SVM_Amitesh_Shukla

```
data1<-read.csv('adult.data',header=FALSE, stringsAsFactors = FALSE)
data2<-read.csv('adult.test', header=FALSE)
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
cdata <- rbind(data1, data2)
cdata$V15[cdata$V15 == " <=50K."] <- -1
cdata$V15[cdata$V15 == " >50K."]<-  1
cdata$V15[cdata$V15 == " <=50K"] <- -1
cdata$V15[cdata$V15 == " >50K"]<-  1
cdata<-cdata[!(cdata$V15==""),]

cdata<-cdata[,-c(2,4,6,7,8,9,10,14)]
cdata$V15<-as.numeric(cdata$V15)
cdata$V1<-as.numeric(cdata$V1)

#Tranform the variables for unit variance
vectorclass<- cdata[7]
vectorclass$V15<-as.numeric(vectorclass$V15)
scaledcdata <- scale(cdata[,], center = FALSE, scale = apply(cdata[,], 2, sd, na.rm = TRUE))
scaledcdata <- as.data.frame(scaledcdata)
scaledcdata <- within(scaledcdata, V15[V15 < 1] <- -1)
scaledcdata <- within(scaledcdata, V15[V15 > 1] <- 1)

partition_idx_1 = createDataPartition(y=scaledcdata$V15, p=.9, list=F, groups=2)
trainingData = scaledcdata[partition_idx_1,]
testData = scaledcdata[partition_idx_1,]
partition_idx_2 = createDataPartition(y=scaledcdata$V15, p=.89, list=F, groups=2)
validationData = trainingData[partition_idx_2,]

a <- matrix(data=NA,nrow=6,ncol=1)
a_list <- matrix(data=NA,nrow=6,ncol=4)
batchsample <- matrix(data=NA,nrow=1,ncol=7)
vec <- matrix(data=NA,nrow=1,ncol=6)
eval_sample <- matrix(data=NA,nrow=50,ncol=7)
training_score<-array(dim=10)
validate_score<-array(dim=50)
lamda_accuracy<-matrix(data=NA,nrow=4,ncol=500)
epoch_accuracy<-array(dim = 500)
epoch_steps<-array(dim = 500)
coef_mag<-matrix(data=NA,nrow=4,ncol=500)
detr = 0
b = 0
b_list <-array(dim=4)
```

#Regularization: Finding appropriate gamma on training and validation data

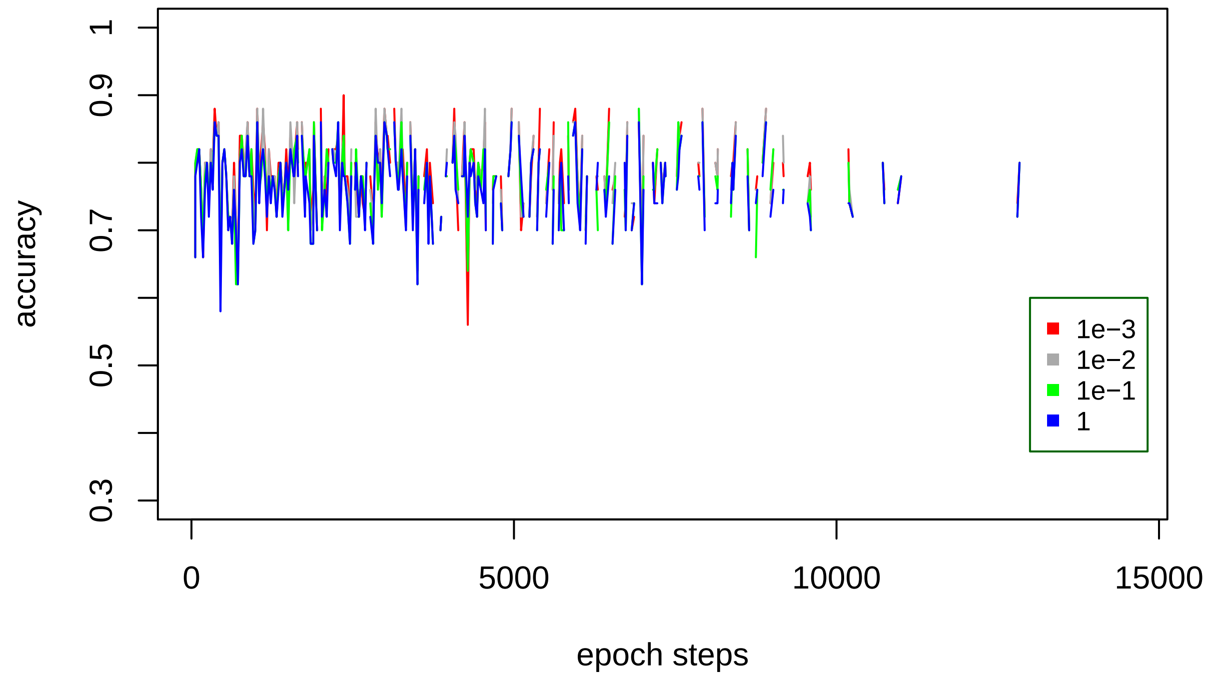
```
stochastic_gradient_descent <- function(lambda,l) {
  set.seed(150)
  a <<- matrix(c(0.01, 0.01, 0.1, 0, 0, 0.2),nrow=6, ncol=1)
  for (epoch in 1:50) {
    #Hold 50 random training examples for evaluation at every 30 steps
    eval_sample<<-trainingData[sample(nrow(trainingData),size=50),]
    steplength = 1/(0.01*epoch + 50)
    sl = steplength*lambda
    counter = 1;
    for (steps in 1:300) {
         if (counter == 30) {
           for (i in 1:50) {
               validate<-as.matrix(eval_sample[i,-7])
               vlable<-eval_sample[i,7]
               cond<-(t(a)%*%as.vector(validate))+b
               if (cond > 1) {
                   result = 1
               } else {
                   result = -1
               }
               gotrightvalidate <- result == vlable
               validate_score[i]<<-sum(gotrightvalidate)/
                  (sum(gotrightvalidate)+sum(!gotrightvalidate))
           }
           average_accuracy <- sum(validate_score)/50
           lamda_accuracy[l,epoch*(steps/30)]<<-average_accuracy
           coef_mag[l,epoch*(steps/30)]<<- t(a)%*%a
           epoch_steps[epoch*(steps/30)]<<-epoch*steps
           epoch_accuracy[epoch*(steps/30)]<<-epoch
           counter = 1;
         }
         counter = counter + 1
         batchsample <<-trainingData[sample(nrow(trainingData),size=1),]
         bsample <- batchsample[,-7]
         label = batchsample$V15
         lbl <- t(bsample) * label
         slbl <- steplength*-label
         vec <<- as.matrix(bsample)
         stlbl<- steplength*lbl
         plane <<- label*(t(a)%*%as.vector(vec) + b)
         detr <<- det(plane)

         if (detr >= 1.0) {
           a <<- (a - sl*a)
            b <<- b
         } else if (detr < 1.0) {
            a <<- (a - (sl*a - stlbl))
            b <<- b - slbl
         }
     }
    #Inner loop ends
  }
  #Outer loop ends
```

```
}
my_svm <- function() {
 set.seed(26)
 lambda <- c(1e-3, 1e-2, 1e-1, 1)
 for (l in 1:4) {
   stochastic_gradient_descent(lambda[l],l)
   a_list[,l]<<-a
   b_list[l]<<-b
 }
}
my_svm()
```

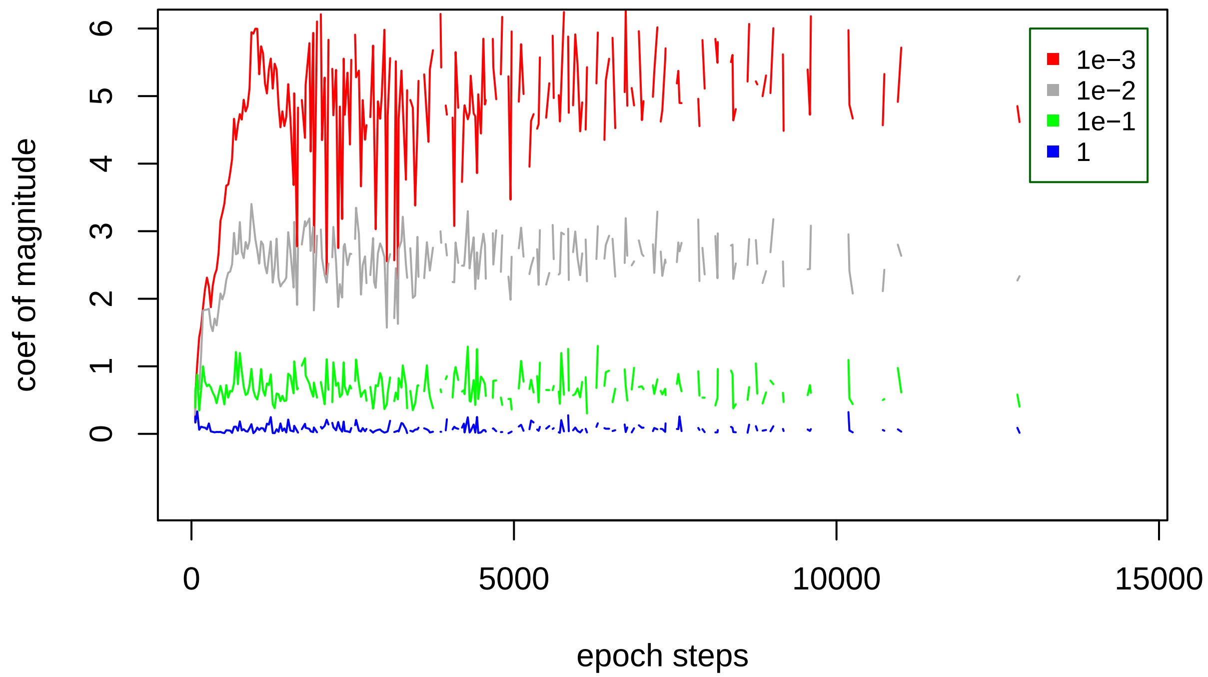
#Problem 1 a

```
plot(epoch_steps,lamda_accuracy[1,],  type = "l",col="red", xlab = "epoch steps",ylab = "accuracy",yaxt=
ticks<-c(0.3,0.4,0.5,0.6,0.7,0.8,0.9,1)
axis(2,at=ticks,labels=ticks)
lines(epoch_steps,lamda_accuracy[2,],col="darkgrey",lty="solid",lwd=1)
lines(epoch_steps,lamda_accuracy[3,],col="green",lty="solid",lwd=1)
lines(epoch_steps,lamda_accuracy[4,],col="blue",lty="solid",lwd=1)
legend(13000, 0.6,pch=c(15,15,15,15),col=c("red","darkgrey","green","blue"),
c("1e-3", "1e-2", "1e-1", "1"),
bty="o",box.col="darkgreen", cex=.8)
```



#Problem 1 b

```
plot(epoch_steps,coef_mag[1,],  type = "l",col="red", xlab = "epoch steps",ylab = "coef of magnitude",ya
ticks<-c(0,1,2,3,4,5,6)
axis(2,at=ticks,labels=ticks)
lines(epoch_steps,coef_mag[2,],col="darkgrey",lty="solid",lwd=1)
lines(epoch_steps,coef_mag[3,],col="green",lty="solid",lwd=1)
lines(epoch_steps,coef_mag[4,],col="blue",lty="solid",lwd=1)
legend(13000, 6, pch=c(15,15,15,15), col=c("red","darkgrey","green","blue"),
c("1e-3", "1e-2", "1e-1", "1"),bty="o",box.col="darkgreen", cex=.8)
```



#Problem 1 c

##Looking at the plots from 4 different chosen regularization constants, lambda=1e-3 looks the best of all the chosen lambda. 1e-1 & 1e are clearly worst performing with multiple low accuracy epochs clearly visible during the training. lamda 1e-3 & 1e-2 are somewhat similar in accuracy but 1e-3 looks to have better accuracy in multiple epochs. Cross validated error on randomly selected 50 training example every 30 steps for regularization constant 1e-3 looks to be better as compared to 1e-2. So 1e-3 is the best regularization constant among the ones chosen and cross-validated/tested on the validation data over the training steps.

#Problem 1 d

```
#Accuracy on held out test data with the chosen regularization constant 1e-3.
for (i in 1:nrow(testData)) {
    validate<-as.matrix(testData[i,-7])
    vlable<-testData[i,7]
    cond<-(t(a_list[,1])%*%as.vector(validate))+b_list[1]
    if (cond > 1) {
        result = 1
```

```r
    } else {
        result = -1
    }
    gotrightvalidate <- result == vlable
    validate_score[i]<-sum(gotrightvalidate)/
         (sum(gotrightvalidate)+sum(!gotrightvalidate))
}
average_accuracy <- sum(validate_score)/nrow(testData)
average_accuracy
```

```
## [1] 0.7822467
```

```r
print(average_accuracy)
```

```
## [1] 0.7822467
```