UDACITY

PROJECT

Predicting Boston Housing Prices

A part of the Machine Learning Engineer Nanodegree Program

PROJECT REVIEW

CODE REVIEW

NOTES

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Meets Specifications

Excellent, you nailed it!
👏👏👏

Awesome work you did there, advancing steadily with each submission, you should be really proud!

You have shown a firm grasp of the concepts presented here and are good to go.

Keep going and good luck!
Paul

PS. If you have further questions remember your have many communication channels with the Udacity support team.

You can find me on Slack as `@viadanna`

Data Exploration

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

Good job calculating statistics, this exploration is very important as a starting point to understand the dataset.

Using `numpy` is recommended as it's a very fast and efficient library commonly used in machine learning projects. Check this reference on statistical functions included.

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

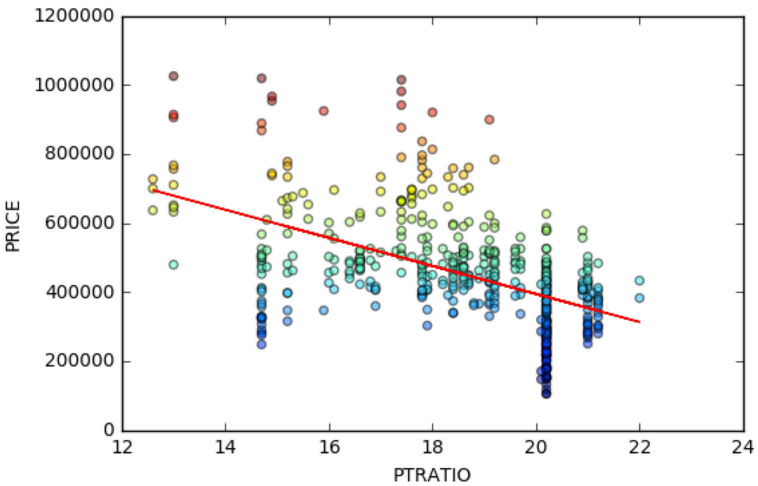
Excellent intuition on the correlation between MEDV and the features.

This intuition is essential in machine learning projects to evaluate if results are reasonable.

Excellent exploration of the features, you can improve it by plotting a linear regression.

```
from sklearn.linear_model import LinearRegression

reg = LinearRegression()
pt_ratio = data['PTRATIO'].reshape(-1, 1)
reg.fit(pt_ratio, prices)
plt.plot(pt_ratio, reg.predict(pt_ratio), color='red', linewidth=1)
plt.scatter(pt_ratio, prices ,alpha=0.5, c=prices)
plt.xlabel('PTRATIO')
plt.ylabel('PRICE')
plt.show()
```



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.

Nice answer!

Metrics like this are important since the datasets found on Machine Learning projects rarely can be evaluated visually as this example.

A correlation coefficient (R2) of 0.923 mean 92.3% of the variation of the dependent variable can be explained by the model.

It is possible to plot the values to get a visual representation in this scenario:

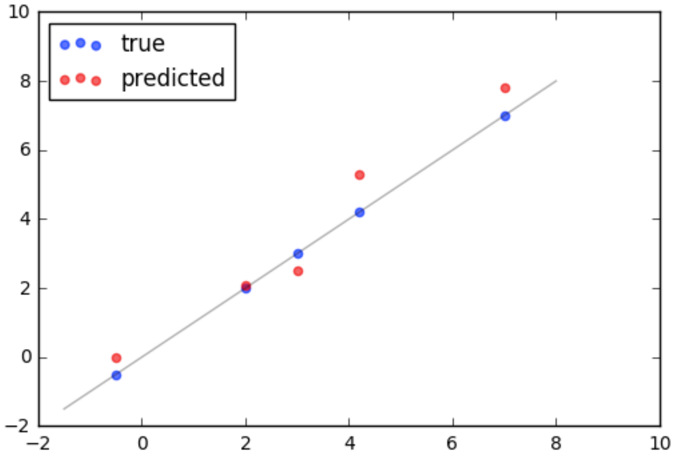
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

true, pred = [3, -0.5, 2, 7, 4.2], [2.5, 0.0, 2.1, 7.8, 5.3]
# Plot true values
true_handle = plt.scatter(true, true, alpha=0.6, color='blue', label='true')

# Reference line
fit = np.poly1d(np.polyfit(true, true, 1))
lims = np.linspace(min(true) - 1, max(true) + 1)
plt.plot(lims, fit(lims), alpha=0.3, color='black')

# Plot predicted values
pred_handle = plt.scatter(true, pred, alpha=0.6, color='red', label='predicted')

# Legend and show
plt.legend(handles=[true_handle, pred_handle], loc='upper left')
plt.show()
```



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.

Good job!

It's really important to have an independent dataset to validate a model and identify its ability to generalize predictions.

Check out this article for an interesting further reading on this subject.

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 job!

There's really no benefit in increasing the size of training dataset further, as it won't improve the validation scores, it would just increase the time needed to train the model.

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.

Nice answer, you correctly identified high bias and high variance.

In short, high bias means the model isn't complex enough to learn the patterns in the data, resulting in low performance on both the training and validation datasets.

On the other hand, high variance means the model starts to learn random noise, losing its capacity to generalize previously unseen data, resulting in a very high training score but low testing score.

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

It's a close call, I'd choose the curve for `max_depth = 4` for the highest validation score.

One argument for `max_depth = 3` would be Occam's Razor which applied here basically means that for two or more equivalent answers, the simplest one is the correct one, but its validation score is smaller.

Let me explain what's going on here: `max_depth = 3` has lower variance, as the curves are closer. But it also has more bias than `max_depth = 4` as both scores are lower. So in this case, I would accept more variance and less bias to get a better performing model, as shown by the highest validation score.

Evaluating Model Performance

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

Excellent description of GridSearch, actually exceeding requirements by also describring RandomSearch! 👍

In short, GridSearch exhaustively searches for a combination of hyperparameters resulting in a model with the best performance.

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.

Excellent description of the k-fold technique!

I like to describe the benefit of this technique as being able to use the training set as multiple training and validation sets, preventing biases on the dataset from skewing the observed performance and causing GridSearch to return a model that's optimal for a subset of the dataset.

You can check some alternatives available in sklearn here.

Student correctly implements the `fit_model` function in code.

Excellent implementation 👍

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

That's alright, check my comments on Question 6.

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.

Good job using the features and statistics here!

You just missed your answer saying if the prices are reasonable, as required on:

> Do these prices seem reasonable given the values for the respective features?

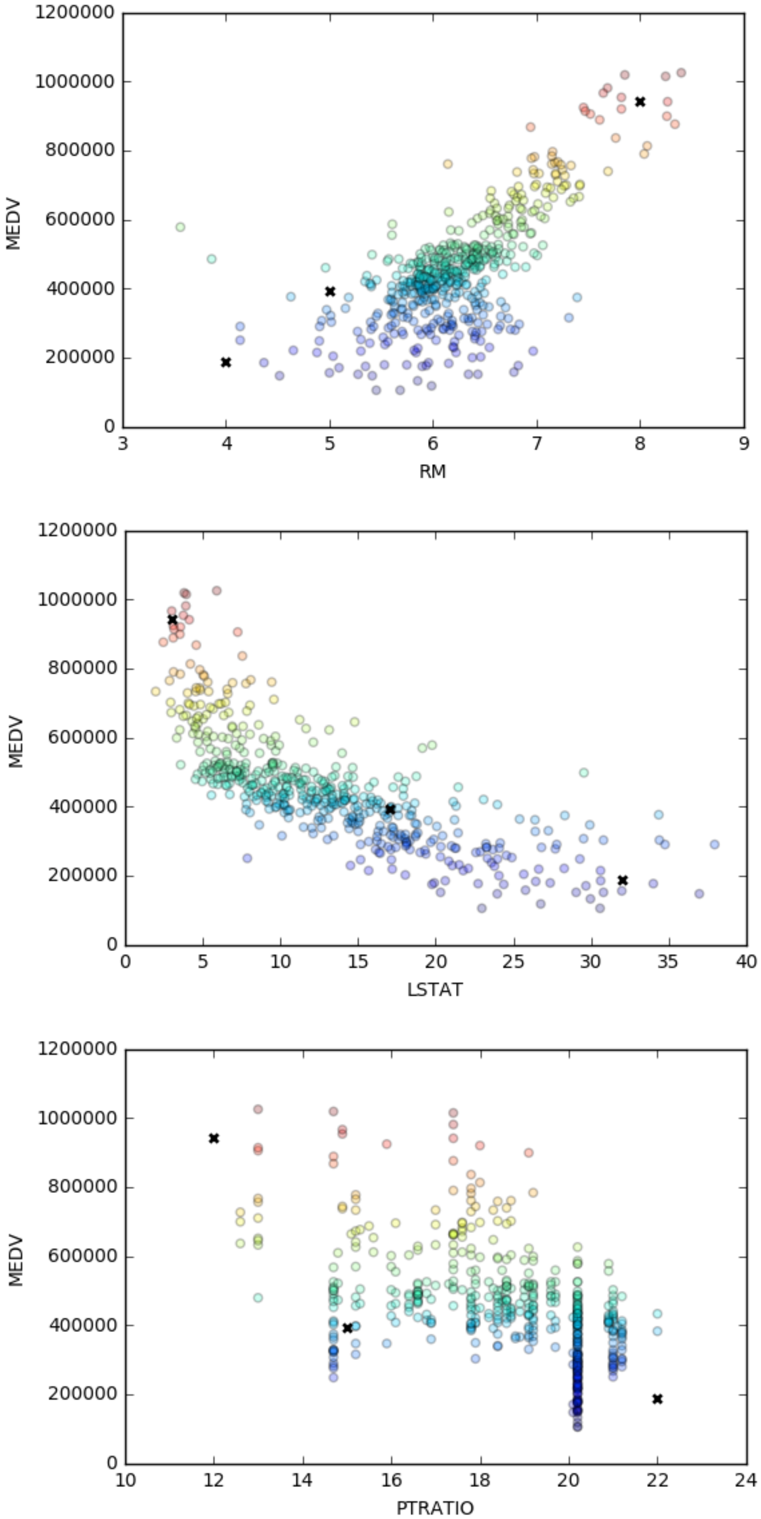
I can infer your answer by the prices you suggested and won't hold you here just for this, as you have shown a firm grasp of the concepts presented.

Just remember to always explicitly answer the questions proposed.

You could also plot the client data against the dataset to get a better view of their features for your justification:

```
from matplotlib import pyplot as plt

clients = np.transpose(client_data)
pred = reg.predict(client_data)
for i, feat in enumerate(['RM', 'LSTAT', 'PTRATIO']):
    plt.scatter(features[feat], prices, alpha=0.25, c=prices)
    plt.scatter(clients[i], pred, color='black', marker='x', linewidths=2)
    plt.xlabel(feat)
    plt.ylabel('MEDV')
    plt.show()
```



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

You have good arguments that show this model shouldn't be trusted in a real-world setting, lacking robustness, features and updated data.

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