

# Final Report

Samuel Burge, Chad Austgen, Skylar Liu

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## Classification Task

### Methodology

For the classification task we approached the problem with a spread of well-known classification algorithms. This included the Naive Bayes classifier, regularized logistic regression (specifically ridge, lasso and elastic net regularization), gradient boosted trees, random forests and support vector machines (using radial and polynomial kernels). For model selection and assessment, we utilized 10-fold cross-validation and, with some algorithms, another nested cross-validation to select tuning hyper-parameter using a grid search. Nested cross-validation is a well-known approach to handling both tuning and assessment of models with hyper-parameters, and we opted to employ this approach to avoid potential over-fitting and bias introduced when the same data used to validate the models is also included in hyper-parameter optimization (Cawley and Talbot 2010).

The only classifier we used that was in covered in the course was the regularized version of the logistic regression model. Before the analysis we created large plot matrices and verified across all predictors that  $X$  and  $Y$  were not well separated suggesting the best linear method might be logistic regression. However, we were not able to fit a logistic regression

model outright since  $p > n$ . We utilized regularization methods to reduce the features in our analysis using lasso, ridge, and elastic net regularization methods (Zou and Hastie 2005). The elastic net regularization simply uses a weighted penalty term  $\lambda[(1 - \alpha) \|\beta\|_2^2 / 2 + \alpha\|\beta\|_1]$  in the objective function, and requires that both tuning parameters  $\lambda$  and  $\alpha$  be selected (which we used nested cross-validation to determine). The lasso and ridge regularization can be viewed as special cases of the elastic net procedure where  $\alpha = 1$  and  $\alpha = 0$ , respectively. We searched for the best tuning parameters  $0 \leq \alpha \leq 1$  in increments of 0.05 and found that lasso regularization yielded the best performance in this category of classifiers.

## Results

The results of our analysis are depicted in the table below. Note the degree to which some classifiers, such as ridge logistic regression, under-performed during the assessment despite a low training error, on average. Overall, the tree-based methods had the best performance of all the classifiers and the boosted classification trees had the best generalization performance with a CV error rate of 31%.

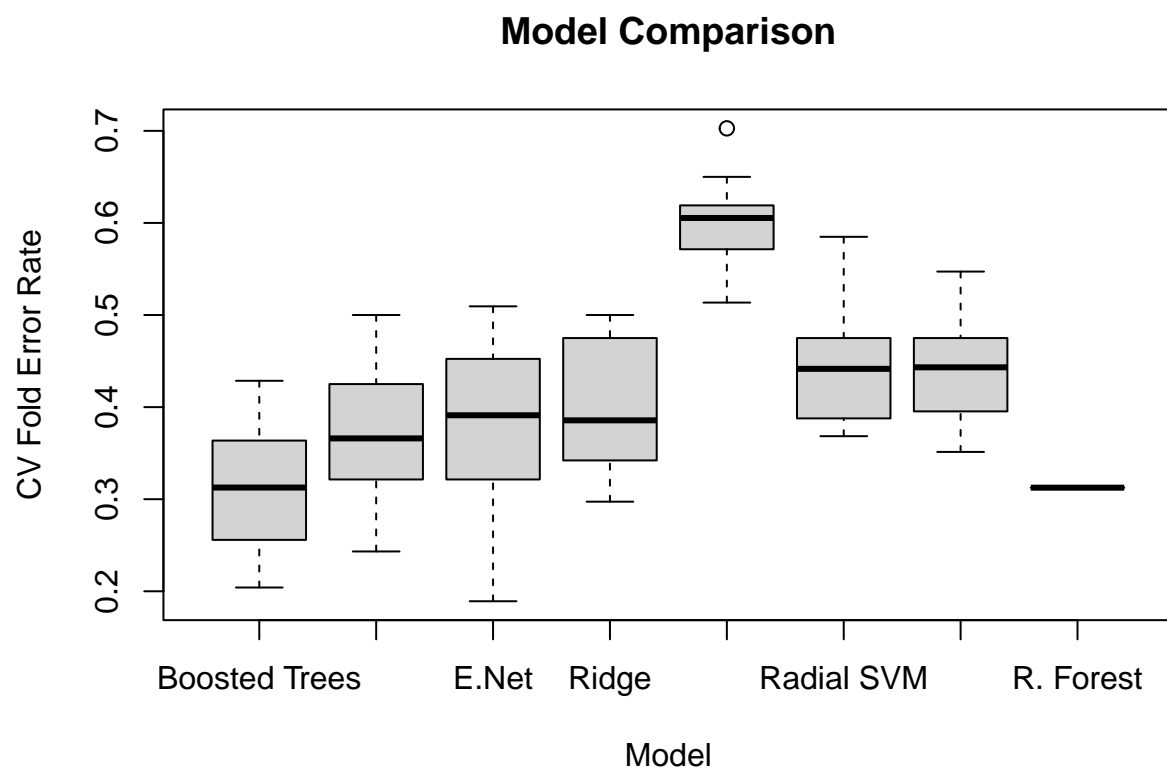


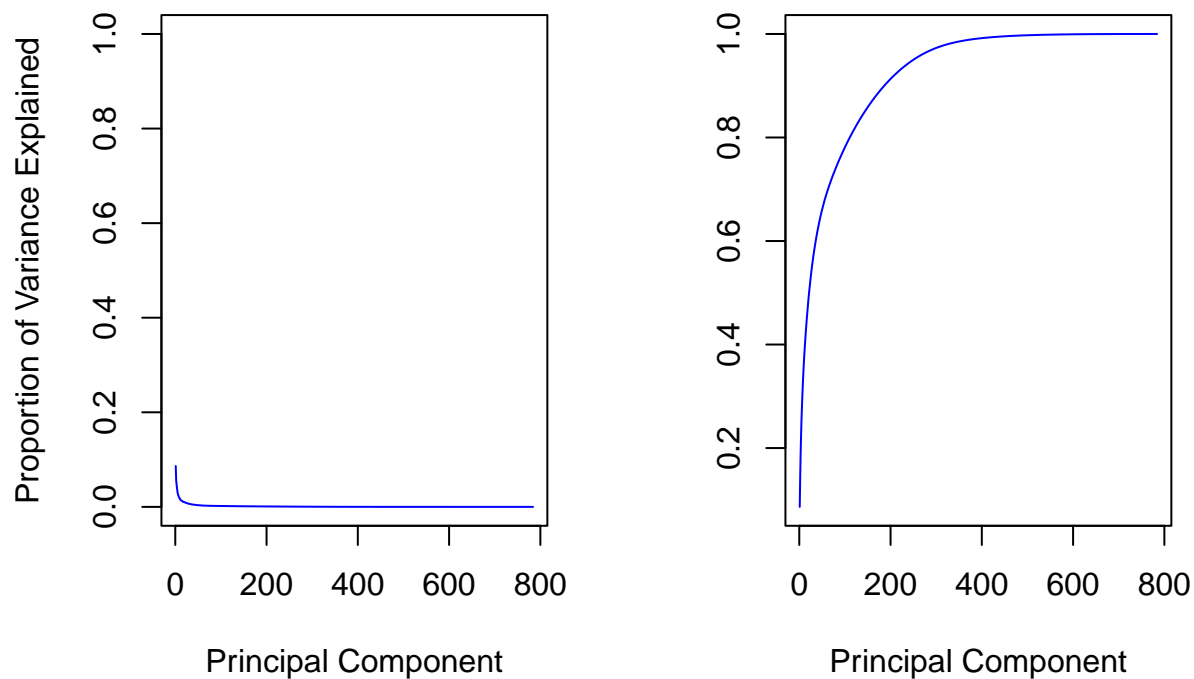
Table 1: Results from 10-fold cross-validation to assess model generalization performance.

	Training Error	Est. Test Error
<b>Lasso</b>	0.3060377	0.3727149
<b>Net</b>	0.3060377	0.3814926
<b>Ridge</b>	0.1786087	0.3972233
<b>Naive Bayes</b>	1.0000000	0.6019532
<b>Radial SVM</b>	0.4468479	0.4460467
<b>Poly. SVM</b>	0.4147253	0.4384205
<b>Random Forest</b>	NA	0.3125000
<b>Boosted Trees</b>	0.0401765	0.3081585

# Clustering Task

## Pre-processing

For the clustering task, we initially looked at performing principal components analysis (PCA) to reduce the number of dimensions in the data set. The two scree plots below show that the number of principal components necessary to capture at least 90% of the variation in the data set was about 187, which did not seem beneficial enough to consider for the analysis. Therefore, we decided to retain all the original features in the data set.



## Methodology

We opted to use k-means and hierarchical clustering, in part because the high-dimensional data is intractable with DBSCAN and due to computing restraints. Since the given data

does not have any contextual basis for selecting the number of clusters  $K$ , we need one or more criteria to determine the number of clusters. Several well-known and widely used approaches include the elbow method, the silhouette method (Rousseeuw 1987), and more recently the use of the gap statistic (Tibshirani, Walther, and Hastie 2001).

## References

- Cawley, Gavin C., and Nicola L. C. Talbot. 2010. “On over-Fitting in Model Selection and Subsequent Selection Bias in Performance Evaluation.” *Journal of Machine Learning Research* 11 (70): 2079–2107. <http://jmlr.org/papers/v11/cawley10a.html>.
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