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, ShuffleSplit,
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_kicking  
\
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	preferred_foot	attacking_
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()
```

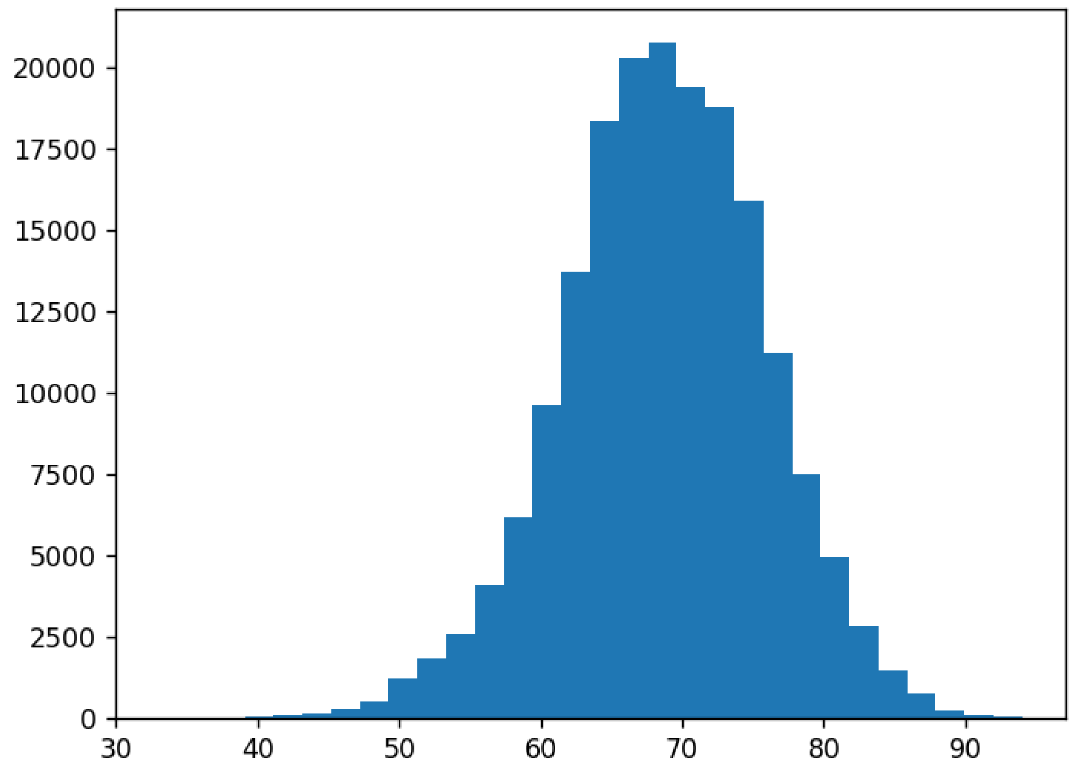
Out[9]:
```
836
```

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: Runtime
Warning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
C:\ProgramData\Anaconda3\lib\site-packages\numpy\lib\histograms.py:840: Runtime
Warning: 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       , 41.13333333,
        43.16666667, 45.2       , 47.23333333, 49.26666667, 51.3       ,
        53.33333333, 55.36666667, 57.4       , 59.43333333, 61.46666667,
        63.5       , 65.53333333, 67.56666667, 69.6       , 71.63333333,
        73.66666667, 75.7       , 77.73333333, 79.76666667, 81.8       ,
        83.83333333, 85.86666667, 87.9       , 89.93333333, 91.96666667,
        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', 'potential',
       'preferred_foot', 'attacking_work_rate', 'defensive_work_rate',
       'crossing', 'finishing', 'heading_accuracy', 'short_passing', 'volleys',
       'dribbling', 'curve', 'free_kick_accuracy', 'long_passing',
       'ball_control', 'acceleration', 'sprint_speed', 'agility', 'reactions',
       'balance', 'shot_power', 'jumping', 'stamina', 'strength', 'long_shots',
       'aggression', 'interceptions', 'positioning', 'vision', 'penalties',
       '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=unique_cat, t
```

```
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_work_rate', '
dummy_df.head()
```

Out[16]:

	id	player_fifa_api_id	player_api_id	date	potential	crossing	finishing	heading_accuracy	s
0	1	218353	505942	2016-02-18 00:00:00	71.0	49.0	44.0	71.0	
1	2	218353	505942	2015-11-19 00:00:00	71.0	49.0	44.0	71.0	
2	3	218353	505942	2015-09-21 00:00:00	66.0	49.0	44.0	71.0	
3	4	218353	505942	2015-03-20 00:00:00	65.0	48.0	43.0	70.0	
4	5	218353	505942	2007-02-22 00:00:00	65.0	48.0	43.0	70.0	

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=0.25, random_
```

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\sklearn\utils
\deprecation.py:66: DeprecationWarning: Class Imputer is deprecated; Imputer wa
s deprecated in version 0.20 and will be removed in 0.22. Import impute.SimpleI
mputer from sklearn instead.
  warnings.warn(msg, category=DeprecationWarning)
```

In [20]:
```
#finding feature_importance for feature selection. from it we'll be able to decid
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 depr
ecated 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, normalize=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 sp

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=None, train
_size=None),
             error_score='raise-deprecating',
             estimator=LinearRegression(copy_X=True, fit_intercept=True,
                                        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=False,
             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_jobs=-1, nor
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)          #e
decision_tree.fit(x_scaled_train, y_train)
```

Out[32]:
```
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_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 validation

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=None, trai
n_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_state=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=False,
             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_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 [38]:
```
new_deci_tree = DecisionTreeRegressor(criterion='friedman_mse', max_depth=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_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=45, splitter='best')
```

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\sklearn\ensem
ble\forest.py:245: FutureWarning: The default value of n_estimators 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=None,
                      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, verbose=
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=None,
                                             oob_score=False, random_state=123,
                                             verbose=0, warm_start=False),
             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=False,
             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=None,
                      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, verbose=
0,
                      warm_start=False)
```

In [45]:
```
new_rand_forest = RandomForestRegressor(bootstrap=True, criterion='mse', max_dept
           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=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)
```

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 depr
ecated 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_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [48]:
```
xgr.score(x_scaled_test, y_test)
```

Out[48]:
```
0.9335978676486084
```

Hyperparameter Tuning:

In [49]:
```
cv = ShuffleSplit(n_splits=10, random_state=0)

param_grid = {'max_depth': [5, 7],
              'learning_rate': [0.1, 0.3]}

grid = GridSearchCV(xgr, param_grid=param_grid, cv=cv, n_jobs= -1)
```

In [50]:
```
grid.fit(x_scaled_train, y_train)
```

```
[14:38:03] WARNING: src/objective/regression_obj.cu:152: reg:linear is now depr
ecated in favor of reg:squarederror.
```

Out[50]:
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=0, test_size=None, train
_size=None),
             error_score='raise-deprecating',
             estimator=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_estimators=100, n_jobs=1, nthread=None,
                                    objective='reg:linear', random_state=42,
                                    reg_alpha=0, reg_lambda=1,
                                    scale_pos_weight=1, seed=None, silent=None,
                                    subsample=1, verbosity=1),
             iid='warn', n_jobs=-1,
             param_grid={'learning_rate': [0.1, 0.3], 'max_depth': [5, 7]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [51]:
```
grid.best_estimator_
```

Out[51]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.3, max_delta_step=0,
             max_depth=7, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [56]:
```
new_xgr = XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.3, max_delta_step=0,
             max_depth=7, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
new_xgr.fit(x_scaled_train, y_train)
```

```
[14:41:57] WARNING: src/objective/regression_obj.cu:152: reg:linear is now depr
ecated in favor of reg:squarederror.
```

Out[56]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.3, max_delta_step=0,
             max_depth=7, min_child_weight=1, missing=None, n_estimators=100,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=42,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [57]:
```
new_xgr.score(x_scaled_test, y_test)
```

Out[57]:
```
0.9655836899933903
```

In [58]:
```
print("""Linear Regressor accuracy is {lin}
DecisionTree Regressor accuracy is {Dec}
RandomForest regressor accuracy is {ran}
XGBoost regressor accuracy is {xgb}""".format(lin=new_linear_reg.score(x_scaled_t
                                                    Dec=new_deci_tree.score(x_
                                                    ran=new_rand_forest.score(
                                                    xgb=new_xgr.score(x_scaled
```

```
Linear Regressor accuracy is 0.8536634604512405
DecisionTree Regressor accuracy is 0.9572660408433513
RandomForest regressor accuracy is 0.9790005019563306
XGBoost regressor accuracy is 0.9655836899933903
```

By accuracy comparision performed above we can say hear that Random Forest regressor gives better result than any other model. and it can predict the target function with approx 98% accuracy.

In [ ]:
```

```