In [1]:

```
# Author: Chidura Santosh
# Importing required Libraries

import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import sklearn
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_boston
```

In [2]:

```
# Loading Data and creating data frame with the data
boston = load_boston()
features = pd.DataFrame(boston.data,columns=boston.feature_names)
targets=boston.target
```

In [3]:

```
#Displaying the first 5 header records
features.head()
```

Out[3]:

| | 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 | 396.90 | 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 | 396.90 | 9.14 |
| **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 |
| **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 |
| **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 |

In [4]:
```python
#summary of the boston data statistics
features.describe()
```

Out[4]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.00 |
| **mean** | 3.593761 | 11.363636 | 11.136779 | 0.069170 | 0.554695 | 6.284634 | 68.574901 | 3.795043 | 9.549407 | 408.237154 | 18.455534 | 356.67 |
| **std** | 8.596783 | 23.322453 | 6.860353 | 0.253994 | 0.115878 | 0.702617 | 28.148861 | 2.105710 | 8.707259 | 168.537116 | 2.164946 | 91.29 |
| **min** | 0.006320 | 0.000000 | 0.460000 | 0.000000 | 0.385000 | 3.561000 | 2.900000 | 1.129600 | 1.000000 | 187.000000 | 12.600000 | 0.32 |
| **25%** | 0.082045 | 0.000000 | 5.190000 | 0.000000 | 0.449000 | 5.885500 | 45.025000 | 2.100175 | 4.000000 | 279.000000 | 17.400000 | 375.37 |
| **50%** | 0.256510 | 0.000000 | 9.690000 | 0.000000 | 0.538000 | 6.208500 | 77.500000 | 3.207450 | 5.000000 | 330.000000 | 19.050000 | 391.44 |
| **75%** | 3.647423 | 12.500000 | 18.100000 | 0.000000 | 0.624000 | 6.623500 | 94.075000 | 5.188425 | 24.000000 | 666.000000 | 20.200000 | 396.22 |
| **max** | 88.976200 | 100.000000 | 27.740000 | 1.000000 | 0.871000 | 8.780000 | 100.000000 | 12.126500 | 24.000000 | 711.000000 | 22.000000 | 396.90 |

In [5]:
```python
# To display the information of teh data frame
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
```

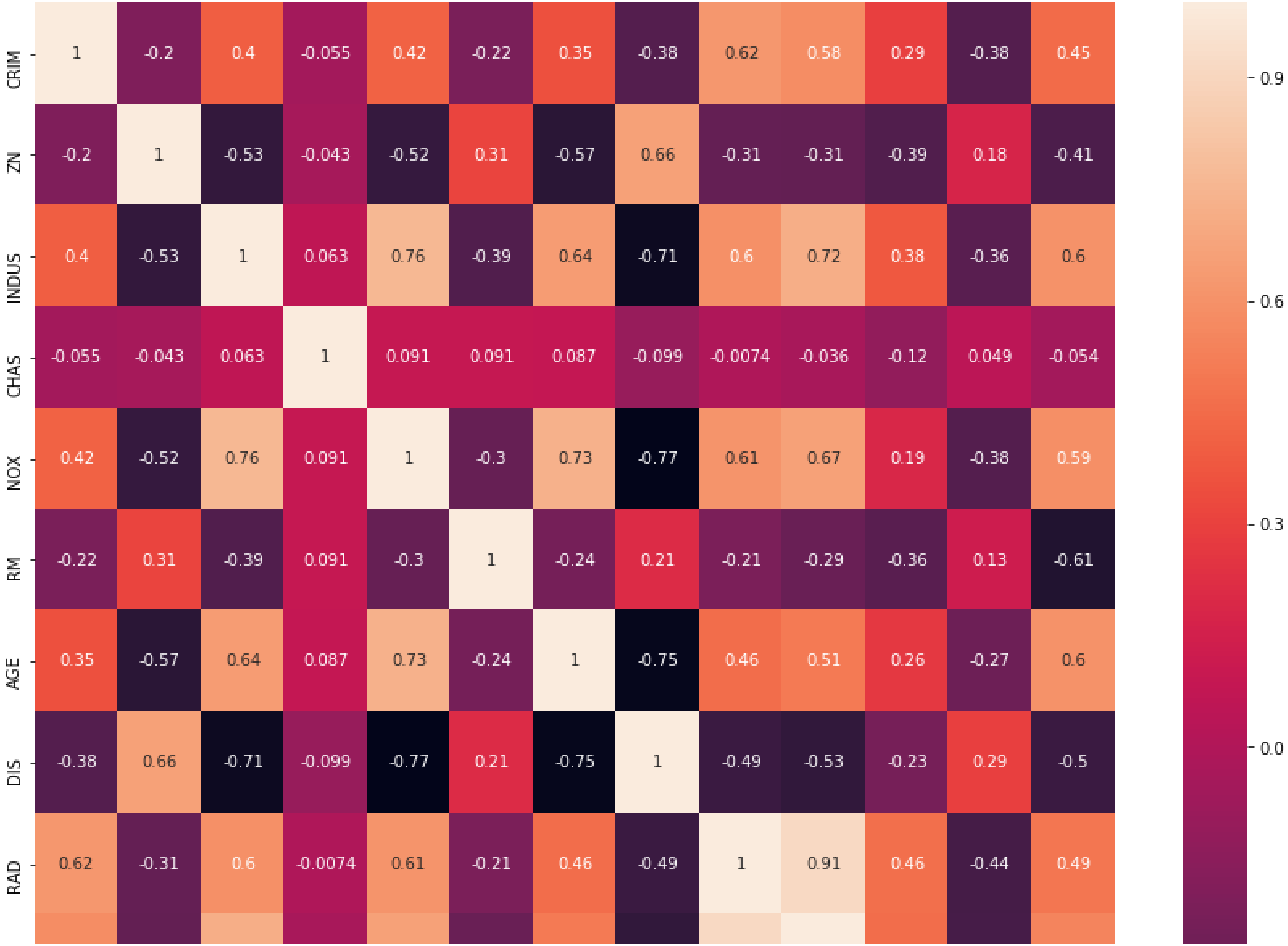
In [6]:
```
# To check and display the sum of null values
features.isnull().sum()
```

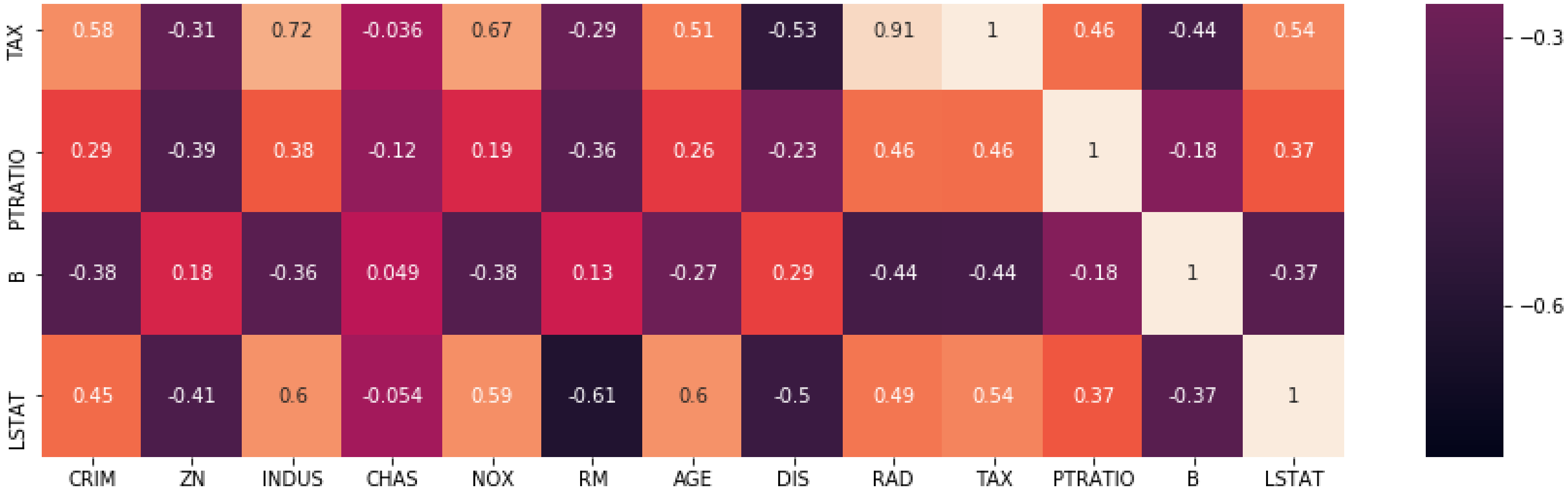
Out[6]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
dtype: int64
```

In [7]:
```python
# Creating heat map for data visualization with correlation and coefficients

f, ax = plt.subplots(figsize=(15, 15))
sns.heatmap(data=features.corr(), annot=True)
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x25dcb4c1588>



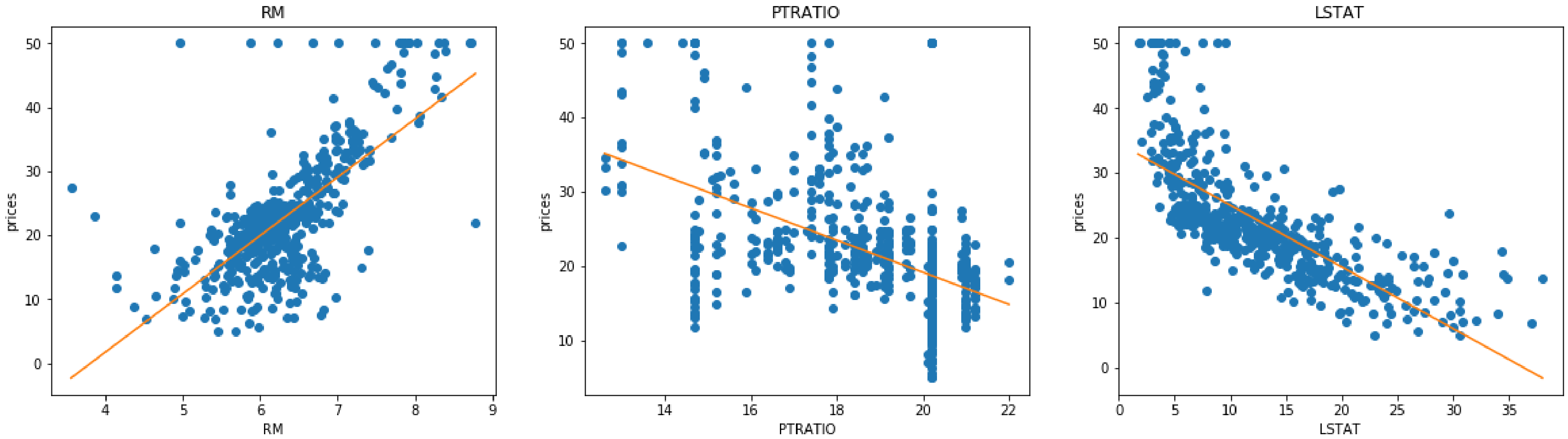



In [8]:
```
#from the above Heat map RM and lstat have higher positive and negative corelation with price values
#RAD TAX have high multi colinearity same goes with DIS and age,dis and nox column values
# displaying all the column names
features.columns
```

Out[8]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT'],
      dtype='object')
```

In [9]:
```python
# Plotting the 'RM','PTRATIO','LSTAT' against Proce
plt.figure(figsize=(20, 5))

# iterating for each column 'RM','PTRATIO','LSTAT'
for i, col in enumerate(['RM','PTRATIO','LSTAT']):
    plt.subplot(1, 3, i+1)
    x = features[col]
    y = targets
    plt.plot(x, y, 'o')
    # Create regression line
    plt.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)))
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('prices')
```



In [10]:

```
# Creating different sizes of room based on their sizes using Quantile-based discretization function

dd=pd.qcut(features.RM,q=[0, .25, .5, .75, 1.])
pd.Categorical(dd)
dd=pd.get_dummies(dd,prefix='RM_')
dd=dd.rename(index=str, columns={"RM__(3.56, 5.885]":"Very_Small_room","RM__(5.885, 6.208]": "Small_room", "RM__(6.208, 6.
features.index=dd.index
features['Very_Small_room']=dd['Very_Small_room']
features['Small_room']=dd['Small_room']
features['Medium_room']=dd['Medium_room']
features['Large_room']=dd['Large_room']
```

In [11]:

```
# Creating different status using Quantile-based discretization function
dd=pd.qcut(features.LSTAT,q=[0, .25, .5, .75, 1.])
pd.Categorical(dd)
dd=pd.get_dummies(dd,prefix='status_')
dd=dd.rename(index=str, columns={"status__(1.729, 6.95]":"Least_lower_Status","status__(6.95, 11.36]": "Medium_lower_Statu
features.index=dd.index
features['Majorly_lower_Status']=dd['Majorly_lower_Status']
features['lower_Status']=dd['lower_Status']
features['Medium_lower_Status']=dd['Medium_lower_Status']
features['Least_lower_Status']=dd['Least_lower_Status']
```

In [12]:

```
# Creating Independent(X) and Dependent(Target-Y) data frames
X = features[['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX',  'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'Very_Small_room', 'Small_room',
       'Medium_room', 'Large_room','Majorly_lower_Status', 'lower_Status',
       'Medium_lower_Status', 'Least_lower_Status']]
Y = targets
```

# Random Forest :

In [13]:
```
from xgboost.sklearn import XGBRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import make_pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import Imputer, StandardScaler
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import train_test_split, GridSearchCV, ShuffleSplit, RandomizedSearchCV
import pickle
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\weight_boosting.py:29: DeprecationWarning: numpy.core.umat
h_tests is an internal NumPy module and should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

In [14]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
```

In [15]:
```
#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)
```

In [16]:
```
#Initialization for random forest
pipe = make_pipeline(StandardScaler(),
                     RandomForestRegressor(n_estimators=500, random_state=123))

cv = ShuffleSplit(test_size=0.2, random_state=0)

param_grid = {'randomforestregressor__max_features':['sqrt', 'log2', 10],
              'randomforestregressor__max_depth':[9, 11, 13]}

grid = GridSearchCV(pipe, param_grid=param_grid, cv=cv)
```

In [17]:
```
#finding feature_importance for feature selection. from it we'll be able to decide threshold value
model = XGBRegressor()
model.fit(X_train, y_train)
print(model.feature_importances_)
```

```
[0.19127516 0.02013423 0.02516779 0.00503356 0.06040268 0.10067114
 0.15939598 0.02181208 0.06711409 0.06040268 0.11912752 0.02013423
 0.00167785 0.01174497 0.03691275 0.03020134 0.00671141 0.02013423
 0.04194631]
```

In [18]:
```
selection = SelectFromModel(model, threshold=0.01, prefit=True)
select_X_train = selection.transform(X_train)
select_X_test = selection.transform(X_test)
# deviding train and test data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
grid.fit(select_X_train, y_train)          #training
```

Out[18]:
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=0, test_size=0.2, train_size=None),
       error_score='raise',
       estimator=Pipeline(memory=None,
     steps=[('standardscaler', StandardScaler(copy=True, with_mean=True, with_std=True)), ('randomforestregressor', Ran
domForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decr...imators=500, n_jobs=1,
           oob_score=False, random_state=123, verbose=0, warm_start=False))]),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'randomforestregressor__max_features': ['sqrt', 'log2', 10], 'randomforestregressor__max_depth': [9,
11, 13]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [19]:
```
grid.best_params_
```

Out[19]:
```
{'randomforestregressor__max_depth': 9,
 'randomforestregressor__max_features': 'sqrt'}
```

In [20]:
```
Randfor_reg = pickle.dumps(grid)
```

In [21]:
```
Randfor_reg = pickle.loads(Randfor_reg)
print("""RandomForest regressor accuracy is {ran}""".format(ran=Randfor_reg.score(select_X_test, y_test)))
```

```
RandomForest regressor accuracy is 0.7990931731692065
```

In [ ]: