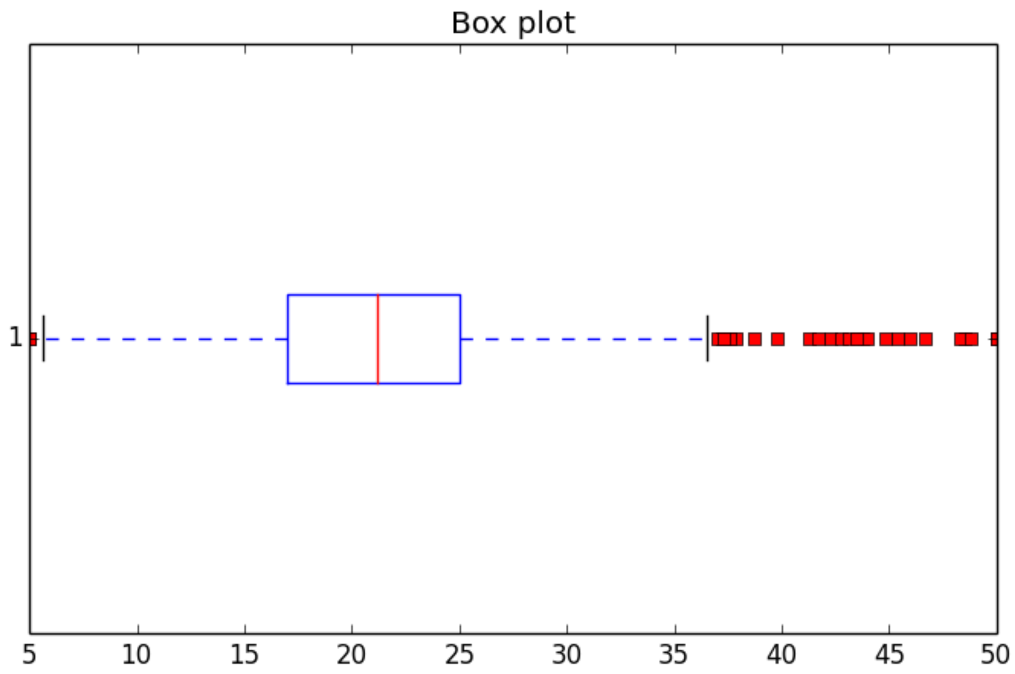
Predicting Boston Housing Prices

Questions

1) Statistical Analysis and Data Exploration

- Number of data points (houses)?
  - 506
- Number of features?
  - 13
- Minimum and maximum housing prices?
  - Min 5.0 -> Max 50.0
- Mean and median Boston housing prices?
  - Mean: 22.532806324
  - Median: 21.2
- Standard deviation?
  - 9.18801154528



2) Evaluating Model Performance

- Which measure of model performance is best to use for predicting Boston housing data and analyzing the errors?
  - For this type of data and regression I believe the mean squared error to be the most appropriate measure of the error.
- Why do you think this measurement most appropriate?
  - Mean squared error is best suited for discrete data like the one we are using here.[1]
  - Mean squared error is more “strict” by assigning little weight to small errors (the square of a very small number is an even smaller number) and assigning a large weight to large errors.
  - Similar to standard deviations, by squaring, negative errors are added instead of subtracted.
- Why might the other measurements not be appropriate here?
  - Because we are dealing with a regression, we can discard all the Classification, Ranking and Clustering metrics.
  - Inside the regression metrics we can choose from:
    - Mean Absolute Error
      - It is vulnerable to negative errors as these are subtracted
      - It is better suited for continuous variables[2]
      - Has no “penalization” for large errors
      - Despite this, it is a viable metric, just not the ideal.
    - R2 Score
      - It does incorporate a squaring that deals with negative values and large error penalization, making it a good candidate.
      - On the other hand, it is a little more complex than Mean squared error, being that the MSE is a good measure, we go with Occam's razor and choose the less complex option.
- Why is it important to split the Boston housing data into training and testing data?
  - Thanks to this split we can train the model and test how good it is against data we already have.
- What happens if you do not do this?
  - We would need to “trust” our model without testing and wait until new data is available to determine if the model is adequate for the data.

[1] http://worldofpiggy.com/squared-or-absolute-how-different-error-can-be/

[2] http://www.eumetcal.org/resources/ukmeteocal/verification/www/english/msg/ver_cont_var/uos3/uos3_ko1.htm

- What does grid search do and why might you want to use it?
    - Grid search takes care of testing different parameters in order to exhaustively determine what is the best combination of parameters for the model based on the provided performance metric.[3]
- Why is cross validation useful and why might we use it with grid search?
    - Cross validation is useful because it allows us to test how well the model will perform against "unknown data" using know results.
    - Grid search is performed against a "cross validated" performance metric, providing the best, tested, result.

3) Analyzing Model Performance

- Look at all learning curve graphs provided. What is the general trend of training and testing error as training size increases?
    - At the start, as the training size increases the train error decreases.
    - On the training side, more training data means an increase in training error.
    - Both trends seem to "slow down" until both training error and test error converge into a value (a different value for training and test).
    - After this convergence, increasing the training size has no meaningful effect.
- Look at the learning curves for the decision tree regressor with max depth 1 and 10 (first and last learning curve graphs). When the model is fully trained does it suffer from either high bias/underfitting or high variance/overfitting?
    - Depth 1:
        - There is evidence of underfitting as there is a high error for both training and test. This indicates the model does not really generalize the data.
    - Depth 10:
        - It is very clear that the model is "overfitting". We can see this because there is practically zero error with the training data, but as soon as we go to test data, we have a much higher error measurement.[4]

[3] https://en.wikipedia.org/wiki/Hyperparameter_optimization

[4] http://www.autonlab.org/tutorials/overfit10.pdf

- Look at the model complexity graph. How do the training and test error relate to increasing model complexity?
    - As the complexity increases, the test error decreases, showing a clear inverse proportionality. This happens until increasing the complexity has no good effect on the test error.
- Based on this relationship, which model (max depth) best generalizes the dataset and why?
    - After a depth of 4-5, increasing the complexity does not seem to impact the performance positively. In fact, increasing the complexity can make the error worse.

4) Model Prediction

- Model makes predicted housing price with detailed model parameters (max depth) reported using grid search. Note due to the small randomization of the code it is recommended to run the program several times to identify the most common/reasonable price/model complexity.
    - Run 1: max_depth=4 -> Prediction: [21.62974359]
    - Run 2: max_depth=4 -> Prediction: [21.62974359]
    - Run 3: max_depth=6 -> Prediction: [20.76598639]
    - Run 4: max_depth=4 -> Prediction: [21.62974359]
    - Run 5: max_depth=6 -> Prediction: [20.76598639]
    - Run 6: max_depth=4 -> Prediction: [21.62974359]
    - After multiple runs it seems clear that the final results are:
        - Max Depth: 4
        - Predicted Price: 21.62974359
- Compare prediction to earlier statistics and make a case if you think it is a valid model.
    - 21.62974359 is less than one standard deviation from the mean and median.
    - 21.62974359 is within the minimum (5) and maximum (50) range of the data.