TimeSeries2

June 2, 2019

0.1 Time Series

```
In [1]: import pandas as pd
        import seaborn as sns
        import numpy as np
        import matplotlib.pylab as plt
        %matplotlib inline
        from matplotlib.pylab import rcParams
        rcParams['figure.figsize'] = 15, 6
        sns.set(style="darkgrid")
```

0.1.1 Loading DataSet

```
In [2]: !pwd

/home/anilla/DataScience/TimeSeries
```

```
In [3]: data=pd.read_csv('AirPassengers.csv')
        data.head(5)

Out[3]:      Month  #Passengers
        0  1949-01          112
        1  1949-02          118
        2  1949-03          132
        3  1949-04          129
        4  1949-05          121
```

```
In [4]: data.dtypes

Out[4]: Month          object
        #Passengers     int64
        dtype: object
```

```
In [5]: date_parse=lambda dates:pd.datetime.strptime(dates,'%Y-%m')
```

```
In [6]: data2=pd.read_csv('AirPassengers.csv',parse_dates=['Month'],index_col='Month',date_parse
```

```
In [7]: data2.head(5)
```

Out[7]:
```
            #Passengers
Month
1949-01-01          112
1949-02-01          118
1949-03-01          132
1949-04-01          129
1949-05-01          121
```

In [8]:
```
data2.dtypes
```

Out[8]:
```
#Passengers    int64
dtype: object
```

In [9]:
```
data2.index
```

Out[9]:
```
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)
```

In [10]:
```
data2.shape
```

Out[10]:
```
(144, 1)
```

In [11]:
```
ts=data2['#Passengers']
```

In [12]:
```
ts.shape
```

Out[12]:
```
(144,)
```

In [13]:
```
ts.head(5)
```

Out[13]:
```
Month
1949-01-01    112
1949-02-01    118
1949-03-01    132
1949-04-01    129
1949-05-01    121
Name: #Passengers, dtype: int64
```

In [14]:
```
ts['1949-01-01']
```

Out[14]:
```
112
```

In [15]:
```
from datetime import datetime
ts[datetime(1949,1,1)]
```

Out[15]: 112

In [16]:
```
#specify an entire range
ts['1949-01-01':'1949-05-01']
```

Out[16]:
```
Month
1949-01-01    112
1949-02-01    118
1949-03-01    132
1949-04-01    129
1949-05-01    121
Name: #Passengers, dtype: int64
```

In [17]:
```
ts[:'1949-03-01']
```

Out[17]:
```
Month
1949-01-01    112
1949-02-01    118
1949-03-01    132
Name: #Passengers, dtype: int64
```

In [18]:
```
#note that the end index are included here unlike the numeric index
```

In [19]:
```
random=ts.sample(5)
```

In [20]:
```
random
```

Out[20]:
```
Month
1952-03-01    193
1955-09-01    312
1951-04-01    163
1955-05-01    270
1956-05-01    318
Name: #Passengers, dtype: int64
```

In [21]:
```
random[:'1958-10-01']
```

Out[21]:
```
Month
1952-03-01    193
1955-09-01    312
1951-04-01    163
1955-05-01    270
1956-05-01    318
Name: #Passengers, dtype: int64
```

In [22]:
```
random['1949-03-01':'1958-10-01']
```

Out[22]:
```
Month
1952-03-01    193
1955-09-01    312
```

```
1951-04-01    163
1955-05-01    270
1956-05-01    318
Name: #Passengers, dtype: int64
```

```
In [23]: #in the above cell , index range doesn't work in random samples
```

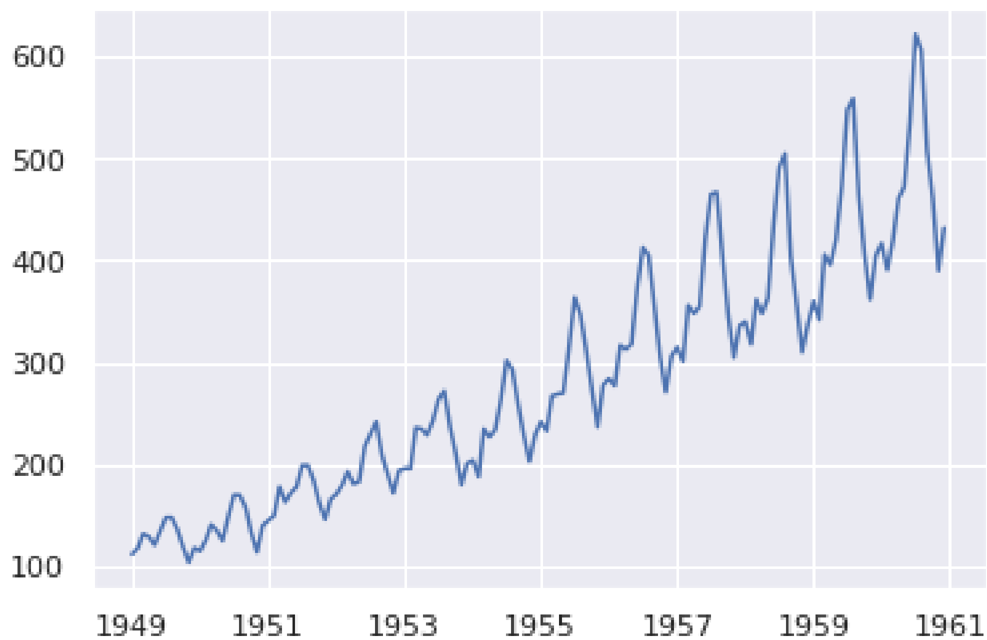
0.2 Analysis of Time Series

0.2.1 Checking Stationarity

a timeseries is said to be stationary if it's statistical properties ie mean variance remai constant overtime

```
In [24]: plt.plot(ts)
```

```
Out[24]: [<matplotlib.lines.Line2D at 0x7f0f35d0ff98>]
```



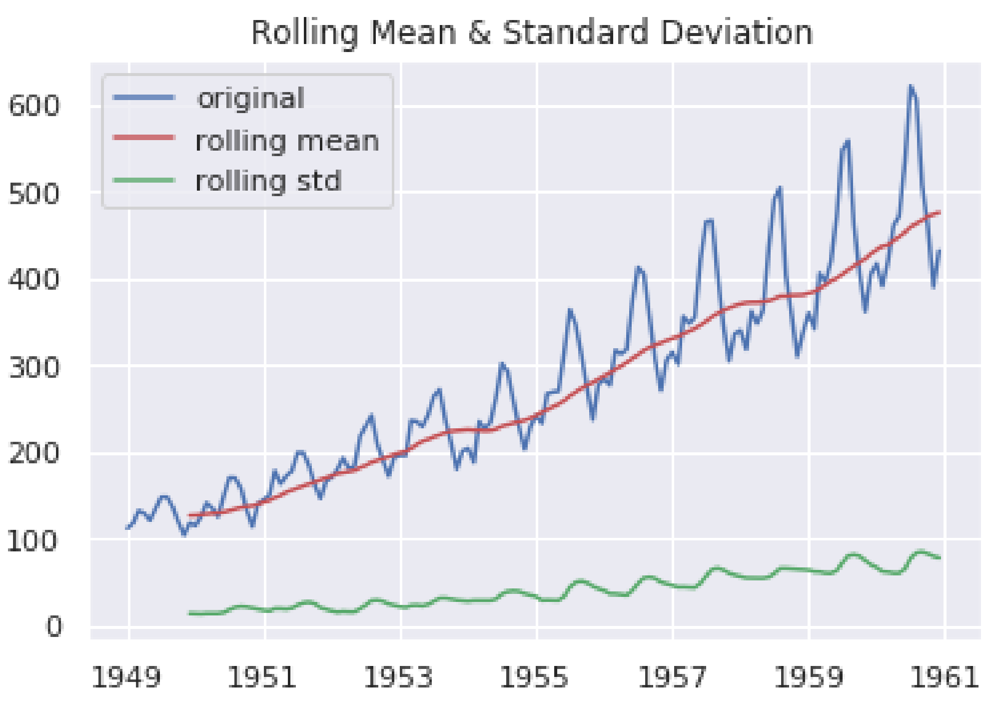

```
In [25]: #it is clear in the above digram that there is an overall increase in trend and seasonl
```

we can check stationarity by either

1. plotting the moving average
2. Using the dickey-fuller test

```
In [26]: from statsmodels.tsa.stattools import  adfuller
         def test_stationarity(timeseries):
             #determine the rolling statistics
             rolling_mean=timeseries.rolling(window=12).mean()
             rolling_std=timeseries.rolling(window=12).std()
             #plot rolling statistics
             original=plt.plot(timeseries,'-b',label='original')
             mean=plt.plot(rolling_mean,'-r',label='rolling mean')
             std=plt.plot(rolling_std,'-g',label='rolling std')
             plt.legend(loc='best')
             plt.title('Rolling Mean & Standard Deviation')
             plt.show(block=False)     #Dickey Fuller Test
             dftest=adfuller(timeseries,autolag='AIC')
             dfoutput=pd.Series(data=dftest[0:4],index=['TestStatistics','p-value','Number of la
             for key,value in dftest[4].items():
                 dfoutput['Critical values %s'%key]=value
             print(dfoutput)
```

```
In [27]: test_stationarity(ts)
```




```
TestStatistics              0.815369
p-value                     0.991880
Number of lags             13.000000
Number of observations    130.000000
Critical values 1%         -3.481682
```

```
Critical values 5%         -2.884042
Critical values 10%        -2.578770
dtype: float64
```

```
In [28]: #from the above results, the ts is non stationary as the test statistics is more than t
```

0.3 Making time series to be stationary

1. To make a non stationary time series stationary,we remove the trend and seasonlity since they rate the reason for aseries to be non stationary

0.3.1 Estimation and Eliminating Trend

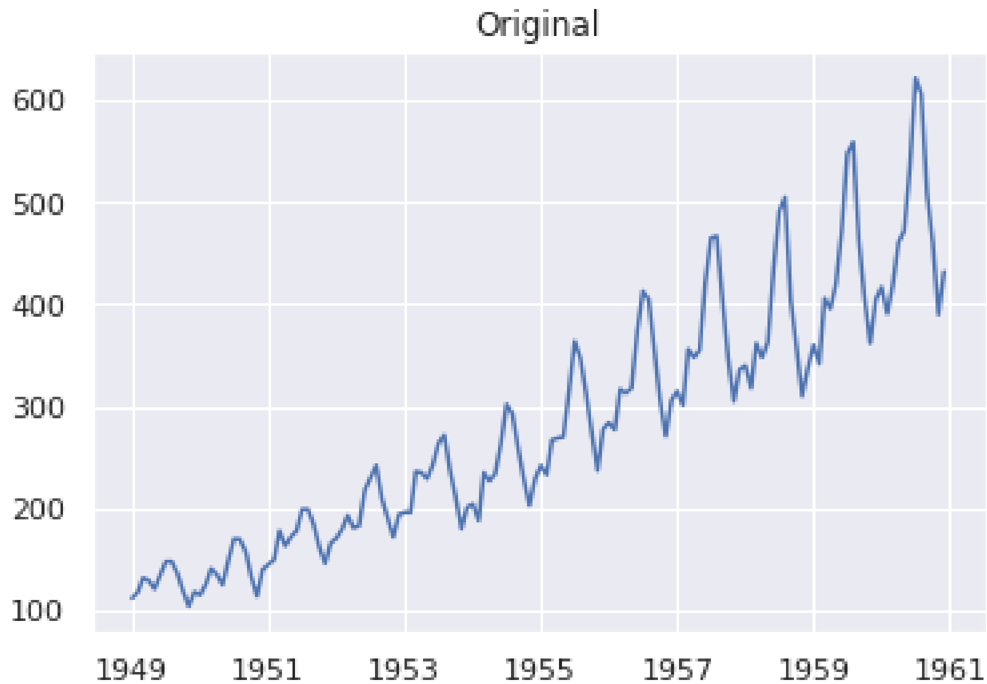
It can be done by transformation ie log ,cube root,square root

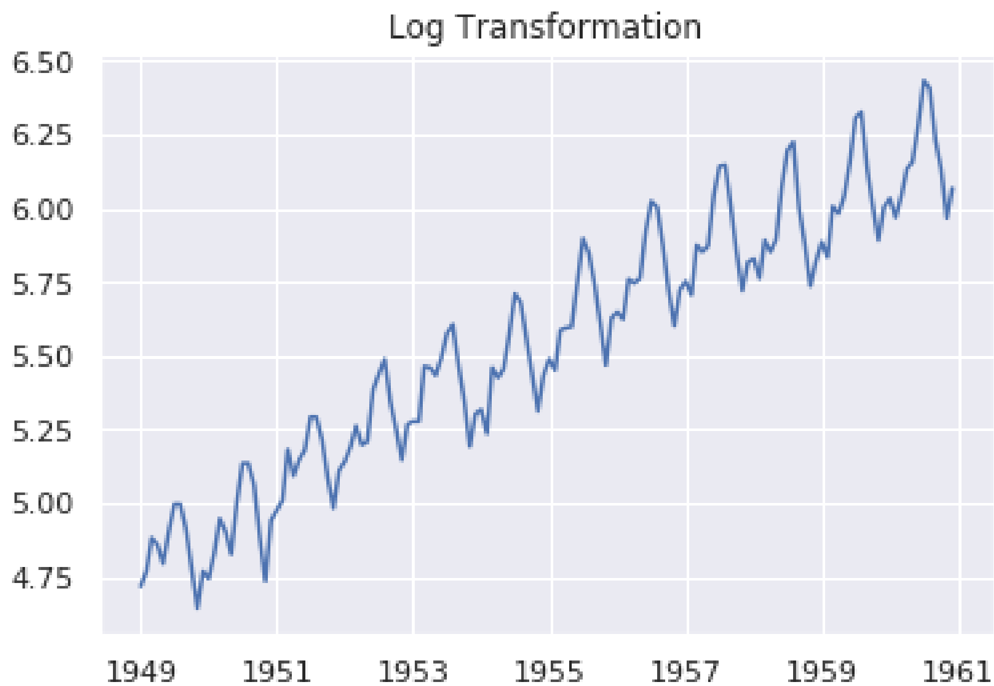
```
In [29]: ts_log=np.log(ts)
```

```
In [30]: ts_log.head(6)
```

```
Out[30]: Month
         1949-01-01    4.718499
         1949-02-01    4.770685
         1949-03-01    4.882802
         1949-04-01    4.859812
         1949-05-01    4.795791
         1949-06-01    4.905275
         Name: #Passengers, dtype: float64
```

```
In [31]: plt.plot(ts)
         plt.title('Original')
         plt.show()
         plt.plot(ts_log)
         plt.title('Log Transformation')
         plt.show()
```


Original
600
500
400
300
200
100
1949
1951
1953
1955
1957
1959
1961

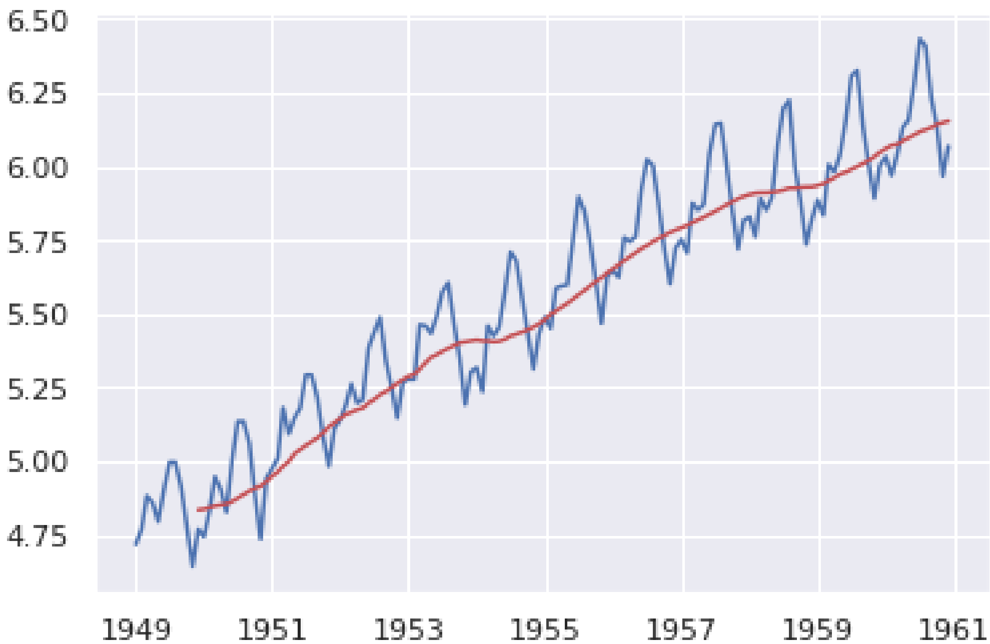

Log Transformation
6.50
6.25
6.00
5.75
5.50
5.25
5.00
4.75
1949
1951
1953
1955
1957
1959
1961

0.4 Moving average

In [32]:
```
mv_avg=ts_log.rolling(window=12).mean()
```

In [33]:
```
plt.plot(ts_log)
plt.plot(mv_avg,'-r')
```

Out[33]:
```
[<matplotlib.lines.Line2D at 0x7f0f306d2710>]
```



In [34]:
```
ts_log_mv_avg_diff=ts_log-mv_avg
```

In [35]:
```
ts_log_mv_avg_diff.head(24)
```

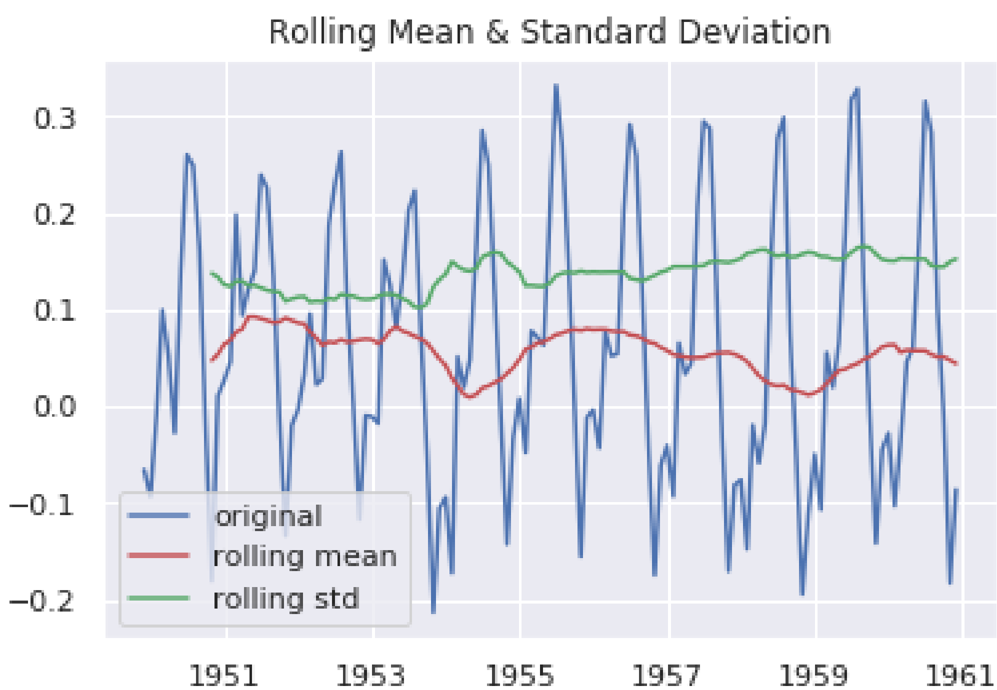
Out[35]:
```
Month
1949-01-01         NaN
1949-02-01         NaN
1949-03-01         NaN
1949-04-01         NaN
1949-05-01         NaN
1949-06-01         NaN
1949-07-01         NaN
1949-08-01         NaN
1949-09-01         NaN
1949-10-01         NaN
1949-11-01         NaN
1949-12-01   -0.065494
```

```
1950-01-01   -0.093449
1950-02-01   -0.007566
1950-03-01    0.099416
1950-04-01    0.052142
1950-05-01   -0.027529
1950-06-01    0.139881
1950-07-01    0.260184
1950-08-01    0.248635
1950-09-01    0.162937
1950-10-01   -0.018578
1950-11-01   -0.180379
1950-12-01    0.010818
Name: #Passengers, dtype: float64
```

In [36]:
```
#drop the first NAN and check the stationarity
```

In [37]:
```
ts_log_mv_avg_diff.dropna(inplace=True)
```

In [38]:
```
test_stationarity(ts_log_mv_avg_diff)
```




```
TestStatistics               -3.162908
p-value                       0.022235
Number of lags               13.000000
Number of observations      119.000000
Critical values 1%           -3.486535
```

```
Critical values 5%         -2.886151
Critical values 10%        -2.579896
dtype: float64
```

```
In [39]: #since the testatistics is less that the critical value hence we reject the null hypoth
```

```
In [40]: exp_weightedavg=pd.DataFrame.ewm(ts_log,halflife=12).mean()
```

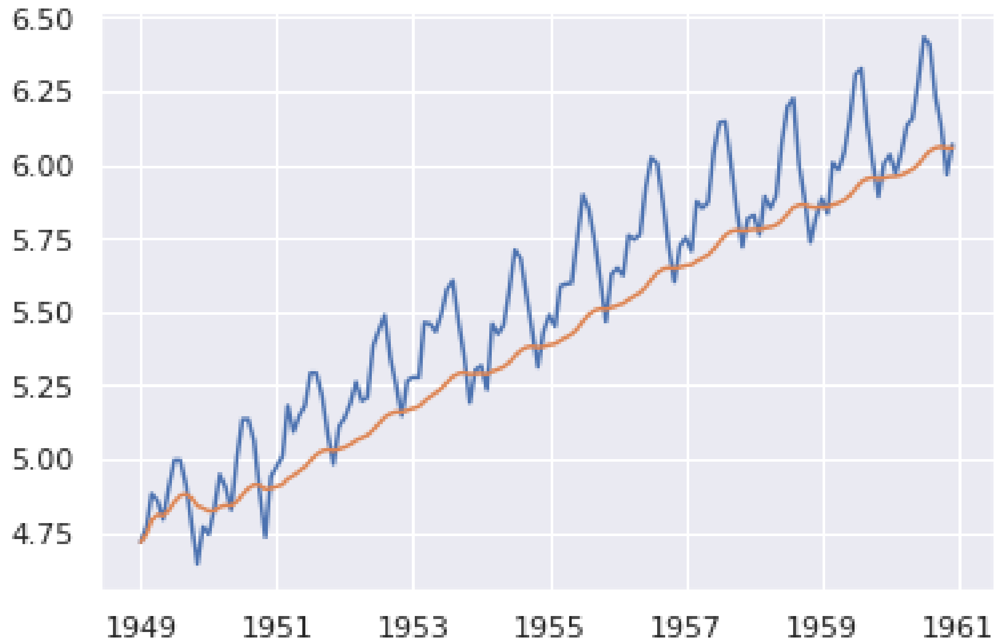
```
In [41]: exp_weightedavg
```

```
Out[41]: Month
         1949-01-01    4.718499
         1949-02-01    4.745345
         1949-03-01    4.793835
         1949-04-01    4.811785
         1949-05-01    4.808206
         1949-06-01    4.826807
         1949-07-01    4.855564
         1949-08-01    4.877049
         1949-09-01    4.881978
         1949-10-01    4.868821
         1949-11-01    4.842036
         1949-12-01    4.834027
         1950-01-01    4.824557
         1950-02-01    4.825744
         1950-03-01    4.837657
         1950-04-01    4.843949
         1950-05-01    4.842546
         1950-06-01    4.856559
         1950-07-01    4.880081
         1950-08-01    4.901033
         1950-09-01    4.913937
         1950-10-01    4.912097
         1950-11-01    4.898667
         1950-12-01    4.901883
         1951-01-01    4.907382
         1951-02-01    4.914838
         1951-03-01    4.933808
         1951-04-01    4.945007
         1951-05-01    4.958991
         1951-06-01    4.974181
                          ...
         1958-07-01    5.832405
         1958-08-01    5.854442
         1958-09-01    5.862700
         1958-10-01    5.863859
         1958-11-01    5.856708
         1958-12-01    5.854650
```

```
1959-01-01    5.856417
1959-02-01    5.855203
1959-03-01    5.863694
1959-04-01    5.870306
1959-05-01    5.879851
1959-06-01    5.895416
1959-07-01    5.918491
1959-08-01    5.941385
1959-09-01    5.952411
1959-10-01    5.955579
1959-11-01    5.951988
1959-12-01    5.954903
1960-01-01    5.959293
1960-02-01    5.959821
1960-03-01    5.964204
1960-04-01    5.973704
1960-05-01    5.983994
1960-06-01    6.000740
1960-07-01    6.025006
1960-08-01    6.046445
1960-09-01    6.056778
1960-10-01    6.061079
1960-11-01    6.055750
1960-12-01    6.056461
Name: #Passengers, Length: 144, dtype: float64
```

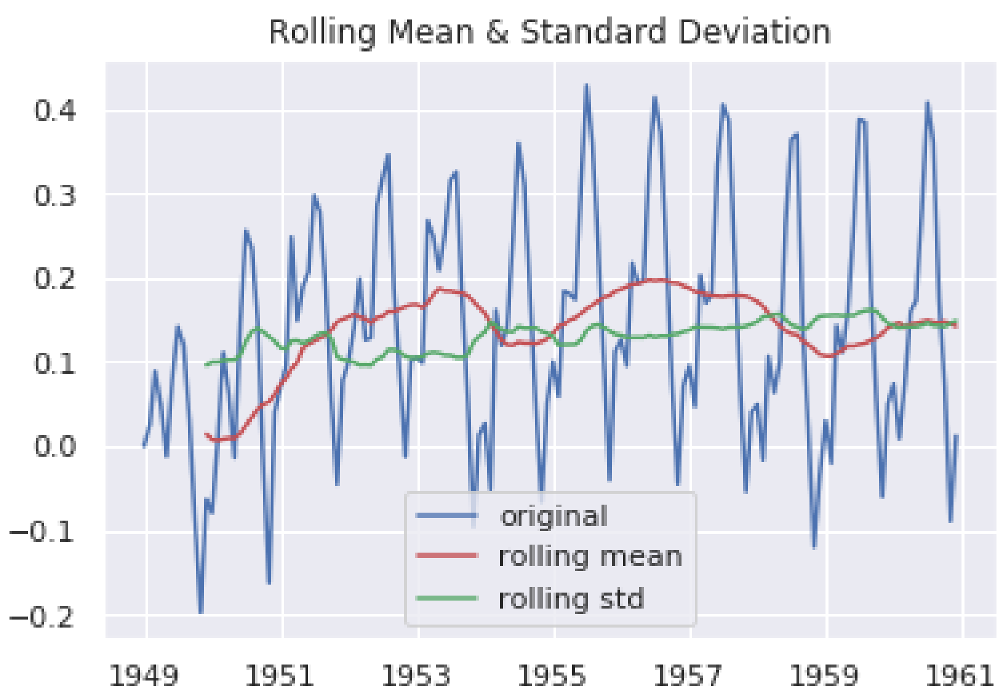
In [42]:
```
plt.plot(ts_log)
plt.plot(exp_weightedavg)
```

Out[42]:
```
[<matplotlib.lines.Line2D at 0x7f0f300a43c8>]
```




```
In [43]: ts_log_wma_diff=ts_log-exp_weightedavg
```

```
In [44]: test_stationarity(ts_log_wma_diff)
```



```
TestStatistics              -3.601262
p-value                      0.005737
Number of lags              13.000000
Number of observations     130.000000
Critical values 1%          -3.481682
Critical values 5%          -2.884042
Critical values 10%         -2.578770
dtype: float64
```

0.5 1. Eliminating trend and seasonality

This can be done by:

1. Decomposition
2. Diffferencing

0.5.1 1.Differencing

Here,we take the difference of a particular instant with that of a previous instant.Below is a simple example

```
In [45]: a=pd.DataFrame({'A':[10, 20, 15, 30, 45],'B':[13, 23, 18, 33, 48],'C':[17, 27, 22, 37,
```

```
In [46]: a
```

```
Out[46]:     A   B   C
         0  10  13  17
         1  20  23  27
         2  15  18  22
         3  30  33  37
         4  45  48  52
```

```
In [47]: a.shift(periods=3)
```

```
Out[47]:       A     B     C
         0   NaN   NaN   NaN
         1   NaN   NaN   NaN
         2   NaN   NaN   NaN
         3  10.0  13.0  17.0
         4  20.0  23.0  27.0
```

```
In [48]: ts_log_shift=ts_log.shift()
```

```
In [49]: ts_log_shift
```

```
Out[49]: Month
         1949-01-01         NaN
         1949-02-01    4.718499
         1949-03-01    4.770685
```

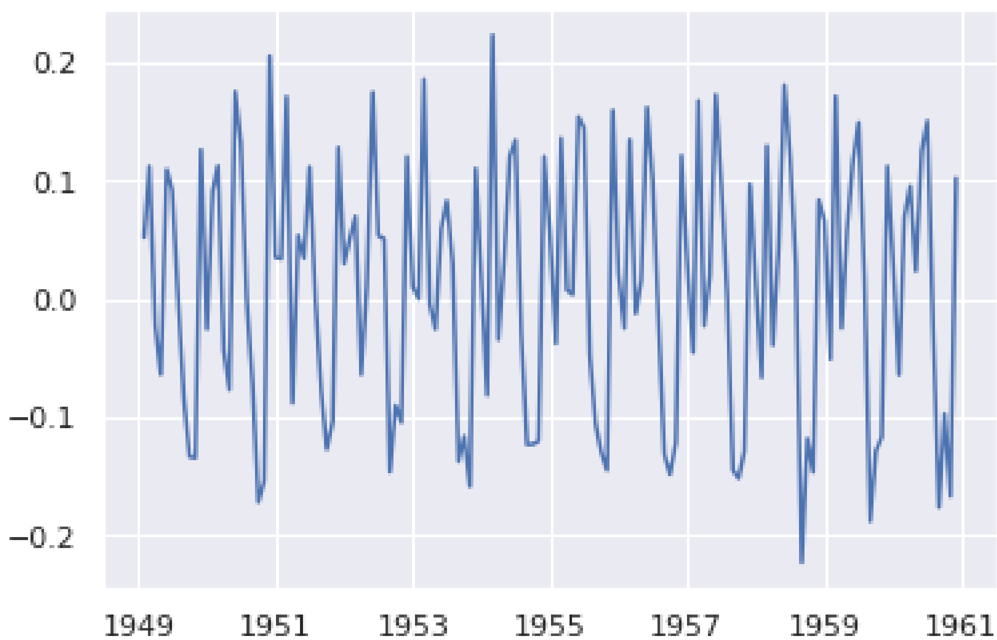
1949-04-01	4.882802
1949-05-01	4.859812
1949-06-01	4.795791
1949-07-01	4.905275
1949-08-01	4.997212
1949-09-01	4.997212
1949-10-01	4.912655
1949-11-01	4.779123
1949-12-01	4.644391
1950-01-01	4.770685
1950-02-01	4.744932
1950-03-01	4.836282
1950-04-01	4.948760
1950-05-01	4.905275
1950-06-01	4.828314
1950-07-01	5.003946
1950-08-01	5.135798
1950-09-01	5.135798
1950-10-01	5.062595
1950-11-01	4.890349
1950-12-01	4.736198
1951-01-01	4.941642
1951-02-01	4.976734
1951-03-01	5.010635
1951-04-01	5.181784
1951-05-01	5.093750
1951-06-01	5.147494
	...
1958-07-01	6.075346
1958-08-01	6.196444
1958-09-01	6.224558
1958-10-01	6.001415
1958-11-01	5.883322
1958-12-01	5.736572
1959-01-01	5.820083
1959-02-01	5.886104
1959-03-01	5.834811
1959-04-01	6.006353
1959-05-01	5.981414
1959-06-01	6.040255
1959-07-01	6.156979
1959-08-01	6.306275
1959-09-01	6.326149
1959-10-01	6.137727
1959-11-01	6.008813
1959-12-01	5.891644
1960-01-01	6.003887
1960-02-01	6.033086

```
1960-03-01    5.968708
1960-04-01    6.037871
1960-05-01    6.133398
1960-06-01    6.156979
1960-07-01    6.282267
1960-08-01    6.432940
1960-09-01    6.406880
1960-10-01    6.230481
1960-11-01    6.133398
1960-12-01    5.966147
Name: #Passengers, Length: 144, dtype: float64
```

```
In [50]: ts_log_diff=ts_log-ts_log_shift
```

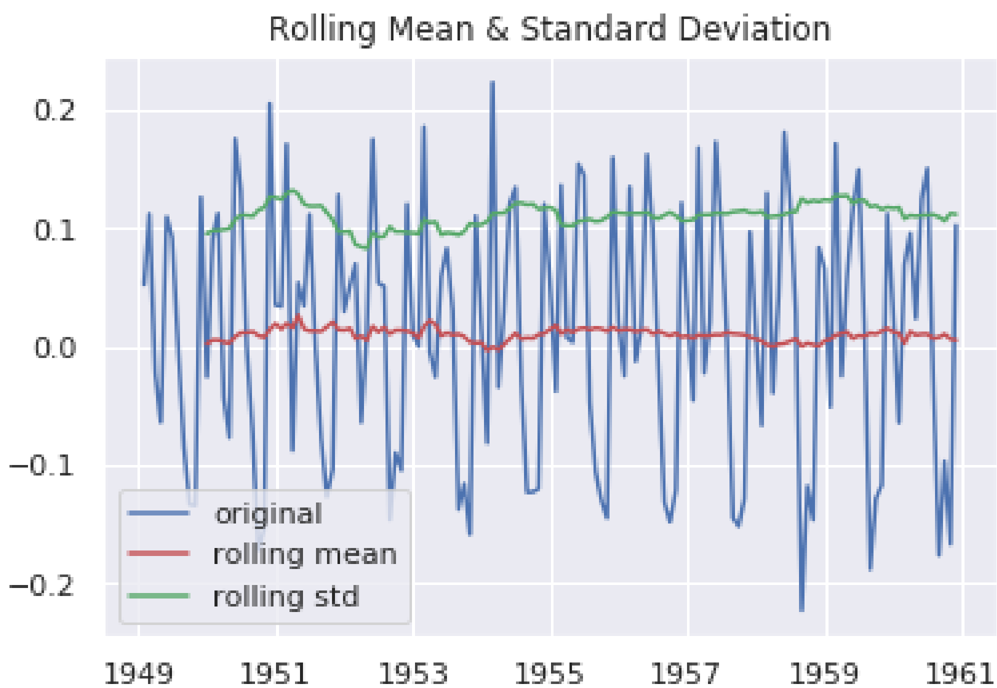
```
In [51]: plt.plot(ts_log_diff)
```

```
Out[51]: [<matplotlib.lines.Line2D at 0x7f0f290b8748>]
```




```
In [52]: ts_log_diff.dropna(inplace=True)
```

```
In [53]: test_stationarity(ts_log_diff)
```




```
TestStatistics                 -2.717131
p-value                         0.071121
Number of lags                 14.000000
Number of observations        128.000000
Critical values 1%             -3.482501
Critical values 5%             -2.884398
Critical values 10%            -2.578960
dtype: float64
```

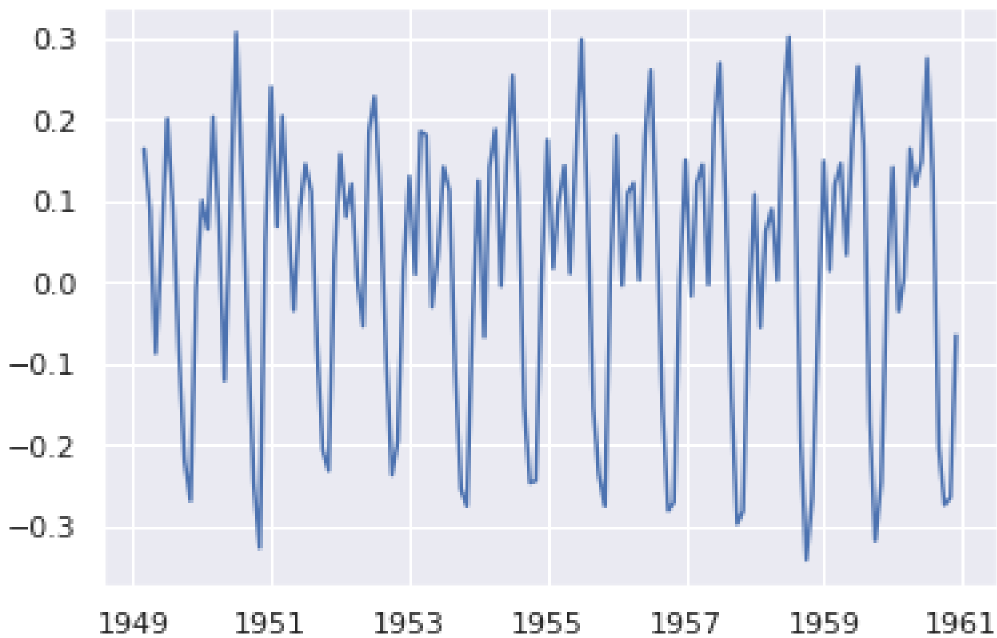
In [54]: #2nd Order

In [55]: ts_log_shift2=ts_log.shift(periods=2)

In [56]: ts_log_diff2=ts_log-ts_log_shift2

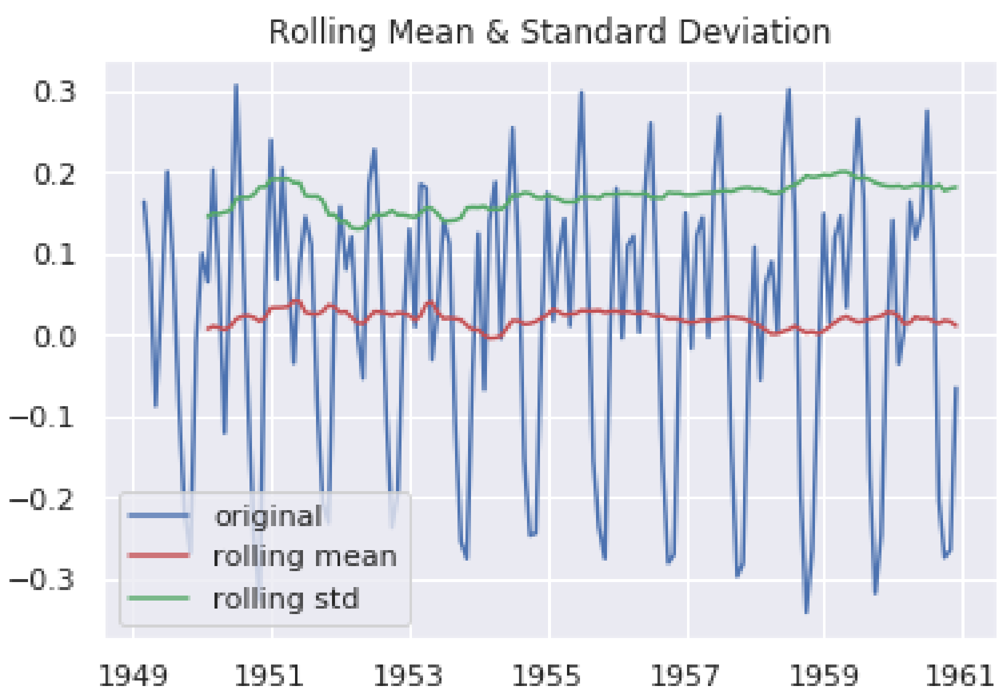
In [57]: plt.plot(ts_log_diff2)

Out[57]: [<matplotlib.lines.Line2D at 0x7f0f29046cf8>]




```
In [58]: ts_log_diff2.dropna(inplace=True)

In [59]: test_stationarity(ts_log_diff2)
```



```
TestStatistics              -3.167907
p-value                      0.021919
Number of lags              11.000000
Number of observations     130.000000
Critical values 1%          -3.481682
Critical values 5%          -2.884042
Critical values 10%         -2.578770
dtype: float64
```

In [60]:
```
#It gets better when the periods of differencing increase
```

0.6 2. Decomposing

Herer the trend and seasonality are modelled differently and the remaining part of the series returned

In [61]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [62]:
```
decomposition=seasonal_decompose(ts_log)
```

In [63]:
```
decomposition
```

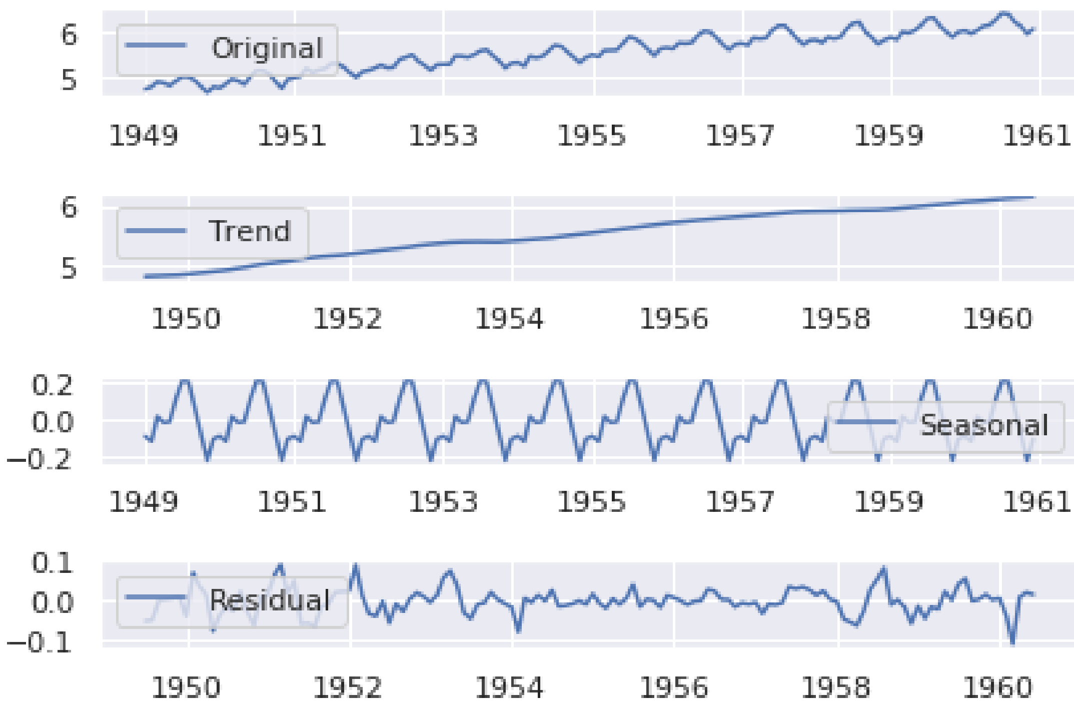
Out[63]:
```
<statsmodels.tsa.seasonal.DecomposeResult at 0x7f0f301383c8>
```

In [64]:
```
trend=decomposition.trend
```

In [65]:
```
seasonal=decomposition.seasonal
```

In [66]:
```
error=decomposition.resid
```

In [67]:
```
plt.subplot(4,1,1)
plt.plot(ts_log,label='Original')
plt.legend(loc='best')
plt.subplot(4,1,2)
plt.plot(trend,label='Trend')
plt.legend(loc='best')
plt.subplot(4,1,3)
plt.plot(seasonal,label='Seasonal')
plt.legend(loc='best')
plt.subplot(4,1,4)
plt.plot(error,label='Residual')
plt.legend(loc='best')
plt.tight_layout()
```

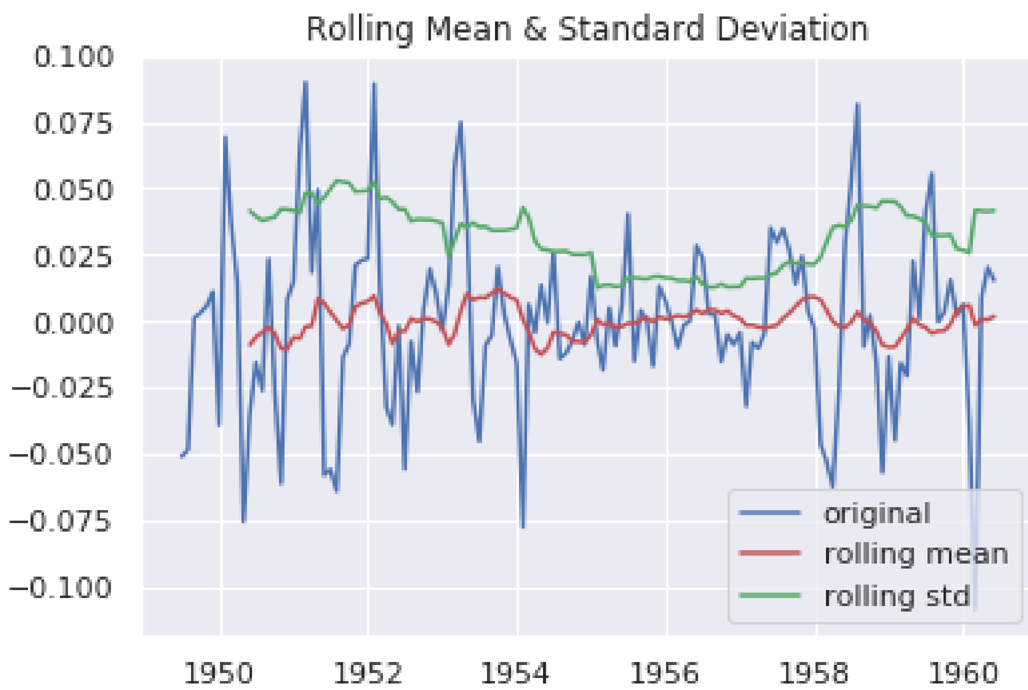



```
In [68]: #Checking Stationarity of the residuals

In [69]: ts_residual_decompose=error

In [70]: ts_residual_decompose.dropna(inplace=True)

In [71]: test_stationarity(ts_residual_decompose)
```




```
TestStatistics             -6.332387e+00
p-value                     2.885059e-08
Number of lags              9.000000e+00
Number of observations      1.220000e+02
Critical values 1%         -3.485122e+00
Critical values 5%         -2.885538e+00
Critical values 10%        -2.579569e+00
dtype: float64
```

As per the above dickey fuller test statistic, the teststatistics is lower than the 1% critical value .Hence we ject the null hypothesis and conclude that the residual is stationary

0.7 Forecasting Time Series

Having Performed the trend seasonality estimation techniques ,there can be two techniques: 1. A Strictly Stationary Series with no dependance among the values,its an easy case but very rare 2. Weakly stationary series with a significant dependance among values thus in this case we use ARIMA to forecast the data.

0.7.1 ARIMA

ARIMA stands for Auto Regressive Intergrated Moving Averages.

- The ARIMA forecasting for a stationary time series is nothing but linear equation.The predictors depend on parameters(p,d,q) of the ARIMA model:

1. Number of AR terms(p)-AR are just lags of dependant variable ie if p is 5 the predictors for X(t) will be from X(t-1)....X(t-5).
2. Number of MA terms(q) MA terms are lagged forecast errors in prediction equation X(t) will be e(t-1).....e(t-5)
3. Number of Differences(d)-These are the number of nonseasonal differences ie in the case we took the first order difference.SO either we can pass that variable and put d=0 or pass the original variable and put d=1. Both will generate same results.

An importance concern here is how to determine the value of p and q . We use two plots to determine these numbers .

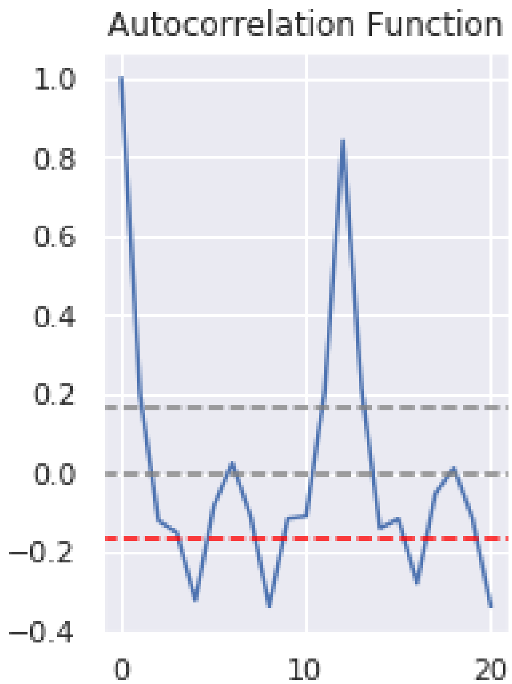
- AutoCorrelation Function(ACF):measure of correlation between the Ts with its lagged version of itself.For Instance at lag 5 ,ACF would compare series at time instant 't1'...'t2' with series
- Partial Autocorrelation Function (PACF):This measures the correlation between TS with a lagged version of itself but after elimating the variations alreday explained by the intervening comparisons.For example at lag 5 ,it will check the correlation but remove the effects already explained by lags 1 to 4.

In [72]:
```
#ACF and PACF:
from statsmodels.tsa.stattools import acf,pacf
```

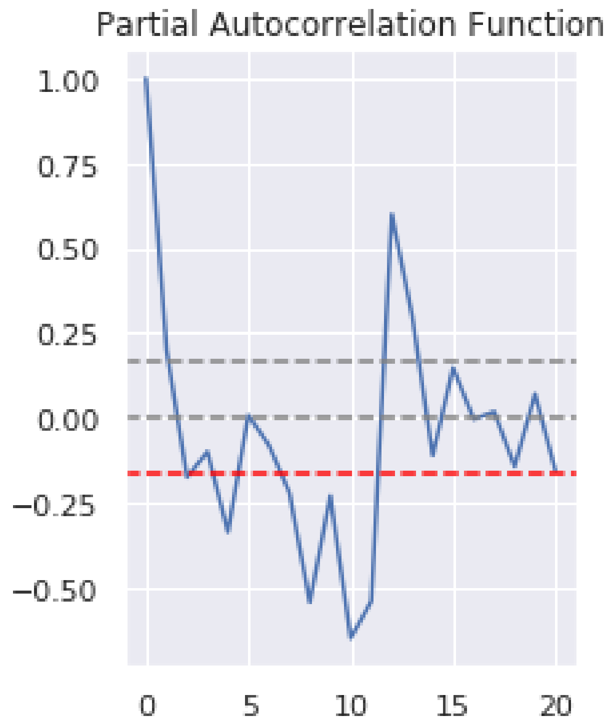
In [73]:
```
lag_acf=acf(ts_log_diff,nlags=20)
lag_pacf=pacf(ts_log_diff,nlags=20,method='ols')
```

In [74]:
```
#Plot ACF
plt.subplot(121)
plt.plot(lag_acf)
plt.axhline(y=0,linestyle='--',color='gray')
plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='red')
plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
plt.title('Autocorrelation Function')
```

Out[74]:
```
Text(0.5,1,'Autocorrelation Function')
```




```
In [75]: #Plot PACF
         plt.subplot(121)#nrows,ncols,index in that order
         plt.plot(lag_pacf)
         plt.axhline(y=0,linestyle='--',color='gray')
         plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='red')
         plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
         plt.title('Partial Autocorrelation Function')
         plt.tight_layout()
```



In the above plots,the dotted lines on either sides of the 0 are the confidence intervals and can be used to determine the 'p','q'. 1. p-the lag value where the **PACF** chart crosses the upper confidence interval for the first time ;here it's p=2 2. q-the lag value where **ACF** chart crosses the upper confidence interval for the first time; here it's q=2

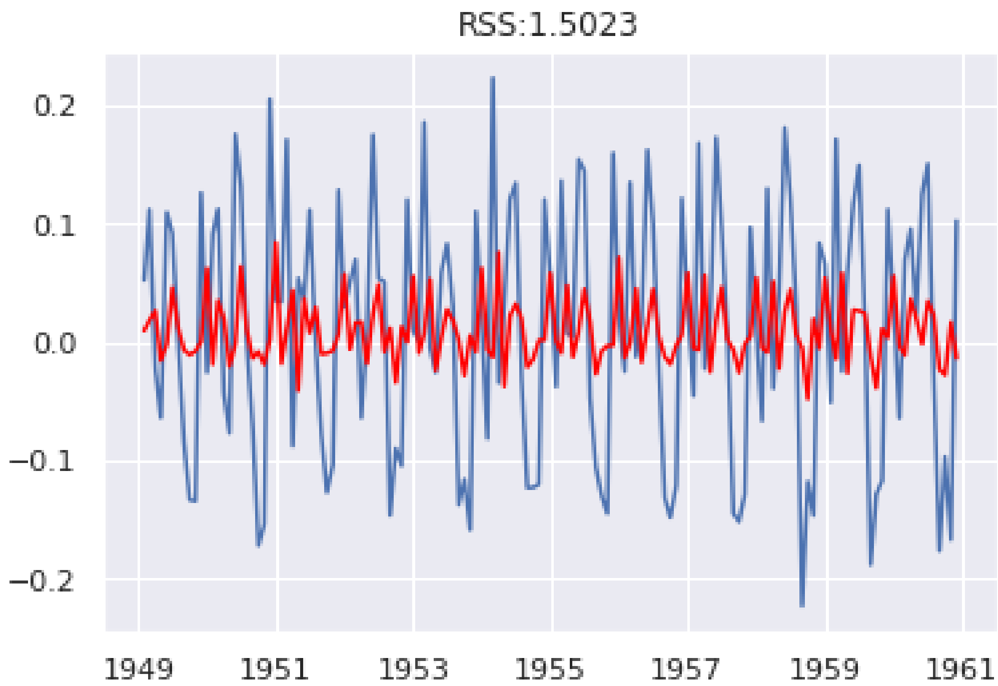
0.7.2 ARIMA

```
In [76]: from statsmodels.tsa.arima_model import ARIMA
```

```
In [77]: model=ARIMA(ts_log,order=(2,1,0))
         results_AR=model.fit(disp=-1)
         plt.plot(ts_log_diff)
         plt.plot(results_AR.fittedvalues,color='red')
         plt.title('RSS:%.4f'% sum((results_AR.fittedvalues-ts_log_diff)**2))
```

```
/home/anilla/anaconda3/lib/python3.6/site-packages/statsmodels/tsa/base/tsa_model.py:171: ValueW
  % freq, ValueWarning)
/home/anilla/anaconda3/lib/python3.6/site-packages/statsmodels/tsa/base/tsa_model.py:171: ValueW
  % freq, ValueWarning)
```

```
Out[77]: Text(0.5,1,'RSS:1.5023')
```

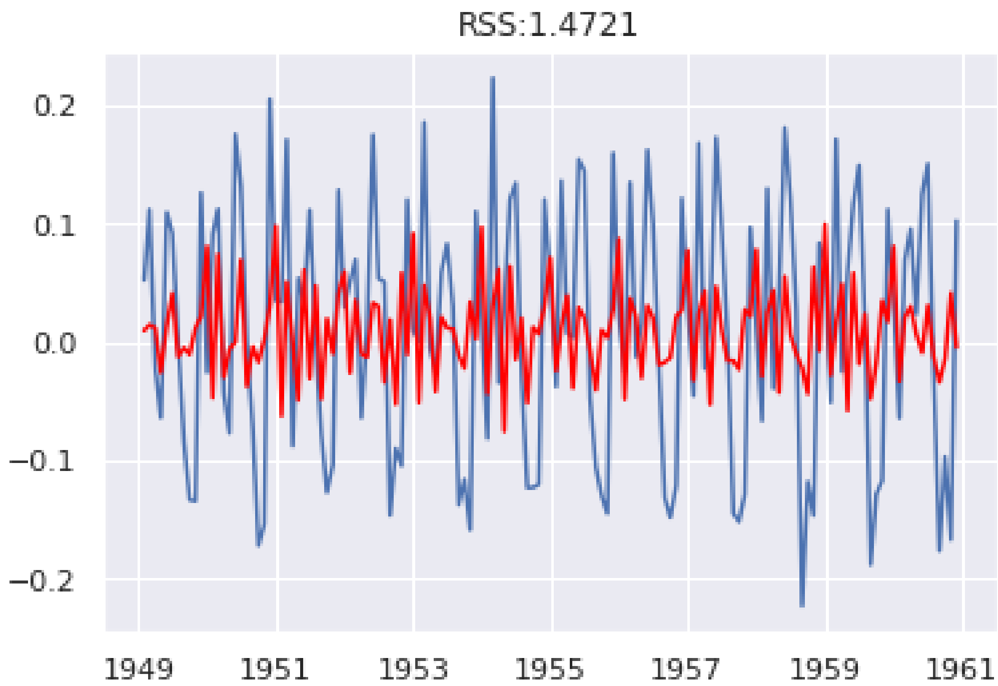


0.7.3 MA Model

```
In [78]: model=ARIMA(ts_log,order=(0,1,2))
         results_MA=model.fit(disp=-1)
         plt.plot(ts_log_diff)
         plt.plot(results_MA.fittedvalues,color='red')
         plt.title('RSS:%.4f'% sum((results_MA.fittedvalues-ts_log_diff)**2))
```

```
/home/anilla/anaconda3/lib/python3.6/site-packages/statsmodels/tsa/base/tsa_model.py:171: ValueW
  % freq, ValueWarning)
/home/anilla/anaconda3/lib/python3.6/site-packages/statsmodels/tsa/base/tsa_model.py:171: ValueW
  % freq, ValueWarning)
```

```
Out[78]: Text(0.5,1,'RSS:1.4721')
```

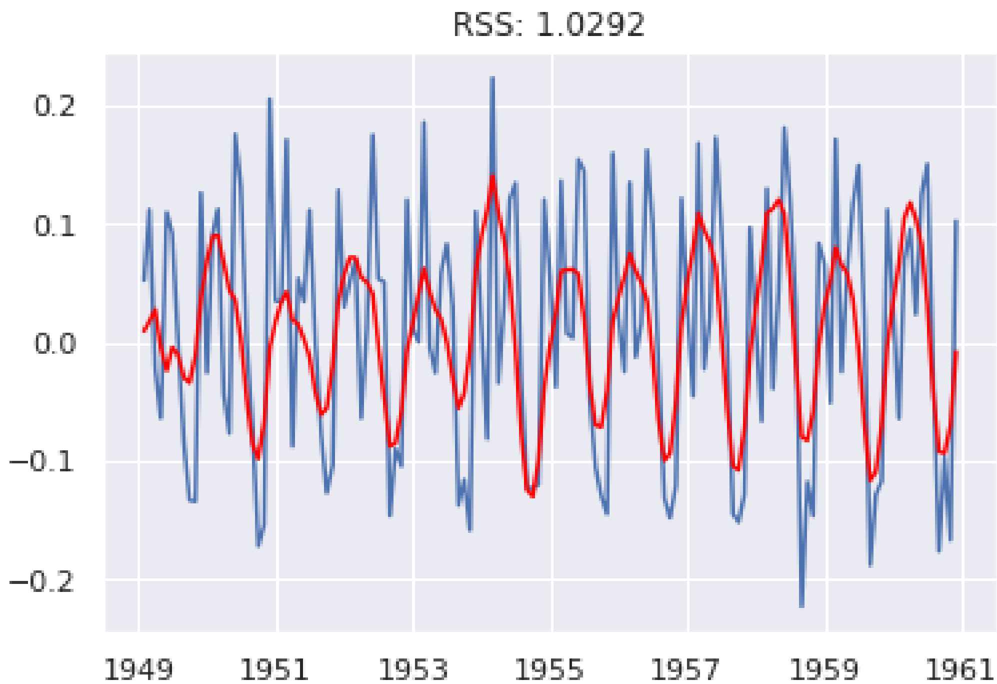


0.7.4 Combined Model

```
In [79]: model=ARIMA(ts_log,order=(2,1,2))
         results_ARIMA=model.fit(disp=-1)
         plt.plot(ts_log_diff)
         plt.plot(results_ARIMA.fittedvalues,color='red')
         plt.title('RSS: %.4f'% sum((results_ARIMA.fittedvalues-ts_log_diff)**2))
```

```
/home/anilla/anaconda3/lib/python3.6/site-packages/statsmodels/tsa/base/tsa_model.py:171: ValueW
  % freq, ValueWarning)
/home/anilla/anaconda3/lib/python3.6/site-packages/statsmodels/tsa/base/tsa_model.py:171: ValueW
  % freq, ValueWarning)
```

```
Out[79]: Text(0.5,1,'RSS: 1.0292')
```



0.8 Taking back to original scale

```
In [80]: predictions_ARIMA_diff=pd.Series(results_ARIMA.fittedvalues,copy=True)
         predictions_ARIMA_diff.head(5)
```

```
Out[80]: Month
         1949-02-01    0.009580
         1949-03-01    0.017491
         1949-04-01    0.027670
         1949-05-01   -0.004521
         1949-06-01   -0.023890
         dtype: float64
```