In this Homework 3, we will be using a public data set called Air Passenger which recorded the number of passenger

every year from 1949 to 1960. We will apply various techniques to the data set in order to obtain

a good SARIMA model that we will be used for forecasting. The accuracy of model will be tested using RMSE.

the references used for this excerce is at the bottom

In [36]:
```
import pandas as pd
import numpy as np
from scipy.stats import norm
import statsmodels.api as sm
import seaborn as sns
import matplotlib.pylab as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.dpi']= 80
sns.set_style("whitegrid")
sns.set_context("poster")
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
```

1.Descriptive Statistics

In [12]:
```
#Load the dataset into pandas dataframe
mydate = lambda dates: pd.datetime.strptime(dates,'%Y-%m')
data =pd.read_csv('AirPassengers.csv',parse_dates=['Month'],index_col='Month',date
data = data.rename(columns={'#Passengers': 'NumberPassenger'})
```

In [13]:
```
# check the first 5 elements
data.head()
```

Out[13]:

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

In [14]:
```
# check the last 5 elements
data.tail()
```

Out[14]:

	NumberPassenger
Month	
1960-08-01	606
1960-09-01	508
1960-10-01	461
1960-11-01	390
1960-12-01	432

In [15]:
```
# check out some descriptive statistics
data.describe()
```

Out[15]:

	NumberPassenger
count	144.000000
mean	280.298611
std	119.966317
min	104.000000
25%	180.000000
50%	265.500000
75%	360.500000
max	622.000000

In [16]:
```
# check the variance
data.var()
```

Out[16]:
```
NumberPassenger    14391.917201
dtype: float64
```

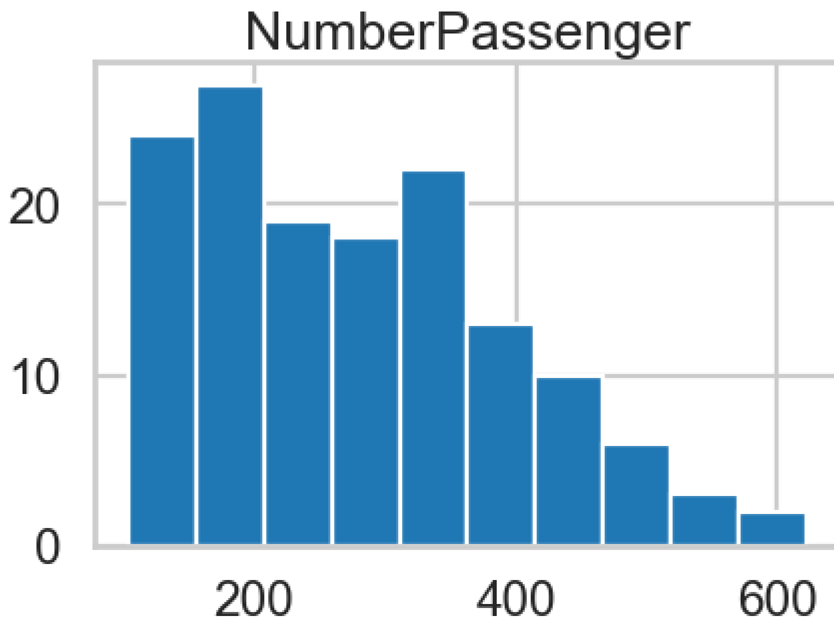
In [17]:
```
# check the data type of the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 144 entries, 1949-01-01 to 1960-12-01
Data columns (total 1 columns):
NumberPassenger    144 non-null int64
dtypes: int64(1)
memory usage: 2.2 KB
```

2.Visualization

In [18]:
```
# check the histogram
data.hist()
```

Out[18]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000288E8884828>]],
      dtype=object)
```



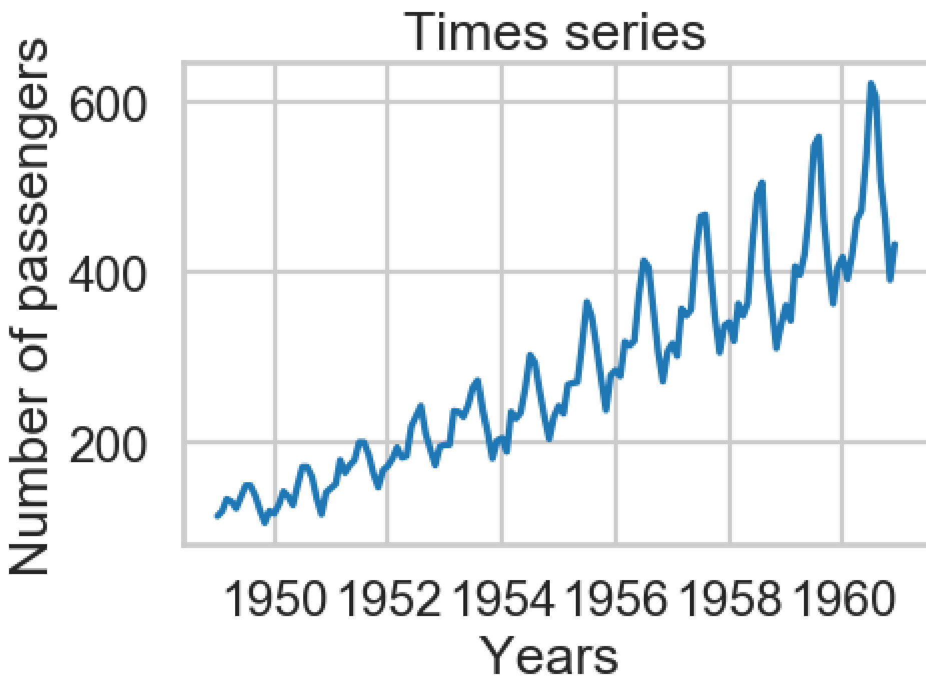
In [19]:
```
# we will consider the column Month as index of the dataset
data.index
```

Out[19]:
```
DatetimeIndex(['1949-01-01', '1949-02-01', '1949-03-01', '1949-04-01',
               '1949-05-01', '1949-06-01', '1949-07-01', '1949-08-01',
               '1949-09-01', '1949-10-01',
               ...
               '1960-03-01', '1960-04-01', '1960-05-01', '1960-06-01',
               '1960-07-01', '1960-08-01', '1960-09-01', '1960-10-01',
               '1960-11-01', '1960-12-01'],
              dtype='datetime64[ns]', name='Month', length=144, freq=None)
```

A time series is stationary if the mean and the variance remain constant over time

In [20]:
```
plt.plot(data)   ## plot the data to see if there is a trend or seasonal
plt.title("Times series")
plt.xlabel("Years ")
plt.ylabel("Number of passengers")
```

Out[20]:
```
Text(0, 0.5, 'Number of passengers')
```



By looking the output, it is very clear there is an overall increasing trend

We will split the data into 70% training and 30% testing

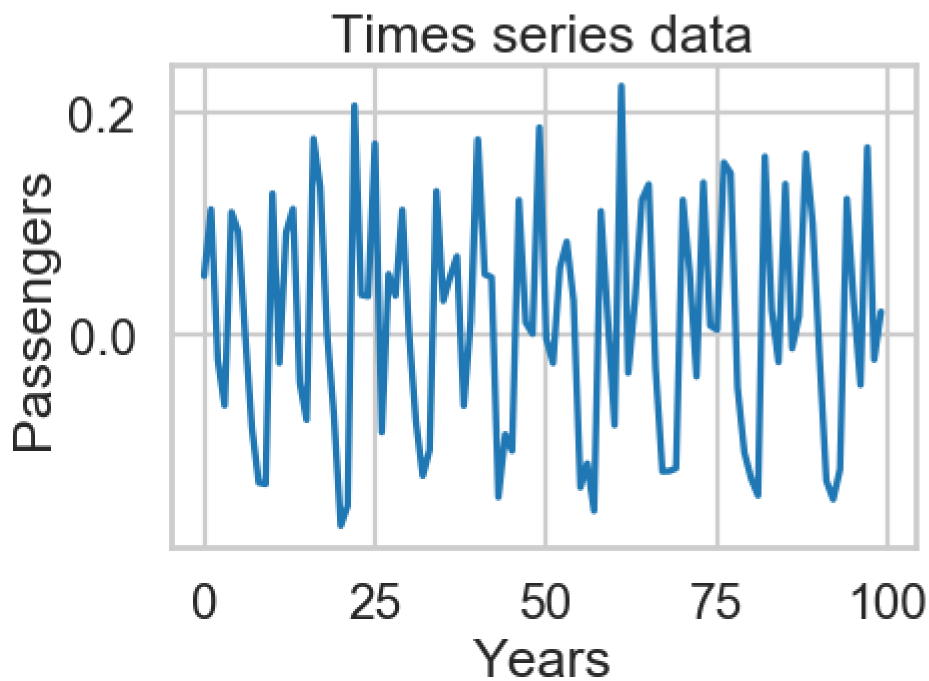
In [21]:
```
trainigPercent =0.70   ## percentage of the training set
splitdata=round(len(data)*trainigPercent)
training, testing=data[0:splitdata],data[splitdata:]  ## we split into training an
```

3.Eliminating trend

We have a multiplicative seasonality, so we will apply a log filter and then analyze the residuals with autocorrelation plots.

In [22]:
```
# data is multiplicative we apply log to transform
training =np.log(training)
# since we have positive linear trend we apply differencing of 1 period
training_diff =training.diff(periods=1).values[1:]

# we plot the residual difference
plt.plot(training_diff)
plt.title("Times series data")
plt.xlabel("Years")
plt.ylabel("Passengers")
```

Out[22]:
```
Text(0, 0.5, 'Passengers')
```



We see here that there is no more a multiplicative affect and no more trend.

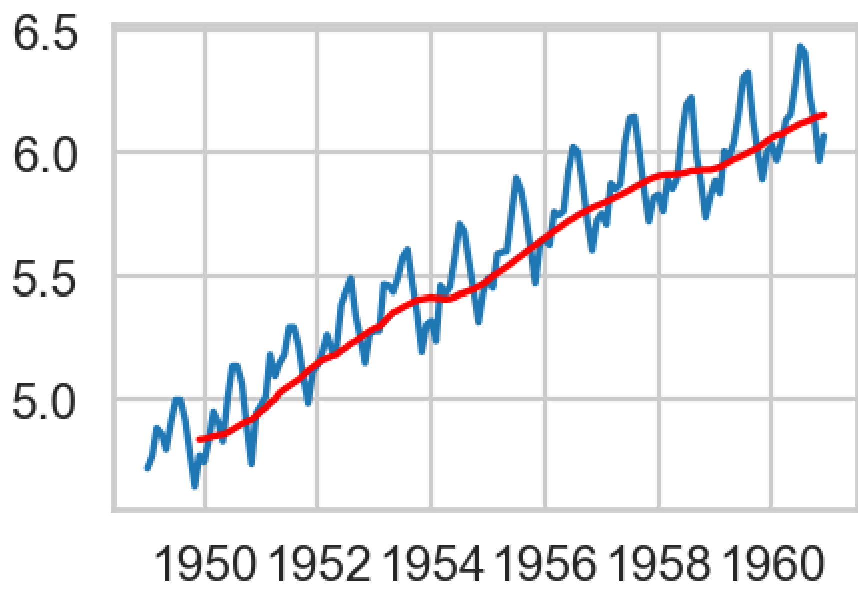
It indicates that we need to remove the seasonal pattern which can be done with SARIMA.

We can select the seasonal pattern parameters of SARIMA by looking at the ACF and PACF plots.

Autocorrelation function(ACF) and Partial autocorrelation function(PACF)

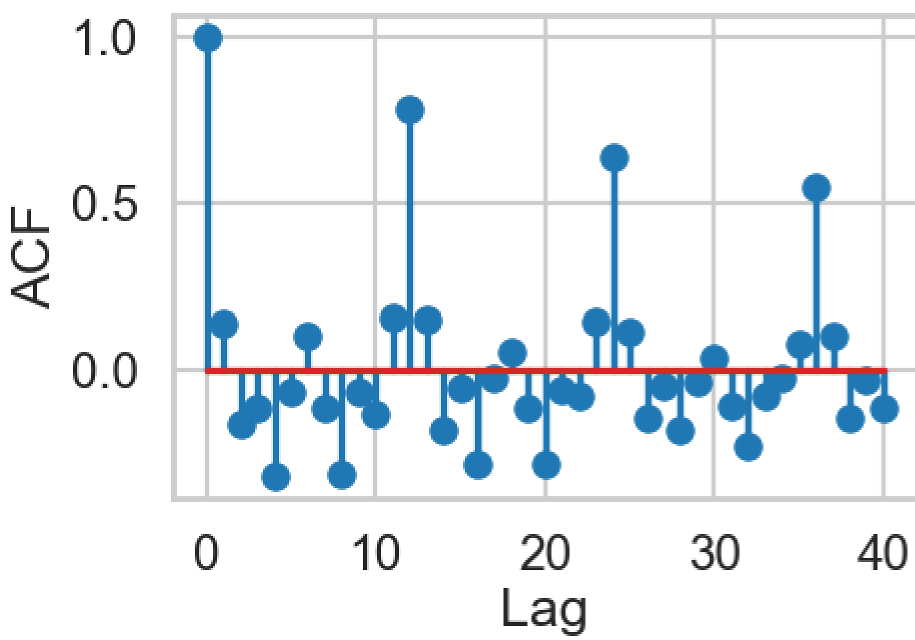
In [23]:
```
data_log=np.log(data)
moving_avg = data_log.rolling(12).mean()
plt.plot(data_log)
plt.plot(moving_avg, color='red')
```

Out[23]: [<matplotlib.lines.Line2D at 0x288e89bd1d0>]



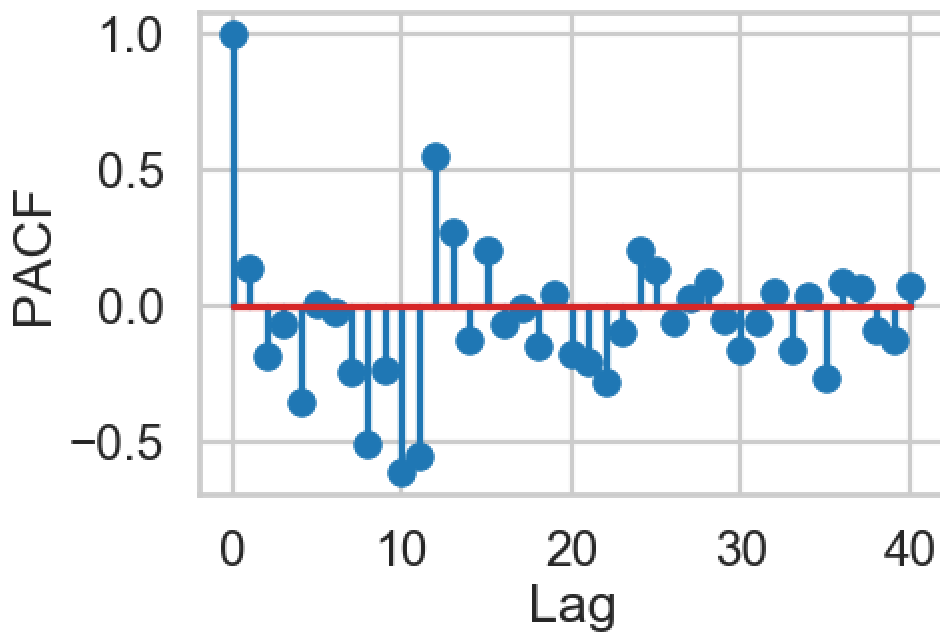
In [24]:
```
#import auto correlation and partial autocorrelation function
from statsmodels.tsa.stattools import acf,pacf
log_acf=acf(training_diff,nlags=40)
log_pacf=pacf(training_diff,nlags=40,method='ols')

#plot ACF
plt.stem(log_acf)
plt.xlabel("Lag")
plt.ylabel("ACF")
```

Out[24]: `Text(0, 0.5, 'ACF')`



In [25]:
```
#plot ACF
plt.stem(log_pacf)
plt.xlabel("Lag")
plt.ylabel("PACF")
```

Out[25]: Text(0, 0.5, 'PACF')



4.Quick rappel of the SARIMA Model is in the form (p,d,q) (P,D,Q)S

Looking at the ACF and PACF plots we see our first significant value at lag 4 for ACF

At the same lag 4 for the PACF which suggest to use p = 4 and q = 4.

We also have a big value at lag 12 in the ACF plot which suggests our season is S = 12 and

since this lag is positive it suggests P = 1 and Q = 0.

Since this is a differenced series for SARIMA we set d = 1

since the seasonal pattern is not stable over time we set D = 0.

All together this gives us a SARIMA(4,1,4)(1,0,0)[12] model.

SARIMA(4,1,4)(1,0,0)[12] model, we will run and fit a model on our training data.

In [26]:
```
# we create the SARIAMX model object
model=SARIMAX(training,order=(4,1,4),seasonal_order=(1,0,0,12),enforce_stationarit
## Fit the model
model_fit =model.fit(disp=False)
```

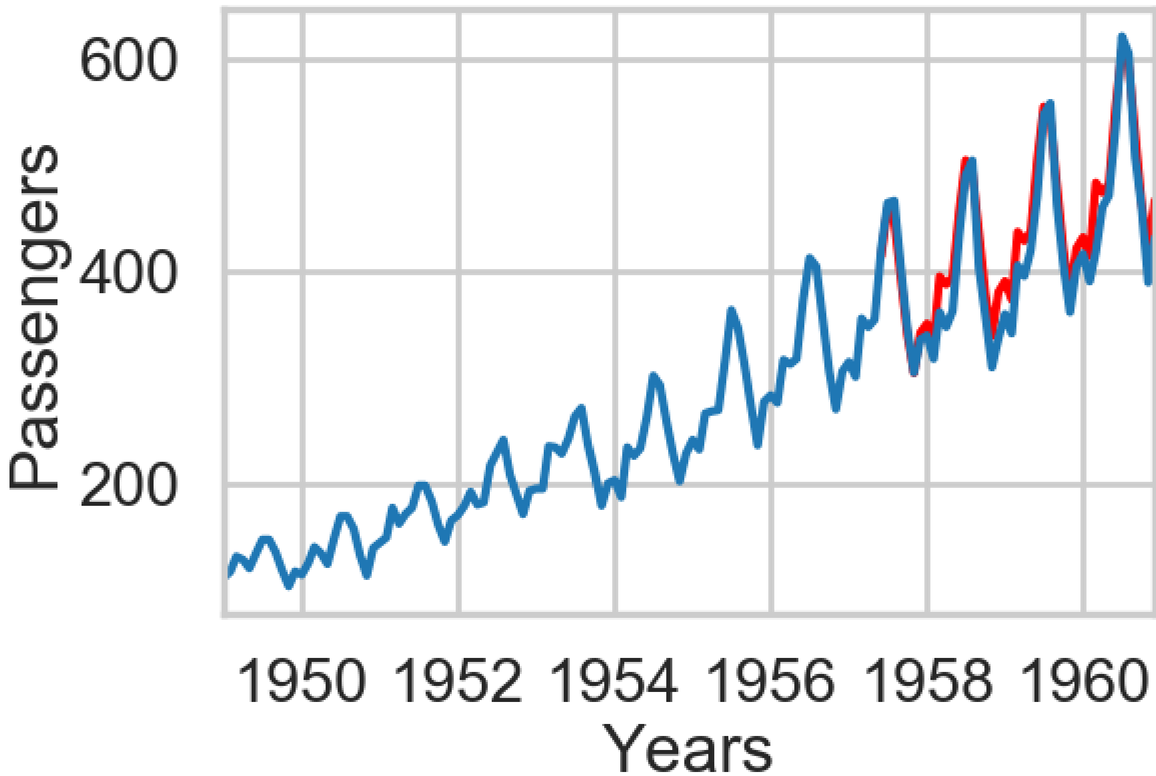
```
c:\users\diall\appdata\local\programs\python\python37\lib\site-packages\statsm
odels\tsa\base\tsa_model.py:171: ValueWarning: No frequency information was pr
ovided, so inferred frequency MS will be used.
  % freq, ValueWarning)
c:\users\diall\appdata\local\programs\python\python37\lib\site-packages\statsm
odels\base\model.py:508: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  "Check mle_retvals", ConvergenceWarning)
```

5.Forecasting processing

In [27]:
```
R =len(testing)        #number of furture steps times we want to forecast
forecast=model_fit.forecast(R) # forcast for k times
forecast=np.exp(forecast) # return to the origin without the log
predictions =model_fit.predict()
```

6.Display forcasting result

In [172]:
```
plt.plot(forecast,'r')
plt.plot(data)
plt.xlabel("Years")
plt.ylabel("Passengers")
plt.autoscale(enable=True,axis='x',tight=True)
```



Test accuracy with Root Mean Square Error (RMSE)

In [37]:
```
ms =mean_squared_error(testing,forecast)
rmse =np.sqrt(ms)
print(rmse)
```

```
24.378405408785316
```

the RMSE is 24.37 which is low that indicates the model fits the data very well

The output shows that the model fit well the data

In [173]:
```python
# we will print the summary of the model
print(model_fit.summary())
```

```
                           Statespace Model Results                           
==============================================================================
============
Dep. Variable:                        #Passengers   No. Observations:         
101
Model:             SARIMAX(4, 1, 4)x(1, 0, 0, 12)   Log Likelihood            
144.138
Date:                            Mon, 25 Feb 2019   AIC                       
-268.275
Time:                                    20:52:20   BIC                       
-243.967
Sample:                                01-01-1949   HQIC                      
-258.504
                                     - 05-01-1957                             
Covariance Type:                              opg                             
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.1331      1.091      0.122      0.903      -2.005       2.271
ar.L2         -0.5250      0.283     -1.852      0.064      -1.081       0.031
ar.L3         -0.4051      0.773     -0.524      0.600      -1.920       1.110
ar.L4          0.3029      0.621      0.488      0.626      -0.914       1.520
ma.L1         -0.5288      1.066     -0.496      0.620      -2.617       1.560
ma.L2          0.7340      0.362      2.027      0.043       0.024       1.444
ma.L3         -0.0374      0.891     -0.042      0.967      -1.784       1.709
ma.L4         -0.2398      0.244     -0.982      0.326      -0.719       0.239
ar.S.L12       0.9681      0.038     25.571      0.000       0.894       1.042
sigma2         0.0018      0.000      4.832      0.000       0.001       0.003
==============================================================================
=====
Ljung-Box (Q):                       41.93   Jarque-Bera (JB):                
0.15
Prob(Q):                              0.39   Prob(JB):                        
0.93
Heteroskedasticity (H):               0.31   Skew:                            
0.10
Prob(H) (two-sided):                  0.00   Kurtosis:                        
2.98
==============================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex
-step).
```

References

[http://www.blackarbs.com/blog/time-series-analysis-in-python-linear-models-to-garch/11/1/2016 (http://www.blackarbs.com/blog/time-series-analysis-in-python-linear-models-to-garch/11/1/2016)](http://www.blackarbs.com/blog/time-series-analysis-in-python-linear-models-to-garch/11/1/2016)

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[https://www.digitalocean.com/community/tutorials/a-guide-to-time-series-visualization-with-python-3 (https://www.digitalocean.com/community/tutorials/a-guide-to-time-series-visualization-with-python-3)](https://www.digitalocean.com/community/tutorials/a-guide-to-time-series-visualization-with-python-3)

https://www.statsmodels.org/dev/examples/notebooks/generated/statespa
(https://www.statsmodels.org/dev/examples/notebooks/generated/statesp

In [ ]: