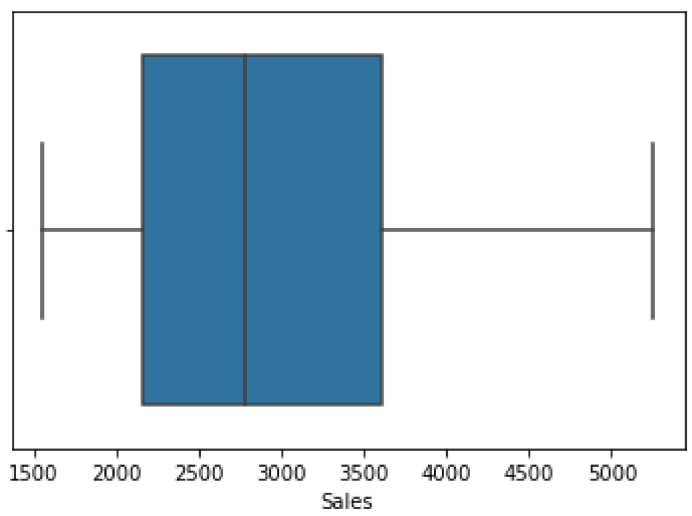
Forecast the CocaCola prices.Prepare a document for each model explaining how many dummy variables you have created and RMSE value for each model. Finally which model you will use for Forecasting.

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.holtwinters import SimpleExpSmoothing # SES
from statsmodels.tsa.holtwinters import Holt # Holts Exponential Smoothing
from statsmodels.tsa.holtwinters import ExponentialSmoothing #
import statsmodels.graphics.tsaplots as tsa_plots
import statsmodels.tsa.statespace as tm_models
from datetime import datetime,time
```

In [4]:
```
cocola = pd.read_excel("CocaCola_Sales_Rawdata.xlsx")


# Boxplot for ever
sns.boxplot("Sales",data=cocola)
```

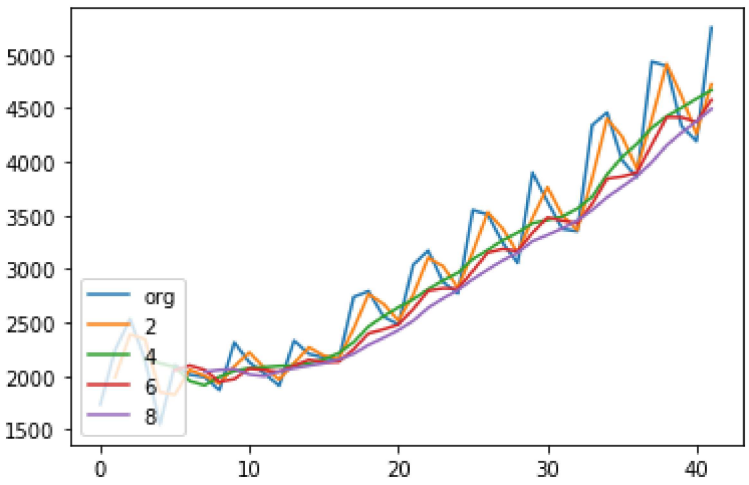
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following var
iable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passin
g other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[4]: <AxesSubplot:xlabel='Sales'>



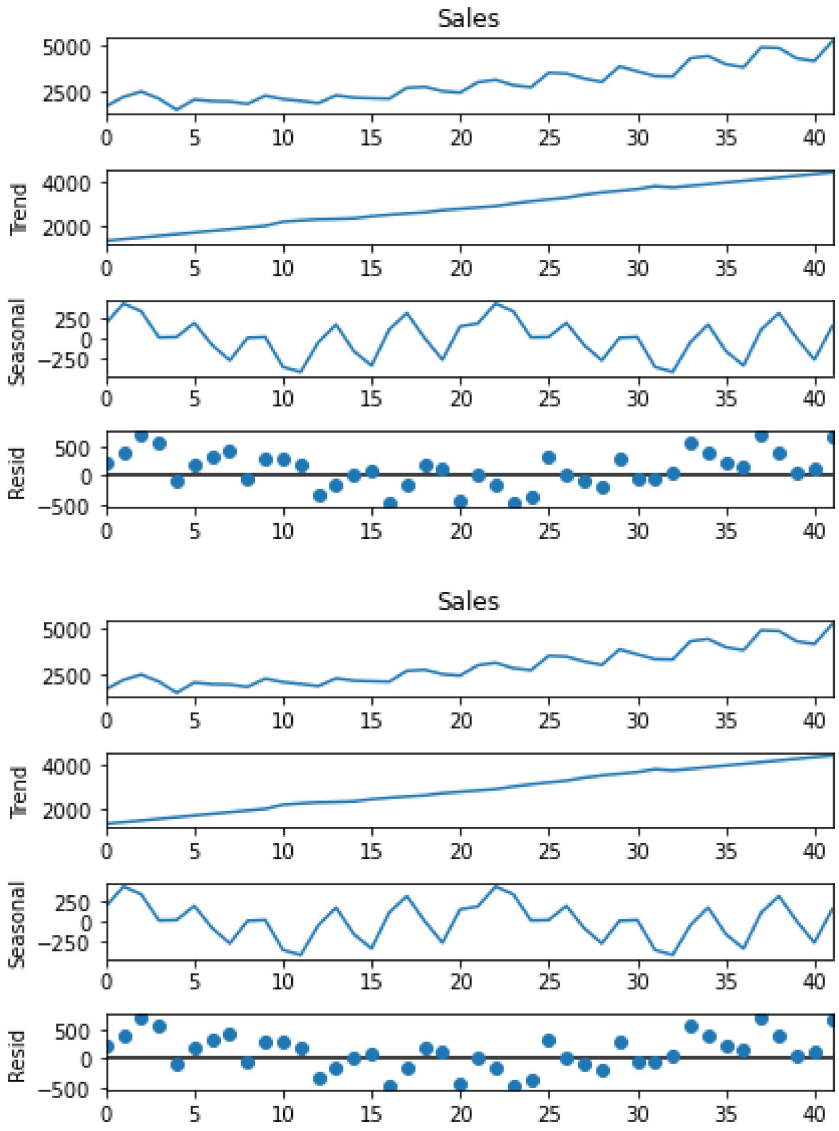
In [5]:
```
# moving average for the time series to understand better about the trend character in Amtrak
cocola.Sales.plot(label="org")
for i in range(2,10,2):
    cocola["Sales"].rolling(i).mean().plot(label=str(i))
plt.legend(loc=3)
```

Out[5]: <matplotlib.legend.Legend at 0x16be795c1f0>



In [6]:
```
# Time series decomposition plot
decompose_ts_add = seasonal_decompose(x=cocola['Sales'], model='additive', extrapolate_trend='freq', period=
decompose_ts_add.plot()
```

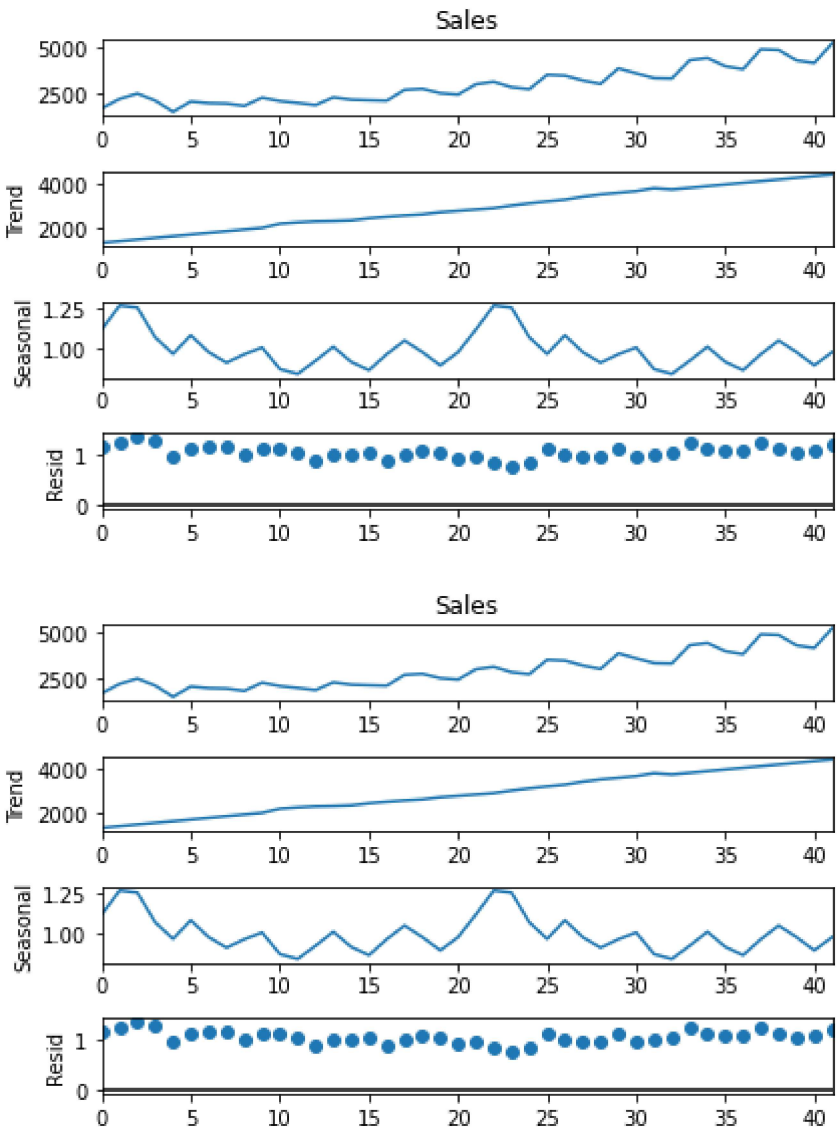
Out[6]:



After looking at the four pieces of decomposed graphs, we can tell that our sales dataset has an overall increasing trend as well as a yearly seasonality.

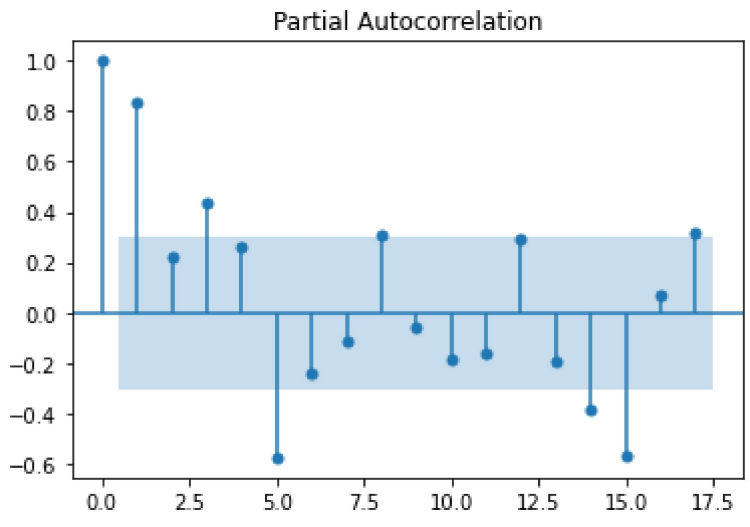
In [7]:
```
decompose_ts_add = seasonal_decompose(x=cocola['Sales'], model='multiplicative', extrapolate_trend='freq', p
decompose_ts_add.plot()
```

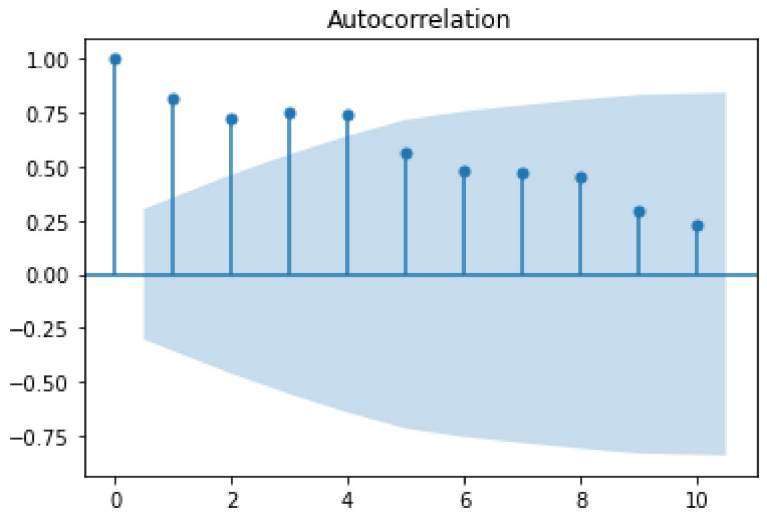
Out[7]:

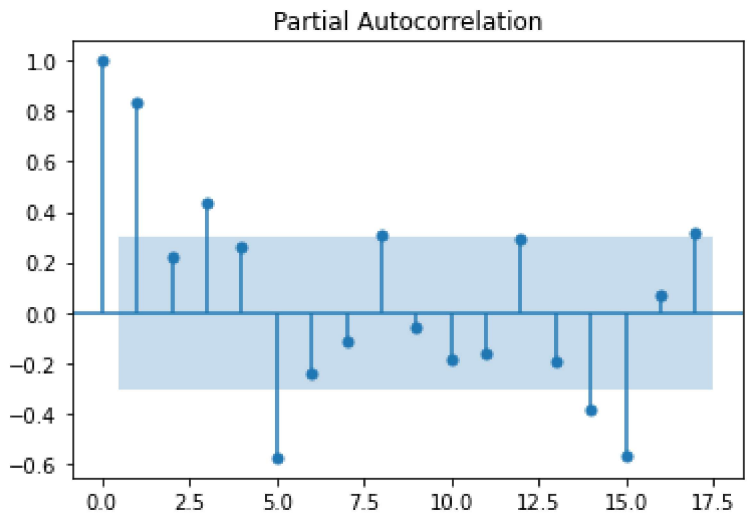


In [18]:
```
# ACF plots and PACF plots on Original data sets
tsa_plots.plot_acf(cocola.Sales,lags=10)
tsa_plots.plot_pacf(cocola.Sales)
```

Out[18]:







Stationarity

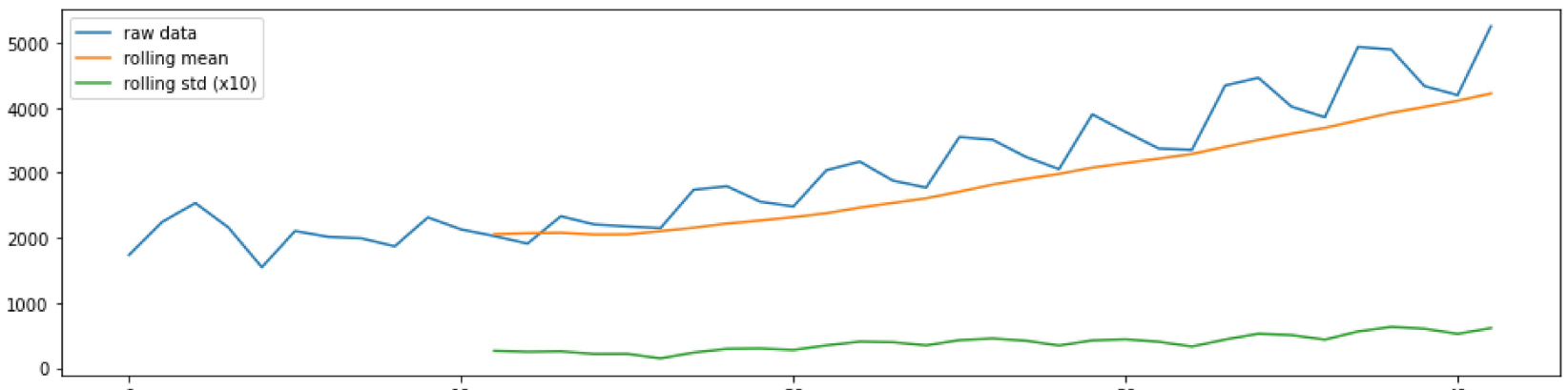
We need to check whether the dataset is stationary or not. A dataset is stationary if its statistical properties like mean, variance, and autocorrelation do not change over time.

Most time series datasets related to business activity are not stationary since there are usually all sorts of non-stationary elements like trends and economic cycles. But, since most time series forecasting models use stationarity—and mathematical transformations related to it—to make predictions, we need to 'stationarize' the time series as part of the process of fitting a model.

Two common methods to check for stationarity are Visualization and the Augmented Dickey-Fuller (ADF) Test.

In [14]:
```
### plot for Rolling Statistic for testing Stationarity
def test_stationarity(timeseries, title):

    #Determing rolling statistics
    rolmean = pd.Series(timeseries).rolling(window=12).mean()
    rolstd = pd.Series(timeseries).rolling(window=12).std()

    fig, ax = plt.subplots(figsize=(16, 4))
    ax.plot(timeseries, label= title)
    ax.plot(rolmean, label='rolling mean');
    ax.plot(rolstd, label='rolling std (x10)');
    ax.legend()
```

In [15]:
```
y = cocola['Sales']
pd.options.display.float_format = '{:.8f}'.format
test_stationarity(y,'raw data')
```



Both the mean and standard deviation for stationary data does not change much over time. But in this case, since the y-axis has such a large scale, we can not confidently conclude that our data is stationary by simply viewing the above graph. Therefore, we should do another test of stationarity.

Augmented Dickey-Fuller Test

The ADF approach is essentially a statistical significance test that compares the p-value with the critical values and does hypothesis testing. Using this test, we can determine whether the processed data is stationary or not with different levels of confidence.

In [17]:
```
# Augmented Dickey-Fuller Test
from statsmodels.tsa.stattools import adfuller

def ADF_test(timeseries, dataDesc):
    print(' > Is the {} stationary ?'.format(dataDesc))
    dftest = adfuller(timeseries.dropna(), autolag='AIC')
    print('Test statistic = {:.3f}'.format(dftest[0]))
    print('P-value = {:.3f}'.format(dftest[1]))
    print('Critical values :')
    for k, v in dftest[4].items():
        print('\t{}: {} - The data is {} stationary with {}% confidence'.format(k, v, 'not' if v<dftest[0] e
```

In [18]:
```
ADF_test(y,'raw data')
```

```
 > Is the raw data stationary ?
Test statistic = 1.309
P-value = 0.997
Critical values :
        1%: -3.639224104416853 - The data is not stationary with 99% confidence
        5%: -2.9512301791166293 - The data is not stationary with 95% confidence
        10%: -2.614446989619377 - The data is not stationary with 90% confidence
```

Looking at both the visualization and ADF test, we can tell that our sample sales data is non-stationary.

Making the data stationary

To proceed with our time series analysis, we need to stationarize the dataset. There are many approaches to stationarize data, but we'll use de-trending, differencing, and then a combination of the two.

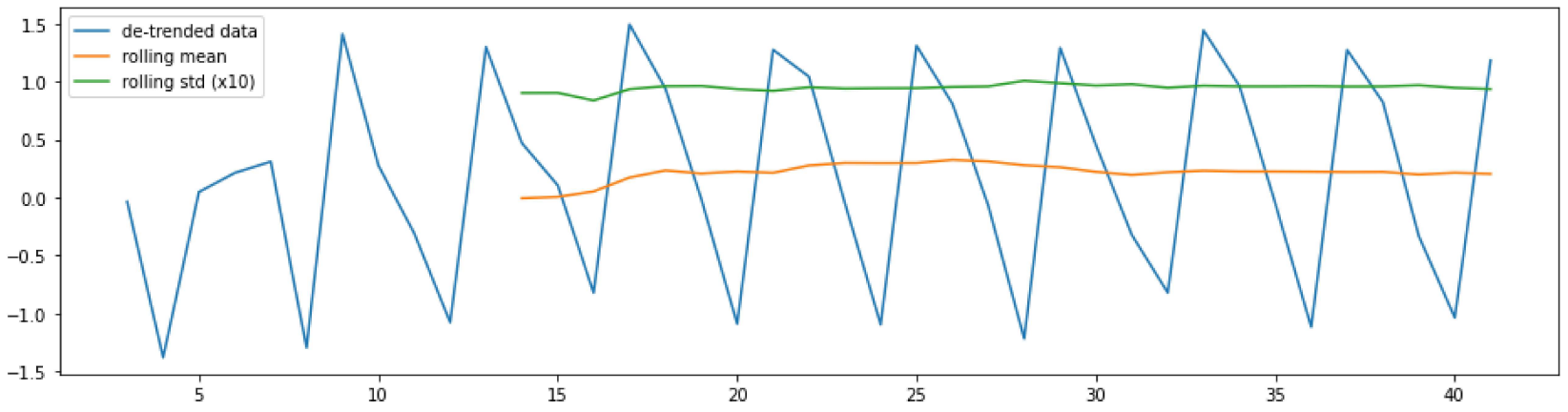
Detrending

This method removes the underlying trend in the time series:

This method removes the underlying seasonal or cyclical patterns in the time series.

In [29]:
```
# Detrending
y_detrend =  (y - y.rolling(window=4).mean())/y.rolling(window=4).std()

test_stationarity(y_detrend,'de-trended data')
ADF_test(y_detrend,'de-trended data')
```

```
 > Is the de-trended data stationary ?
Test statistic = -1.556
P-value = 0.506
Critical values :
        1%: -3.653519805908203 - The data is not stationary with 99% confidence
        5%: -2.9572185644531253 - The data is not stationary with 95% confidence
        10%: -2.6175881640625 - The data is not stationary with 90% confidence
```



Differencing

This method removes the underlying seasonal or cyclical patterns in the time series.

In [30]:
```
# Differencing
y_4lag =  y - y.shift(4)

test_stationarity(y_4lag,'4 lag differenced data')
ADF_test(y_4lag,'4 lag differenced data')
```

```
 > Is the 4 lag differenced data stationary ?
Test statistic = -2.610
P-value = 0.091
Critical values :
        1%: -3.6209175221605827 - The data is not stationary with 99% confidence
        5%: -2.9435394610388332 - The data is not stationary with 95% confidence
        10%: -2.6104002410518627 - The data is not stationary with 90% confidence
```

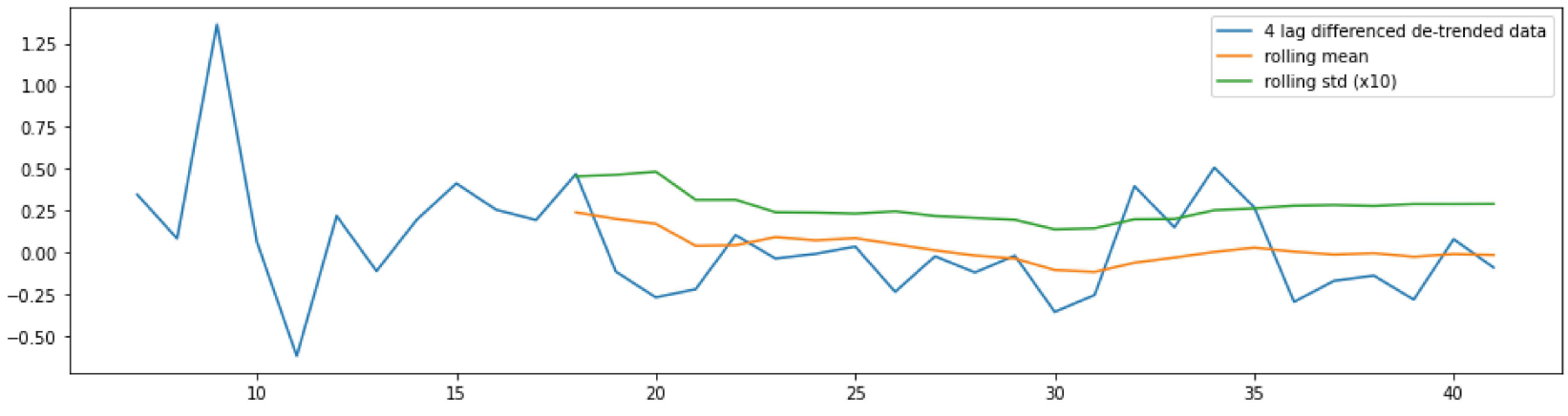

This method did not perform, as indicated by the ADF test which is not stationary within 99 percent of the confidence interval.

Combining detrending and differencing

This approach uses both methods to stationarize the data.

In [31]:
```
# Detrending + Differencing

y_4lag_detrend =  y_detrend - y_detrend.shift(4)

test_stationarity(y_4lag_detrend,'4 lag differenced de-trended data')
ADF_test(y_4lag_detrend,'4 lag differenced de-trended data')
```

```
 > Is the 4 lag differenced de-trended data stationary ?
Test statistic = -4.983
P-value = 0.000
Critical values :
        1%: -3.639224104416853 - The data is  stationary with 99% confidence
        5%: -2.9512301791166293 - The data is  stationary with 95% confidence
        10%: -2.614446989619377 - The data is  stationary with 90% confidence
```



Using the combination of the two methods, we see from both the visualization and the ADF test that the data is now stationary. This is the transformation we will use moving forward with our analysis.

In [79]:
```
#splitting the data into Train and Test data and considering the last 12 months data as
# Test data and left over data as train data

Train = cocola.head(48)
Test =cocola.iloc[30:41]
predict_data = cocola["Quarter"].tail(1)

# to change the index value in pandas data frame
# Test.set_index(np.arange(1,13),inplace=True)
```

In [80]:
```
# Creating a function to calculate the MAPE value for test data
def MAPE(pred,org):
    temp = np.abs((pred-org))*100/org
    return np.mean(temp)
```

Choosing a Time series prediction model

In [84]:
```
# Simple Exponential Method
ses_model = SimpleExpSmoothing(Train["Sales"]).fit()
pred_ses = ses_model.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_ses,Test.Sales)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\holtwinters\model.py:427: FutureWarning: After
0.13 initialization must be handled at model creation
  warnings.warn(
```

Out[84]: 9.017627321108133

In [85]:
```
# Holt method
hw_model = Holt(Train["Sales"]).fit()
pred_hw = hw_model.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hw,Test.Sales)
```

Out[85]: 10.914633014125975

In [86]:
```
# Holts winter exponential smoothing with additive seasonality and additive trend
hwe_model_add_add = ExponentialSmoothing(Train["Sales"],seasonal="add",trend="add",seasonal_periods=4,damped
pred_hwe_add_add = hwe_model_add_add.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hwe_add_add,Test.Sales)
```

```
<ipython-input-86-0da59f3c1cca>:2: FutureWarning: the 'damped'' keyword is deprecated, use 'damped_trend' i
nstead
  hwe_model_add_add = ExponentialSmoothing(Train["Sales"],seasonal="add",trend="add",seasonal_periods=4,dam
ped=True).fit()
```

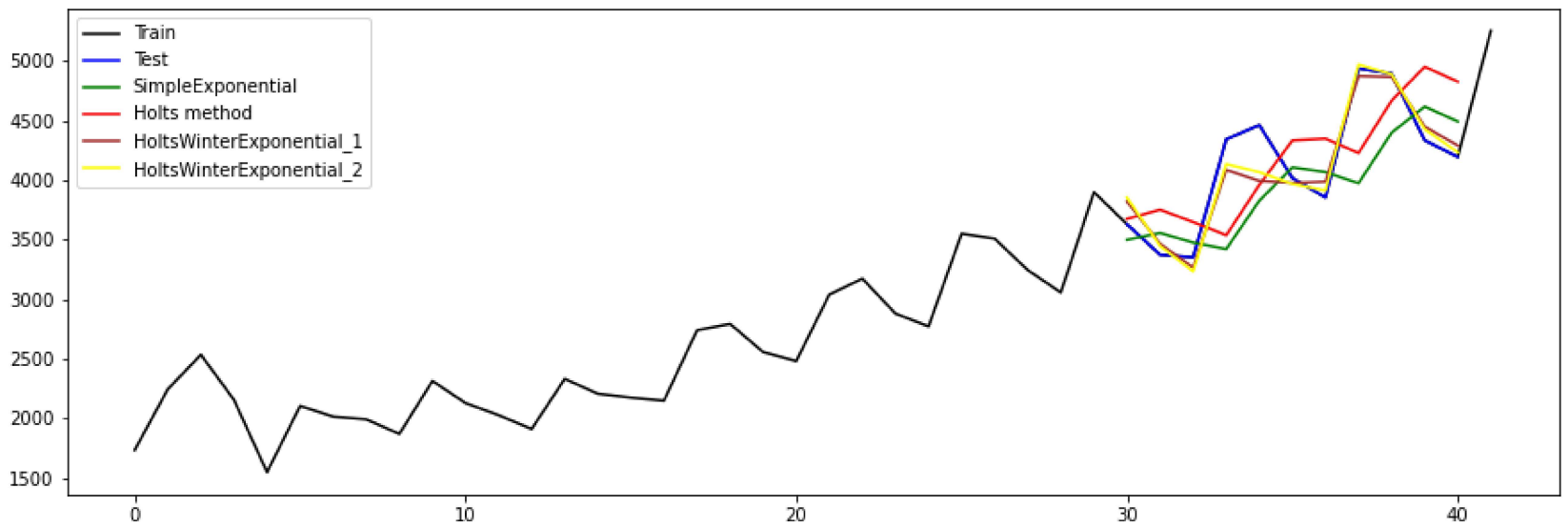
Out[86]: 3.4816551667243236

In [87]:
```
# Holts winter exponential smoothing with multiplicative seasonality and additive trend
hwe_model_mul_add = ExponentialSmoothing(Train["Sales"],seasonal="mul",trend="add",seasonal_periods=4).fit()
pred_hwe_mul_add = hwe_model_mul_add.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hwe_mul_add,Test.Sales)
```

Out[87]: 2.9273783842883727

In [91]:
```
# Visualization of Forecasted values for Test data set using different methods
fig,axes = plt.subplots(figsize=(15,5))
plt.plot(Train.index, Train["Sales"], label='Train',color="black")
plt.plot(Test.index, Test["Sales"], label='Test',color="blue")
plt.plot(pred_ses.index, pred_ses, label='SimpleExponential',color="green")
plt.plot(pred_hw.index, pred_hw, label='Holts method',color="red")
plt.plot(pred_hwe_add_add.index,pred_hwe_add_add,label="HoltsWinterExponential_1",color="brown")
plt.plot(pred_hwe_mul_add.index,pred_hwe_mul_add,label="HoltsWinterExponential_2",color="yellow")
plt.legend(loc='best')
```

Out[91]: <matplotlib.legend.Legend at 0x16be8517ee0>

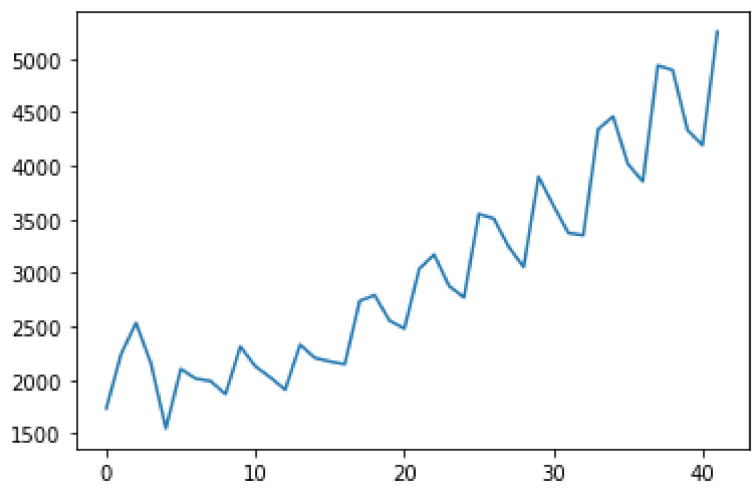


In [134]:
```
import pandas as pd
cococola= pd.read_excel("CocaCola_Sales_Rawdata.xlsx")

import numpy as np
quarter=['Q1','Q2','Q3','Q4']
n=cococola['Quarter'][0]
n[0:2]

cococola['quarter']=0
```

In [135]:
```
for i in range(42):
    n=cococola['Quarter'][i]
    cococola['quarter'][i]=n[0:2]

dummy=pd.DataFrame(pd.get_dummies(cococola['quarter']))

coco=pd.concat((cococola,dummy),axis=1)
t= np.arange(1,43)
coco['t']=t
coco['t_square']=coco['t']*coco['t']

log_Sales=np.log(coco['Sales'])
coco['log_Sales']=log_Sales

train= coco.head(38)
test=coco.tail(4)
coco.Sales.plot()
```

```
<ipython-input-135-271721e68fb2>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  cococola['quarter'][i]=n[0:2]
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\indexing.py:1637: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  self._setitem_single_block(indexer, value, name)
```

Out[135]: <AxesSubplot:>



Model based Forecasting Methods

Linear model

In [136]:
```
import statsmodels.formula.api as smf

#Linear model
linear= smf.ols('Sales~t',data=train).fit()
predlin=pd.Series(linear.predict(pd.DataFrame(test['t'])))
rmselin=np.sqrt((np.mean(np.array(test['Sales'])-np.array(predlin))**2))
rmselin
```

Out[136]: 421.17878760022813

Quadratic model

In [137]:
```
#quadratic model
quad=smf.ols('Sales~t+t_square',data=train).fit()
predquad=pd.Series(quad.predict(pd.DataFrame(test[['t','t_square']])))
rmsequad=np.sqrt(np.mean((np.array(test['Sales'])-np.array(predquad))**2))
rmsequad
```

Out[137]: 475.561835183161

Exponential model

In [138]:
```
#exponential model
expo=smf.ols('log_Sales~t',data=train).fit()
predexp=pd.Series(expo.predict(pd.DataFrame(test['t'])))
predexp
rmseexpo=np.sqrt(np.mean((np.array(test['Sales'])-np.array(np.exp(predexp)))**2))
rmseexpo
```

Out[138]: 466.24797310672005

Additive seasonality model

In [139]:
```
#additive seasonality
additive= smf.ols('Sales~ Q1+Q2+Q3+Q4',data=train).fit()
predadd=pd.Series(additive.predict(pd.DataFrame(test[['Q1','Q2','Q3','Q4']])))
predadd
rmseadd=np.sqrt(np.mean((np.array(test['Sales'])-np.array(predadd))**2))
rmseadd
```

Out[139]: 1860.0238154547278

Additive seasonality with linear trend

In [143]:
```
#additive seasonality with linear trend
addlinear= smf.ols('Sales~t+Q1+Q2+Q3+Q4',data=train).fit()
predaddlinear=pd.Series(addlinear.predict(pd.DataFrame(test[['t','Q1','Q2','Q3','Q4']])))
predaddlinear

rmseaddlinear=np.sqrt(np.mean((np.array(test['Sales'])-np.array(predaddlinear))**2))
rmseaddlinear
```

Out[143]: 464.9829023982247

Additive seasonality with quadratic trend

In [144]:
```
#additive seasonality with quadratic trend
addquad=smf.ols('Sales~t+t_square+Q1+Q2+Q3+Q4',data=train).fit()
predaddquad=pd.Series(addquad.predict(pd.DataFrame(test[['t','t_square','Q1','Q2','Q3','Q4']])))
rmseaddquad=np.sqrt(np.mean((np.array(test['Sales'])-np.array(predaddquad))**2))
rmseaddquad
```

Out[144]: 301.73800719348884

multiplicative seasonality

In [145]:
```
#multiplicative seasonality
mulsea=smf.ols('log_Sales~Q1+Q2+Q3+Q4',data=train).fit()
predmul= pd.Series(mulsea.predict(pd.DataFrame(test[['Q1','Q2','Q3','Q4']])))
rmsemul= np.sqrt(np.mean((np.array(test['Sales'])-np.array(np.exp(predmul)))**2))
rmsemul
```

Out[145]: 1963.3896400779759

multiplicative seasonality with linear trend

In [146]:
```
#multiplicative seasonality with linear trend
mullin= smf.ols('log_Sales~t+Q1+Q2+Q3+Q4',data=train).fit()
predmullin= pd.Series(mullin.predict(pd.DataFrame(test[['t','Q1','Q2','Q3','Q4']])))
rmsemulin=np.sqrt(np.mean((np.array(test['Sales'])-np.array(np.exp(predmullin)))**2))
rmsemulin
```

Out[146]: 225.52439049825708

multiplicative seasonality with quadratic trend

In [147]:
```
#multiplicative seasonality with quadratic trend
mul_quad= smf.ols('log_Sales~t+t_square+Q1+Q2+Q3+Q4',data=train).fit()
pred_mul_quad= pd.Series(mul_quad.predict(test[['t','t_square','Q1','Q2','Q3','Q4']]))
rmse_mul_quad=np.sqrt(np.mean((np.array(test['Sales'])-np.array(np.exp(pred_mul_quad)))**2))
rmse_mul_quad
```

Out[147]: 581.8457187961471

In [148]:
```
#tabulating the rmse values

data={'Model':pd.Series(['rmse_mul_quad','rmseadd','rmseaddlinear','rmseaddquad','rmseexpo','rmselin','rmsem
data

Rmse=pd.DataFrame(data)
Rmse.sort_values(by= "Values").reset_index().drop("index", axis =1)
```

Out[148]:

	Model	Values
0	rmsemulin	225.52439050
1	rmseaddquad	301.73800719
2	rmselin	421.17878760
3	rmseaddlinear	464.98290240
4	rmseexpo	466.24797311
5	rmsequad	475.56183518
6	rmse_mul_quad	581.84571880
7	rmseadd	1860.02381545
8	rmsemul	1963.38964008

we are getting lowest RMSE value for the multiplicative seasonality with linear trend model

In [151]:
```
coco.head()
```

Out[151]:

	Quarter	Sales	quarter	Q1	Q2	Q3	Q4	t	t_square	log_Sales
0	Q1_86	1734.82699966	Q1	1	0	0	0	1	1	7.45866298
1	Q2_86	2244.96099854	Q2	0	1	0	0	2	4	7.71644343
2	Q3_86	2533.80499268	Q3	0	0	1	0	3	9	7.83747740
3	Q4_86	2154.96299744	Q4	0	0	0	1	4	16	7.67552883
4	Q1_87	1547.81899643	Q1	1	0	0	0	5	25	7.34460212

In [155]:
```
#multiplicative seasonality with linear trend
final_model= smf.ols('log_Sales~t+Q1+Q2+Q3+Q4',data=coco).fit()
pred_final= pd.Series(final_model.predict(coco[['t','Q1','Q2','Q3','Q4']]))
rmsemulin=np.sqrt(np.mean((np.array(coco['Sales'])-np.array(np.exp(pred_final)))**2))
rmsemulin
```

Out[155]: 186.07366190239796

In [160]:
```
pred_df = pd.DataFrame({'Actual' : coco.log_Sales, 'Predicted' : pred_final})
pred_df
```

Out[160]:

	Actual	Predicted
0	7.45866298	7.33922388
1	7.71644343	7.57974684
2	7.83747740	7.57132764
3	7.67552883	7.49125357
4	7.34460212	7.43589237
5	7.65179137	7.67641534
6	7.60805829	7.66799613
7	7.59676742	7.58792207
8	7.53318556	7.53256086
9	7.74657386	7.77308383
10	7.66308821	7.76466463
11	7.61422778	7.68459056
12	7.55517470	7.62922936
13	7.75412342	7.86975232
14	7.69918549	7.86133312
15	7.68430935	7.78125905
16	7.67242187	7.72589785
17	7.91546061	7.96642081
18	7.93478348	7.95800161
19	7.84620273	7.87792754
20	7.81640650	7.82256634
21	8.01945587	8.06308931
22	8.06215415	8.05467010
23	7.96519864	7.97459604
24	7.92732436	7.91923483
25	8.17470288	8.15975780
26	8.16280135	8.15133860
27	8.08451926	8.07126453
28	8.02486215	8.01590333
29	8.26847539	8.25642629
30	8.19671241	8.24800709
31	8.12355784	8.16793302
32	8.11731246	8.11257182
33	8.37609035	8.35309478
34	8.40312824	8.34467558
35	8.29829063	8.26460151
36	8.25686685	8.20924031
37	8.50431057	8.44976328
38	8.49596955	8.44134407
39	8.37401542	8.36127000
40	8.34141021	8.30590880
41	8.56655462	8.54643177

In [170]:
```
# Actual Vs Predicted graph

sns.set_style('whitegrid')

plt.rcParams['figure.figsize'] = (10, 6)
_, ax = plt.subplots()
ax.hist(coco.log_Sales, color = 'black', alpha = 0.5, label = 'actual', bins=7)
ax.hist(pred_final, color = 'red', alpha = 0.5, label = 'prediction', bins=7)
ax.yaxis.set_ticks(np.arange(0,11))
ax.legend(loc = 'best')
plt.show()
```

In [173]:

```
# Plot of Actual Sales values and Predicted sales values
plt.plot(coco.log_Sales, color='black',marker='o', label='Actual Sales of CocaCola')
plt.plot(pred_final, color='m',marker='x', label='Predicted Sales of CocaCola')

# Added titles and adjust dimensions
plt.title('Actual Sales values and Predicted sales')
plt.xlabel("Timeline")
plt.ylabel("Sales")
plt.legend()
plt.rcParams['figure.figsize'] = (10,8)

plt.show()
```