Random Forest Continued

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Review

Review **Ensembles / Random Forest**

- What is an ensemble method?
- What is *bagging* short for? How does it help build an ensemble of decision trees?
- What makes a random forest random?
- How do these processes affect the model’s variance? Its bias?
- What hyperparameters can we tune in a random forest?
- Groups! Calculate the probability an observation will not be included in a bootstrap sample as a function of the number of samples (*Hint: Bernoulli Trials)*

Objectives

Morning:

✓ Review **Decisions Trees**

✓ Introduce the concept of **Ensemble Methods**

✓ Discuss **Bagging** (Bootstrap Aggregation) as a type of an Ensemble

✓ Discuss **Random Forest** and how it improves upon bagging

Afternoon:

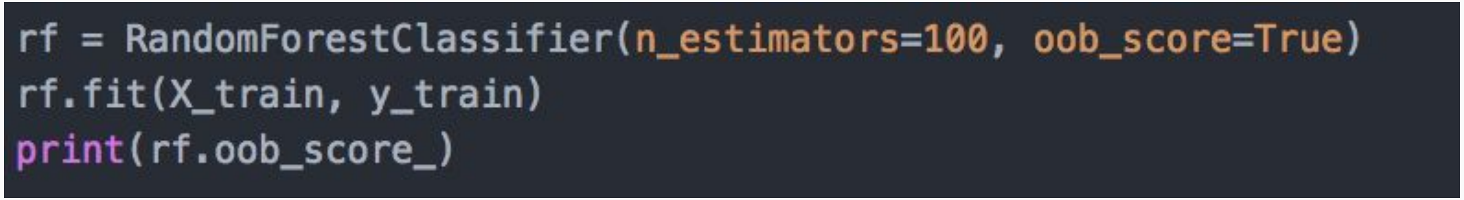
- Discuss **Out-of-Bag (OOB) Score** as a method for evaluating model performance
- Discuss **Feature Importance** for model interpretability

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_)
```

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Interpreting Trees, Bagged Trees and Forests

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

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 Feature Importance

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

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...

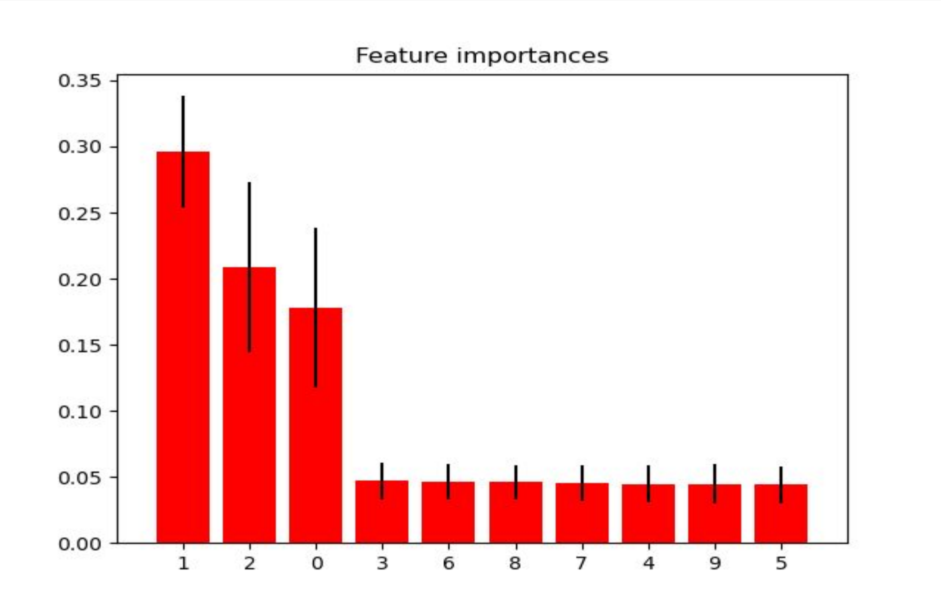
What does feature importance not tell us?

It is difficult to learn the 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.

Discuss: How does the cardinality of the feature affect feature importance?

Feature Importance Continued...



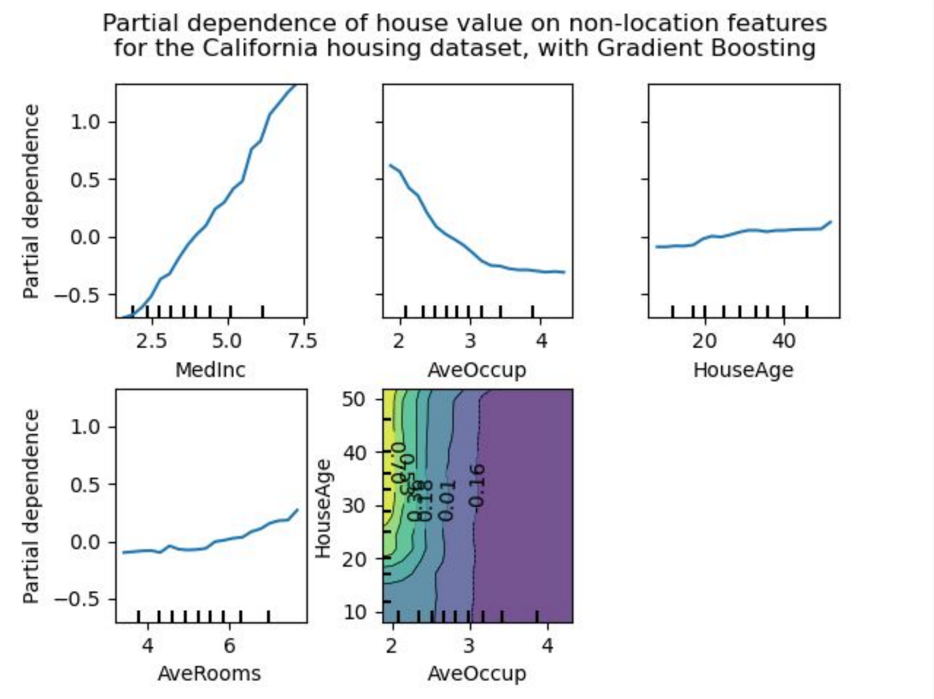
http://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importances.html

Partial Dependence Plots - Group Breakout

https://scikit-learn.org/stable/modules/partial_dependence.html

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

1. What is Partial Dependence?
2. How is Partial Dependence calculated?
3. How can partial dependence plots be used to evaluate feature importance?



Partial Dependence Plots

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.

Recap

- What is OOBS? How is it evaluated?
- How are Random Forests used to evaluate Feature Importance?
- When does feature importance tend to overestimate importance for a feature?
- What is a Partial Dependence Plot?
- How do you interpret such plots?

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