boston_housing

March 18, 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 [15]: # 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, 33

        # 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 [16]: # Number of houses in the dataset
         total_houses = city_data.data.shape[0]

         # Number of features in the dataset
         total_features = housing_features.shape[1]

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

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

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

         # 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
         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
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:

1. CRIM - per capita crime rate by town
2. DIS - weighted distances to five Boston employment centres
3. LSTAT - % lower status of the population

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 [17]: 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: [[11.95, 1.385, 12.13]]

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 [18]: # Put any import statements you need for this code block here
         from sklearn import cross_validation
         from sklearn import svm

         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 = cross_validation.train_test_split(X, y, test_size=0.3, 
         #     X_train = None
         #     y_train = None
         #     X_test = None
         #     y_test = None

             # 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 3

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

Answer:

1. The purpose of machine learning is that given a sample of a population, we want to use the sample to build a model that can make predictions on other data points within that population. Separating training and testing subsets serves somewhat like a simulation where we want to use an independent dataset to test our model (which is also why we need to shuffle the dataset before we split it to eliminate potential confounds).

2. We also use the test set to check if our model is overfitting the data. Because your model can fit the training set very well but fail to generalize for the population. And this can be caught when testing using a independent dataset.

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 [19]: # 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: Mean Squared Error (MSE) - since this is a regression problem, we should use either MSE or MAE. MSE is chosen here due to the way it is calculated. MSE squares the difference between each data point and the model's output of that point, and then averages out across the whole dateset. The reason why this is desirable is because:

1. The overestimations (when the predicted value is higher than the actual) and underestimations (when lower than the actual) of the model don't cancel out when you take the average, therefore you won't underestimate the error.

2. The square of a very small value is even smaller and the square of a big value is even bigger. We are looking for a model that can consistently make predictions that stay close to the actual, and with MSE, we can punish really off predictions even more (for example, being off by 20 is a lot more than twice as bad as being off by 10) to get a consistent model.

3. One problem with MSE tho is that it is more susceptible to outliers. To get a even better result with this metric we may want to preprocess the data and consider dropping the outliers.

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 [20]: # 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 = 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: The grid search algorithm is an algorithm that tries out combinations of parameters for you so that you can better/more efficiently tune the parameters of the regressor or the classfier you're using and gives you better chance of getting a more optimized model. Take the DecisionTreeRegressor for example, one thing we can try here is varying the max depth, where a lower max depth may be susceptible to bias and higher to variance. We can define the range we want to try and get grid search to them of us automatically.

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 method for solving the problem of training/test set dilemma where we want to have as much data as possible and in the mean time having enough test data to verify our model. One popular method is called K-fold where we divide the dataset evenly into k bins, and in turn use one of the bins as the test dataset, and the rest of the bins as the training set. And then we average all of the test results from the k experiments to get a better idea how well our model is performing.

On the other hand, the reason why cross-validation is helpful when using grid search is because it sort of makes best use of the dataset so that the grid search for tuning the parameters can be done more thoroughly with all the data we have.

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 [21]: 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()
```

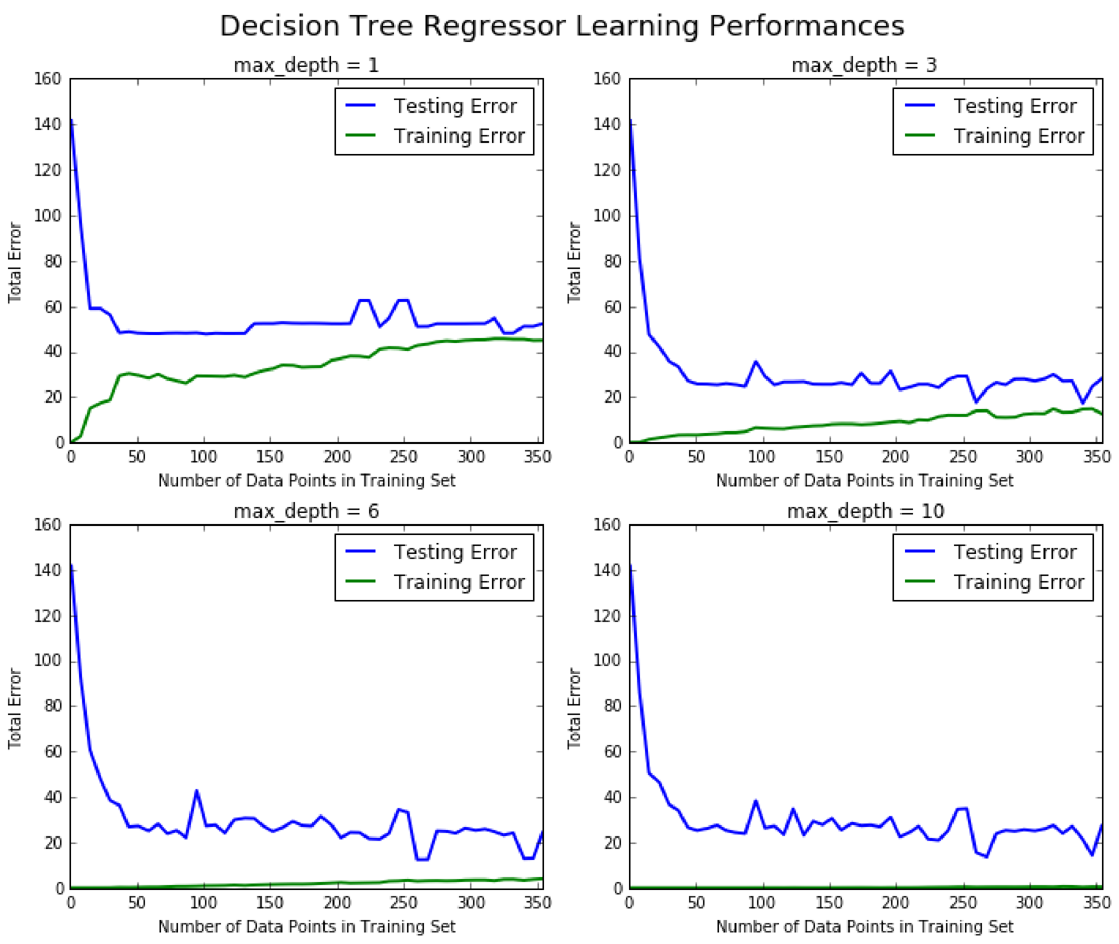
```
In [22]: def model_complexity(X_train, y_train, X_test, y_test):
             """ Calculates the performance of the model as model complexity increases.
                 The learning and testing errors rates are then plotted. """

             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 [23]: 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: Take the model with max_depth = 3 for example. We can see a overall trend that as the size of the training set increases, the training error increases while the testing error decreases. Let's take a closer look at the two curves:

- **Trainineg error:** The training error starts from zero and slowly goes up a bit as the size of the training data increases. This makes sense as the more data there are the harder it becomes for the model to fit them perfectly.
- **Testing error:** The testing error starts high and then drops drastically as the size of the training data increases a bit. This makes sense because when the training dataset is too small we are not able to build a model on it that can make good generalization. As the size of the training dataset goes up a bit, we then get a sufficiently large dataset that is capable of doing so. The gap between the testing and training curves then gradually closes up as the size of the training data increases which means our model is able to make as much use of the data as possible, and improves itself.

6.2 Question 8

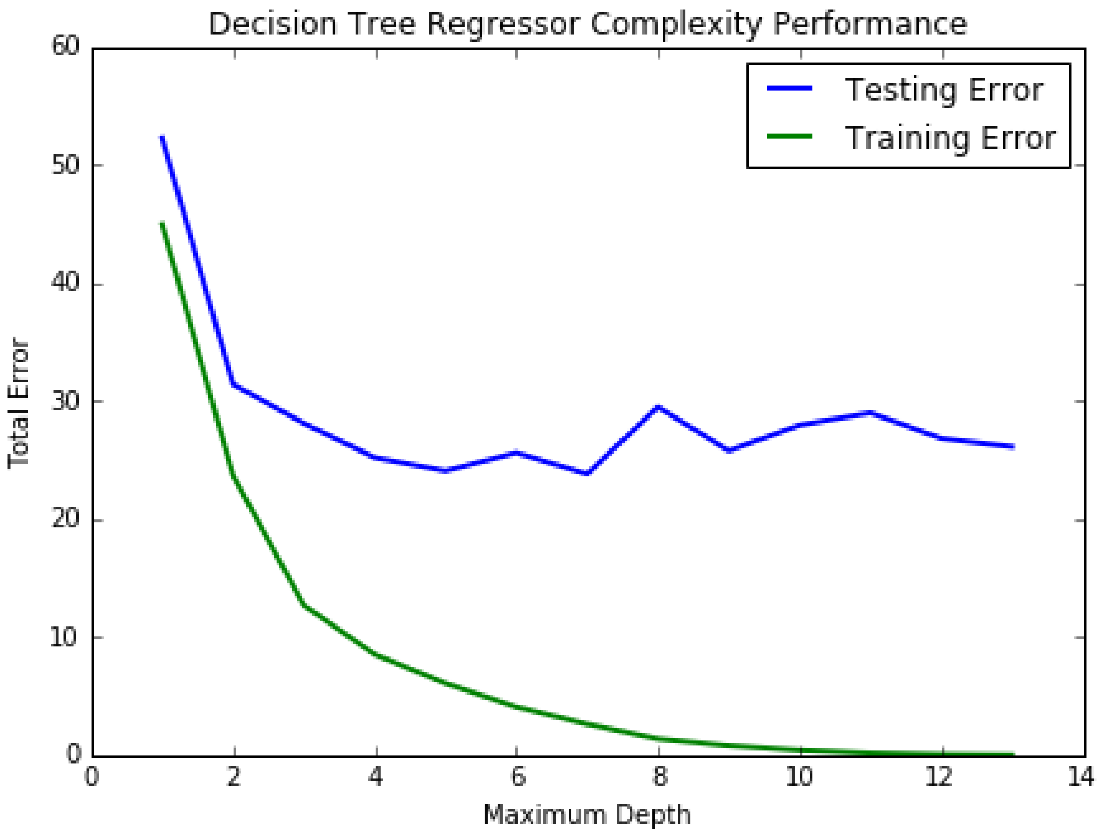
Look at the learning curve graphs for the model with a max depth of 1 and a max depth of 10. When the model is using the full training set, does it suffer from high bias or high variance when the max depth is 1? What about when the max depth is 10?

Answer: For the model with max_depth = 1, apparently the model is suffering from high bias. Because: 1. The training error is very close to the testing error. 2. The training error is very high. 3. The testing error doesn't decrease as we increase the size of the training set (getting more training data doesn't help much).

For the model with max_depth = 10, apparently the model is suffering from high variance. Because: 1. The training error doesn't increase as the size of the training set increases (which is sign of overfitting). 2. The testing error decreases slighly as the size of the training set increases. 3. There's rather large gap between the training error curve and the testing error curve.

```
In [97]: 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 testing error comes down from top and starts to flatten out once it hits max_depth = 2. And the training error comes from the top and doesn't flatten out until it hits somewhere between max_depth = 8 and max_depth = 10, creating a gap between itself and the testing error curve.

This shows that increasing the maximum depth doesn't help much beyond max_depth = 2~4, at least not as much helpful as it is to decreasing the training error (which is a sign of it not being able to generalize for the population).

It also shows that when max_depth > 8, the model is overfitting the data, creating a big gap between the training error curves and the testing error curves (failing to generalize).

The best max depth for generalizing the dataset is max_depth = 4. The reason is we want the testing error to stay reasonably close to the training error (meaning, statistically, the training sample and the model can generalize for the population), and also as low as possible. So in this case when the max_depth > 2, the model starts failing to generalize as the gap between the two curves starts to increase. So we pick the the smallest max depth that minimizes the testing error.

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 [98]: 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: The median of the max_depth is used here, with max_depth = 4. It is the same as my initial intuition.

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 [99]: 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: The best selling price for the client's home is 21.630. It is less than the mean house price = 22.533 and slightly more than the median house price = 21.2, well within one standard deviation from the mean.

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: The model seems to be able to generalize for the population well. I would use this model for predicting the selling price of furture clients' homes in the Greater Boston area.

```
In [ ]:
```