```
In [1]:
         import numpy as np
          import pandas as pd
          import matplotlib.pylab as plt
         %matplotlib inline
         from matplotlib.pylab import rcParams
         rcParams['figure.figsize'] = 10, 6
          import warnings
         warnings.filterwarnings('ignore')
In [2]:
         dataset=pd.read excel("C:\\Users\\Admin\\Downloads\\assignment 10\\Airlines+Data.xlsx")
         dataset.head()
Out[2]:
               Month Passengers
         0 1995-01-01
                             112
          1995-02-01
                             118
           1995-03-01
                             132
           1995-04-01
                             129
          1995-05-01
                             121
In [3]:
         dataset['Month'] = pd.to_datetime(dataset['Month'], infer_datetime_format=True)
          indexedDataset = dataset.set index(['Month'])
In [4]:
         from datetime import datetime
         indexedDataset['1995-03']
          indexedDataset['1995-03':'1995-06']
         indexedDataset['1995']
Out[4]:
                    Passengers
             Month
         1995-01-01
                          112
         1995-02-01
                          118
         1995-03-01
                          132
                          129
         1995-04-01
         1995-05-01
                          121
         1995-06-01
                          135
         1995-07-01
                          148
         1995-08-01
                          148
         1995-09-01
                          136
         1995-10-01
                          119
```

1995-11-01

104

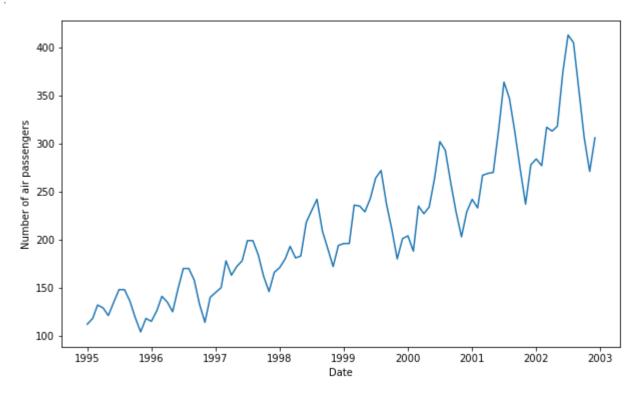
## **Passengers**

#### Month

**1995-12-01** 118

```
plt.xlabel("Date")
  plt.ylabel("Number of air passengers")
  plt.plot(indexedDataset)
```

Out[5]: [<matplotlib.lines.Line2D at 0x203ba0d13d0>]



```
rolmean = indexedDataset.rolling(window=12).mean()
rolstd = indexedDataset.rolling(window=12).std()
print(rolmean, rolstd)
```

	Passengers	
Month		
1995-01-01	NaN	
1995-02-01	NaN	
1995-03-01	NaN	
1995-04-01	NaN	
1995-05-01	NaN	
• • •	• • •	
2002-08-01	316.833333	
2002-09-01	320.416667	
2002-10-01	323.083333	
2002-11-01	325.916667	
2002-12-01	328.250000	
[06 pour v	1 columns]	Dassangans
[96 rows x	I COTUMNS]	Passengers
1995-01-01	NaN	
1995-02-01	NaN	

```
1995-03-01
                    NaN
1995-04-01
                    NaN
1995-05-01
                    NaN
2002-08-01
             54.530781
2002-09-01
             55.586883
2002-10-01
             53.899668
2002-11-01
             49.692616
2002-12-01
             47.861780
[96 rows x 1 columns]
```

```
In [7]:
    orig = plt.plot(indexedDataset, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)
```

# Rolling Mean & Standard Deviation Original 400 Rolling Mean Rolling Std 350 300 250 200 150 100 50 0 1995 1996 1997 1998 1999 2000 2001 2002 2003

```
from statsmodels.tsa.stattools import adfuller

print ('Results of Dickey-Fuller Test:')
   dftest = adfuller(indexedDataset['Passengers'], autolag='AIC')
   dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Numbe
   for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
   print(dfoutput)
```

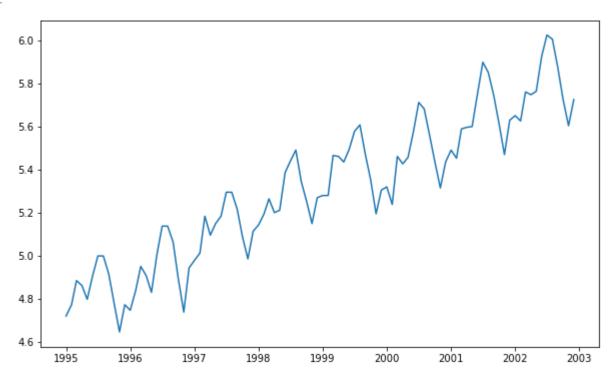
```
Results of Dickey-Fuller Test:
Test Statistic 1.340248
p-value 0.996825
#Lags Used 12.000000
Number of Observations Used 83.000000
Critical Value (1%) -3.511712
```

Critical Value (5%) -2.897048 Critical Value (10%) -2.585713

dtype: float64

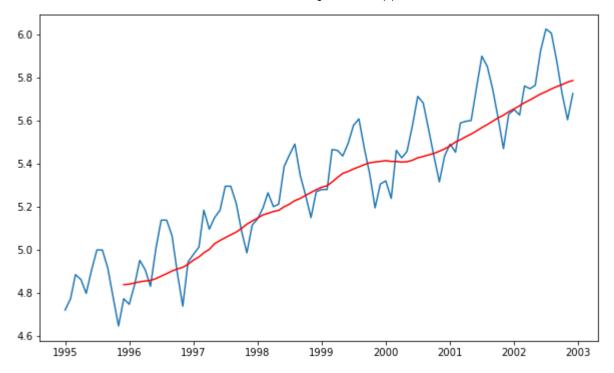
```
indexedDataset_logScale = np.log(indexedDataset)
plt.plot(indexedDataset_logScale)
```

Out[9]: [<matplotlib.lines.Line2D at 0x203bcf002b0>]



```
In [10]:
    movingAverage = indexedDataset_logScale.rolling(window=12).mean()
    movingSTD = indexedDataset_logScale.rolling(window=12).std()
    plt.plot(indexedDataset_logScale)
    plt.plot(movingAverage, color='red')
```

Out[10]: [<matplotlib.lines.Line2D at 0x203bd51d190>]



In [11]:

datasetLogScaleMinusMovingAverage = indexedDataset\_logScale - movingAverage
datasetLogScaleMinusMovingAverage.head(12)

#Remove Nan Values

datasetLogScaleMinusMovingAverage.dropna(inplace=True)
datasetLogScaleMinusMovingAverage.head(10)

### Out[11]:

## **Passengers**

Month	
1995-12-01	-0.065494
1996-01-01	-0.093449
1996-02-01	-0.007566
1996-03-01	0.099416
1996-04-01	0.052142
1996-05-01	-0.027529
1996-06-01	0.139881
1996-07-01	0.260184
1996-08-01	0.248635
1996-09-01	0.162937

In [12]:

```
from statsmodels.tsa.stattools import adfuller
def test_stationarity(timeseries):

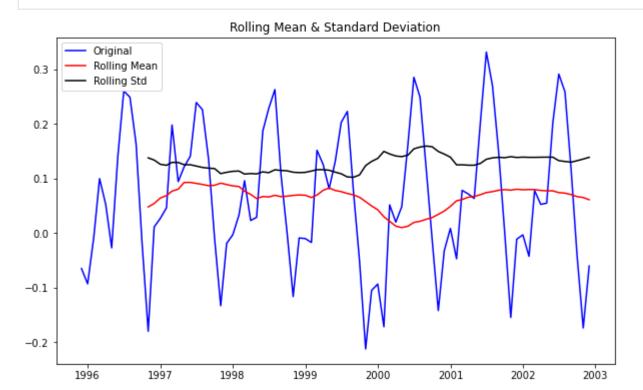
    #Determing rolling statistics
    movingAverage = timeseries.rolling(window=12).mean()
    movingSTD = timeseries.rolling(window=12).std()
```

```
#Plot rolling statistics:
orig = plt.plot(timeseries, color='blue',label='Original')
mean = plt.plot(movingAverage, color='red', label='Rolling Mean')
std = plt.plot(movingSTD, color='black', label = 'Rolling Std')
plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation')
plt.show(block=False)

#Perform Dickey-Fuller test:
print('Results of Dickey-Fuller Test:')
dftest = adfuller(timeseries['Passengers'], autolag='AIC')
dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','N
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value
print(dfoutput)
```

In [13]:

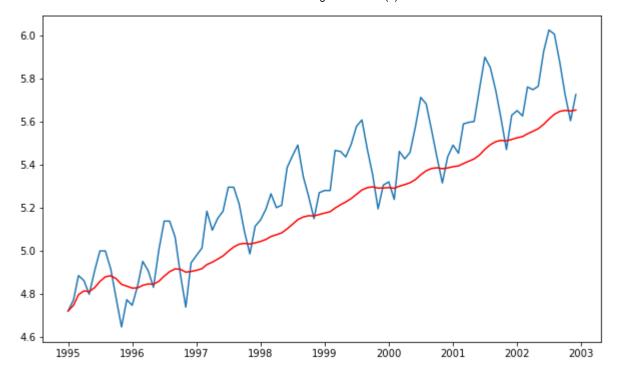
test\_stationarity(datasetLogScaleMinusMovingAverage)



```
Results of Dickey-Fuller Test:
Test Statistic
                                -1.910930
p-value
                                 0.326937
#Lags Used
                                12.000000
Number of Observations Used
                                72.000000
Critical Value (1%)
                                -3.524624
Critical Value (5%)
                                -2.902607
Critical Value (10%)
                                -2.588679
dtype: float64
```

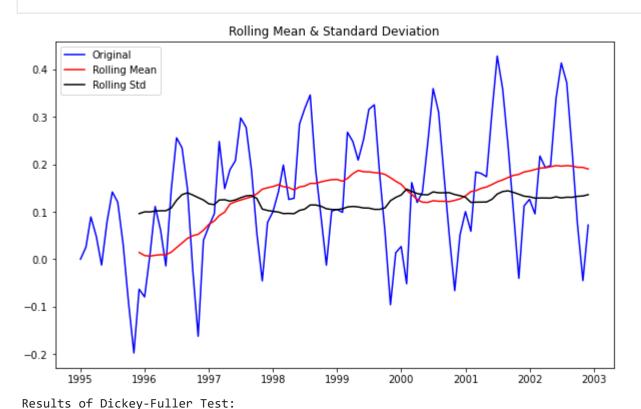
```
exponentialDecayWeightedAverage = indexedDataset_logScale.ewm(halflife=12, min_periods=
plt.plot(indexedDataset_logScale)
plt.plot(exponentialDecayWeightedAverage, color='red')
```

Out[14]: [<matplotlib.lines.Line2D at 0x203bd498f70>]



In [15]:

datasetLogScaleMinusMovingExponentialDecayAverage = indexedDataset\_logScale - exponenti
test\_stationarity(datasetLogScaleMinusMovingExponentialDecayAverage)



Test Statistic -2.835036
p-value 0.053441
#Lags Used 12.000000
Number of Observations Used 83.000000
Critical Value (1%) -3.511712

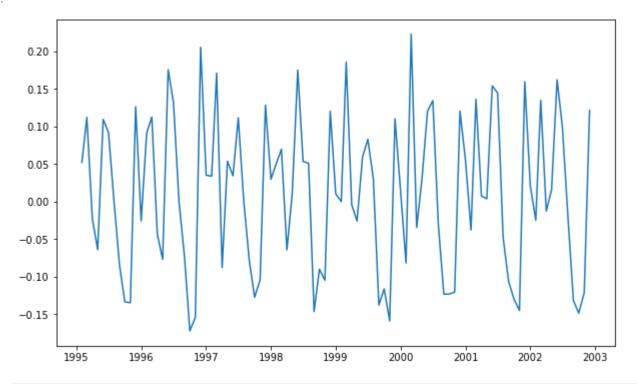
Critical Value (1%) -3.511712 Critical Value (5%) -2.897048 Critical Value (10%) -2.585713

dtype: float64

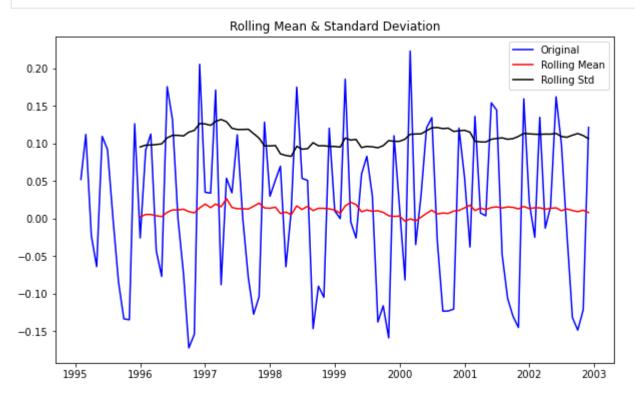
In [16]:

datasetLogDiffShifting = indexedDataset\_logScale - indexedDataset\_logScale.shift()
plt.plot(datasetLogDiffShifting)

Out[16]: [<matplotlib.lines.Line2D at 0x203bd5714f0>]



In [17]: datasetLogDiffShifting.dropna(inplace=True)
 test\_stationarity(datasetLogDiffShifting)



Results of Dickey-Fuller Test:

Test Statistic -2.670823
p-value 0.079225
#Lags Used 12.000000
Number of Observations Used 82.000000

Critical Value (1%)

Critical Value (5%)

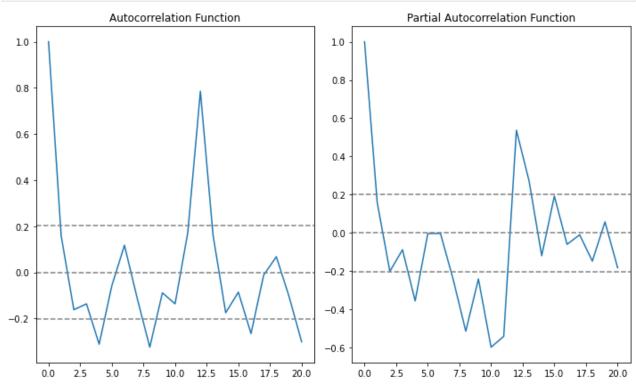
-3.512738

-2.897490

```
Critical Value (10%)
                                            -2.585949
          dtype: float64
In [18]:
           from statsmodels.tsa.seasonal import seasonal decompose
           decomposition = seasonal decompose(indexedDataset logScale)
           trend = decomposition.trend
           seasonal = decomposition.seasonal
           residual = decomposition.resid
           plt.subplot(411)
           plt.plot(indexedDataset logScale, label='Original')
           plt.legend(loc='best')
           plt.subplot(412)
           plt.plot(trend, label='Trend')
           plt.legend(loc='best')
           plt.subplot(413)
           plt.plot(seasonal, label='Seasonality')
           plt.legend(loc='best')
           plt.subplot(414)
           plt.plot(residual, label='Residuals')
           plt.legend(loc='best')
           plt.tight_layout()
                    Original
             5
                 1995
                           1996
                                      1997
                                                1998
                                                           1999
                                                                      2000
                                                                                2001
                                                                                          2002
                                                                                                     2003
                   Trend
           5.5
           5.0
                       1996
                                   1997
                                               1998
                                                           1999
                                                                       2000
                                                                                   2001
                                                                                               2002
           0.2
           0.0
                    Seasonality
          -0.2
                 1995
                           1996
                                      1997
                                                1998
                                                           1999
                                                                      2000
                                                                                2001
                                                                                          2002
                                                                                                     2003
           0.0
                    Residuals
          -0.1
                                   1997
                       1996
                                               1998
                                                           1999
                                                                       2000
                                                                                   2001
                                                                                               2002
In [19]:
           from statsmodels.tsa.stattools import acf, pacf
           lag_acf = acf(datasetLogDiffShifting, nlags=20)
           lag pacf = pacf(datasetLogDiffShifting, nlags=20, method='ols')
           #PLot ACF:
           plt.subplot(121)
```

```
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
plt.title('Autocorrelation Function')

#Plot PACF:
plt.subplot(122)
plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',color='gray')
plt.title('Partial Autocorrelation Function')
plt.tight_layout()
```



```
from statsmodels.tsa.arima_model import ARIMA

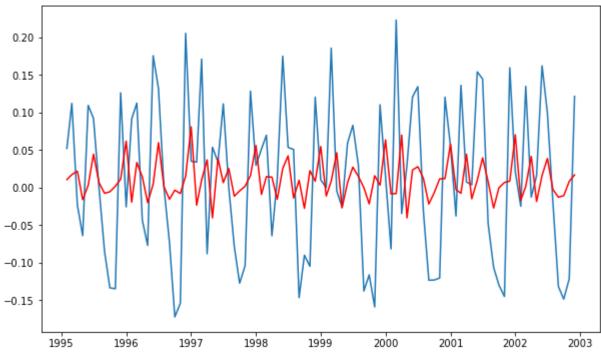
#AR MODEL
model = ARIMA(indexedDataset_logScale, order=(2, 1, 0))
results_AR = model.fit(disp=-1)
plt.plot(datasetLogDiffShifting)
plt.plot(results_AR.fittedvalues, color='red')
plt.title('RSS: %.4f'% sum((results_AR.fittedvalues-datasetLogDiffShifting["Passengers"
print('Plotting AR model')
```

C:\Users\Admin\anaconda3\lib\site-packages\statsmodels\tsa\_base\tsa\_model.py:524: ValueW
arning: No frequency information was provided, so inferred frequency MS will be used.
 warnings.warn('No frequency information was'
C:\Users\Admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:524: ValueW
arning: No frequency information was provided, so inferred frequency MS will be used.

Plotting AR model

warnings.warn('No frequency information was'

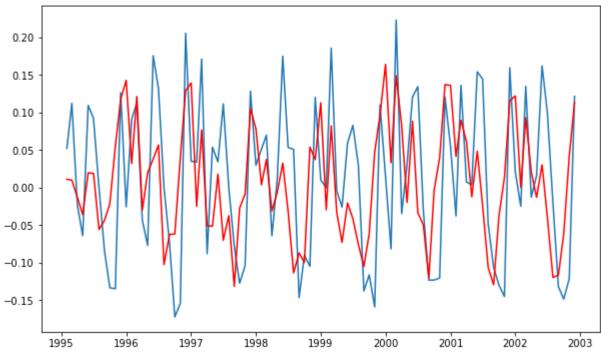
RSS: 0.9508



C:\Users\Admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:524: ValueW
arning: No frequency information was provided, so inferred frequency MS will be used.
 warnings.warn('No frequency information was'

C:\Users\Admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:524: ValueW arning: No frequency information was provided, so inferred frequency MS will be used. warnings.warn('No frequency information was' Plotting AR model

RSS: 0.8278



```
In [22]:
    model = ARIMA(indexedDataset_logScale, order=(2, 1, 2))
    results_ARIMA = model.fit(disp=-1)
    plt.plot(datasetLogDiffShifting)
    plt.plot(results_ARIMA.fittedvalues, color='red')
    plt.title('RSS: %.4f'% sum((results_ARIMA.fittedvalues-datasetLogDiffShifting["Passenge"))
```

C:\Users\Admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:524: ValueW
arning: No frequency information was provided, so inferred frequency MS will be used.
 warnings.warn('No frequency information was'

C:\Users\Admin\anaconda3\lib\site-packages\statsmodels\tsa\base\tsa\_model.py:524: ValueW
arning: No frequency information was provided, so inferred frequency MS will be used.
warnings.warn('No frequency information was'

Out[22]: Text(0.5, 1.0, 'RSS: 0.6931')

RSS: 0.6931

```
0.20
 0.15
 0.10
 0.05
 0.00
-0.05
-0.10
-0.15
        1995
                     1996
                                 1997
                                              1998
                                                          1999
                                                                       2000
                                                                                   2001
                                                                                                2002
                                                                                                            2003
```

 1995-02-01
 0.011261

 1995-03-01
 0.016602

 1995-04-01
 0.021663

 1995-05-01
 -0.008096

 1995-06-01
 -0.017395

dtype: float64

- -

```
In [24]: predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
print (predictions_ARIMA_diff_cumsum.head())
```

```
Month
1995-02-01 0.011261
1995-03-01 0.027863
1995-04-01 0.049526
1995-05-01 0.041430
1995-06-01 0.024035
dtype: float64
```

In [25]: predictions\_ARIMA\_log = pd.Series(indexedDataset\_logScale['Passengers'], index=indexedD
 predictions\_ARIMA\_log = predictions\_ARIMA\_log.add(predictions\_ARIMA\_diff\_cumsum,fill\_va
 predictions\_ARIMA\_log.head()

```
Out[25]: Month

1995-01-01 4.718499

1995-02-01 4.781946

1995-03-01 4.910665

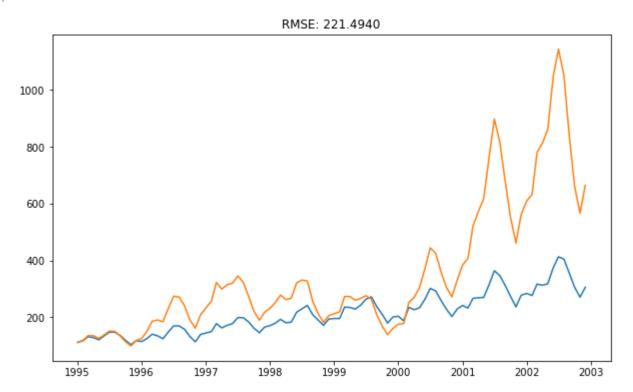
1995-04-01 4.909338

1995-05-01 4.837220

dtype: float64
```

```
In [26]: predictions_ARIMA = np.exp(predictions_ARIMA_log)
    plt.plot(indexedDataset)
    plt.plot(predictions_ARIMA)
    plt.title('RMSE: %.4f'% np.sqrt(sum((predictions_ARIMA-indexedDataset["Passengers"])**2
```

Out[26]: Text(0.5, 1.0, 'RMSE: 221.4940')



In [ ]: