Forecasting Assignment

Data Set - Airlines_data

1. Import Necessary libraries

In [1]:
```python
import pandas as pd
import numpy as np

from matplotlib import pyplot as plt
import seaborn as sns

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

2. Import Data

In [2]:
```python
passengers_data = pd.read_excel('Airlines+Data.xlsx')
passengers_data
```

Out[2]:

	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
...	...	...
91	2002-08-01	405
92	2002-09-01	355
93	2002-10-01	306
94	2002-11-01	271
95	2002-12-01	306

96 rows × 2 columns

3. Data Understanding

3.1 Initial Analysis :

In [3]:
```python
passengers_data.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]:
```python
passengers_data.shape
```

Out[4]:
```
(96, 2)
```

In [5]:
```python
passengers_data.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]:
```python
passengers_data.isna().sum()
```

Out[6]:
```
Month         0
Passengers    0
dtype: int64
```

In [7]:
```python
passengers_data.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]:
```python
passengers_data.dtypes
```

Out[8]:
```
Month         datetime64[ns]
Passengers             int64
dtype: object
```

In [9]:
```python
passengers_data.columns
```

Out[9]:
```
Index(['Month', 'Passengers'], dtype='object')
```

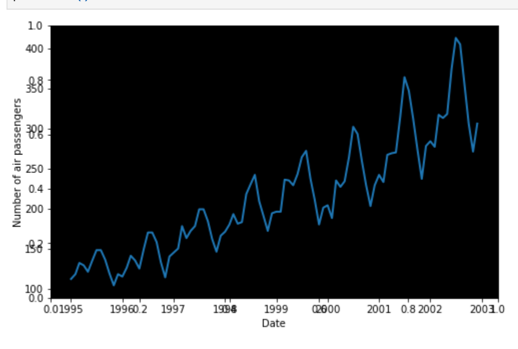
In [10]:
```python
passengers_data.set_index('Month', inplace = True)
passengers_data.head()
```

Out[10]:

Month	Passengers
1995-01-01	112
1995-02-01	118
1995-03-01	132
1995-04-01	129
1995-05-01	121

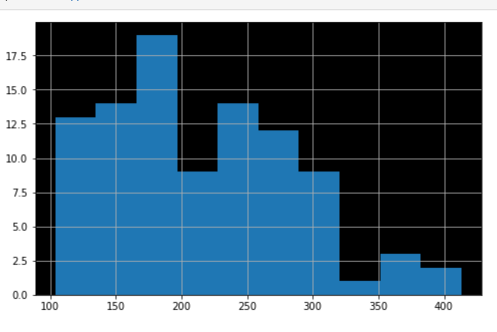
3.2 Visualization using Lineplot for Passengers :

In [11]:
```python
plt.figure(figsize = (8,5))

plt.xlabel("Date")
plt.ylabel("Number of air passengers")
ax = plt.axes()
ax.set_facecolor("black")

plt.plot(passengers_data['Passengers'], linewidth = 2)

plt.show()
```



3.3 Visualization using Histogram :

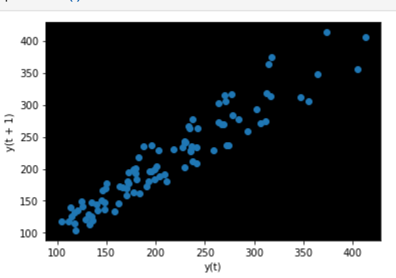
In [12]:
```python
ax = plt.axes()
ax.set_facecolor("black")

passengers_data['Passengers'].hist(figsize = (8,5))

plt.show()
```



3.4 Visualization using Lagplot :

In [13]:
```python
from pandas.plotting import lag_plot
```

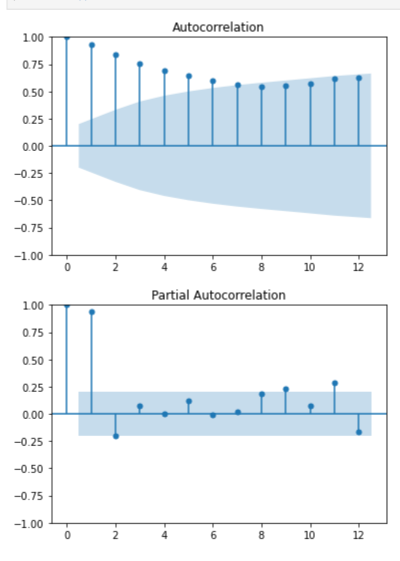
In [14]:
```python
ax = plt.axes()
ax.set_facecolor("black")

lag_plot(passengers_data['Passengers'])

plt.show()
```



3.5 Visualization using TSA Plot :

In [15]:
```python
import statsmodels.graphics.tsaplots as tsa_plots
```

In [16]:
```python
tsa_plots.plot_acf(passengers_data['Passengers'],lags = 12)

tsa_plots.plot_pacf(passengers_data['Passengers'],lags = 12)

plt.show()
```



4. Data Driven Forecasting Methods

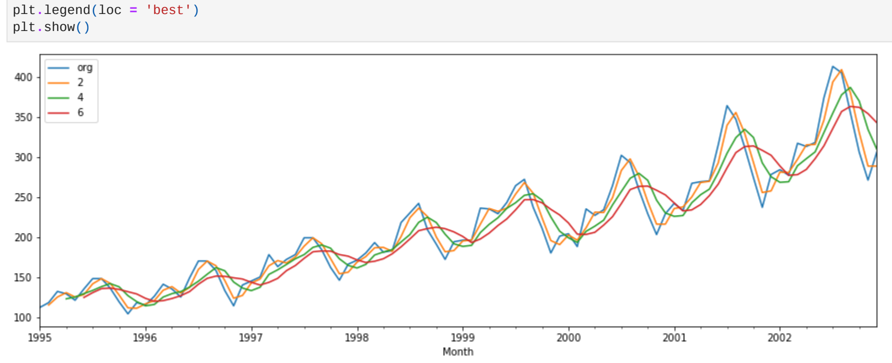
In [17]:
```python
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
from statsmodels.tsa.holtwinters import Holt
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

4.1 Splitting Data :

In [18]:
```python
Train = passengers_data.head(84)
Test = passengers_data.tail(12)
```

4.2 Moving Average Method :

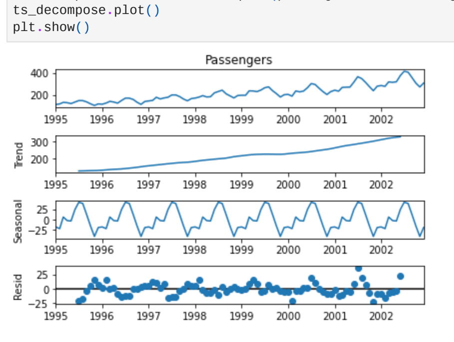
In [19]:
```python
plt.figure(figsize = (15,5))
passengers_data['Passengers'].plot(label = "org")

for i in range(2,8,2):
    passengers_data['Passengers'].rolling(i).mean().plot(label = str(i))

plt.legend(loc = 'best')
plt.show()
```



5. Time series decomposition plot

In [20]:
```python
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [21]:
```python
ts_decompose = seasonal_decompose(passengers_data.Passengers,period = 12)
ts_decompose.plot()
plt.show()
```



6. Evaluation Metric RMSE

In [22]:
```python
def RMSE(org, pred):
    rmse = np.sqrt(np.mean((np.array(org)-np.array(pred))**2))
    return rmse
```

In [23]:
```python
import warnings
warnings.filterwarnings('ignore')
```

6.1 Simple Exponential Method :

In [24]:
```python
simple_model = SimpleExpSmoothing(Train["Passengers"]).fit()
pred_simple_model = simple_model.predict(start = Test.index[0],end = Test.index[-1])
```

In [25]:
```python
rmse_simple_model = RMSE(Test.Passengers, pred_simple_model)
print('RMSE Value of Simple Exponential :',rmse_simple_model)
```

```
RMSE Value of Simple Exponential : 68.00674031350329
```

6.2 Holt method :

In [26]:
```python
holt_model = Holt(Train["Passengers"]).fit()
pred_holt_model = holt_model.predict(start = Test.index[0],end = Test.index[-1])
```

In [27]:
```python
rmse_holt_model = RMSE(Test.Passengers, pred_holt_model)
print('RMSE Value of Holt :',rmse_holt_model)
```

```
RMSE Value of Holt : 58.56209934996357
```

6.3 Holts winter exponential smoothing with additive seasonality and additive trend :

In [28]:
```python
holt_model_add_add = ExponentialSmoothing(Train["Passengers"],seasonal = "add",trend = "add",seasonal_periods = 4).fit()
pred_holt_add_add = holt_model_add_add.predict(start = Test.index[0],end = Test.index[-1])
```

In [29]:
```python
rmse_holt_add_add_model = RMSE(Test.Passengers, pred_holt_add_add)
print('RMSE Value of Holts add and add :',rmse_holt_add_add_model)
```

```
RMSE Value of Holts add and add : 63.07585545619695
```

6.4 Holts winter exponential smoothing with multiplicative seasonality and additive trend

In [30]:
```python
holt_model_multi_add = ExponentialSmoothing(Train["Passengers"],seasonal = "mul",trend = "add",seasonal_periods = 4).fit()
pred_holt_multi_add = holt_model_multi_add.predict(start = Test.index[0],end = Test.index[-1])
```

In [31]:
```python
rmse_holt_model_multi_add_model = RMSE(Test.Passengers, pred_holt_multi_add)
print('RMSE Value of Holts Multi and add :',rmse_holt_model_multi_add_model)
```

```
RMSE Value of Holts Multi and add : 64.62220925087415
```

7. Model based Forecasting Methods

7.1 Data preprocessing for models :

In [32]:
```python
passengers_data_1 = passengers_data.copy()
passengers_data_1.head()
```

Out[32]:

Month	Passengers
1995-01-01	112
1995-02-01	118
1995-03-01	132
1995-04-01	129
1995-05-01	121

In [33]:
```python
passengers_data_1["t"] = np.arange(1,97)
passengers_data_1["t_squared"] = passengers_data_1["t"]*passengers_data_1["t"]

passengers_data_1["log_psngr"] = np.log(passengers_data_1["Passengers"])
passengers_data_1.head()
```

Out[33]:

Month	Passengers	t	t_squared	log_psngr
1995-01-01	112	1	1	4.718499
1995-02-01	118	2	4	4.770685
1995-03-01	132	3	9	4.882802
1995-04-01	129	4	16	4.859812
1995-05-01	121	5	25	4.795791

7.2 Splitting data :

In [34]:
```python
Train = passengers_data_1.head(84)
Test = passengers_data_1.tail(12)
```

7.3 Linear Model :

In [35]:
```python
import statsmodels.formula.api as smf
```

In [36]:
```python
linear_model = smf.ols('Passengers~t',data = Train).fit()
pred_linear =  pd.Series(linear_model.predict(pd.DataFrame(Test['t'])))
```

In [37]:
```python
rmse_linear_model = RMSE(Test['Passengers'], pred_linear)
print('RMSE Value of Linear :',rmse_linear_model)
```

```
RMSE Value of Linear : 53.19923653480267
```

7.4 Exponential Model :

In [38]:
```python
Exp_model = smf.ols('log_psngr~t',data = Train).fit()
pred_Exp = pd.Series(Exp_model.predict(pd.DataFrame(Test['t'])))
```

In [39]:
```python
rmse_Exp_model = RMSE(Test['Passengers'], np.exp(pred_Exp))
print('RMSE Value of Exponential :',rmse_Exp_model)
```

```
RMSE Value of Exponential : 46.05736110315608
```

7.5 Quadratic Model

In [40]:
```python
Quad_model= smf.ols('Passengers~t+t_squared',data = Train).fit()
pred_Quad = pd.Series(Quad_model.predict(Test[["t","t_squared"]]))
```

In [41]:
```python
rmse_Quad_model = RMSE(Test['Passengers'], pred_Quad)
print('RMSE Value of Quadratic :',rmse_Quad_model)
```

```
RMSE Value of Quadratic : 48.05188897933096
```

8. ARIMA model

In [42]:
```python
series = passengers_data.copy()
series
```

Out[42]:

Month	Passengers
1995-01-01	112
1995-02-01	118
1995-03-01	132
1995-04-01	129
1995-05-01	121
...	...
2002-08-01	405
2002-09-01	355
2002-10-01	306
2002-11-01	271
2002-12-01	306

96 rows × 1 columns

8.1 Separate out a validation dataset :

In [43]:
```python
split_point = len(series) - 12
dataset, validation = series[0:split_point], series[split_point:]
print('Dataset %d, Validation %d' % (len(dataset), len(validation)))
dataset.to_csv('dataset.csv', header = False)
validation.to_csv('validation.csv', header = False)
```

```
Dataset 84, Validation 12
```

8.2 Evaluate a Base model :

In [44]:
```python
from pandas import read_csv
from sklearn.metrics import mean_squared_error
from math import sqrt
```

In [45]:
```python
train = read_csv('dataset.csv', header = None, index_col = 0, parse_dates = True, squeeze = True)
```

In [46]:
```python
X = train.values
X = X.astype('float32')
train_size = int(len(X) * 0.715)
train, test = X[0:train_size], X[train_size:]
```

In [47]:
```python
print(train.shape)
print(test.shape)
```

```
(60,)
(24,)
```

8.3 Walk Farward Validation :

In [48]:
```python
history = [x for x in train]
predictions = list()
```

In [49]:
```python
for i in range(len(test)):
    yhat = history[-1]
    predictions.append(yhat)
# observation
    obs = test[i]
    history.append(obs)
    print('>Predicted=%.3f, Expected=%.3f' % (yhat, obs))
```

```
>Predicted=201.000, Expected=204.000
>Predicted=204.000, Expected=188.000
>Predicted=188.000, Expected=235.000
>Predicted=235.000, Expected=227.000
>Predicted=227.000, Expected=234.000
>Predicted=234.000, Expected=264.000
>Predicted=264.000, Expected=302.000
>Predicted=302.000, Expected=293.000
>Predicted=293.000, Expected=259.000
>Predicted=259.000, Expected=229.000
>Predicted=229.000, Expected=203.000
>Predicted=203.000, Expected=229.000
>Predicted=229.000, Expected=242.000
>Predicted=242.000, Expected=233.000
>Predicted=233.000, Expected=267.000
>Predicted=267.000, Expected=269.000
>Predicted=269.000, Expected=270.000
>Predicted=270.000, Expected=315.000
>Predicted=315.000, Expected=364.000
>Predicted=364.000, Expected=347.000
>Predicted=347.000, Expected=312.000
>Predicted=312.000, Expected=274.000
>Predicted=274.000, Expected=237.000
>Predicted=237.000, Expected=278.000
```

In [50]:
```python
rmse = sqrt(mean_squared_error(test, predictions))
print('RMSE Value : %.3f' % rmse)
```

```
RMSE Value : 29.058
```

In [51]:
```python
rmse_Persistence_model = 29.058
```

9. Conclusion

In [69]:
```python
list = [['Simple Exponential Method',rmse_simple_model], ['Holt method',rmse_holt_model],
          ['Holt exp smoothing add',rmse_holt_add_add_model],['Holt exp smoothing multi',rmse_holt_model_multi_add_model],
          ['Linear Model',rmse_linear_model],['Exponential model',rmse_Exp_model],['Quadratic model',rmse_Quad_model],
          ['Persistence/ Base model', rmse_Persistence_model]]
```

In [70]:
```python
df = pd.DataFrame(list, columns = ['Model', 'RMSE_Value'])
df
```

Out[70]:

	Model	RMSE_Value
0	Simple Exponential Method	68.006740
1	Holt method	58.562099
2	Holt exp smoothing add	63.075855
3	Holt exp smoothing multi	64.622209
4	Linear Model	53.199237
5	Exponential model	46.057361
6	Quadratic model	48.051889
7	Persistence/ Base model	29.058000

In [71]:
```python
sns.barplot(data = df,x = 'Model',y = 'RMSE_Value')
plt.show()
```