stsci4740hw5

Nick Gembs

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```
1.

p = 50
N = 100
set.seed(1)
X_train = array(rnorm(p*N),c(N,p))
eps_train = rnorm(N)
Nte = 10^3
X_te = array(rnorm(p*Nte),c(Nte,p))
eps_te = rnorm(Nte)
grid = 10^seq(10,-2,length = 100)
```

Ridge

```
df = as.data.frame(X_train)
#sample(df)

Y_train = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train


library(glmnet)

## Warning: package 'glmnet' was built under R version 4.2.2

## Loading required package: Matrix

## Warning: package 'Matrix' was built under R version 4.2.2

## Loaded glmnet 4.1-4

#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 0, K=10)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min
best_lambda

## [1] 0.2927512

min(cv_model$cvm)

## [1] 1.647019
```

```r
df = as.data.frame(X_te)
#sample(df)

Y_test = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_ridge = mean((Y_test-Y_pred)^2)
MSE_ridge

## [1] 2.387636
```

Lasso

```r
df = as.data.frame(X_train)
#sample(df)

Y_train = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train


library(glmnet)

#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 1, K=10)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min
best_lambda

## [1] 0.03066908

min(cv_model$cvm)

## [1] 1.231167

df = as.data.frame(X_te)
#sample(df)

Y_test = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_lasso = mean((Y_test-Y_pred)^2)
MSE_lasso

## [1] 1.625679
```

Test MSE for Lasso is less than ridge in a sparse model

2

Ridge

```
df = as.data.frame(X_train)
#sample(df)

Y_train =  eps_train

for (i in df) {
  Y_train = Y_train + .5*i
}

library(glmnet)

#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 0, K=10)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min
best_lambda

## [1] 0.1093254

min(cv_model$cvm)

## [1] 1.510946

df = as.data.frame(X_te)
#sample(df)

Y_test = eps_te

for (i in df) {
  Y_test= Y_test + .5*i
}

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_ridge = mean((Y_test-Y_pred)^2)
MSE_ridge

## [1] 2.006925
```

Lasso

```
df = as.data.frame(X_train)
#sample(df)

Y_train =  eps_train
```

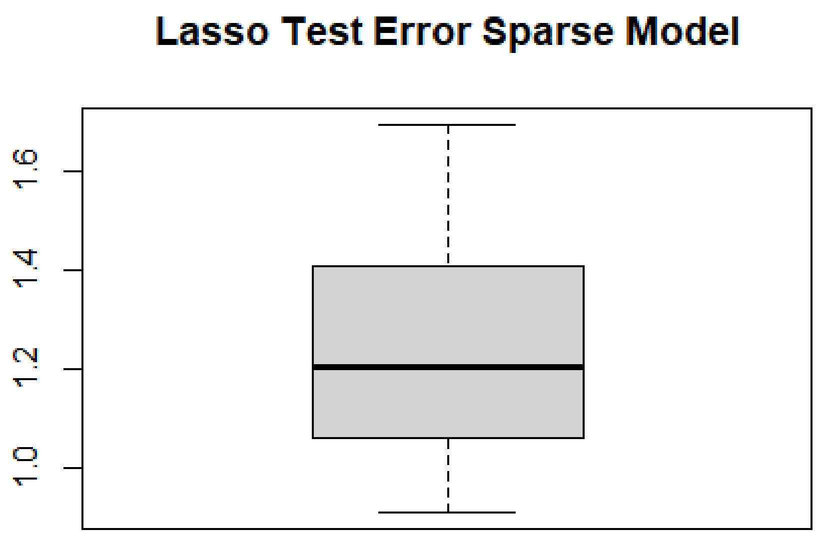
```r
for (i in df) {
  Y_train = Y_train + .5*i
}

library(glmnet)

#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 1, K=10)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min
best_lambda

## [1] 0.002584987

min(cv_model$cvm)

## [1] 2.003724

df = as.data.frame(X_te)
#sample(df)

Y_test = eps_te

for (i in df) {
  Y_test= Y_test + .5*i
}

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_lasso = mean((Y_test-Y_pred)^2)
MSE_lasso

## [1] 2.391959
```

For non-sparse models, ridge has a lower test MSE than lasso.

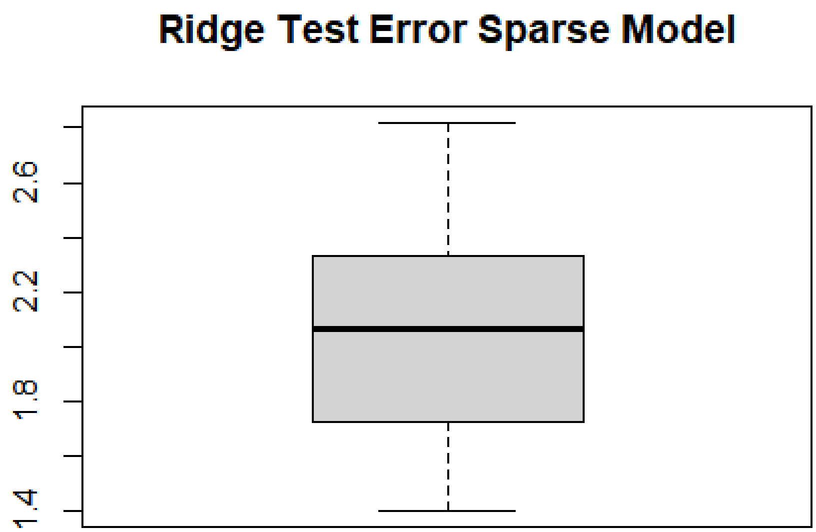
```r
test_errors_ridge = rep(0,50)

for ( i in 1:50){
  set.seed(i)
  X_train = array(rnorm(p*N),c(N,p))
eps_train = rnorm(N)
Nte = 10^3
X_te = array(rnorm(p*Nte),c(Nte,p))
eps_te = rnorm(Nte)
grid = 10^seq(10,-2,length = 100)

df = as.data.frame(X_train)
#sample(df)
```

```r
Y_train = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train


#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 0, K=10)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min

df = as.data.frame(X_te)
#sample(df)

Y_test = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_ridge = mean((Y_test-Y_pred)^2)

test_errors_ridge[i] = MSE_ridge

}

test_errors_lasso = rep(0,50)

for ( i in 1:50){
  set.seed(i)
  X_train = array(rnorm(p*N),c(N,p))
eps_train = rnorm(N)
Nte = 10^3
X_te = array(rnorm(p*Nte),c(Nte,p))
eps_te = rnorm(Nte)
grid = 10^seq(10,-2,length = 100)

df = as.data.frame(X_train)
#sample(df)

Y_train = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train


#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 1, K=10)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min

df = as.data.frame(X_te)
#sample(df)
```

```r
Y_test = 2*df$V1 + 2 * df$V2 + 2*df$V3 +2*df$V4 + 2*df$V5 + eps_train

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_lasso = mean((Y_test-Y_pred)^2)

test_errors_lasso[i] = MSE_lasso

}

boxplot(test_errors_lasso, main = "Lasso Test Error Sparse Model")
```




```r
boxplot(test_errors_ridge, main = "Ridge Test Error Sparse Model")
```

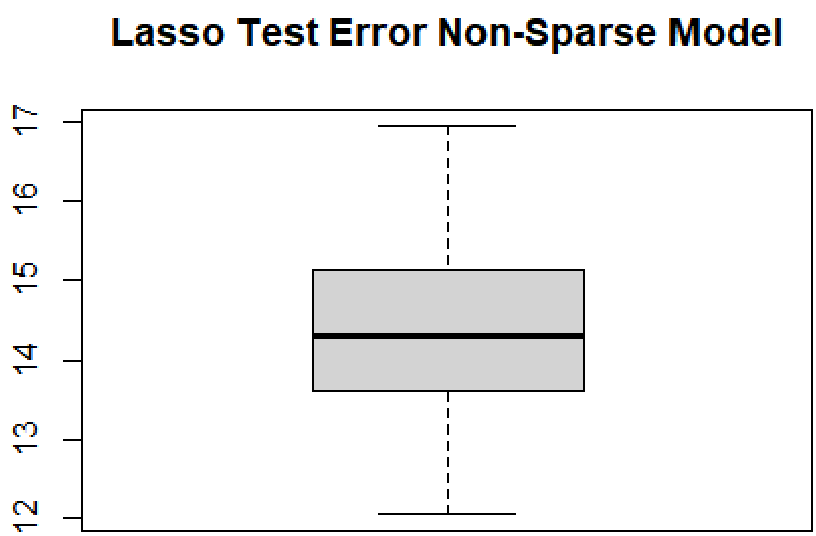


Lasso Test MSE is lower on average for the sparse model

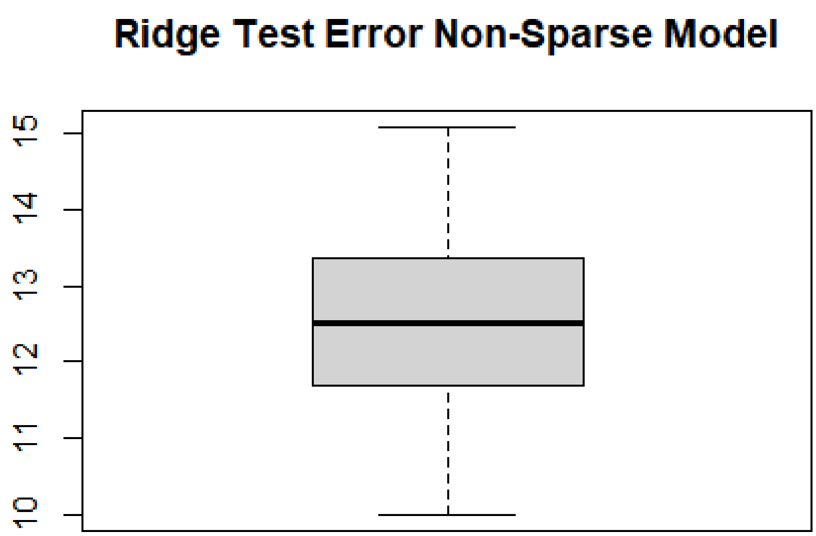
```
test_errors_ridge = rep(0,50)

for ( i in 1:50){
  set.seed(i)
  X_train = array(rnorm(p*N),c(N,p))
eps_train = rnorm(N)
Nte = 10^3
X_te = array(rnorm(p*Nte),c(Nte,p))
eps_te = rnorm(Nte)
grid = 10^seq(10,-2,length = 100)

df = as.data.frame(X_train)
#sample(df)

Y_train =  eps_train

for (q in df) {
  Y_train = Y_train + .5*q
}


#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 0, K=10)
```

```
#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min

df = as.data.frame(X_te)
#sample(df)

Y_test  =  eps_train

for (q in df) {
  Y_train = Y_train + .5*q
}

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_ridge = mean((Y_test-Y_pred)^2)

test_errors_ridge[i] = MSE_ridge

}

test_errors_lasso = rep(0,50)

for ( i in 1:50){
  set.seed(i)
  X_train = array(rnorm(p*N),c(N,p))
eps_train = rnorm(N)
Nte = 10^3
X_te = array(rnorm(p*Nte),c(Nte,p))
eps_te = rnorm(Nte)
grid = 10^seq(10,-2,length = 100)

df = as.data.frame(X_train)
#sample(df)

Y_train  =  eps_train

for (q in df) {
  Y_train = Y_train + .5*q
}


#perform k-fold cross-validation to find optimal lambda value
cv_model <- cv.glmnet(X_train, Y_train, alpha = 1, K=10)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min

df = as.data.frame(X_te)
#sample(df)
```

```
Y_test  =  eps_train

for (q in df) {
  Y_train = Y_train + .5*q
}

Y_pred = predict(cv_model, newx = X_te, s = best_lambda )
MSE_lasso = mean((Y_test-Y_pred)^2)

test_errors_lasso[i] = MSE_lasso

}

boxplot(test_errors_lasso, main = "Lasso Test Error Non-Sparse Model")
```



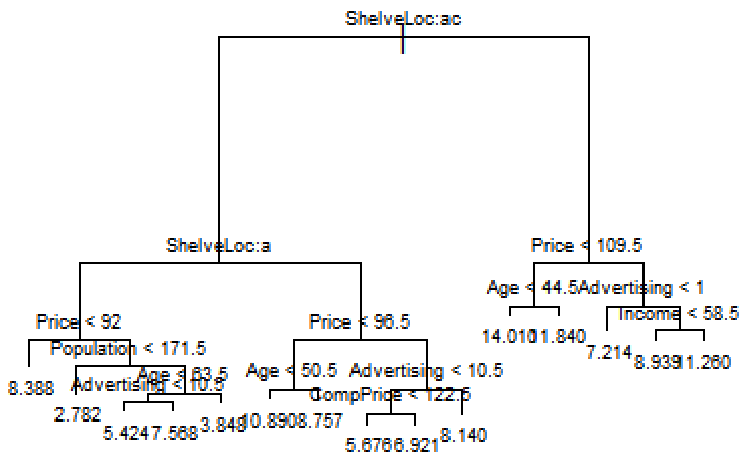

```
boxplot(test_errors_ridge, main = "Ridge Test Error Non-Sparse Model")
```



Ridge Test MSE is lower on average for the non-sparse model

2. (Problem 8)

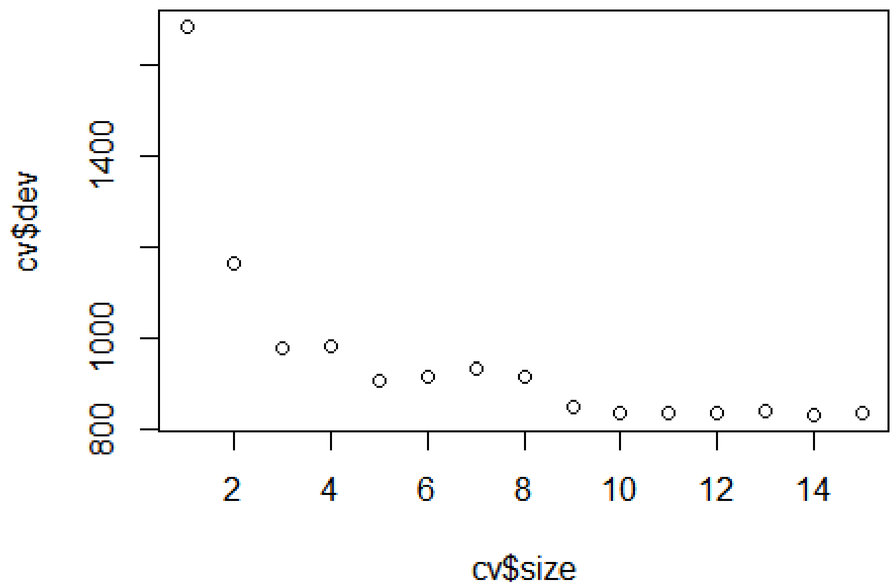
```
library(tree)

## Warning: package 'tree' was built under R version 4.2.2

library(ISLR)

data = Carseats

# a

set.seed(12)

train = sample(length(data$Sales), length(data$Sales)/2)

training = data[train,]
testing = data[-train,]

# b

tree <- tree(Sales ~ ., data = training)
plot(tree)
text(tree, cex = .56)
```




```r
treepred <- predict(tree, newdata = testing)
MSE = mean((treepred - testing$Sales)^2)
MSE

## [1] 5.08059
```

MSE is 5.08059

```r
# c

cv <- cv.tree(tree)
plot(cv$size, cv$dev)
```




```r
# min dev appears at size 9

prunedtree <- prune.tree(tree, best = 9)
prunetreepred <- predict(prunedtree, newdata = testing)
MSE = mean((prunetreepred - testing$Sales)^2)
MSE

## [1] 5.184776
```

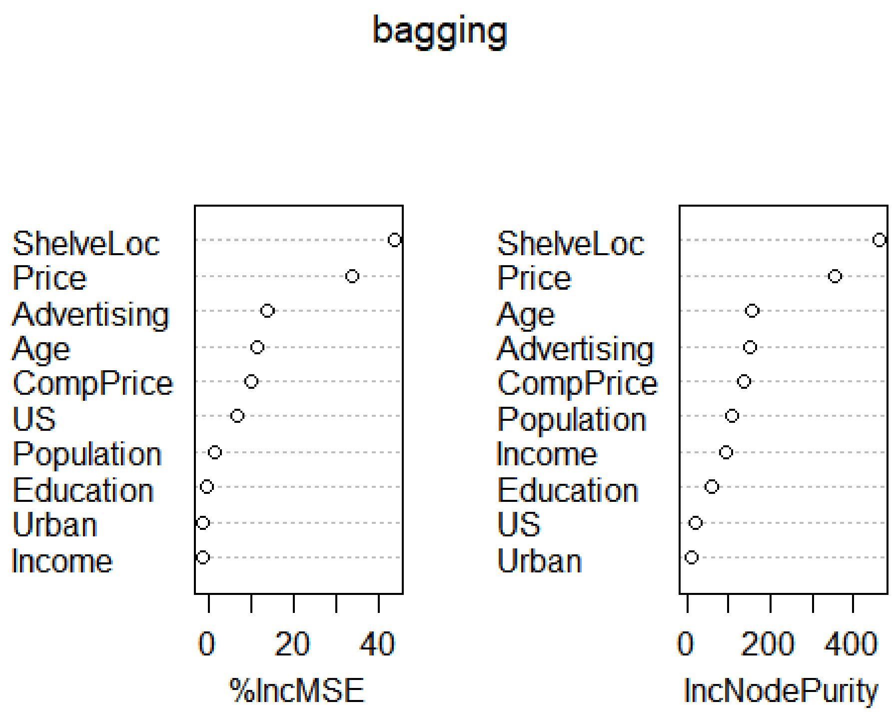
The pruned tree had a greater test MSE (5.184776) than the unpruned tree (5.08059). This indicates that the unpruned tree was not overfitting to the training data.

```r
# d

library(randomForest)

## Warning: package 'randomForest' was built under R version 4.2.2

## randomForest 4.7-1.1

## Type rfNews() to see new features/changes/bug fixes.

bagging <- randomForest(Sales ~ ., data = Carseats, subset = train,
                        importance = TRUE)
bagging

##
## Call:
```

```
##  randomForest(formula = Sales ~ ., data = Carseats, importance = TRUE, 
subset = train)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 3
## 
##           Mean of squared residuals: 3.111895
##                     % Var explained: 62.06

predictbagging <- predict(bagging, newdata = testing)
MSE = mean((predictbagging - testing$Sales)^2)

MSE

## [1] 2.978925
```

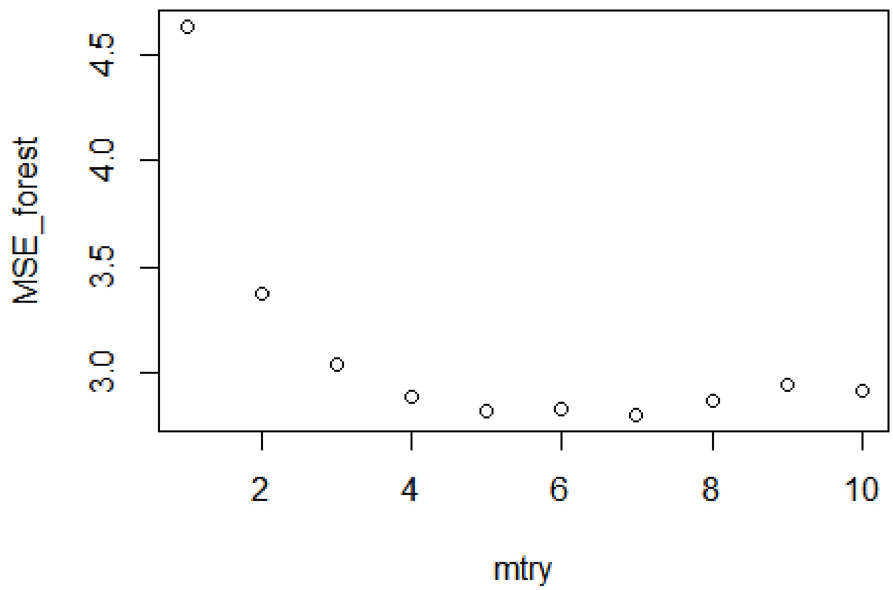
MSE of bagging is 3.044373, lower than the two trees

```
importance(bagging)

##                %IncMSE IncNodePurity
## CompPrice    9.8164095    136.523493
## Income      -1.6603266     92.082628
## Advertising 13.8431083    152.522949
## Population   1.5370312    110.047031
## Price       33.4688136    353.583644
## ShelveLoc   43.8150852    464.048339
## Age         11.5547448    155.528390
## Education   -0.3085175     59.650396
## Urban       -1.4363594      9.837111
## US           6.5590849     23.462175

varImpPlot(bagging)
```



Shelf location and price are the most important variables according to bagging.

```
# e

MSE_forest = rep(0,10)

for (i in 1:10){
  randomf <- randomForest(Sales ~ ., data = Carseats, subset = train, mtry =
i,
                          importance = TRUE)
  randomf.pred <- predict(randomf, newdata = testing)
  MSE_forest[i] = mean((randomf.pred - testing$Sales)^2)
}

mtry = 1:10

plot(mtry,MSE_forest)
```




```
MSE_forest

##  [1] 4.636720 3.368603 3.033561 2.880979 2.820345 2.829977 2.799821
2.868452
##  [9] 2.940906 2.916626
```

The value of m with the minimum test MSE is m=7 with an MSE of 2.833899, lower than any other model MSE tried so far

```
randomf <- randomForest(Sales ~ ., data = Carseats, subset = train, mtry = 7,
                        importance = TRUE)
importance(randomf)

##                  %IncMSE IncNodePurity
## CompPrice   16.62954511     123.28881
## Income       0.04942483      58.87416
## Advertising 17.60889946     142.93691
## Population   6.07750234      84.72412
## Price       46.53321859     401.49444
## ShelveLoc   56.49994157     597.31544
## Age         16.51273087     134.80199
## Education   -1.58469327      34.36782
## Urban        0.33351371       4.15932
## US           4.90317994      13.09051

varImpPlot(randomf)
```

Random forest also claims that shelf location, followed by price are the most important variables

```
# f

library(BayesTree)

## Warning: package 'BayesTree' was built under R version 4.2.2

x = subset(training, select = -Sales )
y = training$Sales

bart = bart(x,y)

##
##
## Running BART with numeric y
##
## number of trees: 200
## Prior:
##   k: 2.000000
##   degrees of freedom in sigma prior: 3
##   quantile in sigma prior: 0.900000
##   power and base for tree prior: 2.000000 0.950000
##   use quantiles for rule cut points: 0
## data:
##   number of training observations: 200
```

```
##  number of test observations: 0
##  number of explanatory variables: 12
##
##
## Cutoff rules c in x<=c vs x>c
## Number of cutoffs: (var: number of possible c):
## (1: 100) (2: 100) (3: 100) (4: 100) (5: 100)
## (6: 100) (7: 100) (8: 100) (9: 100) (10: 100)
## (11: 100) (12: 100)
##
##
## Running mcmc loop:
## iteration: 100 (of 1100)
## iteration: 200 (of 1100)
## iteration: 300 (of 1100)
## iteration: 400 (of 1100)
## iteration: 500 (of 1100)
## iteration: 600 (of 1100)
## iteration: 700 (of 1100)
## iteration: 800 (of 1100)
## iteration: 900 (of 1100)
## iteration: 1000 (of 1100)
## iteration: 1100 (of 1100)
## time for loop: 6
##
## Tree sizes, last iteration:
## 2 2 4 2 2 2 3 2 2 3 4 2 3 2 2 2 2 2 4 3
## 2 2 3 3 2 2 3 2 2 2 4 2 2 2 3 3 2 2 2 2
## 3 3 1 2 2 2 2 2 3 2 2 2 2 3 2 1 2 5 2 2
## 2 2 2 2 2 2 3 3 2 2 2 2 3 2 3 3 2 2 3 3
## 2 2 1 3 2 2 2 2 2 3 3 3 2 3 2 2 3 2 2 2
## 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 3 2 2 4 2
## 2 1 2 2 2 2 2 2 4 2 2 3 6 3 2 3 2 1 2 2
## 2 2 2 2 2 2 2 2 2 2 2 3 2 2 4 2 2 2 2 2
## 2 2 3 2 2 3 3 2 2 3 2 2 3 2 4 5 2 3 4 2
## 3 3 2 3 2 2 1 4 3 3 2 2 2 2 4 2 3 2 3 4
## Variable Usage, last iteration (var:count):
## (1: 21) (2: 22) (3: 23) (4: 23) (5: 34)
## (6: 24) (7: 13) (8: 25) (9: 24) (10: 18)
## (11: 22) (12: 20)
## DONE BART 11-2-2014
```

```r
MSE = mean((bart$y-testing$Sales)^2)
MSE
```

```
## [1] 16.03221
```

BART MSE is highest MSE tested