2.1. Problem Statement: Machine Learning 7

In this assignment, students will be using the K-nearest neighbors algorithm to predict how many points NBA players scored in the 2013-2014 season.

A look at the data Before we dive into the algorithm, let’s take a look at our data. Each row in the data contains information on how a player performed in the 2013-2014 NBA season.

Here are some selected columns from the data:

- player - name of the player
- pos - the position of the player
- g - number of games the player was in
- gs - number of games the player started
- pts - total points the player scored

There are many more columns in the data, mostly containing information about average player game performance over the course of the season.

See this site for an explanation of the rest of them. We can read our dataset in and figure out which columns are present:

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsRegressor
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score , mean_squared_error
import math
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
nba = pd.read_csv('nba_2013.csv')
```

In [3]:
```
nba.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 481 entries, 0 to 480
Data columns (total 31 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   player        481 non-null    object 
 1   pos           481 non-null    object 
 2   age           481 non-null    int64  
 3   bref_team_id  481 non-null    object 
 4   g             481 non-null    int64  
 5   gs            481 non-null    int64  
 6   mp            481 non-null    int64  
 7   fg            481 non-null    int64  
 8   fga           481 non-null    int64  
 9   fg.           479 non-null    float64
 10  x3p           481 non-null    int64  
 11  x3pa          481 non-null    int64  
 12  x3p.          414 non-null    float64
 13  x2p           481 non-null    int64  
 14  x2pa          481 non-null    int64  
 15  x2p.          478 non-null    float64
 16  efg.          479 non-null    float64
 17  ft            481 non-null    int64  
 18  fta           481 non-null    int64  
 19  ft.           461 non-null    float64
 20  orb           481 non-null    int64  
 21  drb           481 non-null    int64  
 22  trb           481 non-null    int64  
 23  ast           481 non-null    int64  
 24  stl           481 non-null    int64  
 25  blk           481 non-null    int64  
 26  tov           481 non-null    int64  
 27  pf            481 non-null    int64  
 28  pts           481 non-null    int64  
 29  season        481 non-null    object 
 30  season_end    481 non-null    int64  
dtypes: float64(5), int64(22), object(4)
memory usage: 116.6+ KB
```

In [4]:
```
nba.describe()
```

Out[4]:

	age	g	gs	mp	fg	fga	fg.	
count	481.000000	481.000000	481.000000	481.000000	481.000000	481.000000	479.000000	481.
mean	26.509356	53.253638	25.571726	1237.386694	192.881497	424.463617	0.436436	39.
std	4.198265	25.322711	29.658465	897.258840	171.832793	368.850833	0.098672	50.
min	19.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.
25%	23.000000	32.000000	0.000000	388.000000	47.000000	110.000000	0.400500	0.
50%	26.000000	61.000000	10.000000	1141.000000	146.000000	332.000000	0.438000	16.
75%	29.000000	76.000000	54.000000	2016.000000	307.000000	672.000000	0.479500	68.
max	39.000000	83.000000	82.000000	3122.000000	849.000000	1688.000000	1.000000	261.

8 rows × 27 columns

In [5]:
```
nba.columns
```

Out[5]:
```
Index(['player', 'pos', 'age', 'bref_team_id', 'g', 'gs', 'mp', 'fg', 'fga',
       'fg.', 'x3p', 'x3pa', 'x3p.', 'x2p', 'x2pa', 'x2p.', 'efg.', 'ft',
       'fta', 'ft.', 'orb', 'drb', 'trb', 'ast', 'stl', 'blk', 'tov', 'pf',
       'pts', 'season', 'season_end'],
      dtype='object')
```

In [6]:
```
nba.isnull().sum()
```

Out[6]:
```
player           0
pos              0
age              0
bref_team_id     0
g                0
gs               0
mp               0
fg               0
fga              0
fg.              2
x3p              0
x3pa             0
x3p.            67
x2p              0
x2pa             0
x2p.             3
efg.             2
ft               0
fta              0
ft.             20
orb              0
drb              0
trb              0
ast              0
stl              0
blk              0
tov              0
pf               0
pts              0
season           0
season_end       0
dtype: int64
```

In [7]:
```
nba[nba["x3p."].isnull()].head()
```

Out[7]:

	player	pos	age	bref_team_id	g	gs	mp	fg	fga	fg.	...	drb	trb	ast	stl	blk
1	Steven Adams	C	20	OKC	81	20	1197	93	185	0.503	...	190	332	43	40	57
2	Jeff Adrien	PF	27	TOT	53	12	961	143	275	0.520	...	204	306	38	24	36
5	Cole Aldrich	C	25	NYK	46	2	330	33	61	0.541	...	92	129	14	8	30
11	Louis Amundson	PF	31	TOT	19	0	185	16	32	0.500	...	27	55	6	9	11
18	Joel Anthony	C	31	TOT	33	0	186	12	32	0.375	...	23	38	2	3	12

5 rows × 31 columns

In [8]:
```
nba.season.value_counts()
```

Out[8]:
```
2013-2014    481
Name: season, dtype: int64
```

In [9]:
```
nba.season_end.value_counts()
```

Out[9]:
```
2013    481
Name: season_end, dtype: int64
```

In [10]:
```
feat_list_obj = []
for i in nba.columns:
    if nba[i].dtype=="object":
        feat_list_obj.append(i)

feat_list_obj
```

Out[10]:
```
['player', 'pos', 'bref_team_id', 'season']
```

In [11]:
```
feat_drop_list = feat_list_obj +["season_end","pts"]
feat_drop_list
```

Out[11]:
```
['player', 'pos', 'bref_team_id', 'season', 'season_end', 'pts']
```

In [12]:
```
Features = nba.drop(feat_drop_list,axis=1)
Lables= nba["pts"]
print(Features.shape)
print(Lables.shape)
```

```
(481, 25)
(481,)
```

In [13]:
```
Features.isnull().sum()
```

Out[13]:
```
age       0
g         0
gs        0
mp        0
fg        0
fga       0
fg.       2
x3p       0
x3pa      0
x3p.     67
x2p       0
x2pa      0
x2p.      3
efg.      2
ft        0
fta       0
ft.      20
orb       0
drb       0
trb       0
ast       0
stl       0
blk       0
tov       0
pf        0
dtype: int64
```

In [14]:
```
Features["fg."].fillna(Features["fg."].mean(),inplace=True)
Features["x2p."].fillna(Features["x2p."].mean(),inplace=True)
Features["efg."].fillna(Features["efg."].mean(),inplace=True)
Features["x3p."].fillna(Features["x3p."].mean(),inplace=True)
Features["ft."].fillna(Features["ft."].mean(),inplace=True)
Y = Lables.values ##--> Dependent Values
```

In [15]:
```
Features.isnull().sum()
```

Out[15]:
```
age      0
g        0
gs       0
mp       0
fg       0
fga      0
fg.      0
x3p      0
x3pa     0
x3p.     0
x2p      0
x2pa     0
x2p.     0
efg.     0
ft       0
fta      0
ft.      0
orb      0
drb      0
trb      0
ast      0
stl      0
blk      0
tov      0
pf       0
dtype: int64
```

In [16]:
```
x_train,x_test,y_train,y_test = train_test_split(Features,Y)
```

In [17]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(360, 25)
(121, 25)
(360,)
(121,)
```

In [18]:
```
sns.set_style("whitegrid")
for k in range(20):
    k_value=1+k
    neu=igh = KNeighborsRegressor(n_neighbors=k_value)
    neu.fit(x_train,y_train)
    y_pred = neu.predict(x_test)
    print("RMSE is :- ",np.sqrt(mean_squared_error(y_pred,y_test)),"For k value {
```

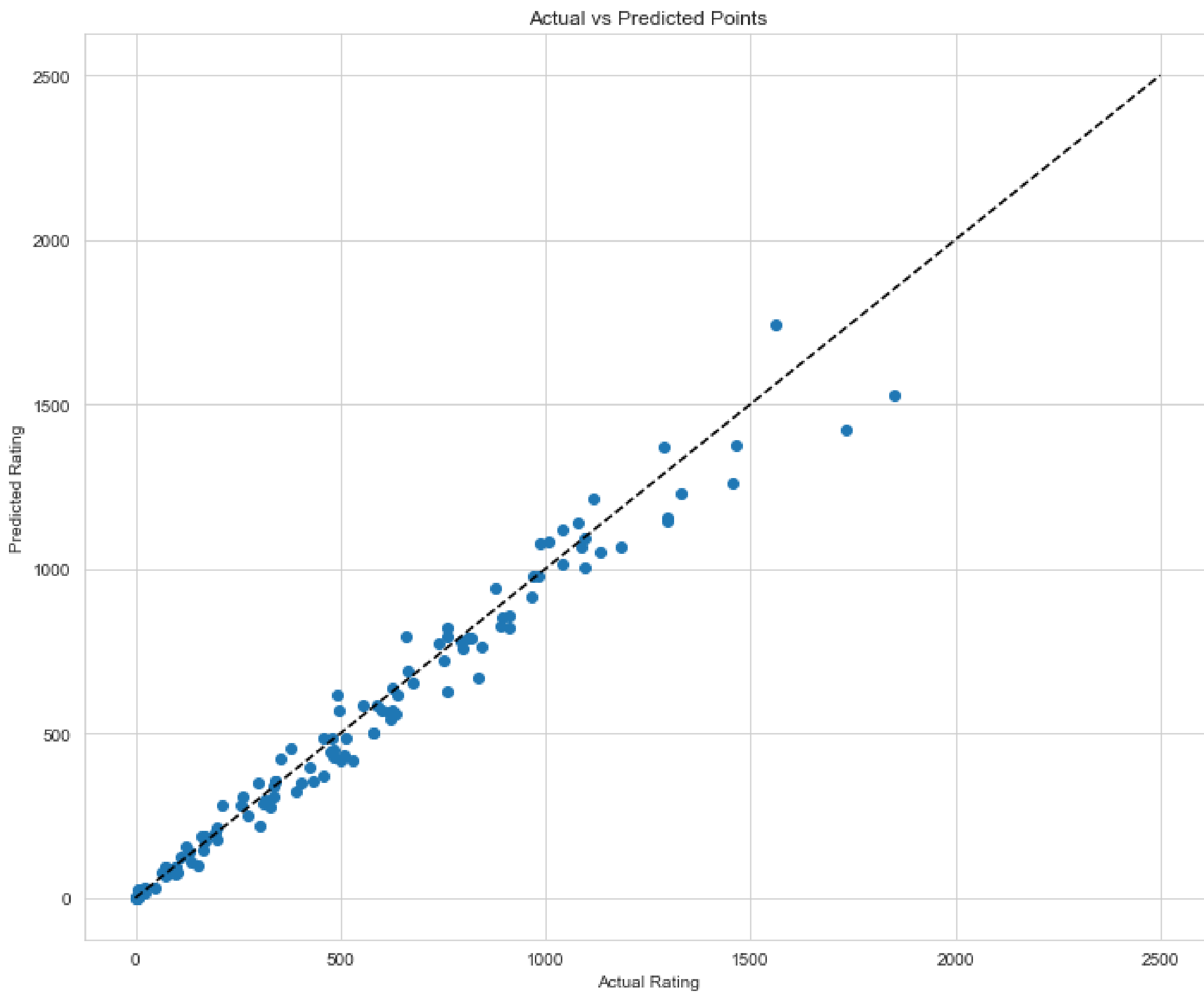
```
RMSE is :-  88.86125316497392 For k value 1
RMSE is :-  82.83955916096772 For k value 2
RMSE is :-  78.93953353096481 For k value 3
RMSE is :-  72.22560284699306 For k value 4
RMSE is :-  73.88683551763411 For k value 5
RMSE is :-  72.13871063502926 For k value 6
RMSE is :-  72.57319485807122 For k value 7
RMSE is :-  76.62458458490929 For k value 8
RMSE is :-  76.37109751909952 For k value 9
RMSE is :-  77.96782235200652 For k value 10
RMSE is :-  75.8551453334614 For k value 11
RMSE is :-  77.2244888054174 For k value 12
RMSE is :-  76.61007712476186 For k value 13
RMSE is :-  77.53038430710822 For k value 14
RMSE is :-  78.04177850305048 For k value 15
RMSE is :-  80.2516382730359 For k value 16
RMSE is :-  81.28241344715694 For k value 17
RMSE is :-  83.62974282094571 For k value 18
RMSE is :-  84.2171561113578 For k value 19
RMSE is :-  83.95040288544241 For k value 20
```

In [19]:
```
#note : It shows that we are get less error for values K =  5 , 6
k_value=5
neuigh=igh = KNeighborsRegressor(n_neighbors=k_value)
neuigh.fit(x_train,y_train)
y_pred = neuigh.predict(x_test)
print("RMSE for KNN Regressor is  :- ",np.sqrt(mean_squared_error(y_pred,y_test)
print("R Squared for KNN Regressor is  :- ",r2_score(y_test,y_pred))
```

```
RMSE for KNN Regressor is  :-  73.88683551763411 For k value 5
R Squared for KNN Regressor is  :-  0.9703610383923194
```

In [20]:
```
#R squared is a statistical measure of how close the data points are to thr fitte


plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred)
plt.plot([0,2500],[0,2500],'--k')
plt.axis("tight")
plt.xlabel("Actual Rating")
plt.ylabel("Predicted Rating")
plt.tight_layout()
plt.title("Actual vs Predicted Points")
```

Out[20]:
```
Text(0.5, 1.0, 'Actual vs Predicted Points')
```

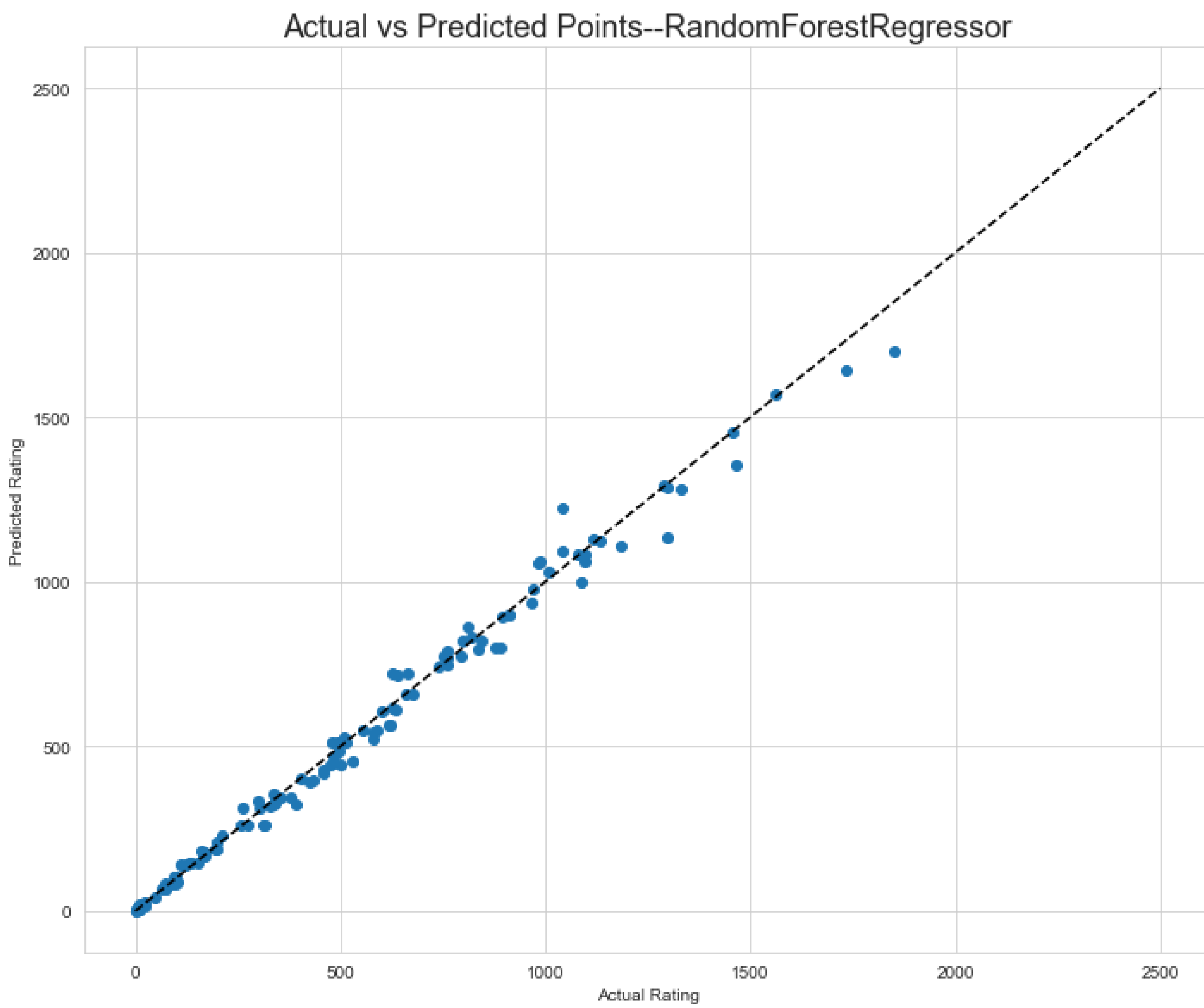


In [21]:
```
from sklearn.ensemble import RandomForestRegressor
Rf = RandomForestRegressor(random_state = 1)
Rf.fit(x_train,y_train)
y_pred=Rf.predict(x_test)
print("RMSE for RandomForest Regressor is  :- ",np.sqrt(mean_squared_error(y_pred
print("R Squared for RandomForest Regressor is  :- ",r2_score(y_test,y_pred))
```

```
RMSE for RandomForest Regressor is  :-  43.25424283397521
R Squared for RandomForest Regressor is  :-  0.9898425129090567
```

In [22]:
```
#R squared is a statistical measure of how close the data points are to thr fitte


plt.figure(figsize=(10,8))
plt.scatter(y_test,y_pred)
plt.plot([0,2500],[0,2500],'--k')
plt.axis("tight")
plt.xlabel("Actual Rating")
plt.ylabel("Predicted Rating")
plt.tight_layout()
plt.title("Actual vs Predicted Points--RandomForestRegressor",fontsize=18)
```

Out[22]:
```
Text(0.5, 1.0, 'Actual vs Predicted Points--RandomForestRegressor')
```



In [23]:
```
for depth in range(30):
    depth+=1
    Rf = RandomForestRegressor(max_depth=depth,random_state =1)
    Rf.fit(x_train,y_train)
    y_pred=Rf.predict(x_test)
    print("RMSE is  :- ",np.sqrt(mean_squared_error(y_pred,y_test)),"For Depth va
```

```
RMSE is  :-  230.5489415724857 For Depth value :- 1
RMSE is  :-  107.58148434819346 For Depth value :- 2
RMSE is  :-  67.55834208828297 For Depth value :- 3
RMSE is  :-  54.60281636989371 For Depth value :- 4
RMSE is  :-  48.56568661113202 For Depth value :- 5
RMSE is  :-  46.33814255372531 For Depth value :- 6
RMSE is  :-  45.82865164515156 For Depth value :- 7
RMSE is  :-  46.0572345946096 For Depth value :- 8
RMSE is  :-  44.3913087385565 For Depth value :- 9
RMSE is  :-  45.03475499611181 For Depth value :- 10
RMSE is  :-  45.52423691405091 For Depth value :- 11
RMSE is  :-  43.94553264841992 For Depth value :- 12
RMSE is  :-  43.308874734690626 For Depth value :- 13
RMSE is  :-  43.25424283397521 For Depth value :- 14
RMSE is  :-  43.25424283397521 For Depth value :- 15
RMSE is  :-  43.25424283397521 For Depth value :- 16
RMSE is  :-  43.25424283397521 For Depth value :- 17
RMSE is  :-  43.25424283397521 For Depth value :- 18
RMSE is  :-  43.25424283397521 For Depth value :- 19
RMSE is  :-  43.25424283397521 For Depth value :- 20
RMSE is  :-  43.25424283397521 For Depth value :- 21
RMSE is  :-  43.25424283397521 For Depth value :- 22
RMSE is  :-  43.25424283397521 For Depth value :- 23
RMSE is  :-  43.25424283397521 For Depth value :- 24
RMSE is  :-  43.25424283397521 For Depth value :- 25
RMSE is  :-  43.25424283397521 For Depth value :- 26
RMSE is  :-  43.25424283397521 For Depth value :- 27
RMSE is  :-  43.25424283397521 For Depth value :- 28
RMSE is  :-  43.25424283397521 For Depth value :- 29
RMSE is  :-  43.25424283397521 For Depth value :- 30
```

In [49]:
```
#NOTE :-the random forest regressor gives a low RMSE value for maxdepth =13 and 1

#CONCLUSION

#The R Squared for KNN Regressor is  0.9703610383923194

#The R Squared for RandomForest Regressor is  0.9898425129090567
```

In [ ]:

In [ ]:

2.2. Problem Statement: Machine Learning 8

In this assignment students have to find the frequency of words in a webpage. User can use urllib and BeautifulSoup to extract text from webpage.

***Hint: ***

from bs4 import BeautifulSoup

import urllib.request

import nltk

response = urllib.request.urlopen('http://php.net/' (http://php.net/'))

html = response.read()

soup = BeautifulSoup(html,"html5lib")

In [24]:
```
from bs4 import BeautifulSoup
import urllib.request
import nltk
```

In [25]:
```
response = urllib.request.urlopen('http://php.net/')
html = response.read()
raw = BeautifulSoup(html,"html5lib").get_text()
```

In [26]:
```
nltk.download('punkt')
words=nltk.word_tokenize(raw)

#removing the singal characters  mostly puncatuations
words=[word for word in words if len(word)>1]

#removing any numbers present in our text
words = [word for word in words if not word.isnumeric()]

#lowercase all words (default stopwords are lowercase too)
words = [word.lower() for word in words]

#calculating frequency distribution
fdist = nltk.FreqDist(words)

#printing the top 10 words with their frequency
for word , frequency in fdist.most_common(10):
    print(u'{}; {}'.format(word , frequency))
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\idofa\AppData\Roaming\nltk_data...

the; 245
php; 153
of; 87
release; 85
for; 81
this; 66
in; 60
is; 56
to; 51
be; 50

[nltk_data]   Package punkt is already up-to-date!
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

2.3. Problem Statement: Machine Learning 9

***In this assignment students have to compress racoon grey scale image into 5 clusters. In the end, visualize both raw and compressed image and look for quality difference. ***

The raw image is available in spicy.misc package with the name face. Hint:

import numpy as np

from sklearn import cluster, datasets

from scipy import misc

In [27]:
```
#Importing libraries
import numpy as np
from sklearn.cluster import KMeans
from sklearn import datasets
from scipy import misc
import matplotlib.pyplot as plt
```

In [28]:
```
face =misc.face(gray=True)
```

In [29]:
```
k_Means= KMeans(n_clusters = 5)
np.random.seed(10)
X = face.reshape((-1,1))

#fitting value of X
k_Means.fit(X)

values = k_Means.cluster_centers_
print("Values :-",values)

labels = k_Means.labels_
print("Labels :-",labels)
```

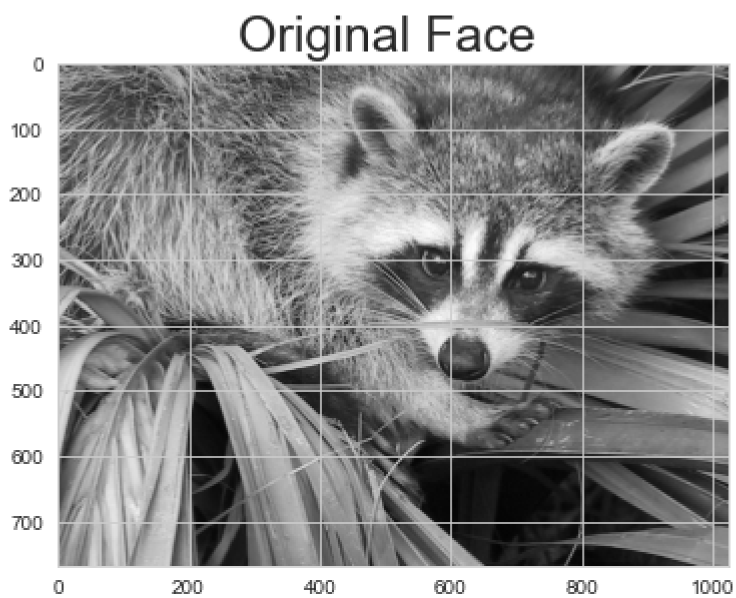
```
Values :- [[114.99362851]
 [ 27.62031146]
 [194.13840989]
 [ 75.41095451]
 [153.31393344]]
Labels :- [0 0 4 ... 4 4 4]
```

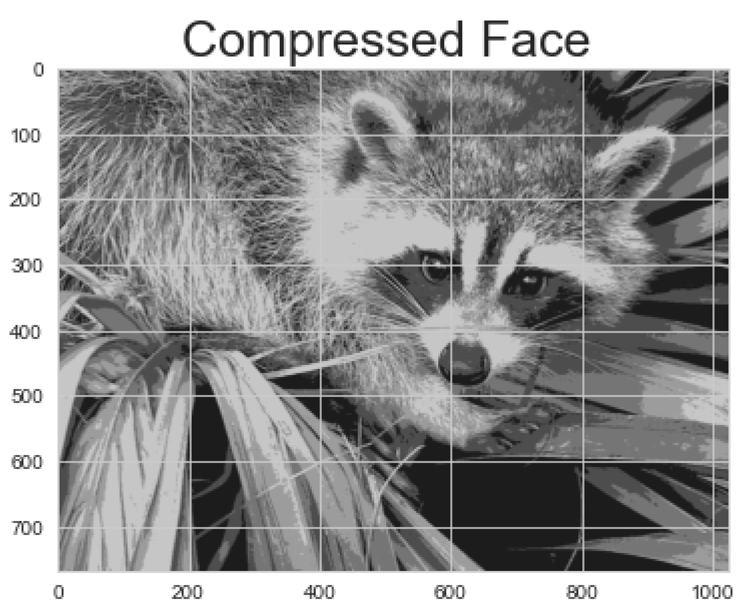
In [30]:
```
#Create an array from label and values
face_compressed = np.choose(labels , values)
face_compressed.shape = face.shape

vmin = face.min()
vmax = face.max()

print("Vmin :-{}\t Vmax :-{}".format(vmin , vmax))
```

```
Vmin :-0         Vmax :-250
```

In [31]:
```
#Original Face
plt.figure(figsize = (6,6))
plt.imshow(face,cmap= plt.cm.gray)
plt.title("Original Face ",fontsize = 25)

#Compressed Face
plt.figure(figsize = (6,6))
plt.imshow(face_compressed,cmap= plt.cm.gray,vmin = vmin,vmax= vmax)
plt.title("Compressed Face ",fontsize = 25)
```

Out[31]:
```
Text(0.5, 1.0, 'Compressed Face ')
```





In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

2.4. Problem Statement: Machine Learning 10

In this assignment students have to transform iris data into 3 dimensions and plot a 3d chart with transformed dimensions and colour each data point with specific class.

Hint:

import numpy as np

import matplotlib.pyplot as plt

from mpl_toolkits.mplot3d import Axes3D

from sklearn import decomposition

from sklearn import datasets

In [32]:

```
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn import decomposition
from sklearn import datasets
import seaborn as sns
import pandas as pd
```

In [33]:

```
iris = sns.load_dataset('iris')
```

In [34]:
```
iris.head(3)
```

Out[34]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa

In [35]:
```
iris['Species'] = pd.factorize(iris.species)[0]
```

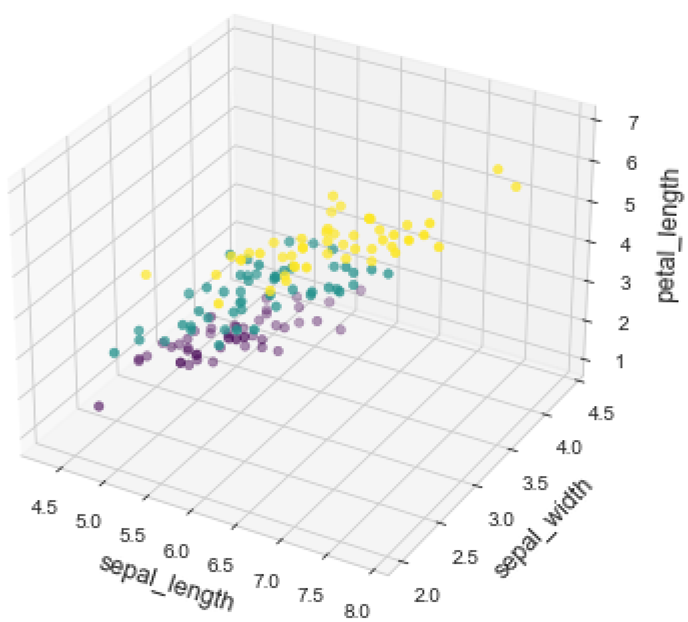
In [36]:
```
iris.tail(3)
```

Out[36]:

	sepal_length	sepal_width	petal_length	petal_width	species	Species
147	6.5	3.0	5.2	2.0	virginica	2
148	6.2	3.4	5.4	2.3	virginica	2
149	5.9	3.0	5.1	1.8	virginica	2

In [37]:
```
plt.figure(figsize = (12,6))
ax = plt.axes(projection='3d')
ax.scatter3D(iris.sepal_length,iris.sepal_width, iris.petal_length,c =iris['Speci
ax.set_xlabel('sepal_length' , fontsize = 12.5)
ax.set_ylabel("sepal_width", fontsize = 12.5)
ax.set_zlabel('petal_length', fontsize = 12.5)
```

Out[37]: Text(0.5, 0, 'petal_length')



In [ ]:

2.5. Problem Statement: Machine Learning 11

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-yearperiod#!ds=22r0&display=line (https://datamarket.com/data/set/22r0/sales-of-shampoo-over-a-three-yearperiod#!ds=22r0&display=line)](https://datamarket.com/data/set/22r0/sales-of-shampoo-over-a-three-yearperiod#!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 [38]:

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

In [39]:

```
def parser(x):
    return datetime.strptime('190'+x, '%Y-%m')
```

In [40]:
```
series = pd.read_csv("sales-of-shampoo-over-a-three-ye.csv", header=0, parse_date
series.head()
```

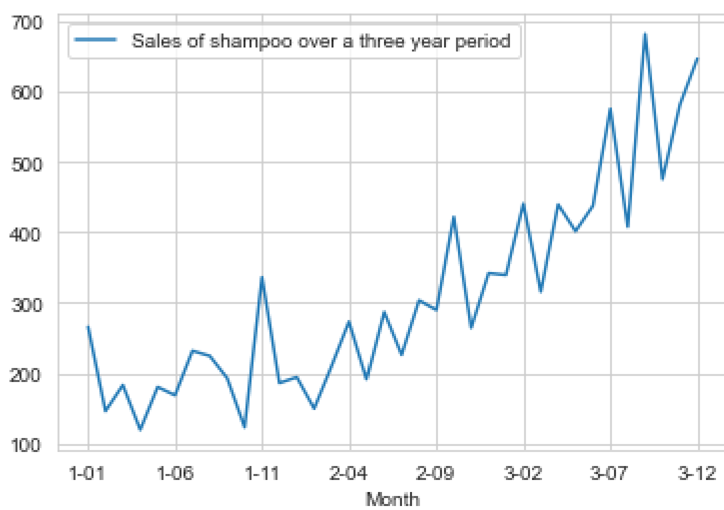
Out[40]:

Month	Sales of shampoo over a three year period
1-01	266.0
1-02	145.9
1-03	183.1
1-04	119.3
1-05	180.3

In [41]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [42]:
```
series.dropna(axis=0,inplace=True)
```

In [43]:
```
series.plot()
pyplot.show()
```



In [44]:
```
X= series.values
X
```

Out[44]:
```
array([[266. ],
       [145.9],
       [183.1],
       [119.3],
       [180.3],
       [168.5],
       [231.8],
       [224.5],
       [192.8],
       [122.9],
       [336.5],
       [185.9],
       [194.3],
       [149.5],
       [210.1],
       [273.3],
       [191.4],
       [287. ],
       [226. ],
       [303.6],
       [289.9],
       [421.6],
       [264.5],
       [342.3],
       [339.7],
       [440.4],
       [315.9],
       [439.3],
       [401.3],
       [437.4],
       [575.5],
       [407.6],
       [682. ],
       [475.3],
       [581.3],
       [646.9]])
```

In [45]:
```
size = int(len(X)*0.6)
print(len(X),'\n',size)
```

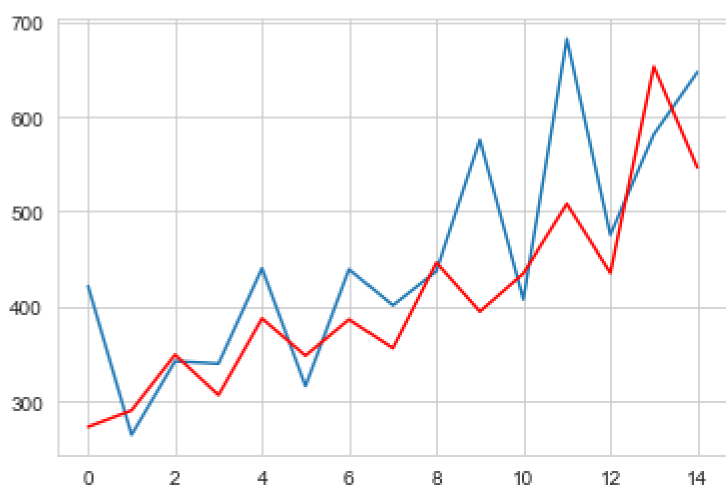
```
36
 21
```

In [46]:
```
train,test=X[0:size],X[size:len(X)]
```

In [47]:
```
history=[x for x in train]
predictions=[]
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 = {}    Excepted = {}".format(yhat,obs))

error = mean_squared_error(test,predictions)
print("\n\n\nTest MSE = {}".format(round(error,ndigits=3)))
```

```
Predicted = [272.96451422]    Excepted = [421.6]
Predicted = [290.31366212]    Excepted = [264.5]
Predicted = [349.11764194]    Excepted = [342.3]
Predicted = [306.51293429]    Excepted = [339.7]
Predicted = [387.37635503]    Excepted = [440.4]
Predicted = [348.15422407]    Excepted = [315.9]
Predicted = [386.30873564]    Excepted = [439.3]
Predicted = [356.08213522]    Excepted = [401.3]
Predicted = [446.37949922]    Excepted = [437.4]
Predicted = [394.73731958]    Excepted = [575.5]
Predicted = [434.9155186]    Excepted = [407.6]
Predicted = [507.92333692]    Excepted = [682.]
Predicted = [435.48297593]    Excepted = [475.3]
Predicted = [652.74379393]    Excepted = [581.3]
Predicted = [546.34341033]    Excepted = [646.9]



Test MSE = 7547.808
```

In [48]:
```
pyplot.plot(test)
pyplot.plot(predictions,color='red')
pyplot.show()
```



In [ ]: