Problem Statement

In this assignment students have to make ARIMA model over shampoo sales data and check the MSE between predicted and actual value.

In [1]:

```
from pandas import read_csv
from pandas import datetime
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error
%matplotlib inline
```

In [2]:

```
def parser(x):
    m = x.split('-')[0]
    if len(m) < 2:
        return datetime.strptime('190'+x, '%Y-%b')
    else:
        return datetime.strptime('19'+x, '%Y-%b')
```

In [36]:

```
df = pd.read_csv('Shampoo_Sales.csv',header=None)
```

In [37]:

```
df.head()
```

Out[37]:

	0	1
0	1-Jan	266.0
1	2-Jan	145.9
2	3-Jan	183.1
3	4-Jan	119.3
4	5-Jan	180.3

In [38]:

```
df.describe()
```

Out[38]:

	1
count	36.000000
mean	312.600000
std	148.937164
min	119.300000
25%	192.450000
50%	280.150000
75%	411.100000
max	682.000000

In [39]:

```
df.isnull().count()
```

Out[39]:

```
0    36
1    36
dtype: int64
```

In [40]:

```
df[0] = df[0].astype(str)
```

In [41]:

```
df.dtypes
```

Out[41]:

```
0     object
1    float64
dtype: object
```

In [42]:

```
df.head()
```

Out[42]:

	0	1
0	1-Jan	266.0
1	2-Jan	145.9
2	3-Jan	183.1
3	4-Jan	119.3
4	5-Jan	180.3

In [43]:

```
df.isnull().count()
```

Out[43]:

```
0    36
1    36
dtype: int64
```

Preparing the Data

In [44]:

```
df.dropna(inplace = True)
```

In [45]:

```
df[0] = df[0].apply(lambda x : parser(x))
```

In [46]:

```
df = df.rename(columns={0:'Month',1:'Shampoo_Sales'})
```

In [47]:

```
df.head()
```

Out[47]:

	Month	Shampoo_Sales
0	1901-01-01	266.0
1	1902-01-01	145.9
2	1903-01-01	183.1
3	1904-01-01	119.3
4	1905-01-01	180.3

In [48]:

```
df['Month'] = pd.to_datetime(df['Month'])
```

In [49]:

```
df.set_index('Month',inplace=True)
```

Autoregressive Integrated Moving Averages

The general process for ARIMA models is the following:

- Visualize the Time Series Data
- Make the time series data stationary
- Plot the Correlation and AutoCorrelation Charts
- Construct the ARIMA Model

Use the model to make predictions

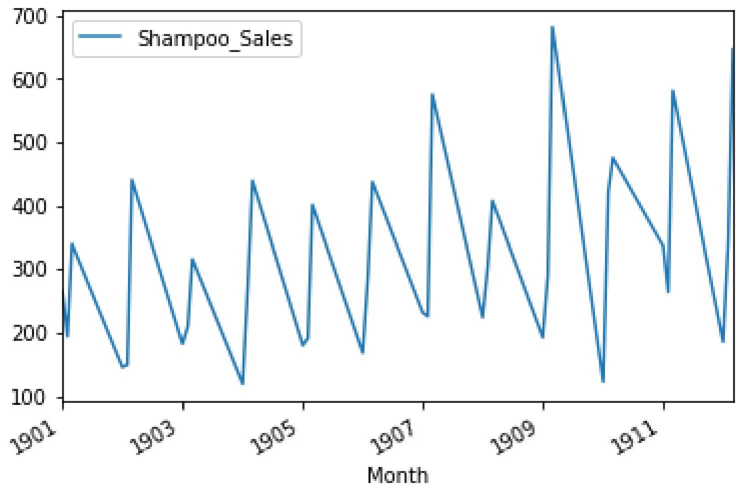
Visualize Data

In [21]:

```
df.plot()
```

Out[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26518e2dc88>
```



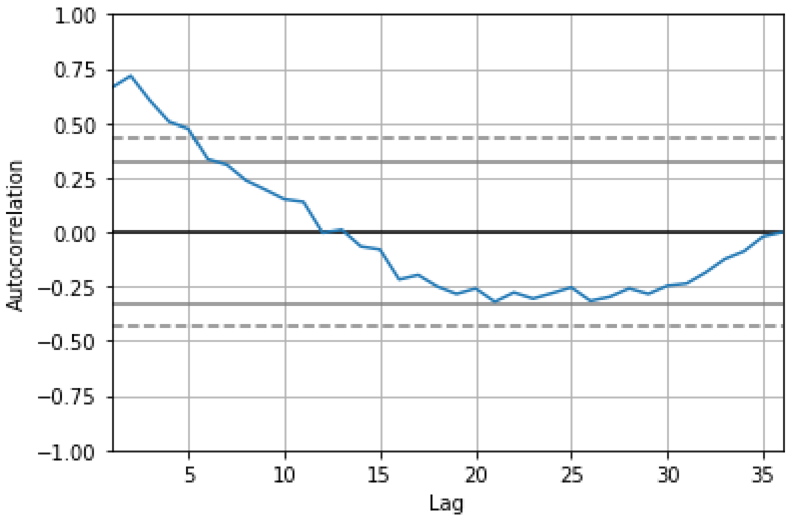
Autocorrelation plot of the time series. This is also built-in to Pandas.

In [22]:

```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df)
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26519012828>
```



Running the example, we can see that there is a positive correlation with the first 10-to-12 lags that is perhaps significant for the first 5 lags.

A good starting point for the AR parameter of the model may be 5.

In [23]:

```
timeseries = df['Shampoo_Sales']
```

In [24]:

```
timeseries.index
```

Out[24]:

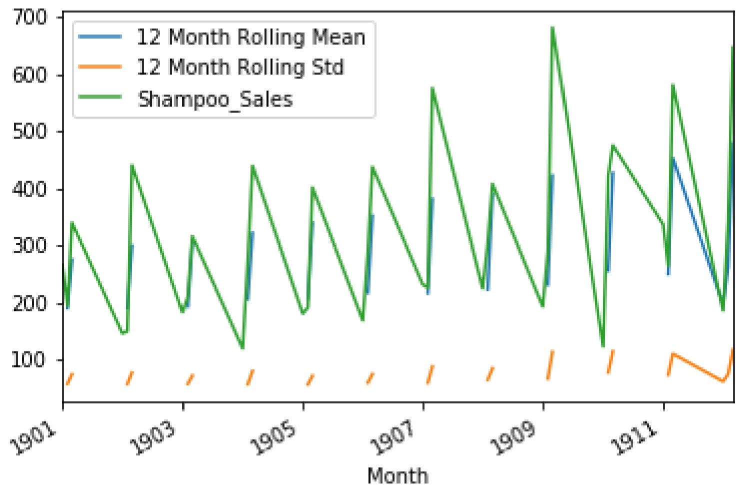
```
DatetimeIndex(['1901-01-01', '1902-01-01', '1903-01-01', '1904-01-01',
               '1905-01-01', '1906-01-01', '1907-01-01', '1908-01-01',
               '1909-01-01', '1910-01-01', '1911-01-01', '1912-01-01',
               '1901-02-01', '1902-02-01', '1903-02-01', '1904-02-01',
               '1905-02-01', '1906-02-01', '1907-02-01', '1908-02-01',
               '1909-02-01', '1910-02-01', '1911-02-01', '1912-02-01',
               '1901-03-01', '1902-03-01', '1903-03-01', '1904-03-01',
               '1905-03-01', '1906-03-01', '1907-03-01', '1908-03-01',
               '1909-03-01', '1910-03-01', '1911-03-01', '1912-03-01'],
              dtype='datetime64[ns]', name='Month', freq=None)
```

In [25]:

```
timeseries.rolling(12).mean().plot(label='12 Month Rolling Mean')
timeseries.rolling(12).std().plot(label='12 Month Rolling Std')
timeseries.plot()
plt.legend()
```

Out[25]:

```
<matplotlib.legend.Legend at 0x265190d7dd8>
```

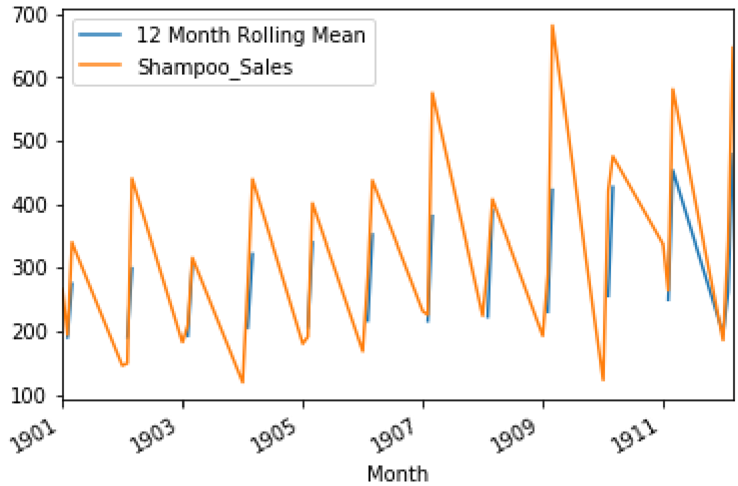


In [89]:

```
timeseries.rolling(12).mean().plot(label='12 Month Rolling Mean')
timeseries.plot()
plt.legend()
```

Out[89]:

```
<matplotlib.legend.Legend at 0x22013497a58>
```



Testing for Stationarity

We can use the Augmented [Dickey-Fuller (https://en.wikipedia.org/wiki/Augmented_Dickey%E2%80%93Fuller_test)](https://en.wikipedia.org/wiki/Augmented_Dickey%E2%80%93Fuller_test) [unit root test (https://en.wikipedia.org/wiki/Unit_root_test)](https://en.wikipedia.org/wiki/Unit_root_test).

In statistics and econometrics, an augmented Dickey–Fuller test (ADF) tests the null hypothesis that a unit root is present in a time series sample. The alternative hypothesis is different depending on which version of the test is used, but is usually stationarity or trend-stationarity.

Basically, we are trying to whether to accept the Null Hypothesis **H0** (that the time series has a unit root, indicating it is non-stationary) or reject **H0** and go with the Alternative Hypothesis (that the time series has no unit root and is stationary).

We end up deciding this based on the p-value return.

- A small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so you reject the null hypothesis.
- A large p-value (> 0.05) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis.

Let's run the Augmented Dickey-Fuller test on our data:

In [26]:

```
df.head()
```

Out[26]:

	Shampoo_Sales
Month	
1901-01-01	266.0
1902-01-01	145.9
1903-01-01	183.1
1904-01-01	119.3
1905-01-01	180.3

In [27]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 36 entries, 1901-01-01 to 1912-03-01
Data columns (total 1 columns):
Shampoo_Sales    36 non-null float64
dtypes: float64(1)
memory usage: 576.0 bytes
```

In [28]:

```
from statsmodels.tsa.stattools import adfuller
result = adfuller(df['Shampoo_Sales'])
result
```

Out[28]:

```
(3.060142083641181,
 1.0,
 10,
 25,
 {'1%': -3.7238633119999998, '10%': -2.6328004, '5%': -2.98648896},
 278.9972644263031)
```

In [29]:

```
print('Augmented Dickey-Fuller Test:')
labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used']

for value,label in zip(result,labels):
    print(label+' : '+str(value) )

if result[1] <= 0.05:
    print("strong evidence against the null hypothesis, reject the null hypothesis. Data ha
else:
    print("weak evidence against null hypothesis, time series has a unit root, indicating i
```

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : 3.060142083641181
p-value : 1.0
#Lags Used : 10
Number of Observations Used : 25
weak evidence against null hypothesis, time series has a unit root, indicati
ng it is non-stationary
```

In [30]:

```
# Store in a function for later use!
def adf_check(time_series):
    """
    Pass in a time series, returns ADF report
    """
    result = adfuller(time_series)
    print('Augmented Dickey-Fuller Test:')
    labels = ['ADF Test Statistic','p-value','#Lags Used','Number of Observations Used']

    for value,label in zip(result,labels):
        print(label+' : '+str(value) )

    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis, reject the null hypothesis. Dat
    else:
        print("weak evidence against null hypothesis, time series has a unit root, indicati
```

In [32]:

```
adf_check(df['Shampoo_Sales'])
```

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : 3.060142083641181
p-value : 1.0
#Lags Used : 10
Number of Observations Used : 25
weak evidence against null hypothesis, time series has a unit root, indicati
ng it is non-stationary
```

Differencing

The first difference of a time series is the series of changes from one period to the next. We can do this easily with pandas. You can continue to take the second difference, third difference, and so on until your data is stationary.

In [50]:

```
df['Shampoo_Sales_first_difference'] = df['Shampoo_Sales'] - df['Shampoo_Sales'].shift(1)
```

In [51]:

```
df.head()
```

Out[51]:

	Shampoo_Sales	Shampoo_Sales_first_difference
Month		
1901-01-01	266.0	NaN
1902-01-01	145.9	-120.1
1903-01-01	183.1	37.2
1904-01-01	119.3	-63.8
1905-01-01	180.3	61.0

In [53]:

```
adf_check(df['Shampoo_Sales_first_difference'].dropna())
```

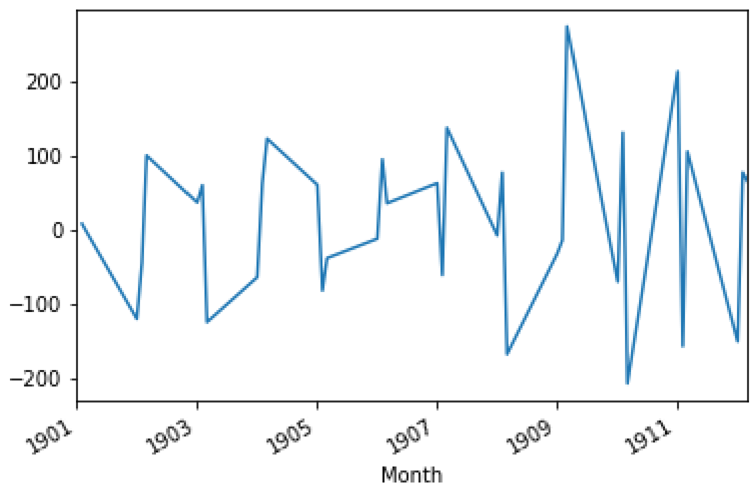
```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -7.249074055553854
p-value : 1.7998574141687034e-10
#Lags Used : 1
Number of Observations Used : 33
strong evidence against the null hypothesis, reject the null hypothesis. Dat
a has no unit root and is stationary
```

In [54]:

```
df['Shampoo_Sales_first_difference'].plot()
```

Out[54]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x265192106d8>
```



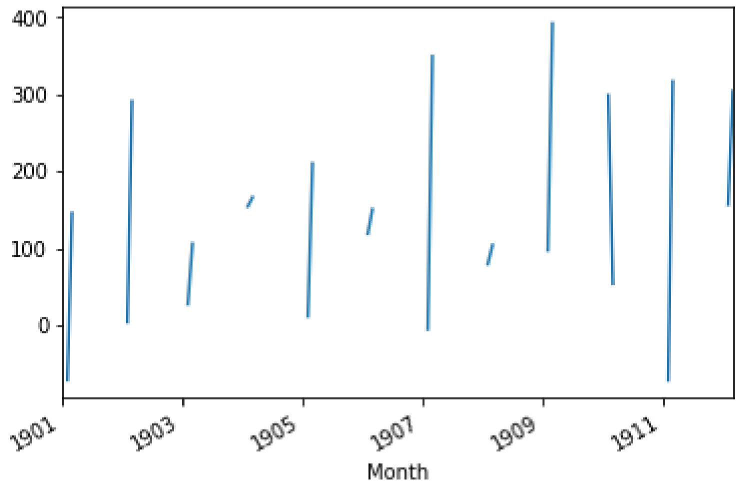
Seasonal Difference

In [55]:

```
df['Seasonal Difference'] = df['Shampoo_Sales'] - df['Shampoo_Sales'].shift(12)
df['Seasonal Difference'].plot()
```

Out[55]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2650d6cc860>
```



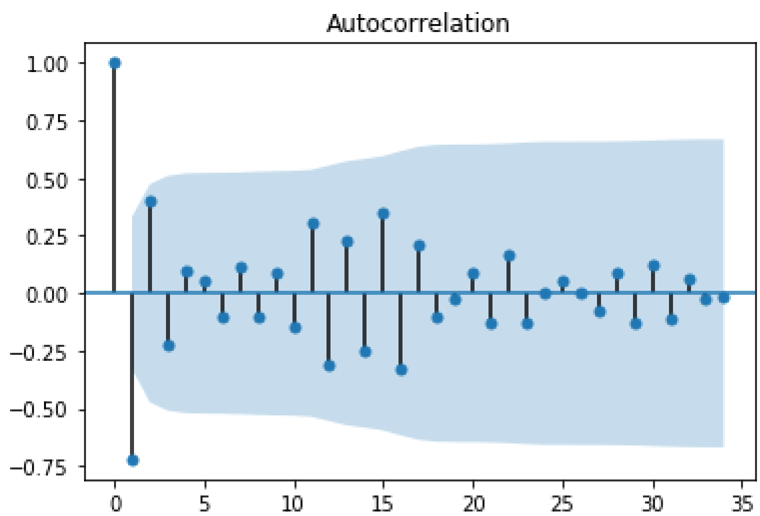
In [56]:

```
# Seasonal Difference by itself was not enough!
adf_check(df['Seasonal Difference'].dropna())
```

```
Augmented Dickey-Fuller Test:
ADF Test Statistic : -0.04561553414248672
p-value : 0.9545931714075301
#Lags Used : 6
Number of Observations Used : 17
weak evidence against null hypothesis, time series has a unit root, indicati
ng it is non-stationary
```

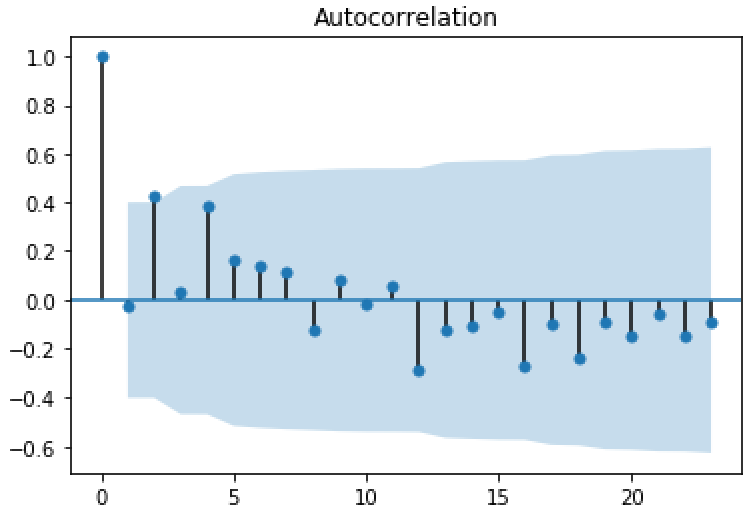
In [57]:

```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf

fig_first = plot_acf(df["Shampoo_Sales_first_difference"].dropna())
```



In [58]:

```
df["Seasonal First Difference"] =  df['Shampoo_Sales'] - df['Shampoo_Sales'].shift(12)
fig_seasonal_first = plot_acf(df["Seasonal First Difference"].dropna())
```

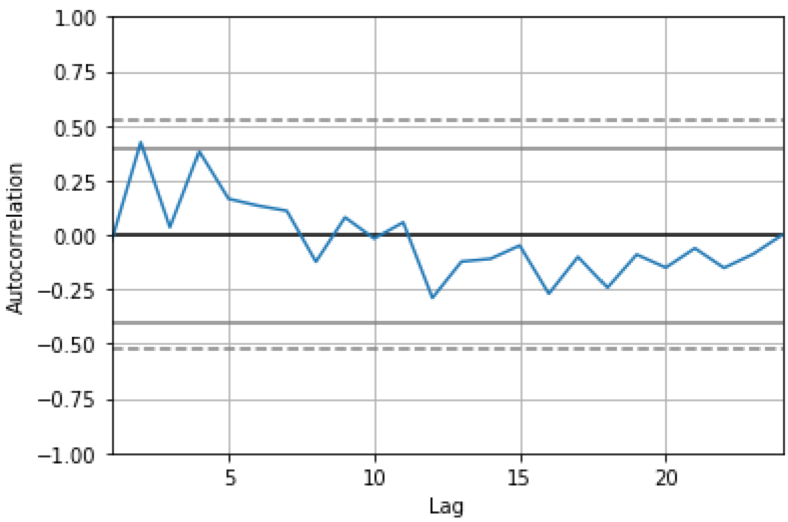


In [59]:

```
autocorrelation_plot(df['Seasonal First Difference'].dropna())
```

Out[59]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x265192770f0>
```



In [26]:

```
# For non-seasonal data
from statsmodels.tsa.arima_model import ARIMA
```

p,d,q parameters

- p: The number of lag observations included in the model.
- d: The number of times that the raw observations are differenced, also called the degree of differencing.
- q: The size of the moving average window, also called the order of moving average.

p: the number before the first inverted bar in the ACF (we begin counting from 0) d: the number of times we differenced our time series to achieve stationarity q: the number before the first inverted bar in our PACF (we begin counting from 0)

In [186]:

```
df.head()
```

Out[186]:

Month	Shampoo_Sales	Milk First Difference	Seasonal First Difference	forecast
1901-01-01	266.0	NaN	NaN	NaN
1902-01-01	145.9	-120.1	NaN	266.0
1903-01-01	183.1	37.2	NaN	266.0
1904-01-01	119.3	-63.8	NaN	266.0
1905-01-01	180.3	61.0	NaN	266.0

ARIMA with Python

The statsmodels library provides the capability to fit an ARIMA model.

An ARIMA model can be created using the statsmodels library as follows:

Define the model by calling ARIMA() and passing in the p, d, and q parameters. The model is prepared on the training data by calling the fit() function. Predictions can be made by calling the predict() function and specifying the index of the time or times to be predicted. Let’s start off with something simple. We will fit an ARIMA model to the entire Shampoo Sales dataset and review the residual errors.

First, we fit an ARIMA(5,1,0) model. This sets the lag value to 5 for autoregression, uses a difference order of 1 to make the time series stationary, and uses a moving average model of 0.

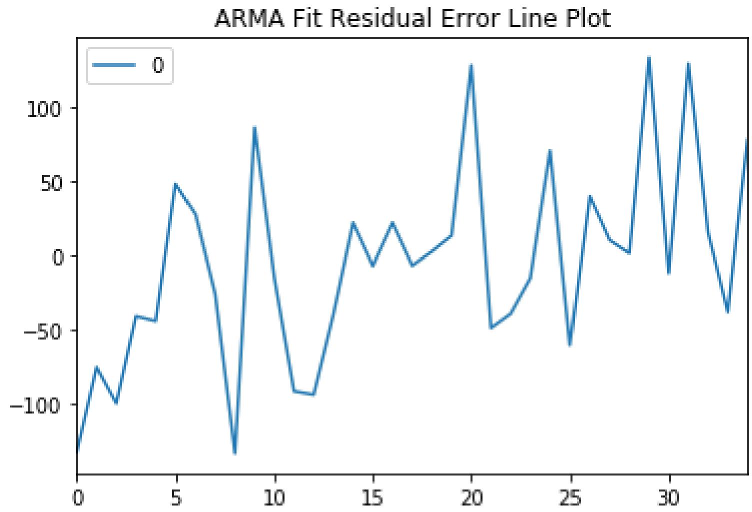
When fitting the model, a lot of debug information is provided about the fit of the linear regression model. We can turn this off by setting the disp argument to 0.

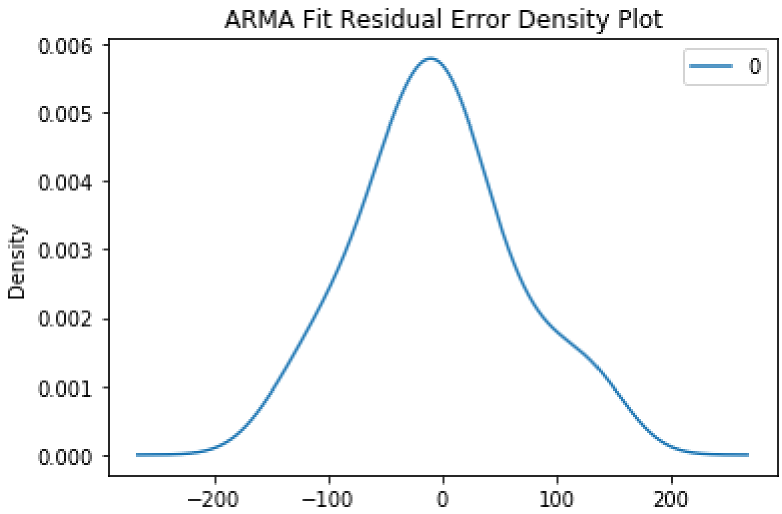
In [62]:

```
# fit model
model = ARIMA(df['Shampoo_Sales'].values, order=(5,1,0))
model_fit = model.fit(disp=0)
print(model_fit.summary())
# plot residual errors
residuals = pd.DataFrame(model_fit.resid)
residuals.plot()
plt.title('ARMA Fit Residual Error Line Plot')
plt.show()
residuals.plot(kind='kde')
plt.title('ARMA Fit Residual Error Density Plot')
plt.show()
print(residuals.describe())
```

```
                              ARIMA Model Results                              

=============================================================================
==
Dep. Variable:                    D.y   No. Observations:                   
35
Model:                 ARIMA(5, 1, 0)   Log Likelihood                -196.1
70
Method:                       css-mle   S.D. of innovations             64.2
41
Date:                Sun, 30 Sep 2018   AIC                            406.3
40
Time:                        22:26:09   BIC                            417.2
27
Sample:                             1   HQIC                           410.0
98                                                                          


=============================================================================
==
                 coef    std err          z      P>|z|      [0.025      0.97
5]
-----------------------------------------------------------------------------
--
const         12.0649      3.652      3.304      0.003       4.908      19.2
22
ar.L1.D.y     -1.1082      0.183     -6.063      0.000      -1.466      -0.7
50
ar.L2.D.y     -0.6203      0.282     -2.203      0.036      -1.172      -0.0
68
ar.L3.D.y     -0.3606      0.295     -1.222      0.231      -0.939       0.2
18
ar.L4.D.y     -0.1252      0.280     -0.447      0.658      -0.674       0.4
24
ar.L5.D.y      0.1289      0.191      0.673      0.506      -0.246       0.5
04
                                    Roots                                    

=============================================================================
=
                  Real          Imaginary           Modulus         Frequenc
y
-----------------------------------------------------------------------------
-
AR.1           -1.0617           -0.5064j            1.1763           -0.429
```

```
2
AR.2           -1.0617            +0.5064j            1.1763            0.429
2
AR.3            0.0816            -1.3804j            1.3828           -0.240
6
AR.4            0.0816            +1.3804j            1.3828            0.240
6
AR.5            2.9315            -0.0000j            2.9315           -0.000
0
-----------------------------------------------------------------------------
-
```






```
                0
count   35.000000
mean    -5.495254
std     68.132879
min   -133.296630
25%    -42.477923
50%     -7.186696
75%     24.748294
max    133.237951
```

In [66]:

```
X = df['Shampoo_Sales'].values
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()
for t in range(len(test)):
    model = ARIMA(history, order=(5,1,0))
    model_fit = model.fit(disp=0)
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
error = mean_squared_error(test, predictions)
print('\n-------------------------------------------------------------')
print('Test MSE : %.3f' % error)
print('\n-------------------------------------------------------------')
# plot
plt.plot(test)
plt.plot(predictions, color='red')
plt.title('ARIMA Rolling Forecast Line Plot')
plt.show()
```

```
predicted=349.117623, expected=342.300000
predicted=306.512928, expected=339.700000
predicted=387.376405, expected=440.400000
predicted=348.154206, expected=315.900000
predicted=386.308782, expected=439.300000
predicted=356.082061, expected=401.300000
predicted=446.379487, expected=437.400000
predicted=394.737317, expected=575.500000
predicted=434.915513, expected=407.600000
predicted=507.923355, expected=682.000000
predicted=435.482830, expected=475.300000
predicted=652.743749, expected=581.300000
predicted=546.343527, expected=646.900000

-------------------------------------------------------------
Test MSE : 6958.326

-------------------------------------------------------------
```