Homework 2

CS 498, Spring 2018, Xiaoming Ji

The UC Irvine machine learning data repository hosts a collection of data on adult income, donated by Ronny Kohavi and Barry Becker. You can find this data at https://archive.ics.uci.edu/ml/datasets/Adult For each record, there is a set of continuous attributes, and a class "less than 50K" or "greater than 50K". There are 48842 examples. You should use only the continuous attributes (see the description on the web page) and drop examples where there are missing values of the continuous attributes. Separate the resulting dataset randomly into 10% validation, 10% test, and 80% training examples.

Write a program to train a support vector machine on this data using stochastic gradient descent. We will ignore the id number, and use the continuous variables as a feature vector. You should scale these variables so that each has unit variance. We will search for an appropriate value of the regularization constant, trying at least the values [1e-3, 1e-2, 1e-1, 1]. Use the validation set for this search. We will use at least 50 epochs of at least 300 steps each. In each epoch, we will separate out 50 training examples at random for evaluation (call this the set held out for the epoch). We will compute the accuracy of the current classifier on the set held out for the epoch every 30 steps. We will produce:

- A plot of the accuracy every 30 steps, for each value of the regularization constant.
- A plot of the magnitude of the coefficient vector every 30 steps, for each value of the regularization constant.
- Estimate of the best value of the regularization constant, together with a brief description of why you believe that is a good value.
- Estimate of the accuracy of the best classifier on the 10% test dataset data.

```r
library(readr)
set.seed(19720816)

#Read data from 2 data files and combine them
data1 = read.csv("./data/adult.data", header = FALSE)[,c(1, 3, 5, 11, 12, 13, 15)]
data2 = read.csv("./data/adult.test", header = FALSE, skip = 1)[,c(1, 3, 5, 11, 12, 13, 15)]
str(data1)
```

```
## 'data.frame':    32561 obs. of  7 variables:
##  $ V1 : int  39 50 38 53 28 37 49 52 31 42 ...
##  $ V3 : int  77516 83311 215646 234721 338409 284582 160187 209642 45781 159449 ...
##  $ V5 : int  13 13 9 7 13 14 5 9 14 13 ...
##  $ V11: int  2174 0 0 0 0 0 0 0 14084 5178 ...
##  $ V12: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ V13: int  40 13 40 40 40 40 16 45 50 40 ...
##  $ V15: Factor w/ 2 levels " <=50K"," >50K": 1 1 1 1 1 1 1 2 2 2 ...
```

```r
str(data2)
```

```
## 'data.frame':    16281 obs. of  7 variables:
##  $ V1 : int  25 38 28 44 18 34 29 63 24 55 ...
##  $ V3 : int  226802 89814 336951 160323 103497 198693 227026 104626 369667 104996 ...
##  $ V5 : int  7 9 12 10 10 6 9 15 10 4 ...
##  $ V11: int  0 0 0 7688 0 0 0 3103 0 0 ...
##  $ V12: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ V13: int  40 50 40 40 30 30 40 32 40 10 ...
##  $ V15: Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1 1 ...
```

```r
data1[, 7] = as.numeric(data1[, 7])
data1[data1[, 7] == 1, 7] = -1
```

```
data1[data1[, 7] == 2, 7] = 1

data2[, 7] = as.numeric(data2[, 7])
data2[data2[, 7] == 1, 7] = -1
data2[data2[, 7] == 2, 7] = 1

adult_data = rbind(data1, data2)

#Normalize the data
for (i in 1:6) {
  s = sd(adult_data[,i])
  m = mean(adult_data[,i])

  adult_data[,i] = (adult_data[,i] - m) / s
}

#Calculate train/validation/test split
total_count = dim(adult_data)[1]
test_count = round(total_count * 0.1)
valid_count = round(total_count * 0.1)

test_indexes = sample(1:total_count,test_count)
```

We don't see missing data.

$$a^{(n+1)} = a^n - \frac{\eta}{N_b}(\sum_i^{N_b} \begin{cases} 0 & \text{if } y_i(a^T x_i + b) \geq 1 \\ -y_i x_i & otherwise \end{cases} + \lambda a)$$

$$b^{(n+1)} = b^n - \frac{\eta}{N_b} \sum_i^{N_b} \begin{cases} 0 & \text{if } y_i(a^T x_i + b) \geq 1 \\ -y_i & otherwise \end{cases}$$

$$\beta^T X + \beta_0$$

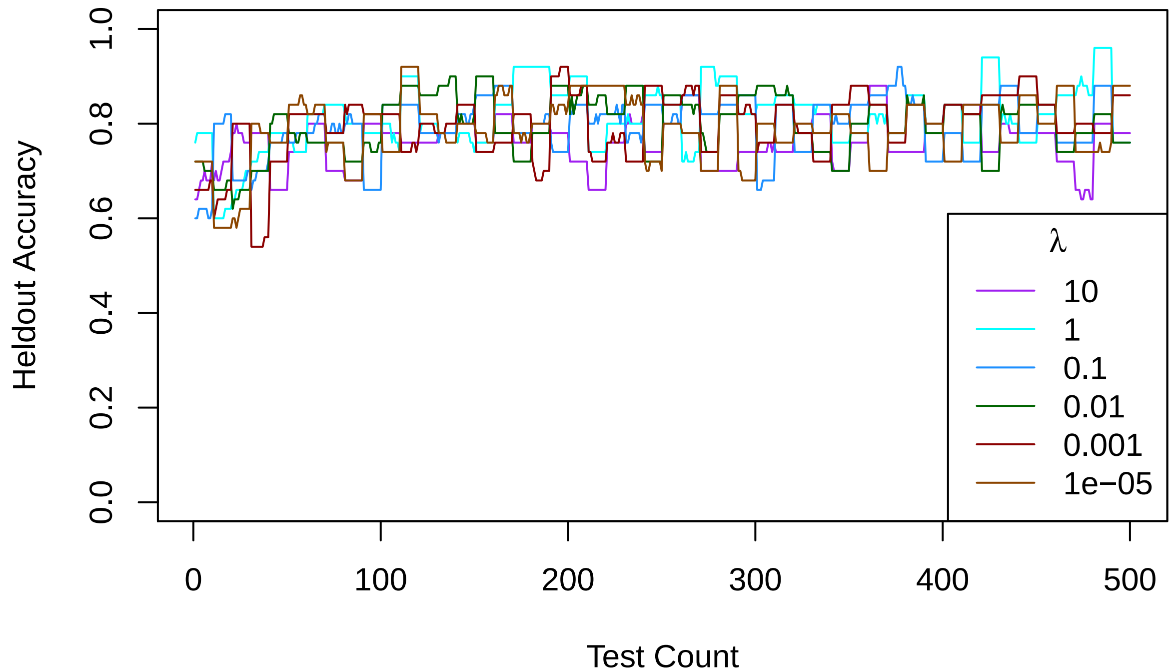
```
predict = function(a, b, features) {
  pred_y = c(a %*% t(features) + b)
  pred_y[pred_y <= 0] = -1
  pred_y[pred_y > 0] = 1

  return (pred_y)
}

sgd = function(epoch, n_steps, sample_count, valid_count, heldout_count, steps_before_testing, data, pa
  feature_count = dim(data)[2] - 1
  accuracy = c()
  w = c()
  v_a = parameters[1:feature_count]
  b = parameters[feature_count + 1]
  heldout_accuracies = rep(0, epoch * n_steps / steps_before_testing)
  coef_magnitude     = rep(0, length(heldout_accuracies))
  valid_accuracies   = rep(0, epoch)

  total_step = 1
```

```
  test_count = 1

  for (epoch in 1:epoch) {
    #split heldout_data
    heldout_indexes = sample(1: dim(data)[1], heldout_count)
    heldout_data = data[heldout_indexes,]
    #make the remaining the test and validation data
    r_indexes     = (1: dim(data)[1])[-heldout_indexes]
    train_indexes = sample(1:length(r_indexes), length(r_indexes) - valid_count)
    train_data  = data[r_indexes[train_indexes], ]
    valid_data  = data[r_indexes[-train_indexes],]
    steplength  = 1 / (0.01 * epoch + 50)

    for (step in 1:n_steps){
      sample_indexes = sample(1:dim(train_data)[1], sample_count)
      x = train_data[sample_indexes, 1:feature_count]
      y = train_data[sample_indexes, feature_count + 1]

      h = y * (v_a %*% t(x) + b)

      #update a and b
      v_a = v_a - steplength/sample_count * (colSums(-y[h < 1] * x[h < 1,]) + lambda * v_a)
      b   = b - steplength/sample_count * sum(-y[h < 1])

      if(total_step %% steps_before_testing == 0){
        pred_y = predict(v_a, b, heldout_data[, 1:feature_count])
        heldout_accuracies[test_count] = sum(pred_y == heldout_data[, feature_count + 1]) / heldout_cou
        coef_magnitude[test_count] = sqrt(t(v_a) %*% v_a + b ^ 2)
        test_count = test_count + 1
      }
      total_step = total_step + 1
    }
    #calculate accuracy on validation data
    pred_y = predict(v_a, b, valid_data[, 1:feature_count])
    valid_accuracies[epoch] =  sum(pred_y == valid_data[, feature_count + 1]) / length(pred_y)
  }
  return (list(a = v_a, b = b,
               heldout_accuracies = heldout_accuracies,
               coef_magnitude = coef_magnitude,
               valid_accuracies = valid_accuracies))
}

lambdas =  c(10, 1, 1e-1, 1e-2, 1e-3, 1e-5)
params = runif(7, 0, 10)
results = list()

for (i in 1:length(lambdas)){
  results[[i]] = sgd(50, 300, 50, valid_count, 50, 30, adult_data[-test_indexes,], params, lambdas[i])
}
```

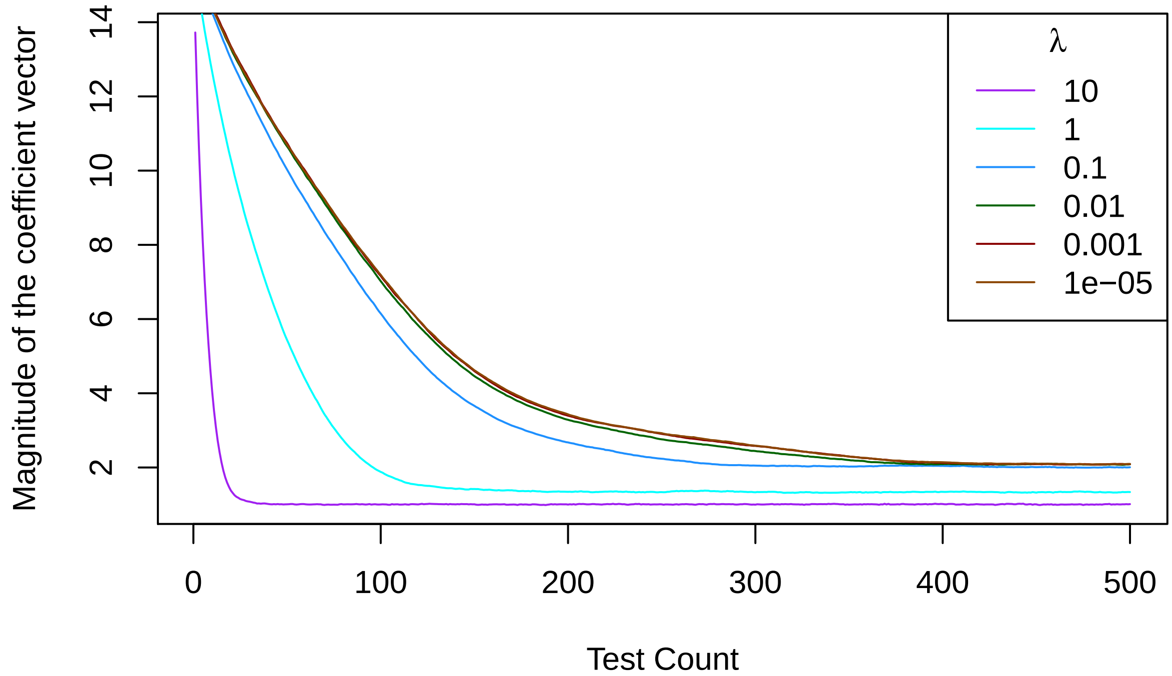
Draw diagram

```
colors = c("purple", "cyan", "dodgerblue", "darkgreen", "darkred", "darkorange4")
```

```r
plot(1:500, results[[1]]$heldout_accuracies, type = "l", ylim=c(0,1), xlab="Test Count", ylab="Heldout A

for (i in 2:length(lambdas)) {
  lines(1:500, results[[i]]$heldout_accuracies, col=colors[i])
}

legend("bottomright", title = expression(lambda), legend = lambdas, lwd = 1, col = colors)
```




```r
plot(1:500, results[[1]]$coef_magnitude, type = "l", xlab="Test Count", ylab="Magnitude of the coeffici

for (i in 2:length(lambdas)) {
  lines(1:500, results[[i]]$coef_magnitude, col=colors[i])
}

legend("topright", title = expression(lambda), legend = lambdas, lwd = 1, col = colors)
```




```
df = data.frame()
for (i in 1:length(lambdas)){
  df = rbind(df, data.frame(y = results[[i]]$valid_accuracies, lambda=lambdas[i]))
}

boxplot(y ~ lambda, data = df, xlab=expression(lambda), ylab="Validation Accuracy", pch = 20, cex = 2,
```