Machine Learning with Python

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EDA Recap

After getting to know the data during EDA, some general statements can be made with regard to survival status:

- A passenger's probability of surviving decreases as their socioeconomic status decreases.
- Given a passenger is male, he almost certainly died.
- Given a passenger is female, she most likely survived.
- Children had a higher probability of surviving than the elderly.
- A passenger's probability of surviving decreases as the number of siblings (or spouse) they have on board increases.

Machine Learning Outline

Using some of the insights (summarized above) that were extracted from the exploratory analysis, this part of the analysis will shift to machine learning, with the overarching goal being to correctly classify those who lived and those who died aboard the Titanic.

This section will be broken down into four parts:

1. **Data Cleaning** - As mentioned in the Exploratory Analysis, there are some Null and NaN value that needs to be taken care of.
2. **Create a Benchmark** - Logistic Regression with a few select coefficients.
3. **Multi-Model Testing** - Cross validate a variety of classification algorithms, performing minor grid searches over each.
4. **Algorithm Tuning and Explanation** - Choose the model with the highest accuracy, perform a more granular grid search and explain the mathematical foundations of the algorithm.
5. **Test Set Scoring** - Use the refined model on the test set.

Data Cleaning

First and Foremost, as mentioned briefly in the exploratory analysis with R, there is a small amount of data cleaning that needs to be performed before modeling. As it turns out, over 75% of the values in the Cabin column are empty strings. Initially, one might try grouping on the SipSp and Parch columns and then looking at the last names to determine any families that were traveling together. Hypothetically, this would then lead to some of the family members having entries in the Cabin column, and one could then impute the values from there. Unfortunately, when this was performed the theoretical family groupings either all had no entries in the Cabin column or they were all complete. This, paired with the fact that imputing over 75% of the values for a column could only be considered guesswork at best, leads to the decision to not include this column in the modeling process.

In addition, there are 177 NaN values in the Age column, which amounts to roughly 20% of the data set. Since this variable *will* be used in the modeling process, some imputation will be necessary. Instead of imputing the **entire** column mean for **all** of the missing values, the distortion to the distribution of the values can be minimized by getting a little more granular.

In order to do this, any NaN values in the Age column were imputed with the mean of a *subset* of the data. For each of the possible combinations of the distinct values in the Gender, Pclass and Title (a feature constructed out of the Name column, which appears to be a rough proxy for Age) columns, a subset was created by masking the entire data set to only include observations in *that specific group,* and then the mean **of that subset** was imputed was for the NaN values **in that subset.** Doing this for all of the possible subsets results in the 177 NaN being imputed in an intelligent manner.

Lastly, there were two observations that didn't have values in the Embarked column, which were droppped since there will be close to no affect going from 891 observations to 889 observations. In addition, if there hypothetically were an improvement in the error rate, it is unlikely that it would have been worth the time spent to work through an intelligent manner to impute those values.

Benchmark Model - Logistic Regression

Using a total of eight columns ($Pclass$, Sex, Age, $SibSp$, $Parch$, $Fare$, *Embarked*, $Title$), some of which were one hot encoded, K-Fold cross validation with $K = 8$ was used to get a sense of how simple logistic regression with ridge regularization would perform. The results are summarized in the table below.

Metrics	Score
8-Fold Accuracy	82.45%
8-Fold Precision	79.36%
8-Fold Recall	75.51%

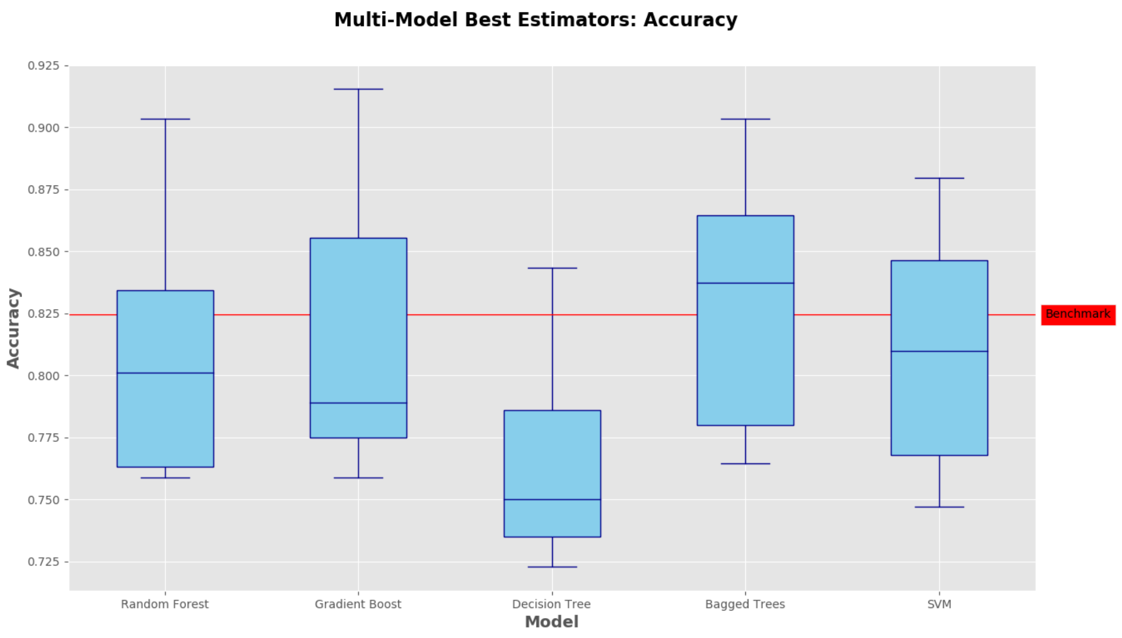
Since there is no obvious reason why a false positive should be considered more costly than a false negative, accuracy will be the metric to beat for all subsequent modeling (precision and recall will still be reported). For all subsequent model evaluation, accuracy must be greater than 84% for the increase in model complexity to be worth the scrapping of the benchmark model.

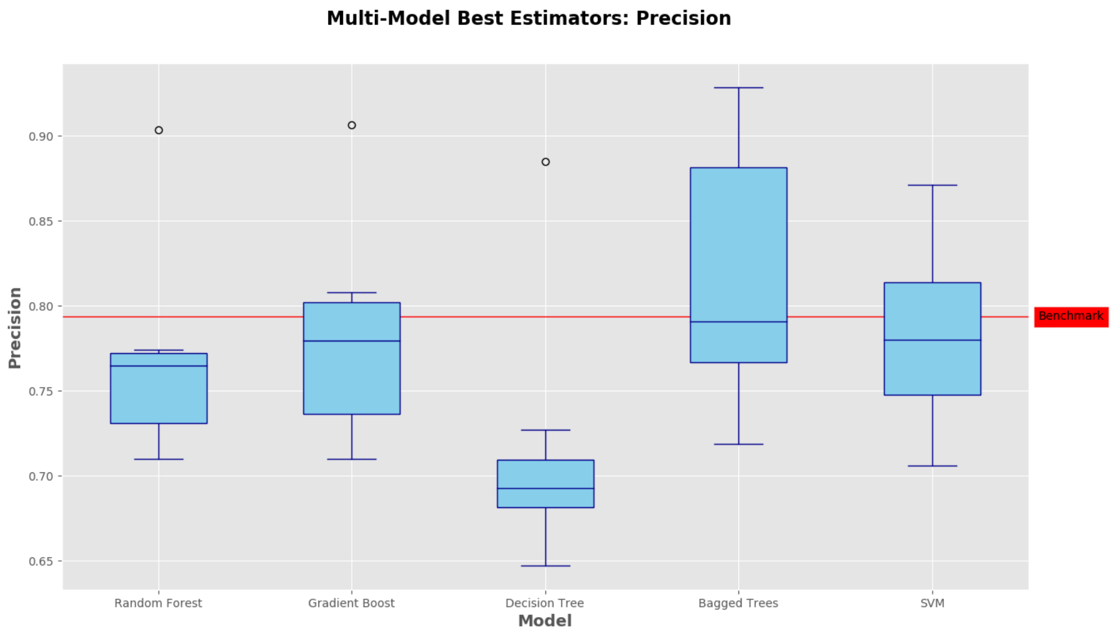
Multi-Model Testing

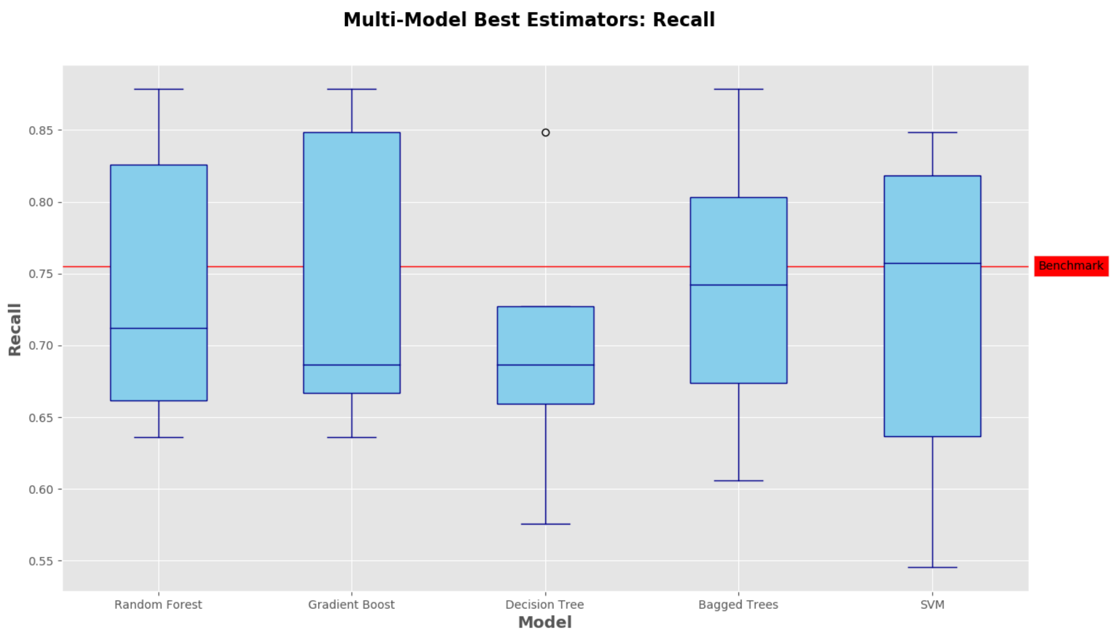
In order to determine if there is a model that will beat the benchmark, I chose five model frameworks to grid search over, ideally one of which would be a more superior model than the benchmark.

For each model architecture, a number of different models were built, the best model (*for the model architecture*) being determined using GridSearchCV's 3-Fold cross validation. Once the best estimator for a given framework was selected, I used 8-Fold cross validation on the training data to estimate which model, if any, has the highest chance of beating the benchmark. The training run times are summarized in the table below, and the Accuracy, Precision and Recall of all model architectures are illustrated on the following pages against the benchmark model.

Model Architecture	Number of possible models tested	Run Time
Random Forest	36	41 sec
Gradient Boosting	90	33.7 sec
Decision Tree	4	0 sec
Bagging	24	30.9 sec
Support Vector Machine	32	318.7 min


Multi-Model Best Estimators: Accuracy
Accuracy
0.925
0.900
0.875
0.850
0.825
0.800
0.775
0.750
0.725
Benchmark
Random Forest
Gradient Boost
Decision Tree
Bagged Trees
SVM
Model


Multi-Model Best Estimators: Precision
Precision
0.90
0.85
0.80
0.75
0.70
0.65
Benchmark
Random Forest
Gradient Boost
Decision Tree
Bagged Trees
SVM
Model



Algorithm Tuning and Explanation

Upon first glance, it seems rather shocking that Bagged Decision Tree's outperformed some of the more complex architectures, such as Gradient Boosting or a Random Forest. However, with a closer look, the $max\ features$ parameter, **when not equal to 1**, allows each decision tree to have access to only a subset of the feature space. In a 1998 paper by T.Ho[1], this ensemble method was coined a *Decision Forest*, a different albiet similar method to Random Forests.

Recall that a Random Forest is a collection of decision trees, each tree being built a bootstrapped data set. At each split within any given tree, only a random sample of the predictors are available as candidates on which to create the split. This decorrelates the trees so that when multiple learners are averaged together, variance is reduced and the algorithm generalizes well.

A Decision Forest is slightly different in that each decision tree within the ensemble **only has access to a random subset of the predictors.** Every node within a tree is then allowed to consider the full feature space **withing the already filtered feature space for that tree.** For example, if one is working with a **n x 12** data set, each tree within a Decision Forest will utilized all n observations, but only a random subset of the 12 features

References

[1] T. Ho, "The random subspace method for constructing decision forests", Pattern Analysis and Machine Intelligence, 20(8), 832-844, 1998.