

Introduction to Machine Learning

Lab 2 Block 2

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Assignment 1a

Assumptions:

$$\begin{aligned} \mathbb{E} [\epsilon^b(x)] &= 0, \\ \forall_{i,j}, i \neq j : \mathbb{E} [\epsilon^i(x)\epsilon^j(x)] &= 0 \end{aligned}$$

Prove:

$$\mathbb{E}_X [(f_{bag}(x) - h(x))^2] = \frac{1}{B} \left[\frac{1}{B} \sum_b \mathbb{E}_X [(f^b(x) - h(x))^2] \right]$$

We know:

$$\begin{aligned} f^b(x) &= h(x) + \epsilon^b(x) \\ f_{bag}(x) &= \frac{1}{B} \sum_b f^b(x) \end{aligned}$$

Proof:

$$\begin{aligned} \mathbb{E}_X [(f_{bag}(x) - h(x))^2] &= \\ \mathbb{E}_X \left[\left(\frac{1}{B} \sum_b f^b(x) - h(x) \right)^2 \right] &= \\ \mathbb{E}_X \left[\left(\frac{1}{B} \sum_b \epsilon^b(x) \right)^2 \right] &= \\ \frac{1}{B^2} \mathbb{E}_X [(\epsilon^1(x))^2 + 2\epsilon^1(x)\epsilon^2(x) + \dots + 2\epsilon^{b-1}(x)\epsilon^b(x) + (\epsilon^b(x))^2] &= \\ \frac{1}{B^2} (\mathbb{E}_X [(\epsilon^1(x))^2] + 2\mathbb{E}_X [\epsilon^1(x)\epsilon^2(x)] + \dots + 2\mathbb{E}_X [\epsilon^{b-1}(x)\epsilon^b(x)] + \mathbb{E}_X [(\epsilon^b(x))^2]) &= \\ \frac{1}{B^2} \sum_b \mathbb{E}_X [(\epsilon^b(x))^2] &= \\ \frac{1}{B^2} \sum_b \mathbb{E}_X [(f^b(x) - h(x))^2] &= \\ \frac{1}{B} \left[\frac{1}{B} \sum_b \mathbb{E}_X [(f^b(x) - h(x))^2] \right] \end{aligned}$$

Assignment 2a

1

An estimated upperbound of the squared error of the bagging regression tree using 2/3 of the data set as training data and 1/3 for testing.

```
set.seed(1234567890)
tree_count <- 100
test_errors <- rep(0, tree_count)

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

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)
#> [1] 37.20882
```

2

An estimated upperbound of the squared error of the bagging regression tree using 3-fold cross-validation.

```
set.seed(1234567890)
tree_count <- 100
fold_count <- 3
test_errors <- matrix(0, nrow=tree_count, ncol=fold_count)

folds <- suppressWarnings(split(1:nrow(data), f=1:fold_count))

for (j in 1:fold_count) {
  train <- data[-folds[[j]],]
  test <- data[folds[[j]],]

  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, j] <- test_error
  }
}

mean(test_errors)
#> [1] 40.19377
```

3

The resulting bagging regression tree and its predicted value where data is the complete data set and newdata is the data to predict. I would return this result for both the techniques used to estimate the upperbound of the squared error.

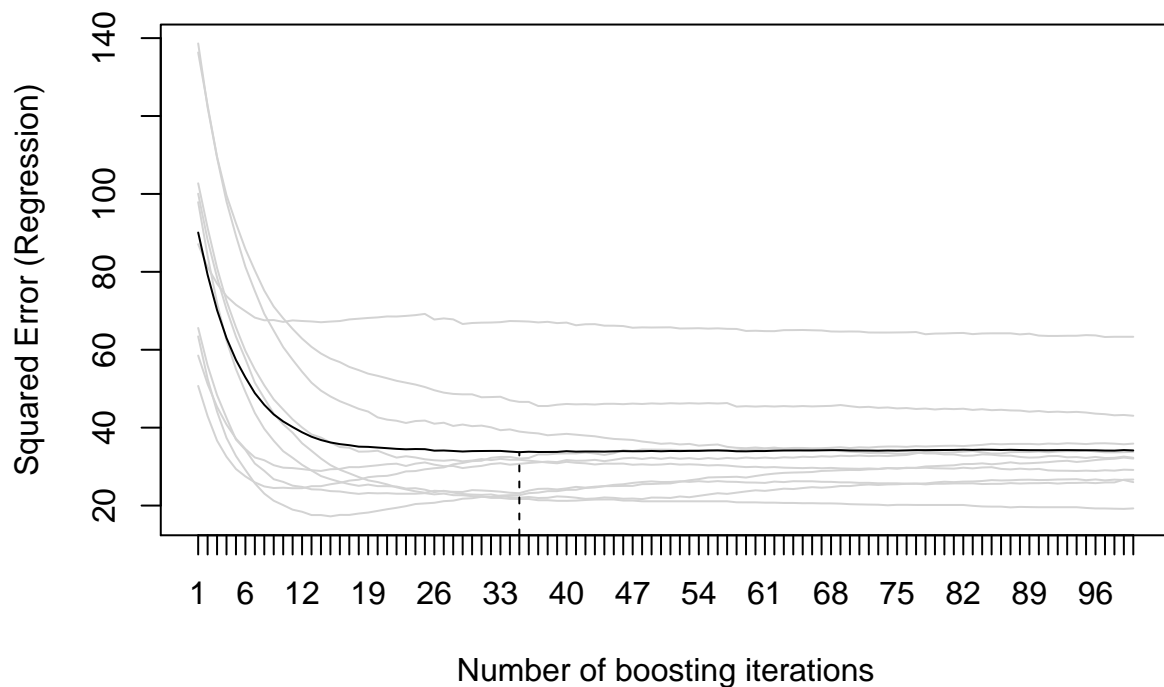
```
bagging.regtrees <- function(formula, data, newdata, b) {  
  predictions <- matrix(0, nrow=nrow(newdata), ncol=b)  
  trees <- list()  
  
  for (i in 1:b) {  
    bootstrap_sample <- data[sample(nrow(data), replace=TRUE),]  
    fit <- tree(formula, data=bootstrap_sample, split="deviance")  
    trees[[i]] <- fit  
    predictions[, i] <- predict(fit, newdata)  
  }  
  
  list(trees=trees, predictions=rowMeans(predictions))  
}
```

Assignment 3a

1

In boosting the number of iterations is a hyper-parameter and the plot below shows estimated squared errors using 10-fold cross-validation as the number of iterations increases from 1 to 100. The gray curves are the mean squared errors from each validation set and the black curve shows the mean of the those errors. The optimal seems to be around 35 iterations. By the elbow method we would rather choose around 15-19 iterations.

10-fold kfold



2

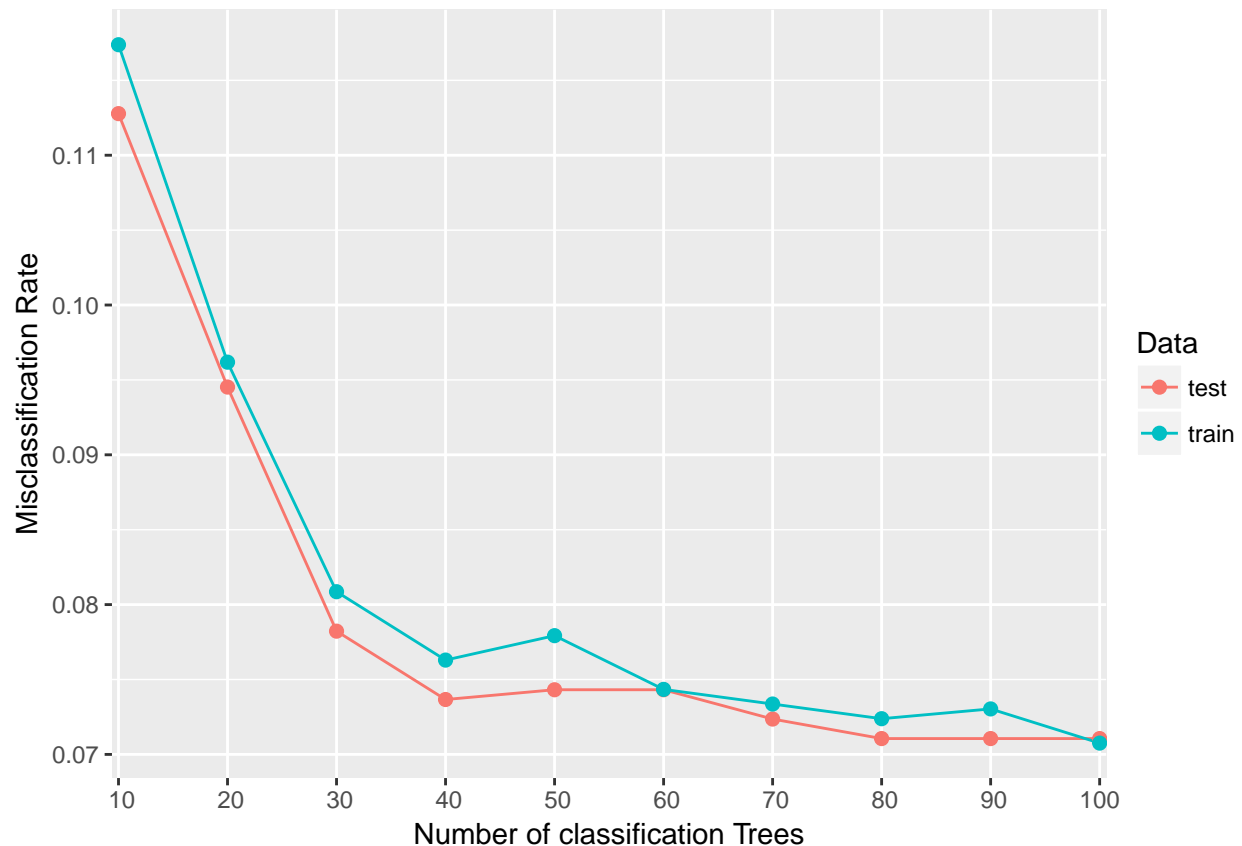
Here I used 2/3 of the data for training and 1/3 as test data and created a boosting regression tree using the optimal number of iterations, i.e. the number of trees, found above. The squared errors for the two data sets were the following.

```
#> Test Error: 954.394614354515  
#> Train Error: 1530.30207953437
```

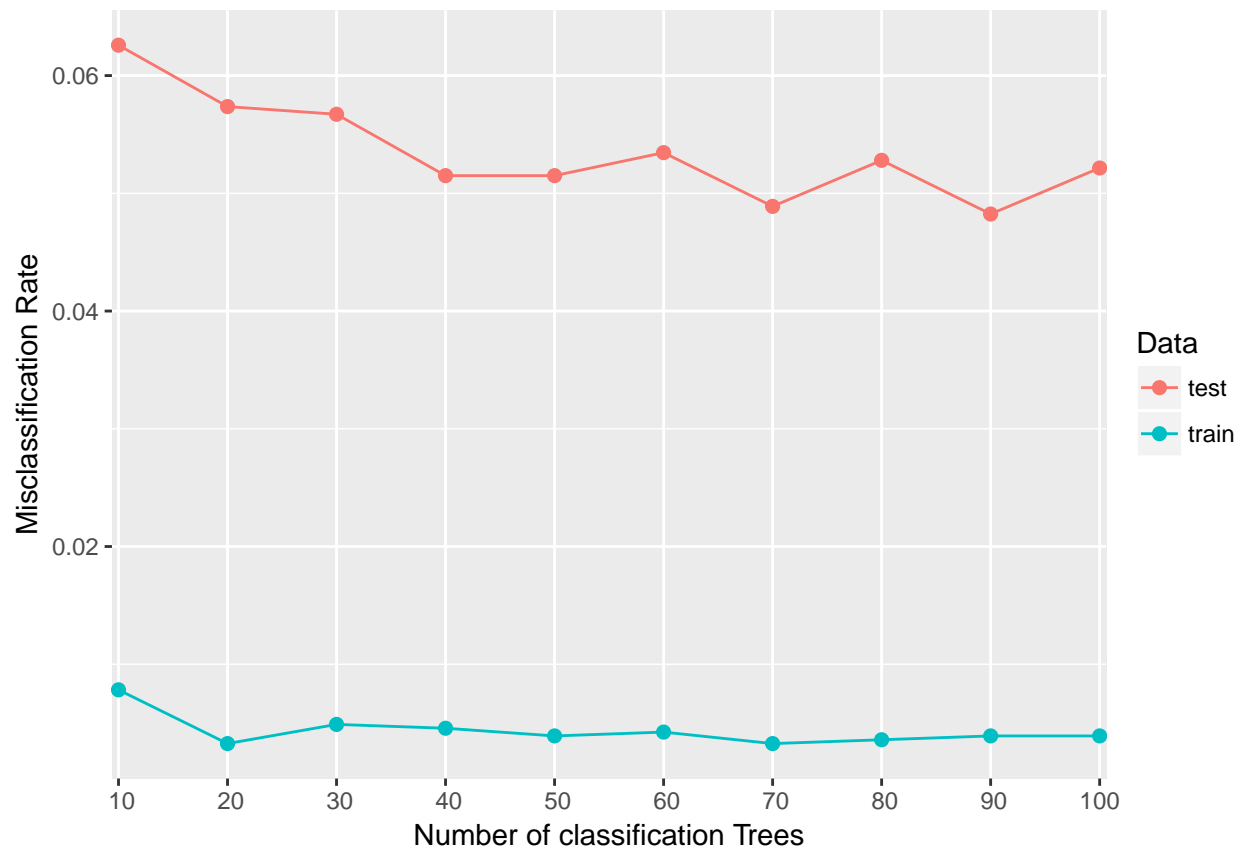
Assignment 4a

In this exercise I have used Adaboost classification trees and random forests to evaluate their performance on spam data. The data set have been divided into two parts, 2/3 for training and 1/3 as test data.

The performance of the Adaboost classification trees can be seen below. We can see that the optimal would be roughly 40 trees then it barely decreases as the number of trees grows. At 80 trees the test error seems to halt so if you want to push the limit and create a substantially more complex model it may be preferable to use 80 trees. However, since the error on the test data stops monotonically decrease after 40 trees that is the choice I would choose.



The performance of the random forest can be seen below. Same as above, the test error seem to stop monotonically decreasing after 40 trees and that should be the preferred choice. We can see that the train error barely moves as the number of trees increases after 20 trees so the model have almost fit the training data perfectly with 20 trees.



Assignment 1b

```
x_given_mu <- function(x, mu) {
  x_mu <- matrix(1, nrow=nrow(x), ncol=nrow(mu))

  for (n in 1:N) {
    for (k in 1:K) {
      for (i in 1:D) {
        prob <- mu[k, i]^x[n, i] * (1 - mu[k, i])^(1 - x[n, i])
        x_mu[n, k] <- x_mu[n, k] * prob
      }
    }
  }

  x_mu
}

expectation.step <- function(x, x_given_mu, pi) {
  z <- matrix(nrow=nrow(x), ncol=length(pi))

  for (n in 1:N) {
    denominator <- sum(pi * x_given_mu[n,])

    for (k in 1:K) {
      nominator <- pi[k] * x_given_mu[n, k]

      z[n, k] <- nominator / denominator
    }
  }

  z
}

loglikelihood <- function(x, x_given_mu, pi) {
  llik <- 0
  for (n in 1:N) {
    inner_summation <- 0
    for (k in 1:K) {
      inner_summation <- inner_summation + pi[k] * x_given_mu[n, k]
    }
    llik <- llik + log(inner_summation)
  }

  llik
}

maximization.step <- function(x, z) {
  pi <- vector(length=ncol(z))
  mu <- matrix(nrow=ncol(z), ncol=ncol(x))

  for (k in 1:K) {
    pi[k] <- sum(z[, k]) / nrow(x)
  }
}
```



```

}

for (k in 1:K) {
  denominator <- sum(z[, k])
  for (i in 1:D) {
    nominator <- sum(x[, i] * z[, k])
    mu[k, i] <- nominator / denominator
  }
}

list(pi=pi, mu=mu)
}

EM <- function(N, D, K, max_it, min_change, true_pi, true_mu) {

  ## Producing the training data
  x <- matrix(nrow=N, ncol=D)

  for(n in 1:N) {
    k <- sample(1:K, 1, prob=true_pi)
    for(d in 1:D) {
      x[n, d] <- rbinom(1, 1, true_mu[k, d])
    }
  }

  z <- matrix(nrow=N, ncol=K) # fractional component assignments
  pi <- vector(length=K) # mixing coefficients
  mu <- matrix(nrow=K, ncol=D) # conditional distributions
  llik <- vector(length=max_it) # log likelihood of the EM iterations

  ## Random initialization of the paramters
  pi <- runif(K, 0.49, 0.51)
  pi <- pi / sum(pi)
  for(k in 1:K) {
    mu[k,] <- runif(D, 0.49, 0.51)
  }

  for(it in 1:max_it) {
    x_mu <- x_given_mu(x, mu)

    ## E-step: Computation of the fractional component assignments
    z <- expectation.step(x, x_mu, pi)

    ## Log likelihood computation.
    llik[it] <- loglikelihood(x, x_mu, pi)

    ## Stop if the log likelihood has not changed significantly
    if (it > 1 && abs(llik[it] - llik[it-1]) < min_change) break

    ## M-step: ML parameter estimation from the data and fractional component assignments
    result <- maximization.step(x, z)
    pi <- result$pi
    mu <- result$mu
  }
}

```

```

    }

    list(pi=pi, mu=mu, llik=llik, it=it)
}

max_it <- 100 # max number of EM iterations
min_change <- 0.1 # min change in log likelihood between two consecutive EM iterations

N <- 1000 # number of training points
D <- 10 # number of dimensions
K <- 3 # number of guessed components

## true mixing coefficients
true_pi <- vector(length=3)
true_pi <- c(1/3, 1/3, 1/3)

## true conditional distributions
true_mu <- matrix(nrow=3, ncol=D)
true_mu[1,] <- c(0.5, 0.6, 0.4, 0.7, 0.3, 0.8, 0.2, 0.9, 0.1, 1)
true_mu[2,] <- c(0.5, 0.4, 0.6, 0.3, 0.7, 0.2, 0.8, 0.1, 0.9, 0)
true_mu[3,] <- c(0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5)

```

Assignment 2b

The plot below shows the three true multivariate Bernoulli distributions from which the data set have been generated.

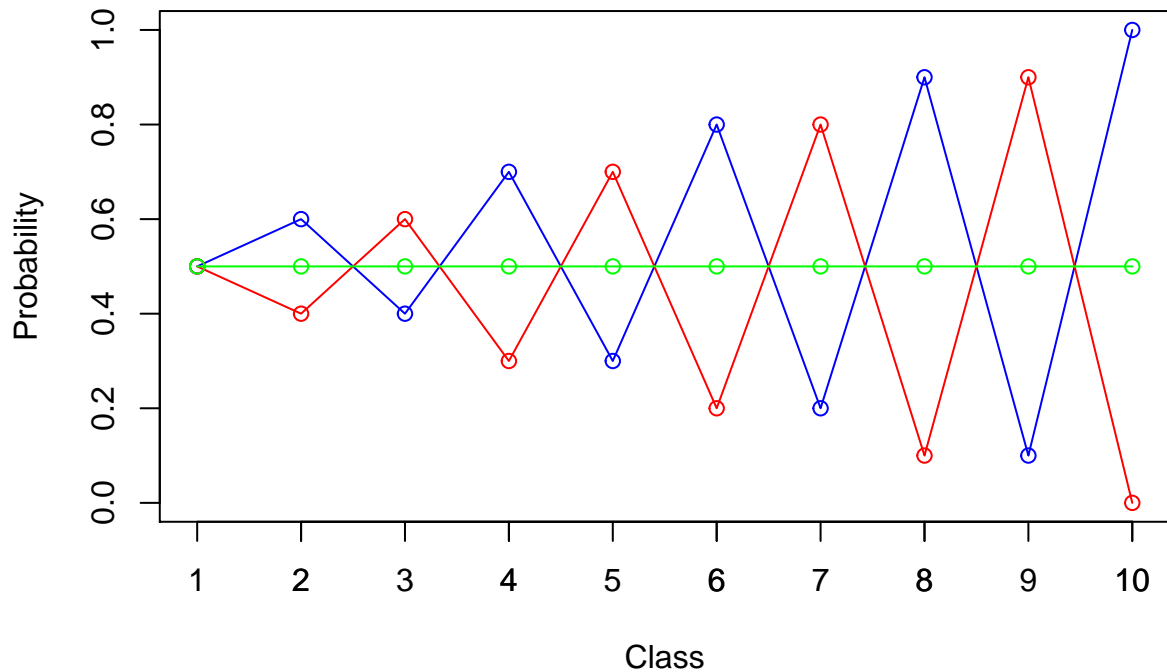


Figure 1: The true probabilities of the multivariate Bernoulli distributions.

The plot below shows two multivariate Bernoulli distributions estimated by the expectation-maximization (EM) algorithm. We can see that the multivariate Bernoulli with equal probabilities for each class has not affected EM particular much in order to find the other two distributions. This is probably because equal probabilities even out in the long run, i.e. the noise from that distribution is approximately equal for both sides of the coin.

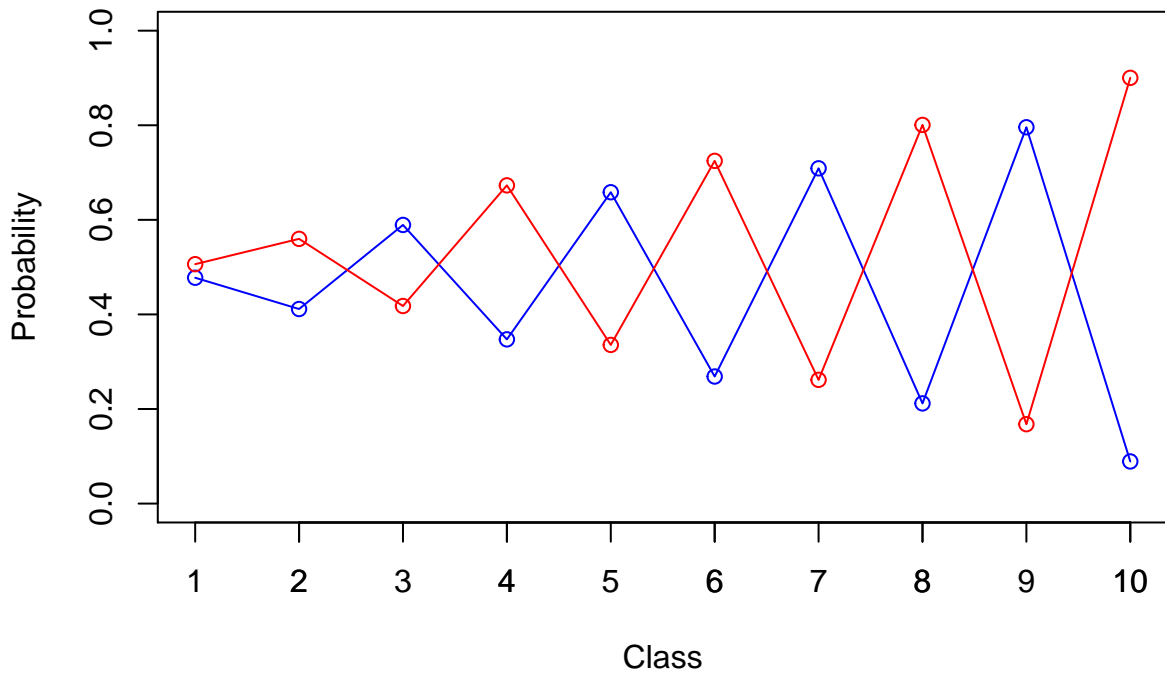


Figure 2: The estimated probabilities of the multivariate Bernoulli distributions.

The prior probabilities for each distribution.

```
#> [1] 0.497125 0.502875
```

The plot below shows the log-likelihood versus the number of iterations.

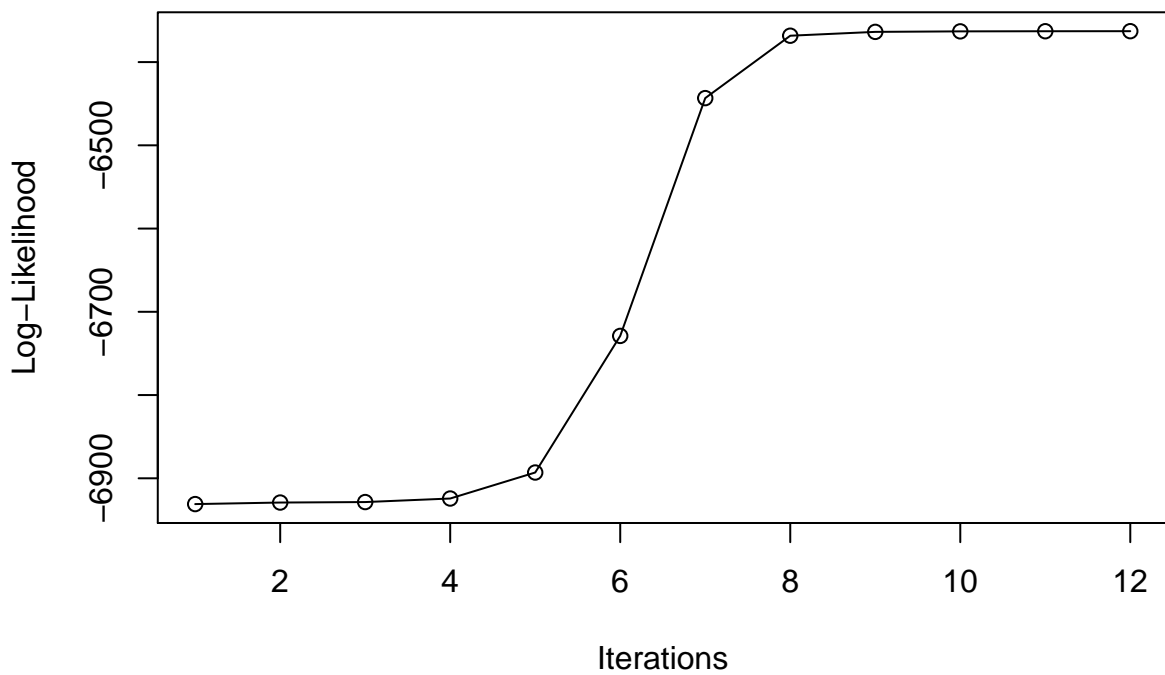


Figure 3: The log-likelihood versus the number of iterations.

The plot below shows three multivariate Bernoulli distributions estimated by the EM algorithm. The

distributions found are pretty similar to the true ones with exception of the uniform one which have been influenced by the other two distributions and/or bad luck on the coin flips that have resulted in seemingly unfair coins.

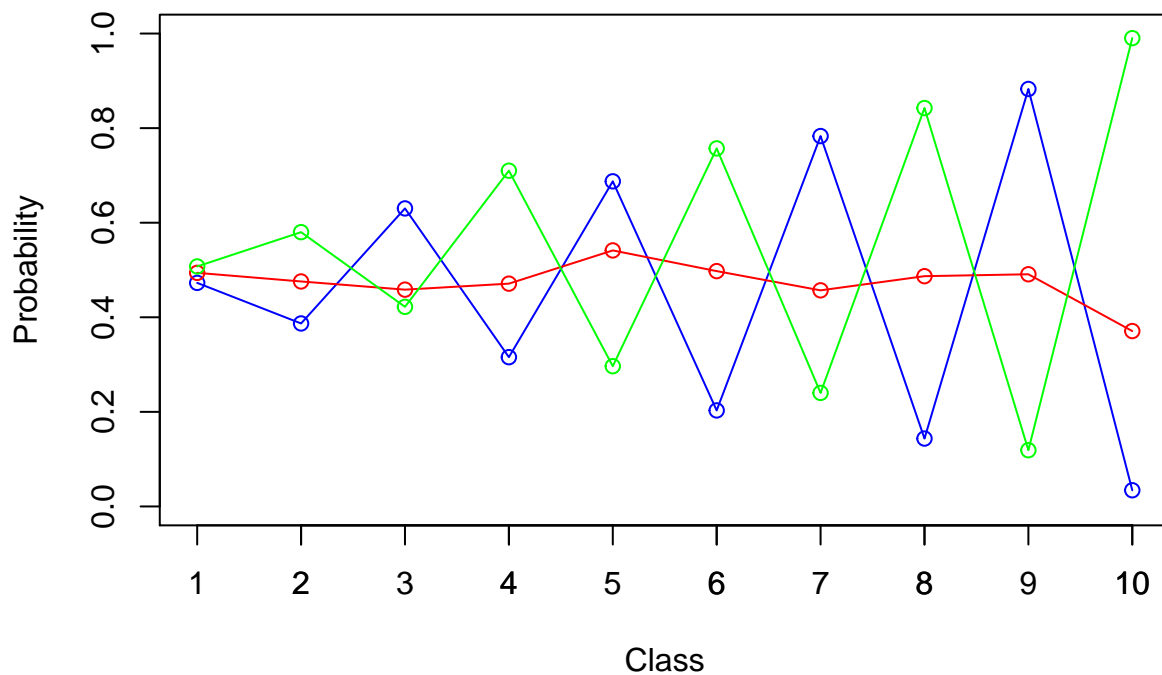


Figure 4: The estimated probabilities of the multivariate Bernoulli distributions.

The prior probabilities for each distribution.

```
#> [1] 0.3416794 0.2690298 0.3892909
```

The plot below shows the log-likelihood versus the number of iterations.

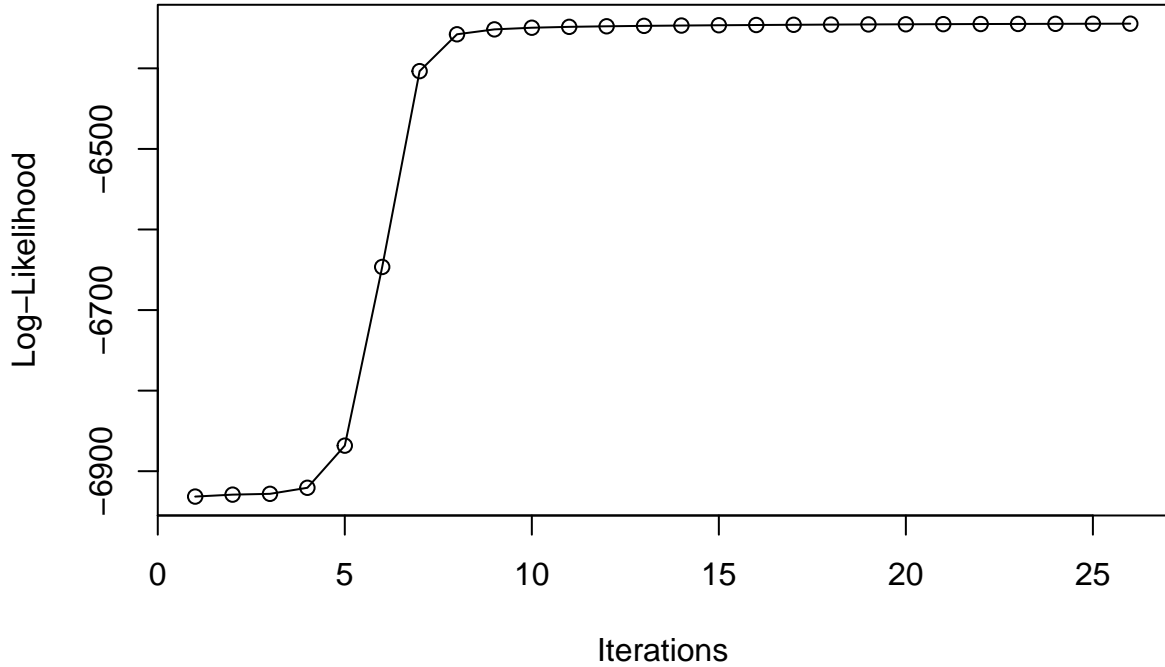


Figure 5: The log-likelihood versus the number of iterations.

The plot below shows four multivariate Bernoulli distributions estimated by the EM algorithm. The blue and red curves are quite chaotic that do not resemble any of the true ones but taking the average would approximate the multivariate Bernoulli distribution with uniform parameters pretty well. So the EM algorithm have basically modelled two distributions based on the noise from the uniform one which is not surprising given that there are only three true distributions and that one is the most unpredictable.

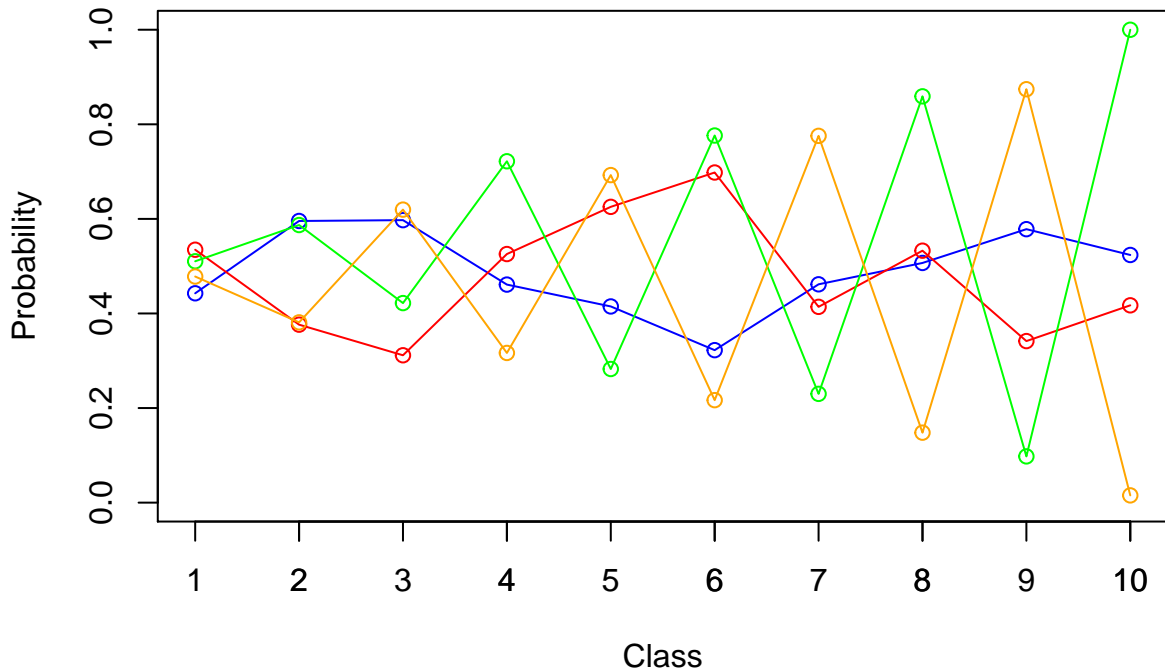


Figure 6: The estimated probabilities of the multivariate Bernoulli distributions.

The prior probabilities for each distribution.

```
#> [1] 0.1547196 0.1418652 0.3514089 0.3520062
```

The plot below shows the log-likelihood versus the number of iterations.

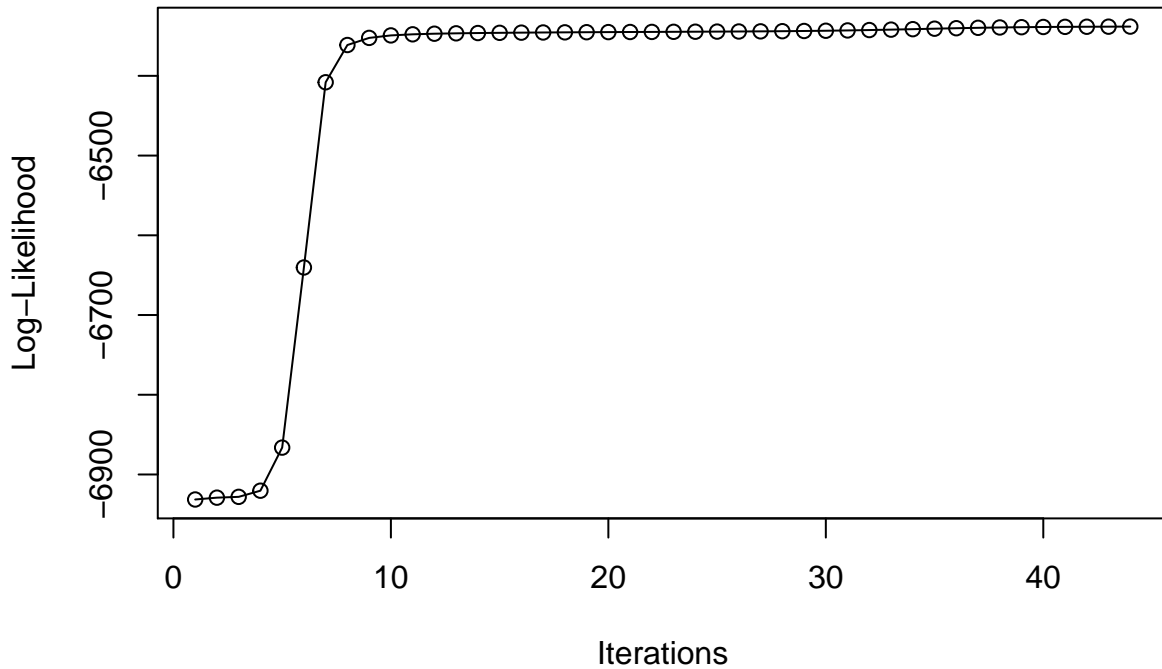


Figure 7: The log-likelihood versus the number of iterations.

The maximum log-likelihood have been found after roughly 10 iterations for all experiments which indicates that it does not really matter in terms of iterations how many distributions the EM tries to find. However, the more distributions the more fluctuations in the log-likelihood after each iterations which may suggest that the threshold should be a function of the number of distributions.

Appendix

Code for Assignment 2a

```
library(tree)

data <- read.csv2("../data/bodyfatregression.csv")
names(data) <- c("Waist", "Weight", "Bodyfat")
set.seed(1234567890)
tree_count <- 100
test_errors <- rep(0, tree_count)

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

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
fold_count <- 3
test_errors <- matrix(0, nrow=tree_count, ncol=fold_count)

folds <- suppressWarnings(split(1:nrow(data), f=1:fold_count))

for (j in 1:fold_count) {
  train <- data[-folds[[j]],]
  test <- data[folds[[j]],]

  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, j] <- test_error
  }
}

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

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



```

    trees[[i]] <- fit
    predictions[, i] <- predict(fit, newdata)
  }

  list(trees=trees, predictions=rowMeans(predictions))
}

```

Code for Assignment 3a

```

library(mboost)

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

set.seed(1234567890)
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)

cat(paste("Test Error:", test_error, "\n"))
cat(paste("Train Error:", train_error, "\n"))

```

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 classification Trees") +
  ylab("Misclassification Rate") +
  geom_line(aes(x=Trees, y=Error, color=Data)) +
  geom_point(aes(x=Trees, y=Error, color=Data), size=2) +
  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 classification Trees") +
  ylab("Misclassification Rate") +
  geom_line(aes(x=Trees, y=Error, color=Data)) +
  geom_point(aes(x=Trees, y=Error, color=Data), size=2) +
  scale_x_discrete(limits=tree_counts)

```

Code for Assignment 2b

```

plot(true_mu[1,], type="o", col="blue", ylim=c(0,1),
     xlab="Class", ylab="Probability")
axis(side=1, at=c(1:D))
points(true_mu[2,], type="o", col="red")
points(true_mu[3,], type="o", col="green")
set.seed(1234567890)

K <- 2
result <- EM(N, D, K, max_it, min_change, true_pi, true_mu)
mu <- result$mu
pi <- result$pi
llik <- result$llik
it <- result$it

```

```

plot(mu[1,], type="o", col="blue", ylim=c(0,1),
      xlab="Class", ylab="Probability")
axis(side=1, at=c(1:D))
points(mu[2,], type="o", col="red")
plot(llik[1:it], type="o", xlab="Iterations",
      ylab="Log-Likelihood")
set.seed(1234567890)

K <- 3
result <- EM(N, D, K, max_it, min_change, true_pi, true_mu)
mu <- result$mu
pi <- result$pi
llik <- result$llik
it <- result$it
plot(mu[1,], type="o", col="blue", ylim=c(0,1),
      xlab="Class", ylab="Probability")
axis(side=1, at=c(1:D))
points(mu[2,], type="o", col="red")
points(mu[3,], type="o", col="green")
plot(llik[1:it], type="o", xlab="Iterations",
      ylab="Log-Likelihood")
set.seed(1234567890)

K <- 4
result <- EM(N, D, K, max_it, min_change, true_pi, true_mu)
mu <- result$mu
pi <- result$pi
llik <- result$llik
it <- result$it
plot(mu[1,], type="o", col="blue", ylim=c(0,1),
      xlab="Class", ylab="Probability")
axis(side=1, at=c(1:D))
points(mu[2,], type="o", col="red")
points(mu[3,], type="o", col="green")
points(mu[4,], type="o", col="orange")
plot(llik[1:it], type="o", xlab="Iterations",
      ylab="Log-Likelihood")

```