Acadgild Machine Learning Assignment 5

Import Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import tree, datasets
from sklearn.metrics import mean_squared_error, r2_score, roc_auc_score
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor
```

Load boston dataset

In [2]:

```
boston = datasets.load_boston()
features = pd.DataFrame(boston.data, columns=boston.feature_names)
targets = boston.target
```

In [3]:

```
boston.keys()
```

Out[3]:

```
dict_keys(['data', 'target', 'feature_names', 'DESCR'])
```

In [4]:

```
boston.feature_names
```

Out[4]:

```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [5]:

```
print(boston.DESCR)
```

```
Boston House Prices dataset
===========================

Notes
------
Data Set Characteristics:

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive

    :Median Value (attribute 14) is usually the target

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000
sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river;
0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by
town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
http://archive.ics.uci.edu/ml/datasets/Housing (http://archive.ics.uci.edu/m
l/datasets/Housing)


This dataset was taken from the StatLib library which is maintained at Carne
gie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostic
s
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers th
at address regression
problems.

**References**
```

```
   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential
 Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. I
n Proceedings on the Tenth International Conference of Machine Learning, 236
-243, University of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing) (htt
p://archive.ics.uci.edu/ml/datasets/Housing))
```

DataFrame using boston dataset features and target values

In [6]:

```
df_x = pd.DataFrame(boston.data, columns=boston.feature_names)
df_y = boston.target
```

Statistical analysis of features in DataFrame df_x

In [7]:

```
df_x.describe()
```

Out[7]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	50
mean	3.593761	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	
std	8.596783	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	
75%	3.647423	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	1.

Data Preprocessing

Function to handle missing data

In [8]:

```
def data_preprocessing(df):
    df.convert_objects(convert_numeric=True)
    df.fillna(0, inplace=True)

    return df
```

Function to handle categorical data

In [9]:

```
def handle_non_numeric_data(df):
    columns = df.columns.values

    for column in columns:
        text_digit_vals = {}
        def convert_to_int(val):
            return text_digit_vals[val]

        if df[column].dtype != np.int64 and df[column].dtype != np.float64:
            column_contents = df[column].values.tolist()
            unique_elements = set(column_contents)

            x = 0
            for unique in unique_elements:
                if unique not in text_digit_vals:
                    text_digit_vals[unique] = x
                    x+=1
            df[column] = list(map(convert_to_int, df[column]))

    return df
```

Perform data preprocessing on boston dataset

In [10]:

```
df_x = data_preprocessing(df_x)
df_x = handle_non_numeric_data(df_x)
df_x.head()
```

```
C:\Users\santhu\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureW
arning: convert_objects is deprecated.  To re-infer data dtypes for object c
olumns, use DataFrame.infer_objects()
For all other conversions use the data-type specific converters pd.to_dateti
me, pd.to_timedelta and pd.to_numeric.
```

Out[10]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	[illegible]
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	[illegible]
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	[illegible]
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	[illegible]
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	[illegible]

Spliting boston dataset into test and traning dataset

In [11]:

```
x_train,x_test,y_train,y_test = train_test_split(df_x,df_y,test_size=0.2,random_state=5)
```

Apply RandomForest Model on boston dataset

In [12]:

```
rfc1 = RandomForestRegressor(random_state=10)
rfc1.fit(x_train, y_train)
```

Out[12]:

```
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=1,
           oob_score=False, random_state=10, verbose=0, warm_start=False)
```

In [13]:

```
#Applying model by changing the max_features parameter
rfc2 = RandomForestRegressor(max_features=8, random_state=10)
rfc2.fit(x_train, y_train)

rfc3 = RandomForestRegressor(max_features=6, random_state=10)
rfc3.fit(x_train, y_train)
```

Out[13]:

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features=6, 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=10,
           verbose=0, warm_start=False)
```

Feature engineering

Analyze features importance

In [14]:

```
rfc1.feature_importances_
```

Out[14]:

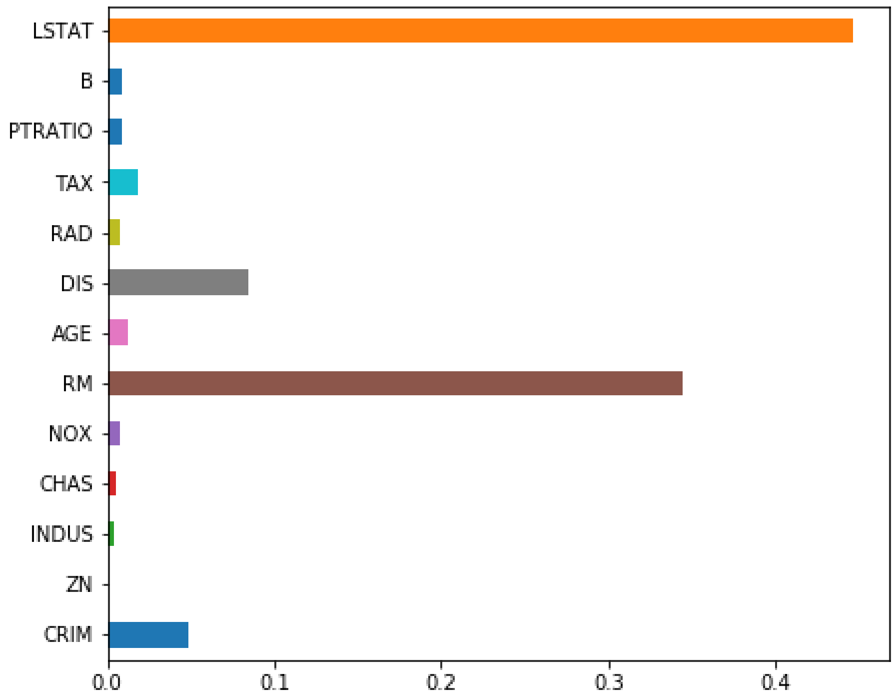
```
array([0.04903067, 0.00108498, 0.00374297, 0.00511706, 0.00817035,
       0.34495785, 0.01275462, 0.08436785, 0.00822323, 0.01818498,
       0.0092608 , 0.00921063, 0.44589401])
```

In [15]:

```
%matplotlib inline
feature_importances = pd.Series(rfc1.feature_importances_,index=df_x.columns)
feature_importances.plot(kind='barh',figsize=(7,6))
```

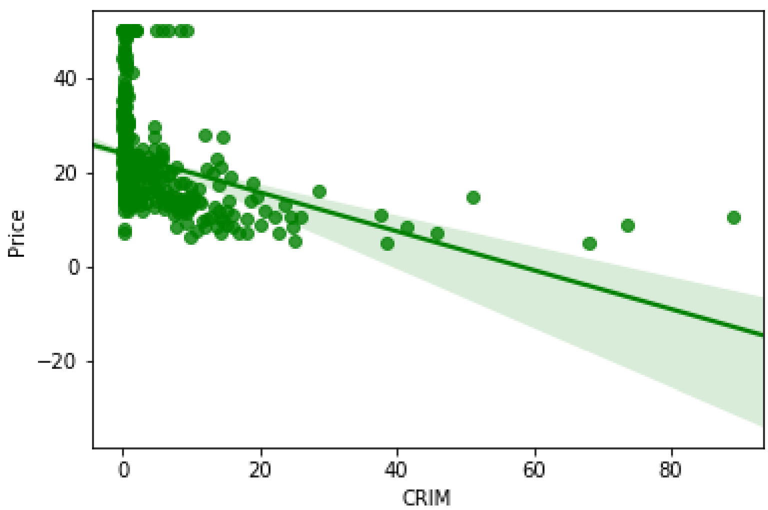
Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xaf22198>
```



In [16]:

```
#Graph between features and target price
for var in boston.feature_names:
    sns.regplot(features[var], targets, color='g')
    plt.ylabel('Price')
    plt.show()
```



Model Evaluation

Model efficiency by considering all the parameters of boston dataset for analysis

In [17]:

```
pred1 = rfc1.predict(x_test)
# The mean squared error
print("Mean squared error: %f" % mean_squared_error(y_test, pred1))
# Explained variance score: 1 is perfect prediction
print('Variance score: %f' % r2_score(y_test, pred1))
```

```
Mean squared error: 14.061522
Variance score: 0.820401
```

Model efficiency by considering n most important features (n=8) of boston dataset for analysis

In [18]:

```
pred2 = rfc2.predict(x_test)
# The mean squared error
print("Mean squared error: %f" % mean_squared_error(y_test, pred2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %f' % r2_score(y_test, pred2))
```

```
Mean squared error: 12.088211
Variance score: 0.845605
```

Model efficiency by considering n most important features (n=6) of boston dataset for analysis

In [19]:

```
pred3 = rfc3.predict(x_test)
# The mean squared error
print("Mean squared error: %f" % mean_squared_error(y_test, pred3))
# Explained variance score: 1 is perfect prediction
print('Variance score: %f' % r2_score(y_test, pred3))
```

```
Mean squared error: 9.728154
Variance score: 0.875748
```

Data Normalization and model evaluation

In [20]:

```
from sklearn.preprocessing import StandardScaler
scalerx = StandardScaler().fit(x_train)
scalery = StandardScaler().fit(y_train.reshape(-1, 1))

x_train1 = scalerx.transform(x_train)
y_train1 = scalery.transform(y_train.reshape(-1, 1))
x_test1 = scalerx.transform(x_test)
y_test1 = scalery.transform(y_test.reshape(-1, 1))

#print (np.max(x_train1), np.min(x_train1), np.mean(x_train1), np.max(y_train1), np.min(y_t

# Best Model accuracy was provided when we were using 6 features,
# So Normalized data is given as input into RandomForestRegressor with  max_features=6
rfc4 = RandomForestRegressor(max_features=6, random_state=10)
rfc4.fit(x_train1, y_train1)
pred4 = rfc4.predict(x_test1)
# The mean squared error
print("Mean squared error after normalizing data with 6 features: %f" % mean_squared_error(
# Explained variance score: 1 is perfect prediction
print('Variance score after normalizing data with 6 features: %f' % r2_score(y_test1, pred4
```

```
Mean squared error after normalizing data with 6 features: 0.112758
Variance score after normalizing data with 6 features: 0.876285

C:\Users\santhu\Anaconda3\lib\site-packages\ipykernel_launcher.py:15: DataCo
nversionWarning: A column-vector y was passed when a 1d array was expected.
Please change the shape of y to (n_samples,), for example using ravel().
  from ipykernel import kernelapp as app
```

Visulization between predicted and actual price

In [21]:

```
#Between y_test (actual price) and predicted price (pred4)
plt.xlabel("Actual Price ( $1000 )")
plt.ylabel("Predicted Price ( $1000 )")
plt.title("Actual vs Predicted Price")
plt.scatter(y_test, pred4, color='black')
plt.show()
```