Data Science Masters :Assignment 24

Problem:

Build a random forest model after normalizing the variable to house pricing from boston data set.

Solution:

Importing Libraries...

In [1]:

```
# Mathematical computation
import numpy as np

# DateFrame setup
import pandas as pd

# Data Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning pkgs
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
from sklearn import datasets
```

Data Pre-processing Steps

In [2]:

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

Out[2]:

	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	4
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	9
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	4
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	2
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	5

Exploring Data - Analysis

In [3]:

```
features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
CRIM       506 non-null float64
ZN         506 non-null float64
INDUS      506 non-null float64
CHAS       506 non-null float64
NOX        506 non-null float64
RM         506 non-null float64
AGE        506 non-null float64
DIS        506 non-null float64
RAD        506 non-null float64
TAX        506 non-null float64
PTRATIO    506 non-null float64
B          506 non-null float64
LSTAT      506 non-null float64
dtypes: float64(13)
memory usage: 51.5 KB
```

In [4]:

```
# Statictical observation
features.describe()
```

Out[4]:

	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 Visualisation

In [5]:

```
#Analyze both Feature and Targe
df=features
df['ACTUAL_PRICE']= boston.target
df.head()
```

Out[5]:

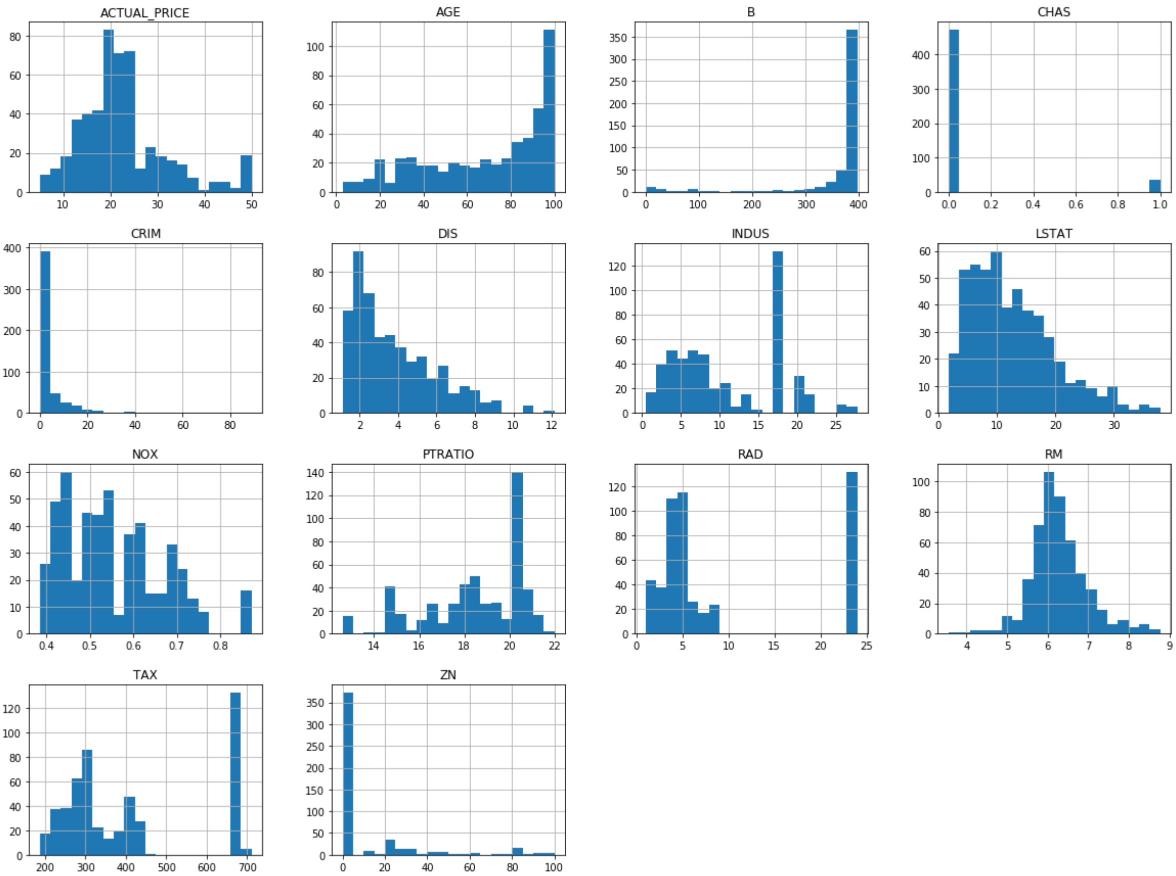
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	
3	0.03237	0.0	2.18	0.0	0.458	6.998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

In [6]:

```
df.hist(bins=20,figsize=(20,15))
```

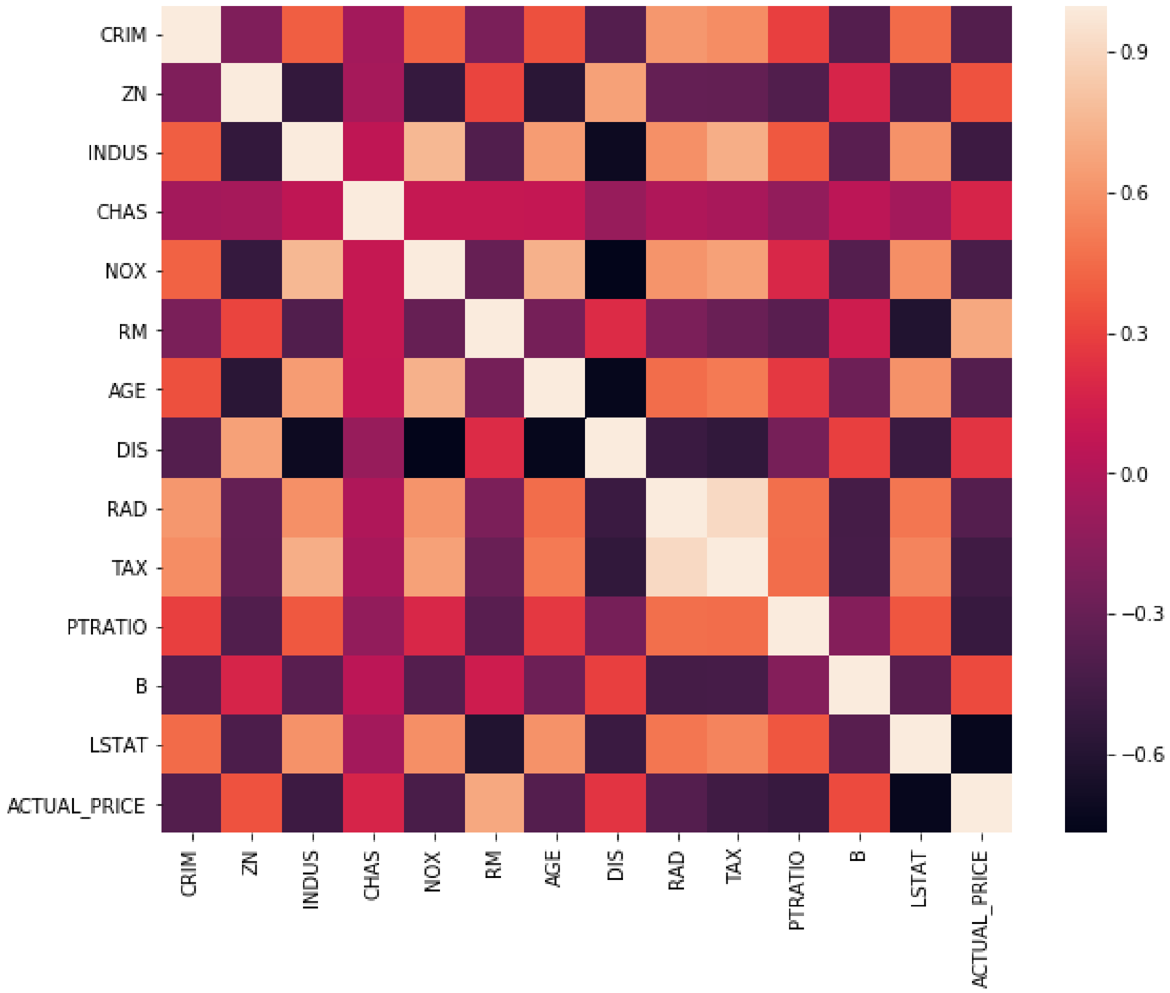
Out[6]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000287C06A8B00
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C09A2128
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C09CF438
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C09F7748
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0A22A20
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0A22A58
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0A7D080
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0AA7390
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0AD16A0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0AFB9B0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0B25CC0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0B4EFD0
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0B81320
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0BAA630
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0BD5940
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000287C0BFDC50
>]],
      dtype=object)
```


ACTUAL_PRICE
AGE
B
CHAS
CRIM
DIS
INDUS
LSTAT
NOX
PTRATIO
RAD
RM
TAX
ZN

In [7]:

```
#Analyze Data by using Different Plot
#Show the Coorelations in the picture
plt.figure(figsize=(10,8))
sns.heatmap(df.corr())
plt.show()
```



Train & Test sets

In [8]:

```
# Spliting Data to Train and test
X_train, X_test, y_train, y_test = train_test_split(df[boston.feature_names], df['ACTUAL_PR
X_train.shape,X_test.shape, y_train.shape,y_test.shape
```

Out[8]:

```
((354, 13), (152, 13), (354,), (152,))
```

Scaling:

In [9]:

```
# Normalazing the variables using StandardScaler
sc_X = StandardScaler()
X_train_trans = sc_X.fit_transform(X_train)
X_test_trans = sc_X.fit_transform(X_test)

#taking log values for house prices to make them stable and as we scale X values..
y_train = np.log(y_train)
y_test = np.log(y_test)
```

Modeling - Random Forest Regression

In [10]:

```
#Random Forest Regression and Fit the train data
randomForest = RandomForestRegressor(n_estimators=500, oob_score=True, n_jobs=-1,random_sta
randomForest.fit(X_train_trans, y_train)
```

Out[10]:

```
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=500, n_jobs=-1,
           oob_score=True, random_state=10, verbose=0, warm_start=False)
```

In [11]:

```
predictions = randomForest.predict(X_test_trans)
r_sq_score = r2_score(y_test, predictions)
r_sq_score
```

Out[11]:

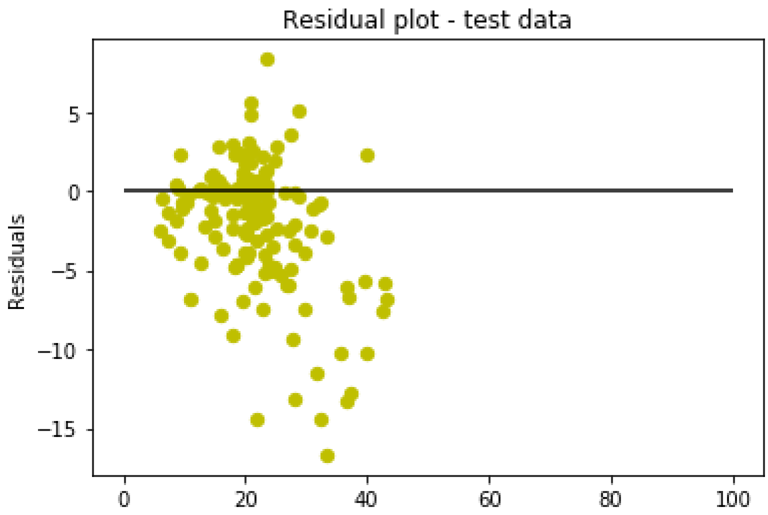
```
0.8312479085333367
```

In [12]:

```
predictions = np.exp(predictions)
y_test = np.exp(y_test)
```

In [13]:

```
#Evaluate the Model
#Plot using Test Data with caluclated Residual
plt.scatter(predictions,(predictions-y_test),c='y',s=40)
plt.hlines(y=0,xmin=0,xmax=100)
plt.title('Residual plot - test data')
plt.ylabel('Residuals')
plt.show()
```



Looks like, the model is good with 0.831 as r2 score and the residuals are scattered randomly around line zero.

In [14]:

```
#Comparing actual and predicted prices...
comparison = pd.DataFrame()
comparison['ACTUAL_PRICE']=y_test
comparison['PREDICTED_PRICE']= predictions
comparison.head(20)
```

Out[14]:

	ACTUAL_PRICE	PREDICTED_PRICE
305	28.4	23.246171
193	31.1	25.790637
65	23.5	23.480651
349	26.6	26.485112
151	19.6	19.421957
433	14.3	14.456882
161	50.0	37.274205
129	14.3	14.799346
269	20.7	20.467459
226	37.6	39.864085
107	20.4	18.041539
222	27.5	25.151470
181	36.2	21.790910
275	32.0	30.891005
277	33.1	27.109935
262	48.8	42.947558
325	24.6	23.850029
184	26.4	19.411622
176	23.2	21.147039
154	17.0	16.571668

In [15]:

```
#Visulaize both Actual and Predicted price
plt.scatter(comparison.ACTUAL_PRICE,comparison.PREDICTED_PRICE)
plt.ylabel('Predicted values')
plt.xlabel('Actual values')
plt.show()
```