Assignment - 32 - MACHINE LEARNING - 11

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Problem Statement: Make ARIMA model over shampoo sales data and check the MSE between predicted and actual value.

Student can download data in .csv format from the following link:

https://datamarket.com/data/set/22r0/sales-of-shampoo-over-a-three-year-period#!ds=22r0&display=line (https://datamarket.com/data/set/22r0/sales-of-shampoo-over-a-three-year-period#!ds=22r0&display=line)

Hint:

Following is the command import packages and data

from pandas import read_csv
from pandas import datetime
from matplotlib import pyplot
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error
def parser(x):
return datetime.strptime('190'+x, '%Y-%m')
series = read_csv('shampoo-sales.csv', header=0, parse_dates=[0], index_col=0,
squeeze=True, date_parser=parser)

In [24]:
```
# Loading Libraries
import numpy as np
import pandas as pd
from pandas import read_csv, datetime

from matplotlib import pyplot
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.stattools import adfuller
from sklearn.metrics import mean_squared_error

import statsmodels.api as sm
from pandas.tools.plotting import autocorrelation_plot

import warnings
warnings.filterwarnings('ignore')
```

Load Data

In [10]:
```
# From the link https://datamarket.com/data/set/22r0/sales-of-shampoo-over-a-three-year-period#!ds=22r0&display=line
# Data has been down loaded to the csv "shampoo-sales.csv"
FileName = "shampoo-sales.csv"

## parser function for parsing date into yyyy-mm-dd format
def parser(x):
    return datetime.strptime('190'+x, '%Y-%m')
## create dataset
series = read_csv(FileName,
                  header=0,
                  parse_dates=[0],
                  index_col=0,
                  squeeze=True,
                  date_parser=parser)
```

In [11]:
```
series.head(10)
```

Out[11]:
```
Month
1901-01-01    266.0
1901-02-01    145.9
1901-03-01    183.1
1901-04-01    119.3
1901-05-01    180.3
1901-06-01    168.5
1901-07-01    231.8
1901-08-01    224.5
1901-09-01    192.8
1901-10-01    122.9
Name: Sales of shampoo over a three year period, dtype: float64
```

Analyze Data

In [14]:
```
series.describe()
```

Out[14]:
```
count     36.000000
mean     312.600000
std      148.937164
min      119.300000
25%      192.450000
50%      280.150000
75%      411.100000
max      682.000000
Name: Sales of shampoo over a three year period, dtype: float64
```

In [17]:
```
# Check Null
series.isnull().values.any()
```

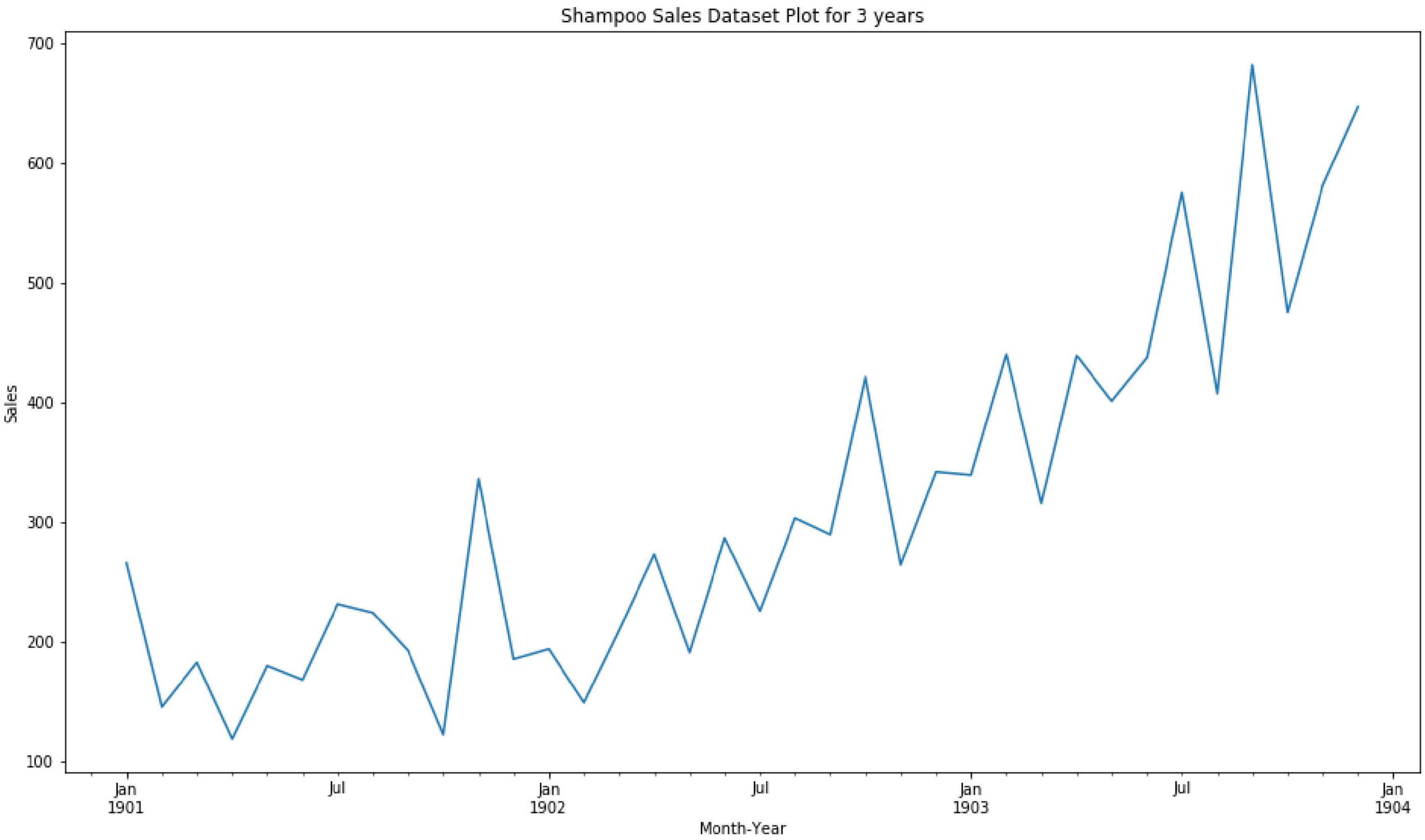
Out[17]:
```
False
```

In [18]:
```
# Check duplicate
series.duplicated().values.any()
```

Out[18]:
```
False
```

Visualize Data

In [20]:
```
# Visualize Data in a graph
series.plot(figsize=(16,9))
pyplot.title('Shampoo Sales Dataset Plot for 3 years')
pyplot.xlabel('Month-Year')
pyplot.ylabel('Sales')
pyplot.show()
```



- **Observation-1 : Year on year increase of sales**

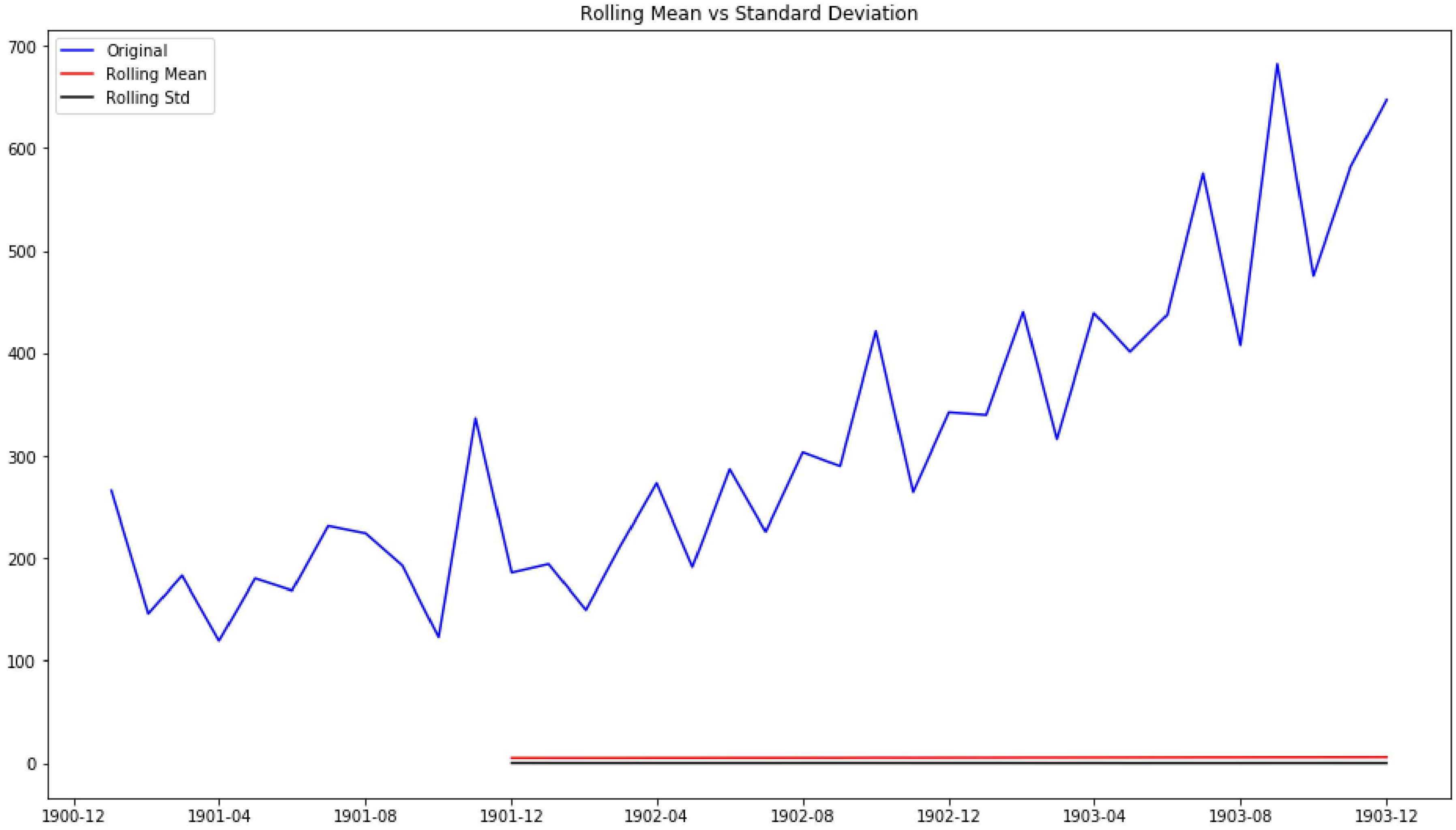
Dicker-Fuller test

Check for whether mentioned time series data is stationary or non-stationary using rolling statistic

In [23]:
```
df_log = np.log(series)
rolling_mean = df_log.rolling(window=12).mean()
rolling_std = df_log.rolling(window=12).std()

pyplot.figure(figsize=(16,9))
original = pyplot.plot(series, color='blue',label='Original' )
mean = pyplot.plot(rolling_mean, color='red', label='Rolling Mean')
std = pyplot.plot(rolling_std, color='black', label = 'Rolling Std')

pyplot.legend(loc='best')
pyplot.title('Rolling Mean vs Standard Deviation')
pyplot.show(block=False)
```



- **Observation-2 : Difference between rolling mean and standard devaition with time indicates the series is non-stationary**

- **Augmented dicker fuller test**

  Null Hypothesis: The series has a unit root
  Alternate Hypothesis: The series has no unit root.

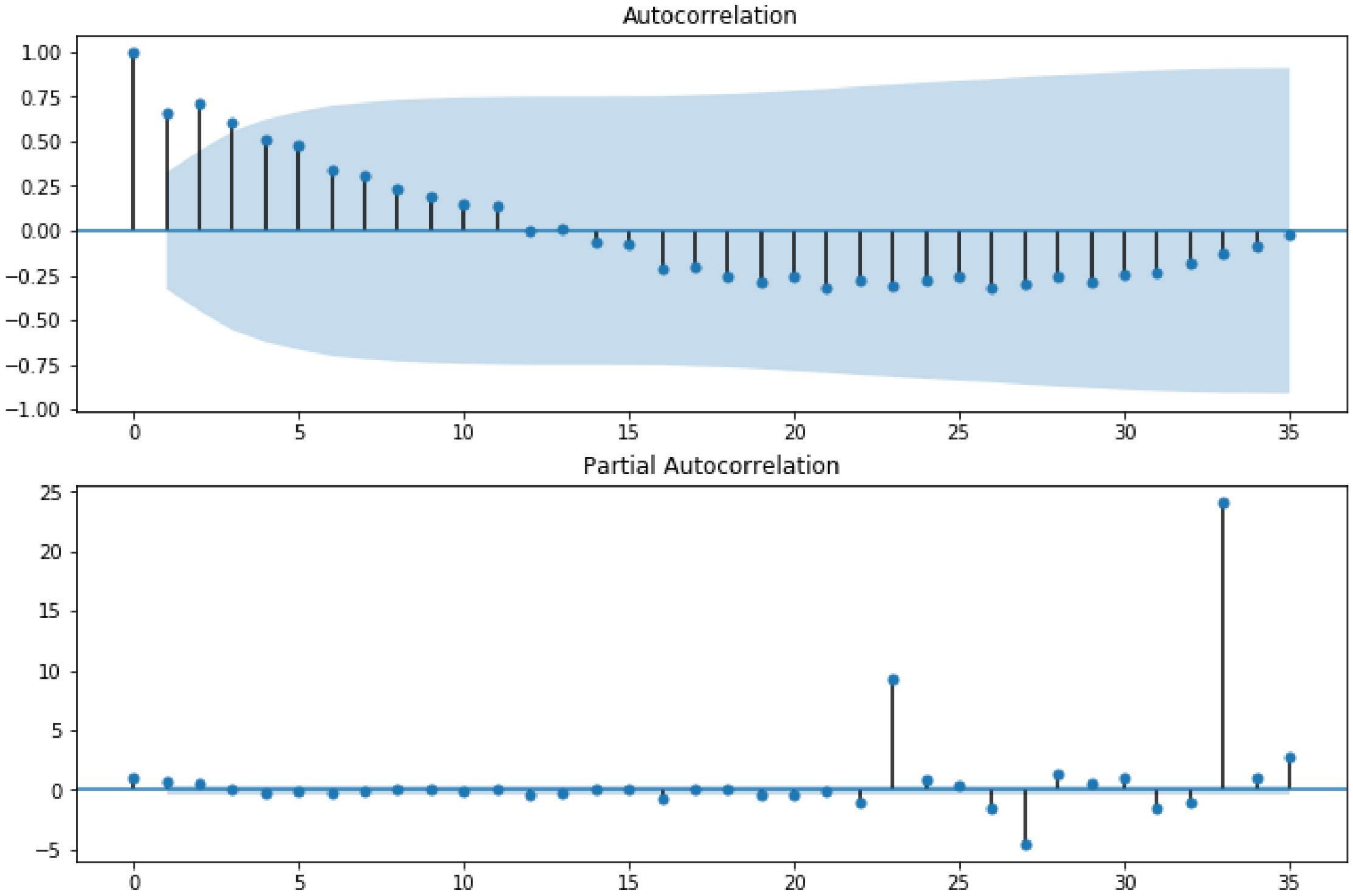
In [33]:
```
adftest = adfuller(series, autolag='AIC')
adfoutput = pd.Series(adftest[0:4],
                      index=['Test Statistic',
                             'p-value',
                             'Lags',
                             'Observation#'])
for key,value in adftest[4].items():
    adfoutput['Critical Value (%s)'%key] = value
print(adfoutput)
```

```
Test Statistic           3.060142
p-value                  1.000000
Lags                    10.000000
Observation#            25.000000
Critical Value (1%)     -3.723863
Critical Value (5%)     -2.986489
Critical Value (10%)    -2.632800
dtype: float64
```

- **Observation-3 : Test statistics > Critical value indicates the series is not stationary**

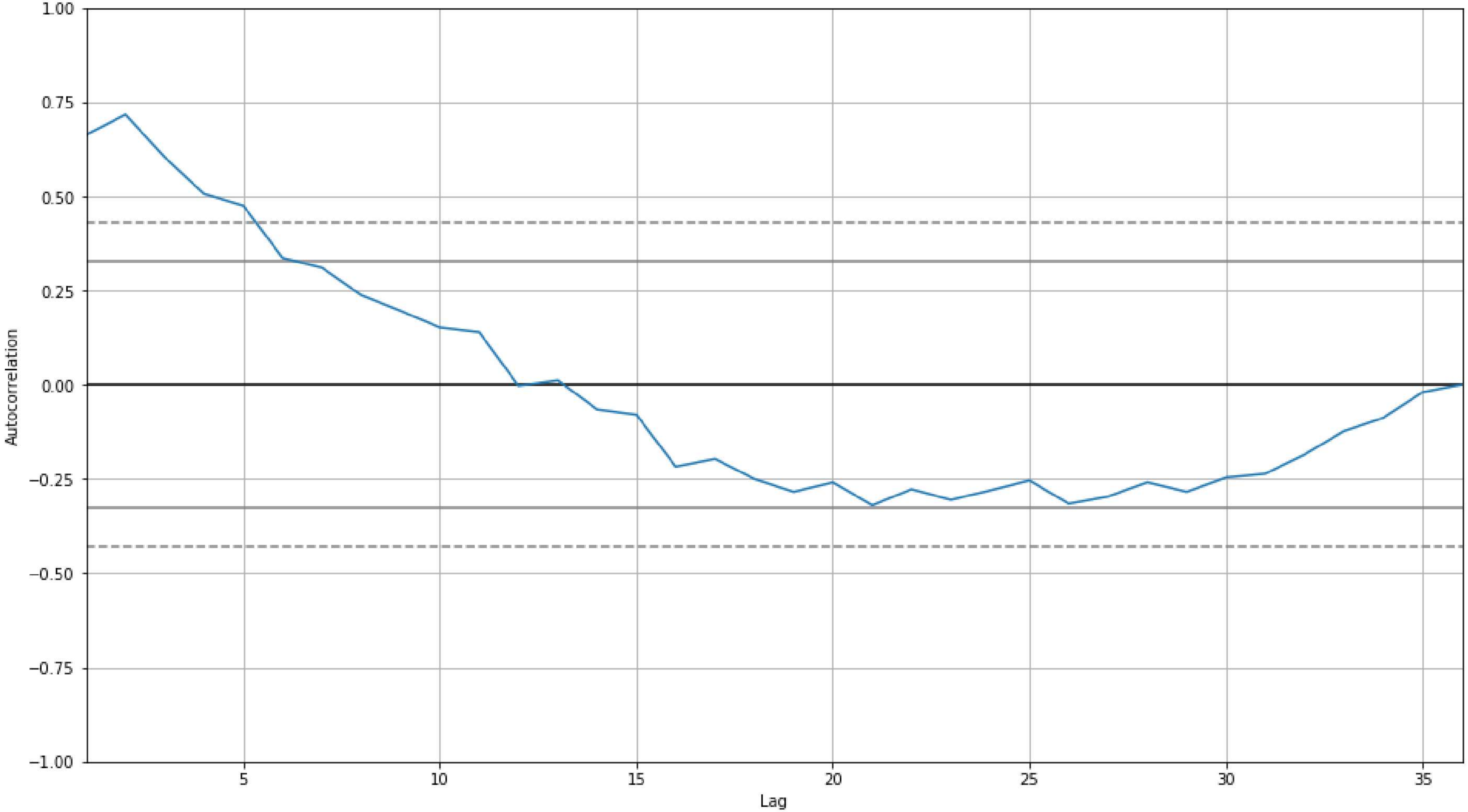
Correlation plot using statsmodel

In [34]:
```
plot = pyplot.figure(figsize=(12,8))
ax1 = plot.add_subplot(211)
plot = sm.graphics.tsa.plot_acf(series.values.squeeze(), lags=35, ax=ax1)
ax2 = plot.add_subplot(212)
plot = sm.graphics.tsa.plot_pacf(series, lags=35, ax=ax2)
```



Autocorrelation Plot

In [35]:
```
pyplot.figure(figsize=(16,9))
autocorrelation_plot(series)
pyplot.show()
```



- **Observation-4 : Positive correlation with the first 12 lags(approx). Choose starting point for the AR parameter of the model at 5.**

ARIMA Modelling on time series data

ARIMA(p,d,q) where

p: Lag order.

d: Degree of differencing.

q: Order of moving average.

In [82]:
```
# Intialize ARIMA model
p=5  # lag order
d=1  # take moving average
q=0  # take moving average
arima_model = ARIMA(series , order=(p,d,q))
```

In [83]:
```
# fit the model
arima_model_fit = arima_model.fit(disp=0)
```

In [84]:
```
arima_model_fit.summary()
```

Out[84]:

ARIMA Model Results

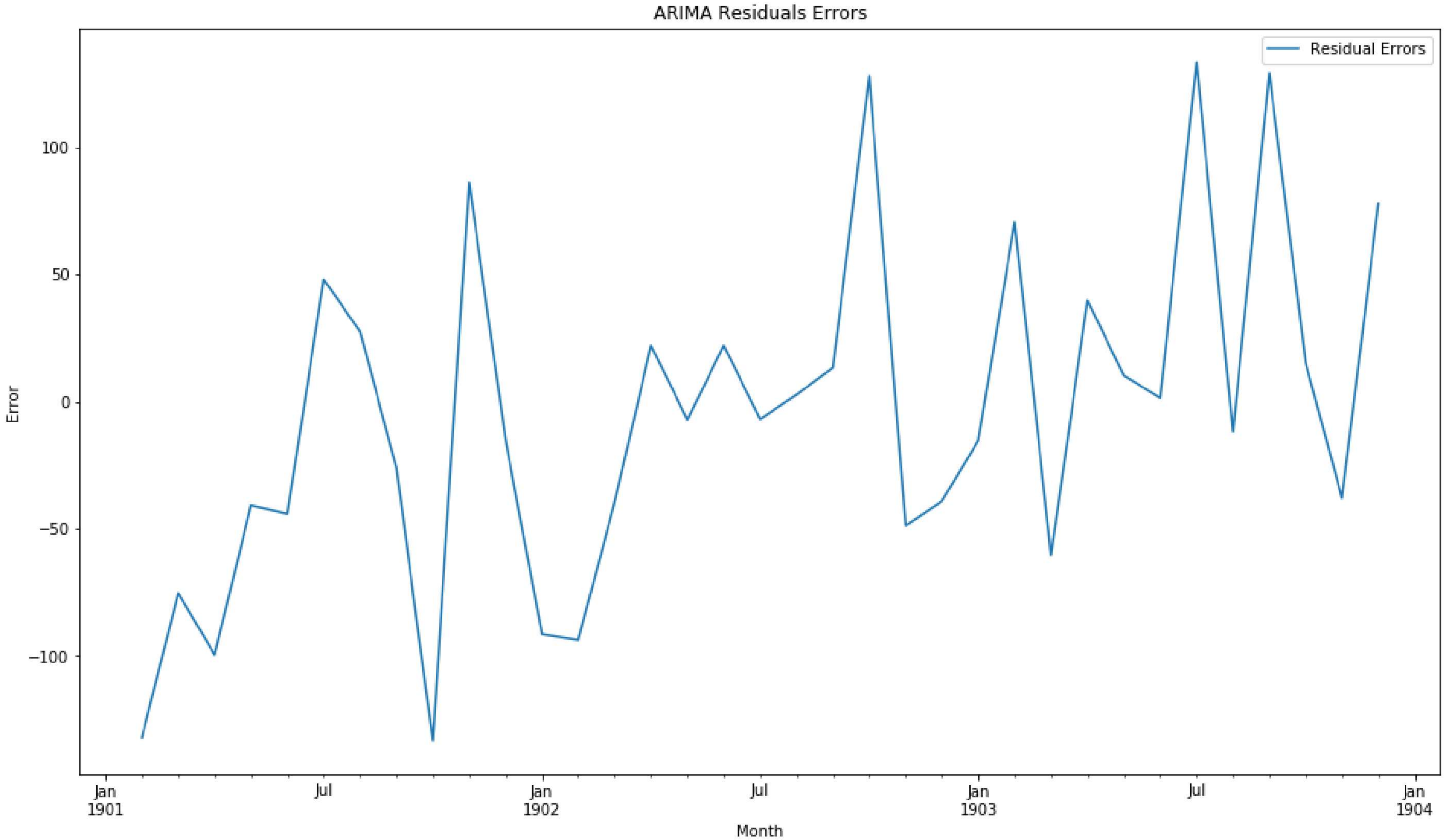
Dep. Variable:	D.Sales of shampoo over a three year period	No. Observations:	35
Model:	ARIMA(5, 1, 0)	Log Likelihood	-196.170
Method:	css-mle	S.D. of innovations	64.241
Date:	Sun, 30 Dec 2018	AIC	406.340
Time:	21:13:37	BIC	417.227
Sample:	02-01-1901	HQIC	410.098
	- 12-01-1903		

	coef	std err	z	P>|z|	[0.025	0.975]
const	12.0649	3.652	3.304	0.003	4.908	19.222
ar.L1.D.Sales of shampoo over a three year period	-1.1082	0.183	-6.063	0.000	-1.466	-0.750
ar.L2.D.Sales of shampoo over a three year period	-0.6203	0.282	-2.203	0.036	-1.172	-0.068
ar.L3.D.Sales of shampoo over a three year period	-0.3606	0.295	-1.222	0.231	-0.939	0.218
ar.L4.D.Sales of shampoo over a three year period	-0.1252	0.280	-0.447	0.658	-0.674	0.424
ar.L5.D.Sales of shampoo over a three year period	0.1289	0.191	0.673	0.506	-0.246	0.504

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-1.0617	-0.5064j	1.1763	-0.4292
AR.2	-1.0617	+0.5064j	1.1763	0.4292
AR.3	0.0816	-1.3804j	1.3828	-0.2406
AR.4	0.0816	+1.3804j	1.3828	0.2406
AR.5	2.9315	-0.0000j	2.9315	-0.0000

In [85]:
```
# Plots residual errors
arima_residuals = pd.DataFrame(arima_model_fit.resid , columns=['Residual Errors'])
arima_residuals.plot(figsize=(16,9))
pyplot.ylabel("Error")
pyplot.title('ARIMA Residuals Errors')
pyplot.show()
```

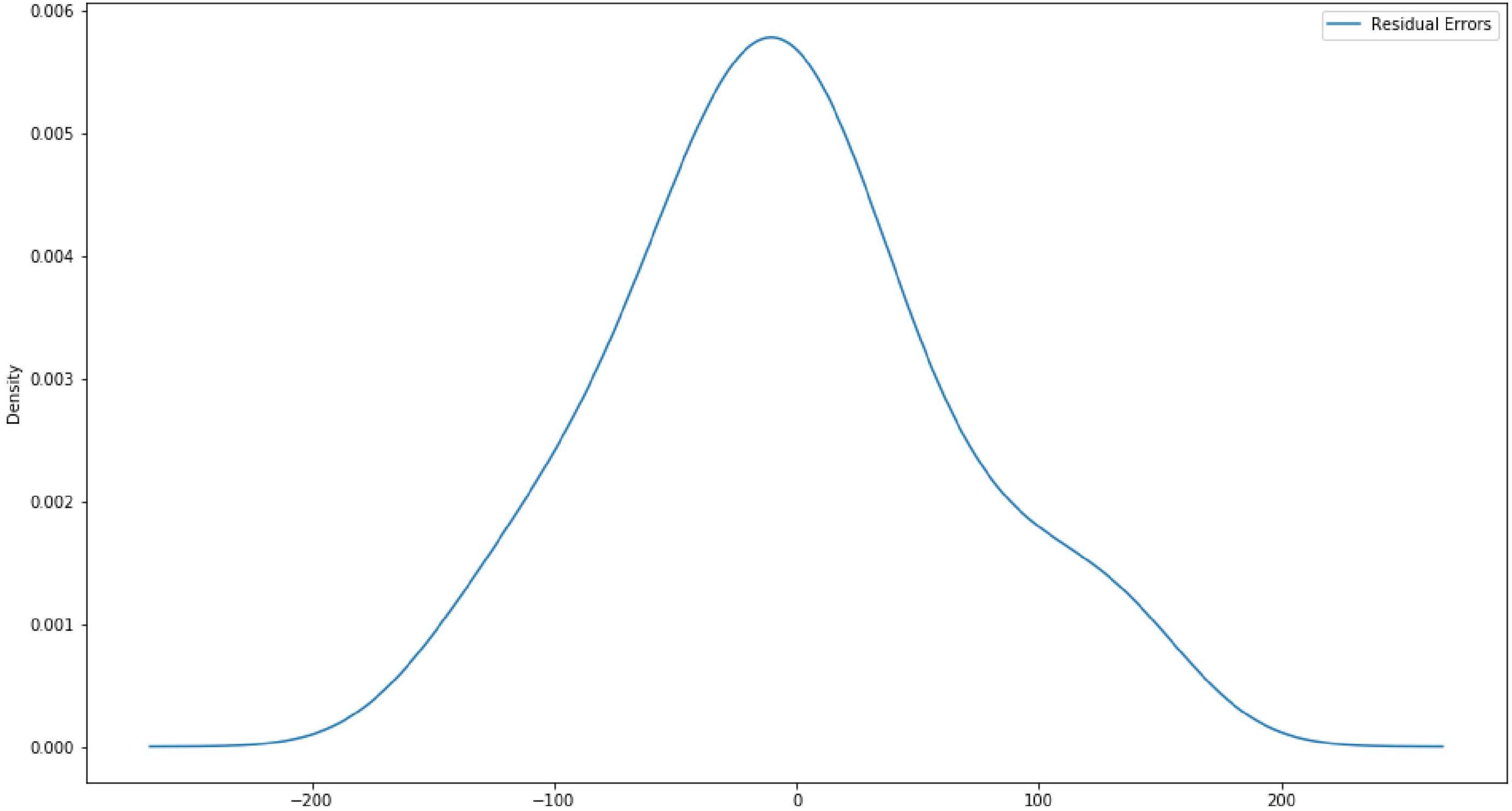


In [86]:
```
arima_residuals.describe()
```

Out[86]:

	Residual Errors
count	35.000000
mean	-5.495218
std	68.132882
min	-133.296637
25%	-42.477890
50%	-7.186512
75%	24.748330
max	133.237936

In [87]:
```
# Density Plot of the residual error values
arima_residuals.plot(kind='kde',figsize=(16,9))
pyplot.show()
```



Evaluate the ARIMA Model

In [135]:
```
train_set_len = int(len(series.values) * 0.7)
train, test = series.values[0:train_set_len], series.values[train_set_len:len(series.values)]

list_train = list(train)
list_predictions = list()

for i in range(len(test)):
    model = ARIMA(list_train, order=(p,d,q))
    model_fit = model.fit(disp=0)
    output = model_fit.forecast()
    list_predictions.append(output[0])
    list_train.append(test[i])
    print('Predicted=%f, Actual=%f' % (output[0], test[i]))
```

```
Predicted=387.376449, Actual=440.400000
Predicted=348.154255, Actual=315.900000
Predicted=386.308818, Actual=439.300000
Predicted=356.082087, Actual=401.300000
Predicted=446.379462, Actual=437.400000
Predicted=394.737224, Actual=575.500000
Predicted=434.915402, Actual=407.600000
Predicted=507.923547, Actual=682.000000
Predicted=435.482779, Actual=475.300000
Predicted=652.743826, Actual=581.300000
Predicted=546.343519, Actual=646.900000
```

In [136]:
```
pyplot.figure(figsize=(16,9))
pyplot.plot(test , label='Actual Sales')
pyplot.plot(list_predictions, color='red' , label='Predicted Sales')
pyplot.legend(loc='best')
pyplot.xlabel("Months")
pyplot.ylabel("Sales")
pyplot.show()
```