

In [194...]

```
import pandas as pd
import numpy as np
```

In [195...]

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

In [196...]

```
del df['ID']
df.head()
```

Out[196...]

	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 [197...]

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18288 entries, 0 to 18287
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
 ---  --          --          --      
 0   Datetime    18288 non-null   object 
 1   Count       18288 non-null   int64  
dtypes: int64(1), object(1)
memory usage: 285.9+ KB
```

In [198...]

```
df.Timestamp = pd.to_datetime(df.Datetime,format='%d-%m-%Y %H:%M')
df.index = df.Timestamp
df = df.resample('D').mean() # reduce rows
# df.drop(['ID'], axis = 1,inplace=True)
```

```
C:\Users\GOD'SF~1\AppData\Local\Temp/ipykernel_7656/3706016313.py:1: UserWarning: Pandas doesn't allow columns to be created via a new attribute name - see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access
df.Timestamp = pd.to_datetime(df.Datetime,format='%d-%m-%Y %H:%M')
```

In []:

In [199...]

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

In [200...]

```
df['SMA_2'] = df.Count.rolling(2, min_periods=1).mean()
df['SMA_12'] = df.Count.rolling(12, min_periods=6).mean()
df.head(20)
```

Out[200...]

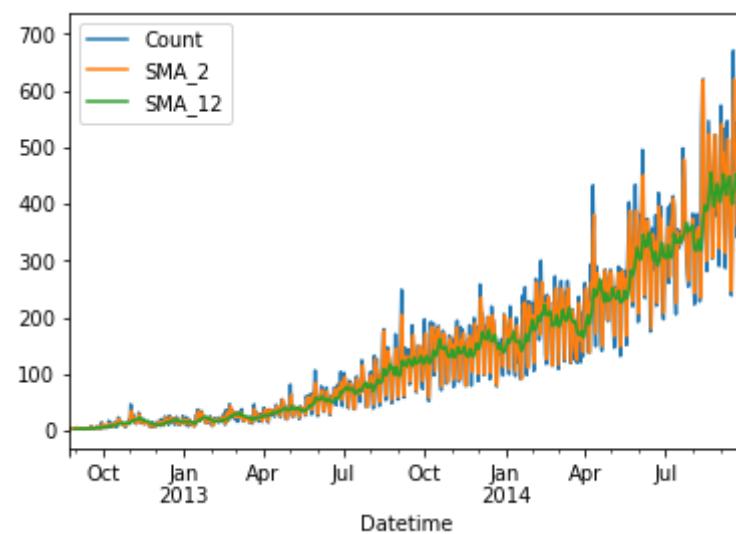
	Count	SMA_2	SMA_12
Datetime			
2012-08-25	3.166667	3.166667	NaN
2012-08-26	3.666667	3.416667	NaN
2012-08-27	2.583333	3.125000	NaN
2012-08-28	2.416667	2.500000	NaN
2012-08-29	2.500000	2.458333	NaN
2012-08-30	3.083333	2.791667	2.902778
2012-08-31	3.250000	3.166667	2.952381
2012-09-01	4.666667	3.958333	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

	Count	SMA_2	SMA_12
Datetime			
2012-08-25	3.166667	3.166667	NaN
2012-08-26	3.666667	3.416667	NaN
2012-08-27	2.583333	3.125000	NaN
2012-08-28	2.416667	2.500000	NaN
2012-08-29	2.500000	2.458333	NaN
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

	Count	SMA_2	SMA_12
Datetime			
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 [201... df.plot()
```

```
Out[201... <AxesSubplot:xlabel='Datetime'>
```



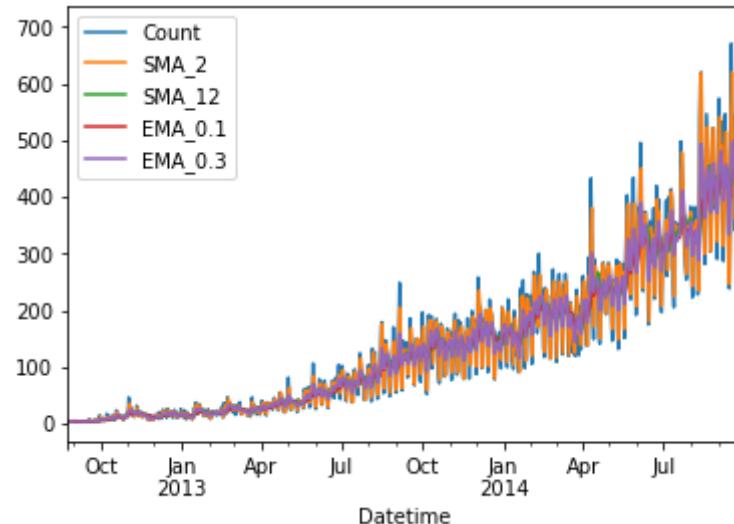
```
In [202... # EMA Sales
df1 = pd.DataFrame()
#Exponential Moving Average (EMA) does a superb job in capturing the pattern of the data (0,1)
# Let's smoothing factor - 0.1
df['EMA_0.1'] = df.Count.ewm(alpha=0.1, adjust=False).mean()
```

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

In [203...]

```
df.plot()
```

Out[203...]



In [204...]

```
# import matplotlib.pyplot as plt
# rolmean = df.Count.rolling(window=12).mean()

# rolstd = df.Count.rolling(window=12).std()

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

```
In [206...]: # df.isna().value_counts()
```

```
In [207...]: test_result=adfuller(df['Count'])
test_result # 'ADF Test Statistic', 'p-value', '#Lags Used', 'Number of Observations Used'\
```

```
Out[207...]: (2.986350959013852,
 1.0,
 20,
 741,
 {'1%': -3.4392057325732104,
 '5%': -2.8654483492874236,
 '10%': -2.5688512291811225},
 7212.068059584322)
```

```
In [ ]:
```

```
In [ ]:
```

```
In [208...]: 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 [209...]: 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
```

```
In [210...]: from statsmodels.tsa.seasonal import seasonal_decompose
```

```
In [211...]: # Decompose the data frame to get the trend, seasonality and noise
decompose_result = seasonal_decompose(df['Count'], model='additive', period=1)
```

```
In [212...]: import matplotlib.pyplot as plt
# plt.show()
```

```
In [213...]: # Detrending
df_detrend = (df['Count'] - df['Count'].rolling(window=12).mean())/df['Count'].rolling(window=46).std()
```

```
In [214...]: # S_df= df['Seasonal_Difference']
n_df = pd.DataFrame(df['Count'].T)
n_df.dropna(inplace=True)
n_df.shape
```

```
Out[214...]: (762, 1)
```

```
In [215...]: y_to_train = n_df.iloc[:600] # dataset to train
y_to_val = n_df.iloc[600:] # last X months for test
predict_date = len(n_df) - len(n_df.iloc[:75])
```

```
In [216...]: y_to_val
```

```
Out[216...]:
```

Count

Datetime

2014-04-17 257.583333

2014-04-18 247.000000

Count	
Datetime	
2014-04-19	158.250000
2014-04-20	140.583333
2014-04-21	223.333333
...	...
2014-09-21	379.250000
2014-09-22	588.166667
2014-09-23	554.333333
2014-09-24	702.333333
2014-09-25	589.666667

162 rows × 1 columns

In [217]:

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

In [218]:

```
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")
```

12/30/21, 5:46 PM

TimeSeriesData_Assignment

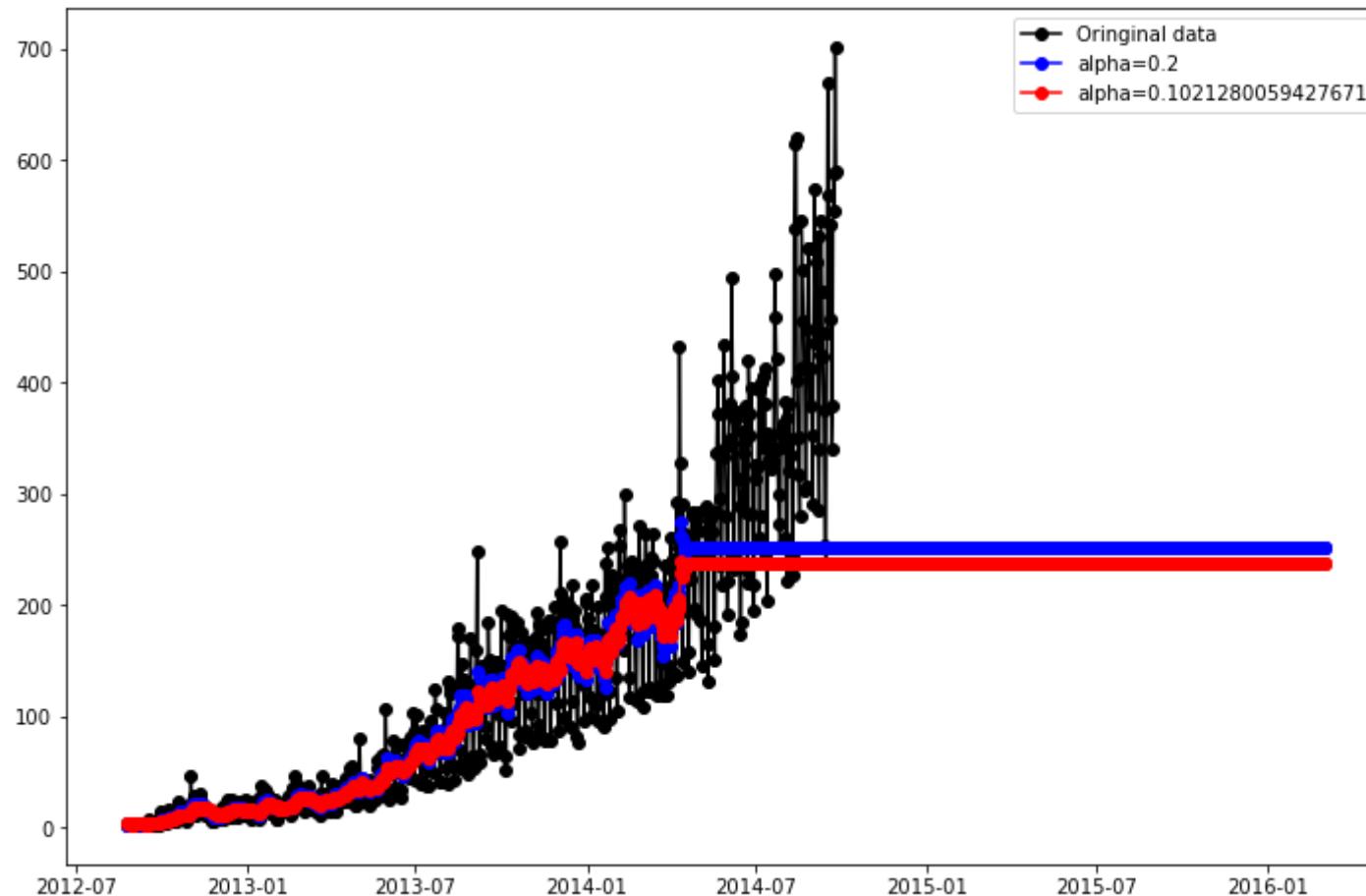
```
line2 = plt.plot(fcast2, marker="o", color="red",label=f'alpha={alpha}')
```

```
plt.legend()
```

```
plt.show
```

0.1021280059427671

Out[218...]



In [219...]

```
#square sum error
```

```
sse1 =fit1.sse
```

```
print(sse1)
```

```
sse2 =fit2.sse
```

```
print(sse2)
```

```
699410.4850384595  
683326.7805020371
```

In [220...]

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

In [221...]

```
fit1 = Holt(y_to_train).fit(smoothing_level=0.8, smoothing_trend=0.2, optimized=False)  
fcast1 = fit1.forecast(predict_date)
```

```
fit2 = Holt(y_to_train).fit()  
fcast2 = fit2.forecast(predict_date)
```

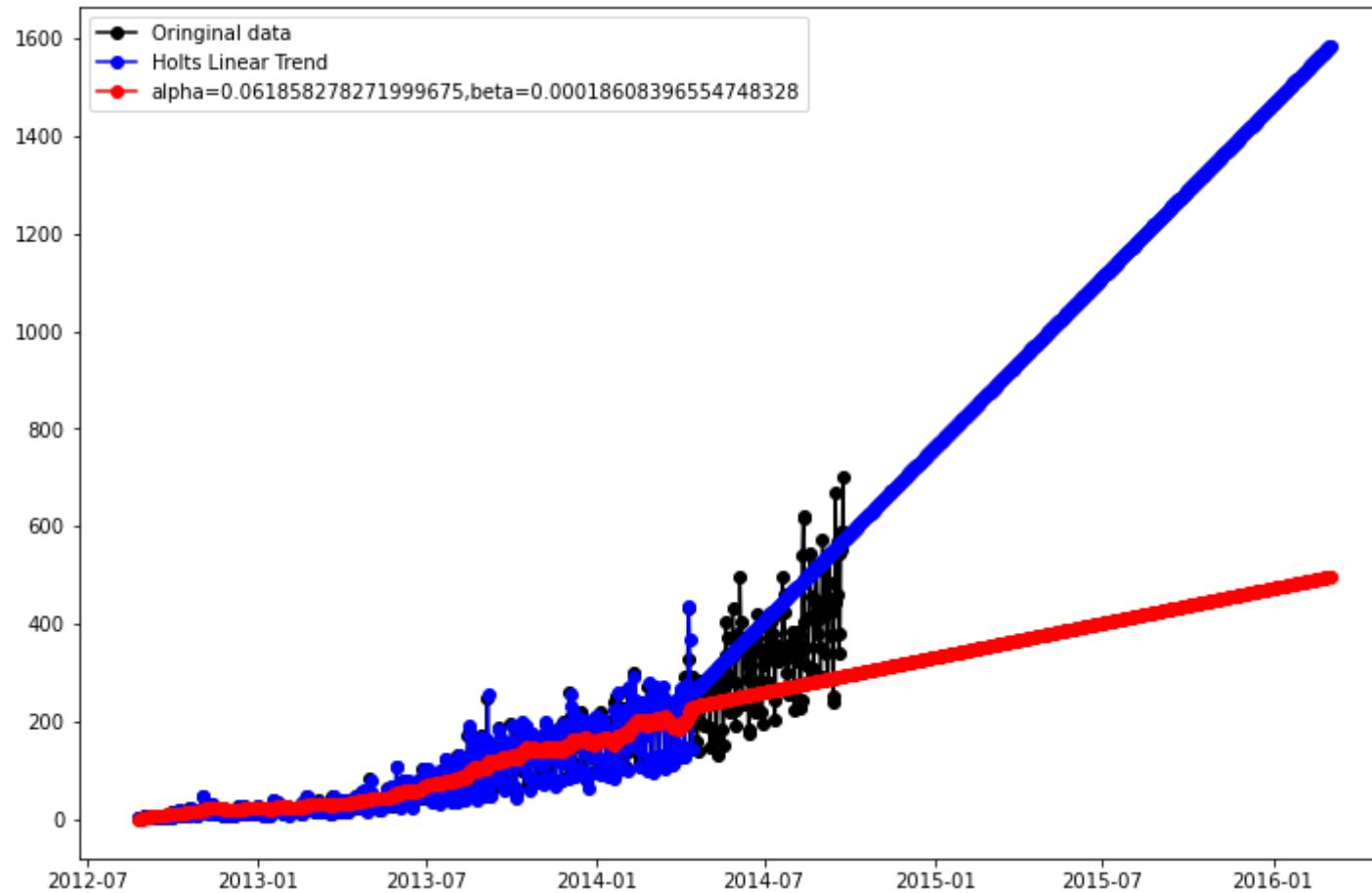
```
alpha = fit2.params["smoothing_level"]  
print(alpha)  
beta = fit2.params["smoothing_trend"]  
print(beta)
```

```
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
```

```
0.061858278271999675  
0.00018608396554748328
```

Out[221...]

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



In [222...]

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

```
936009.625865363
670561.7363438432
```

In [223...]

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

In [224...]

```
fit1 = ExponentialSmoothing(y_to_train,seasonal_periods = 12, trend='add', seasonal='add').fit()
fcast1 = fit1.forecast(predict_date)

fit2 = ExponentialSmoothing(y_to_train).fit() # use_boxcox=True
fcast2 = fit2.forecast(predict_date)

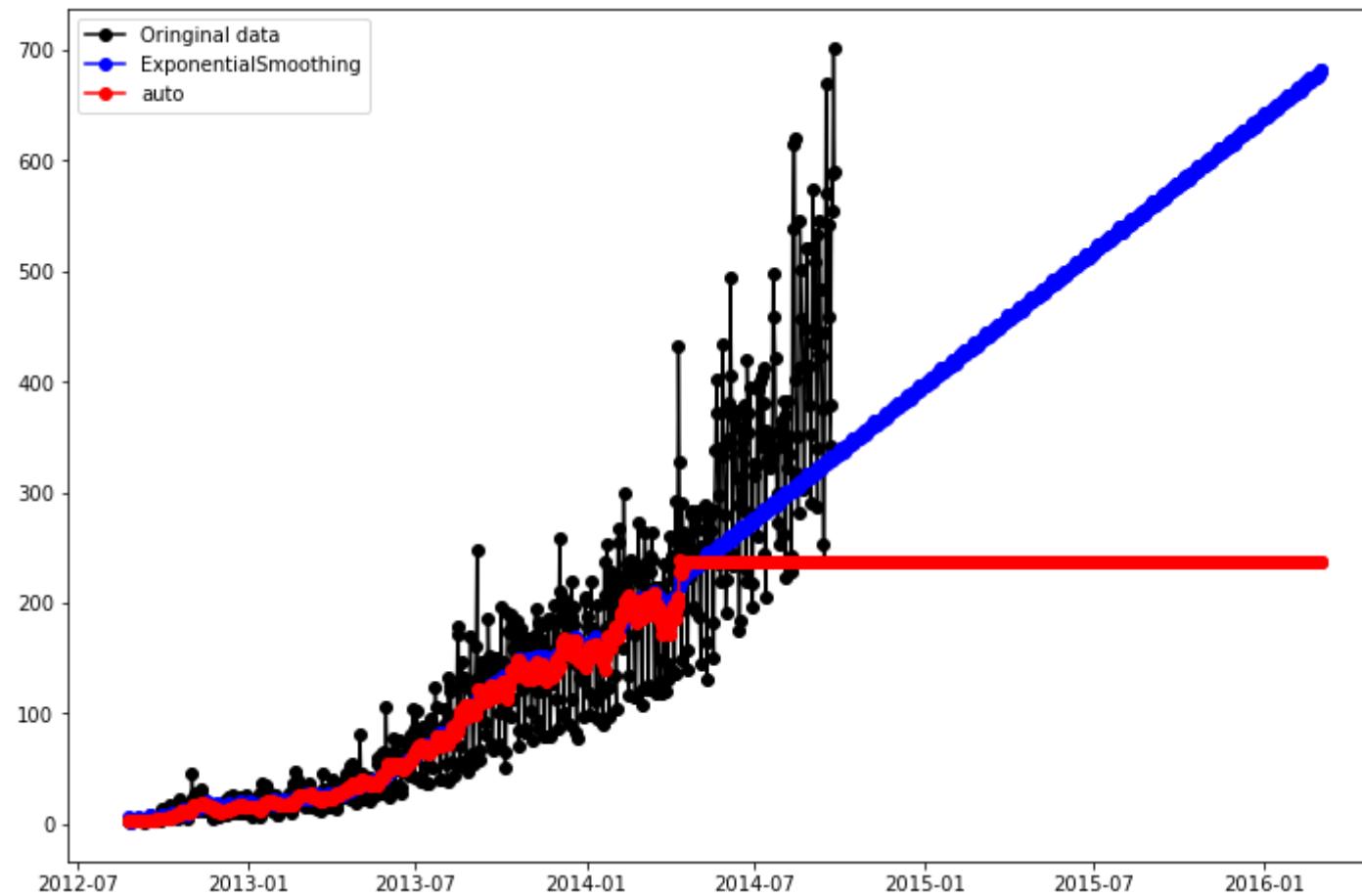
plt.figure(figsize=(12, 8))
plt.plot(n_df, marker="o", color="black",label='Oringinal data')

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

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

plt.legend()
plt.show
```

```
Out[224... <function matplotlib.pyplot.show(close=None, block=None)>
```



In [225...]

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

```
671631.8615754868
683326.7804999587
```