Final Report

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March 18, 2016

Introduction

Over the course of this project we tried out a number of different machine learning algorithms. This report explains in detail which ones we tried out, how they worked, and what we decided to do with them.

This document is split into 2 main sections:

1. **Variable Selection and Feature Engineering**
2. **Algorithm Selection**

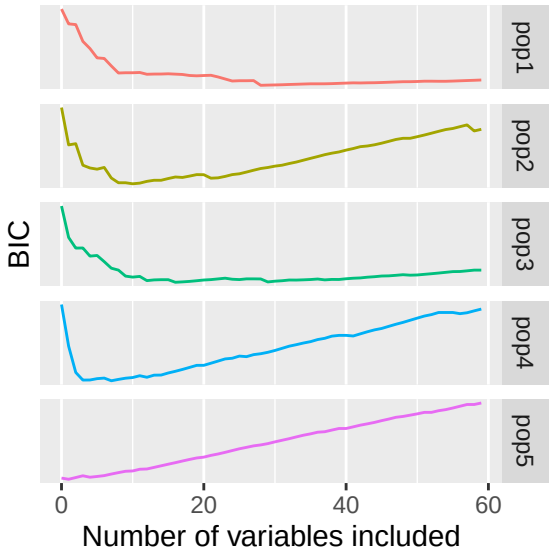
1. Variable Selection and Feature Engineering

Below are detailed results from variable selection and feature engineering test:

- Fisher Score-Based Logistic Regression
- Penalized Logistic Regression
- Interaction Terms
- PCA

Fisher Score-Based Logistic Regression

To find the right variables for logistic regression, first we applied a simple strategy: We computed fisher scores between popularity and each of the possible explanatory variables and ranked the variables based on this score. Starting from the simplest model we added variables by fisher score ranking one-by-one. Finally, we selected the best performing model based on Bayesian information criterion. This method can be considered as a version of stepwise regression where the models considered are based on a specific variable ranking. The best model obtained this way had an accuracy arond 49%.



We also tried to fit an ordered logit model to take into account the fact the outcome measure is not a simple categorical but an ordinal variable. Using ordered logit yielded very similar results as the multinomial logit.

The highest accuracy acheived was 49%. Since these approaches were more ad-hoc than k-nn and yield very similar prediction accuracy, we decided not to use these for prediction.

Penalized Logistic Regression

We also fitted and optimized lasso and ridge logistic regressions. Interestingly, the optimal version of lasso and ridge both yielded approximately 50% accuracy, which is 1% higher than the performance of the logistic regression with variable selection based on BIC and fisher score.

Interaction Terms

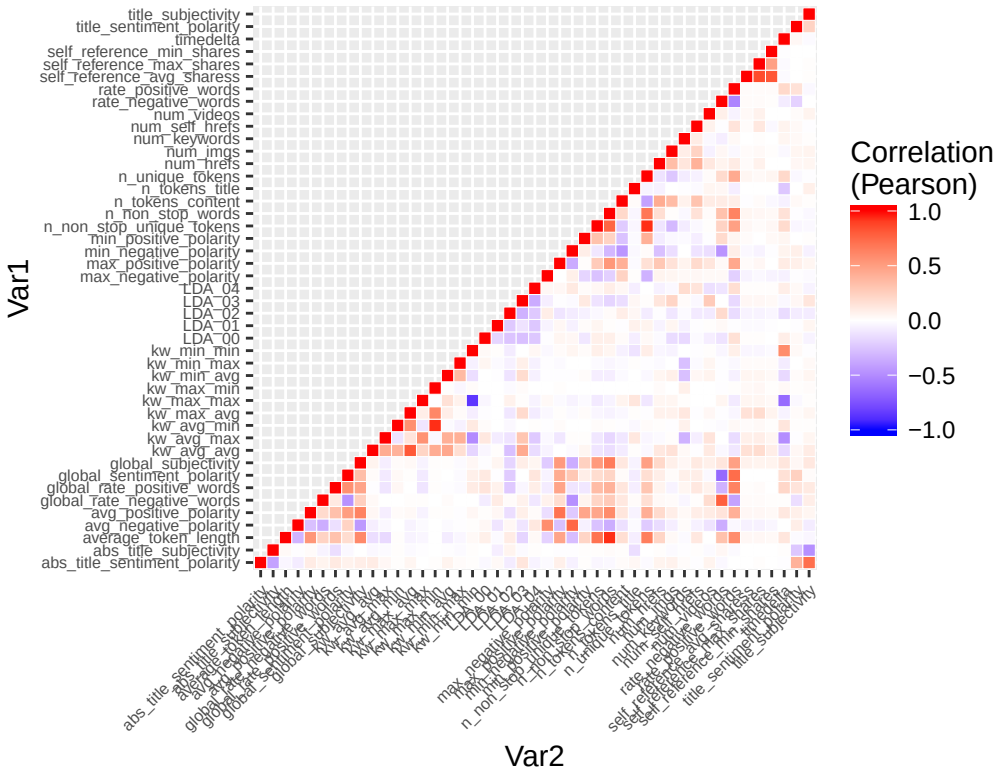
Relatively poor performance of these models is likely related to lack of interaction terms so we decided to examine feature interactions to increase analytical leverage over the data. To this end, we ran logistic regressions examining interaction terms for each of the binary variables - that is, the `weekday` and `data_channel` variables. This examines a fairly limited scope of interactions, but was a good starting point.

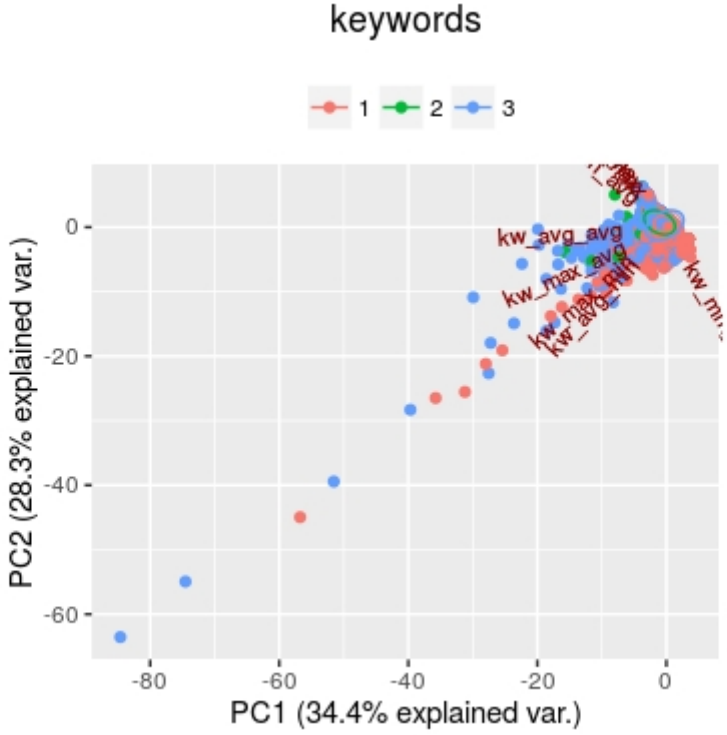
The key problem was these logistic regressions almost entirely predicted 2s, with the occasional 1. This gave us a poor accuracy of circa 46%. Using the engineered features (see below) we managed to get this up to about 48%. However, in general these methods were very clearly out-performed by other methods.

PCA

An other approach of feature engineering we tried was PCA. We started off trying out a vanilla PCA approach. This proved to have very poor predictive performance, so we modified our approach. Instead we tried a PCA-in-groups approach. As it can be seen in the graph below there are numerous groups of variables in the database that are highly correlated, so we took the principal components of these groups and ran our algorithms on those instead of on the plain features.

Unfortunately, using this approach usually worsened the accuracy of whichever algorithm we ran on the transformed dataset, rather than improved it.





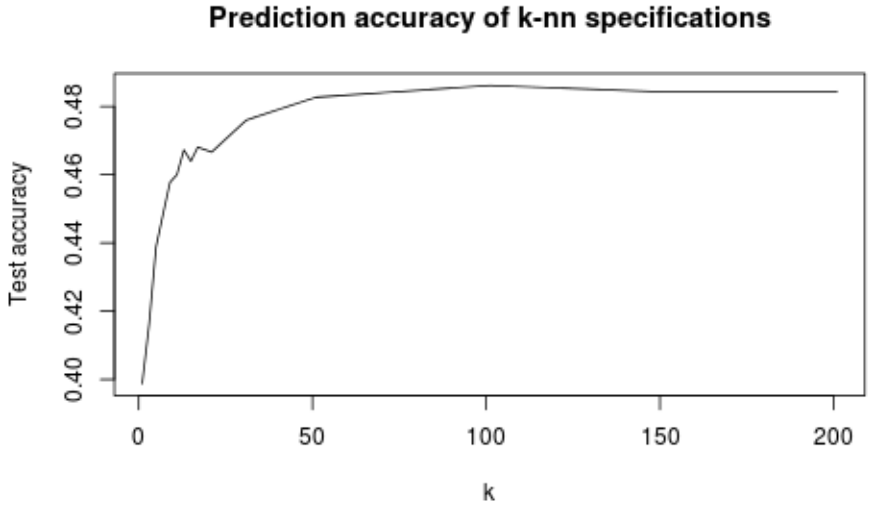
2. Algorithm Selection

We evaluated the following algorithms and tuning methos:

- K-NN
- Logistic Regression
- K-means
- Removing Outliers
- Boosting
- Tree methods
- Ensembles

K-NN

To have a reference point in terms of prediction accuracy we ran an optimized k-nn specification on the standardised variables. We optimized the k-value based on accuracy on a test set. The best specification had approximately 49% accuracy which is approxiemately 3% higher than if we had predicted every article having popularity 2, the most frequent outcome value in the sample. We also tried to run k-nn separately for different channels and separately for articles published on weekends and weekdays since the treatment of categorical variables is problematic in k-nn. The overall accuracy of these k-nn was very similar to the simple k-nn approach run on standardised data.



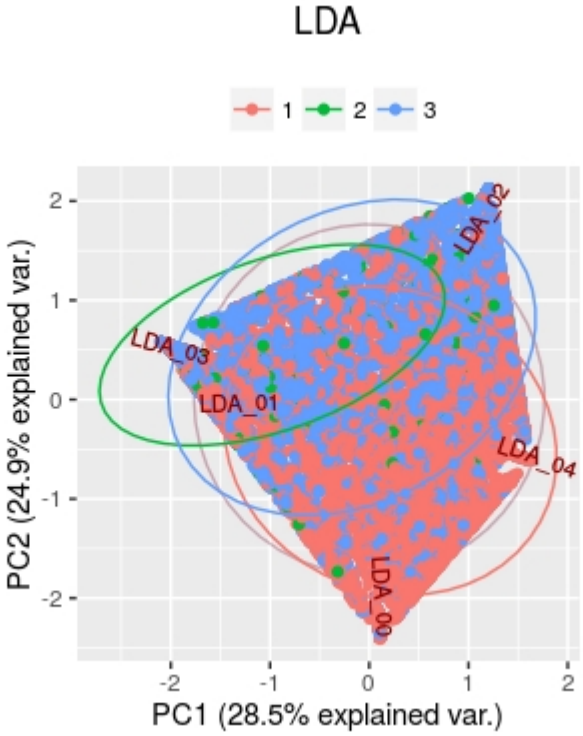
Logistic regression

The second approach we tried was various versions of logistic regression. We experimented with different variable selection and regularization approaches with moderate success.

K-means

Logically, articles are written with a particular target market in mind. Different target markets will react differently to the various features captured in the dataset, and the writer will change aspects of their writing in order to reflect this. This is the logic behind seeking clusters in the data: authors who are targeting readers who are looking for in-depth articles with many long words will use more complex sentence structures than those who are targeting readers who want a short humour article. For this reason, it makes sense to split the data into clusters and then measure the differential impact of the different features dependent on the cluster. This approach using three clusters yielded around the 50% mark during cross-validation, though dropping again to about 48% on our actual submission.

The graph below shows some of the relationships between variables and clusters.



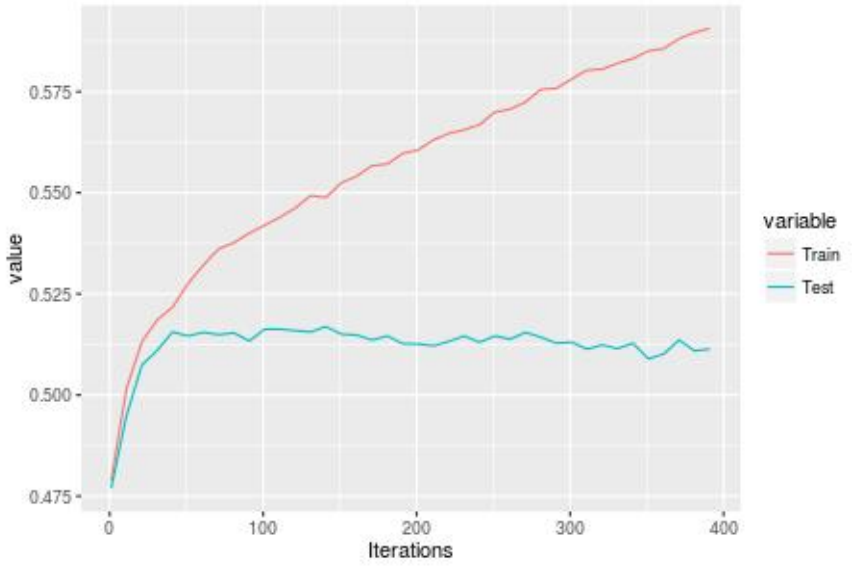
These graphs illustrate a number of things: firstly, cluster is not merely a proxy for weekday (the same result holds for the other categorical variables); secondly, that the clustering shows a clear relationship with some of the variables, and a less clear relationship with other variables.

Removing outliers

We tried removing outliers to improve our model. We noticed that roughly 95% of the observations in the dataset were classified as a 1, a 2 or a 3. There is also anecdotal evidence that suggests that which articles go 'viral' is a matter of luck and random chance rather than anything predictable. Most of our algorithms were not correctly classifying any of the 4s or 5s anyway, so it seemed sensible to suppose that all those articles classed as a 4 or a 5 unusual events, and that removing them would improve the training of our model. In general the outlier-removed version of our algorithms had roughly the same accuracy.

Boosting

Boosted classifications models provided similar test accuracy results as random tree models, around 51.4%. See below the test and training accuracy of a multinomial specifications as the function of iterations.



Tree methods

Since in the simple regression models with many possible explanatory variables it is difficult to determine the best set of predictors and the proper model form (e.g.: interactions and functional form) in a systematic manner we expected the tree methods combined with ensemble methods to yield relatively better prediction accuracy.

Indeed, basic random forest specifications turned out to have around 51.5% test accuracy, better than the best regression models.

Ensembles

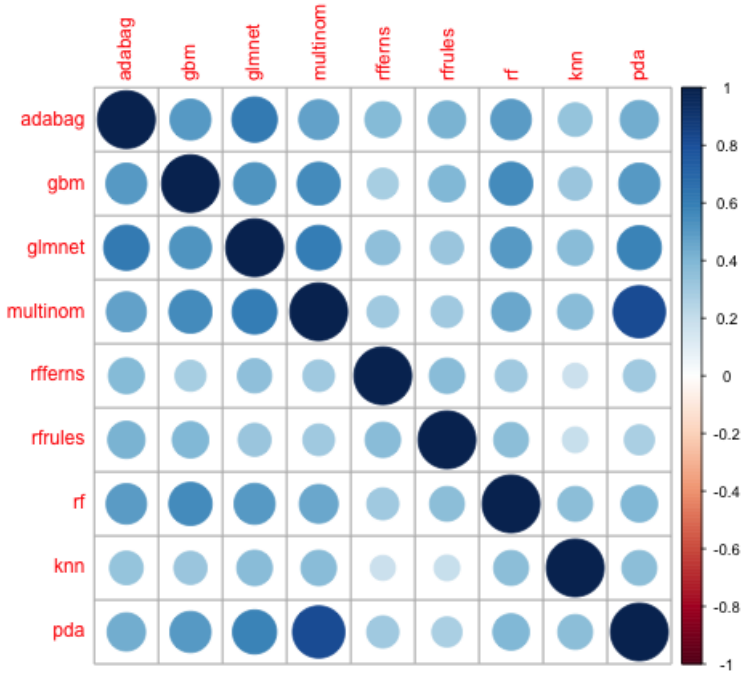
The concept of ensembling has become popular from the intuitive idea that more heads are better than one. *Are more models better than one?* It has been shown that making predicions from a collection of models can have greater predictive power than one very good model.

The process to create an ensemble was as follows:

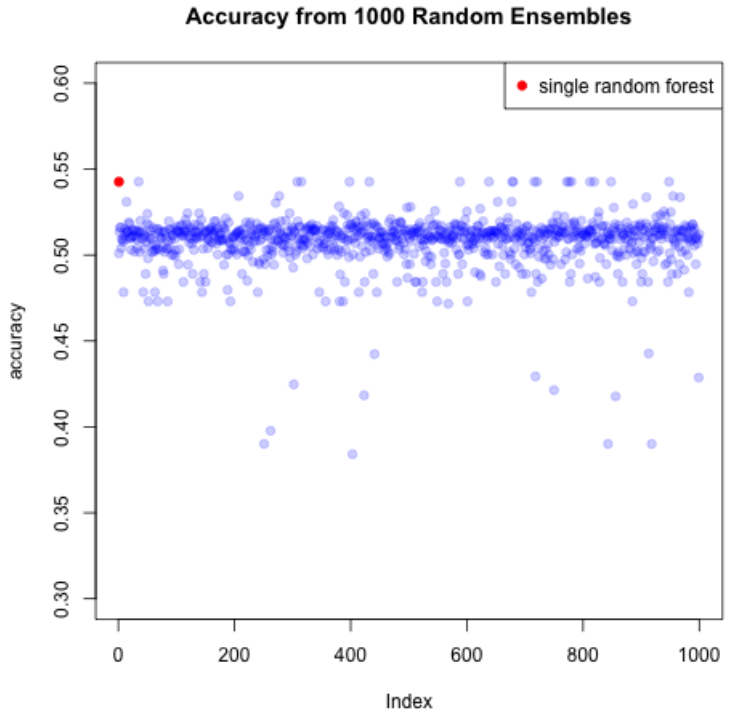
1. Train a collection of models, using caret for tuning, on a smallish data set to iterate faster, on the same training set
2. Evaluate the accuracy of each model on the same test (e.g. validation) data set
3. Evaluate the accuracy of an ensemble of models having low correlation in predictions

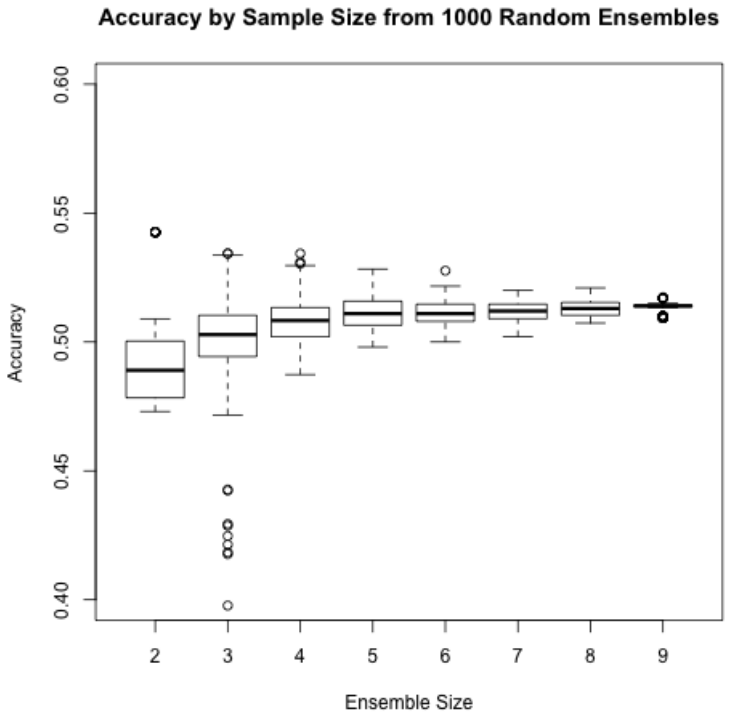
The results of this experiment on the Mashable data set are that while it improved on predictive power of nearly all models used in isolation, it still did not improve on the predictive accuracy we achieved via random forest.

Below is a plot of the correlations:



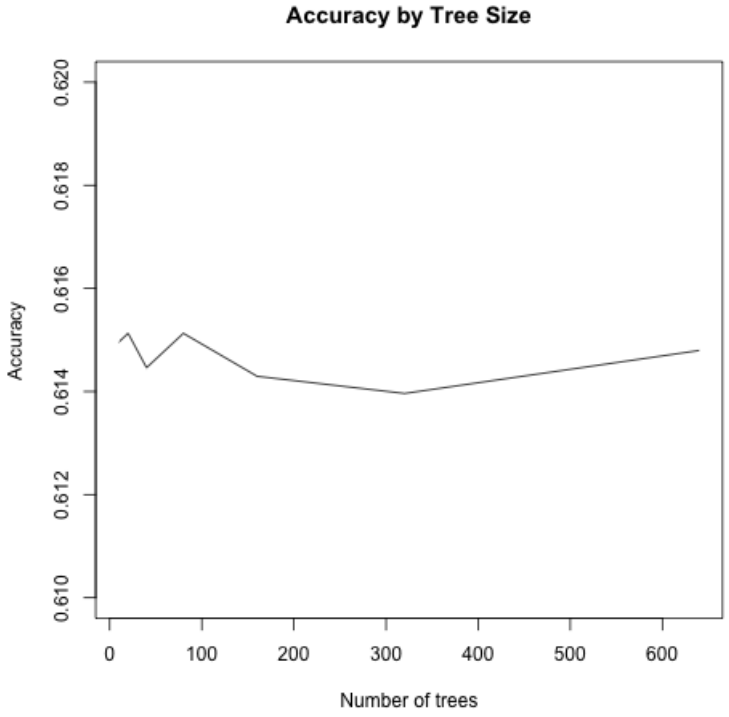
Ensembling predictions from the least correlated models resulted in lower predictive power. In order to affirm this result, we ran 1000 simulations with different random sizes and selections of the model predictions available.

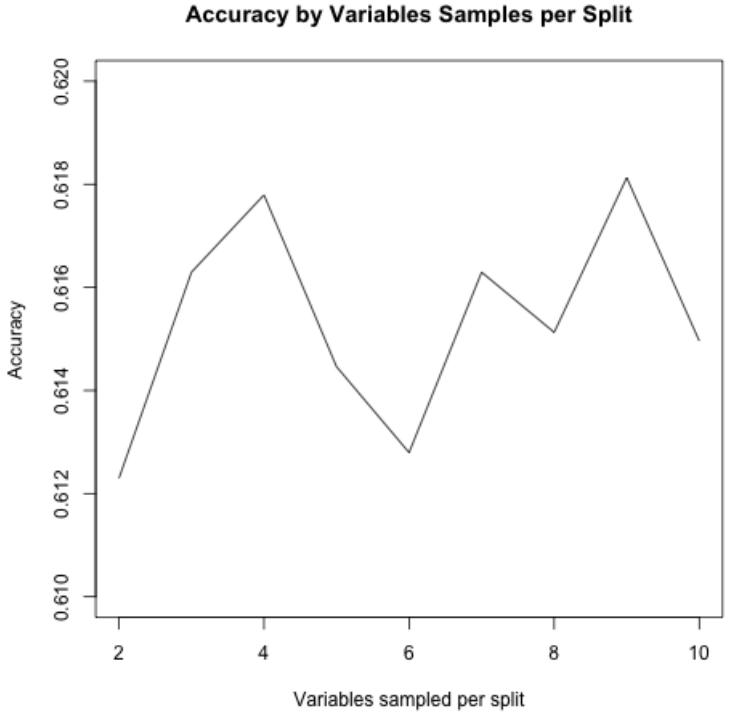




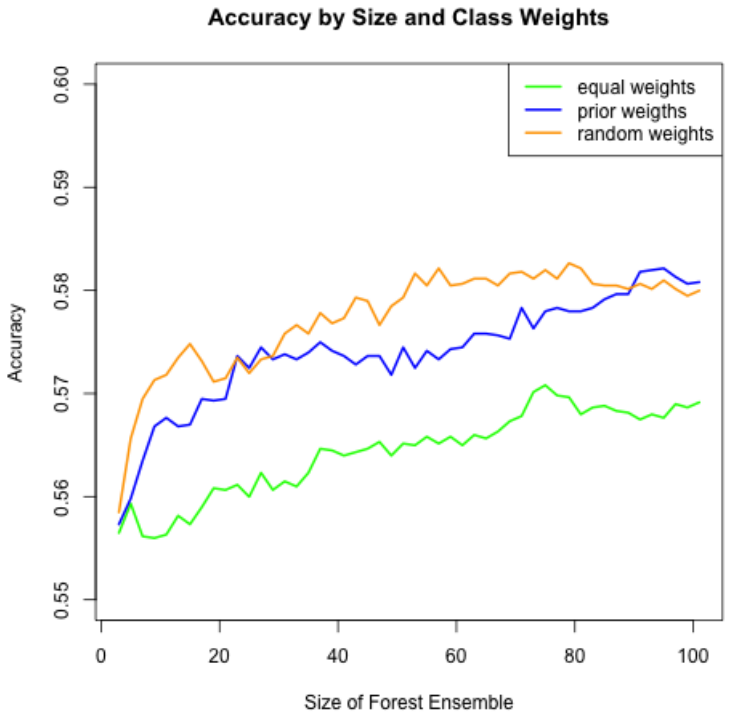
Ensembling Random Forests

Since ensembling different models was unsuccessful, we doubled down on random forest. Most parameters were tested for optimal tuning and it was found the default tuning (e.g. nodesize, mtry, ntrees) were hard to improve upon.





We were particularly interested in the effect of tuning `classwt` parameter: Could it be ensembled randomly to produce greater predictive power?



As can be seen in the plots above, ultimately the highest predictive power came from an ensemble of forests using class priors. By passing to the `randomForest` algorithm the `classwt = classwts` parameter, we arrived at our highest prediction.

```
no.classes <- length(unique(data.train[,label]))
classwts <- sapply(1:no.classes, function(cl) {
  sum(data.train[,label] == cl)/nrow(data.train)
})
```

Conclusion

Some concluding remarks about model evaluation:

TL;DR: Keep lots of data on your data

- Keep systematic track of seeds and data indices when using random algorithms and random samples
- Keep systematic track of models evaluated, parameters used and accuracies / error rates
- Visualize results to motivate decisions

Ultimately, we found a single randomForest using priors on the class probabilities as an argument gave the best predictive power. Ensembling `randomForest` with itself or other algorithms did not improve accuracy over a lonesome forest.