DATA MINING ASSIGNMENT

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B150310CS

10

About the dataset:

buying v-high, high, med, low
maint v-high, high, med, low
doors 2, 3, 4, 5-more
persons 2, 4, more
lug_boot small, med, big
safety low, med, high

The dataset has 6 feature variables and 1 class variable

Number of Instances: 1728 (instances completely cover the attribute space)

Number of Attributes: 6

1 a. Decision Tree with Gini index as the impurity measure

Loading the data

```
data_url <- c("https://archive.ics.uci.edu/ml/machine-learning-
databases/car/car.data");
```

```
download.file(url=data_url,destfile = "car.data");
```

```
mydata <- read.csv("car.data",sep=",",header=FALSE)
```

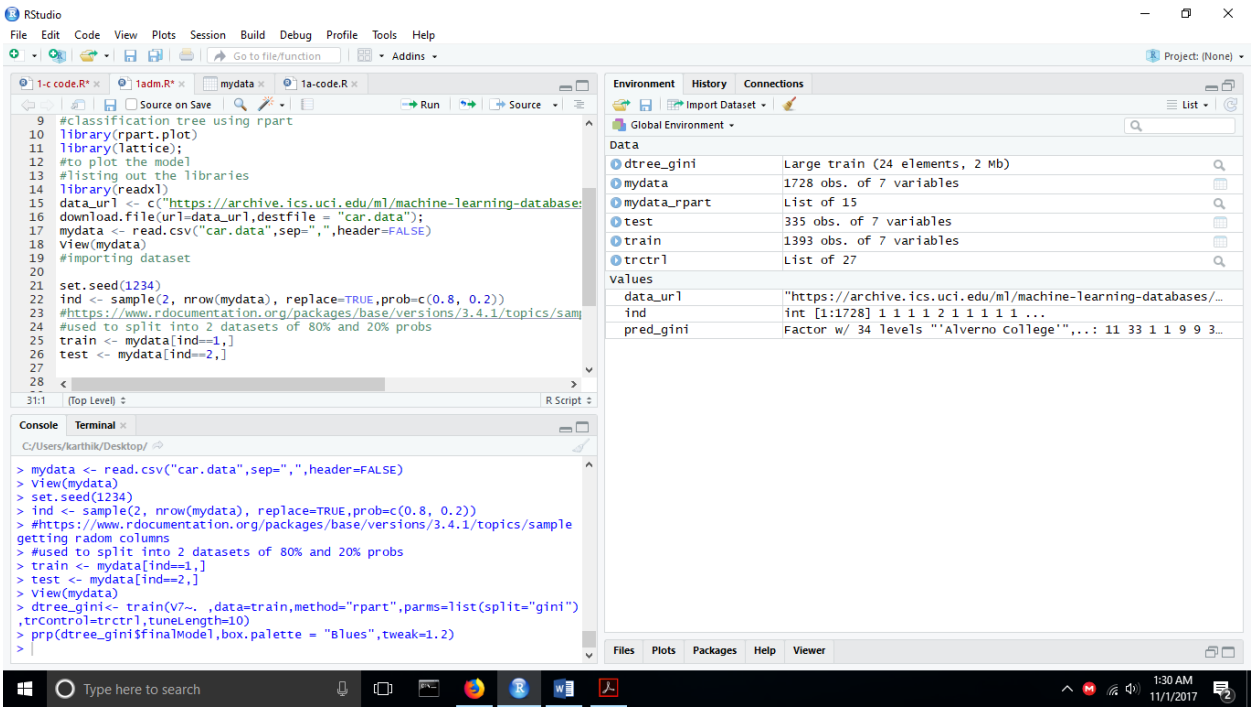
Data Slicing

Splitting the data into training set and test set

```
ind <- sample(2, nrow(mydata), replace=TRUE,prob=c(0.8, 0.2))
```

```
train <- mydata[ind==1,]
```

```
test <- mydata[ind==2,]
```

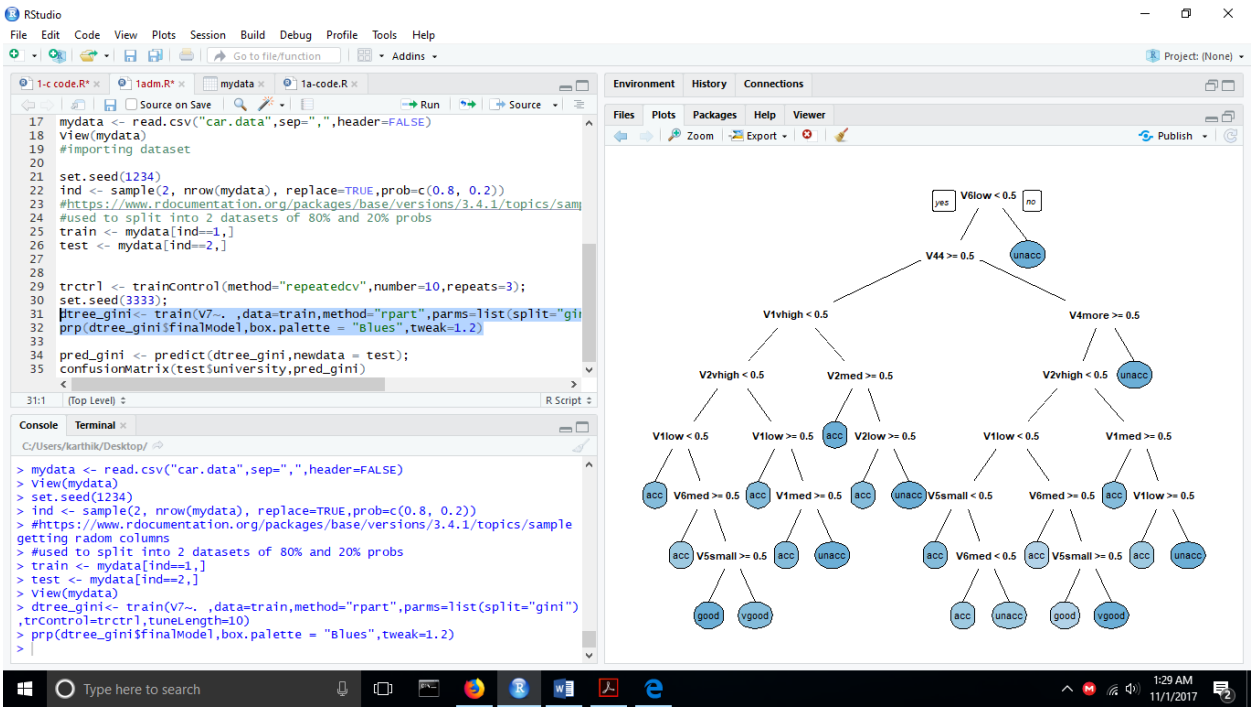


Training the dataset using the caret library based on decision on gini index on university column

```
trctrl <- trainControl(method="repeatedcv",number=10,repeats=3);
set.seed(3333);
dtree_gini<- train(V7 ~.
,data=train,method="rpart",parms=list(split="gini"),trControl=trctrl,tuneLeng
th=10)
```

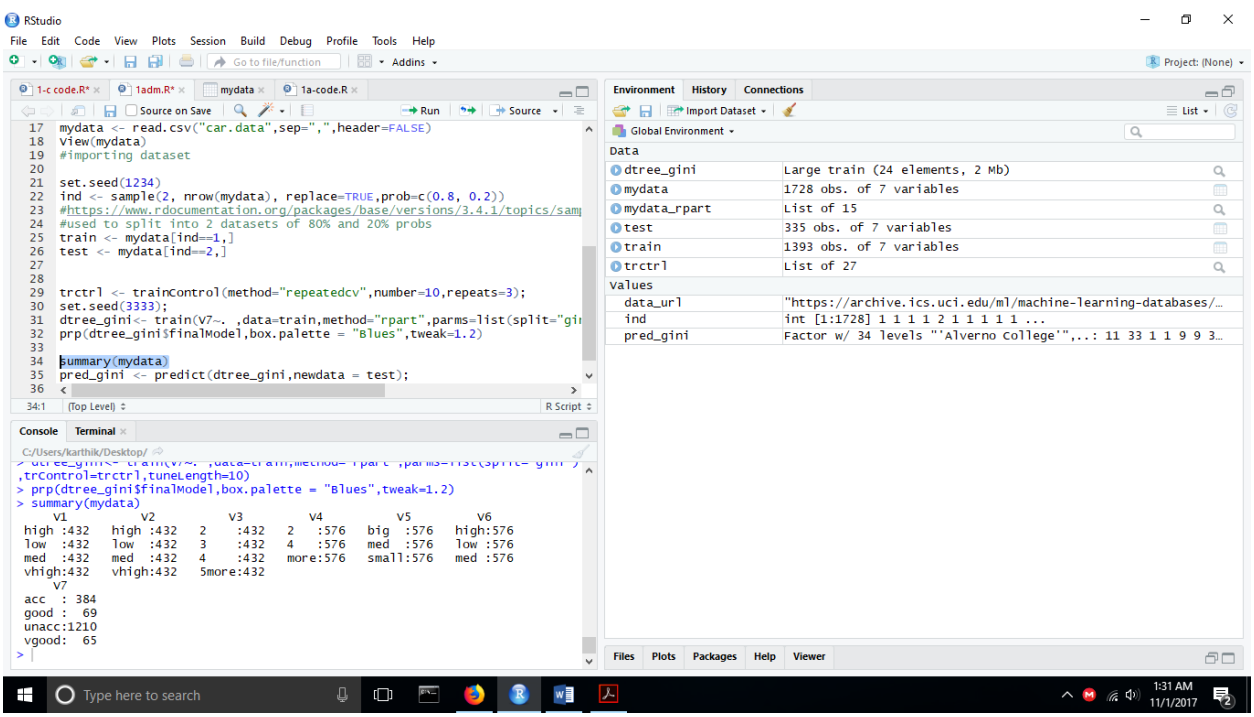
Displaying the dataset

```
prp(dtree_gini$finalModel,box.palette = "Blues",tweak=1.2)
```



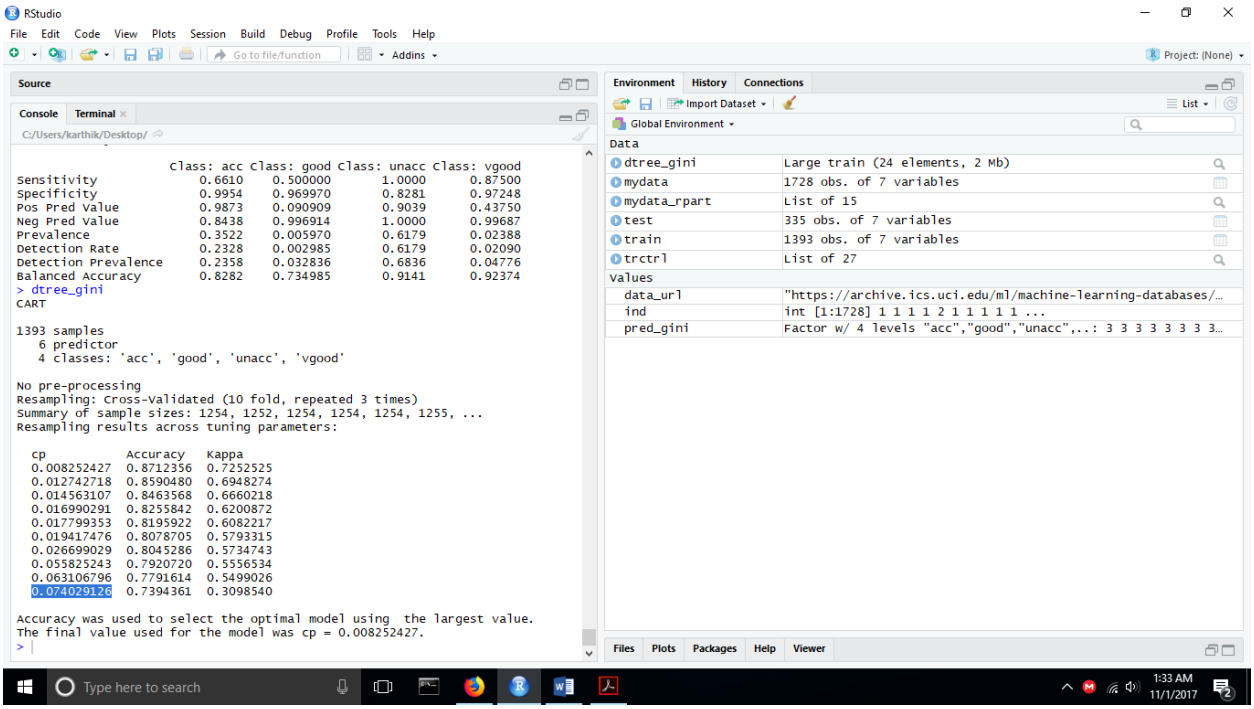
We can check if our dataset contains any missing values using the anyNA(dataset) function

To check the summary of the dataset we can use summary(dataset)



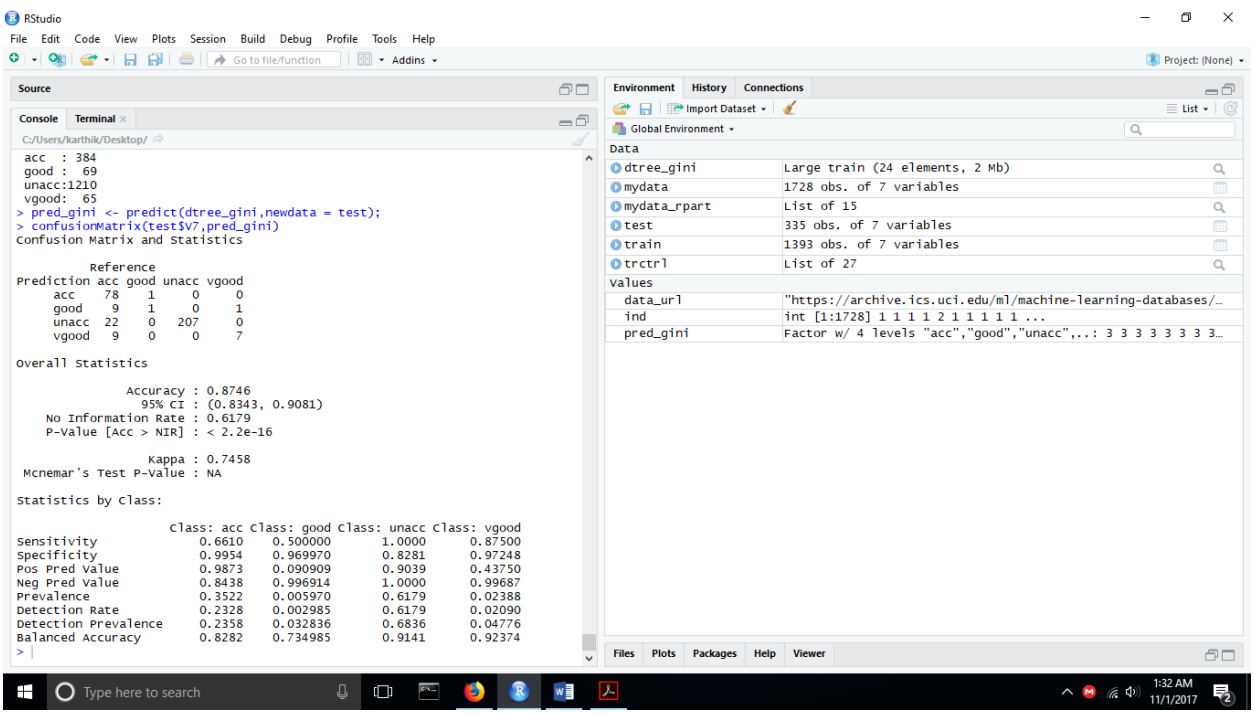
Prediction

Our model is trained with a cp of 0.008252427



Confusion Matrix and statistics

```
pred_gini <- predict(dtree_gini,newdata = test);
confusionMatrix(test$V7,pred_gini)
```

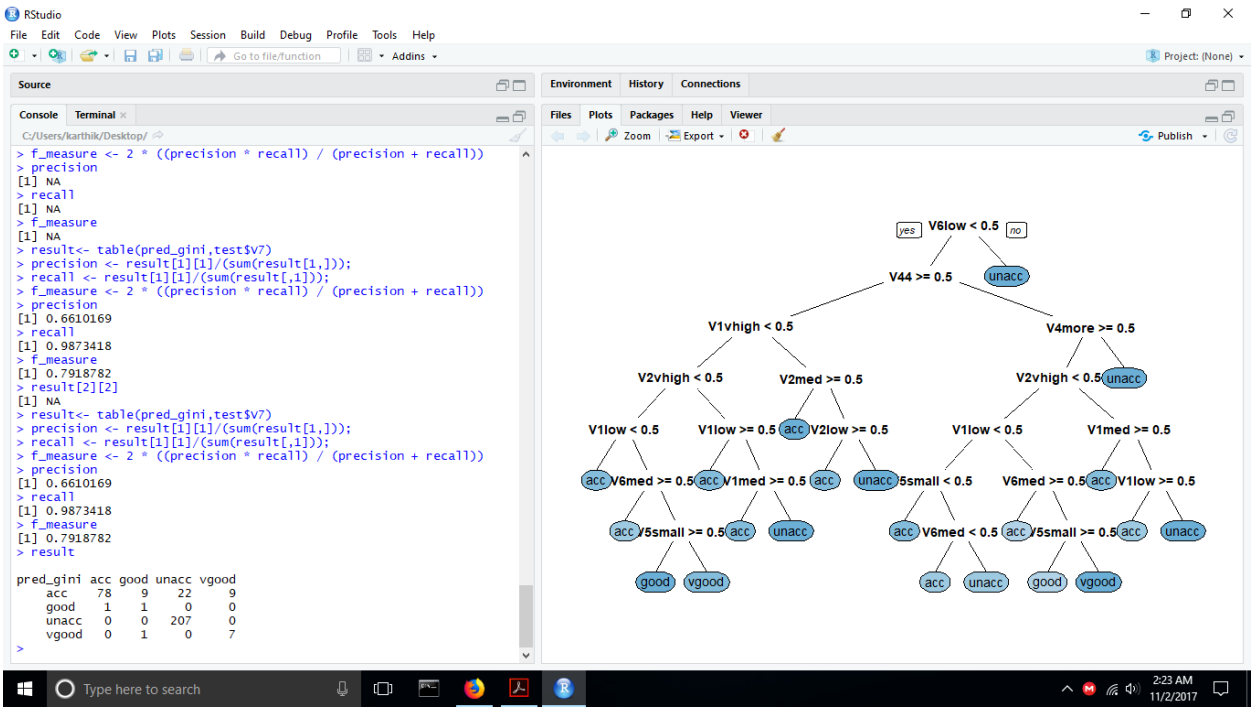


Accuracy : 87.46%

The values of fmeasure,recall,precision are as follows:

Precision, Recall and f- measure

```
result<- table(pred_gini,test$V7)
precision <- result[1][1]/(sum(result[1,]));
recall <- result[1][1]/(sum(result[,1]));
f_measure <- 2 * ((precision * recall) / (precision + recall))
precision
recall
f_measure
```



10 fold cross validation

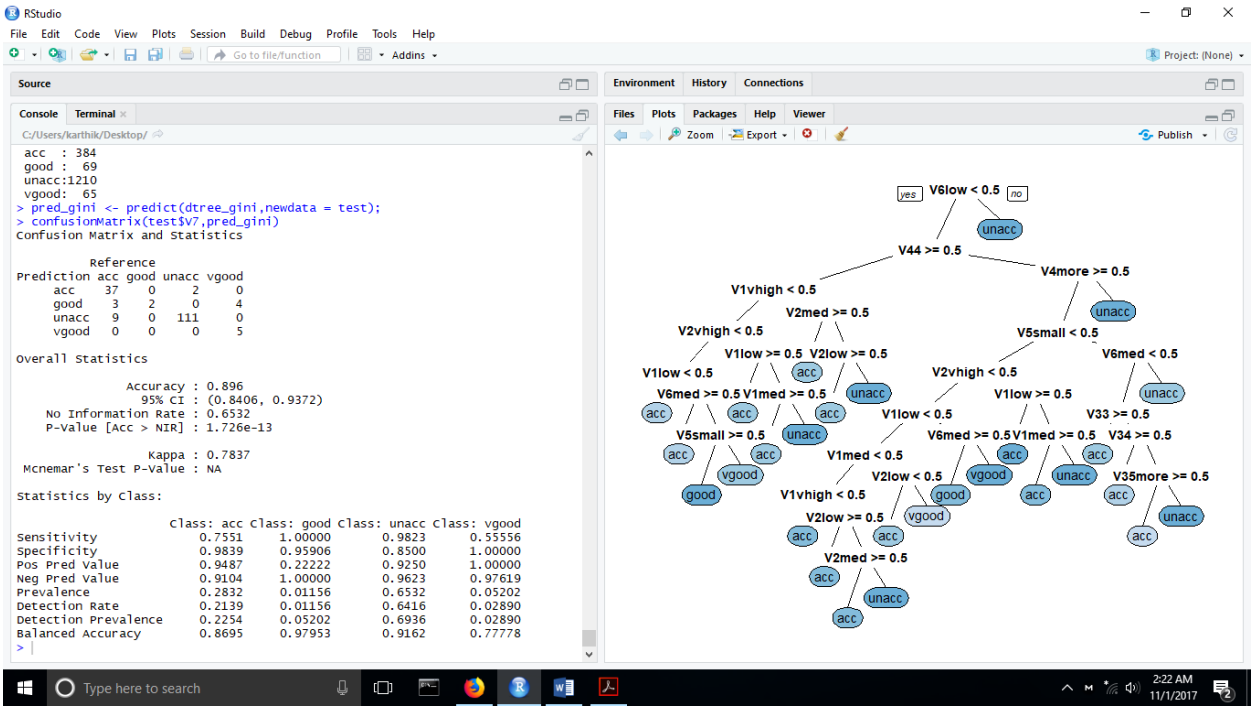
```
set.seed(1234)
mydata<-mydata[sample(nrow(mydata)),]

#Create 10 equally size folds
folds <- cut(seq(1,nrow(mydata)),breaks=10,labels=FALSE)

#Perform 10 fold cross validation
for(i in 1:10){
  #Segement your data by fold using the which() function
  testIndexes <- which(folds==i,arr.ind=TRUE)
  test <- mydata[testIndexes, ]
```

```
  train <- mydata[-testIndexes, ]
  #Use the test and train data partitions however you desire...
}
```

We use this code for 10 fold cross validation



Now the accuracy is 89.6%

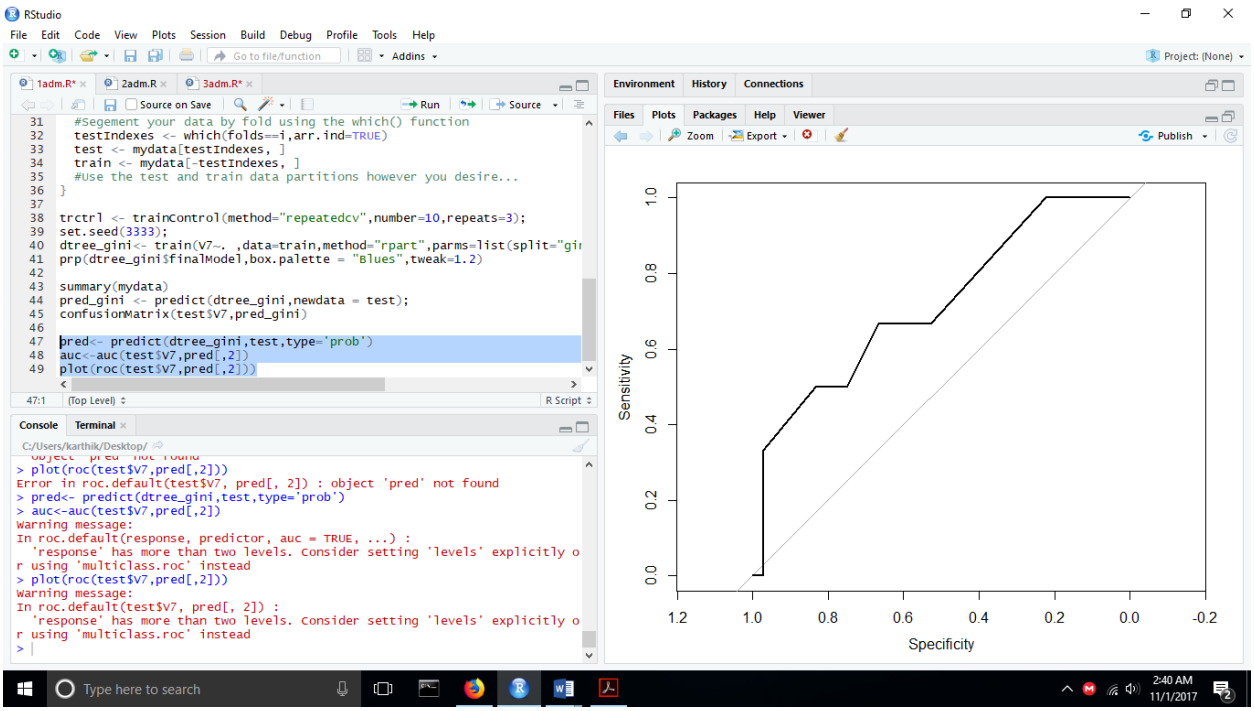
This classifier performs better with case 2 i.e 10 fold cross validation

ROC Curve

Install pROC library before proceeding

```
pred<- predict(dtree_gini,test,type='prob')
auc<-auc(test$V7,pred[,2])
plot(roc(test$V7,pred[,2]))
```

In a ROC curve the true positive rate (Sensitivity) is plotted in function of the false positive rate (Specificity) for different cut-off points of a parameter. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish between two class groups.

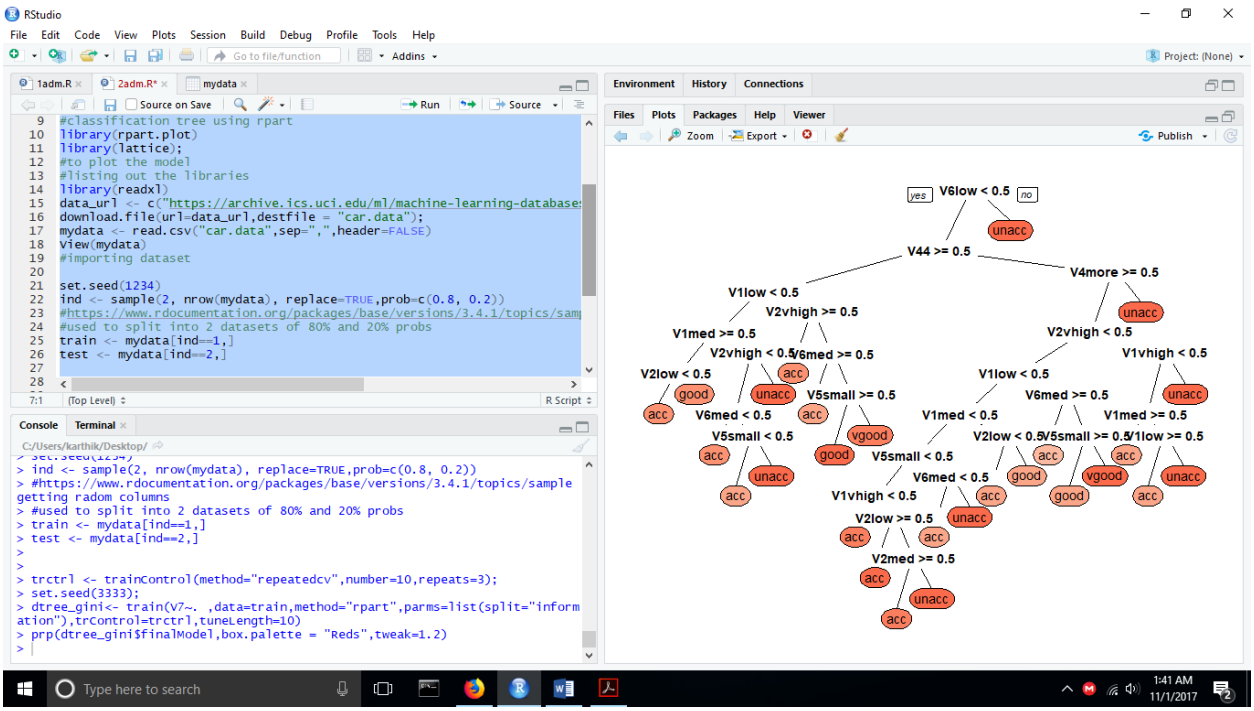


Area under the curve: 0.8621

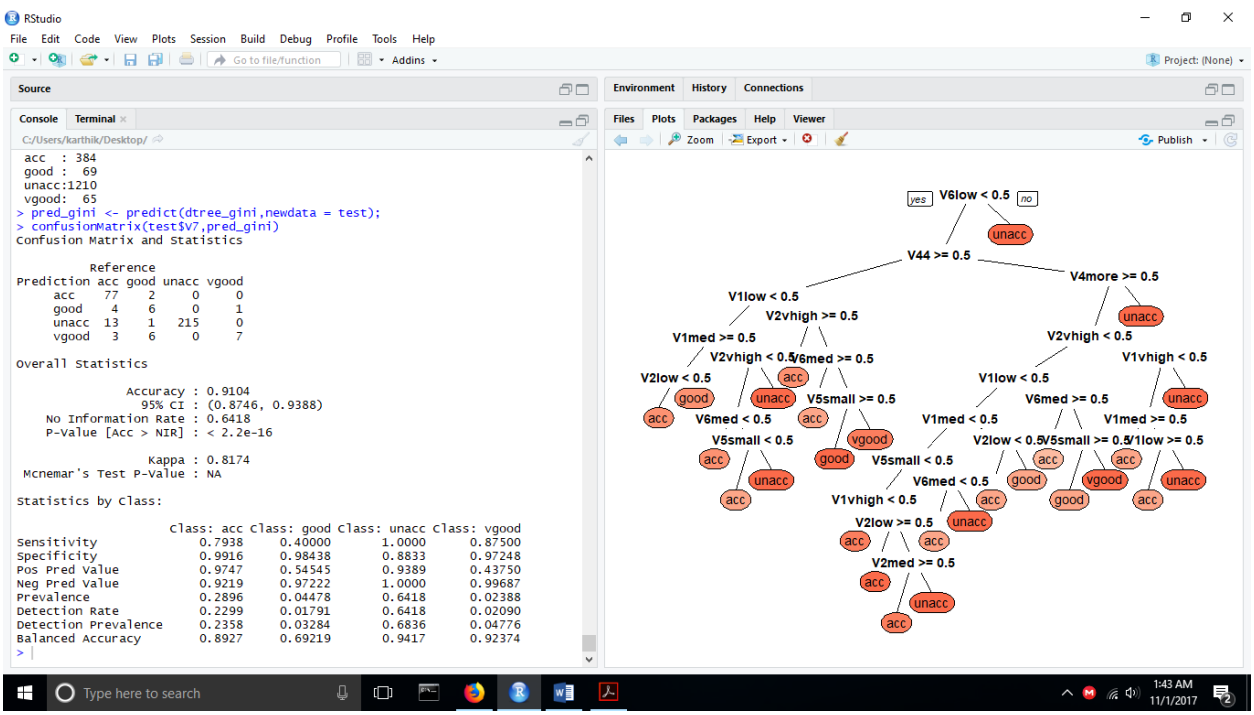
1 b. Decision Tree with Entropy as the impurity measure

We now simulate the steps in 1 a and change the statement to obtain the impurity measure

```
dtree_gini<- train(university ~.
,data=train,method="rpart",parms=list(split="gini"),trControl=trctrl,tuneLeng
th=10)
```

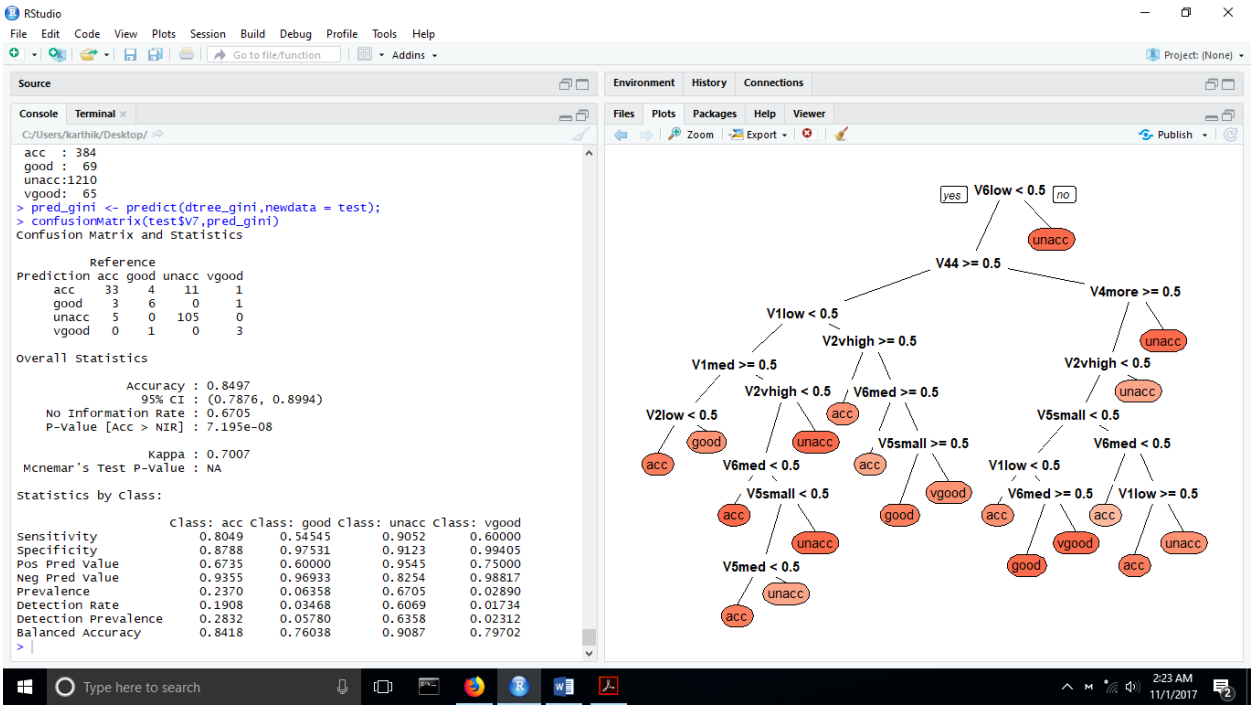


Confusion matrix and Statistics



Accuracy: 91.04%

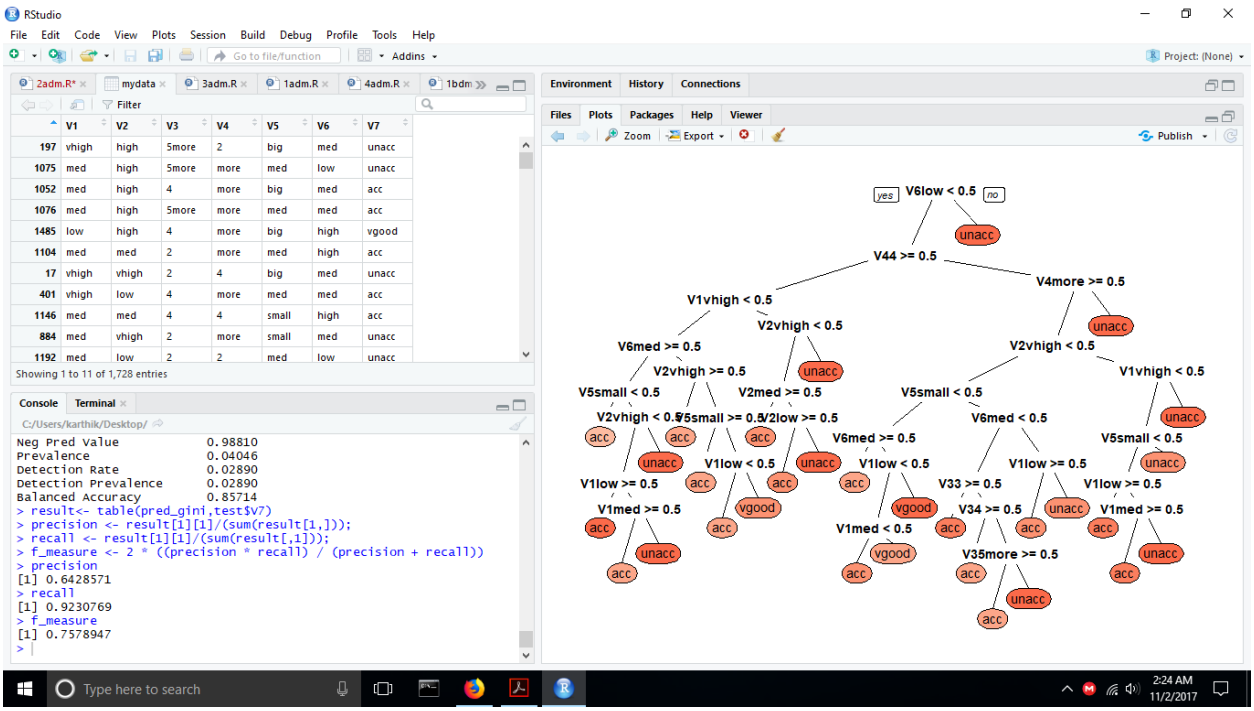
Using **10 fold cross validation** similar to 1 a



The accuracy now is 84.97%.

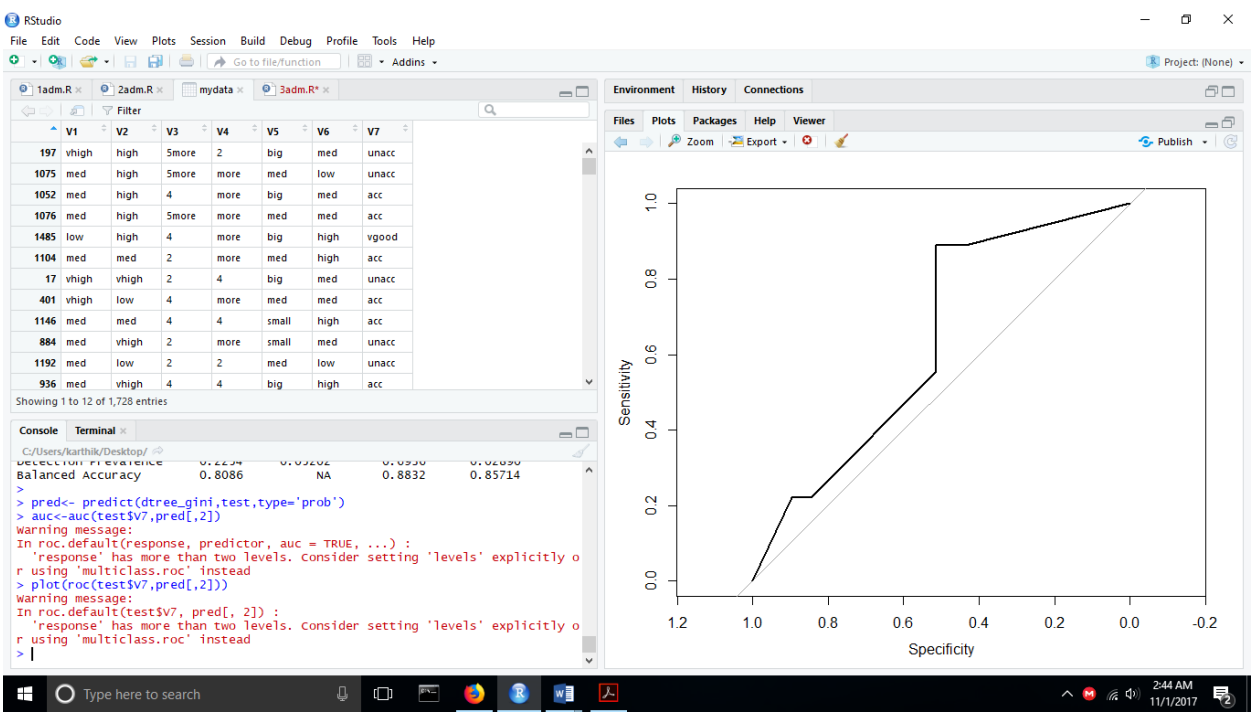
This classifier performs better with case 1 i.e random sampling

Precision, Recall and f- measure



ROC Curve

Find the ROC curve similar to 1 a

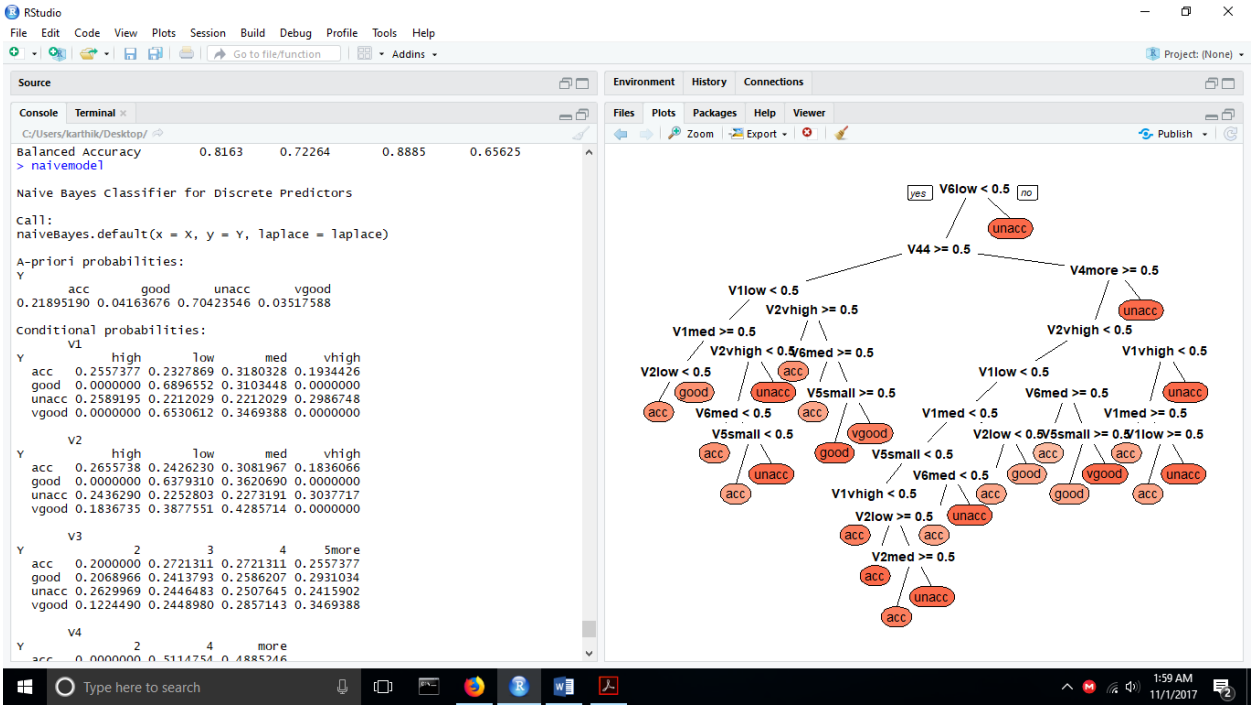


Area under the curve: 0.8694

1 c. Naïve Bayesian Classifier

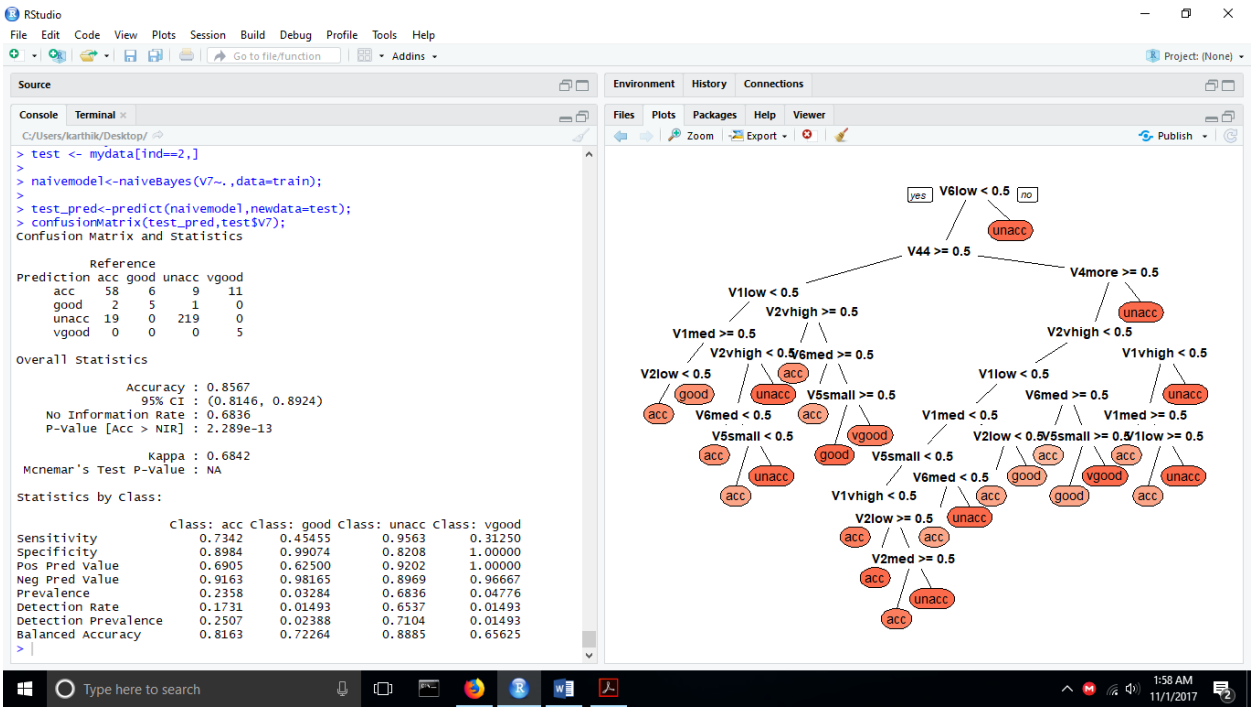
We now install and include the libraries rminer and e1071.

```
naivemodel<-naiveBayes(V7~.,data=train);
```



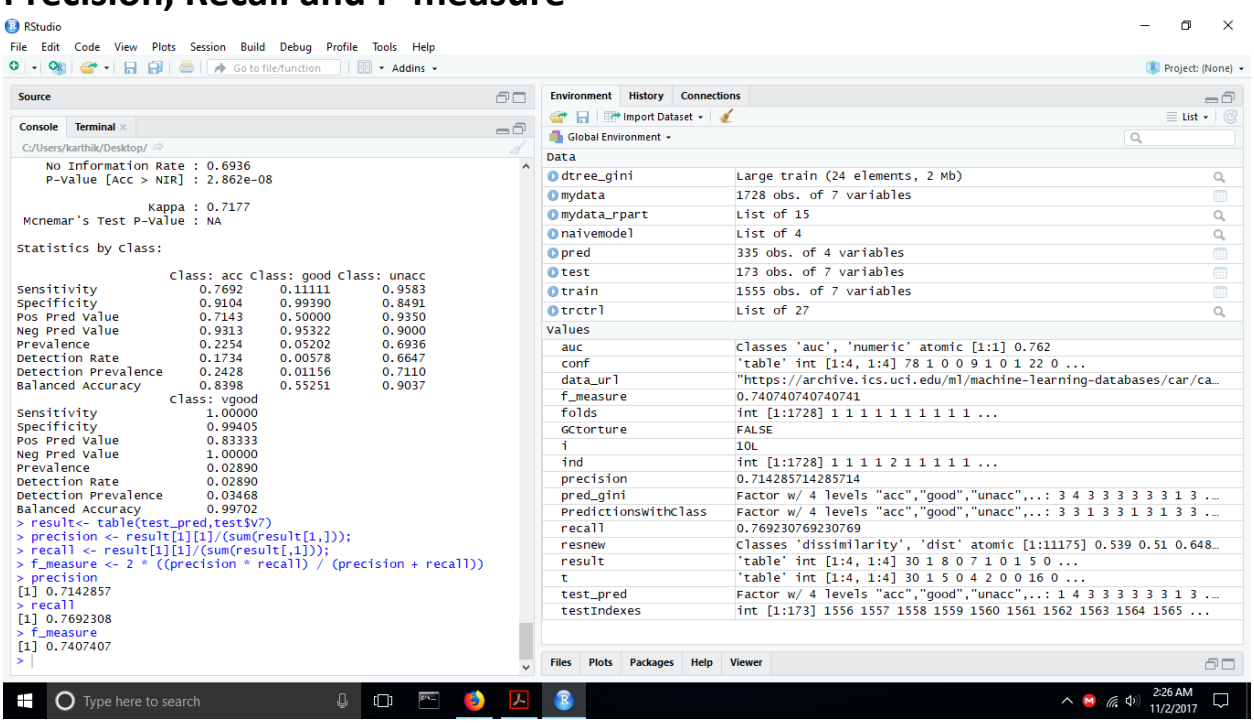

```
test_pred<-predict(naivemodel,newdata=test);
confusionMatrix(test_pred,test$V7);
```

Confusion Matrix and statistics:

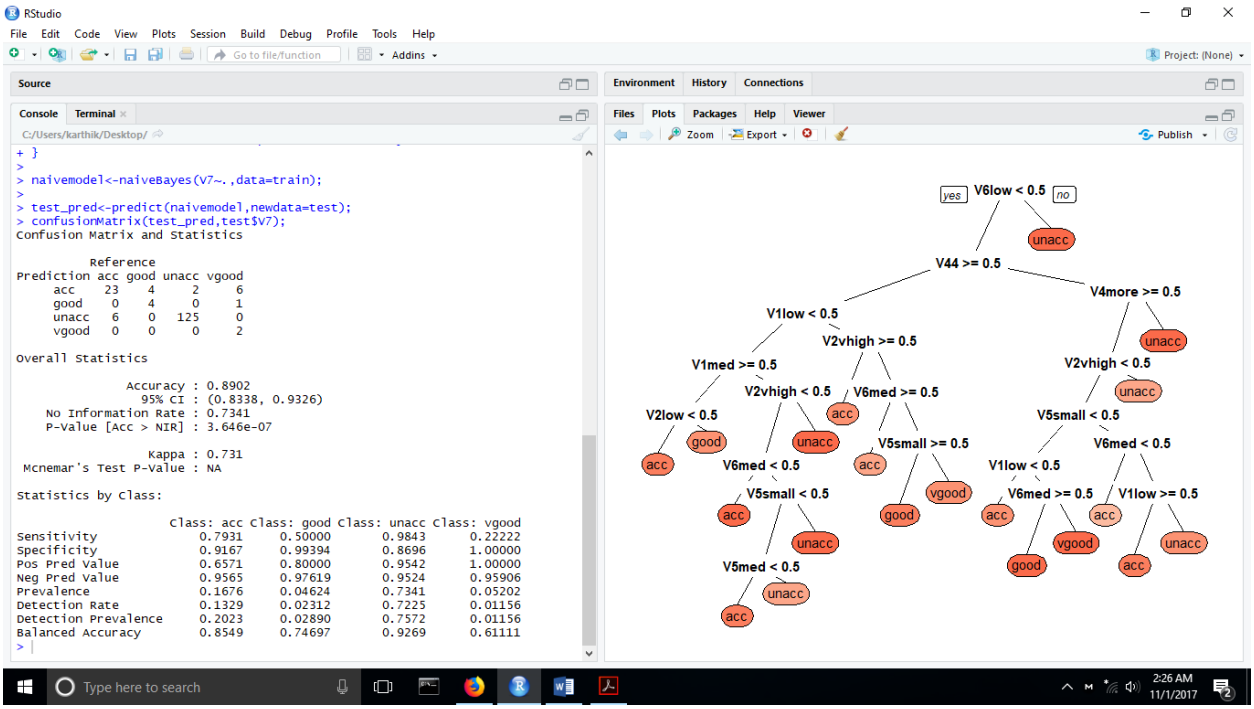


Accuracy: 85.6%

Precision, Recall and f- measure



Using 10 fold cross validation similar to 1 a

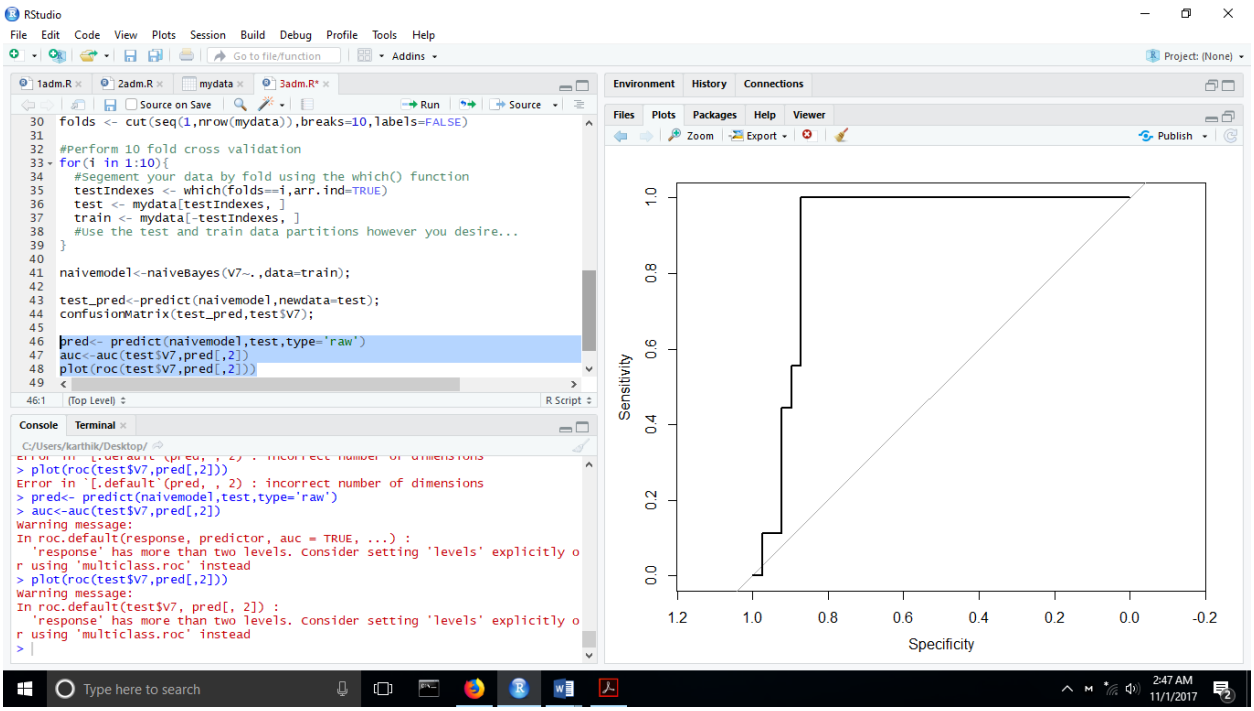


Accuracy now : 89.02%

This classifier performs better with case 2 i.e 10 fold cross validation

ROC Curve

```
pred<- predict(naivemodel,test,type='raw')
auc<-auc(test$V7,pred[,2])
plot(roc(test$V7,pred[,2]))
```



Area under the curve: 0.9031

1.d Artificial Neural Network – with and without hidden layers

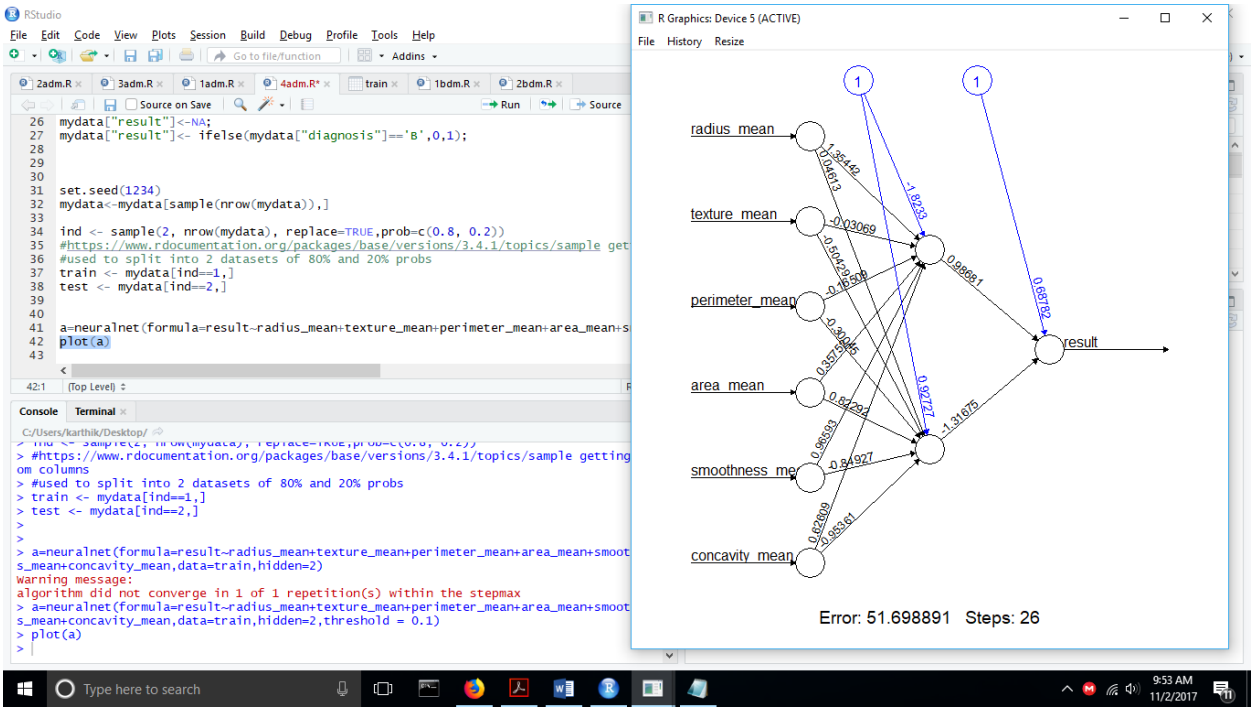
A change in dataset as artificial neural network requires numerical data to compute weights;

Dataset-url: https://www.kaggle.com/uciml/breast-cancer-wisconsin-data/data

Include the library neuralnet

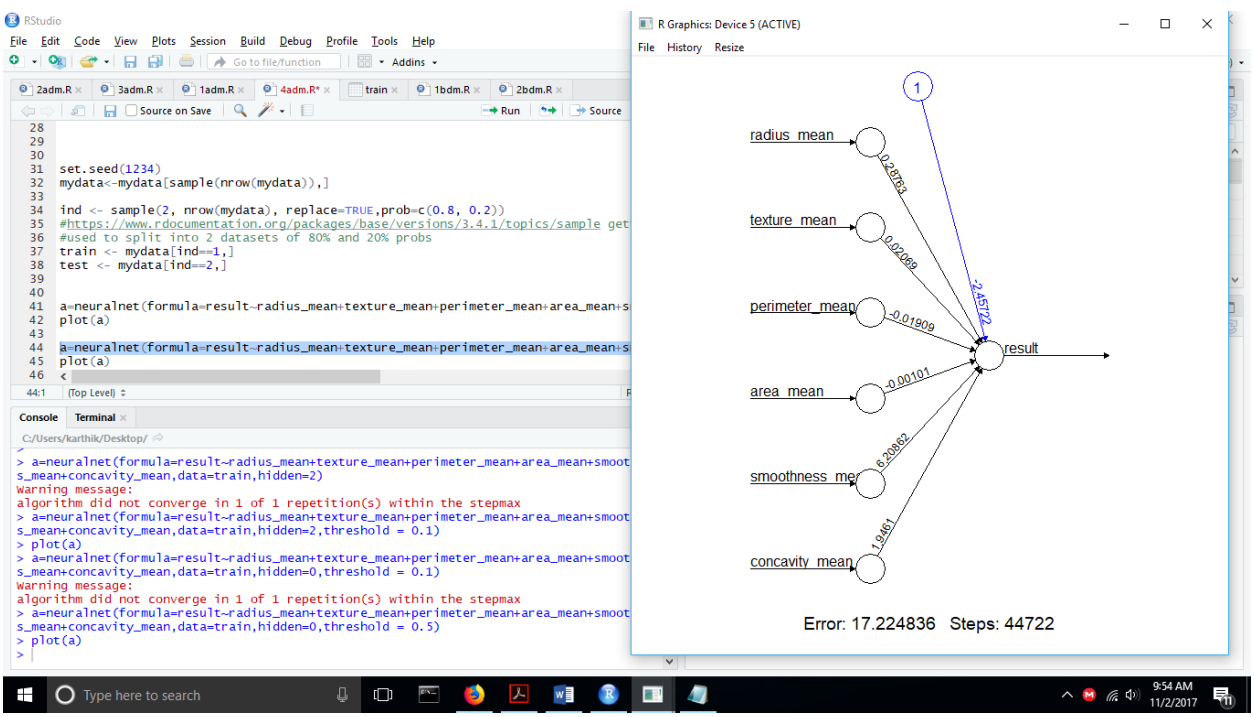
Neural Network with two hidden layer:

a=neuralnet(formula=result~radius_mean+texture_mean+perimeter_mean+area_mean+smoothness_mean+concavity_mean,data=train,hidden=2)



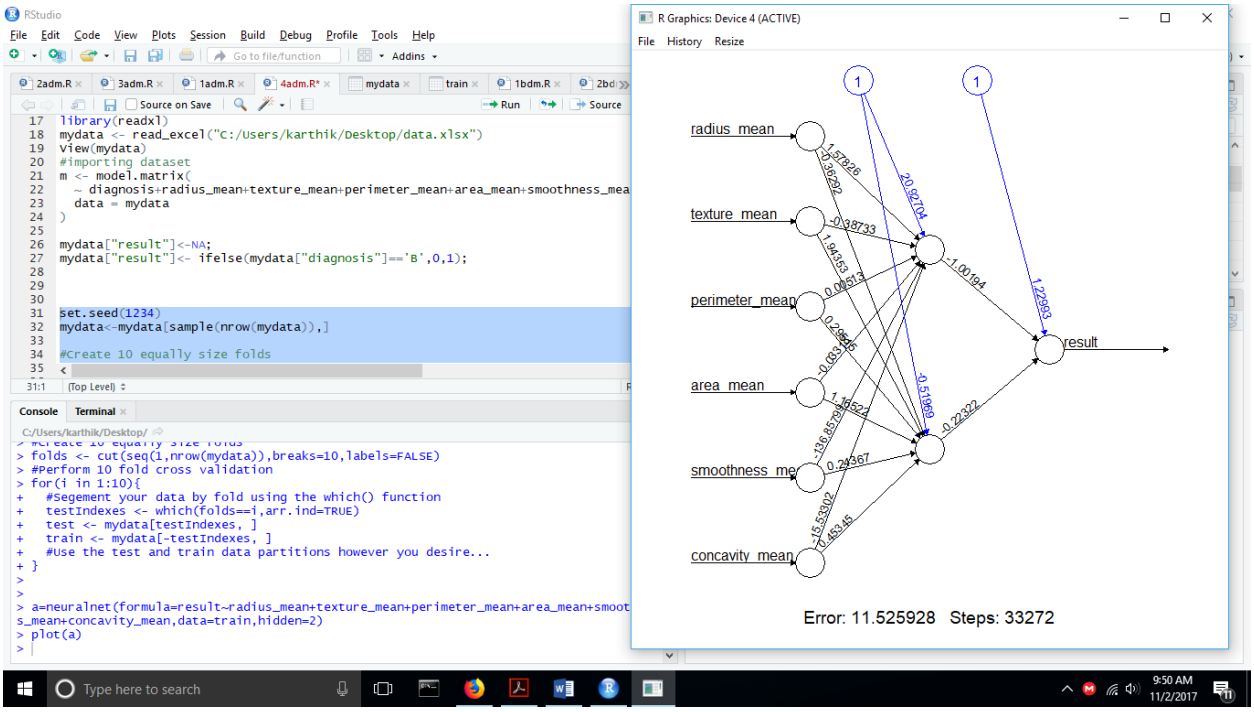
Neural Network with no hidden layer:

```
a=neuralnet(formula=result~radius_mean+texture_mean+perimeter_mean+area_mean+
smoothness_mean+concavity_mean,data=train,hidden=0,threshold = 0.1)
```



10 fold cross validation

Neural Network with two hidden layer:



Neural Network with no hidden layer: