import numpy as np import pandas as pd import matplotlib.pyplot as plt

In [310…

```
df = pd.read_csv(r"D:\PG-DAI\MachineLearning\Dec 29 & 30 TimeSeries\Train.csv")
df.head()
```

Out[310…

	ID	Datetime	Count
0	0	25-08-2012 00:00	8
1	1	25-08-2012 01:00	2
2	2	25-08-2012 02:00	6
3	3	25-08-2012 03:00	2
4	4	25-08-2012 04:00	2

In [311…

```
## Cleaning up the data
df.columns=["ID","DateTime","Count"]
del df["ID"]
df.head()
```

Out[311…

	DateTime	Count
0	25-08-2012 00:00	8
1	25-08-2012 01:00	2
2	25-08-2012 02:00	6
3	25-08-2012 03:00	2
4	25-08-2012 04:00	2

In [312…

```
df.DateTime = pd.to_datetime(df.DateTime,format='%d-%m-%Y %H:%M')
df.index = df.DateTime
df = df.resample('D').mean()
```

In [313…

```
# ## Drop last 2 rows
# df.drop(106,axis=0,inplace=True)
```

```
# df.drop(105,axis=0,inplace=True)
```

In [314…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 762 entries, 2012-08-25 to 2014-09-25
Freq: D
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Count   762 non-null    float64
dtypes: float64(1)
memory usage: 11.9 KB
```

In [ ]:

```

```

In [315…

```
# # Convert DateTime into Datetime
# df['DateTime']=pd.to_datetime(df['DateTime'])
# df.info()
```

In [316…

```
# df.set_index('DateTime',inplace=True)
# df.head()
```

In [317…

```
df.describe()
```

Out[317…

	Count
count	762.000000
mean	138.958115
std	135.911437
min	2.416667
25%	24.250000
50%	99.125000

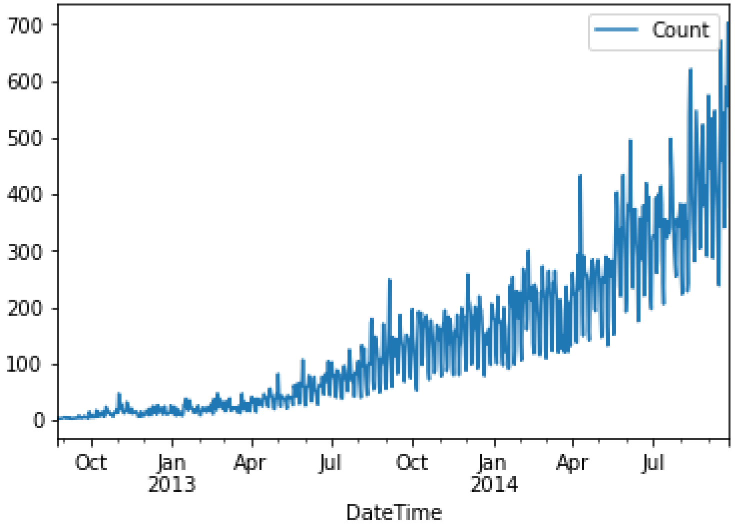
	Count
75%	215.958333
max	702.333333

In [318…

```
df.plot()
```

Out[318…

```
<AxesSubplot:xlabel='DateTime'>
```



Moving Average

This method removes the underlying trend in the time series also known as Detrending

In [319…

```
# SMA over a period of 2 and 12 DateTime
#min_period = min value to start calculation

df['SMA_2'] = df.Count.rolling(2, min_periods=1).mean()
df['SMA_12'] = df.Count.rolling(12, min_periods=1).mean()
df.head(20)
```

Out[319…

	Count	SMA_2	SMA_12

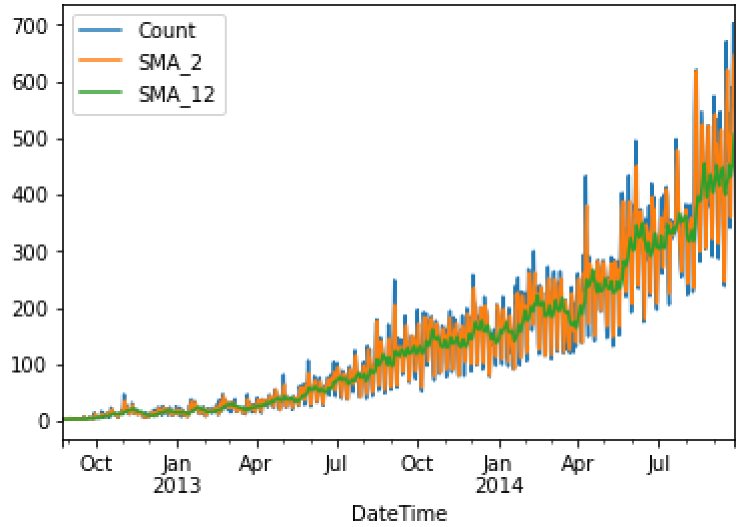
DateTime	Count	SMA_2	SMA_12
DateTime			
2012-08-25	3.166667	3.166667	3.166667
2012-08-26	3.666667	3.416667	3.416667
2012-08-27	2.583333	3.125000	3.138889
2012-08-28	2.416667	2.500000	2.958333
2012-08-29	2.500000	2.458333	2.866667
2012-08-30	3.083333	2.791667	2.902778
2012-08-31	3.250000	3.166667	2.952381
2012-09-01	4.666667	3.958333	3.166667
2012-09-02	4.916667	4.791667	3.361111
2012-09-03	4.500000	4.708333	3.475000
2012-09-04	2.750000	3.625000	3.409091
2012-09-05	4.333333	3.541667	3.486111
2012-09-06	4.166667	4.250000	3.569444
2012-09-07	2.833333	3.500000	3.500000
2012-09-08	4.166667	3.500000	3.631944
2012-09-09	2.833333	3.500000	3.666667
2012-09-10	2.666667	2.750000	3.680556
2012-09-11	2.416667	2.541667	3.625000
2012-09-12	3.500000	2.958333	3.645833
2012-09-13	3.000000	3.250000	3.506944

In [320…

```
df.plot()
```

Out[320…

```
<AxesSubplot:xlabel='DateTime'>
```



In [321…

```
df['CMA']= df.Count.expanding(min_periods=1).mean()  # cummulative moving average the cumulative moving average considers all of t
df.head(15)
```

Out[321…

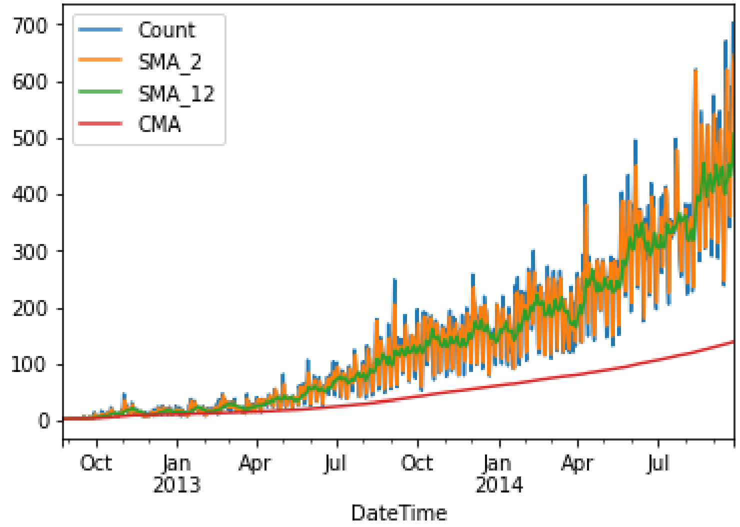
DateTime	Count	SMA_2	SMA_12	CMA
2012-08-25	3.166667	3.166667	3.166667	3.166667
2012-08-26	3.666667	3.416667	3.416667	3.416667
2012-08-27	2.583333	3.125000	3.138889	3.138889
2012-08-28	2.416667	2.500000	2.958333	2.958333
2012-08-29	2.500000	2.458333	2.866667	2.866667
2012-08-30	3.083333	2.791667	2.902778	2.902778
2012-08-31	3.250000	3.166667	2.952381	2.952381
2012-09-01	4.666667	3.958333	3.166667	3.166667
2012-09-02	4.916667	4.791667	3.361111	3.361111
2012-09-03	4.500000	4.708333	3.475000	3.475000

	Count	SMA_2	SMA_12	CMA
DateTime				
2012-09-04	2.750000	3.625000	3.409091	3.409091
2012-09-05	4.333333	3.541667	3.486111	3.486111
2012-09-06	4.166667	4.250000	3.569444	3.538462
2012-09-07	2.833333	3.500000	3.500000	3.488095
2012-09-08	4.166667	3.500000	3.631944	3.533333

In [322…

```
df.plot()
```

Out[322… <AxesSubplot:xlabel='DateTime'>



Exponential Moving Average

Simple Exponential Smoothing (SES) for data without trend or seasonality

In [323…

```
# EMA Count
#Exponential Moving Average (EMA) does a superb job in capturing the pattern of the data (0,1)
# Let's smoothing factor - 0.1
```

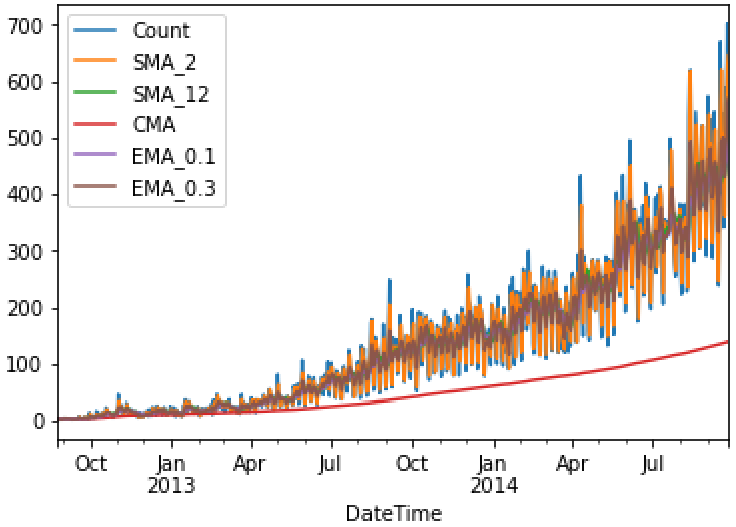
```
df['EMA_0.1'] = df.Count.ewm(alpha=0.1, adjust=False).mean()
# Let's smoothing factor  - 0.3
df['EMA_0.3'] = df.Count.ewm(alpha=0.3, adjust=False).mean()
```

In [324…

```
df.plot()
```

Out[324…

```
<AxesSubplot:xlabel='DateTime'>
```



Check for Stationarity

Two common methods to check for stationarity are Visualization and the Augmented Dickey-Fuller (ADF) Test. Python makes both approaches easy:

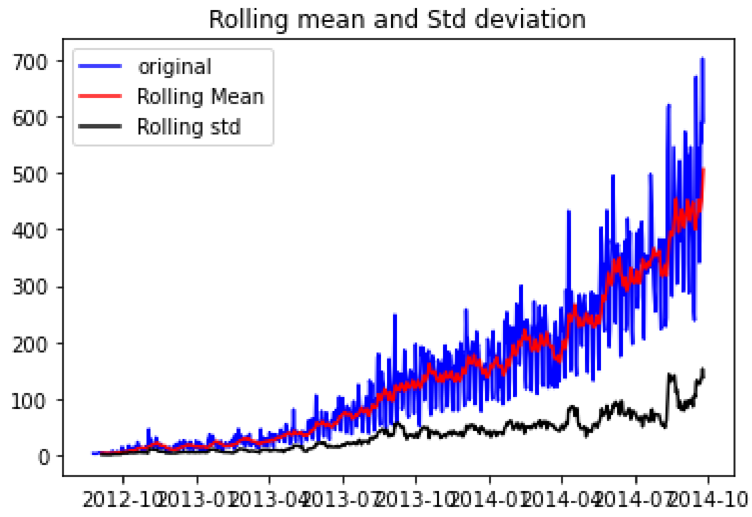
In [325…

```
# Rolling Statistics or Visualization

rolmean = df.Count.rolling(window=12).mean()
rolstd = df.Count.rolling(window=12).std()
```

In [326…

```
orig = plt.plot(df.Count,color='blue',label='original')
mean = plt.plot(rolmean,color='red',label='Rolling Mean')
std = plt.plot(rolstd,color='black',label='Rolling std')
```

```
plt.legend()
plt.title('Rolling mean and Std deviation')
plt.show()
```



In [327…

```
### Testing For Stationarity using Dickey-fuller test

from statsmodels.tsa.stattools import adfuller
```

In [328…

```
test_result=adfuller(df['Count'])
test_result  # 'ADF Test Statistic','p-value','#Lags Used','Number of Observations Used'
```

Out[328…

```
(2.986350959013852,
 1.0,
 20,
 741,
 {'1%': -3.4392057325732104,
  '5%': -2.8654483492874236,
  '10%': -2.5688512291811225},
 7212.068059584322)
```

In [329…

```
#Ho: It is not stationary
#H1: It is stationary
```

```
def adfuller_test(sales):
    result=adfuller(sales)
    #print(result)
    labels = ['ADF Test Statistic','p-value','Lags Used','Number of Observations Used']
    for value,label in zip(result,labels):
        print(label+' : '+str(value) )
    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis(Ho), reject the null hypothesis. Data is stationary")
    else:
        print("weak evidence against null hypothesis, indicating it is non-stationary ")
```

In [330…

```
adfuller_test(df['Count'])
```

```
ADF Test Statistic : 2.986350959013852
p-value : 1.0
Lags Used : 20
Number of Observations Used : 741
weak evidence against null hypothesis, indicating it is non-stationary
```

Converting Non- stationary into stationary

Detrending

This method removes the underlying trend in the time series:

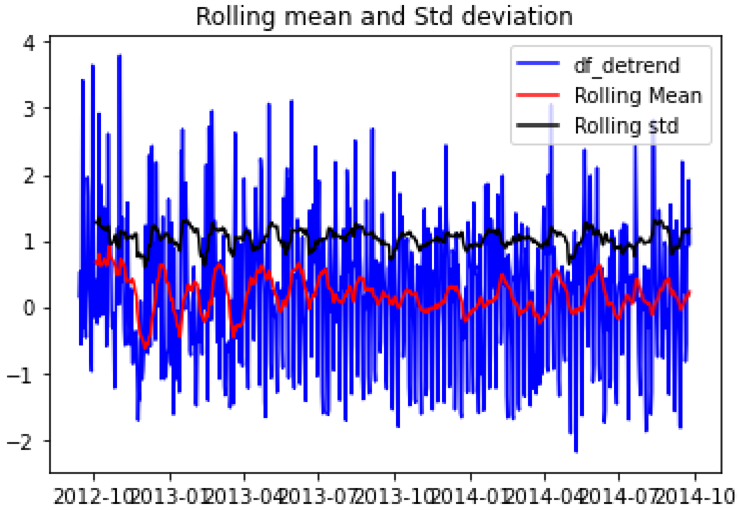
In [331…

```
# Detrending
df_detrend =  (df['Count'] - df['Count'].rolling(window=21).mean())/df['Count'].rolling(window=21).std()
```

In [332…

```
# Rolling Statistics or Visualization

rolmean = df_detrend.rolling(window=21).mean()
rolstd = df_detrend.rolling(window=21).std()

orig = plt.plot(df_detrend,color='blue',label='df_detrend')
mean = plt.plot(rolmean,color='red',label='Rolling Mean')
std = plt.plot(rolstd,color='black',label='Rolling std')
plt.legend()
```

```
plt.title('Rolling mean and Std deviation')
plt.show()
```



In [333…

```
df_detrend = df_detrend.dropna()
```

In [334…

```
#ad fuller test
adfuller_test(df_detrend.dropna())
```

```
ADF Test Statistic : -6.858601721956723
p-value : 1.6241878203855054e-09
Lags Used : 20
Number of Observations Used : 721
strong evidence against the null hypothesis(Ho), reject the null hypothesis. Data is stationary
```

In [335…

```
df_detrend
```

Out[335…

```
DateTime
2012-09-14    0.155035
2012-09-15    0.532111
2012-09-16   -0.568583
2012-09-17    0.509060
2012-09-18    3.420736
                ...
```

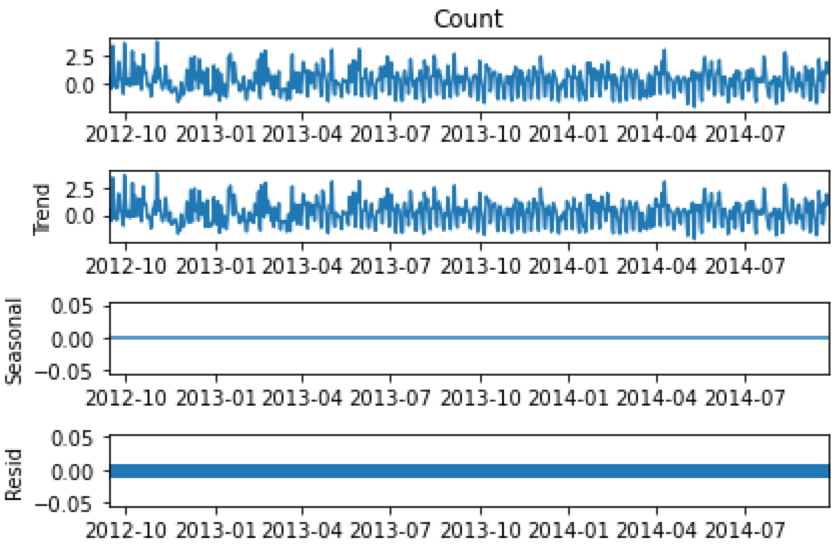
```
2014-09-21   -0.556363
2014-09-22    1.192368
2014-09-23    0.917834
2014-09-24    1.915742
2014-09-25    0.957778
Freq: D, Name: Count, Length: 742, dtype: float64
```

In [ ]:

```

```

In [336…

```
from statsmodels.tsa.seasonal import seasonal_decompose
decompose_result = seasonal_decompose(df_detrend,model='additive',period=1)
decompose_result.plot()
plt.show()
```



Differencing

This method removes the underlying seasonal or cyclical patterns in the time series. Since the sample dataset has a 12-DateTime seasonality, I used a 12-lag difference:

In [337…

```
# df['Seasonal_Difference']=df['Count']-df['Count'].shift(21)
```

In [338…
```
# df.head(15)
```

In [339…
```
# # Again test dickey fuller test
# adfuller_test(df['Seasonal_Difference'].dropna())
```

In [340…
```
# # Rolling Statistics

# rolmean = df['Seasonal_Difference'].rolling(window=21).mean()
# rolstd = df['Seasonal_Difference'].rolling(window=21).std()
# #orig = plt.plot(df.Count,color='yellow',label='original')
# Seasonal_Difference = plt.plot(df['Seasonal_Difference'],color='blue',label='Seasonal_Difference')
# mean = plt.plot(rolmean,color='red',label='Rolling Mean')
# std = plt.plot(rolstd,color='black',label='Rolling std')
# plt.legend()
# plt.title('Rolling mean and Std deviation')
# plt.show()
```

Forcasting on Stationary dataset

from statsmodels.tsa.seasonal import seasonal_decompose decompose_result = seasonal_decompose(df['Count'],model='additive',period=1) decompose_result.plot() plt.show()

In [341…
```
# from statsmodels.tsa.seasonal import seasonal_decompose
# df = df.dropna()
# decompose_result = seasonal_decompose(df['Seasonal_Difference'],model='additive',period=1)
# decompose_result.plot()
# plt.show()
```

In [342…
```
# S_df= df['Seasonal_Difference']
# n_df = pd.DataFrame(S_df.T)
# n_df.dropna(inplace=True)
```

In [343…
```
df
```

Out[343…

	Count	SMA_2	SMA_12	CMA	EMA_0.1	EMA_0.3

DateTime	Count	SMA_2	SMA_12	CMA	EMA_0.1	EMA_0.3
DateTime						
2012-08-25	3.166667	3.166667	3.166667	3.166667	3.166667	3.166667
2012-08-26	3.666667	3.416667	3.416667	3.416667	3.216667	3.316667
2012-08-27	2.583333	3.125000	3.138889	3.138889	3.153333	3.096667
2012-08-28	2.416667	2.500000	2.958333	2.958333	3.079667	2.892667
2012-08-29	2.500000	2.458333	2.866667	2.866667	3.021700	2.774867
...	...	...	...	...	...	...
2014-09-21	379.250000	360.166667	431.750000	136.479661	434.678741	430.384255
2014-09-22	588.166667	483.708333	440.513889	137.074769	450.027534	477.718978
2014-09-23	554.333333	571.250000	451.361111	137.623794	460.458114	500.703285
2014-09-24	702.333333	628.333333	478.604167	138.365856	484.645636	561.192299
2014-09-25	589.666667	646.000000	506.631944	138.958115	495.147739	569.734610

762 rows × 6 columns

Set the y_to_train, y_to_test, and the length of predict units

In [344...

```
n_df = df_detrend
y_to_train = n_df.iloc[:600] # dataset to train
y_to_test = n_df.iloc[600:] # last X DateTimes for test
predict_date = len(n_df) - len(y_to_train)  #lenght of dataset - len of training dataset
```

In [345...

```
y_to_train
```

Out[345...

```
DateTime
2012-09-14    0.155035
2012-09-15    0.532111
2012-09-16   -0.568583
2012-09-17    0.509060
```

```
2012-09-18    3.420736
                 ...
2014-05-02    0.037836
2014-05-03   -1.052706
2014-05-04   -1.906897
2014-05-05    0.372087
2014-05-06    0.210462
Freq: D, Name: Count, Length: 600, dtype: float64
```

In [346…

```
df_detrend
```

Out[346…

```
DateTime
2012-09-14    0.155035
2012-09-15    0.532111
2012-09-16   -0.568583
2012-09-17    0.509060
2012-09-18    3.420736
                 ...
2014-09-21   -0.556363
2014-09-22    1.192368
2014-09-23    0.917834
2014-09-24    1.915742
2014-09-25    0.957778
Freq: D, Name: Count, Length: 742, dtype: float64
```

Exponential Moving Average

In [347…

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

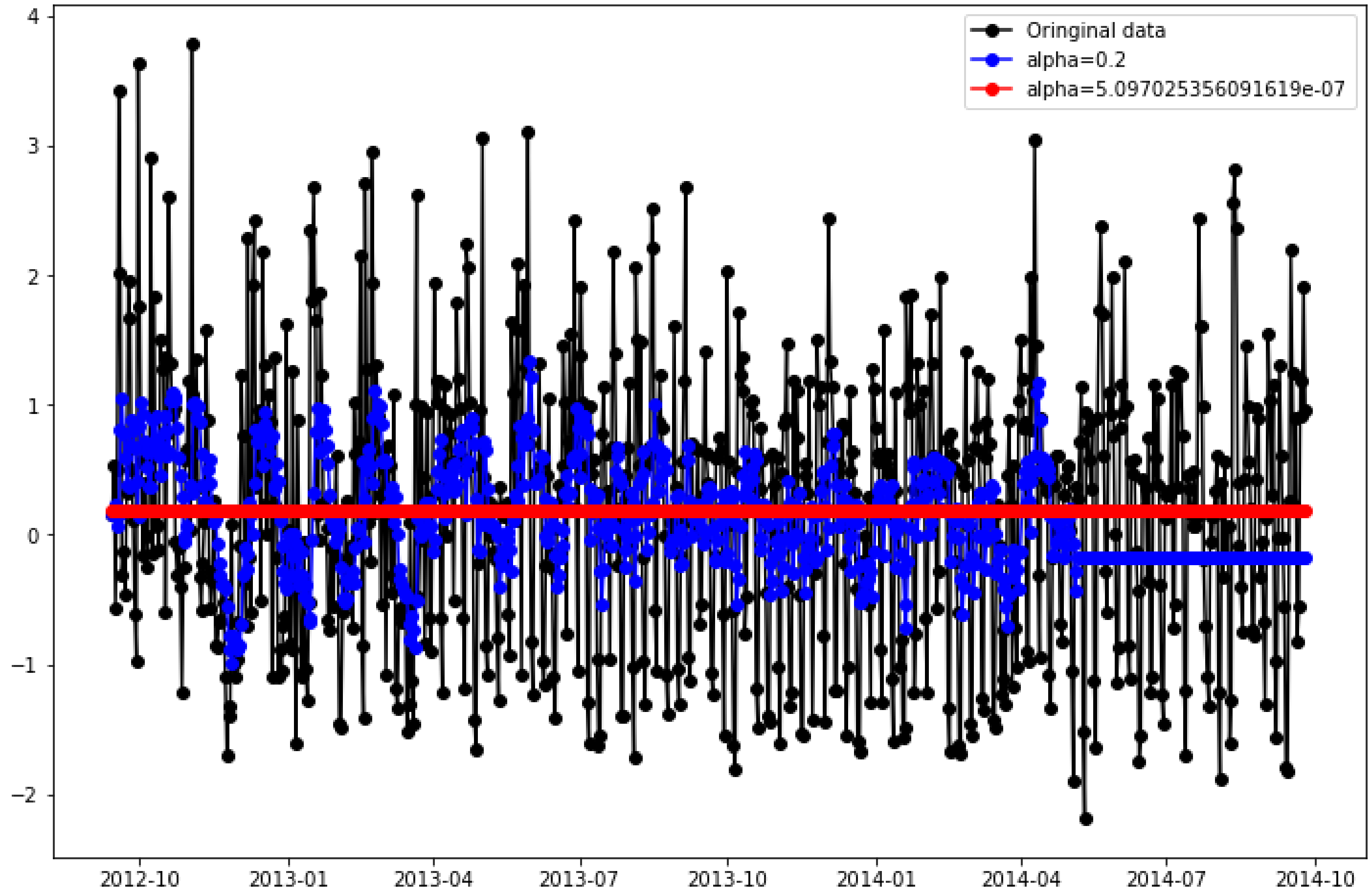
In [348…

```
fit1 = SimpleExpSmoothing(y_to_train).fit(smoothing_level=0.2, optimized=False)
fcast1 = fit1.forecast(predict_date)

fit2 = SimpleExpSmoothing(y_to_train).fit()
#statsmodels to automatically find an optimized alpha value for us.
fcast2 = fit2.forecast(predict_date)

alpha = fit2.params["smoothing_level"]
print(alpha)

plt.figure(figsize=(12, 8))
```

```
plt.plot(n_df, marker="o", color="black",label='Oringinal data')

plt.plot(fit1.fittedvalues, marker="o", color="blue")
line1 = plt.plot(fcast1, marker="o", color="blue",label='alpha=0.2')

plt.plot(fit2.fittedvalues, marker="o", color="red")
line2 = plt.plot(fcast2, marker="o", color="red",label=f'alpha={alpha}')

plt.legend()
plt.show
```

```
5.097025356091619e-07
<function matplotlib.pyplot.show(close=None, block=None)>
```

Out[348…



In [349…

```
#square sum error
sse1 =fit1.sse
print(sse1)
sse2 =fit2.sse
print(sse2)
```

```
700.2791231624221
667.7327009093299
```

Holt’s Linear Trend Method

Suitable for time series data with a trend component but without a seasonal component

In [350…

```
from statsmodels.tsa.api import Holt
```

The fit1 is the default Holt’s additive modelother option is exponential model and damped model. An exponential model would be appropriate for situations where the increase or decrease starts slowly but then accelerates rapidly. An damped model would be appropriate for situations where the trend component curve is damped (flattens over time) instead of being linear

In [351…

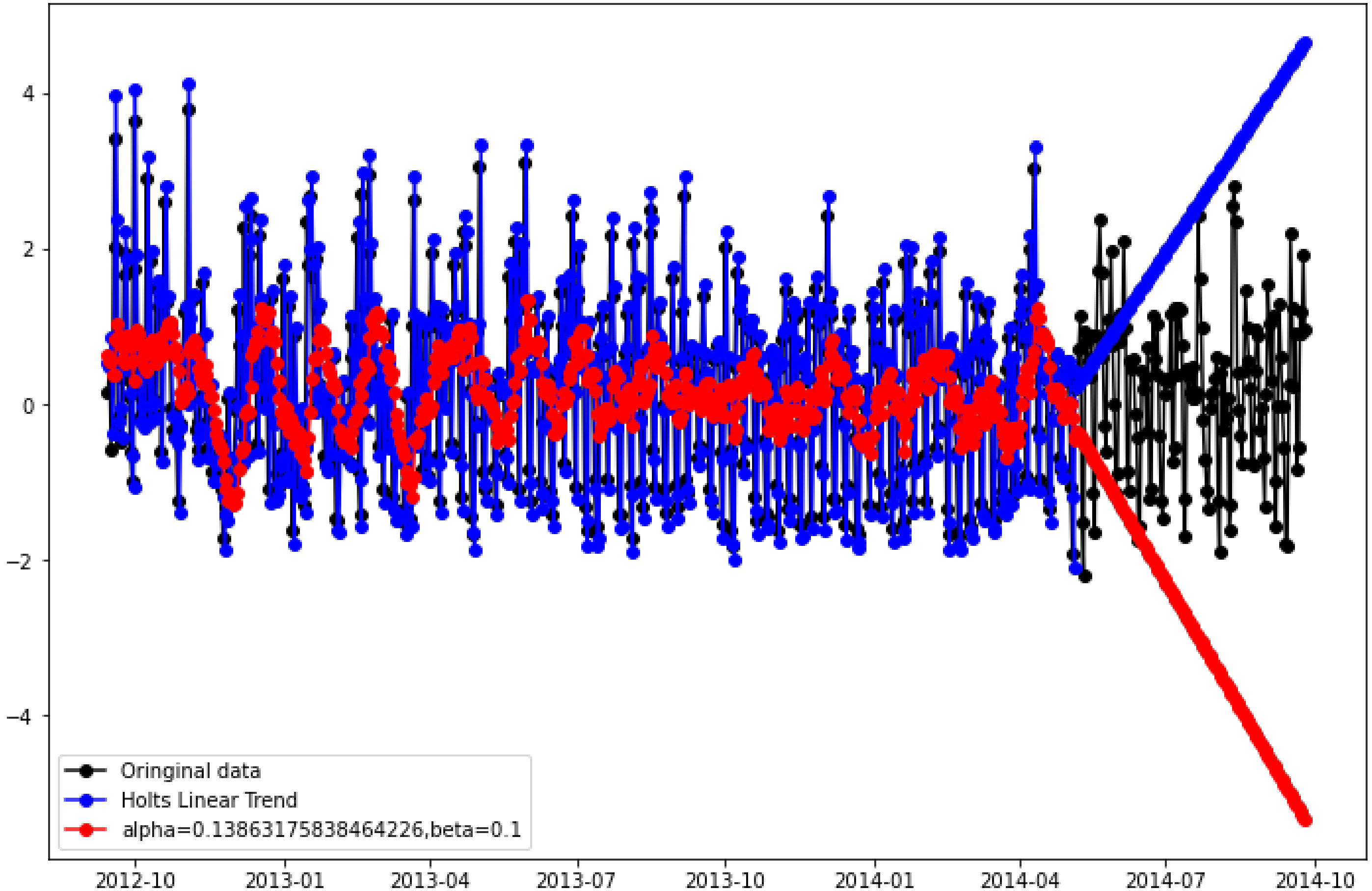
```
fit1 = Holt(y_to_train).fit(smoothing_level=1, smoothing_slope=0.1, optimized=False)  #smoothing_trend
fcast1 = fit1.forecast(predict_date)

fit2 = Holt(y_to_train).fit(smoothing_slope=0.1, optimized=True)
fcast2 = fit2.forecast(predict_date)


alpha = fit2.params["smoothing_level"]
print(alpha)
beta = fit2.params["smoothing_trend"]
print(beta)


plt.figure(figsize=(12, 8))
plt.plot(n_df, marker="o", color="black",label='Oringinal data')

plt.plot(fit1.fittedvalues, marker="o", color="blue")
line1 = plt.plot(fcast1, marker="o", color="blue",label='Holts Linear Trend')

plt.plot(fit2.fittedvalues, marker="o", color="red")
line2 = plt.plot(fcast2, marker="o", color="red",label=f'alpha={alpha},beta={beta}')
```

```
plt.legend()
plt.show
```

```
0.13863175838464226
0.1
C:\Users\GOD'SF~1\AppData\Local\Temp/ipykernel_2084/541267126.py:1: FutureWarning: the 'smoothing_slope'' keyword is deprecated, u
se 'smoothing_trend' instead
  fit1 = Holt(y_to_train).fit(smoothing_level=1, smoothing_slope=0.1, optimized=False)  #smoothing_trend
C:\Users\GOD'SF~1\AppData\Local\Temp/ipykernel_2084/541267126.py:4: FutureWarning: the 'smoothing_slope'' keyword is deprecated, u
se 'smoothing_trend' instead
  fit2 = Holt(y_to_train).fit(smoothing_slope=0.1, optimized=True)
```

Out[351…

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [352…

```
#square sum error
sse1 =fit1.sse
print(sse1)
sse2 =fit2.sse
print(sse2)
```

```
944.6269398360666
749.7053031436049
```

Holt-Winters’ Seasonal Method

Suitable for time series data with trend and/or seasonal components

In [353…

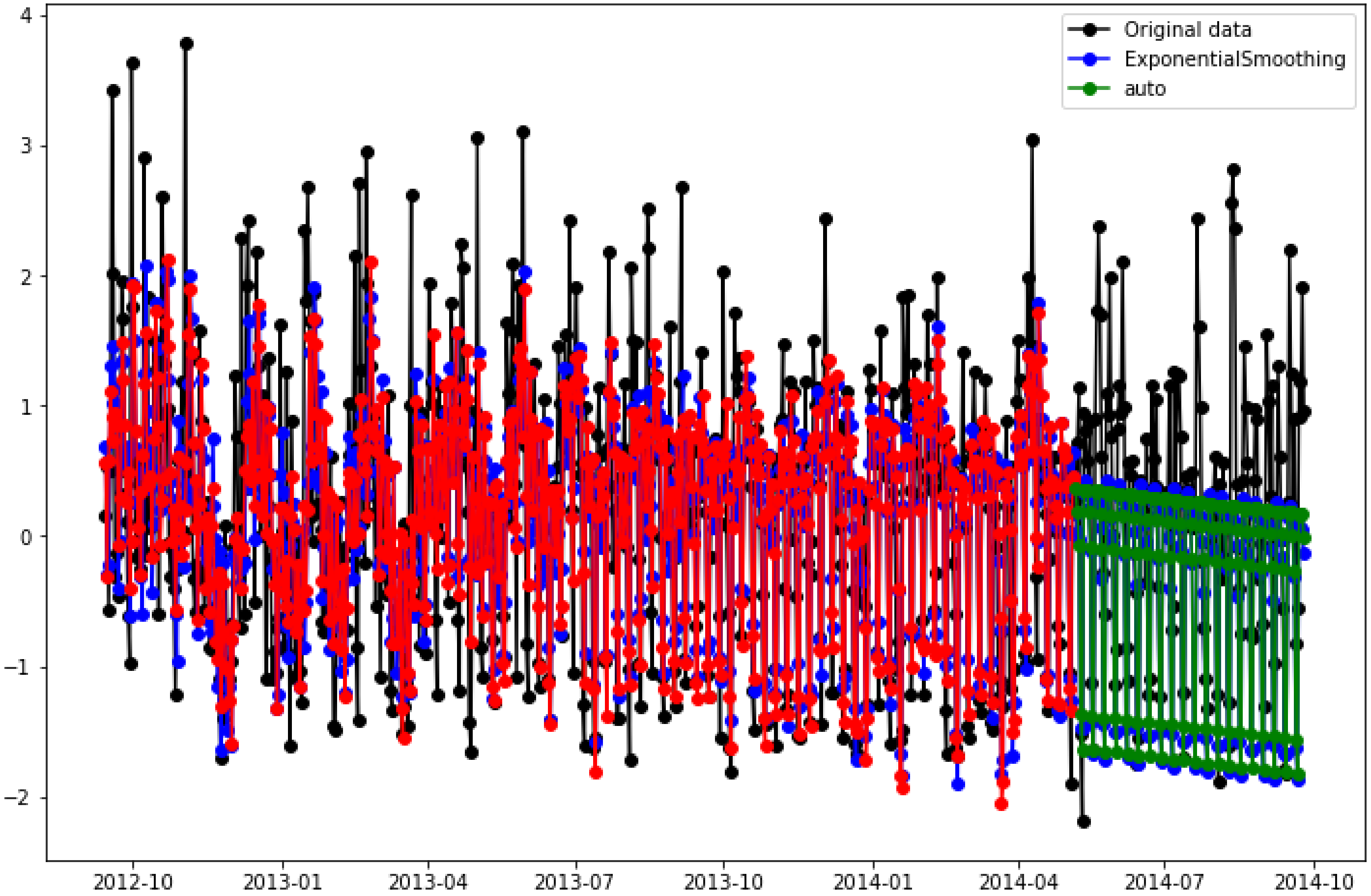
```
from statsmodels.tsa.api import ExponentialSmoothing
```

In [354…

```
fit1 = ExponentialSmoothing(y_to_train,seasonal_periods = 21, trend='add', seasonal='add').fit()
fcast1 = fit1.forecast(predict_date)

fit2 = ExponentialSmoothing(y_to_train, trend='add', seasonal='add').fit()  # use_boxcox=True
fcast2 = fit2.forecast(predict_date)

plt.figure(figsize=(12, 8))
plt.plot(n_df, marker="o", color="black",label='Original data')

plt.plot(fit1.fittedvalues, marker="o", color="blue")
line1 = plt.plot(fcast1, marker="o", color="blue",label='ExponentialSmoothing')

plt.plot(fit2.fittedvalues, marker="o", color="red")
line2 = plt.plot(fcast2, marker="o", color="green",label='auto')

plt.legend()
plt.show
```

Out[354…

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [355…

```
#square sum error
sse1 =fit1.sse
print(sse1)
sse2 =fit2.sse
print(sse2)
```

```
389.81182537250345
362.9432107523461
```

In [356…

```
389.81182537250345
362.9432107523461
```

Out[356…

```
362.9432107523461
```

In [ ]: