In [94]:

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

In [95]:

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

In [96]:

```
df = pd.read_csv('/content/Airline_Passangers.csv')
```

In [97]:

```
df.head(3)
```

Out[97]:

	Month	Passengers
0	1949-01	112
1	1949-02	118
2	1949-03	132

In [98]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima_model import ARIMA
```

In [99]:

```
from statsmodels.stats.stattools import durbin_watson
from statsmodels.tsa.stattools import adfuller
```

In [100]:

```
from sklearn.metrics import mean_squared_error
```

In [101]:

```
dw_stats = durbin_watson(df.Passengers)
dw_stats
```

Out[101]:

```
0.0121527966037621
```

Inference from dw stats = Positively autocorrelated data

In [102]:

```
dickey_fuller = adfuller(x = df.Passengers)
dickey_fuller
```

Out[102]:

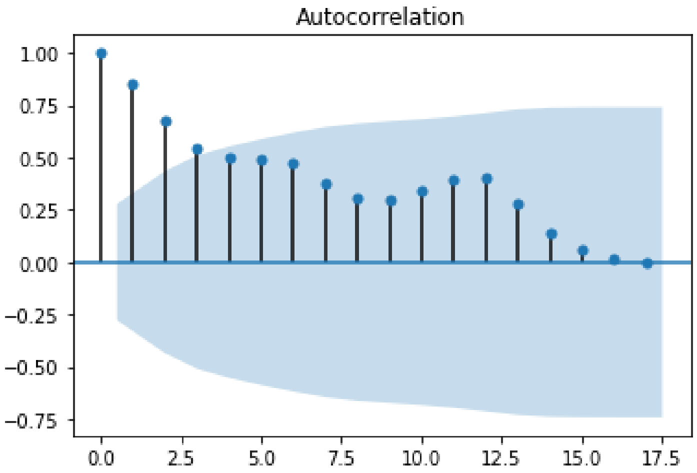
```
(0.8153688792060472,
 0.991880243437641,
 13,
 130,
 {'1%': -3.4816817173418295,
  '5%': -2.8840418343195267,
```

```
'10%': -2.578770059171598},
996.6929308390189)
```

Inference from dickey_fuller stats: p-val > 0.05, Hence we fail to reject null hypothesis. So, data is non stationary

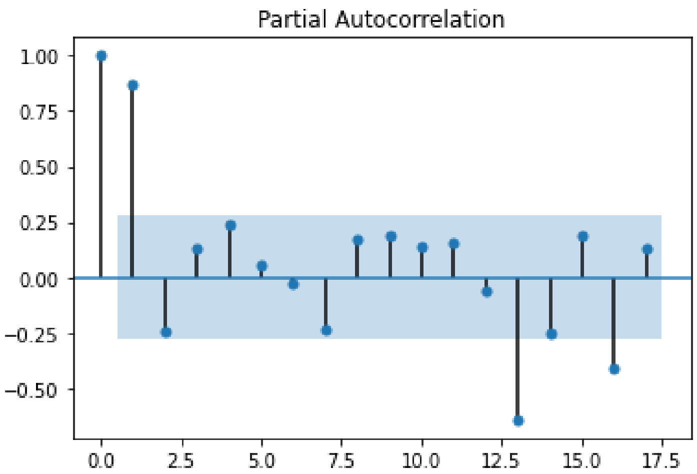
In [103]:

```
acf = plot_acf(df.Passengers[0:50])
```



In [104]:

```
pacf = plot_pacf(df.Passengers[0:50])
```



Inference:

- **ACF plot gradually reduces to 0 after several 'q' lags (data shows signs of non-stationarity) => the same was confirmed by Dickey Fuller Test**
- **PACF plot immediately reduces to 0 after p = 1 lag**

Building AR(p) model:

- **order = (1,0,0)**

In [105]:

```
order = (1,0,0)
```

In [106]:

```
model = ARIMA(df.Passengers[0:50], order = order)
```

In [107]:

```
AR_model = model.fit()
```

In [108]:

```
AR_model.summary2()
```

Out[108]:

Model:	ARMA	**BIC:**	427.9663
Dependent Variable:	Passengers	**Log-Likelihood:**	-208.12
Date:	2022-08-29 11:12	**Scale:**	1.0000
No. Observations:	50	**Method:**	css-mle
Df Model:	2	**Sample:**	0
Df Residuals:	48		0
Converged:	1.0000	**S.D. of innovations:**	15.289
No. Iterations:	15.0000	**HQIC:**	424.415
AIC:	422.2303		

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
const	158.3756	17.9118	8.8420	0.0000	123.2692	193.4821
ar.L1.Passengers	0.8958	0.0618	14.4952	0.0000	0.7747	1.0169

	Real	Imaginary	Modulus	Frequency
AR.1	1.1164	0.0000	1.1164	0.0000

Since, p-val < 0 => Hence, p = 1 lag (1st lag in PACF plot) is a significant variable in determining the autoregression of Passengers

In [109]:

```
AR_model.pvalues
```

Out[109]:

```
const               9.403805e-19
ar.L1.Passengers    1.300136e-47
dtype: float64
```

In [110]:

```
AR_forecast = np.round(AR_model.predict(50,60),0)
```

In [111]:

```
AR_actual = df.Passengers[50:60]
```

In [112]:

```
df_forecast = pd.DataFrame({'AR_actual':AR_actual,'AR_forecast':AR_forecast})
```

In [113]:

```
df_forecast
```

Out[113]:

	AR_actual	AR_forecast
50	236.0	192.0
51	235.0	189.0
52	229.0	185.0
53	243.0	183.0

	AR_actual	AR_forecast
54	264.0	180.0
55	272.0	178.0
56	237.0	176.0
57	211.0	174.0
58	180.0	172.0
59	201.0	171.0
60	NaN	170.0

In [114]:

```
def get_mape(actual, pred):
  mape = np.round(np.mean(np.abs(100*(actual-pred)/actual)),2)
  return mape
```

In [115]:

```
AR_mape = get_mape(df_forecast.AR_actual[:9], df_forecast.AR_forecast[:9])
AR_mape
```

Out[115]:

```
21.8
```

In [116]:

```
AR_rmse = np.round(np.sqrt(mean_squared_error(df_forecast.AR_actual[:9], df_forecast.AR_
forecast[:9])),2)
AR_rmse
```

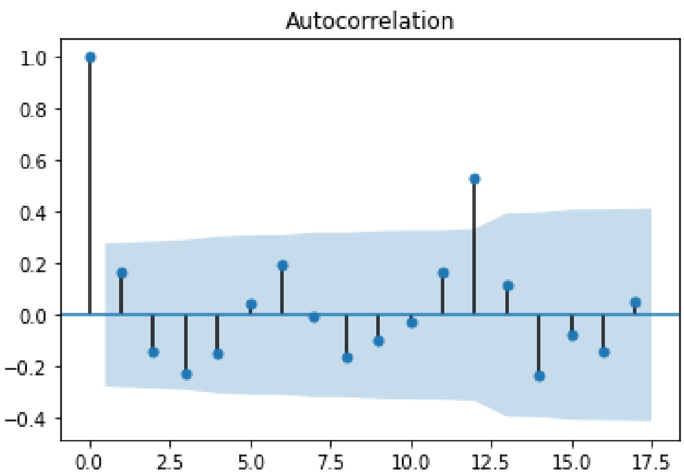
Out[116]:

```
58.34
```

Plotting ACF and PACF plots for AR model residuals:

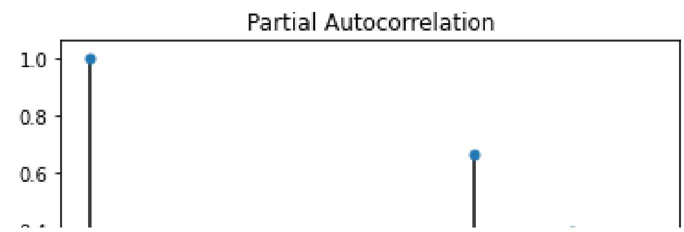
In [117]:

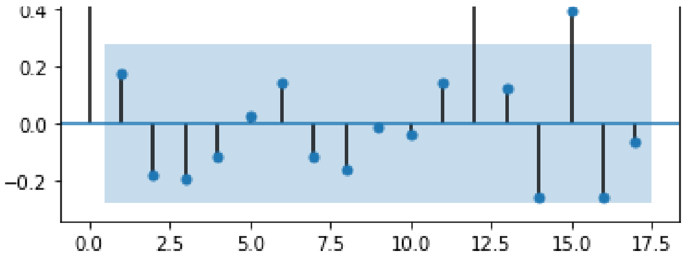
```
acf_resid = plot_acf(AR_model.resid)
```



In [118]:

```
pacf_resid = plot_pacf(AR_model.resid)
```





Both ACF and PACF plots of AR model residuals immediately reduce to 0. This shows that AR model residuals are white noise and are not autocorrelated.

In [ ]: