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.
Download 'nba_2013.csv' file from this link:
https://www.dropbox.com/s/b3nv38jjo5dxcl6/nba_2013.csv?dl=0 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:
import pandas
with open("nba_2013.csv", 'r') as csvfile:
nba = pandas.read_csv(csvfile)
```

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 :-  88.14361871775607 For k value 1
RMSE is :-  81.34522391969583 For k value 2
RMSE is :-  72.85064031500823 For k value 3
RMSE is :-  77.57868239929006 For k value 4
RMSE is :-  81.33551570932885 For k value 5
RMSE is :-  82.92611108082846 For k value 6
RMSE is :-  87.92879849240383 For k value 7
RMSE is :-  88.97359289383573 For k value 8
RMSE is :-  90.58101632414188 For k value 9
RMSE is :-  91.29329947441717 For k value 10
RMSE is :-  92.16674138023905 For k value 11
RMSE is :-  91.2252293510743 For k value 12
RMSE is :-  90.5259853963601 For k value 13
RMSE is :-  93.9551023981956 For k value 14
RMSE is :-  95.37743147758651 For k value 15
RMSE is :-  97.42398399542753 For k value 16
RMSE is :-  98.78410995872197 For k value 17
RMSE is :-  96.5671266687894 For k value 18
RMSE is :-  98.62167831755075 For k value 19
RMSE is :-  101.73117101962796 For k value 20
```

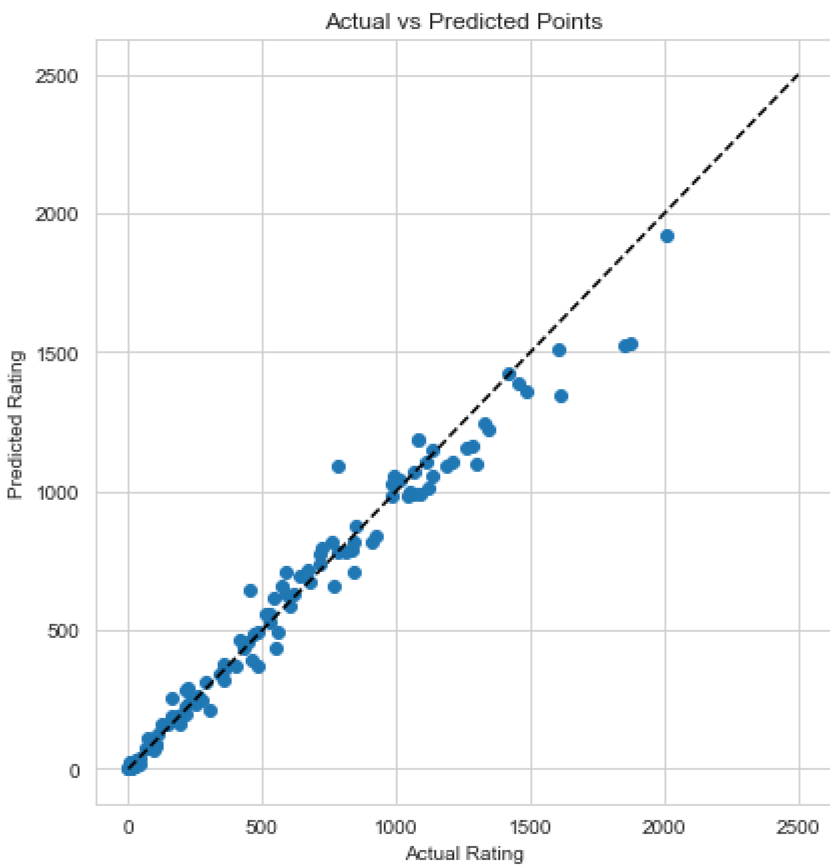
In [19]:
```
#note : It shows that we are get less error for values K =  5 , 6
k_value=5
neuigh=igh = KNeighborsRegressor(n_neighbors=k_value)
neuigh.fit(x_train,y_train)
y_pred = neuigh.predict(x_test)
print("RMSE for KNN Regressor is  :- ",np.sqrt(mean_squared_error(y_pred,y_test))
print("R Squared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

```
RMSE for KNN Regressor is  :-  81.33551570932885 For k value 5
R Squared for KNN Regressor is  :-  0.9726611329606782
```

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


plt.figure(figsize=(6,6))
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')
```



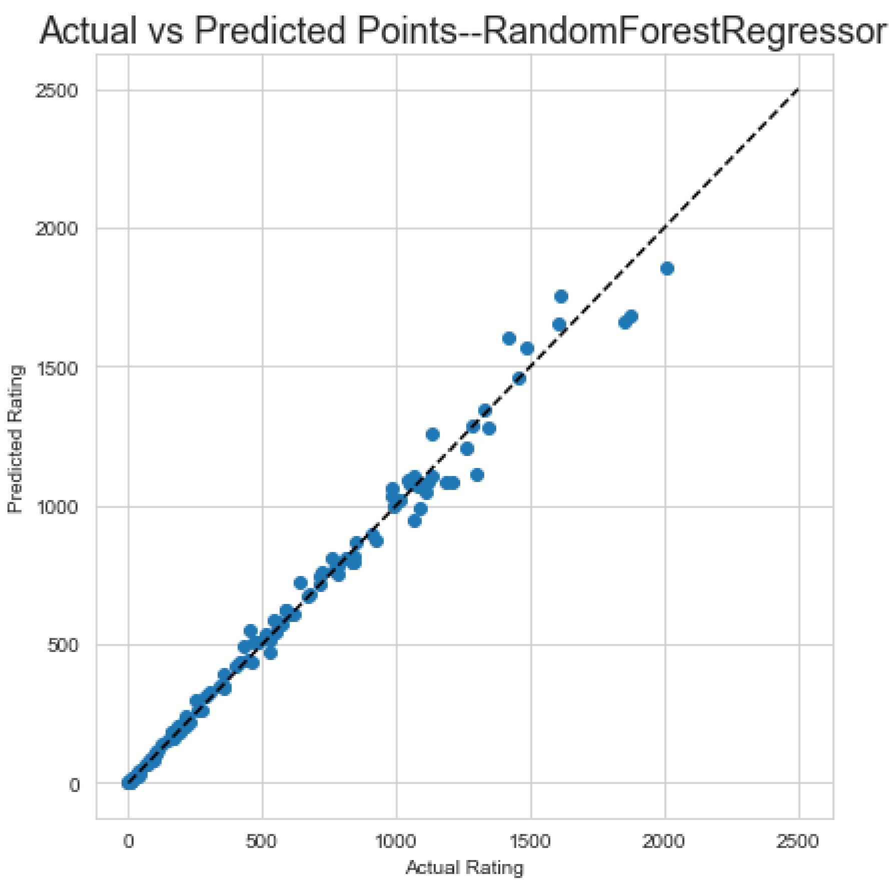
In [21]:
```
from sklearn.ensemble import RandomForestRegressor
Rf = RandomForestRegressor(random_state = 1)
Rf.fit(x_train,y_train)
y_pred=Rf.predict(x_test)
print("RMSE for RandomForest Regressor is  :- ",np.sqrt(mean_squared_error(y_pred
print("R Squared for RandomForest Regressor is  :- ",r2_score(y_test,y_pred))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

```
RMSE for RandomForest Regressor is  :-  52.744436367910836
R Squared for RandomForest Regressor is  :-  0.9885032953349514
```

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


plt.figure(figsize=(6,6))
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  :-  241.97474246484296 For Depth value :- 1
RMSE is  :-  120.12885179433188 For Depth value :- 2
RMSE is  :-  70.01110593091636 For Depth value :- 3
RMSE is  :-  59.50580786687762 For Depth value :- 4
RMSE is  :-  55.29846210031686 For Depth value :- 5
RMSE is  :-  53.81523169064212 For Depth value :- 6
RMSE is  :-  54.41103469474289 For Depth value :- 7
RMSE is  :-  53.138815243339586 For Depth value :- 8
RMSE is  :-  53.43299603950885 For Depth value :- 9
RMSE is  :-  50.93145610514773 For Depth value :- 10
RMSE is  :-  53.051465627387074 For Depth value :- 11
RMSE is  :-  52.26235308930614 For Depth value :- 12
RMSE is  :-  52.42349688322346 For Depth value :- 13
RMSE is  :-  52.06751951088634 For Depth value :- 14
RMSE is  :-  52.744436367910836 For Depth value :- 15
RMSE is  :-  52.744436367910836 For Depth value :- 16
RMSE is  :-  52.744436367910836 For Depth value :- 17
RMSE is  :-  52.744436367910836 For Depth value :- 18
RMSE is  :-  52.744436367910836 For Depth value :- 19
RMSE is  :-  52.744436367910836 For Depth value :- 20
RMSE is  :-  52.744436367910836 For Depth value :- 21
RMSE is  :-  52.744436367910836 For Depth value :- 22
RMSE is  :-  52.744436367910836 For Depth value :- 23
RMSE is  :-  52.744436367910836 For Depth value :- 24
RMSE is  :-  52.744436367910836 For Depth value :- 25
RMSE is  :-  52.744436367910836 For Depth value :- 26
RMSE is  :-  52.744436367910836 For Depth value :- 27
RMSE is  :-  52.744436367910836 For Depth value :- 28
RMSE is  :-  52.744436367910836 For Depth value :- 29
RMSE is  :-  52.744436367910836 For Depth value :- 30
```

NOTE :-the random forest regressor gives a low RMSE value for maxdepth =13 and The RMSE remains constant aftermath.

CONCLUSION

The R Squared for KNN Regressor is 0.9703610383923194

The R Squared for RandomForest Regressor is 0.9898425129090567

In [ ]:

In [ ]:

In [ ]:
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```

In [ ]:
```

```