Data Mining Assignment 8

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```
> load('realEstate.RData')
> binQua = ifelse(realEstate$Quality == 1, 1, 0)
> binQua = as.factor(binQua)
> all.data = data.frame(realEstate, binQua)
> totalInstance = dim(realEstate)[1]
> trainSize = 350
> testSize = totalInstance - trainSize
> set.seed(1)
> trainIndex = sample(1:522, 350)
> trainSet = all.data[trainIndex, c(-1, -10)]
> validateSet = all.data[-trainIndex, c(-1, -10)]
```

1: Tree

(b)

```
> library(tree)
> tree.realEstate = tree(binQua~., trainSet)
> summary(tree.realEstate)

Classification tree:
tree(formula = binQua ~ ., data = trainSet)
Variables actually used in tree construction:
[1] "Sales"   "SqFeet"  "Year"    "LotSize"
Number of terminal nodes:  10
Residual mean deviance:  0.09508 = 32.33 / 340
Misclassification error rate: 0.02286 = 8 / 350
```

1. Training error rate is 0.02286.
2. There are 10 terminal nodes.
3. Training error changes everytime with different samples.

(c)

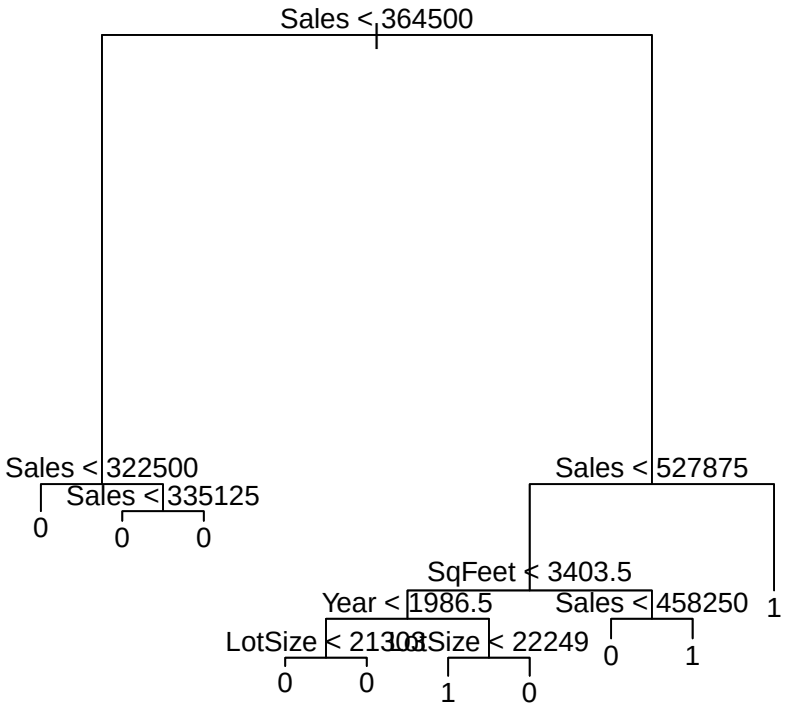
```
> tree.realEstate

node), split, n, deviance, yval, (yprob)
      * denotes terminal node

 1) root 350 294.200 0 ( 0.85143 0.14857 )
   2) Sales < 364500 271  23.620 0 ( 0.99262 0.00738 )
     4) Sales < 322500 248   0.000 0 ( 1.00000 0.00000 ) *
     5) Sales > 322500 23  13.590 0 ( 0.91304 0.08696 )
      10) Sales < 335125 10  10.010 0 ( 0.80000 0.20000 ) *
      11) Sales > 335125 13   0.000 0 ( 1.00000 0.00000 ) *
   3) Sales > 364500 79 103.900 1 ( 0.36709 0.63291 )
```

```
6) Sales < 527875 48  64.440 0 ( 0.60417 0.39583 )
 12) SqFeet < 3403.5 35  39.900 0 ( 0.74286 0.25714 )
   24) Year < 1986.5 22   8.136 0 ( 0.95455 0.04545 )
     48) LotSize < 21303 5   5.004 0 ( 0.80000 0.20000 ) *
     49) LotSize > 21303 17   0.000 0 ( 1.00000 0.00000 ) *
   25) Year > 1986.5 13  17.320 1 ( 0.38462 0.61538 )
     50) LotSize < 22249 5   0.000 1 ( 0.00000 1.00000 ) *
     51) LotSize > 22249 8  10.590 0 ( 0.62500 0.37500 ) *
 13) SqFeet > 3403.5 13  14.050 1 ( 0.23077 0.76923 )
   26) Sales < 458250 5   6.730 0 ( 0.60000 0.40000 ) *
   27) Sales > 458250 8   0.000 1 ( 0.00000 1.00000 ) *
7) Sales > 527875 31   0.000 1 ( 0.00000 1.00000 ) *
```

1. Let's look at node 2:
2. The split criterion is Sales $<$ 322500
3. There are 271 data points in this node.
4. This terminal node label is 0.
5. Deviance is 23.62.
6. 0.99262 percent of the data points are labeled 0, and 0.00738 of the data points are labeled 1.

(d)

```
> plot(tree.realEstate)
> text(tree.realEstate, pretty = 0)
```



1. This tree has depth 4.

2. The most important predictor is Sales. The first split differentiated most of the data points. And it appeared 5 times.

(e)

```
> tree.pred = predict(tree.realEstate, validateSet, type = 'class')
> table(tree.pred, validateSet$binQua)

tree.pred   0   1
        0 152   6
        1   4  10

> (6 + 4) / 172

[1] 0.05813953
```

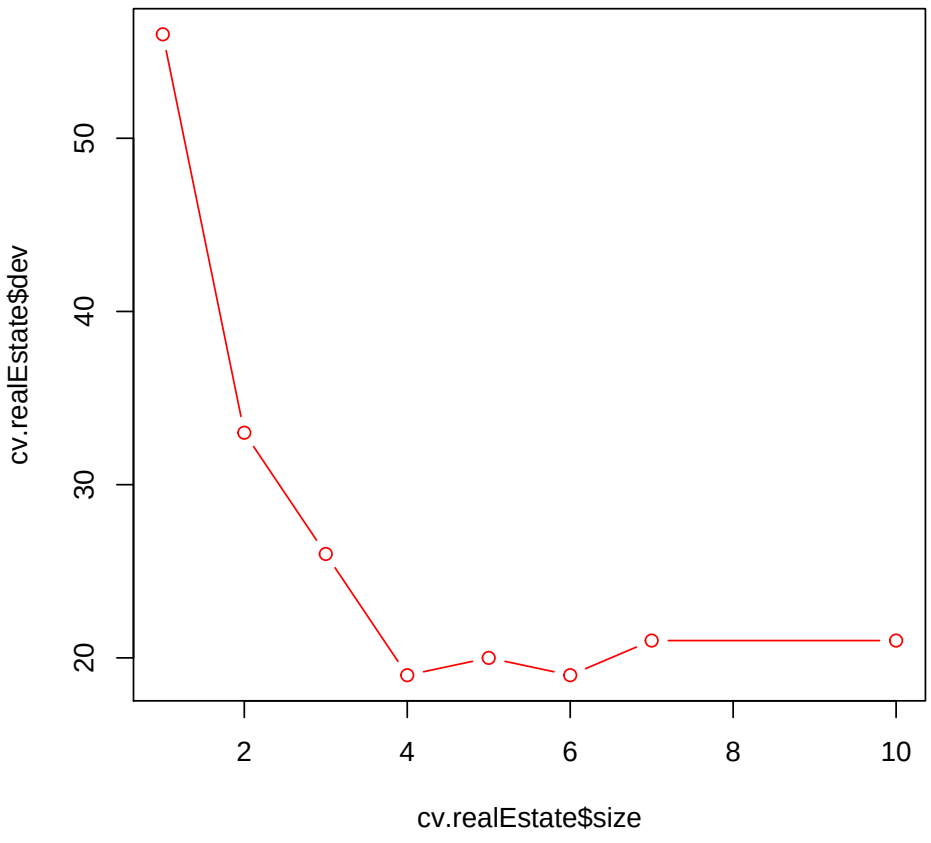
1. Test error rate is 0.05813953.

(f)

```
> cv.realEstate = cv.tree(tree.realEstate, FUN = prune.misclass)
```

(g)

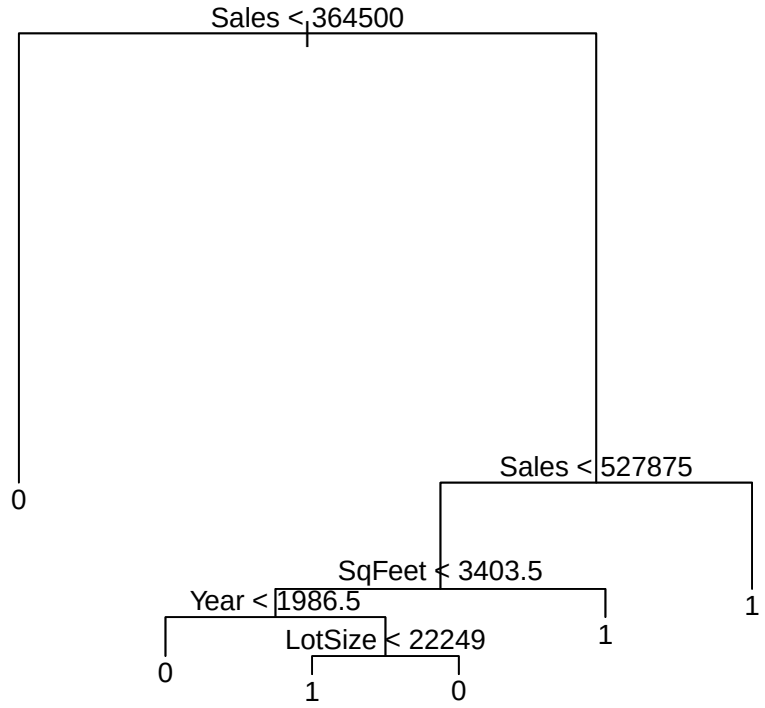
```
> plot(cv.realEstate$size, cv.realEstate$dev, type = 'b', col = 'red')
```



1. As show in the plot, tree size 4 and 6 corresponding to the lowest cross-validated error rate.

(h)

```
> prune.realEstate = prune.misclass(tree.realEstate, best = 6)
> plot(prune.realEstate)
> text(prune.realEstate, pretty = 0)
```



(j)

```
> prune.pred.train = predict(prune.realEstate, trainSet, type = 'class')
> table(prune.pred.train, trainSet$binQua)

prune.pred.train   0   1
               0 295   6
               1   3  46

> (6 + 3) / 350

[1] 0.02571429
```

1. Train error rate after prune if 0.0257, which is higher than unpruned tree.

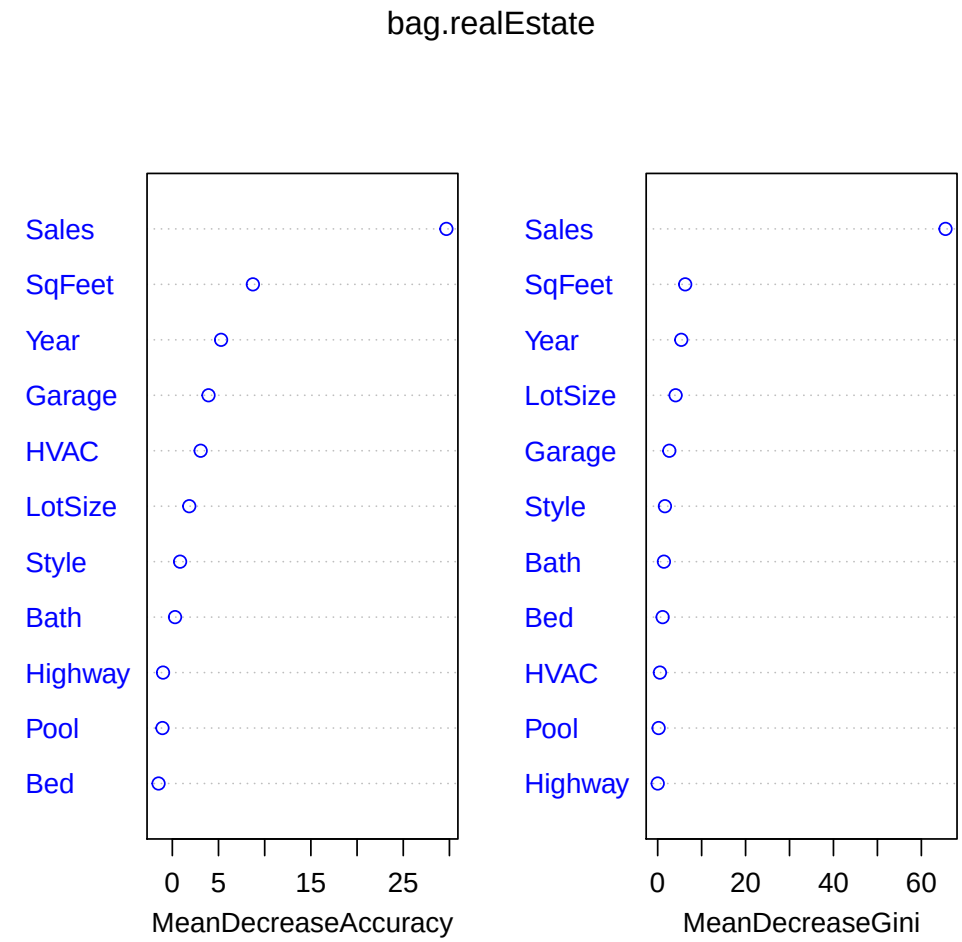
(k)

```
> prune.pred.validate = predict(prune.realEstate, validateSet, type = 'class')
> table(prune.pred.validate, validateSet$binQua)

prune.pred.validate   0   1
                  0 148   5
                  1   8  11

> (8 + 5) / 172

[1] 0.0755814
```

1. Test error rate after prune if 0.0755814, which is higher than unpruned tree.

2: Bagging

```
> library(randomForest)
> set.seed(1)
> bag.realEstate = randomForest(binQua ~ ., data = trainSet, mtry = 11, importance = T, ntree = 100)
> bag.realEstate

Call:
 randomForest(formula = binQua ~ ., data = trainSet, mtry = 11,      importance = T, ntree = 100)
               Type of random forest: classification
                     Number of trees: 100
No. of variables tried at each split: 11

        OOB estimate of  error rate: 6.29%
Confusion matrix:
    0  1 class.error
0 289  9  0.03020134
1  13 39  0.25000000

> varImpPlot(bag.realEstate, col = 'blue')
> yhat.bag = predict(bag.realEstate, newdata = validateSet)
> table(yhat.bag, validateSet$binQua)

yhat.bag   0   1
       0 150   4
       1   6  12

> (6 + 4) / 172

[1] 0.05813953
```



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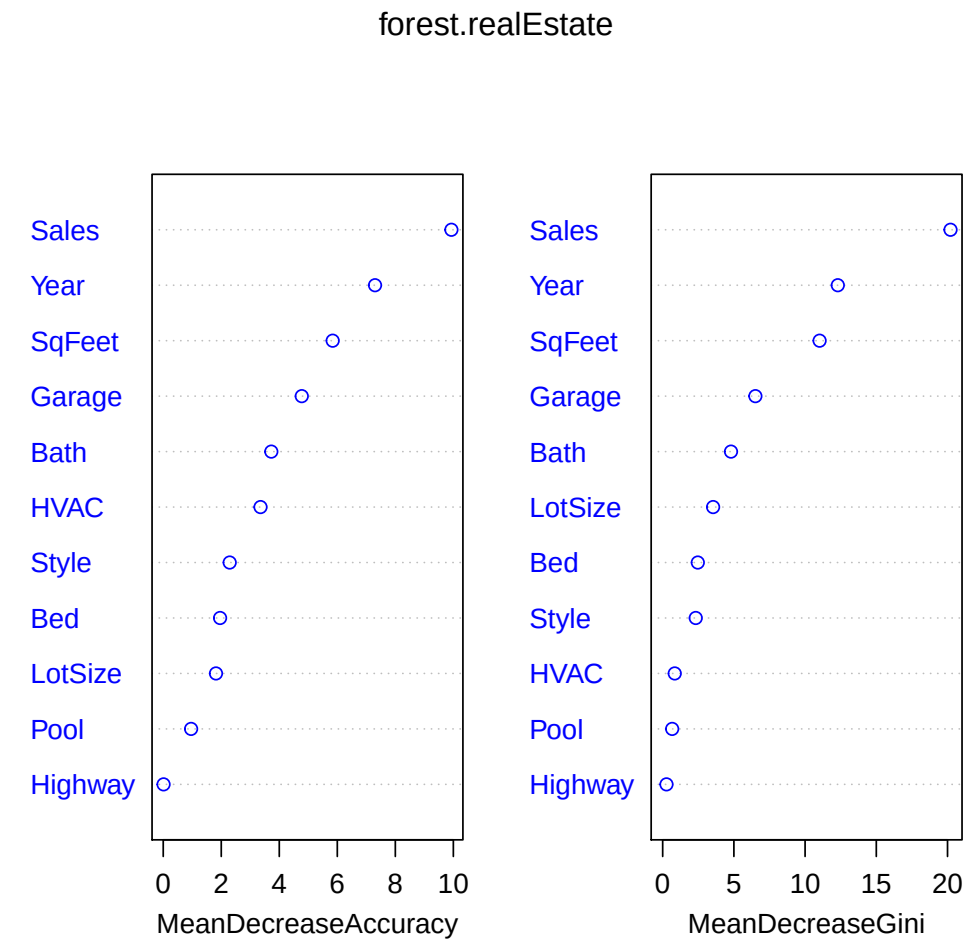
1. We can see that Sales is the most important predictor.
2. Train error rate is 0.0629, higher than the best single-tree classification.
3. Test error rate is 0.05813953, equal with the best single-tree classification.

3: RandomForest

```
> set.seed(1)
> forest.realEstate = randomForest(binQua ~ ., data = trainSet, mtry = 1, importance = T, ntree = 10
> forest.realEstate

Call:
 randomForest(formula = binQua ~ ., data = trainSet, mtry = 1,      importance = T, ntree = 100)
               Type of random forest: classification
                     Number of trees: 100
No. of variables tried at each split: 1

        OOB estimate of  error rate: 6.29%
Confusion matrix:
    0  1 class.error
0 295  3  0.01006711
1  19 33  0.36538462

> varImpPlot(forest.realEstate, col = 'blue')
> yhat.forest = predict(forest.realEstate, newdata = validateSet)
> table(yhat.forest, validateSet$binQua)

yhat.forest   0   1
          0 153   4
          1   3  12

> (4 + 3) / 172

[1] 0.04069767
```



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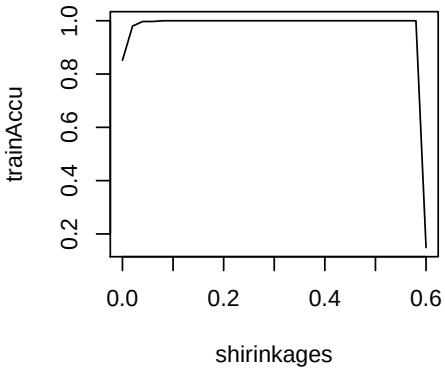
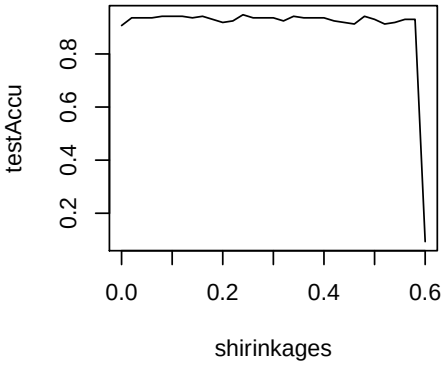
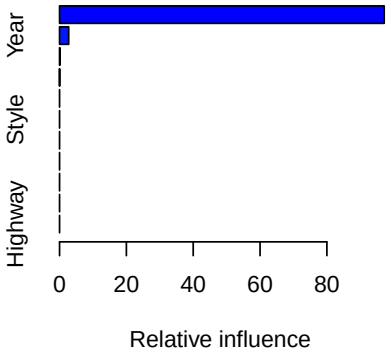
1. Train is 0.629, higher than best single tree.
2. Test error is 0.04069767, lower than best single tree.
3. Importance map changed a litter bit. Other variables have more infulence now, which is as expected.
4. Note that I set mtry = 1, which gives the best test error.

4: Boosting

```
> require(gbm)
> set.seed(1)
> shirinkages = seq(from = 0, to = 0.6, by = 0.02)
> trainAccu = rep(NA, length(shirinkages))
> testAccu = rep(NA, length(shirinkages))
> counter = 1
> trainSet$binQua = as.numeric(trainSet$binQua) - 1
> validateSet$binQua = as.numeric(validateSet$binQua) - 1
> for (s in shirinkages) {
+     boost.realEstate = gbm(binQua ~ ., data = trainSet, distribution = "bernoulli", n.trees = 1000
+     yhat.boost.vali.probs = predict(boost.realEstate, newdata = validateSet, n.trees = 1000, type =
+     yhat.boost.vali.preds = ifelse(yhat.boost.vali.probs > 0.5, 1, 0)
+     yhat.boost.train.probs = predict(boost.realEstate, newdata = trainSet, n.trees = 1000, type =
+     yhat.boost.train.preds = ifelse(yhat.boost.train.probs > 0.5, 1, 0)
+
+     trainAccu[counter] = sum(yhat.boost.train.preds == trainSet$binQua) / 350
+     testAccu[counter] = sum(yhat.boost.vali.preds == validateSet$binQua) / 172
+     counter = counter + 1
+ }
> par(mfrow = c(2, 2))
> plot(shirinkages, trainAccu, type = 'l')
> plot(shirinkages, testAccu, type = 'l')
> best = which.max(testAccu)
> 1 - testAccu[best]

[1] 0.05232558

> 1 - trainAccu[best]

[1] 0

> summary(boost.realEstate)

            var      rel.inf
Sales     Sales 9.715107e+01
Year       Year 2.728681e+00
SqFeet   SqFeet 1.142591e-01
Bed         Bed 3.947412e-03
Garage   Garage 1.459663e-03
Style     Style 5.799144e-04
Bath       Bath 0.000000e+00
HVAC       HVAC 0.000000e+00
Pool       Pool 0.000000e+00
LotSize LotSize 0.000000e+00
Highway Highway 0.000000e+00
```







1. Test error rate is 0.05232558, lower than best single tree model.
2. Train error rate is 0, lower than best single tree.
3. The most important variable is Sales and Year