In [1]:
```
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```

Boston Housing with Linear Regression

With this data our objective is create a model using linear regression to predict the houses price

The data contains the following columns:

- **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**: nitrogen 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 mean of 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
- **BLACK**: 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town.
- **LSTAT**: lower status of the population (percent).
- **MEDV**: median value of owner-occupied homes in $$1000s

Prepare our enviroment

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [3]:
```
# Importing DataSet and take a look at Data
Boston = pd.read_csv("boston.csv")
Boston.head()
```

Out[3]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	BLACK	LSTAT	M
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	

In [4]:
```
Boston.info()
Boston.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    int64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  BLACK    506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

Out[4]:

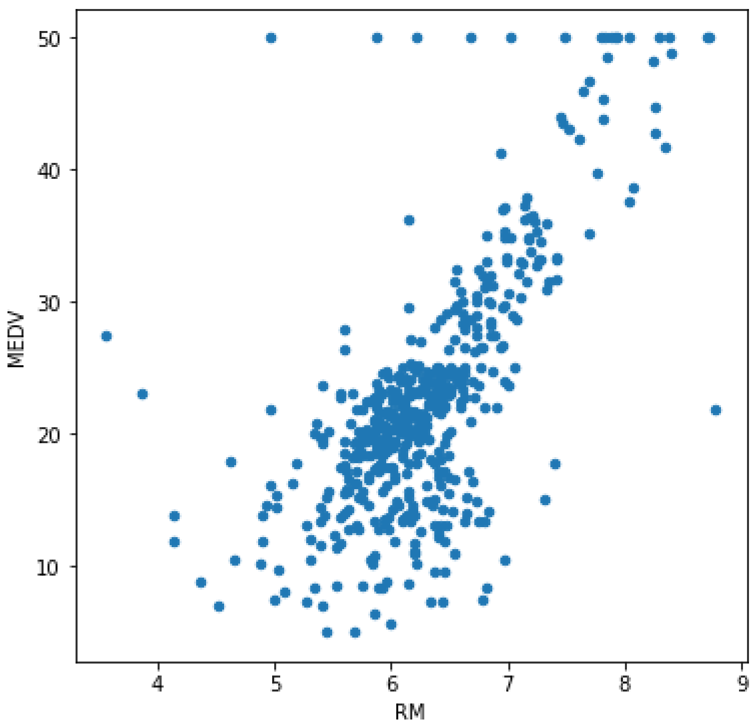
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500

In [5]:

```
Boston.plot.scatter('RM', 'MEDV', figsize=(6, 6))
```

Out[5]:

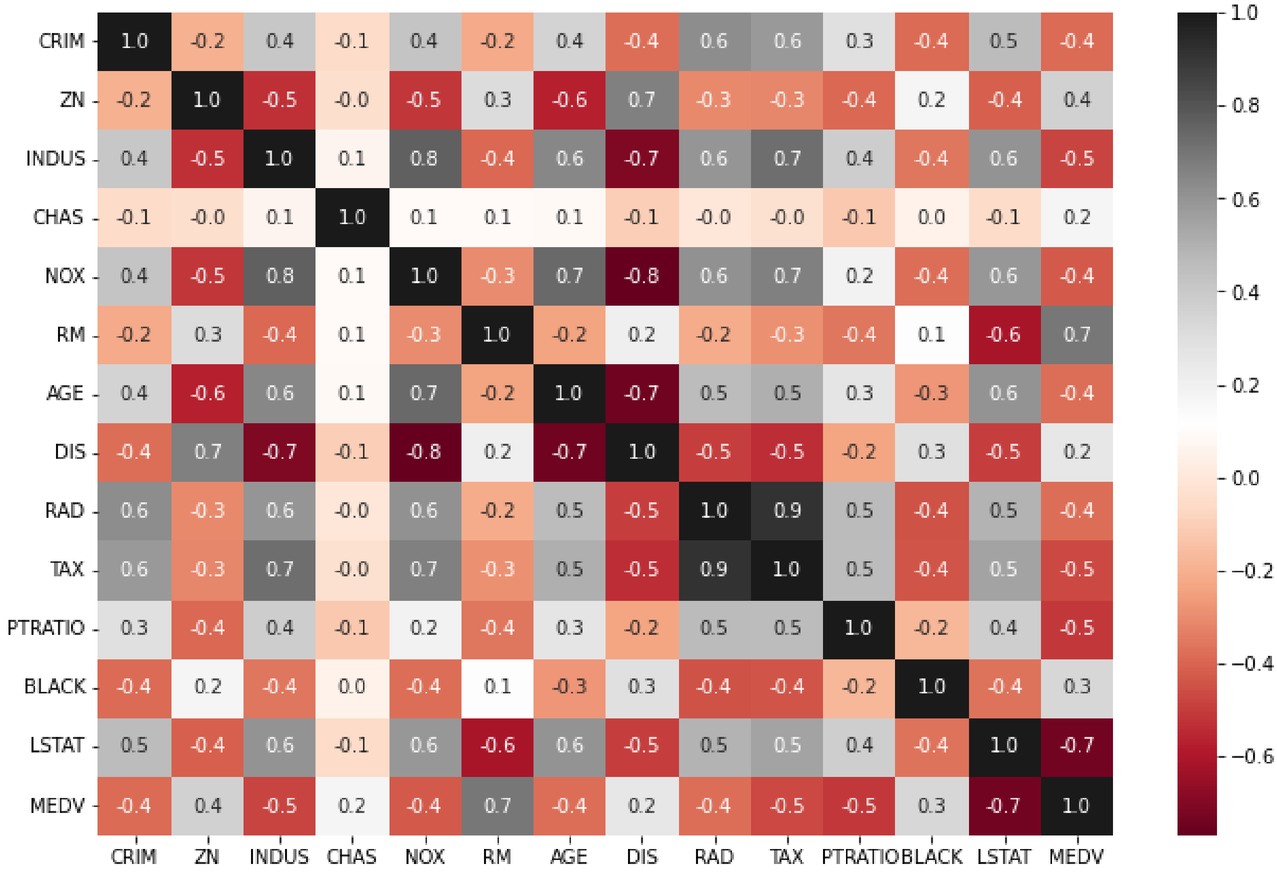
```
<AxesSubplot:xlabel='RM', ylabel='MEDV'>
```



In this plot its clearly to see a linear pattern. Wheter more average number of rooms per dwelling, more expensive the median value is.

In [6]:
```
plt.subplots(figsize=(12,8))
sns.heatmap(Boston.corr(), cmap = 'RdGy', annot = True, fmt = '.1f')
```

Out[6]:
```
<AxesSubplot:>
```



At this heatmap plot, we can do our analysis better than the pairplot.

Lets focus at the last line, where y = MEDV:

When shades of Red/Orange: the more red the color is on X axis, smaller the MEDV. Negative correlation
When light colors: those variables at axis x and y, they dont have any relation. Zero correlation
When shades of Gray/BLACK : the more BLACK the color is on X axis, more higher the value med is. Positive correlation

Trainning Linear Regression Model

Define X and Y

X: Varibles named as predictors, independent variables, features.
Y: Variable named as response or dependent variable

In [7]:
```
X = Boston[['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX'
Y = Boston['MEDV']
```

Import sklearn librarys:

train_test_split, to split our data in two DF, one for build a model and other to validate.
LinearRegression, to apply the linear regression.

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [9]:
```
# Split DataSet
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3)
```

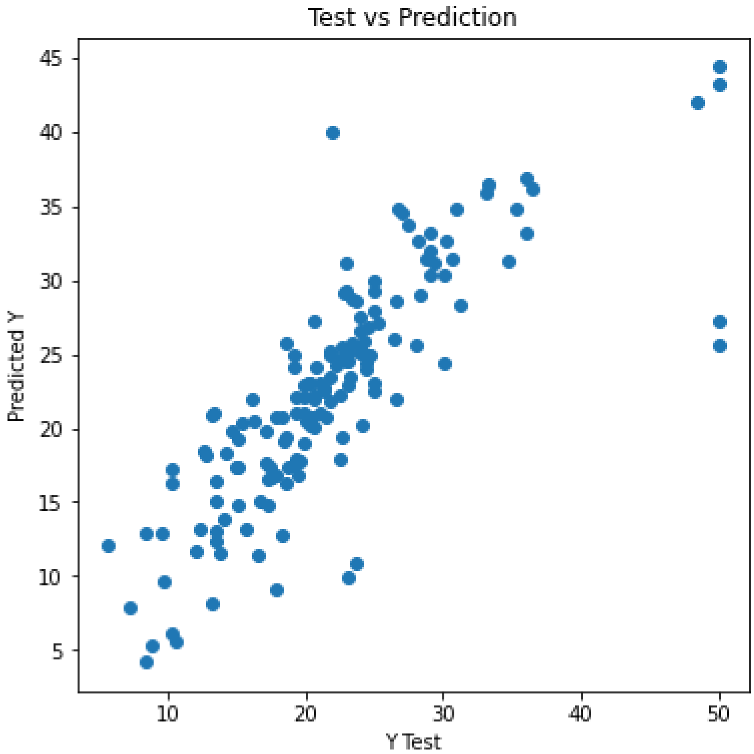
In [10]:
```
print(f'Train Dataset Size - X: {X_train.shape}, Y: {Y_train.shape}')
print(f'Test  Dataset Size - X: {X_test.shape}, Y: {Y_test.shape}')
```

```
Train Dataset Size - X: (354, 13), Y: (354,)
Test  Dataset Size - X: (152, 13), Y: (152,)
```

In [11]:
```
# Model Building
lm = LinearRegression()
lm.fit(X_train,Y_train)
predictions = lm.predict(X_test)
```

In [12]:
```
# Model Visualization
plt.figure(figsize=(6, 6))
plt.scatter(Y_test, predictions)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
plt.title('Test vs Prediction')
```

Out[12]:
```
Text(0.5, 1.0, 'Test vs Prediction')
```



In [13]:
```
plt.figure(figsize=(6, 6))
sns.regplot(x = X_test['RM'], y = predictions, scatter_kws={'s':5})
plt.scatter(X_test['RM'], Y_test, marker = '+')
plt.xlabel('Average number of rooms per dwelling')
plt.ylabel('Median value of owner-occupied homes')
plt.title('Regression Line Tracing')
```

Out[13]:
```
Text(0.5, 1.0, 'Regression Line Tracing')
```

In [14]:
```
from sklearn import metrics

print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test, predictions))
print('Mean Square Error:', metrics.mean_squared_error(Y_test, predictions))
print('Root Mean Square Error:', np.sqrt(metrics.mean_squared_error(Y_test, predic
```

```
Mean Absolute Error: 3.373916998524693
Mean Square Error: 24.201703414184955
Root Mean Square Error: 4.919522681539842
```

In [15]:
```
# Model Coefficients
coefficients = pd.DataFrame(lm.coef_.round(2), X.columns)
coefficients.columns = ['coefficients']
coefficients
```

Out[15]:

	coefficients
CRIM	-0.11
ZN	0.03
INDUS	0.06
CHAS	3.60
NOX	-21.13
RM	4.28
AGE	0.00
DIS	-1.50
RAD	0.31
TAX	-0.01
PTRATIO	-1.05
BLACK	0.01
LSTAT	-0.53