boston_housing

March 30, 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 [1]: # 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 [2]:
```
# Number of houses in the dataset
total_houses = np.array(city_data.data).shape[0]

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

# Minimum housing value in the dataset
minimum_price = np.amin(np.array(city_data.target), axis=0)

# Maximum housing value in the dataset
maximum_price = np.amax(np.array(city_data.target), axis=0)

# Mean house value of the dataset
mean_price = np.mean(np.array(city_data.target), axis=0)

# Median house value of the dataset
median_price = np.median(np.array(city_data.target), axis=0)

# Standard deviation of housing values of the dataset
std_dev = np.std(np.array(city_data.target), axis=0)

# 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: - **CRIM** It measures how much safe of the location and it is one of most important concern when people buying a house - **DIS** It measures how much convinient for owner to commute which is another important considerations when people buying a house - **TAX** The property tax is totally depended on property value

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 [3]: 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 DIS = 1.385 TAX = 680

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

```
In [4]: # Put any import statements you need for this code block here
        import random
        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. """

            X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=42)

            # 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: We need to evaluate the performace of our model and then we can decide wheather we should use the model or not. We split the data into traning and testing because if we test the prediction on training data is like knowing the answer before test so it will not reflect the real situation when predicting real world data. e.g. If we test agaist training data, the error will always small and we won't know if the model is overfiting or underfitting.

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 if the `performance_metric` function is working if the statement *"Successfully performed a metric calculation!"* is printed.

```
In [5]: # 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*, *F1 Score* are for classification which the outputs are discrete labels. *Mean Squared Error (MSE)* and *Mean Absolute Error (MAE)* are for regression which the outputs are continous values. So for our prices prediction problem, we should choose from MSE and MAE. MSE has better performance here so I will choose MSE.

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

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

        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 = grid_search.GridSearchCV(regressor, parameters, scoring=scoring_function, cv=20)

            # 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
    try:
        reg = fit_model(X_train, y_train)
        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 is a algorithm that test parameters in the paramter space one by one and select the optimal paramters based on performance metric.

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 that we split the training data again into two parts. One part is for trainning and the other part is used for testing because we can not use test data when training the model. Cross-validation can performed in many ways: e.g. randomly select N% of tranining data as test data or k-fold cross validation which equally divide data into serveral fold and use one fold as test data and the remaining folds as trainning data.
And we can repeat with different fold data as test data. The cross-validation is helpful for grid search because cross-validation can evaluate a model's perfromance without using test data to avoid cheating, overfit and make the performence metric more generalized. Here I choose 20-fold cross validation as smaller k leads to high bias while larger k leads to high computation time. And usually 10 fold is enough for cross validation. This data is realatively small, so 20 fold cross validation won't take too much computation time and has smaller bias.

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 [7]: 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.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 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 [8]:
```
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()
```

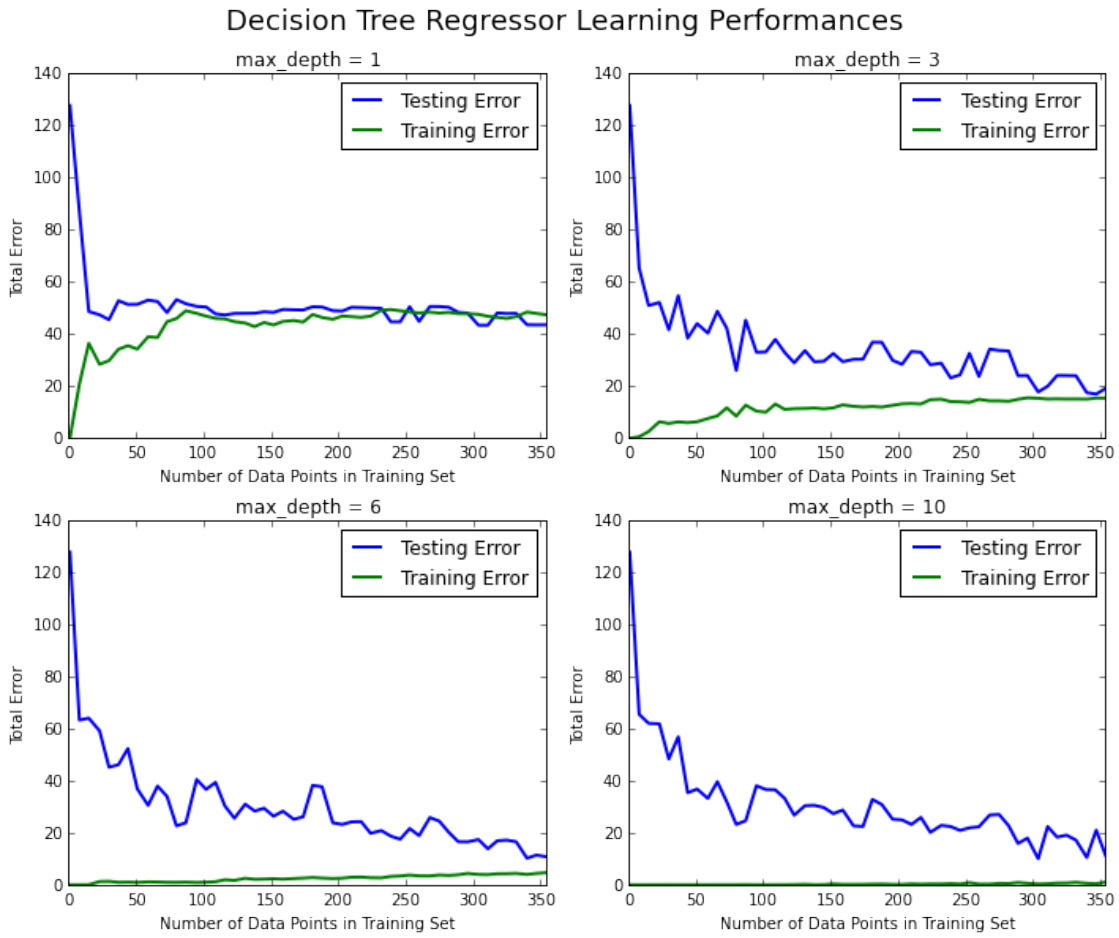
6 Analyzing Model Performance

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

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

```
/Users/Alice/anaconda/lib/python2.7/site-packages/matplotlib/figure.py:387: UserWarning: matplotlib is c
  "matplotlib is currently using a non-GUI backend, "
```



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: I will choose the top right graph, the max depth is 3. As the trainning set increase, first the trainning error increases and the testing error decreases dramatically and then trainning error keep increasing and testing error keep increasing with noticable pertubations and in the end, the two errors seems converge and stable.

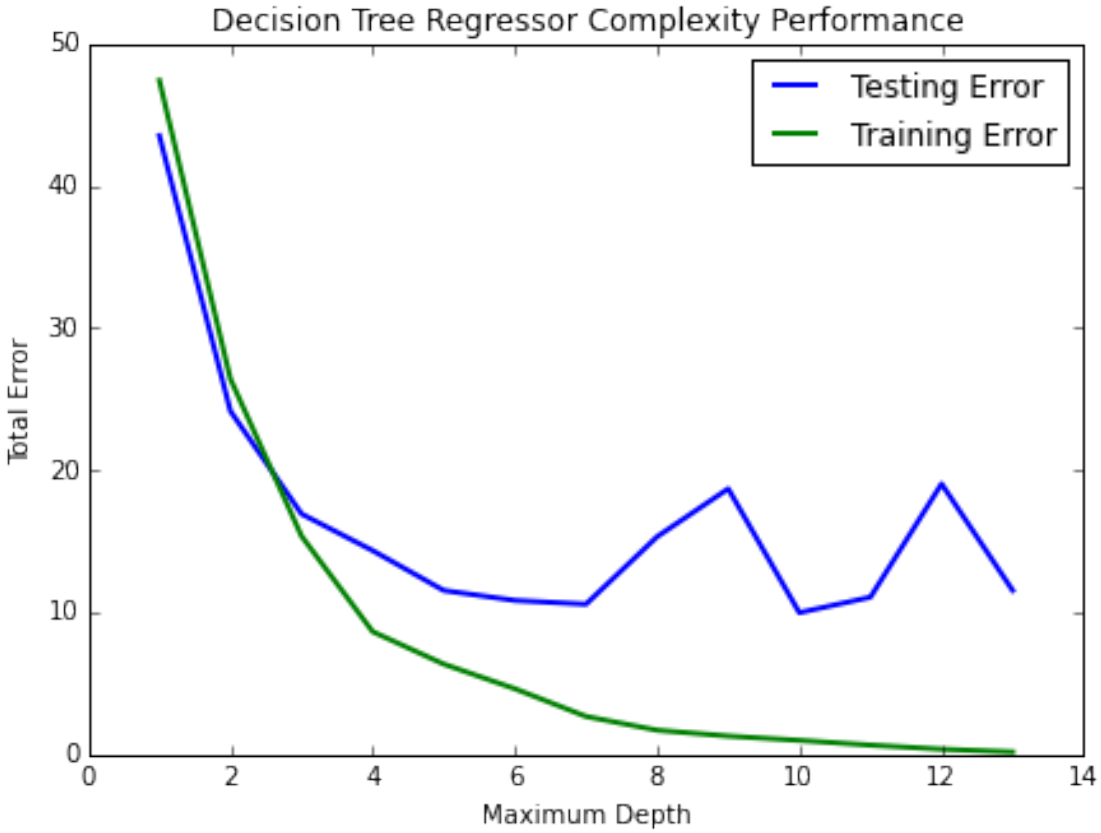
6.2 Question 8

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: When the model is using the full training set and the max depth is 1, the testing error shows high bias and low varaince as it looks very stable and the curve is very falt both the trainning error and testing are constantly high. In contrast, the model with max depth of 10 shows very low bias as the traning error is almost zero, but the testing error is still very high, so there is very large difference between traning error and testing error which indicate high variance.

```
In [10]: 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 keep decreasing untill reach zero. However testing errors decreasing dramatically first but stays at a level after a max depth of 8 and the gap between the tranning error and testing error are increasing which may cause high variance. So the max depath of 8 is the one that beast generlizes the dataset.

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`. *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, 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 [11]: print "Final model optimal parameters:", reg.best_params_
```

```
Final model optimal parameters: {'max_depth': 10}
```

Answer: The result is close to my analysis in Question 9.

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 [12]: 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: 21.519
```

Answer: I think the best selling price for your client's home is 21.519. The result is close to mean and median and within the range between min and max. So it is a reasonable prediction.

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, definitely I would use the prediction price. The prediction may not be very precise, but it can narrow down the price to a reasonable range for clients' home and avoid clients selling their houses in a underevaluate price. besides of using the prediction price, I will track on how well prediction can help clients sell their home. And I will also try improving the model by taking more data in.

```
In [ ]:
```

```
In [ ]:
```