In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

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

In [2]:

```
df = pd.read_csv('AirPassengers.csv')
df.head()
```

Out[2]:

	Month	Passengers
0	15-01-1949	112
1	15-02-1949	118
2	15-03-1949	132
3	15-04-1949	129
4	15-05-1949	121

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Month       144 non-null    object
 1   Passengers  144 non-null    int64
dtypes: int64(1), object(1)
memory usage: 2.4+ KB
```

In [4]:

```
df = df.set_index('Month')
df.head()
```

Out[4]:

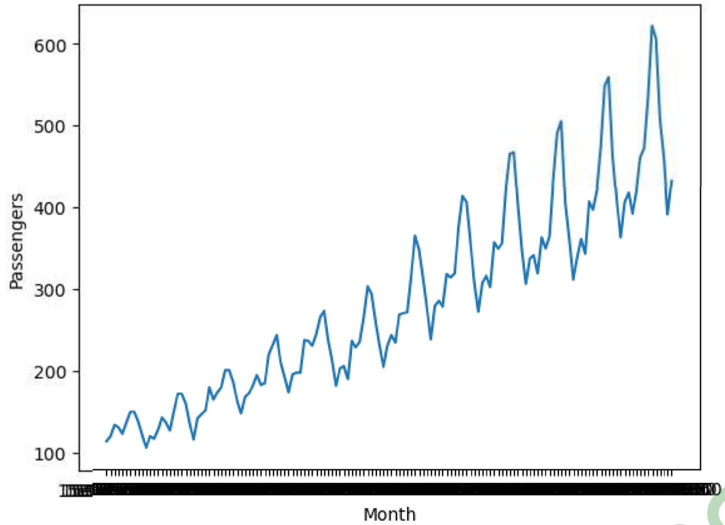
	Passengers
Month	
15-01-1949	112
15-02-1949	118
15-03-1949	132
15-04-1949	129
15-05-1949	121

Visualize the time series

Check for trend, seasonality or random patterns

In [5]:

```
sns.lineplot(x=df.index, y=df['Passengers'])
plt.show()
```



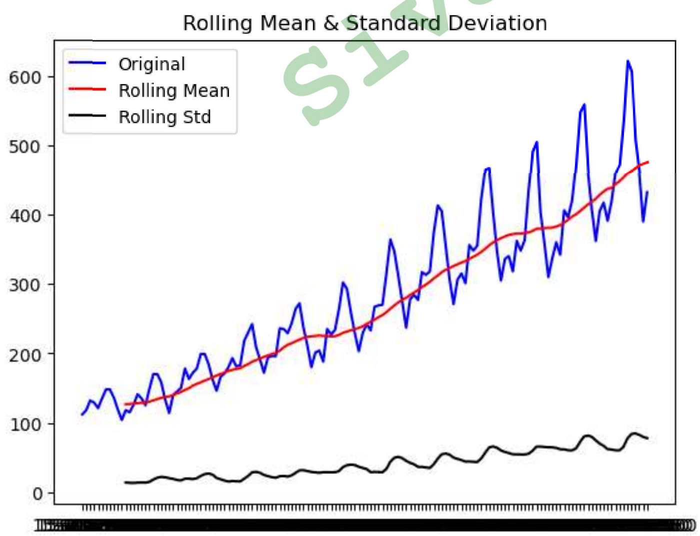
Check for stationarity

Method-1: Rolling Statistics

In [6]:

```
#Determing rolling statistics
rolmean = df['Passengers'].rolling(window=12).mean()
rolstd = df['Passengers'].rolling(window=12).std()

#Plot rolling statistics:
orig = plt.plot(df['Passengers'], color='blue',label='Original')
mean = plt.plot(rolmean, color='red', label='Rolling Mean')
std = plt.plot(rolstd, color='black', label = 'Rolling Std')
plt.title('Rolling Mean & Standard Deviation')
plt.legend()
plt.show()
```



Method 2: Augmented Dicky Fuller Test

- for the ADF Test
  - H0: data is non-stationary
  - H1: data is stationary
- Based on pvalue, we will accept or reject H0 (if p-value < 5% reject null hypothesis)

In [7]:

```
from statsmodels.tsa.stattools import adfuller
adfuller_result = adfuller(df['Passengers'])
adfuller_result
```

Out[7]:

```
(0.8153688792060543,
 0.9918802434376411,
 13,
 130,
 {'1%': -3.4816817173418295,
  '5%': -2.8840418343195267,
  '10%': -2.578770059171598},
 996.692930839019)
```

In [8]:

```
print('p-value:',adfuller_result[1])
```

```
p-value: 0.9918802434376411
```

The time series is not stationary

Now, we have to convert the non-stationary data to stationary data

Differencing

In [9]:

```
# apply differencing
diff = df['Passengers']- df['Passengers'].shift(2)

diff.dropna(inplace=True)

# Applying ADF Test
adfuller_result = adfuller(diff)
print('p-value of adf test:',adfuller_result[1])
```

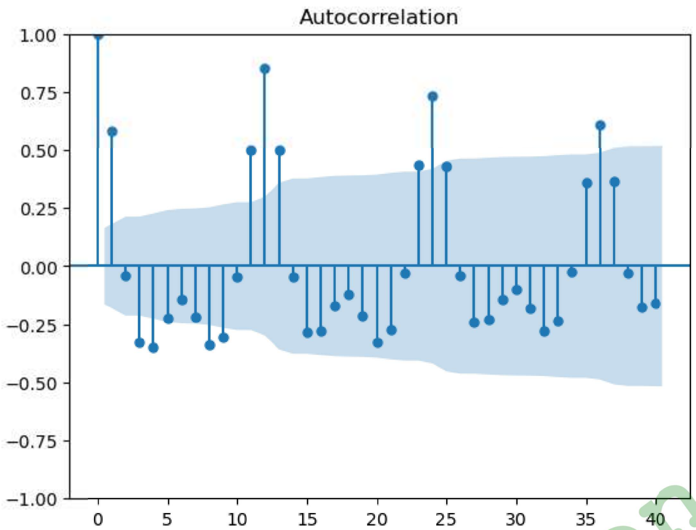
```
p-value of adf test: 0.03862975767698741
```

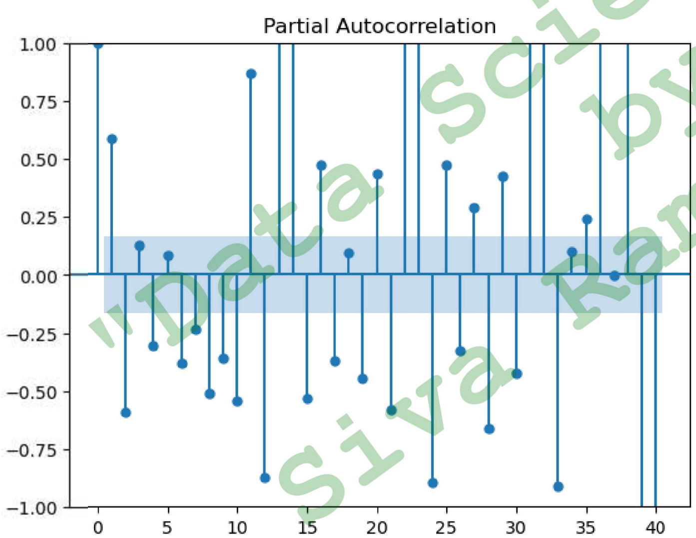
Now, the time series is stationary.

Step-4: Plot ACF/PACF and find p,d,q parameters

In [10]:

```
from statsmodels.tsa.stattools import acf,pacf
import statsmodels.api as sm
fig = sm.graphics.tsa.plot_acf(diff,lags=40)
fig = sm.graphics.tsa.plot_pacf(diff,lags=40)
```





From ACF curve, optimal value of q in the ARIMA model must be 1

From PACF curve, optimal value of p in the ARIMA model is 1

Train-test Split

Split the data into train (80%) & test(20%)

- for time series data, we have use first 80% of records for training & next 20% of records for testing
- here 80% = 0.8*142 = 114 records, so first 114 records we have to use for training

Note: We should not apply train-test split function, because it divides the data randomly

In [11]:

```
y_train = diff[:114]
y_test = diff[114:]
```

Build ARIMA Model

ARIMA Model is build by using p,d,q values

- p is AR value (determined from PACF plot)
- d is intergration
- q is MA value (determined from ACF plot)

Modelling

In [12]:

```
from statsmodels.tsa.arima.model import ARIMA
model = ARIMA(diff, order=(1,2,1))
ARIMA = model.fit()
```

```
C:\Users\admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has been provi
ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has been provi
ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has been provi
ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Prediction

In [13]:

```
ypred_test = ARIMA.predict(start=y_test.index[0], end=y_test.index[-1])
ypred_train = ARIMA.predict(start=y_train.index[0], end=y_train.index[-1])
```

Evaluation

In [14]:

```
from sklearn.metrics import r2_score
print("Train R2",r2_score(ypred_train,y_train))
print("Test R2",r2_score(ypred_test,y_test))
```

```
Train R2 0.34022485430256666
Test R2 0.4239665875806876
```

- **Here, ARIMA model is not performing well, because there is seasonality in the given data**

Build SARIMAX Model

Whenever, there is seasonality in given data, apply SARIMAX

SARIMAX Model is build by using p,d,q,s values

- p is AR value (determined from PACF plot)
- d is intergration
- q is MA value (determined from ACF plot)
- s is seasonality value

Modelling

In [15]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
model = SARIMAX(diff,seasonal_order=(1,2,1,12))
SARIMAX = model.fit()
```

```
C:\Users\admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has been provi
ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: A date index has been provi
ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

Prediction

In [16]:

```
ypred_train = SARIMAX.predict(start=y_train.index[0], end=y_train.index[-1])
ypred_test = SARIMAX.predict(start=y_test.index[0], end=y_test.index[-1])
```

Evaluation

In [17]:

```
from sklearn.metrics import r2_score
print("Train R2 of SARIMAX model: ",r2_score(ypred_train,y_train))
print("Test R2 of SARIMAX model: ",r2_score(ypred_test,y_test))
```

```
Train R2 of SARIMAX model:  0.9053226759209412
Test R2 of SARIMAX model:  0.9540352226751071
```