# boston_housing

March 28, 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 [8]:
```
# Importing a few necessary libraries
import numpy as np
import matplotlib.pyplot as pl
from sklearn import datasets
from sklearn.tree import DecisionTreeRegressor
import pandas as pd

# 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 [9]:
```
        # Number of houses in the dataset
        total_houses = city_data.data.shape[0]

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

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

        # Maximum housing value in the dataset
        maximum_price = 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
        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:** I performed a correlation between the house_price and the features. The correlation vector is given by, [-0.385832 0.360445 -0.483725 0.175260 -0.427321 0.695360 -0.376955 0.249929 -0.381626 -0.468536 -0.507787 0.333461 -0.737663 ] which the correlation of MEDV with respect to ,[CRIM ZN INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO B LSTAT MEDV] . From the vector the ones (three) those are highly correlated are LSTAT, RM and PTRATIO. The method used here, is by converting the dataset to dataframe and using .corr() method . The code I used follows

```
In [11]: #The code to answer #Question 1
         df1=pd.DataFrame(housing_features)
         df2=pd.DataFrame(housing_prices)
         fullDataFrame=pd.concat([df1,df2],axis=1, join_axes=[df1.index])
         fullDataFrame.columns = ['CRIM','ZN','INDUS','CHAS','NOX','RM','AGE','DIS','RAD','TAX','PTRATI
         #print fullDataFrame.describe()
         print fullDataFrame.corr()
```

```
CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
CRIM     1.000000 -0.199458  0.404471 -0.055295  0.417521 -0.219940  0.350784
ZN      -0.199458  1.000000 -0.533828 -0.042697 -0.516604  0.311991 -0.569537
INDUS    0.404471 -0.533828  1.000000  0.062938  0.763651 -0.391676  0.644779
CHAS    -0.055295 -0.042697  0.062938  1.000000  0.091203  0.091251  0.086518
NOX      0.417521 -0.516604  0.763651  0.091203  1.000000 -0.302188  0.731470
RM      -0.219940  0.311991 -0.391676  0.091251 -0.302188  1.000000 -0.240265
AGE      0.350784 -0.569537  0.644779  0.086518  0.731470 -0.240265  1.000000
DIS     -0.377904  0.664408 -0.708027 -0.099176 -0.769230  0.205246 -0.747881
RAD      0.622029 -0.311948  0.595129 -0.007368  0.611441 -0.209847  0.456022
TAX      0.579564 -0.314563  0.720760 -0.035587  0.668023 -0.292048  0.506456
PTRATIO  0.288250 -0.391679  0.383248 -0.121515  0.188933 -0.355501  0.261515
B       -0.377365  0.175520 -0.356977  0.048788 -0.380051  0.128069 -0.273534
LSTAT    0.452220 -0.412995  0.603800 -0.053929  0.590879 -0.613808  0.602339
MEDV    -0.385832  0.360445 -0.483725  0.175260 -0.427321  0.695360 -0.376955

              DIS       RAD       TAX   PTRATIO         B     LSTAT      MEDV
```

```
CRIM    -0.377904  0.622029  0.579564  0.288250 -0.377365  0.452220 -0.385832
ZN       0.664408 -0.311948 -0.314563 -0.391679  0.175520 -0.412995  0.360445
INDUS   -0.708027  0.595129  0.720760  0.383248 -0.356977  0.603800 -0.483725
CHAS    -0.099176 -0.007368 -0.035587 -0.121515  0.048788 -0.053929  0.175260
NOX     -0.769230  0.611441  0.668023  0.188933 -0.380051  0.590879 -0.427321
RM       0.205246 -0.209847 -0.292048 -0.355501  0.128069 -0.613808  0.695360
AGE     -0.747881  0.456022  0.506456  0.261515 -0.273534  0.602339 -0.376955
DIS      1.000000 -0.494588 -0.534432 -0.232471  0.291512 -0.496996  0.249929
RAD     -0.494588  1.000000  0.910228  0.464741 -0.444413  0.488676 -0.381626
TAX     -0.534432  0.910228  1.000000  0.460853 -0.441808  0.543993 -0.468536
PTRATIO -0.232471  0.464741  0.460853  1.000000 -0.177383  0.374044 -0.507787
B        0.291512 -0.444413 -0.441808 -0.177383  1.000000 -0.366087  0.333461
LSTAT   -0.496996  0.488676  0.543993  0.374044 -0.366087  1.000000 -0.737663
MEDV     0.249929 -0.381626 -0.468536 -0.507787  0.333461 -0.737663  1.000000
```

### 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 [12]: 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:** LSTAT = 12.13, RM = 5.609 , PTRATIO = 20.2

## 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
         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
             n_samples = city_data.data.shape[0]
             #print city_data.data.shape
             rs = cross_validation.ShuffleSplit(n_samples, test_size=0.3, random_state=0)
             for train_index, test_index in rs:
                 #print("TRAIN:", train_index, "TEST:", test_index)
```

```
            X_train = housing_features[train_index]
            y_train = housing_prices[train_index]
            X_test = housing_features[test_index]
            y_test = housing_prices[test_index]
            break;

        # 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:** To evaluate the model by performing cross-validation or any other model va;idation methods. A good way is to build another function that determines a performance metric for the model.

## 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 [23]:
```
# 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) . Because Accuracy, Precision, Recall, F1 Score are all for classification but our target is continuous. MSE and MAE are for continuous variables, but I prefer MSE over MAE, because MSE squares the error, therefore higher magnitude errors are amplified, and derivatives do not vanish.

## 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 [25]:
```
# Put any import statements you need for this code block

from sklearn.grid_search import GridSearchCV
from sklearn.svm import LinearSVC
from sklearn.metrics import fbeta_score, make_scorer

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':(1,2,3,4,5,6,7,8,9,10,11,12,13)}

    # Make an appropriate scoring function
    scoring_function = make_scorer(mean_squared_error, 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:** Grid search algorithm performs an intense search over the parameter space to get the best estimate. Therefore, it needs the following information, cross-validation method, scoring function, regressor and a method for searching the candidates.

### 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 (CV) is validation estimation techniques for surrogate models. This method gives an estimate of how a predictive model behaves with respect to an independent data sample.In K-fold CV, the data set is divided into k subsets, with each subset comprising of N/k data samples. Remmebr that N is the total number of samples. Now the hold out method is repeated k times, where in each time, k subsets are used as the test set and the other k-1 subsets are put together to form the training set. The average error of all the k trials is computed as our final score. —-CV is particularly useful because it maximizes both the training and the test substes. So we maximize learning as well as maximize validation. ——-If we limit the grid search into a single dataset, yes overfir will happen.

## 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 [30]: 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 [28]:
```
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))
```

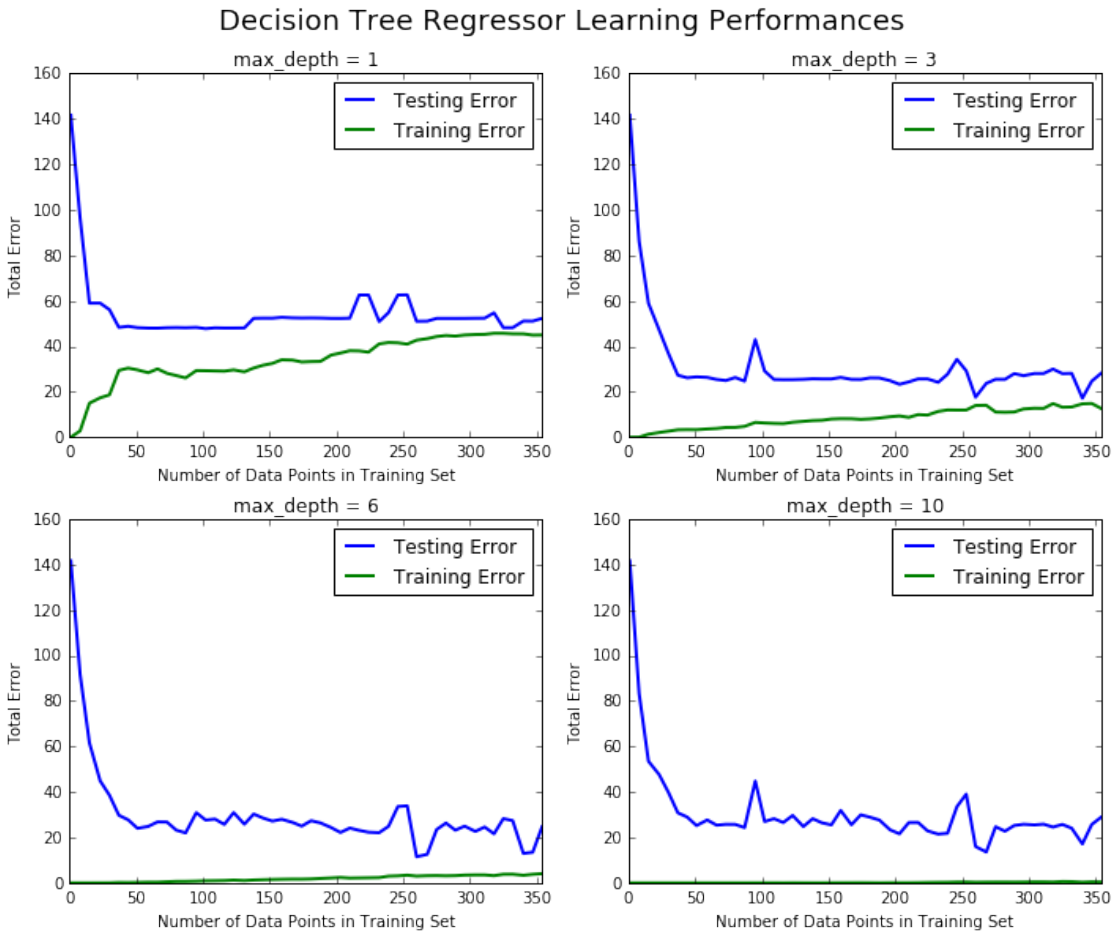
```
# Plot the model complexity graph
pl.figure(figsize=(7, 5))
pl.title('Decision Tree Regressor Complexity Performance')
pl.plot(max_depth, test_err, lw=2, label = 'Testing Error')
pl.plot(max_depth, train_err, lw=2, label = 'Training Error')
pl.legend()
pl.xlabel('Maximum Depth')
pl.ylabel('Total 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 [31]: 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:** Maximum depth is 10. As the training set increase, the training error increases while the testing error stabilizes to a saturated value. The testring error reduces with the number of points in the training set. This means that with addition of points the fit is learnign about model. The error rates initially start with being biased (when number of testing points is low), this can also be thought of as the model is getting "memorized" with the small amount of data and, then as the number of training data increases gradually the model becomes more generalised. Apaprently the model starts with being underfit and then with addition of training points starts becoming overfit.

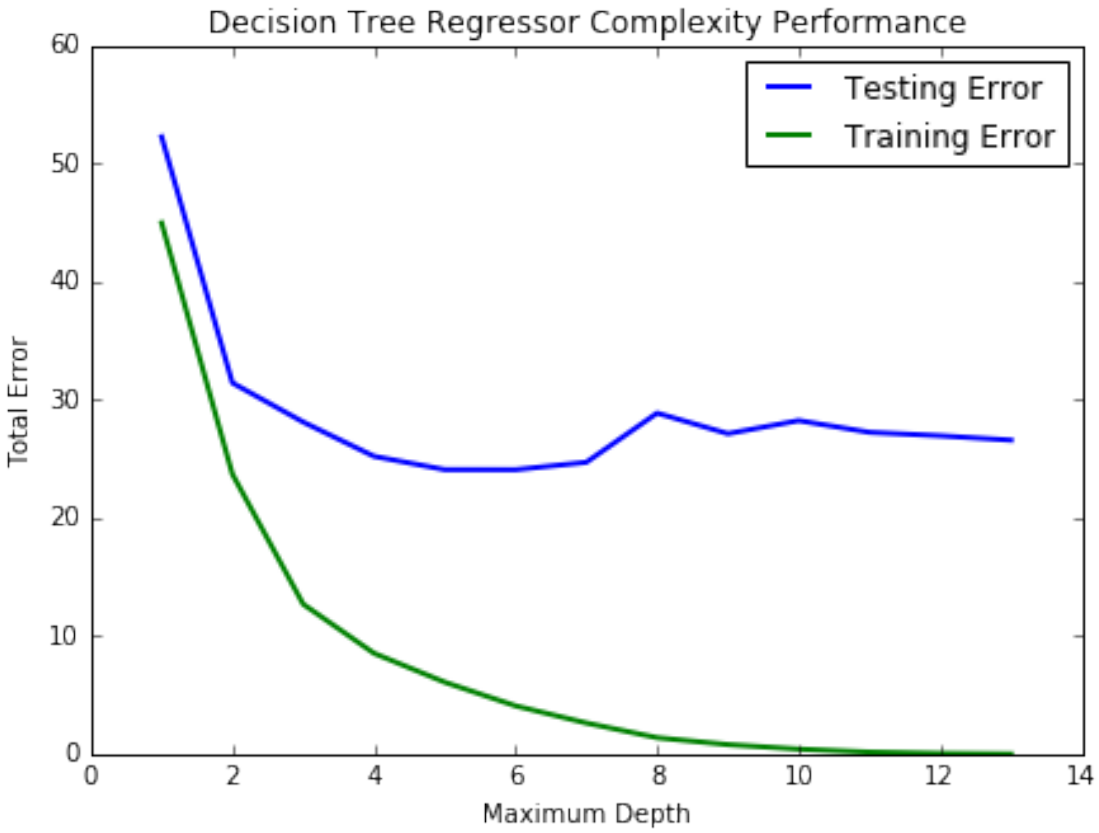
## 6.2 Question 8

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:** Max depth-1 : High Biased , because the gap between the training and testing error is less, and the testing error has not saturated yet. ..... Max depth-10 : High variance because the gap between training and testing error is large.

```
In [32]: 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:** 5 seems to be the max depth.. Because after 5 the testing error almost constant. The testing curve becomes saturated when the model moves from underfitting to over fitting. Apparently, the training error also becomes saturated, but it saturates at a lower error value as compared to 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 [33]: print "Final model has an optimal max_depth parameter of", reg.get_params()['max_depth']
```

```
Final model has an optimal max_depth parameter of 5
```

**Answer:** I have predicted 5 as the optimum depth. Because at this point, the model transits from underfitting to ooverfitting i.e. the training error is low and the testing error is global minimum.

### 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 [34]: 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: 20.968
```

**Answer:** Predicted value of client's home: 20.968 . This number is very close to the median and the mean and is also inside one standard deviation from the mean. So the number looks reasonable.

### 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:** Yes. Because of the following reasons, 1> The estimated value we got for the client looks statisticall ok 2> The curves give a good analysis of the depth and the optimizer seems working fine 3> I do not see any outleirs

```
In [ ]:
```