In [1]:
```
import sqlite3
import numpy as np
import pandas as pd
%matplotlib notebook
import matplotlib.pyplot as plt
import xgboost as xgb
from xgboost.sklearn import XGBRegressor
from xgboost import plot_importance

from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import Imputer, StandardScaler
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import train_test_split, GridSearchCV, Shu
ffleSplit, RandomizedSearchCV
from sklearn.pipeline import make_pipeline

import pickle
```

Reading Data from the Database into pandas

In [2]:
```
cnx = sqlite3.connect('database.sqlite')
```

In [3]:
```
df= pd.read_sql_query("SELECT * FROM Player_Attributes", cnx)
```

In [4]:
```
print(df)
```

```
            id  player_fifa_api_id  player_api_id                 date  
\
0            1              218353         505942  2016-02-18 00:00:00
1            2              218353         505942  2015-11-19 00:00:00
2            3              218353         505942  2015-09-21 00:00:00
3            4              218353         505942  2015-03-20 00:00:00
4            5              218353         505942  2007-02-22 00:00:00
...        ...                 ...            ...                  ...
183973  183974              102359          39902  2009-08-30 00:00:00
183974  183975              102359          39902  2009-02-22 00:00:00
183975  183976              102359          39902  2008-08-30 00:00:00
183976  183977              102359          39902  2007-08-30 00:00:00
183977  183978              102359          39902  2007-02-22 00:00:00

        overall_rating  potential preferred_foot attacking_work_rate  \
0                 67.0       71.0          right              medium
1                 67.0       71.0          right              medium
2                 62.0       66.0          right              medium
3                 61.0       65.0          right              medium
4                 61.0       65.0          right              medium
...                ...        ...            ...                 ...
183973            83.0       85.0          right              medium
183974            78.0       80.0          right              medium
183975            77.0       80.0          right              medium
183976            78.0       81.0          right              medium
183977            80.0       81.0          right              medium
```

```
       defensive_work_rate  crossing  ...  vision  penalties  marking  \
0                   medium      49.0  ...    54.0       48.0     65.0
1                   medium      49.0  ...    54.0       48.0     65.0
2                   medium      49.0  ...    54.0       48.0     65.0
3                   medium      48.0  ...    53.0       47.0     62.0
4                   medium      48.0  ...    53.0       47.0     62.0
...                    ...       ...  ...     ...        ...      ...
183973                 low      84.0  ...    88.0       83.0     22.0
183974                 low      74.0  ...    88.0       70.0     32.0
183975                 low      74.0  ...    88.0       70.0     32.0
183976                 low      74.0  ...    88.0       53.0     28.0
183977                 low      74.0  ...    88.0       53.0     38.0

        standing_tackle  sliding_tackle  gk_diving  gk_handling  gk_kic
king  \
0                  69.0            69.0        6.0         11.0
10.0
1                  69.0            69.0        6.0         11.0
10.0
2                  66.0            69.0        6.0         11.0
10.0
3                  63.0            66.0        5.0         10.0
9.0
4                  63.0            66.0        5.0         10.0
9.0
...                 ...             ...        ...          ...
...
183973             31.0            30.0        9.0         20.0
84.0
183974             31.0            30.0        9.0         20.0
73.0
183975             31.0            30.0        9.0         20.0
73.0
183976             32.0            30.0        9.0         20.0
73.0
183977             32.0            30.0        9.0          9.0
78.0

        gk_positioning  gk_reflexes
0                  8.0          8.0
1                  8.0          8.0
2                  8.0          8.0
3                  7.0          7.0
4                  7.0          7.0
...                ...          ...
183973            20.0         20.0
183974            20.0         20.0
183975            20.0         20.0
183976            20.0         20.0
183977             7.0         15.0

[183978 rows x 42 columns]
```

In [5]:
```
df.head()
```

Out[5]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferre

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferre
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right

5 rows × 42 columns

Creating Target variable:

In [6]:
```
target = df.pop('overall_rating')
```

In [7]:
```
df.shape
```

Out[7]:
```
(183978, 41)
```

In [8]:
```
target.head()
```

Out[8]:
```
0    67.0
1    67.0
2    62.0
3    61.0
4    61.0
Name: overall_rating, dtype: float64
```

Imputing target funtion :

In [9]:
```
target.isnull().values.sum()
```

Out[9]:
```
836
```

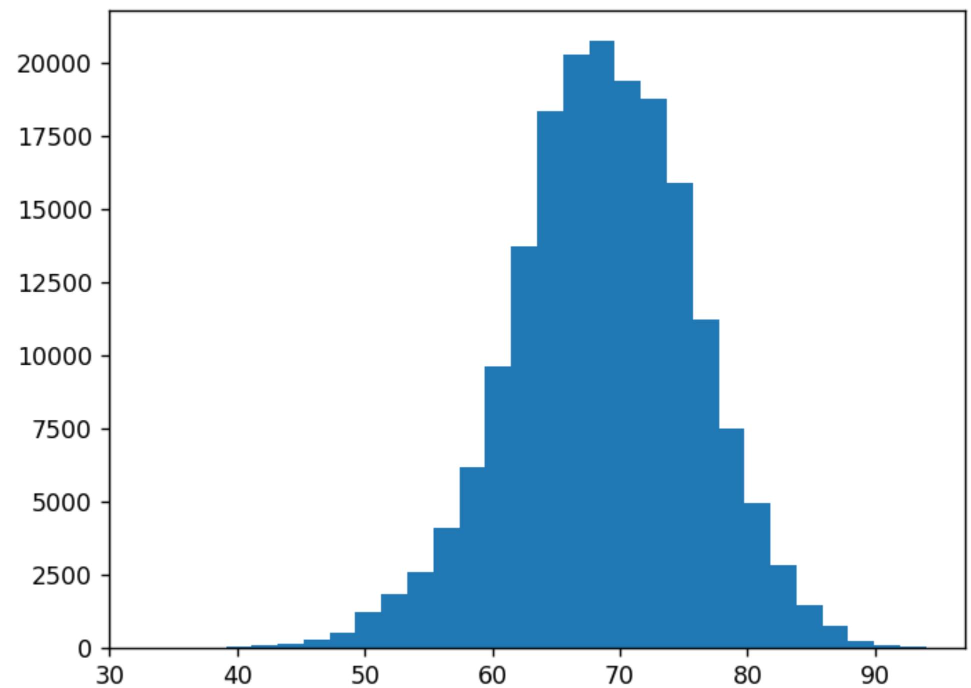
In [10]:
```
target.describe()
```

Out[10]:
```
count    183142.000000
mean         68.600015
std           7.041139
min          33.000000
25%          64.000000
```

```
50%          69.000000
75%          73.000000
max          94.000000
Name: overall_rating, dtype: float64
```

In [11]:
```
plt.hist(target, 30, range=(33, 94))
```

```
<IPython.core.display.Javascript object>
```




```
C:\ProgramData\Anaconda3\lib\site-packages\numpy\lib\histograms.py:839:
RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
C:\ProgramData\Anaconda3\lib\site-packages\numpy\lib\histograms.py:840:
RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

Out[11]:
```
(array([7.0000e+00, 6.0000e+00, 2.0000e+01, 6.5000e+01, 9.4000e+01,
        1.4200e+02, 2.9400e+02, 5.2600e+02, 1.2510e+03, 1.8450e+03,
        2.5780e+03, 4.0870e+03, 6.1890e+03, 9.6500e+03, 1.3745e+04,
        1.8366e+04, 2.0310e+04, 2.0773e+04, 1.9382e+04, 1.8784e+04,
        1.5915e+04, 1.1254e+04, 7.5250e+03, 4.9470e+03, 2.8290e+03,
        1.4590e+03, 7.4800e+02, 2.2800e+02, 8.4000e+01, 3.9000e+01]),
 array([33.        , 35.03333333, 37.06666667, 39.1       , 41.1333333
3,
        43.16666667, 45.2       , 47.23333333, 49.26666667, 51.3
,
        53.33333333, 55.36666667, 57.4       , 59.43333333, 61.4666666
7,
        63.5       , 65.53333333, 67.56666667, 69.6       , 71.6333333
3,
        73.66666667, 75.7       , 77.73333333, 79.76666667, 81.8
,
        83.83333333, 85.86666667, 87.9       , 89.93333333, 91.9666666
7
```

```
,
        94.        ]),
 <a list of 30 Patch objects>)
```

It's almost normal distribution so we can impute mean value for missing value in target.

In [12]:
```
y = target.fillna(target.mean())
```

In [13]:
```
y.isnull().values.any()
```

Out[13]:
```
False
```

Data Exploration :

In [14]:
```
df.columns
```

Out[14]:
```
Index(['id', 'player_fifa_api_id', 'player_api_id', 'date', 'potentia
l',
       'preferred_foot', 'attacking_work_rate', 'defensive_work_rate',
       'crossing', 'finishing', 'heading_accuracy', 'short_passing', 'v
olleys',
       'dribbling', 'curve', 'free_kick_accuracy', 'long_passing',
       'ball_control', 'acceleration', 'sprint_speed', 'agility', 'reac
tions',
       'balance', 'shot_power', 'jumping', 'stamina', 'strength', 'long
_shots',
       'aggression', 'interceptions', 'positioning', 'vision', 'penalti
es',
       'marking', 'standing_tackle', 'sliding_tackle', 'gk_diving',
       'gk_handling', 'gk_kicking', 'gk_positioning', 'gk_reflexes'],
      dtype='object')
```

In [15]:
```
for col in df.columns:
    unique_cat = len(df[col].unique())
    print("{col}--> {unique_cat}..{typ}".format(col=col, unique_cat=uni
que_cat, typ=df[col].dtype))
```

```
id--> 183978..int64
player_fifa_api_id--> 11062..int64
player_api_id--> 11060..int64
date--> 197..object
potential--> 57..float64
preferred_foot--> 3..object
attacking_work_rate--> 9..object
defensive_work_rate--> 20..object
crossing--> 96..float64
finishing--> 98..float64
heading_accuracy--> 97..float64
short_passing--> 96..float64
volleys--> 94..float64
dribbling--> 98..float64
curve--> 93..float64
free_kick_accuracy--> 98..float64
long_passing--> 96..float64
ball_control--> 94..float64
acceleration--> 87..float64
```

```
sprint_speed--> 86..float64
agility--> 82..float64
reactions--> 79..float64
balance--> 82..float64
shot_power--> 97..float64
jumping--> 80..float64
stamina--> 85..float64
strength--> 83..float64
long_shots--> 97..float64
aggression--> 92..float64
interceptions--> 97..float64
positioning--> 96..float64
vision--> 98..float64
penalties--> 95..float64
marking--> 96..float64
standing_tackle--> 96..float64
sliding_tackle--> 95..float64
gk_diving--> 94..float64
gk_handling--> 91..float64
gk_kicking--> 98..float64
gk_positioning--> 95..float64
gk_reflexes--> 93..float64
```

In [16]:

```
dummy_df = pd.get_dummies(df, columns=['preferred_foot', 'attacking_wor
k_rate', 'defensive_work_rate'])
dummy_df.head()
```

Out[16]:

	id	player_fifa_api_id	player_api_id	date	potential	crossing	finishing	hea
0	1	218353	505942	2016-02-18 00:00:00	71.0	49.0	44.0	71.
1	2	218353	505942	2015-11-19 00:00:00	71.0	49.0	44.0	71.
2	3	218353	505942	2015-09-21 00:00:00	66.0	49.0	44.0	71.
3	4	218353	505942	2015-03-20 00:00:00	65.0	48.0	43.0	70.
4	5	218353	505942	2007-02-22 00:00:00	65.0	48.0	43.0	70.

5 rows × 67 columns

In [17]:

```
X = dummy_df.drop(['id', 'date'], axis=1)
```

Feature selection :

As tree model doesn't gets affected by missing values present in data set. but feature selection by SelectFromModel can not be done on datasets that carries null value. Therefore, we should also perform imputation on dataset.

In [18]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2
5, random_state=42)
```

In [19]:
```
#imputing null value of each column with the mean of that column
imput = Imputer()
X_train = imput.fit_transform(X_train)
X_test = imput.fit_transform(X_test)
```

```
C:\Users\Shridhar M\AppData\Roaming\Python\Python37\site-packages\sklea
rn\utils\deprecation.py:66: DeprecationWarning: Class Imputer is deprec
ated; Imputer was deprecated in version 0.20 and will be removed in 0.2
2. Import impute.SimpleImputer from sklearn instead.
  warnings.warn(msg, category=DeprecationWarning)
```

In [20]:
```
#finding feature_importance for feature selection. from it we'll be abl
e to decide threshold value
model = XGBRegressor()
model.fit(X_train, y_train)
print(model.feature_importances_)
```

```
[13:50:34] WARNING: src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
[0.05115651 0.02897777 0.13911739 0.02826106 0.00595768 0.04332646
 0.01590659 0.         0.01287898 0.         0.         0.00348626
 0.13141693 0.00436716 0.0058711  0.0065089  0.16110069 0.
 0.05513685 0.0040621  0.00863542 0.03761797 0.00898127 0.0139806
 0.01894557 0.02671051 0.0015188  0.         0.03219567 0.0530614
 0.00176505 0.02725989 0.02712863 0.01008714 0.02617038 0.00840923
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.        ]
```

In [21]:
```
selection = SelectFromModel(model, threshold=0.01, prefit=True)

select_X_train = selection.transform(X_train)
select_X_test = selection.transform(X_test)
select_X_train.shape
```

Out[21]:
```
(137983, 20)
```

Scaling the data:

In [22]:
```
scalar = StandardScaler()
x_scaled_train = scalar.fit_transform(select_X_train)
x_scaled_train
```

Out[22]:
```
array([[ 1.0567811 ,  2.90118168, -0.37370531, ..., -0.69862488,
        -0.65367807, -0.31949444],
       [ 0.83239093,  1.11023832, -0.67788964, ..., -0.25617622,
```

```
        -0.51352154, -0.25716519],
       [ 0.17077907,  1.07420333,  0.38675551, ..., -0.12976231,
        -0.60695922, -0.19483593],
       ...,
       [-2.07758255, -0.8212941 ,  1.2993085 , ...,  0.31268635,
         2.4764844 ,  0.30379811],
       [ 0.44157109, -0.11639067,  0.99512417, ...,  0.37589331,
         1.02820027,  0.36612736],
       [ 0.22002412, -0.64891505,  1.755585  , ..., -0.69862488,
        -0.56024038, -0.50648221]])
```

In [23]:

```
x_scaled_test = scalar.fit_transform(select_X_test)
x_scaled_test
```

Out[23]:

```
array([[ 0.5825465 ,  0.37577743,  1.14364038, ..., -0.69951284,
        -0.65497804, -0.19548251],
       [ 0.7131656 ,  0.14588373, -0.22328168, ..., -0.63646818,
        -0.60825467, -0.19548251],
       [ 0.2307514 , -0.78242149, -0.52704214, ..., -0.51037885,
        -0.23446774, -0.00935998],
       ...,
       [ 0.7233016 ,  0.76992259,  0.83987993, ..., -0.13211088,
        -0.37463784, -0.13344167],
       [ 0.71524098,  1.61776501,  0.6879997 , ..., -0.25820021,
        -0.65497804, -0.50568674],
       [ 0.90691696,  2.24229255, -1.74208398, ..., -0.25820021,
        -0.5615313 , -0.38160505]])
```

Training different models :

1. Linear Regression :

In [24]:

```
linear_reg = LinearRegression()
linear_reg.fit(x_scaled_train, y_train)
```

Out[24]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=False)
```

In [25]:

```
linear_reg.score(x_scaled_test, y_test)
```

Out[25]:

```
0.8536634604512405
```

Hyperparameter Tuning:

In [26]:

```
cv = ShuffleSplit(random_state=0)   #defining type of cross_validation
(shuffle spliting)

param_grid = {'n_jobs': [-1]}     #parameters for model tunning

grid = GridSearchCV(linear_reg, param_grid=param_grid, cv=cv)
```

In [27]:

```
grid.fit(select_X_train, y_train)
```

Out[27]:

```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=0, test_size=Non
```

```
e, train_size=None),
             error_score='raise-deprecating',
             estimator=LinearRegression(copy_X=True, fit_intercept=Tru
e,
                                        n_jobs=None, normalize=False),
             iid='warn', n_jobs=None, param_grid={'n_jobs': [-1]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring=None, verbose=0)
```

In [28]:
```
grid.best_params_
```

Out[28]:
```
{'n_jobs': -1}
```

In [29]:
```
grid.best_estimator_
```

Out[29]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=-1, normalize=
False)
```

In [30]:
```
new_linear_reg = LinearRegression(copy_X=True, fit_intercept=True, n_jo
bs=-1, normalize=False)
new_linear_reg.fit(x_scaled_train, y_train)
```

Out[30]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=-1, normalize=
False)
```

In [31]:
```
new_linear_reg.score(x_scaled_test, y_test)
```

Out[31]:
```
0.8536634604512405
```

2. Decision Tree :

In [32]:
```
decision_tree = DecisionTreeRegressor(criterion='mse', random_state=0)
#estimator
decision_tree.fit(x_scaled_train, y_train)
```

Out[32]:
```
DecisionTreeRegressor(criterion='mse', max_depth=None, max_features=Non
e,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.
0,
                      presort=False, random_state=0, splitter='best')
```

In [33]:
```
decision_tree.score(x_scaled_test, y_test)
```

Out[33]:
```
0.9576184490579795
```

In [34]:
```
cv = ShuffleSplit(n_splits=10, random_state=42)       #cross validatio
n

param_grid = {'max_depth': [3, 5, 7, 9, 13],
             'criterion': ['mse', 'friedman_mse']}

grid = GridSearchCV(decision_tree, param_grid=param_grid, cv=cv)
```

In [35]:
```
grid.fit(select_X_train, y_train)          #training
```

Out[35]:
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=42, test_size=No
ne, train_size=None),
             error_score='raise-deprecating',
             estimator=DecisionTreeRegressor(criterion='mse', max_depth
=None,
                                             max_features=None,
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=
0.0,
                                             presort=False, random_stat
e=0,
                                             splitter='best'),
             iid='warn', n_jobs=None,
             param_grid={'criterion': ['mse', 'friedman_mse'],
                         'max_depth': [3, 5, 7, 9, 13]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring=None, verbose=0)
```

In [36]:
```
grid.best_params_
```

Out[36]:
```
{'criterion': 'friedman_mse', 'max_depth': 13}
```

In [37]:
```
grid.best_estimator_
```

Out[37]:
```
DecisionTreeRegressor(criterion='friedman_mse', max_depth=13, max_featu
res=None,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.
0,
                      presort=False, random_state=0, splitter='best')
```

In [38]:
```
new_deci_tree = DecisionTreeRegressor(criterion='friedman_mse', max_dep
th=24,
           max_features=None, max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, presort=False, random_state=45
,
           splitter='best')
new_deci_tree.fit(x_scaled_train, y_train)
```

Out[38]:
```
DecisionTreeRegressor(criterion='friedman_mse', max_depth=24, max_featu
res=None,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.
0,
                      presort=False, random_state=45, splitter='best')
```

In [39]:
```
new_deci_tree.score(x_scaled_test, y_test)
```

```
In [39]: new_deci_tree.score(x_scaled_test, y_test)
```

Out[39]: 0.9572660408433513

3. Random Forest :

In [40]:
```
rand_forest = RandomForestRegressor(random_state=123)
rand_forest.fit(x_scaled_train, y_train)
```

```
C:\Users\Shridhar M\AppData\Roaming\Python\Python37\site-packages\sklea
rn\ensemble\forest.py:245: FutureWarning: The default value of n_estima
tors will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Out[40]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=10,
                      n_jobs=None, oob_score=False, random_state=123, v
erbose=0,
                      warm_start=False)
```

In [41]:
```
rand_forest.score(x_scaled_test, y_test)
```

Out[41]: 0.976235810489465

Hyperparameter Tuning:

In [42]:
```
cv = ShuffleSplit(test_size=0.2, random_state=0)

param_grid = {'max_features':['sqrt', 'log2', 10],
              'max_depth':[9, 11, 13]}

grid = GridSearchCV(rand_forest, param_grid=param_grid, cv=cv)
```

In [43]:
```
grid.fit(x_scaled_train, y_train)
```

Out[43]:
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=0, test_size=0.
2, train_size=None),
             error_score='raise-deprecating',
             estimator=RandomForestRegressor(bootstrap=True, criterion
='mse',
                                             max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=
0.0,
                                             n_estimators=10, n_jobs=No
ne,
                                             oob_score=False, random_st
```

```
                                                oob_score=False, random_st
ate=123,
                                                verbose=0, warm_start=Fals
e),
             iid='warn', n_jobs=None,
             param_grid={'max_depth': [9, 11, 13],
                         'max_features': ['sqrt', 'log2', 10]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring=None, verbose=0)
```

In [44]:
```
grid.best_estimator_
```

Out[44]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=13,
                      max_features=10, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=10,
                      n_jobs=None, oob_score=False, random_state=123, v
erbose=0,
                      warm_start=False)
```

In [45]:
```
new_rand_forest = RandomForestRegressor(bootstrap=True, criterion='mse'
, max_depth=33,
           max_features=10, max_leaf_nodes=None, min_impurity_decrease=
0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=10, n_jobs=1, oob_score=False, random_state=42,
           verbose=0, warm_start=False)
new_rand_forest.fit(x_scaled_train, y_train)
```

Out[45]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=33,
                      max_features=10, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=10, n_
jobs=1,
                      oob_score=False, random_state=42, verbose=0,
                      warm_start=False)
```

In [46]:
```
new_rand_forest.score(x_scaled_test, y_test)
```

Out[46]:
```
0.9790005019563306
```

4. Xgboost regressor :

In [47]:
```
xgr = XGBRegressor(random_state=42)
xgr.fit(x_scaled_train, y_train)
```

```
[14:28:50] WARNING: src/objective/regression_obj.cu:152: reg:linear is
now deprecated in favor of reg:squarederror.
```

Out[47]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=
```

```
0,
             max_depth=3, min_child_weight=1, missing=None, n_estimator
s=100,
```