

Introduction to Machine Learning

Lab 2 Block 2

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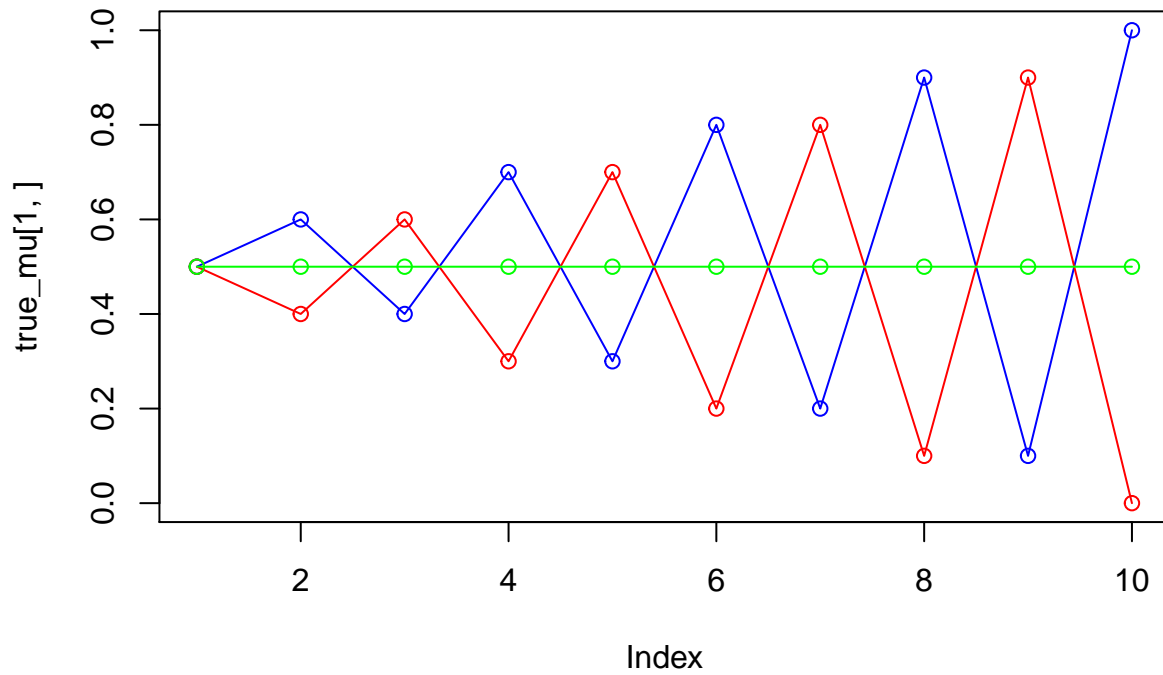
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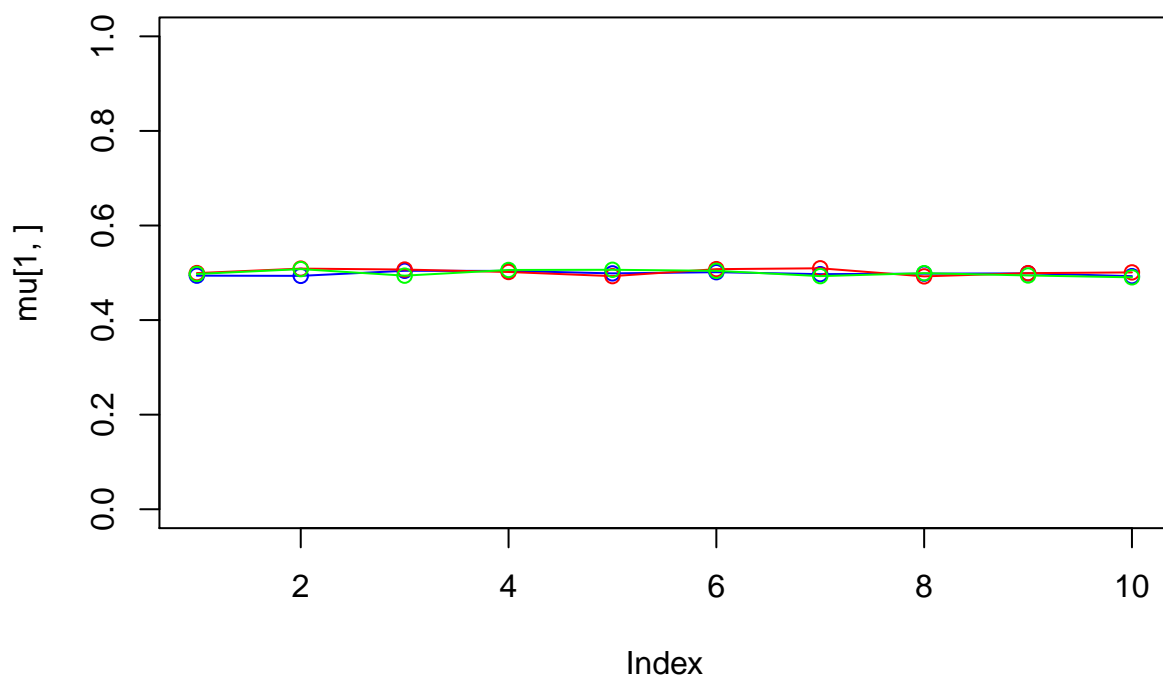
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Assignment 1a

Assignment 1b



```
#> [1] 0.3326090 0.3336558 0.3337352
#>      [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
#> [1,] 0.4939877 0.4935375 0.5042511 0.5040286 0.4987810 0.5012754 0.4971036
#> [2,] 0.4993719 0.5088453 0.5068730 0.5016720 0.4929275 0.5077146 0.5095075
#> [3,] 0.4975302 0.5077926 0.4939841 0.5059821 0.5063490 0.5041462 0.4929400
#>      [,8]      [,9]     [,10]
#> [1,] 0.4982144 0.4987654 0.4929075
#> [2,] 0.4924574 0.4992470 0.5008651
#> [3,] 0.4992362 0.4943482 0.4903974
```



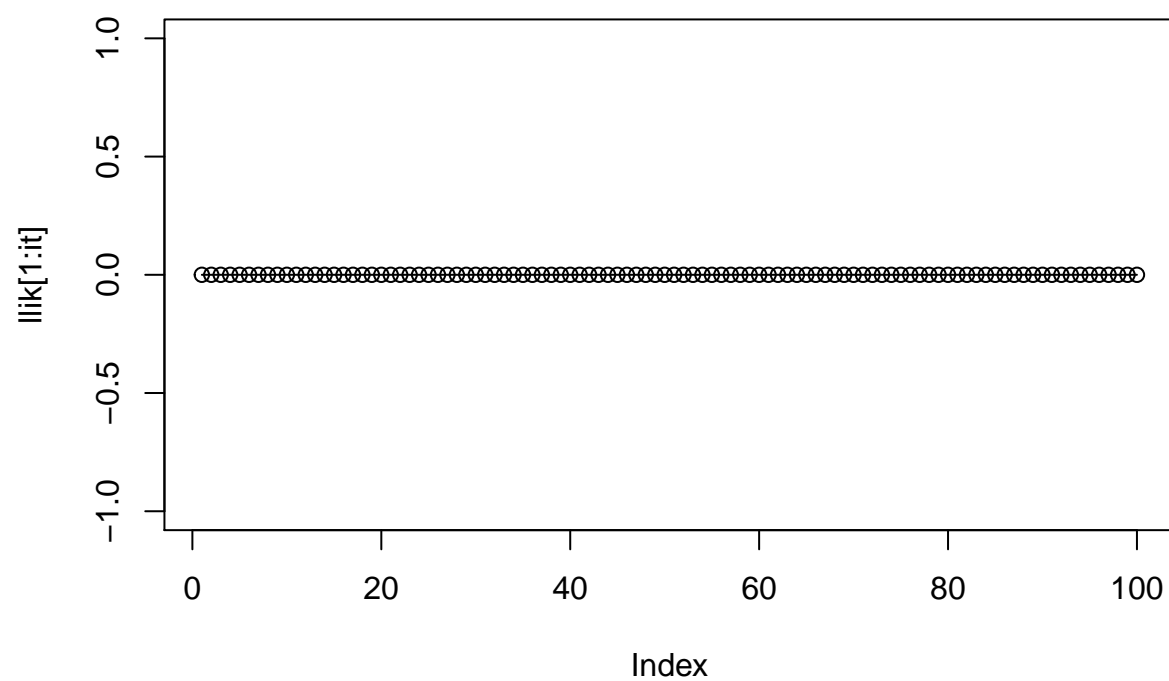
```
#> iteration: 1 log likelihood: FALSE
#> iteration: 2 log likelihood: FALSE
#> iteration: 3 log likelihood: FALSE
#> iteration: 4 log likelihood: FALSE
#> iteration: 5 log likelihood: FALSE
#> iteration: 6 log likelihood: FALSE
#> iteration: 7 log likelihood: FALSE
#> iteration: 8 log likelihood: FALSE
#> iteration: 9 log likelihood: FALSE
#> iteration: 10 log likelihood: FALSE
#> iteration: 11 log likelihood: FALSE
#> iteration: 12 log likelihood: FALSE
#> iteration: 13 log likelihood: FALSE
#> iteration: 14 log likelihood: FALSE
#> iteration: 15 log likelihood: FALSE
#> iteration: 16 log likelihood: FALSE
#> iteration: 17 log likelihood: FALSE
#> iteration: 18 log likelihood: FALSE
#> iteration: 19 log likelihood: FALSE
#> iteration: 20 log likelihood: FALSE
#> iteration: 21 log likelihood: FALSE
#> iteration: 22 log likelihood: FALSE
#> iteration: 23 log likelihood: FALSE
#> iteration: 24 log likelihood: FALSE
#> iteration: 25 log likelihood: FALSE
#> iteration: 26 log likelihood: FALSE
```

[illegible]

```

#> iteration: 81 log likelihood: FALSE
#> iteration: 82 log likelihood: FALSE
#> iteration: 83 log likelihood: FALSE
#> iteration: 84 log likelihood: FALSE
#> iteration: 85 log likelihood: FALSE
#> iteration: 86 log likelihood: FALSE
#> iteration: 87 log likelihood: FALSE
#> iteration: 88 log likelihood: FALSE
#> iteration: 89 log likelihood: FALSE
#> iteration: 90 log likelihood: FALSE
#> iteration: 91 log likelihood: FALSE
#> iteration: 92 log likelihood: FALSE
#> iteration: 93 log likelihood: FALSE
#> iteration: 94 log likelihood: FALSE
#> iteration: 95 log likelihood: FALSE
#> iteration: 96 log likelihood: FALSE
#> iteration: 97 log likelihood: FALSE
#> iteration: 98 log likelihood: FALSE
#> iteration: 99 log likelihood: FALSE
#> iteration: 100 log likelihood: FALSE
#> [1] 0.3326090 0.3336558 0.3337352
#>      [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
#> [1,] 0.4939877 0.4935375 0.5042511 0.5040286 0.4987810 0.5012754 0.4971036
#> [2,] 0.4993719 0.5088453 0.5068730 0.5016720 0.4929275 0.5077146 0.5095075
#> [3,] 0.4975302 0.5077926 0.4939841 0.5059821 0.5063490 0.5041462 0.4929400
#>      [,8]      [,9]     [,10]
#> [1,] 0.4982144 0.4987654 0.4929075
#> [2,] 0.4924574 0.4992470 0.5008651
#> [3,] 0.4992362 0.4943482 0.4903974

```



Assignment 2a

1

```
#> [1] 37.10301
```

2

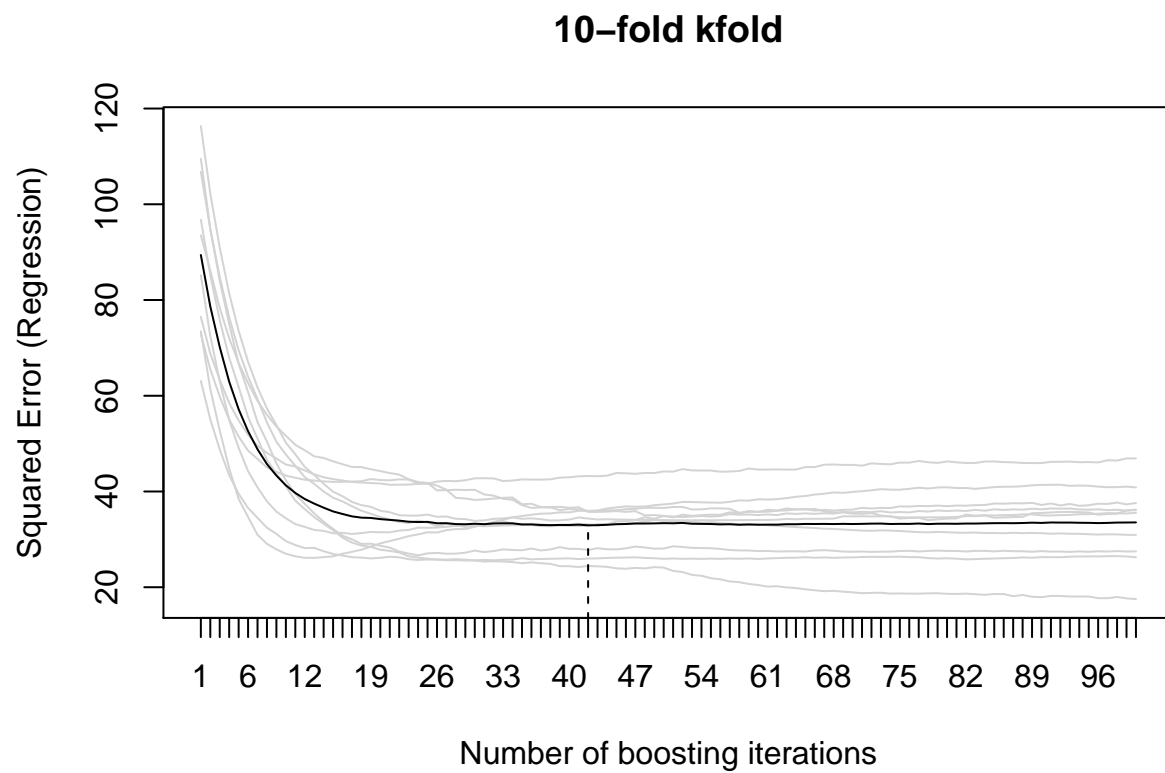
```
#> [1] 30.8038
```

3

Assignment 2b

Assignment 3a

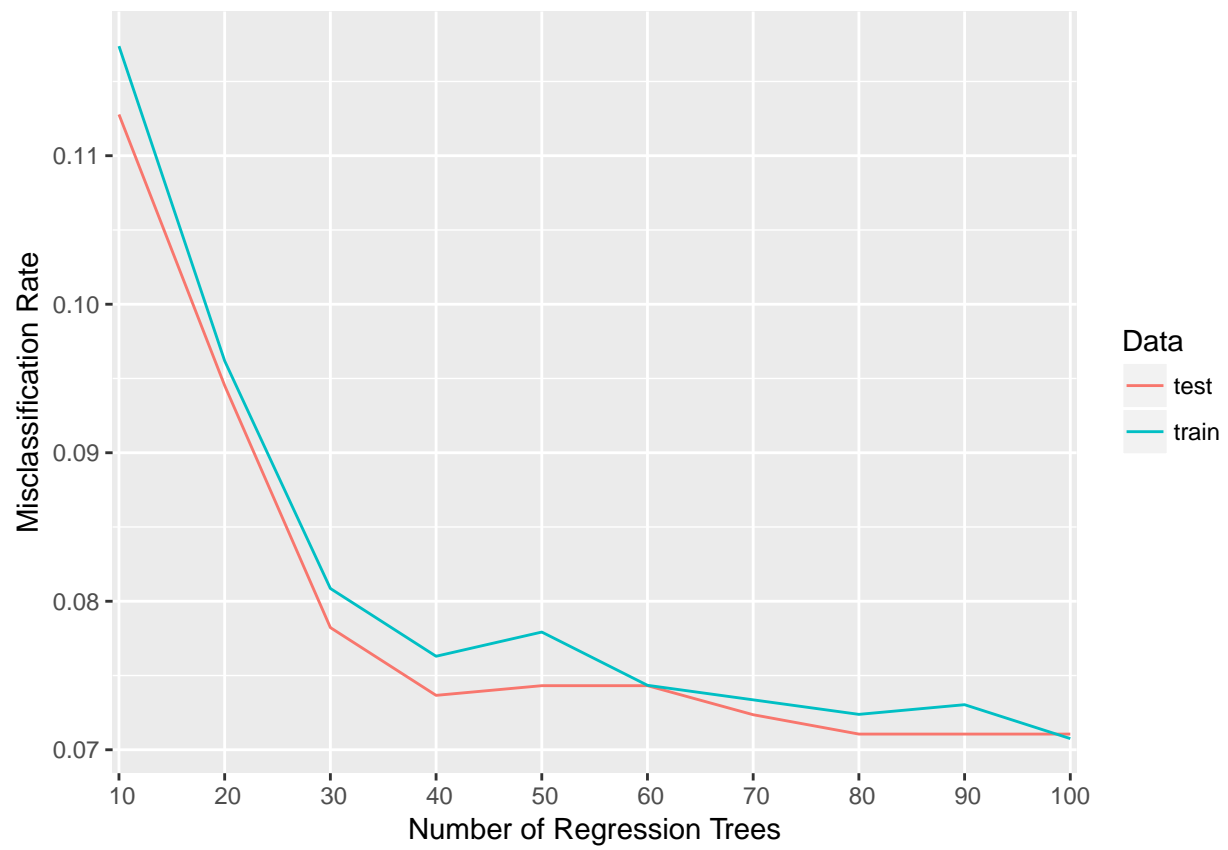
1

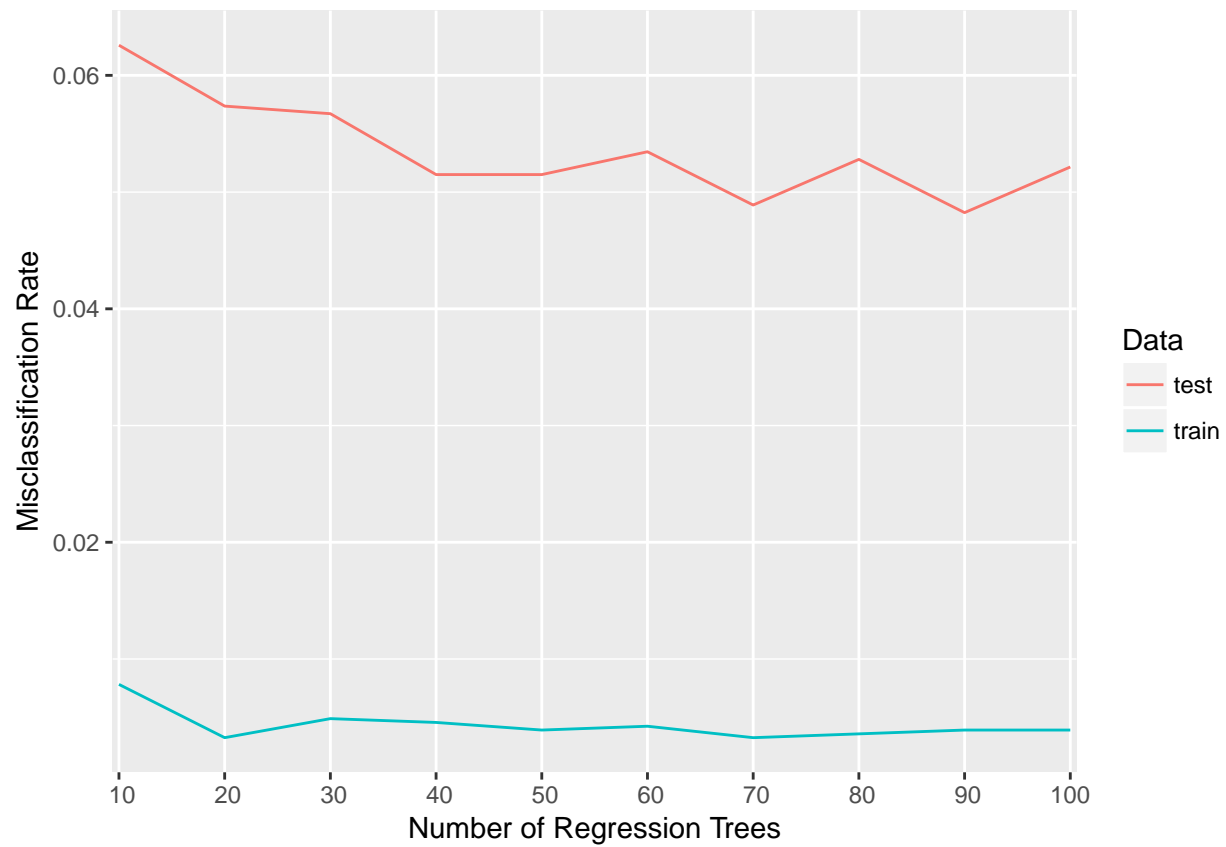


2

```
#> [1] 988.8233  
#> [1] 1433.941
```

Assignment 4a





Appendix

Code for Assignment 1a

Code for Assignment 1b

Code for Assignment 2a

```
library(tree)

data <- read.csv2("../data/bodyfatregression.csv")
names(data) <- c("Waist", "Weight", "Bodyfat")

set.seed(1234567890)
train_idx <- sample(nrow(data), floor(nrow(data) * (2 / 3)))
train <- data[train_idx,]
test <- data[-train_idx,]
set.seed(1234567890)

tree_count <- 100
test_errors <- rep(0, tree_count)

for (i in 1:tree_count) {
  newdata <- train[sample(nrow(train), replace=TRUE),]
  fit <- tree(Bodyfat ~ ., data=newdata, split="deviance")
  test_error <- mean((predict(fit, test) - test$Bodyfat)^2)
  test_errors[i] <- test_error
}

mean(test_errors)
set.seed(1234567890)

tree_count <- 100
k <- 3
errors <- rep(0, tree_count * k)

for (i in 1:tree_count) {
  newdata <- data[sample(nrow(data), replace=TRUE),]
  datasets <- suppressWarnings(split(newdata, 1:k))

  train1 <- rbind(datasets[[1]], datasets[[2]])
  test1 <- datasets[[3]]

  train2 <- rbind(datasets[[1]], datasets[[3]])
  test2 <- datasets[[2]]

  train3 <- rbind(datasets[[2]], datasets[[3]])
  test3 <- datasets[[1]]

  fit1 <- tree(Bodyfat ~ ., data=train1, split="deviance")
  error1 <- mean((predict(fit1, test1) - test1$Bodyfat)^2)
```

```

fit2 <- tree(Bodyfat ~ ., data=train2, split="deviance")
error2 <- mean((predict(fit2, test2) - test2$Bodyfat)^2)

fit3 <- tree(Bodyfat ~ ., data=train3, split="deviance")
error3 <- mean((predict(fit3, test3) - test3$Bodyfat)^2)

errors[(i - 1) * k + 1] <- error1
errors[(i - 1) * k + 2] <- error2
errors[(i - 1) * k + 3] <- error3
}

mean(errors)
bagging.regtrees <- function(formula, data, newdata, b) {
  predictions <- matrix(0, nrow=nrow(newdata), ncol=b)

  for (i in 1:k) {
    bootstrap_sample <- data[sample(nrow(data), replace=TRUE),]
    fit <- tree(formula, data=bootstrap_sample, split="deviance")
    predictions[, i] <- predict(fit, newdata)
  }

  rowMeans(predictions)
}

cv.regtrees <- function(formula, data, newdata, b, k) {
  predictions <- matrix(0, nrow(nrow(newdata)), ncol=b*k)

  for (i in 1:tree_count) {
    bootstrap_sample <- data[sample(nrow(data), replace=TRUE),]
    datasets <- suppressWarnings(split(bootstrap_sample, 1:k))

    train1 <- rbind(datasets[[1]], datasets[[2]])
    test1 <- datasets[[3]]

    train2 <- rbind(datasets[[1]], datasets[[3]])
    test2 <- datasets[[2]]

    train3 <- rbind(datasets[[2]], datasets[[3]])
    test3 <- datasets[[1]]

    fit1 <- tree(Bodyfat ~ ., data=train1, split="deviance")
    prediction1 <- predict(fit1, newdata)

    fit2 <- tree(Bodyfat ~ ., data=train2, split="deviance")
    prediction2 <- predict(fit2, newdata)

    fit3 <- tree(Bodyfat ~ ., data=train3, split="deviance")
    prediction2 <- predict(fit2, newdata)

    predictions[, (i - 1) * k + 1] <- prediction1
    predictions[, (i - 1) * k + 2] <- prediction2
    predictions[, (i - 1) * k + 3] <- prediction3
  }
}

```

```
    rowMeans(predictions)
  }
```

Code for Assignment 2b

Code for Assignment 3a

```
library(mboost)

data <- read.csv2("../data/bodyfatregression.csv")

fit <- blackboost(Bodyfat_percent ~ Waist_cm + Weight_kg, data=data)

cvf <- cv(model.weights(fit), type="kfold")
cvm <- cvrisk(fit, folds=cvf, grid=1:100)
plot(cvm)
set.seed(1234567890)
train_idx <- sample(nrow(data), floor(nrow(data) * (2 / 3)))
train <- data[train_idx,]
test <- data[-train_idx,]

fit <- blackboost(Bodyfat_percent ~ Waist_cm + Weight_kg, data=train,
                  control=boost_control(mstop=mstop(cvm)))
test_error <- sum((predict(fit, test) - test$Bodyfat_percent)^2)
train_error <- sum((predict(fit, train) - train$Bodyfat_percent)^2)

test_error
train_error
```

Code for Assignment 4a

```
library(mboost)
library(randomForest)
library(ggplot2)
library(reshape2)

data <- read.csv2("../data/spambase.csv")
data$Spam <- as.factor(data$Spam)

set.seed(1234567890)
train_idx <- sample(nrow(data), floor(nrow(data) * (2 / 3)))
train <- data[train_idx,]
test <- data[-train_idx,]
tree_counts <- seq(10, 100, by=10)
test_errors <- rep(0, length(tree_counts))
train_errors <- rep(0, length(tree_counts))

for (i in 1:length(tree_counts)) {
  fit <- blackboost(Spam ~ ., data=train, family=AdaExp(),
                    control=boost_control(mstop=tree_counts[i]))
}
```

```

test_error <- 1 - (sum(predict(fit, test, type="class") == test$Spam) / nrow(test))
train_error <- 1 - (sum(predict(fit, train, type="class") == train$Spam) / nrow(train))
test_errors[i] <- test_error
train_errors[i] <- train_error
}
plot_data <- data.frame(Trees=tree_counts, test=test_errors, train=train_errors)
plot_data <- melt(plot_data, id="Trees", value.name="Error", variable.name="Data")

ggplot(plot_data) +
  xlab("Number of Regression Trees") +
  ylab("Misclassification Rate") +
  geom_line(aes(x=Trees, y=Error, color=Data)) +
  scale_x_discrete(limits=tree_counts)
test_errors <- rep(0, length(tree_counts))
train_errors <- rep(0, length(tree_counts))

for (i in 1:length(tree_counts)) {
  fit <- randomForest(Spam ~ ., data=train, ntree=tree_counts[i])
  test_error <- 1 - (sum(predict(fit, test, type="class") == test$Spam) / nrow(test))
  train_error <- 1 - (sum(predict(fit, train, type="class") == train$Spam) / nrow(train))
  test_errors[i] <- test_error
  train_errors[i] <- train_error
}
plot_data <- data.frame(Trees=tree_counts, test=test_errors, train=train_errors)
plot_data <- melt(plot_data, id="Trees", value.name="Error", variable.name="Data")

ggplot(plot_data) +
  xlab("Number of Regression Trees") +
  ylab("Misclassification Rate") +
  geom_line(aes(x=Trees, y=Error, color=Data)) +
  scale_x_discrete(limits=tree_counts)

```