HOMEWORK 4

Read the data

We will read dataset that is about the stores. The data contains following information.

```
1.UsesID: Id of a user.
2.Gender: Gender of the customer.
3.Age: Age of customer is years.
4.EstimatedSalary: Yearly estimated salary of the customer.
5.Purchased: Binary value with value 1 if the customer purchased the item, 0 otherwise.
```

In [103…

```
options(warn=-1)
library(ggplot2)
storeData <- read.csv('social.csv')
```

Inspect the data read

In [104…

```
head(storeData)
```

User.ID	Gender	Age	EstimatedSalary	Purchased
15624510	Male	19	19000	0
15810944	Male	35	20000	0
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	0
15728773	Male	27	58000	0

Spends are already reduced in given data.

In [105…

```
cat("Size of Store data",dim.data.frame(storeData))
```

```
Size of Store data 400 5
```

Aim is to train a support vector machine(SVM) that will predict whether a customer will purchase or not.

Spliting the data as training and testing data

In [106…

```
# sampling data to generate 75% training data and 25% test data
sdata <- sample(nrow(storeData), nrow(storeData)*0.75)
sampledata <- sort(sample(nrow(storeData), nrow(storeData)*0.75))
trainingData<-storeData[sampledata,]
testingData<-storeData[-sampledata,]
```

In [107…

```
cat("Trainig Data :: ","Size :: ", dim.data.frame(trainingData))
head(trainingData)
cat("Testing Data :: ","Size :: ", dim.data.frame(testingData))
head(testingData)
```

```
Trainig Data ::  Size ::  300 5
```

	User.ID	Gender	Age	EstimatedSalary	Purchased
2	15810944	Male	35	20000	0
3	15668575	Female	26	43000	0
5	15804002	Male	19	76000	0
9	15600575	Male	25	33000	0
11	15570769	Female	26	80000	0
13	15746139	Male	20	86000	0

```
Testing Data ::  Size ::  100 5
```

	User.ID	Gender	Age	EstimatedSalary	Purchased
1	15624510	Male	19	19000	0
4	15603246	Female	27	57000	0
6	15728773	Male	27	58000	0
7	15598044	Female	27	84000	0
8	15694829	Female	32	150000	1
10	15727311	Female	35	65000	0

Preprocessing data for modelling

In [108…

```
# converting dataframe into matrix with required data. We are using only Age and EstimatedSalary
ytrain <- as.matrix(trainingData$Purchased)
# creating yn for computation assigning +1 to 1 and -1 to 0
ytrain <- matrix(apply(ytrain, 1, function (var) {if (var == 1) return (1) else return (-1)}))
colnames(ytrain) <- c("Purchased")
ones <- matrix(rep(1,nrow(ytrain)), nrow = nrow(ytrain), ncol = 1)
# Adding ones in first column of data for bias parameter
xtrain <- cbind(ones,trainingData$Age,trainingData$EstimatedSalary)
colnames(xtrain) <- c("ones","Age","EstimatedSalary")
cat("Trainig Data:: Input and Output" )
head(xtrain)
head(ytrain)
ytest <- as.matrix(testingData$Purchased)
# creating yn for computation assigning +1 to 1 and -1 to 0
ytest <- matrix(apply(ytest, 1, function (var) {if (var == 1) return (1) else return (-1)}))
colnames(ytest) <- c("Purchased")
ones <- matrix(rep(1,nrow(ytest)), nrow = nrow(ytest), ncol = 1)
# Adding ones in first column of data for bias parameter
xtest <- cbind(ones,testingData$Age,testingData$EstimatedSalary)
colnames(xtest) <- c("ones","Age","EstimatedSalary")
cat("Testing Data:: Input and Output" )
head(xtest)
head(ytest)
```

```
Trainig Data:: Input and Output
```

ones	Age	EstimatedSalary
1	35	20000
1	26	43000
1	19	76000
1	25	33000
1	26	80000
1	20	86000

Purchased
-1
-1
-1
-1
-1
-1

```
Testing Data:: Input and Output
```

ones	Age	EstimatedSalary
1	19	19000
1	27	57000
1	27	58000
1	27	84000
1	32	150000
1	35	65000

Purchased
-1
-1
-1
-1
1
-1

In [109…

```
#Scaling predictor variables for training data
xtrain[,2] <- (xtrain[,2] - mean(xtrain[,2]))/sd(xtrain[,2])
xtrain[,3] <- (xtrain[,3]- mean(xtrain[,3]))/sd(xtrain[,3])
cat("Training Input data after normalization")
head(xtrain)

#Scaling predictor variables for testing data
xtest[,2] <- (xtest[,2] - mean(xtest[,2]))/sd(xtest[,2])
xtest[,3] <- (xtest[,3]- mean(xtest[,3]))/sd(xtest[,3])
cat("Testing Input data after normalization")
head(xtest)
```

```
Training Input data after normalization
```

ones	Age	EstimatedSalary
1	-0.3249205	-1.4065133
1	-1.1824821	-0.7552187
1	-1.8494744	0.1792476
1	-1.2777667	-1.0383903
1	-1.1824821	0.2925163
1	-1.7541898	0.4624192

```
Testing Input data after normalization
```

ones	Age	EstimatedSalary
1	-1.61236437	-1.6809336
1	-0.82536529	-0.4274902
1	-0.82536529	-0.3945048
1	-0.82536529	0.4631144
1	-0.33349086	2.6401477
1	-0.03836621	-0.1636074

Defining functions for subgradient and loss function

In [110…

```
g <- function(t){
    if (t < 1)
        return (-1)
    else
        return (0)
}

# define tn = yn(<w,xn>)
    # yn is the output for nth index
    # xn is the input for nth index
    # x = [b w1 w2]'

tn <- function(yn, x, xn){
    t <- yn * ((xn%*%x))
    return (t)
}


#compute loss as terminating condition
loss <-function(x,C){
    N <- dim(xtrain)[1]
    distances <- 1 - ytrain * (xtrain%*%x)
    distances[distances < 0] <- 0  # equivalent to max(0, distance)
    hinge_loss <- C * (sum(distances) / N)
    # calculate cost
    cost <- 1 / 2 * t(x)%*%x + hinge_loss
    return (cost)
}


gradient <- function(x, C){
    deltaF <- matrix(rep(0,3), nrow = 3, ncol = 1)
    sum<- matrix(rep(0,3), nrow = 3, ncol = 1)
    for (n in seq(length(ytrain)))
        {
        t = tn(ytrain[n],x,xtrain[n,])
        gn = g(t)
        diff <- x + (C * gn * ytrain[n] * xtrain[n,])
        sum <- sum + diff
    }
    deltaF <- sum/length(ytrain)
    return (deltaF)
}
```

Defining functions execute gradient descent for SVM, generate prediction, compute accuracy and genearte confusion matrix

In [111…

```
# Run gradient descent for SVM
gradientDescent <- function(x, C, alpha,thrs,maxi){
    converged<-FALSE
    i<-1
    x1<-x
    prev_lossvalue <- 0
     while((!converged  && i <= maxi))
            {
                deltafx <- gradient(x1,C)
                if(is.infinite(deltafx) || is.nan(norm(deltafx,type = "2"))){
                    break
                }
                x1 <- x1 - (alpha*deltafx)
                lossvalue <- loss(x1,C)
                # terminating condition based on loss function
                converged <-abs(prev_lossvalue - lossvalue) < thrs * prev_lossvalue
                prev_lossvalue <- lossvalue
                i <- i+1
            }

    return (list("x1"= x1,"iteration" = i-1,"converged" = converged, "lossValue" = prev_lossvalue))
}

# generate prediction
predict <- function(data,featurecoffiecients)
    {
    result <- data%*%featurecoffiecients
    result[result < 0] <- -1
    result[result > 0] <- 1
    return(result)
}

# compute accuracy
accuracy <- function(predicted, actual)
    {
    return((sum(predicted==actual)/dim(predicted)[1])*100)
}

# generate confusion matrix
generateconfusionmatrix <- function(predicted, actual)
{
    consfusionMatrix <- matrix(rep(0,4), nrow = 2, ncol = 2)
    colnames(consfusionMatrix) <- c("actual(1)","actual(-1)")
    rownames(consfusionMatrix) <- c("pred(1)","pred(-1)")
    consfusionMatrix

    for (i in seq(length(actual)))
    {
        if (actual[i] ==1 & predicted[i] ==1)
            {
            consfusionMatrix[1,1] = consfusionMatrix[1,1] + 1
        }

        else if (actual[i] ==1 & predicted[i] ==-1)
        {
            consfusionMatrix[2,1] = consfusionMatrix[2,1] + 1
        }

        else if (actual[i] ==-1 & predicted[i] ==1)
        {
            consfusionMatrix[1,2] = consfusionMatrix[1,2] + 1
        }

        else if (actual[i] ==-1 & predicted[i] ==-1)
        {
            consfusionMatrix[2,2] = consfusionMatrix[2,2] + 1
        }

    }

    return (consfusionMatrix)
}
```

Running SVM for tradeoff factor = 50

In [112…

```
#setting tradoff parameter to 50
C <- 50
# x = [w1 w2 b]'
x <- matrix(rep(0,3), nrow = 3, ncol = 1)
thres <- 10**(-2)
maxiter <- 1000
alpha <- 0.01
answer <- gradientDescent(x, C,alpha,thres,maxiter)
wstar <- answer$x
cat("Coffiecients")
wstar
#prediction
prediction <- predict(xtest,wstar)
#accuracy
accuracyper1 <- accuracy(prediction,ytest)
cat("Accuarcy is :: ", accuracyper1,"%","\n")
#confusion matrix
cat("Confusion Matrix")
cmatrix1 <- generateconfusionmatrix(prediction,ytest)
cmatrix1
```

```
Coffiecients
```

-0.5130687
0.9951247
0.4937978

```
Accuarcy is ::  87 %
Confusion Matrix
```

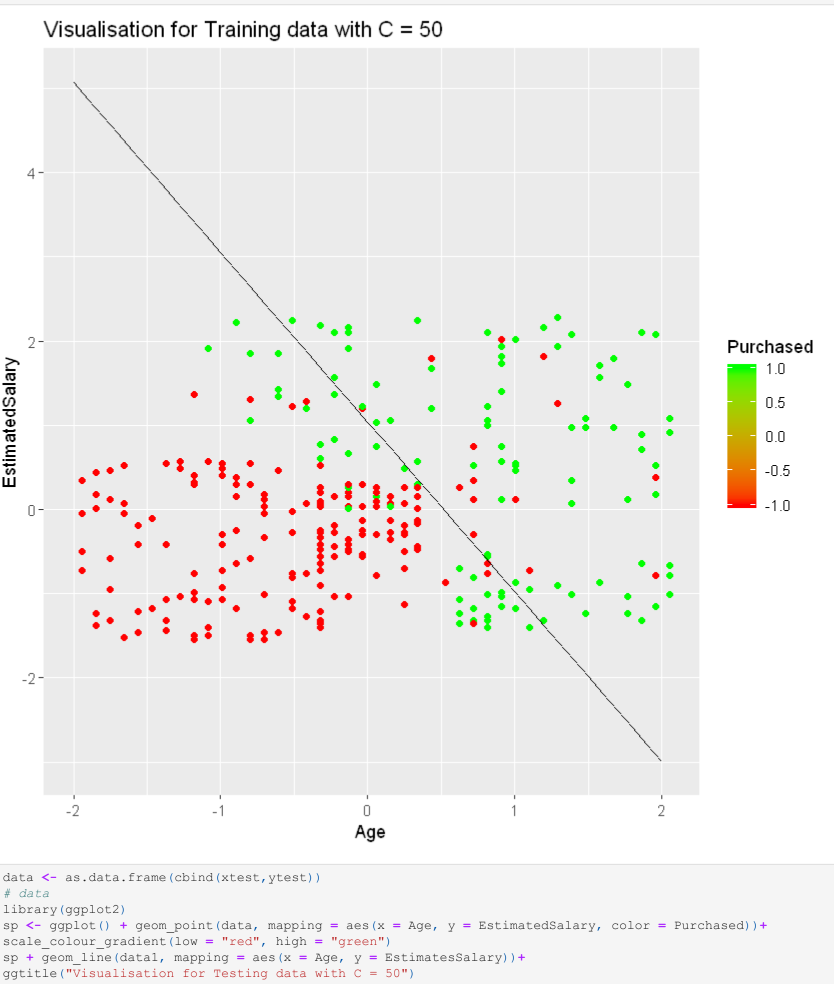
	actual(1)	actual(-1)
pred(1)	26	6
pred(-1)	7	61

In [113…

```
# generating points to plot classification line
Age = seq(-2,2,0.1)
# wstar[1] represents b, wstar[2] and wstar[3] represents the parameter for Age and salary
EstimatesSalary = -(wstar[2]*Age+wstar[1])/wstar[3]
data1 <- as.data.frame(cbind(Age,EstimatesSalary))
```

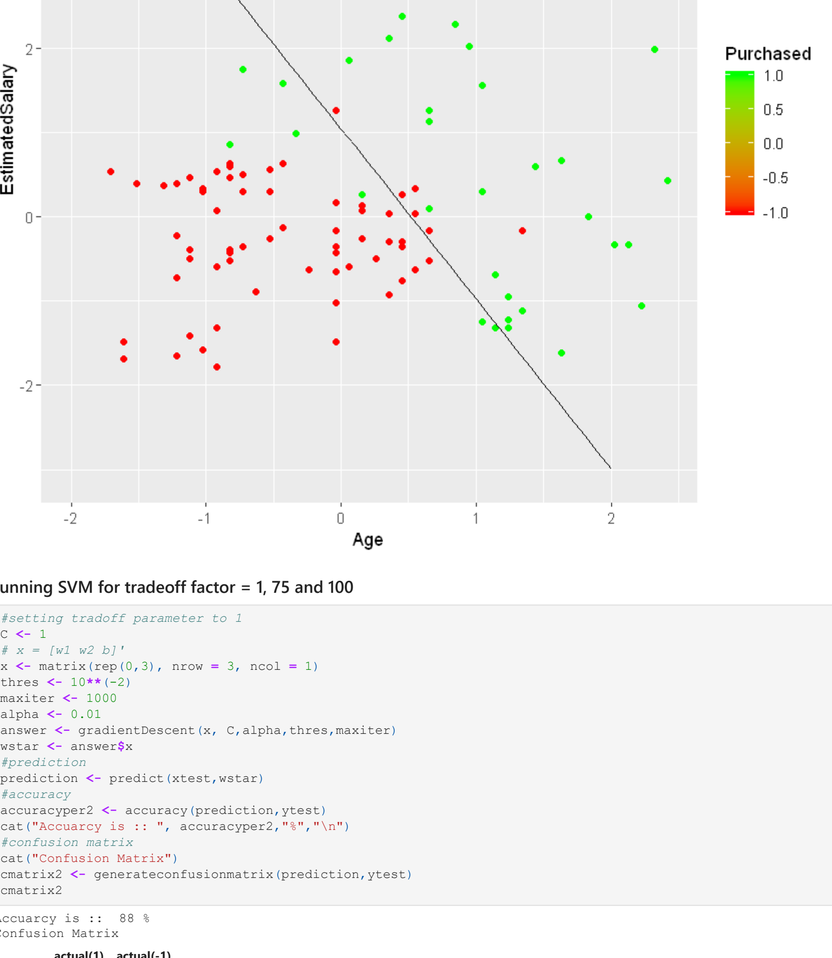
In [114…

```
data <- as.data.frame(cbind(xtrain,ytrain))
sp <- ggplot() + geom_point(data, mapping = aes(x = Age, y = EstimatedSalary,color = Purchased)) +
scale_colour_gradient(low = "red", high = "green")
sp + geom_line(data1, mapping = aes(x = Age, y = EstimatesSalary)) +
ggtitle("Visualisation for Training data with C = 50")
```



In [115…

```
data <- as.data.frame(cbind(xtest,ytest))
# data
library(ggplot2)
sp <- ggplot() + geom_point(data, mapping = aes(x = Age, y = EstimatedSalary, color = Purchased))+
scale_colour_gradient(low = "red", high = "green")
sp + geom_line(data1, mapping = aes(x = Age, y = EstimatesSalary))+
ggtitle("Visualisation for Testing data with C = 50")
```



Running SVM for tradeoff factor = 1, 75 and 100

In [116…

```
#setting tradoff parameter to 1
C <- 1
# x = [w1 w2 b]'
x <- matrix(rep(0,3), nrow = 3, ncol = 1)
thres <- 10**(-2)
maxiter <- 1000
alpha <- 0.01
answer <- gradientDescent(x, C,alpha,thres,maxiter)
wstar <- answer$x
#prediction
prediction <- predict(xtest,wstar)
#accuracy
accuracyper2 <- accuracy(prediction,ytest)
cat("Accuarcy is :: ", accuracyper2,"%","\n")
#confusion matrix
cat("Confusion Matrix")
cmatrix2 <- generateconfusionmatrix(prediction,ytest)
cmatrix2
```

```
Accuarcy is ::  88 %
Confusion Matrix
```

	actual(1)	actual(-1)
pred(1)	27	6
pred(-1)	6	61

In [117…

```
#setting tradoff parameter to 75
C <- 75
# x = [w1 w2 b]'
x <- matrix(rep(0,3), nrow = 3, ncol = 1)
thres <- 10**(-2)
maxiter <- 1000
alpha <- 0.01
answer <- gradientDescent(x, C,alpha,thres,maxiter)
wstar <- answer$x
#prediction
prediction <- predict(xtest,wstar)
#accuracy
accuracyper3 <- accuracy(prediction,ytest)
cat("Accuarcy is :: ", accuracyper3,"%","\n")
#confusion matrix
cat("Confusion Matrix")
cmatrix3 <- generateconfusionmatrix(prediction,ytest)
cmatrix3
```

```
Accuarcy is ::  87 %
Confusion Matrix
```

	actual(1)	actual(-1)
pred(1)	26	6
pred(-1)	7	61

In [118…

```
#setting tradoff parameter to 100
C <- 100
# x = [b w1 w2]'
x <- matrix(rep(0,3), nrow = 3, ncol = 1)
thres <- 10**(-2)
maxiter <- 1000
alpha <- 0.01
answer <- gradientDescent(x, C,alpha,thres,maxiter)
wstar <- answer$x
#prediction
prediction <- predict(xtest,wstar)
#accuracy
accuracyper4 <- accuracy(prediction,ytest)
cat("Accuarcy is :: ", accuracyper4,"%","\n")
#confusion matrix
cat("Confusion Matrix")
cmatrix4 <- generateconfusionmatrix(prediction,ytest)
cmatrix4
```

```
Accuarcy is ::  87 %
Confusion Matrix
```

	actual(1)	actual(-1)
pred(1)	26	6
pred(-1)	7	61

In [119…

```
cat("Confusion Matrix and accuracy (%)  for C = 1")
cmatrix2
accuracyper2
cat("Confusion Matrix and accuracy (%) for C = 50")
cmatrix1
accuracyper1
cat("Confusion Matrixa and accuracy (%) for C = 75")
cmatrix3
accuracyper3
cat("Confusion Matrix and accuracy (%) for C = 100")
cmatrix4
accuracyper4
```

```
Confusion Matrix and accuracy (%)  for C = 1
```

	actual(1)	actual(-1)
pred(1)	27	6
pred(-1)	6	61

88

```
Confusion Matrix and accuracy (%) for C = 50
```

	actual(1)	actual(-1)
pred(1)	26	6
pred(-1)	7	61

87

```
Confusion Matrixa and accuracy (%) for C = 75
```

	actual(1)	actual(-1)
pred(1)	26	6
pred(-1)	7	61

87

```
Confusion Matrix and accuracy (%) for C = 100
```

	actual(1)	actual(-1)
pred(1)	26	6
pred(-1)	7	61

87

What happens to the confusion matrix if you use C = 100? What happens to the confusion matrix if you use C = 1? Comment on what the effect of C is on the entries of the confusion matrix. What choice of C gives you the best classification accuracy results on the test data?

I ran SVM for trade-off factors 1, 50, 75 and 100. Accuracy is best (88%) for trade-off fator C = 1 while accuracy for trade-off 50, 75 and 100 is same 87%. Also as trade-off is increased from 1, there is decrease in "TRUE POSITIVE" cases from 27 to 26 and increase in "TRUE NEGATIVE" cases from 6 to 7.

Given the observation, C = 1 gives the best accuracy.

Github link for the code

https://github.com/jainsanyam786/OptimizationForMachineLearning.git