impro_v5_timeSeries

July 3, 2018

1 Time series Analysis

In [86]:
```
from pandas import Series
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
from matplotlib.pylab import rcParams
from datetime import datetime
rcParams['figure.figsize'] = 15, 6
```

In [80]:
```
data=pd.read_csv('a40282n.csv',header=None,index_col=None)
print(data.head())
# print(data.dtypes)
```

```
                        0     1      2     3     4    5     6    7  8  9  10
0  '[10:00:00 30/06/2016]'  60.3  102.7  56.5  71.5  0.0  16.8  0.0  -  -  -
1  '[10:01:00 30/06/2016]'  64.3  101.6  55.3  70.3  0.0  21.4  0.0  -  -  -
2  '[10:02:00 30/06/2016]'  60.9  112.5  60.1  77.3  0.0  12.1  0.0  -  -  -
3  '[10:03:00 30/06/2016]'  59.8  115.1  59.7  77.8  0.0  10.6  0.0  -  -  -
4  '[10:04:00 30/06/2016]'  60.5  111.5  58.6  75.5  0.0  16.2  0.0  -  -  -
```

In [81]:
```
#extract previous 5 columns
data=data[list(range(5))]
```

In [82]:
```
# format the timestamp
rawtime=[]
timeformat=[]
for i in range(len(data)):
    rawtime.append(data[0][i][2:21])
    timeformat.append(pd.to_datetime(rawtime[i],format='%H:%M:%S %d/%m/%Y'))
data[0]=timeformat
```

In [83]:
```
#rename the columns
data.columns=['Time and date','HR','ABPSys','ABPDias','ABPMean']
```

In [84]:
```
data.head()
```

```
Out[84]:          Time and date    HR  ABPSys  ABPDias  ABPMean
         0 2016-06-30 10:00:00  60.3   102.7     56.5     71.5
         1 2016-06-30 10:01:00  64.3   101.6     55.3     70.3
         2 2016-06-30 10:02:00  60.9   112.5     60.1     77.3
         3 2016-06-30 10:03:00  59.8   115.1     59.7     77.8
         4 2016-06-30 10:04:00  60.5   111.5     58.6     75.5
```

```
In [91]: ts=data['ABPMean']
         # ts[datetime(2016,6,20,10,0,0)]
         # plt.plot(data['ABPMean'])
```

```
In [93]: print(data['Time and date'][0])
```

```
2016-06-30 10:00:00
```

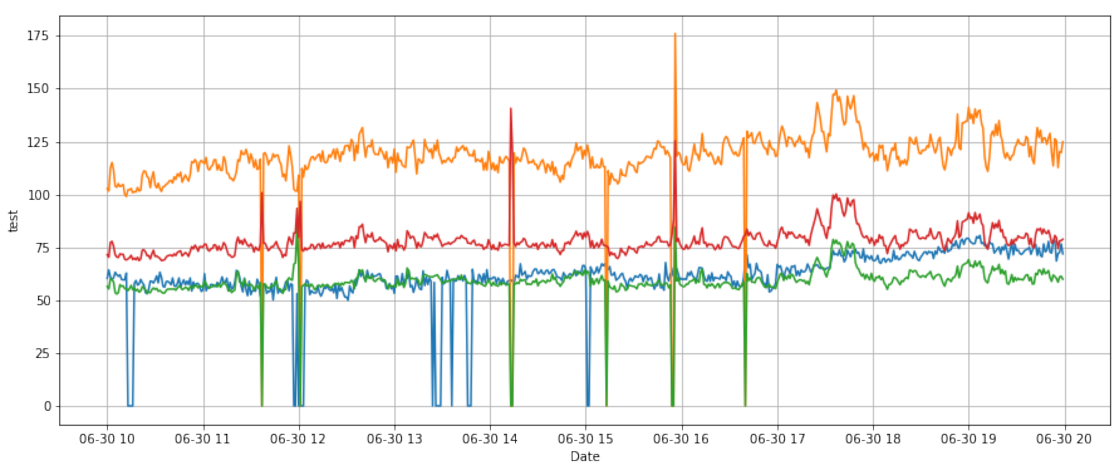
```
In [96]: data['Time and date']=pd.to_datetime(data['Time and date'],infer_datetime_format=True
         indexedDataset=data.set_index(['Time and date'])
```

```
In [97]: indexedDataset.head()
```

```
Out[97]:                        HR  ABPSys  ABPDias  ABPMean
         Time and date
         2016-06-30 10:00:00  60.3   102.7     56.5     71.5
         2016-06-30 10:01:00  64.3   101.6     55.3     70.3
         2016-06-30 10:02:00  60.9   112.5     60.1     77.3
         2016-06-30 10:03:00  59.8   115.1     59.7     77.8
         2016-06-30 10:04:00  60.5   111.5     58.6     75.5
```

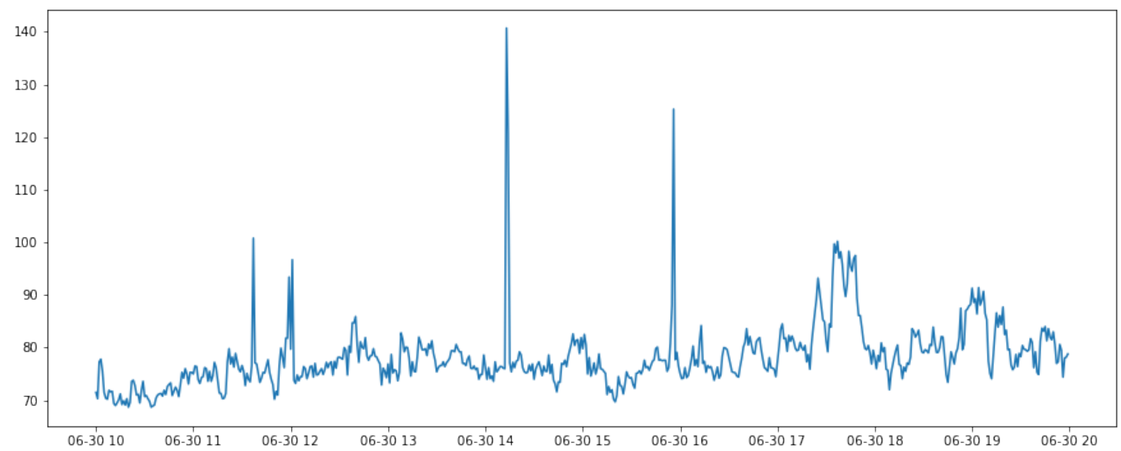
```
In [115]: plt.xlabel('Date')
          plt.ylabel('test')
          plt.grid(True)
          plt.plot(indexedDataset)
```

```
Out[115]: [<matplotlib.lines.Line2D at 0x11c30b5c0>,
           <matplotlib.lines.Line2D at 0x11c31e7f0>,
           <matplotlib.lines.Line2D at 0x11c31e978>,
           <matplotlib.lines.Line2D at 0x11c31eac8>]
```



```
In [118]: ABPm=indexedDataset[['ABPMean']]
          plt.plot(ABPm)
```

```
Out[118]: [<matplotlib.lines.Line2D at 0x11c4ac5f8>]
```




```
In [121]: #Determing rolling statistics
          #30 minutes
          rolmean=ABPm.rolling(window=30).mean()
          rolstd=ABPm.rolling(window=30).std()
          print(rolmean,rolstd)
```

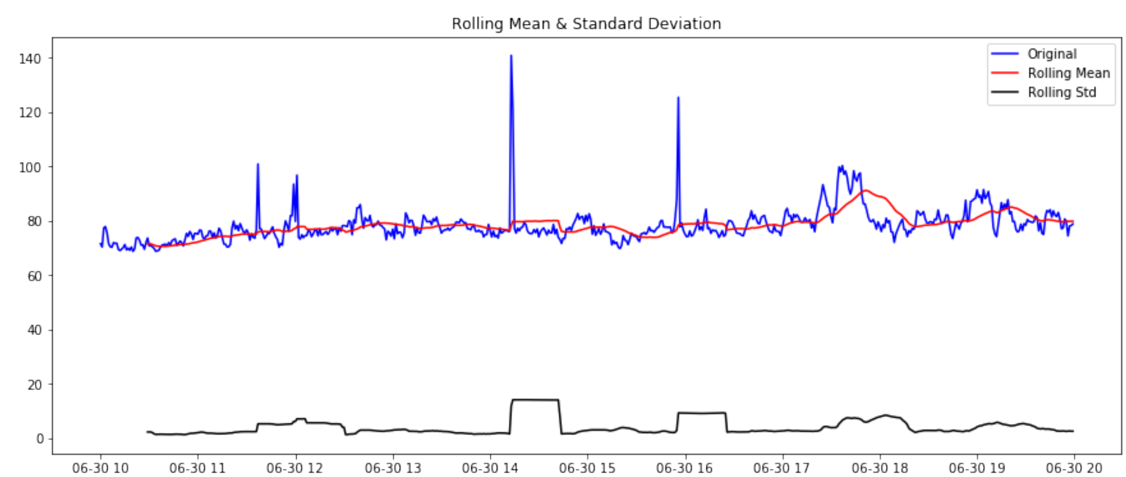
```
                     ABPMean
Time and date
2016-06-30 10:00:00      NaN
2016-06-30 10:01:00      NaN
2016-06-30 10:02:00      NaN
2016-06-30 10:03:00      NaN
2016-06-30 10:04:00      NaN
2016-06-30 10:05:00      NaN
2016-06-30 10:06:00      NaN
2016-06-30 10:07:00      NaN
2016-06-30 10:08:00      NaN
2016-06-30 10:09:00      NaN
2016-06-30 10:10:00      NaN
2016-06-30 10:11:00      NaN
2016-06-30 10:12:00      NaN
2016-06-30 10:13:00      NaN
2016-06-30 10:14:00      NaN
2016-06-30 10:15:00      NaN
```

```
2016-06-30 10:16:00        NaN
2016-06-30 10:17:00        NaN
2016-06-30 10:18:00        NaN
2016-06-30 10:19:00        NaN
2016-06-30 10:20:00        NaN
2016-06-30 10:21:00        NaN
2016-06-30 10:22:00        NaN
2016-06-30 10:23:00        NaN
2016-06-30 10:24:00        NaN
2016-06-30 10:25:00        NaN
2016-06-30 10:26:00        NaN
2016-06-30 10:27:00        NaN
2016-06-30 10:28:00        NaN
2016-06-30 10:29:00  71.433333
...                        ...
2016-06-30 19:30:00  82.600000
2016-06-30 19:31:00  82.326667
2016-06-30 19:32:00  82.006667
2016-06-30 19:33:00  81.780000
2016-06-30 19:34:00  81.376667
2016-06-30 19:35:00  81.093333
2016-06-30 19:36:00  80.850000
2016-06-30 19:37:00  80.526667
2016-06-30 19:38:00  80.183333
2016-06-30 19:39:00  79.980000
2016-06-30 19:40:00  79.906667
2016-06-30 19:41:00  79.900000
2016-06-30 19:42:00  80.136667
2016-06-30 19:43:00  80.310000
2016-06-30 19:44:00  80.326667
2016-06-30 19:45:00  80.240000
2016-06-30 19:46:00  80.153333
2016-06-30 19:47:00  80.070000
2016-06-30 19:48:00  79.990000
2016-06-30 19:49:00  79.783333
2016-06-30 19:50:00  79.800000
2016-06-30 19:51:00  79.710000
2016-06-30 19:52:00  79.623333
2016-06-30 19:53:00  79.543333
2016-06-30 19:54:00  79.673333
2016-06-30 19:55:00  79.796667
2016-06-30 19:56:00  79.733333
2016-06-30 19:57:00  79.710000
2016-06-30 19:58:00  79.770000
2016-06-30 19:59:00  79.766667

[600 rows x 1 columns]                    ABPMean
Time and date
```

```
2016-06-30 10:00:00         NaN
2016-06-30 10:01:00         NaN
2016-06-30 10:02:00         NaN
2016-06-30 10:03:00         NaN
2016-06-30 10:04:00         NaN
2016-06-30 10:05:00         NaN
2016-06-30 10:06:00         NaN
2016-06-30 10:07:00         NaN
2016-06-30 10:08:00         NaN
2016-06-30 10:09:00         NaN
2016-06-30 10:10:00         NaN
2016-06-30 10:11:00         NaN
2016-06-30 10:12:00         NaN
2016-06-30 10:13:00         NaN
2016-06-30 10:14:00         NaN
2016-06-30 10:15:00         NaN
2016-06-30 10:16:00         NaN
2016-06-30 10:17:00         NaN
2016-06-30 10:18:00         NaN
2016-06-30 10:19:00         NaN
2016-06-30 10:20:00         NaN
2016-06-30 10:21:00         NaN
2016-06-30 10:22:00         NaN
2016-06-30 10:23:00         NaN
2016-06-30 10:24:00         NaN
2016-06-30 10:25:00         NaN
2016-06-30 10:26:00         NaN
2016-06-30 10:27:00         NaN
2016-06-30 10:28:00         NaN
2016-06-30 10:29:00    2.329175
...                         ...
2016-06-30 19:30:00    5.209673
2016-06-30 19:31:00    5.097933
2016-06-30 19:32:00    4.944097
2016-06-30 19:33:00    4.891329
2016-06-30 19:34:00    4.558258
2016-06-30 19:35:00    4.386887
2016-06-30 19:36:00    4.128016
2016-06-30 19:37:00    3.686128
2016-06-30 19:38:00    3.588976
2016-06-30 19:39:00    3.459559
2016-06-30 19:40:00    3.536405
2016-06-30 19:41:00    3.545954
2016-06-30 19:42:00    3.378480
2016-06-30 19:43:00    3.424692
2016-06-30 19:44:00    3.437414
2016-06-30 19:45:00    3.303979
2016-06-30 19:46:00    3.238106
```

```
2016-06-30 19:47:00  3.109402
2016-06-30 19:48:00  3.023853
2016-06-30 19:49:00  2.669894
2016-06-30 19:50:00  2.688930
2016-06-30 19:51:00  2.611823
2016-06-30 19:52:00  2.658322
2016-06-30 19:53:00  2.691837
2016-06-30 19:54:00  2.643526
2016-06-30 19:55:00  2.540904
2016-06-30 19:56:00  2.652303
2016-06-30 19:57:00  2.664757
2016-06-30 19:58:00  2.607304
2016-06-30 19:59:00  2.608518

[600 rows x 1 columns]
```

```
In [122]: #plot rolling statistics
          orig=plt.plot(ABPm,color='b',label='Original')
          mean=plt.plot(rolmean,color='red',label='Rolling Mean')
          std=plt.plot(rolstd,c='k',label='Rolling Std')
          plt.legend(loc='best')
          plt.title('Rolling Mean & Standard Deviation')
          plt.show(block=False)
```



1.1 Stationarity

the standard deviation is not constant, so our data is not stationary

dickey-fuller testunit root

-Dickey-Fuller test-Augmented Dickey-Fuller testunit root http://www.pengfoo.com/post/machine-learning/2017-01-24

```
In [125]: #Perform Dickey-Fuller test
          from statsmodels.tsa.stattools import adfuller
          print('Results of Dickey-Fuller Test:')
          dftest=adfuller(ABPm['ABPMean'],autolag='AIC')

          dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#Lags Used','Numbe
          for k,v in dftest[4].items():
              dfoutput['Critical Value (%s)'%k]=v

          print(dfoutput)
```

```
Results of Dickey-Fuller Test:
Test Statistic                  -4.962266
p-value                          0.000026
#Lags Used                       6.000000
Number of Observations Used    593.000000
Critical Value (1%)             -3.441426
Critical Value (5%)             -2.866426
Critical Value (10%)            -2.569372
dtype: float64
```

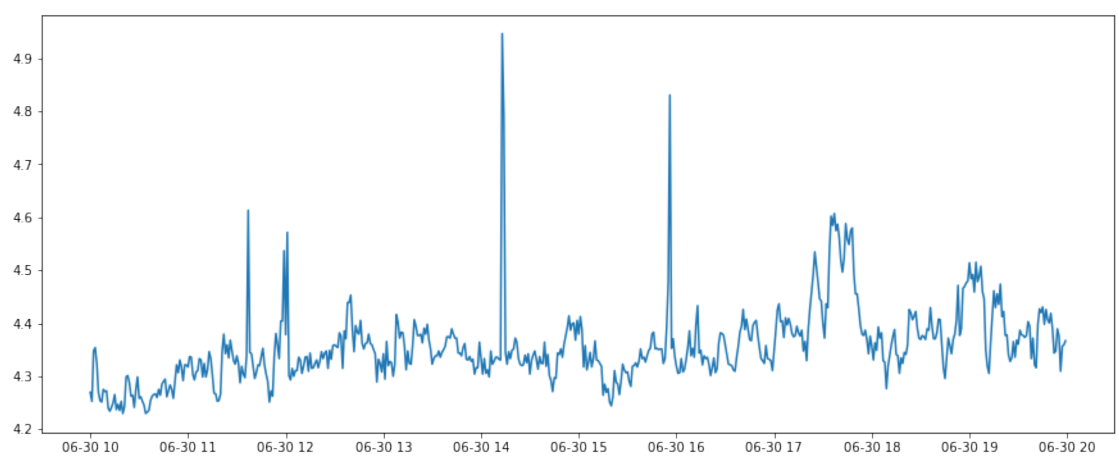
1.2 Note

p-value should be always small, here is close to 0, it's good

Critical Value should be always more than Test Statistic, it's good shows that it can reject the hypothesis and we can say the data is stationary

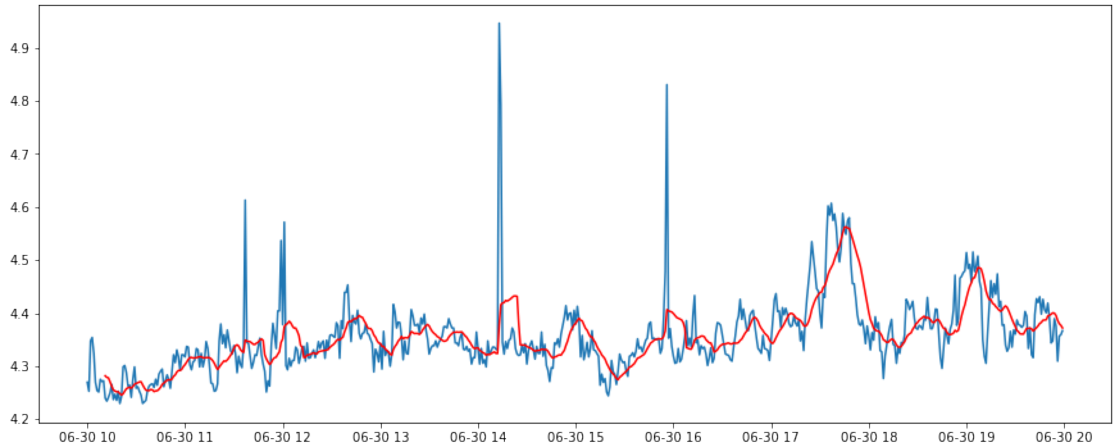
```
In [126]: #Estimating trend
          ABPm_logScale=np.log(ABPm)
          plt.plot(ABPm_logScale)
```

```
Out[126]: [<matplotlib.lines.Line2D at 0x11eb8e748>]
```



```
In [127]: movingAverage=ABPm_logScale.rolling(window=12).mean()
          movingSTD=ABPm_logScale.rolling(window=12).mean()
          plt.plot(ABPm_logScale)
          plt.plot(movingAverage,c='red')
```

```
Out[127]: [<matplotlib.lines.Line2D at 0x11873d550>]
```



1.3 Note

1.3.1 some standard ways to make a time series stationary

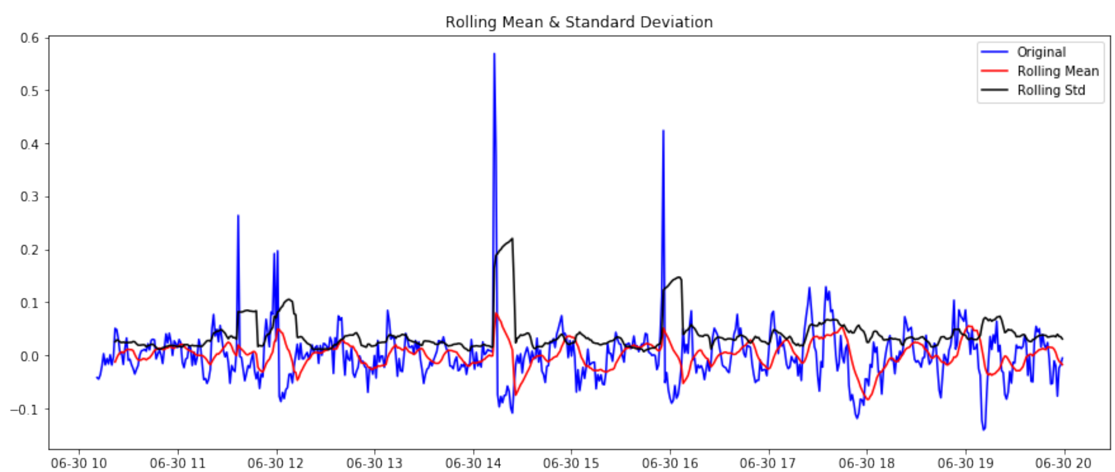
make it stationary like take log, take a square, cube roots all depends on data what it holds so here we're going to log scale

```
In [130]: datasetLogScaleMinusMovingAverage=ABPm_logScale-movingAverage
          datasetLogScaleMinusMovingAverage.head(12)

          #remove Nan Values
          datasetLogScaleMinusMovingAverage.dropna(inplace=True)
          datasetLogScaleMinusMovingAverage.head(10)
```

```
Out[130]:                      ABPMean
          Time and date
          2016-06-30 10:11:00 -0.041982
          2016-06-30 10:12:00 -0.044796
          2016-06-30 10:13:00 -0.036622
          2016-06-30 10:14:00 -0.019879
          2016-06-30 10:15:00  0.003079
          2016-06-30 10:16:00 -0.018152
          2016-06-30 10:17:00 -0.006202
          2016-06-30 10:18:00 -0.016159
          2016-06-30 10:19:00  0.000939
          2016-06-30 10:20:00 -0.018289
```

```
In [134]: 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='b',label='Original')
              mean=plt.plot(movingAverage,c='red',label='Rolling Mean')
              std=plt.plot(movingSTD,c='k',label='Rolling Std')
              plt.legend(loc='best')
              plt.title('Rolling Mean & Standard Deviation')
              plt.show(block=False)

              #Perform Dickey-Fuller test
              from statsmodels.tsa.stattools import adfuller
              print('Results of Dickey-Fuller Test:')
              dftest=adfuller(timeseries['ABPMean'],autolag='AIC')

              dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#Lags Used','Nu
              for k,v in dftest[4].items():
                  dfoutput['Critical Value (%s)'%k]=v

              print(dfoutput)
```

```
In [135]: test_stationarity(datasetLogScaleMinusMovingAverage)
```

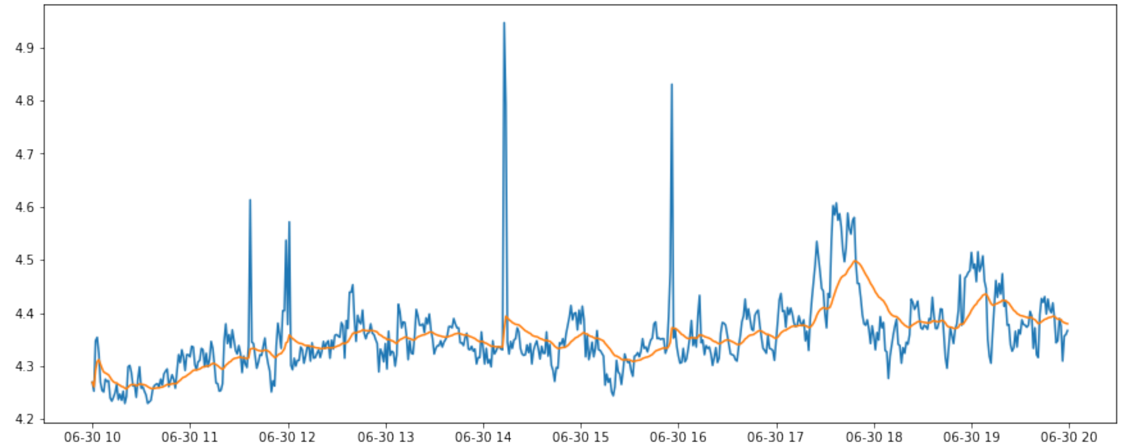



```
Results of Dickey-Fuller Test:
Test Statistic                -1.317320e+01
p-value                        1.238328e-24
#Lags Used                     0.000000e+00
```

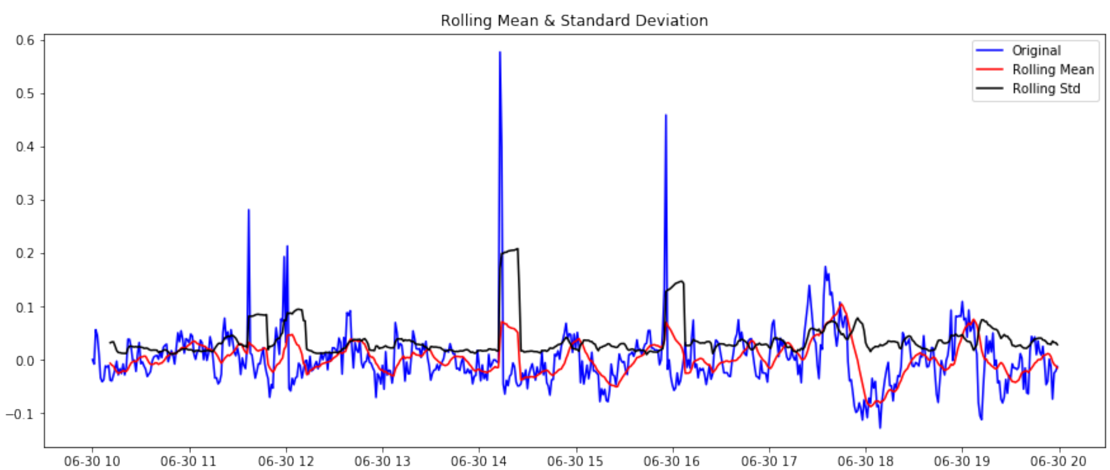
```
Number of Observations Used    5.880000e+02
Critical Value (1%)           -3.441520e+00
Critical Value (5%)           -2.866468e+00
Critical Value (10%)          -2.569394e+00
dtype: float64
```

In [136]:
```
#weighted mean
exponentialDecayWeightedAverage=ABPm_logScale.ewm(halflife=12,min_periods=0,adjust=Tr
plt.plot(ABPm_logScale)
plt.plot(exponentialDecayWeightedAverage)
```

Out[136]: [<matplotlib.lines.Line2D at 0x11a6f2a58>]



In [137]:
```
#substract weighted mean instead of simple mean
#and then check for stationarity
datasetLogScaleMinusMovingExponentialDecayAverage=ABPm_logScale-exponentialDecayWeigh
test_stationarity(datasetLogScaleMinusMovingExponentialDecayAverage)
```



```
Results of Dickey-Fuller Test:
Test Statistic                 -1.266196e+01
p-value                         1.299104e-23
#Lags Used                      0.000000e+00
Number of Observations Used     5.990000e+02
Critical Value (1%)            -3.441314e+00
Critical Value (5%)            -2.866377e+00
Critical Value (10%)           -2.569346e+00
dtype: float64
```

1.4 Note

the std is quite flat and in fact you can also say that this doesn't have any trend

use the function called a shift to shift all of these values below we take a lag of 1 so here we just shift the values by 1

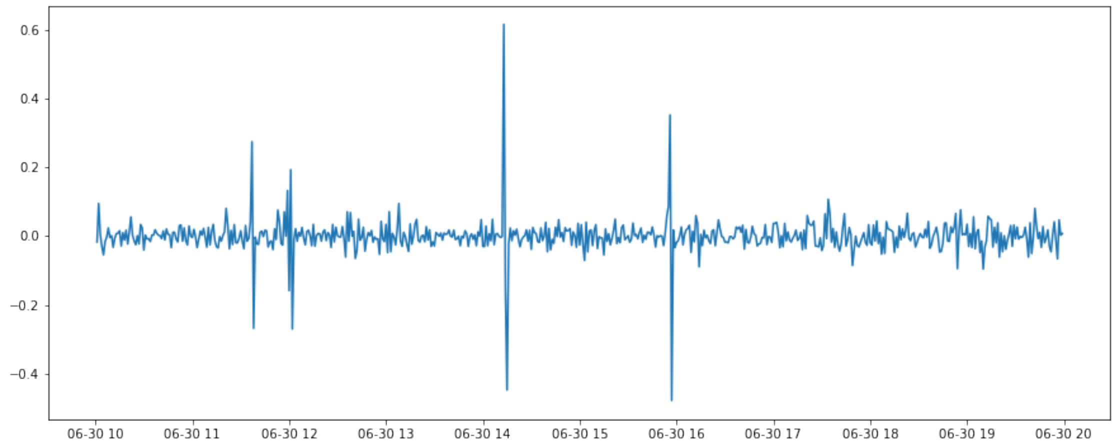
1.4.1 ARIMA model

ARIMA model have three models in it: * AR model: stand for auto regressive * MA model: for moving average * IS model: for integration

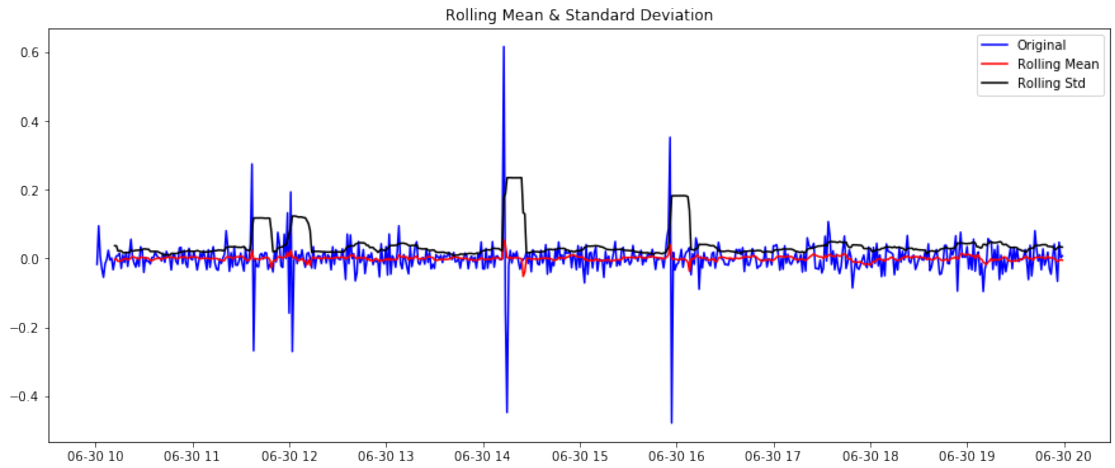
so Arima model basically takes three parameters

```
In [138]: #shift the value into series so that we can use it in the forecasting
          datasetLogDiffShifting=ABPm_logScale-ABPm_logScale.shift()
          plt.plot(datasetLogDiffShifting)
```

```
Out[138]: [<matplotlib.lines.Line2D at 0x11b19a898>]
```



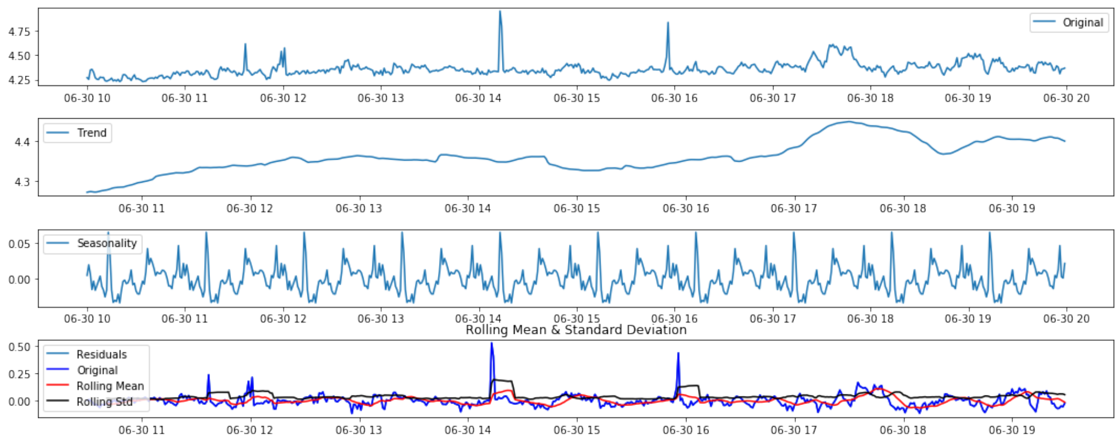
```
In [139]: datasetLogDiffShifting.dropna(inplace=True)
          test_stationarity(datasetLogDiffShifting)
```




```
Results of Dickey-Fuller Test:
Test Statistic                -1.143874e+01
p-value                        6.254018e-21
#Lags Used                     9.000000e+00
Number of Observations Used    5.890000e+02
Critical Value (1%)           -3.441501e+00
Critical Value (5%)           -2.866460e+00
Critical Value (10%)          -2.569390e+00
dtype: float64
```

```
In [148]: from statsmodels.tsa.seasonal import seasonal_decompose
          # sm.tsa.seasonal_decompose(ABPm_logScale.G.values, freq=1440)
          #freq is calculated based on the time window, which is 10 mins,
          #so the freqency actually is half a day. freq=6*12
          #frep=6*10 ten hours???
          decomposition = seasonal_decompose(ABPm_logScale,freq=60)
          trend=decomposition.trend
          seasonal=decomposition.seasonal
          residual=decomposition.resid

          plt.subplot(411)
          plt.plot(ABPm_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()
```




```
Results of Dickey-Fuller Test:
Test Statistic                 -1.164580e+01
p-value                         2.093817e-21
#Lags Used                      0.000000e+00
Number of Observations Used     5.390000e+02
Critical Value (1%)            -3.442541e+00
Critical Value (5%)            -2.866917e+00
Critical Value (10%)           -2.569634e+00
dtype: float64
```

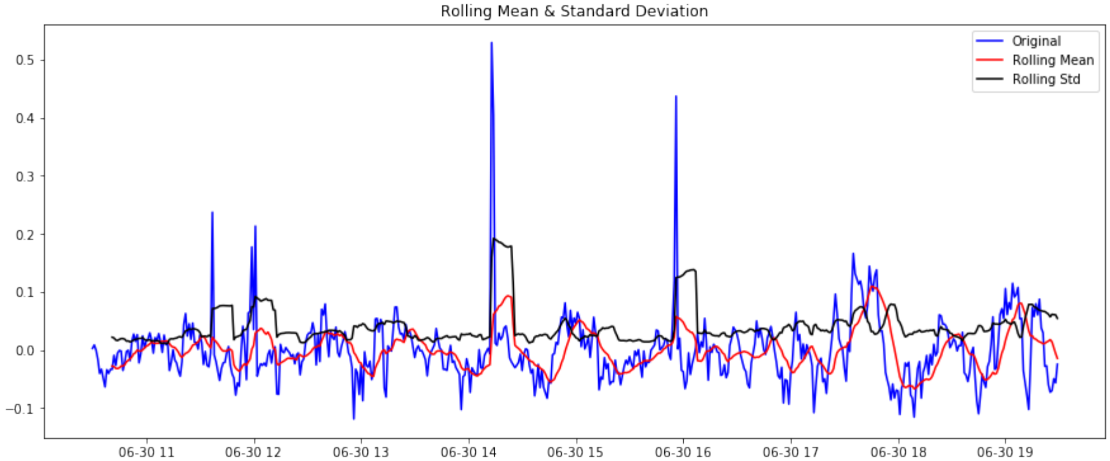
1.5 Note

residuals is nothing, the irregularities that is present in your data

so they don't have any shape any size and it cannot find out what is going to happen next it's quite regular in nature

so now we are going to check the noise if it's stationary or not

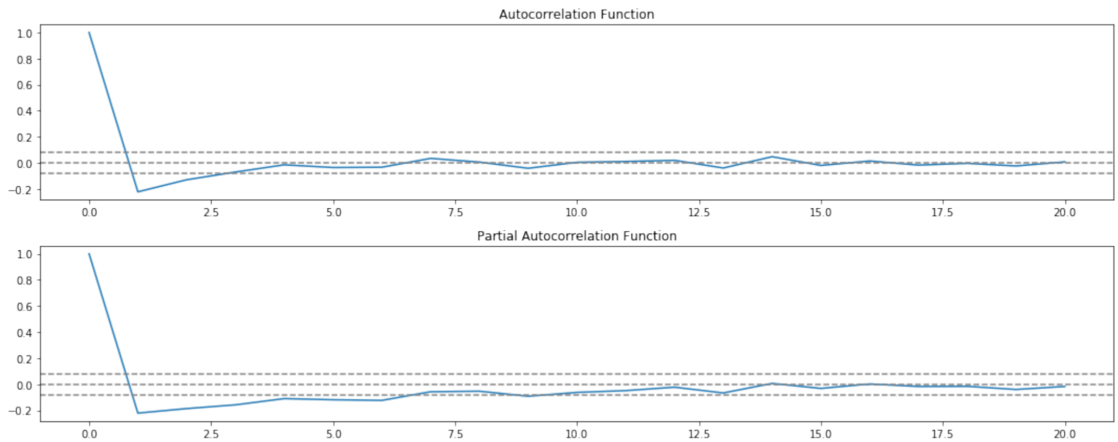
```
In [149]: decomposeLogData=residual
          decomposeLogData.dropna(inplace=True)
          test_stationarity(decomposeLogData)
```




```
Results of Dickey-Fuller Test:
Test Statistic                -1.164580e+01
p-value                        2.093817e-21
#Lags Used                     0.000000e+00
Number of Observations Used    5.390000e+02
Critical Value (1%)           -3.442541e+00
Critical Value (5%)           -2.866917e+00
Critical Value (10%)          -2.569634e+00
dtype: float64
```

In [150]:
```
#determine how to calculate p-value and Q-value(left graph) using acf
#according to the graph we need to check that what is the value where the graph cuts
#or you can set drops to zero for the first time

'''
it touches the confidence level over here so here if you see the p-values (right gra
almost around 1 or 2
Q valueit cut
drops to zeroOQ value1

'''

#ACF and PACF plots
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(211)
plt.plot(lag_acf)
```

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

#plot PACF
plt.subplot(212)
plt.plot(lag_pacf)
plt.axhline(y=0,linestyle='--',c='gray')
plt.axhline(y=-1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',c='gray')
plt.axhline(y=1.96/np.sqrt(len(datasetLogDiffShifting)),linestyle='--',c='gray')
plt.title('Partial Autocorrelation Function')

plt.tight_layout()
```



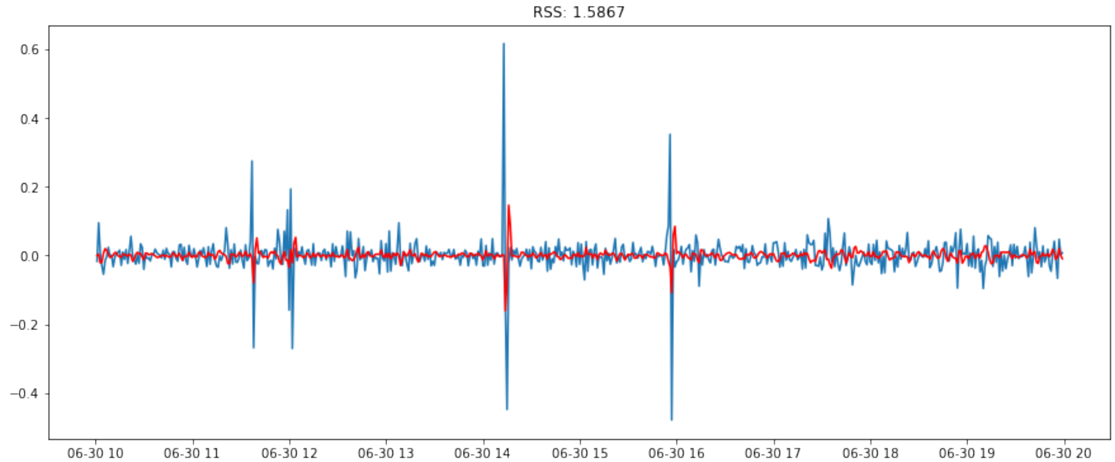
1.6 Note

we can simply substitute these values in the ARIMA model
with respect to AR that is your auto regressive part

In [188]:
```
from statsmodels.tsa.arima_model import ARIMA
# AR Model
#(2,1,2)means P value is 2, differenced it 1, so D value becomes 1, Q value is again
#(1,1,0)(0,1,1)
model= ARIMA(ABPm_logScale,order=(2,1,0))
results_AR=model.fit(disp=-1)
plt.plot(datasetLogDiffShifting)
plt.plot(results_AR.fittedvalues,color='red')
#RSS is the residual sum of squares
# the greater the RSS the bad is for you
plt.title('RSS: %.4f'%sum((results_AR.fittedvalues-datasetLogDiffShifting['ABPMean']]
print('Plotting AR model')
```

```
/usr/local/Cellar/python3/3.6.4_2/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-p
  % freq, ValueWarning)
/usr/local/Cellar/python3/3.6.4_2/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-p
  % freq, ValueWarning)
```

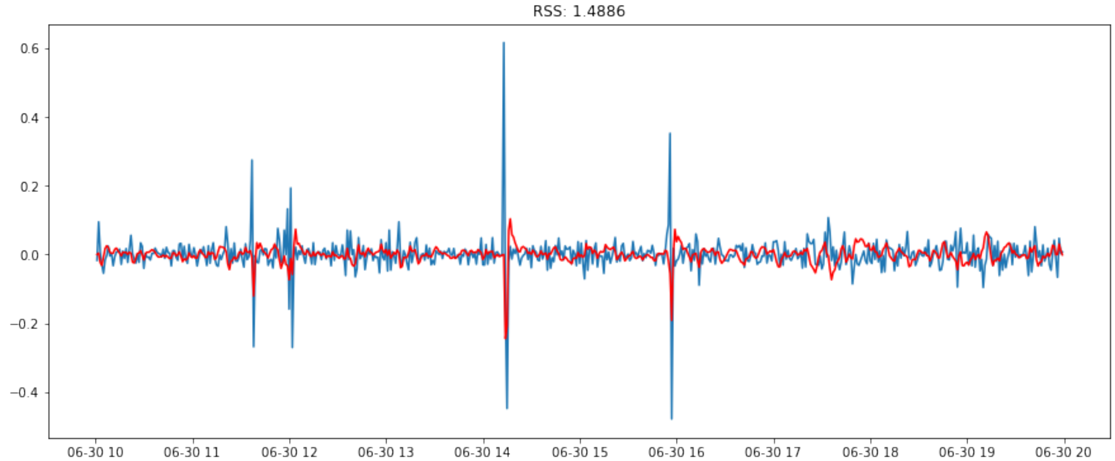
```
Plotting AR model
```



In [187]:
```
#MA model
model=ARIMA(ABPm_logScale,order=(0,1,2))
results_MA=model.fit(disp=-1)
plt.plot(datasetLogDiffShifting)
plt.plot(results_MA.fittedvalues,color='red')
plt.title('RSS: %.4f'%sum((results_MA.fittedvalues-datasetLogDiffShifting['ABPMean'])
print('Plotting MA model')
```

```
/usr/local/Cellar/python3/3.6.4_2/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-p
  % freq, ValueWarning)
/usr/local/Cellar/python3/3.6.4_2/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-p
  % freq, ValueWarning)
```

```
Plotting MA model
```

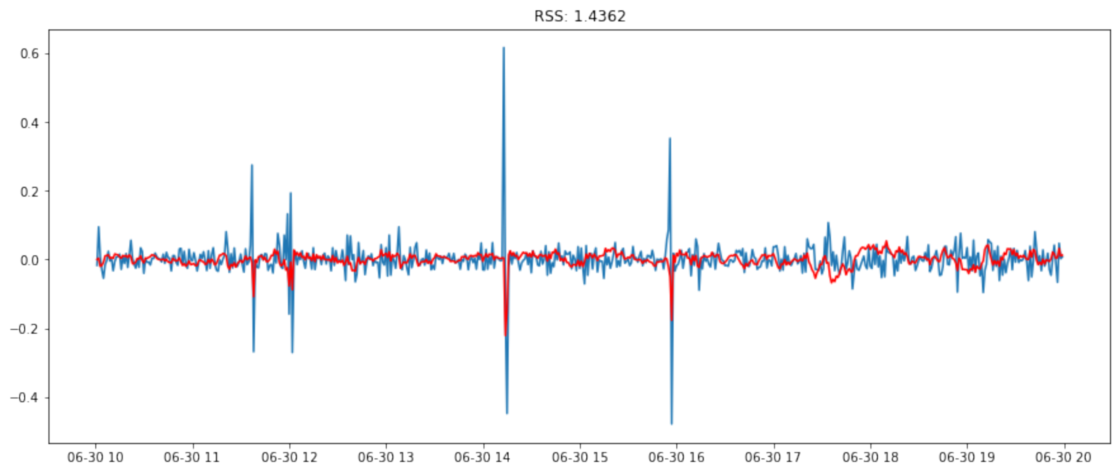


1.7 Note

here we conclude that with respect to auto regressive part, we have the RSS as 1.5867 with respect to moving average we have the RSS 1.4886 and if we combine both of them and make a ARIMA out of it that is (2,1,2)

```
In [189]: model=ARIMA(ABPm_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['ABPMea
          print('Plotting ARIMA model')
```

```
/usr/local/Cellar/python3/3.6.4_2/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-
  % freq, ValueWarning)
/usr/local/Cellar/python3/3.6.4_2/Frameworks/Python.framework/Versions/3.6/lib/python3.6/site-
  % freq, ValueWarning)


Plotting ARIMA model
```




```
In [190]: #do some fitting on the time series on what data we have
          predictions_ARIMA_diff=pd.Series(results_ARIMA.fittedvalues,copy=True)
          print(predictions_ARIMA_diff.head())
```

```
Time and date
2016-06-30 10:01:00    0.000193
2016-06-30 10:02:00    0.003794
2016-06-30 10:03:00   -0.020167
2016-06-30 10:04:00   -0.016795
2016-06-30 10:05:00   -0.007855
dtype: float64
```

```
In [191]: #convert to cumulative sum
          predictions_ARIMA_diff_cumsum=predictions_ARIMA_diff.cumsum()
          print(predictions_ARIMA_diff_cumsum.head())
```

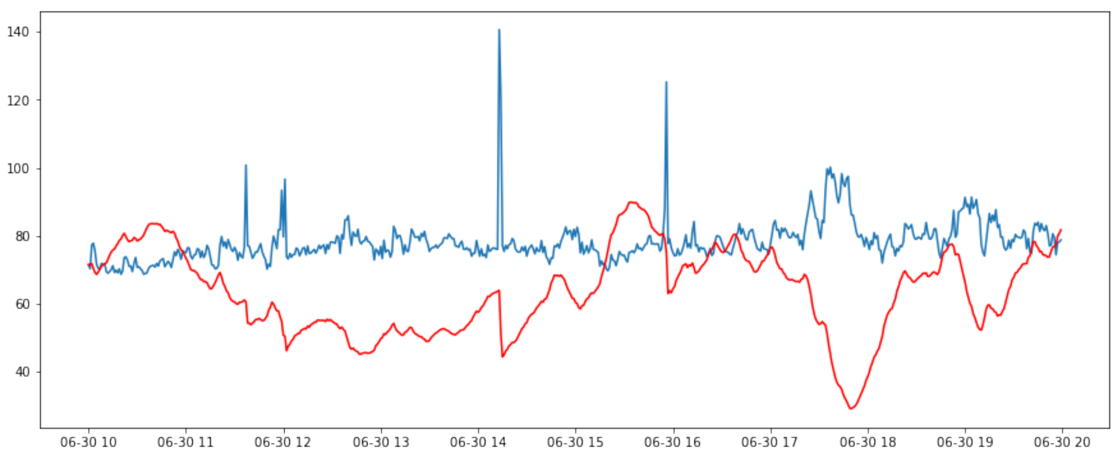
```
Time and date
2016-06-30 10:01:00    0.000193
2016-06-30 10:02:00    0.003987
2016-06-30 10:03:00   -0.016180
2016-06-30 10:04:00   -0.032975
2016-06-30 10:05:00   -0.040829
dtype: float64
```

```
In [201]: # finally we are going to have the predictions done for the fitted values
          predictions_ARIMA_log=pd.Series(ABPm_logScale['ABPMean'].iloc[0],index=ABPm_logScale
          predictions_ARIMA_log=predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum,fill_va
          predictions_ARIMA_log.head()
```

Out[201]:
```
Time and date
2016-06-30 10:00:00    4.269697
2016-06-30 10:01:00    4.269890
2016-06-30 10:02:00    4.273684
2016-06-30 10:03:00    4.253517
2016-06-30 10:04:00    4.236723
dtype: float64
```

In [202]:
```
#come back to the original form
# plot the actual values to how our model has fited
predictions_ARIMA=np.exp(predictions_ARIMA_log)
plt.plot(ABPm)
plt.plot(predictions_ARIMA,c='r')
```

Out[202]:
```
[<matplotlib.lines.Line2D at 0x12202c7b8>]
```



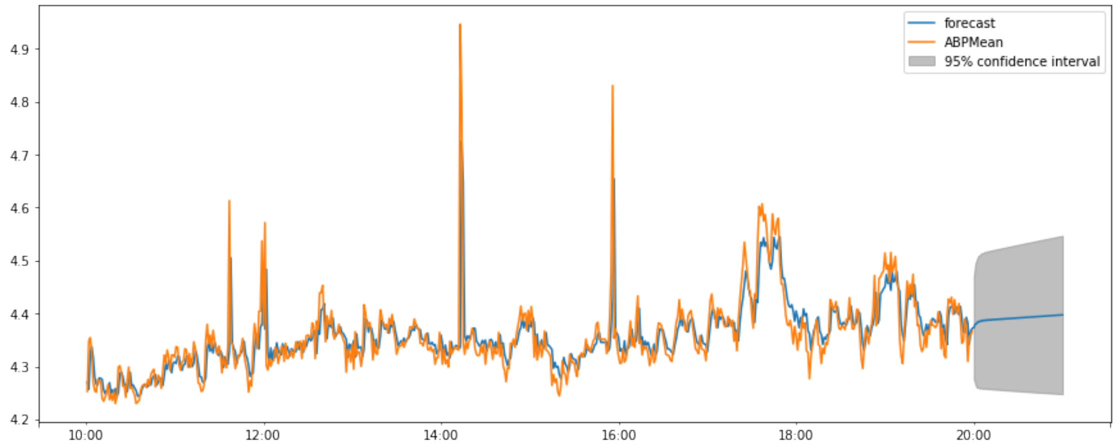
In [203]:
```
ABPm_logScale
```

Out[203]:
```
                     ABPMean
Time and date
2016-06-30 10:00:00  4.269697
2016-06-30 10:01:00  4.252772
2016-06-30 10:02:00  4.347694
2016-06-30 10:03:00  4.354141
2016-06-30 10:04:00  4.324133
2016-06-30 10:05:00  4.269697
2016-06-30 10:06:00  4.254193
2016-06-30 10:07:00  4.251348
2016-06-30 10:08:00  4.275276
2016-06-30 10:09:00  4.271095
2016-06-30 10:10:00  4.272491
2016-06-30 10:11:00  4.239887
```

```
2016-06-30 10:12:00  4.234107
2016-06-30 10:13:00  4.241327
2016-06-30 10:14:00  4.249923
2016-06-30 10:15:00  4.265493
2016-06-30 10:16:00  4.237001
2016-06-30 10:17:00  4.247066
2016-06-30 10:18:00  4.235555
2016-06-30 10:19:00  4.252772
2016-06-30 10:20:00  4.229749
2016-06-30 10:21:00  4.242765
2016-06-30 10:22:00  4.298645
2016-06-30 10:23:00  4.301359
2016-06-30 10:24:00  4.287716
2016-06-30 10:25:00  4.262680
2016-06-30 10:26:00  4.264087
2016-06-30 10:27:00  4.241327
2016-06-30 10:28:00  4.275276
2016-06-30 10:29:00  4.298645
...                       ...
2016-06-30 19:30:00  4.360548
2016-06-30 19:31:00  4.387014
2016-06-30 19:32:00  4.378270
2016-06-30 19:33:00  4.377014
2016-06-30 19:34:00  4.373238
2016-06-30 19:35:00  4.377014
2016-06-30 19:36:00  4.403054
2016-06-30 19:37:00  4.394449
2016-06-30 19:38:00  4.333361
2016-06-30 19:39:00  4.371976
2016-06-30 19:40:00  4.321480
2016-06-30 19:41:00  4.316154
2016-06-30 19:42:00  4.396915
2016-06-30 19:43:00  4.427239
2016-06-30 19:44:00  4.420045
2016-06-30 19:45:00  4.430817
2016-06-30 19:46:00  4.398146
2016-06-30 19:47:00  4.426044
2016-06-30 19:48:00  4.406719
2016-06-30 19:49:00  4.400603
2016-06-30 19:50:00  4.418841
2016-06-30 19:51:00  4.389499
2016-06-30 19:52:00  4.343805
2016-06-30 19:53:00  4.347694
2016-06-30 19:54:00  4.389499
2016-06-30 19:55:00  4.375757
2016-06-30 19:56:00  4.309456
2016-06-30 19:57:00  4.356709
2016-06-30 19:58:00  4.359270
```

```
2016-06-30 19:59:00  4.366913

[600 rows x 1 columns]
```

```
In [210]: #to predict next 60 points
          results_ARIMA.plot_predict(1,660)
```



1.8 Note

the blue is the forecasted value and this gray part is the confidence level so now whatever happens or however you do the foreasting this value will not exceed the confidence level so it means for the next 1 hour you have the prediction somewhat like this

```
In [211]: x=results_ARIMA.forecast(steps=60)

In [206]: x[1]

Out[206]: array([0.04893829, 0.0579196 , 0.06169574, 0.06335123, 0.06434122,
                 0.06488896, 0.06533437, 0.06563456, 0.06593559, 0.06616533,
                 0.06641941, 0.06662624, 0.06686254, 0.06706145, 0.06728976,
                 0.06748583, 0.06770965, 0.06790462, 0.06812528, 0.06831974,
                 0.06853778, 0.06873188, 0.06894759, 0.06914136, 0.06935489,
                 0.0695483 , 0.06975978, 0.06995279, 0.07016232, 0.07035489,
                 0.07056256, 0.07075466, 0.07096054, 0.07115213, 0.07135631,
                 0.07154735, 0.0717499 , 0.07194037, 0.07214134, 0.07233122,
                 0.07253068, 0.07271994, 0.07291795, 0.07310657, 0.07330318,
                 0.07349115, 0.0736864 , 0.0738737 , 0.07406764, 0.07425426,
                 0.07444694, 0.07463287, 0.07482432, 0.07500956, 0.07519982,
                 0.07538435, 0.07557345, 0.07575727, 0.07594525, 0.07612836])

In [207]: len(x[1])

Out[207]: 60
```

```
In [208]: np.exp(x[1])

Out[208]: array([1.05015555, 1.0596298 , 1.06363867, 1.06540098, 1.06645623,
                 1.06704054, 1.06751591, 1.06783641, 1.06815792, 1.06840335,
                 1.06867484, 1.06889589, 1.0691485 , 1.06936119, 1.06960536,
                 1.0698151 , 1.07005457, 1.07026323, 1.07049941, 1.0707076 ,
                 1.07094109, 1.07114898, 1.07138006, 1.07158767, 1.07181652,
                 1.07202384, 1.07225057, 1.07245755, 1.07268228, 1.07288887,
                 1.0731117 , 1.07331786, 1.07353886, 1.07374456, 1.07396382,
                 1.07416901, 1.0743866 , 1.07459126, 1.07480725, 1.07501135,
                 1.0752258 , 1.07542931, 1.07564228, 1.07584518, 1.07605672,
                 1.07625901, 1.07646917, 1.07667081, 1.07687965, 1.07708063,
                 1.07728818, 1.0774885 , 1.07769481, 1.07789445, 1.07809955,
                 1.07829851, 1.07850244, 1.07870071, 1.07890351, 1.07910108])
```