# Forecasting (CocaCola\_Sales)

Forecast the CocaCola prices data set. 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.

# 1. Import Libs

#### In [223]:

```
import pandas as pd
import numpy as np
from numpy import sqrt
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
from datetime import datetime,time
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 matplotlib
from pandas import DataFrame
from pandas import Grouper
from numpy import log
from statsmodels.tsa.seasonal import seasonal decompose
from statsmodels.tsa.arima_model import ARIMA
from pylab import rcParams
from sklearn.metrics import mean_squared_error
from pandas.plotting import lag_plot
from statsmodels.graphics.tsaplots import plot acf
from statsmodels.tsa.holtwinters import Holt
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import statsmodels.graphics.tsaplots as tsa_plots
import statsmodels.tsa.statespace as tm models
import itertools
import warnings
warnings.filterwarnings('ignore')
```

# 2. Import Data

## In [224]:

```
df = pd.read_excel('CocaCola_Sales_Rawdata.xlsx')
df
```

## Out[224]:

	_	
	Quarter	Sales
0	Q1_86	1734.827000
1	Q2_86	2244.960999
2	Q3_86	2533.804993
3	Q4_86	2154.962997
4	Q1_87	1547.818996
5	Q2_87	2104.411995
6	Q3_87	2014.362999
7	Q4_87	1991.746998
8	Q1_88	1869.049999
9	_ Q2_88	
10		2128.320000
11	Q4_88	2026.828999
12	Q1_89	1910.603996
13	_ Q2_89	2331.164993
14	Q3_89	
15	Q4_89	
16	Q1_90	2148.278000
17	Q2_90	2739.307999
18		2792.753998
19	Q4_90	2556.009995
20	Q4_90 Q1_91	2480.973999
21	_	3039.522995
21	Q2_91 Q3_91	
	Q3_91 Q4_91	
23		
24		2772.000000
25	Q2_92	3550.000000
26	Q3_92	
27	Q4_92	
28	Q1_93	3056.000000
29	Q2_93	
30	Q3_93	3629.000000
31	Q4_93	
32		3352.000000
33	Q2_94	4342.000000

	Quarter	Sales
34	Q3_94	4461.000000
35	Q4_94	4017.000000
36	Q1_95	3854.000000
37	Q2_95	4936.000000
38	Q3_95	4895.000000
39	Q4_95	4333.000000
40	Q1_96	4194.000000
41	Q2_96	5253.000000

# 3. EDA

## In [225]:

```
df.isna().sum()
```

#### Out[225]:

Quarter 0 Sales 0 dtype: int64

## In [226]:

```
df.dtypes
```

## Out[226]:

Quarter object Sales float64

dtype: object

## In [227]:

```
df.describe()
```

## Out[227]:

	Sales
count	42.000000
mean	2994.353308
std	977.930896
min	1547.818996
25%	2159.714247
50%	2782.376999
75%	3609.250000
max	5253.000000

#### convert quarterly periods to datetime

```
In [228]:
```

```
df['Quarter_Year'] = df['Quarter'].str.split('_').apply(lambda x: ' 19'.join(x[:]))
```

## In [229]:

df

## Out[229]:

	Quarter	Sales	Quarter_Year
0	Q1_86	1734.827000	Q1 1986
1	Q2_86	2244.960999	Q2 1986
2	Q3_86	2533.804993	Q3 1986
3	Q4_86	2154.962997	Q4 1986
4	Q1_87	1547.818996	Q1 1987
5	Q2_87	2104.411995	Q2 1987
6	Q3_87	2014.362999	Q3 1987
7	Q4_87	1991.746998	Q4 1987
8	Q1_88	1869.049999	Q1 1988
9	Q2_88	2313.631996	Q2 1988
10	Q3_88	2128.320000	Q3 1988
11	Q4_88	2026.828999	Q4 1988
12	Q1_89	1910.603996	Q1 1989
13	Q2_89	2331.164993	Q2 1989
14	Q3_89	2206.549995	Q3 1989
15	Q4_89	2173.967995	Q4 1989
16	Q1_90	2148.278000	Q1 1990
17	Q2_90	2739.307999	Q2 1990
18	Q3_90	2792.753998	Q3 1990
19	Q4_90	2556.009995	Q4 1990
20	Q1_91	2480.973999	Q1 1991
21	Q2_91	3039.522995	Q2 1991
22	Q3_91	3172.115997	Q3 1991
23	Q4_91	2879.000999	Q4 1991
24	Q1_92	2772.000000	Q1 1992
25	Q2_92	3550.000000	Q2 1992
26	Q3_92	3508.000000	Q3 1992
27	Q4_92	3243.859993	Q4 1992
28	Q1_93	3056.000000	Q1 1993
29	Q2_93	3899.000000	Q2 1993
30	Q3_93	3629.000000	Q3 1993
31	Q4_93	3373.000000	Q4 1993
32	Q1_94	3352.000000	Q1 1994
33	Q2_94	4342.000000	Q2 1994
34	Q3_94	4461.000000	Q3 1994

	Quarter	Sales	Quarter_Year
35	Q4_94	4017.000000	Q4 1994
36	Q1_95	3854.000000	Q1 1995
37	Q2_95	4936.000000	Q2 1995
38	Q3_95	4895.000000	Q3 1995
39	Q4_95	4333.000000	Q4 1995
40	Q1_96	4194.000000	Q1 1996
41	Q2 96	5253.000000	Q2 1996

converting into datetime formate as the index was not in correct formate.

## In [230]:

```
df['date'] = (pd.to_datetime(df['Quarter_Year'].str.split(' ').apply(lambda x: ''.join(x[::
```

## In [231]:

df

## Out[231]:

	Quarter	Sales	Quarter_Year	date
0	Q1_86	1734.827000	Q1 1986	1986-01-01
1	Q2_86	2244.960999	Q2 1986	1986-04-01
2	Q3_86	2533.804993	Q3 1986	1986-07-01
3	Q4_86	2154.962997	Q4 1986	1986-10-01
4	Q1_87	1547.818996	Q1 1987	1987-01-01
5	Q2_87	2104.411995	Q2 1987	1987-04-01
6	Q3_87	2014.362999	Q3 1987	1987-07-01
7	Q4_87	1991.746998	Q4 1987	1987-10-01
8	Q1_88	1869.049999	Q1 1988	1988-01-01
9	Q2_88	2313.631996	Q2 1988	1988-04-01
10	Q3_88	2128.320000	Q3 1988	1988-07-01
11	Q4_88	2026.828999	Q4 1988	1988-10-01
12	Q1_89	1910.603996	Q1 1989	1989-01-01
13	Q2_89	2331.164993	Q2 1989	1989-04-01
14	Q3_89	2206.549995	Q3 1989	1989-07-01
15	Q4_89	2173.967995	Q4 1989	1989-10-01
16	Q1_90	2148.278000	Q1 1990	1990-01-01
17	Q2_90	2739.307999	Q2 1990	1990-04-01
18	Q3_90	2792.753998	Q3 1990	1990-07-01
19	Q4_90	2556.009995	Q4 1990	1990-10-01
20	Q1_91	2480.973999	Q1 1991	1991-01-01
21	Q2_91	3039.522995	Q2 1991	1991-04-01
22	Q3_91	3172.115997	Q3 1991	1991-07-01
23	Q4_91	2879.000999	Q4 1991	1991-10-01
24	Q1_92	2772.000000	Q1 1992	1992-01-01
25	Q2_92	3550.000000	Q2 1992	1992-04-01
26	Q3_92	3508.000000	Q3 1992	1992-07-01
27	Q4_92	3243.859993	Q4 1992	1992-10-01
28	Q1_93	3056.000000	Q1 1993	1993-01-01
29	Q2_93	3899.000000	Q2 1993	1993-04-01
30	Q3_93	3629.000000	Q3 1993	1993-07-01
31	Q4_93	3373.000000	Q4 1993	1993-10-01
32	Q1_94	3352.000000	Q1 1994	1994-01-01
33	Q2_94	4342.000000	Q2 1994	1994-04-01
34	Q3_94	4461.000000	Q3 1994	1994-07-01

	Quarter	Sales	Quarter_Year	date
35	Q4_94	4017.000000	Q4 1994	1994-10-01
36	Q1_95	3854.000000	Q1 1995	1995-01-01
37	Q2_95	4936.000000	Q2 1995	1995-04-01
38	Q3_95	4895.000000	Q3 1995	1995-07-01
39	Q4_95	4333.000000	Q4 1995	1995-10-01
40	Q1_96	4194.000000	Q1 1996	1996-01-01
41	Q2_96	5253.000000	Q2 1996	1996-04-01

#### In [232]:

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42 entries, 0 to 41
Data columns (total 4 columns):
    Column
                  Non-Null Count Dtype
                  -----
    -----
                                 _ _ _ _ _
0
    Quarter
                 42 non-null
                                  object
 1
                  42 non-null
                                  float64
    Sales
 2
    Quarter_Year 42 non-null
                                  object
                  42 non-null
                                  datetime64[ns]
 3
dtypes: datetime64[ns](1), float64(1), object(2)
memory usage: 1.4+ KB
```

## droping the Column Quarter and Quarter\_Year from the data

```
In [233]:
```

```
df.drop(columns=['Quarter','Quarter_Year'],inplace=True)
```

## In [234]:

df

## Out[234]:

	Sales	date
0	1734.827000	1986-01-01
1	2244.960999	1986-04-01
2	2533.804993	1986-07-01
3	2154.962997	1986-10-01
4	1547.818996	1987-01-01
5	2104.411995	1987-04-01
6	2014.362999	1987-07-01
7	1991.746998	1987-10-01
8	1869.049999	1988-01-01
9	2313.631996	1988-04-01
10	2128.320000	1988-07-01
11	2026.828999	1988-10-01
12	1910.603996	1989-01-01
13	2331.164993	1989-04-01
14	2206.549995	1989-07-01
15	2173.967995	1989-10-01
16	2148.278000	1990-01-01
17	2739.307999	1990-04-01
18	2792.753998	1990-07-01
19	2556.009995	1990-10-01
20	2480.973999	1991-01-01
21	3039.522995	1991-04-01
22	3172.115997	1991-07-01
23	2879.000999	1991-10-01
24	2772.000000	1992-01-01
25	3550.000000	1992-04-01
26	3508.000000	1992-07-01
27	3243.859993	1992-10-01
28	3056.000000	1993-01-01
29	3899.000000	1993-04-01
30	3629.000000	1993-07-01
31	3373.000000	1993-10-01
32	3352.000000	1994-01-01
33	4342.000000	1994-04-01
34	4461.000000	1994-07-01

	Sales	date
35	4017.000000	1994-10-01
36	3854.000000	1995-01-01
37	4936.000000	1995-04-01
38	4895.000000	1995-07-01
39	4333.000000	1995-10-01
40	4194.000000	1996-01-01
41	5253.000000	1996-04-01

## In [235]:

```
df.isnull().sum()
```

#### Out[235]:

Sales 0 date 0 dtype: int64

## In [236]:

```
df[df.duplicated()].shape
```

## Out[236]:

(0, 2)

## In [237]:

```
Df = df[['date','Sales']]
```

## In [238]:

## Df.head()

## Out[238]:

	date	Sales
0	1986-01-01	1734.827000
1	1986-04-01	2244.960999
2	1986-07-01	2533.804993
3	1986-10-01	2154.962997
4	1987-01-01	1547 818996

#### In [239]:

## Df.describe()

#### Out[239]:

	Sales
count	42.000000
mean	2994.353308
std	977.930896
min	1547.818996
25%	2159.714247
50%	2782.376999
75%	3609.250000
max	5253.000000

#### converte date column to index

#### In [240]:

```
Df.set_index('date',inplace=True)
```

## In [241]:

## Df.head()

## Out[241]:

#### Sales

date	
1986-01-01	1734.827000
1986-04-01	2244.960999
1986-07-01	2533.804993
1986-10-01	2154.962997
1987-01-01	1547.818996

#### In [242]:

```
Df.index.year
```

#### Out[242]:

#### In [243]:

```
DF = Df.copy()
```

#### In [244]:

```
DF.head()
```

## Out[244]:

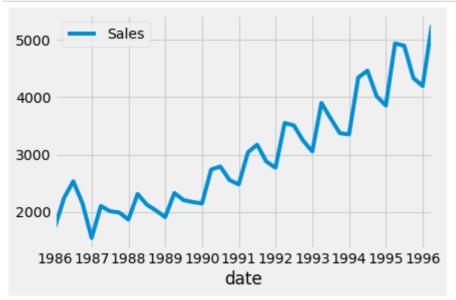
#### **Sales**

date	
1986-01-01	1734.827000
1986-04-01	2244.960999
1986-07-01	2533.804993
1986-10-01	2154.962997
1987-01-01	1547.818996

# 4. Visulization

#### In [245]:

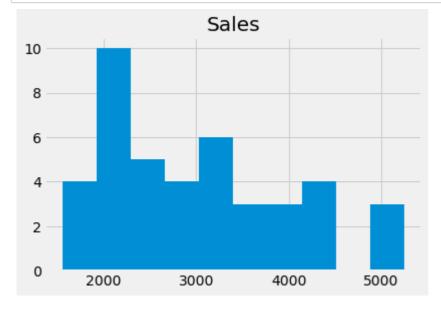
```
DF.plot()
plt.show()
```



here we can say that the trend is upward and the sessionality is not so clear but may be quadratic or exponential,

## In [246]:

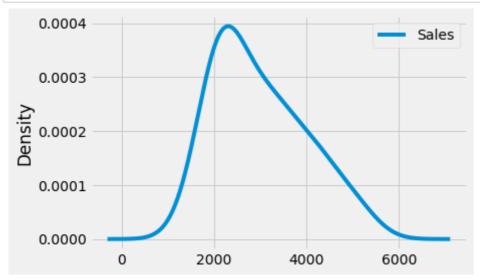
DF.hist()
plt.show()



## density plot

#### In [247]:

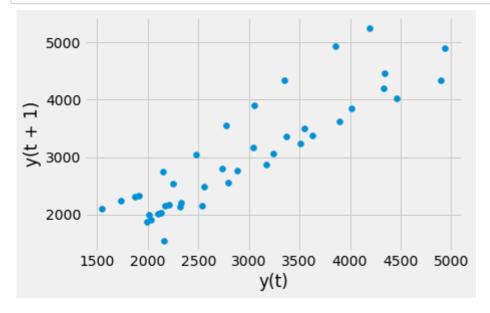
```
DF.plot(kind='kde')
plt.show()
```



#### Lag\_plot

#### In [249]:

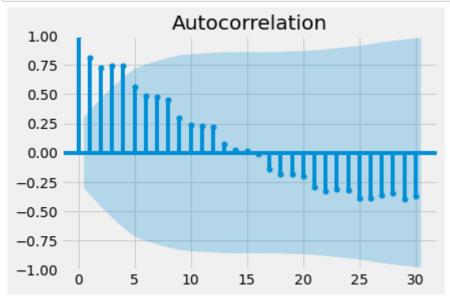
```
lag_plot(DF)
plt.show()
```



#### **Autocorrelation Plot**

## In [250]:

plot\_acf(DF,lags=30)
plt.show()



# **UpSampling**

## In [251]:

```
upsampled = DF.resample('M').mean()
print(upsampled.head(32))
```

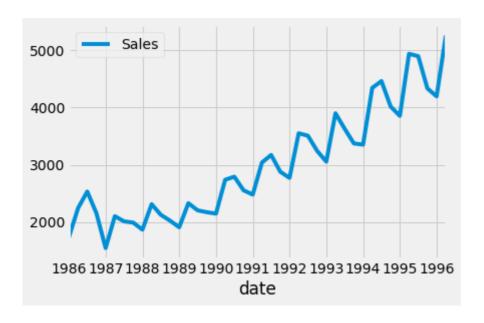
	Sales
date	
1986-01-31	1734.827000
1986-02-28	NaN
1986-03-31	NaN
1986-04-30	2244.960999
1986-05-31	NaN
1986-06-30	NaN
1986-07-31	2533.804993
1986-08-31	NaN
1986-09-30	NaN
1986-10-31	2154.962997
1986-11-30	NaN
1986-12-31	NaN
1987-01-31	1547.818996
1987-02-28	NaN
1987-03-31	NaN
1987-04-30	2104.411995
1987-05-31	NaN
1987-06-30	NaN
1987-07-31	2014.362999
1987-08-31	NaN
1987-09-30	NaN
1987-10-31	1991.746998
1987-11-30	NaN
1987-12-31	NaN
1988-01-31	1869.049999
1988-02-29	NaN
1988-03-31	NaN
1988-04-30	2313.631996
1988-05-31	NaN
1988-06-30	NaN
1988-07-31	2128.320000
1988-08-31	NaN

## interplation is done for nan values

#### In [252]:

```
interpolated = upsampled.interpolate(method='linear')
print(interpolated.head(15))
interpolated.plot()
plt.show()
```

#### Sales date 1986-01-31 1734.827000 1986-02-28 1904.871666 1986-03-31 2074.916332 1986-04-30 2244.960999 1986-05-31 2341.242330 1986-06-30 2437.523661 1986-07-31 2533.804993 1986-08-31 2407.524328 1986-09-30 2281.243663 1986-10-31 2154.962997 1986-11-30 1952.581664 1986-12-31 1750.200330 1987-01-31 1547.818996 1987-02-28 1733.349996 1987-03-31 1918.880995



#### In [253]:

#### interpolated

#### Out[253]:

#### Sales

date	
1986-01-31	1734.827000
1986-02-28	1904.871666
1986-03-31	2074.916332
1986-04-30	2244.960999
1986-05-31	2341.242330
1995-12-31	4240.333333
1996-01-31	4194.000000
1996-02-29	4547.000000
1996-03-31	4900.000000
1996-04-30	5253.000000
124 rows ×	1 columns

# 5. Tranformations

# **Square Root Transformation**

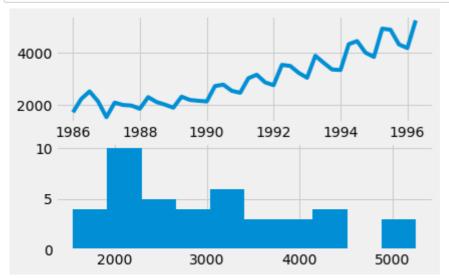
#### In [254]:

```
dataframe = DataFrame(DF.values)
dataframe.columns = ['Sales']
dataframe['Sales'] = sqrt(dataframe['Sales'])
```

#### In [255]:

```
plt.subplot(211)
plt.plot(DF['Sales'])

plt.subplot(212)
plt.hist(DF['Sales'])
plt.show()
```



# **Log Transformation**

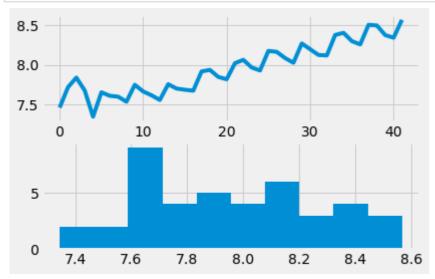
## In [256]:

```
dataframe = DataFrame(DF.values)
dataframe.columns = ['Sales']
dataframe['Sales'] = log(dataframe['Sales'])
```

## In [257]:

```
plt.subplot(211)
plt.plot(dataframe['Sales'])

plt.subplot(212)
plt.hist(dataframe['Sales'])
plt.show()
```



# **Moving Average**

#### In [258]:

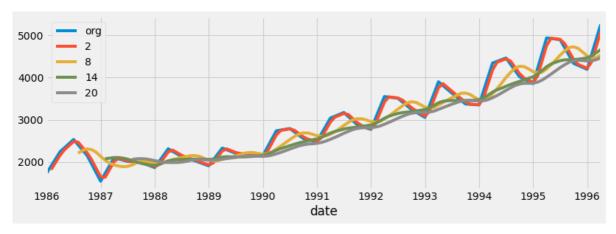
```
Train = interpolated.head(112)
Test = interpolated.tail(12)
```

#### In [259]:

```
plt.figure(figsize=(12,4))
interpolated.Sales.plot(label="org")
for i in range(2,24,6):
    interpolated["Sales"].rolling(i).mean().plot(label=str(i))
plt.legend(loc='best')
```

#### Out[259]:

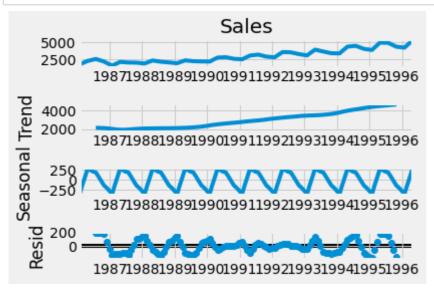
<matplotlib.legend.Legend at 0x2873b9074c0>



# Time series decomposition plot

#### In [260]:

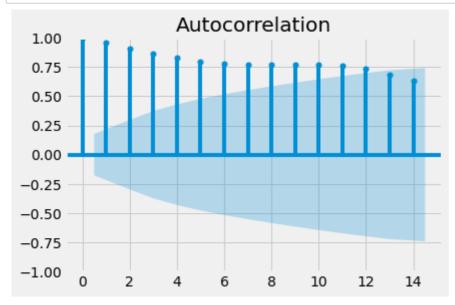
```
decompose_ts_add = seasonal_decompose(interpolated.Sales,period=12)
decompose_ts_add.plot()
plt.show()
```

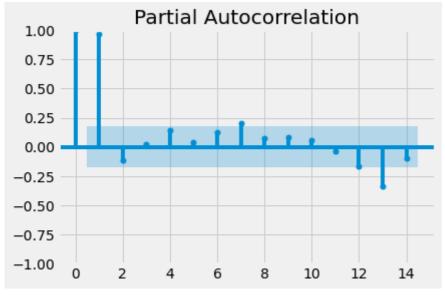


# **ACF plots and PACF plots**

#### In [261]:

```
tsa_plots.plot_acf(interpolated.Sales,lags=14)
tsa_plots.plot_pacf(interpolated.Sales,lags=14)
plt.show()
```





## **Evaluation Metric MAPE**

#### In [262]:

```
def MAPE(pred,org):
   temp = np.abs((pred-org)/org)*100
   return np.mean(temp)
```

# **Simple Exponential Method**

```
In [263]:
```

```
ses_model = SimpleExpSmoothing(Train["Sales"]).fit(smoothing_level=0.2)
pred_ses = ses_model.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_ses,Test.Sales)
```

#### Out[263]:

7.528920151221705

## Holt method

#### In [264]:

```
hw_model = Holt(Train["Sales"]).fit(smoothing_level=0.1, smoothing_trend=0.2)
pred_hw = hw_model.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hw,Test.Sales)
```

#### Out[264]:

7.9715447532695825

# Holts winter exponential smoothing with additive seasonality and additive trend

```
In [265]:
```

```
hwe_model_add_add = ExponentialSmoothing(Train["Sales"],seasonal="add",trend="add",seasonal
pred_hwe_add_add = hwe_model_add_add.predict(start = Test.index[0],end = Test.index[-1])
MAPE(pred_hwe_add_add,Test.Sales)
```

#### Out[265]:

4.980642076778319

# Holts winter exponential smoothing with multiplicative seasonality and additive trend

```
In [266]:
```

```
hwe_model_mul_add = ExponentialSmoothing(Train["Sales"],seasonal="mul",trend="add",seasonal
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[266]:

4.760059857710733

#### In [267]:

```
rmse_hwe_mul_add = sqrt(mean_squared_error(pred_hwe_mul_add,Test.Sales))
rmse_hwe_mul_add
```

#### Out[267]:

249.77163694491563

# Final Model by combining train and test

```
In [268]:
```

```
hwe_model_add_add = ExponentialSmoothing(interpolated["Sales"],seasonal="add",trend="add",s
```

## Forecasting for next 10 time periods

#### In [269]:

```
hwe_model_add_add.forecast(10)
```

#### Out[269]:

```
1996-05-31
             5645.853877
1996-06-30
            6044.108417
1996-07-31
             6424.580532
1996-08-31
             6796.899936
             7100.361465
1996-09-30
            7422.984410
1996-10-31
1996-11-30
             7677.114691
1996-12-31
             8025.662468
1997-01-31 8323.526408
1997-02-28
             8690.513977
Freq: M, dtype: float64
```

## In [270]:

## interpolated

## Out[270]:

#### Sales

date	
1986-01-31	1734.827000
1986-02-28	1904.871666
1986-03-31	2074.916332
1986-04-30	2244.960999
1986-05-31	2341.242330
1995-12-31	4240.333333
1996-01-31	4194.000000
1996-02-29	4547.000000
1996-03-31	4900.000000
1996-04-30	5253.000000

124 rows × 1 columns

## In [271]:

```
interpolated.reset_index(inplace=True)
```

## In [272]:

```
interpolated['t'] = 1
```

## In [273]:

#### interpolated

#### Out[273]:

	date	Sales	t
0	1986-01-31	1734.827000	1
1	1986-02-28	1904.871666	1
2	1986-03-31	2074.916332	1
3	1986-04-30	2244.960999	1
4	1986-05-31	2341.242330	1
119	1995-12-31	4240.333333	1
120	1996-01-31	4194.000000	1
121	1996-02-29	4547.000000	1
122	1996-03-31	4900.000000	1
123	1996-04-30	5253.000000	1

124 rows × 3 columns

## In [274]:

```
for i,row in interpolated.iterrows():
   interpolated['t'].iloc[i] = i+1
```

#### In [275]:

## interpolated

#### Out[275]:

	date	Sales	t
0	1986-01-31	1734.827000	1
1	1986-02-28	1904.871666	2
2	1986-03-31	2074.916332	3
3	1986-04-30	2244.960999	4
4	1986-05-31	2341.242330	5
119	1995-12-31	4240.333333	120
120	1996-01-31	4194.000000	121
121	1996-02-29	4547.000000	122
122	1996-03-31	4900.000000	123
123	1996-04-30	5253.000000	124

124 rows × 3 columns

#### inserting t\_sq column with values

## In [276]:

```
interpolated['t_sq'] = (interpolated['t'])**2
```

## In [277]:

#### interpolated

#### Out[277]:

	date	Sales	t	t_sq
0	1986-01-31	1734.827000	1	1
1	1986-02-28	1904.871666	2	4
2	1986-03-31	2074.916332	3	9
3	1986-04-30	2244.960999	4	16
4	1986-05-31	2341.242330	5	25
119	1995-12-31	4240.333333	120	14400
120	1996-01-31	4194.000000	121	14641
121	1996-02-29	4547.000000	122	14884
122	1996-03-31	4900.000000	123	15129
123	1996-04-30	5253.000000	124	15376

#### 124 rows × 4 columns

## In [278]:

```
interpolated["month"] = interpolated.date.dt.strftime("%b") # month extraction
interpolated["year"] = interpolated.date.dt.strftime("%Y") # year extraction
```

## In [279]:

## interpolated

## Out[279]:

	date	Sales	t	t_sq	month	year
0	1986-01-31	1734.827000	1	1	Jan	1986
1	1986-02-28	1904.871666	2	4	Feb	1986
2	1986-03-31	2074.916332	3	9	Mar	1986
3	1986-04-30	2244.960999	4	16	Apr	1986
4	1986-05-31	2341.242330	5	25	May	1986
119	1995-12-31	4240.333333	120	14400	Dec	1995
120	1996-01-31	4194.000000	121	14641	Jan	1996
121	1996-02-29	4547.000000	122	14884	Feb	1996
122	1996-03-31	4900.000000	123	15129	Mar	1996
123	1996-04-30	5253.000000	124	15376	Apr	1996

124 rows × 6 columns

## In [280]:

```
months = pd.get_dummies(interpolated['month'])
```

## In [281]:

months

## Out[281]:

	Apr	Aug	Dec	Feb	Jan	Jul	Jun	Mar	May	Nov	Oct	Sep
0	0	0	0	0	1	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	1	0	0	0	0
3	1	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	1	0	0	0
119	0	0	1	0	0	0	0	0	0	0	0	0
120	0	0	0	0	1	0	0	0	0	0	0	0
121	0	0	0	1	0	0	0	0	0	0	0	0
122	0	0	0	0	0	0	0	1	0	0	0	0
123	1	0	0	0	0	0	0	0	0	0	0	0

124 rows × 12 columns

```
In [282]:
```

```
months = months[['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']]
```

#### In [283]:

```
Coka_Cola = pd.concat([interpolated,months],axis=1)
```

#### In [284]:

```
Coka_Cola.head()
```

#### Out[284]:

	date	Sales	t	t_sq	month	year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
0	1986- 01-31	1734.827000	1	1	Jan	1986	1	0	0	0	0	0	0	0	0
1	1986- 02-28	1904.871666	2	4	Feb	1986	0	1	0	0	0	0	0	0	0
2	1986- 03-31	2074.916332	3	9	Mar	1986	0	0	1	0	0	0	0	0	0
3	1986- 04-30	2244.960999	4	16	Apr	1986	0	0	0	1	0	0	0	0	0
4	1986- 05-31	2341.242330	5	25	May	1986	0	0	0	0	1	0	0	0	0
4															•

#### In [285]:

```
Coka_Cola['log_sales'] = np.log(Coka_Cola['Sales'])
```

## In [286]:

Coka\_Cola

## Out[286]:

	date	Sales	t	t_sq	month	year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
0	1986- 01-31	1734.827000	1	1	Jan	1986	1	0	0	0	0	0	0	0
1	1986- 02-28	1904.871666	2	4	Feb	1986	0	1	0	0	0	0	0	0
2	1986- 03-31	2074.916332	3	9	Mar	1986	0	0	1	0	0	0	0	0
3	1986- 04-30	2244.960999	4	16	Apr	1986	0	0	0	1	0	0	0	0
4	1986- 05-31	2341.242330	5	25	May	1986	0	0	0	0	1	0	0	0
119	1995- 12-31	4240.333333	120	14400	Dec	1995	0	0	0	0	0	0	0	0
120	1996- 01-31	4194.000000	121	14641	Jan	1996	1	0	0	0	0	0	0	0
121	1996- 02-29	4547.000000	122	14884	Feb	1996	0	1	0	0	0	0	0	0
122	1996- 03-31	4900.000000	123	15129	Mar	1996	0	0	1	0	0	0	0	0
123	1996- 04-30	5253.000000	124	15376	Apr	1996	0	0	0	1	0	0	0	0

124 rows × 19 columns

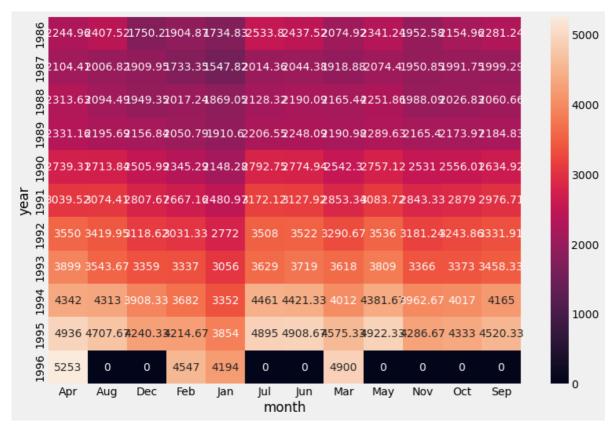
 $local host: 8888/notebooks/python\ for\ ds\ john/Assignments/Forecasting/Forecasting\ (CocaCola\_Sales). ipynblue and the property of the control of the co$ 

#### In [287]:

```
plt.figure(figsize=(12,8))
heatmap_y_month = pd.pivot_table(data=Coka_Cola,values="Sales",index="year",columns="month"
sns.heatmap(heatmap_y_month,annot=True,fmt="g")
```

#### Out[287]:

<AxesSubplot:xlabel='month', ylabel='year'>

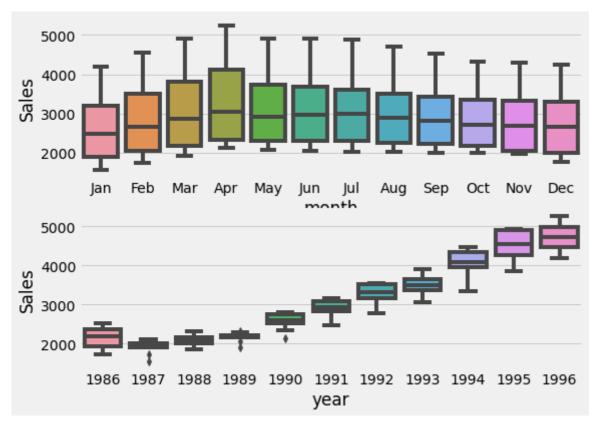


#### In [288]:

```
plt.figure(figsize=(8,6))
plt.subplot(211)
sns.boxplot(x="month",y="Sales",data= Coka_Cola)
plt.subplot(212)
sns.boxplot(x="year",y="Sales",data=Coka_Cola)
```

#### Out[288]:

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

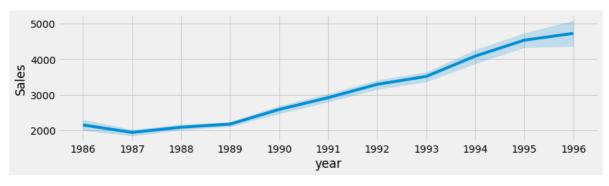


#### In [289]:

```
plt.figure(figsize=(12,3))
sns.lineplot(x="year",y="Sales",data=Coka_Cola)
```

#### Out[289]:

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



# 6. Comparing Multiple Models

```
In [290]:
```

```
Train = Coka_Cola.head(110)
Test = Coka_Cola.tail(14)
```

## **Linear Model**

```
In [291]:
```

```
linear_model = smf.ols('Sales~t',data=Train).fit()
pred_linear = pd.Series(linear_model.predict(pd.DataFrame(Test['t'])))
rmse_linear = np.sqrt(np.mean((np.array(Test['Sales'])-np.array(pred_linear))**2))
rmse_linear
```

#### Out[291]:

638.120822592281

# **Exponential Model**

```
In [292]:
```

```
Exp = smf.ols('log_sales~t',data=Train).fit()
pred_Exp = pd.Series(Exp.predict(pd.DataFrame(Test['t'])))
rmse_Exp = np.sqrt(np.mean((np.array(Test['Sales'])-np.array(np.exp(pred_Exp)))**2))
rmse_Exp
```

#### Out[292]:

494.4406930545973

# **Quadratic Model**

```
In [293]:
```

```
Quad = smf.ols('Sales~t+t_sq',data=Train).fit()
pred_Quad = pd.Series(Quad.predict(Test[["t","t_sq"]]))
rmse_Quad = np.sqrt(np.mean((np.array(Test['Sales'])-np.array(pred_Quad))**2))
rmse_Quad
```

#### Out[293]:

387.28160082928383

# Additive seasonality

```
In [294]:
```

```
add_sea = smf.ols('Sales~Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data=Train).fit()
pred_add_sea = pd.Series(add_sea.predict(Test[['Jan','Feb','Mar','Apr','May','Jun','Jul','A
rmse_add_sea = np.sqrt(np.mean((np.array(Test['Sales'])-np.array(pred_add_sea))**2))
rmse_add_sea
```

#### Out[294]:

1881.813589906022

# **Additive Seasonality Quadratic**

```
In [295]:
```

```
add_sea_Quad = smf.ols('Sales~t+t_sq+Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data=Trai
pred_add_sea_quad = pd.Series(add_sea_Quad.predict(Test[['Jan','Feb','Mar','Apr','May','Jun
rmse_add_sea_quad = np.sqrt(np.mean((np.array(Test['Sales'])-np.array(pred_add_sea_quad))**
rmse_add_sea_quad
```

#### Out[295]:

242.77660443468957

# **Multiplicative Seasonality**

```
In [296]:
```

```
Mul_sea = smf.ols('log_sales~Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data = Train).fit
pred_Mult_sea = pd.Series(Mul_sea.predict(Test))
rmse_Mult_sea = np.sqrt(np.mean((np.array(Test['Sales'])-np.array(np.exp(pred_Mult_sea)))**
rmse_Mult_sea
```

#### Out[296]:

1973.2620608123086

# **Multiplicative Additive Seasonality**

#### In [297]:

```
Mul_Add_sea = smf.ols('log_sales~t+Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data = Trai
pred_Mult_add_sea = pd.Series(Mul_Add_sea.predict(Test))
rmse_Mult_add_sea = np.sqrt(np.mean((np.array(Test['Sales'])-np.array(np.exp(pred_Mult_add_
rmse_Mult_add_sea
```

#### Out[297]:

275.27503211175105

# Compareing the results

#### In [298]:

```
data = {"MODEL":pd.Series(["rmse_linear","rmse_Exp","rmse_Quad","rmse_add_sea","rmse_add_se
table_rmse=pd.DataFrame(data)
table_rmse.sort_values(['RMSE_Values'])
```

#### Out[298]:

	MODEL	RMSE_Values
4	rmse_add_sea_quad	242.776604
6	rmse_Mult_add_sea	275.275032
2	rmse_Quad	387.281601
1	rmse_Exp	494.440693
0	rmse_linear	638.120823
3	rmse_add_sea	1881.813590
5	rmse_Mult_sea	1973.262061

## **End**

## In [ ]: