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

Very nice adjustments here, check out the corresponding sections for even more insight! If the rest of your projects are on this level, this program will be a breeze. Wish you the best of luck throughout this program!

Data Exploration

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

Good job utilizing the power of Numpy!! Always important to get a basic understanding of our dataset before diving in. As we now know that a "dumb" classifier that only predicts the mean would predict $454,342.94 for all houses.

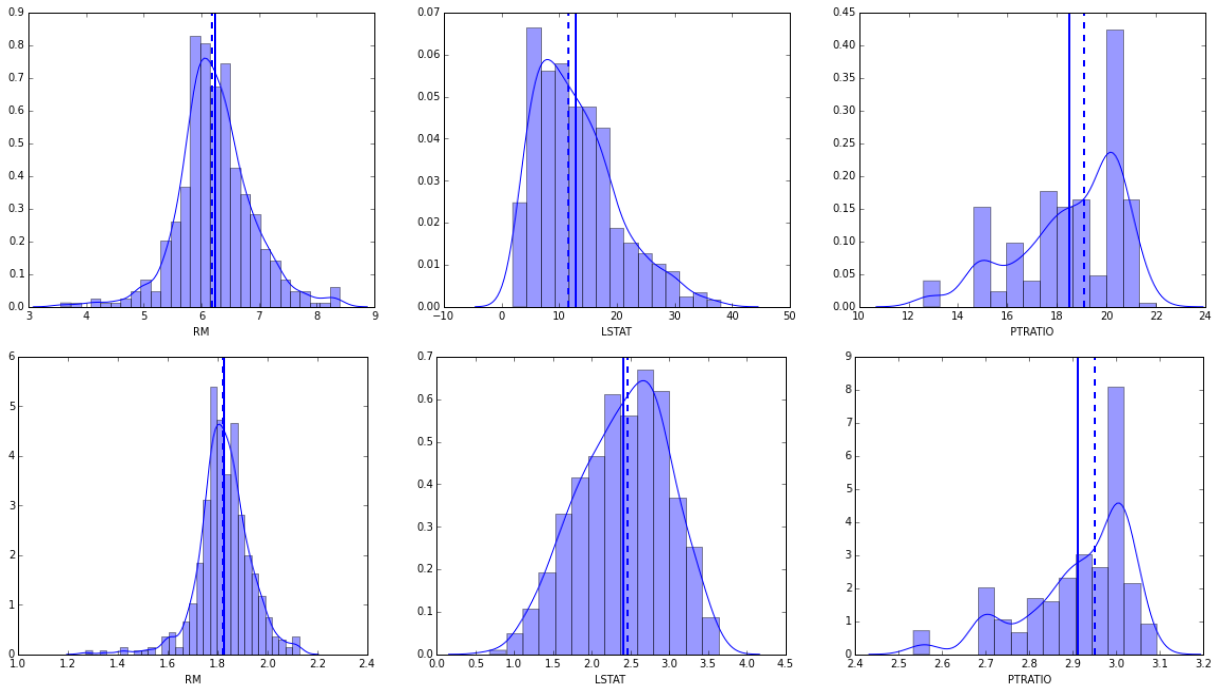
Student correctly justifies how each feature correlates with an increase or decrease in the target variable.

Typically, in machine learning we desire to have our features to be Gaussian distributed. Therefore, could also plot histograms. Do we need any feature transformations? Maybe a log transformation could be ideal.

```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(20, 5))

# original data
for i, col in enumerate(features.columns):
    plt.subplot(131 + i)
    sns.distplot(data[col])
    plt.axvline(data[col].mean(), linestyle='solid', linewidth=2)
    plt.axvline(data[col].median(), linestyle='dashed', linewidth=2)

# plot the log transformed data
plt.figure(figsize=(20, 5))
for i, col in enumerate(features.columns):
    plt.subplot(131 + i)
    sns.distplot(np.log(data[col]))
    plt.axvline(np.log(data[col]).mean(), linestyle='solid', linewidth=2)
    plt.axvline(np.log(data[col]).median(), linestyle='dashed', linewidth=
2)
```



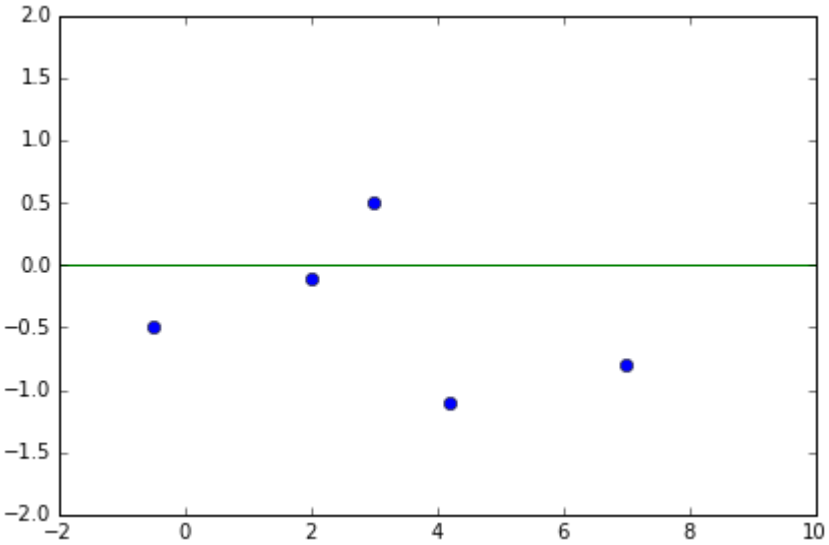
Developing a Model

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.

Another interesting thing to check out for regression problems would be a residual plot. A residual plot is a graph that shows the residuals on the vertical axis and the independent variable on the horizontal axis. If the

points in a residual plot are randomly dispersed around the horizontal axis, a linear regression model is appropriate for the data; otherwise, a non-linear model is more appropriate.

```
import matplotlib.pyplot as plt
trueValues = [3, -0.5, 2, 7, 4.2]
predictions = [2.5, 0.0, 2.1, 7.8, 5.3]
residuals = [i - j for i, j in zip(trueValues, predictions)]
plt.plot(trueValues, residuals, 'o',[-2,10], [0,0], '-')
plt.ylim(-2, 2)
plt.tight_layout()
```



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.

Great ideas. You have captured the need of a testing set for evaluation of our model. The purpose and benefit of having training and testing subsets from a dataset is the opportunity to quantify the model performance on an independent dataset and to check for overfitting. Evaluating and measuring the performance of the model over the testing subset provides estimations of the metrics that reflect how good the model predictions will be when the model is used to estimate the output using independent data (that was not used by a learning algorithm when the model was being tuned). If there is no testing subset available, there would be no way to estimate the performance of the model.

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.

To go into a bit more detail in terms of the training and testing curves for a depth of 3

- Analysis of the training score curve: for a very small number of training points, training score is 1, or close. This happens due to model overfitting. As more training points are added, training score drops because the model cannot explain all the variance anymore. It converges to a value close to 0.8.
- Analysis of the testing score curve: for a very small number of training points, testing score is 0, or close. This happens due to model overfitting (decision tree model explains well a few points but doesn't generalizes well). As more training points are added, testing score increases rapidly and converges to a value also close to 0.8. The model seems to generalize well.

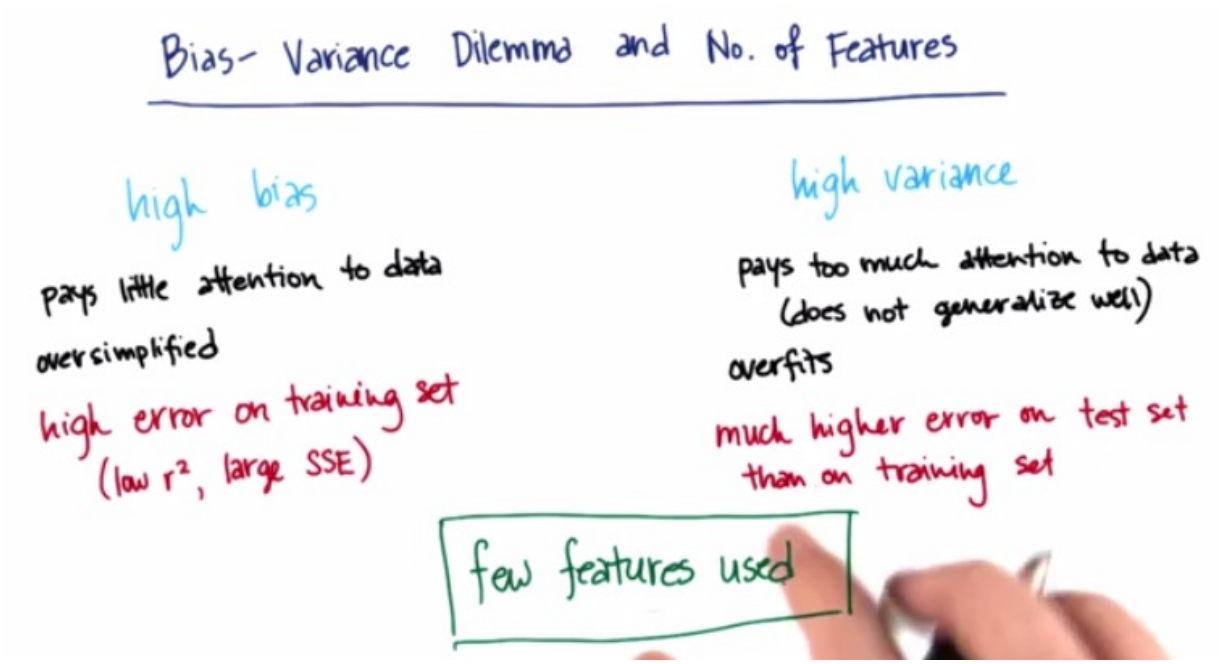
> "Typically, more data benefits high variance models but not in this case. Looking closely at the testing curve (when the number of data points is >200>200), we see that it has started to diverge from its optimal score. Therefore, it's evident that adding more data points is not necessary."

Correct! Typically we do reduce the overfitting issue, but not always true. In this case, we gain no benefit from the testing(unseen data) if we were to receive more data. We would continue to see the testing curve to remain flat.

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.

Glad that you fixed the 'typo'! You clearly have an excellent understanding of the bias/variance tradeoff. If you would like to learn more, check out these links and visual

- http://scott.fortmann-roe.com/docs/BiasVariance.html
- http://machinelearningmastery.com/gentle-introduction-to-the-bias-variance-trade-off-in-machine-learning/
- http://insidebigdata.com/2014/10/22/ask-data-scientist-bias-vs-variance-tradeoff/



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

Evaluating Model Performance

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

Nice ideas! As GridSearch simply is an exhaustive searching through a manually specified subset of the hyperparameter space of a learning algorithm. A grid search algorithm must be guided by some performance metric, typically measured by cross-validation on the training set or evaluation on a held-out validation set.

In our example we are passing 10 different values [1,2,..9,10] for 'max_depth' to grid search, meaning, we are asking to run the decision tree regression for each value of 'max_depth'. Therefore we first fit the decision tree regression model with max_depth = 1, evaluate the model based on out scoring function (r2_score in this project) based on our train/validation data(which is actually 10 sets of train/validation data produced using the ShuffleSplit method). Then we do the same for a max depth = 2 and so on. And at the end we are returned the highest scoring max depth for the validation set.

If you would like to learn about some more advanced techniques and combining gridSearch with other techniques, with the notion of Pipelining, check out this blog post brought to you by Katie from lectures

- (https://civisanalytics.com/blog/data-science/2016/01/06/workflows-python-using-pipeline-gridsearchcv-for-compact-code/)

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.

Looks good! To go into a bit more detail here, I would say that k-fold cross-validation with 5 splits is described as the following:

- The training data is split into k folds, (cv = 5)
- We train a model on the k-1 folds, k times, and use the remaining fold as the validation set (4 for train and 1 for validation here)
- For each model we calculate the validation error (5 errors rates here)
- Then at the end, all of the error rates are averaged together. (single number)

> "If we used a single validation set to tune the model's hyperparameters, they are likely to favour/overfit the validation set we used. By rotating the data, we are able to assess the model's hyperparameters multiple times on different subsets of the data."

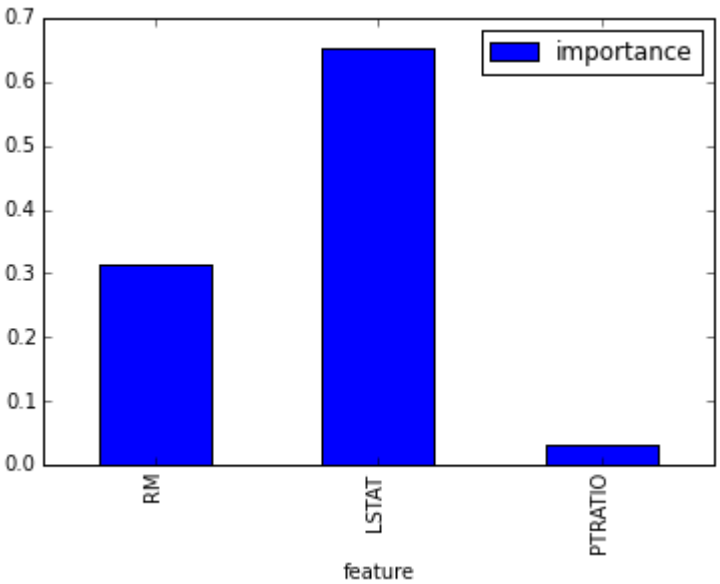
Yes! The additional benefit is to prevent overfitting from over tuning the model during grid search. There is a risk of overfitting on the test set because the parameters can be tweaked until the estimator performs optimally. CV comes in handy instead of using a validation set.

Student correctly implements the `fit_model` function in code.

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

Another cool thing with tree based method is that we can use feature_importances to determine the most important features for the predictions. Check this out(which one of these features contributes to the model the most?)

```
%matplotlib inline
pd.DataFrame(zip(X_train.columns, reg.feature_importances_), columns=['fea
ture', 'importance']).set_index('feature').plot(kind='bar')
```



You will see this more in the next project!

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.

Just remember to keep in mind the testing error here.

```
reg.score(X_test, y_test)
```

Pro Tip: We can also plot a histogram of all of the housing prices in this dataset and see where each of these predictions fall

```
import matplotlib.pyplot as plt
for i,price in enumerate(reg.predict(client_data)):
    plt.hist(prices, bins = 30)
```

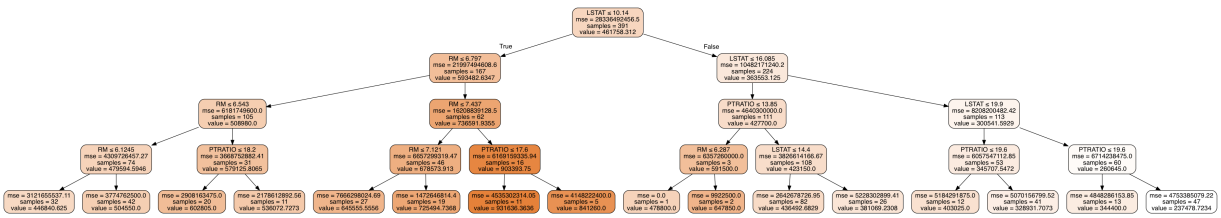
```
    plt.axvline(price, lw = 3)
    plt.text(price-50000, 50, 'Client '+str(i+1), rotation=90)
```

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

One of the biggest advantages when using a decision tree as a classifier in the interpretability of the model. Therefore we can actually visualize this exact tree with the use of export_graphviz

```
from IPython.display import Image
from sklearn.externals.six import StringIO
import pydot
from sklearn import tree

clf = DecisionTreeRegressor(max_depth=4)
clf = clf.fit(X_train, y_train)
dot_data = StringIO()
tree.export_graphviz(clf, out_file=dot_data,
    feature_names=X_train.columns,
    class_names="PRICES",
    filled=True, rounded=True,
    special_characters=True)
graph = pydot.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```



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