Problem Set 3

Seth Harrison

2/17/2020

```
library(tidyverse)
library(gbm)
library(rsample)
library(randomForest)
library(e1071)
library(ISLR)
library(caret)
```

Decision Trees

Set Up

```
set.seed(1)

nes2008 <- read_csv("./data/nes2008.csv")

noBiden <- nes2008 %>%
            select(-nes2008$biden)

p <- ncol(noBiden)

lambda <- seq(from = 0.0001, to = 0.04, by = 0.001)
```

Create a training set consisting of 75% of the observations, and a test set with all remaining obs. Note: because you will be asked to loop over multiple λ values below, these training and test sets should only be integer values corresponding with row IDs in the data. This is a little tricky, but think about it carefully. If you try to set the training and testing sets as before, you will be unable to loop below.

```
set.seed(1)

train_ind <- sample(nrow(nes2008), size = nrow(nes2008)*.75)

train <- nes2008[train_ind,]
test <- nes2008[-train_ind,]
```

Create empty objects to store training and testing MSE, and then write a loop to perform boosting on the training set with 1,000 trees for the pre-defined range of values of the shrinkage parameter, λ. Then, plot the training set and test set MSE across shrinkage values.

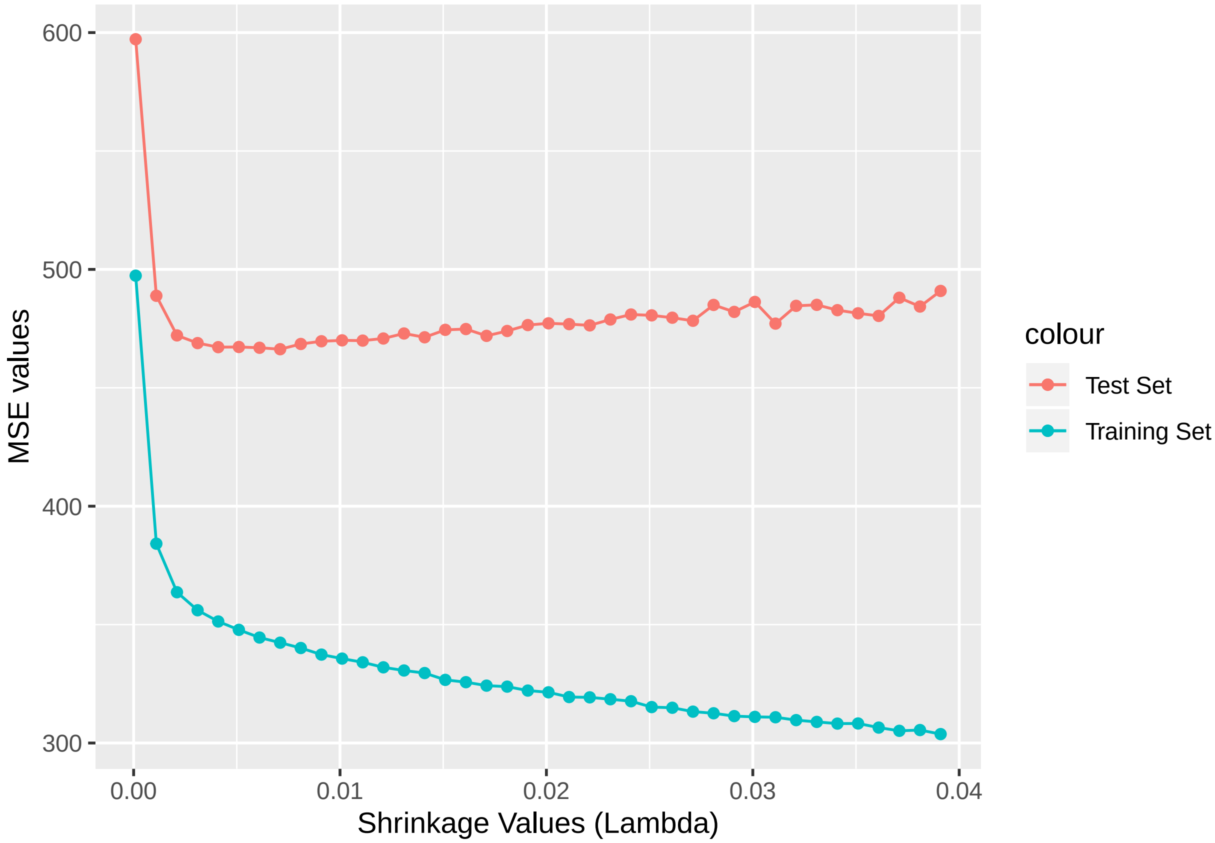
```r
TestMSE <- vector(mode = "numeric", length = length(lambda))
TrainingMSE <- vector(mode = "numeric", length = length(lambda))
for(i in seq_along(lambda)) {
# boosting training set
  boost.train <- gbm(biden ~.,
                   data = train,
                   distribution = "gaussian",
                   n.trees = 1000,
                   shrinkage = lambda[i],
                   interaction.depth = 4
                   )
  training.pred <- predict(boost.train, newdata = train, n.trees = 1000)
  training.mse <- Metrics::mse(training.pred, train$biden)
# predict on test set
  test.pred <- predict(boost.train, newdata = test, n.trees = 1000)
  test.mse <- Metrics::mse(test.pred, test$biden)
# extract MSE and lambda
  TrainingMSE[i] <- training.mse
  TestMSE[i] <- test.mse
  result <- cbind(lambda, TrainingMSE, TestMSE)
  result <- result %>%
    as_tibble()
}
#Plot
result %>%
  ggplot(aes(x = lambda)) +
  geom_point(aes(y = TrainingMSE, color = "Training Set")) +
```

```r
  geom_point(aes(y = TestMSE, color = "Test Set")) +

  geom_line(aes(y = TrainingMSE, color = "Training Set")) +

  geom_line(aes(y = TestMSE, color = "Test Set")) +

labs(x = "Shrinkage Values (Lambda)", y = "MSE values")
```



The test MSE values are insensitive to some precise value of λ as long as its small enough. Update the boosting procedure by setting λ equal to 0.01 (but still over 1000 trees). Report the test MSE and discuss the results. How do they compare?

```r
boost.train2 <- gbm(biden ~.,

                   data = train,

                   distribution = "gaussian",

                   n.trees = 1000,

                   shrinkage = lambda[1]*100,

                   interaction.depth = 4
```

```r
                    )


training.pred2 <- predict(boost.train2, newdata = train, n.trees = 1000)

training.mse2 <- Metrics::mse(training.pred2, train$biden)

# predict on test set

test.pred2 <- predict(boost.train2, newdata = test, n.trees = 1000)

test.mse2 <- Metrics::mse(test.pred2, test$biden)

# extract MSE and lambda

TrainingMSE2 <- training.mse2

TestMSE2 <- test.mse2

result <- cbind(lambda, TrainingMSE2, TestMSE2)

result <- result %>%
            as_tibble()

TestMSE2
```

```
## [1] 470.9239
```

The MSE changes only marginally once lambda became greater than .002.

Now apply bagging to the training set. What is the test set MSE for this approach?

```r
bag_biden <- randomForest(data = train,
                          x = train[,2:6],
                          y = train$biden,
                          mtry = p)

# predict on test set

test.predbag <- predict(bag_biden, newdata = test)

test.msebag <- Metrics::mse(test.predbag, test$biden)

test.msebag
```

```
## [1] 550.5081
```

Now apply random forest to the training set. What is the test set MSE for this approach?

```r
rf_biden <- randomForest(data = train,
                          x = train [,2:6],
```

```
                        y = train$biden)

# predict on test set

test.predrf <- predict(rf_biden, newdata = test)

test.mserf <- Metrics::mse(test.predrf, test$biden)

test.mserf
```

```
## [1] 475.1519
```

Now apply linear regression to the training set. What is the test set MSE for this approach?

```
lm_biden <- glm(biden~female+age+educ+dem+rep, data = train)

# predict on test set

test.predlm <- predict(lm_biden, newdata = test)

test.mselm <- Metrics::mse(test.predlm, test$biden)

test.mselm
```

```
## [1] 469.9226
```

Compare test errors across all fits. Discuss which approach generally fits best and how you concluded this.

```
mse.table <- cbind(test.mse,test.mse2,test.msebag, test.mserf, test.mselm)

mse.table
```

```
##      test.mse test.mse2 test.msebag test.mserf test.mselm
## [1,] 490.9084  470.9239    550.5081   475.1519   469.9226
```

In terms of test MSE, the boosted MSE with lambda at 0.01 did only marginally better than a simple linear regression. This is because boosting and its subsequent derivations provide a sequence of coefficient vectors, which is the functional form of a linear regression, which minimizes the sum of square errors.

Support Vector Machines

Create a training set with a random sample of size 800, and a test set containing the remaining observations.

```
set.seed(1)

OJ <- ISLR::OJ

OJtrain_ind <- sample(nrow(OJ), size = 800)
```

```
OJtrain <- OJ[OJtrain_ind,]
OJtest <- OJ[-OJtrain_ind,]
```

Fit a support vector classifier to the training data with `cost = 0.01`, with `Purchase` as the response and *all* other features as predictors. Discuss the results.

```
svmfit <- svm(Purchase ~ .,
             data = OJtrain,
             kernel = "linear",
             cost = .01,
             scale = FALSE); summary(svmfit)
```

```
##
## Call:
## svm(formula = Purchase ~ ., data = OJtrain, kernel = "linear",
##     cost = 0.01, scale = FALSE)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.01
##
## Number of Support Vectors:  615
##
##  ( 306 309 )
##
##
## Number of Classes:  2
##
## Levels:
##  CH MM
```

There were 615 support vectors; 306 in one class and 309 in the other.

Display the confusion matrix for the classification solution, and also report both the training and test set error rates.

```
train.prediction <- predict(svmfit, OJtrain)

confusionMatrix(train.prediction, OJtrain$Purchase, dnn = c("Prediction", "Reference"))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  CH  MM
##         CH 473 189
##         MM  21 117
##
##                Accuracy : 0.7375
##                  95% CI : (0.7055, 0.7677)
```

```
##     No Information Rate : 0.6175
##     P-Value [Acc > NIR] : 5.044e-13
##
##                   Kappa : 0.3795
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9575
##             Specificity : 0.3824
##          Pos Pred Value : 0.7145
##          Neg Pred Value : 0.8478
##              Prevalence : 0.6175
##          Detection Rate : 0.5913
##    Detection Prevalence : 0.8275
##       Balanced Accuracy : 0.6699
##
##        'Positive' Class : CH
##
```

```r
test.prediction <- predict(svmfit, OJtest)

confusionMatrix(test.prediction, OJtest$Purchase, dnn = c("Prediction", "Reference") )
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  CH  MM
##         CH 156  68
##         MM   3  43
##
##                Accuracy : 0.737
##                  95% CI : (0.6802, 0.7885)
##     No Information Rate : 0.5889
##     P-Value [Acc > NIR] : 2.668e-07
##
##                   Kappa : 0.4043
##
##  Mcnemar's Test P-Value : 3.068e-14
##
##             Sensitivity : 0.9811
##             Specificity : 0.3874
##          Pos Pred Value : 0.6964
##          Neg Pred Value : 0.9348
##              Prevalence : 0.5889
##          Detection Rate : 0.5778
##    Detection Prevalence : 0.8296
##       Balanced Accuracy : 0.6843
##
##        'Positive' Class : CH
##
```