011-12-09    C581484     23843  PAPER CRAFT , LITTLE BIRDIE    -80995
 2011-12-09     581483     23843  PAPER CRAFT , LITTLE BIRDIE     80995

             UnitPrice  CustomerID        Country
 InvoiceDate
```

```
2011-12-09        2.08     16446.0  United Kingdom
2011-12-09        2.08     16446.0  United Kingdom  ,
             InvoiceNo StockCode                     Description  Quantity  \
InvoiceDate
2011-01-18    C541433     23166  MEDIUM CERAMIC TOP STORAGE JAR    -74215
2011-06-20    C557508     23166  MEDIUM CERAMIC TOP STORAGE JAR      -240
2011-08-04    C562375     23166  MEDIUM CERAMIC TOP STORAGE JAR       -12
2011-10-12    C570867     23166  MEDIUM CERAMIC TOP STORAGE JAR       -12
2011-05-24    C554527     23166  MEDIUM CERAMIC TOP STORAGE JAR        -9
...               ...       ...                             ...       ...
2011-05-12     552882     23166  MEDIUM CERAMIC TOP STORAGE JAR        96
2011-07-24     561051     23166  MEDIUM CERAMIC TOP STORAGE JAR       144
2011-05-18     553607     23166  MEDIUM CERAMIC TOP STORAGE JAR       240
2011-07-31     561901     23166  MEDIUM CERAMIC TOP STORAGE JAR       288
2011-01-18     541431     23166  MEDIUM CERAMIC TOP STORAGE JAR     74215

             UnitPrice  CustomerID         Country
InvoiceDate
2011-01-18        1.04     12346.0  United Kingdom
2011-06-20        1.04     16684.0  United Kingdom
2011-08-04        1.25     14911.0            EIRE
2011-10-12        1.25     12607.0             USA
2011-05-24        1.04     15251.0  United Kingdom
...                ...         ...             ...
2011-05-12        1.04     14646.0     Netherlands
2011-07-24        1.04     16684.0  United Kingdom
2011-05-18        1.04     16684.0  United Kingdom
2011-07-31        1.25     14156.0            EIRE
2011-01-18        1.04     12346.0  United Kingdom

[260 rows x 7 columns],
             InvoiceNo StockCode                          Description  \
InvoiceDate
2010-12-02    C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2010-12-06    C537251     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2011-01-05    C540164     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2011-10-24    C572473     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2011-02-28     545217     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
...               ...       ...                                  ...
2010-12-10     538191     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2010-12-02     536784     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2010-12-15     538998     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2011-10-24     572325     84347  ROTATING SILVER ANGELS T-LIGHT HLDR
2011-11-22     577822     84347  ROTATING SILVER ANGELS T-LIGHT HLDR

             Quantity  UnitPrice  CustomerID         Country
InvoiceDate
2010-12-02      -9360       0.03     15838.0  United Kingdom
2010-12-06         -9       2.55         NaN  United Kingdom
2011-01-05         -6       2.55     14911.0            EIRE
2011-10-24         -1       2.55     18188.0  United Kingdom
2011-02-28          1       4.96         NaN  United Kingdom
...               ...        ...         ...             ...
2010-12-10        240       1.88     15061.0  United Kingdom
2010-12-02        240       1.88     15061.0  United Kingdom
2010-12-15        480       1.88     15061.0  United Kingdom
2011-10-24        600       1.74     14607.0  United Kingdom
2011-11-22        600       1.74     14607.0  United Kingdom

[475 rows x 7 columns],
             InvoiceNo StockCode                         Description  Quantity
\
InvoiceDate
2011-04-18    C550456     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
2011-11-22    C577832     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR       -18
```

```
2011-12-01    C580131     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR       -18
2011-07-28     561658     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR         1
2011-06-20     557502     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR         1
...               ...       ...                                ...       ...
2011-11-23     578125     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR        90
2011-11-14     576180     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR       180
2011-11-09     575296     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR       540
2011-01-11     540815     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR      3114
2011-04-18     550461     21108  FAIRY CAKE FLANNEL ASSORTED COLOUR      3114

             UnitPrice  CustomerID         Country
InvoiceDate
2011-04-18        2.10     15749.0  United Kingdom
2011-11-22        0.79     18274.0  United Kingdom
2011-12-01        2.10     17576.0  United Kingdom
2011-07-28        2.55     12743.0     Unspecified
2011-06-20        4.96         NaN  United Kingdom
...                ...         ...             ...
2011-11-23        0.79     17511.0  United Kingdom
2011-11-14        0.79     13694.0  United Kingdom
2011-11-09        0.79     16041.0  United Kingdom
2011-01-11        2.10     15749.0  United Kingdom
2011-04-18        2.10     15749.0  United Kingdom

[270 rows x 7 columns],
            InvoiceNo StockCode                  Description  Quantity  \
InvoiceDate
2011-04-18    C550456     21175  GIN + TONIC DIET METAL SIGN     -2000
2011-10-10    C570290     21175  GIN + TONIC DIET METAL SIGN       -12
2011-06-13    C556647     21175  GIN + TONIC DIET METAL SIGN       -12
2011-05-27    C554870     21175  GIN + TONIC DIET METAL SIGN        -3
2010-12-10    C538350     21175  GIN + TONIC DIET METAL SIGN        -1
...               ...       ...                          ...       ...
2011-07-14     560080     21175  GIN + TONIC DIET METAL SIGN       192
2011-09-20     567458     21175  GIN + TONIC DIET METAL SIGN       192
2011-11-21     577747     21175  GIN + TONIC DIET METAL SIGN       240
2011-01-11     540815     21175  GIN + TONIC DIET METAL SIGN      2000
2011-04-18     550461     21175  GIN + TONIC DIET METAL SIGN      2000

             UnitPrice  CustomerID         Country
InvoiceDate
2011-04-18        1.85     15749.0  United Kingdom
2011-10-10        2.55     14665.0  United Kingdom
2011-06-13        2.55     13012.0  United Kingdom
2011-05-27        2.55     15078.0  United Kingdom
2010-12-10        1.85     13798.0  United Kingdom
...                ...         ...             ...
2011-07-14        2.08     17450.0  United Kingdom
2011-09-20        2.66     17450.0  United Kingdom
2011-11-21        2.67     17450.0  United Kingdom
2011-01-11        1.85     15749.0  United Kingdom
2011-04-18        1.69     15749.0  United Kingdom

[825 rows x 7 columns]]
```

In [22]:

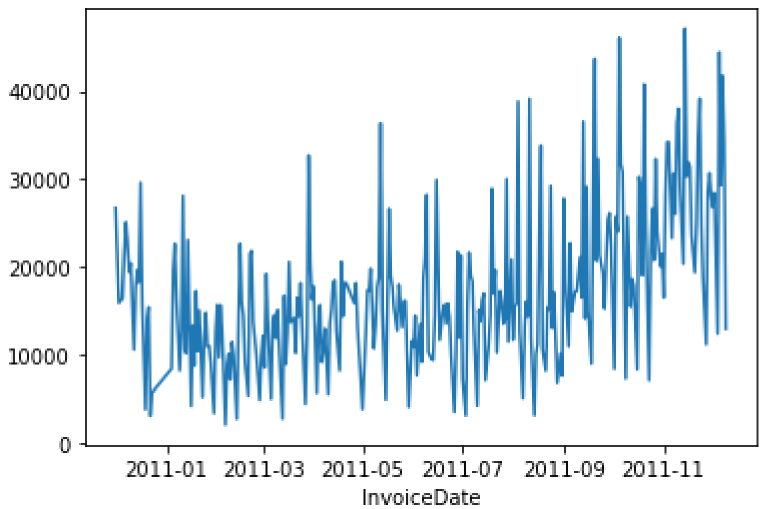
```
#By looking at top 5, it is reasonable to assume that the majority of cancelled
# The exception is item 84347, which doesn't have a reasonable explanation witho
# For now, we will not be removing cancelled transaction, since many are voided
# However, we will define a function and remove transactions that have a negativ
```

In [23]:

```
def remove_writeoffs(df):
    qnegat=[x for x in df.InvoiceNo if x.startswith('C')]
    return df[(df.Quantity>0) | (df.InvoiceNo.isin(qnegat))].sort_values(by='Qua
df1=remove_writeoffs(df1)
```

In [24]:
```
# View daily sales volume by day
df2=df1.groupby(['InvoiceDate'])['Quantity'].sum()
df2.plot()

# The plot doesn't look stationary. While we take a note of it, we will coninue
```

Out[24]: <AxesSubplot:xlabel='InvoiceDate'>



In [25]:
```
# Check how many quantity of products have been sold online from each country
a = df1['Quantity'].groupby(df1['Country']).agg('sum').sort_values(ascending = F
print(a)
```

```
Country
United Kingdom    4399357
Netherlands        199552
EIRE               142363
Germany            117446
France             110479
Australia           83345
Sweden              35637
Switzerland         30324
Spain               26813
Japan               25218
Name: Quantity, dtype: int64
```

In [26]:
```
# Since the dates range from 12/01/2010-12/09/2011, it looks like there are miss
len(df2.index)
```

Out[26]: 305

In [27]:
```
# Define a function to reinstate dates
import datetime
def zero_sales(df):
    idx = pd.date_range(df.index.min(),datetime.date(2011,12,9))
    return df.reindex(idx, fill_value=0)
```

In [28]:
```
df2=zero_sales(df2)
```

In [29]:
```
# Review which days of the week we have no sales reported
pd.DataFrame(df2.index[df2.values==0])[0].dt.day_name().value_counts()
```

Out[29]: Saturday   53

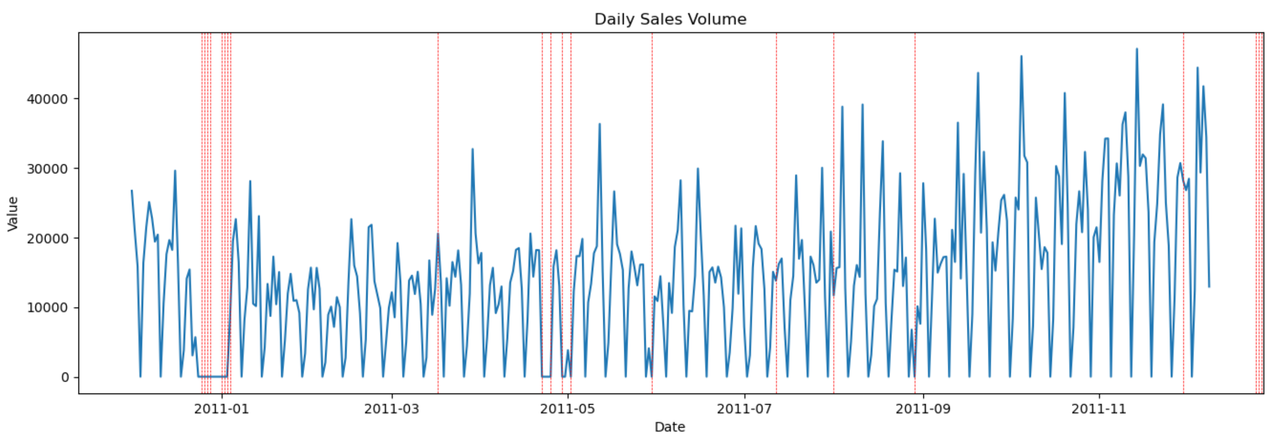
```
Monday        6
Friday        4
Sunday        3
Thursday      1
Wednesday     1
Tuesday       1
Name: 0, dtype: int64
```

In [30]:
```
#!pip install holidays
```

In [31]:
```
from datetime import date
import holidays
```

In [32]:
```
uk_holidays=pd.Series(holidays.UnitedKingdom(years= [2010,2011] ).keys())
```

In [33]:
```
# Plot data with holidays
from matplotlib import pylab
def plot_df(data, x, y, title="", xlabel='Date', ylabel='Value', dpi=100):
    plt.figure(figsize=(16,5), dpi=dpi)
    plt.plot(x, y, color='tab:blue')
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
    holidays = uk_holidays[uk_holidays.between(data.index.min(), datetime.date(2
    [pylab.axvline(_x, linewidth=0.5, color='r', ls='--') for _x in holidays]
    plt.show()

plot_df(df2, x=df2.index, y=df2.values, title='Daily Sales Volume')
```



In [34]:
```
# Define a week between 2011-11-27 and 2011-12-3 and identify the top 3 per obje
week=df1[(df1.index>=datetime.date(2011,11,27) ) & (df1.index<=datetime.date(201
top3=week[['StockCode','Quantity']].groupby('StockCode').sum().sort_values(by='Q
top3
```

Out[34]:

	Quantity
StockCode	
23084	4588
22197	3195
23582	1851

In [35]:
```
# Since the dataset has various descriptions per SKU, let's review the Descripti
df1[df1['StockCode']==top3.index[0]]['Description'].unique()
```

Out[35]: array(['RABBIT NIGHT LIGHT'], dtype=object)

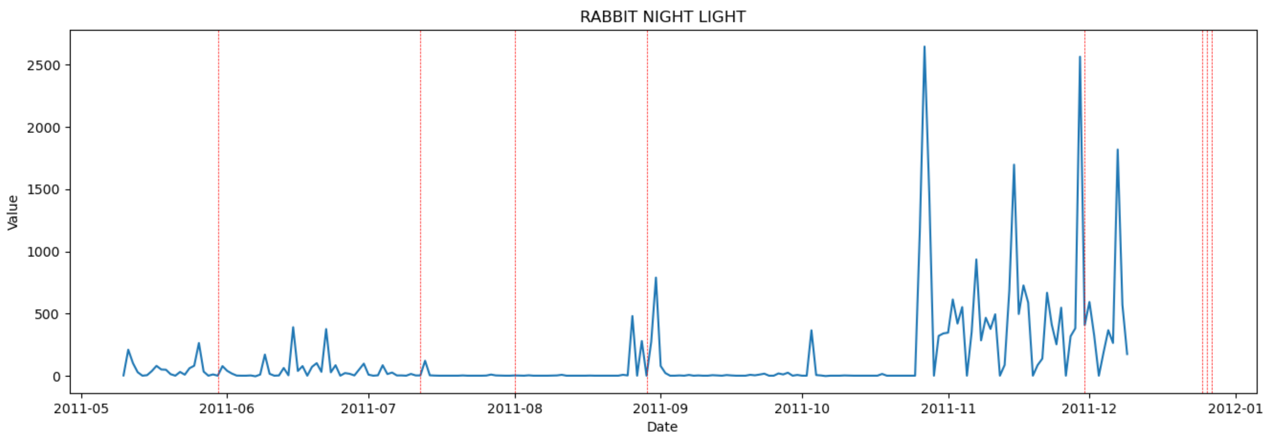
In [36]:
```
df1[df1['StockCode']==top3.index[1]]['Description'].unique()
```

Out[36]: array(['POPCORN HOLDER', 'SMALL POPCORN HOLDER'], dtype=object)

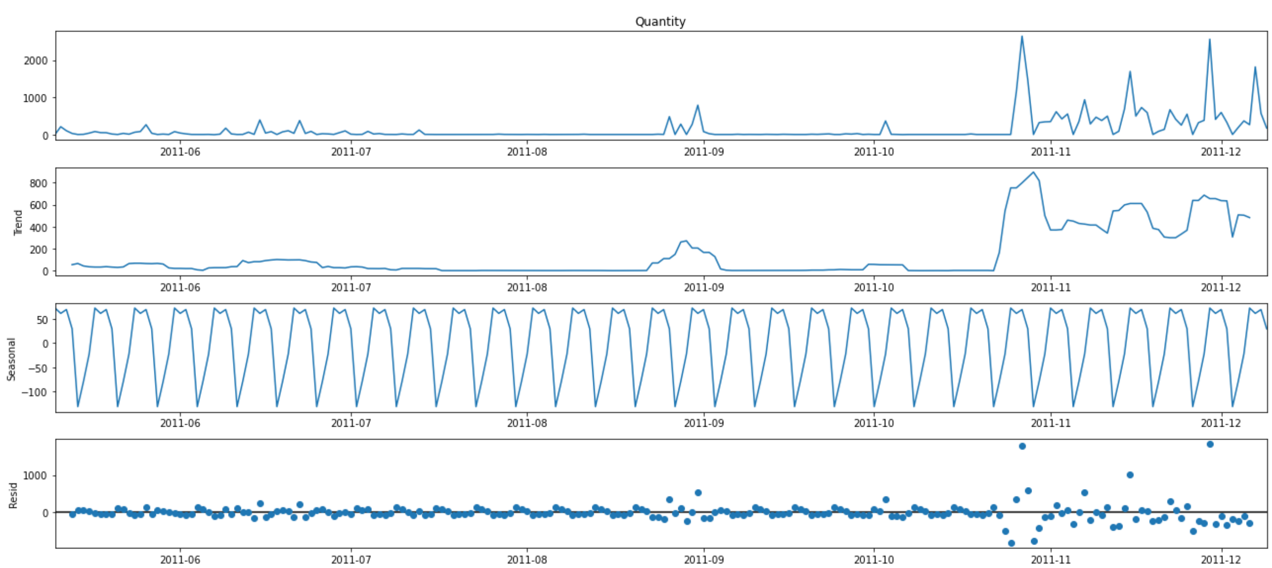
In [37]:
```
df1[df1['StockCode']==top3.index[2]]['Description'].unique()
```

Out[37]: array(['VINTAGE DOILY JUMBO BAG RED '], dtype=object)

In [38]:
```
# Plot the sales quantity timeseries of each item
rabl=df1[df1.StockCode==top3.index[0]].sort_values(by='InvoiceDate')
rabl2=zero_sales(rabl.groupby(['InvoiceDate'])['Quantity'].sum())
plot_df(rabl2, x=rabl2.index, y=rabl2.values, title="RABBIT NIGHT LIGHT", xlabel
```

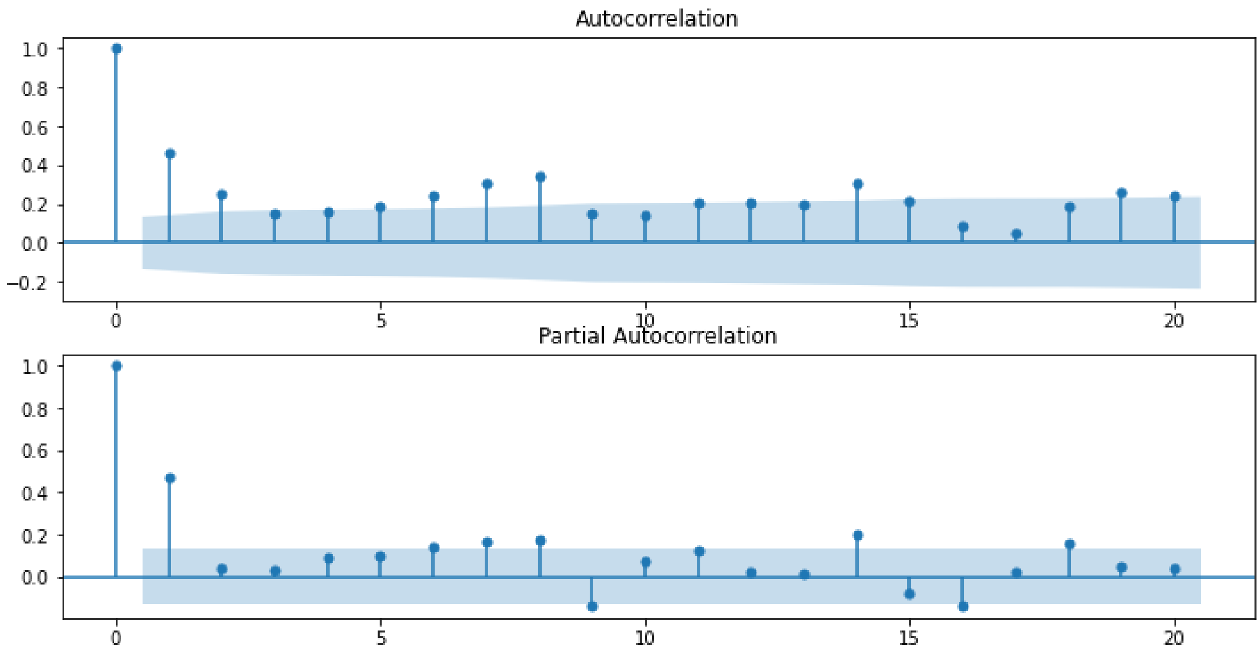


In [39]:
```
# By looking at the RABBIT NIGHT LIGHT, we can infer that there is an increasing
#There is a somewhat seasonality in the observed data. Also, the data may not be
import statsmodels.api as sm
decomposition = sm.tsa.seasonal_decompose(rabl2, model='additive')
from pylab import rcParams
rcParams['figure.figsize'] = 18, 8
fig = decomposition.plot()
plt.show()
```



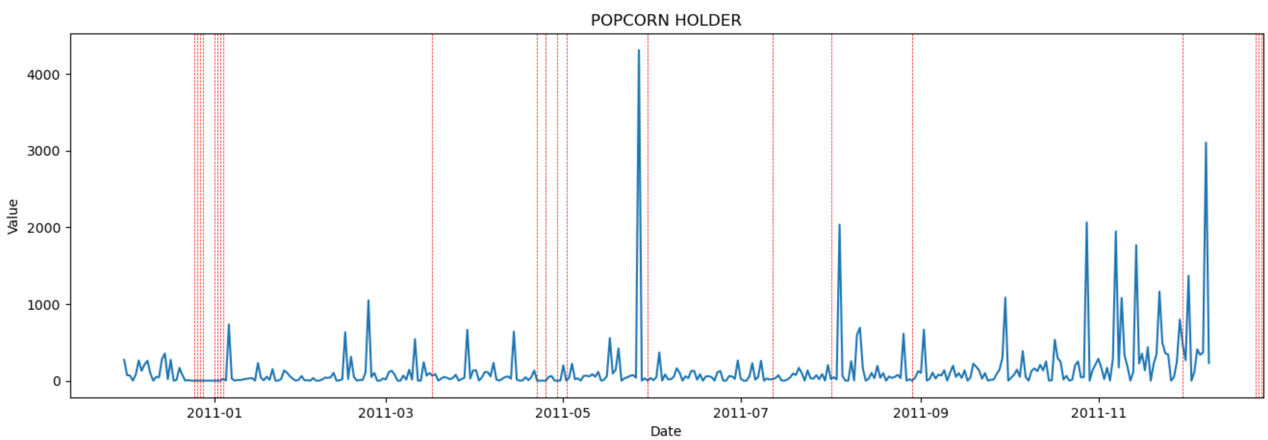
In [40]:
```
# Review autocorrelation function plots
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

```
fig, ax = plt.subplots(2, figsize=(12,6))
ax[0]=plot_acf(rabl2, ax=ax[0], lags=20)
ax[1]=plot_pacf(rabl2, ax=ax[1], lags=20)
```



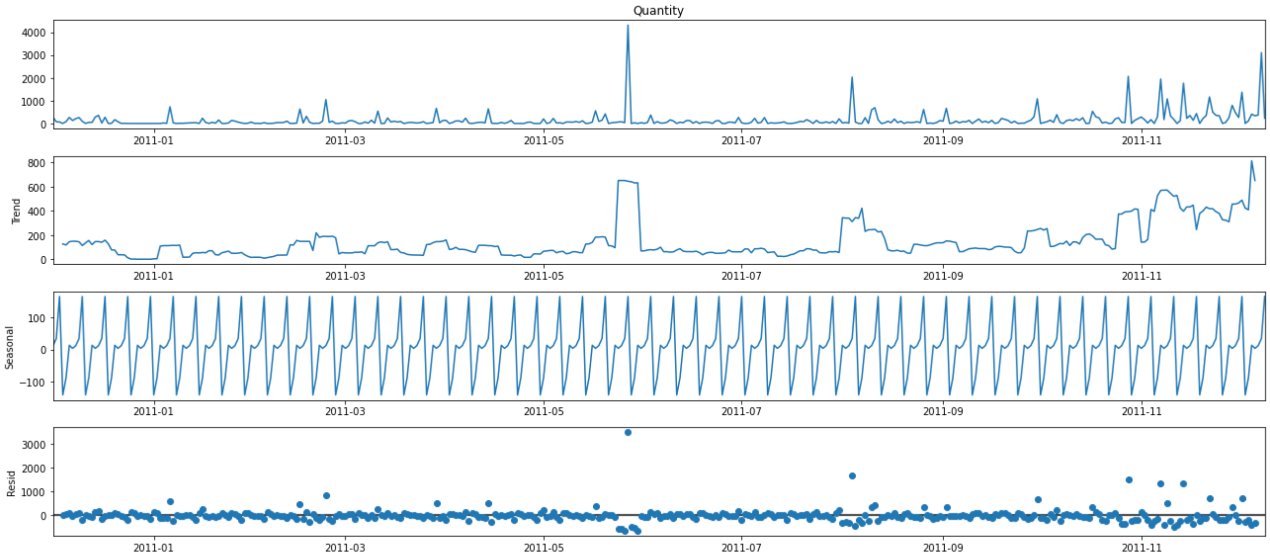
In [41]:

```
# Plot the Popcorn Holder data
poph=df1[df1.StockCode==top3.index[1]].sort_values(by='InvoiceDate')
poph2=zero_sales(poph.groupby(['InvoiceDate'])['Quantity'].sum())
plot_df(poph2, x=poph2.index, y=poph2.values, title="POPCORN HOLDER", xlabel='Da
```

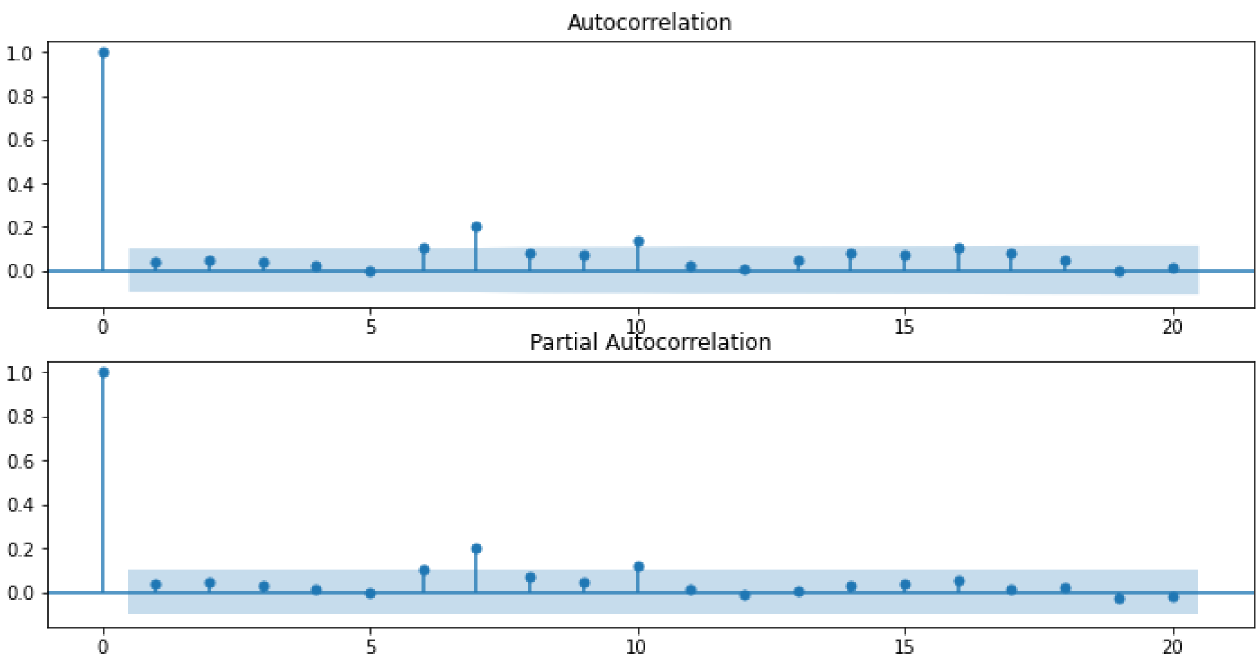


In [42]:

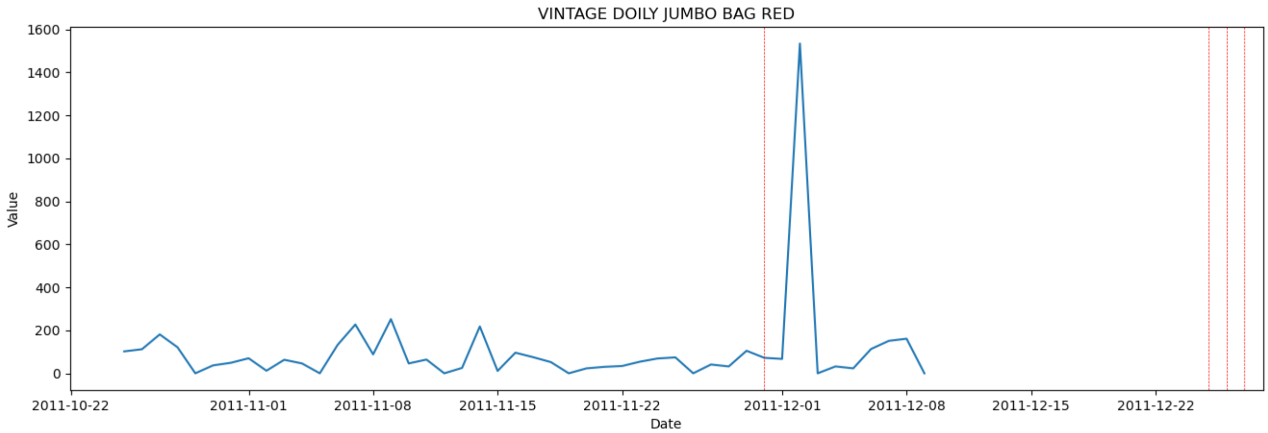
```
# By looking at it, we can also infer that there is an unusual spike around June
import statsmodels.api as sm
from pylab import rcParams
decomposition = sm.tsa.seasonal_decompose(poph2, model='additive')
rcParams['figure.figsize'] = 18, 8
fig = decomposition.plot()
plt.show()
```



In [43]:
```
fig, ax = plt.subplots(2, figsize=(12,6))
ax[0]=plot_acf(poph2, ax=ax[0], lags=20)
ax[1]=plot_pacf(poph2, ax=ax[1], lags=20)
```

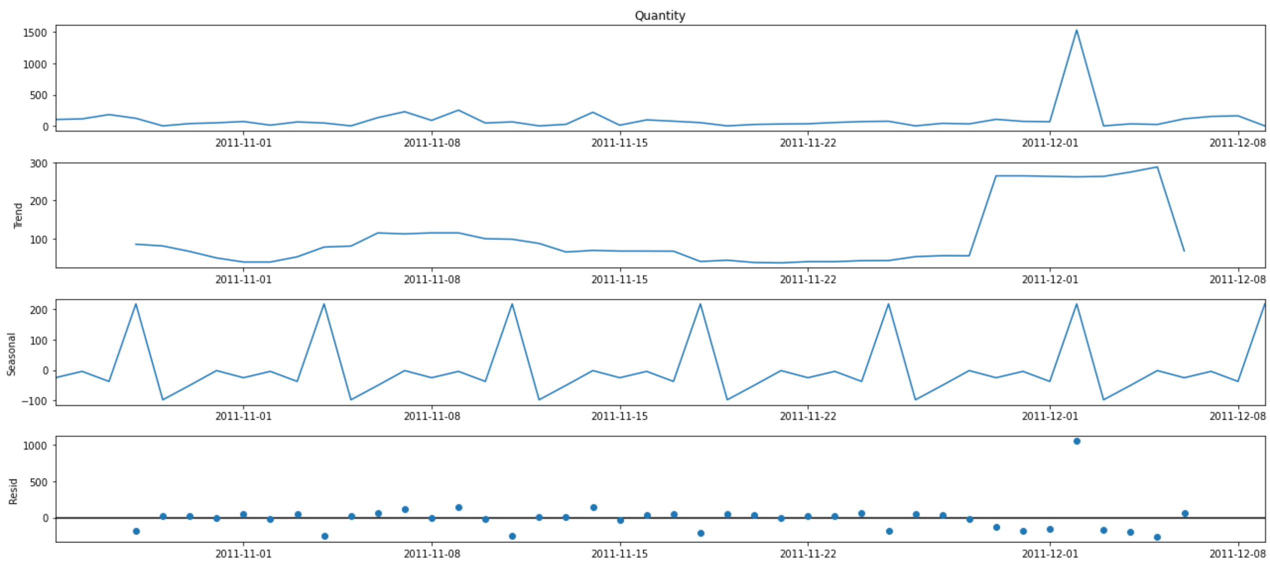


In [44]:
```
# Plot sales of the VINTAGE DOILY JUMBO BAG RED
vinb=df1[df1.StockCode==top3.index[2]].sort_values(by='InvoiceDate')
vinb2=zero_sales(vinb.groupby(['InvoiceDate'])['Quantity'].sum())
plot_df(vinb2, x=vinb2.index, y=vinb2.values, title="VINTAGE DOILY JUMBO BAG RED
```



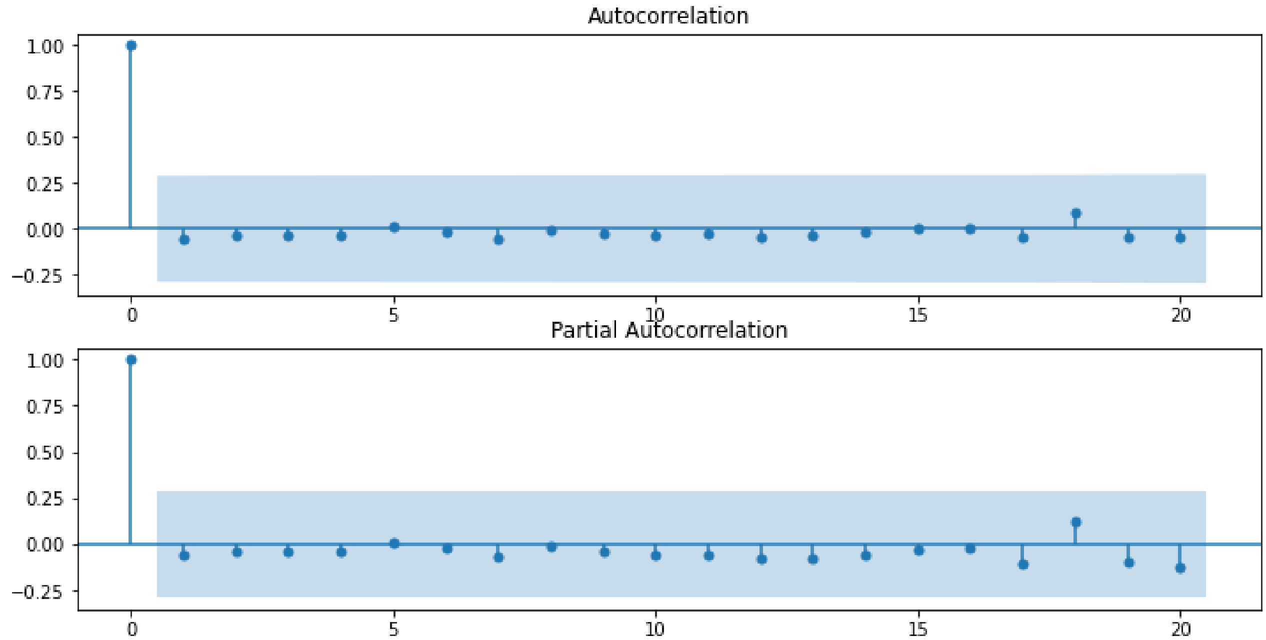
In [45]:

```
# By looking at the VINTAGE DOILY JUMBO BAG RED, we can also infer that there is
decomposition = sm.tsa.seasonal_decompose(vinb2, model='additive')
rcParams['figure.figsize'] = 18, 8
fig = decomposition.plot()
plt.show()
```



In [46]:

```
fig, ax = plt.subplots(2, figsize=(12,6))
ax[0]=plot_acf(vinb2, ax=ax[0], lags=20)
ax[1]=plot_pacf(vinb2, ax=ax[1], lags=20)
#The data is stationary and appears to have daily and weekly seasonality alog wi
```



In [47]:
```
#It is evident that three items have a different history of sales: Over a year f
#for RABBIT NIGHT LIGHT, and a month and a half for VINTAGE DOILY JUMBO BAG RED.
```

Models

In [48]:
```
from sklearn.metrics import mean_squared_error
from matplotlib import pyplot

# Begin with modeling the POPCORN HOLDER data

poph2_train=poph2[poph2.index<'2011-11-27']
poph2_test=poph2[poph2.index>='2011-11-27']

#rabl2_train=rabl2[rabl2.index<'2011-11-27']
#rabl2_test=rabl2[rabl2.index>='2011-11-27']

#vinb2_train=vinb2[vinb2.index<'2011-11-27']
#vinb2_test=vinb2[vinb2.index>='2011-11-27']
```

In [49]:
```
train_dates, test_dates = poph2_train.index, poph2_test.index
train_data, test_data = poph2_train.values, poph2_test.values

#train_dates, test_dates = rabl2_train.index, rabl2_test.index
#train_data, test_data = rabl2_train.values, rabl2_test.values

#train_dates, test_dates = vinb2_train.index, vinb2_test.index
#train_data, test_data = vinb2_train.values, vinb2_test.values
```

In [50]:
```
# Define a dataframe to view the performance of fitted models
perform=pd.DataFrame()
perform.index.name='Models Popcorn Holder'
perform['RMSE']=None
perform['Parameters']=None
```

In [51]:
```
# Define a function for RMSE
from sklearn.metrics import mean_squared_error
```

```
def rmse(actual, predicted):
    rmse=np.sqrt(mean_squared_error(actual,predicted))
    return rmse
```

In [52]:
```
# Define a plot function for actual vs predicted:
import plotly.graph_objects as go
def plot_actual_predicted(actual, predicted, model_name):
    fig = go.Figure()
    fig.add_trace(go.Scatter(x=test_dates, y=actual, name = "Expected", line = d
    fig.add_trace(go.Scatter(x=test_dates, y=predicted, name = model_name, line
    fig.show()
```

Model 1: Moving Average

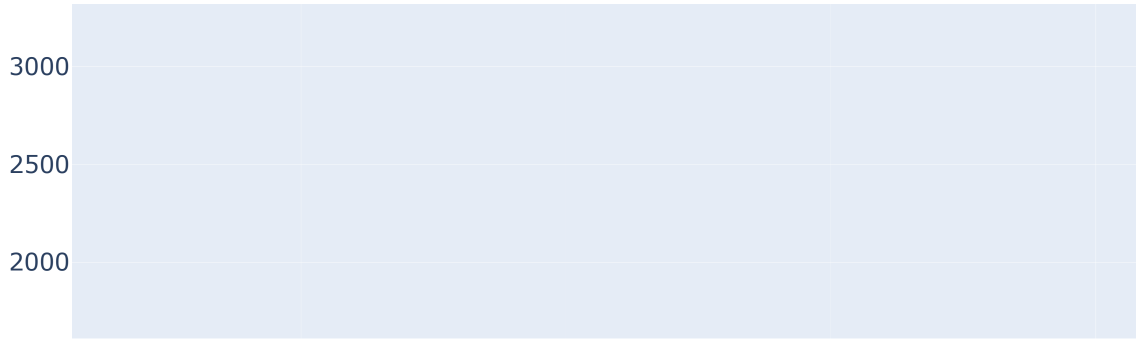
In [53]:
```
# Begin selecting the best window size

X=poph2.values
for a in range(1,13):
    window = a
    history = [X[i] for i in range(window)]
    test = [X[i] for i in range(window, (len(X)-14))]
    predictions = list()
    # walk forward over time steps in test
    for t in range(len(test)):
        length = len(history)
        preds = np.mean([history[i] for i in range(length-window,length)])
        obs = test[t]
        predictions.append(preds)
        history.append(obs)
    error = rmse(test, predictions)
    print ('RMSE: %.3f' % round(error), 'Window size: %.3f' % a)
```

```
RMSE: 476.000 Window size: 1.000
RMSE: 409.000 Window size: 2.000
RMSE: 389.000 Window size: 3.000
RMSE: 376.000 Window size: 4.000
RMSE: 370.000 Window size: 5.000
RMSE: 364.000 Window size: 6.000
RMSE: 352.000 Window size: 7.000
RMSE: 350.000 Window size: 8.000
RMSE: 349.000 Window size: 9.000
RMSE: 346.000 Window size: 10.000
RMSE: 346.000 Window size: 11.000
RMSE: 346.000 Window size: 12.000
```

In [54]:
```
# Apply a window size of 10 and predict
window = 10
predict=pd.DataFrame(X)[0].rolling(window).mean()[-13:]
observ=pd.DataFrame(X)[0][-13:]
error_ma = rmse(observ, predict)
print('RMSE error: %.3f' % error_ma, 'Window size: %.3f' % window)
```

```
RMSE error: 745.817 Window size: 10.000
```

In [55]:
```
plot_actual_predicted(observ, predict, "Moving Average Predictions")
```



In [56]:
```
perform.loc['Moving Average', ('RMSE','Parameters')]= round(error_ma,0), 'Window
perform
```

Out[56]:

Models Popcorn Holder	RMSE	Parameters
Moving Average	746	Window size: 10

Model 2: Exponential Smoothing

In [57]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_squared_error
```

In [58]:
```
#!pip install pmdarima
```

In [59]:
```
#from statsmodels.tsa.statespace.sarimax import SARIMAX
#from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [60]:
```
mod_ex=ExponentialSmoothing(np.array(train_data), seasonal_periods=52, trend='ad
```

In [61]:
```
fit=mod_ex.fit()
pred_es=fit.forecast(13)
```

In [62]:
```
error_es = rmse(test_data, pred_es)
print('RMSE: %.3f' % error_es)
```

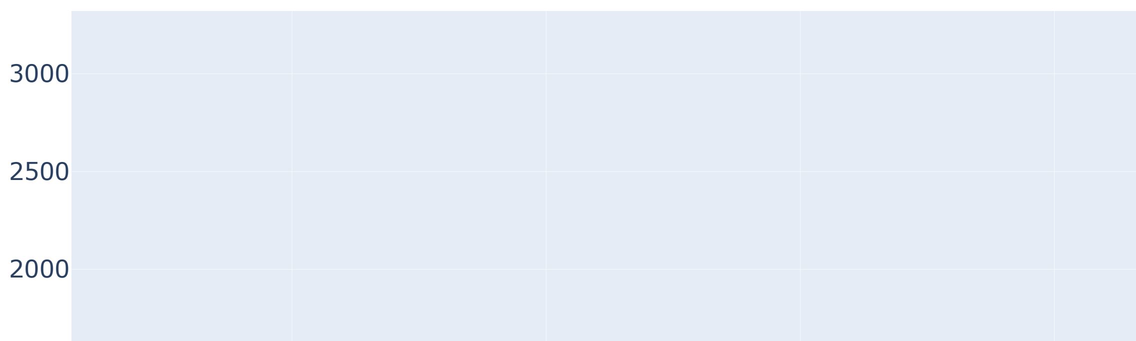
```
RMSE: 781.167
```

In [63]:
```
perform.loc['Exponential Smoothing', ('RMSE','Parameters')]= round(error_es), 'S
perform
```

Out[63]:

	RMSE	Parameters
Models Popcorn Holder		
Moving Average	746	Window size: 10
Exponential Smoothing	781	Seasonal_periods =52

In [64]:
```
plot_actual_predicted(test_data, pred_es, "Exponential Smoothing Prediction")
```



Model 3: Arima

In [65]:
```
#!pip install pmdarima
from pmdarima.arima import auto_arima
from statsmodels.tsa.stattools import adfuller
```

In [66]:
```
# Let's use auto_arima. We know our data shows seasonality and needs differencin
stepwise_model = auto_arima(train_data, start_p=1, start_q=1, max_p=3, max_q=3,
                           trace=True, error_action='ignore', suppress_warnings=
```

```
Performing stepwise search to minimize aic
```

```
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=inf, Time=0.54 sec
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=5531.538, Time=0.02 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=5334.731, Time=0.15 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=inf, Time=0.28 sec
 ARIMA(1,1,0)(0,1,0)[12]             : AIC=5445.079, Time=0.03 sec
 ARIMA(1,1,0)(2,1,0)[12]             : AIC=5291.955, Time=0.32 sec
 ARIMA(1,1,0)(2,1,1)[12]             : AIC=inf, Time=0.94 sec
 ARIMA(1,1,0)(1,1,1)[12]             : AIC=inf, Time=0.36 sec
 ARIMA(0,1,0)(2,1,0)[12]             : AIC=5387.740, Time=0.28 sec
 ARIMA(2,1,0)(2,1,0)[12]             : AIC=5256.161, Time=0.44 sec
 ARIMA(2,1,0)(1,1,0)[12]             : AIC=5300.342, Time=0.21 sec
 ARIMA(2,1,0)(2,1,1)[12]             : AIC=inf, Time=1.17 sec
 ARIMA(2,1,0)(1,1,1)[12]             : AIC=inf, Time=0.53 sec
 ARIMA(3,1,0)(2,1,0)[12]             : AIC=5235.364, Time=0.48 sec
 ARIMA(3,1,0)(1,1,0)[12]             : AIC=5282.255, Time=0.27 sec
 ARIMA(3,1,0)(2,1,1)[12]             : AIC=inf, Time=1.38 sec
 ARIMA(3,1,0)(1,1,1)[12]             : AIC=inf, Time=0.63 sec
 ARIMA(3,1,1)(2,1,0)[12]             : AIC=inf, Time=1.28 sec
 ARIMA(2,1,1)(2,1,0)[12]             : AIC=inf, Time=1.25 sec
 ARIMA(3,1,0)(2,1,0)[12] intercept   : AIC=5237.368, Time=0.97 sec

Best model:  ARIMA(3,1,0)(2,1,0)[12]
Total fit time: 11.532 seconds
```

In [67]:

```
stepwise_model.fit(train_data)
preds = stepwise_model.predict(n_periods=13)
preds
```

Out[67]:

```
array([  88.78128757,  118.38078031,   25.54930964,  140.30679137,
        585.01505017,   41.36413624, 1147.21044358,  323.36986013,
        156.51130324,   79.41973066,  139.3972984 ,  543.33842197,
          3.84710817])
```

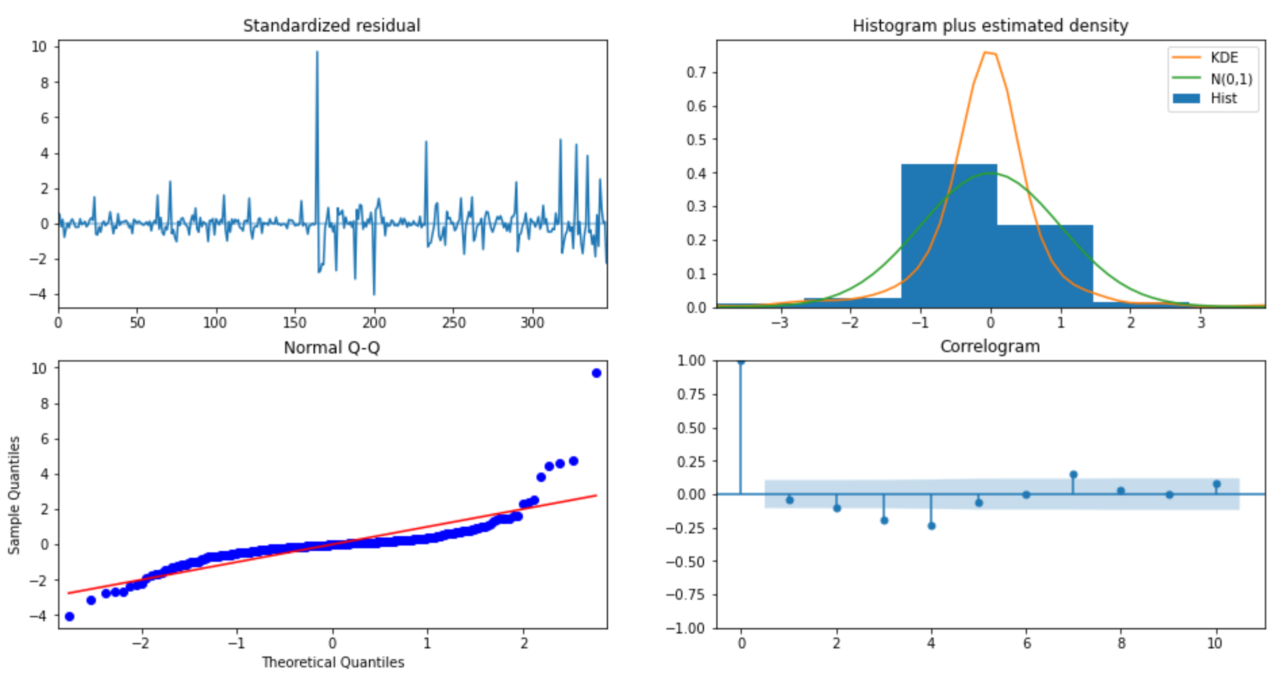
In [68]:

```
error_ar=rmse(test_data, preds)

print('RMSE: %.3f' % error_ar)
```

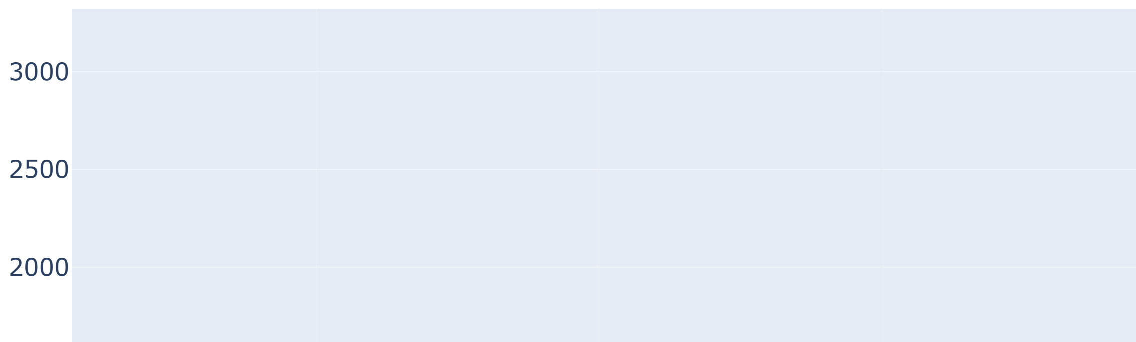
```
RMSE: 909.169
```

In [69]:

```
stepwise_model.plot_diagnostics(figsize=(16, 8))
plt.show()
```



In [70]:
```
plot_actual_predicted(test_data, preds, 'Arima Predictions')
```



In [71]:
```
perform.loc['Arima', ('RMSE','Parameters')]=round(error_ar), stepwise_model
perform
```

Out[71]:

Models Popcorn Holder	RMSE	Parameters
Moving Average	746	Window size: 10
Exponential Smoothing	781	Seasonal_periods =52
Arima	909	ARIMA(3,1,0)(2,1,0)[12]

Model 4: XGBoost

In [72]:
```
#!pip install xgboost
```

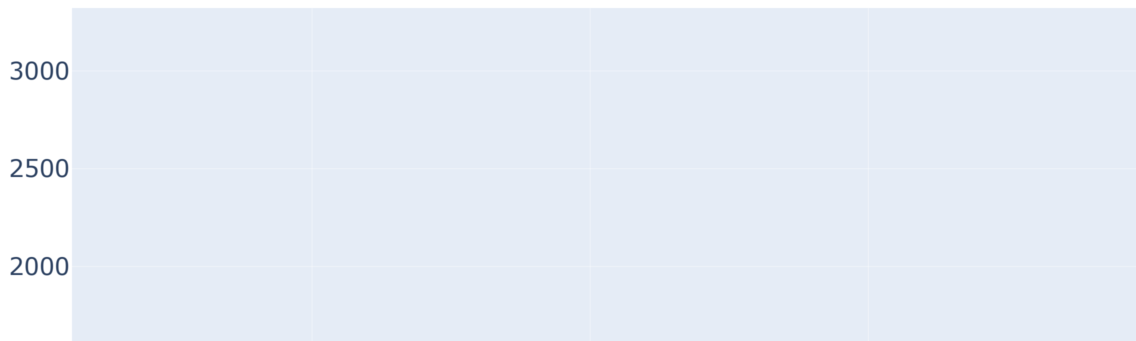
In [73]:
```
import xgboost as xgb
from xgboost import DMatrix
from pandas import concat
from numpy import asarray
from xgboost import XGBRegressor
```

In [74]:
```
# Define functions to apply XGBoost model:
data=poph2.values

# Transform a time series dataset into a supervised learning dataset
def series_to_supervised(data, n_in, n_out=1, dropnan=True):
    df = pd.DataFrame(data)
    cols = list()
    # input sequence (t-n, ... t-1)
    for i in range(n_in, 0, -1):
        cols.append(df.shift(i))
    # forecast out
    for i in range(0, n_out):
        cols.append(df.shift(-i))
    # aggregate
    agg = concat(cols, axis=1)
    # drop rows with NaN values
    if dropnan:
        agg.dropna(inplace=True)
    return agg.values

# Split a dataset into train/test sets
def train_test_split(data, n_test):
    return data[:-n_test, :], data[-n_test:, :]

# Fit an xgboost model and make a one step prediction
def xgboost_forecast(train, testX):
    train = asarray(train)
    # split into input and output columns
    trainX, trainY = train[:, :-1], train[:, -1]
    # fit model
    model = XGBRegressor(objective='reg:squarederror', n_estimators=1000, max_de
 min_child_weight=1)
    model.fit(trainX, trainY)
    preds = model.predict(asarray([testX]))
    return preds[0]

# Validation
def walk_forward_test(data, n_test):
    predictions = list()
    train, test = train_test_split(data, n_test)
    # add history with training dataset
    history = [x for x in train]
    # step over each time-step in the test set
    for i in range(len(test)):
        # split test row into input and output columns
        testX, testY = test[i, :-1], test[i, -1]
        # make a prediction
        preds = xgboost_forecast(history, testX)
        predictions.append(preds)
        # add actual observation for the next loop to history
        history.append(test[i])
    # estimate error
    error_xgboost = np.sqrt(mean_squared_error(test[:,-1], predictions))
    return error_xgboost, test[:, -1], predictions
```

In [75]:
```
# Transform the time series data into supervised learning
data = series_to_supervised(data, n_in=17)
# Evaluate
error_xgboost, y, preds = walk_forward_test(data, n_test=13)
print('RMSE: %.3f' % error_xgboost)
```

```python
# Plot expected vs preducted
plot_actual_predicted(y, preds, "XGBoost Predictions")
```

RMSE: 714.233



In [76]:
```python
perform.loc['XGBoost', ('RMSE','Parameters')]=round(error_xgboost), "n_estimator
perform
```

Out[76]:

Models Popcorn Holder	RMSE	Parameters
Moving Average	746	Window size: 10
Exponential Smoothing	781	Seasonal_periods =52
Arima	909	ARIMA(3,1,0)(2,1,0)[12]
XGBoost	714	n_estimators=1000, max_depth=5,min_child_weight=1

Model 5: FB Prophet

In [77]:
```python
#!pip install fbprophet
```

In [78]:
```python
from fbprophet import Prophet
```

In [79]:
```
# Prepare data
df_train, df_test  =poph2_train.reset_index(), poph2_test.reset_index()
#df_train, df_test  =rabl2_train.reset_index(), rabl2_test.reset_index()
#df_train, df_test  =vinb2_train.reset_index(), rabl2_test.reset_index()
df_train.columns, df_test.columns = ['ds','y'], ['ds','y']
```

In [80]:
```
# Add holidays

holi = pd.DataFrame(list(holidays.UnitedKingdom(years= [2010,2011]).items()))
holi.columns=['ds','holiday']
```

In [81]:
```
# Define a model
m=Prophet(holidays=holi, holidays_prior_scale=0.05) #weekly_seasonality=True, da

m.add_seasonality(name='weekly', period=7, fourier_order=3, prior_scale=5)
m.add_seasonality(name='daily', period=8, fourier_order=3, prior_scale=0.1)
m.add_seasonality(name='yearly', period=6, fourier_order=3, prior_scale=0.1)
```

Out[81]:
```
<fbprophet.forecaster.Prophet at 0x7fa441cde5e0>
```

In [82]:
```
m.fit(df_train)
```

```
INFO:fbprophet:Found custom seasonality named 'yearly', disabling built-in 'year
ly' seasonality.
INFO:fbprophet:Found custom seasonality named 'weekly', disabling built-in 'week
ly' seasonality.
INFO:fbprophet:Found custom seasonality named 'daily', disabling built-in 'dail
y' seasonality.
```

Out[82]:
```
<fbprophet.forecaster.Prophet at 0x7fa441cde5e0>
```

In [83]:
```
future=m.make_future_dataframe(periods=13, freq='D')
```

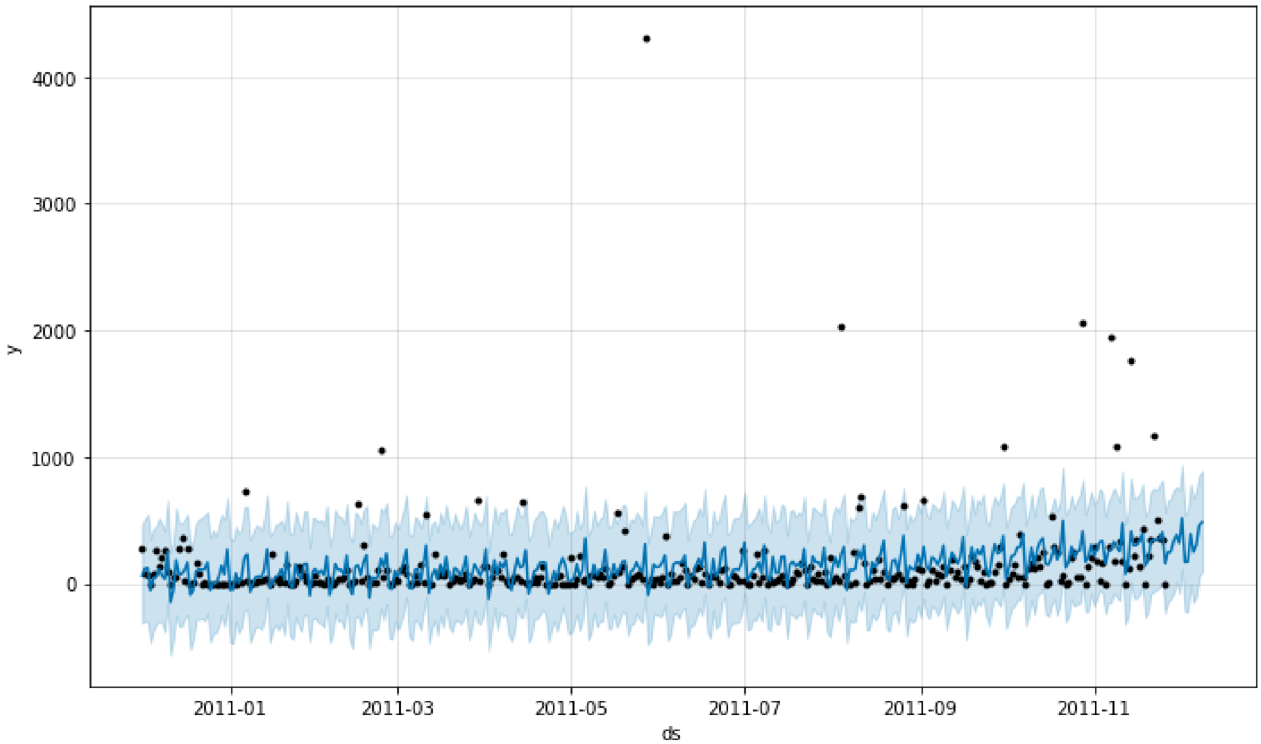
In [84]:
```
prophet_pred=m.predict(future)
prophet_pred.tail()
```

Out[84]:

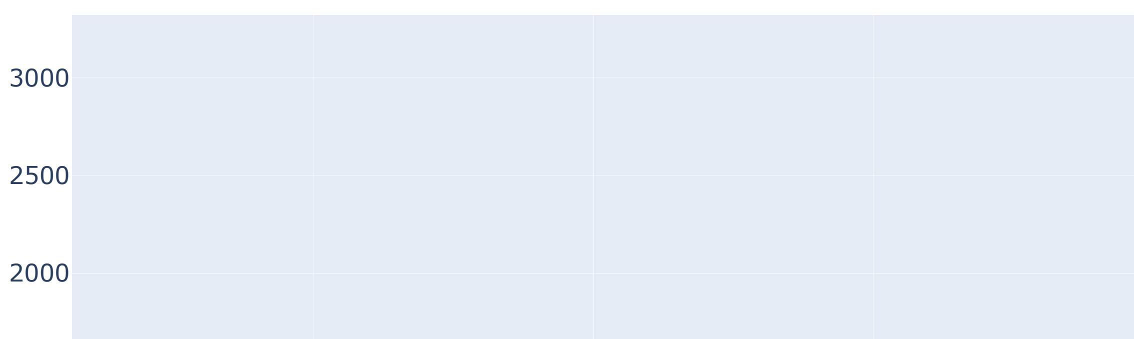
	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	Battle of the Boyne [Northern Ireland]	Battle (E [Nor Ireland]_
369	2011-12-05	318.564071	-7.675460	785.822680	318.383531	318.741389	0.0	
370	2011-12-06	320.122080	-150.624089	672.610332	319.889838	320.344679	0.0	
371	2011-12-07	321.680090	-106.786993	730.466544	321.391054	321.955181	0.0	
372	2011-12-08	323.238099	56.800815	855.213451	322.874798	323.591524	0.0	
373	2011-12-09	324.796109	91.167244	888.424066	324.362337	325.205168	0.0	

5 rows × 79 columns

In [85]:
```
import matplotlib.pyplot as plt
m.plot(prophet_pred)
plt.show()
```



In [86]:
```
plot_actual_predicted(poph2_test.values, prophet_pred[prophet_pred.ds>='2011-11-
```



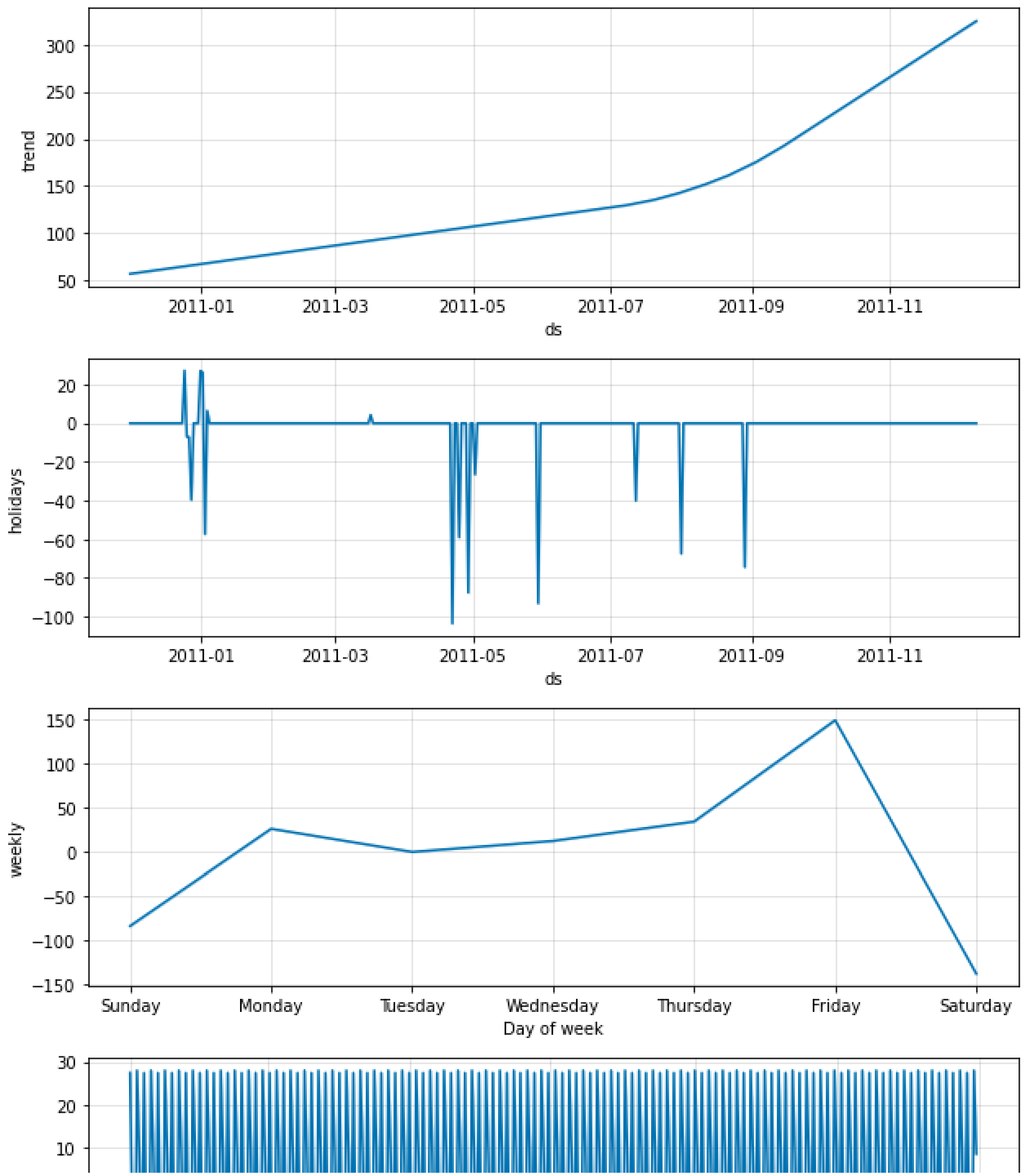
In [87]:
```
preds_prophet=prophet_pred[prophet_pred.ds>='2011-11-27']['yhat'].values
```

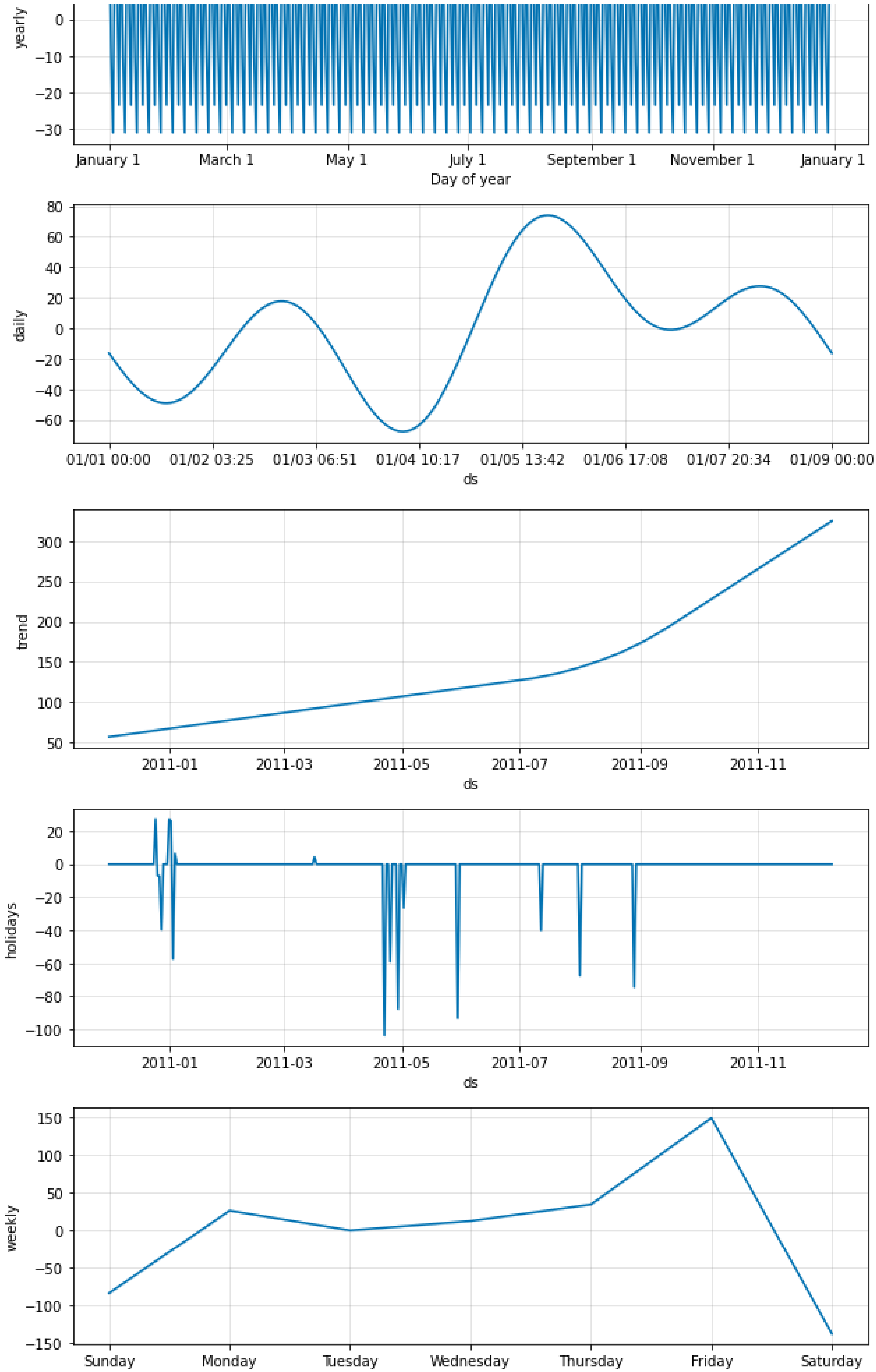
In [88]:
```
error_prophet=np.sqrt(mean_squared_error(poph2_test.values, preds_prophet))

print('RMSE: %.3f' % error_prophet)
```

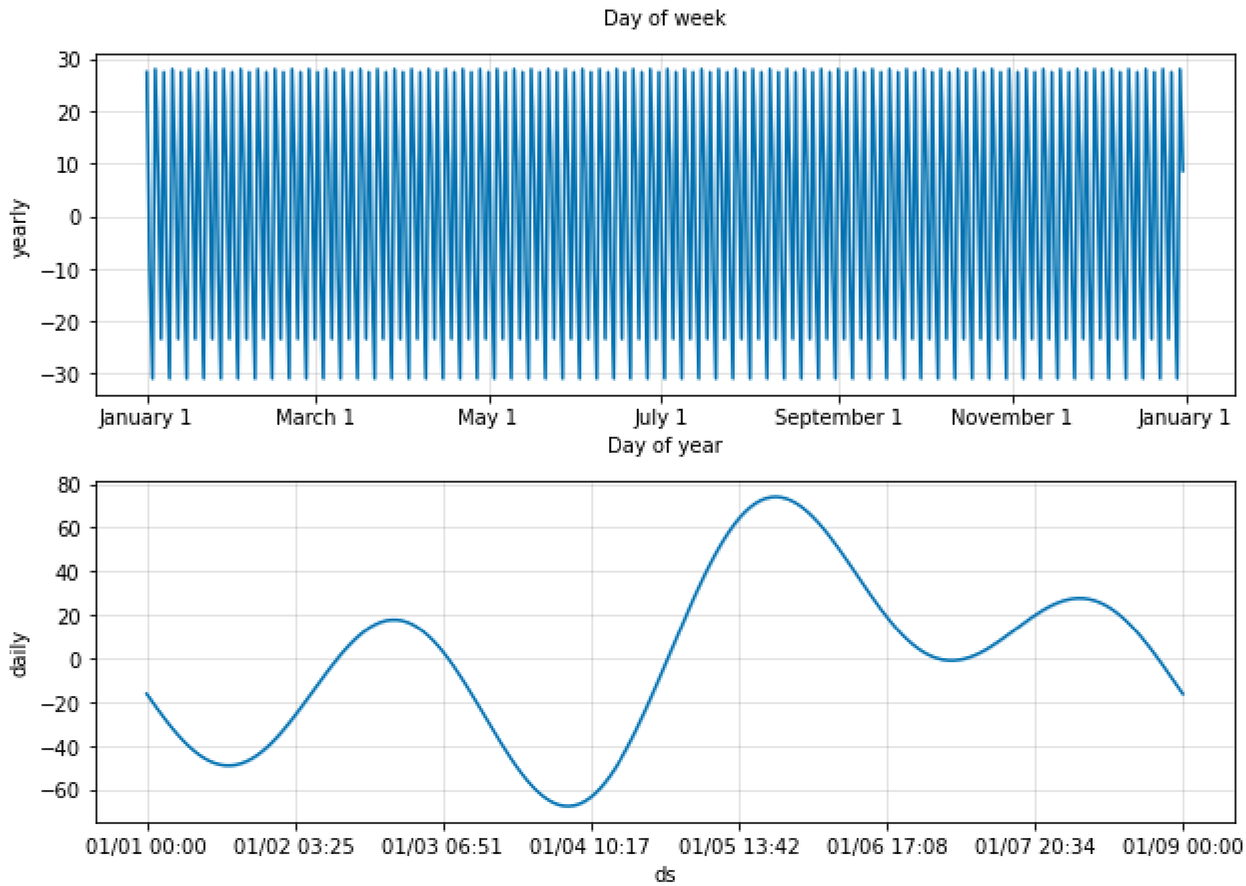
```
RMSE: 790.290
```

In [89]:
```
m.plot_components(prophet_pred)
```

Out[89]:




yearly
0
−10
−20
−30
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year
daily
80
60
40
20
0
−20
−40
−60
01/01 00:00
01/02 03:25
01/03 06:51
01/04 10:17
01/05 13:42
01/06 17:08
01/07 20:34
01/09 00:00
ds
trend
300
250
200
150
100
50
2011-01
2011-03
2011-05
2011-07
2011-09
2011-11
ds
holidays
20
0
−20
−40
−60
−80
−100
2011-01
2011-03
2011-05
2011-07
2011-09
2011-11
ds
weekly
150
100
50
0
−50
−100
−150
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday



In [90]:

```
perform.loc['Prophet', ('RMSE','Parameters')]=round(error_prophet), "Holidays, S
perform
```

Out[90]:

	RMSE	Parameters
Models Popcorn Holder		
Moving Average	746	Window size: 10
Exponential Smoothing	781	Seasonal_periods =52
Arima	909	ARIMA(3,1,0)(2,1,0)[12]
XGBoost	714	n_estimators=1000, max_depth=5,min_child_weight=1
Prophet	790	Holidays, Seasonality: W, D, Y

Model 6: LSTM

In [91]:

```
# Now, let's fit LSTM. Please note, no parameter tuning was performed and it is
# A model is required to learn from the series of past observations to predict t
```

In [92]:

```
#!pip install tensorflow
#!pip install keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.preprocessing.sequence import TimeseriesGenerator
from sklearn.preprocessing import MinMaxScaler

scaler=MinMaxScaler()
```

In [93]:
```
# Prepare data
train_data, test_data = pd.DataFrame(train_data), pd.DataFrame(test_data)
```

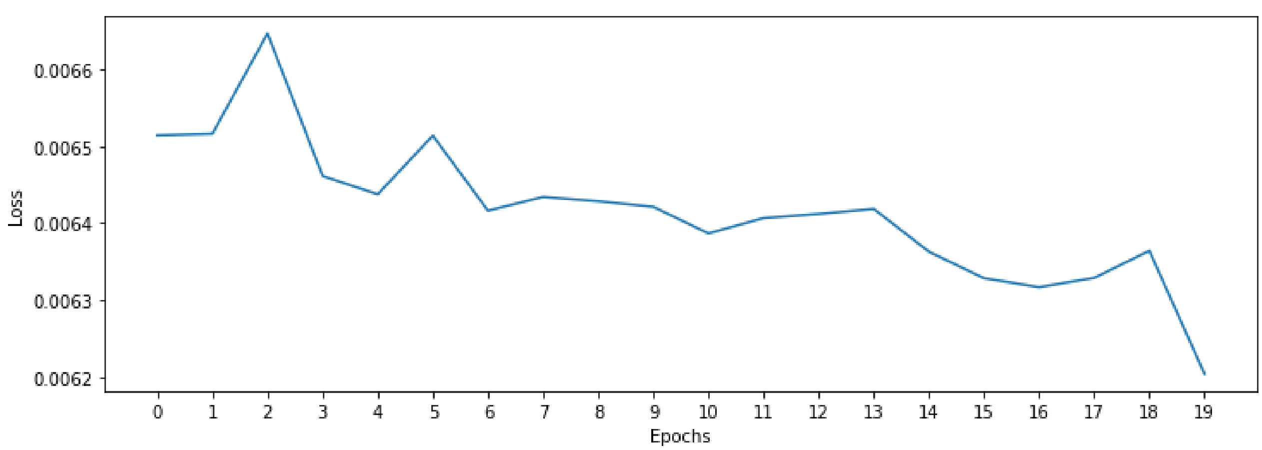
In [94]:
```
# Normalize the dataset
scaler.fit(train_data)
scaled_train_data=scaler.transform(train_data)
scaled_test_data=scaler.transform(test_data)
```

In [95]:
```
# Build a model
n_input = 16
n_features = 1
generator = TimeseriesGenerator(scaled_train_data, scaled_train_data, length = n
lstm_model = Sequential()
lstm_model.add(LSTM(100, activation='relu', input_shape=(n_input, n_features)))
lstm_model.add(Dense(1))
lstm_model.compile(optimizer='adam', loss='mse')
lstm_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm (LSTM)                  (None, 100)               40800     
_________________________________________________________________
dense (Dense)                (None, 1)                 101       
=================================================================
Total params: 40,901
Trainable params: 40,901
Non-trainable params: 0
_________________________________________________________________
```

In [96]:
```
# Fit a model
lstm_model.fit(generator, epochs=20, verbose=0)

losses_lstm=lstm_model.history.history['loss']
plt.figure(figsize=(12,4))
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.xticks(np.arange(0,21,1))
plt.plot(range(len(losses_lstm)), losses_lstm)
```

Out[96]: [<matplotlib.lines.Line2D at 0x7fa456c9e850>]



In [97]:
```
# Predict and inverse scaling
lstm_predictions_scaled=list()
```

```
batch = scaled_train_data[-n_input:]
current_batch = batch.reshape((1, n_input, n_features))

for i in range(len(test_data)):
    lstm_pred = lstm_model.predict(current_batch)[0]
    lstm_predictions_scaled.append(lstm_pred)
    current_batch = np.append(current_batch[:, 1:, :], [[lstm_pred]], axis=1)

lstm_predictions=scaler.inverse_transform(lstm_predictions_scaled)
```

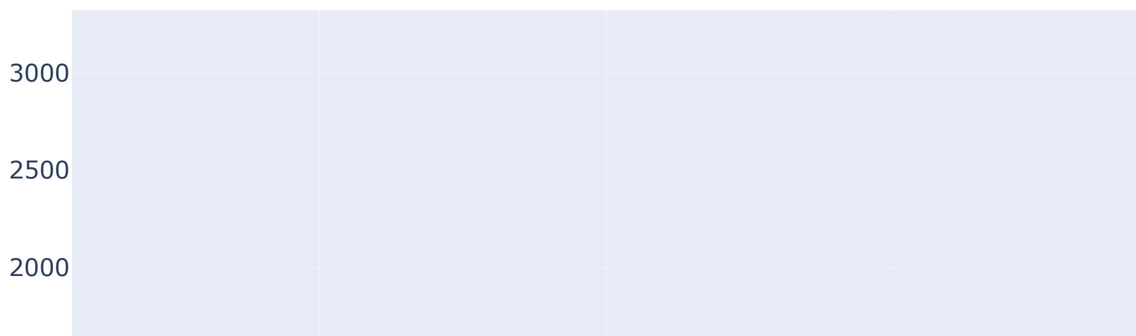
In [98]:

```
# Calculate error
error_lstm=np.sqrt(mean_squared_error(test_data.values, lstm_predictions))
error_lstm
```

Out[98]: 904.9477093089544

In [99]:

```
plot_actual_predicted(test_data[0], pd.DataFrame(lstm_predictions)[0], "LSTM Pre
```



In [100…

```
perform.loc['LSTM', ('RMSE','Parameters')]=round(error_lstm), "LSTM: 100, act =
perform
```

Out[100…

	RMSE	Parameters
Models Popcorn Holder		
Moving Average	746	Window size: 10

Models Popcorn Holder	RMSE	Parameters
Exponential Smoothing	781	Seasonal_periods =52
Arima	909	ARIMA(3,1,0)(2,1,0)[12]
XGBoost	714	n_estimators=1000, max_depth=5,min_child_weight=1
Prophet	790	Holidays, Seasonality: W, D, Y
LSTM	905	LSTM: 100, act = 'relu', input_shape: 16x1

In [101…
```
#By looking at the results so far, it is evident that seasonality doesn't have s
#My assumption is that lagged, differenciated values and rolling mean will posit
#Let's test it out with Random Forrest by adding these features in the model's i
```

Model 7: Random Forest

In [102…
```
# Prepare the data by differencing, adding 4 lags and rolling mean
df_forecasting=pd.DataFrame(poph2)
df_forecasting = df_forecasting.diff()
df_forecasting.columns=['Values']
for i in range(4,0,-1):
    df_forecasting['t-'+str(i)] = df_forecasting['Values'].shift(i)
df_forecasting=df_forecasting.dropna()
df_forecasting['Values_Rolling'] = df_forecasting['Values'].rolling(window = 16)
df_forecasting= df_forecasting.dropna()
df_forecasting
```

Out[102…

	Values	t-4	t-3	t-2	t-1	Values_Rolling
2010-12-21	-92.0	253.0	-272.0	8.0	159.0	-0.3750
2010-12-22	-75.0	-272.0	8.0	159.0	-92.0	-16.5000
2010-12-23	8.0	8.0	159.0	-92.0	-75.0	-7.5625
2010-12-24	-8.0	159.0	-92.0	-75.0	8.0	-13.2500
2010-12-25	0.0	-92.0	-75.0	8.0	-8.0	-16.2500
...	...	...	...	...	...	...
2011-12-05	296.0	-203.0	1103.0	-1369.0	113.0	25.5625
2011-12-06	-72.0	1103.0	-1369.0	113.0	296.0	7.4375
2011-12-07	31.0	-1369.0	113.0	296.0	-72.0	1.1875
2011-12-08	2738.0	113.0	296.0	-72.0	31.0	121.5000
2011-12-09	-2876.0	296.0	-72.0	31.0	2738.0	-16.6250

354 rows × 6 columns

In [103…
```
from sklearn.ensemble import RandomForestRegressor
from random import seed
x=df_forecasting.iloc[:,1:]
y=df_forecasting.iloc[:,0]
x_train, x_valid = x.loc[x.index < '2011-11-27'], x.loc[x.index >= '2011-11-27']
```

```
y_train, y_valid = y.loc[y.index < '2011-11-27'], y.loc[y.index >= '2011-11-27']
mdl = RandomForestRegressor(n_estimators=100)
np.random.seed(55)
mdl.fit(x_train, y_train)
pred=mdl.predict(x_valid)
pred=pd.Series(pred, index=y_valid.index)
```

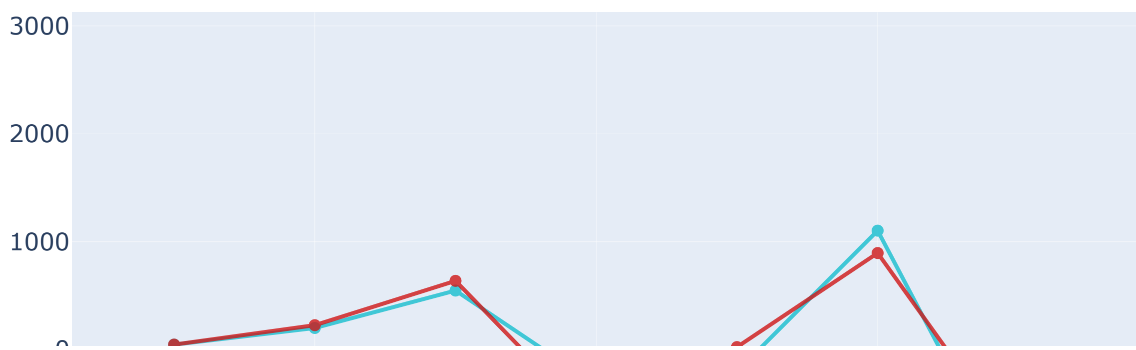
In [104…

```
error_rf_dif=np.sqrt(mean_squared_error(y_valid, pred))
print('RMSE_dif: %.3f' % error_rf_dif)
```

```
RMSE_dif: 359.950
```

In [105…

```
plot_actual_predicted(y_valid, pred, "Random Forest Fit")
```



In [106…

```
# Inverse differencing and plot predicted values
converted=pd.DataFrame()
last_obs=train_data.iloc[-1][0]
converted['Conv']=np.r_[last_obs, pred[0:]].cumsum()[1:]
```

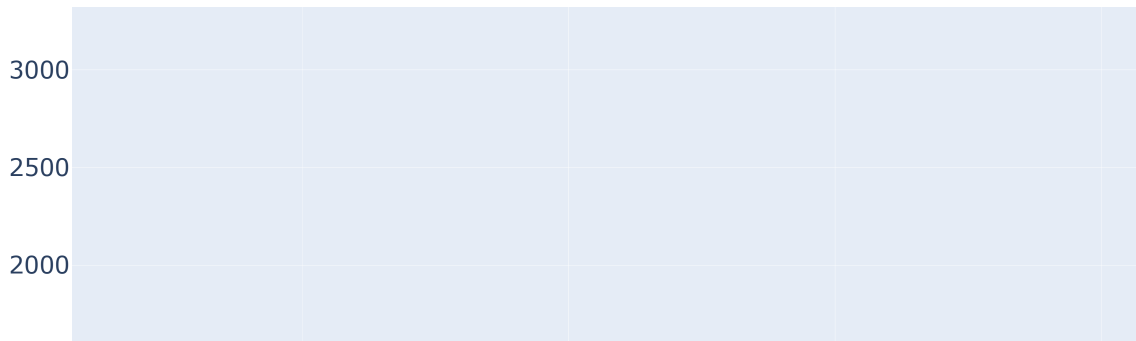
In [107…

```
error_rf=np.sqrt(mean_squared_error(test_data, converted))
print('RMSE: %.3f' % error_rf)
```

```
RMSE: 261.448
```

In [108…

```
plot_actual_predicted(test_data[0], converted['Conv'], "Random Forest Prediction
```



In [109…
```
perform.loc['RF', ('RMSE','Parameters')]=round(error_rf), "Differenced: 1, Lags:
perform
```

Out[109…

Models Popcorn Holder	RMSE	Parameters
Moving Average	746	Window size: 10
Exponential Smoothing	781	Seasonal_periods =52
Arima	909	ARIMA(3,1,0)(2,1,0)[12]
XGBoost	714	n_estimators=1000, max_depth=5,min_child_weight=1
Prophet	790	Holidays, Seasonality: W, D, Y
LSTM	905	LSTM: 100, act = 'relu', input_shape: 16x1
RF	261	Differenced: 1, Lags: 4 , RM Window: 16

In [110…
```
#Random forrest seems to have the best fit by far. We will apply that model to t
```

In [111…
```
# Therefore, the predicted order quantity for the 7 days from 11/27/2011 - 12/3/
PO_poph2=converted[0:7].sum()[0]
print('Predicted Sales Quantity Total 11/27-12/3: %.3f' % PO_poph2)
```

```
Predicted Sales Quantity Total 11/27-12/3: 3001.460
```

In [112…
```
print('Actual Sales Quantity Total 11/27-12/3: %.3f' % test_data[0:7].sum()[0])
```

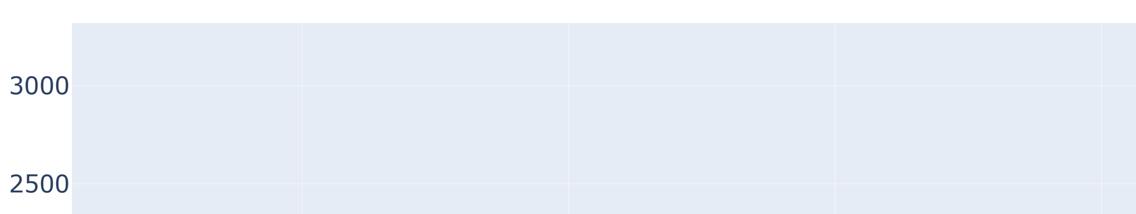
```
Actual Sales Quantity Total 11/27-12/3: 3195.000
```

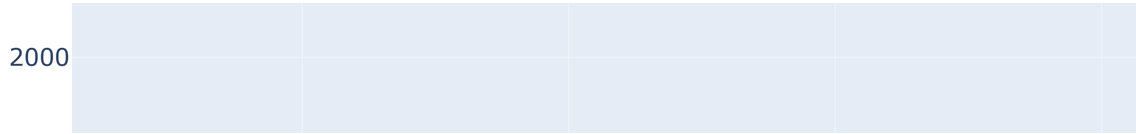
In [113…
```
# Define a function to fit RF

def RF_fit(data,lags, window):
    df_forecasting=pd.DataFrame(data)
    df_forecasting = df_forecasting.diff()
    df_forecasting.columns=['Values']
    for i in range(lags,0,-1):
        df_forecasting['t-'+str(i)] = df_forecasting['Values'].shift(i)
    df_forecasting=df_forecasting.dropna()
    df_forecasting['Values_Rolling'] = df_forecasting['Values'].rolling(window).
    df_forecasting= df_forecasting.dropna()
    x=df_forecasting.iloc[:,1:]
    y=df_forecasting.iloc[:,0]
    x_train, x_valid = x.loc[x.index < '2011-11-27'], x.loc[x.index >= '2011-11-
    y_train, y_valid = y.loc[y.index < '2011-11-27'], y.loc[y.index >= '2011-11-
    mdl = rf=RandomForestRegressor(n_estimators=100)
    np.random.seed(55)
    mdl.fit(x_train, y_train)
    pred=mdl.predict(x_valid)
    pred=pd.Series(pred, index=y_valid.index)
    error_rf_dif=np.sqrt(mean_squared_error(y_valid, pred))
    print('RMSE_dif: %.3f' % error_rf_dif)
    test_data=pd.DataFrame(data[data.index>='2011-11-27'].values)
    train_data=pd.DataFrame(data[data.index<'2011-11-27'].values)
    last_obs=train_data.iloc[-1][0]
    #Let's inverse differencing and plot predicted values
    converted=pd.DataFrame()
    converted['Conv']=np.r_[last_obs, pred[0:]].cumsum()[1:]
    error_rf=np.sqrt(mean_squared_error(test_data, converted))
    print('RMSE: %.3f' % error_rf)
    plot_actual_predicted(test_data[0], converted['Conv'], "Random Forest Predic
    #Therefore, the predicted order quantity for the 7 days from 11/27/2011 - 12
    purchase_order=converted[0:7].sum()[0]
    print('Predicted Sales Quantity Total 11/27-12/3: %.3f' % purchase_order)
    print('Actual Sales Quantity Total 11/27-12/3: %.3f' % test_data[0:7].sum()[
    return purchase_order
```

Predicting Quantities: Popcorn Holder

In [114…
```
# Let's test it and ensure it works
PO_poph2=RF_fit(poph2, 4, 16)
```

```
RMSE_dif: 359.950
RMSE: 261.448
```






```
Predicted Sales Quantity Total 11/27-12/3: 3001.460
Actual Sales Quantity Total 11/27-12/3: 3195.000
```

In [115…
```
# While we can regress the quantities over counties and dates to come up with co
```

In [116…
```
# Define a function for it
def predict_orders (data, predicted_order):
    data_train=data[(data.index<datetime.date(2011,11,27)) & (data.index>=(datet
    data_test=data[(data.index>=datetime.date(2011,11,27)) & (data.index<=dateti
    pred_countries=pd.DataFrame(data_train.groupby('Country')['Quantity'].sum().
    actual_countries_data=pd.DataFrame(data_test.groupby('Country')['Quantity'].
    countries_data=pd.merge(pred_countries, actual_countries_data, on=['Country'
    countries_data['Ratio']=round(countries_data.Quantity_x/countries_data.Quant
    countries_data['Predictions']=round(countries_data.Ratio*predicted_order)
    countries_data.rename(columns = {'Quantity_y':'Actual'}, inplace = True)
    countries_data.rename(columns = {'Quantity_x':'Historical'}, inplace = True)
    return (countries_data) #.head(15))
```

In [117…
```
predict_orders (poph, PO_poph2).head()
```

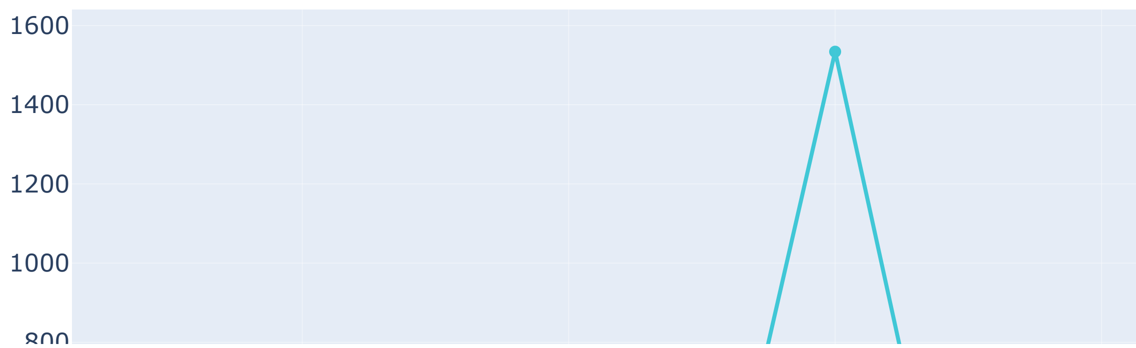
Out[117…

	Historical	Actual	Ratio	Predictions
Country				
United Kingdom	12783	3083	0.98	2941.0
Italy	100	0	0.01	30.0
EIRE	92	12	0.01	30.0
France	54	0	0.00	0.0
Belgium	36	0	0.00	0.0

Predicting quantities: Vintage Doily Jumbo Bag Red

In [118…
```
# Fit RF model
PO_vinb2=RF_fit(vinb2, 4, 1)
```

```
RMSE_dif: 521.429
RMSE: 362.303
```




```
Predicted Sales Quantity Total 11/27-12/3: 602.360
Actual Sales Quantity Total 11/27-12/3: 1851.000
```

In [119…

```
predict_orders(vinb, PO_vinb2).head()
```

Out[119…

	Historical	Actual	Ratio	Predictions
Country				
United Kingdom	2125	1830	0.94	566.0
Portugal	40	0	0.02	12.0
France	35	10	0.02	12.0
Germany	20	10	0.01	6.0
Finland	20	0	0.01	6.0

Predicting Quantities: Rabbit Night Light

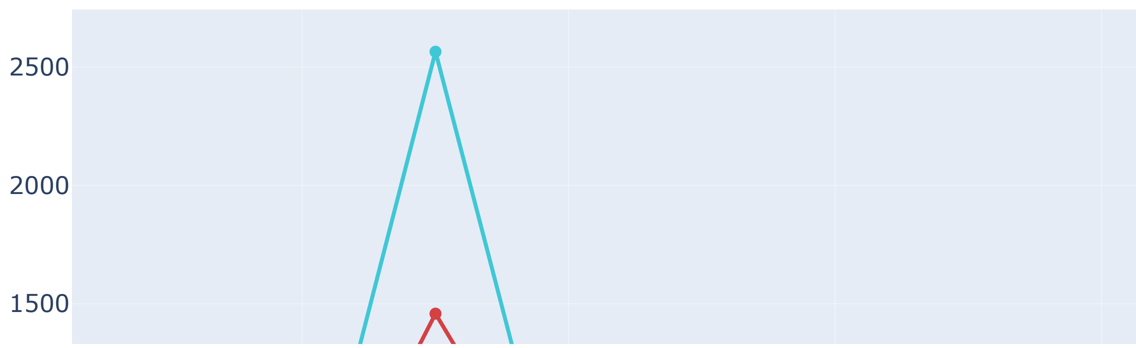
In [120…

```
# Fit the Random Forest to Rabbit Night Light data
```

In [121…

```
PO_rabl2=RF_fit(rabl2, 4, 1)
```

```
RMSE_dif: 485.418
RMSE: 337.100
```




```
Predicted Sales Quantity Total 11/27-12/3: 3906.450
Actual Sales Quantity Total 11/27-12/3: 4588.000
```

In [122…

```
predict_orders(rabl, PO_rabl2).head()
```

Out[122…

Country	Historical	Actual	Ratio	Predictions
United Kingdom	8784	1985	0.51	1992.0
Netherlands	2616	0	0.15	586.0
France	2326	383	0.14	547.0
Australia	1632	0	0.10	391.0
Japan	1080	2040	0.06	234.0

In [123…

```
# Japan's order is obviously underpredicted
```

In [124…

```
rabl[rabl.Country=="Japan"] #It was unusual order for that country
```

Out[124…

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country

InvoiceDate	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	Country
2011-06-22	557670	23084	RABBIT NIGHT LIGHT	288	1.79	12798.0	Japan
2011-10-26	572869	23084	RABBIT NIGHT LIGHT	960	1.79	12798.0	Japan
2011-11-17	576923	23084	RABBIT NIGHT LIGHT	120	1.79	12753.0	Japan
2011-11-29	579498	23084	RABBIT NIGHT LIGHT	2040	1.79	12798.0	Japan
2011-12-06	C580832	23084	RABBIT NIGHT LIGHT	-7	1.79	12753.0	Japan

In [125…
```
# Add predicted orders to top3 dataframe
orders={'Rabbit_Night_Light': round(PO_rabl2), 'Popcorn_Holder': round(PO_poph2)
```

In [126…
```
top3['Description']=[x for x in pd.DataFrame(orders.items())[0]]
```

In [127…
```
top3['Predicted_Order_ML']=[x for x in pd.DataFrame(orders.items())[1]]
```

In [128…
```
top3
```

Out[128…

StockCode	Quantity	Description	Predicted_Order_ML
23084	4588	Rabbit_Night_Light	3906
22197	3195	Popcorn_Holder	3001
23582	1851	Vintage_Doily_Jumbo_Bag	602

In [129…
```
# A workable solution to address understock is to add a safety stock:
# Safety stock ss = std(delivery_lead_time) * importance_factor
# Since we don't have that data, we can substitute:
# ss = std(daily_quantity) * (days_of_prediction) * (model_confidence_factor)
# Therefore, our prediction could be the following:
# Predicted_Order = Predicted_Order_ML + ss
```

In [130…
```
model_confidence_factor=[0.3, 0.1, 0.9]
stdevs=[np.std(rabl2.values)*6,np.std(poph2)*6,np.std(vinb2)*6]
```

In [131…
```
ss = [round(a * b) for a, b in zip(model_confidence_factor, stdevs)]
print(ss)
```

```
[645, 224, 1201]
```

In [132…
```
top3.insert(2, "Safety_Stock", ss)
```

In [133…
```
top3['Final_Order']=top3.Safety_Stock+top3.Predicted_Order_ML
```

In [134…
```
top3
```

Out[134...

StockCode	Quantity	Description	Safety_Stock	Predicted_Order_ML	Final_Order
23084	4588	Rabbit_Night_Light	645	3906	4551
22197	3195	Popcorn_Holder	224	3001	3225
23582	1851	Vintage_Doily_Jumbo_Bag	1201	602	1803

In [135...

```
# Aggregate the results
rabbit_light=predict_orders(rabl, top3.Final_Order.values[0])
rabbit_light.head()
```

Out[135...

Country	Historical	Actual	Ratio	Predictions
United Kingdom	8784	1985	0.51	2321.0
Netherlands	2616	0	0.15	683.0
France	2326	383	0.14	637.0
Australia	1632	0	0.10	455.0
Japan	1080	2040	0.06	273.0

In [136...

```
popcorn_holder=predict_orders(poph, top3.Final_Order.values[1])
popcorn_holder.head()
```

Out[136...

Country	Historical	Actual	Ratio	Predictions
United Kingdom	12783	3083	0.98	3160.0
Italy	100	0	0.01	32.0
EIRE	92	12	0.01	32.0
France	54	0	0.00	0.0
Belgium	36	0	0.00	0.0

In [137...

```
vintage_bag=predict_orders(vinb, top3.Final_Order.values[2])
vintage_bag.head()
```

Out[137...

Country	Historical	Actual	Ratio	Predictions
United Kingdom	2125	1830	0.94	1695.0
Portugal	40	0	0.02	36.0
France	35	10	0.02	36.0
Germany	20	10	0.01	18.0
Finland	20	0	0.01	18.0

```
step1=pd.merge(rabbit_light, popcorn_holder, on = 'Country', how='outer')
```

In [138…

```

```

In [139…

```
final_data=pd.merge(step1, vintage_bag, on = 'Country', how='outer')
```

In [140…

```
final_data.columns=['Hist_rabbbit_light', 'Act_rabbit_light', 'R_rabbit_light',
                    'Preds_popcorn_holder', 'Hist_vintage_bag', 'Act_vintage_bag
```

In [141…

```
final_data
```

Out[141…

	Hist_rabbbit_light	Act_rabbit_light	R_rabbit_light	Preds_rabbit_light	Hist_popcorn_hc
Country					
United Kingdom	8784	1985	0.51	2321.0	1:
Netherlands	2616	0	0.15	683.0	
France	2326	383	0.14	637.0	
Australia	1632	0	0.10	455.0	
Japan	1080	2040	0.06	273.0	
Germany	192	72	0.01	46.0	
Belgium	108	0	0.01	46.0	
Finland	96	48	0.01	46.0	
Sweden	84	0	0.00	0.0	
EIRE	48	0	0.00	0.0	
Iceland	48	0	0.00	0.0	
Italy	48	0	0.00	0.0	
Denmark	24	12	0.00	0.0	
Portugal	18	48	0.00	0.0	
Unspecified	12	0	0.00	0.0	
Norway	12	0	0.00	0.0	
Switzerland	12	0	0.00	0.0	
Spain	6	0	0.00	0.0	
Lithuania	0	0	0.00	0.0	
USA	0	0	0.00	0.0	
Austria	0	0	0.00	0.0	
Bahrain	0	0	0.00	0.0	
United Arab Emirates	0	0	0.00	0.0	
Brazil	0	0	0.00	0.0	
Canada	0	0	0.00	0.0	
Channel Islands	0	0	0.00	0.0	

	Hist_rabbbit_light	Act_rabbit_light	R_rabbit_light	Preds_rabbit_light	Hist_popcorn_hc
Country					
Cyprus	0	0	0.00	0.0	
Czech Republic	0	0	0.00	0.0	
European Community	0	0	0.00	0.0	
Lebanon	0	0	0.00	0.0	
Singapore	0	0	0.00	0.0	
Saudi Arabia	0	0	0.00	0.0	
Greece	0	0	0.00	0.0	
Hong Kong	0	0	0.00	0.0	
RSA	0	0	0.00	0.0	
Poland	0	0	0.00	0.0	
Malta	0	0	0.00	0.0	
Israel	0	0	0.00	0.0	

In [142…

```
final_data.to_csv(r'Tatsiana_Sokalava}_result.csv', index = True, header=True)
```

Thank you!