Data Science II Homework 4

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Contents

Question 1

```
set.seed(0409)

# data import and cleaning
df = read_csv("College.csv") %>%
  janitor::clean_names() %>%
  select(-college) %>%
  select(outstate, everything()) %>%
  na.omit()

# data partition
indexTrain = createDataPartition(y = df$outstate,
                                 p = 0.8,
                                 list = FALSE)


train_df = df[indexTrain, ]
test_df = df[-indexTrain, ]
```

```
# data dimension and summary
dim(train_df)
```

```
## [1] 453  17
```

```
summary(train_df)
```

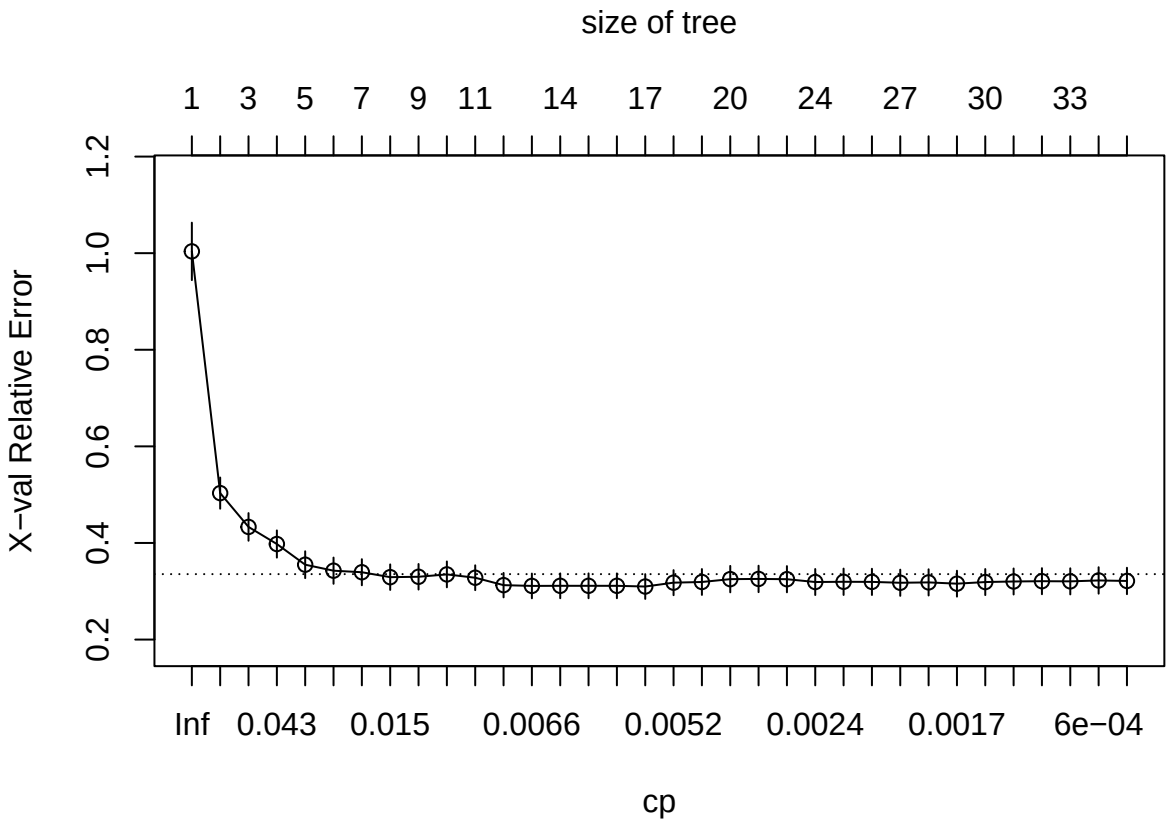
```
##     outstate          apps           accept          enroll
##  Min.   : 2340   Min.   :   81   Min.   :   72   Min.   :  35.0
##  1st Qu.: 9100   1st Qu.:  632   1st Qu.:  501   1st Qu.: 207.0
##  Median :11200   Median : 1179   Median :  884   Median : 335.0
##  Mean   :11810   Mean   : 1970   Mean   : 1304   Mean   : 457.8
##  3rd Qu.:13960   3rd Qu.: 2212   3rd Qu.: 1580   3rd Qu.: 527.0
##  Max.   :21700   Max.   :20192   Max.   :13007   Max.   :4615.0
##    top10perc       top25perc      f_undergrad     p_undergrad
##  Min.   : 2.00   Min.   :  9.00   Min.   :  139   Min.   :    1.0
##  1st Qu.:17.00   1st Qu.: 44.00   1st Qu.:  847   1st Qu.:   62.0
##  Median :26.00   Median : 56.00   Median : 1298   Median :  205.0
##  Mean   :29.76   Mean   : 57.75   Mean   : 1872   Mean   :  430.5
##  3rd Qu.:37.00   3rd Qu.: 71.00   3rd Qu.: 2074   3rd Qu.:  541.0
##  Max.   :96.00   Max.   :100.00   Max.   :27378   Max.   :10221.0
##    room_board       books           personal         ph_d
##  Min.   :2370   Min.   : 250.0   Min.   : 250   Min.   : 10.00
##  1st Qu.:3740   1st Qu.: 450.0   1st Qu.: 800   1st Qu.: 61.00
##  Median :4400   Median : 500.0   Median :1100   Median : 74.00
##  Mean   :4567   Mean   : 540.4   Mean   :1225   Mean   : 72.02
##  3rd Qu.:5330   3rd Qu.: 600.0   3rd Qu.:1500   3rd Qu.: 85.00
##  Max.   :8124   Max.   :2000.0   Max.   :6800   Max.   :100.00
##     terminal        s_f_ratio      perc_alumni        expend
##  Min.   : 24.00   Min.   : 2.50   Min.   : 2.00   Min.   : 3186
##  1st Qu.: 70.00   1st Qu.:11.10   1st Qu.:16.00   1st Qu.: 7477
```

```
##  Median : 81.00   Median :12.80   Median :25.00   Median : 9060
##  Mean   : 79.32   Mean   :13.03   Mean   :25.99   Mean   :10475
##  3rd Qu.: 92.00   3rd Qu.:14.50   3rd Qu.:34.00   3rd Qu.:11487
##  Max.   :100.00   Max.   :39.80   Max.   :64.00   Max.   :56233
##    grad_rate
##  Min.   : 15.00
##  1st Qu.: 59.00
##  Median : 69.00
##  Mean   : 69.26
##  3rd Qu.: 81.00
##  Max.   :118.00
```

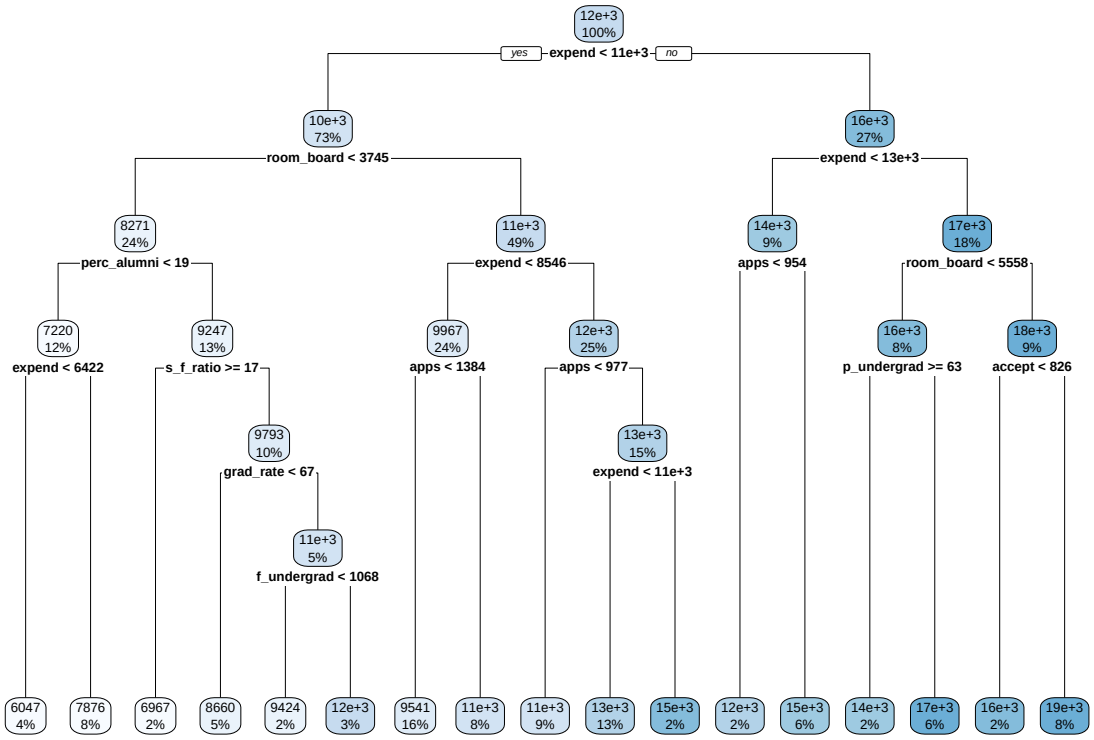
There are 453 rows and 17 columns in training data, all the variables are numeric.

(a) Build a regression tree on the training data to predict the response. Create a plot of the tree.

```
set.seed(0409)

reg_tree = rpart(formula = outstate ~ . ,
                 data = train_df,
                 control = rpart.control(cp = 0))

# cp table
reg_tree_cptable = reg_tree$cptable

# cross-validation plot
plotcp(reg_tree)
```




```
# minimum cross_validation error
min_err = which.min(reg_tree_cptable[,4])

# pruning
reg_tree_prune = prune(reg_tree,
                       cp = reg_tree_cptable[min_err,1])

#summary(reg_tree_prune)

# plot final tree
rpart.plot(reg_tree_prune)
```




```
# make prediction
reg_tree_pred = predict(reg_tree_prune, newdata = test_df)

head(reg_tree_pred)
```

```
##         1         2         3         4         5         6
## 12702.934  7875.794 11145.372 14950.897  8659.818 12702.934
```

```
RMSE(reg_tree_pred, test_df$outstate)
```

```
## [1] 2239.096
```

(b) Perform random forest on the training data. Report the variable importance and the test error.

```
set.seed(0409)

# using randomForest
rf = randomForest(outstate ~ .,
                  data = train_df,
                  mtry = 6)

rf_pred = predict(rf, newdata = test_df)

RMSE(rf_pred, test_df$outstate)
```

```
## [1] 1733.612
```

```
set.seed(0409)

# fast implementation using ranger
rf2 = ranger(outstate ~ .,
             data = train_df,
             mtry = 6)

rf2_pred = predict(rf2, data = test_df)$predictions

# test error
RMSE(rf2_pred, test_df$outstate)
```

```
## [1] 1724.522
```

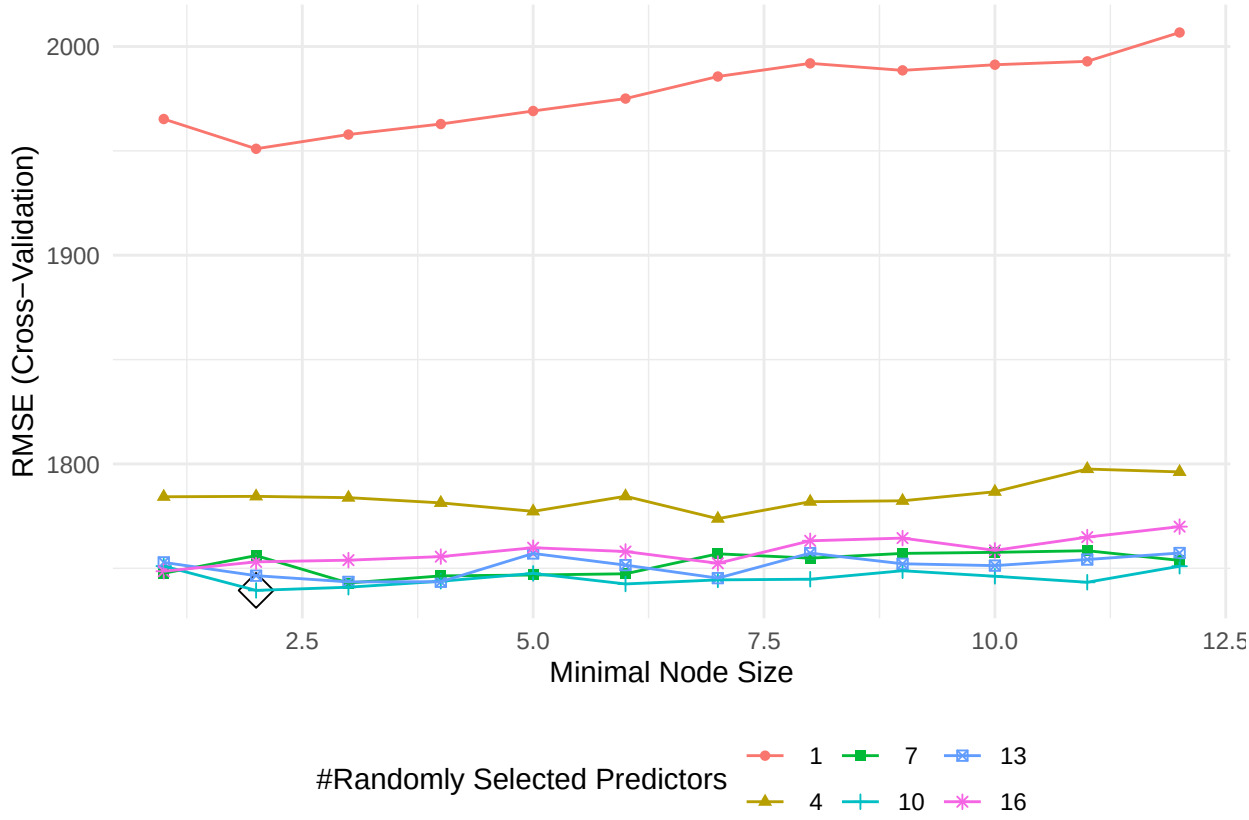
- The function `randomForest()` implements Breiman's random forest algorithm. The test error is 1733.6117039.

- `ranger()` is a fast implementation of the algorithm above, particularly suit for high dimentional data. The test error is 1724.5216241.

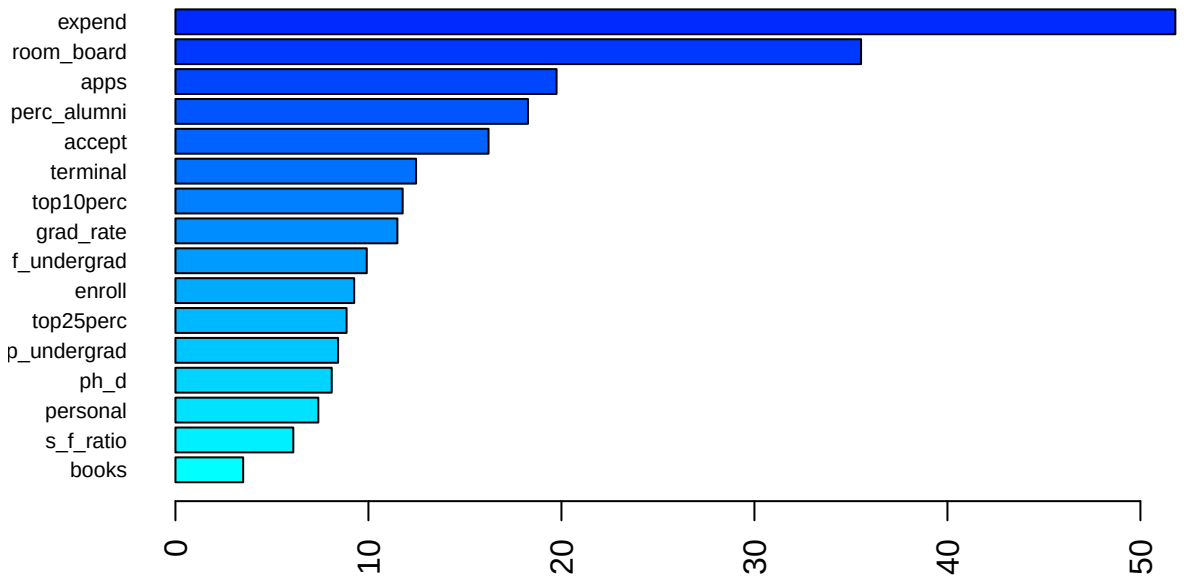
```
set.seed(0409)

# train random forest model using caret
ctrl = trainControl(method = "cv")

rf_grid = expand.grid(mtry = seq(1, 16, 3),
                      splitrule = "variance",
                      min.node.size = 1:12)

rf_grid_fit = train(outstate ~ .,
               data = train_df,
               method = "ranger",
               tuneGrid = rf_grid,
               trControl = ctrl)

rf_grid_fit$bestTune
```

```
##    mtry splitrule min.node.size
## 38   10  variance             2
```

```
ggplot(rf_grid_fit, highlight = TRUE)
```




```
set.seed(0409)

# extract variable importance using permutation
rf_per = ranger(outstate ~ . ,
                data = train_df,
                mtry = rf_grid_fit$bestTune[[1]],
                splitrule = "variance",
                min.node.size = rf_grid_fit$bestTune[[3]],
                importance = "permutation",
                scale.permutation.importance = TRUE)

# variable importance
barplot(sort(ranger::importance(rf_per), decreasing = FALSE),
        las = 2, horiz = TRUE, cex.names = 0.7,
        col = colorRampPalette(colors = c("cyan", "blue"))(19))
```

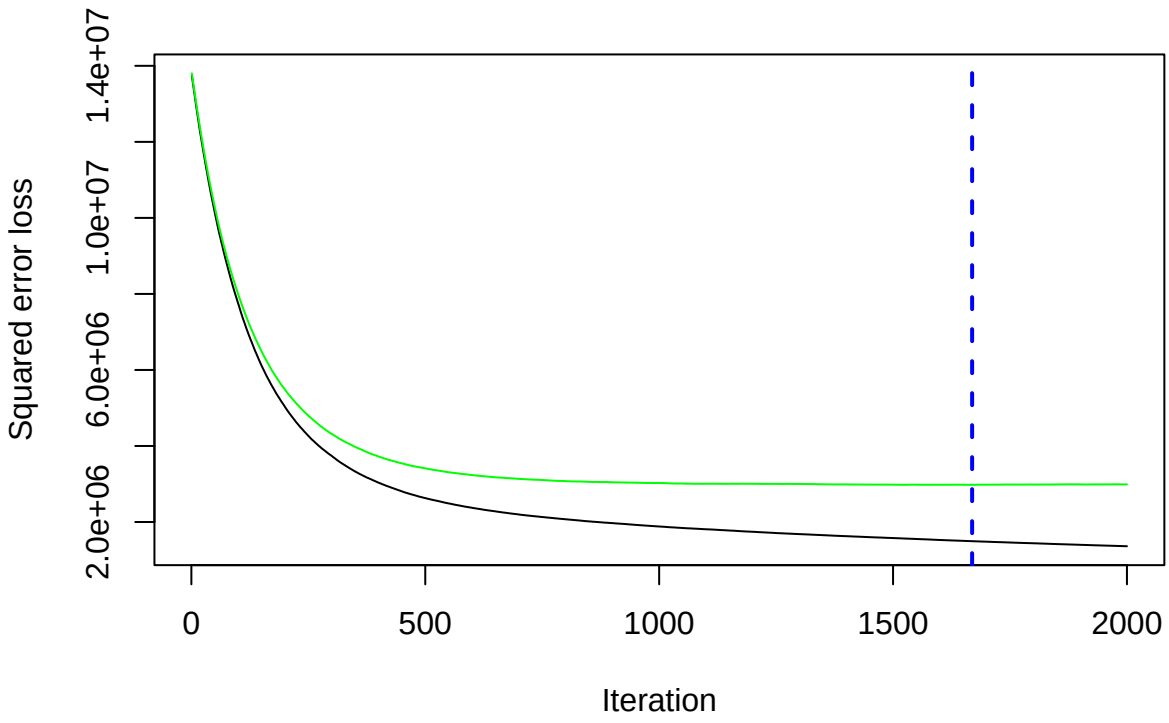



```
# make prediction
rf_grid_pred = predict(rf_grid_fit, newdata = test_df)

# test error
RMSE(rf_grid_pred, test_df$outstate)
```

```
## [1] 1785.281
```

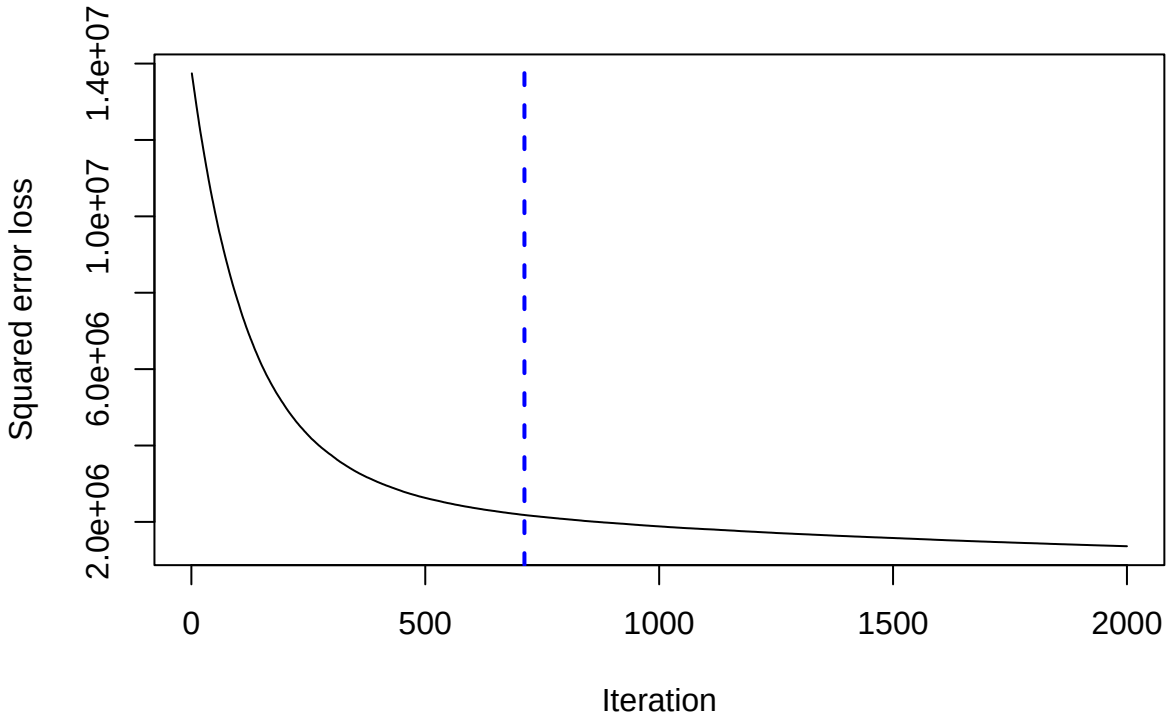
(c) Perform boosting on the training data. Report the variable importance and the test error.

```
set.seed(0409)

# fit a gradient boosting model with Gaussian loss function
boost = gbm(outstate ~ .,
            data = train_df,
            distribution = "gaussian",
            n.trees = 2000,
            interaction.depth = 3,
            shrinkage = 0.005,
            cv.folds = 10,
            n.cores = 2)

# plot loss function as a result of number of trees added to the ensemble
gbm.perf(boost, method = "cv")
```




```
## [1] 1669
```

```
best.iter = 1669

# check performance using the out-of-bag (OOB) error
# the OOB error typically underestimates the optimal number of iterations
gbm.perf(boost, method = "OOB")
```




```
## [1] 712
## attr(,"smoother")
## Call:
## loess(formula = object$oobag.improve ~ x, enp.target = min(max(4,
##     length(x)/10), 50))
##
## Number of Observations: 2000
## Equivalent Number of Parameters: 39.99
## Residual Standard Error: 1098
```

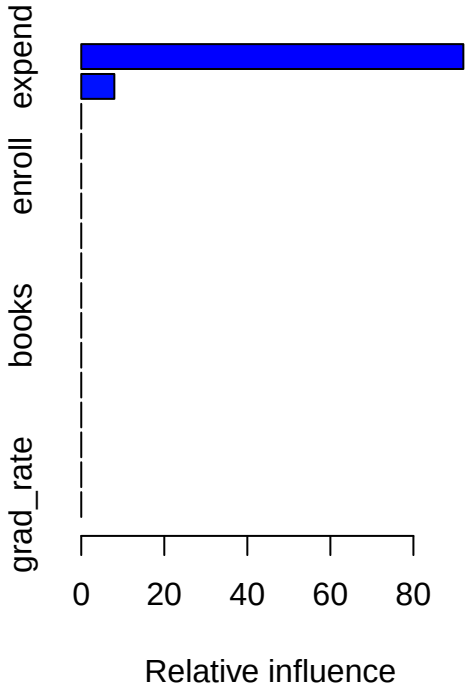
- The green curve represents the cross-validation error, and the black curve represents the training error.
- The best cross-validation iteration was 1669, as is shown by the vertical dash line.

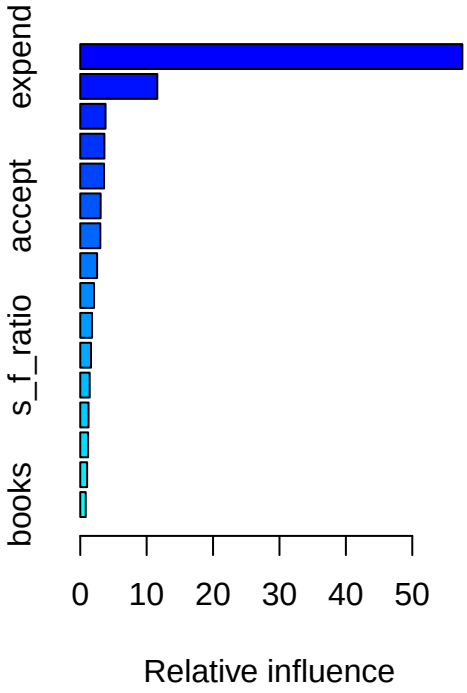
```
# plot relative influence of each variable
par(mfrow = c(1, 2))
summary(boost, n.trees = 1) # using first tree
```

```
##                    var   rel.inf
## expend          expend 92.030971
## top10perc     top10perc  7.969029
## apps              apps  0.000000
## accept          accept  0.000000
## enroll          enroll  0.000000
```

```
## top25perc     top25perc  0.000000
## f_undergrad f_undergrad  0.000000
## p_undergrad p_undergrad  0.000000
## room_board   room_board  0.000000
## books             books  0.000000
## personal       personal  0.000000
## ph_d               ph_d  0.000000
## terminal       terminal  0.000000
## s_f_ratio     s_f_ratio  0.000000
## perc_alumni perc_alumni  0.000000
## grad_rate     grad_rate  0.000000
```

```
summary(boost, n.trees = best.iter) # using estimated best number of trees
```






```
##                     var    rel.inf
## expend           expend 57.5426958
## room_board   room_board 11.6002893
## perc_alumni perc_alumni  3.8092300
## grad_rate     grad_rate  3.6396079
## apps               apps  3.5866388
## accept           accept  3.0722912
## terminal       terminal  3.0227693
## ph_d               ph_d  2.5399454
## f_undergrad f_undergrad  2.0796704
## personal       personal  1.7792895
```

```
## s_f_ratio     s_f_ratio  1.6170697
## top10perc     top10perc  1.4212408
## top25perc     top25perc  1.2473544
## p_undergrad p_undergrad  1.1843613
## enroll           enroll  1.0359470
## books             books  0.8215991
```

- The left plot shows the variable influence of the first tree, the right plot shows the variable influence of the estimated best number of trees.

- `expend`, `apps`, `ph_d`, `top10perc`, and `books` are important variables, which are consistent with the variable importance in caret.

```
# predict on the new data using the "best" number of trees
# by default, predictions will be on the link scale
boost_pred = predict(boost,
                     newdata = test_df,
                     n.trees = best.iter,
                     type = "link")

# test error
RMSE(boost_pred, test_df$outstate)
```

```
## [1] 1713.395
```

- The test error is 1713.3953364, which is smaller than the test error 1785.2810445 from the tuned model from caret.

Question 2

```
# data import and cleaning
data(OJ)

OJ_df = OJ %>%
  janitor::clean_names() %>%
  relocate("purchase", .after = "store") %>%
  mutate(purchase = as.factor(purchase)) %>%
  na.omit()

dim(OJ_df)
```

```
## [1] 1070   18
```

```
summary(OJ_df)
```

```
##  weekof_purchase    store_id       price_ch        price_mm
##  Min.   :227.0   Min.   :1.00   Min.   :1.690   Min.   :1.690
##  1st Qu.:240.0   1st Qu.:2.00   1st Qu.:1.790   1st Qu.:1.990
##  Median :257.0   Median :3.00   Median :1.860   Median :2.090
##  Mean   :254.4   Mean   :3.96   Mean   :1.867   Mean   :2.085
```

```
##  3rd Qu.:268.0   3rd Qu.:7.00   3rd Qu.:1.990   3rd Qu.:2.180
##  Max.   :278.0   Max.   :7.00   Max.   :2.090   Max.   :2.290
##     disc_ch           disc_mm         special_ch       special_mm
##  Min.   :0.00000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.00000   Median :0.0000   Median :0.0000   Median :0.0000
##  Mean   :0.05186   Mean   :0.1234   Mean   :0.1477   Mean   :0.1617
##  3rd Qu.:0.00000   3rd Qu.:0.2300   3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :0.50000   Max.   :0.8000   Max.   :1.0000   Max.   :1.0000
##     loyal_ch        sale_price_mm   sale_price_ch     price_diff      store7
##  Min.   :0.000011   Min.   :1.190   Min.   :1.390   Min.   :-0.6700   No :714
##  1st Qu.:0.325257   1st Qu.:1.690   1st Qu.:1.750   1st Qu.: 0.0000   Yes:356
##  Median :0.600000   Median :2.090   Median :1.860   Median : 0.2300
##  Mean   :0.565782   Mean   :1.962   Mean   :1.816   Mean   : 0.1465
##  3rd Qu.:0.850873   3rd Qu.:2.130   3rd Qu.:1.890   3rd Qu.: 0.3200
##  Max.   :0.999947   Max.   :2.290   Max.   :2.090   Max.   : 0.6400
##   pct_disc_mm      pct_disc_ch      list_price_diff     store       purchase
##  Min.   :0.0000   Min.   :0.00000   Min.   :0.000   Min.   :0.000   CH:653
##  1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:0.140   1st Qu.:0.000   MM:417
##  Median :0.0000   Median :0.00000   Median :0.240   Median :2.000
##  Mean   :0.0593   Mean   :0.02731   Mean   :0.218   Mean   :1.631
##  3rd Qu.:0.1127   3rd Qu.:0.00000   3rd Qu.:0.300   3rd Qu.:3.000
##  Max.   :0.4020   Max.   :0.25269   Max.   :0.440   Max.   :4.000
```

```
set.seed(0409)

# data partition
OJ_indexTrain = createDataPartition(y = OJ_df$purchase,
                                    p = 0.653,
                                    list = FALSE)

OJ_train_df = OJ_df[OJ_indexTrain, ]
OJ_test_df = OJ_df[-OJ_indexTrain, ]
```

(a) Build a classification tree using the training data, with Purchase as the response and the other variables as predictors. Use cross-validation to determine the tree size and create a plot of the final tree. Which tree size corresponds to the lowest cross-validation error? Is this the same as the tree size obtained using the 1 SE rule?

Min MSE rule:

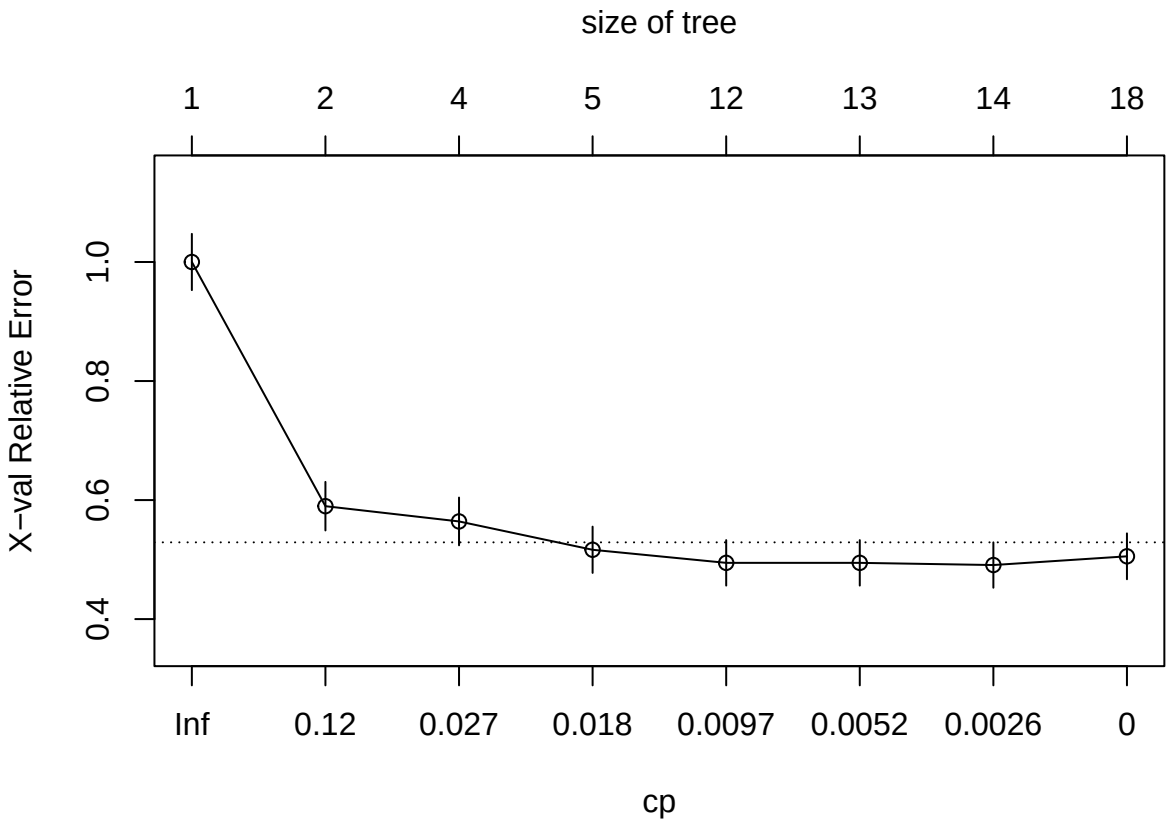
The tree with depth = 7 and 14 terminal nodes corresponds to the lowest cross-validation error.

```
set.seed(0409)

# fit classification model using rpart
class_tree = rpart(purchase ~ . ,
                   data = OJ_train_df,
                   control = rpart.control(cp = 0))

# tract cp table
OJ_cp_table = printcp(class_tree)
```

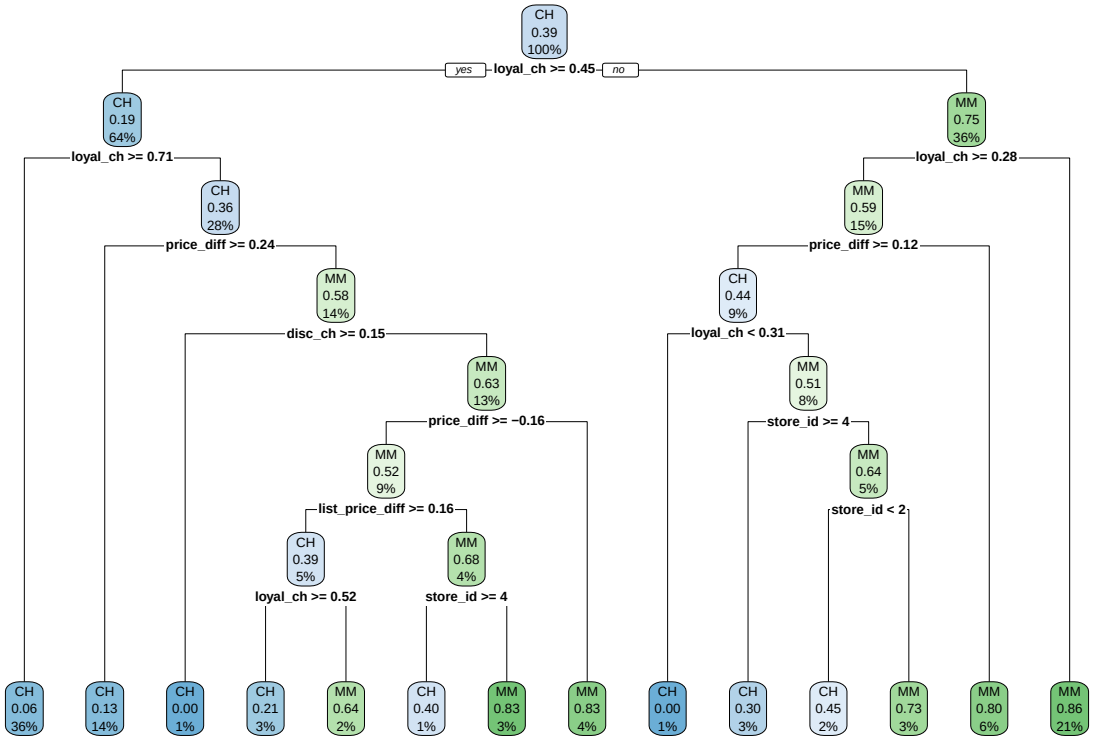
```
##
```

```
## Classification tree:
## rpart(formula = purchase ~ ., data = OJ_train_df, control = rpart.control(cp = 0))
##
## Variables actually used in tree construction:
## [1] disc_ch         list_price_diff loyal_ch        price_ch
## [5] price_diff      store_id
##
## Root node error: 273/700 = 0.39
##
## n= 700
##
##          CP nsplit rel error  xerror     xstd
## 1 0.4542125      0   1.00000 1.00000 0.047270
## 2 0.0293040      1   0.54579 0.58974 0.040785
## 3 0.0256410      3   0.48718 0.56410 0.040146
## 4 0.0128205      4   0.46154 0.51648 0.038869
## 5 0.0073260     11   0.36264 0.49451 0.038237
## 6 0.0036630     12   0.35531 0.49451 0.038237
## 7 0.0018315     13   0.35165 0.49084 0.038128
## 8 0.0000000     17   0.34432 0.50549 0.038556
```

```
# extract min MSE
OJ_min_MSE = which.min(OJ_cp_table[ , 4])

# plot cross-validation error agiainst cp
plotcp(class_tree)
```



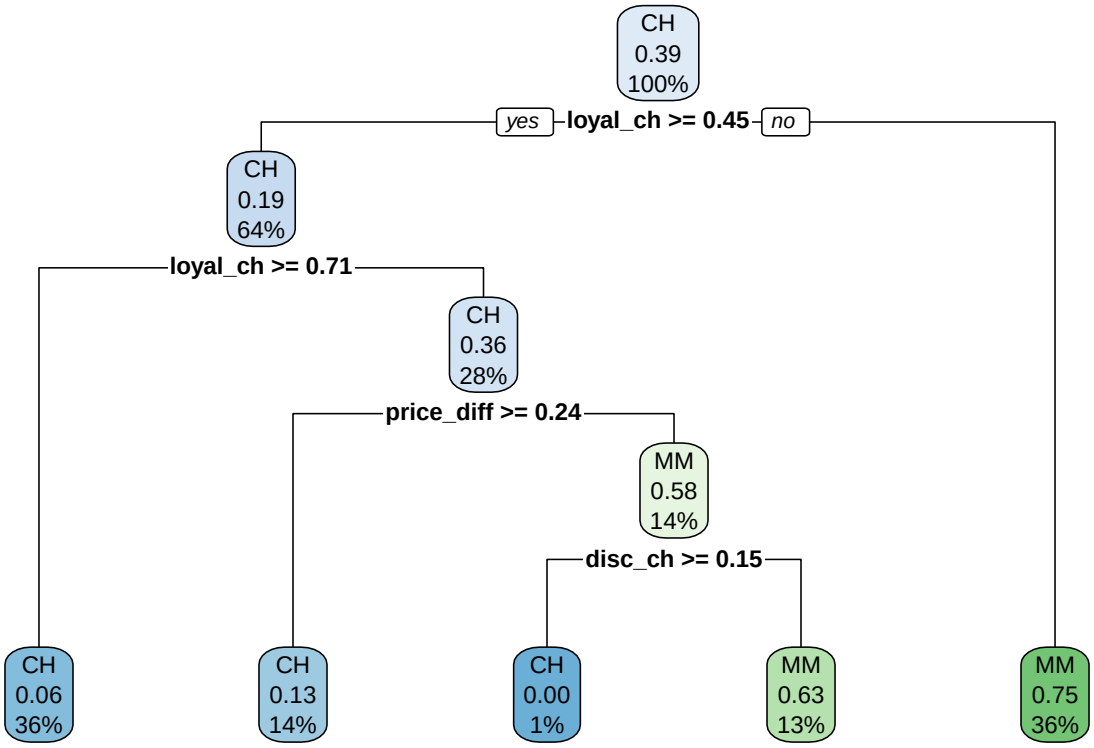
```
# obtain final tree using min MSE
cp_MSE = OJ_cp_table[OJ_min_MSE, 1]

class_tree_prune = prune(class_tree, cp = cp_MSE)

# plot final tree
rpart.plot(class_tree_prune)
```



1 SE rule:

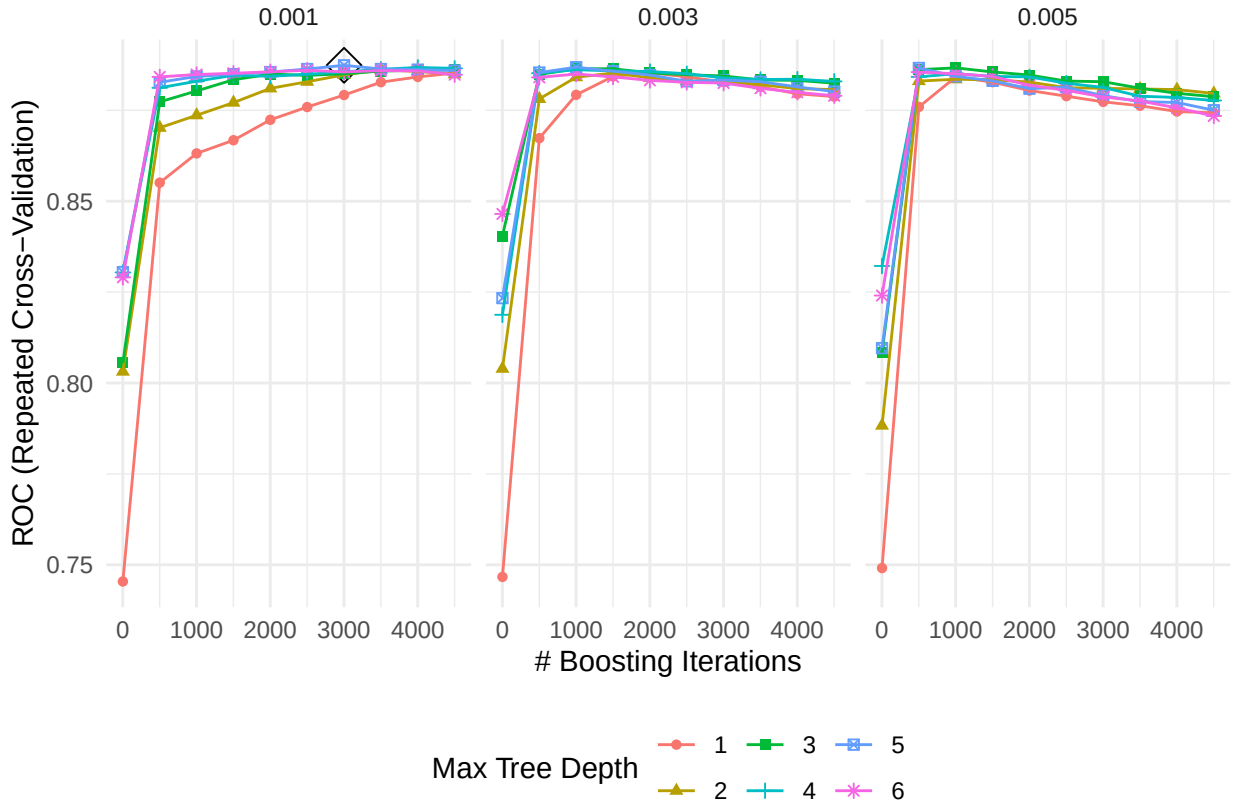
The tree with depth = 4 and 5 terminal nodes corresponds to the lowest cross-validation error, which is smaller than the tree obtained using min MSE.

```
set.seed(0409)

# obtain final tree using 1SE
cp_1SE = OJ_cp_table[OJ_cp_table[ , 4] < OJ_cp_table[OJ_min_MSE, 4] + OJ_cp_table[OJ_min_MSE, 5], 1][1]

class_tree_prune_1SE = prune(class_tree,
                             cp = cp_1SE)

# plot fianl tree
rpart.plot(class_tree_prune_1SE)
```

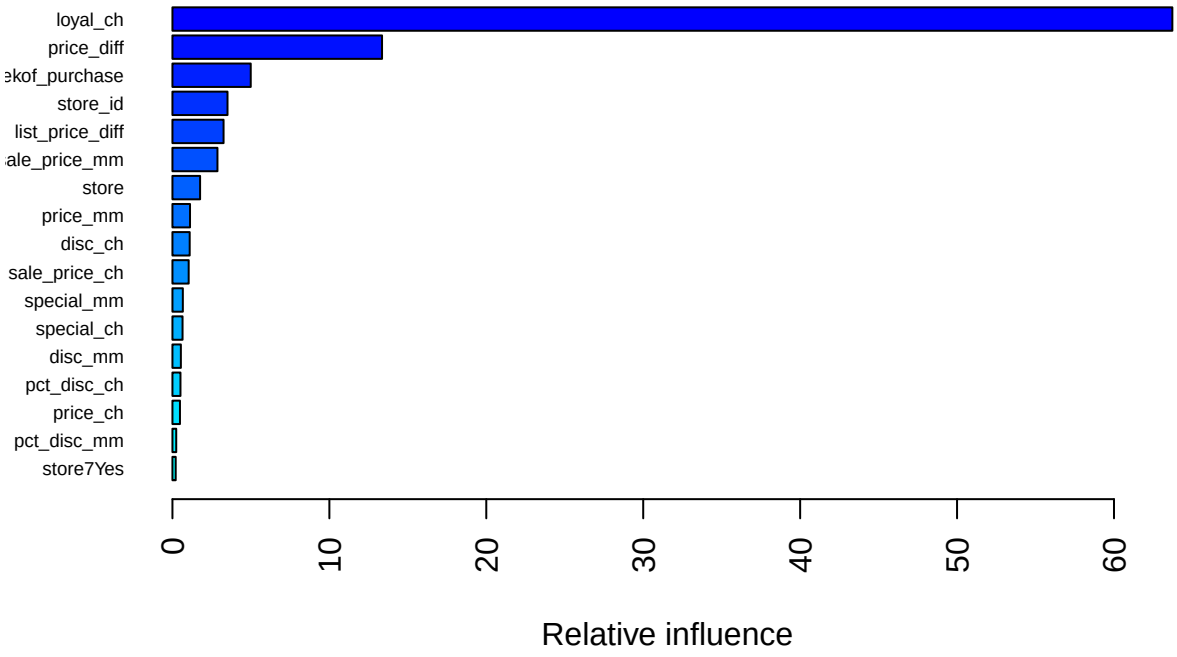


(b) Perform boosting on the training data and report the variable importance. What is the test error rate?

```
set.seed(0409)

ctrl_class = trainControl(method = "repeatedcv",
                          classProbs = TRUE,
                          summaryFunction = twoClassSummary)

# fit adaboost model for classification
OJ_boost_grid = expand.grid(n.trees = seq(1, 5000, 500),
                            interaction.depth = 1:6,
                            shrinkage = c(0.001, 0.003, 0.005),
                            n.minobsinnode = 1)

OJ_boost = train(purchase ~ .,
                 data = OJ_train_df,
                 method = "gbm",
                 tuneGrid = OJ_boost_grid,
                 trControl = ctrl_class,
                 distribution = "adaboost",
                 metric = "ROC",
                 verbose = FALSE)

ggplot(OJ_boost, highlight = TRUE)
```




```
set.seed(0409)

# variable importance plot
summary(OJ_boost$finalModel, las = 2, cBars = 19, cex.names = 0.6)
```




```
##                              var    rel.inf
## loyal_ch                loyal_ch 63.7202343
## price_diff            price_diff 13.3570869
## weekof_purchase weekof_purchase  4.9890061
## store_id                store_id  3.5098099
## list_price_diff list_price_diff  3.2583526
## sale_price_mm     sale_price_mm  2.8686560
## store                      store  1.7627601
## price_mm                price_mm  1.1190379
## disc_ch                  disc_ch  1.0989890
## sale_price_ch     sale_price_ch  1.0345569
## special_mm           special_mm  0.6622408
## special_ch           special_ch  0.6440243
## disc_mm                 disc_mm  0.5362988
## pct_disc_ch         pct_disc_ch  0.5114526
## price_ch               price_ch  0.4787856
## pct_disc_mm         pct_disc_mm  0.2419161
## store7Yes             store7Yes  0.2067920
```

```
# test error rate
OJ_boost_pred = predict(OJ_boost, newdata = OJ_test_df)

mean(OJ_boost_pred != OJ_test_df$purchase) * 100
```

```
## [1] 15.40541
```

- From the plot above, the most important variable is `loyal_ch`.
- The test error rate is 15.4054054.