Machine Learning Engineer Nanodegree

Model Evaluation & Validation

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 (https://archive.ics.uci.edu/ml/datasets/Housing), which is provided by the **UCI Machine Learning Repository**.

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 (http://daringfireball.net/projects/markdown/syntax), 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 [23]:

```
# 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 noteboo
k)
%matplotlib inline

# Create our client's feature set for which we will be predicting a sell
ing price
CLIENT_FEATURES = [[11.95, 0.00, 18.100, 0, 0.6590, 5.6090, 90.00, 1.38
5, 24, 680.0, 20.20, 332.09, 12.13]]

# 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!
```

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.

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 [24]:

```
# Number of houses in the dataset
total_houses = len(housing_features)

# Number of features in the dataset
total_features = len(housing_features[0,:])

# 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
```

Question 1

As a reminder, you can view a description of the Boston Housing dataset here (https://archive.ics.uci.edu/ml/datasets/Housing), 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.RAD: index of accessibility to radial highways 3.TAX: full-value property-tax rate per $10,000

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 [25]: 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: CRIM = 11.95, RAD = 24, TAX = 680.0

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.

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 if the `shuffle_split_data` function is working if the statement *"Successfully shuffled and split the data!"* is printed.

In [26]:

```
# 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 subse
ts,
        then returns the training and testing subsets. """

    # Shuffle and split the data
    ##X_train = None
    ##y_train = None
    ##X_test = None
    ##y_test = None
    X_train, X_test, y_train, y_test = train_test_split(
     X, y, test_size=0.3, random_state=0)
    # 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_featur
es, 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!
```

Question 4

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

Answer:We split the data into training and testing subsets to estimate the performance of our model on two independent data sets and also to have a check on overfitting and underfitting of the model.

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 (http://scikit-learn.org/stable/modules/classes.html#sklearn-metrics-metrics) 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 if the `performance_metric` function is working if the statement *"Successfully performed a metric calculation!"* is printed.

In [27]:

```
# Put any import statements you need for this code block here
from sklearn.metrics import mean_squared_error
#from sklearn.metrics import mean_absolute_error

def performance_metric(y_true, y_predict):
    """ Calculates and returns the total error between true and predicte
d 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!
```

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: This is a regression problem and MSE has more statistical advantage than MAE. So Mean Squared Error(MSE) would be the most appropriate performance matric in this case. May be I should have said mathematical advantage rather than statistical. But the advantages of MSE would be: 1) MSE emphasizes larger errors rather than smaller errors. 2) It's differentiable from calculus standpoint, allowing to find min and max values. 3) Squaring function converts all values automatically into positives there by allowing to derive the mean.

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 (http://scikit-learn.org/stable/modules/generated/sklearn.metrics.make_scorer.html).
- Build a GridSearchCV object using `regressor`, `parameters`, and `scoring_function`. See the sklearn documentation on GridSearchCV (http://scikit-learn.org/stable/modules/generated/sklearn.grid_search.GridSearchCV.html).

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 if the `fit_model` function is working if the statement *"Successfully fit a model to the data!"* is printed.

```
In [28]: # 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(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


         # 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!
```

Question 5

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

Answer:Grid search is a method of hyperparameter optimization which exhaustively searches through manually specified grid of parameter values and evaluates a model for each combination of parameters specified in a grid. It is applicable when selecting the best among the set of competing models.

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 that assesses how well can the model generalize to an independent dataset. It involves partitioning of data into complementary subsets: training and test datasets. Training dataset is used to perform analysis as well as build the model, and the test dataset is used to validate the model (built on training). Specifically in k-fold cross validation, the dataset is randomly partitioned into k equal sized subsets. Of the k subsets, a single subset is retained as the validation/test dataset for testing the model, and the remaining k − 1 subsets are used together as a training dataset. The cross-validation process is then repeated k times (k folds), making each of the k subsets once as the validation dataset. When using grid search, cross validation helps to identify and eliminate the model that overfits or underfits. Grid search works through combinations of given parameters, and for each combination it cross validates the model using k fold technique and selects the model with best performance. For example, if there were 4 different combintations of parameters, thus forming 4 different models, Grid Search with CV would perform k fold validation on for all 4 models and choose the one that has the least average error.

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 [29]:

```
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 plo
tted. """

    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 si
zes
    sizes = np.round(np.linspace(1, len(X_train), 50))
    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 w
ith 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.pre
dict(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', fontsi
ze=18, y=1.03)
    fig.tight_layout()
    fig.show()
```

In [30]:

```
def model_complexity(X_train, y_train, X_test, y_test):
    """ Calculates the performance of the model as model complexity incr
eases.
        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_t
rain))

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

    # 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()
```

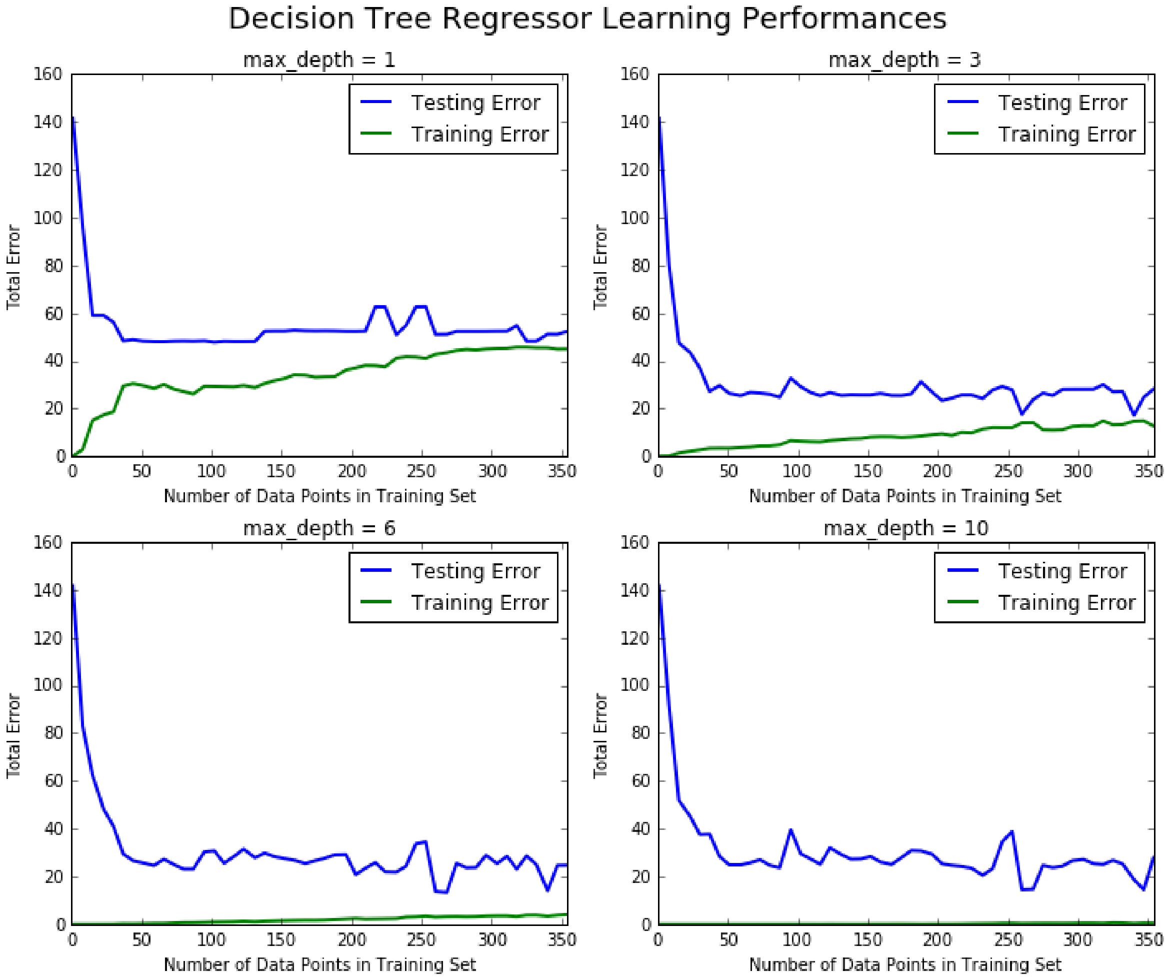
Analyzing Model Performance

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)
```

```
C:\Anaconda2\lib\site-packages\ipykernel\__main__.py:24: DeprecationWar
ning: using a non-integer number instead of an integer will result in a
n error in the future
C:\Anaconda2\lib\site-packages\ipykernel\__main__.py:27: DeprecationWar
ning: using a non-integer number instead of an integer will result in a
n error in the future
C:\Anaconda2\lib\site-packages\matplotlib\figure.py:397: UserWarning: m
atplotlib is currently using a non-GUI backend, so cannot show the figu
re
  "matplotlib is currently using a non-GUI backend, "

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



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: Learning curve graph 1: Max depth for the chosen model is 1 and it is highly biased; hence both training and testing errors remain high even with more training data. With fewer data points (far left on x-axis) there's less variance to accommodate, so the training error remains low (even though the model is highly biased); but testing error high, since the model (built from fewer training data) does not generalize well on unseen test data points. As the number of data points in training set increase, training error grows because the model fails to accommodate more data points (underfitting), however the testing error decreases because the model starts to generalize better (than the model built from fewer data). After some point in training data size increase, both training and testing errors start to come closer and performance (on both training and testing) ends up being similar (but poor). Any further increase in training set (far right on x-axis) ceases to have any effect on testing because the model just fails to fit new data points.

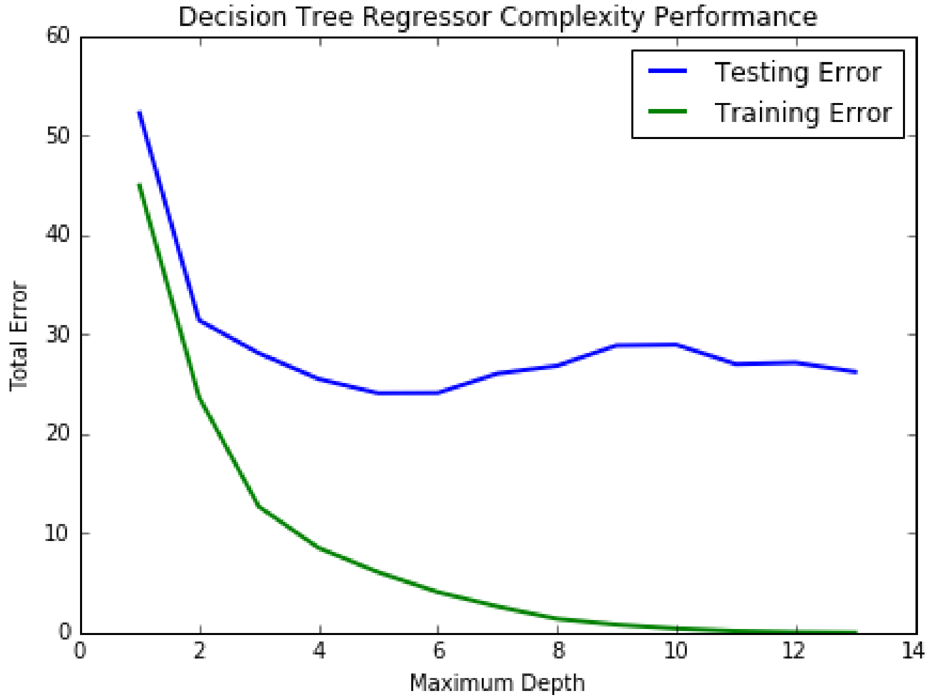
Question 8

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: With full training set, when the max depth is 1: model suffers from high bias (underfitting). And when max depth is 10: model suffers from high variance (overfitting). For the "max depth 1", training and testing curves start to converge into a high error area as the training set size increases. This indicates that the model underfits and is making more training errors as data points increase. Thus at some point on the farther right of the x-axis, training error increases all the way so as to converge into testing. For the "max depth 10", low training error is the result of overfitting i.e. the model tries to fit every possible data point, thus keeping training error very low. But the same model does not generalize well on testing data and makes large errors indicating high testing curves. This results in a large gap between the low training error and high testing error curves.

```
In [32]: model_complexity(X_train, y_train, X_test, y_test)
```

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



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: Initially as Max Depth increases, Total Error decreases for both Training and Testing datasets. However, further increase in Max Depth would not decrease Total Error for Testing dataset after it attains the best fit at some point; although the Total Error for Training could further decrease. As Max Depth increases, the decrease in the Training error towards zero but not in Testing shows overfitting of the data. Max Depth value ~ 4 results in a model that best generalizes the dataset because further increase in Max Depth overfits training data and does not help generalize any further. We can see from the graph that training error continues to drop with the increase in max depth, but test error does not decrease after max depth 4. This shows that models with higher complexity than Max Depth ~ 4 do not generalize any better and they start to overfit training data. Hence the model for Max Depth ~ 4 is optimal.

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`. *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.*

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 optimal parameters:", reg.best_params_
```

```
Final model optimal parameters: {'max_depth': 4}
```

Answer:Optimal max_depth parameter for my model is 4,which is one of the values in my initial intuition.

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: 21.630
```

Answer: Best selling price for client's home would be 21.63(in $1000's) which is almost same as the median value and mean value the dataset.

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:Here are some of the things I would do, 1.Although most of the features from the model seem important, I would do a little bit more research on the Boston housing market and possibly get other important features in my model. 2.I would model this data using other algorithms and compare the models for better prediction/fit. 3.I would try to get more data if possible about Boston Housing market.Beacause an avarage algorithm does better on more data than a better algorithm on fewer/less data.