Lab 08: Bagging and Random Forests

PSTAT 131/231, Spring 2021

Learning Objectives

- Bagged trees and random forest by randomForest()
- Variable importance by importance() and varImpPlot()
- Boosting by gbm()

In Lab 04 - Decision Trees, we used classification trees to analyze the Carseats data set. In this data, Sales is a continuous variable, and so we begin by recoding it as a binary variable. We use the `ifelse()` function to create a variable, called *High*, which takes on a value of *Yes* if the Sales variable exceeds the median of Sales, and takes a value *No* otherwise.

```
library(dplyr)
#install.packages("randomForest")
library(randomForest)
#install.packages("gbm")
library(gbm)
library(ISLR)
library(tree)
```

Let's have a glance at the data.

```
attach(Carseats)
Carseats = Carseats %>%
    mutate(High=as.factor(ifelse(Sales <= median(Sales), "No", "Yes"))) %>%
    select(-Sales)

# Check the structure of above data frame we just created
glimpse(Carseats)
```

```
## Registered S3 method overwritten by 'cli':
##   method     from
##   print.tree tree
```

```
## Rows: 400
## Columns: 11
## $ CompPrice   <dbl> 138, 111, 113, 117, 141, 124, 115, 136, 132, 132, 121, ...
## $ Income      <dbl> 73, 48, 35, 100, 64, 113, 105, 81, 110, 113, 78, 94, 35...
## $ Advertising <dbl> 11, 16, 10, 4, 3, 13, 0, 15, 0, 0, 9, 4, 2, 11, 11, 5, ...
## $ Population  <dbl> 276, 260, 269, 466, 340, 501, 45, 425, 108, 131, 150, 5...
## $ Price       <dbl> 120, 83, 80, 97, 128, 72, 108, 120, 124, 124, 100, 94, ...
## $ ShelveLoc   <fct> Bad, Good, Medium, Medium, Bad, Bad, Medium, Good, Medi...
## $ Age         <dbl> 42, 65, 59, 55, 38, 78, 71, 67, 76, 76, 26, 50, 62, 53,...
## $ Education   <dbl> 17, 10, 12, 14, 13, 16, 15, 10, 10, 17, 10, 13, 18, 18,...
## $ Urban       <fct> Yes, Yes, Yes, Yes, Yes, No, Yes, Yes, No, No, No, Yes,...
## $ US          <fct> Yes, Yes, Yes, Yes, No, Yes, No, Yes, No, Yes, Yes, Yes...
## $ High        <fct> Yes, Yes, Yes, No, No, Yes, No, Yes, No, No, Yes, Yes, ...
```

1. Review of a single tree model

As usual, we split the data into training and test set.

```
# Sample 250 observations as training data
set.seed(3)
train = sample(1:nrow(Carseats), 250)
train.carseats = Carseats[train,]

# The rest as test data
test.carseats = Carseats[-train,]
```

As a review, we use 10-fold CV to select the best tree size and prune the original large tree to this target number. We calculate the test error rate for future comparison.

```
tree.carseats = tree(High~., data = Carseats, subset = train)
summary(tree.carseats)
```

```
##
## Classification tree:
## tree(formula = High ~ ., data = Carseats, subset = train)
## Variables actually used in tree construction:
## [1] "ShelveLoc"   "Price"       "CompPrice"   "Advertising" "Income"
## [6] "Population"  "Age"
## Number of terminal nodes:  23
## Residual mean deviance:  0.4573 = 103.8 / 227
## Misclassification error rate: 0.092 = 23 / 250
```

```
# 10-fold CV for selecting best tree size
tree.cv = cv.tree(tree.carseats, FUN=prune.misclass, K=10)

# Best size
best.cv = min(tree.cv$size[tree.cv$dev==min(tree.cv$dev)])
best.cv
```

```
## [1] 5
```

```
# Prune the tree to the optimal size
tree.prune = prune.misclass(tree.carseats, best=best.cv)

# Test error for tree.prune
tree.err = table(treePred=predict(tree.prune, newdata=test.carseats, type="class"),
                 truth=test.carseats$High)
test.tree.err = 1 - sum(diag(tree.err))/sum(tree.err)
test.tree.err
```

```
## [1] 0.26
```

2. Bagging

The test error rate for the best-size pruned tree is 0.26. In the following, we apply bagging and random forests to the Carseats data, using the randomForest package in R and compare the same metric for bagged tree and random forest. Note that the exact results obtained in this section may depend on the version of R and the version of the randomForest package installed on your computer. Recall that bagging is simply a special case of a random forest with m = p. Therefore, the randomForest() function can be used to perform both random forests and bagging. We perform bagging as follows:

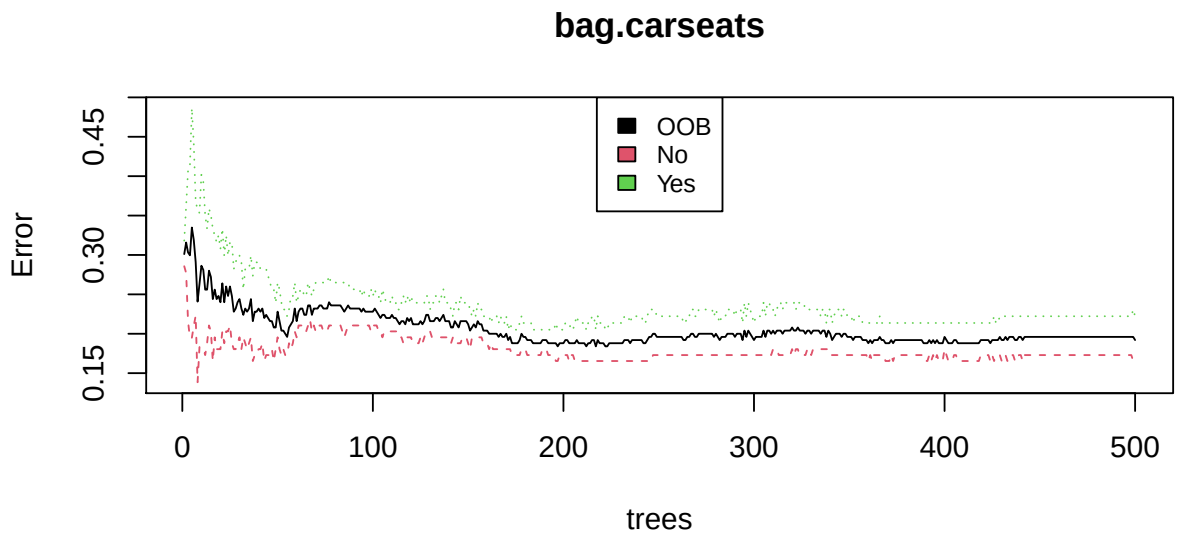
```
bag.carseats = randomForest(High ~ ., data=train.carseats, mtry=10, importance=TRUE)
bag.carseats
```

```
##
## Call:
##  randomForest(formula = High ~ ., data = train.carseats, mtry = 10,      importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 10
##
##         OOB estimate of  error rate: 19.2%
## Confusion matrix:
##      No Yes class.error
## No  111  22   0.1654135
## Yes  26  91   0.2222222
```

```
# equivalently, you can do
# bag.carseats = randomForest(High ~ ., data=Carseats, subset=train, mtry=4, importance=TRUE)
```

The argument `mtry=10` indicates that 10 predictors should be considered for each split of the tree -in other words, that bagging should be done. The argument `importance=TRUE` tells whether independent variable importance in bagged trees should be assessed.

```
plot(bag.carseats)
legend("top", colnames(bag.carseats$err.rate),col=1:4,cex=0.8,fill=1:4)
```



How well does this bagged model perform on the test set?

```
yhat.bag = predict(bag.carseats, newdata = test.carseats)

# Confusion matrix
bag.err = table(pred = yhat.bag, truth = test.carseats$High)
test.bag.err = 1 - sum(diag(bag.err))/sum(bag.err)
test.bag.err
```

```
## [1] 0.1733333
```

The test set error rate associated with the bagged classification tree is 0.1733, 4.67% lower than that obtained using an optimally-pruned single tree (0.26). You may consider this a minor improvement, however there are many cases that the improvement could be as half. We could change the number of trees grown by randomForest() using the `ntree` argument. For simplicity of output, we set the following code chunk option as `eval=FALSE`.

```
bag.carseats = randomForest(High ~ ., data=train.carseats, mtry=10, ntree=700,importance=TRUE)
yhat.bag = predict (bag.carseats, newdata = test.carseats)

# Confusion matrix
bag.err = table(pred = yhat.bag, truth = test.carseats$High)
test.bag.err = 1 - sum(diag(bag.err))/sum(bag.err)
test.bag.err
```

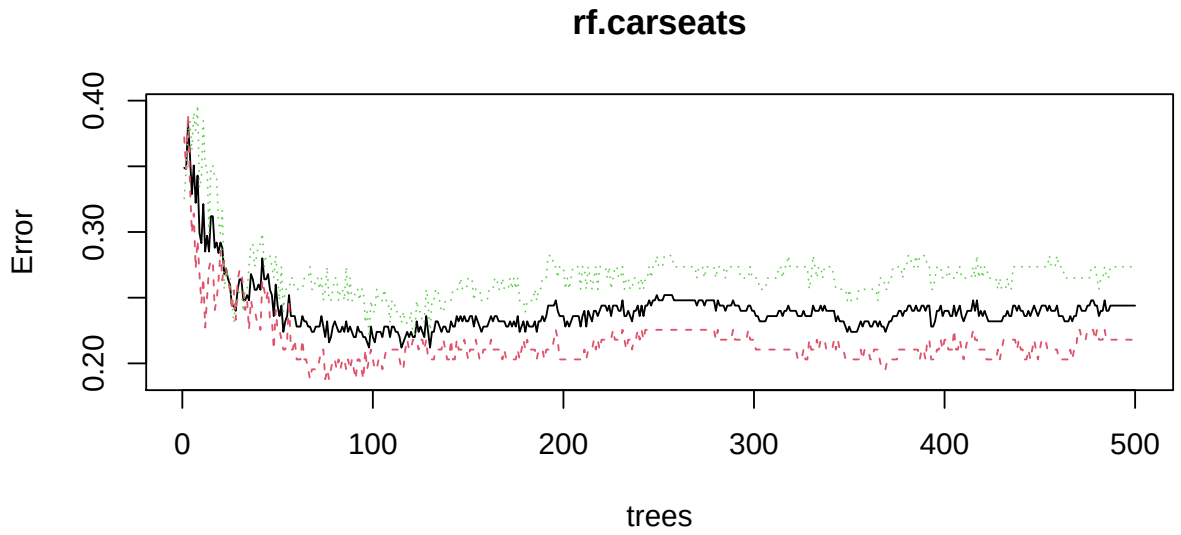
3. Random Forests

Growing a random forest proceeds in exactly the same way, except that we use a smaller value of the `mtry` argument. By default, randomForest() uses p/3 variables when building a random forest of regression trees, and $\sqrt{p}$ variables when building a random forest of classification trees. Here we use `mtry = 3`.

```
rf.carseats = randomForest(High ~ ., data=train.carseats, mtry=3, ntree=500, importance=TRUE)
rf.carseats
```

```
##
## Call:
##  randomForest(formula = High ~ ., data = train.carseats, mtry = 3,      ntree = 500, importance = TRU
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 3
##
##         OOB estimate of  error rate: 24.4%
## Confusion matrix:
##      No Yes class.error
## No  104  29   0.2180451
## Yes  32  85   0.2735043
```

```
plot(rf.carseats)
```




```
yhat.rf = predict (rf.carseats, newdata = test.carseats)

# Confusion matrix
rf.err = table(pred = yhat.rf, truth = test.carseats$High)
test.rf.err = 1 - sum(diag(rf.err))/sum(rf.err)
test.rf.err
```

```
## [1] 0.2133333
```

The test set error rate is 0.2133; this indicates that random forests yielded an improvement over bagging in this case.

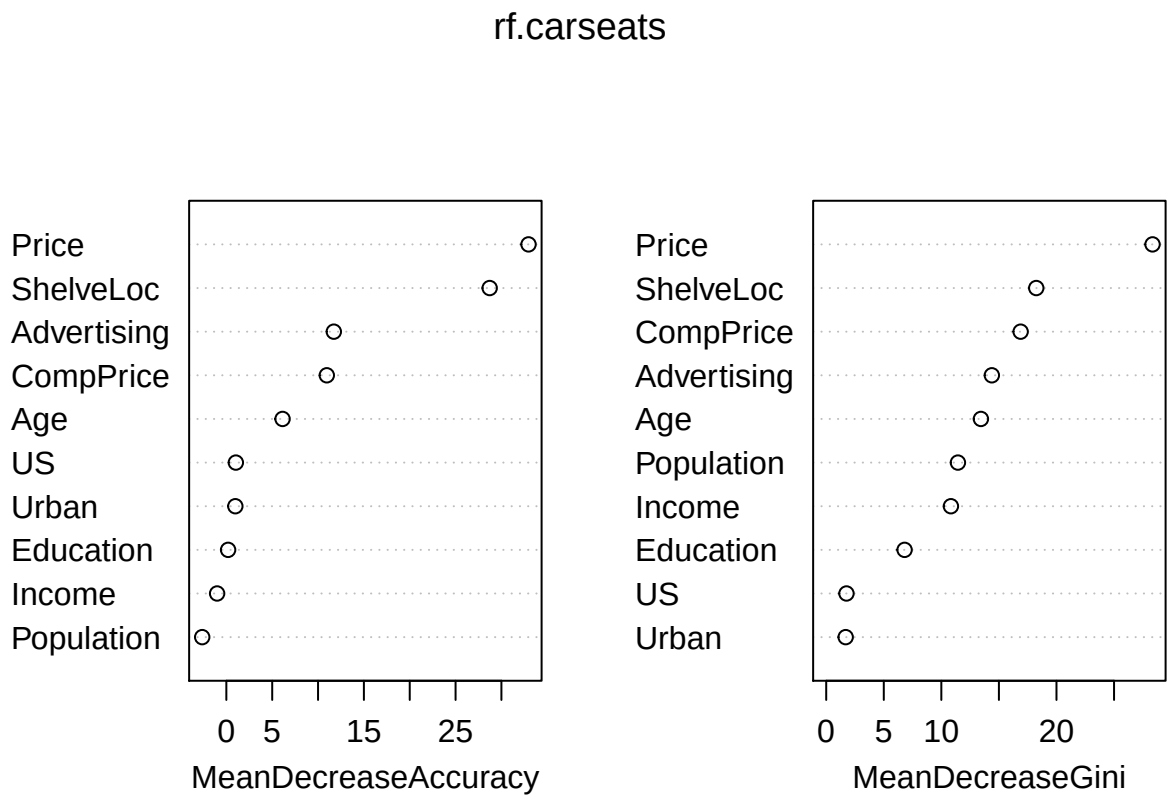
Using the importance() function, we can view the importance of each importance() variable.

```
importance(rf.carseats)
```

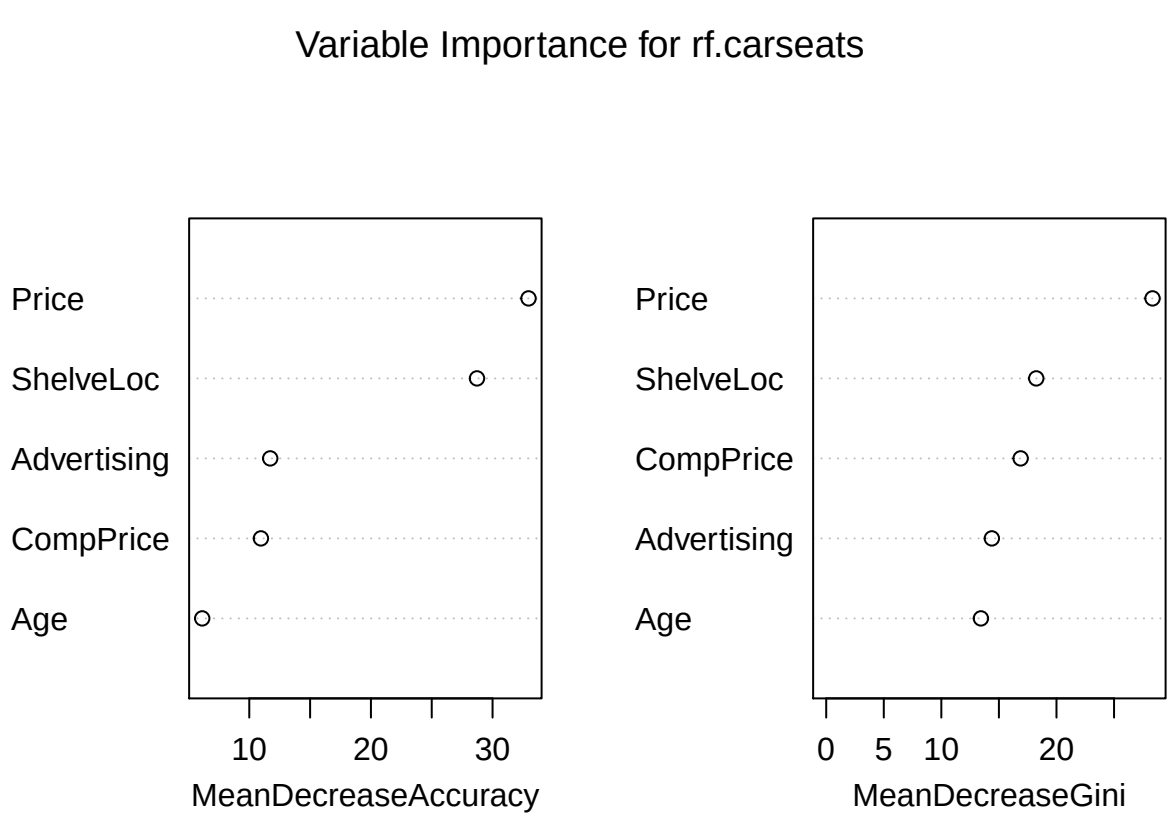
```
##                    No         Yes MeanDecreaseAccuracy MeanDecreaseGini
## CompPrice    8.278234  7.65663343           10.9548335        16.886477
## Income      -1.445034 -0.07327523           -1.0086464        10.830753
## Advertising  6.917362 10.34377865           11.7209445        14.384443
## Population  -1.543855 -2.30145192           -2.6341856        11.438341
## Price       25.086230 24.29665119           32.9587707        28.342814
## ShelveLoc   22.815372 22.42648569           28.7199135        18.244238
## Age          4.400962  4.60579270            6.1291999        13.436181
## Education   -1.129159  1.46141321            0.1909577         6.806345
## Urban        1.618487 -0.36146563            0.9794098         1.691061
## US          -1.447985  3.13310779            1.0353288         1.761979
```

Variable importance plot is also a useful tool and can be plotted using varImpPlot() function. By default, top 10 variables are selected and plotted based on Model Accuracy and Gini value. We can also get a plot with decreasing order of importance based on Model Accuracy and Gini value.

```
varImpPlot(rf.carseats)
```




```
varImpPlot(rf.carseats, sort=T, main="Variable Importance for rf.carseats", n.var=5)
```



The results indicate that across all of the trees considered in the random forest, the price is by far the most important variable in terms of Model Accuracy and Gini index.

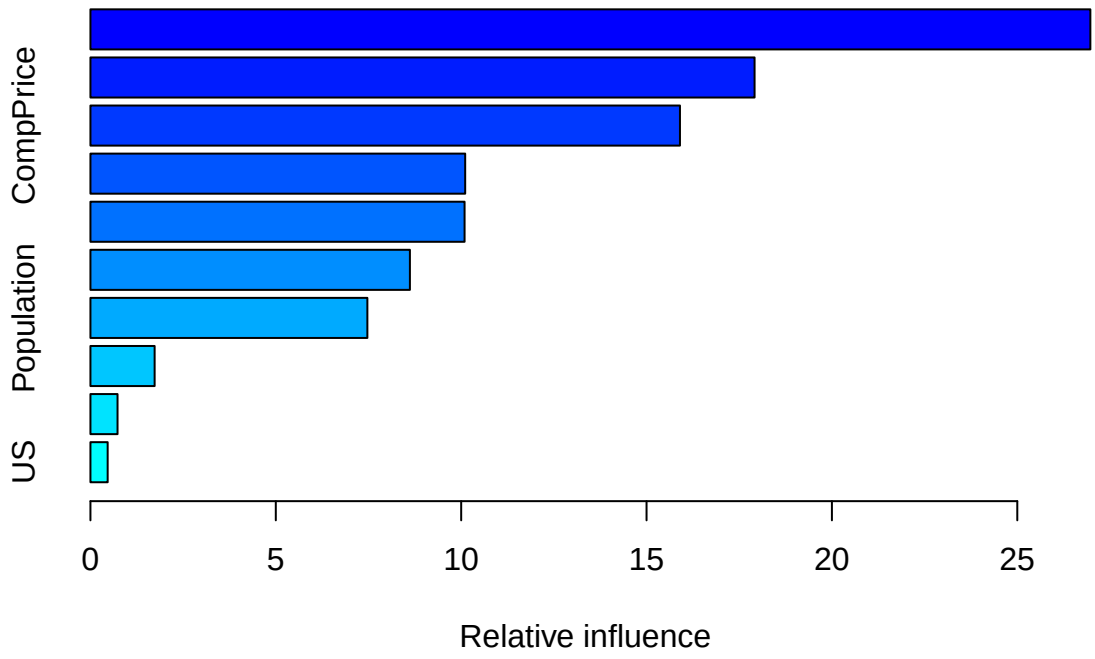
4. Boosting

Here we use the gbm package, and within it the `gbm()` function, to fit boosted classification trees to the Carseats data set. To use gbm(), we have to guarantee that the response variable is coded as $\{0, 1\}$ instead of two levels. We run `gbm()` with the option `distribution="bernoulli"` since this is a binary classification problem; if it were a regression problem, we would use `distribution="gaussian"`. The argument `n.trees=500` indicates that we want 500 trees, and the option `interaction.depth=4` limits the depth of each tree. The argument `shrinkage` is the learning rate or step-size reduction in every step of the boosting. Its default value is 0.001.

```
set.seed(1)
boost.carseats = gbm(ifelse(High=="Yes",1,0)~., data=train.carseats,
                     distribution="bernoulli", n.trees=500, interaction.depth=4)
```

The `summary()` function produces a relative influence plot and also outputs the relative influence statistics.

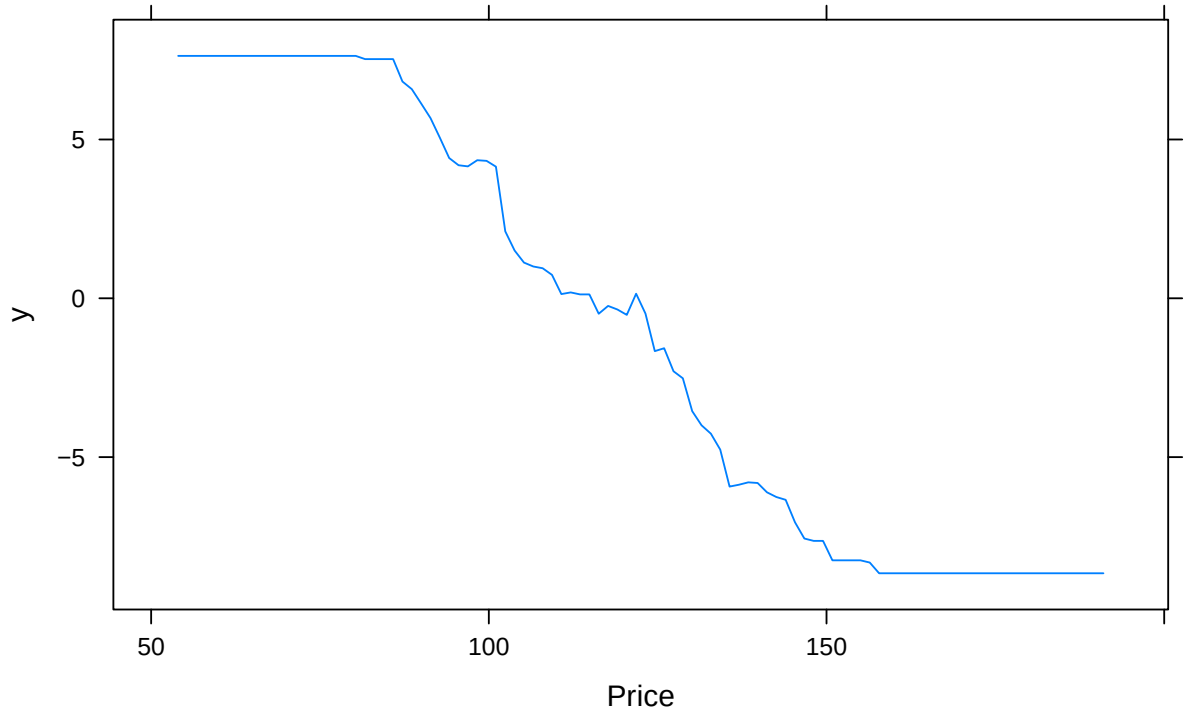
```
summary(boost.carseats)
```



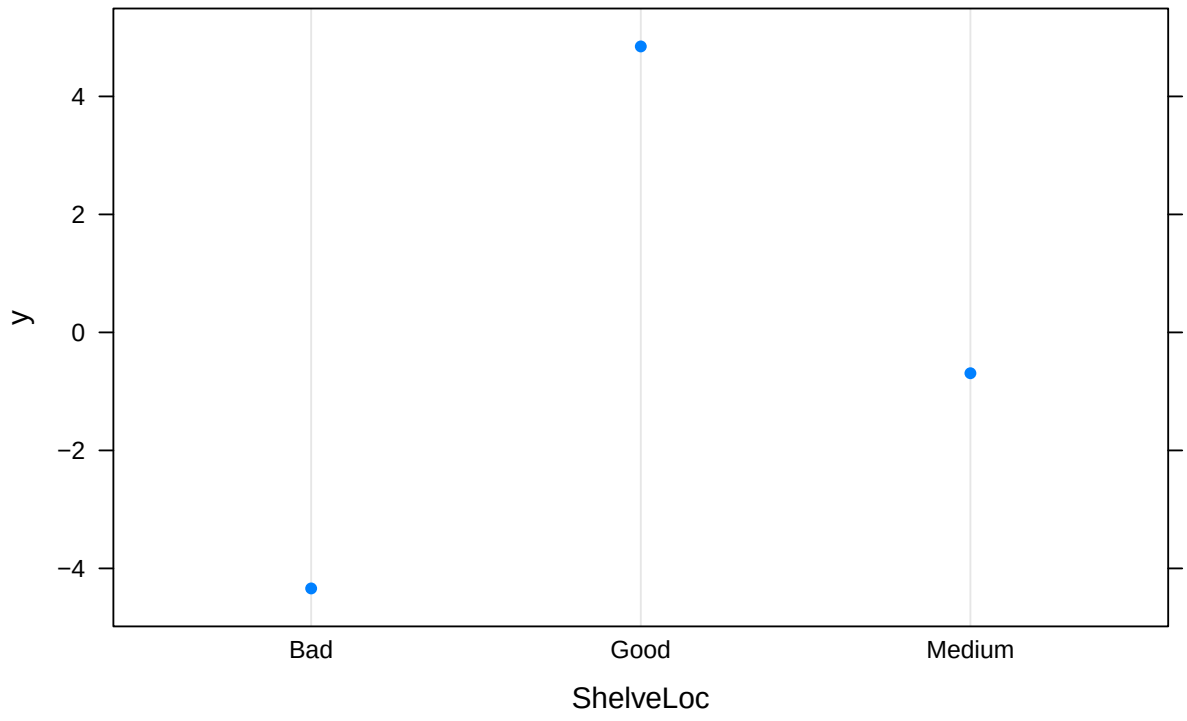

```
##                       var    rel.inf
## Price               Price 26.9710020
## ShelveLoc       ShelveLoc 17.9136017
## CompPrice       CompPrice 15.9010814
## Advertising Advertising 10.1082886
## Age                 Age 10.0914961
## Income           Income  8.6173681
## Population   Population  7.4700990
## Education     Education  1.7315267
## Urban             Urban  0.7308327
## US                   US  0.4647037
```

We see that Price and ShelveLoc are by far the most important variables. We can also produce partial dependence plots for these variables. These plots illustrate the marginal effect of the selected variables on the response after integrating out the other variables.

```
par(mfrow =c(1,2))
plot(boost.carseats ,i="Price")
```




```
plot(boost.carseats ,i="ShelveLoc")
```



We now use the boosted model to predict `High` on the test set:

```
yhat.boost = predict(boost.carseats, newdata = test.carseats, n.trees=500)

# Confusion matrix
boost.err = table(pred = yhat.rf, truth = test.carseats$High)
test.boost.err = 1 - sum(diag(boost.err))/sum(boost.err)
test.boost.err
```

```
## [1] 0.2133333
```

The test error rate obtained is 0.2133; similar to the test error rate for random forests and superior to that for bagging.