forecasting_AirPassengers

June 5, 2018

```
In [70]: # Load the relevant packages
         import math
         import pandas as pd
         import numpy as np
         import matplotlib.pylab as plt
         %matplotlib inline
         from matplotlib.pylab import rcParams
         from statsmodels.tsa.stattools import adfuller
         from statsmodels.tsa.stattools import acf, pacf
         from statsmodels.tsa.arima_model import ARIMA
         import statsmodels.api as sm

         rcParams['figure.figsize'] = 15, 6
```

```
In [2]: # Load the dataset
        dateparse = lambda dates: pd.datetime.strptime(dates, '%Y-%m')
        data = pd.read_csv('AirPassengers.csv', parse_dates=['Month'], index_col='Month',date_
        data.head()
```

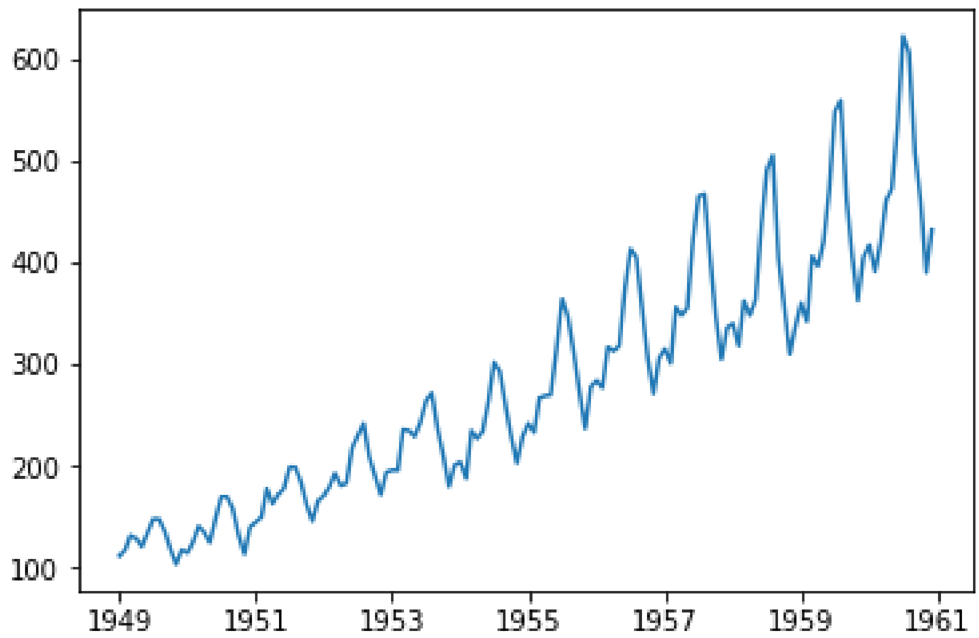
```
Out[2]:             #Passengers
        Month
        1949-01-01          112
        1949-02-01          118
        1949-03-01          132
        1949-04-01          129
        1949-05-01          121
```

```
In [3]: # save the number of passengers in ts for ease of access
        ts = data['#Passengers']
        ts.head()
```

```
Out[3]: 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
```

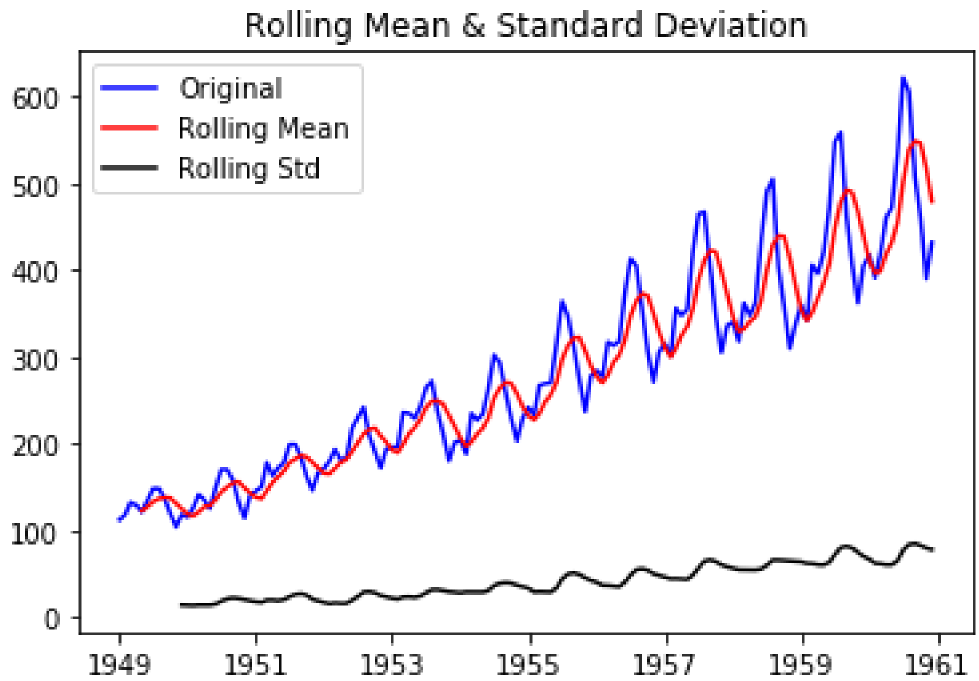
In [4]:
```
# visualize the data
plt.plot(ts)
```

Out[4]: [<matplotlib.lines.Line2D at 0x1c13ff0dd8>]



In [5]:
```
# Function to test the stationarity of a time series
def test_stationarity(timeseries):

    #Determing rolling statistics
    rolmean = timeseries.rolling(window=5).mean()
    rolstd = timeseries.rolling(window=12).std()

    #Plot rolling statistics:
    orig = plt.plot(timeseries, 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)

    #Perform Dickey-Fuller test:
    print('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, 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 [6]: # Test for stationarity
        test_stationarity(ts)
```

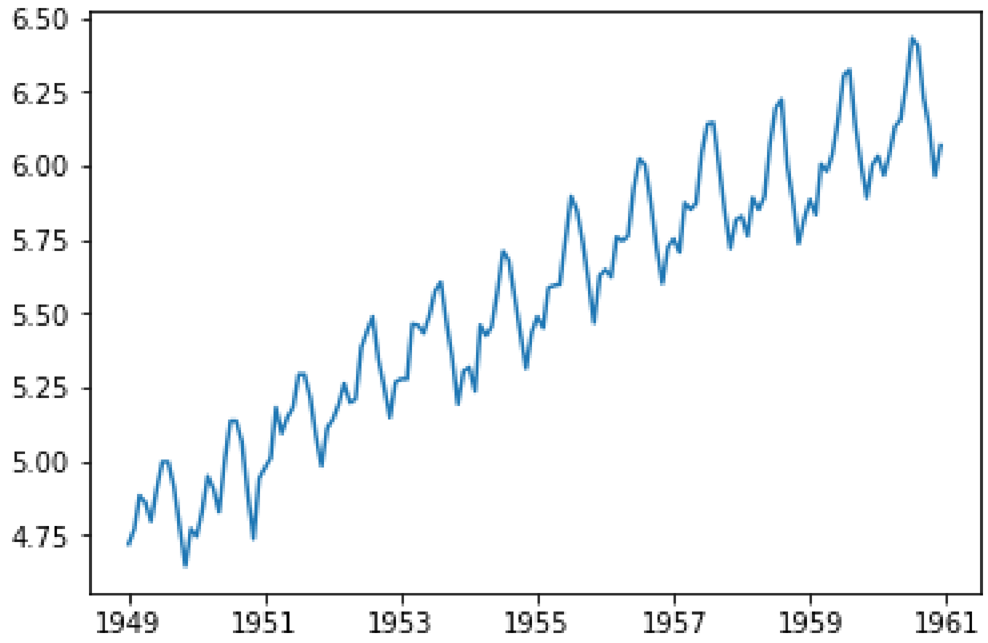



```
Results of Dickey-Fuller Test:
Test Statistic                   0.815369
p-value                          0.991880
#Lags Used                      13.000000
Number of Observations Used    130.000000
Critical Value (1%)             -3.481682
dtype: float64
Test Statistic                   0.815369
p-value                          0.991880
#Lags Used                      13.000000
Number of Observations Used    130.000000
Critical Value (1%)             -3.481682
Critical Value (5%)             -2.884042
dtype: float64
Test Statistic                   0.815369
p-value                          0.991880
#Lags Used                      13.000000
Number of Observations Used    130.000000
Critical Value (1%)             -3.481682
Critical Value (5%)             -2.884042
Critical Value (10%)            -2.578770
```

```
dtype: float64
```

```
In [7]: # Lets Estimate or model the trend in the data and then remove it from the series. Tak
        ts_log = np.log(ts)
        plt.plot(ts_log)
```

```
Out[7]: [<matplotlib.lines.Line2D at 0x1c1e5b0be0>]
```



In this approach, we take average of ‘k’ consecutive values depending on the frequency of time series. Here we can take the average over the past 1 year, i.e. last 12 values. First compute the rolling mean:

```
In [8]: ts.head()
```

```
Out[8]: 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 [36]: newData = pd.DataFrame({'Passengers': ts.values, 'RolMean' : ts.rolling(window=12).mea
         newData['DiffRolMean'] = newData.apply(lambda x: x['RolMean']-x['Passengers'] if not n
         newData = newData.dropna()
         newData.head(13)
```

Out[36]:

Month	Passengers	RolMean	TSLog	DiffRolMean
1949-12-01	118	126.666667	4.770685	8.666667
1950-01-01	115	126.916667	4.744932	11.916667
1950-02-01	126	127.583333	4.836282	1.583333
1950-03-01	141	128.333333	4.948760	-12.666667
1950-04-01	135	128.833333	4.905275	-6.166667
1950-05-01	125	129.166667	4.828314	4.166667
1950-06-01	149	130.333333	5.003946	-18.666667
1950-07-01	170	132.166667	5.135798	-37.833333
1950-08-01	170	134.000000	5.135798	-36.000000
1950-09-01	158	135.833333	5.062595	-22.166667
1950-10-01	133	137.000000	4.890349	4.000000
1950-11-01	114	137.833333	4.736198	23.833333
1950-12-01	140	139.666667	4.941642	-0.333333

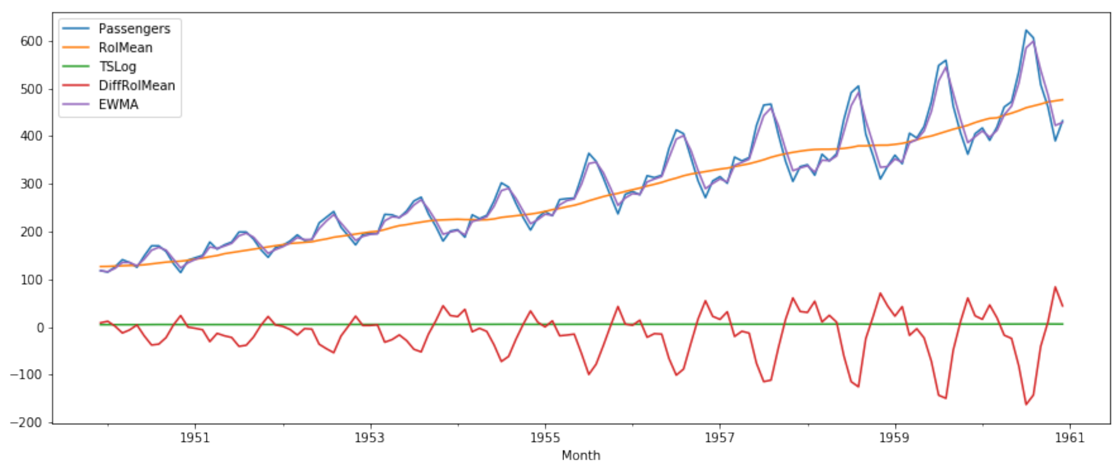
In [37]:
```
newData['EWMA'] = newData['Passengers'].ewm(com=0.5).mean()
newData.head()
```

Out[37]:

Month	Passengers	RolMean	TSLog	DiffRolMean	EWMA
1949-12-01	118	126.666667	4.770685	8.666667	118.000000
1950-01-01	115	126.916667	4.744932	11.916667	115.750000
1950-02-01	126	127.583333	4.836282	1.583333	122.846154
1950-03-01	141	128.333333	4.948760	-12.666667	135.100000
1950-04-01	135	128.833333	4.905275	-6.166667	135.033058

In [38]:
```
newData.plot()
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1c1ee4a1d0>



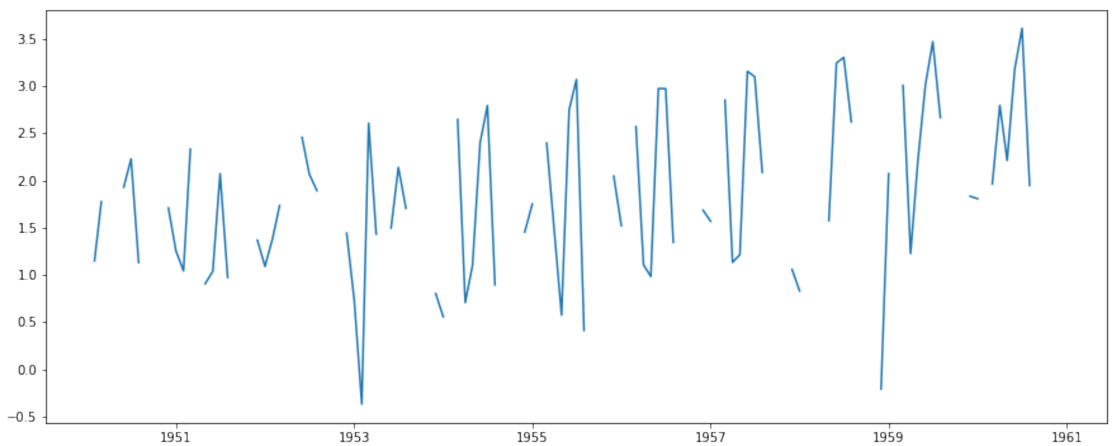
In [41]:
```
newTSLog = newData.apply(lambda x: x['Passengers']-x['EWMA'] if not math.isnan(x['Pas
newTSLog.head()
```

Out[41]: Month
```
1949-12-01    0.000000
1950-01-01   -0.750000
1950-02-01    3.153846
1950-03-01    5.900000
1950-04-01   -0.033058
Freq: MS, dtype: float64
```

In [42]:
```
new_ts_log = np.log(newTSLog)
plt.plot(new_ts_log)
```

```
/Volumes/MacHD01/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: RuntimeWarning
  """Entry point for launching an IPython kernel.
/Volumes/MacHD01/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: RuntimeWarning
  """Entry point for launching an IPython kernel.
```

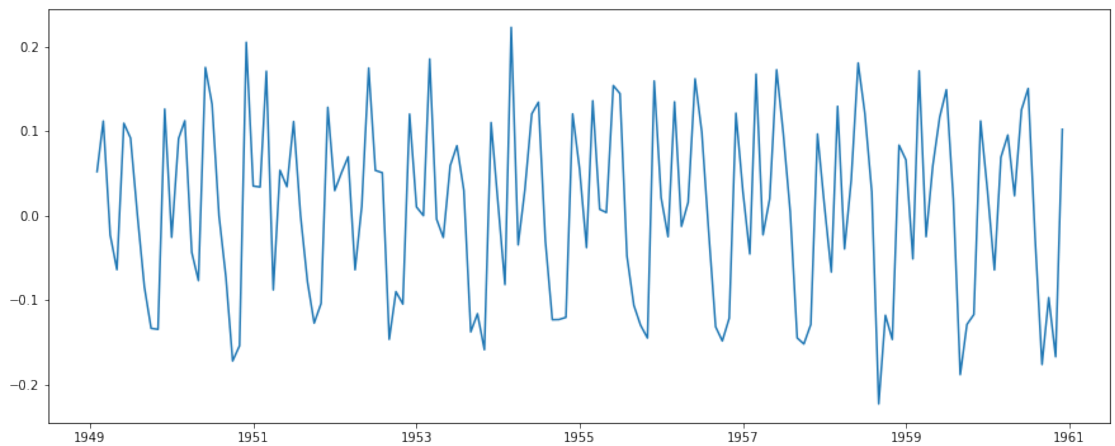
Out[42]: [<matplotlib.lines.Line2D at 0x1c1f9b4be0>]



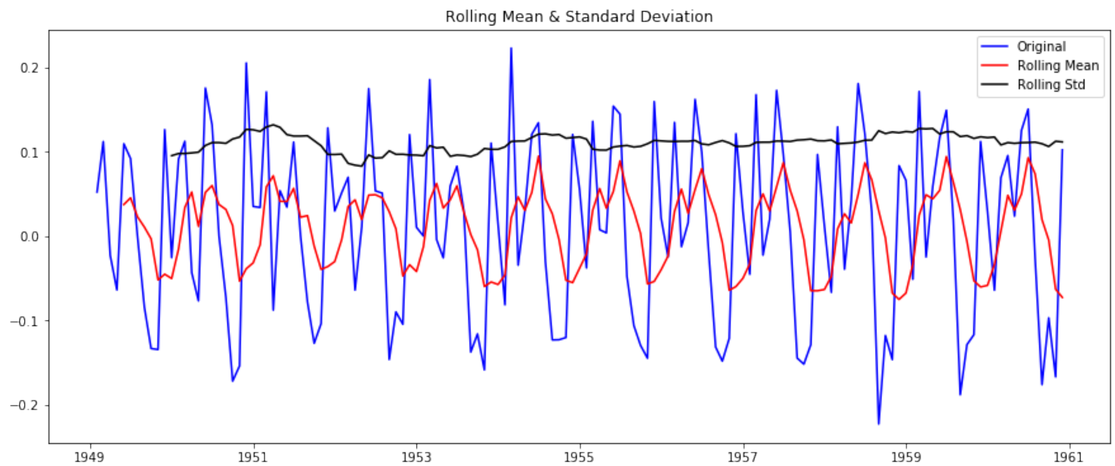
One of the most common methods of dealing with both trend and seasonality is differencing. In this technique, we take the difference of the observation at a particular instant with that at the previous instant.

In [43]:
```
# Use the following formula
ts_log_diff = ts_log - ts_log.shift()
plt.plot(ts_log_diff)
```

Out[43]: [<matplotlib.lines.Line2D at 0x1c1fb5ab38>]




```
In [45]: ts_log_diff.dropna(inplace=True)
         # Test for stationarity
         test_stationarity(ts_log_diff)
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -2.717131
p-value                          0.071121
#Lags Used                      14.000000
Number of Observations Used    128.000000
Critical Value (1%)             -3.482501
dtype: float64
Test Statistic                  -2.717131
p-value                          0.071121
#Lags Used                      14.000000
```

```
Number of Observations Used    128.000000
Critical Value (1%)             -3.482501
Critical Value (5%)             -2.884398
dtype: float64
Test Statistic                  -2.717131
p-value                          0.071121
#Lags Used                      14.000000
Number of Observations Used    128.000000
Critical Value (1%)             -3.482501
Critical Value (5%)             -2.884398
Critical Value (10%)            -2.578960
dtype: float64
```

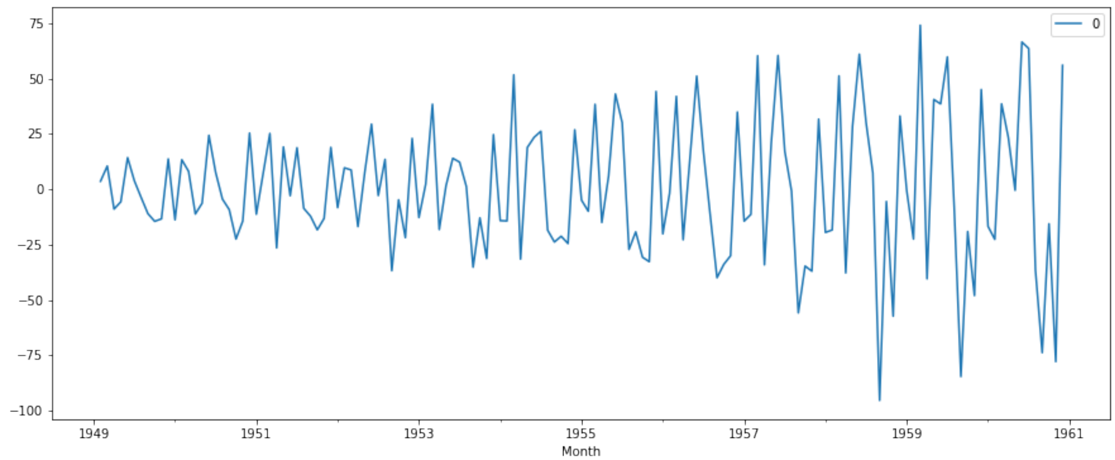
ARIMA

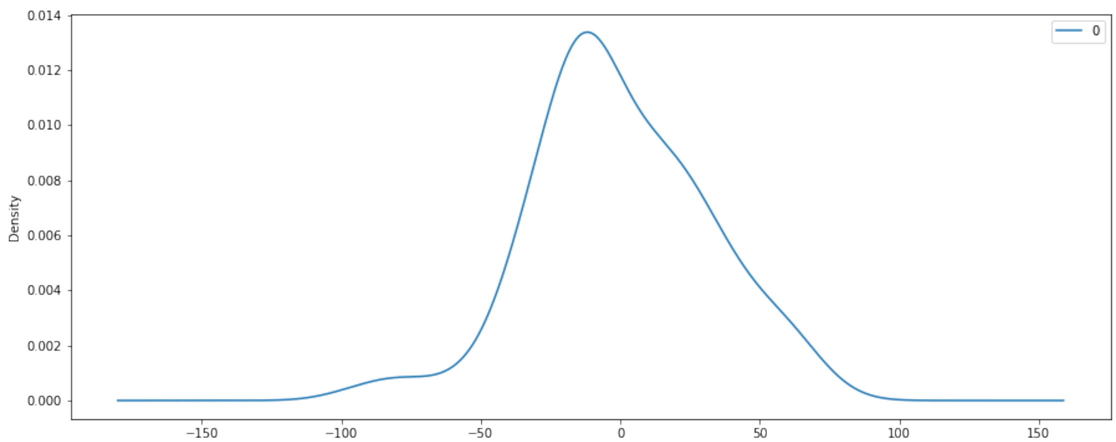
```
In [46]: lag_acf = acf(ts_log_diff, nlags=20)
         lag_pacf = pacf(ts_log_diff, nlags=20, method='ols')
```

```
In [56]: model = ARIMA(ts, order=(2,1,0))
         model_fit = model.fit(disp=0)
         print(model_fit.summary())

         # plot residual errors
         residuals = pd.DataFrame(model_fit.resid)
         residuals.plot()
         plt.show()

         residuals.plot(kind='kde')
         plt.show()

         print(residuals.describe())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:           D.#Passengers   No. Observations:                  143
Model:                  ARIMA(2, 1, 0)   Log Likelihood                -694.988
Method:                        css-mle   S.D. of innovations             31.199
Date:                 Tue, 05 Jun 2018   AIC                           1397.975
Time:                         13:40:22   BIC                           1409.827
Sample:                     02-01-1949   HQIC                          1402.791
                          - 12-01-1960
=========================================================================================
                            coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     2.4075      3.064      0.786      0.433      -3.597       8.412
ar.L1.D.#Passengers       0.3792      0.082      4.605      0.000       0.218       0.541
ar.L2.D.#Passengers      -0.2314      0.083     -2.777      0.006      -0.395      -0.068
                                    Roots
```

```
==============================================================================
                    Real          Imaginary           Modulus         Frequency
------------------------------------------------------------------------------
AR.1              0.8191           -1.9104j            2.0787           -0.1855
AR.2              0.8191           +1.9104j            2.0787            0.1855
------------------------------------------------------------------------------
```



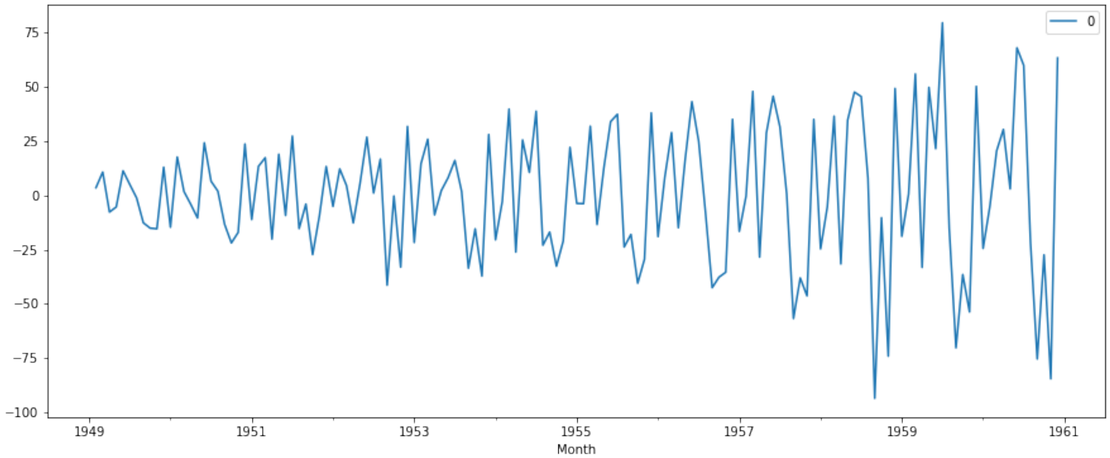


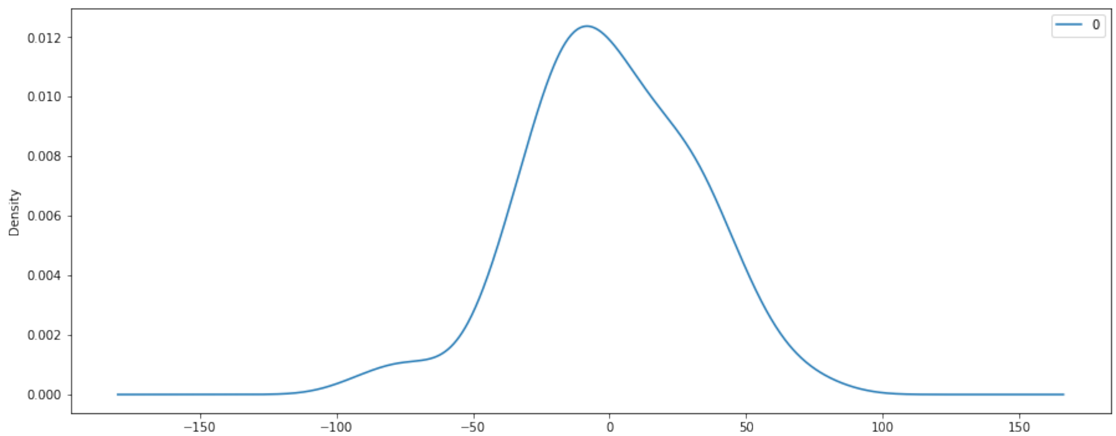

```
                0
count  143.000000
mean     0.016841
std     31.309377
min    -95.399565
25%    -18.811532
50%     -4.459782
```

```
75%      21.848521
max      74.096243
```

In [57]:
```python
model = ARIMA(ts, order=(0,1,2))
model_fit = model.fit(disp=0)
print(model_fit.summary())

# plot residual errors
residuals = pd.DataFrame(model_fit.resid)
residuals.plot()
plt.show()

residuals.plot(kind='kde')
plt.show()

print(residuals.describe())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:          D.#Passengers   No. Observations:                  143
Model:                 ARIMA(0, 1, 2)   Log Likelihood                -695.193
Method:                       css-mle   S.D. of innovations             31.214
Date:                Tue, 05 Jun 2018   AIC                           1398.386
Time:                        13:40:43   BIC                           1410.237
Sample:                    02-01-1949   HQIC                          1403.201
                         - 12-01-1960
=========================================================================================
                            coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     2.4329      2.850      0.854      0.395      -3.154       8.020
ma.L1.D.#Passengers       0.3736      0.097      3.860      0.000       0.184       0.563
ma.L2.D.#Passengers      -0.2830      0.156     -1.819      0.071      -0.588       0.022
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
MA.1           -1.3322           +0.0000j            1.3322            0.5000
MA.2            2.6520           +0.0000j            2.6520            0.0000
-----------------------------------------------------------------------------
```



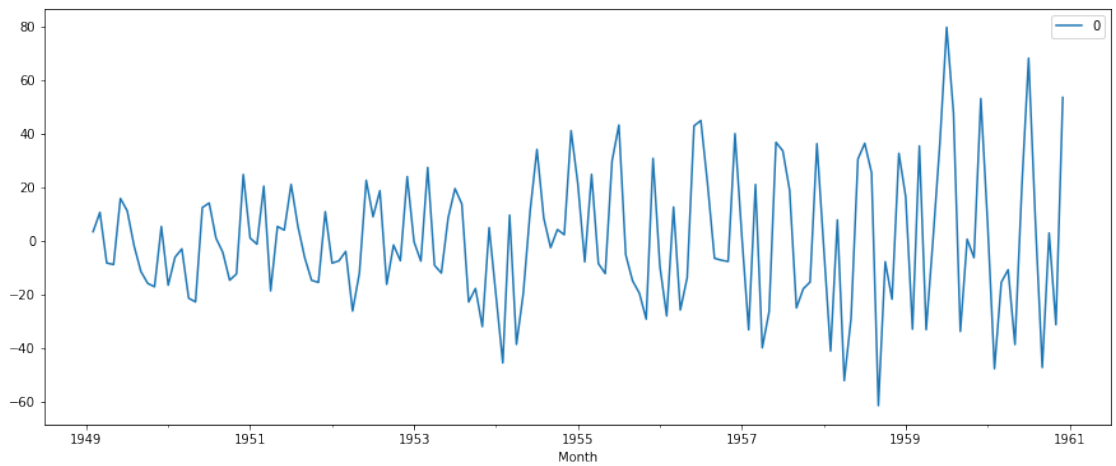


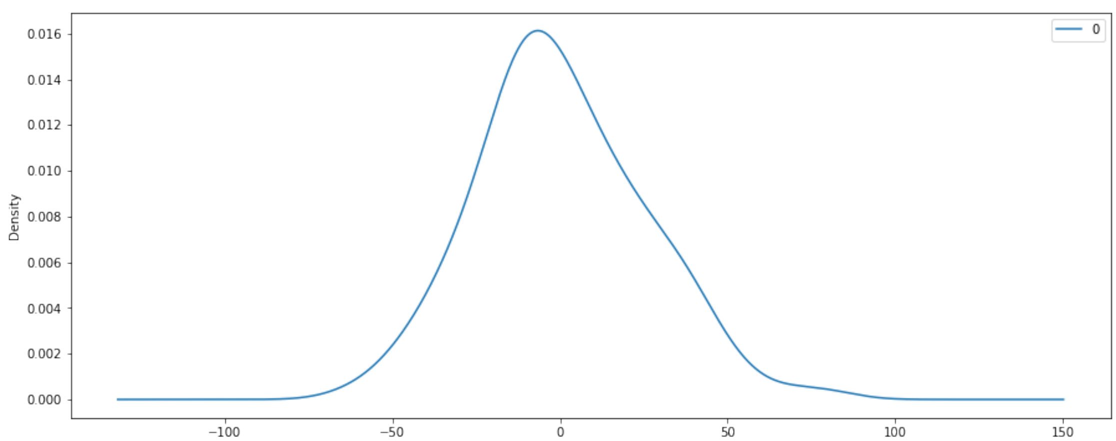

```
                0
count  143.000000
mean     0.015679
std     31.326445
min    -93.526112
25%    -19.559210
50%     -0.301836
75%     22.958166
max     79.616546
```

```
In [64]: model = ARIMA(ts, order=(2,1,2))
         model_fit = model.fit(disp=0)
         print(model_fit.summary())
```

```python
# plot residual errors
residuals = pd.DataFrame(model_fit.resid)
residuals.plot()
plt.show()

residuals.plot(kind='kde')
plt.show()

print(residuals.describe())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:           D.#Passengers   No. Observations:                  143
Model:                  ARIMA(2, 1, 2)   Log Likelihood                -666.022
Method:                        css-mle   S.D. of innovations             24.715
Date:                 Tue, 05 Jun 2018   AIC                           1344.043
Time:                         13:51:13   BIC                           1361.820
Sample:                     02-01-1949   HQIC                          1351.267
                          - 12-01-1960
=======================================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------
const                   2.5310      0.708      3.573      0.000       1.143       3.919
ar.L1.D.#Passengers     1.6477      0.033     49.929      0.000       1.583       1.712
ar.L2.D.#Passengers    -0.9094      0.033    -27.877      0.000      -0.973      -0.845
ma.L1.D.#Passengers    -1.9098      0.065    -29.475      0.000      -2.037      -1.783
ma.L2.D.#Passengers     0.9996      0.068     14.790      0.000       0.867       1.132
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            0.9060           -0.5281j            1.0487           -0.0840
AR.2            0.9060           +0.5281j            1.0487            0.0840
MA.1            0.9552           -0.2965j            1.0002           -0.0479
MA.2            0.9552           +0.2965j            1.0002            0.0479
-----------------------------------------------------------------------------
```



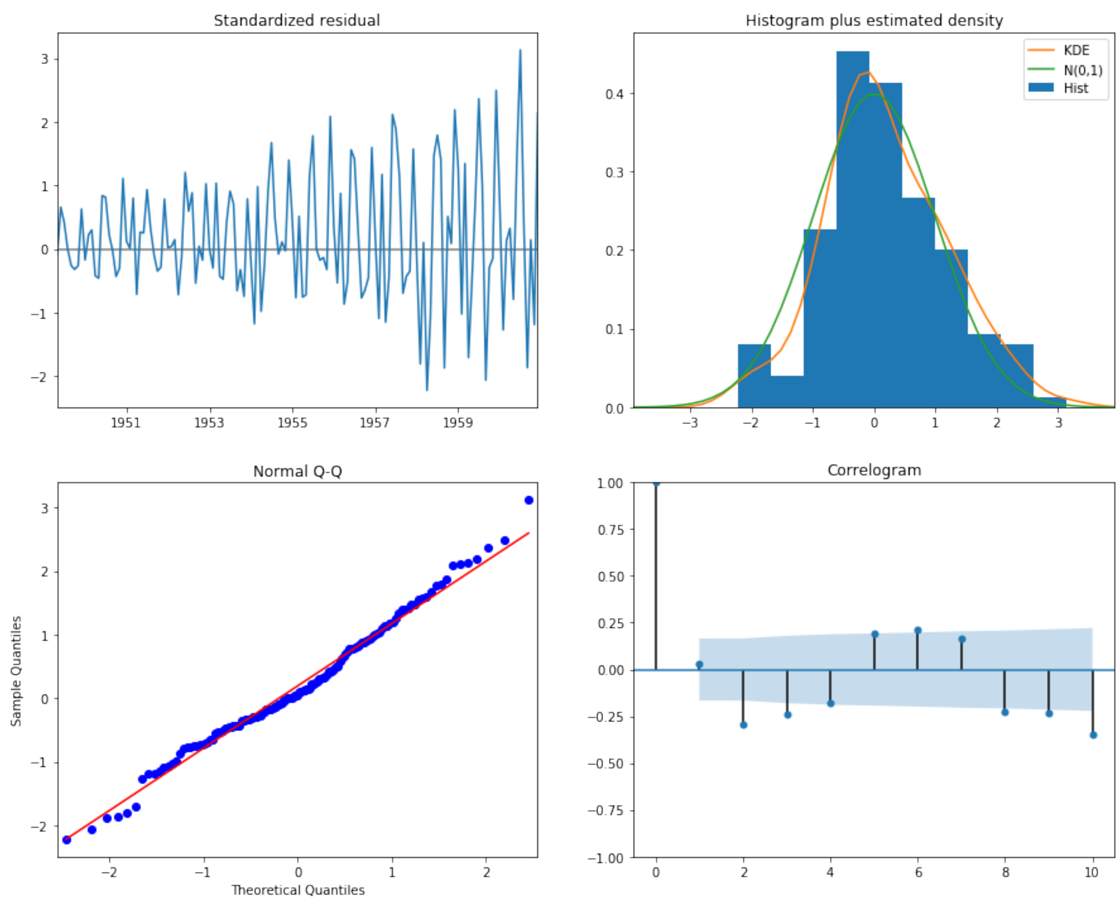



```
                0
count  143.000000
mean     0.371723
std     25.142955
min    -61.345169
25%    -15.612496
50%     -2.309301
75%     17.612061
max     79.639519
```

```
In [72]: mod = sm.tsa.statespace.SARIMAX(ts,
                                        order=(2, 1, 2),
                                        enforce_stationarity=False,
                                        enforce_invertibility=False)
```

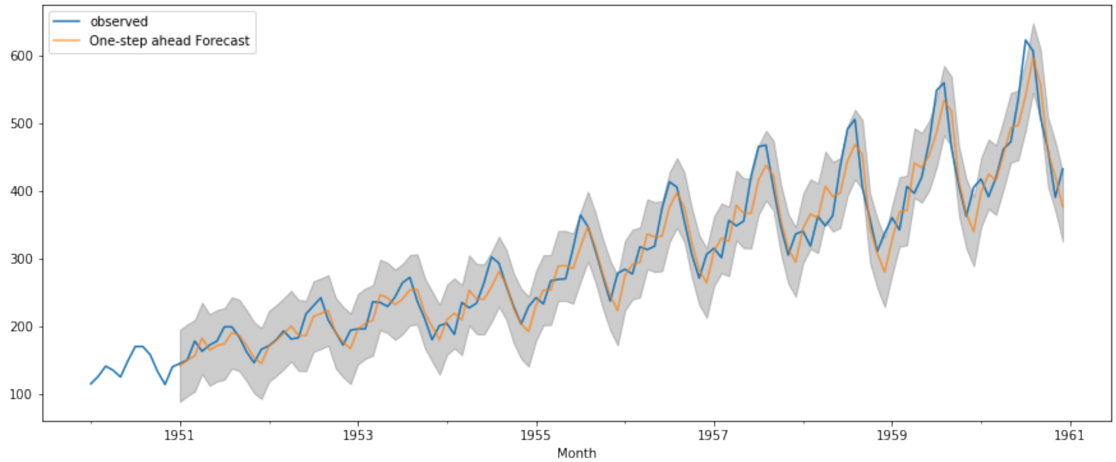
```
results = mod.fit()

print(results.summary().tables[1])

results.plot_diagnostics(figsize=(15, 12))
plt.show()
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.6917      0.021     82.361      0.000       1.651       1.732
ar.L2         -0.9654      0.018    -54.946      0.000      -1.000      -0.931
ma.L1         -1.8617      0.051    -36.159      0.000      -1.963      -1.761
ma.L2          1.0135      0.054     18.654      0.000       0.907       1.120
sigma2       664.6345     85.215      7.799      0.000     497.616     831.653
==============================================================================
```




```
In [73]: pred = results.get_prediction(start=pd.to_datetime('1951-01-01'), dynamic=False)
         pred_ci = pred.conf_int()
```

In [76]:
```
ax = ts['1950':].plot(label='observed')
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast', alpha=.7)

ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)

plt.legend()
plt.show()
```

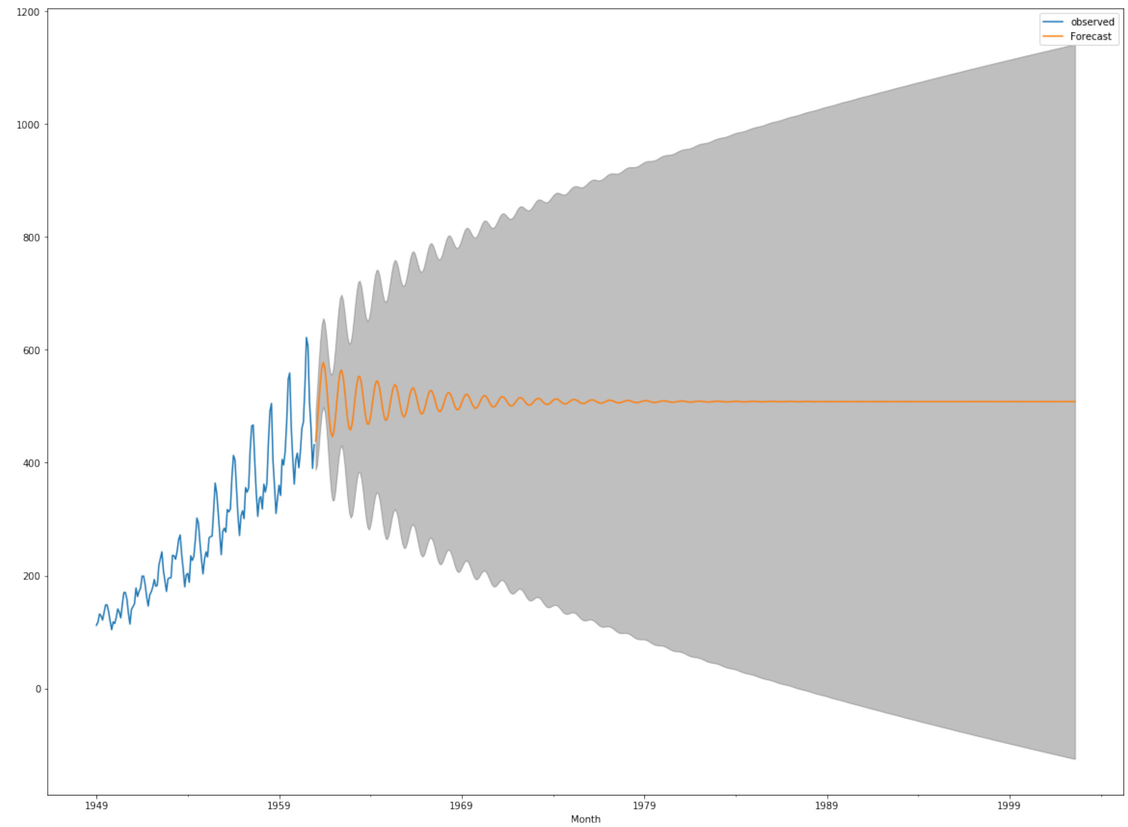


In [77]:
```
ts_forecasted = pred.predicted_mean
ts_truth = ts['1950-01-01':]

# Compute the mean square error
mse = ((ts_forecasted - ts_truth) ** 2).mean()
print('The Mean Squared Error of our forecasts is {}'.format(round(mse, 2)))
```

```
The Mean Squared Error of our forecasts is 778.32
```

In [78]:
```
# Get forecast 500 steps ahead in future
pred_uc = results.get_forecast(steps=500)

# Get confidence intervals of forecasts
pred_ci = pred_uc.conf_int()

ax = ts.plot(label='observed', figsize=(20, 15))
pred_uc.predicted_mean.plot(ax=ax, label='Forecast')
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.25)
```

```
plt.legend()
plt.show()
```



In [ ]: