Predicting Boston Housing Prices

Requires Changes

7 SPECIFICATIONS REQUIRE CHANGES

Great work as a first submission..!!

You have understood most of the concepts well. There are still a few misconceptions that still need some clarity and hence I urge you to dive deeper. Read the materials that I have provided and soon you will have clarity. Keep up the good work. 😃

Thanks and do rate my review.

Happy Learning..!!

Data Exploration

All requested statistics for the Boston Housing dataset are accurately calculated.
Student correctly leverages NumPy functionality to obtain these results.

You are correct in a sense, but you need to implement the code in NumPy. 😃

We urge students to use NumPy because it is fast and works well with matrices.

Here is an example:

```
import numpy as np
a = [1,2,3,4,5,6]
minimum = np.min(a)
```

Student correctly justifies how each feature correlates with an increase or decrease in the target variable.

Wow..!! You understand the features and their relationships well. 😃

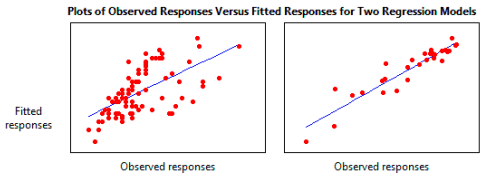
Developing a Model

Student correctly identifies whether the hypothetical model successfully captures the variation of the target variable based on the model's R^2 score.
The performance metric is correctly implemented in code.

You are in the right direction here..!! But what I really want from you is an explanation of how R^2 score is a measure of goodness of fit. Think about the distance between the actual point (Y) and the predicted point (Y') on the regression line.

Here is something that should help you gain intuition on how R^2 score is a measure of goodness of fit:

Plotting fitted values by observed values graphically illustrates different R-squared values for regression models.



The regression model on the left accounts for 38.0% of the variance while the one on the right accounts for 87.4%. The more variance that is accounted for by the regression model the closer the data points will fall to the fitted regression line. Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line.

Some more info for you to dive deeper: link

Student provides a valid reason for why a dataset is split into training and testing subsets for a model. Training and testing split is correctly implemented in code.

Here I want you to explain how the test set helps prevent overfitting and underfitting. We could have used a part of train data to test our model right? But we didn't. Why?

Here are a few additional points that should help you gain some intuition:

- Suppose you use all your data for training. What do you think will happen in this scenario?
- Your model might overfit or underfit or it might be a good fit as well. If your model is underfitting you will know that from your train scores (which will be low). But if your model is overfitting, your train scores will be high. By first look it would seem you have done a great job in training, but most probably you have not. It is only after you test your model with the test set that you will know the real performance of your model. Using part of train set to test will always give good results if you are getting good train score (since your model is biased towards that data)
- That's why you always need a test set. But while training you cannot use your test set performance to improve your model, because that would make your model biased towards the test set. Hence you need to do cross-validation.

Further let me define the concepts of underfitting, overfitting and the concept of being a good fit:

- UNDERFITTING: In this scenario, the model is not able to learn from the training (it is too simple) and hence it doesnot perform well on the test set (it wont perform well on train data as well).
- OVERFITTING: In this scenario, the model is over-complex and is trying to just memorize the train data, hence it doesnot generalize well on the test data.
- GOOD FIT: In this scenario, the model is neither too simple nor too complex, it is able to learn from the training data and hence it generalizes well to test data as well.

If you further want to know why we split our data, here is a good explanation: link

Analyzing Model Performance

Student correctly identifies the trend of both the training and testing curves from the graph as more training points are added. Discussion is made as to whether additional training points would benefit the model.

Good work..!! You understand how to check the performance of a model using learning curves. 😃

Here is another blog that explains learning curves in depth: link

Student correctly identifies whether the model at a max depth of 1 and a max depth of 10 suffer from either high bias or high variance, with justification using the complexity curves graph.

Here I want you to answer two more questions:

- What visual cues from graph made you believe that `max_depth=1` has high bias?
- `max_depth=10` has high bias or high variance? What visual cues from graph made you believe that?

Bias-variance tradeoff is a very important concept in machine learning and hence I urge you to dive deeper.

Here is some more info on bias-variance tradeoff:

Types of learning curves

- Bad Learning Curve: High Bias
  - When training and testing errors converge and are high
    - No matter how much data we feed the model, the model cannot represent the underlying relationship and has high systematic errors
    - Poor fit
    - Poor generalization
- Bad Learning Curve: High Variance
  - When there is a large gap between the errors
    - Require data to improve
    - Can simplify the model with fewer or less complex features
- Ideal Learning Curve
  - Model that generalizes to new data
  - Testing and training learning curves converge at similar values
  - Smaller the gap, the better our model generalizes

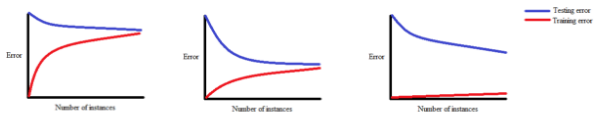


Image #1 (high bias) Image #2 (ideal) Image #3 (high variance)

Some more info for you to dive deeper: link

Student picks a best-guess optimal model with reasonable justification using the model complexity graph.

Wow..!! Even I believe the same. 😃

Evaluating Model Performance

Student correctly describes the grid search technique and how it can be applied to a learning algorithm.

Here I want you to explain your points a little bit more:

- What are the inputs to a gridSearch?
- What is the output?
- Do we need a performance metric to find the best hyper-parameter?
- What does the grid signify in a gridSearch?

Here are a few points on gridSearch that should help you answer these questions:

- It is an algorithm with the help of which we can tune hyper-parameters of a model. We pass the hyper-parameters to tune, the possible values for each hyper-parameter and a performance metric as input to the grid search algorithm. The algorithm will then place all the possible hyper-parameter combination in a grid and then find the performance of the model for each combination against some cross-validation set. Then it outputs the hyper-parameter combination that gives the best result.

Here is the official sklearn page on gridSearch: link

Here is another great answer on how gridSearch works: link

Student correctly describes the k-fold cross-validation technique and discusses the benefits of its application when used with grid search when optimizing a model.

There is a slight misconception in your answer here:

- k-fold cross-validation is technique where, the data is split in to k-buckets and then training happens on these buckets k-times. Each time, we choose one of the buckets as our testing set.

We donot apply k-fold on the whole dataset. Instead we first split our data into train and test and then apply k-fold on the train dataset. This is how cross-validation works. Now after this step we train our model on (k-1) folds and use 1 fold for cross-validation. This process is repeated k times, each time with a different cross-validation set. The average cross-validation score is used to check the performance of the model. Once you have selected the best parameters using gridSearch along with k-fold cross-validation, we will use the test set to check the final performance of the model.

Here are a few more points on k-fold that should help you gain the intuition:

- There is a `huge` difference between `testing` and `cross-validation`.

- K-fold is a cross-validation technique and not a testing technique.
- Suppose you use all your data for training. What do you think will happen in this scenario?
- Your model might overfit or underfit or it might be a good fit as well. If your model is underfitting you will know that from your train scores (which will be low). But if your model is overfitting, your train scores will be high. By first look it would seem you have done a great job in training, but most probably you have not. It is only after you test your model with the test set that you will know the real performance of your model. Using part of train set to test will always give good results if you are getting good train score (since your model is biased towards that data)
- That's why you always need a test set. But while training you cannot use your test set performance to improve your model, because that would make your model biased towards the test set. Hence you need to do cross-validation.
- Using normal cross-validation also has its disadvantages, since you use up a part of your training data. Hence, here k-fold comes to the rescue.

Here is some more info on k-fold CV: link

You can check the difference between cross-validation and testing here: link

Student correctly implements the `fit_model` function in code.

Good implementation..!! 😃

Student reports the optimal model and compares this model to the one they chose earlier.

Correct..!! 😃

Student reports the predicted selling price for the three clients listed in the provided table. Discussion is made for each of the three predictions as to whether these prices are reasonable given the data and the earlier calculated descriptive statistics.

Here I want you to explain the predictions for each of the client one by one. 😃

The main idea here is to explain your predictions to a person who has not seen the data or doesnot know what features you have selected to reach these predictions.

You can follow the below steps to answer this question:

- First try to compare the predictions to the descriptive statistics that you calculated in first TODO (min, max, mean etc.)
- Then compare the predictions for each client with each other.
- Finally dive deeper into the features for each client and then justify if the prices are reasonable.

Student thoroughly discusses whether the model should or should not be used in a real-world setting.

Great discussion..!! I agree with your points. 😃

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Student FAQ