In this assignment students have to 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)

In [1]: import pandas as pd
 from pandas import datetime
 import matplotlib.pyplot as plt
 %matplotlib inline

### Out[2]:

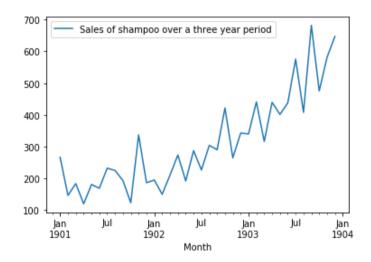
Month	
1901-01-01	266.0
1901-02-01	145.9
1901-03-01	183.1
1901-04-01	119.3
1901-05-01	180.3
1901-06-01	168.5
1901-07-01	231.8
1901-08-01	224.5
1901-09-01	192.8
1901-10-01	122.9
1901-11-01	336.5
1901-12-01	185.9
1902-01-01	194.3
1902-02-01	149.5
1902-03-01	210.1
1902-04-01	273.3
1902-05-01	191.4
1902-06-01	287.0
1902-07-01	226.0
1902-08-01	303.6
1902-09-01	289.9
1902-10-01	421.6
1902-11-01	264.5
1902-12-01	342.3
1903-01-01	339.7
1903-02-01	440.4
1903-03-01	315.9
1903-04-01	439.3
1903-05-01	401.3
1903-06-01	437.4
1903-07-01	575.5
1903-08-01	407.6
1903-09-01	682.0

#### Sales of shampoo over a three year period

Month	
1903-10-01	475.3
1903-11-01	581.3
1903-12-01	646.9

```
In [3]: sales.plot()
```

Out[3]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1febf1945f8>



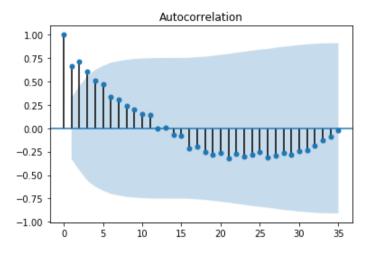
Stationary means mean, variance and covariance is constant over periods.

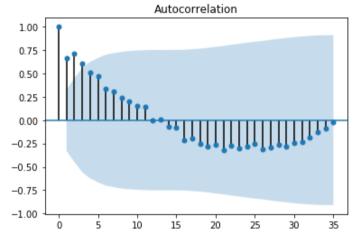
In [4]: from statsmodels.graphics.tsaplots import plot\_acf
 plot\_acf(sales)

C:\Users\prashant\_gupta1\AppData\Local\Continuum\anaconda3\lib\site-packages\statsmodels\c
ompat\pandas.py:56: FutureWarning: The pandas.core.datetools module is deprecated and will
be removed in a future version. Please use the pandas.tseries module instead.

from pandas.core import datetools







# **Converting series to stationary**

# In [5]: sales.head()

### Out[5]:

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

In [6]: sales.shift(1)

Out[6]:

Month	
1901-01-01	NaN
1901-02-01	266.0
1901-03-01	145.9
1901-04-01	183.1
1901-05-01	119.3
1901-06-01	180.3
1901-07-01	168.5
1901-08-01	231.8
1901-09-01	224.5
1901-10-01	192.8
1901-11-01	122.9
1901-12-01	336.5
1902-01-01	185.9
1902-02-01	194.3
1902-03-01	149.5
1902-04-01	210.1
1902-05-01	273.3
1902-06-01	191.4
1902-07-01	287.0
1902-08-01	226.0
1902-09-01	303.6
1902-10-01	289.9
1902-11-01	421.6
1902-12-01	264.5
1903-01-01	342.3
1903-02-01	339.7
1903-03-01	440.4
1903-04-01	315.9
1903-05-01	439.3
1903-06-01	401.3
1903-07-01	437.4
1903-08-01	575.5
1903-09-01	407.6
1903-10-01	682.0
1903-11-01	475.3
1903-12-01	581.3

```
In [7]: sales_diff = sales.diff(periods=1)
#integrated of order 1, denoted by d(for diff), one of the parameter of ARIMA model
```

```
In [8]: sales_diff = sales_diff[1:]
sales_diff.head()
```

### Out[8]:

Month	
1901-02-01	-120.1
1901-03-01	37.2
1901-04-01	-63.8
1901-05-01	61.0
1901-06-01	-11.8

In [9]: sales.shift(1)

Out[9]:

	Sales of snampoo over a three year period
Month	
1901-01-01	NaN
1901-02-01	266.0
1901-03-01	145.9
1901-04-01	183.1
1901-05-01	119.3
1901-06-01	180.3
1901-07-01	168.5
1901-08-01	231.8
1901-09-01	224.5
1901-10-01	192.8
1901-11-01	122.9
1901-12-01	336.5
1902-01-01	185.9
1902-02-01	194.3
1902-03-01	149.5
1902-04-01	210.1
1902-05-01	273.3
1902-06-01	191.4
1902-07-01	287.0
1902-08-01	226.0
1902-09-01	303.6
1902-10-01	289.9
1902-11-01	421.6
1902-12-01	264.5
1903-01-01	342.3
1903-02-01	339.7
1903-03-01	440.4
1903-04-01	315.9
1903-05-01	439.3
1903-06-01	401.3
1903-07-01	437.4
1903-08-01	575.5
1903-09-01	407.6
1903-10-01	682.0
1903-11-01	475.3
1903-12-01	581.3

```
In [10]: sales_diff = sales.diff(periods=1)
#integrated of order 1, denoted by d(for diff), one of the parameter of ARIMA model
```

```
In [11]: sales_diff = sales_diff[1:]
    sales_diff.head()
```

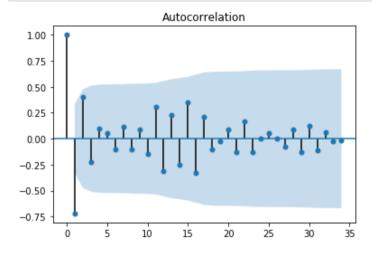
### Out[11]:

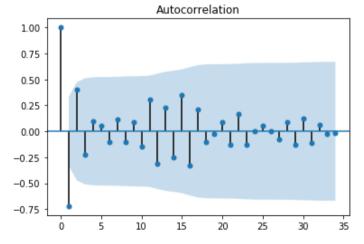
#### Sales of shampoo over a three year period

Month	
1901-02-01	-120.1
1901-03-01	37.2
1901-04-01	-63.8
1901-05-01	61.0
1901-06-01	-11.8

# In [12]: plot\_acf(sales\_diff)

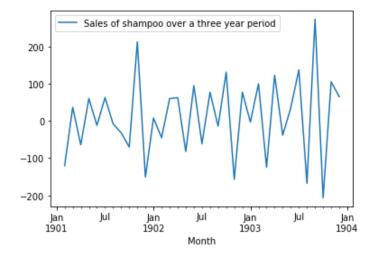
### Out[12]:





```
In [13]: sales_diff.plot()
```

Out[13]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1fec30dbc18>



```
In [14]: X = sales.values
    train = X[0:28] # 27 data as train data
    test = X[28:] # 9 data as test data
    print(train.size)
    print(test.size)
    predictions = []
```

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### **ARIMA** model

In [15]: from statsmodels.tsa.arima\_model import ARIMA

```
In [16]:
          import itertools
          p=d=q=range(0,6)
          pdq=list(itertools.product(p,d,q))
          pdq
            (0, 2, 5),
           (0, 3, 0),
           (0, 3, 1),
(0, 3, 2),
           (0, 3, 3),
           (0, 3, 4),
           (0, 3, 5),
           (0, 4, 0),
           (0, 4, 1),
(0, 4, 2),
           (0, 4, 3),
           (0, 4, 4),
           (0, 4, 5),
           (0, 5, 0),
           (0, 5, 1),
           (0, 5, 2),
           (0, 5, 3),
           (0, 5, 4),
           (0, 5, 5),
```

(1, 0, 0),

```
In [17]: import warnings
warnings.filterwarnings('ignore')
for param in pdq:
    try:
        model_arima = ARIMA(train, order=param)
        model_arima_fit = model_arima.fit()
        print(param,model_arima_fit.aic)
    except:
        continue

(0, 0, 0) 335.09040511436183
(0, 0, 1) 334.3872829960065
(0, 0, 2) 329.3188116463245
(0, 0, 3) 330.92416191329755
```

```
(0, 0, 4) 326.20991814556083
(0, 0, 5) nan
(0, 1, 0) 324.4220452613395
(0, 1, 1) 308.00170527527325
(0, 1, 2) 306.76985736180313
(0, 2, 0) 343.4502397203673
(0, 2, 1) 318.2621879566042
(1, 0, 0) 330.891809426
(1, 0, 1) 325.6333949306371
(1, 0, 2) 322.4525346634769
(1, 1, 0) 309.11887677524066
(1, 1, 1) 306.79093608912103
(1, 1, 2) 306.91086651441833
(1, 1, 3) 311.87130308527367
(1, 1, 4) 309.11946068137985
(1, 1, 5) 314.62738257879744
(1, 2, 0) 317.80308367611093
(1, 2, 1) 304.28854627184654
(1, 2, 4) 301.84243592770645
(2, 0, 0) 322.0934945916866
(2, 0, 1) 323.6906512129914
(2, 1, 0) 310.4797159942252
(2, 1, 1) 308.67508697382726
(2, 1, 4) 310.7392463440925
(2, 1, 5) 309.26130294792756
(2, 2, 0) 317.2438967005482
(2, 2, 1) 305.70536447196343
(2, 2, 3) 301.9734131614505
(3, 0, 0) 324.0564894664129
(3, 0, 1) 345.56189420353957
(3, 1, 0) 305.2133148241061
(3, 1, 1) 306.4702994791127
(3, 1, 2) 303.36848271124654
(3, 1, 3) 305.18376856738263
(3, 1, 4) 306.97823625865476
(3, 2, 0) 309.7952134616359
(3, 2, 1) 300.1087027284869
(3, 2, 2) 303.66039523146463
(3, 2, 3) 298.77068698523084
(3, 2, 4) 300.6672665956482
(4, 0, 0) 330.7646131531544
(4, 0, 1) 333.30147262133727
(4, 1, 0) 306.53005409134755
(4, 1, 1) 308.44169440230746
(4, 1, 2) 305.2617876918041
(4, 1, 3) 307.17530796213805
(4, 1, 4) 335.2735615876484
(4, 2, 0) 307.1934977443044
```

```
(4, 2, 1) 301.1607743489167

(4, 2, 2) 304.81455102589587

(5, 0, 0) 333.44426873756004

(5, 1, 0) 308.3655922901959

(5, 1, 1) 310.09896254081184

(5, 1, 2) 306.1810888934841

(5, 1, 3) 308.8768446366264

(5, 2, 0) 306.8900144573346

(5, 2, 1) 302.8531580359661

(5, 2, 2) 302.5657340585613

(5, 2, 3) 308.3799433205256
```

It seems that out of different combinations ranging from order (0,0,0) to (5,5,5) param with values as p=3, d=2 and q=3 is the best because of lowest AIC value

```
In [18]: #p,d,q
#p -> Periods taken for auto regressive model
#d -> Integrated order, difference
#q -> Periods in moving average model
model_arima = ARIMA(train, order=(3,2,3))
model_arima_fit = model_arima.fit()
print(model_arima_fit.aic)

298.77068698523084

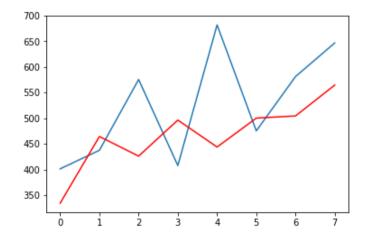
In [19]: predictions = model_arima_fit.forecast(steps=8)[0]
predictions

Out[19]: array([334.25497944, 464.33196912, 426.08758442, 496.34781322,
```

In [20]: plt.plot(test)
plt.plot(predictions, color='red')

443.78522094, 500.24819382, 504.44186036, 564.70722907])

Out[20]: [<matplotlib.lines.Line2D at 0x1fec32697f0>]



In [21]: from sklearn.metrics import mean\_squared\_error
 mean\_squared\_error(test,predictions)

Out[21]: 13181.51607295262