In [1]:
```
# In this assignment students will build the random forest model after normali
zing the
# variable to house pricing from boston data set.
# Following the code to get data into the environment:
# 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 datasets
# boston = datasets.load_boston()
# features = pd.DataFrame(boston.data, columns=boston.feature_names)
# targets = boston.target
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.datasets import load_boston
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Loading the data
boston = load_boston()
print("Keys:", boston.keys())
print("Shape:", boston.data.shape)
print("Columns", boston.feature_names)
```

```
Keys: dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
Shape: (506, 13)
Columns ['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRAT
IO'
 'B' 'LSTAT']
```

In [4]:
```
# Creating a data frame
bos = pd.DataFrame(boston.data, columns=boston.feature_names)
bos['PRICE'] = boston.target
bos.head()
```

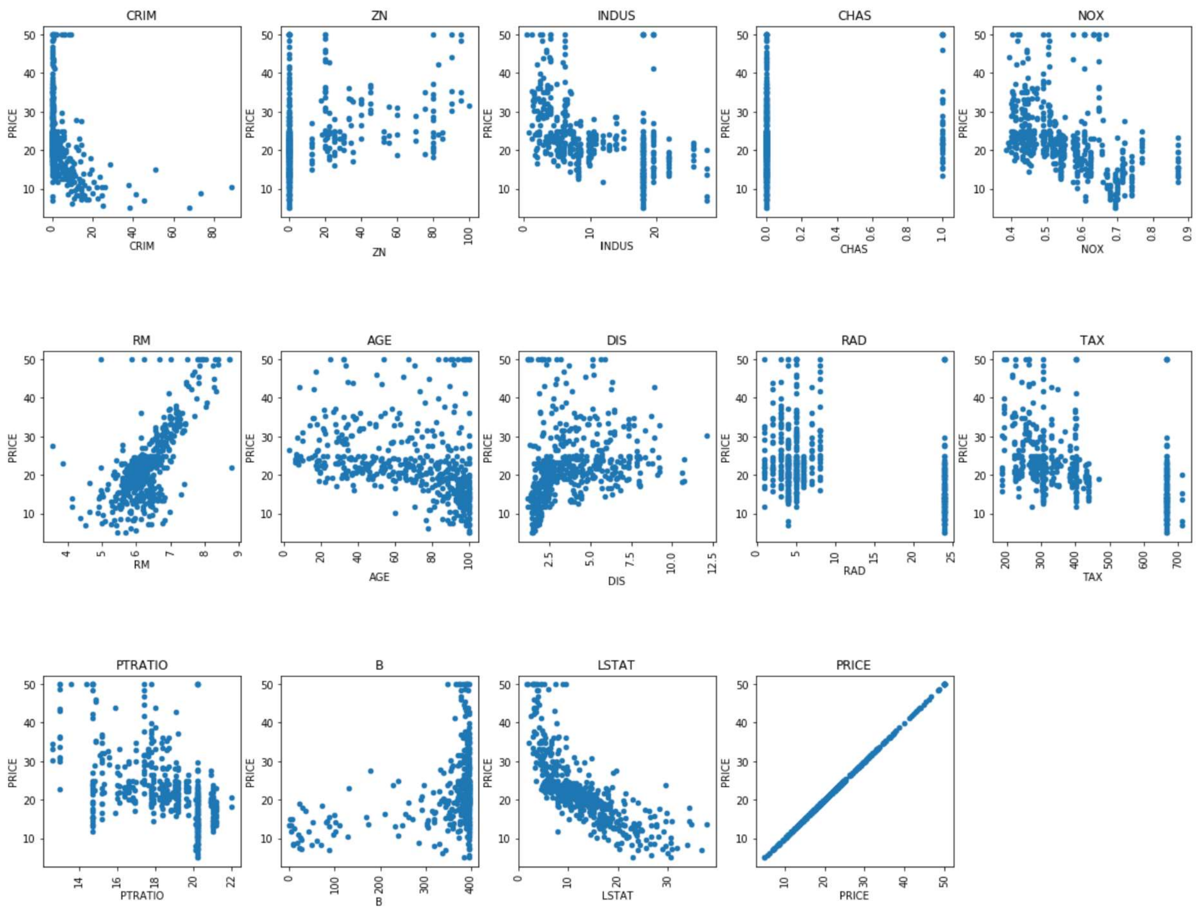
Out[4]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
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.

In [5]:
```
# Minimum price of the data
minimum_price = np.min(boston.target)

# Maximum price of the data
maximum_price = np.max(boston.target)

# Mean price of the data
mean_price = np.mean(boston.target)

# Median price of the data
median_price = np.median(boston.target)

# Standard deviation of prices of the data
std_price = np.std(boston.target)

# Show the calculated statistics
print("Statistics for Boston housing dataset:\n")
print( "Minimum price: ${:,.2f}".format(minimum_price * 1000))
print( "Maximum price: ${:,.2f}".format(maximum_price * 1000))
print( "Mean price: ${:,.2f}".format(mean_price * 1000))
print( "Median price ${:,.2f}".format(median_price * 1000))
```

```
Statistics for Boston housing dataset:

Minimum price: $5,000.00
Maximum price: $50,000.00
Mean price: $22,532.81
Median price $21,200.00
```

In [6]:
```python
from matplotlib import pyplot as plt
from math import ceil

fig = plt.figure(figsize=(20,15))
cols = 5
rows = ceil(float(bos.shape[1]) / cols)
for i, column in enumerate(bos.columns):
    axs = fig.add_subplot(rows, cols, i + 1)
    axs.set_title(column)
    bos.plot(kind='scatter', x=column, y='PRICE', ax=axs)
    plt.xticks(rotation="vertical")
plt.subplots_adjust(hspace=0.7, wspace=0.2)
```



In [7]:
```python
# The column that we want to predict.
y_column = bos['PRICE']

# The columns that we will be making predictions with.
x_columns = bos.drop('PRICE', axis=1)
```

In [27]:
```
# split the data into training and test sets and scale the variables
X_train, X_test, y_train, y_test = train_test_split(x_columns, y_column, test_
size = 0.3, random_state = 25)

X_scaler = StandardScaler()
X_train = X_scaler.fit_transform(X_train)
X_test = X_scaler.transform(X_test)

y_scaler = StandardScaler()
y_train = y_scaler.fit_transform(y_train[:, None])[:, 0]
y_test = y_scaler.transform(y_test[:, None])[:, 0]
```

In [28]:
```
# Instantiate a random forest regressor since we have to predic on continous v
ariables, and fit the training set

model = RandomForestRegressor()
model.fit(X_train, y_train)
```

Out[28]:
```
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=None, verbose=0, warm_start=False)
```

In [29]:
```
y_pred = model.predict(X_test)
print("Test Accuracy:", format(metrics.r2_score(y_test, y_pred) * 100, '.2f'),
'%')
print("Mean Squared Error:", format(metrics.mean_squared_error(y_test, y_pred
), '.5f'))
```

```
Test Accuracy: 80.92 %
Mean Squared Error: 0.16277
```

In [30]:
```
# Performing gridserach to tune the hyper parameters, then use the best estima
tor for scoring on the test set.
parameters = {"min_samples_split": [2, 5, 10],
              "max_depth": [None, 2, 5, 10],
              "min_samples_leaf": [1, 3, 5],
              "max_features": ['auto', 'sqrt', 'log2'],
              "n_estimators": [50, 75, 100]
              }

grid_search = GridSearchCV(RandomForestRegressor(), param_grid=parameters, n_j
obs=-1, verbose=1)
grid_search.fit(X_train, y_train)

print("Best parameters set found on development set:\n")
print(grid_search.best_params_)
```

```
Fitting 3 folds for each of 324 candidates, totalling 972 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  52 tasks      | elapsed:    1.0s
[Parallel(n_jobs=-1)]: Done 352 tasks      | elapsed:    4.6s
[Parallel(n_jobs=-1)]: Done 852 tasks      | elapsed:   12.1s

Best parameters set found on development set:

{'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_sampl
es_split': 2, 'n_estimators': 75}

[Parallel(n_jobs=-1)]: Done 972 out of 972 | elapsed:   14.1s finished
```

In [31]:
```
print("Accuracy for test data set:\n")
y_pred = grid_search.predict(X_test)
print("Test Accuracy:", format(metrics.r2_score(y_test, y_pred) * 100, '.2f'),
'%')
print("Mean Squared Error:", format(metrics.mean_squared_error(y_test, y_pred
), '.5f'))
```

```
Accuracy for test data set:

Test Accuracy: 86.92 %
Mean Squared Error: 0.11160
```

In [32]:
```
print("Accuaracy score has increased by 5% after tuning the hyper parameters a
nd mean squared error is reduced from 0.16 to 0.11.")
```

```
Accuaracy score has increased by 5% after tuning the hyper parameters and mea
n squared error is reduced from 0.16 to 0.11.
```