

In [1]:

```
# Load Libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

In [3]:

```
# Import dataset
airline = pd.read_excel('Airlines+Data.xlsx')
airline.head()
```

Out[3]:

| | Month | Passengers |
|---|------------|------------|
| 0 | 1995-01-01 | 112 |
| 1 | 1995-02-01 | 118 |
| 2 | 1995-03-01 | 132 |
| 3 | 1995-04-01 | 129 |
| 4 | 1995-05-01 | 121 |

In [4]:

```
airline.isna().sum()
```

Out[4]:

```
Month      0
Passengers 0
dtype: int64
```

In [5]:

```
airline.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 96 entries, 0 to 95
Data columns (total 2 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   Month       96 non-null    datetime64[ns]
1   Passengers  96 non-null    int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 1.6 KB
```

In [6]:

```
airline[ 'Month' ].unique()
```

Out[6]:

[illegible]

In [7]:

```
airline.describe()
```

Out[7]:

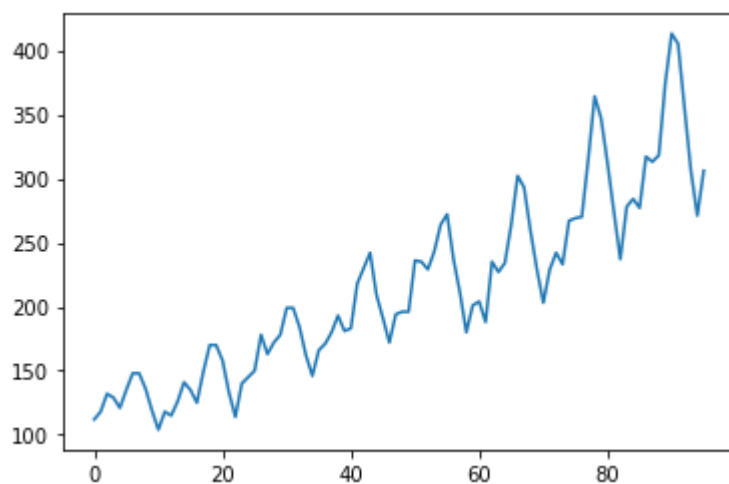
| Passengers | |
|------------|------------|
| count | 96.000000 |
| mean | 213.708333 |
| std | 71.918216 |
| min | 104.000000 |
| 25% | 156.000000 |
| 50% | 200.000000 |
| 75% | 264.750000 |
| max | 413.000000 |

In [8]:

```
airline.Passengers.plot()
```

Out[8]:

<AxesSubplot:>



In [9]:

```
airline['Date'] = pd.to_datetime(airline.Month, format='%b-%y')
airline['Months'] = airline.Date.dt.strftime('%b')
airline['Year'] = airline.Date.dt.strftime('%Y')
```

In [10]:

airline

Out[10]:

| | Month | Passengers | Date | Months | Year |
|-----|------------|------------|------------|--------|------|
| 0 | 1995-01-01 | 112 | 1995-01-01 | Jan | 1995 |
| 1 | 1995-02-01 | 118 | 1995-02-01 | Feb | 1995 |
| 2 | 1995-03-01 | 132 | 1995-03-01 | Mar | 1995 |
| 3 | 1995-04-01 | 129 | 1995-04-01 | Apr | 1995 |
| 4 | 1995-05-01 | 121 | 1995-05-01 | May | 1995 |
| ... | ... | ... | ... | ... | ... |
| 91 | 2002-08-01 | 405 | 2002-08-01 | Aug | 2002 |
| 92 | 2002-09-01 | 355 | 2002-09-01 | Sep | 2002 |
| 93 | 2002-10-01 | 306 | 2002-10-01 | Oct | 2002 |
| 94 | 2002-11-01 | 271 | 2002-11-01 | Nov | 2002 |
| 95 | 2002-12-01 | 306 | 2002-12-01 | Dec | 2002 |

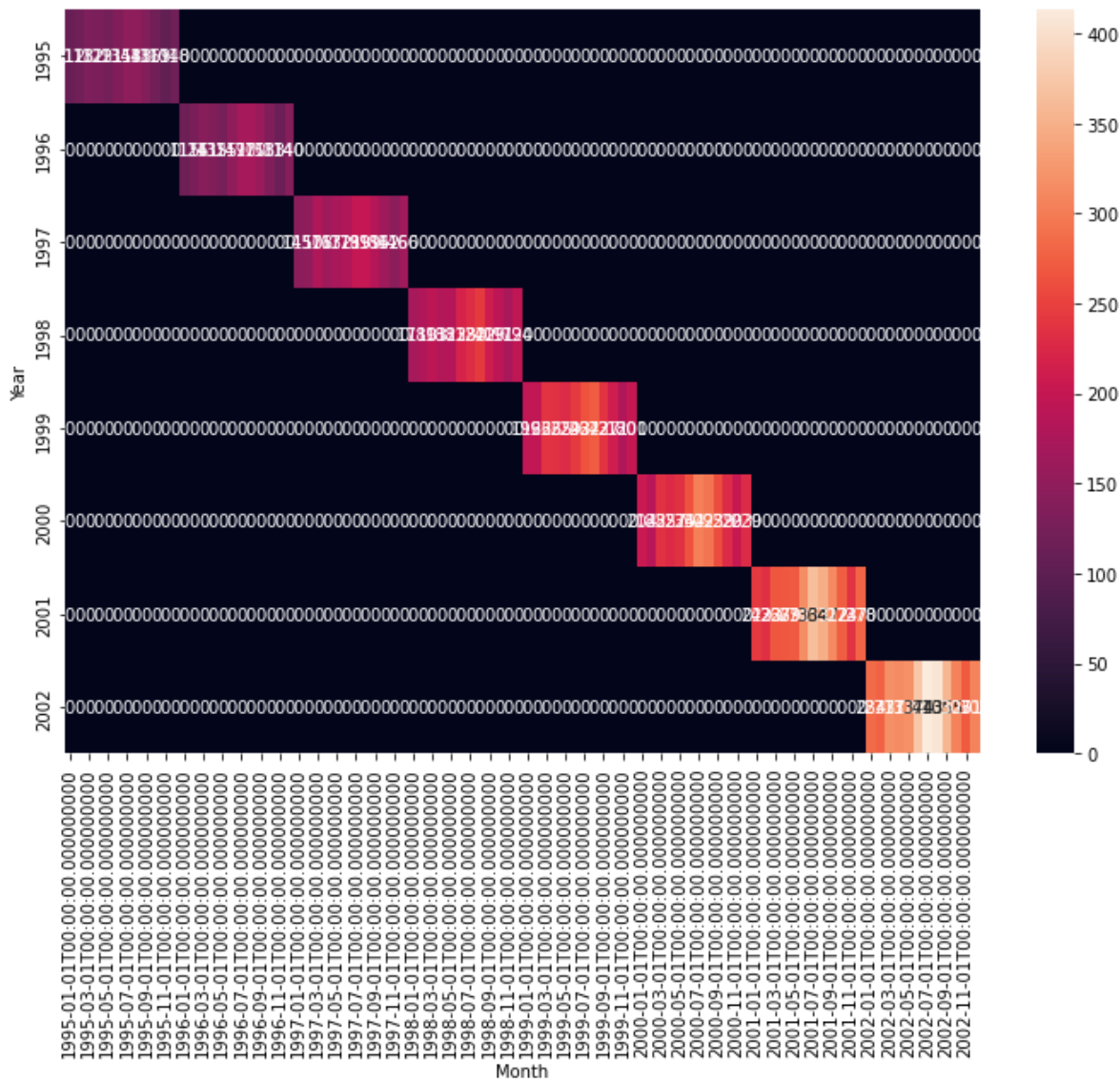
96 rows × 5 columns

In [11]:

```
# Heatmap
plt.figure(figsize=(12,8))
heatmap_y_month = pd.pivot_table(data=airline,values='Passengers',index='Year',columns='Month',
sns.heatmap(heatmap_y_month,annot=True,fmt='g') # fmt is format of the grid values
```

Out[11]:

<AxesSubplot:xlabel='Month', ylabel='Year'>

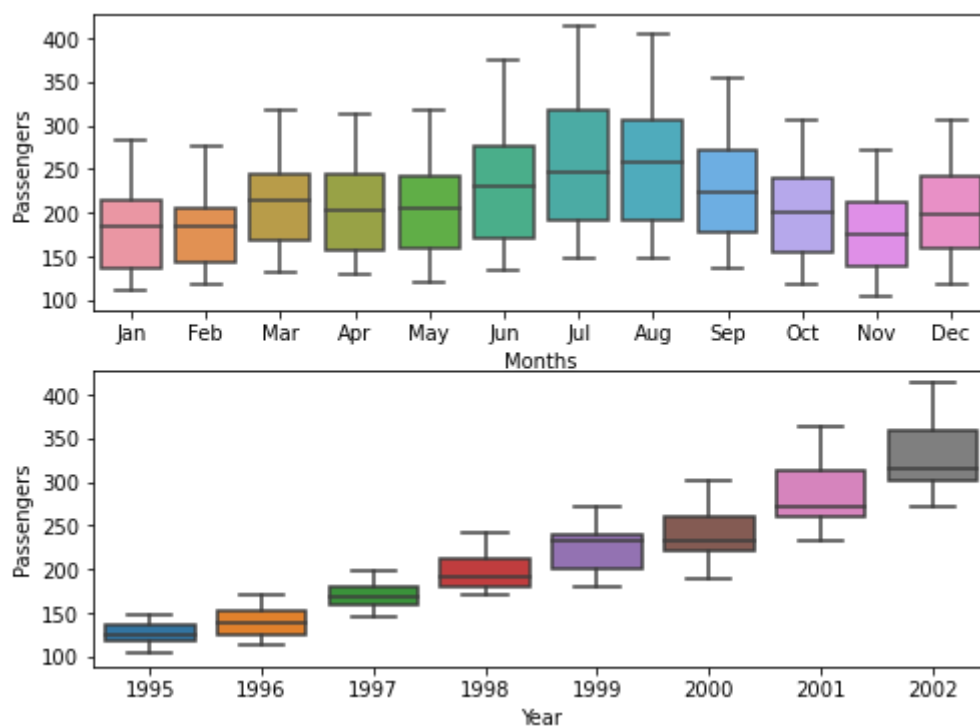


In [12]:

```
# Boxplot
plt.figure(figsize=(8,6))
plt.subplot(211)
sns.boxplot(x='Months',y='Passengers',data=airline)
plt.subplot(212)
sns.boxplot(x='Year',y='Passengers', data=airline)
```

Out[12]:

<AxesSubplot:xlabel='Year', ylabel='Passengers'>



In [13]:

```
#Preparing dummies
Month_Dummies= pd.DataFrame(pd.get_dummies(airline['Months']))
airline1 = pd.concat([airline,Month_Dummies],axis =1)
```

In [14]:

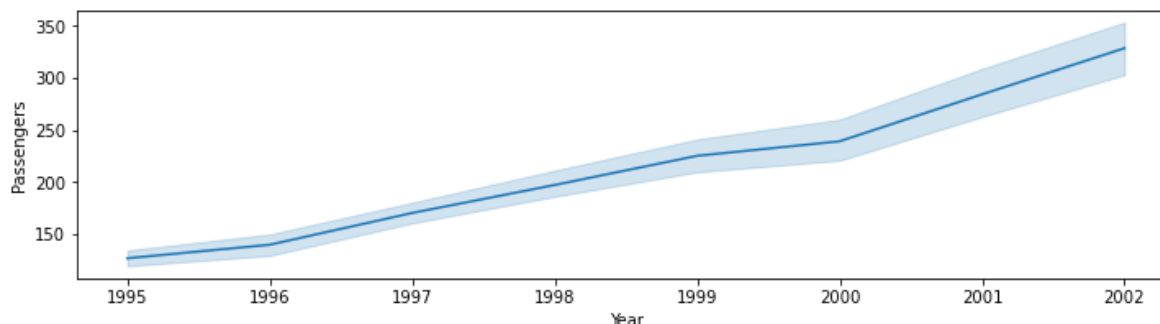
```
airline1["t"] = np.arange(1,97)
airline1["t_squared"] = airline1["t"] * airline1["t"]
airline1["Log_Passengers"] = np.log(airline1["Passengers"])
```

In [15]:

```
plt.figure(figsize=(12,3))
sns.lineplot(x='Year', y='Passengers', data=airline)
```

Out[15]:

<AxesSubplot:xlabel='Year', ylabel='Passengers'>



In [16]:

```
#Splitting data
Train = airline1.head(80)
Test = airline1.tail(16)
```

In [17]:

```
#Linear Model
import statsmodels.formula.api as smf

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

Out[17]:

47.542624067726734

In [18]:

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

Out[18]:

43.79373939334317

In [19]:

```
#Quadratic Model
Quad = smf.ols('Passengers~t+t_squared',data=Train).fit()
pred_Quad = pd.Series(Quad.predict(Test[['t', 't_squared']]))
rmse_Quad = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(pred_Quad))**2))
rmse_Quad
```

Out[19]:

43.65440369584248

In [20]:

```
#Additive seasonality
add_sea = smf.ols('Passengers~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['Passengers'])- np.array(pred_add_sea))**2))
rmse_add_sea
```

Out[20]:

129.26647641443313

In [21]:

```
#Additive Seasonality quadratic
add_sea_Quad = smf.ols('Passengers~t+t_squared+Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov'
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['Passengers'])-np.array(pred_add_sea_qua
rmse_add_sea_quad
```

Out[21]:

23.91098357010659

In [22]:

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

Out[22]:

135.3264841462111

In [23]:

```
#Multiplicative Additive Seasonality
Mul_Add_sea = smf.ols('Log_Passengers~t+Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov',data=T
pred_Mult_add_sea = pd.Series(Mul_Add_sea.predict(Test))
rmse_Mult_add_sea = np.sqrt(np.mean((np.array(Test['Passengers'])-np.array(np.exp(pred_Mult
rmse_Mult_add_sea
```

Out[23]:

9.469000230303608

In [24]:

```
#Tabulating the rmse values
data= {'Model':pd.Series(['rmse_linear','rmse_Exp','rmse_Quad','rmse_add_sea','rmse_add_sea
table_rmse = pd.DataFrame(data)
table_rmse.sort_values(['RMSE_Values'])
```

Out[24]:

| | Model | RMSE_Values |
|---|-------------------|-------------|
| 6 | rmse_Mult_add_sea | 9.469000 |
| 4 | rmse_add_sea_quad | 23.910984 |
| 2 | rmse_Quad | 43.654404 |
| 1 | rmse_Exp | 43.793739 |
| 0 | rmse_linear | 47.542624 |
| 3 | rmse_add_sea | 129.266476 |
| 5 | rmse_Mult_sea | 135.326484 |

Conclusion:- From the above rmse values (rmse_Mult_ADD_sea - 9.469) is the best fit model

In [25]:

```
# Forecasting using Multiplicative Additive Seasonality Model
# Forecasting for next 12 months
data = [['2003-01-01', 'Jan'], ['2003-02-01', 'Feb'], ['2003-03-01', 'Mar'], ['2003-04-01', 'Apr']]
# Print(data)
forecast = pd.DataFrame(data, columns = ['Date', 'Months'])
forecast
```

Out[25]:

| | Date | Months |
|----|------------|--------|
| 0 | 2003-01-01 | Jan |
| 1 | 2003-02-01 | Feb |
| 2 | 2003-03-01 | Mar |
| 3 | 2003-04-01 | Apr |
| 4 | 2003-05-01 | May |
| 5 | 2003-06-01 | Jun |
| 6 | 2003-07-01 | Jul |
| 7 | 2003-08-01 | Aug |
| 8 | 2003-09-01 | Sep |
| 9 | 2003-10-01 | Oct |
| 10 | 2003-11-01 | Nov |
| 11 | 2003-12-01 | Dec |

In [26]:

```
# Create dummies and T and T-Squared columns

dummies = pd.DataFrame(pd.get_dummies(forecast['Months']))
forecast1 = pd.concat([forecast, dummies], axis =1)
print('After dummy\n',forecast1.head())

forecast1['t'] = np.arange(1,13)
forecast1['t_squared'] = forecast1['t'] * forecast1['t']
print('\nAfter T and T-Squared\n', forecast1.head())
```

After dummy

| | Date | Months | Apr | Aug | Dec | Feb | Jan | Jul | Jun | Mar | May | Nov | Oct |
|---|------------|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 0 | 2003-01-01 | Jan | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 2003-02-01 | Feb | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 2003-03-01 | Mar | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 3 | 2003-04-01 | Apr | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 2003-05-01 | May | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |

Sep

| | |
|---|---|
| 0 | 0 |
| 1 | 0 |
| 2 | 0 |
| 3 | 0 |
| 4 | 0 |

After T and T-Squared

| | Date | Months | Apr | Aug | Dec | Feb | Jan | Jul | Jun | Mar | May | Nov | Oct |
|---|------------|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 0 | 2003-01-01 | Jan | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 2003-02-01 | Feb | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 2003-03-01 | Mar | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 3 | 2003-04-01 | Apr | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 2003-05-01 | May | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |

Sep t t_squared

| | | | |
|---|---|---|----|
| 0 | 0 | 1 | 1 |
| 1 | 0 | 2 | 4 |
| 2 | 0 | 3 | 9 |
| 3 | 0 | 4 | 16 |
| 4 | 0 | 5 | 25 |

In [27]:

```
# Forecasting using Multiplicative Additive Seasonality Model

model_full = smf.ols('Log_Passengers~t+Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov+Dec',data)
pred_new = pd.Series(model_full.predict(forecast1))
pred_new

forecast1["Forecasted_log"] = pd.Series(pred_new)
forecast1['Forecasted_Passengers'] = np.exp(forecast1['Forecasted_log'])
```

In [28]:

```
# Final Prediction

Final_predict = forecast1.loc[:, ['Months', 'Forecasted_Passengers']]
Final_predict
```

Out[28]:

| | Months | Forecasted_Passengers |
|----|--------|-----------------------|
| 0 | Jan | 109.176148 |
| 1 | Feb | 110.331245 |
| 2 | Mar | 127.315234 |
| 3 | Apr | 123.200587 |
| 4 | May | 122.399578 |
| 5 | Jun | 138.536397 |
| 6 | Jul | 154.066959 |
| 7 | Aug | 153.741209 |
| 8 | Sep | 137.693733 |
| 9 | Oct | 120.894736 |
| 10 | Nov | 106.109309 |
| 11 | Dec | 121.633998 |

In []: