CodeNotebook

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2/27/2021

Mobile Price Classification - Team 1

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Models

Linear Models

Neural Net Multiclass Linear Model

There are a number of methods that can be applied to a multiclass classification problem.

Of the various models we applied to our problem, the best performing was a log-linear neural network model.

We used this as a baseline to inform our strategy and compare results to the methods discussed in the course.

```
set.seed(430)
library(data.table)
library(nnet)
mo <- fread('~/R/mobile/train.csv')
mo_obs <- nrow(mo)
mo_idx <- sample(mo_obs, size = trunc(0.70 * mo_obs))
mo_trn <- mo[mo_idx, ]
mo_test <- mo[-mo_idx, ]

Y_train <- mo_trn[,price_range]
Y_test <- mo_test[,price_range]

model_multi <- multinom(price_range ~ ., data = mo_trn) # instantiating model
```

```
## # weights:  88 (63 variable)
## initial  value 1940.812106
## iter  10 value 1539.449569
## iter  20 value 1372.517934
## iter  30 value 1328.431365
## iter  40 value 1203.483614
## iter  50 value 826.577171
## iter  60 value 446.763231
## iter  70 value 59.572210
## iter  80 value 31.622093
## iter  90 value 21.277743
## iter 100 value 15.526852
## final  value 15.526852
## stopped after 100 iterations
```

```
# train predictions
Y_train_hat_df <- predict(model_multi, newdata = mo_trn, type = "prob")

Y_train_hat <- data.table(colnames(Y_train_hat_df)[max.col(Y_train_hat_df,ties.method="first")])
Y_train_hat <- transform(Y_train_hat, V1 = as.numeric(V1))

train_accuracy <- mean(Y_train == Y_train_hat)

#test predictions
Y_test_hat_df <- predict(model_multi, newdata = mo_test, type = "prob")

Y_test_hat <- data.table(colnames(Y_test_hat_df)[max.col(Y_test_hat_df,ties.method="first")])
Y_test_hat <- transform(Y_test_hat, V1 = as.numeric(V1))[,V1]

test_accuracy <- mean(Y_test == Y_test_hat)

# Evaluation:
cm <- table(observed=Y_test, predicted=Y_test_hat) # confusion matrix

diag = diag(cm) # number of correctly classified instances per class
rowsums = apply(cm, 1, sum) # number of instances per class
colsums = apply(cm, 2, sum) # number of predictions per class


precision = diag / colsums
recall = diag / rowsums
f1 = 2 * precision * recall / (precision + recall)

scores <- data.frame(precision, recall, f1)


train_accuracy
```

```
## [1] 0.9971429
```

```
test_accuracy
```

```
## [1] 0.9716667
```

```
print(cm)
```

```
##          predicted
## observed   0   1   2   3
##        0 147   1   0   0
##        1   2 147   2   0
##        2   0   5 147   6
##        3   0   0   1 142
```

```
print(scores)
```

```
##   precision    recall        f1
## 0 0.9865772 0.9932432 0.9898990
## 1 0.9607843 0.9735099 0.9671053
## 2 0.9800000 0.9303797 0.9545455
## 3 0.9594595 0.9930070 0.9759450
```

We have a test accuracy of 97% for this model. This high accuracy of this linear model indicates that there is likely a strong linear relationship between the predictors and price_range.

Binary Logistic Regression

Because we have more than 2 classes of predictors, we cannot simply predict between all 4 with a simple logistic regression.

Our first approach was to predict between the the lowest price range (0,1) and the highest price (2,3) with a binomial model.

```
set.seed(430)
defaultW <- getOption("warn")
options(warn = -1)


library(caTools)
library(caret)
mo_p <- fread('~/R/mobile/processed_train.csv')
m_binary <- mo_p[, !c("price_range", "p0", "p1", "p2", "p3")]
sampleSplit <- sample.split(Y=m_binary$price_binary, SplitRatio=0.7)
trainSet <- subset(x=m_binary, sampleSplit==TRUE)
testSet <- subset(x=m_binary, sampleSplit==FALSE)

log_model_binary <- glm(price_binary ~ .,
family=binomial(link='logit'), data=trainSet)

probabs <- predict(log_model_binary, testSet[,!c("price_binary")],type='response')
preds <- ifelse(probabs > 0.5, 1, 0)



test_accuracy <- mean(testSet$price_binary == preds)

cm <- table(observed=testSet$price_binary, predicted=preds)

diag = diag(cm) # number of correctly classified instances per class
rowsums = apply(cm, 1, sum) # number of instances per class
colsums = apply(cm, 2, sum) # number of predictions per class


precision = diag / colsums
recall = diag / rowsums
f1 = 2 * precision * recall / (precision + recall)

scores <- data.frame(precision, recall, f1)

print(paste0("test accuracy: ", test_accuracy))
```

```
## [1] "test accuracy: 0.988333333333333"
```

```
cat('\nConfusion Matrix\n\n')
```

```
##
## Confusion Matrix
```

```
print(cm)
```

```
##          predicted
## observed   0   1
##        0 296   4
##        1   3 297
```

```
print(scores)
```

```
##   precision    recall        f1
## 0 0.9899666 0.9866667 0.9883139
## 1 0.9867110 0.9900000 0.9883527
```

This model does an excellent job differentiating between low prices and high prices.

Multiple Binary Logistic Regression

Our next step was to run multiple binomial models, one for each class of price range.

We can select between all 4 classes by ultimately predicting the class with the highest probability between all 4 models.

```
set.seed(430)
mo_obs <- nrow(mo_p)
mo_idx <- sample(mo_obs, size = trunc(0.70 * mo_obs))
mo_trn <- mo_p[mo_idx, ]
mo_test <- mo_p[-mo_idx, ]

# 4 separate train and test sets
X_train <- mo_trn[,1:20]
Y_train <- mo_trn[,price_range]
Y_train0 <- mo_trn[,p0]
Y_train1 <- mo_trn[,p1]
Y_train2 <- mo_trn[,p2]
Y_train3 <- mo_trn[,p3]
X_train0 <- data.table(X_train)
X_train0[,p0 := Y_train0]
X_train1 <- data.table(X_train)
X_train1[,p1 := Y_train1]
X_train2 <- data.table(X_train)
X_train2[,p2 := Y_train2]
X_train3 <- data.table(X_train)
X_train3[,p3 := Y_train3]

X_test <- mo_test[,1:20]
Y_test <- mo_test[,price_range]
Y_test0 <- mo_test[,p0]
Y_test1 <- mo_test[,p1]
Y_test2 <- mo_test[,p2]
Y_test3 <- mo_test[,p3]
X_test0 <- data.table(X_test)
X_test0[,p0 := Y_test0]
X_test1 <- data.table(X_test)
X_test1[,p1 := Y_test1]
X_test2 <- data.table(X_test)
X_test2[,p2 := Y_test2]
X_test3 <- data.table(X_test)
X_test3[,p3 := Y_test3]

# fitting models
glm.fit0 <- glm(p0 ~ ., data = X_train0, family = binomial)
glm.fit1 <- glm(p1 ~ ., data = X_train1, family = binomial)
glm.fit2 <- glm(p2 ~ ., data = X_train2, family = binomial)
glm.fit3 <- glm(p3 ~ ., data = X_train3, family = binomial) # binomial for logistic regression

# train predictions
Y_train_hat0 <- predict(glm.fit0, newdata = X_train0, type = "response")
Y_train_hat1 <- predict(glm.fit1, newdata = X_train1, type = "response")
Y_train_hat2 <- predict(glm.fit2, newdata = X_train2, type = "response")
Y_train_hat3 <- predict(glm.fit3, newdata = X_train3, type = "response")

Y_train_hat_df <- data.table("0" = Y_train_hat0, "1" = Y_train_hat1, '2' = Y_train_hat2, "3" = Y
_train_hat3)

Y_train_hat <- data.table(colnames(Y_train_hat_df)[max.col(Y_train_hat_df,ties.method="first")])
```

```
Y_train_hat <- lapply(Y_train_hat[,], as.numeric)

train_accuracy <- mean(Y_train == Y_train_hat$V1)

#test predictions
Y_test_hat0 <- predict(glm.fit0, newdata = X_test0, type = "response")
Y_test_hat1 <- predict(glm.fit1, newdata = X_test1, type = "response")
Y_test_hat2 <- predict(glm.fit2, newdata = X_test2, type = "response")
Y_test_hat3 <- predict(glm.fit3, newdata = X_test3, type = "response")

Y_test_hat_df <- data.table("0" = Y_test_hat0, "1" = Y_test_hat1, '2' = Y_test_hat2, "3" = Y_tes
t_hat3)

Y_test_hat <- data.table(colnames(Y_test_hat_df)[max.col(Y_test_hat_df,ties.method="first")])
Y_test_hat <- lapply(Y_test_hat[,], as.numeric)

test_accuracy <- mean(Y_test == Y_test_hat$V1)

# Evaluation
cm <- table(observed=Y_test, predicted=Y_test_hat$V1)

diag = diag(cm) # number of correctly classified instances per class
rowsums = apply(cm, 1, sum) # number of instances per class
colsums = apply(cm, 2, sum) # number of predictions per class

precision = diag / colsums
recall = diag / rowsums
f1 = 2 * precision * recall / (precision + recall)

scores <- data.frame(precision, recall, f1)

print(paste0("train accuracy: ", train_accuracy))
```

```
## [1] "train accuracy: 0.892142857142857"
```

```
print(paste0("test accuracy: ", test_accuracy))
```

```
## [1] "test accuracy: 0.843333333333333"
```

```
cat('\nConfusion Matrix\n\n')
```

```
##
## Confusion Matrix
```

```
print(cm)
```

```
##          predicted
## observed   0   1   2   3
##        0 148   0   0   0
##        1   2 113  36   0
##        2   0  45 104   9
##        3   0   0   2 141
```

```
print(scores) # has trouble distinguishing between 1 and 2
```

```
##   precision    recall        f1
## 0 0.9866667 1.0000000 0.9932886
## 1 0.7151899 0.7483444 0.7313916
## 2 0.7323944 0.6582278 0.6933333
## 3 0.9400000 0.9860140 0.9624573
```

This set of models identifies the lowest and highest price ranges well, but has trouble distinguishing between price range 1 and 2.

Layered Binary Regressions

Our binary first model predicts well between low and high prices (0,1) vs (2,3), and our multiple binary models do a good job predicting the lowest (0) and highest (3) price ranges.

We decided to combine the strengths of both sets of models by initially predicting high vs low, then predicting 0 vs 1 for low predictions, or 2 vs 3 for high predictions.

```
set.seed(430)
Y_train <- mo_trn[,price_binary]
X_train <- mo_trn[, 1:20]
X_train[,price_binary := Y_train]                  # training set - first binary (low-high) mode
l
X_train01 <- mo_trn[price_range < 2, c(1:20,24) ]  # training set - second layer binary model
 (0,1)
X_train23 <- mo_trn[price_range > 1, c(1:20,26) ]  # training set - second layer binary model
 (2,3)


Y_test <- mo_test[,price_binary]
X_test <- mo_test[, 1:20]
X_test[, price_binary := Y_test]

# fitting models
glm.fit <- glm(price_binary ~ ., data = X_train, family = binomial) # binomial for logistic regr
ession

glm.fit01 <- glm(p1 ~ ., data = X_train01, family = binomial)
glm.fit23 <- glm(p3 ~ ., data = X_train23, family = binomial)

######################
# 1st Prediction Layer

#test predictions
Y_test_hat <- predict(glm.fit, newdata = X_test, type = "response")
Y_test_hat <- data.table(Y_test_hat > 0.5)
Y_test_hat <- transform(Y_test_hat, V1 = as.numeric(V1))[,V1]

binary1_accuracy <- mean(Y_test == Y_test_hat)

x2 <- data.table(mo_test)
x2[, hi_lo_prediction := Y_test_hat]

low_table <- x2[hi_lo_prediction == 0, c(1:20, 24, 21)]
high_table <-  x2[hi_lo_prediction == 1, c(1:20, 26, 21)] # split based on prediction from first
layer

######################
# 2nd Prediction Layer

# if first layer predicted low, second layer predicts 0 or 1
# if first layer predicted high, second layer predicts 2 or 3

#test predictions
Y_test_hat_low <- predict(glm.fit01, newdata = low_table[, 1:21], type = "response")
Y_test_hat_low <- data.table(Y_test_hat_low > 0.5)
Y_test_hat_low <- transform(Y_test_hat_low, V1 = as.numeric(V1))[,V1]

test_accuracy_low <- mean(low_table$price_range == Y_test_hat_low) # price_range column - not us
ed as input, just for checking results
```

```
Y_test_hat_high <- predict(glm.fit23, newdata = high_table[, 1:21], type = "response")
Y_test_hat_high <- data.table(Y_test_hat_high > 0.5)
Y_test_hat_high <- Y_test_hat_high + 2
Y_test_hat_high <- transform(Y_test_hat_high, V1 = as.numeric(V1))[,V1]

test_accuracy_high <- mean(high_table$price_range == Y_test_hat_high)  # price_range column - no
t used as input, just for checking results

# Combining Results
matrix1 <- data.table(low_table)
matrix1[, prediction := Y_test_hat_low]
matrix1[, p1 := NULL]
matrix2 <- data.table(high_table)
matrix2[, prediction := Y_test_hat_high]
matrix2[, p3 := NULL]

results <- rbind(matrix1, matrix2)

# Evaluation

test_accuracy <- mean(results$price_range == results$prediction)

cm <- table(observed=results$price_range, predicted=results$prediction)

diag = diag(cm) # number of correctly classified instances per class
rowsums = apply(cm, 1, sum) # number of instances per class
colsums = apply(cm, 2, sum) # number of predictions per class

precision = diag / colsums
recall = diag / rowsums
f1 = 2 * precision * recall / (precision + recall)

scores <- data.frame(precision, recall, f1)




print(paste0("test binary 1st layer accuracy: ", binary1_accuracy))
```

```
## [1] "test binary 1st layer accuracy: 0.988333333333333"
```

```
print(paste0("test accuracy 2nd layer low: ", test_accuracy_low))
```

```
## [1] "test accuracy 2nd layer low: 0.98"
```

```
print(paste0("test accuracy 2nd layer high: ", test_accuracy_high))
```

```
## [1] "test accuracy 2nd layer high: 0.953333333333333"
```

```
print(paste0("test accuracy: ", test_accuracy)) #overall accuracy for final output through both
 layers
```

```
## [1] "test accuracy: 0.966666666666667"
```

```
cat('\nConfusion Matrix\n\n')
```

```
##
## Confusion Matrix
```

```
print(cm)
```

```
##          predicted
## observed   0   1   2   3
##        0 148   0   0   0
##        1   2 146   3   0
##        2   0   4 145   9
##        3   0   0   2 141
```

```
print(scores)
```

```
##   precision    recall        f1
## 0 0.9866667 1.0000000 0.9932886
## 1 0.9733333 0.9668874 0.9700997
## 2 0.9666667 0.9177215 0.9415584
## 3 0.9400000 0.9860140 0.9624573
```

This approach yields accuracy almost as high as our baseline neural net model.

Logistic Models Summary:

- Having more than 2 predictors complicated problem, and we had to be creative with models we applied to this dataset.
- These models overall had high accuracy, indicating a linear relationship between predictors and price range.

Tree-based Models

Tree Models have the advantage of being easily adaptable to a multiclass classification problem, and are easily interpretable.

We apply several multiclass and multiple binary tree models below.

Simple Decision Tree

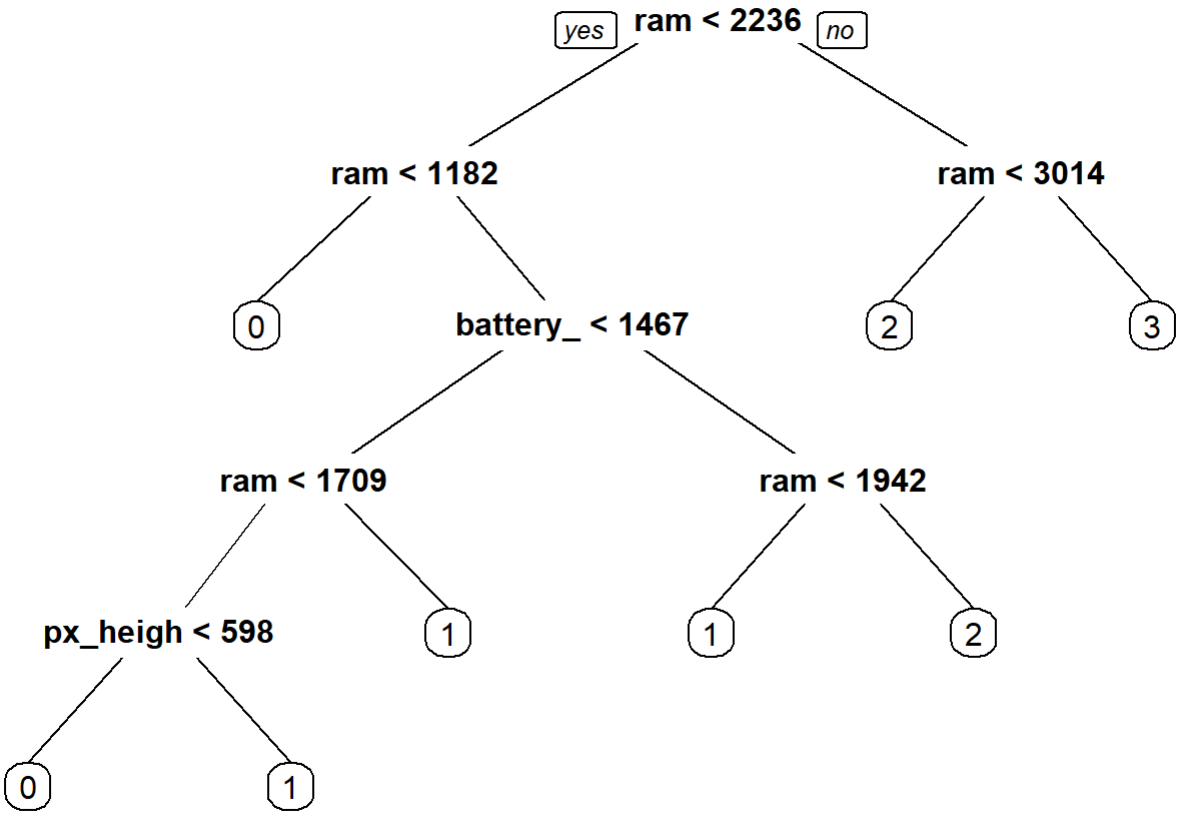
Here we apply a simple decision tree:

To solve the potential problem of overfitting, we tried on cost complexity pruning and tried to find the best shrinkage level of decision tree.

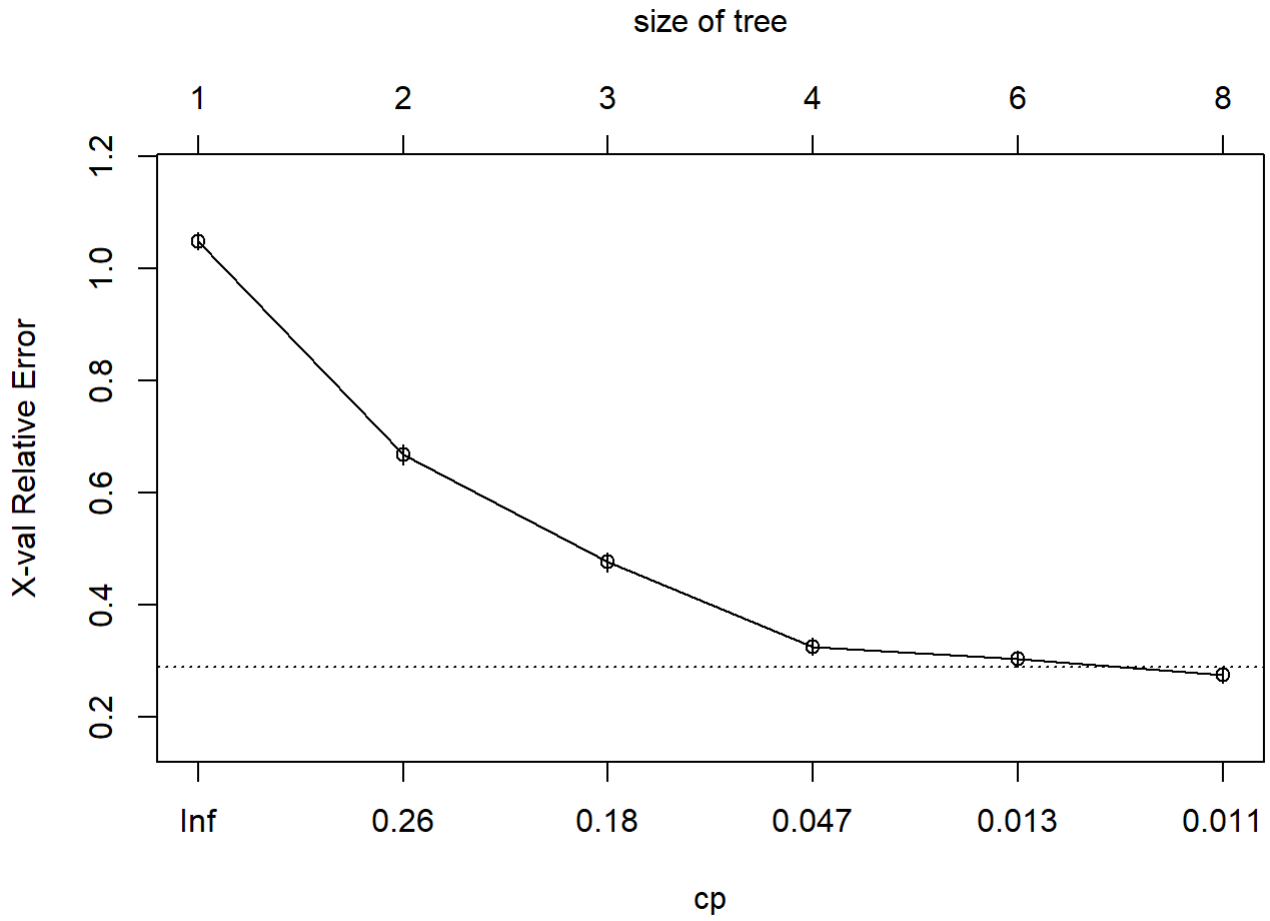
Since decision tree models can have high variance, it means if we divided the training dataset randomly into 2 parts, we could get completely different results.

To decrease the variance, we also tried to combine bagging method with random forest as well as boosting method to increase the prediction accuracy of model.

```
set.seed(810)
library(rpart)
library(rpart.plot)

split = sample.split(mo$price_range, SplitRatio = 0.7)
data_train = subset(mo, split == TRUE)
data_test = subset(mo, split == FALSE)

tree = rpart(price_range ~ .,method = "class", data = data_train,control = rpart.control(minspli
t = 1) , parms = list(split = "information"), cp = 0.01000000)
prp(tree)
```



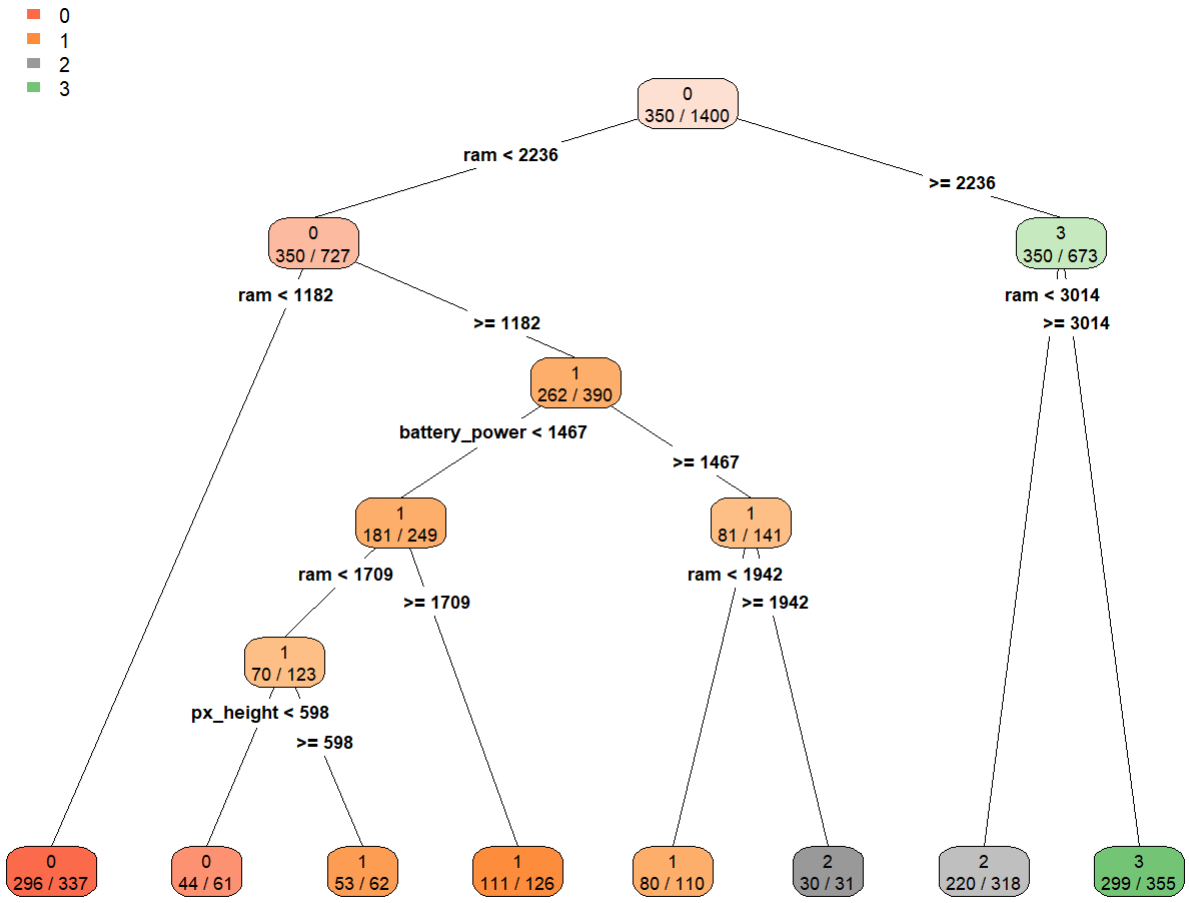

```
plotcp(tree)
```




```
tree.pred = predict(tree, newdata = data_test, type = 'class')
tree.accuracy = mean(tree.pred == data_test$price_range)
tree.accuracy
```

```
## [1] 0.775
```

```
# Pruning Tree
tree2 <- prune(tree, cp = 0.01000000)
rpart.plot(tree2, type = 4, branch = 0, extra = 2)
```



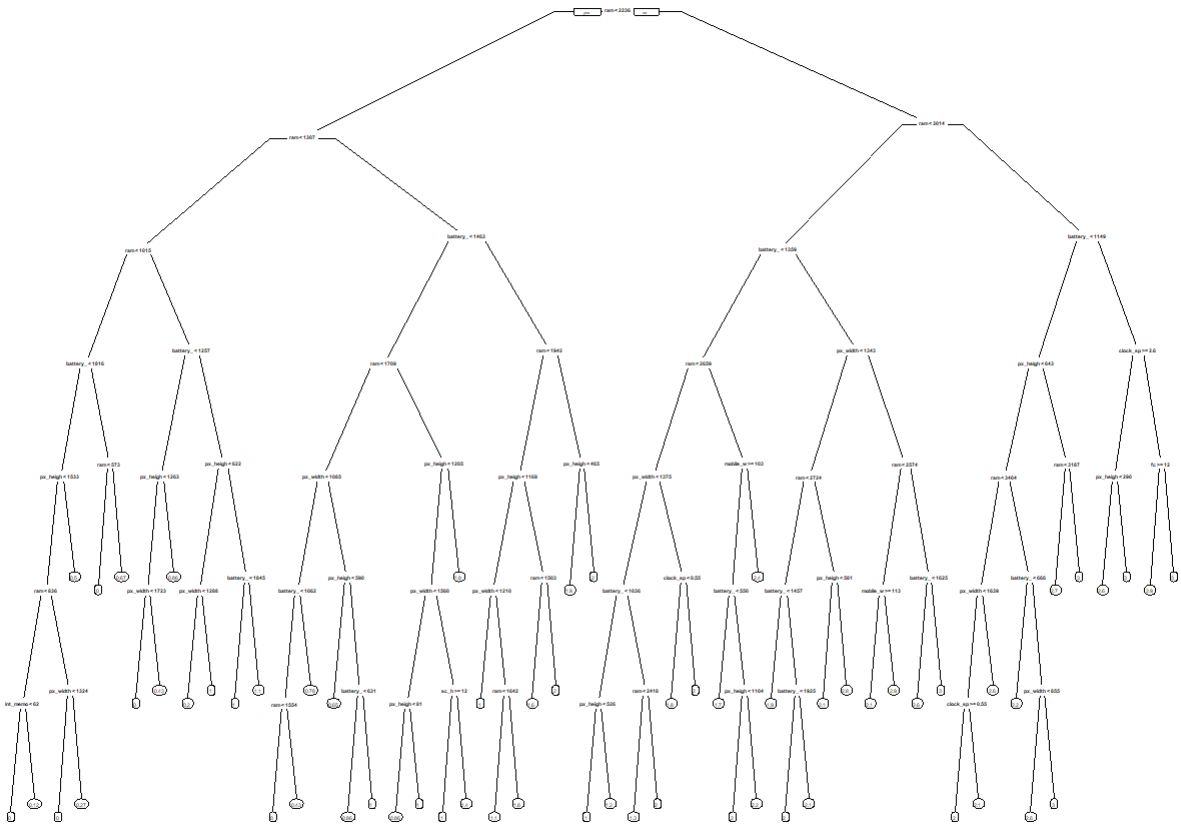

```
CFit1 <- predict(tree2, data_test, type = "class")
#ConfM1 <- table(data_train$price_range, CFit1)
#(E1 <- (sum(ConfM1) - sum(diag(ConfM1)))/sum(ConfM1))
tree.accuracy = mean(CFit1 == data_test$price_range)
tree.accuracy
```

```
## [1] 0.775
```

```
# Cross Validation
tr.control = trainControl(method = "cv", number = 10)
cp.grid = expand.grid(.cp = (0:10)*0.01)
tr = train(price_range ~., data = data_train, method = "rpart", trControl = tr.control, tuneGrid
= cp.grid)
tr
```

```
## CART
##
## 1400 samples
##   20 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1260, 1260, 1260, 1260, 1260, 1260, ...
## Resampling results across tuning parameters:
##
##   cp    RMSE       Rsquared   MAE
##   0.00  0.3419279  0.9058512  0.1784105
##   0.01  0.4392330  0.8458431  0.3393374
##   0.02  0.4770649  0.8177951  0.3178361
##   0.03  0.4770649  0.8177951  0.3178361
##   0.04  0.4770649  0.8177951  0.3178361
##   0.05  0.4770649  0.8177951  0.3178361
##   0.06  0.4770649  0.8177951  0.3178361
##   0.07  0.5493317  0.7586751  0.4394886
##   0.08  0.5684387  0.7401151  0.4689417
##   0.09  0.6016143  0.7083425  0.5131030
##   0.10  0.6493827  0.6632262  0.5897471
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was cp = 0.
```

```
# Predictions with best tree from CV
best.tree = tr$finalModel
prp(best.tree)
```



```
best.tree.pred = predict(best.tree, newdata = data_test)
tree.accuracy = mean(best.tree.pred == data_test$price_range)
tree.accuracy
```

```
## [1] 0.63
```

Though more interpretable, our decision tree model has lower accuracy than our linear classification models.

We also compared the accuracy score of decision tree model with random forest model. We next show that random forest method improves the accuracy score of fitting the testing dataset by around 10.2%.

Random Forests

Multiple Binary Random Forest Classifiers

We decided to apply random forest models with each individual price range, as this would make results more interpretable.

```
set.seed(430)
library(mltools)
library(randomForest)
library(tidyr)
library(tidyselect)
library(ggplot2)
library(dplyr)

mobile_data <- fread('~/R/mobile/train.csv', stringsAsFactors = T)

#set price_range as factor for one hot encoding
mobile_data$price_range <- as.factor(mobile_data$price_range)

#one hot encode the data for price range
mobile_data_one = one_hot(mobile_data,cols='price_range')

#split the data into training and test
mobile_data_one[, test:=0]
mobile_data_one[sample(nrow(mobile_data_one), 300), test:=1] # take 300 random rows and stick th
em in the test set
# now split
mobile_data_one_test <- mobile_data_one[test==1]
mobile_data_one_train <- mobile_data_one[test==0]

### Train data for each price level randomForest model, setting target variable as a factor
mobile_train_0 <- mobile_data_one_train %>% select(-(price_range_1:test))
mobile_train_0$price_range_0 <- as.factor(mobile_train_0$price_range_0)

mobile_train_1 <- mobile_data_one_train %>% select(-c(price_range_0,(price_range_2:test)))
mobile_train_1$price_range_1 <- as.factor(mobile_train_1$price_range_1)

mobile_train_2 <- mobile_data_one_train %>% select(-c((price_range_0:price_range_1),(price_range
_3:test)))
mobile_train_2$price_range_2 <- as.factor(mobile_train_2$price_range_2)

mobile_train_3 <- mobile_data_one_train %>% select(-c((price_range_0:price_range_2),test))
mobile_train_3$price_range_3 <- as.factor(mobile_train_3$price_range_3)

###Test data
mobile_predictors_test <- mobile_data_one_test %>% select(-(price_range_0:test))
#instantiate test Ys
price_0_test <- mobile_data_one_test %>% select(price_range_0)
price_0_test_f <- as.factor(price_0_test$price_range_0)

price_1_test <- mobile_data_one_test %>% select(price_range_1)
price_1_test_f <- as.factor(price_1_test$price_range_1)

price_2_test <- mobile_data_one_test %>% select(price_range_2)
price_2_test_f <- as.factor(price_2_test$price_range_2)

price_3_test <- mobile_data_one_test %>% select(price_range_3)
price_3_test_f <- as.factor(price_3_test$price_range_3)
```

```
##############################################################################
####Code below did not work for the random Forest model but
###could be used for other applications

#cross validation (?)

#separate X (predictors)
mobile_predictors_train <- mobile_data_one_train %>% select(-(price_range_0:test))

#instantiate each individual train Ys and obtain the vector of the values
price_0_train <- mobile_data_one_train %>% select(price_range_0)
y_0_train <- price_0_train$price_range_0

price_1_train <- mobile_data_one_train %>% select(price_range_1)
y_1_train <- price_1_train$price_range_1

price_2_train <- mobile_data_one_train %>% select(price_range_2)
y_2_train <- price_2_train$price_range_2

price_3_train <- mobile_data_one_train %>% select(price_range_3)
y_3_train <- price_3_train$price_range_3


##############################################################################
#fit the models for each price level
#Random Forest Classifier for price range 0
fit.rndfor_0 <- randomForest(price_range_0 ~.,
                             data = mobile_train_0,
                             importance = TRUE,
                             xtest = mobile_predictors_test,
                             ytest = price_0_test_f)
#Random Forest Classifier for price range 1
fit.rndfor_1 <- randomForest(price_range_1 ~.,
                               data = mobile_train_1,
                               importance=TRUE,
                               xtest = mobile_predictors_test,
                               ytest = price_1_test_f)
#Random Forest Classifier for price range 2
fit.rndfor_2 <- randomForest(price_range_2 ~.,
                               data = mobile_train_2,
                               importance=TRUE,
                               xtest = mobile_predictors_test,
                               ytest = price_2_test_f)
#Random Forest Classifier for price range 3
fit.rndfor_3 <- randomForest(price_range_3 ~.,
                               data = mobile_train_3,
                               importance=TRUE,
                               xtest = mobile_predictors_test,
                               ytest = price_3_test_f)

#Analyze the results
# Price Range 0 train
y_hat_0 <- fit.rndfor_0$predicted
price_0_acc <- mean(y_hat_0 == y_0_train)
```

```
# Price Range 0 test
y_test_hat_0 <- fit.rndfor_0$test$predicted
price_0_acc_test <- mean(y_test_hat_0 == price_0_test$price_range_0)

#Price Range 1 train
y_hat_1 <- fit.rndfor_1$predicted
price_1_acc <- mean(y_hat_1 == y_1_train)
# Price Range 1 test
y_test_hat_1 <- fit.rndfor_1$test$predicted
price_1_acc_test <- mean(y_test_hat_1 == price_1_test$price_range_1)

#Price Range 2 train
y_hat_2 <- fit.rndfor_2$predicted
price_2_acc <- mean(y_hat_2 == y_2_train)
# Price Range 2 test
y_test_hat_2 <- fit.rndfor_2$test$predicted
price_2_acc_test <- mean(y_test_hat_2 == price_2_test$price_range_2)

#Price Range 3 train
y_hat_3 <- fit.rndfor_3$predicted
price_3_acc <- mean(y_hat_3 == y_3_train)
# Price Range 3 test
y_test_hat_3 <- fit.rndfor_3$test$predicted
price_3_acc_test <- mean(y_test_hat_3 == price_3_test$price_range_3)

#############################################################################################################
#Code below has the purpose of combining all 4 previous models

#Building a model for a prediction with all models
#set up y_test as a 4 level factor
price_levels <- mobile_data_one_test %>% select((price_range_0:price_range_3))
colnames(price_levels) <- c("0","1","2","3")
w <- which(price_levels==1,arr.ind = T)
mobile_data_one_test$price_level <- toupper(names(price_levels)[w[order(w[,1]),2]])
#Add these values into a data table
prediction_dt <- data.table("0" = fit.rndfor_0$test$votes[,2],
                            "1" = fit.rndfor_1$test$votes[,2],
                            "2" = fit.rndfor_2$test$votes[,2],
                            "3" = fit.rndfor_3$test$votes[,2])

label_rf <- apply(prediction_dt,1,which.max)-1
decision_dt <- data.table("predicted values"= label_rf)

decision_dt$actualvalues <- mobile_data_one_test$price_level



#Evaluate decisions
y_test <- as.numeric(decision_dt$actualvalues)
predictions <- as.numeric(decision_dt$`predicted values`)
analysis_table <- table(y_test,predictions)

diag = diag(analysis_table) # number of correctly classified instances per class
rowsums = apply(analysis_table, 1, sum) # number of instances per class
```

```
colsums = apply(analysis_table, 2, sum) # number of predictions per class

precision = diag / colsums
recall = diag / rowsums
f1 = 2 * precision * recall / (precision + recall)

scores <- data.frame(precision, recall, f1)
test_accuracy <- mean(y_test == predictions)

scores
```

```
##   precision    recall        f1
## 0 0.8750000 0.9390244 0.9058824
## 1 0.8219178 0.7407407 0.7792208
## 2 0.7323944 0.8387097 0.7819549
## 3 0.9705882 0.8800000 0.9230769
```

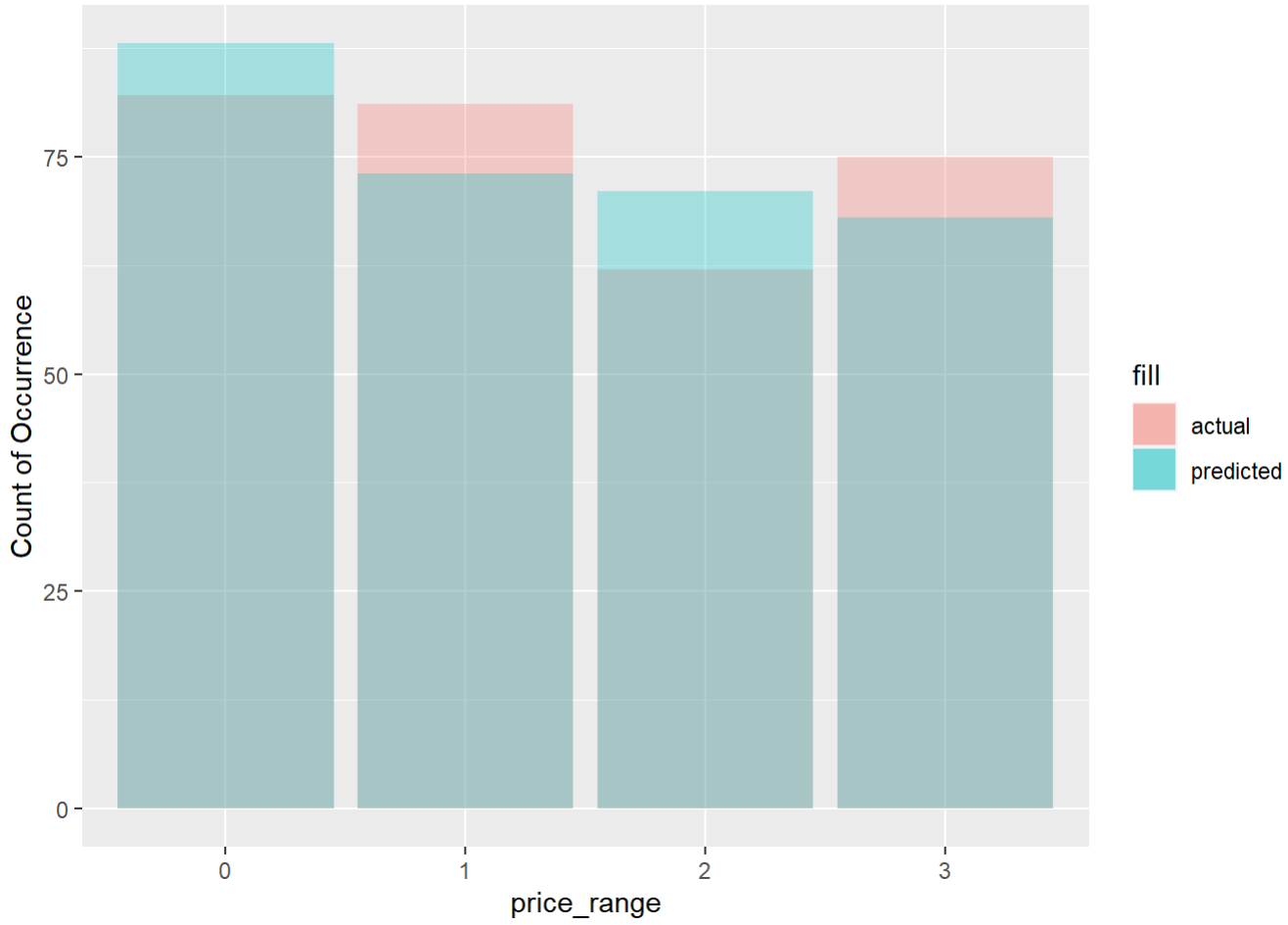
```
analysis_table
```

```
##       predictions
## y_test  0  1  2  3
##      0 77  5  0  0
##      1 11 60 10  0
##      2  0  8 52  2
##      3  0  0  9 66
```

```
test_accuracy
```

```
## [1] 0.85
```

```
#graphing the results
df_rf <- data.table(rowsums)
df_rf$pred <- colsums
df_rf$price_range <- c("0",'1','2','3')
colnames(df_rf) <- c('actual','predicted','price_range')
ggplot(NULL,aes(x=price_range,y=actual))+
  geom_bar(aes(fill="actual"), data= df_rf, stat = 'identity',position = "dodge",alpha=0.3)+
  geom_bar(aes(y=predicted,fill="predicted"),data=df_rf,stat = 'identity',position = "dodge",alp
ha = 0.3)+
  ylab("Count of Occurrence")
```



This model proved to be good, as accuracy for values in the test set was 0.83. As seen with our other methods as well, the model had the most trouble differentiating between phones in the middle price ranges of 1-2.

However, as these tree based models performed worse than our linear models, we were led to believe that our data follows a more linear relationship.

Multiclass Random Forest Classifier

Here we use cross validation to find optimal values of 2 Random Forest hyperparameters

- m - the number of predictors randomly selected for each split
- number of trees

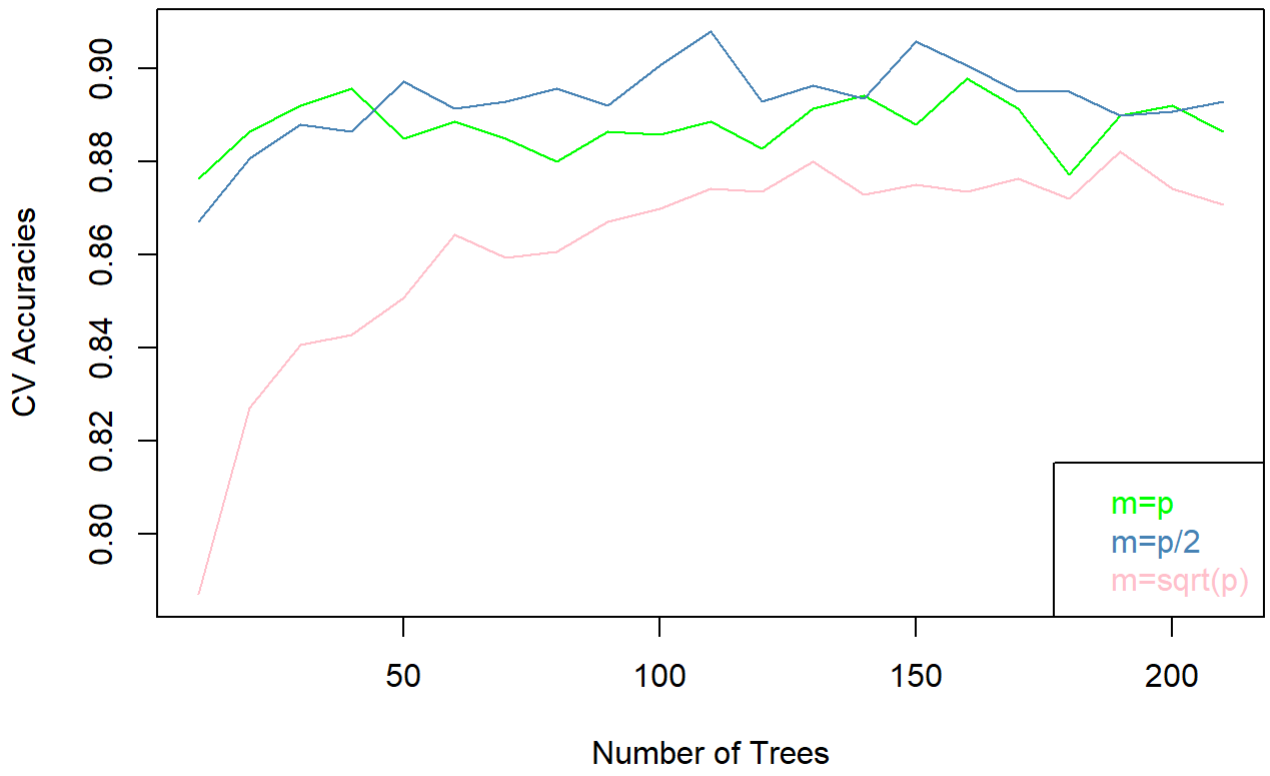
```
set.seed(430)
mo <- fread('~/R/mobile/train.csv')
mo$price_range <- as.factor(mo$price_range)
mo_obs <- nrow(mo)
mo_idx <- sample(mo_obs, size = trunc(0.70 * mo_obs))
mo_trn <- mo[mo_idx, ]
mo_test <- mo[-mo_idx, ]

Y_test <- mo_test[,price_range]

#https://www.blopig.com/blog/2017/04/a-very-basic-introduction-to-random-forests-using-r/


dd <- data.table()
dd
```

```
## Null data.table (0 rows and 0 cols)
```

```
p <- length(colnames(mo_trn)) -1
p_ov2 <- p / 2
p_sqrt <- sqrt(length(colnames(mo_trn)) -1)

trees <- seq(from = 10, to = 210, by = 10)


for (num_pred in c(p, p_ov2, p_sqrt)) {
  CV_accuracies = c()
  for (num_trees in trees){

    #Perform K-fold cross validation
    k = 5
    #Randomly shuffle the data
    mo_trn_cross <- mo_trn[sample(nrow(mo_trn)),]

    #Create K equally size folds
    folds <- cut(seq(1,nrow(mo_trn_cross)),breaks=k,labels=FALSE)

    accuracies <- c()

    #Perform K-fold cross validation

    for(i in 1:k){
      #Segement  data by fold with which() function
      testIndexes <- which(folds==i,arr.ind=TRUE)
      testData <- mo_trn_cross[testIndexes, ]
      trainData <- mo_trn_cross[-testIndexes, ]
      Y_CV <- testData$price_range


      #num_features <- sqrt(length(colnames(mo_trn)) -1)


      rf_classifier <- randomForest(price_range ~ ., data = trainData, ntree = num_trees, mtry =
num_pred, importance = TRUE )
      Y_test_hat <- predict(rf_classifier, newdata = testData, type = "class")

      accuracy <- mean(Y_test_hat == Y_CV)

      accuracies <- c(accuracies, accuracy)
    }
    CV_accuracy <- mean(accuracies)
    CV_accuracies <- c(CV_accuracies, CV_accuracy)
  }
  dd <- cbind(dd, CV_accuracies)


}
dd[, num_tree := trees]
dd
```

```
##     CV_accuracies CV_accuracies CV_accuracies num_tree
##  1:     0.8764286     0.8671429     0.7871429       10
##  2:     0.8864286     0.8807143     0.8271429       20
##  3:     0.8921429     0.8878571     0.8407143       30
##  4:     0.8957143     0.8864286     0.8428571       40
##  5:     0.8850000     0.8971429     0.8507143       50
##  6:     0.8885714     0.8914286     0.8642857       60
##  7:     0.8850000     0.8928571     0.8592857       70
##  8:     0.8800000     0.8957143     0.8607143       80
##  9:     0.8864286     0.8921429     0.8671429       90
## 10:     0.8857143     0.9007143     0.8700000      100
## 11:     0.8885714     0.9078571     0.8742857      110
## 12:     0.8828571     0.8928571     0.8735714      120
## 13:     0.8914286     0.8964286     0.8800000      130
## 14:     0.8942857     0.8935714     0.8728571      140
## 15:     0.8878571     0.9057143     0.8750000      150
## 16:     0.8978571     0.9007143     0.8735714      160
## 17:     0.8914286     0.8950000     0.8764286      170
## 18:     0.8771429     0.8950000     0.8721429      180
## 19:     0.8900000     0.8900000     0.8821429      190
## 20:     0.8921429     0.8907143     0.8742857      200
## 21:     0.8864286     0.8928571     0.8707143      210
##     CV_accuracies CV_accuracies CV_accuracies num_tree
```

```
colnames(dd) <- c("m=p", "m=p/2", "m=sqrt(p)", "num_tree")

plot(dd$`m=p` ~ dd$num_tree, type = 'l', ylim = c(min(dd[,1:3]), max(dd[,1:3])), col = 'green',
 xlab = 'Number of Trees', ylab = "CV Accuracies")
lines(dd$num_tree, dd$`m=p/2`, col = "steelblue")
lines(dd$num_tree, dd$`m=sqrt(p)`, col = "pink")

legend("bottomright",
       legend = c("m=p", "m=p/2", "m=sqrt(p)"),
       text.col = c("green", "steelblue", "pink")

)
```




```
which.max(dd$`m=p/2`) # 110 trees with m = p/2 is max cv accuracy
```

```
## [1] 11
```

```
rf_classifier <- randomForest(price_range ~ ., data = mo_trn, ntree = 110, mtry = p_ov2, importa
nce = TRUE )

Y_test_hat <- predict(rf_classifier, newdata = mo_test, type = "class")

test_accuracy <- mean(Y_test_hat == Y_test)


cm <- table(observed=Y_test, predicted=Y_test_hat)

diag = diag(cm) # number of correctly classified instances per class
rowsums = apply(cm, 1, sum) # number of instances per class
colsums = apply(cm, 2, sum) # number of predictions per class

precision = diag / colsums
recall = diag / rowsums
f1 = 2 * precision * recall / (precision + recall)

scores <- data.frame(precision, recall, f1)



print(paste0("test accuracy: ", test_accuracy))
```

```
## [1] "test accuracy: 0.893333333333333"
```

```
cat('\nConfusion Matrix\n\n')
```

```
##
## Confusion Matrix
```

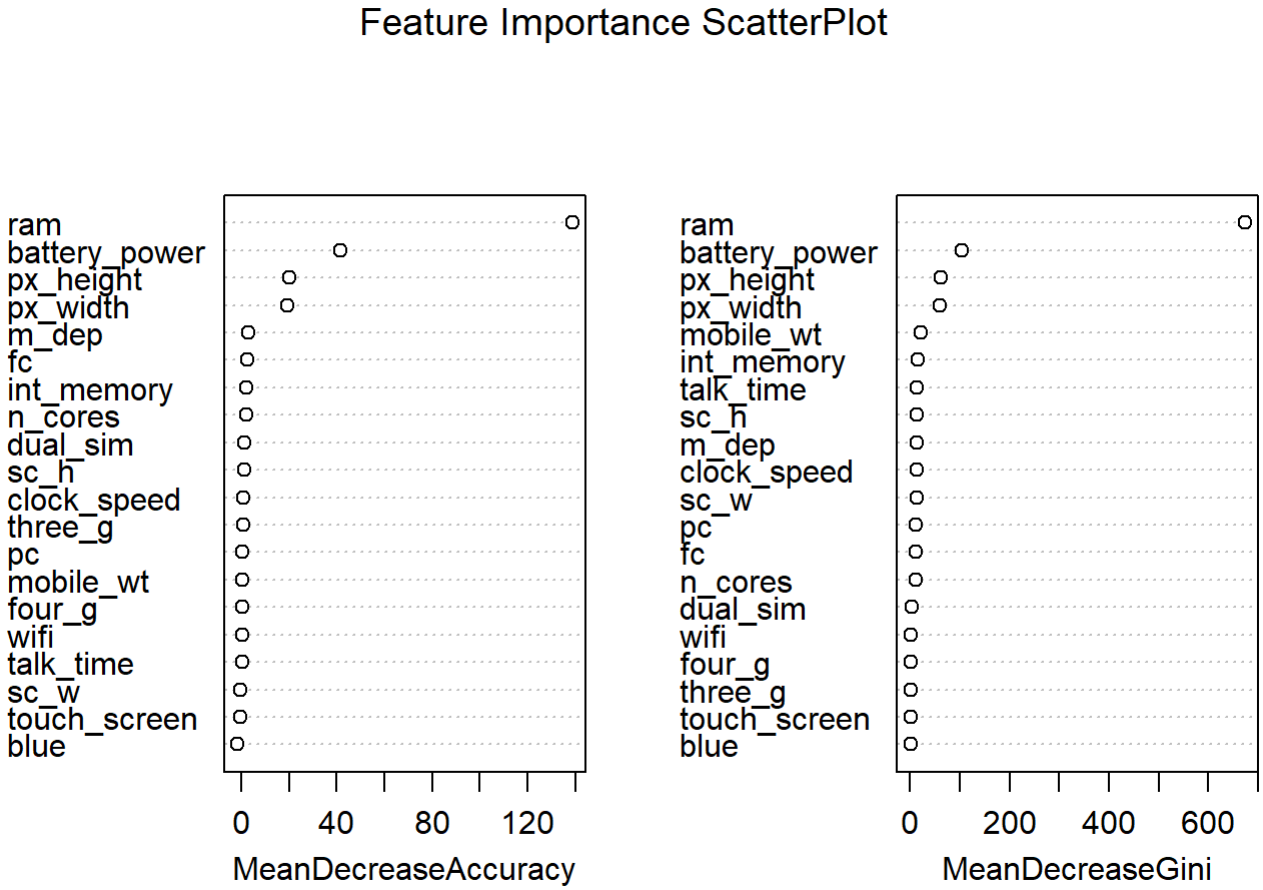
```
print(cm)
```

```
##          predicted
## observed   0   1   2   3
##        0 139   9   0   0
##        1   9 135   7   0
##        2   0  15 127  16
##        3   0   0   8 135
```

```
print(scores)
```

```
##   precision    recall        f1
## 0 0.9391892 0.9391892 0.9391892
## 1 0.8490566 0.8940397 0.8709677
## 2 0.8943662 0.8037975 0.8466667
## 3 0.8940397 0.9440559 0.9183673
```

```
# Variable Importance

varImpPlot(rf_classifier, sort = TRUE, n.var = nrow(rf_classifier$importance), main = "Feature I
mportance ScatterPlot")
```



Typically the recommended value for m in a random forest is the square root of the number of predictors, but that approach consistently under preformed compared to m = p (same as bagging), and m = p / 2.

The best cv accuracy came from a model with 140 trees and m = p / 2.

Boosting Classification Tree

Finally we run a boosting classification tree.

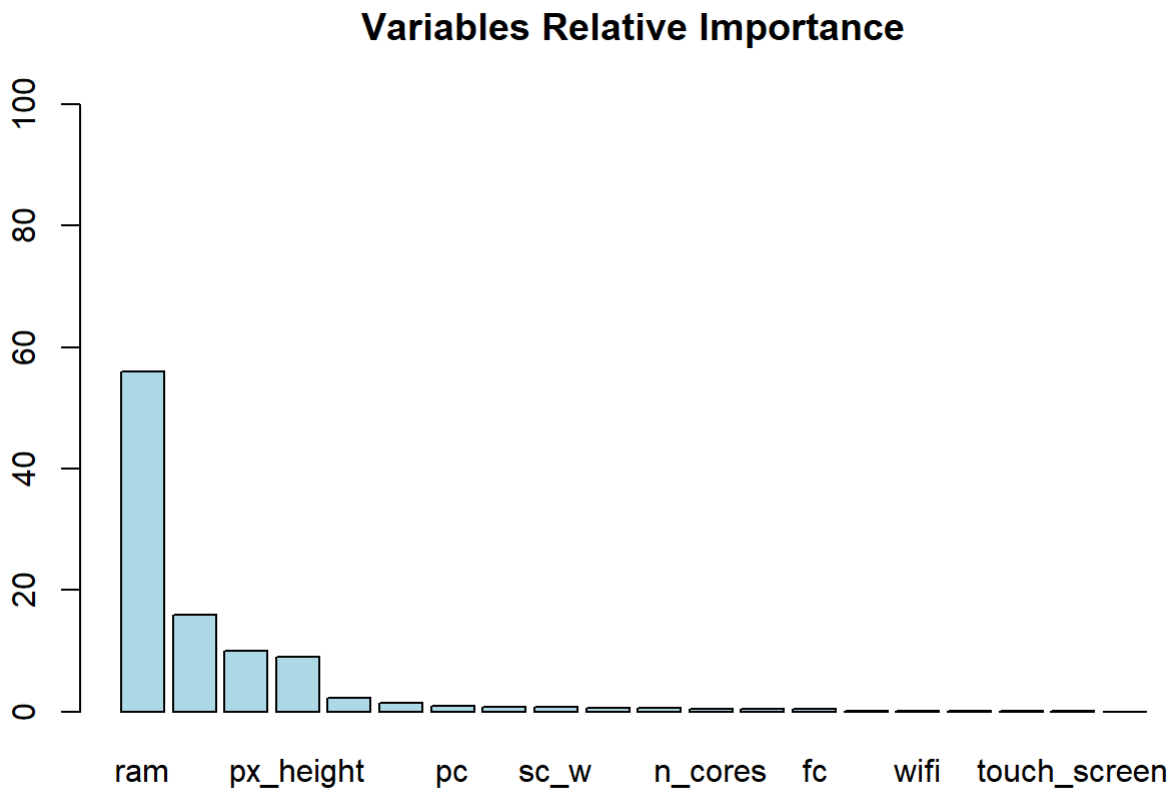
```
set.seed(430)

mo$price_range <- as.factor(mo$price_range)
split = sample.split(mo$price_range, SplitRatio = 0.7)
data_train = subset(mo, split == TRUE)
data_test = subset(mo, split == FALSE)

library(adabag)

data.adaboost <- boosting(price_range ~., data = data_train, mfinal = 100, control = rpart.contr
ol(maxdepth = 5))
#data.adaboost
data.predboosting <- predict.boosting(data.adaboost, newdata = data_test)
#data.predboosting
#data.boostcv <- boosting.cv(price_range ~., v = 10, data = data_train, mfinal = 10, control = r
part.control(maxdepth = 1))
#data.boostcv

cm <- data.predboosting$confusion

test_accuracy <- 1 - data.predboosting$error

cm
```

```
##                Observed Class
## Predicted Class   0   1   2   3
##               0 142   3   0   0
##               1   8 143   9   0
##               2   0   4 137   9
##               3   0   0   4 141
```

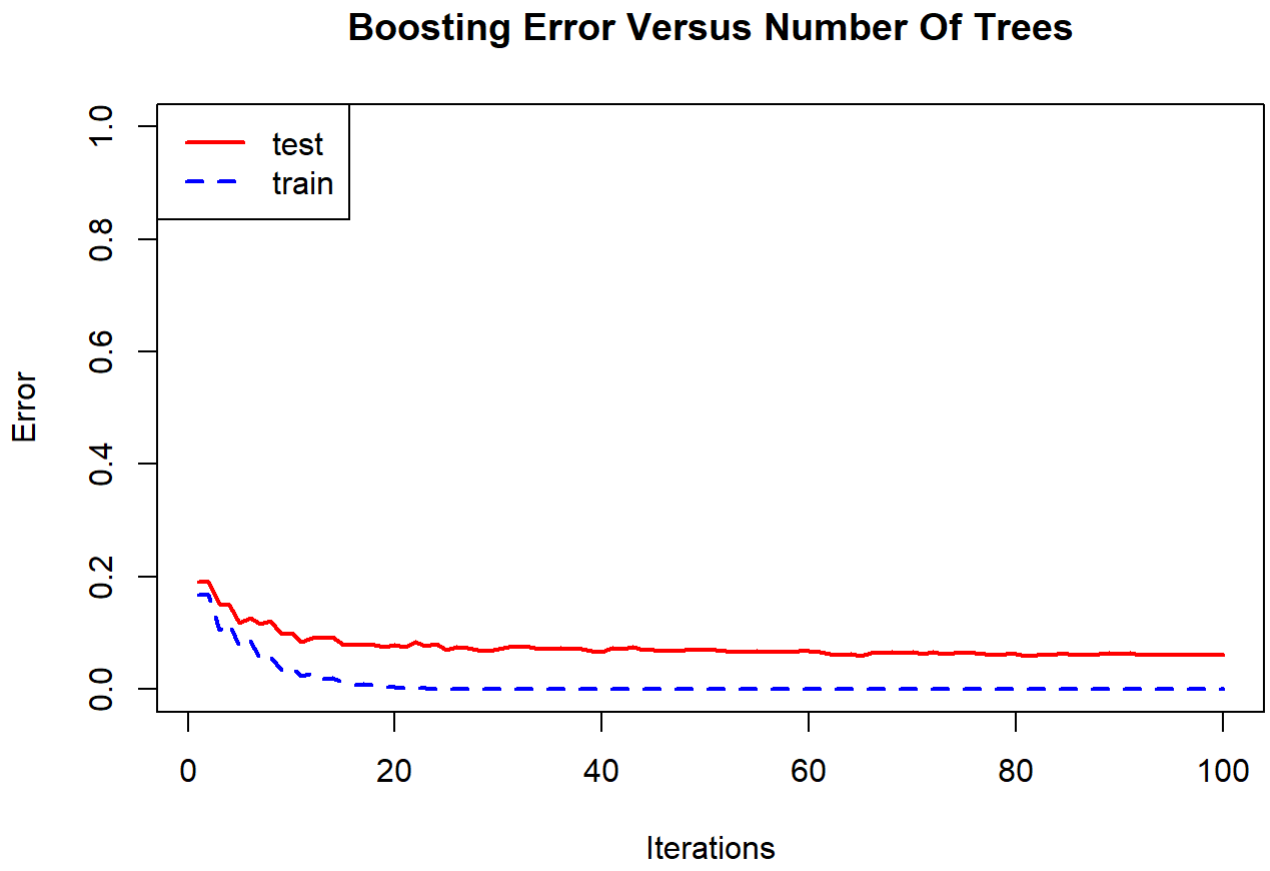
```
test_accuracy
```

```
## [1] 0.9383333
```

```
barplot(data.adaboost$imp[order(data.adaboost$imp, decreasing = TRUE)], ylim = c(0, 100), main =
"Variables Relative Importance", col = "lightblue")
```




```
evol.test <- errorevol(data.adaboost, data_test)
evol.train <- errorevol(data.adaboost, data_train)
plot(evol.test$error, type = "l", ylim = c(0, 1),
main = "Boosting Error Versus Number Of Trees", xlab = "Iterations",
ylab = "Error", col = "red", lwd = 2)
lines(evol.train$error, cex = .5, col = "blue", lty = 2, lwd = 2)
legend("topleft", c("test", "train"), col = c("red", "blue"), lty = 1:2, lwd = 2)
```



This model performed better than our top performing Random Forest with a value of 5 for max splits in each tree and 100 trees.

Summary

Accuracies for various models:

- Multinomial Neural Net - 97.16%
- Layered Binary Logistic Regressions - 96.66%
- Boosting Decision Tree - 93.83%
- Random Forest Decision Tree - 89.33%
- Multiple Binary Random Forest - 85%
- Simple Decision Tree - 77.5%

Though Decision trees are more interpretable for multiclass classification problem we see that the linear models perform better. This indicates that the relationship between predictors and price_range is linear.

Having more than 2 predictors complicates the problem and we had to come up with creative solutions like the layered binary logistic Regressions.

The random forest and boosting models improve accuracy over a simple decision tree by over 10%.

Variable importance measures show that ram is by far the most important feature for predicting price_range.