Assignment - 24 - MACHINE LEARNING - 5

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Problem Statement:

Build the Random Forest Model after normalizing the variable to House Pricing from Boston Dataset.

Solution:

In [1]:
```
# Loading Data and modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor, RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import r2_score, accuracy_score, roc_auc_score, confusion_matrix
from sklearn.metrics import classification_report, mean_squared_error, mean_absolute_error
from scipy.stats import spearmanr, pearsonr
```

In [2]:
```
# Create Datsframe from boston dataset
boston = datasets.load_boston()
features = pd.DataFrame(boston.data, columns=boston.feature_names)
targets = boston.target
# Show features (first 2 rows)
features.head(2)
```

Out[2]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.9	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.9	9.14

In [3]:
```
#  Description of boston dataset
print(boston.DESCR)
```

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

Notes
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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


This dataset was taken from the StatLib library which is maintained at Carnegie 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 diagnostics
...', 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 that address regression
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wile
y, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In 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)
```

Data Exploration

- Structure of data

In [4]:
```
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 [5]:
```
# Combine Feature and Target to create complete DataFrame
df_boston=features
df_boston['PRICE']= boston.target
df_boston.head()
```

Out[5]:

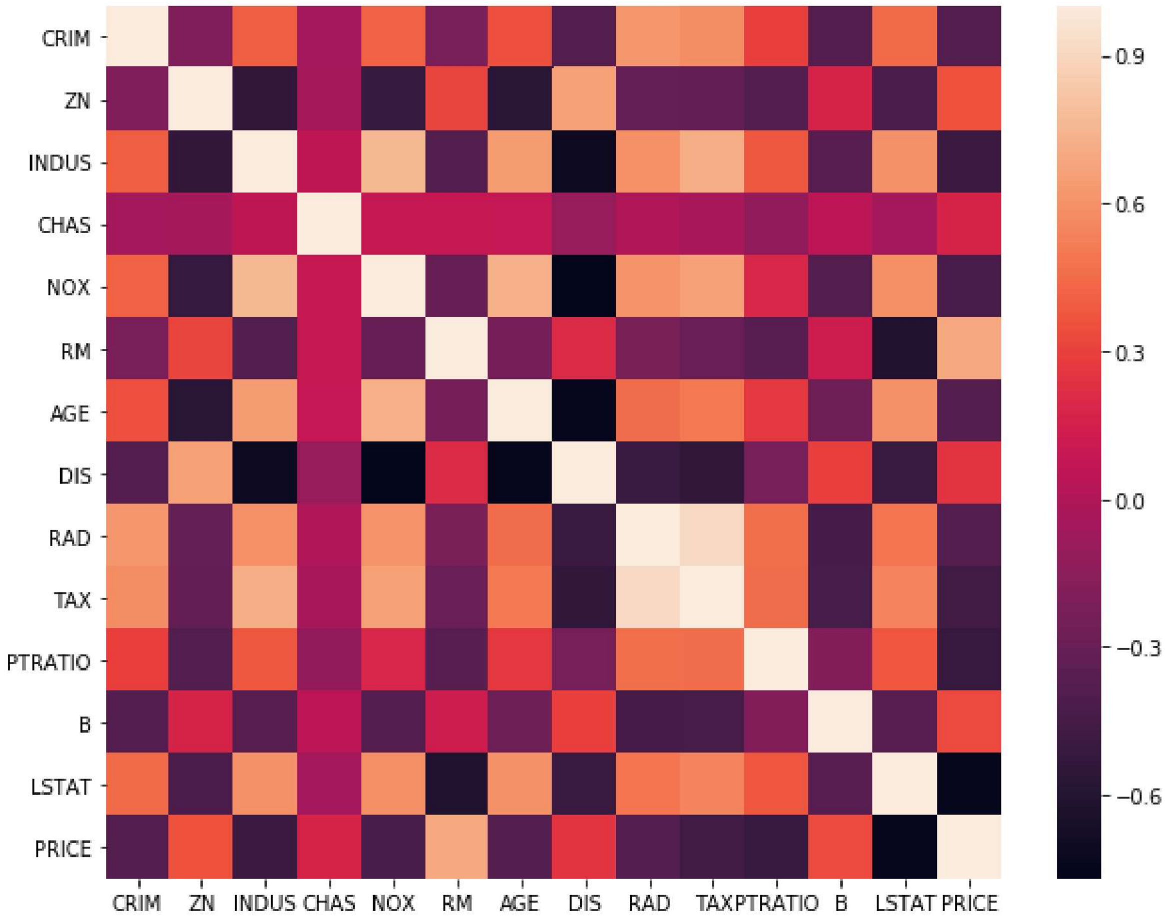
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
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	2.94	33.4
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	5.33	36.2

In [6]:
```
# Statictical observation
df_boston.describe()
```

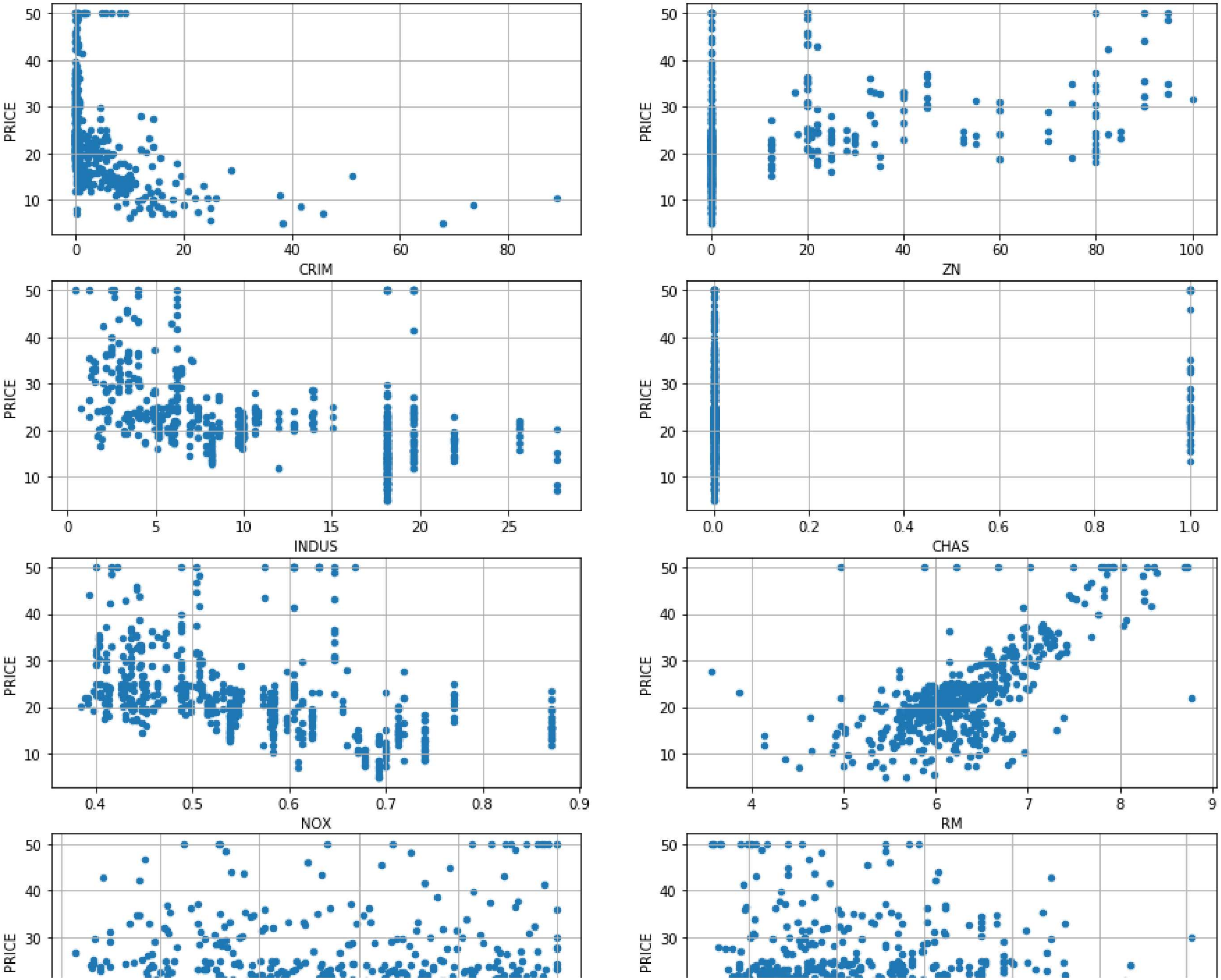
Out[6]:

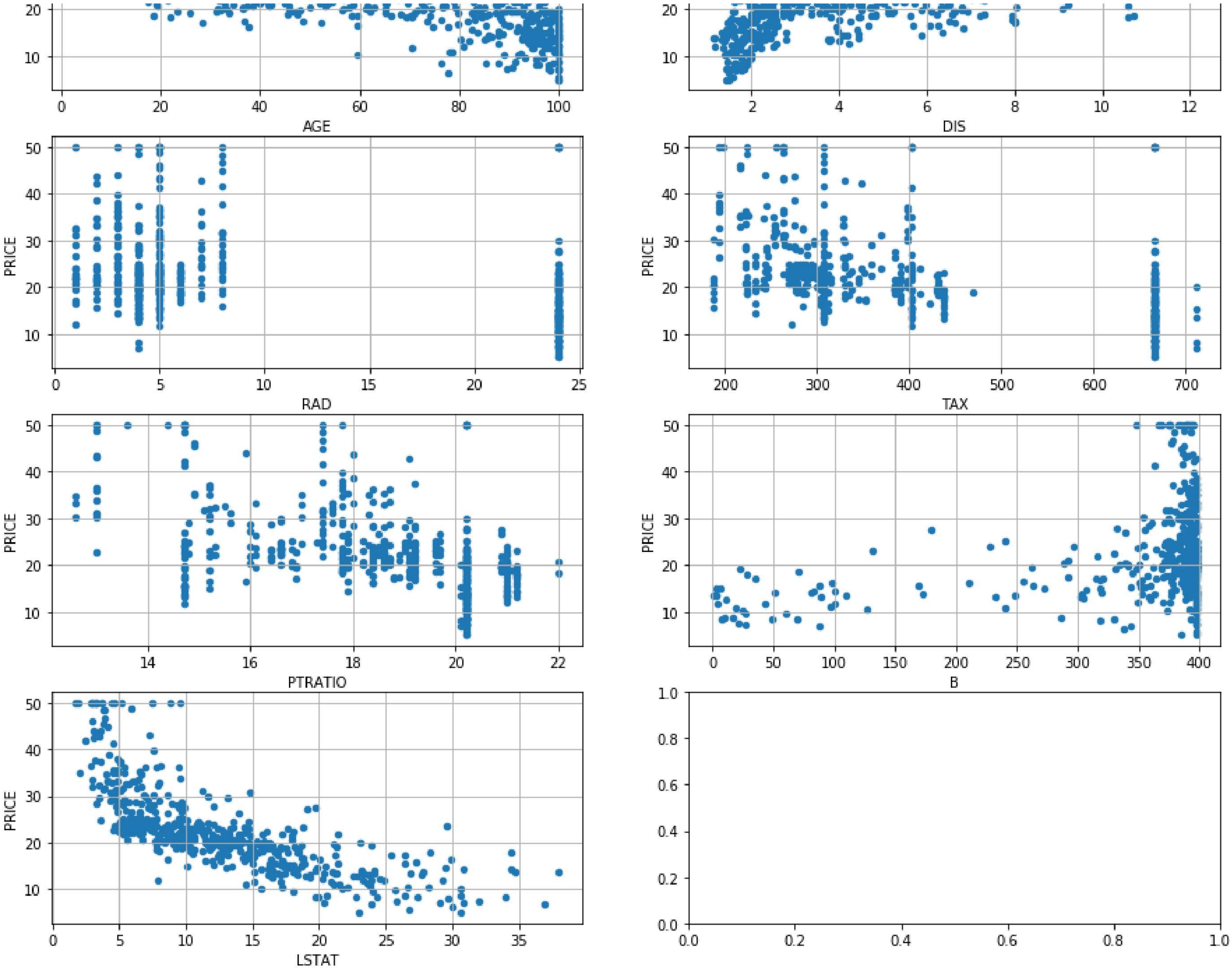
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PT
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.
mean	3.593761	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.4
std	8.596783	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.16
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.6
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.4
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.0
75%	3.647423	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.2
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0

In [7]:
```
# Visual analysis between target variable and other features

#Show the Coorelations in the Heatmap
plt.figure(figsize=(10,8))
sns.heatmap(df_boston.corr())
plt.show()
```



In [8]:
```
# Show the Correlation between target variable and other features using scatter plot
fig, axs = plt.subplots(7, 2 , sharey=False)
df_boston.plot(kind='scatter', x=df_boston.columns[0], y='PRICE', ax=axs[0][0] , figsize=(15,25) , grid=True )
df_boston.plot(kind='scatter', x=df_boston.columns[1], y='PRICE', ax=axs[0][1], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[2], y='PRICE', ax=axs[1][0], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[3], y='PRICE', ax=axs[1][1], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[4], y='PRICE', ax=axs[2][0], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[5], y='PRICE', ax=axs[2][1], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[6], y='PRICE', ax=axs[3][0], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[7], y='PRICE', ax=axs[3][1], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[8], y='PRICE', ax=axs[4][0], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[9], y='PRICE', ax=axs[4][1], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[10], y='PRICE', ax=axs[5][0], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[11], y='PRICE', ax=axs[5][1], grid=True)
df_boston.plot(kind='scatter', x=df_boston.columns[12], y='PRICE', ax=axs[6][0], grid=True)
plt.show()
```


PRICE
CRIM
ZN
INDUS
CHAS
NOX
RM


AGE
DIS
PRICE
RAD
PRICE
TAX
PRICE
PTRATIO
PRICE
B
PRICE
LSTAT

Split the Target variable and Feature variable into Train and Test dataset

In [9]:
```
# Train set 70%, Test set 30%
X_train, X_test, y_train, y_test = train_test_split(df_boston[boston.feature_names],
                                                    df_boston['PRICE'],
                                                    test_size=0.3,
                                                    random_state=1)
print("X_train:\t" , X_train.shape)
print("y_train:\t" , y_train.shape)

print("X_test:\t\t" , X_test.shape)
print("y_test:\t\t" , y_test.shape)
```

```
X_train:         (354, 13)
y_train:         (354,)
X_test:          (152, 13)
y_test:          (152,)
```

Random Forest Model

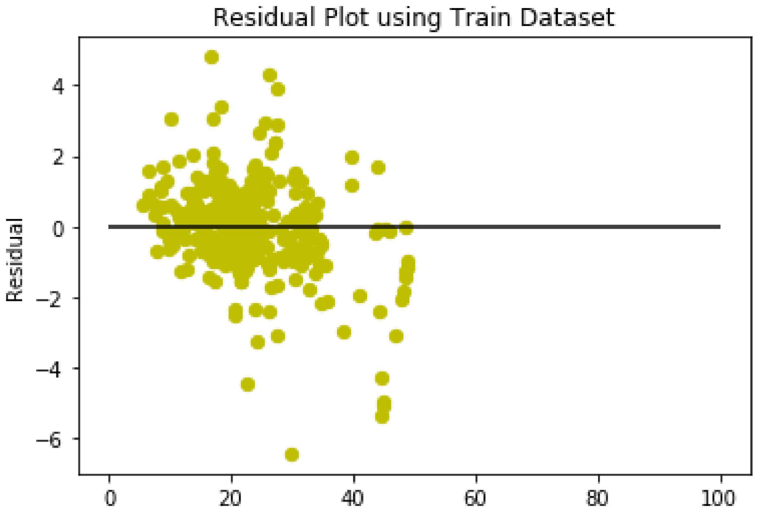
In [10]:
```
#  Define Random Forest Regression with train data
rf = RandomForestRegressor(n_estimators=50, oob_score=True, random_state=1)
rf.fit(X_train, y_train)

# Create Prediction for both train and test
predicted_train = rf.predict(X_train)
predicted_test = rf.predict(X_test)

print("The Predicted Price for Train data (First 5 rows):\t", predicted_train[0:5])
print("The Predicted Price for Test data (First 5 rows):\t", predicted_test[0:5])
```

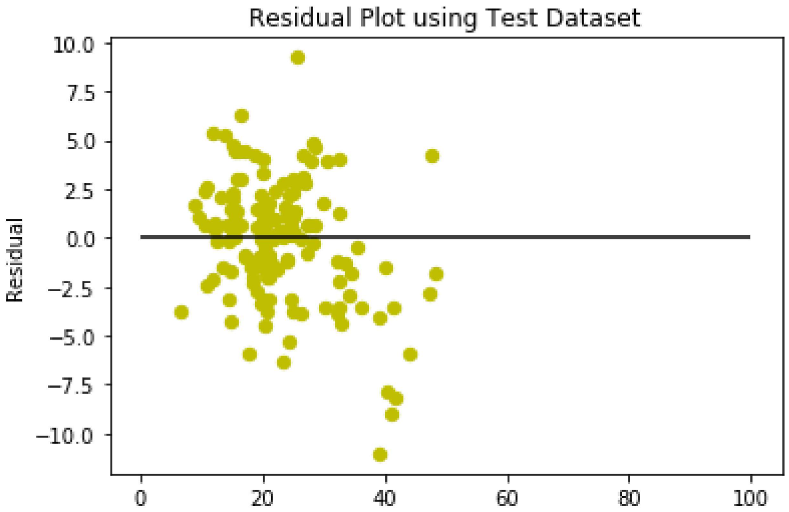
```
The Predicted Price for Train data (First 5 rows):       [19.67  17.514 13.462 30.196 26.554]
The Predicted Price for Test data (First 5 rows):        [29.96  27.826 19.964 21.122 20.304]
```

In [11]:
```
# Check different parameter related to the Model
oob_score = rf.oob_score_
r2_score_test = r2_score(y_test, predicted_test)
spearman_correlation =spearmanr(y_test, predicted_test)
pearson_correlation = pearsonr(y_test, predicted_test)

print('oob_score: \t\t',oob_score)
print('r2_score_test: \t\t',r2_score_test)
print('spearman_correlation: \t', spearman_correlation[0])
print('pearson_correlation: \t', pearson_correlation[0])

# Train Dataset
no_of_tree= len(rf.estimators_)
accuracy_score_train= rf.score(X=X_train, y=y_train)
mean_abs_error_train= mean_absolute_error(y_train , predicted_train)
mean_squared_error_train= mean_squared_error(y_train , predicted_train)
root_mean_squared_error_train = np.sqrt(mean_squared_error_train)

print('\nTrain Dataset:')
print('no_of_tree: \t\t\t',no_of_tree)
print('accuracy_score_train: \t\t',accuracy_score_train)
print('mean_abs_error_train: \t\t', mean_abs_error_train)
print('mean_squared_error_train: \t', mean_squared_error_train)
print('root_mean_squared_error_train: \t', root_mean_squared_error_train)

# Test Dataset
no_of_tree= len(rf.estimators_)
accuracy_score_test= rf.score(X=X_test, y=y_test)
mean_abs_error_test= mean_absolute_error(y_test , predicted_test)
mean_squared_error_test= mean_squared_error(y_test , predicted_test)
root_mean_squared_error_test = np.sqrt(mean_squared_error_test)

print('\nTest Dataset:')
print('no_of_tree: \t\t\t',no_of_tree)
print('accuracy_score_test: \t\t',accuracy_score_test)
print('mean_abs_error_test: \t\t', mean_abs_error_test)
print('mean_squared_error_test: \t', mean_squared_error_test)
print('root_mean_squared_error_test: \t', root_mean_squared_error_test)
```

```
oob_score:               0.8566200860402604
r2_score_test:           0.8973029801175374
spearman_correlation:    0.9267454184299099
pearson_correlation:     0.9529694125360377

Train Dataset:
no_of_tree:                      50
accuracy_score_train:            0.9800864947632482
mean_abs_error_train:            0.8634971751412422
mean_squared_error_train:        1.6167588361581893
root_mean_squared_error_train:   1.2715183192381418

Test Dataset:
no_of_tree:                      50
accuracy_score_test:             0.8973029801175374
mean_abs_error_test:             2.3524473684210525
mean_squared_error_test:         9.412642684210528
root_mean_squared_error_test:    3.0680030450132425
```

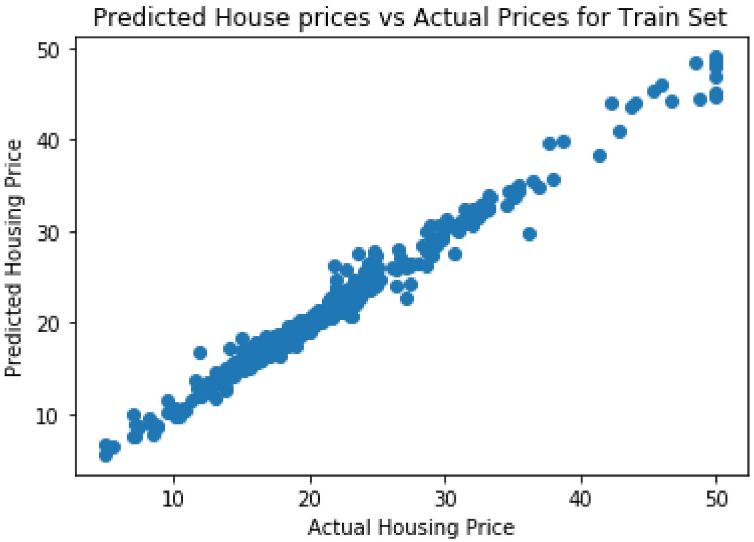
In [12]:
```
#Plot using Train Data with caluclated Residual
plt.scatter(predicted_train,(predicted_train-y_train),c='y',s=40)
plt.hlines(y=0,xmin=0,xmax=100)
plt.title('Residual Plot using Train Dataset')
plt.ylabel('Residual')
plt.show()

#Plot using Test Data with caluclated Residual
plt.scatter(predicted_test,(predicted_test-y_test),c='y',s=40)
plt.hlines(y=0,xmin=0,xmax=100)
plt.title('Residual Plot using Test Dataset')
plt.ylabel('Residual')
plt.show()
```

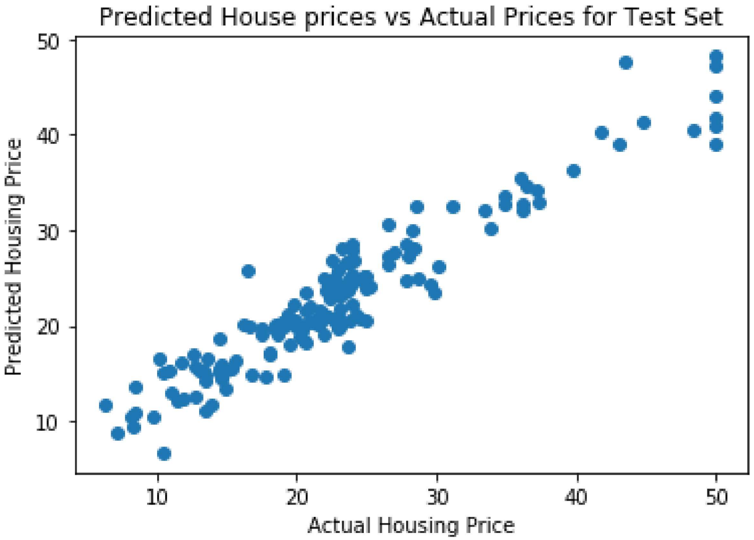




Observation: The Residual are randomly scattered around line zero for both Train and Test Dataset. So it can be considereded as Good Model.

In [13]:
```
#Visulaize with both Actual Price and Predicted price

plt.scatter(y_train, rf.predict(X_train[boston.feature_names]))
plt.title('Predicted House prices vs Actual Prices for Train Set')
plt.ylabel('Predicted Housing Price')
plt.xlabel('Actual Housing Price')
plt.show()

plt.scatter(y_test, rf.predict(X_test[boston.feature_names]))
plt.title('Predicted House prices vs Actual Prices for Test Set')
plt.ylabel('Predicted Housing Price')
plt.xlabel('Actual Housing Price')
plt.show()
```


Predicted House prices vs Actual Prices for Train Set
Predicted Housing Price
Actual Housing Price
10
20
30
40
50


Predicted House prices vs Actual Prices for Test Set
Predicted Housing Price
Actual Housing Price
10
20
30
40
50