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Stat 154

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Final Project Report

Introduction:

Income level has become a topic people pay a lot of attention to. In this project, I will analyze people's income level, below or above 50,000, from census income data set denoted by Ronny Kohavi and Barry Becker to the UCI Machine Learning Repository. The features I will use to for the analysis are age, work class, final weight, marital status, occupation, relationship in the family, race, sex, capital gain, capital loss, working hours per week, and native country. The goal of this project is to use the feature to build a reasonable model in order to be able to determine if a new observation with all the features stated above has income less than or more than 50,000. To accomplish the goal, I am going to utilize classification tree model, bagging tree, and random forest, and, in the end, I will pick a model that fits the data the best to consider as the final model.

Data Cleaning and EDA:

I will begin with preprocessing (i.e. data cleaning) and exploratory data analysis. First of all, I know that the dataset has 32561 observations by simply check the number of rows in the dataset. Then, by looking at the summary statistics (figure shown below) of the training data, we can see there are some "?", which indicates missing values, in some of the variable. As a result, I will need to investigate further to handle these missing values.

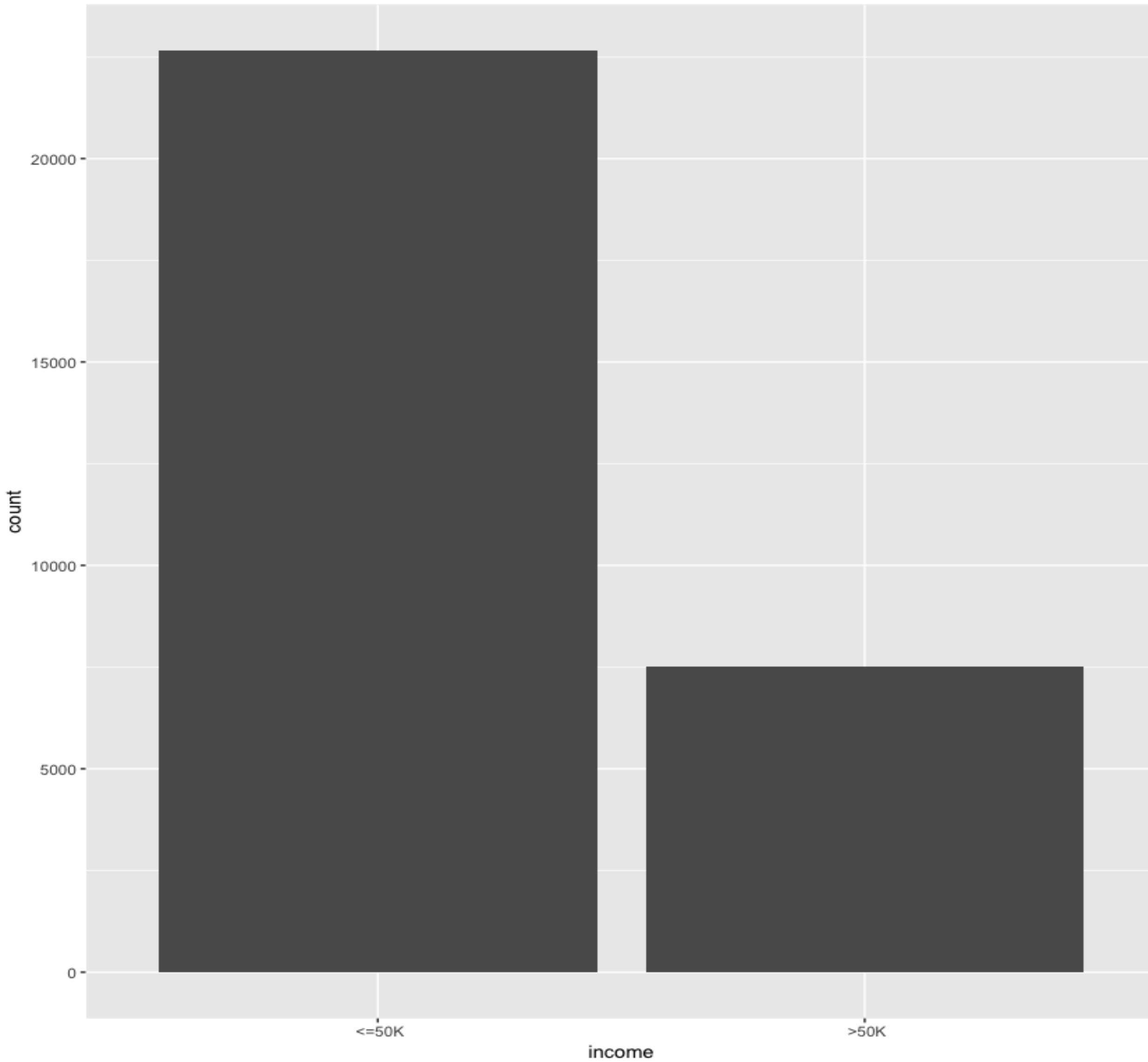
```
      age                    workclass          fnlwgt               education      education.num                 marital.status              occupation
 Min.   :17.00   Private          :22696   Min.   :  12285   HS-grad     :10501   Min.   : 1.00   Divorced             : 4443   Prof-specialty :4140
 1st Qu.:28.00   Self-emp-not-inc: 2541   1st Qu.: 117827   Some-college: 7291   1st Qu.: 9.00   Married-AF-spouse    :   23   Craft-repair   :4099
 Median :37.00   Local-gov       : 2093   Median : 178356   Bachelors   : 5355   Median :10.00   Married-civ-spouse   :14976   Exec-managerial:4066
 Mean   :38.58   ?               : 1836   Mean   : 189778   Masters     : 1723   Mean   :10.08   Married-spouse-absent:  418   Adm-clerical   :3770
 3rd Qu.:48.00   State-gov       : 1298   3rd Qu.: 237051   Assoc-voc   : 1382   3rd Qu.:12.00   Never-married        :10683   Sales          :3650
 Max.   :90.00   Self-emp-inc    : 1116   Max.   :1484705   11th        : 1175   Max.   :16.00   Separated            : 1025   Other-service  :3295
                (Other)          :  981                    (Other)      : 5134                   Widowed              :  993  (Other)         :9541
         relationship                    race            sex          capital.gain    capital.loss     hours.per.week        native.country      income
 Husband       :13193   Amer-Indian-Eskimo:  311   Female:10771   Min.   :    0   Min.   :   0.0   Min.   : 1.00   United-States:29170   <=50K:24720
 Not-in-family : 8305   Asian-Pac-Islander: 1039   Male  :21790   1st Qu.:    0   1st Qu.:   0.0   1st Qu.:40.00   Mexico       :  643   >50K : 7841
 Other-relative:  981   Black             : 3124                  Median :    0   Median :   0.0   Median :40.00   ?            :  583
 Own-child     : 5068   Other             :  271                  Mean   : 1078   Mean   :  87.3   Mean   :40.44   Philippines  :  198
 Unmarried     : 3446   White             :27816                  3rd Qu.:    0   3rd Qu.:   0.0   3rd Qu.:45.00   Germany      :  137
 Wife          : 1568                                             Max.   :99999   Max.   :4356.0   Max.   :99.00   Canada       :  121
                                                                                                                  (Other)       : 1709
```

By looking at the summary statistic and the unique values in categorical variables, there seems to be no missing values in variables age, fnlwgt, education, education-num, marital-status, relationship, race, sex, hours-per-week, and income. Therefore, for these variables, we do not need to handle the missing values. Also, I found that there are 29849 of the data in capital gain equal to 0, and 31042 of the data in capital loss equal to 0. Therefore, I decide to omit these two features for building the model later on since they may not provide useful information since most of the data are missing. Furthermore, I noticed that the missing values seems to be non-systematic (i.e. data missing just due to chance), and the number observations having missing values is not large (1836 in workclass, 1843 in occupation, and 583 in native country) comparing to the total number of observations 32561. Accordingly, I choose to simply remove these individuals from the dataset.

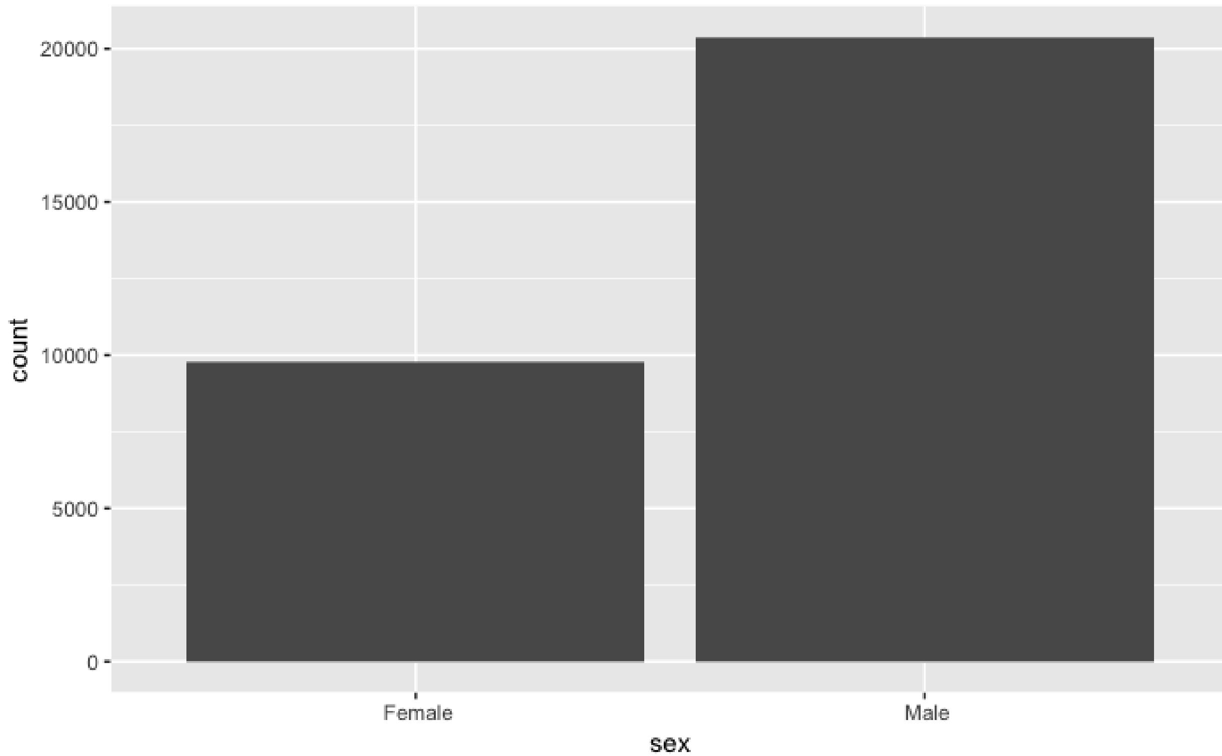
Some people bin the variables to maybe make their classification models run more efficiently. However, since discretizing variables may lose some information, I just decide not to do so.

In addition, I change the scale of all the numeric variables into standard unit (i.e. subtract by their mean and divide by their standard deviation). By doing so, all the variables have the same scale, and doing to can make the variable comparisons much easier.

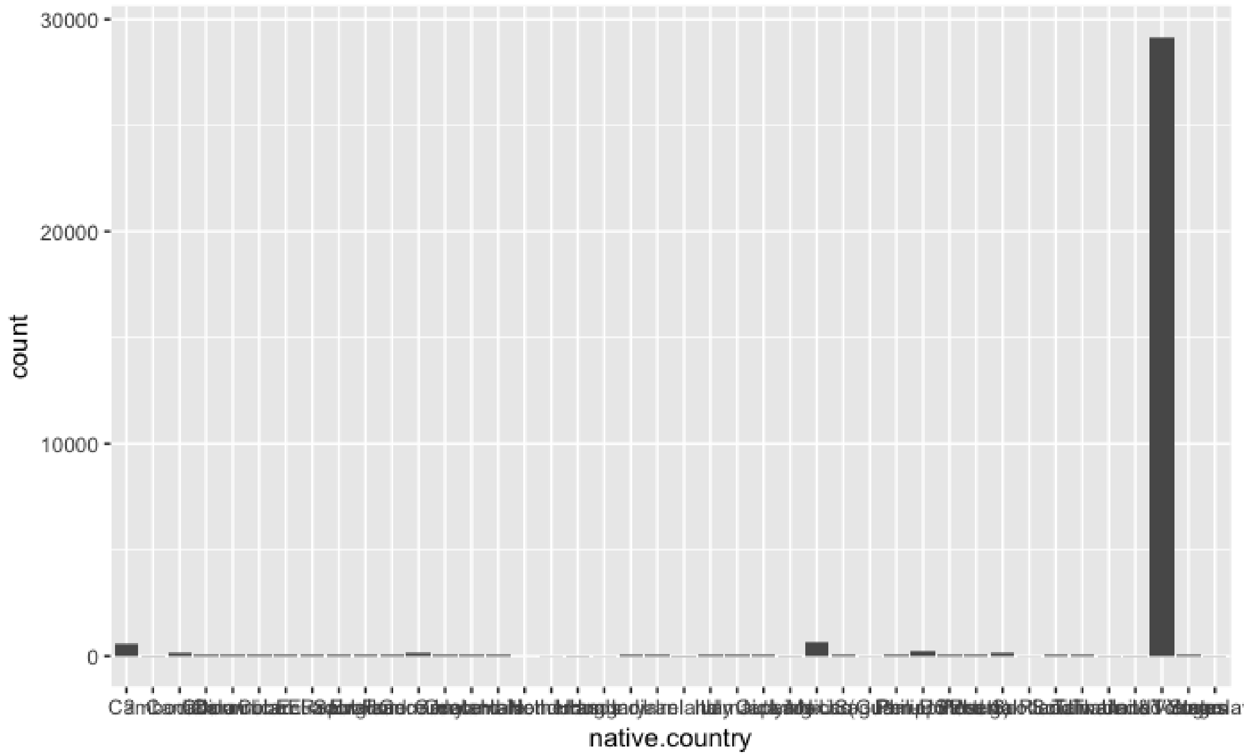
To further explore the variables, a good approach is to visualize the distributions of each variables. I would like to plot the numeric variables with density plots and categorical features with boxplots. First of all, I look at the plot for income, and notice that the number of people who earn less than 50K is way more than the number of people who earn more than in this dataset. I may need to take this fact into account when I build the model and/or make the conclusion.



Then, we can look at the plot for sex. We can see that there are more males than females in the dataset. This may raise up a question: combining the fact that there are more people earn less that 50K than more than 50K, does that mean males earn less than females? I will say no. Before we do any data analysis, we can guarantee anything. Also, this dataset may not be collected at random, so there may be a lot of different factors that we have not explore yet that may affect the income.



We can see that most of the individuals in the dataset are from the United State since the dataset came from US Census data.



Now, we can further look at the correlation between explanatory variables and response variable. We can see that although basically all the variables are not highly correlated to the response variable. However, since I am going to build the model with not just one variable, I can still use all these variables to build the classification models.

[1] "The correlation between age and income is 0.242"

[1] "The correlation between workclass and income is 0"

[1] "The correlation between fnlwgt and income is -0.009"

[1] "The correlation between education and income is 0.079"

[1] "The correlation between education.num and income is 0.3353"

[1] "The correlation between marital.status and income is -0.1935"

[1] "The correlation between occupation and income is 0.0516"

[1] "The correlation between relationship and income is -0.251"

[1] "The correlation between race and income is 0.0717"

[1] "The correlation between sex and income is 0.2167"

[1] "The correlation between hours.per.week and income is 0.2295"

[1] "The correlation between native.country and income is 0.0233"

Model Building:

Classification Tree

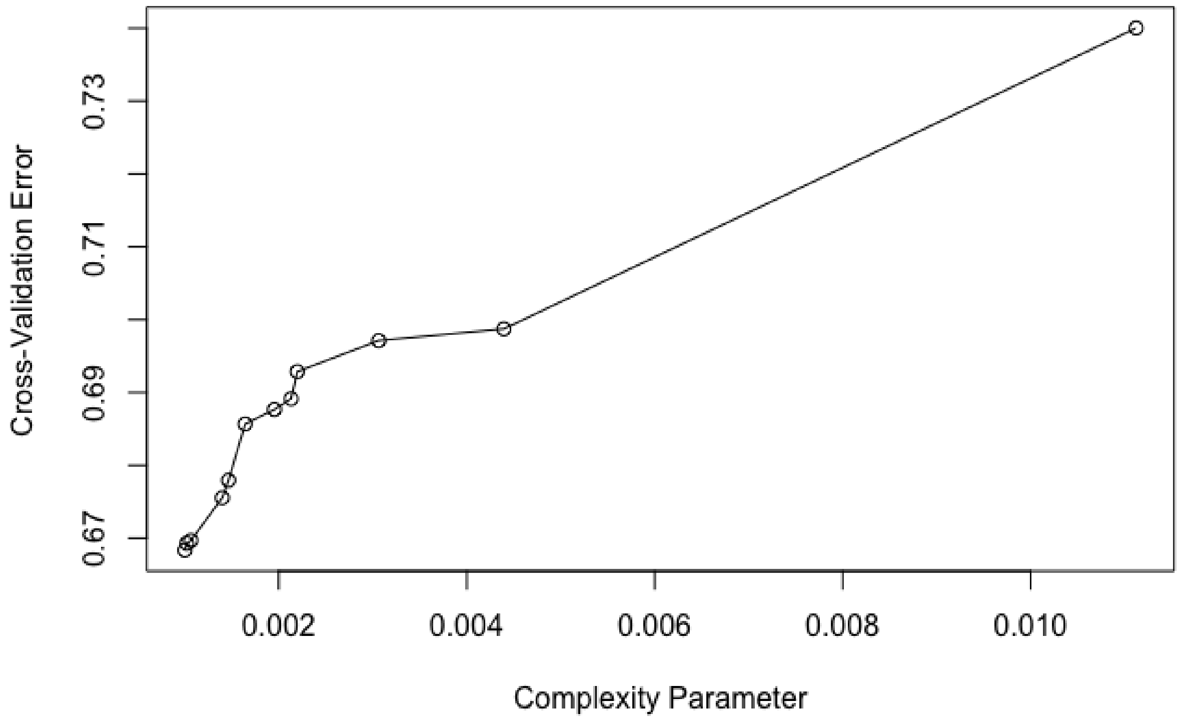
In this part, I will use the R package "rpart" to build the classification model, and I will try to find out the best hyper parameter in order to fit the model more to the data. At the same time, I will need to prevent from overfitting the model.

First of all, I fit the classification tree with default values in rpart. The default complexity parameter is 0.01. And, within rpart, I internally use cross validation to test on complexity parameter. We can see the complexity parameter table shown below. The way to read the cross-validation errors is that we look at the column "xerror" and multiply it be root node error (0.24892 in this case). However, we can simply look for the minimum values from "xerror" column since multiply by a scaler greater than 1 does not affect the sorted order of numbers.

```
Classification tree:
rpart(formula = income ~ ., data = dat)

Variables actually used in tree construction:
[1] age          education    occupation   relationship

Root node error: 7508/30162 = 0.24892

n= 30162

        CP nsplit rel error  xerror      xstd
1 0.129995      0   1.00000 1.00000 0.0100018
2 0.011121      2   0.74001 0.74001 0.0089670
3 0.010000      5   0.69579 0.70844 0.0088158
```

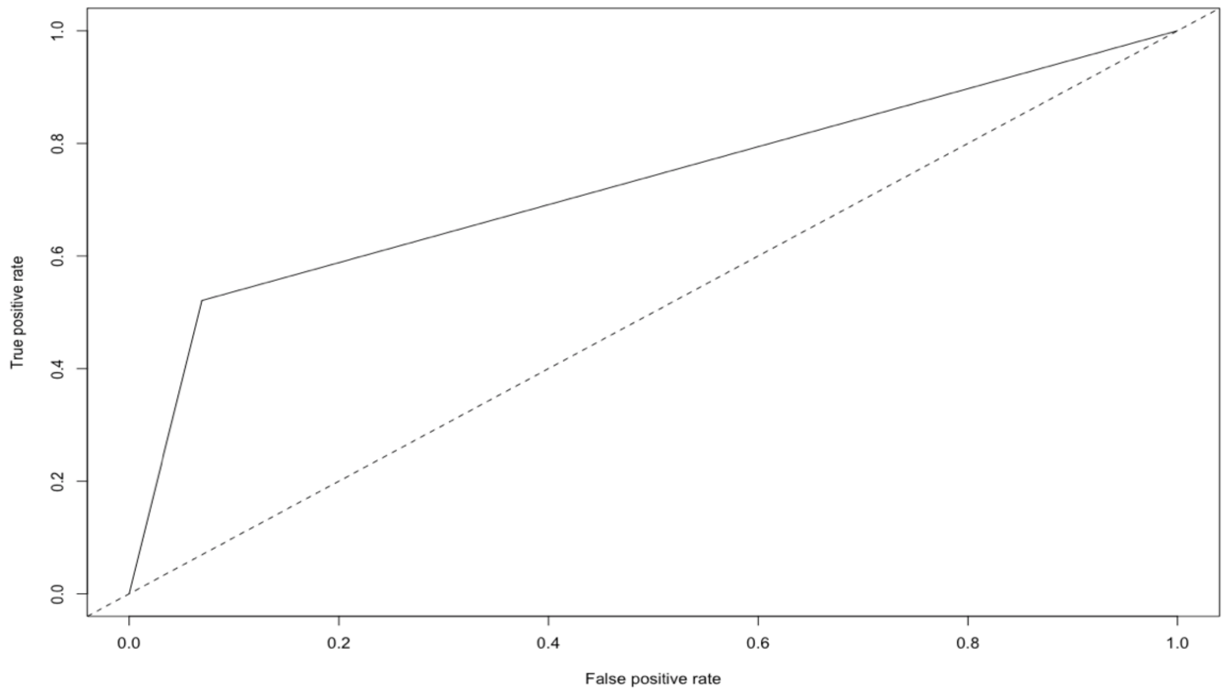
Knowing that there are actually only two complexity parameters that I can really choose since the one with no split is not useful, I redo the cross-validation process by setting the complexity parameter to 0.001 instead of default 0.01. Now, we can see from the table shown below, all the complexity parameters less than 0.003 have almost no difference in cross-validation errors (by taking the “xerror” column times root node error). As a result, I can choose any of them which will give me around the same cross-validation error. Furthermore, in order to prevent from overfitting, I need to choose a complexity parameter that does not give a high number of splits. Therefore, I decide to choose 0.0022 as my complexity parameter which gives me around 7 splits.

```
Classification tree:
rpart(formula = income ~ ., data = dat, cp = 0.001)

Variables actually used in tree construction:
[1] age            education      hours.per.week native.country occupation     relationship   sex
workclass

Root node error: 7508/30162 = 0.24892

n= 30162

          CP nsplit rel error  xerror      xstd
1  0.1299947      0   1.00000 1.00000 0.0100018
2  0.0111215      2   0.74001 0.74001 0.0089670
3  0.0043953      5   0.69579 0.69872 0.0087680
4  0.0030634      6   0.69140 0.69712 0.0087600
5  0.0021977      7   0.68833 0.69286 0.0087388
6  0.0021311     11   0.67954 0.68913 0.0087202
7  0.0019535     15   0.67035 0.68767 0.0087128
8  0.0016427     18   0.66449 0.68567 0.0087028
9  0.0014651     23   0.65357 0.67794 0.0086636
10 0.0013985     24   0.65210 0.67555 0.0086514
11 0.0010655     26   0.64931 0.66969 0.0086213
12 0.0010211     28   0.64718 0.66929 0.0086193
13 0.0010000     31   0.64411 0.66835 0.0086145
```

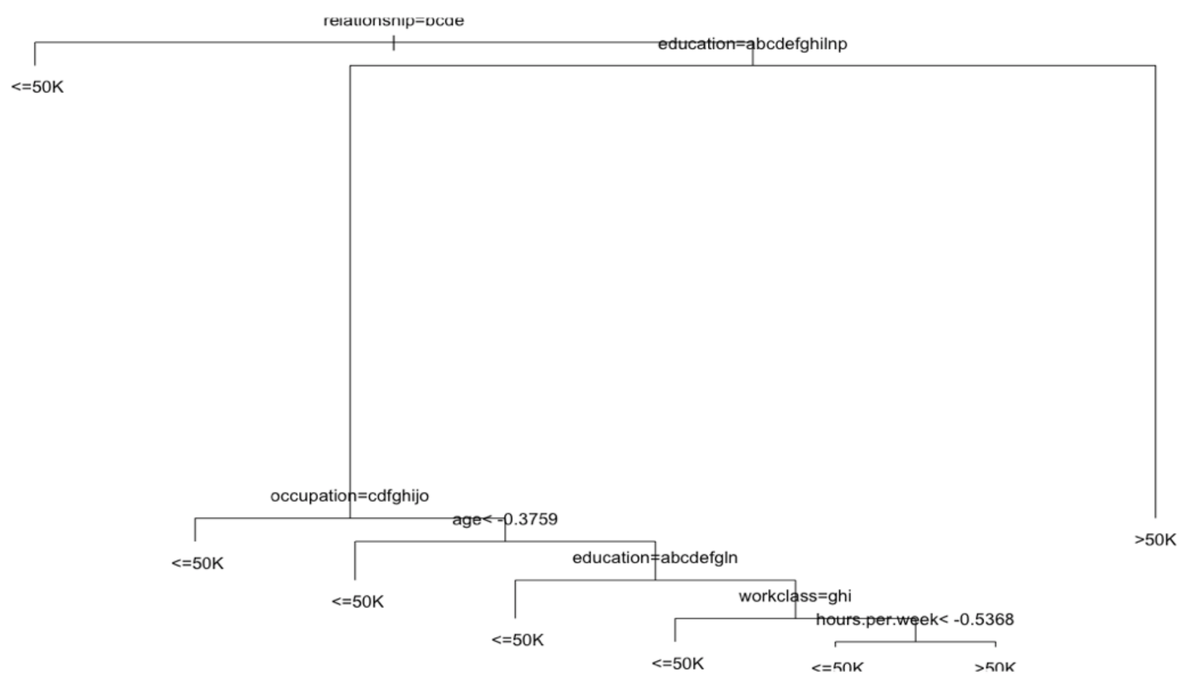


One way to measure whether a model is good is to look at the ROC (Receiver Operating Characteristic) curve (shown below) and the AUC (area under curve). The model selected has

AUC of 0.7258, which is not so good, but it's not so bad as well.

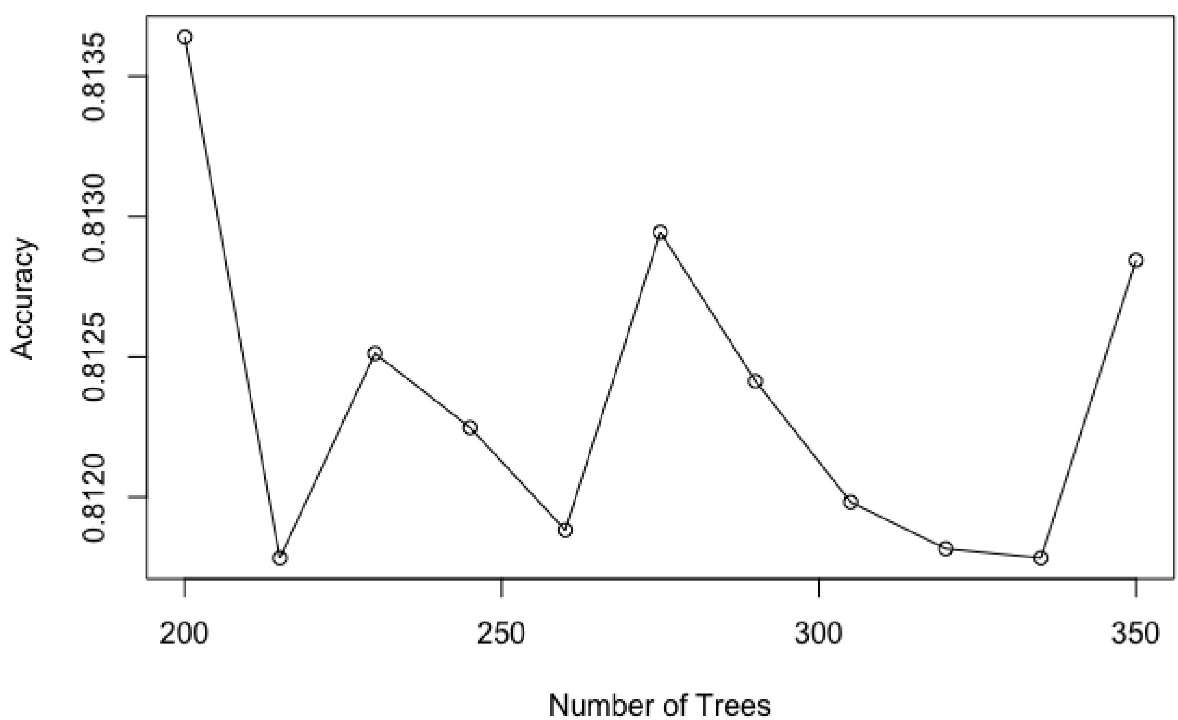


To summarize, the classification tree model I select has complexity parameter of 0.0022 with 7 splits. It has an in-sample accuracy of around 83%.



Bagged Tree

The idea is that build a random forest with all the features, but I need to choose the number of trees in the forest via parameter tuning. The way I choose to tune the hyperparameter is to utilize cross-validation. First of all, a reason range for a random forest is 200 to 350, in my opinion. After running cross-validation with sequence 200, 215, …, 350, 200 gives me the lowest cross-validation error although they are all really close (plot of cv accuracy shown below). The reason that the cross-validation errors are close may be random forest models predict the results base on majority votes.



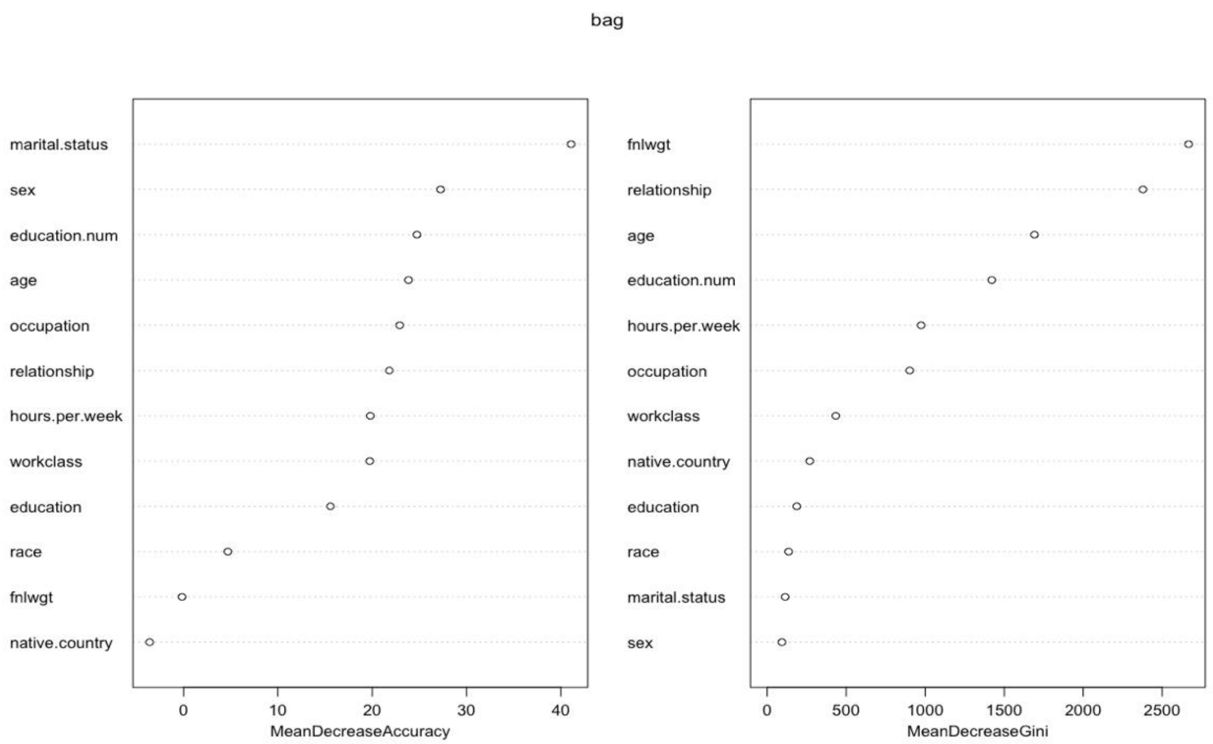
We can also look at the importance of each variable to the model. By looking at mean decrease accuracy, the 5 most important features and its variable importance statistics are shown below.

marital.status	sex	education.num	age	occupation
41.07545	27.23939	24.74220	23.85257	22.92289

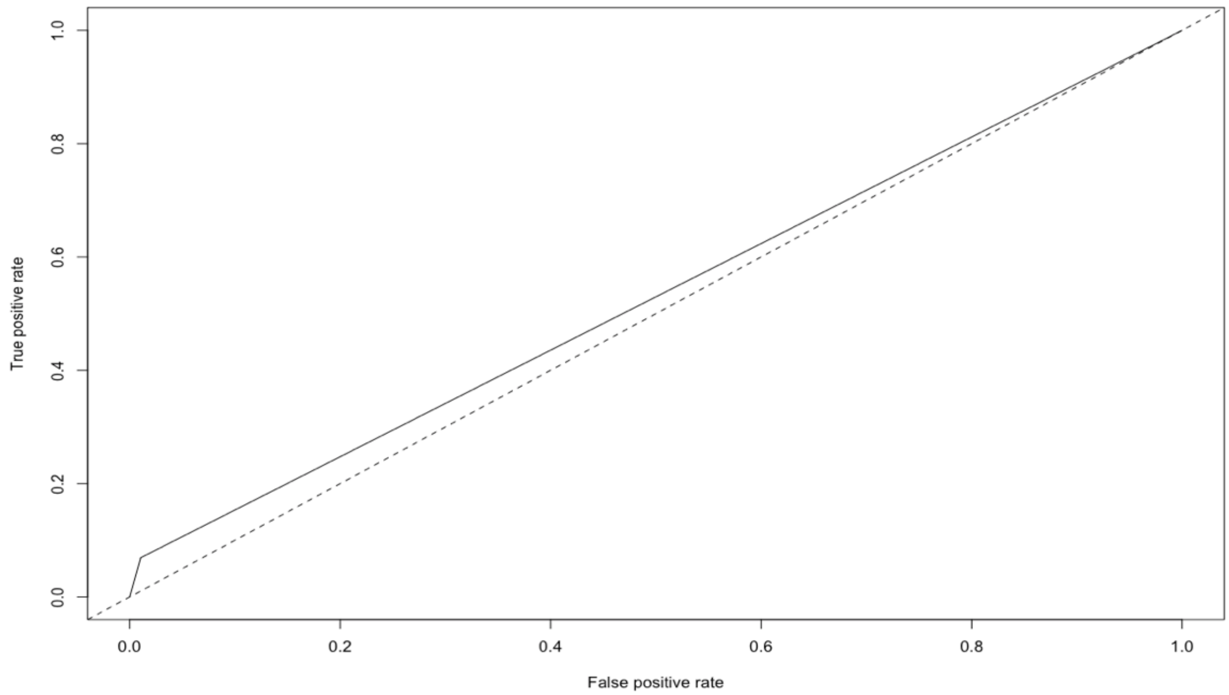
However, by looking at mean decrease gini, the 5 most important features and its variable importance statistics are shown below.

fnlwgt	relationship	age	education.num	hours.per.week
2666.7308	2378.8149	1691.8624	1421.2200	973.9281

We can also see a more explicit plot below to see the importance statistics.



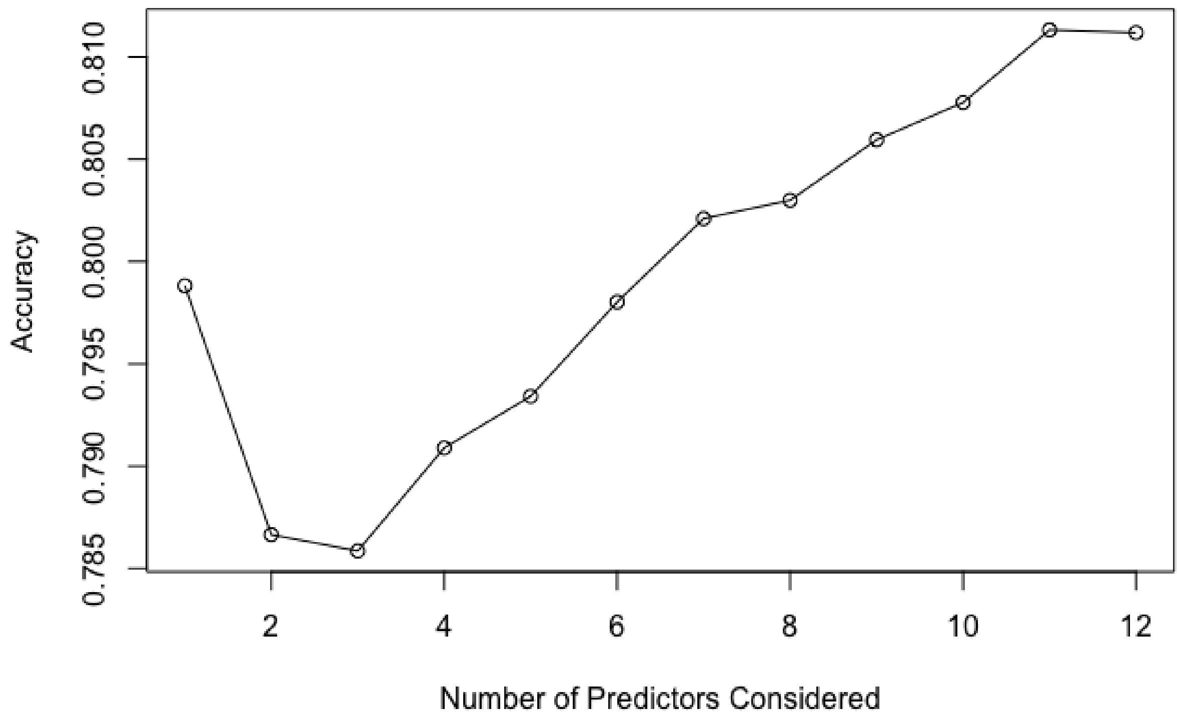
Again, ROC curve and its AUC is a way to measure a model. The bagged tree model selected has AUC of 0.5294.



In conclusion, the bagging tree model selected has a structure of 200 trees, and it achieves an accuracy of 76%.

Random Forest

There are two hyperparameters to tune which are number of trees in the forest and number of features used to construct the trees. Since I have already tuned the number of trees while working with bagging tree, I will just keep the number of trees the same as before. Again, I utilize cross-validation to tune the number of features, and the one gives me the highest cross-validation accuracy is to use 11 features (plot of cv accuracy shown below).



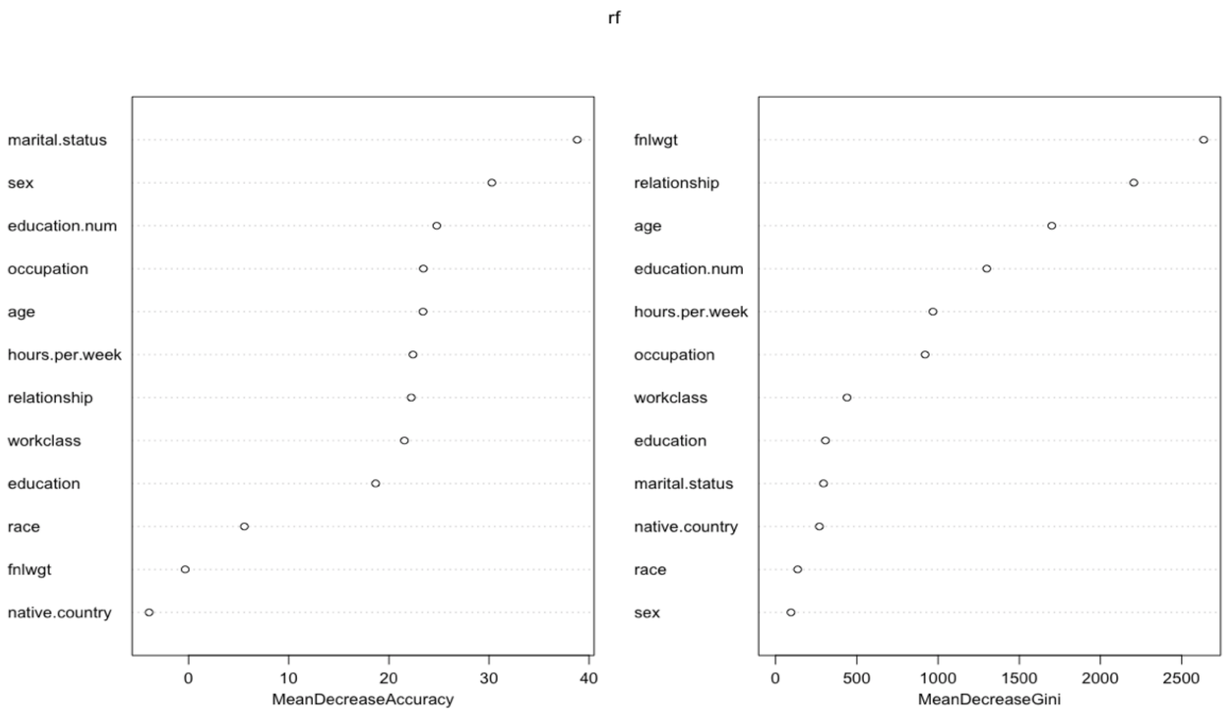
We can also see how important is a variable to this model. By looking at mean decrease accuracy, the 5 most important features and its variable importance statistics are shown below.

```
marital.status           sex  education.num     occupation            age
      38.79456      30.28084       24.77849       23.44628       23.40998
```

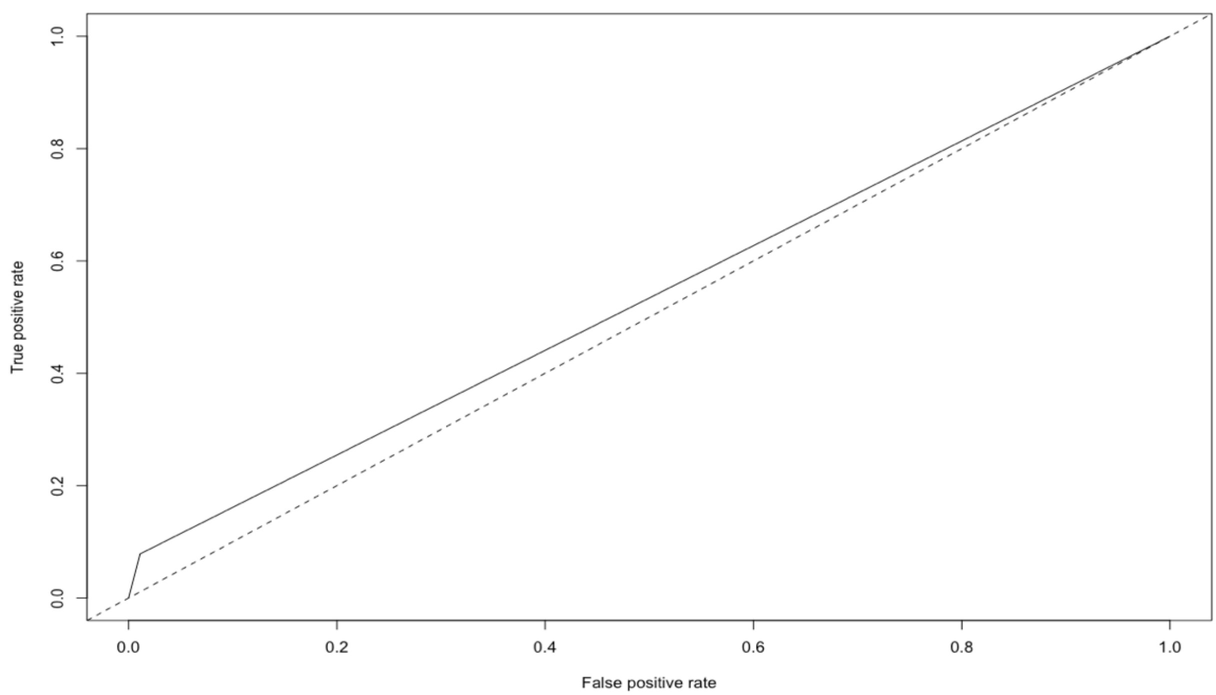
However, by looking at mean decrease gini, the 5 most important features and its variable importance statistics are shown below.

```
   fnlwgt   relationship            age  education.num hours.per.week
2635.0573      2204.8492      1700.4514      1300.2550       968.4396
```

We can also see the plot for the importance statistics.



One way to measure whether a model is good is to look at the ROC curve (shown below) and the AUC. The model has AUC of 0.5337.



In summary, the random forest model chosen has structures of 200 trees, and uses 11 variables to build each tree. It has an in-sample arruracy of 76%.

Model Selection:

In conclusion, I have a classification tree model, a bagging tree model, and a random forest model, and want to pick a model that best describes the data. In order to measure how good a model is better, I use the models trained above to predict on the test set, which has the same explanatory variables. Since I did not build the model from any observation in the test set, the measure has lower bias on performance measures.

First of all, we use the models to predict the income from the test set, and we can look at the confusion matrix, specificity, and sensitivity from each model.

Classification Tree:

```
          Reference
Prediction     0     1
         0 11027  1497
         1  1408  2349
Sensitivity Specificity
  0.6107644   0.8867712
```

Bagged Tree:

```
          Reference
Prediction  <=50K  >50K
     <=50K  11154  3230
     >50K    1281   616
Sensitivity Specificity
  0.1601664   0.8969843
```

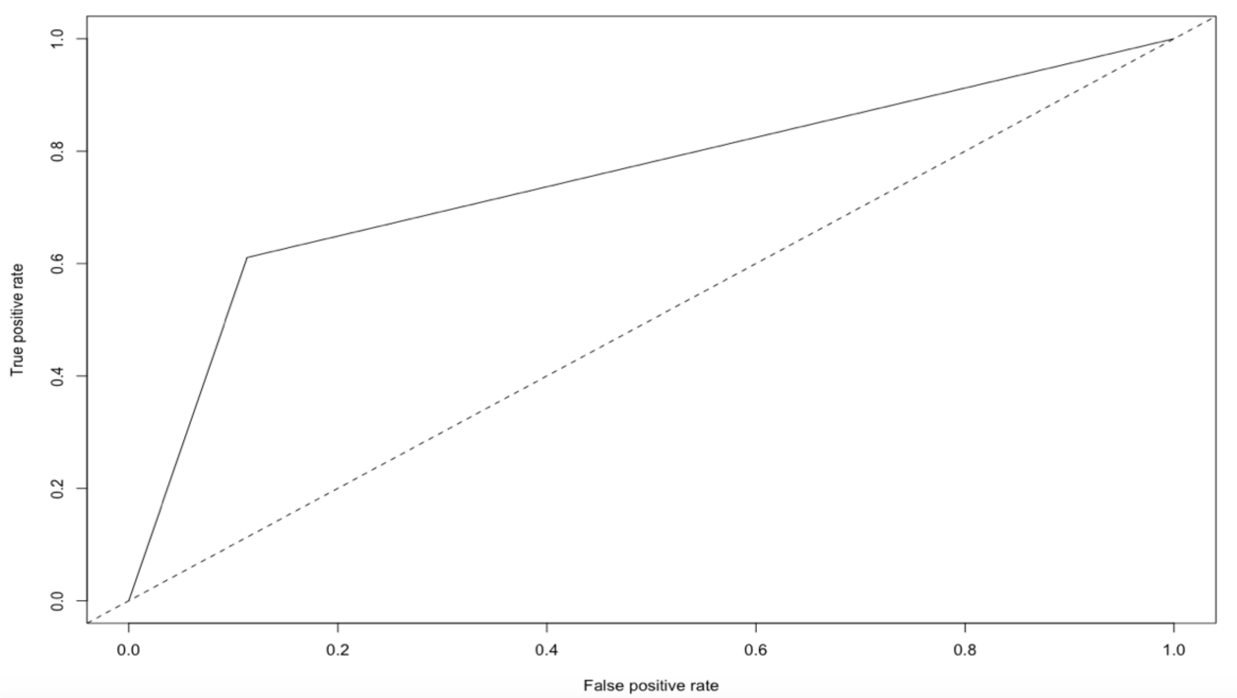
Random Forest:

```
            Reference
Prediction  <=50K  >50K
     <=50K  11989  3526
     >50K     446   320
Sensitivity Specificity
 0.08320333  0.96413349
```

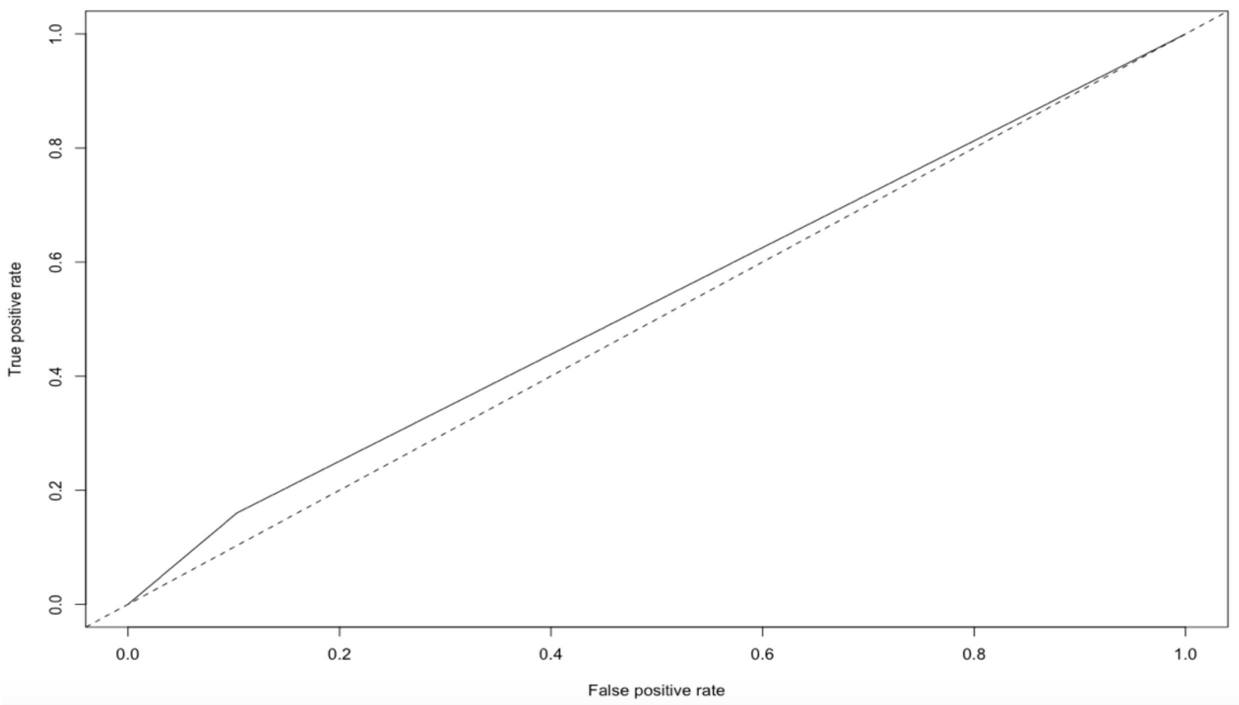
Additionally, we can also simply look at the test set accuracy. Classification tree model achieves an accuracy of 82.16%, bagged tree models has accuracy of 72.29%, and random forest has 75.6% accuracy.

Furthermore, we can look at the ROC curve and AUC.

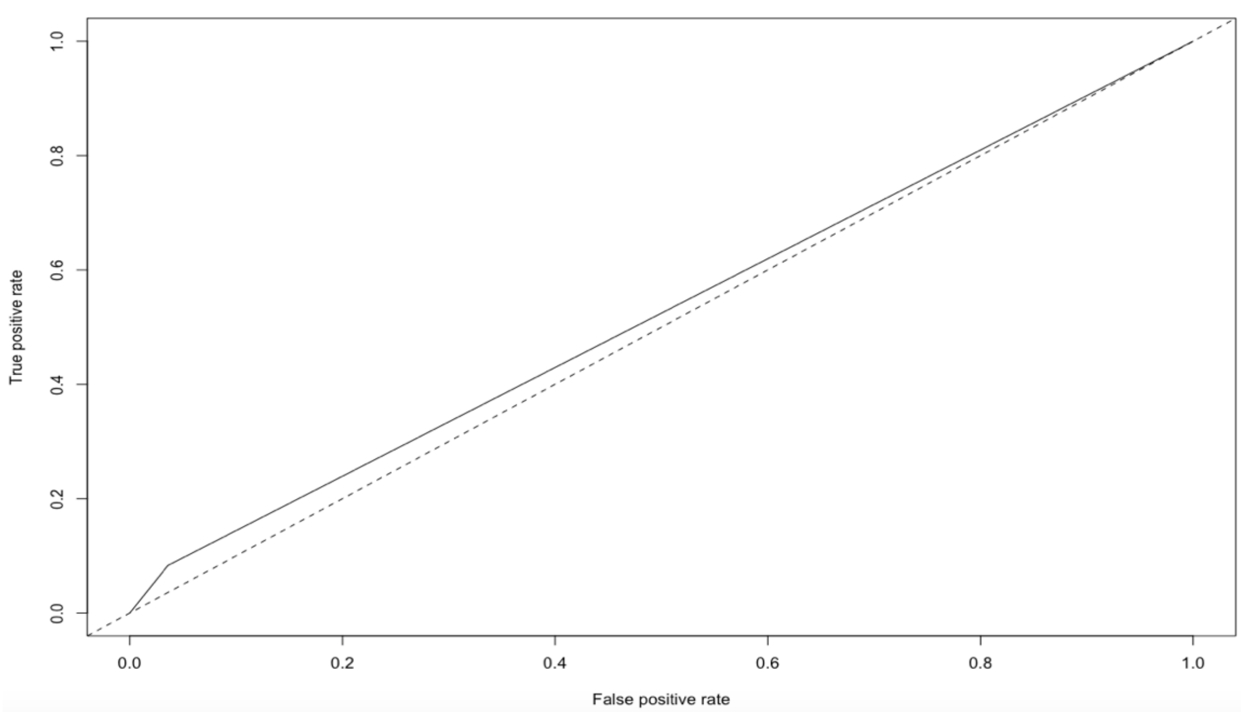
Classification Tree:



Bagged Tree:



Random Forest:



```
"The AUC statistic of classification tree model is 0.7488"
"The AUC statistic of bagged tree model is 0.5286"
"The AUC statistic of random forest model is 0.5237"
```

In conclusion, by comparing confusion matrix, specificity, sensitivity, testing accuracy, ROC curve, and AUC, I will select the classification tree with complexity parameter of 0.0022 as my final model to fit this dataset.