Random Forest II

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DSI Lecture

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Learning Objectives

- Discuss **Out-of-Bag (OOB) Score** as a method for evaluating model performance

- Discuss **Feature Importance and Partial Dependence** for model interpretability

Review

What is “bagging” short for? How does this algorithm work?

What are the two things that make a random forest “random”?

Why does random forest make better predictions than bagging?

What are the hyper-parameters you can tune in a random forest?

Review: Bagging vs. Random Forest

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Bagging - The average of many low bias, high variance trees created in parallel; the trees are highly correlated.

Random Forests - The average of many low bias, high variance trees created in parallel; selects a subset of features at each split to create trees with more differences.

Out of Bag Score (OOB Score)

OOB Score is a quick and dirty “replacement” for cross validation

- We already have data that each tree has not seen yet -- each bootstrapped sample only includes about ⅔ of the data.
- We can feed the data that wasn’t used in a tree as a **test set** for that tree.
- We can then aggregate the *accuracy score** for each of our points (each test data point tested on ~⅓ of our trees)

The downside is that oob_score_ in sklearn only computes accuracy or R^2, so if we want precision, recall, or other metrics we will still need to cross validate :(

```
rf = RandomForestClassifier(n_estimators=100, oob_score=True)
rf.fit(X_train, y_train)
print(rf.oob_score_)
```

Interpreting your ensemble model

Interpreting Trees, Bagged Trees and Forests

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Recall, one of the main strengths of Decision Trees is interpretability.

However, when we aggregate our trees with simple Bagging or Random Forests, it's not so easy…

- We can no longer simply rank our features in the order in which they were split on

But… We can look at ***Feature Importances*** *(Note: nowhere near as reliable as coefficients for a linear regression)*

Measuring Feature Importance

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There are a several ways we can go about identifying important features:

1. Measure the total amount the information gain increases due to splits over a given feature

2. Record what portion of points pass through a single split -- the higher in a tree a feature is split on, the more important

3. **Combine 1 & 2 with rf.feature_importances_ (where rf is your fit RandomForestClassifier / RandomForestRegressor)**

More Ways to Measure Feature Importance

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Two more methods...

1. When tree B_i is grown score it with OOB, then remove that feature and score it again to measure the change in your validation metric(s) **--** This is called **Leave One Out Feature Importances**

2. **Iterate through features dropping m_i out and plotting feature importances -- help with "multicollinearity"**

Measuring Feature Importances

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Let's get some intuition for how we calculate feature importances…

1. For each feature m_j, we calculate the decrease in our impurity criterion (MSE, Gini, etc.) for the node(s) that split on m_j
2. We then weight it by how many points passed through the nodes that split on m_j
3. And finally, we average the calculations for steps 1 and 2 across our entire forest

Feature Importance Continued...

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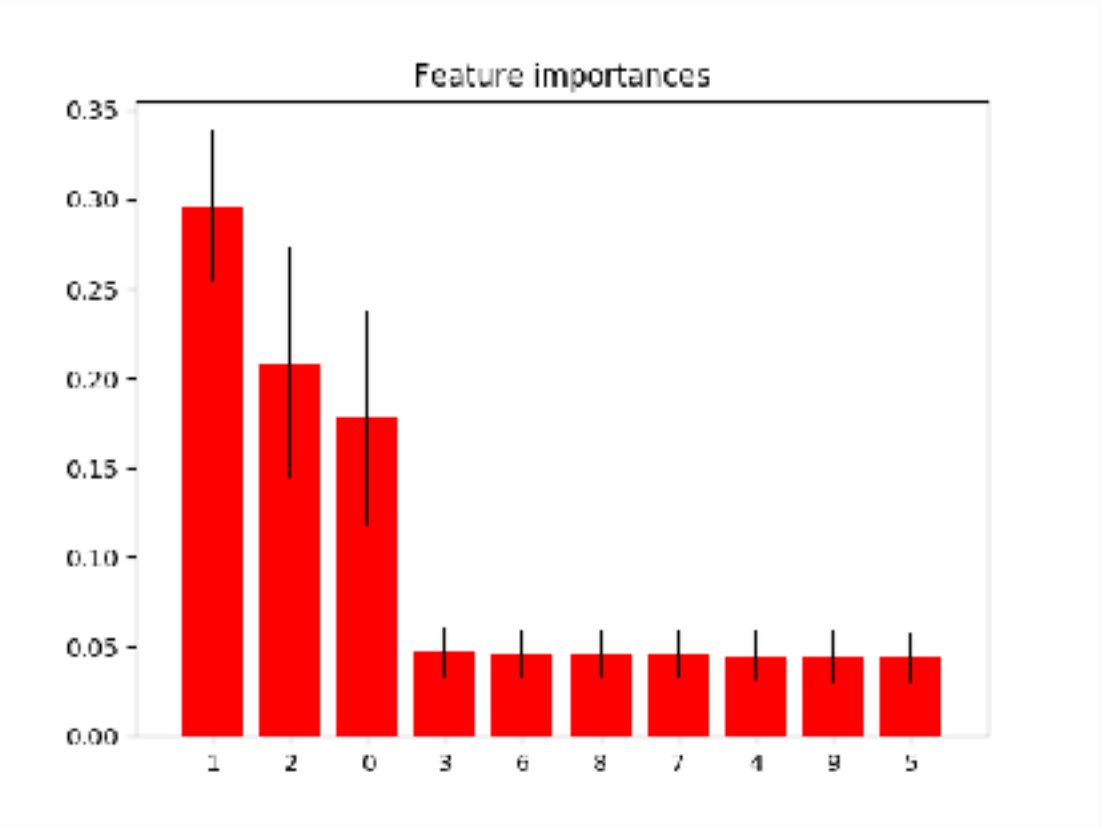
What does feature importance not tell us?

It does NOT tell you effect size and direction of a feature… But this is the *price we pay* for a model that can handle *nonlinear relationships*.

For most real world problems, *features don't have a constant effect size* across all X-values, and sometimes the *effect direction can even reverse* at different levels of X.

What it does tell us: what proportion of our splits (weighted by how much data passed through the split) used this feature - LOOSELY translates to how much variance in y is explained by this feature.

Feature Importances



http://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importances.html

Partial Dependence Plots

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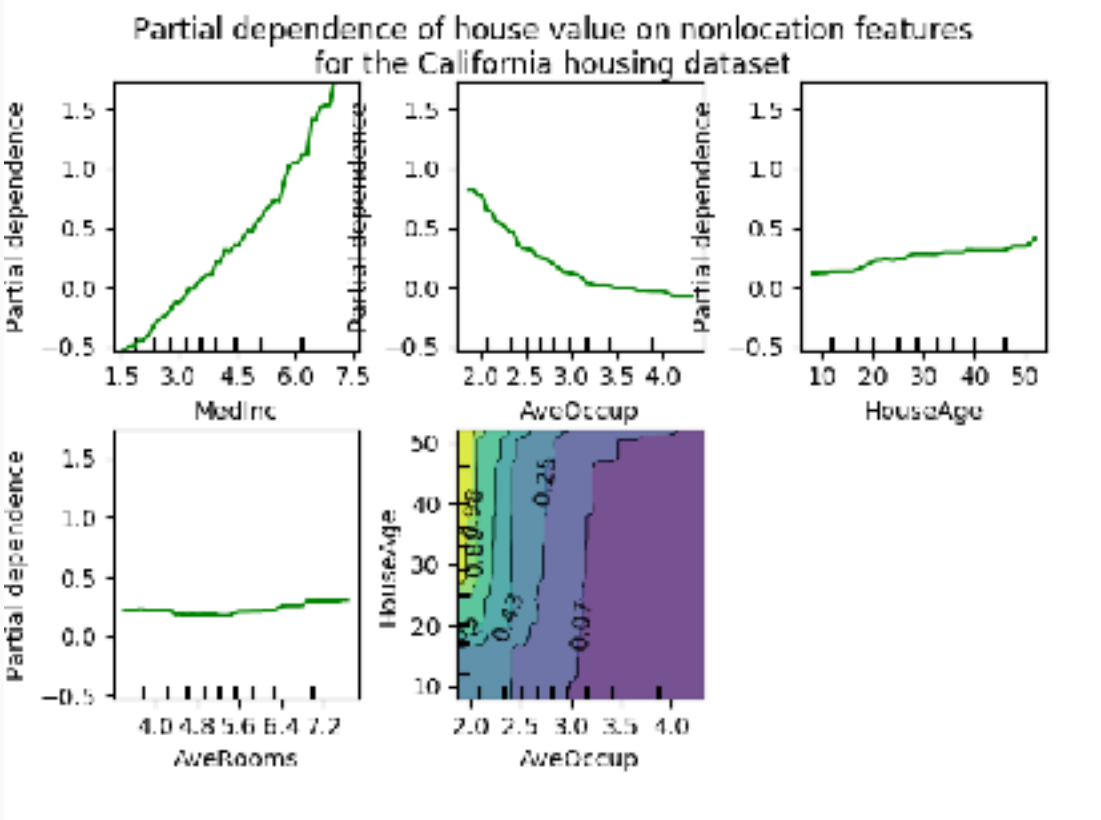
Permute values for each feature column and compare predictive “success” of the feature at each value.

Compare one (or two, if you use a 3D plot) features and how predictive they are at different values.

How to interpret y - axis: It’s all relative. For a classification example, a negative value means for that particular value of predictor variable it is less likely to predict the positive class on that observation and having a positive value means it more likely to predict the positive class. Same applies to two variable plots, color represents the intensity of effect on model.

https://www.kaggle.com/dansbecker/partial-dependence-plots

Partial Dependence Plots



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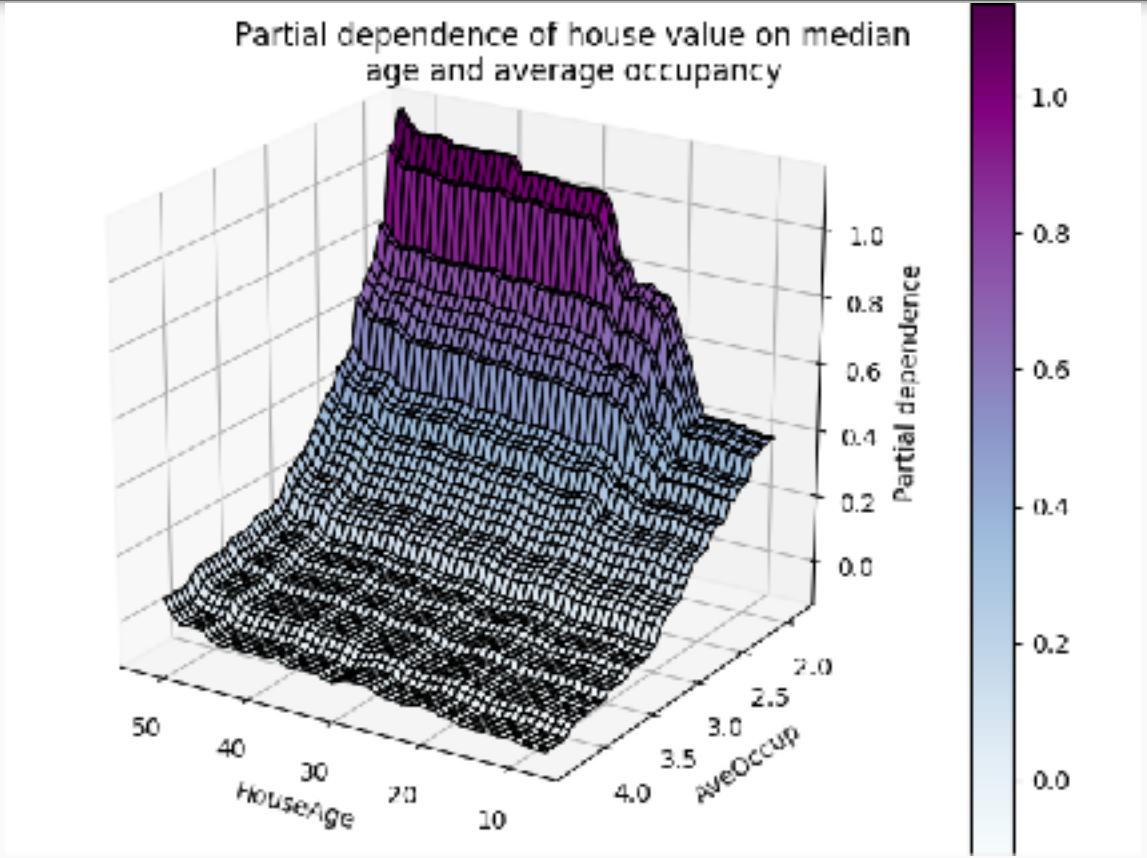
Partial Dependence Plots



Recap: Learning Objectives

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