In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [25]:

```
cococola_data=pd.read_excel('CocaCola_Sales_Rawdata (1).xlsx')
cococola_data.tail()
```

Out[25]:

	Quarter	Sales
37	Q2_95	4936.0
38	Q3_95	4895.0
39	Q4_95	4333.0
40	Q1_96	4194.0
41	Q2_96	5253.0

Initial investigation

In [26]:

```
cococola_data.shape
```

Out[26]:

```
(42, 2)
```

In [27]:

```
cococola_data.dtypes
```

Out[27]:

```
Quarter     object
Sales      float64
dtype: object
```

In [28]:

```
cococola_data.isnull().sum()
```

Out[28]:

```
Quarter    0
Sales      0
dtype: int64
```

The data have 2 features and 42 records

The datatype of the features are assigned coorectly and there is no null values

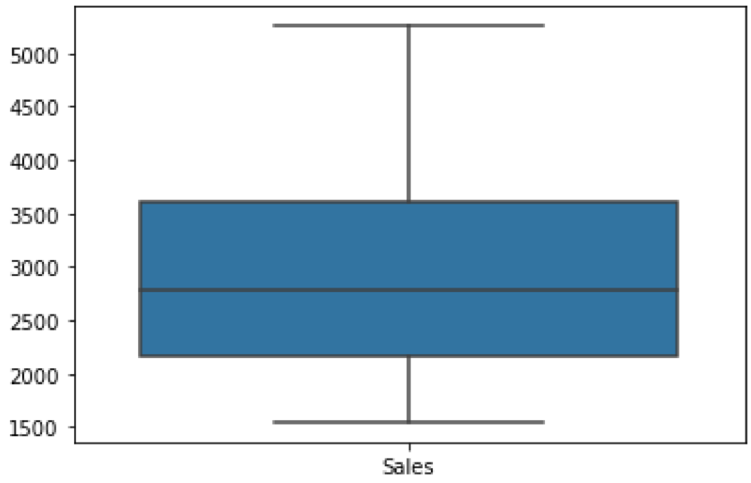
Data visualization

In [29]:

```
sns.boxplot(data=cococola_data)
```

Out[29]:

<AxesSubplot:>

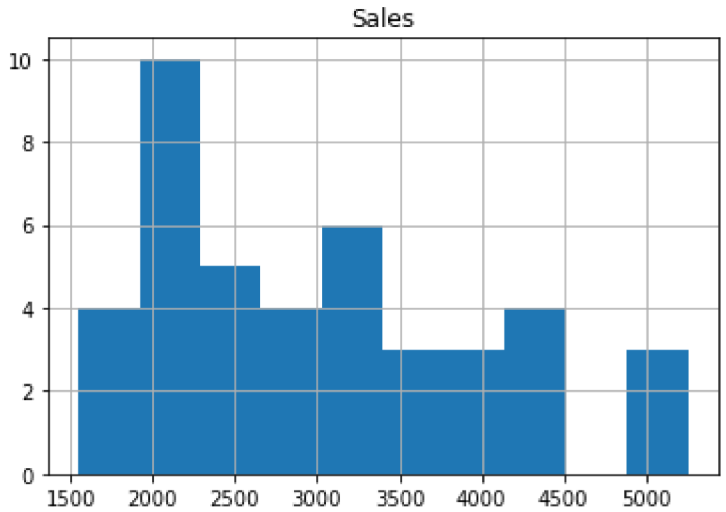


In [8]:

```
cococola_data.hist()
```

Out[8]:

array([[<AxesSubplot:title={'center':'Sales'}>]], dtype=object)

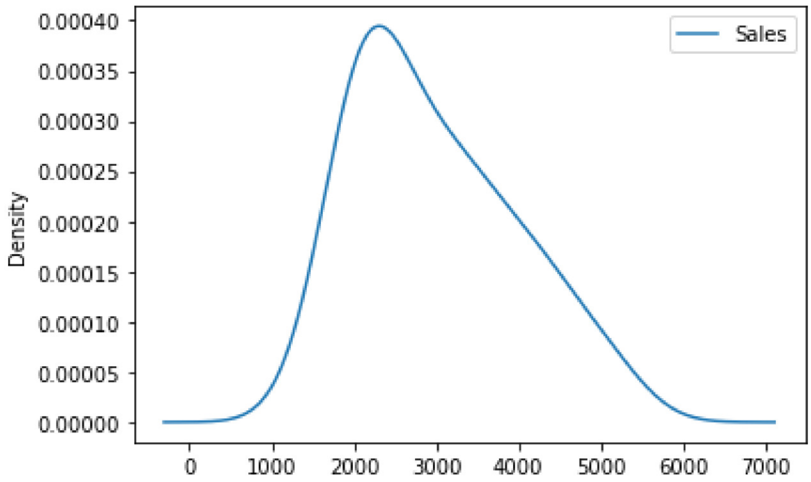


In [10]:

```
cococola_data.plot(kind='kde')
```

Out[10]:

<AxesSubplot:ylabel='Density'>

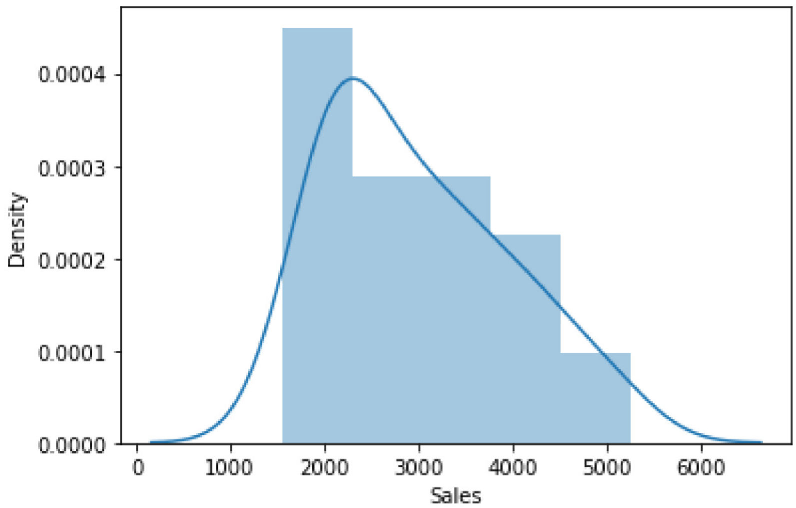


In [12]:

```
sns.distplot(cococola_data['Sales'])
```

Out[12]:

<AxesSubplot:xlabel='Sales', ylabel='Density'>

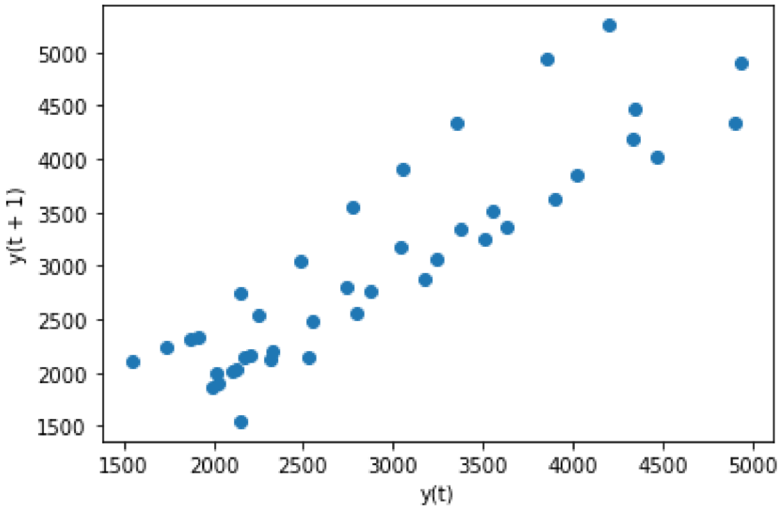


In [14]:

```
from pandas.plotting import lag_plot

lag_plot(cococola_data['Sales'])
```

Out[14]:

```
<AxesSubplot:xlabel='y(t)', ylabel='y(t + 1)'>
```



In [10]:

```
from pandas import DataFrame
from numpy import sqrt
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
```

Model based forecasting

In [6]:

```
cococola_data_model=cococola_data
```

In [7]:

```
cococola_data['quater_list']=cococola_data_model['Quarter']
```

In [11]:

```
cococola_data_model['quater_list']=0
for i in range(len(cococola_data_model)):
    p=cococola_data_model['Quarter'][i]
    cococola_data_model['quater_list'][i]=p[1:2]
```

In [12]:

```
cococola_data_model['year_list']=0
for i in range(len(cococola_data_model)):
    p=cococola_data_model['Quarter'][i]
    cococola_data_model['year_list'][i]=p[3:5]
```

In [13]:

```
cococola_data_model.head()
```

Out[13]:

	Quarter	Sales	quater_list	year_list
0	Q1_86	1734.827000	1	86
1	Q2_86	2244.960999	2	86
2	Q3_86	2533.804993	3	86
3	Q4_86	2154.962997	4	86
4	Q1_87	1547.818996	1	87

In [14]:

```
df_dummies = pd.DataFrame(pd.get_dummies(cococola_data_model['quater_list']))
```

In [15]:

```
cococola_data_df =pd.concat([cococola_data_model,df_dummies],axis= 1)
cococola_data_df.head()
```

Out[15]:

	Quarter	Sales	quater_list	year_list	1	2	3	4
0	Q1_86	1734.827000	1	86	1	0	0	0
1	Q2_86	2244.960999	2	86	0	1	0	0
2	Q3_86	2533.804993	3	86	0	0	1	0
3	Q4_86	2154.962997	4	86	0	0	0	1
4	Q1_87	1547.818996	1	87	1	0	0	0

In [16]:

```
cococola_data_df['quater_sqaure']=cococola_data_df['quater_list'].apply(lambda x:x**2)
```

In [17]:

```
from numpy import log

cococola_data_df['log_sales']=cococola_data_df['Sales'].apply(lambda x:log(x))
```

In [18]:

```
cococola_data_df.head()
```

Out[18]:

	Quarter	Sales	quater_list	year_list	1	2	3	4	quater_sqaure	log_sales
0	Q1_86	1734.827000	1	86	1	0	0	0	1	7.458663
1	Q2_86	2244.960999	2	86	0	1	0	0	4	7.716443
2	Q3_86	2533.804993	3	86	0	0	1	0	9	7.837477
3	Q4_86	2154.962997	4	86	0	0	0	1	16	7.675529
4	Q1_87	1547.818996	1	87	1	0	0	0	1	7.344602

In [19]:

```
cococola_data_df=cococola_data_df.rename(columns={1:'Q1',2:'Q2',3:'Q3',4:'Q4'})
cococola_data_df.head()
```

Out[19]:

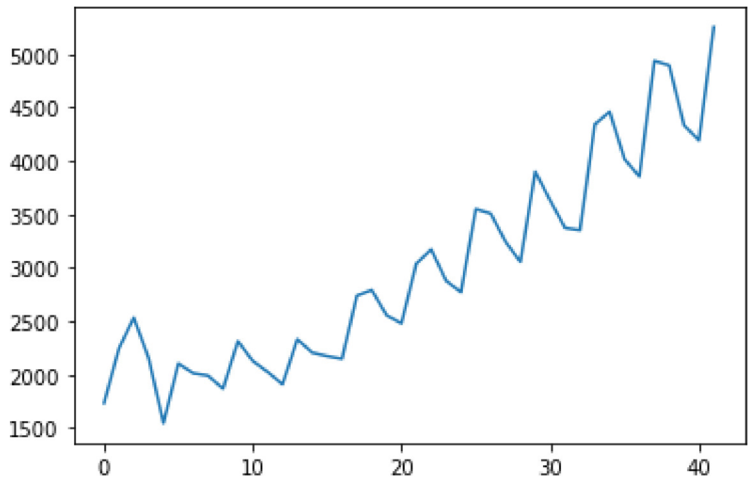
	Quarter	Sales	quater_list	year_list	Q1	Q2	Q3	Q4	quater_sqaure	log_sales
0	Q1_86	1734.827000	1	86	1	0	0	0	1	7.458663
1	Q2_86	2244.960999	2	86	0	1	0	0	4	7.716443
2	Q3_86	2533.804993	3	86	0	0	1	0	9	7.837477
3	Q4_86	2154.962997	4	86	0	0	0	1	16	7.675529
4	Q1_87	1547.818996	1	87	1	0	0	0	1	7.344602

In [20]:

```
cococola_data_df['Sales'].plot()
```

Out[20]:

<AxesSubplot:>



In [21]:

```
cococola_data_df.shape
```

Out[21]:

```
(42, 10)
```

In [22]:

```
train_model=cococola_data_df.head(30)
test_model=cococola_data_df.tail(12)
```

Linear model

In [23]:

```
import statsmodels.formula.api as smf
from sklearn.metrics import mean_absolute_percentage_error

linear_model = smf.ols('Sales~quater_list',data=train_model).fit()
linear_pred=linear_model.predict(test_model['quater_list'])

linear_rms=mean_absolute_percentage_error(test_model['Sales'],linear_pred)*100
linear_rms
```

Out[23]:

```
39.383373853440155
```

Exponential model

In [49]:

```
exponential_model = smf.ols('log_sales~quater_list',data=train_model).fit()
exponential_pred=exponential_model.predict(test_model['quater_list'])

exp_rms=mean_absolute_percentage_error(test_model['Sales'],exponential_pred)*100
exp_rms
```

Out[49]:

```
99.81145421571463
```

Quaratic model

In [51]:

```
quaratic_model = smf.ols('Sales~quater_list+quater_sqaure',data=train_model).fit()
#quaratic_model.fit()
quaratic_pred=quaratic_model.predict(test_model[['quater_list','quater_sqaure']])

qua_rms=mean_absolute_percentage_error(test_model['Sales'],quaratic_pred)*100
qua_rms
```

Out[51]:

```
39.799293820383724
```

Additional seasonality model

In [53]:

```
add_sea = smf.ols("Sales~Q1+Q2+Q3+Q4",data=train_model).fit()
add_pred=add_sea.predict(test_model[['Q1','Q2','Q3','Q4']])

add_rms=mean_absolute_percentage_error(test_model['Sales'],add_pred)*100
add_rms
```

Out[53]:

```
39.924193475512794
```

Additional seasonality with quaratic model

In [54]:

```
add_qua_model=smf.ols("Sales~quater_list+quater_sqaure+Q1+Q2+Q3+Q4",data=train_model).fit()
add_qua_pred=add_qua_model.predict(test_model[['quater_list','quater_sqaure','Q1','Q2','Q3'

add_qua_rms=mean_absolute_percentage_error(test_model['Sales'],add_qua_pred)*100
add_qua_rms
```

Out[54]:

```
39.92419347551282
```

Multiplicative seasonality model

In [55]:

```
mul_sea = smf.ols("log_sales~Q1+Q2+Q3+Q4",data=train_model).fit()
mul_pred=mul_sea.predict(test_model[['Q1','Q2','Q3','Q4']])

mul_rms=mean_absolute_percentage_error(test_model['Sales'],mul_pred)*100
mul_rms
```

Out[55]:

```
99.81166869304352
```

Multiplicative with additional seasonality

In [56]:

```
mul_add_model=smf.ols("Sales~quater_list+Q1+Q2+Q3+Q4",data=train_model).fit()
mul_add_pred=mul_add_model.predict(test_model[['quater_list','Q1','Q2','Q3','Q4']])

mul_add_rms=mean_absolute_percentage_error(test_model['Sales'],mul_add_pred)*100
mul_add_rms
```

Out[56]:

```
39.92419347551281
```

Data driven model

In [53]:

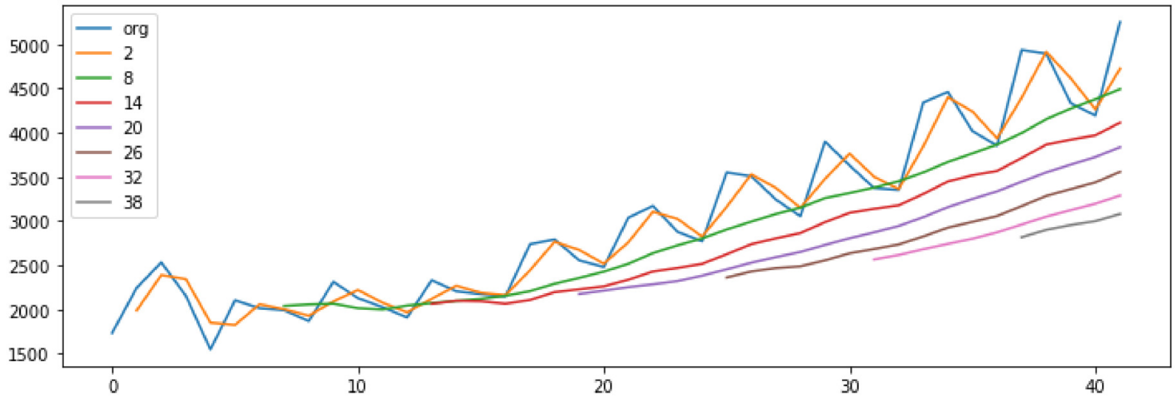
```
train_data=cococola_data.head(30)
test_data=cococola_data.tail(12)
```

In [34]:

```
plt.figure(figsize=(12,4))
cococola_data['Sales'].plot(label="org")
for i in range(2,43,6):
    cococola_data['Sales'].rolling(i).mean().plot(label=str(i))
plt.legend(loc='best')
```

Out[34]:

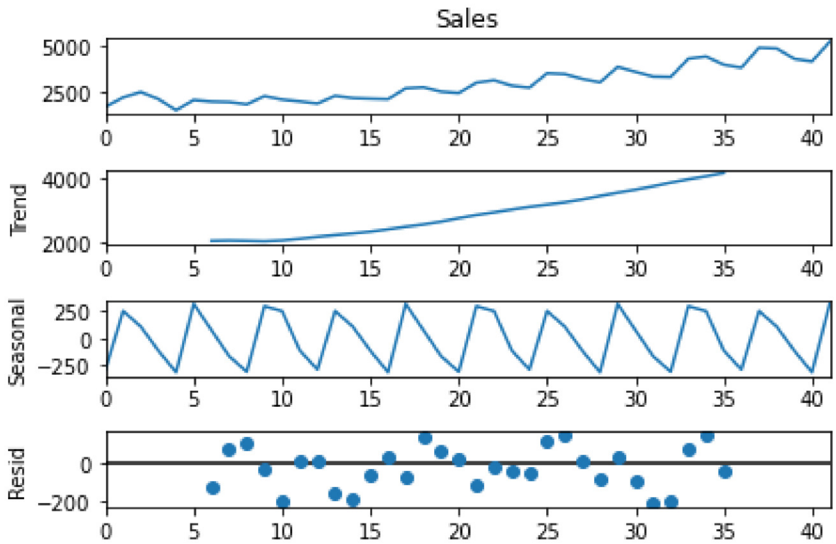
```
<matplotlib.legend.Legend at 0x25c48a74f10>
```



Time series decomposition plot

In [35]:

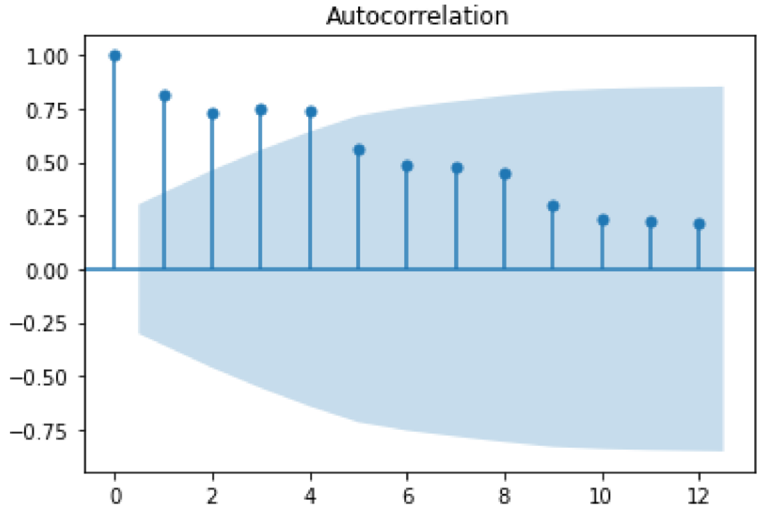
```
from statsmodels.tsa.seasonal import seasonal_decompose

decompose_ts_add = seasonal_decompose(cococola_data['Sales'],period=12)
decompose_ts_add.plot()
plt.show()
```

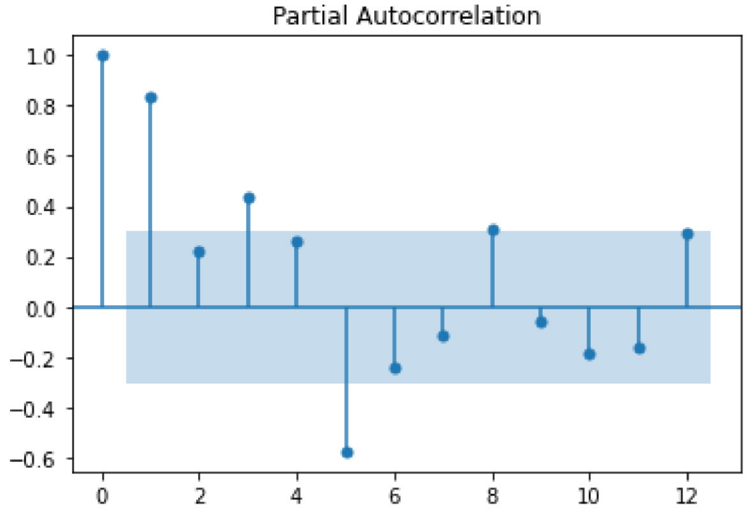


ACF Plot and PACF Plot

In [36]:

```
import statsmodels.graphics.tsaplots as tsa_plots
tsa_plots.plot_acf(cococola_data['Sales'],lags=12)
tsa_plots.plot_pacf(cococola_data['Sales'],lags=12)
plt.show()
```





In [61]:

```
train_data=cococola_data.head(30)
test_data=cococola_data.tail(12)
```

Simple Exponential Smoothing model

In [63]:

```
from statsmodels.tsa.holtwinters import SimpleExpSmoothing

ses_model = SimpleExpSmoothing(train_data["Sales"]).fit(smoothing_level=0.2)
pred_ses = ses_model.predict(start = test_data.index[0],end = test_data.index[-1])

ses_rms=mean_absolute_percentage_error(pred_ses,test_data['Sales'])*100
ses_rms
```

Out[63]:

```
30.811045381255248
```

Holt model

In [64]:

```
from statsmodels.tsa.holtwinters import Holt

hw_model = Holt(train_data["Sales"]).fit(smoothing_level=0.8, smoothing_slope=0.2)
pred_hw = hw_model.predict(start = test_data.index[0],end = test_data.index[-1])
hw_rms=mean_absolute_percentage_error(pred_hw,test_data['Sales'])*100
hw_rms
```

Out[64]:

```
9.474439491339446
```

Holts winter exponential smoothing with multiplicative seasonality and additive trend

In [57]:

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing

hwe_model_mul_add = ExponentialSmoothing(train_data["Sales"],seasonal="mul",trend="add",sea
pred_hwe_mul_add = hwe_model_mul_add.predict(start = test_data.index[0],end = test_data.ind

hw_ma_rms=mean_absolute_percentage_error(pred_hwe_mul_add,test_data['Sales'])*100
hw_ma_rms
```

Out[57]:

```
4.4755974482245255
```

Holts winter exponential smoothing with additive seasonality and additive trend

In [59]:

```
hwe_model_add_add = ExponentialSmoothing(train_data["Sales"],seasonal="add",trend="add",sea
pred_hwe_add_add = hwe_model_add_add.predict(start = test_data.index[0],end = test_data.ind

hw_aa_rms=mean_absolute_percentage_error(pred_hwe_add_add,test_data['Sales'])*100
hw_aa_rms
```

Out[59]:

```
8.501749972939315
```

ARMA Model

In [54]:

```
from statsmodels.tsa.arima_model import ARMA

ARMAmodel = ARMA(train_data['Sales'], order=(1, 1)) #model with AR=0 and MA=1
ARMAmodel_fit = ARMAmodel.fit()

ARMA_pred = ARMAmodel_fit.predict(0,11)
ARMA_pred

arma_rms=mean_absolute_percentage_error(ARMA_pred,test_data['Sales'])*100
arma_rms
```

Out[54]:

```
99.33840793503349
```

ARIMA Model

In [55]:

```
from statsmodels.tsa.arima_model import ARIMA

ARIMAmodel = ARIMA(train_data['Sales'], order=(1, 1, 2)) #notice p,d and q value here
ARIMA_model_fit = ARIMAmodel.fit()

ARIMA_pred = ARIMA_model_fit.predict(1,12,typ='levels')

arima_rms=mean_absolute_percentage_error(ARIMA_pred,test_data['Sales'])*100
arima_rms
```

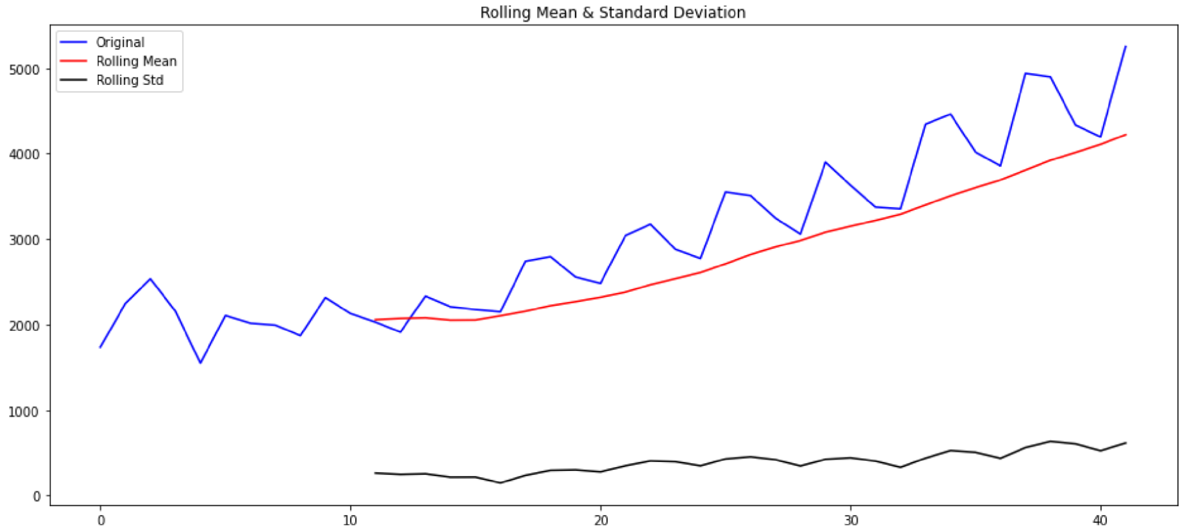
Out[55]:

```
95.05939132370956
```

Converting non stationary data to stationary data to improve ARIMA model

In [37]:

```
rolLmean = cococola_data['Sales'].rolling(12).mean() # 12 entries
rolLstd = cococola_data['Sales'].rolling(12).std()

plt.figure(figsize=(16,7))
fig = plt.figure(1)

#Plot rolling statistics:
orig = plt.plot(cococola_data['Sales'], color='blue',label='Original')
mean = plt.plot(rolLmean, color='red', label='Rolling Mean')
std = plt.plot(rolLstd, color='black', label = 'Rolling Std')
plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation')
plt.show(block=False)
```



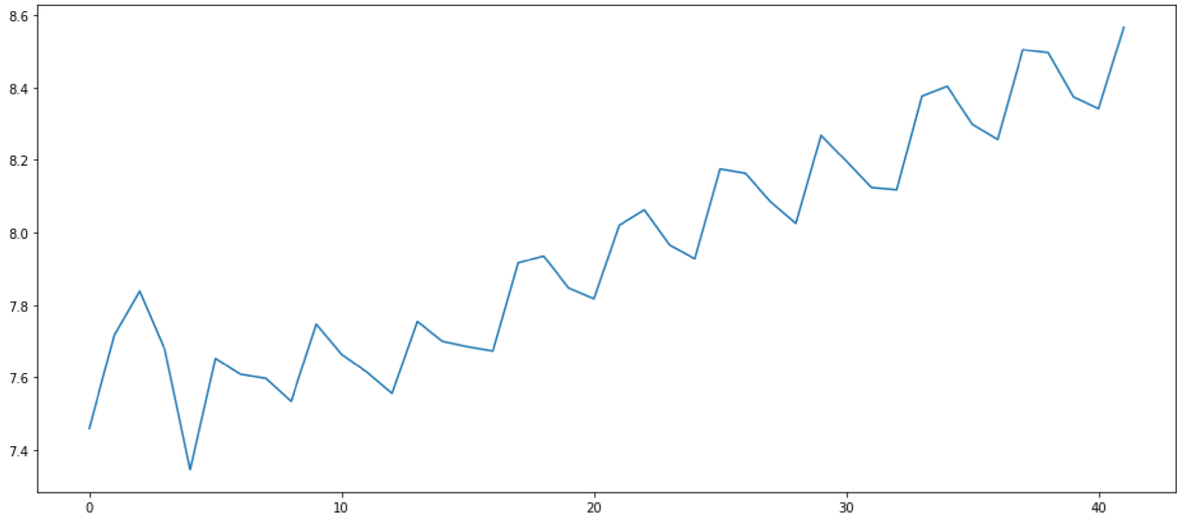
Log transform

In [39]:

```
plt.figure(figsize=(16,7))
fig = plt.figure(1)

import numpy as np
ts_log = np.log(cococola_data['Sales'])#to transform to stationary from non-stationary
plt.plot(ts_log)
```

Out[39]:

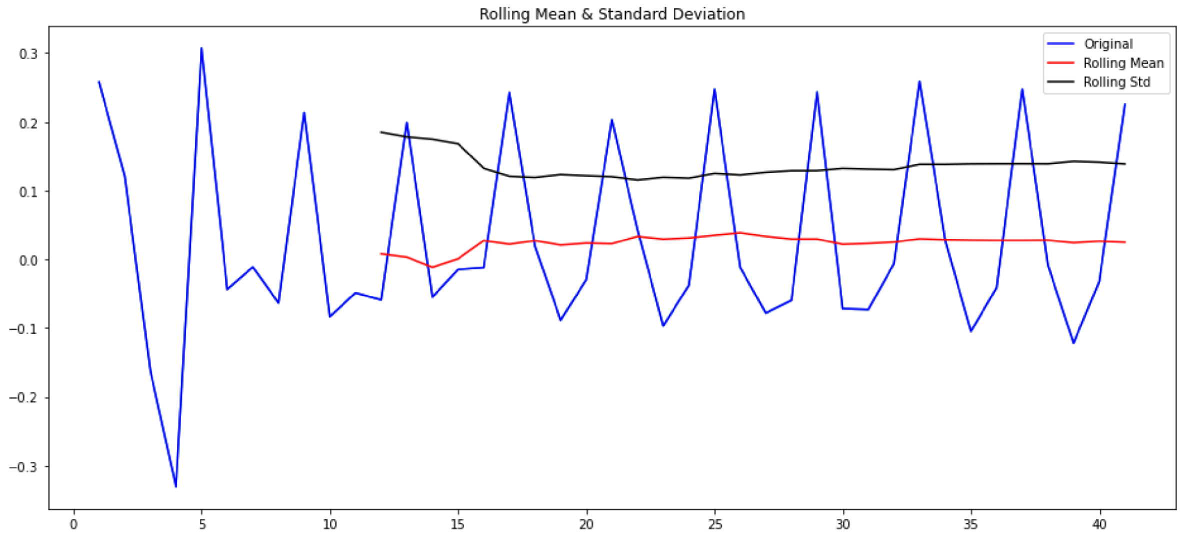
```
[<matplotlib.lines.Line2D at 0x25c4a442790>]
```



Differencing

In [40]:

```
plt.figure(figsize=(16,7))
fig = plt.figure(1)
ts_log_diff = ts_log - ts_log.shift() # I will shift the time series by 1 and subtract from
plt.plot(ts_log_diff)

#Determing rolling statistics
rolLmean = ts_log_diff.rolling(12).mean()
rolLstd = ts_log_diff.rolling(12).std()



#Plot rolling statistics:
orig = plt.plot(ts_log_diff, color='blue',label='Original')
mean = plt.plot(rolLmean, color='red', label='Rolling Mean')
std = plt.plot(rolLstd, color='black', label = 'Rolling Std')
plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation')
plt.show(block=False)
```



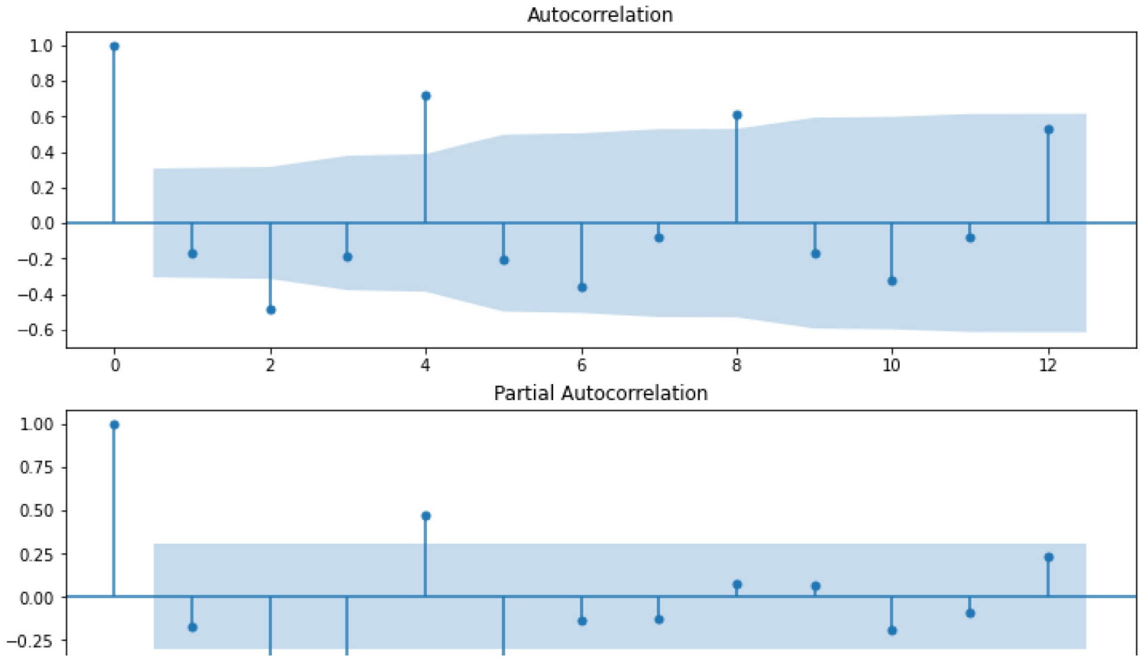
ACF and PACF plot

In [41]:

```
from statsmodels.tsa.stattools import acf, pacf
lag_acf = acf(ts_log_diff, nlags=12)
lag_pacf = pacf(ts_log_diff, nlags=12)
```

In [42]:

```
import statsmodels.api as sm
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(ts_log_diff.dropna(),lags=12,ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(ts_log_diff.dropna(),lags=12,ax=ax2)
```



In [43]:

```
ts_log_diff = ts_log_diff[~ts_log_diff.isnull()]
```

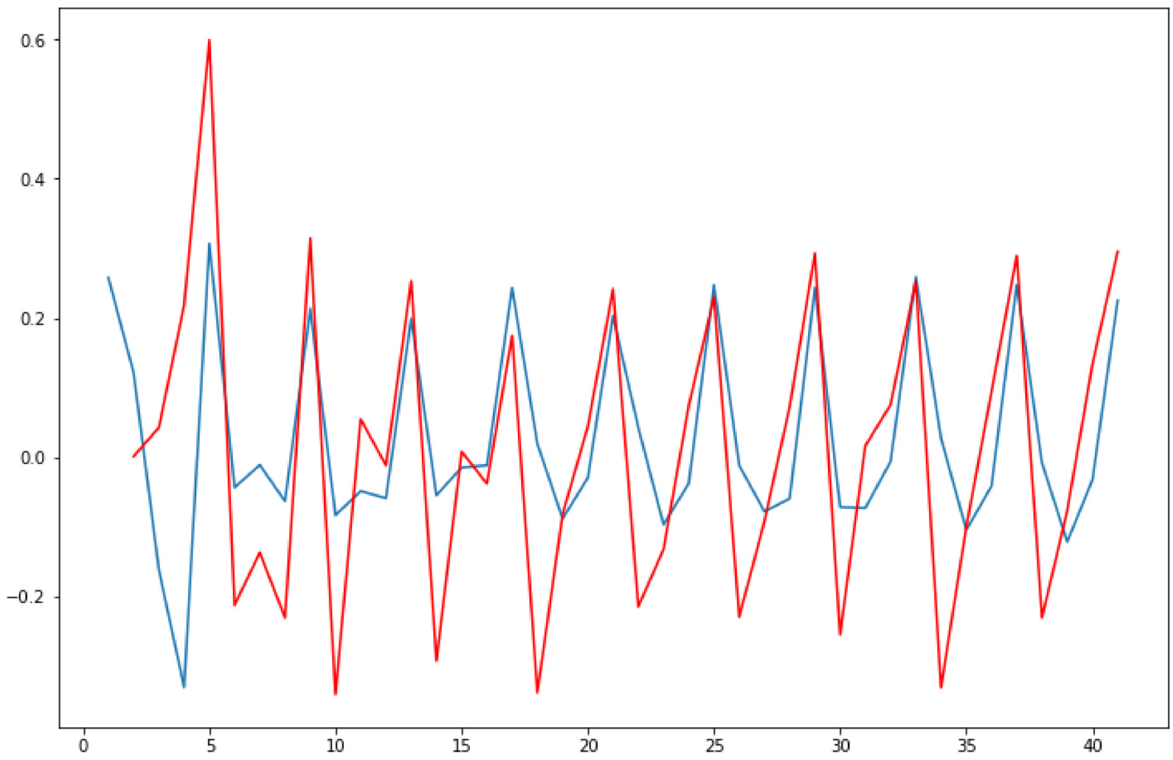
In [56]:

```
plt.figure(figsize=(12,8))
ts_log_diff.dropna(inplace=True)
model = ARIMA(ts_log_diff, order=(4,1,2))
results_ARIMA = model.fit()
plt.plot(ts_log_diff)
plt.plot(results_ARIMA.fittedvalues, color='red')
```

```
C:\Users\ROOBA\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:578: ValueWarning: An unsupported index was provided and will be ignored w
hen e.g. forecasting.
  warnings.warn('An unsupported index was provided and will be'
C:\Users\ROOBA\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.p
y:578: ValueWarning: An unsupported index was provided and will be ignored w
hen e.g. forecasting.
  warnings.warn('An unsupported index was provided and will be'
```

Out[56]:

```
[<matplotlib.lines.Line2D at 0x25c4ba308b0>]
```



List of models based of RMSE value

In [72]:

```
data = {"MODEL":pd.Series(["rmse_linear","rmse_Exp","rmse_Quad","rmse_add_sea","rmse_add_se
        "RMSE_Values":pd.Series([linear_rms,exp_rms,qua_rms,add_rms,add_qua_rms,mul_rms,mul
table_rmse=pd.DataFrame(data)
table_rmse.sort_values(['RMSE_Values'])
```

Out[72]:

	MODEL	RMSE_Values
9	rmse_holt_ma	4.475597
10	rmse_holt_aa	8.501750
8	rmse_holt	9.474439
7	rmse_ses	30.811045
0	rmse_linear	39.383374
2	rmse_Quad	39.799294
3	rmse_add_sea	39.924193
6	rmse_Mult_add_sea	39.924193
4	rmse_add_sea_quad	39.924193
12	rmse_arima	95.059391
11	rmse_arma	99.338408
1	rmse_Exp	99.811454
5	rmse_Mult_sea	99.811669

Inference

The mean absolute percentage error of Holts winter exponential smoothing with multiplicative seasonality and additive trend model is comparitively low compared to all other model

Hence, the forecast model can be built by Holts winter exponential smoothing with multiplicative seasonality and additive trend