boston_housing

March 12, 2016

1 Machine Learning Engineer Nanodegree

1.1 Model Evaluation & Validation

1.2 Project 1: Predicting Boston Housing Prices

Welcome to the first project of the Machine Learning Engineer Nanodegree! In this notebook, some template code has already been written. You will need to implement additional functionality to successfully answer all of the questions for this project. Unless it is requested, do not modify any of the code that has already been included. In this template code, there are four sections which you must complete to successfully produce a prediction with your model. Each section where you will write code is preceded by a **STEP X** header with comments describing what must be done. Please read the instructions carefully!

In addition to implementing code, there will be questions that you must answer that relate to the project and your implementation. Each section where you will answer a question is preceded by a **QUESTION X** header. Be sure that you have carefully read each question and provide thorough answers in the text boxes that begin with "**Answer:**". Your project submission will be evaluated based on your answers to each of the questions.

A description of the dataset can be found here, which is provided by the **UCI Machine Learning Repository**.

2 Getting Started

To familiarize yourself with an iPython Notebook, **try double clicking on this cell**. You will notice that the text changes so that all the formatting is removed. This allows you to make edits to the block of text you see here. This block of text (and mostly anything that's not code) is written using Markdown, which is a way to format text using headers, links, italics, and many other options! Whether you're editing a Markdown text block or a code block (like the one below), you can use the keyboard shortcut **Shift + Enter** or **Shift + Return** to execute the code or text block. In this case, it will show the formatted text.

Let's start by setting up some code we will need to get the rest of the project up and running. Use the keyboard shortcut mentioned above on the following code block to execute it. Alternatively, depending on your iPython Notebook program, you can press the **Play** button in the hotbar. You'll know the code block executes successfully if the message "Boston Housing dataset loaded successfully!" is printed.

```
In [2]: # Importing a few necessary libraries
        import numpy as np
        import matplotlib.pyplot as pl
        from sklearn import datasets
        from sklearn.tree import DecisionTreeRegressor

        # Make matplotlib show our plots inline (nicely formatted in the notebook)
        %matplotlib inline

        # Create our client's feature set for which we will be predicting a selling price
```

```
CLIENT_FEATURES = [[11.95, 0.00, 18.100, 0, 0.6590, 5.6090, 90.00, 1.385, 24, 680.0, 20.20, 332

# Load the Boston Housing dataset into the city_data variable
city_data = datasets.load_boston()

# Initialize the housing prices and housing features
housing_prices = city_data.target
housing_features = city_data.data

print "Boston Housing dataset loaded successfully!"
```

```
Boston Housing dataset loaded successfully!
```

3 Statistical Analysis and Data Exploration

In this first section of the project, you will quickly investigate a few basic statistics about the dataset you are working with. In addition, you'll look at the client's feature set in `CLIENT_FEATURES` and see how this particular sample relates to the features of the dataset. Familiarizing yourself with the data through an explorative process is a fundamental practice to help you better understand your results.

3.1 Step 1

In the code block below, use the imported `numpy` library to calculate the requested statistics. You will need to replace each `None` you find with the appropriate `numpy` coding for the proper statistic to be printed. Be sure to execute the code block each time to test if your implementation is working successfully. The print statements will show the statistics you calculate!

```
In [6]: # Number of houses in the dataset
        total_houses = np.size(housing_prices)

        # Number of features in the dataset
        total_features = np.size(housing_features[0])

        # Minimum housing value in the dataset
        minimum_price = np.min(housing_prices)

        # Maximum housing value in the dataset
        maximum_price = np.max(housing_prices)

        # Mean house value of the dataset
        mean_price = np.mean(housing_prices)

        # Median house value of the dataset
        median_price = np.median(housing_prices)

        # Standard deviation of housing values of the dataset
        std_dev = np.std(housing_prices)


        # Show the calculated statistics
        print "Boston Housing dataset statistics (in $1000's):\n"
        print "Total number of houses:", total_houses
        print "Total number of features:", total_features, "(%d if including house price)" %(total_featu
        print "Minimum house price:", minimum_price
        print "Maximum house price:", maximum_price
        print "Mean house price: {0:.3f}".format(mean_price)
        print "Median house price:", median_price
        print "Standard deviation of house price: {0:.3f}".format(std_dev)
```

```
Boston Housing dataset statistics (in $1000's):

Total number of houses: 506
Total number of features: 13 (14 if including house price)
Minimum house price: 5.0
Maximum house price: 50.0
Mean house price: 22.533
Median house price: 21.2
Standard deviation of house price: 9.188
```

3.2 Question 1

As a reminder, you can view a description of the Boston Housing dataset here, where you can find the different features under **Attribute Information**. The `MEDV` attribute relates to the values stored in our `housing_prices` variable, so we do not consider that a feature of the data.

Of the features available for each data point, choose three that you feel are significant and give a brief description for each of what they measure.

Remember, you can **double click the text box below** to add your answer!

Answer: From some basic research and exploring some simple relationships between features of the data in Excel, I've identified the following features as significant indicators of house value: 1. **LSTAT** - A homebuyer's income level is going to dictate the price of house she can afford. Therefore, the lower the average income in an area, the lower the average house price will be. LSTAT, measuring the percentage of the population in the area considered "lower class" (lower income), is probably the feature with the most obvious relationship to house price. 2. **RM** - The average number of rooms per house in an area. The market in an area that has mostly 5+ bedroom houses is likely to behave differently from an area of mostly studio and 1-bedroom apartments. 3. **CRIM** - Number of crimes committed in an area divided by the number of residents of the area. Homebuyers are usually looking to put down roots, and so would logically prefer an area where they feel their families are safe.

3.3 Question 2

Using your client's feature set `CLIENT_FEATURES`, which values correspond with the features you've chosen above?

Hint: Run the code block below to see the client's data.

```
In [4]: print CLIENT_FEATURES
```

```
[[11.95, 0.0, 18.1, 0, 0.659, 5.609, 90.0, 1.385, 24, 680.0, 20.2, 332.09, 12.13]]
```

Answer: 1. LSTAT: 12.13 2. RM: 5.609 3. CRIM: 11.95

4 Evaluating Model Performance

In this second section of the project, you will begin to develop the tools necessary for a model to make a prediction. Being able to accurately evaluate each model's performance through the use of these tools helps to greatly reinforce the confidence in your predictions.

4.1 Step 2

In the code block below, you will need to implement code so that the `shuffle_split_data` function does the following: - Randomly shuffle the input data `X` and target labels (housing values) `y`. - Split the data into training and testing subsets, holding 30% of the data for testing.

If you use any functions not already acessible from the imported libraries above, remember to include your import statement below as well!
Ensure that you have executed the code block once you are done. You'll know the `shuffle_split_data` function is working if the statement "Successfully shuffled and split the data!" is printed.

```
In [5]: # Put any import statements you need for this code block here
        from sklearn.cross_validation import train_test_split

        def shuffle_split_data(X, y):
            """ Shuffles and splits data into 70% training and 30% testing subsets,
                then returns the training and testing subsets. """

            # Shuffle and split the data
            X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

            # Return the training and testing data subsets
            return X_train, y_train, X_test, y_test


        # Test shuffle_split_data
        try:
            X_train, y_train, X_test, y_test = shuffle_split_data(housing_features, housing_prices)
            print "Successfully shuffled and split the data!"
        except:
            print "Something went wrong with shuffling and splitting the data."
```

```
Successfully shuffled and split the data!
```

4.2 Question 4

Why do we split the data into training and testing subsets for our model?

Answer: A model is only useful if its performance holds when fed new data. By splitting into training and testing data, are able to test our model against a data set distinct from the one used to train it. This helps avoid overfitting to training data.

4.3 Step 3

In the code block below, you will need to implement code so that the `performance_metric` function does the following: - Perform a total error calculation between the true values of the `y` labels `y_true` and the predicted values of the `y` labels `y_predict`.

You will need to first choose an appropriate performance metric for this problem. See the sklearn metrics documentation to view a list of available metric functions. **Hint:** Look at the question below to see a list of the metrics that were covered in the supporting course for this project.

Once you have determined which metric you will use, remember to include the necessary import statement as well!
Ensure that you have executed the code block once you are done. You'll know the `performance_metric` function is working if the statement "Successfully performed a metric calculation!" is printed.

```
In [6]: # Put any import statements you need for this code block here
        from sklearn.metrics import mean_squared_error
```

```
def performance_metric(y_true, y_predict):
    """ Calculates and returns the total error between true and predicted values
        based on a performance metric chosen by the student. """

    error = mean_squared_error(y_true, y_predict)
    return error


# Test performance_metric
try:
    total_error = performance_metric(y_train, y_train)
    print "Successfully performed a metric calculation!"
except:
    print "Something went wrong with performing a metric calculation."
```

```
Successfully performed a metric calculation!
```

4.4 Question 4

Which performance metric below did you find was most appropriate for predicting housing prices and analyzing the total error. Why? - Accuracy - Precision - Recall - F1 Score - Mean Squared Error (MSE) - Mean Absolute Error (MAE)

Answer: Accuracy, precision, recall, and F1 score apply to classification and so are not appropriate for this model. Between MSE and MAE, I believe MSE to be more appropriate for this problem since squared error will be more sensitive to extreme deviations from the predicted value. Houses represent a significant portion of their owner's net-worth, so under-valuing a house for sale compromises the time and money the owner has invested in that house. Also, over-valuing a house will lead to a longer time-to-sale, which makes the sale more costly overall.

4.5 Step 4 (Final Step)

In the code block below, you will need to implement code so that the `fit_model` function does the following: - Create a scoring function using the same performance metric as in **Step 2**. See the sklearn `make_scorer` documentation. - Build a GridSearchCV object using `regressor`, `parameters`, and `scoring_function`. See the sklearn documentation on GridSearchCV.

When building the scoring function and GridSearchCV object, be sure that you read the parameters documentation thoroughly. It is not always the case that a default parameter for a function is the appropriate setting for the problem you are working on.

Since you are using `sklearn` functions, remember to include the necessary import statements below as well!

Ensure that you have executed the code block once you are done. You'll know the `fit_model` function is working if the statement "Successfully fit a model to the data!" is printed.

```
In [48]: # Put any import statements you need for this code block
         from sklearn.metrics import make_scorer
         from sklearn.grid_search import GridSearchCV

         def fit_model(X, y):
             """ Tunes a decision tree regressor model using GridSearchCV on the input data X
                 and target labels y and returns this optimal model. """

             # Create a decision tree regressor object
             regressor = DecisionTreeRegressor()
```

```
    # Set up the parameters we wish to tune
    parameters = {'max_depth':(1,2,3,4,5,6,7,8,9,10)}

    # Make an appropriate scoring function
    scoring_function = make_scorer(performance_metric, greater_is_better=False)

    # Make the GridSearchCV object
    reg = GridSearchCV(regressor, parameters, scoring_function)

    # Fit the learner to the data to obtain the optimal model with tuned parameters
    reg.fit(X, y)

    # Return the optimal model
    return reg.best_estimator_


# Test fit_model on entire dataset
try:
    reg = fit_model(housing_features, housing_prices)
    print "Successfully fit a model!"
except:
    print "Something went wrong with fitting a model."
```

```
Successfully fit a model!
```

4.6 Question 5

What is the grid search algorithm and when is it applicable?

Answer: A grid search algorithm finds the optimal parameter values for a given estimator by brute-force. Using the parameter space defined by the `parameters` argument, it tests the given estimator with each combination of parameter values and finds the parameter set that results in the best score (as determined by the `scoring_function` argument).

4.7 Question 6

What is cross-validation, and how is it performed on a model? Why would cross-validation be helpful when using grid search?

Answer: Cross-validation is a technique for validating model performance. A dataset is split into training and testing subsets, and the model is trained and evaluated. The dataset is then re-partitioned, and the training/testing process is repeated. This process is repeated multiple times, and the model's performance is then evaluated as some weighted average of the performance for each partitioning.

When used in combination with grid search, cross-validation maximizes the amounts of data available for training. Were the test set held constant throughout the grid search, the process might overfit the model to the test set. This is because the grid search algorithm would simply find the parameters which performed best on that set. One method to avoid this would be to separate the data into three sets, with the third set used to evaluate the tuned model after the grid search and not used during the tuning process. However, this would reduce the size of the dataset available for tuning. Cross-validation allows us to avoid this issue, at the expense of computation time.

5 Checkpoint!

You have now successfully completed your last code implementation section. Pat yourself on the back! All of your functions written above will be executed in the remaining sections below, and questions will be asked about various results for you to analyze. To prepare the **Analysis** and **Prediction** sections, you will need to intialize the two functions below. Remember, there’s no need to implement any more code, so sit back and execute the code blocks! Some code comments are provided if you find yourself interested in the functionality.

```
In [37]: def learning_curves(X_train, y_train, X_test, y_test):
             """ Calculates the performance of several models with varying sizes of training data.
                 The learning and testing error rates for each model are then plotted. """

             print "Creating learning curve graphs for max_depths of 1, 3, 6, and 10. . ."

             # Create the figure window
             fig = pl.figure(figsize=(10,8))

             # We will vary the training set size so that we have 50 different sizes
             sizes = np.rint(np.linspace(1, len(X_train), 50)).astype(int)
             train_err = np.zeros(len(sizes))
             test_err = np.zeros(len(sizes))

             # Create four different models based on max_depth
             for k, depth in enumerate([1,3,6,10]):

                 for i, s in enumerate(sizes):

                     # Setup a decision tree regressor so that it learns a tree with max_depth = depth
                     regressor = DecisionTreeRegressor(max_depth = depth)

                     # Fit the learner to the training data
                     regressor.fit(X_train[:s], y_train[:s])

                     # Find the performance on the training set
                     train_err[i] = performance_metric(y_train[:s], regressor.predict(X_train[:s]))

                     # Find the performance on the testing set
                     test_err[i] = performance_metric(y_test, regressor.predict(X_test))

                 # Subplot the learning curve graph
                 ax = fig.add_subplot(2, 2, k+1)
                 ax.plot(sizes, test_err, lw = 2, label = ’Testing Error’)
                 ax.plot(sizes, train_err, lw = 2, label = ’Training Error’)
                 ax.legend()
                 ax.set_title(’max_depth = %s’%(depth))
                 ax.set_xlabel(’Number of Data Points in Training Set’)
                 ax.set_ylabel(’Total Error’)
                 ax.set_xlim([0, len(X_train)])

             # Visual aesthetics
             fig.suptitle(’Decision Tree Regressor Learning Performances’, fontsize=18, y=1.03)
             fig.tight_layout()
             fig.show()
```

```
In [38]: def model_complexity(X_train, y_train, X_test, y_test):
             """ Calculates the performance of the model as model complexity increases.
                 The learning and testing errors rates are then plotted. """

             print "Creating a model complexity graph. . . "
```

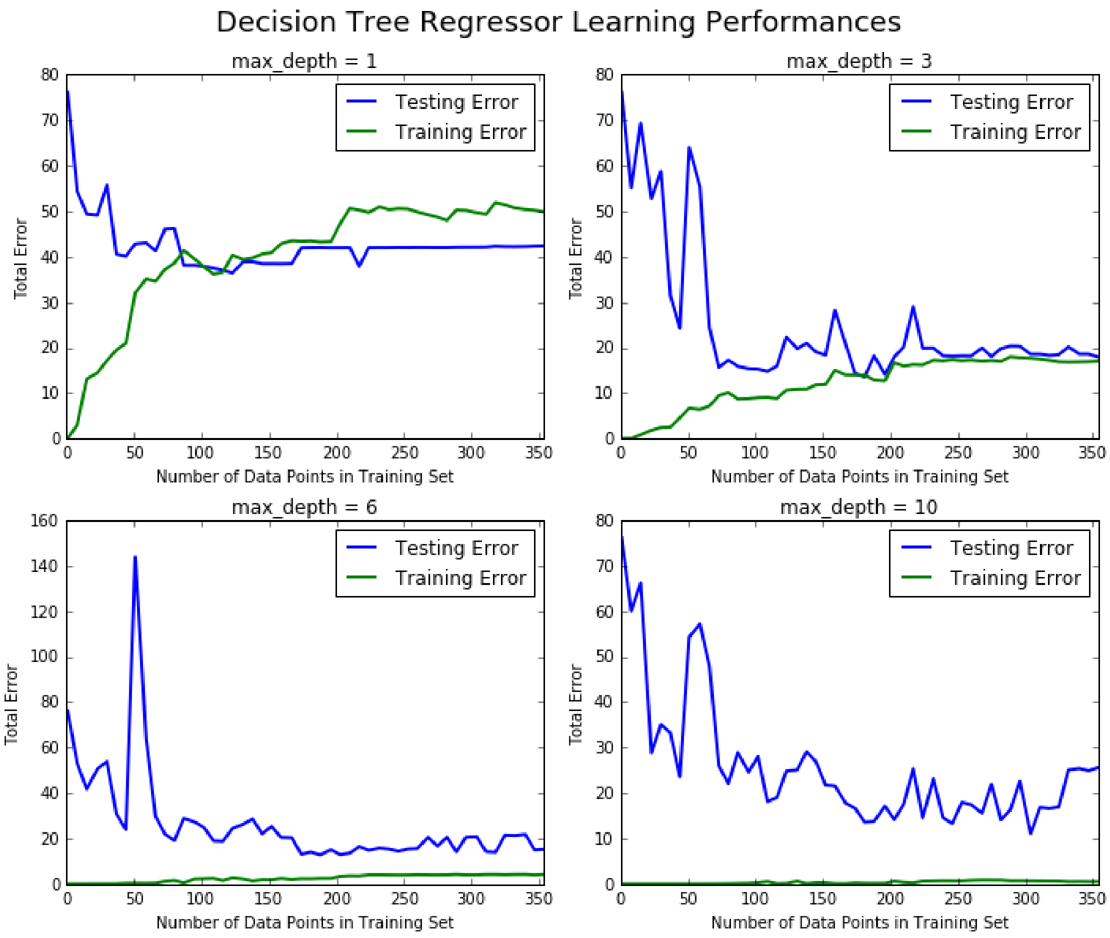
```
# We will vary the max_depth of a decision tree model from 1 to 14
max_depth = np.arange(1, 14)
train_err = np.zeros(len(max_depth))
test_err = np.zeros(len(max_depth))

for i, d in enumerate(max_depth):
    # Setup a Decision Tree Regressor so that it learns a tree with depth d
    regressor = DecisionTreeRegressor(max_depth = d)

    # Fit the learner to the training data
    regressor.fit(X_train, y_train)

    # Find the performance on the training set
    train_err[i] = performance_metric(y_train, regressor.predict(X_train))

    # Find the performance on the testing set
    test_err[i] = performance_metric(y_test, regressor.predict(X_test))

# Plot the model complexity graph
pl.figure(figsize=(7, 5))
pl.title(’Decision Tree Regressor Complexity Performance’)
pl.plot(max_depth, test_err, lw=2, label = ’Testing Error’)
pl.plot(max_depth, train_err, lw=2, label = ’Training Error’)
pl.legend()
pl.xlabel(’Maximum Depth’)
pl.ylabel(’Total Error’)
pl.show()
```

6 Analyzing Model Performance

In this third section of the project, you’ll take a look at several models’ learning and testing error rates on various subsets of training data. Additionally, you’ll investigate one particular algorithm with an increasing max_depth parameter on the full training set to observe how model complexity affects learning and testing errors. Graphing your model’s performance based on varying criteria can be beneficial in the analysis process, such as visualizing behavior that may not have been apparent from the results alone.

```
In [39]: learning_curves(X_train, y_train, X_test, y_test)
```

```
Creating learning curve graphs for max_depths of 1, 3, 6, and 10. . .
```



6.1 Question 7

Choose one of the learning curve graphs that are created above. What is the max depth for the chosen model? As the size of the training set increases, what happens to the training error? What happens to the testing error?

Answer:

`max_depth`: 3

As the size of the training set increases, the training error steadily increases before reaching a plateau.

The testing error generally decreases as the training set increases, though the behavior is a bit more interesting: the testing error drops sharply between 0 and ˜60 data points; between ˜60 and ˜225 data points, it oscillates significantly; and above 225 data points it stabilizes around the same level as the training error. There is also a large spike at 50 points which is shared with the learning curves of the other max_depths.

6.2 Question 8

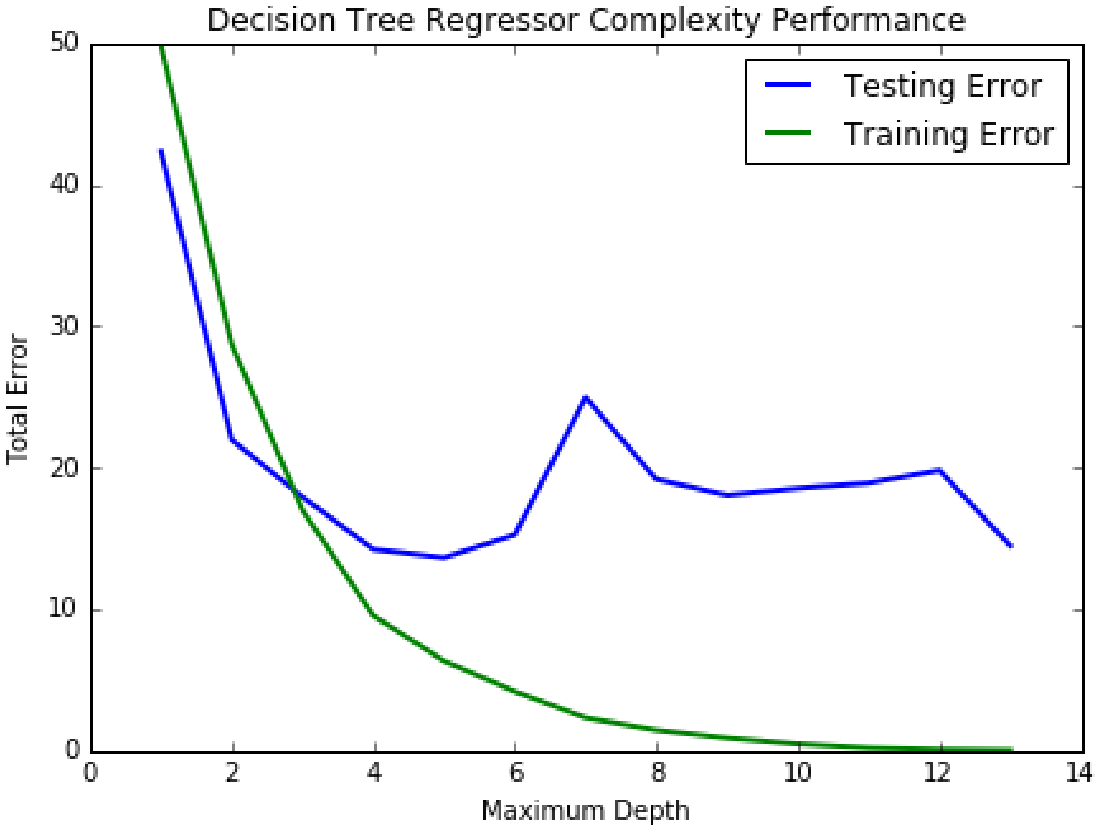
Look at the learning curve graphs for the model with a max depth of 1 and a max depth of 10. When the model is using the full training set, does it suffer from high bias or high variance when the max depth is 1? What about when the max depth is 10?

Answer: At a `max_depth` of 1, the model suffers from high bias. It is not complex enough and so maintains a high level of error.

At a max_depth of 10, the model suffers from high variance. The training error is near-zero while the testing error never stabilizes regardless of the size of the training set.

```
In [79]: model_complexity(X_train, y_train, X_test, y_test)
```

```
Creating a model complexity graph. . .
```



6.3 Question 9

From the model complexity graph above, describe the training and testing errors as the max depth increases. Based on your interpretation of the graph, which max depth results in a model that best generalizes the dataset? Why?

Answer: The training error decreases as the model complexity increases, which is to be expected. At a certain point, the model is overfitted to the training set and the training error approaches zero.

The testing error also decreases as the model complexity increases. However, starting around at a max_depth of 6 or 7, the error starts to increase and oscillate wildly as the model becomes overfitted. This behavior is consistent over repeated fittings.

Based on the behavior described above, I would choose a max_depth of 5 or 6.

7 Model Prediction

In this final section of the project, you will make a prediction on the client's feature set using an optimized model from fit_model. When applying grid search along with cross-validation to optimize your model, it would typically be performed and validated on a training set and subsequently evaluated on a **dedicated test set**. In this project, the optimization below is performed on the entire dataset (as opposed to the training set you made above) due to the many outliers in the data. Using the entire dataset for training provides for a less volatile prediction at the expense of not testing your model's performance.

To answer the following questions, it is recommended that you run the code blocks several times and use the median or mean value of the results.

7.1 Question 10

Using grid search on the entire dataset, what is the optimal `max_depth` parameter for your model? How does this result compare to your intial intuition?
Hint: Run the code block below to see the max depth produced by your optimized model.

```
In [80]: print "Final model has an optimal max_depth parameter of", reg.get_params()['max_depth']
```

```
Final model has an optimal max_depth parameter of 4
```

Answer: After running the fitting algorithm 15 times, the mean tuned `max_depth` is 5.8. I would therefore choose 6 as the optimal `max_depth`, which aligns well with the graphical analysis performed above.

7.2 Question 11

With your parameter-tuned model, what is the best selling price for your client's home? How does this selling price compare to the basic statistics you calculated on the dataset?

Hint: Run the code block below to have your parameter-tuned model make a prediction on the client's home.

```
In [81]: sale_price = reg.predict(CLIENT_FEATURES)
         print "Predicted value of client's home: {0:.3f}".format(sale_price[0])
```

```
Predicted value of client's home: 21.630
```

Answer: After running the fitting algorithm 15 times, the mean predicted home value is $20,615. This is just below the median home value in the dataset.

7.3 Question 12 (Final Question):

In a few sentences, discuss whether you would use this model or not to predict the selling price of future clients' homes in the Greater Boston area.

Answer: This model is tuned to data from 1978, when houses were significantly less expensive than they are now. As it is currently tuned, it would not be very useful for today's market. However, even if it were tuned to a more contemporary dataset, I'm not sure it would be very useful. Consecutive fittings are highly variable. This could be due to only having a few hundred data points for training, but my intuition is that a decision tree regressor might not be the best regressor type for this problem, as my first instinct when considering this problem was to use a k-nearest neighbor regressor. I'm looking forward to learning more about various regressors and classifiers and when each is most appropriate.