In [1]:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
```

```
Bad key "text.kerning_factor" on line 4 in
C:\Users\91920\anaconda3\lib\site-packages\matplotlib\mpl-data\stylelib\_cla
ssic_test_patch.mplstyle.
You probably need to get an updated matplotlibrc file from
https://github.com/matplotlib/matplotlib/blob/v3.1.3/matplotlibrc.template
 (https://github.com/matplotlib/matplotlib/blob/v3.1.3/matplotlibrc.templat
e)
or from the matplotlib source distribution
```

In [2]:

```
filename="E:\python\perrin-freres-monthly-champagne-.csv"

df=pd.read_csv(filename)
df.head()
```

Out[2]:

	Month	Perrin Freres monthly champagne sales millions ?64-?72
0	1964-01	2815.0
1	1964-02	2672.0
2	1964-03	2755.0
3	1964-04	2721.0
4	1964-05	2946.0

In [3]:

```
## Cleaning up the data
df.columns=["Month","Sales"]
df.head()
```

Out[3]:

	Month	Sales
0	1964-01	2815.0
1	1964-02	2672.0
2	1964-03	2755.0
3	1964-04	2721.0
4	1964-05	2946.0

In [4]:

```
df.tail()
```

Out[4]:

	Month	Sales
102	1972-07	4298.0
103	1972-08	1413.0
104	1972-09	5877.0
105	NaN	NaN
106	Perrin Freres monthly champagne sales millions...	NaN

In [5]:

```
## Drop last 2 rows
df.drop(106,axis=0,inplace=True)
df.drop(105,axis=0,inplace=True)
```

In [6]:

```
df.tail()
```

Out[6]:

	Month	Sales
100	1972-05	4618.0
101	1972-06	5312.0
102	1972-07	4298.0
103	1972-08	1413.0
104	1972-09	5877.0

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 105 entries, 0 to 104
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Month   105 non-null    object 
 1   Sales   105 non-null    float64
dtypes: float64(1), object(1)
memory usage: 2.5+ KB
```

In [8]:

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 105 entries, 0 to 104
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Month   105 non-null    datetime64[ns]
 1   Sales   105 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 2.5 KB
```

In [9]:

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

Out[9]:

Month	Sales
1964-01-01	2815.0
1964-02-01	2672.0
1964-03-01	2755.0
1964-04-01	2721.0
1964-05-01	2946.0

In [10]:

```
df.describe()
```

Out[10]:

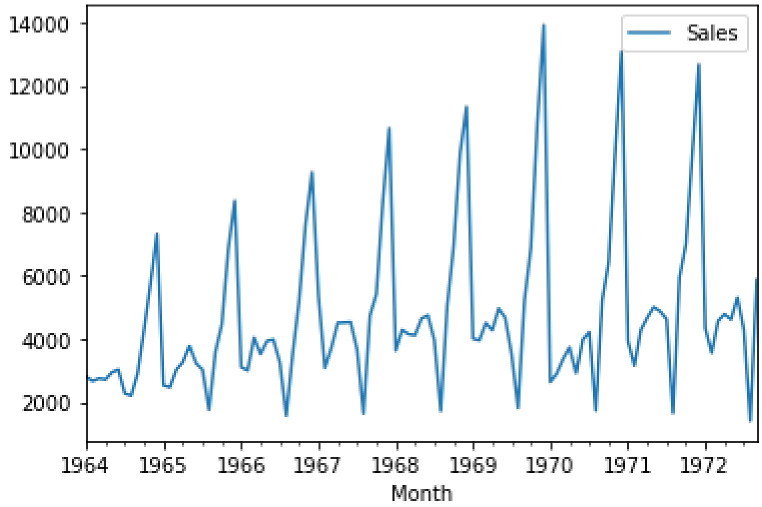
	Sales
count	105.000000
mean	4761.152381
std	2553.502601
min	1413.000000
25%	3113.000000
50%	4217.000000
75%	5221.000000
max	13916.000000

In [11]:

```
df.plot()
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20e8c6cbe88>
```



Moving Average

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

In [12]:

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

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

Out[12]:

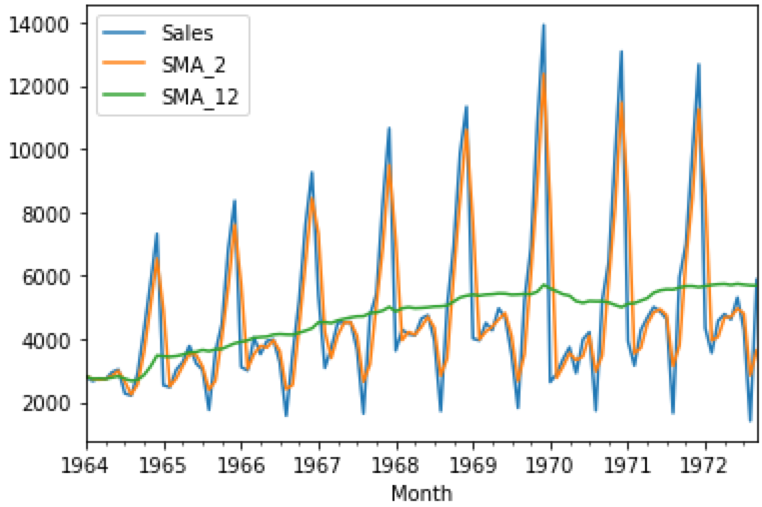
Month	Sales	SMA_2	SMA_12
1964-01-01	2815.0	2815.0	2815.000000
1964-02-01	2672.0	2743.5	2743.500000
1964-03-01	2755.0	2713.5	2747.333333
1964-04-01	2721.0	2738.0	2740.750000
1964-05-01	2946.0	2833.5	2781.800000
1964-06-01	3036.0	2991.0	2824.166667
1964-07-01	2282.0	2659.0	2746.714286
1964-08-01	2212.0	2247.0	2679.875000
1964-09-01	2922.0	2567.0	2706.777778
1964-10-01	4301.0	3611.5	2866.200000
1964-11-01	5764.0	5032.5	3129.636364
1964-12-01	7312.0	6538.0	3478.166667
1965-01-01	2541.0	4926.5	3455.333333
1965-02-01	2475.0	2508.0	3438.916667
1965-03-01	3031.0	2753.0	3461.916667
1965-04-01	3266.0	3148.5	3507.333333
1965-05-01	3776.0	3521.0	3576.500000
1965-06-01	3230.0	3503.0	3592.666667
1965-07-01	3028.0	3129.0	3654.833333
1965-08-01	1759.0	2393.5	3617.083333

In [13]:

```
df.plot()
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a84ede1d88>
```



In [14]:

```
df['CMA']= df.Sales.expanding(min_periods=1).mean()  # cummulative moving average the cumul
df.head(15)
```

Out[14]:

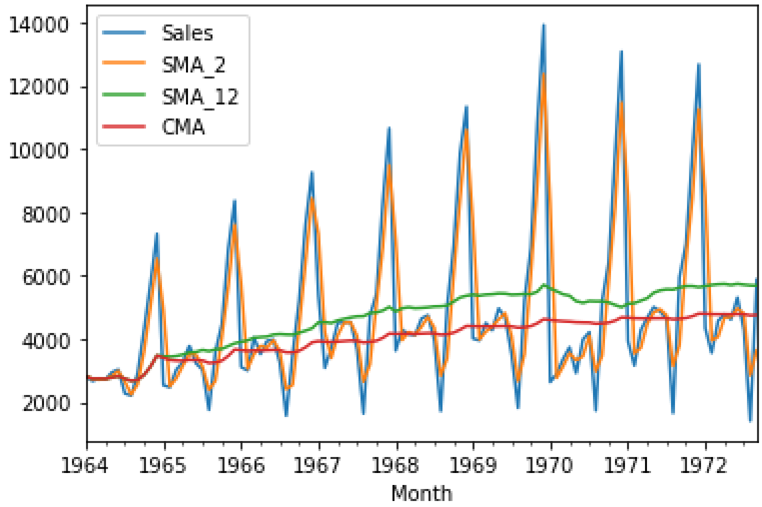
Month	Sales	SMA_2	SMA_12	CMA
1964-01-01	2815.0	2815.0	2815.000000	2815.000000
1964-02-01	2672.0	2743.5	2743.500000	2743.500000
1964-03-01	2755.0	2713.5	2747.333333	2747.333333
1964-04-01	2721.0	2738.0	2740.750000	2740.750000
1964-05-01	2946.0	2833.5	2781.800000	2781.800000
1964-06-01	3036.0	2991.0	2824.166667	2824.166667
1964-07-01	2282.0	2659.0	2746.714286	2746.714286
1964-08-01	2212.0	2247.0	2679.875000	2679.875000
1964-09-01	2922.0	2567.0	2706.777778	2706.777778
1964-10-01	4301.0	3611.5	2866.200000	2866.200000
1964-11-01	5764.0	5032.5	3129.636364	3129.636364
1964-12-01	7312.0	6538.0	3478.166667	3478.166667
1965-01-01	2541.0	4926.5	3455.333333	3406.076923
1965-02-01	2475.0	2508.0	3438.916667	3339.571429
1965-03-01	3031.0	2753.0	3461.916667	3319.000000

In [15]:

```
df.plot()
```

Out[15]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a84eeb8448>



Exponential Moving Average

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

In [16]:

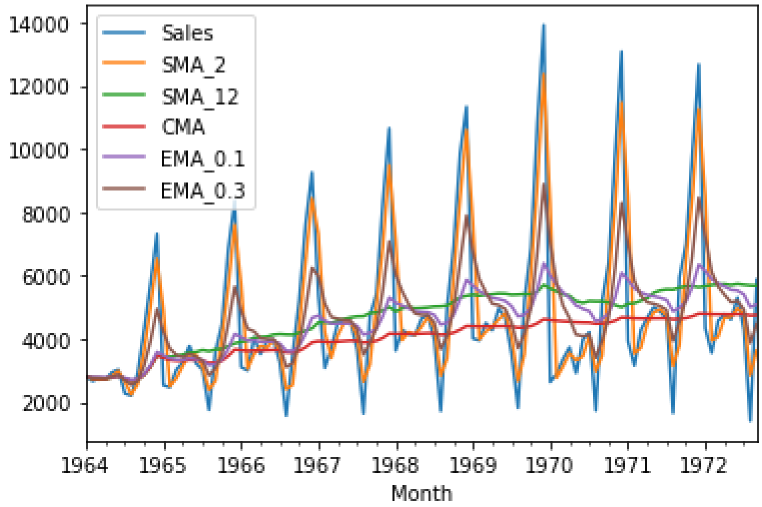
```
# EMA Sales
#Exponential Moving Average (EMA) does a superb job in capturing the pattern of the data (0
# Let's smoothing factor - 0.1
df['EMA_0.1'] = df.Sales.ewm(alpha=0.1, adjust=False).mean()
# Let's smoothing factor  - 0.3
df['EMA_0.3'] = df.Sales.ewm(alpha=0.3, adjust=False).mean()
```

In [17]:

```
df.plot()
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a84ef97fc8>
```



Check for Stationarity

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

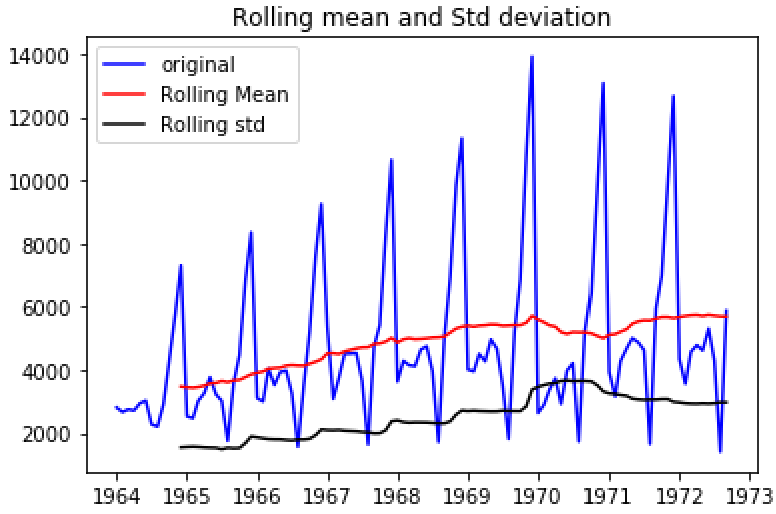
In [15]:

```
# Rolling Statistics or Visualization

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

In [16]:

```
orig = plt.plot(df.Sales,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 [17]:

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

from statsmodels.tsa.stattools import adfuller
```

In [18]:

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

Out[18]:

```
(-1.8335930563276297,
 0.3639157716602417,
 11,
 93,
 {'1%': -3.502704609582561,
  '5%': -2.8931578098779522,
  '10%': -2.583636712914788},
 1478.4633060594724)
```

In [19]:

```
#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.
    else:
        print("weak evidence against null hypothesis, indicating it is non-stationary ")
```

In [20]:

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

```
ADF Test Statistic : -1.8335930563276297
p-value : 0.3639157716602417
Lags Used : 11
Number of Observations Used : 93
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 [29]:

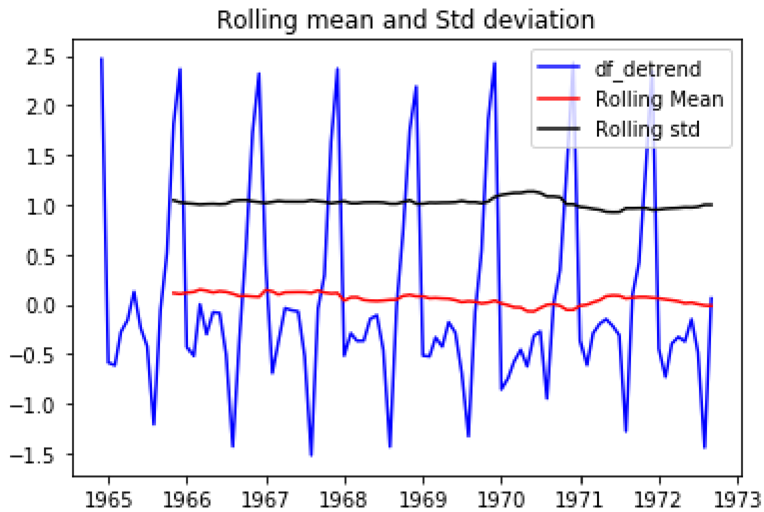
```
# Detrending
df_detrend =  (df['Sales'] - df['Sales'].rolling(window=12).mean())/df['Sales'].rolling(win
```

In [30]:

```
# Rolling Statistics or Visualization

rolmean = df_detrend.rolling(window=12).mean()
rolstd = df_detrend.rolling(window=12).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 [31]:

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

```
ADF Test Statistic : -1.5854241126412958
p-value : 0.4909112123799473
Lags Used : 11
Number of Observations Used : 82
weak evidence against null hypothesis, indicating it is non-stationary
```

Differencing

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

In [12]:

```
df['Seasonal_Difference']=df['Sales']-df['Sales'].shift(12)
```

In [13]:

```
df.head(15)
```

Out[13]:

Month	Sales	Seasonal_Difference
1964-01-01	2815.0	NaN
1964-02-01	2672.0	NaN
1964-03-01	2755.0	NaN
1964-04-01	2721.0	NaN
1964-05-01	2946.0	NaN
1964-06-01	3036.0	NaN
1964-07-01	2282.0	NaN
1964-08-01	2212.0	NaN
1964-09-01	2922.0	NaN
1964-10-01	4301.0	NaN
1964-11-01	5764.0	NaN
1964-12-01	7312.0	NaN
1965-01-01	2541.0	-274.0
1965-02-01	2475.0	-197.0
1965-03-01	3031.0	276.0

In [21]:

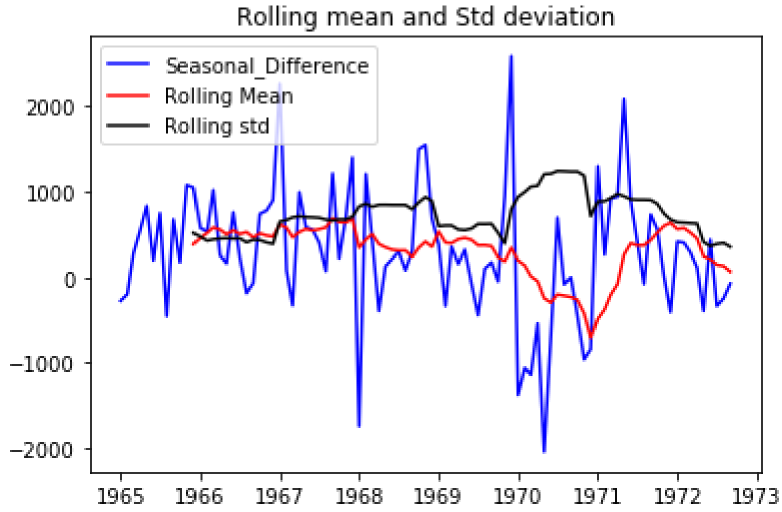
```
## Again test dickey fuller test
adfuller_test(df['Seasonal_Difference'].dropna())
```

```
ADF Test Statistic : -7.626619157213163
p-value : 2.060579696813685e-11
Lags Used : 0
Number of Observations Used : 92
strong evidence against the null hypothesis(Ho), reject the null hypothesis.
Data is stationary
```

In [22]:

```
# Rolling Statistics

rolmean = df['Seasonal_Difference'].rolling(window=12).mean()
rolstd = df['Seasonal_Difference'].rolling(window=12).std()
#orig = plt.plot(df.Sales,color='yellow',label='original')
Seasonal_Difference = plt.plot(df['Seasonal_Difference'],color='blue',label='Seasonal_Diffe
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['Sales'],model='additive',period=1)
decompose_result.plot()
plt.show()
```

In [23]:

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

In [24]:

```
n_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 93 entries, 1965-01-01 to 1972-09-01
Data columns (total 1 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Seasonal_Difference  93 non-null     float64
dtypes: float64(1)
memory usage: 1.5 KB
```

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

In [25]:

```
y_to_train = n_df.iloc[:75] # dataset to train
y_to_test = n_df.iloc[75:] # last X months for test
predict_date = len(n_df) - len(y_to_train)  #lenght of dataset - len of training dataset
```

In [26]:

```
predict_date  # len(y_to_val)
```

Out[26]:

```
18
```

Exponential Moving Average

In [74]:

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

In [80]:

```
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}')

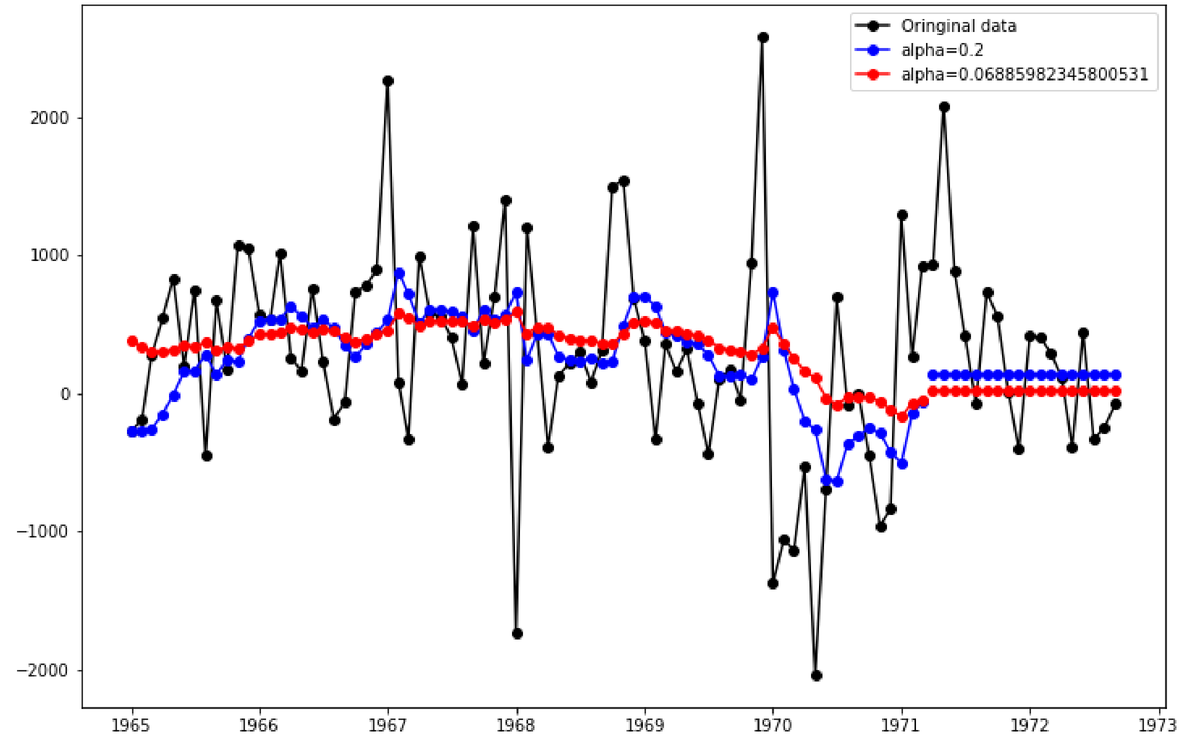
plt.legend()
plt.show
```

```
0.06885982345800531

C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:162: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  % freq, ValueWarning)
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:162: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  % freq, ValueWarning)
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters.py:73
1: RuntimeWarning: invalid value encountered in greater_equal
  loc = initial_p >= ub
```

Out[80]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [84]:

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

```
48770904.168382205
46338230.633439496
```

Holt’s Linear Trend Method

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

In [82]:

```
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 [89]:

```
fit1 = Holt(y_to_train).fit(smoothing_level=0.8, smoothing_slope=0.2, optimized=False)  #sm
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_slope"]
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}')

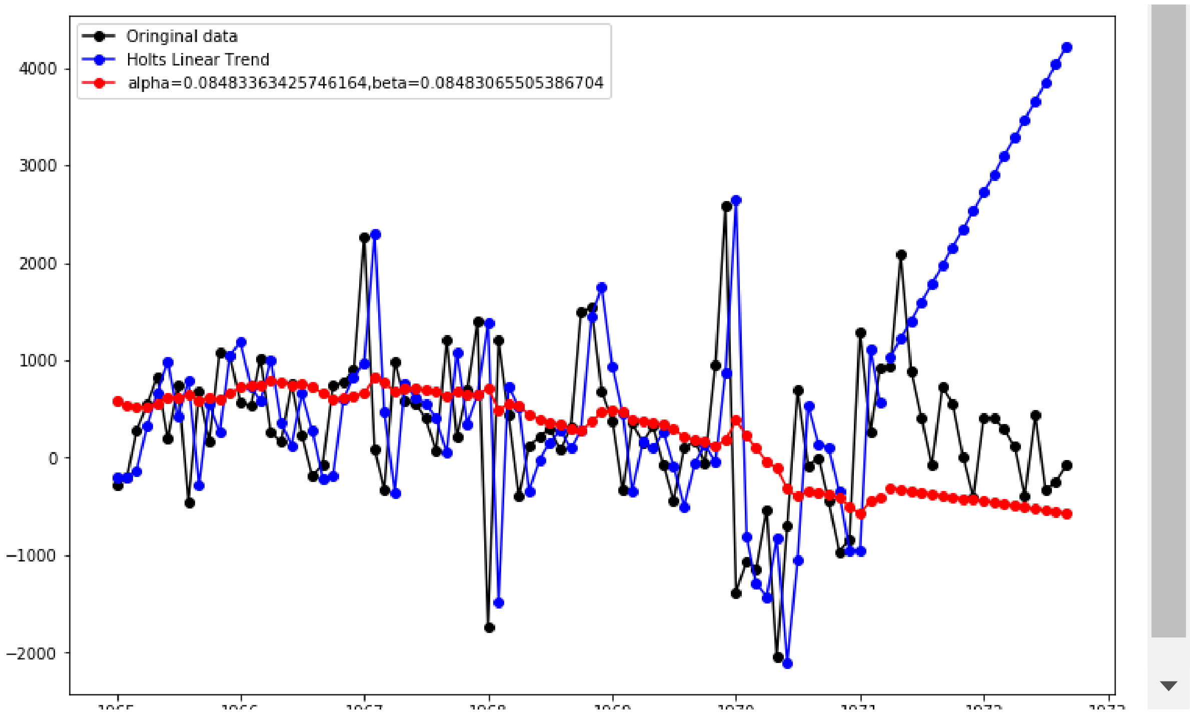
plt.legend()
plt.show
```

```
0.08483363425746164
0.08483065505386704

C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:162: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  % freq, ValueWarning)
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:162: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  % freq, ValueWarning)
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters.py:74
4: ConvergenceWarning: Optimization failed to converge. Check mle_retvals.
  ConvergenceWarning)
```

Out[89]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [90]:

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

```
76710338.37726729
48405678.50179307
```

Holt-Winters' Seasonal Method

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

In [27]:

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

In [28]:

```
fit1 = ExponentialSmoothing(y_to_train,seasonal_periods = 12, trend='add', seasonal='add').
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')

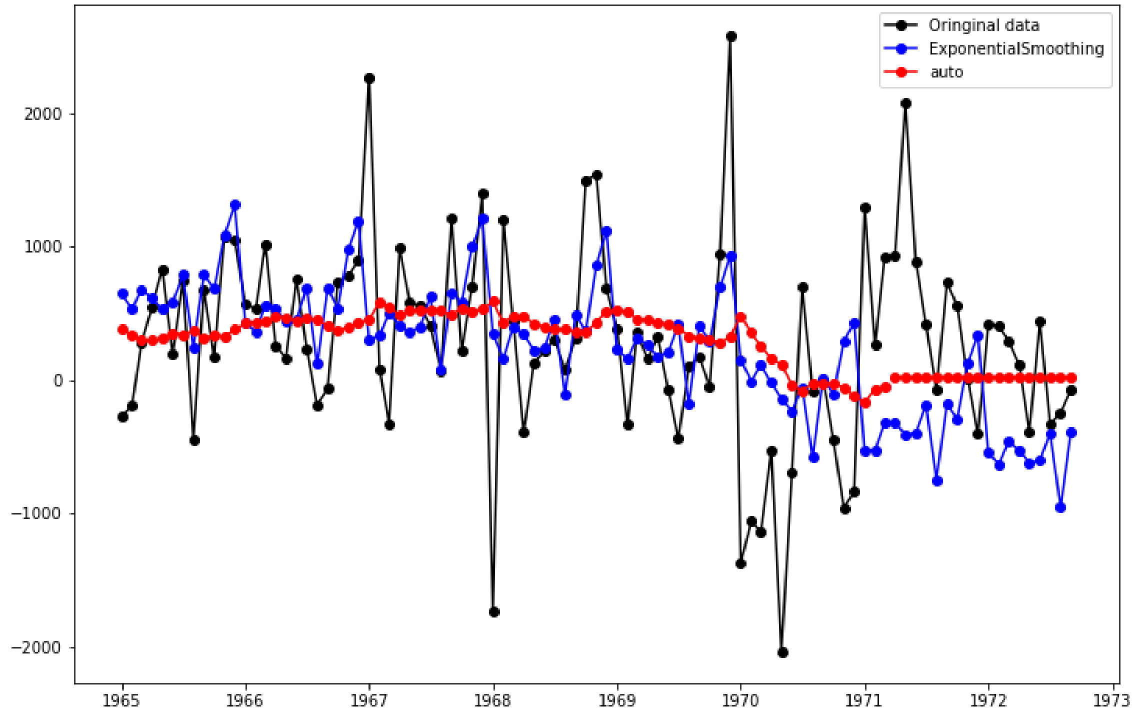
plt.plot(fit2.fittedvalues, marker="o", color="red")
line2 = plt.plot(fcast2, marker="o", color="red",label='auto')

plt.legend()
plt.show
```

```
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:162: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  % freq, ValueWarning)
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters.py:72
5: RuntimeWarning: invalid value encountered in less_equal
  loc = initial_p <= lb
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters.py:73
1: RuntimeWarning: invalid value encountered in greater_equal
  loc = initial_p >= ub
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters.py:74
4: ConvergenceWarning: Optimization failed to converge. Check mle_retvals.
  ConvergenceWarning)
C:\Users\91920\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:162: ValueWarning: No frequency information was provided, so inferred freq
uency MS will be used.
  % freq, ValueWarning)
```

Out[28]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [29]:

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

```
40667304.40999994
46338230.633439496
```

In [30]:

```
fcast1 = fit1.forecast(30)
fcast1
```

Out[30]:

```
1971-04-01    -318.835930
1971-05-01    -411.941693
1971-06-01    -397.377452
1971-07-01    -189.384556
1971-08-01    -747.690978
1971-09-01    -179.018627
1971-10-01    -295.125461
1971-11-01     123.107110
1971-12-01     336.874258
1972-01-01    -545.779387
1972-02-01    -633.483027
1972-03-01    -463.865414
1972-04-01    -528.349250
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1972-11-01     -86.406210
1972-12-01     127.360938
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1973-03-01    -673.378734
1973-04-01    -737.862570
1973-05-01    -830.968333
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1973-08-01   -1166.717619
1973-09-01    -598.045268
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