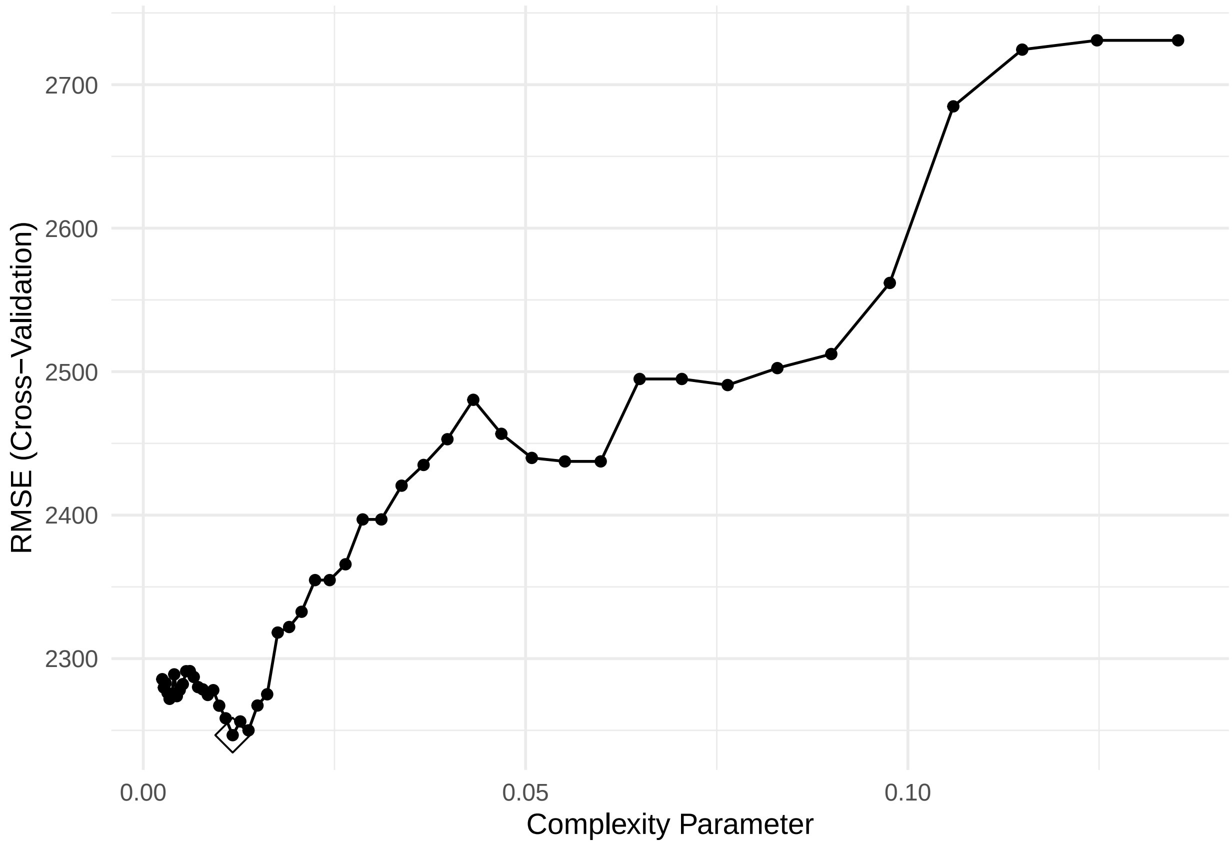
Hw4 regression/classification trees

Problem 1

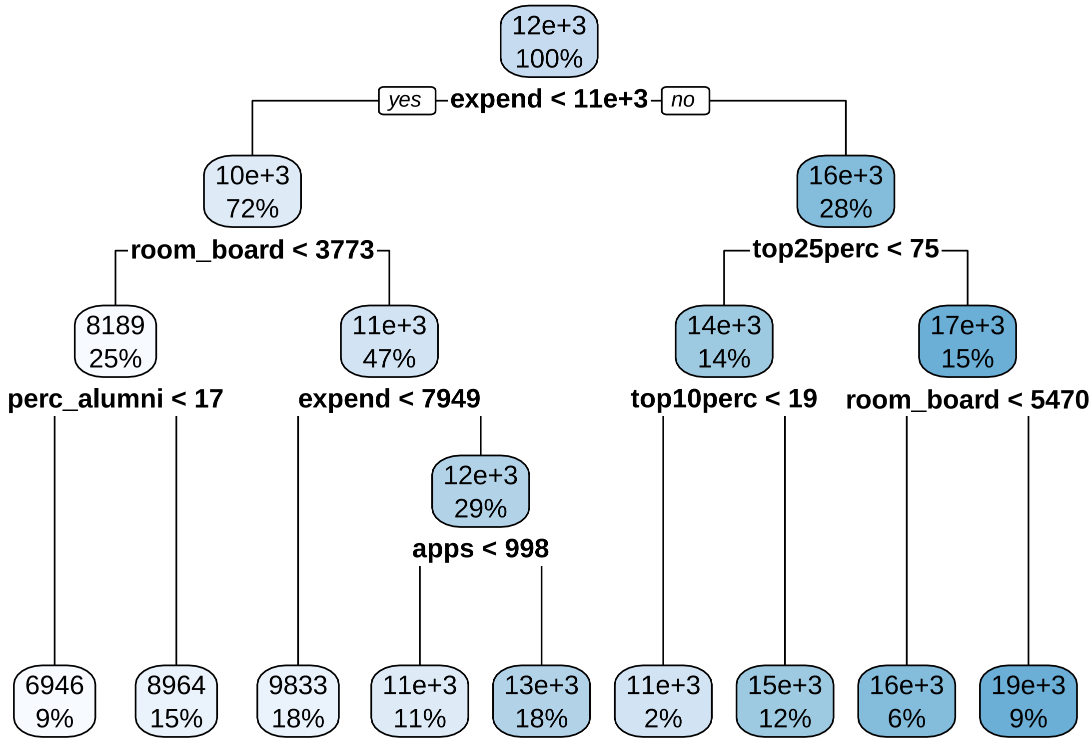
```r
# load dataset
college_df = read_csv("College.csv", show_col_types = FALSE) %>%
  janitor::clean_names() %>%
  select(-college) %>%
  na.omit()

# data partition
set.seed(2023)
index_train = createDataPartition(y = college_df$outstate, p = 0.8, list = FALSE)
```

Recursive Partitioning and Regression Trees

```r
# set train method
ctrl_1 = trainControl(method = "cv", number = 10)
set.seed(1)
rpart_model = train(outstate ~ . ,
                   data = college_df,
                   subset = index_train,
                   method = "rpart",
                   tuneGrid = data.frame(cp = exp(seq(-6,-2, length = 50))),
                   trControl = ctrl_1)
ggplot(rpart_model, highlight = TRUE)
```

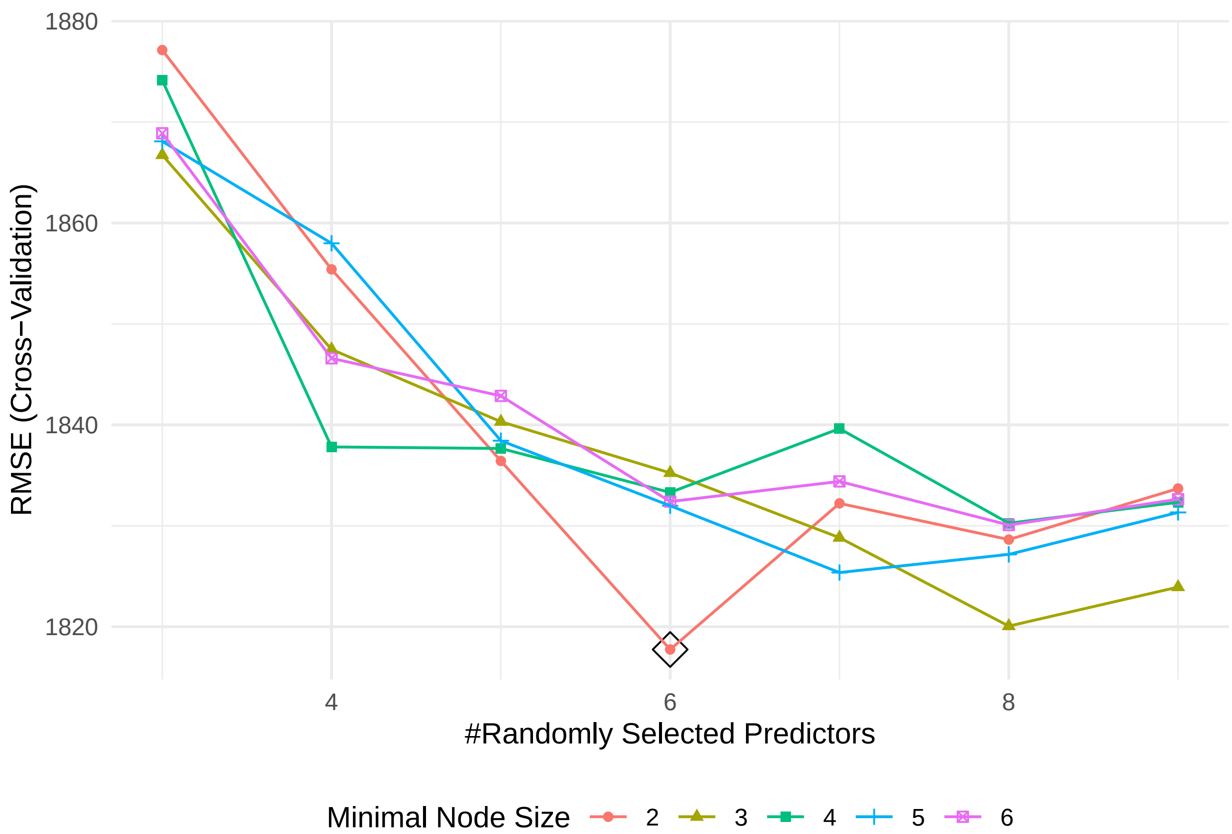



```
# Create a plot of the selected tree
rpart.plot(rpart_model$finalModel)
```



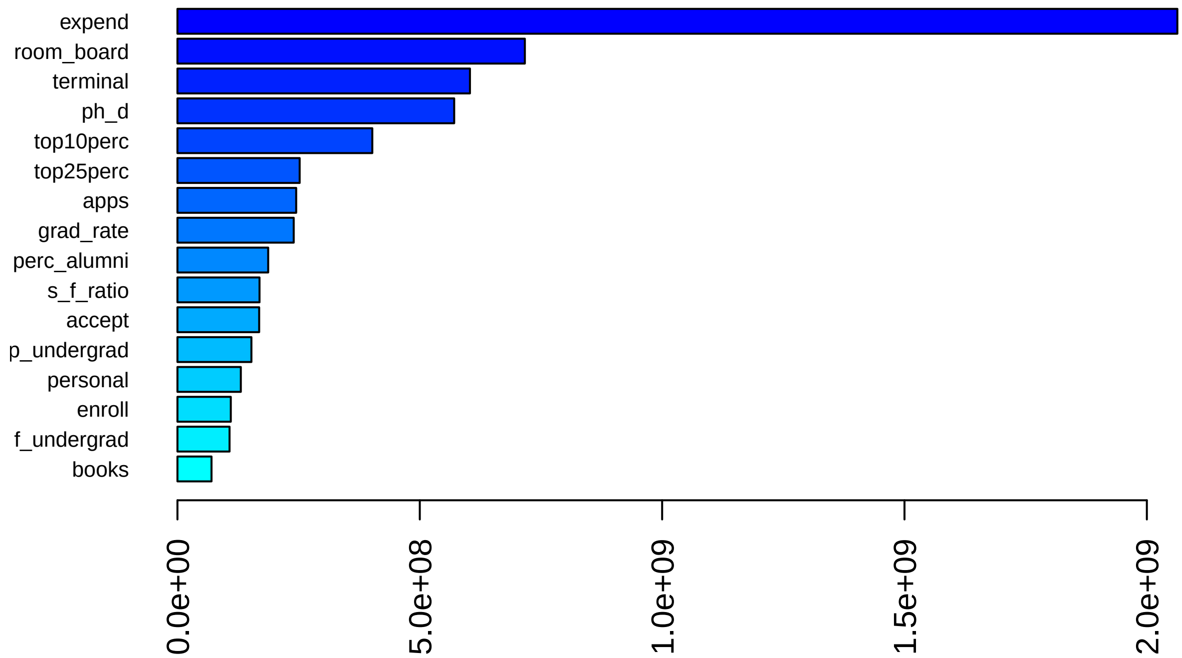
Random Forest Regression

```r
# For number of predictors included in each tree, p/3 and sqrt{p} are commonly selected. For 17 predict
set.seed(1)
rf_grid = expand.grid(mtry = 3:9,
                       splitrule = "variance",
                       min.node.size = 2:6)
rf_model = train(outstate ~ . ,
                 data = college_df[index_train,],
                 method = "ranger",
                 tuneGrid = rf_grid,
                 trControl = ctrl_1)
ggplot(rf_model, highlight = TRUE)
```




```
set.seed(1)
rf_model_final = ranger(outstate ~ . ,
                        data = college_df[index_train,],
                        mtry = rf_model$bestTune[[1]],
                        splitrule = "variance",
                        min.node.size = rf_model$bestTune[[3]],
                        importance = "impurity")
barplot(sort(ranger::importance(rf_model_final), decreasing = FALSE),
        las = 2, horiz = TRUE, cex.names = 0.7,
        col = colorRampPalette(colors = c("cyan","blue"))(16))
```

Variable importance and test MSE of Random Forest




```r
# test mse of final model from ranger
pred_y = predict(rf_model_final, college_df[-index_train,])
mean((college_df[-index_train,]$outstate-pred_y$predictions)^2)
```

```
## [1] 2090869
```

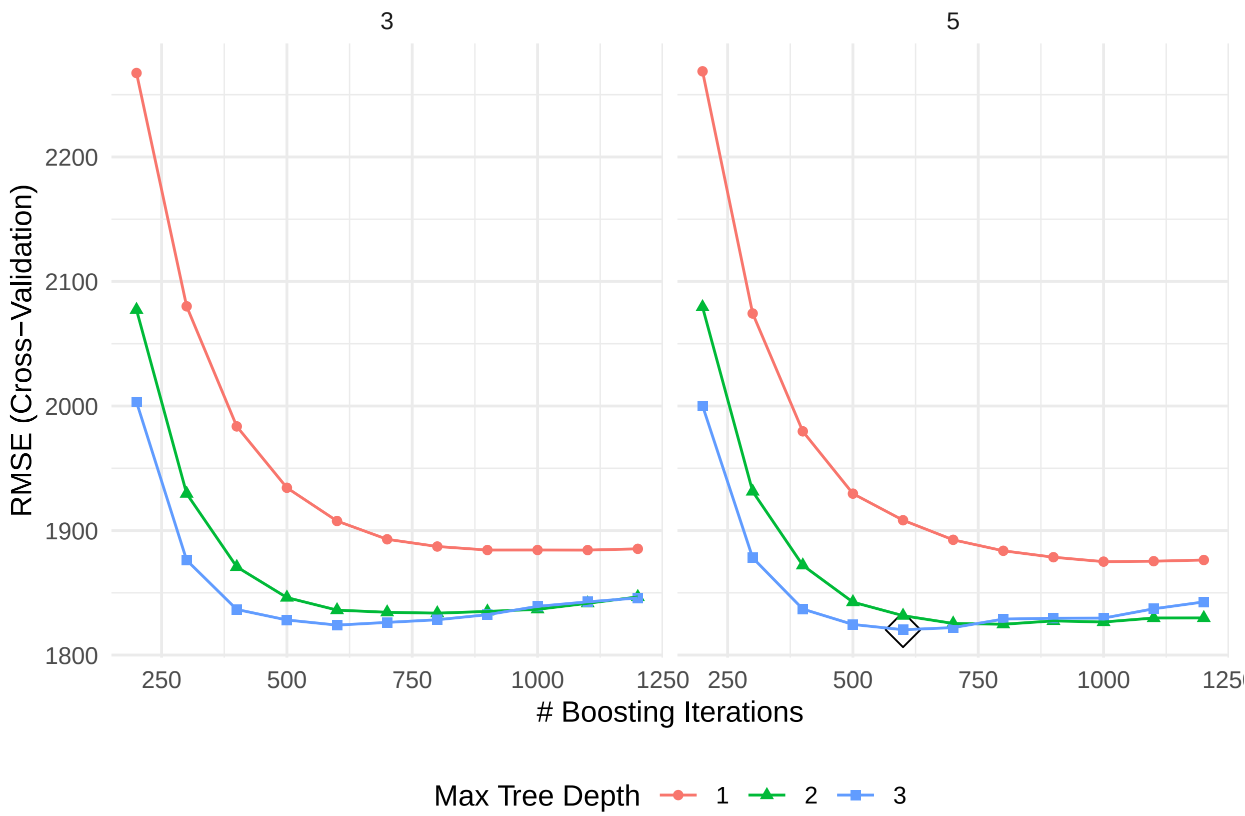
```r
# OR test mse of final model from caret
# pred_z = predict(rf_model, college_df[-index_train,])
# mean((college_df[-index_train,]$outstate-pred_z)^2)
```

`expend` is the most important variable which accounts most reduction to the loss function given this set of predictors. `room_board`, `terminal`, and `ph_d` are followed. The test MSE is 2090869.

Gradient Boosting regression

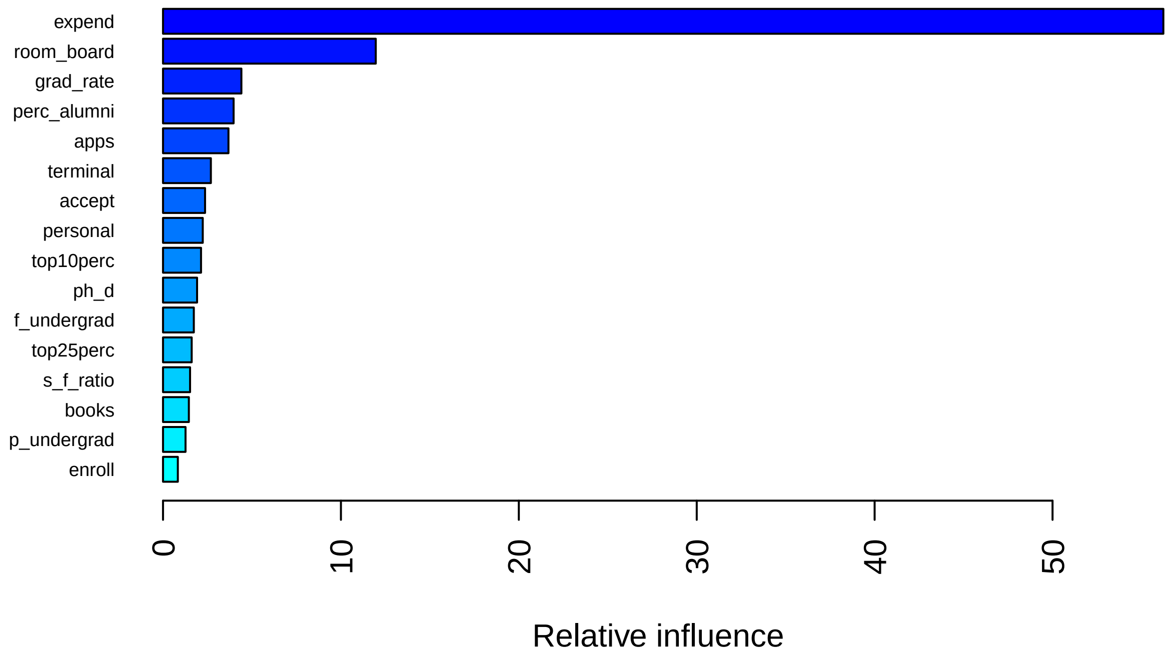
```r
set.seed(1)
# learning rate selection criterion : max(0.01, 0.1*(min(1, nl/10000)))
gbm_grid = expand.grid(n.trees = c(seq(200, 1200, by = 100)),
                       interaction.depth = 1:3,
                       shrinkage = 0.01,
                       n.minobsinnode = c(3,5))
gbm_model = train(outstate ~ . ,
                  data = college_df[index_train,],
```

```
                  method = "gbm",
                  trControl = ctrl_1,
                  tuneGrid = gbm_grid,
                  verbose = FALSE)
ggplot(gbm_model, highlight = TRUE)
```




```
par(mfrow = c(1, 1))
var_df = summary(gbm_model$finalModel, las = 2, cBars = 16, cex.names = 0.6)
```

Variable importance and test MSE of Boosting Model




```
var_df %>%
  as.data.frame() %>%
  select(-var) %>%
  knitr::kable()
```

	rel.inf
expend	56.2293479
room_board	11.9594374
grad_rate	4.4057356
perc_alumni	3.9678975
apps	3.6780434
terminal	2.6908159
accept	2.3637394
personal	2.2336687
top10perc	2.1375602
ph_d	1.9150704
f_undergrad	1.7312571
top25perc	1.6123081
s_f_ratio	1.5213065
books	1.4536362
p_undergrad	1.2658496
enroll	0.8343261

```r
# test mse of final model from caret
pred_z = predict(gbm_model, college_df[-index_train,])
mean((college_df[-index_train,]$outstate-pred_z)^2)
```

```
## [1] 1827409
```

`expend` and `room_board` are the most important variable which accounts for more than 56% and 12% of the reduction to the loss function given this set of predictors. The test MSE is 1827409.

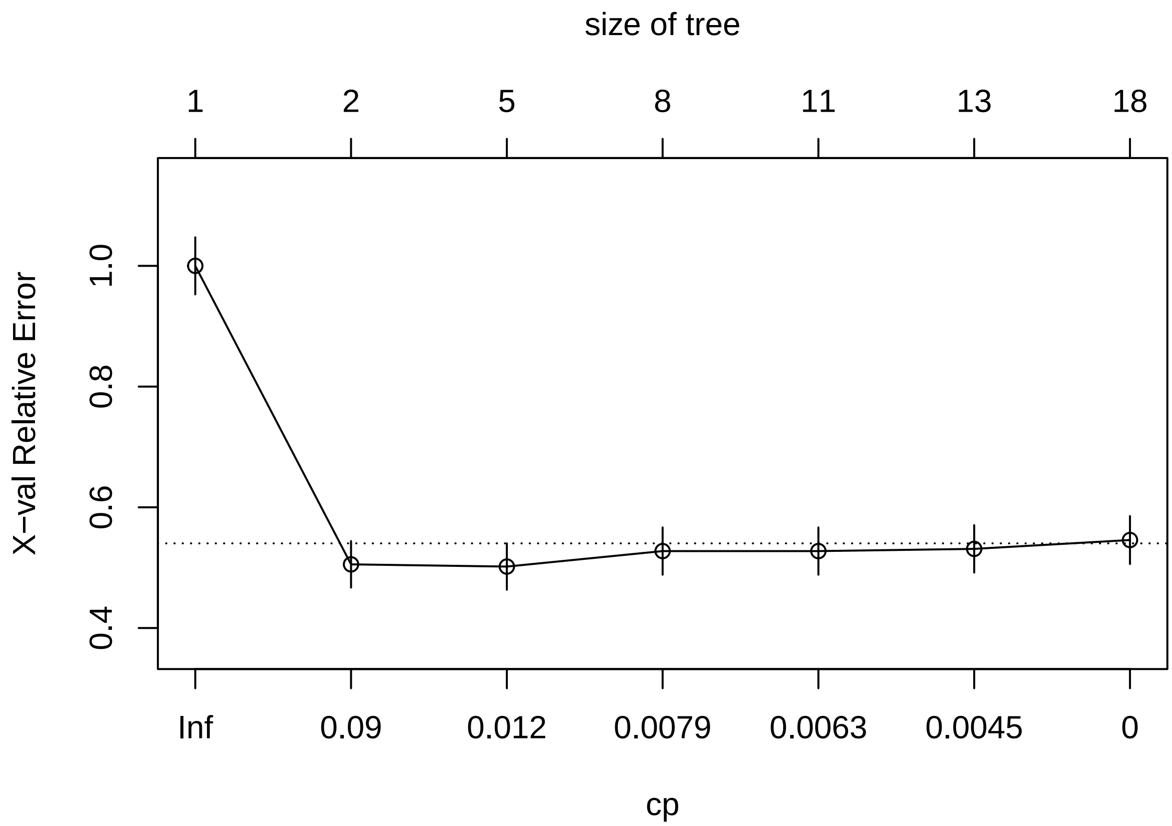
Problem 2

Classification Trees

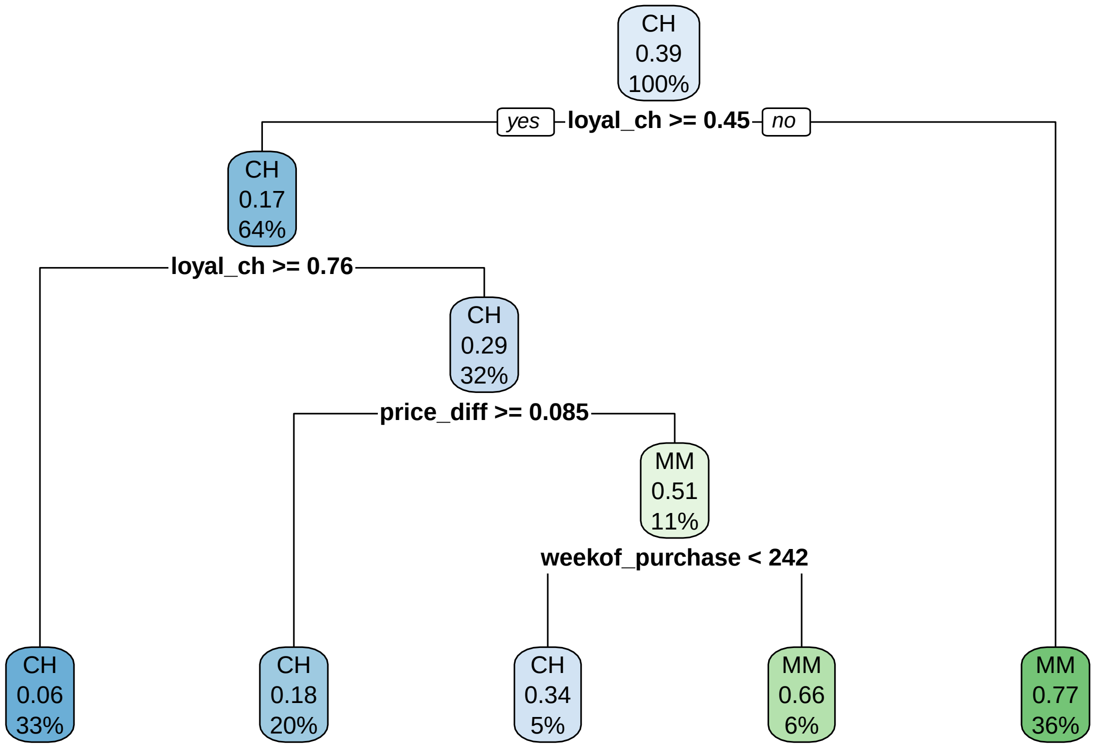
```r
data(OJ)
oj_df = OJ %>% janitor::clean_names()
set.seed(2022)
train_index = createDataPartition(oj_df$purchase, p = 700/1070, list = FALSE)

set.seed(3)
tree1 = rpart(purchase ~ . ,
              data = oj_df,
              subset = train_index,
              control = rpart.control(cp = 0))
cpTable = printcp(tree1)
```

```
##
## Classification tree:
## rpart(formula = purchase ~ ., data = oj_df, subset = train_index,
##     control = rpart.control(cp = 0))
##
## Variables actually used in tree construction:
## [1] list_price_diff loyal_ch        price_diff      sale_price_mm
## [5] special_ch      special_mm      store           weekof_purchase
##
## Root node error: 273/701 = 0.38944
##
## n= 701
##
##          CP nsplit rel error  xerror     xstd
## 1 0.5054945      0   1.00000 1.00000 0.047291
## 2 0.0158730      1   0.49451 0.50549 0.038563
## 3 0.0085470      4   0.44689 0.50183 0.038457
## 4 0.0073260      7   0.42125 0.52747 0.039182
## 5 0.0054945     10   0.39927 0.52747 0.039182
## 6 0.0036630     12   0.38828 0.53114 0.039283
## 7 0.0000000     17   0.36996 0.54579 0.039677
```

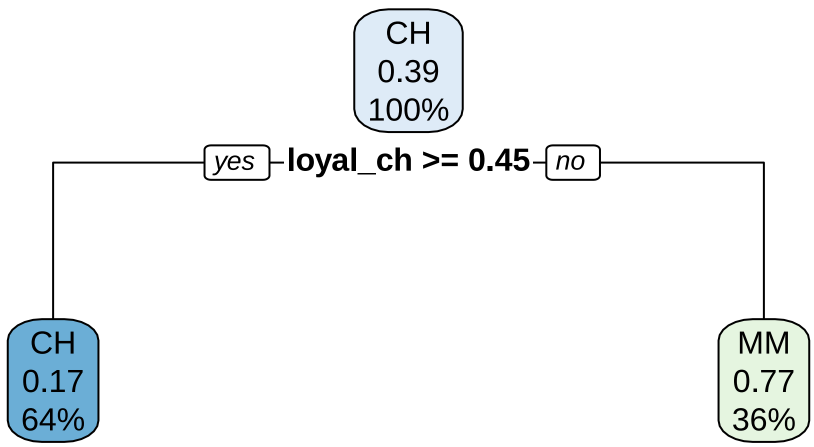
```r
# cv error
plotcp(tree1)
```




```
# tree size based on minimum cross-validation error
minErr = which.min(cpTable[,4])
tree2 = prune(tree1, cp = cpTable[minErr,1])
rpart.plot(tree2)
```




```
# tree size based on 1SE rule
tree4 = prune(tree1, cp = cpTable[cpTable[,4]< cpTable[minErr,4]+cpTable[minErr,5],1][1])
rpart.plot(tree4)
```



(a) The tree with lowest cross-validation error has a size of 5, which is different from the tree size of 2 based on the selection of 1 SE rule.

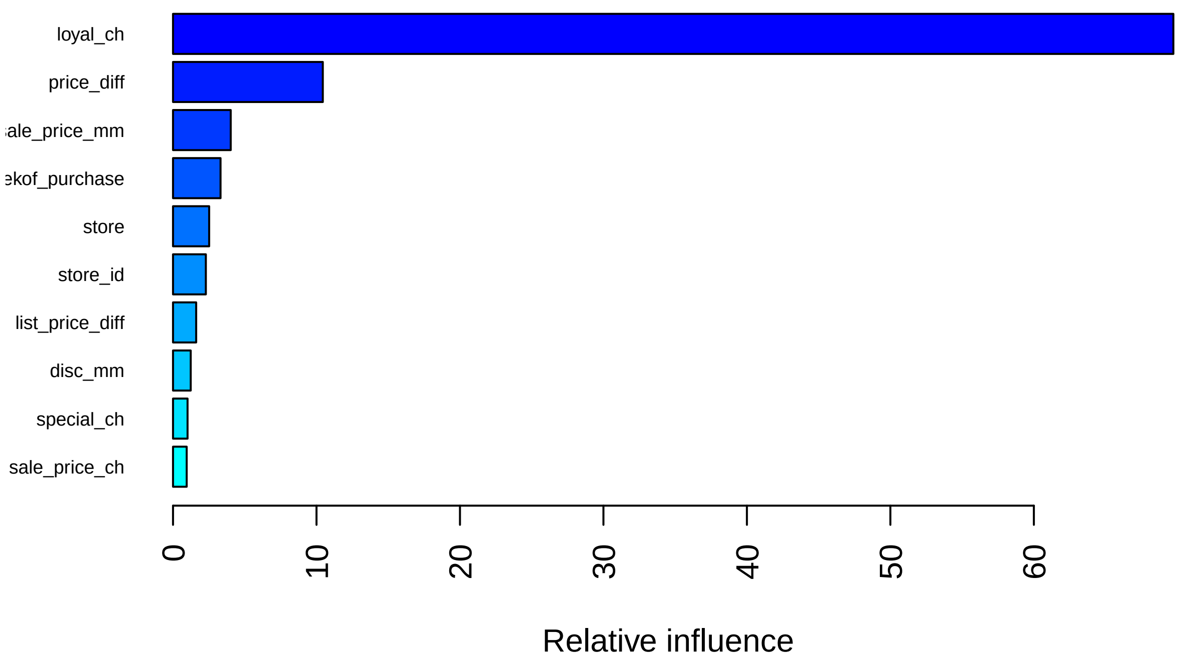
Adaptive boosting classfier

```
ctrl_2 = trainControl(method = "cv",
                      classProbs = TRUE,
                      summaryFunction = twoClassSummary)
# set tunning parameters
# learning rate selection criterion : max(0.01, 0.1*(min(1, nl/10000)))
gbmA_grid <- expand.grid(n.trees = c(seq(200, 1200, by = 100)),
                         interaction.depth = 1:3,
                         shrinkage = 0.01,
                         n.minobsinnode = c(3, 5))
set.seed(5)
gbmA_model = train(purchase ~ . ,
                  data = oj_df,
                  subset = train_index,
                  tuneGrid = gbmA_grid,
                  trControl = ctrl_2,
                  method = "gbm",
                  distribution = "adaboost",
                  metric = "ROC",
```

```
                    verbose = FALSE)
ggplot(gbmA_model, highlight = TRUE)
```


```
par(mfrow = c(1, 1))
# show relative importance of 10 most important variables
var_df = summary(gbmA_model$finalModel, las = 2, cBars = 10, cex.names = 0.6)
```

Variable importance of Adaptive boosting classfier




```
var_df %>%
  as.data.frame() %>%
  select(-var) %>%
  knitr::kable()
```

	rel.inf
loyal_ch	69.7231932
price_diff	10.4413927
sale_price_mm	4.0231151
weekof_purchase	3.3112194
store	2.5199953
store_id	2.2890655
list_price_diff	1.6142087
disc_mm	1.2340747
special_ch	1.0129561
sale_price_ch	0.9545172
price_mm	0.8461131
pct_disc_mm	0.5225001
price_ch	0.4238247
disc_ch	0.3919234
pct_disc_ch	0.2632321
store7Yes	0.2207418
special_mm	0.2079269

```
postResample(predict(gbmA_model, oj_df[-train_index,]),
             oj_df[-train_index,]$purchase) %>% knitr::kable()
```

Test error rate of Adaptive boosting classfier

	x
Accuracy	0.8672087
Kappa	0.7185092

(b) The test error rate is given by (1 - accuracy) which is 0.133 for this adaptive boosting classfier.