housing

May 6, 2015

1 Boston Housing data

This part of the tutorial loads data about Boston housing and median house prices. The goal is to predict the housing price in each district given a series of features.

Features include race, air quality and plot size.

```
In [1]: # Load the data
        import warnings
        from sklearn.datasets import load_boston

        TRAIN_SIZE = 200

        warnings.filterwarnings('ignore')

        boston = load_boston()
        X_train = boston["data"][:TRAIN_SIZE]
        y_train = boston["target"][:TRAIN_SIZE]
        X_test = boston["data"][TRAIN_SIZE:]
        y_test = boston["target"][TRAIN_SIZE:]

        all_features = boston["feature_names"]
```

```
/Library/Python/2.7/site-packages/numpy/core/fromnumeric.py:2499: VisibleDeprecationWarning: `rank` is d
  VisibleDeprecationWarning)
```

2 Feature Explanation

What do these features mean?

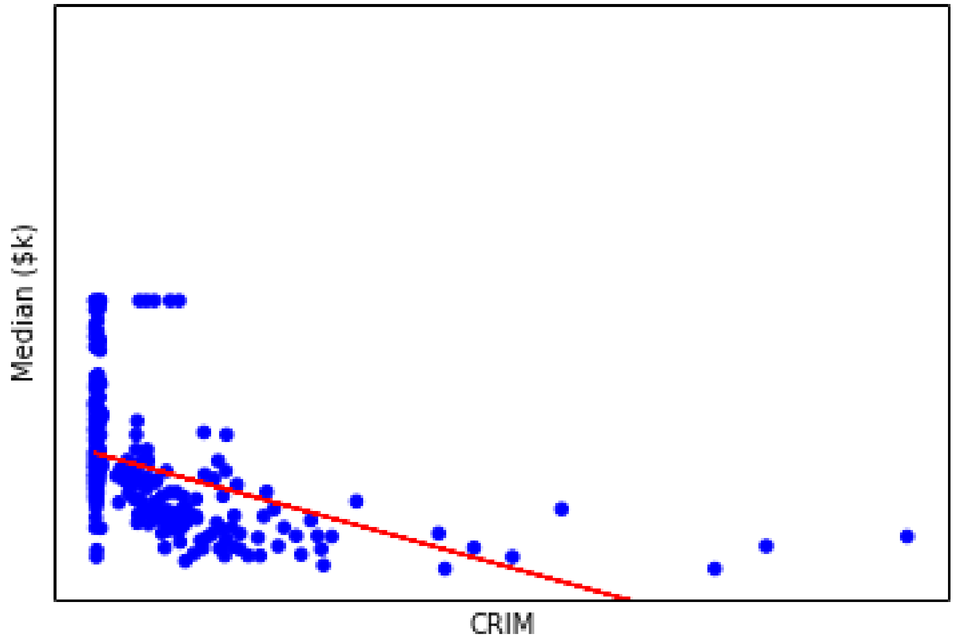
1. CRIM: per capita crime rate by town
2. ZN: proportion of residential land zoned for lots over 25,000 sq.ft.
3. INDUS: proportion of non-retail business acres per town
4. CHAS: Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
5. NOX: nitric oxides concentration (parts per 10 million)
6. RM: average number of rooms per dwelling
7. AGE: proportion of owner-occupied units built prior to 1940
8. DIS: weighted distances to five Boston employment centres
9. RAD: index of accessibility to radial highways
10. TAX: full-value property-tax rate per 10,000 dollars
11. PTRATIO: pupil-teacher ratio by town
12. B: 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
13. LSTAT: Percent lower status of the population
14. MEDV: Median value of owner-occupied homes in 1000s of dollars

3 Plot Data

Fet a feel for plotting data. FOR THE STUDENT: Increase FEATURES_TO_SHOW to see all 13 features.

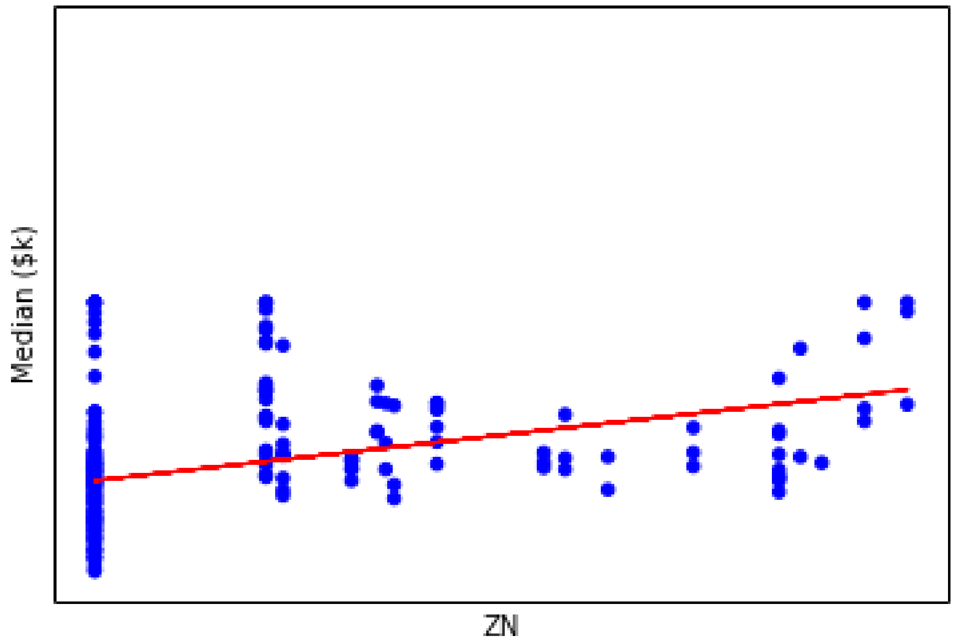
In [2]:
```
# LET's plot it
import matplotlib.pyplot as plt
import numpy
import pylab
import scipy
# ALLOW inline graphs
%matplotlib inline

# FOR THE student:
# Look at more graphs of features and find those that look to be the best
# fits

FEATURES_TO_SHOW = 2

for feature_name in all_features[:FEATURES_TO_SHOW]:
    print
    print 'Feature: %s' % feature_name
    idx = list(all_features).index(feature_name)
    x_vals = [x[idx] for x in X_test]
#    plt.scatter([x[idx] for x in X_test], y_test, color='blue')
    plt.scatter(x_vals, y_test, color='blue')

    plt.xticks(())
    plt.yticks(())
    z = numpy.polyfit(x_vals, y_test, 1)
    p = numpy.poly1d(z)
    pylab.plot(x_vals, p(x_vals),'r-')

    plt.ylim([-0.05, 100.0])
    plt.xlabel(feature_name)
    plt.ylabel('Median ($k)')
    plt.show()
    slope, intercept, r_value, p_value, std_err = scipy.stats.linregress(x_vals, y_test)
    print "y=%.6fx+(%.6f), R^2 = %.2f" % (z[0], z[1], r_value**2)


#housing.main()
```

```
Feature: CRIM
```



y=-0.421677x+(24.415939), R^2 = 0.20

Feature: ZN



y=0.160753x+(20.109698), R^2 = 0.15

Next let's see some of the data. X is a matrix of all feature values. y is a vector of target data.

```
In [3]: all_features = boston["feature_names"]
        print str(all_features)
        print 'y training size is %d' % len(y_train)
        print 'X training size is %d x %d' % (len(X_train[0]), len(X_train))
        print 'y training set is in $k %s' % str(y_train[:5])
```

```
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT' 'MEDV']
y training size is 200
X training size is 13 x 200
y training set is in $k [ 24.   21.6  34.7  33.4  36.2]
```

4 First Linear regression

Let's try a couple of models. First a linear regression based on least squares. The variance should be close to 1 if the model is good. Don't be fooled by the R^2 on the training set. It's a line that does not describe the reality of taking on a real set of new random data.

```
In [4]: from sklearn import linear_model
        from sklearn.metrics import r2_score

        clf_linear_simple = linear_model.LinearRegression()

        clf_linear_simple.fit (X_train, y_train)
        linear_r2 = r2_score(y_train, clf_linear_simple.predict(X_train))
        print 'R^2 train is %f # bogus' % linear_r2
        linear_test_r2 = r2_score(y_test, clf_linear_simple.predict(X_test))
        print 'R^2 test is %f # Needs improvement' % linear_test_r2
        print 'Coefficients: ' + str(clf_linear_simple.coef_)
```

```
R^2 train is 0.847066 # bogus
R^2 test is -2.204567 # Needs improvement
Coefficients: [  1.21702620e+00   2.28358110e-02   4.05630994e-03   1.55045296e-02
  -7.33657559e+00   9.01161321e+00  -3.88193998e-02  -1.13348841e+00
   4.60084845e-01  -1.76861359e-02  -6.84160019e-01   1.86722634e-02
  -1.86732207e-01]
```

5 Feature Scaling

Feature scaling helps prevent some features from appearing to dominate a training set.

```
In [5]: # SCALE it
        from sklearn.preprocessing import StandardScaler
        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_test_scaled = scaler.fit_transform(X_test)
```

6 Rank Features

Here we want to order the features by r-squared value.

In [6]:
```
import operator
r2_values = {}
for feature_name in all_features[:-1]:
    idx = list(all_features).index(feature_name)
    x_vals = [x[idx] for x in X_train_scaled]
    slope, intercept, r_value, p_value, std_err = scipy.stats.linregress(x_vals, y_train)
    r2_values[feature_name] = r_value ** 2
sorted_features = sorted(r2_values.items(), key=operator.itemgetter(1), reverse=True)
print 'Sorted features: ' + str(sorted_features)
good_features = [x[0] for x in sorted_features]
print 'Good features: ' + str(good_features)
```

```
Sorted features: [('RM', 0.73894619361181768), ('LSTAT', 0.52769518464243903), ('PTRATIO', 0.13342654496
Good features: ['RM', 'LSTAT', 'PTRATIO', 'AGE', 'NOX', 'INDUS', 'ZN', 'TAX', 'CRIM', 'B', 'RAD', 'DIS'
```

7 Feature Selection

We try to find the best features using a series of random sets. Starty by importing the data and using the random forest regressor to select features.

8 Make a reduced set

Make slimmed down training and test set. Try to get over .5 R-squared.

In [10]:
```
# TO THE STUDENT:
# Change this to use different top features

FEATURE_COUNT = 13

# USE good features to train next model
X_selected_train = []
X_selected_test = []

for line in X_train_scaled:
    x_out = []
    feature_num = 0
    for feature_name in all_features:
        if feature_name in good_features[:FEATURE_COUNT]:
            x_out.append(line[feature_num])
        feature_num += 1
    X_selected_train.append(x_out)

for line in X_test_scaled:
    x_out = []
    feature_num = 0
    for feature_name in all_features:
        if feature_name in good_features[:FEATURE_COUNT]:
            x_out.append(line[feature_num])
        feature_num += 1
    X_selected_test.append(x_out)
    clf_select = linear_model.LinearRegression()

clf_select.fit (X_selected_train, y_train)
```

```
print('R^2 selected train linear score: %.2f # bogus' % clf_select.score(X_selected_train, y_t
print('R^2 selected test linear score: %.2f' % clf_select.score(X_selected_test, y_test))
```

```
R^2 selected train linear score: 0.85 # bogus
R^2 selected test linear score: 0.58
```

9 Test Scaled Data

Test the scaled version.

```
In [11]: clf = linear_model.LinearRegression()

         clf.fit(X_train_scaled, y_train)
         #X_test_scaled = scaler.fit_transform(X_test)

         print('R^2 test scaled linear score: %.2f' % clf.score(X_test_scaled, y_test))
```

```
R^2 test scaled linear score: 0.58
```

10 Test Scaled and Selected Data

```
In [12]: X_train_select_scaled = scaler.fit_transform(X_selected_train)
         X_test_select_scaled = scaler.fit_transform(X_selected_test)


         clf_select_scaled = linear_model.LinearRegression()
         clf_select_scaled.fit(X_train_select_scaled, y_train)
         print('R^2 test select scaled linear score: %.2f' % clf_select_scaled.score(X_test_select_scal
```

```
R^2 test select scaled linear score: 0.58
```

11 Ridiculously Easy Alert

12 Random Forest

The random forest optimizes the results under the hood. This is the easy way. This is an overestimate of the R^2 again. This really is random. Try play twice and watch the score.

```
In [14]: from sklearn.ensemble import RandomForestRegressor
         rf_first = RandomForestRegressor(n_estimators=20, max_depth=4)
         rf_first.fit(X_train, y_train)
         print('R^2 score: %.2f' % rf_first.score(X_test, y_test))
```

```
R^2 score: 0.61
```

13 Ridge Regression

TO THE STUDENT, BROKEN. Fix me

```
In [15]: ridge = linear_model.Ridge (alpha = .5)
         ridge.fit(X_train, y_train)
         print('R^2 score: %.2f' % ridge.score(X_test, y_test))
```

```
R^2 score: -1.42
```

14 Lasso

```
In [16]: lasso = linear_model.Lasso(alpha = 0.1)
         lasso.fit(X_train, y_train)
         print('R^2 score: %.2f' % lasso.score(X_test, y_test))
```

```
R^2 score: 0.20
```

```
In [ ]:
```