DS2_HW4_REGRESSION_TREE

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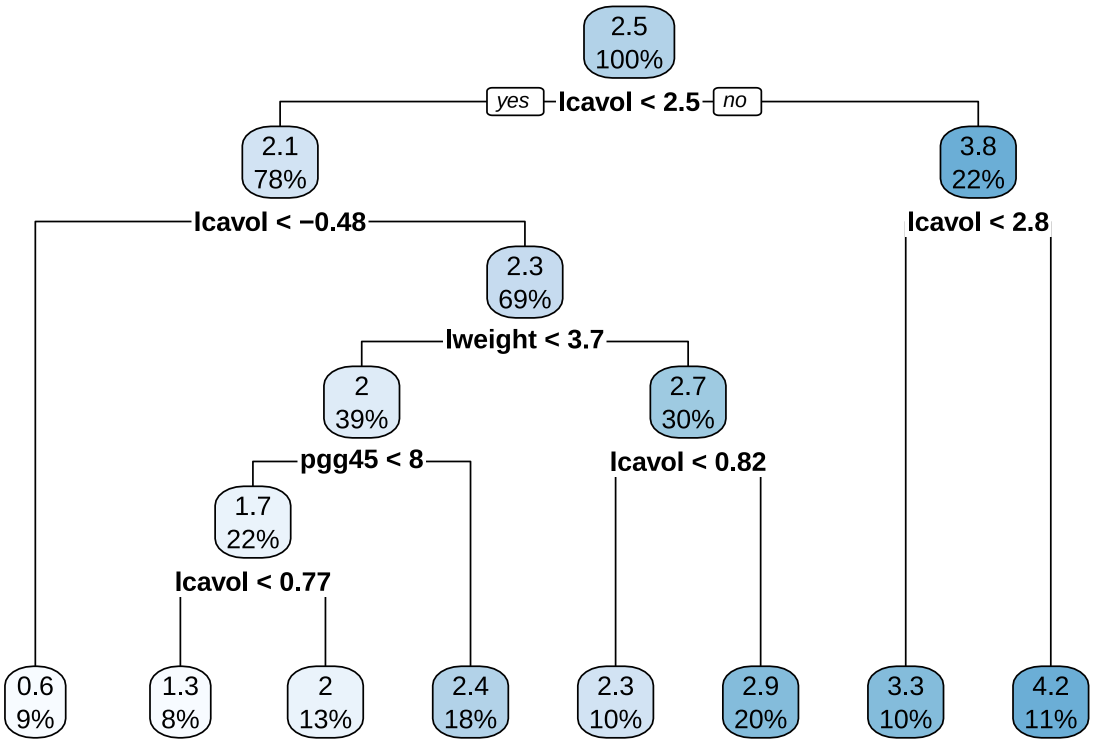
```
data(Prostate)
head(Prostate)
```

```
##       lcavol  lweight age      lbph svi       lcp gleason pgg45       lpsa
## 1 -0.5798185 2.769459  50 -1.386294   0 -1.386294       6     0 -0.4307829
## 2 -0.9942523 3.319626  58 -1.386294   0 -1.386294       6     0 -0.1625189
## 3 -0.5108256 2.691243  74 -1.386294   0 -1.386294       7    20 -0.1625189
## 4 -1.2039728 3.282789  58 -1.386294   0 -1.386294       6     0 -0.1625189
## 5  0.7514161 3.432373  62 -1.386294   0 -1.386294       6     0  0.3715636
## 6 -1.0498221 3.228826  50 -1.386294   0 -1.386294       6     0  0.7654678
```

```
set.seed(1)
rowtrain = createDataPartition(y = Prostate$lpsa,
                               p = 0.75,
                               list = FALSE)
ctr1 = trainControl(method = "cv")
```

1a) Fit a regression tree withlpsaas the response;Use cross-validation to determine the optimal tree size. Which tree size correspondsto the lowest cross-validation error? Is this the same as the tree size obtained usingthe 1 SE rule?

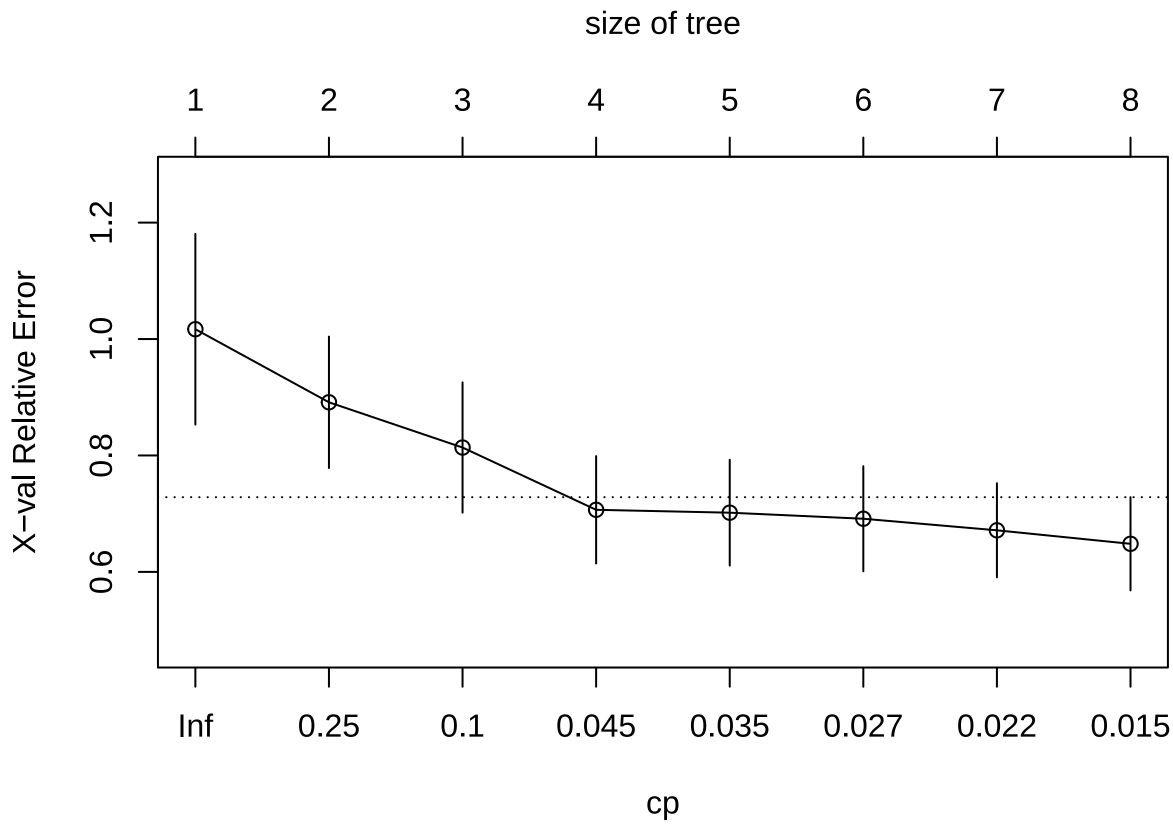
```
set.seed(1)
rpart.fit = train(lpsa~., Prostate,
                  method = "rpart",
                  tuneGrid = data.frame(cp = exp(seq(-6,-2,length=20))), trControl = ctr1)
rpart.plot(rpart.fit$finalModel)

#####
set.seed(1)
tree1 = rpart(formula = lpsa~., data = Prostate)
rpart.plot(tree1)
```



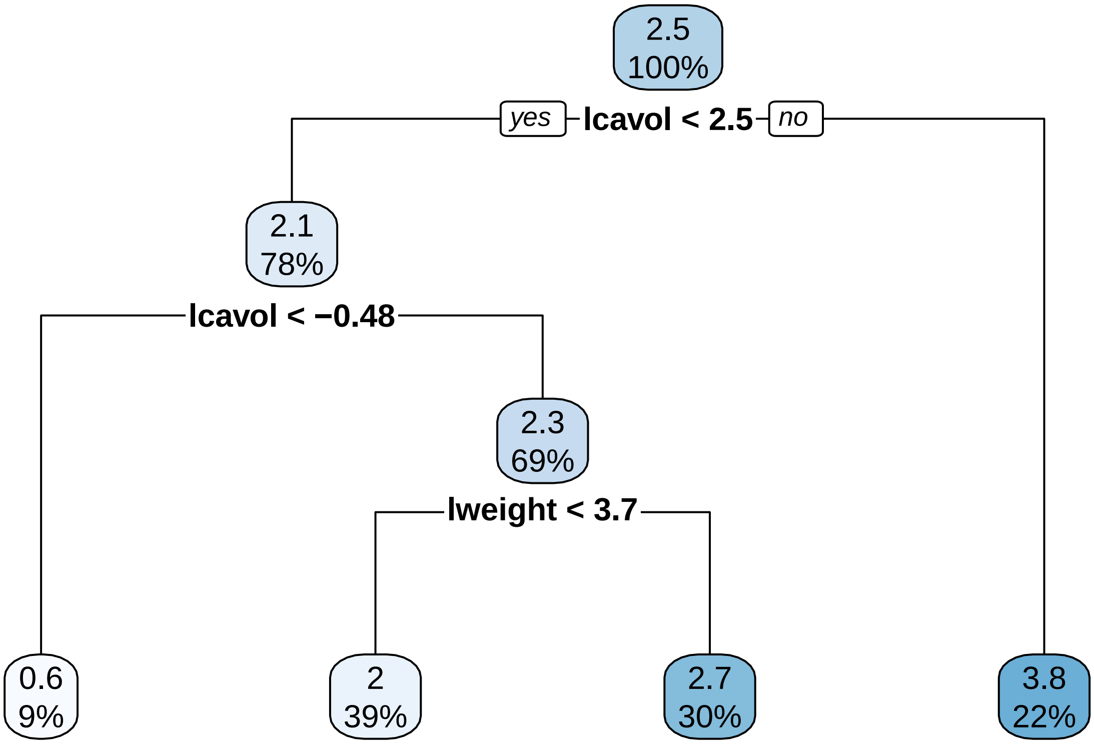

```
cp_table = printcp(tree1)### cross validation built in rpart; large cp give smaller tree
```

```
##
## Regression tree:
## rpart(formula = lpsa ~ ., data = Prostate)
##
## Variables actually used in tree construction:
## [1] lcavol  lweight pgg45
##
## Root node error: 127.92/97 = 1.3187
##
## n= 97
##
##          CP nsplit rel error  xerror     xstd
## 1 0.347108      0   1.00000 1.01687 0.163742
## 2 0.184647      1   0.65289 0.89137 0.112926
## 3 0.059316      2   0.46824 0.81363 0.111838
## 4 0.034756      3   0.40893 0.70667 0.092263
## 5 0.034609      4   0.37417 0.70171 0.090879
## 6 0.021564      5   0.33956 0.69128 0.090257
## 7 0.021470      6   0.31800 0.67139 0.080849
## 8 0.010000      7   0.29653 0.64826 0.080048
```

```
plotcp(tree1)
```



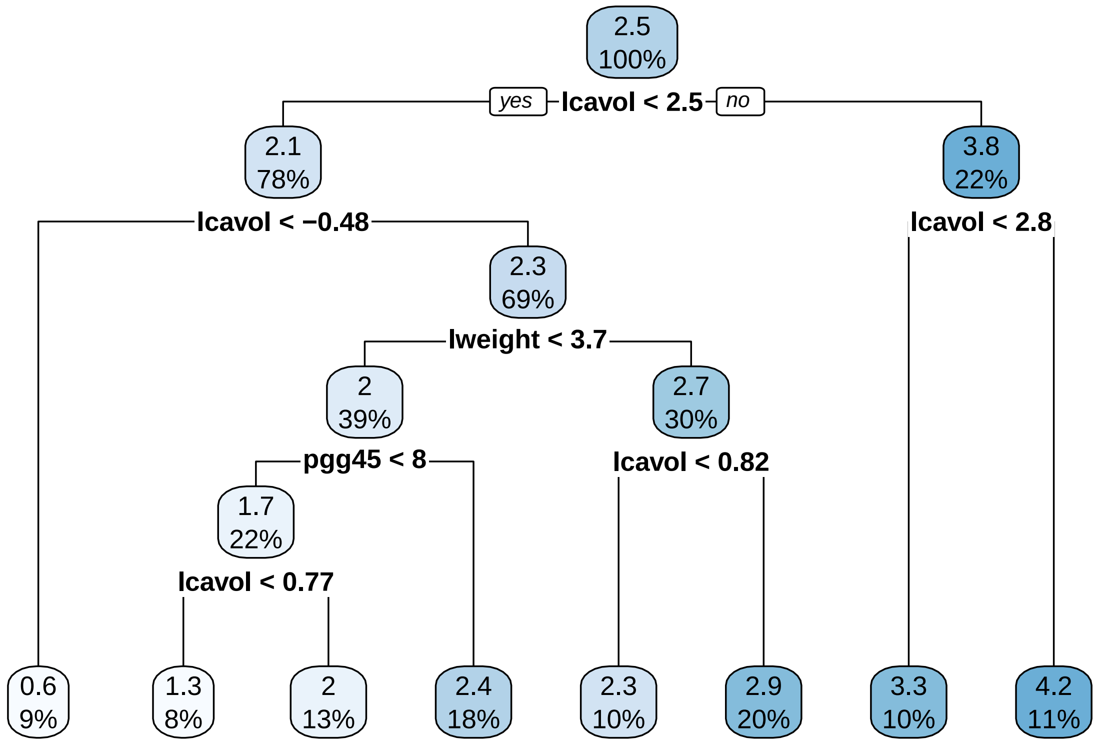

```r
### tree by minimium cross validation error
minerror = which.min(cp_table[,4])
tree2 = prune(tree1, cp = cp_table[minerror,1])
### 1SE rule- simplest model with error smaller than the line
tree3 = prune(tree1, cp = cp_table[cp_table[,4]<cp_table[minerror,4]+cp_table[minerror,5],1][1])
# split 3
rpart.plot(tree3)
```



According to the plot. the optimal tree size is 7+1 = 8 by cross validation. According to 1SE rule, the optimal split is 3. Therefore, the tree size are different.

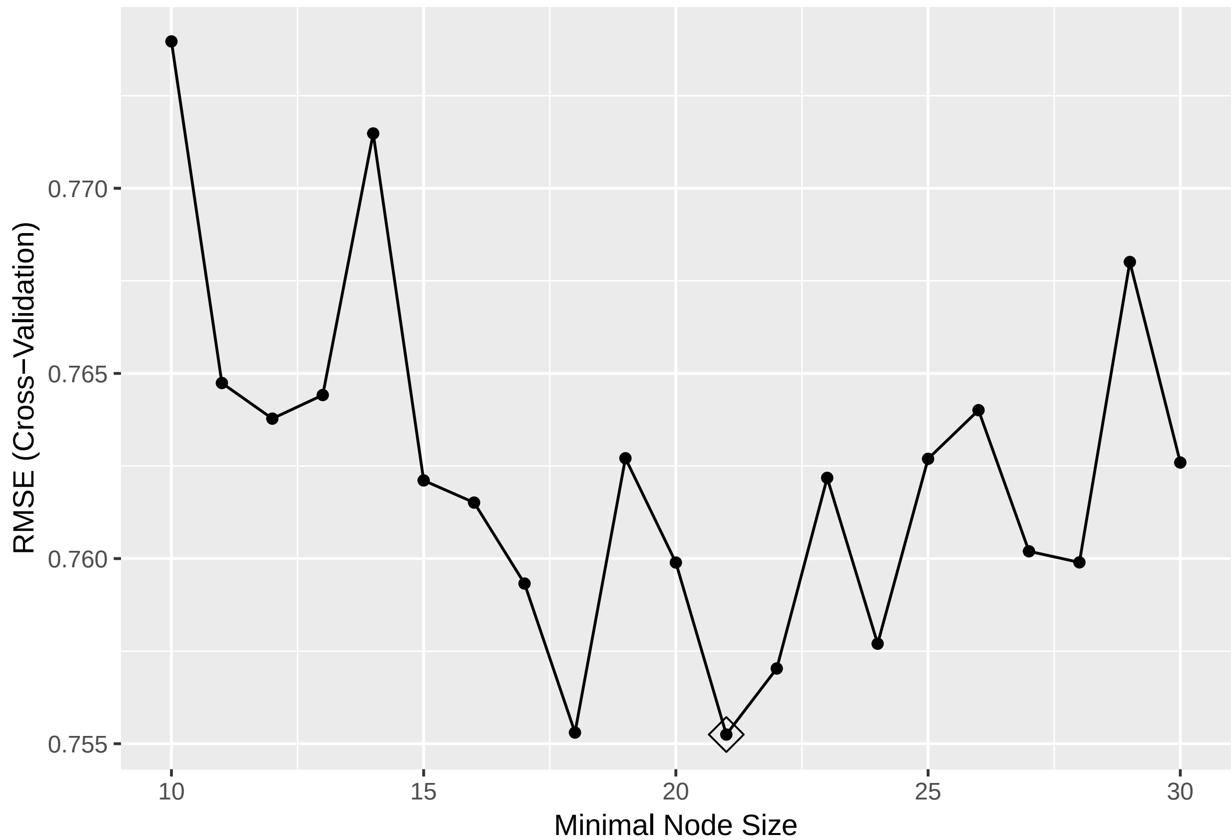
2 Create a plot of the final tree you choose. Pick one of the terminal nodes, andinterpret the information displayed.

```r
rpart.plot(tree2)
```

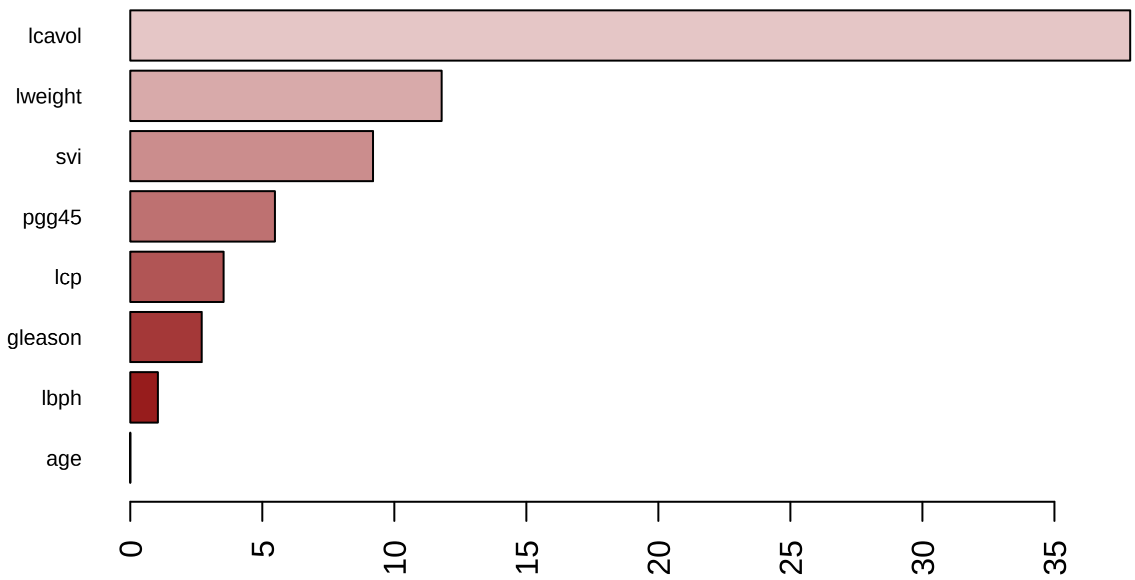


(c) Perform bagging and report the variable importance.

```
set.seed(2)
rf.grid = expand.grid(mtry = 8,
                      splitrule = "variance",
                     min.node.size = 10:30)
bagging.fit = train(lpsa~., Prostate,
                    method = "ranger",
                    tuneGrid = rf.grid,
                    trControl = ctrl)
ggplot(bagging.fit , highlight = TRUE)
```

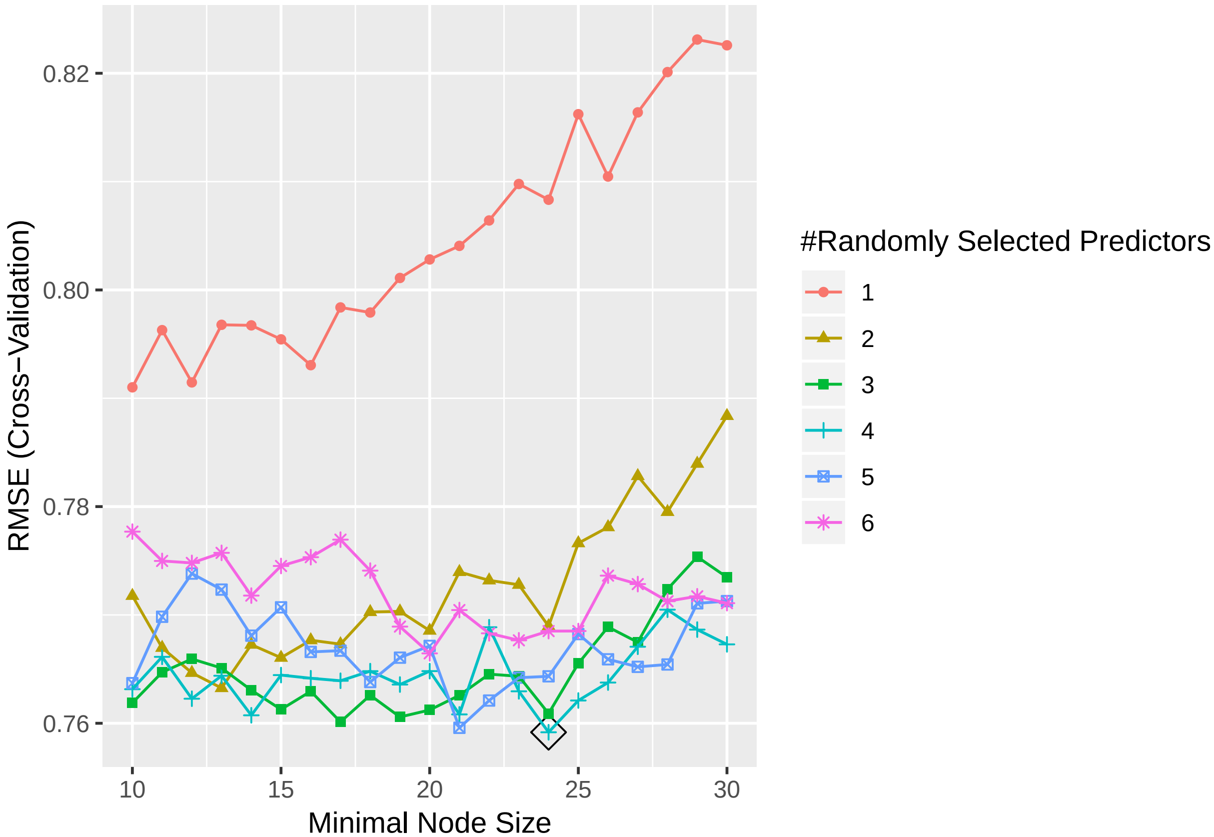



```r
bagging.imp = ranger(lpsa~., Prostate,
                     mtry = 8,
                     splitrule = "variance",
                     min.node.size = 11,
                     importance = "permutation",
                     scale.permutation.importance = TRUE)
barplot(sort(ranger::importance(bagging.imp), decreasing = FALSE),
        las = 2, horiz = TRUE, cex.names = 0.7, col = colorRampPalette(colors = c("darkred", "white", "
```

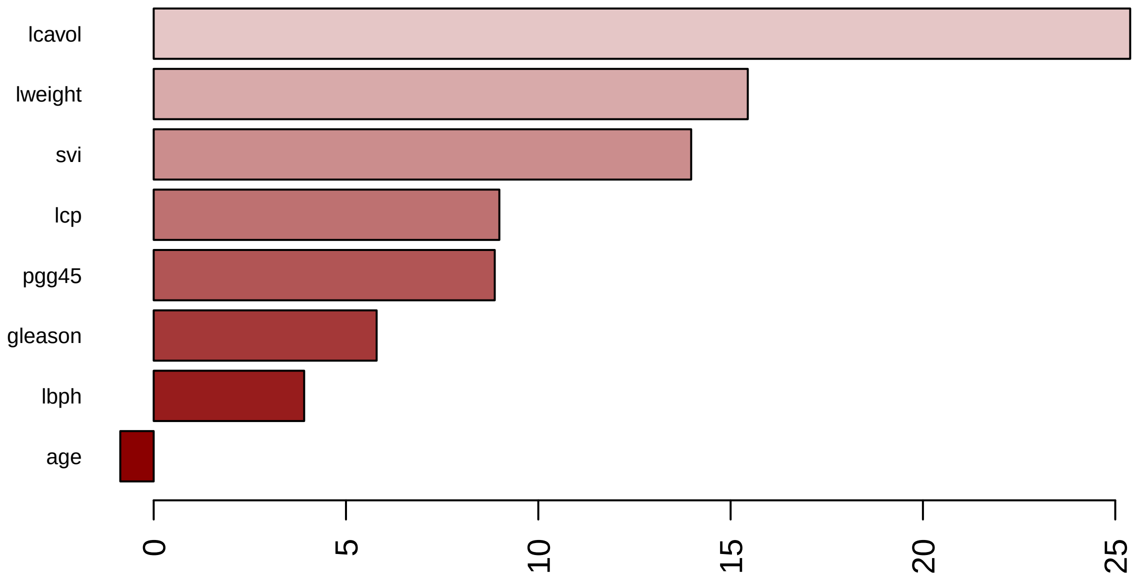


(d) Perform random forests and report the variable importance.

```r
### tuning parameter
rf.grid = expand.grid(mtry = 1:6,
                      splitrule = "variance",
                      min.node.size = 10:30)### ?
### fit model
set.seed(3)
rf.fit = train(lpsa~., Prostate,
               method = "ranger",
               tuneGrid = rf.grid,
               trControl = ctr1)
### tuning parameter choosen
ggplot(rf.fit, highlight = TRUE)
```

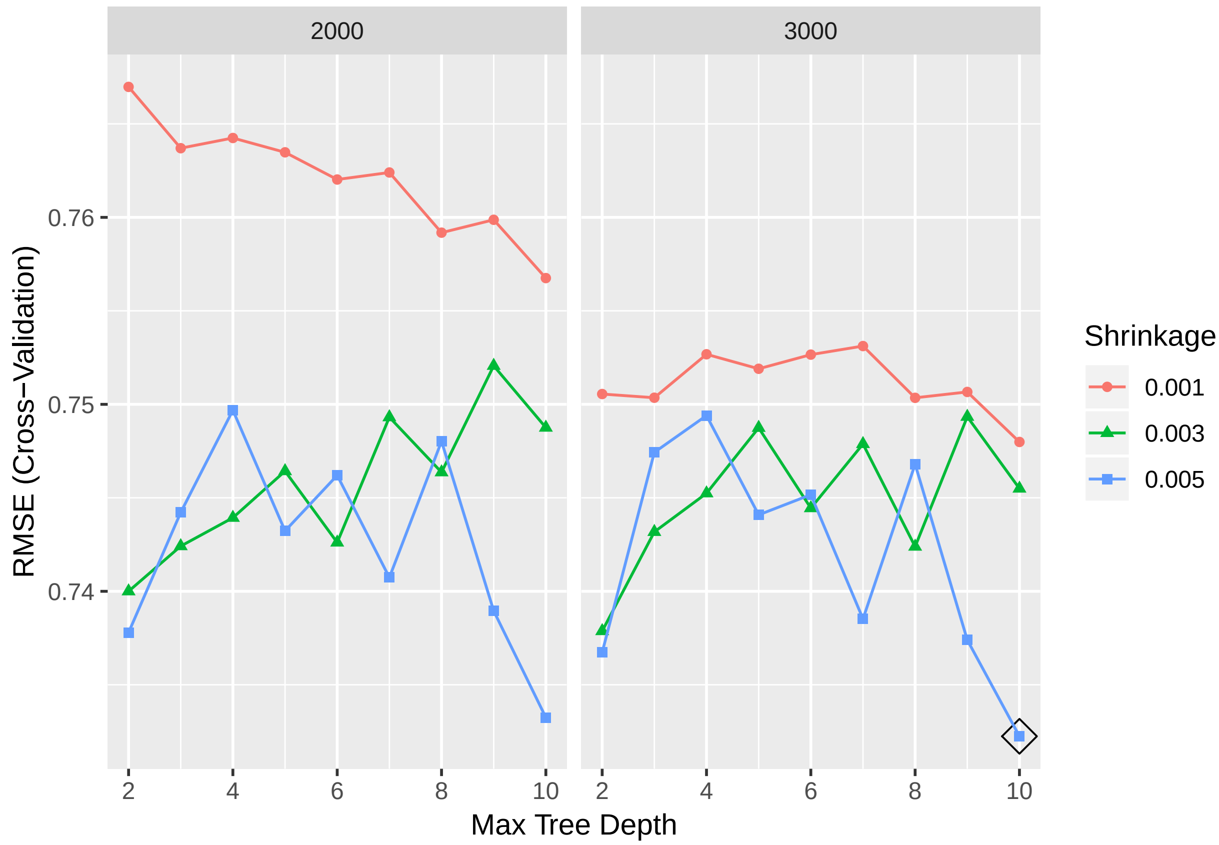



```r
### variable importance.
rf.final.imp = ranger(lpsa~., Prostate,
                      mtry = 4, splitrule = "variance",
                      min.node.size = 24,
                      importance = "permutation",
                      scale.permutation.importance = TRUE)
barplot(sort(ranger::importance(rf.final.imp), decreasing = FALSE),
        las = 2, horiz = TRUE, cex.names = 0.7, col = colorRampPalette(colors = c("darkred", "white", "
```

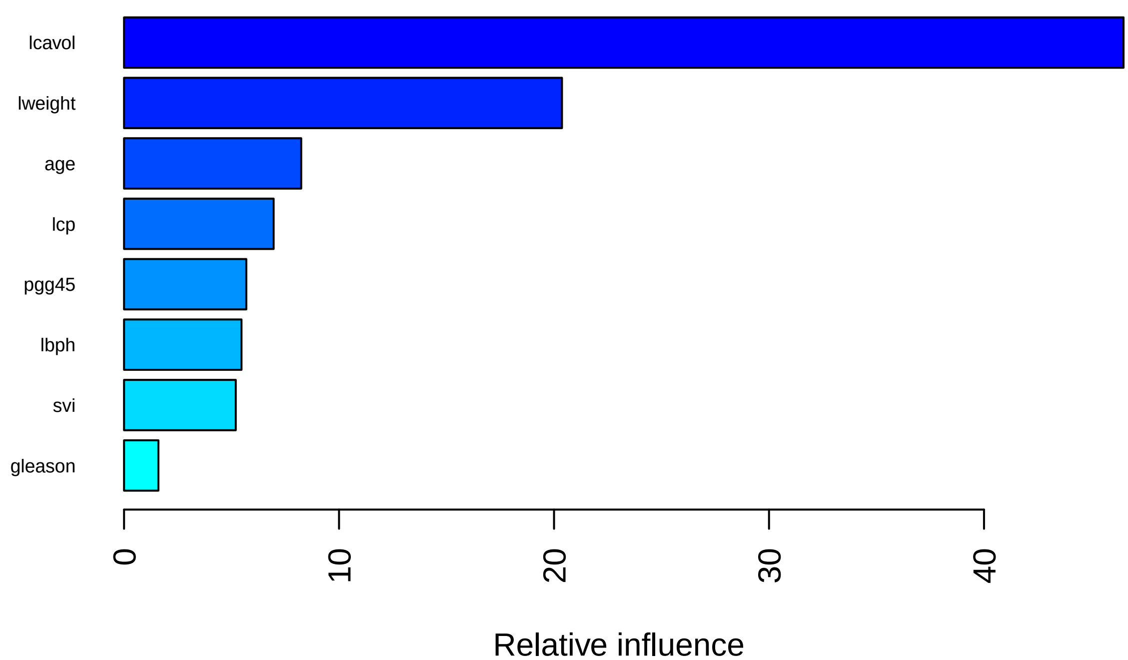


(e) Perform boosting and report the variable importance.

```
### tuning parameter
gbm.grid = expand.grid(n.trees = c(2000,3000),  ###?
                       interaction.depth = 2:10,
                       shrinkage = c(0.001, 0.003, 0.005),
                       n.minobsinnode = 1)
### fit model
gbm.fit = train(lpsa~.,Prostate,
                method = "gbm",
                tuneGrid = gbm.grid,
                trControl = ctrl1,
                verbose = FALSE)
ggplot(gbm.fit, highlight = TRUE)
```




```r
summary(gbm.fit$finalModel, las = 2, cBars = 19, cex.names = 0.6)
```




```
##             var   rel.inf
## lcavol   lcavol 46.491222
## lweight lweight 20.369375
## age         age  8.239670
```

```
## lcp         lcp  6.957807
## pgg45     pgg45  5.685430
## lbph       lbph  5.463286
## svi         svi  5.195660
## gleason gleason  1.597550
```

(f) Which of the above models will you select to predict PSA level? Explain

```r
resamp = resamples(list(rpart = rpart.fit, bagging = bagging.fit, rf = rf.fit, gbm = gbm.fit))
summary(resamp)
```

```
##
## Call:
## summary.resamples(object = resamp)
##
## Models: rpart, bagging, rf, gbm
## Number of resamples: 10
##
## MAE
##              Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## rpart   0.6029257 0.6833061 0.7132861 0.7481058 0.7878006 1.0108929    0
## bagging 0.4132455 0.5733499 0.6171783 0.6242907 0.6717655 0.8203720    0
## rf      0.3207104 0.4336260 0.6678633 0.6367605 0.7578791 1.0413658    0
## gbm     0.4073739 0.5278648 0.5467414 0.5822022 0.6558448 0.8031722    0
##
## RMSE
##              Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## rpart   0.6940977 0.7916380 0.8659767 0.8688293 0.9202064 1.1161271    0
## bagging 0.5690718 0.6507318 0.7658300 0.7552480 0.8558485 0.9142573    0
## rf      0.3852574 0.5493899 0.8002497 0.7591698 0.9212254 1.1998445    0
## gbm     0.4994624 0.6739685 0.7284938 0.7322453 0.7914498 0.9575104    0
##
## Rsquared
##               Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## rpart   0.10742511 0.4435906 0.5507225 0.4869429 0.5676906 0.6732530    0
## bagging 0.30582778 0.5199532 0.6269879 0.6297696 0.7633807 0.9030913    0
## rf      0.05163731 0.4903155 0.6836592 0.5723541 0.7337990 0.8431251    0
## gbm     0.18153923 0.4188219 0.6308190 0.5685605 0.7310841 0.7685486    0
```

Problem 2

```r
data(OJ)
head(OJ)
```

```
##   Purchase WeekofPurchase StoreID PriceCH PriceMM DiscCH DiscMM SpecialCH
## 1       CH            237       1    1.75    1.99   0.00    0.0         0
## 2       CH            239       1    1.75    1.99   0.00    0.3         0
## 3       CH            245       1    1.86    2.09   0.17    0.0         0
## 4       MM            227       1    1.69    1.69   0.00    0.0         0
## 5       CH            228       7    1.69    1.69   0.00    0.0         0
## 6       CH            230       7    1.69    1.99   0.00    0.0         0
```

```
##   SpecialMM  LoyalCH SalePriceMM SalePriceCH PriceDiff Store7 PctDiscMM
## 1         0 0.500000        1.99        1.75      0.24     No  0.000000
## 2         1 0.600000        1.69        1.75     -0.06     No  0.150754
## 3         0 0.680000        2.09        1.69      0.40     No  0.000000
## 4         0 0.400000        1.69        1.69      0.00     No  0.000000
## 5         0 0.956535        1.69        1.69      0.00    Yes  0.000000
## 6         1 0.965228        1.99        1.69      0.30    Yes  0.000000
##   PctDiscCH ListPriceDiff STORE
## 1  0.000000          0.24     1
## 2  0.000000          0.24     1
## 3  0.091398          0.23     1
## 4  0.000000          0.00     1
## 5  0.000000          0.00     0
## 6  0.000000          0.30     0
```

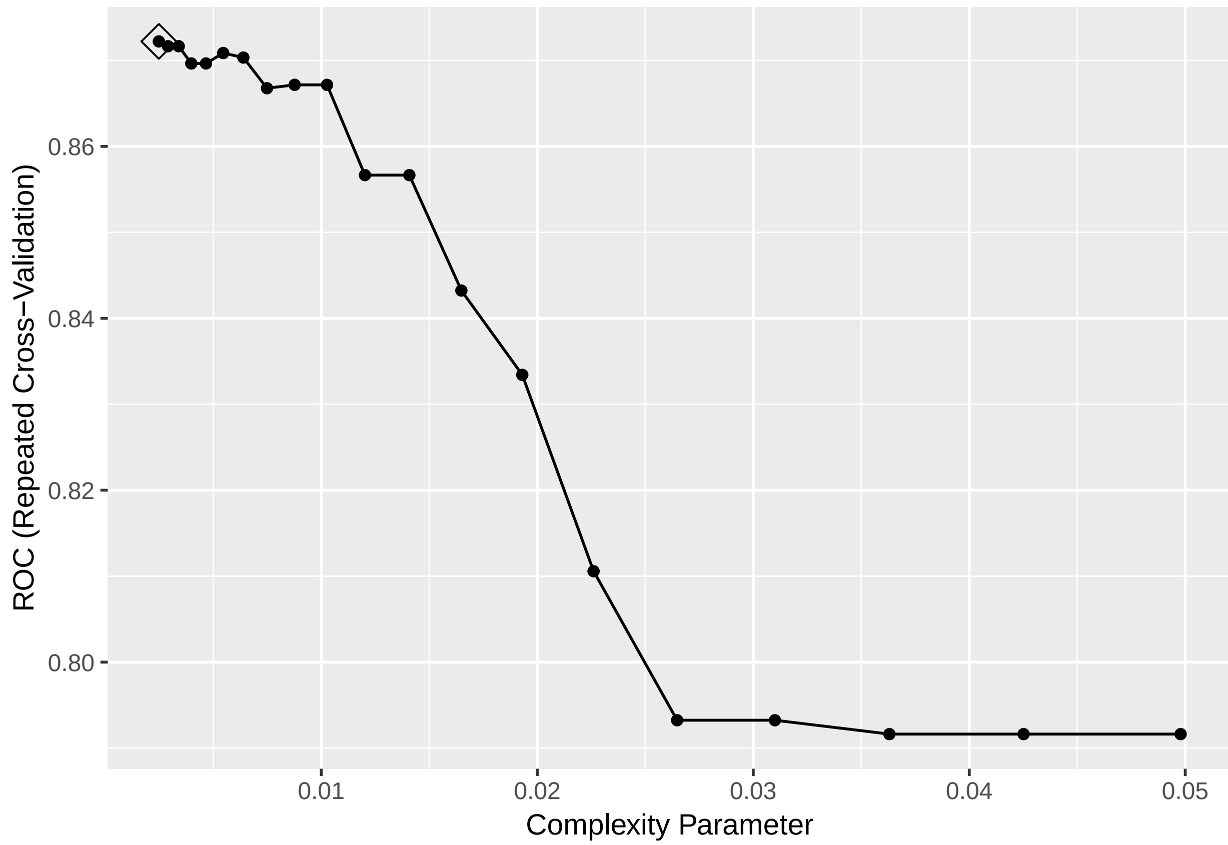
```r
levels(OJ$Purchase)
```

```
## [1] "CH" "MM"
```

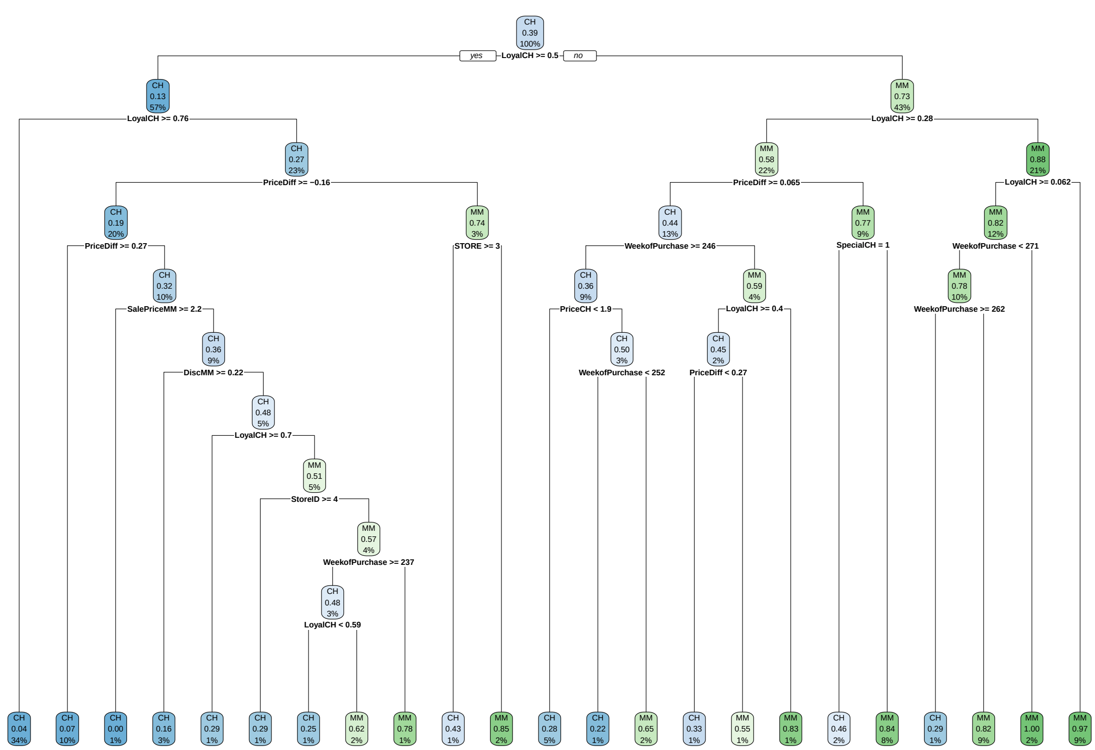
```r
rowtrain2 = createDataPartition(y = OJ$Purchase,
                                p = 800/1070,
                                list = FALSE)
```

(a) Fit a classification tree to the training set, withPurchaseas the response and theother variables as predictors. Use cross-validation to determine the tree size andcreate a plot of the final tree. Predict the response on the test data. What is the testclassification error rate?

```r
ctr1 = trainControl(method = "repeatedcv",
                    summaryFunction = twoClassSummary,
                    classProbs = TRUE)
set.seed(1)
rpart.fit2 = train(Purchase~.,OJ,
                   subset = rowtrain2,
                   method = "rpart",
                   tuneGrid = data.frame(cp = exp(seq(-6,-3,len=20))),
                   trControl = ctr1,
                   metric = "ROC")
ggplot(rpart.fit2, highlight = TRUE)
```




```r
### plot of final tree
rpart.plot(rpart.fit2$finalModel)
```



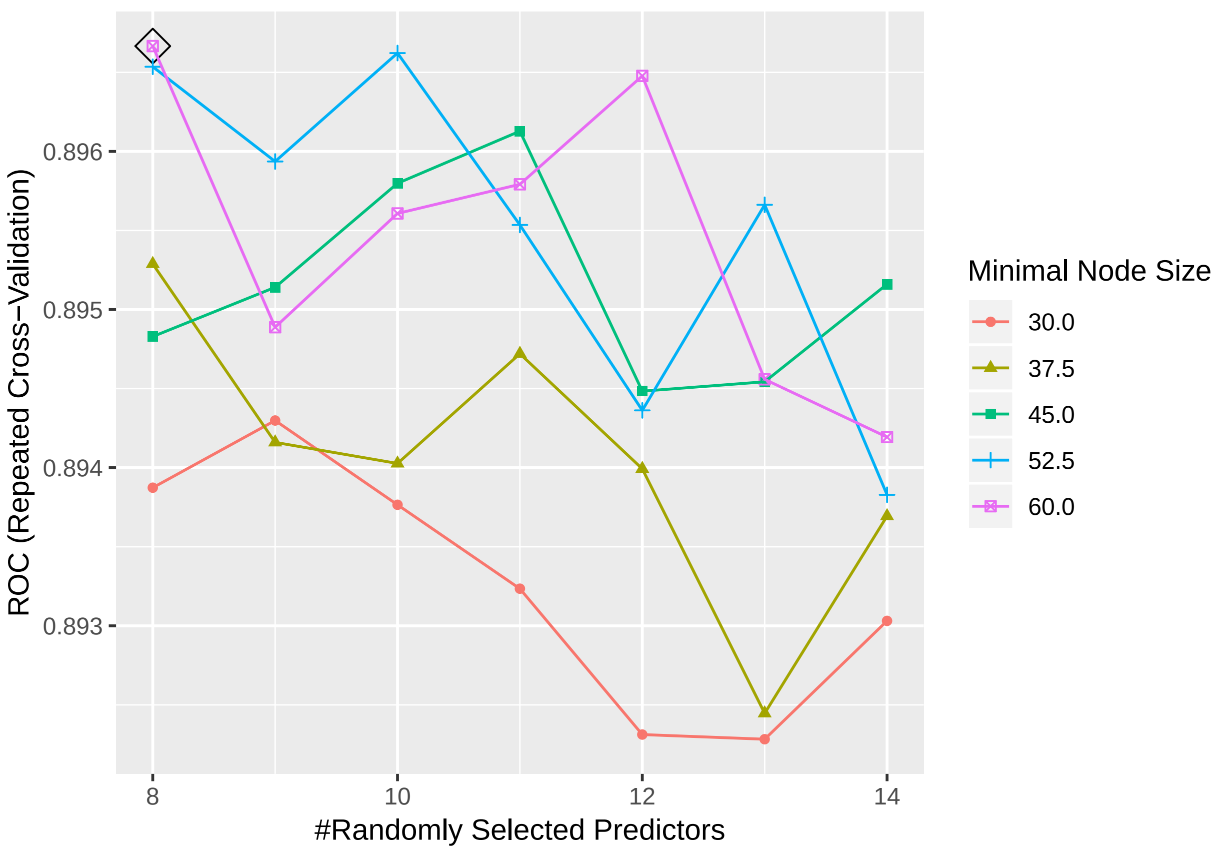
```r
### predict
pred = predict(rpart.fit2, newdata = OJ[-rowtrain2,])
### test classification error rate
mean(pred != OJ[-rowtrain2,]$Purchase)
```

```
## [1] 0.1821561
```

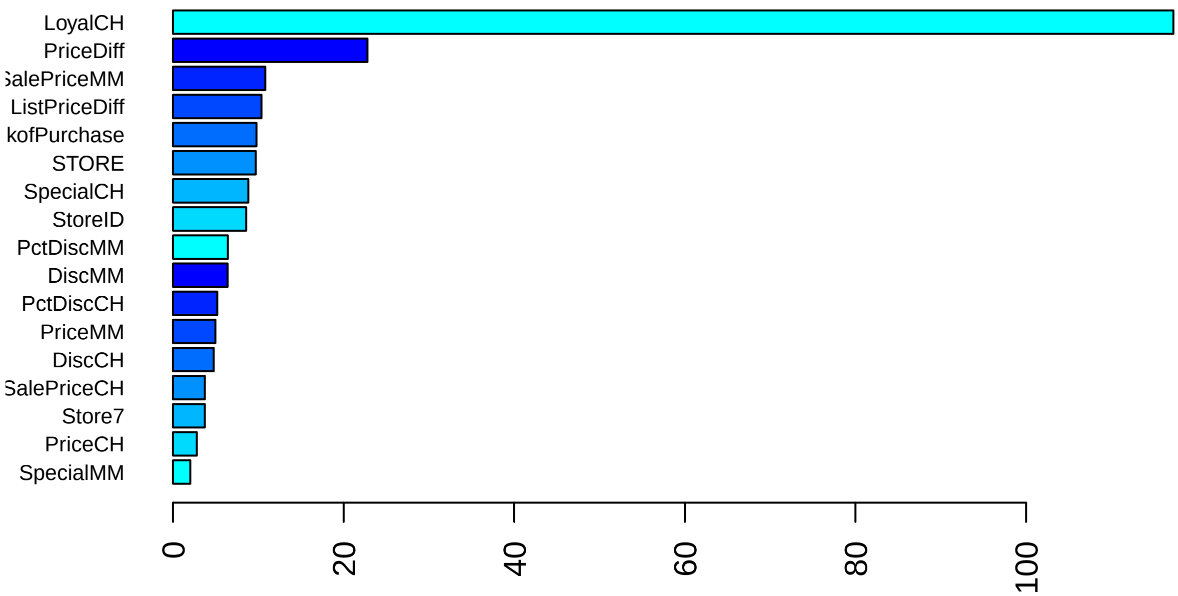
According to cross validation, the optimal tree size is 11.

(b) Perform random forests on the training set and report variable importance. What isthe test error rate?

```r
rf.grid2 = expand.grid(mtry = 8:14,
                       splitrule = "gini",
                       min.node.size = seq(30,60,length = 5))
set.seed(1)
rf.fit2 = train(Purchase~., OJ,
                subset = rowtrain2,
                method = "ranger",
                tuneGrid =  rf.grid2,
                metric = "ROC",
                trControl = ctrl)

ggplot(rf.fit2, highlight = TRUE)
```



```r
### VARIABLE IMPORTANCE
rf2.final.imp = ranger(Purchase~., OJ[rowtrain2,],
                       mtry = 9 ,
                       min.node.size = 45,
                        splitrule = "gini",
                       importance = "permutation",
                       scale.permutation.importance = TRUE)
barplot(sort(ranger::importance(rf2.final.imp), decreasing = FALSE),
        las = 2, hori = TRUE, cex.names = 0.7,
        col = colorRampPalette(colors = c("cyan","blue"))(8))
```

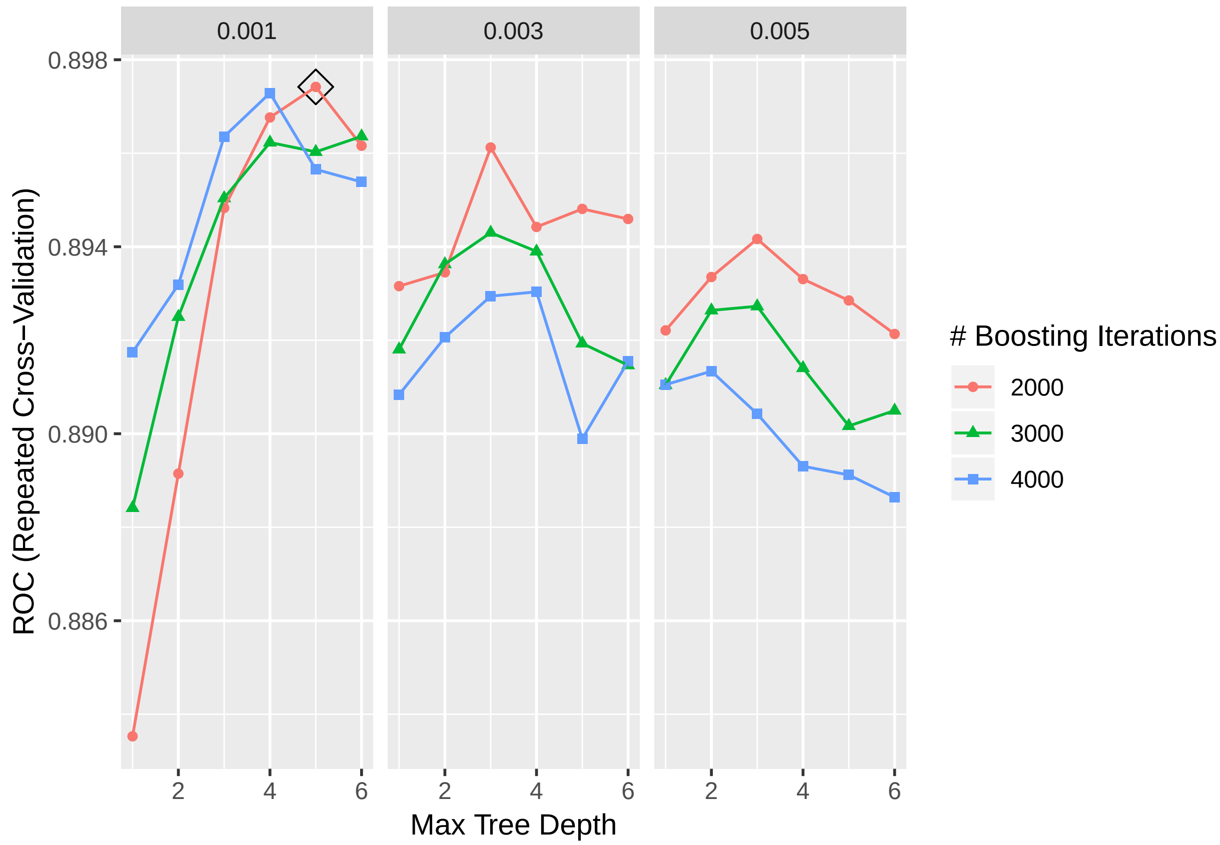



```r
### test error rate

pred_rf = predict(rf.fit2, newdata = OJ[-rowtrain2,])
mean(pred_rf!= OJ[-rowtrain2,]$Purchase)
```

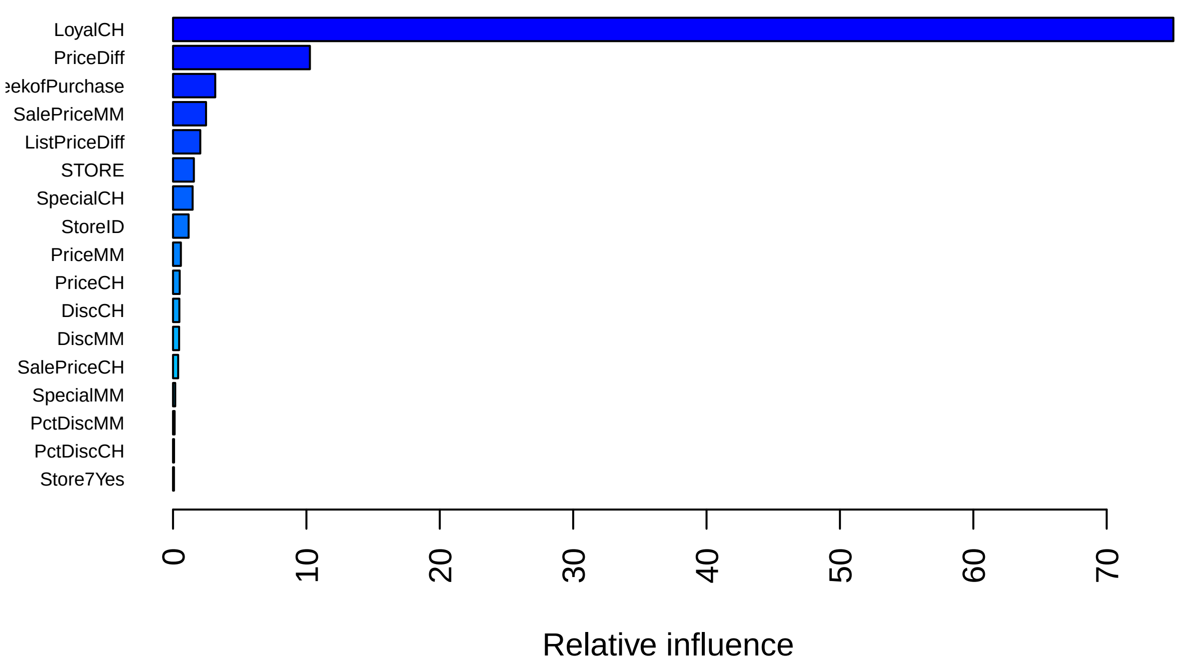
```
## [1] 0.1710037
```

(c) Perform boosting on the training set and report variable importance. What is thetest error rate?

```r
gbm2.grid = expand.grid(n.trees = c(2000, 3000, 4000),
                        interaction.depth = 1:6,
                        shrinkage = c(0.001,0.003,0.005),
                        n.minobsinnode = 1)
gbm2.fit = train(Purchase~., OJ[rowtrain2,],
                 tuneGrid = gbm2.grid,
                 trControl = ctrl,
                 method = "gbm",
                 distribution = "bernoulli",
                 metric = "ROC",
                 verbose = FALSE)
ggplot(gbm2.fit, highligh = TRUE)
```




```r
### important variable
summary(gbm2.fit$finalModel, las = 2, cBars = 19, cex.names = 0.6)
```




```
##                                var     rel.inf
## LoyalCH                    LoyalCH 75.00017781
## PriceDiff                PriceDiff 10.26319526
```

```
## WeekofPurchase WeekofPurchase  3.16546239
## SalePriceMM       SalePriceMM  2.47592453
## ListPriceDiff   ListPriceDiff  2.04450990
## STORE                   STORE  1.56394329
## SpecialCH           SpecialCH  1.46930112
## StoreID               StoreID  1.17043846
## PriceMM               PriceMM  0.59068255
## PriceCH               PriceCH  0.50269348
## DiscCH                 DiscCH  0.47539396
## DiscMM                 DiscMM  0.45799764
## SalePriceCH       SalePriceCH  0.38504642
## SpecialMM           SpecialMM  0.16546476
## PctDiscMM           PctDiscMM  0.12021707
## PctDiscCH           PctDiscCH  0.07733877
## Store7Yes           Store7Yes  0.07221257
```

```r
### test error rate
pred_gbm2 = predict(gbm2.fit, newdata = OJ[-rowtrain2,])
mean(pred_gbm2!=OJ[-rowtrain2,]$Purchase)
```

```
## [1] 0.1710037
```