Stat 154 Final Project

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Introduction

Using the data from the Census Income Dataset, we wanted to see which tree-based method had the highest predicitve accuracy and which variables have the strongest predictive power in regards to whether an individual earns over $50000 in income. We compare three methods - classification trees, bagged, trees, and random forest.We begin with preprocessing and exploration of the data. Then, we fit the three models using the training data. With the most accurate model, we fit the test data.

Exploratory Data Analysis(All graphs are attached in appendix)

First, we needed to remove missing values that were found in the workclass, native_country, and occupation variables. Removal was appropriate as observations with these missing values made up about 2400 of the 32561 observations. To be used with the models, we needed to aggregate some of the countries of the native_country variable. We chose to aggregate the countries with the 10 fewest occurances in the data into the “other” label, which totaled 137 observations. Based on our prior knowledge, we believed that age, education, and occupation would be important variables. Looking at the proportion of income levels, age and education appear the most different for the two groups. For many of the variables, initial plots were not too insightful due to the fact that the data was not very well balanced. We noticed that the training data had a much larger proportion of incomes greater than $50K, so the AUC metric would be useful.

Our last step for this phase was to remove some of the variables. We felt that “education” and “education_num” variables were very well correlated so we would only use one to fit our models.

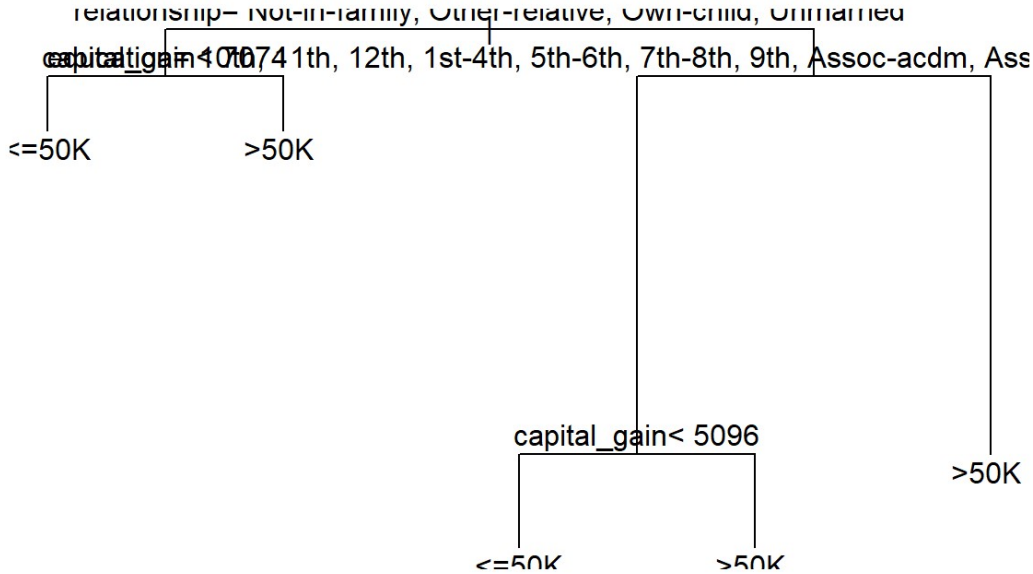
Looking at boxplots and histograms, we also saw that “capital_gain” and “capital_loss” contained many outliers and were heavely skewed. This amount of variability just from the fact that these two variables had most occurances around 0 but also very large outlier values would severely bias their importance. Although decision trees and random forest are quite robust, it should be a point of attention.

The last variable of interest was “fnlwgt”, which is a stastical metric for each invididual. We felt that this was not relevant to the individual’s income level based on the variable’s meaning so we decided to not use it in our analysis.

Looking at boxplots and barplots of various variables, it seems that there is a noticeable difference in age and education of the two income groups. The occupation boxplot showed large differences in income distributions of the respective occupations. These can be seen in the provided images.

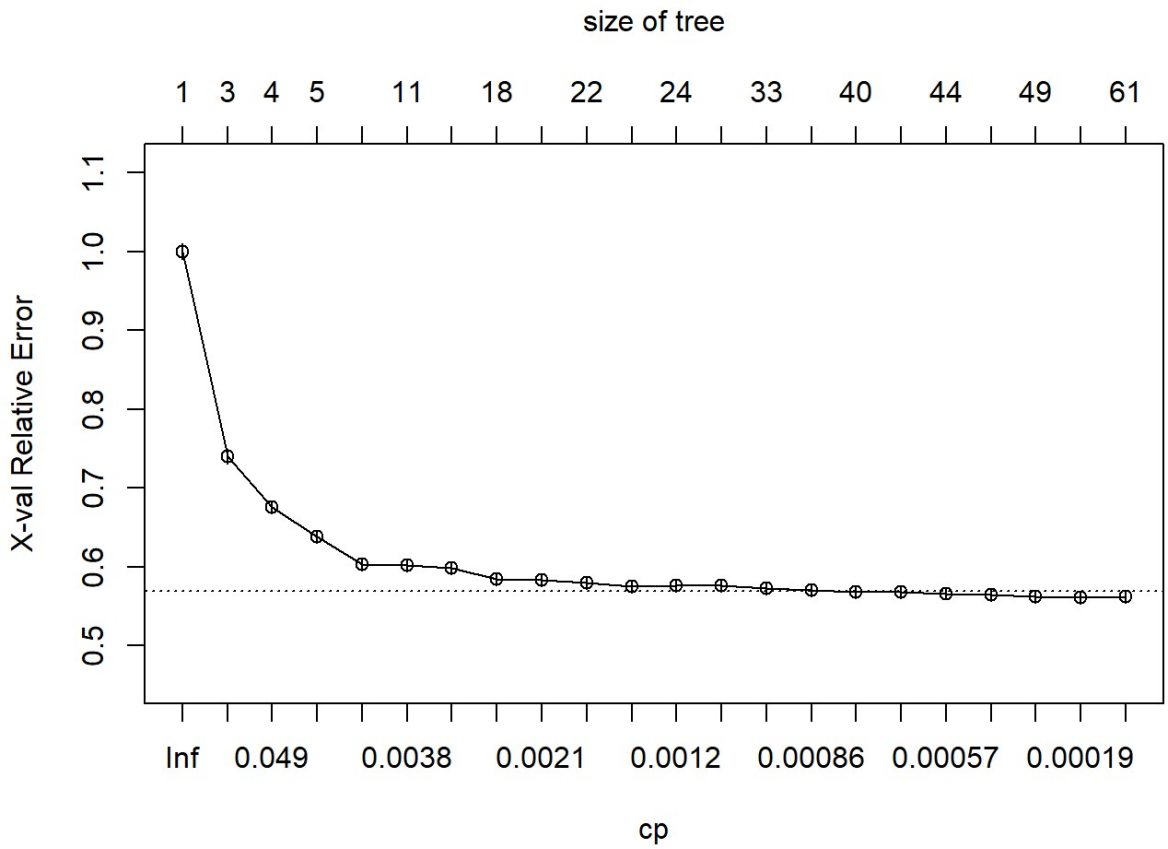
Analysis

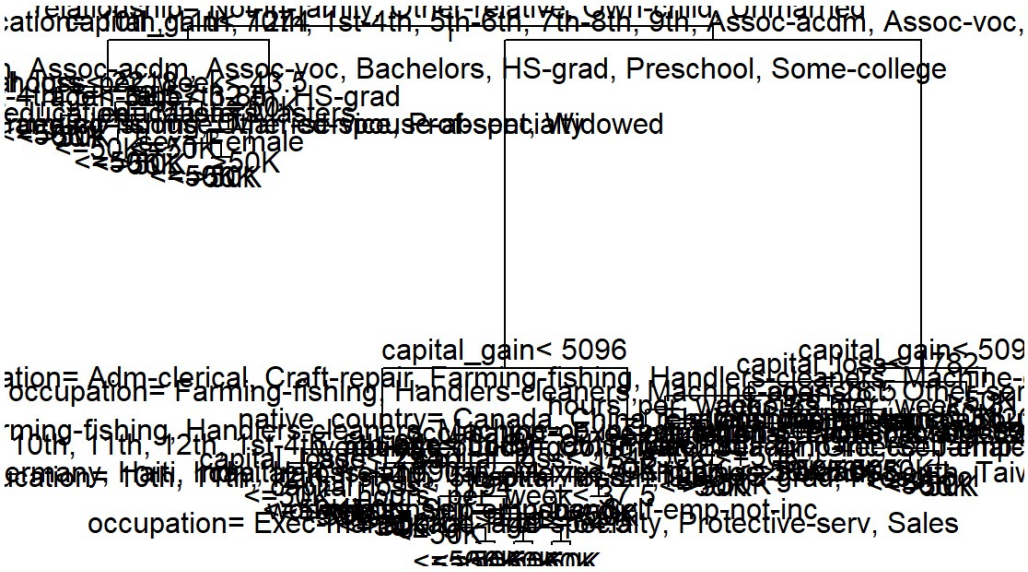
Classification Tree:



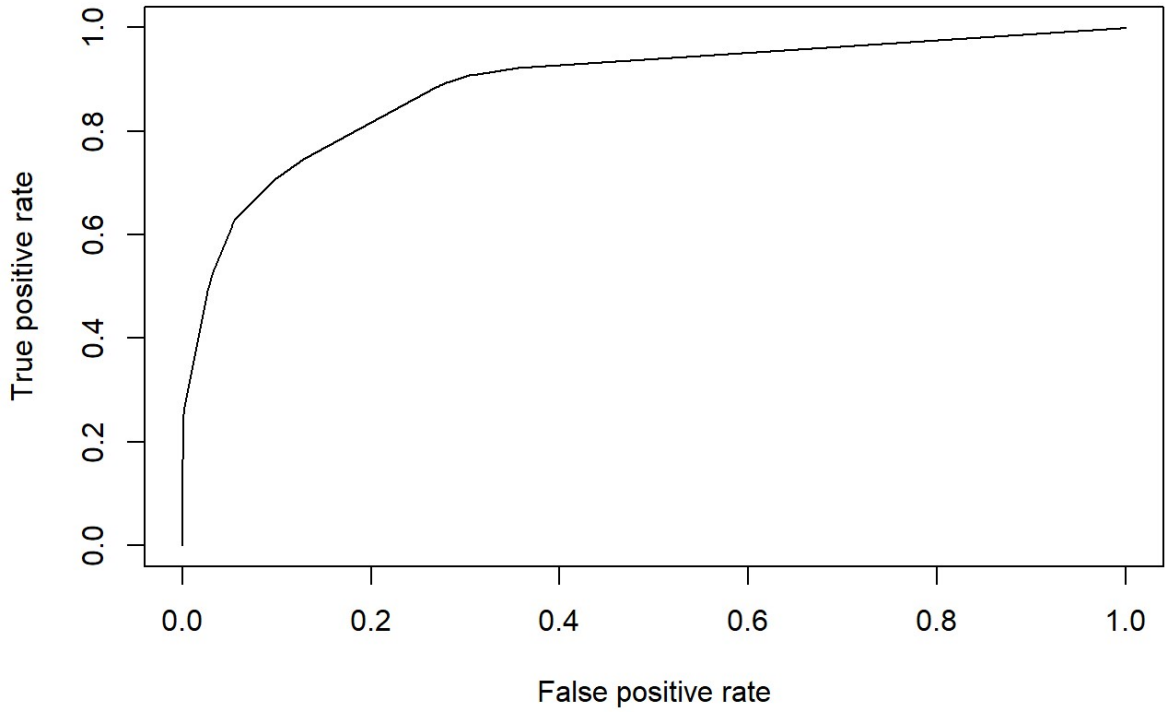
We decided to use the “education_num” variable over the “education” variable as it was cleaner for the tree model.For the tuning, 10-fold cross validation was used to tune the complexity parameter and the minimum split size,and max depth by the tune.wrapper function in the e1071 package.

```
##
## Error estimation of 'rpart.wrapper' using 10-fold cross validation: 0.1416353
```





We found the max depth = 10 , minimum split size =50, cp= 0.0003 minimized the error. We pruned the tree at cp =0.0003.Decreasing CP and increasing minsplit would help to prevent overfitting by growing too large of a tree as CP decreases.



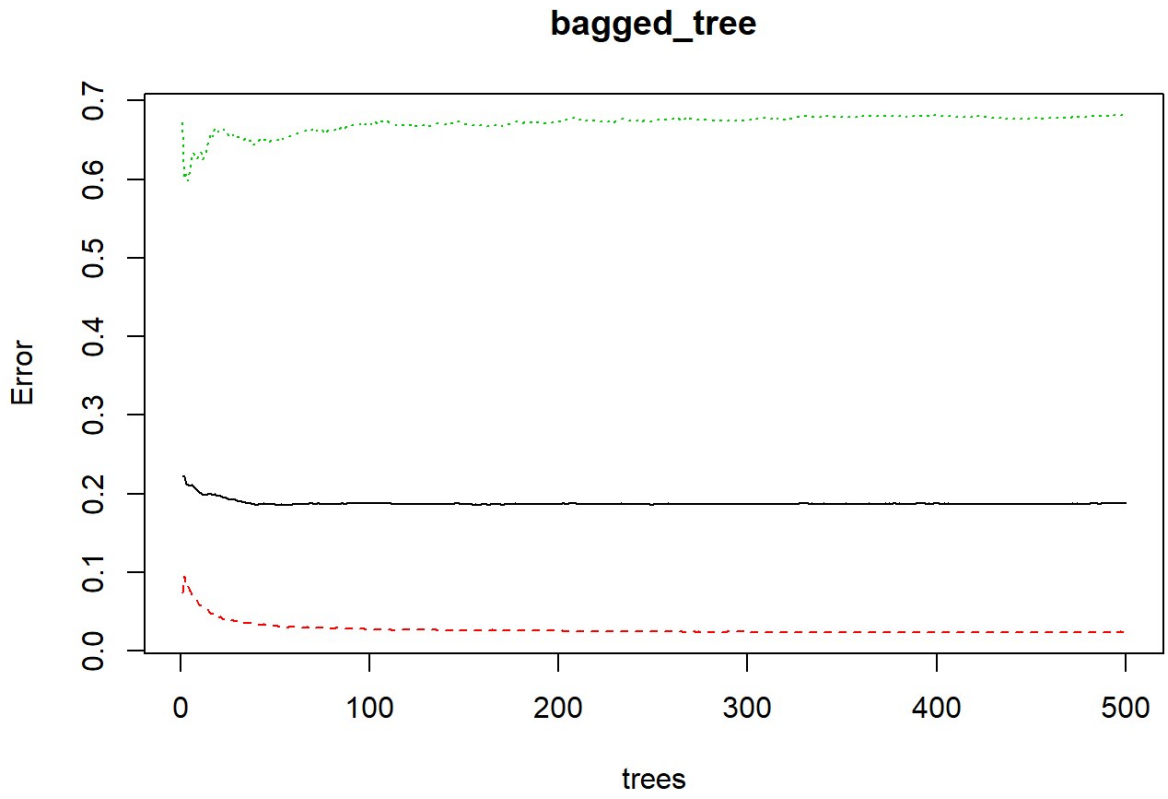
We fit the training data with the combination with the lowest misclassification error, using rpart from the rpart library, then pruned the tree with the CP with the lowest error. This produced a training accuracy of 0.8657. The AUC value was 0.89.

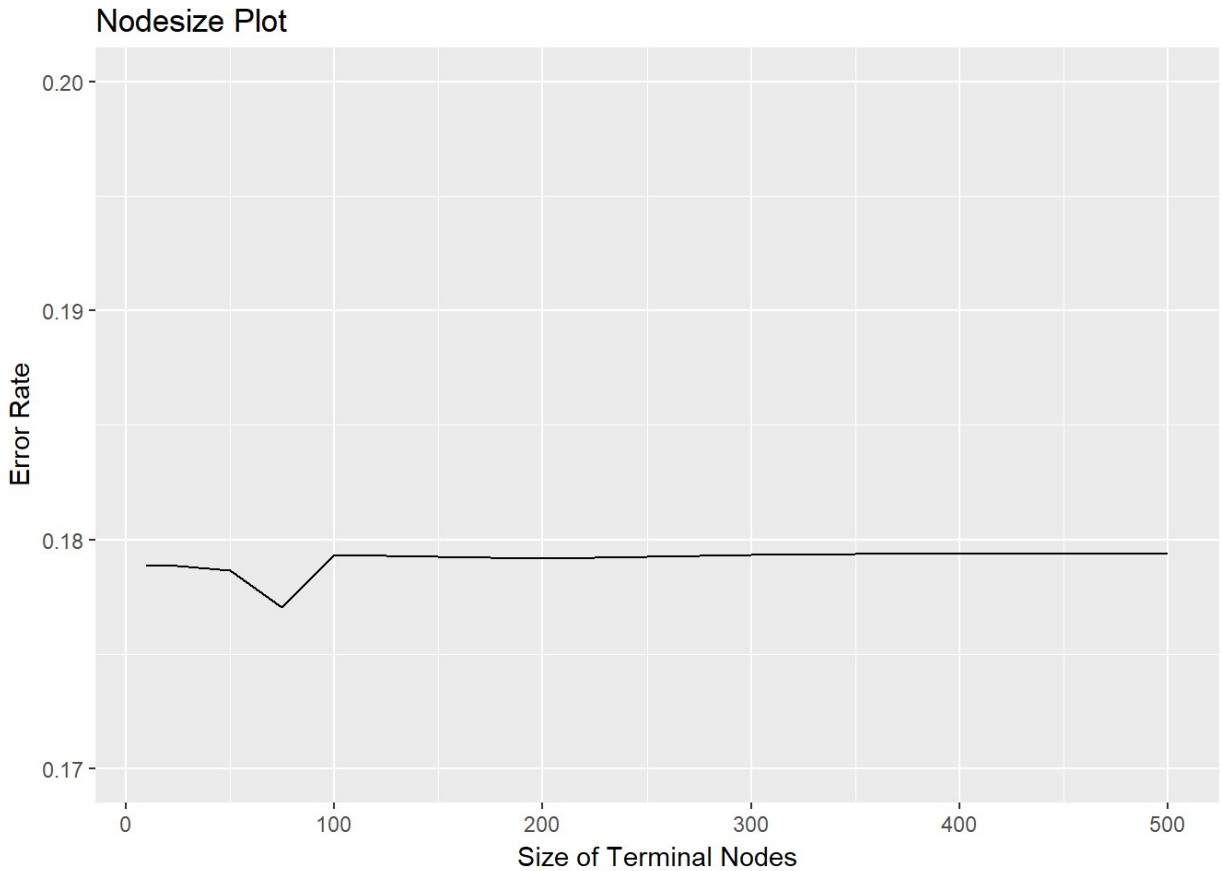
The following are the 7 most important varibales as measured by the average decrease in gini:

```
##   relationship marital_status      education   capital_gain     occupation
##      2313.3385      2252.7651      1127.6795      1096.4274       957.7924
##            sex            age
##       770.4282       679.4851
```

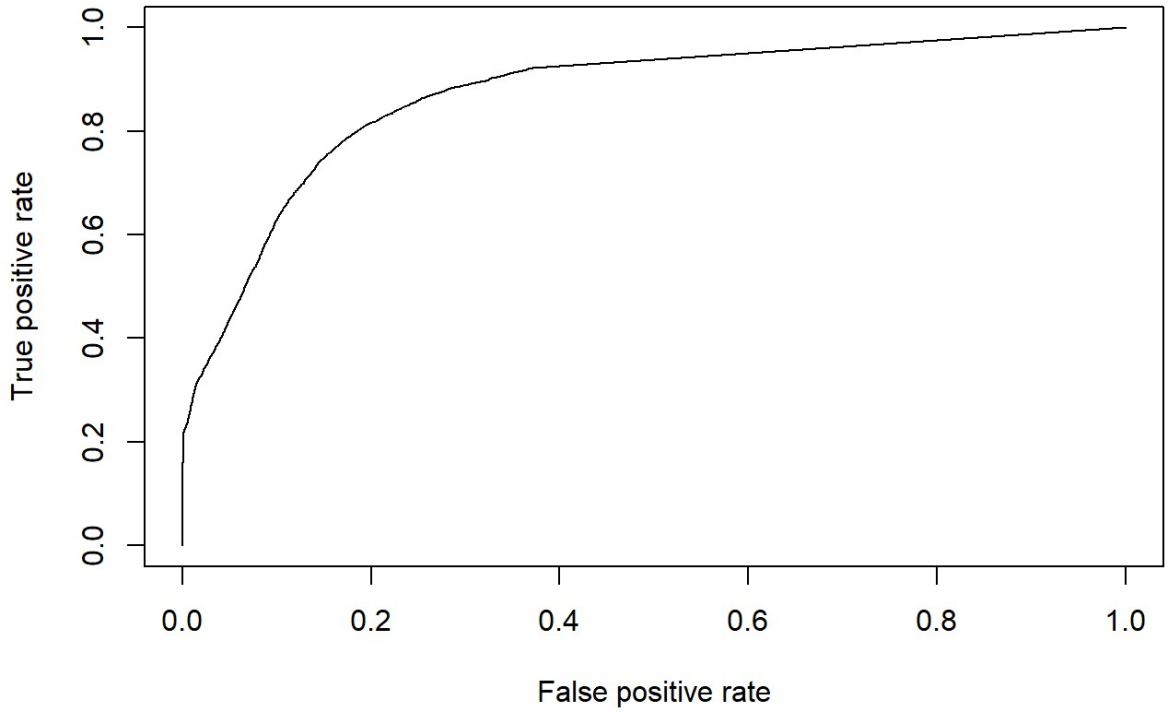
Bagged Tree:

A bagged tree is a special case of a random forest where all the predictors are considered at each split, which is reflected in the mtry parameter. We decided to tune the number of trees and minimum node size.





It can be seen from the graph of errors and number of trees that 300 trees stabilizes the error rate. Calculating the errors for different minimum node sizes, the plot shows that around a minimum of 75 produces the optimal error. Choosing 75 allows for controlling the size of the trees.

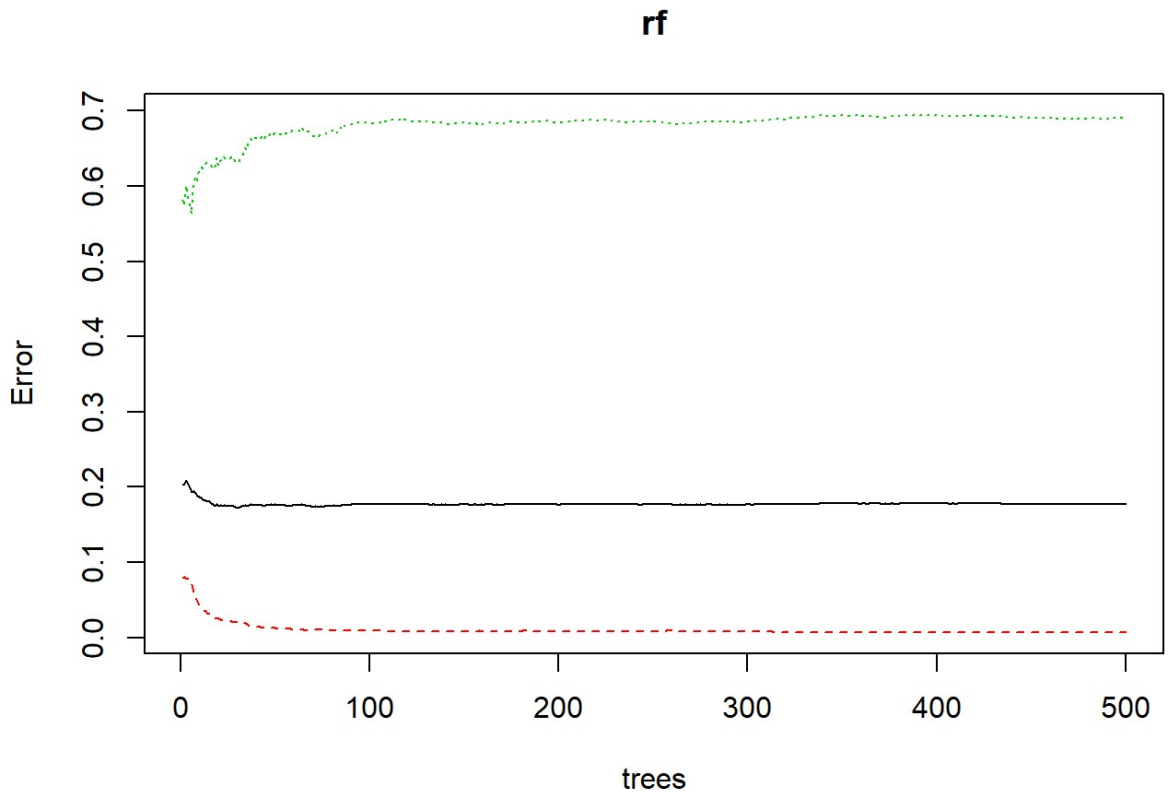


Using randomForest from the randomForest library, we fit the training data, getting a training accuracy of 0.81. The AUC was 0.87.

The seven most important variables were:

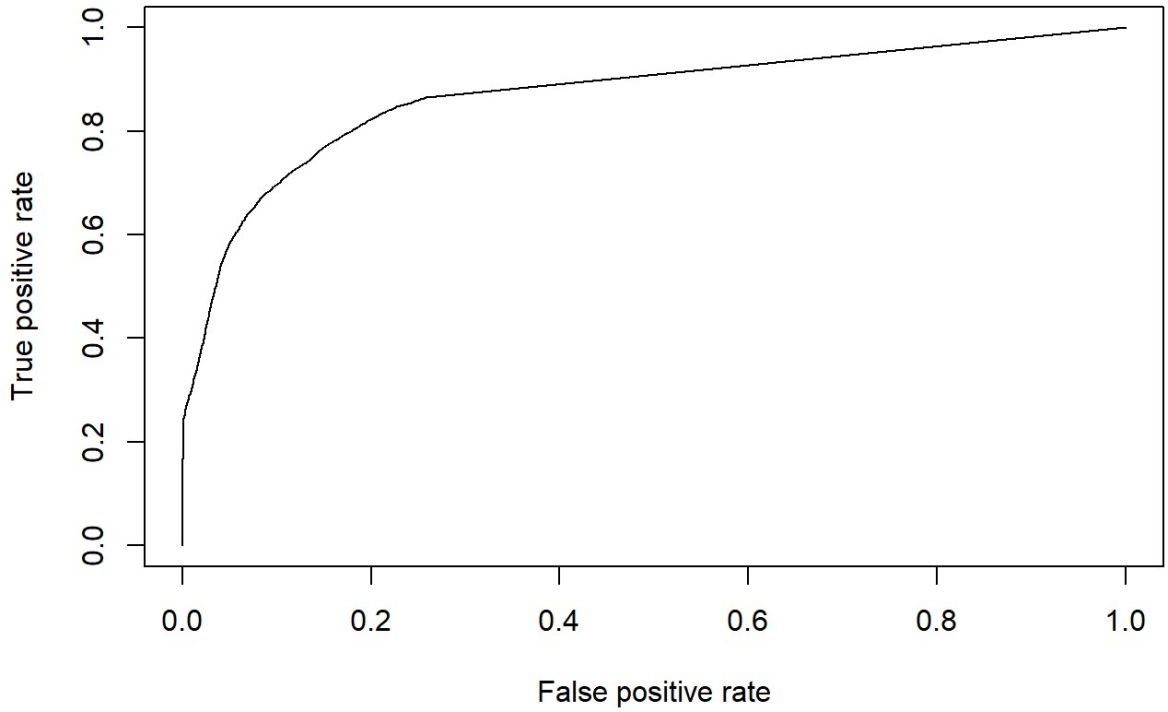
```
##   relationship      education   capital_gain     occupation            age
##      2294.4472      1143.5576      1102.4702       484.5694       407.3874
##   capital_loss hours_per_week
##       308.2347       257.7376
```

Random Forest:



A random forest of size 300 trees was fitted using randomForest from the randomForest library.When number of trees reached 300, three lines are stable and no significant change after 300. 300 trees is sufficient to provide our results with robustness.

Three parameters that are commonly used in tuning are the number of tree , minimum node size (implicitly set the depth of tree) and the number of predictors. We use the randon search in MLR package to find the hyperparameter. The hyperparameter with lowest error are mtry:4, nodesize:400, ntree:300. The minimum leaf size was chosen because the data is fairly unbalanced.

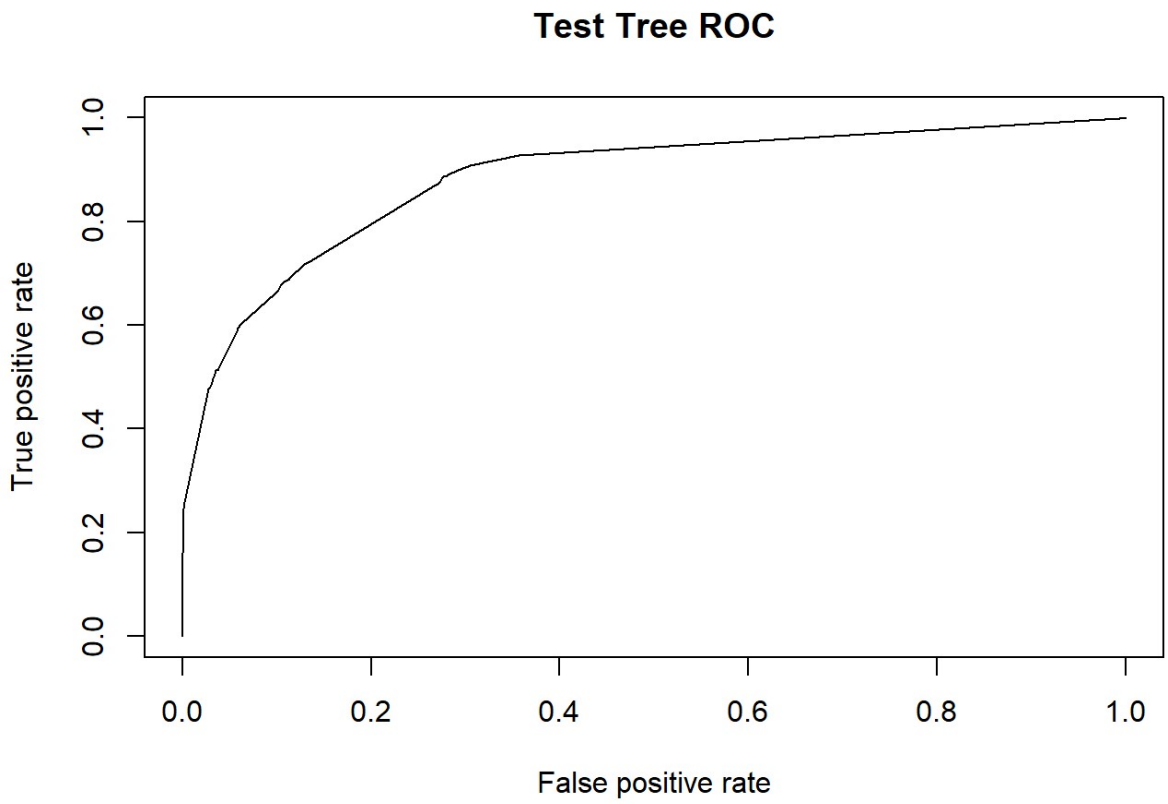


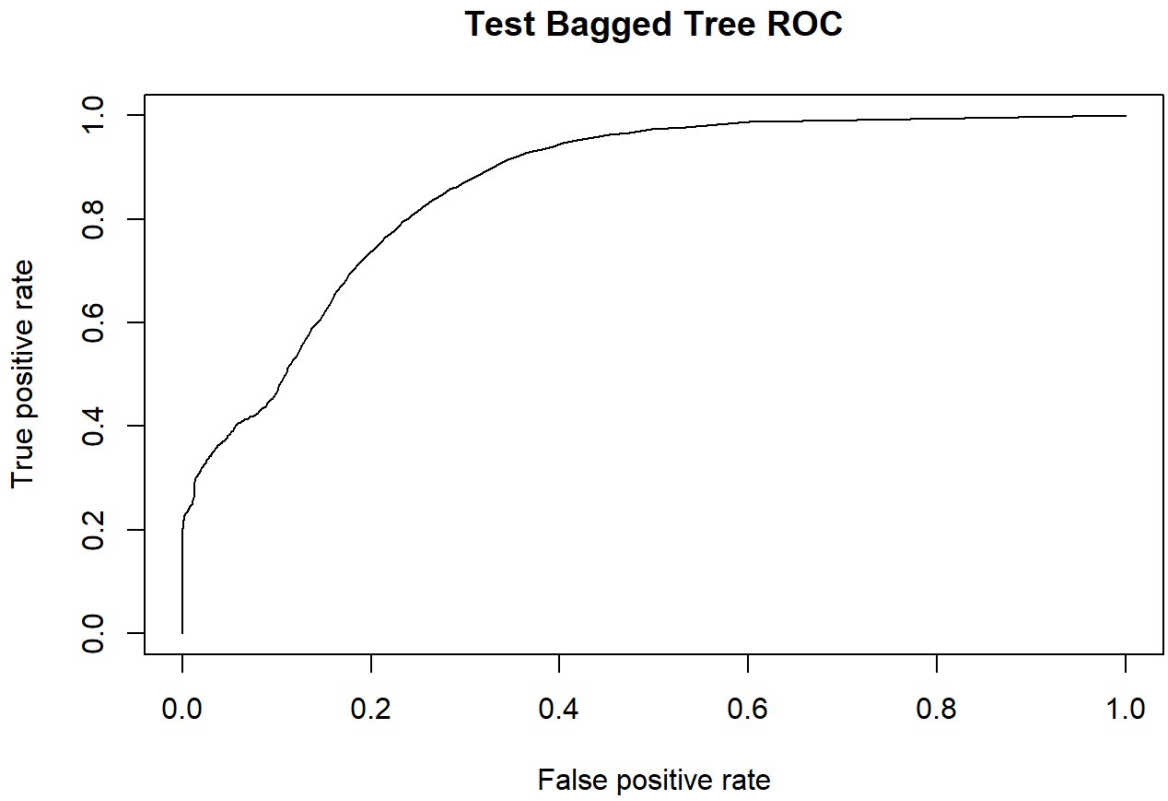
The random forest model has a training accuracy of 0.84, The AUC value was 0.87, lower than that of the tree. It would be useful to look at the false positive rate, which was around 2%.

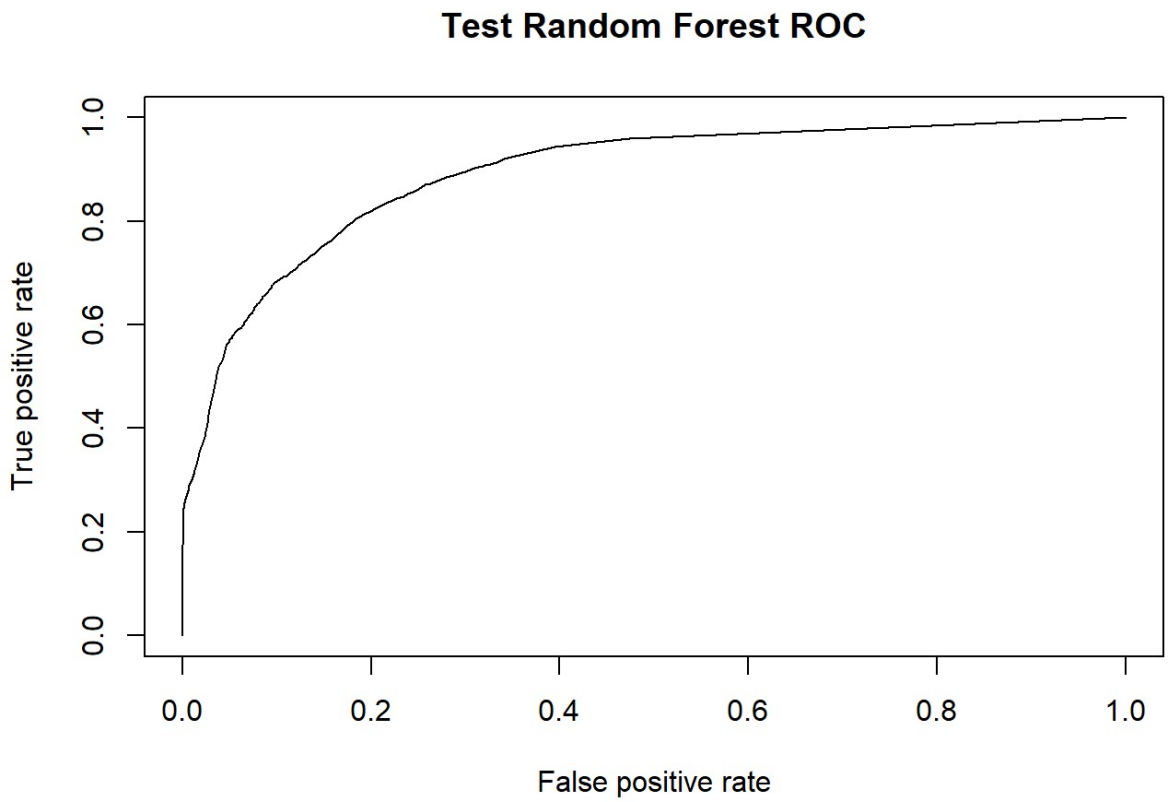
```
##   relationship   capital_gain marital_status      education     occupation
##      1234.6693      1006.6616       839.2736       797.1107       587.3411
##            age   capital_loss
##       281.5575       193.4349
```

Mostly the same variables had the most importance as measured by the mean decrease in gini as for the classification tree, although the values of the mean decrease in gini are noticably lower. This could be due to the fact that the mtry parameter restricted the selection of variables for splitting.

Test Data


Test Tree ROC
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0


Test Bagged Tree ROC
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0



Based on the training accuracy the tree is the strongest model. After fitting the tree, the test accuracy was 0.8562 and the AUC for the ROC curve was 0.868. Based on the plots, this is the highest AUC of the three, which would indicate that this classifier addresses the unbalanced data classes the best. The confusion matrix was (observed is the columns, predicted is the rows):

```
tree_confusion_Matrix$table
```

```
##            Reference
## Prediction <=50K  >50K
##      <=50K 10679  1485
##      >50K    684  2215
```

The true positive rate (senstivity) was:

```
## Pos Pred Value
##      0.8779184
```

The true negative rate (specificity) was:

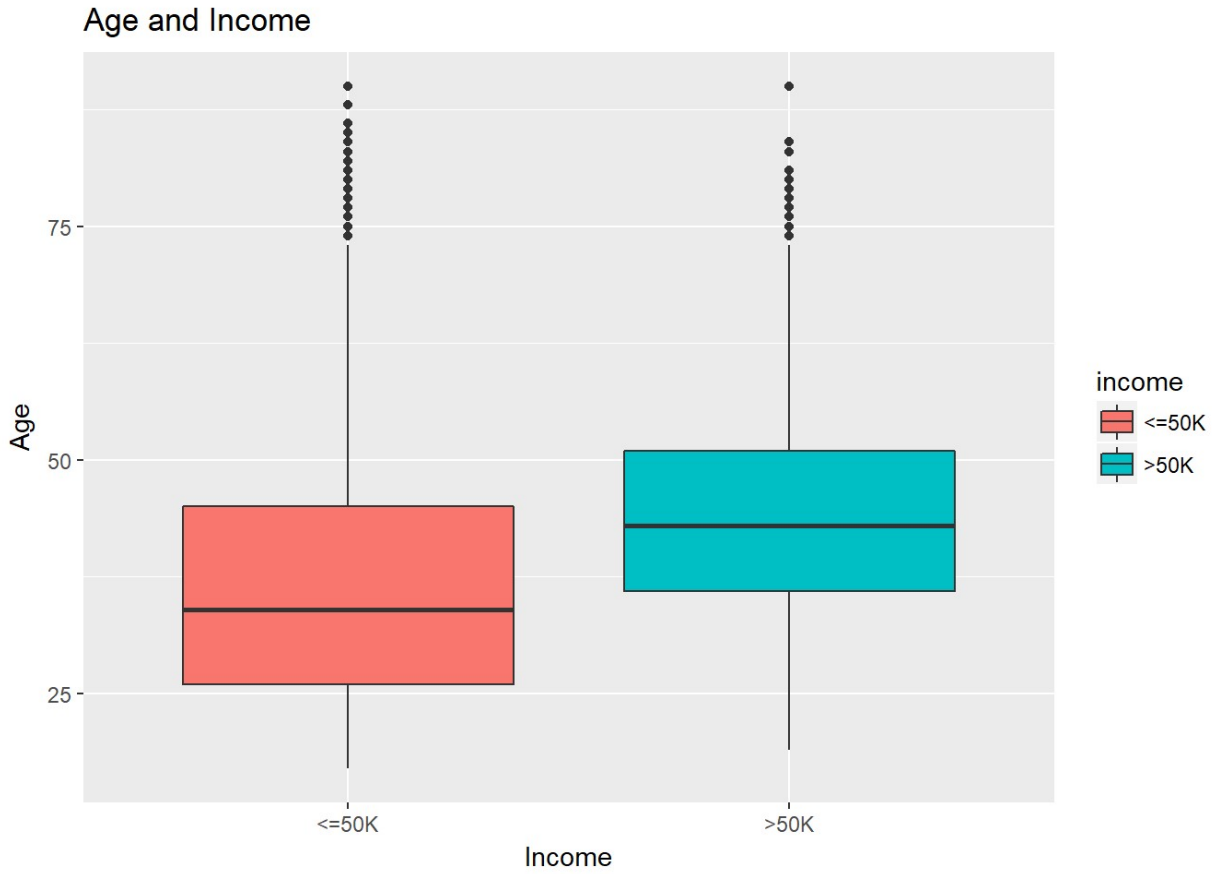
```
## Neg Pred Value
##      0.7640566
```

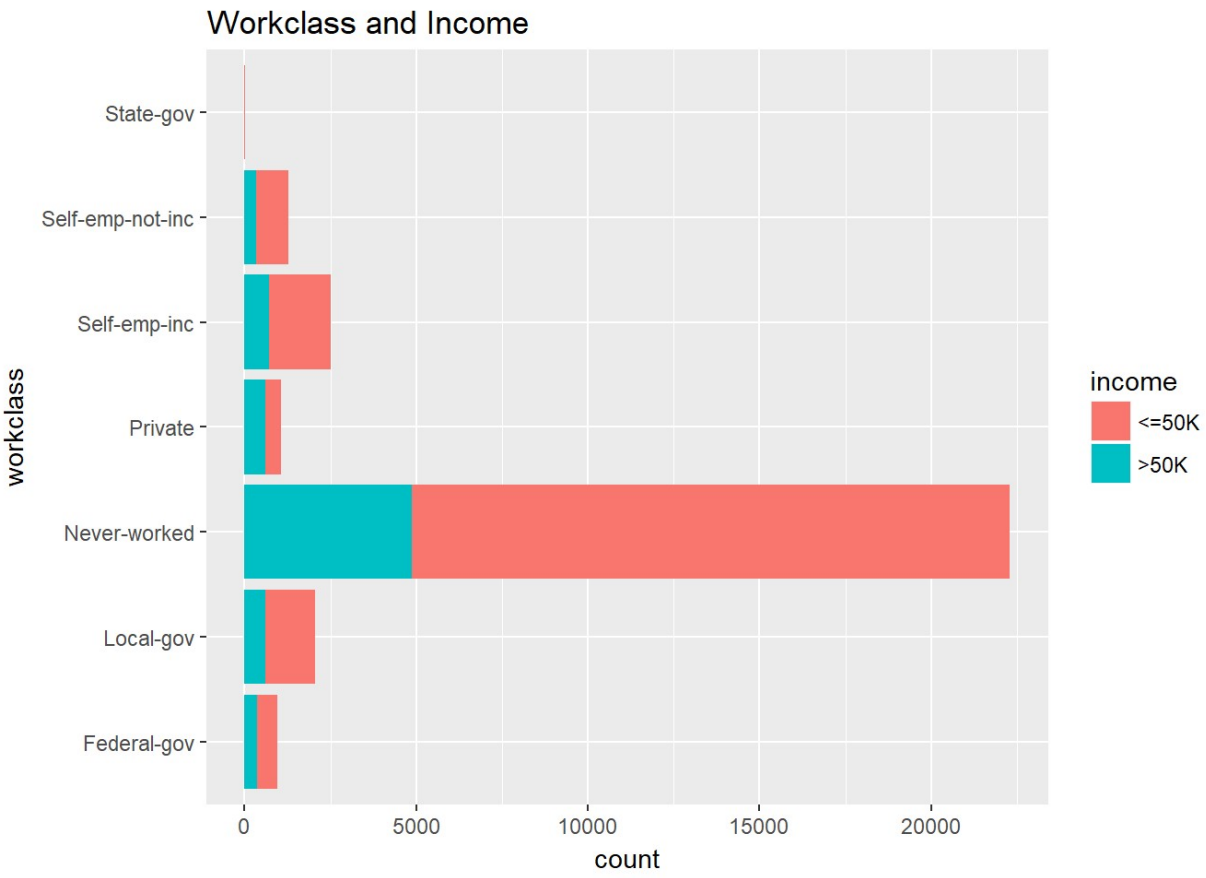
Conclusion

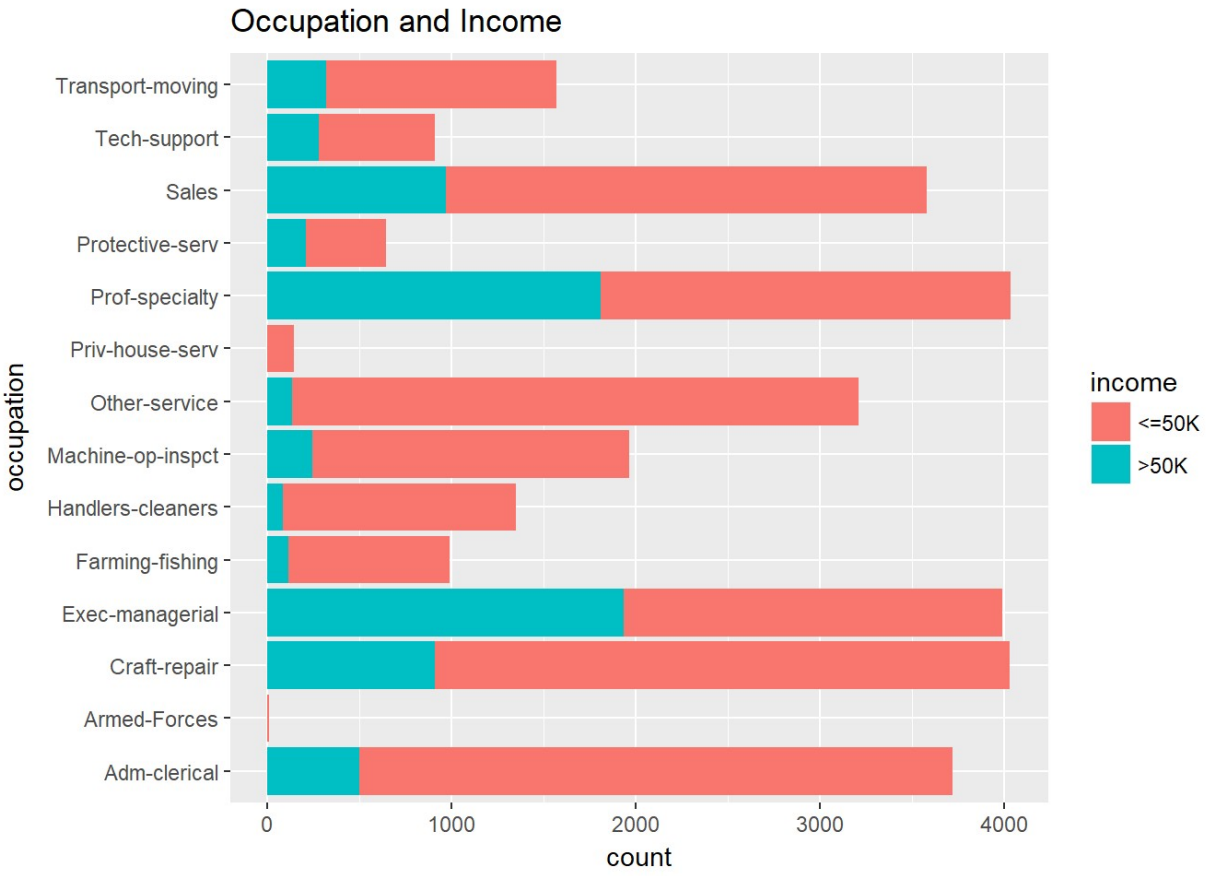
The classification tree is the strongest classifier of the three methods. The accuracy was 0.856 which was lower than the training accuracy of 0.883. This does indicate some overfitting of the training model. All three models indicated that the most discriminative variables were relationship, education, age, and occupation, although there were some differences in ranking. This is in line with our expecations that age, job, and level of education are strong indicators of income. It was interesting that race and gender didn't appear to be significant variables for the three models since these are widely thought of as key factors of income inequality.

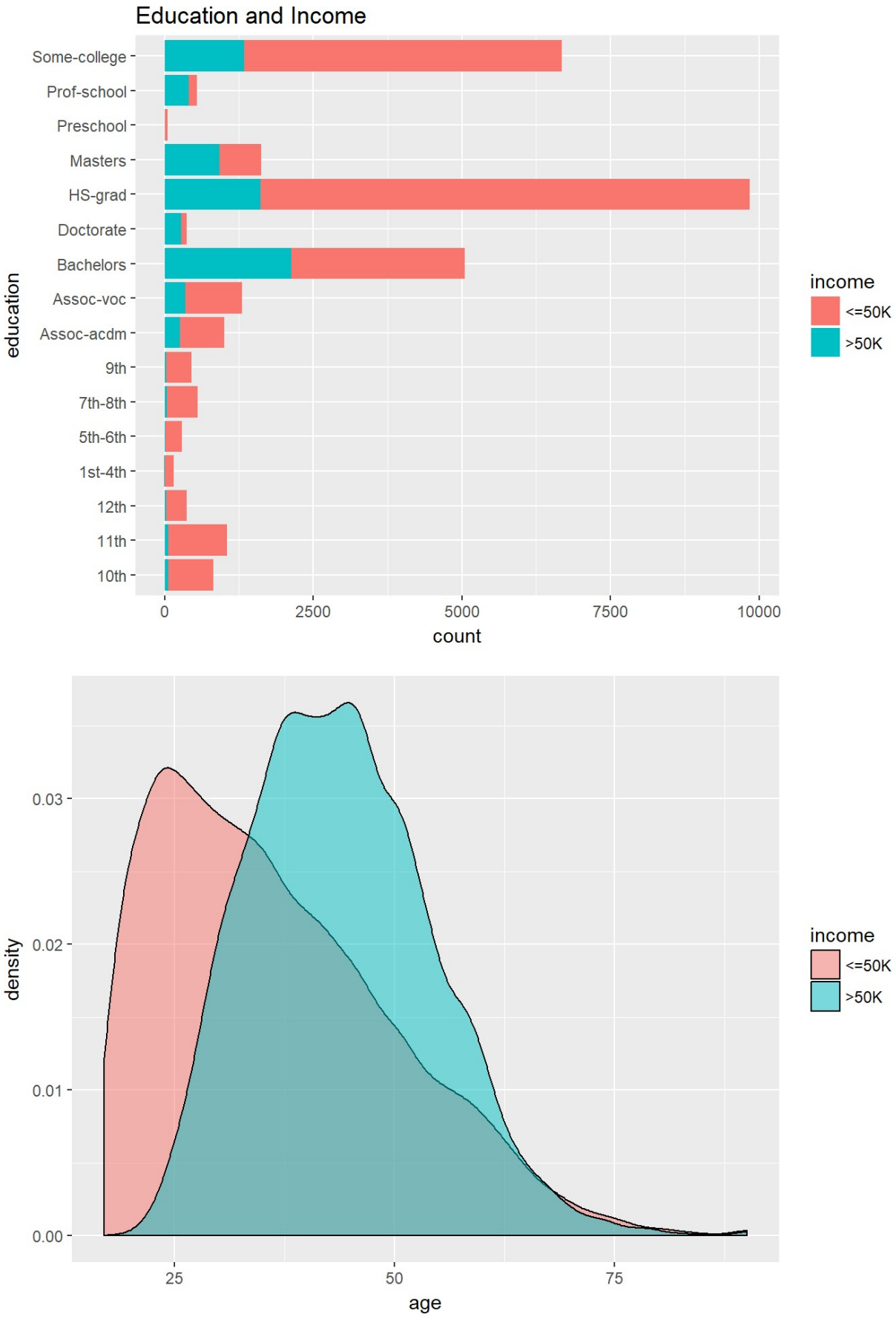
Due to computational limits, more granular tuning of parameters could not be done, but it would be useful to tune more of the parameters and more values for each parameter to address the unbalanced nature of the data.

Appendix

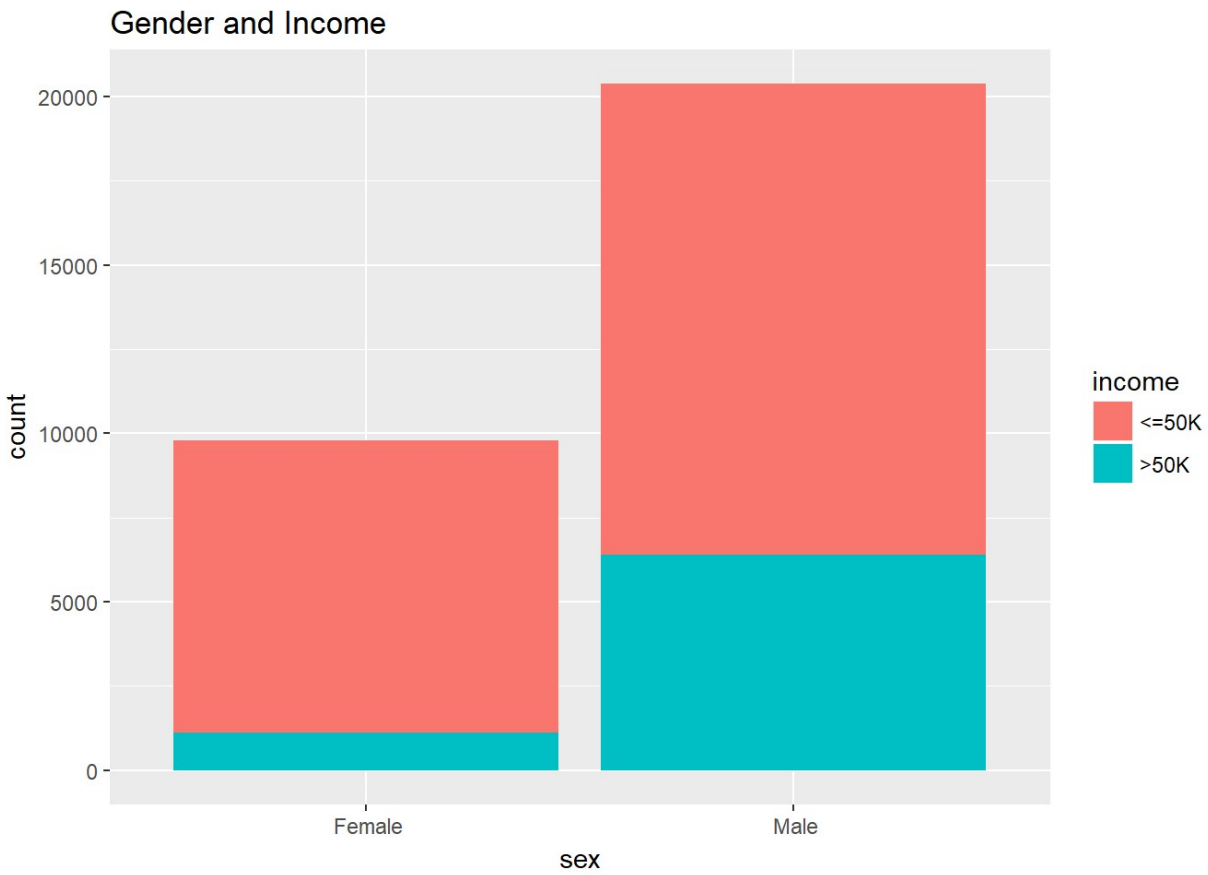



Workclass and Income
State-gov
Self-emp-not-inc
Self-emp-inc
Private
Never-worked
Local-gov
Federal-gov
workclass
0
5000
10000
15000
20000
count
income
<=50K
>50K

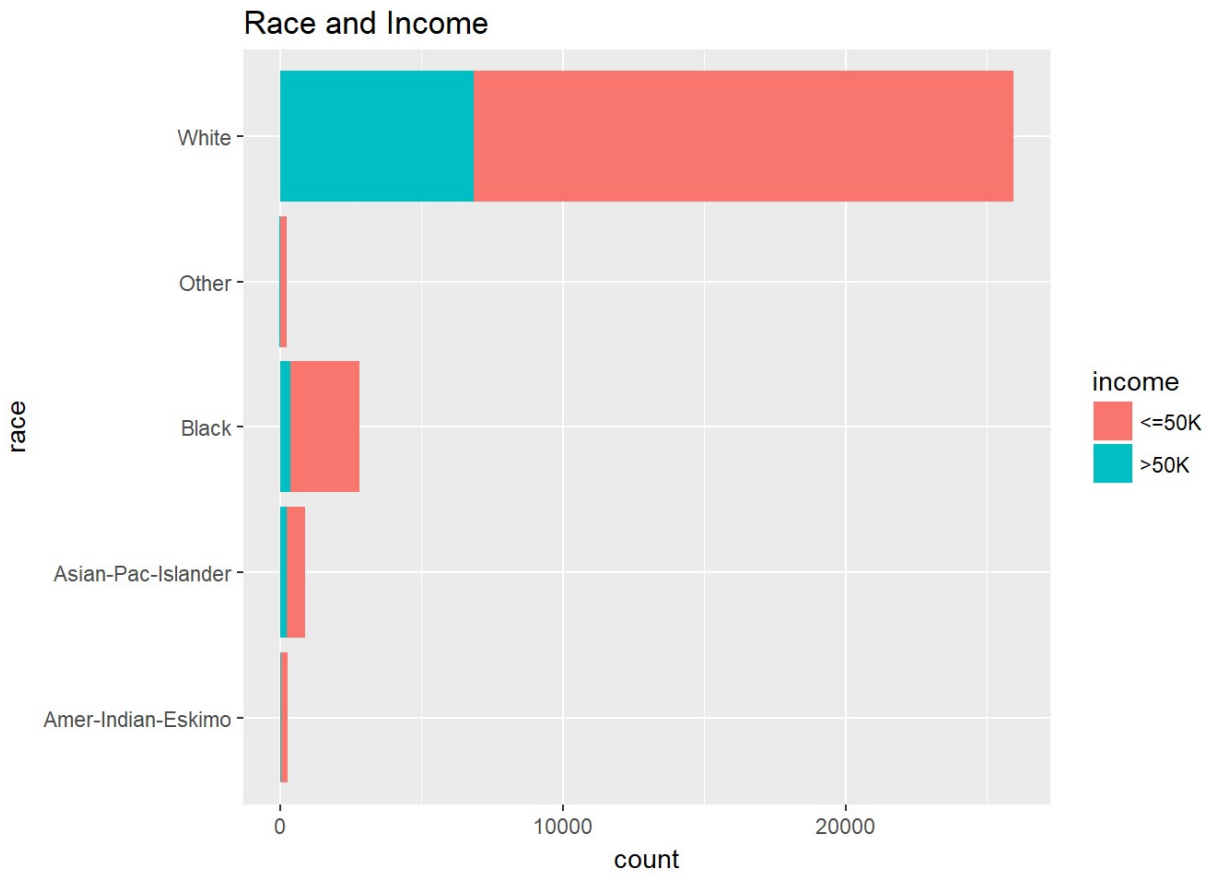

Occupation and Income
Transport-moving
Tech-support
Sales
Protective-serv
Prof-specialty
Priv-house-serv
Other-service
Machine-op-inspct
Handlers-cleaners
Farming-fishing
Exec-managerial
Craft-repair
Armed-Forces
Adm-clerical
occupation
0
1000
2000
3000
4000
count
income
<=50K
>50K



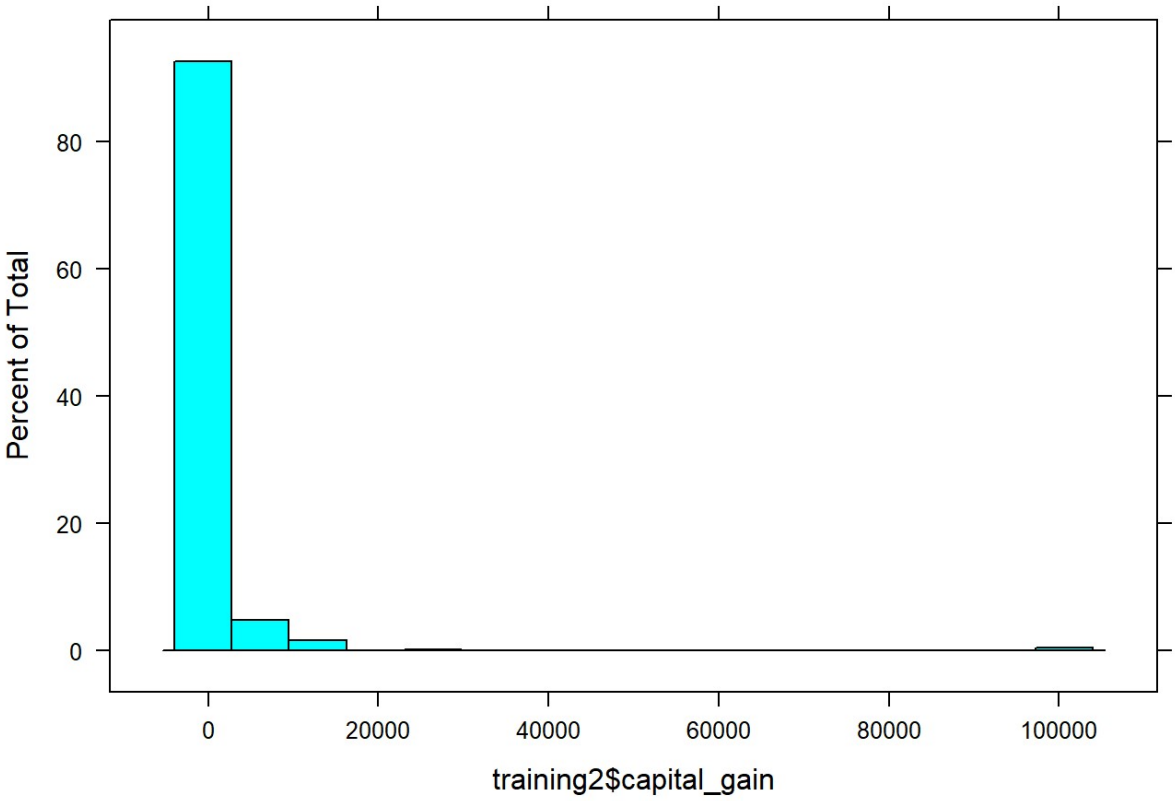
The median age of people making more than 50K is higher than the median age of people making less than 50k. Most people earning more than 50K are around 50 years old. This is consistent with the logic that older people tend to earn more.

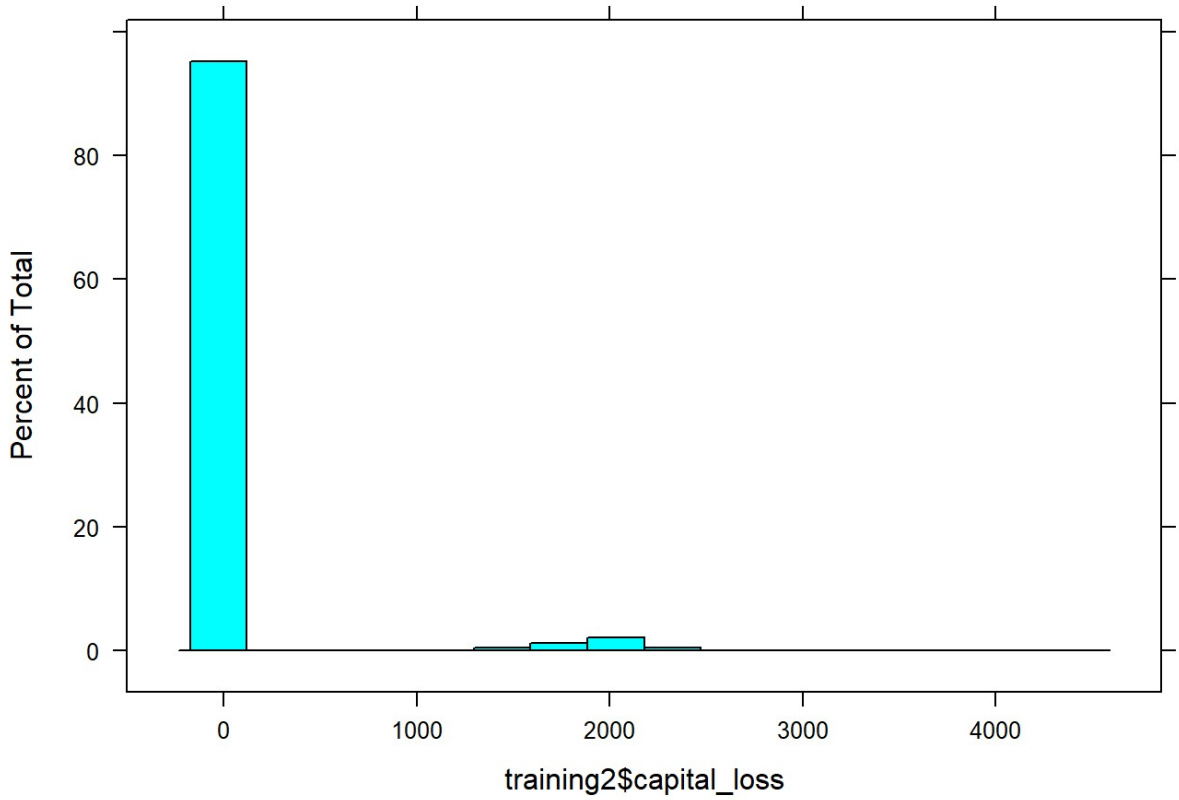


The data has much more males than females so the barplot is not balanced. It appears that a people making less than 50K make up a larger portion of the female population than they do for males, although for the dataset, people making fewer than 50K make up the large majority of the data, so it is not too different from the overall sample.



From the barplot, it appears that a larger proportion of whites have an income greater than 50k compared to the proportion for the other races.





Education and age appear to be the variables that are most different between the two income levels.