Supervised Learning - Linear Regression 1

October 10, 2016

Original notepad for this lecture

In [1]:
```
import numpy as np
import pandas as pd
from pandas import Series,DataFrame

#Imports for plotting
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
%matplotlib inline

from sklearn.datasets import load_boston

# Load the housing dataset
boston = load_boston()
#Let's see what the data set contains
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 other
        - NOX      nitric oxides concentration (parts per 10 million)
```
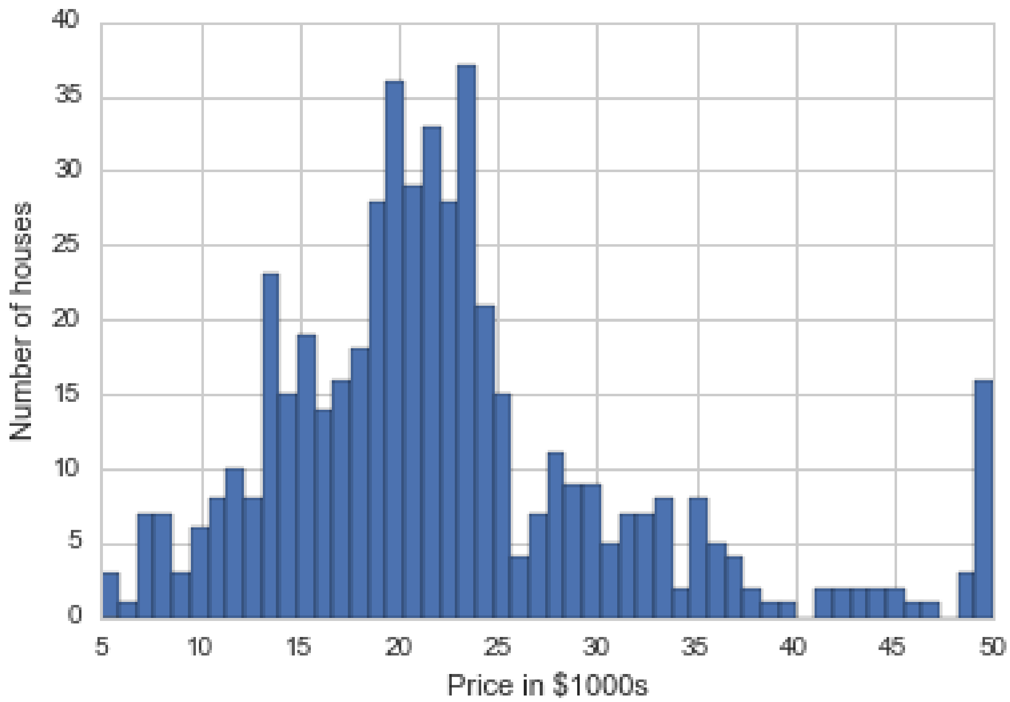

```
        - RTM       average number of rooms per dwelling
```

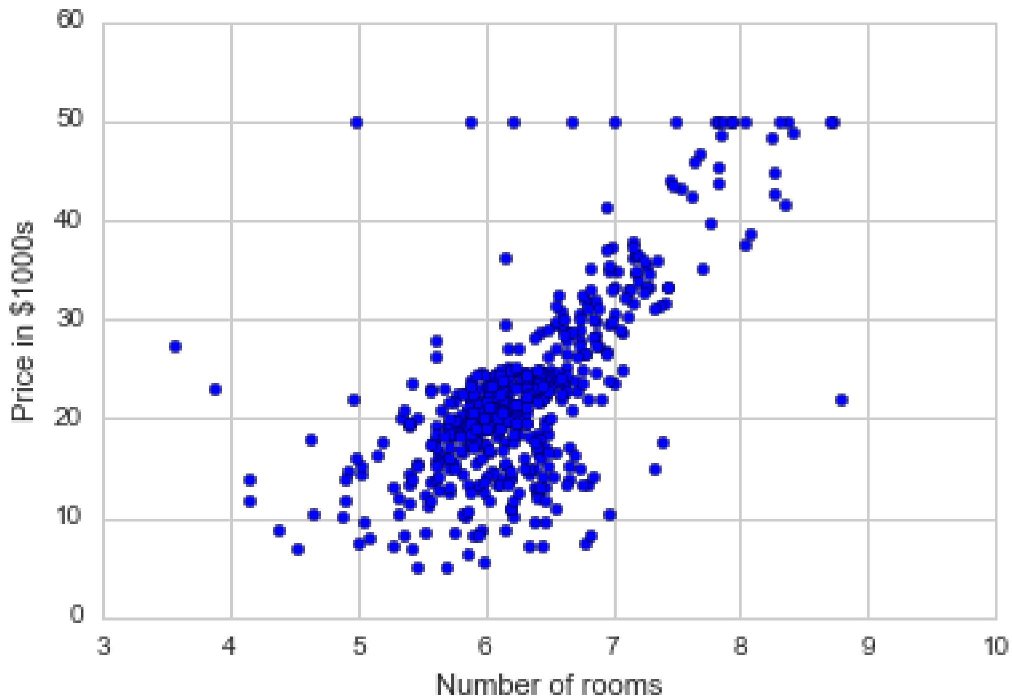
```
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax 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 Mel

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 addr
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data a
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proce
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

In [2]:
```
# Histogram of prices (this is the target of our dataset)
plt.hist(boston.target,bins=50)

#label
plt.xlabel('Price in $1000s')
plt.ylabel('Number of houses')
```

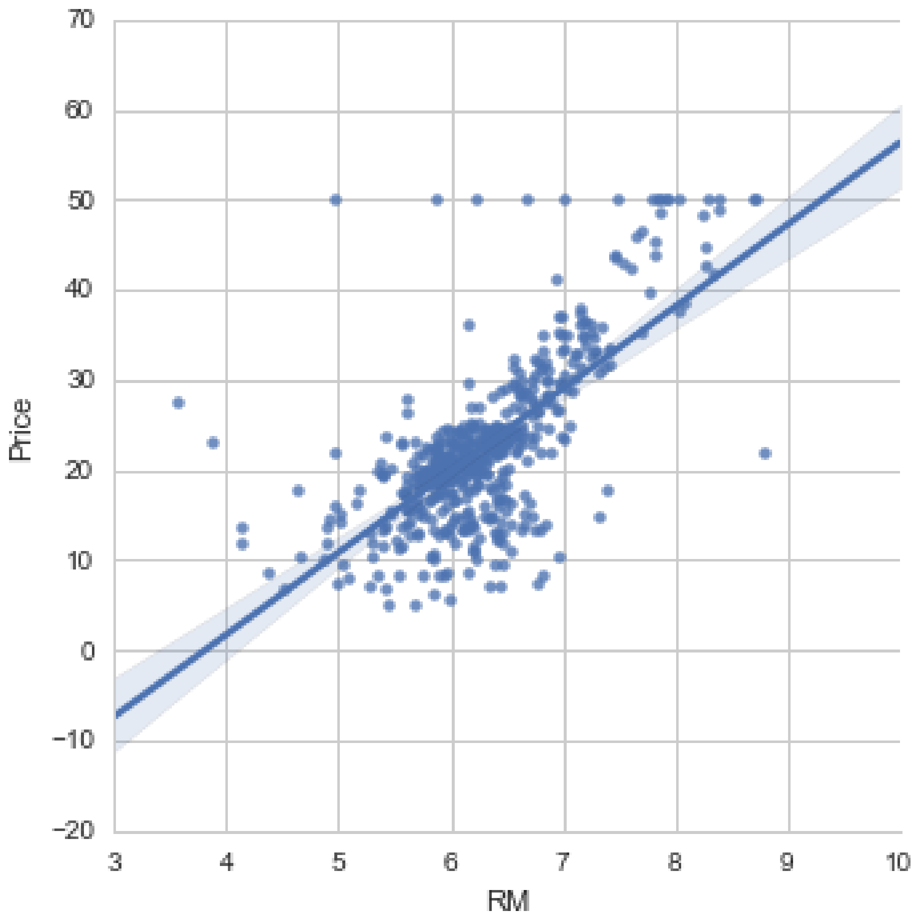
Out[2]:
```
<matplotlib.text.Text at 0xb167f60>
```




```
In [3]: # Plot the column at the 5 index (Labeled RM)
        plt.scatter(boston.data[:,5],boston.target)

        #label
        plt.ylabel('Price in $1000s')
        plt.xlabel('Number of rooms')

Out[3]: <matplotlib.text.Text at 0xb5209b0>
```




```
In [4]: # reset data as pandas DataFrame
        boston_df = DataFrame(boston.data)

        #show This prints dataset without columns headers
        #boston_df.head()

        # label columns
        boston_df.columns = boston.feature_names

        #show without price column
        #boston_df.head()

        # Set price column for target
        boston_df['Price'] = boston.target
        #Now let's see the resultign DataFrame!

        # Show result
        boston_df.head()

        # Using seabron to create a linear fit
        sns.lmplot('RM','Price',data = boston_df)

Out[4]: <seaborn.axisgrid.FacetGrid at 0xbaafd30>
```



Previous result done by seaborn
Let's do the same with numpy code
Note: np.vstack tranform

```
0       6.575
1       6.421
2       7.185
3       6.998
4       7.147
5       6.430
...
```

to:

```
array([[ 6.575],
       [ 6.421],
       [ 7.185],
       [ 6.998],
       [ 7.147],
```

```
       [ 6.43 ],
       ...])
```

And

```
# Create the X array in the form [X 1]
X = np.array( [ [value,1] for value in X ] )
```

Create

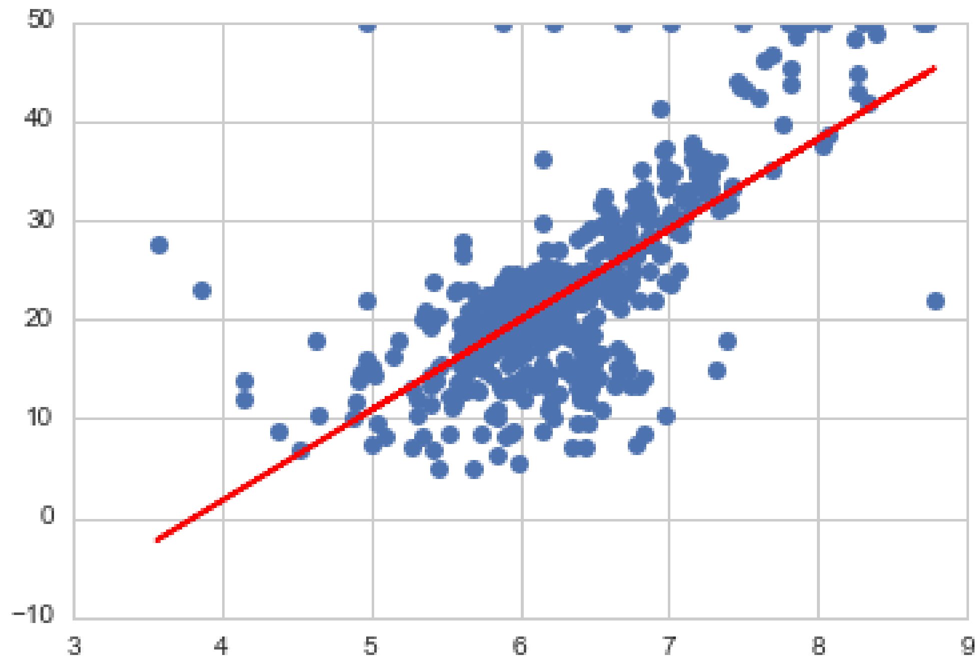
```
array([[array([ 6.575]), 1],
       [array([ 6.421]), 1],
       [array([ 7.185]), 1],
       ...,
       [array([ 6.976]), 1],
       [array([ 6.794]), 1],
       [array([ 6.03]), 1]], dtype=object)
```

This is form of array required by np.linalg.lstsq

```
# Now get out m and b values for our best fit line
m, b = np.linalg.lstsq(X, Y)[0]
```

Google `np.linalg.lstsq` and pick numpy doc from results to read about **least square** function

```
In [5]: # Set up X as median room values
        X = boston_df.RM

        # Use v to make X two-dimensional
        X = np.vstack(boston_df.RM)

        # Set up Y as the target price of the houses.
        Y = boston_df.Price

        # Create the X array in the form [X 1]
        X = np.array( [ [value,1] for value in X ] )

        # Now get out m and b values for our best fit line
        m, b = np.linalg.lstsq(X, Y)[0]

        # First the original points, Price vs Avg Number of Rooms
        plt.plot(boston_df.RM,boston_df.Price,'o')

        # Next the best fit line
        x= boston_df.RM
        plt.plot(x, m*x + b,'r',label='Best Fit Line')

Out[5]: [<matplotlib.lines.Line2D at 0xc006128>]
```




```
In [6]: # Get the resulting array
        result = np.linalg.lstsq(X,Y)

        # Get the total error
        error_total = result[1]

        # Get the root mean square error
        rmse = np.sqrt(error_total/len(X) )

        # Print
        print("The root mean squared error was %.2f " %rmse)
```

```
The root mean squared error was 6.60
```

```
In [12]: # Import for Linear Regression
         import sklearn
         from sklearn.linear_model import LinearRegression
         # Create a LinearRegression Object
         lreg = LinearRegression()
         # Data Columns
         X_multi = boston_df.drop('Price',1)

         # Targets
         Y_target = boston_df.Price
```

```
# X_multi
#Y_target
# Implement Linear Regression
lreg.fit(X_multi,Y_target)
print(' The estimated intercept coefficient is %.2f ' %lreg.intercept_)
print(' The number of coefficients used was %d ' % len(lreg.coef_))
```

```
 The estimated intercept coefficient is 36.49
 The number of coefficients used was 13
```

In [13]:
```
# Set a DataFrame from the Features
coeff_df = DataFrame(boston_df.columns)
coeff_df.columns = ['Features']

# Set a new column lining up the coefficients from the linear regression
coeff_df["Coefficient Estimate"] = pd.Series(lreg.coef_)

# Show
coeff_df
```

Out[13]:

	Features	Coefficient Estimate
0	CRIM	-0.107171
1	ZN	0.046395
2	INDUS	0.020860
3	CHAS	2.688561
4	NOX	-17.795759
5	RM	3.804752
6	AGE	0.000751
7	DIS	-1.475759
8	RAD	0.305655
9	TAX	-0.012329
10	PTRATIO	-0.953464
11	B	0.009393
12	LSTAT	-0.525467
13	Price	NaN

In [14]:
```
# Grab the output and set as X and Y test and train data sets!
X_train, X_test, Y_train, Y_test = sklearn.cross_validation.train_test_spl

#Let's go ahead and see what the output of the train_test_split was:

# Print shapes of the training and testing data sets
print(X_train.shape, X_test.shape, Y_train.shape, Y_test.shape)
```

```
(379, 2) (127, 2) (379,) (127,)
```

In [15]:
```
# Create our regression object
lreg = LinearRegression()
```

```
# Once again do a linear regression, except only on the training sets this
lreg.fit(X_train,Y_train)
#Output:LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normal
#Now run a prediction on both the X training set and the testing set.
# Predictions on training and testing sets
pred_train = lreg.predict(X_train)
pred_test = lreg.predict(X_test)

#Now we will get the mean square error

print("Fit a model X_train, and calculate MSE with Y_train: %.2f"  % np.me

print("Fit a model X_train, and calculate MSE with X_test and Y_test: %.2f
```

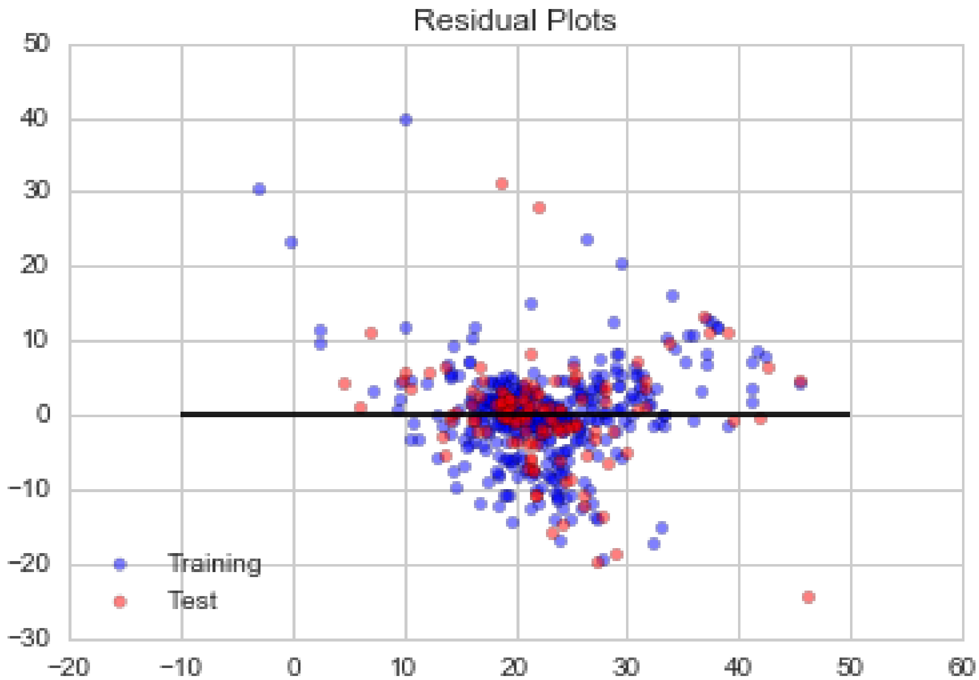
```
Fit a model X_train, and calculate MSE with Y_train: 41.68
Fit a model X_train, and calculate MSE with X_test and Y_test: 49.55
```

In [16]:

```
# Scatter plot the training data
train = plt.scatter(pred_train,(Y_train-pred_train),c='b',alpha=0.5)

# Scatter plot the testing data
test = plt.scatter(pred_test,(Y_test-pred_test),c='r',alpha=0.5)

# Plot a horizontal axis line at 0
plt.hlines(y=0,xmin=-10,xmax=50)

#Labels
plt.legend((train,test),('Training','Test'),loc='lower left')
plt.title('Residual Plots')
```

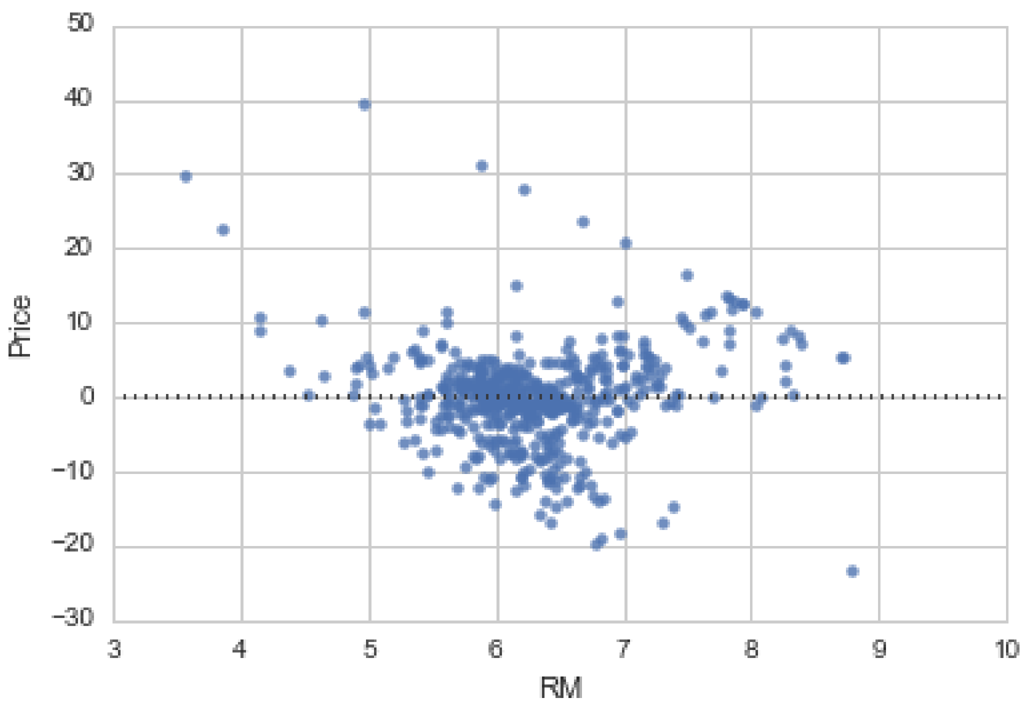
Out[16]:

```
<matplotlib.text.Text at 0xc472588>
```




```
In [17]: # Residual plot of all the dataset using seaborn
         sns.residplot('RM', 'Price', data = boston_df)
```

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0xc4f9128>
```



```
In [ ]:
```