HW4

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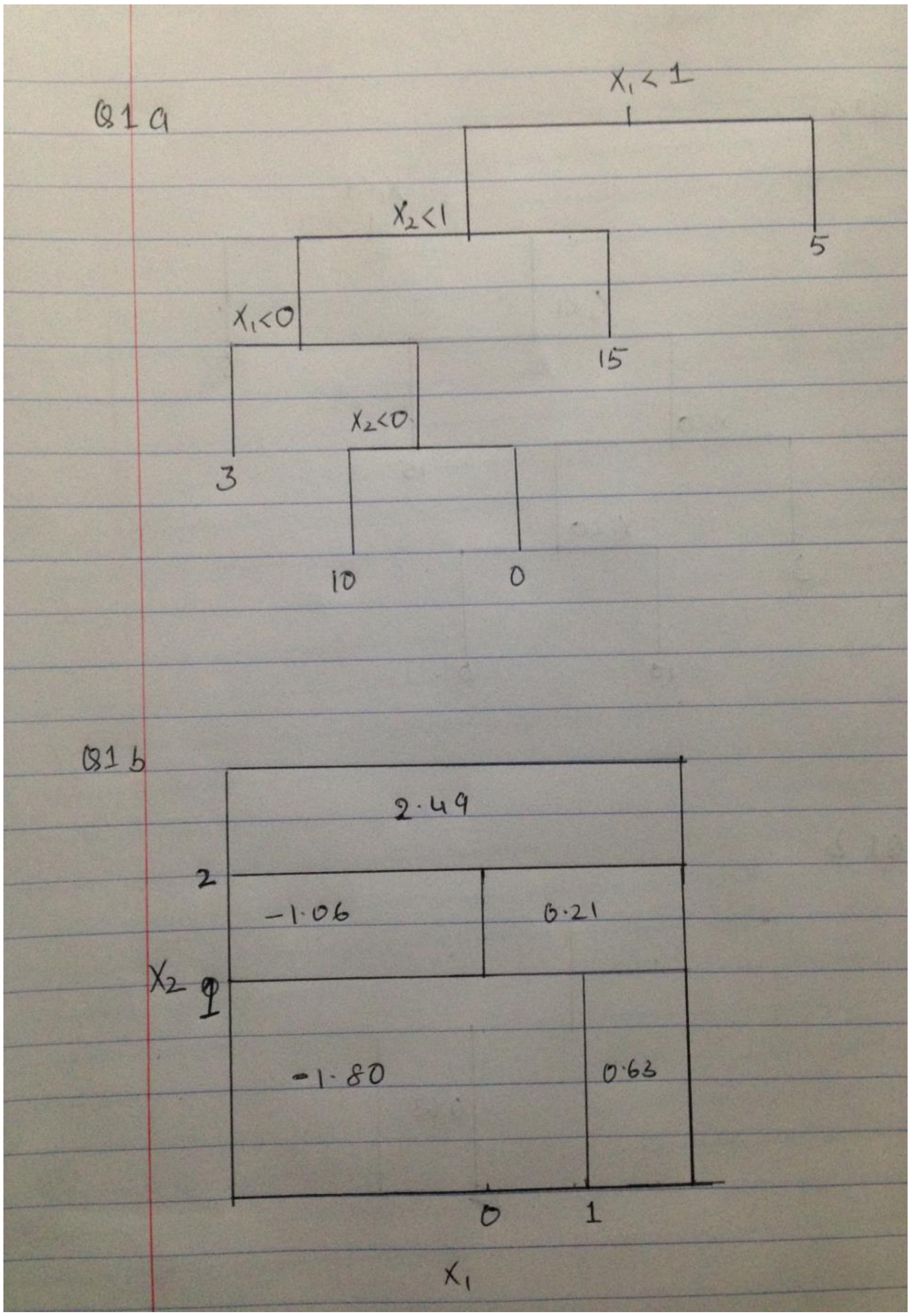
1. Q1.

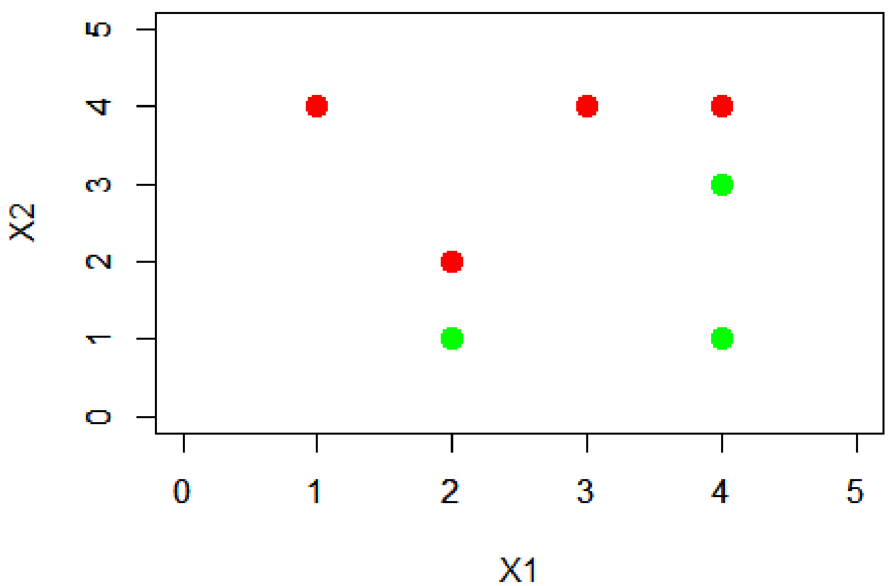


-

2. Q2.

- 2a.

```
X1op=c(3,2,4,1,2,4,4)
X2op=c(4,2,4,4,1,3,1)
Yop=c("Red","Red", "Red", "Red", "Blue", "Blue","Blue")

plot(X1op[5:7],X2op[5:7],col="green", xlim=c(0,5), ylim=c(0,5),xlab="X1",
ylab="X2", type="p",lwd=6)
par(new=T)
plot(X1op[1:4],X2op[1:4],col="red", xlim=c(0,5), ylim=c(0,5),xlab="",ylab
="",type="p", lwd=6)
```

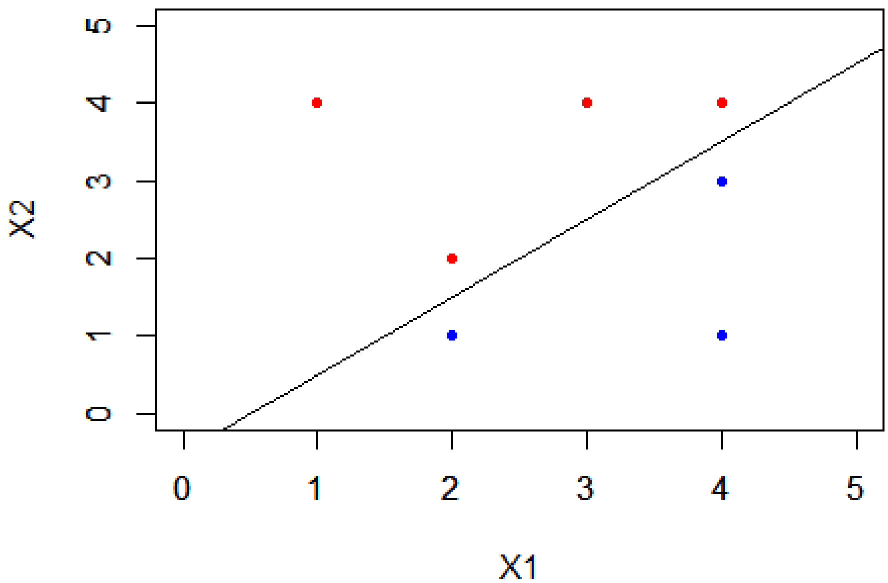



```
par(new=F)
```

- 2b.

```
X1op=c(3,2,4,1,2,4,4)
X2op=c(4,2,4,4,1,3,1)
Yop=c("Red","Red", "Red", "Red", "Blue", "Blue","Blue")

plot(X1op[5:7],X2op[5:7],col="blue", xlim=c(0,5), ylim=c(0,5),xlab="X1",
ylab="X2", type="p",pch=20)
par(new=T)
plot(X1op[1:4],X2op[1:4],col="red", xlim=c(0,5), ylim=c(0,5),xlab="",ylab
="",type="p", pch=20)
```

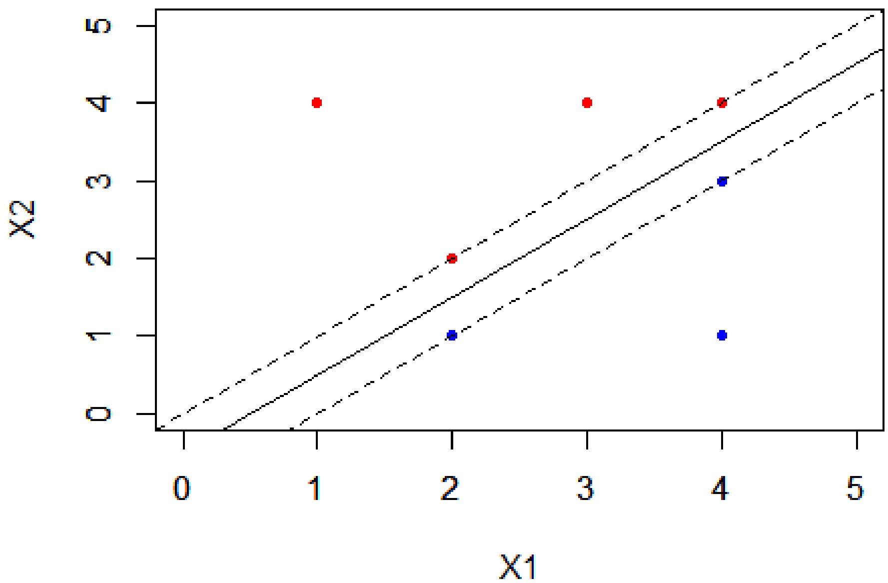
```
par(new=F)
abline(-0.5,1)
```



- Equation of the hyperplane is $2 * X1 - 2 * X2 - 1 = 0$
- 2c.
  - Eqn of hyperplane is $2 * X1 - 2 * X2 - 1 = 0$, so subbing values
  - Blue (2,1)= 2(2)-2(1)-1= 4-3=1
  - Red (2,2)=2(2)-2(2)-1=4-4-1=-1
  - -> $2 * X1 - 2 * X2 - 1 > 0$ == Blue
  - -> $2 * X1 - 2 * X2 - 1 < 0$== Red
- 2d
  - margin is the perpendicular distance from a point to line e.g red point at (2,2) intersects the line at (2.25, 1.75) distance between them is about 0.3

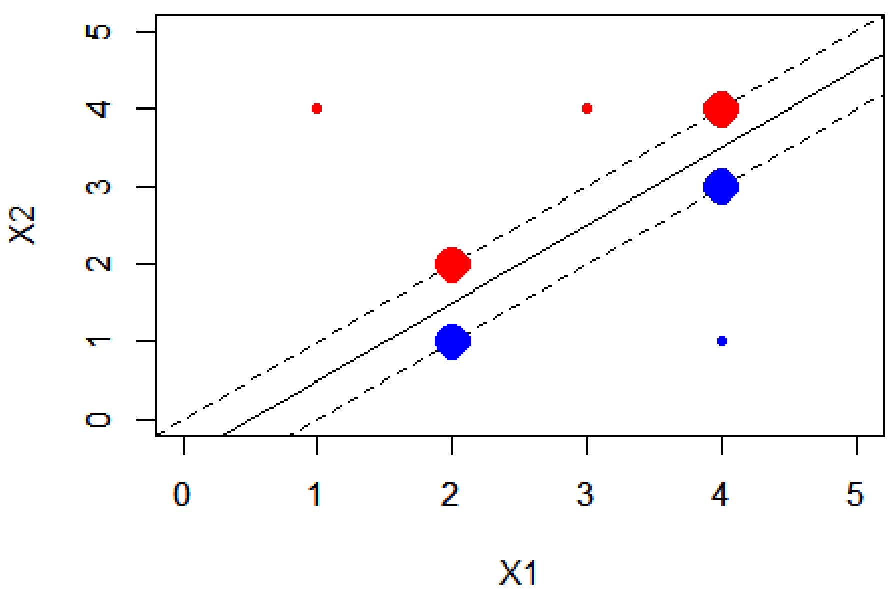
```
   X1op=c(3,2,4,1,2,4,4)
X2op=c(4,2,4,4,1,3,1)
Yop=c("Red","Red", "Red", "Red", "Blue", "Blue","Blue")

plot(X1op[5:7],X2op[5:7],col="blue", xlim=c(0,5), ylim=c(0,5),xlab="X1",
ylab="X2", type="p",pch=20)
par(new=T)
plot(X1op[1:4],X2op[1:4],col="red", xlim=c(0,5), ylim=c(0,5),xlab="",ylab
="",type="p", pch=20)
par(new=F)
abline(-0.5,1)
```

```r
abline(-1,1,lty=2)
abline(0,1,lty=2)
```



- 2e

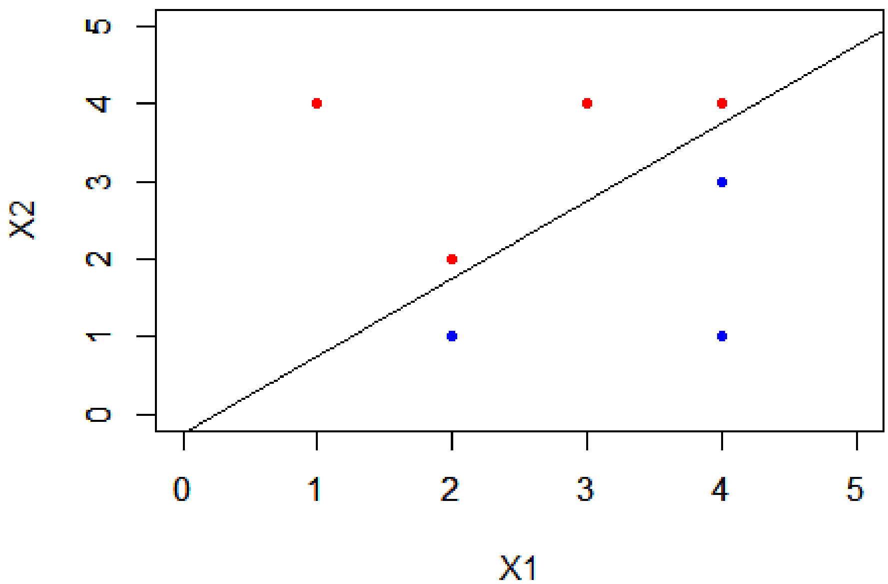
```
    plot(X1op[5:7],X2op[5:7],col="blue", xlim=c(0,5), ylim=c(0,5),xlab="X
1", ylab="X2", type="p",pch=20)
par(new=T)
plot(X1op[1:4],X2op[1:4],col="red", xlim=c(0,5), ylim=c(0,5),xlab="",ylab
="",type="p", pch=20)
par(new=F)
abline(-0.5,1)
abline(-1,1,lty=2)
abline(0,1,lty=2)

points(2,2,pch=23, lwd=10, col="red")
points(4,4,pch=23, lwd=10, col="red")
points(4,3,pch=23, lwd=10, col="blue")
points(2,1,pch=23, lwd=10, col="blue")
```



  - Support vectors have been marked with larger points. They are at(2,2),(4,4),(4,3) and (2,1)
- 2f. The 7th point is (4,1) in the blue category. A slight movement of this point will not have an effect on the maximal margin classifer as it would not move within the support vectors of the classifier; However if it moves beyond the margin of the support vectors it will change the hyperplane

- 2g.

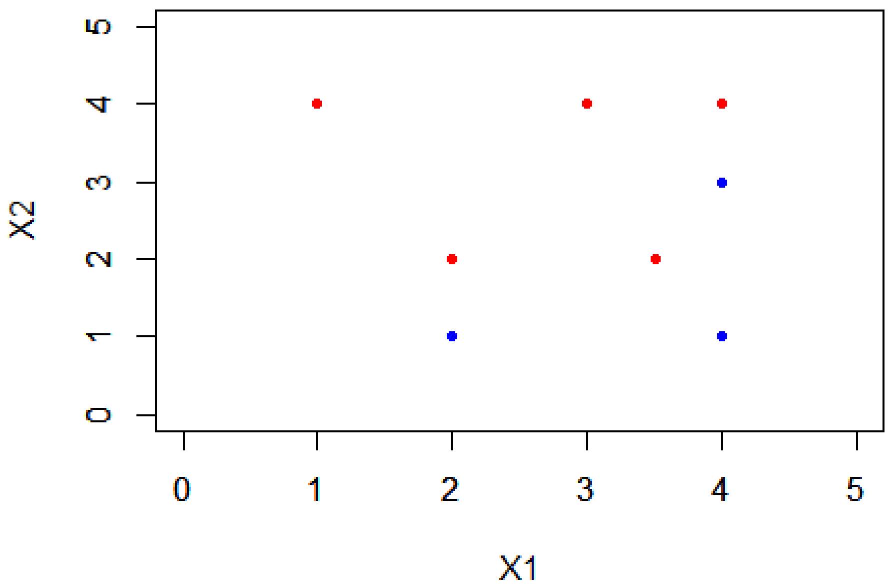
```
 plot(X1op[5:7],X2op[5:7],col="blue", xlim=c(0,5), ylim=c(0,5),xlab="X1",
ylab="X2", type="p",pch=20)
par(new=T)
plot(X1op[1:4],X2op[1:4],col="red", xlim=c(0,5), ylim=c(0,5),xlab="",ylab
="",type="p", pch=20)
par(new=F)
#abline(-0.5,1)
abline(-0.25,1)
```



  - The new hyper plane has the same slope as the original hyperplane but the intercept is a bit larger hence it moves this towards the red points
  - Equation of the plane is $2 * X1 - 2 * X2 - 0.5 = 0$

- 2h.

```
    plot(X1op[5:7],X2op[5:7],col="blue", xlim=c(0,5), ylim=c(0,5),xlab="
X1", ylab="X2", type="p",pch=20)
par(new=T)
plot(X1op[1:4],X2op[1:4],col="red", xlim=c(0,5), ylim=c(0,5),xlab="",ylab
="",type="p", pch=20)
par(new=F)

points(3.5,2,col="red", pch=20)
```

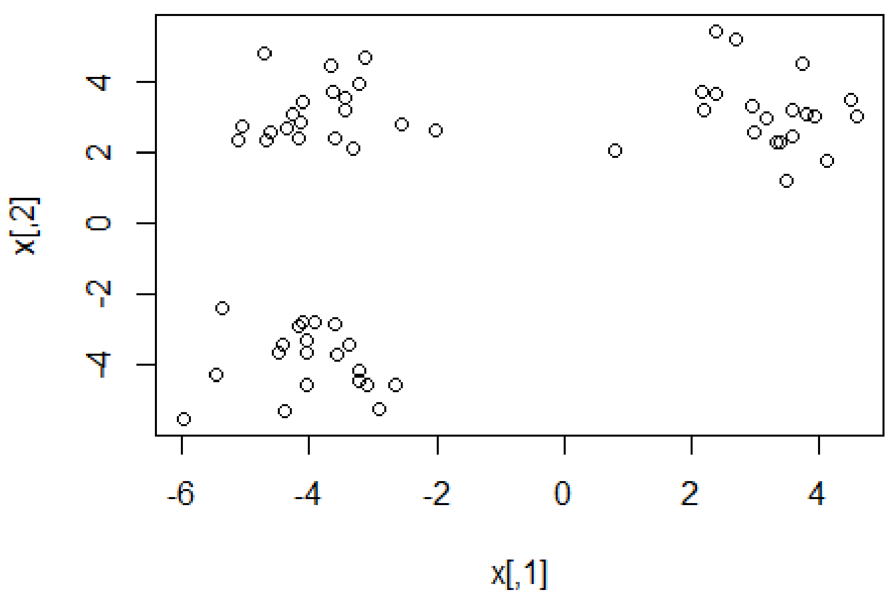


X2
X1
0
1
2
3
4
5
0
1
2
3
4
5

3. Q3.

- 3a.

```
set.seed(1)
x=matrix(rnorm(20*3*50),ncol=50)
x[1:20,1]=x[1:20,1]+3
x[1:20,2]= x[1:20,2]+3
x[21:40,1]=x[21:40,1]-4
x[21:40,2]=x[21:40,2]-4
x[41:60,2]=x[41:60,2]+3
x[41:60,1]=x[41:60,1]-4
plot(x)
```



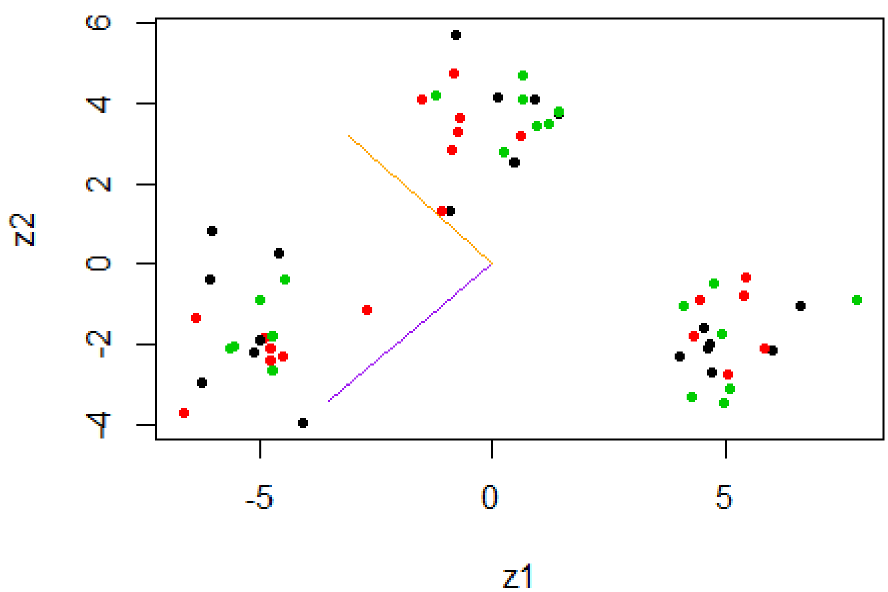

```
y=rep(NA,60)
y[1:20]=1
y[21:40]=2
y[41:60]=3
```

- 3b.

```
  pr.out=prcomp(x)
  pr.out$x[,1:2]

##                PC1        PC2
##  [1,] -6.0316190  0.8104626
##  [2,] -4.8930257 -1.8341547
##  [3,] -4.9721506 -0.8745783
```

```
##  [4,] -6.2443600 -2.9464527
##  [5,] -4.4891223 -2.2956106
##  [6,] -4.4806259 -0.3980923
##  [7,] -4.0600421 -3.9462011
##  [8,] -6.3820029 -1.3394883
##  [9,] -5.5263153 -2.0411504
## [10,] -6.0564751 -0.3971925
## [11,] -6.6470155 -3.7023009
## [12,] -4.7248186 -1.7947830
## [13,] -4.5981938  0.2557031
## [14,] -2.7016751 -1.1502436
## [15,] -4.7065350 -2.6468746
## [16,] -4.9784070 -1.9088544
## [17,] -4.7690020 -2.0744746
## [18,] -5.6416904 -2.1008847
## [19,] -5.0938766 -2.2030256
## [20,] -4.7710345 -2.3769676
## [21,]  5.0942207 -3.1067133
## [22,]  4.6161724 -2.0894476
## [23,]  4.3323709 -1.7911289
## [24,]  7.8273416 -0.8952682
## [25,]  4.0449609 -2.2980823
## [26,]  5.0495862 -2.7300858
## [27,]  4.7444407 -0.5043218
## [28,]  6.6224744 -1.0225696
## [29,]  5.4258099 -0.7801509
## [30,]  4.2975817 -3.2855168
## [31,]  4.7348472 -2.6958419
## [32,]  4.4511228 -0.8810681
## [33,]  4.1238047 -1.0210527
## [34,]  4.5500881 -1.6091786
## [35,]  5.4323430 -0.3185482
## [36,]  4.9294724 -1.7263383
## [37,]  6.0172545 -2.1335221
## [38,]  5.8414077 -2.0752837
## [39,]  4.9714181 -3.4505238
## [40,]  4.6910077 -1.9655946
## [41,]  0.5934246  3.2092440
## [42,]  0.6486150  4.0892988
## [43,]  0.4571165  2.5568799
## [44,] -0.6950646  3.6618987
## [45,]  1.2286169  3.5115401
## [46,] -0.7644803  5.7127450
## [47,] -0.8735983  2.8253423
## [48,] -1.2019669  4.2231795
## [49,]  0.1249432  4.1316382
## [50,] -1.5107489  4.0805204
## [51,]  0.2467589  2.7973085
## [52,]  1.4101946  3.7683626
## [53,] -0.8299349  4.7652238
```

```
## [54,]  1.4080769  3.8128667
## [55,] -0.9318156  1.3084279
## [56,] -1.0815189  1.3320545
## [57,]  0.6373622  4.7102320
## [58,]  0.8897862  4.1057428
## [59,] -0.7257057  3.3162644
## [60,]  0.9402005  3.4266312

  plot(pr.out$x[,1:2],col=1:3, xlab="z1", ylab="z2", pch=20)

  c=c(0,pr.out$rotation[1,1])
  d=c(0,pr.out$rotation[2,1])
  lines(5*c,5*d,col="purple")

  c=c(0,pr.out$rotation[1,2])
  d=c(0,pr.out$rotation[2,2])
  lines(5*c,5*d,col="orange")
```



- The 2 principal compoents (Purple=1st principal component, Orange=2nd principal components) are plotted and shown in the graph

- 3c.

```
set.seed(1)
km.out=kmeans(x,3,nstart=20)
table(y,km.out$cluster)

##
## y    1  2  3
##   1 20  0  0
##   2  0 20  0
##   3  0  0 20
```

  - All the cluster points are correctly classified

- 3d.

```
set.seed(1)
km.out=kmeans(x,2,nstart=20)
table(y,km.out$cluster)

##
## y    1  2
##   1 20  0
##   2  0 20
##   3 20  0
```

  - All the points from class 3 are categorized as points from a class 1.

- 3e.

```
set.seed(1)
km.out=kmeans(x,4,nstart=20)
table(y,km.out$cluster)

##
## y    1  2  3  4
##   1  0 10  0 10
##   2 20  0  0  0
##   3  0  0 20  0
```

  - Points from one of the classes are split into two clusters. Points of the remaining clusters are classified correctly
- 3f.

```
set.seed(1)
km.out=kmeans(pr.out$x[,1:2],3,nstart=20)
table(y,km.out$cluster)

##
## y    1  2  3
##   1 20  0  0
##   2  0 20  0
##   3  0  0 20
```

  - All the points are classified correctly
- 3g.

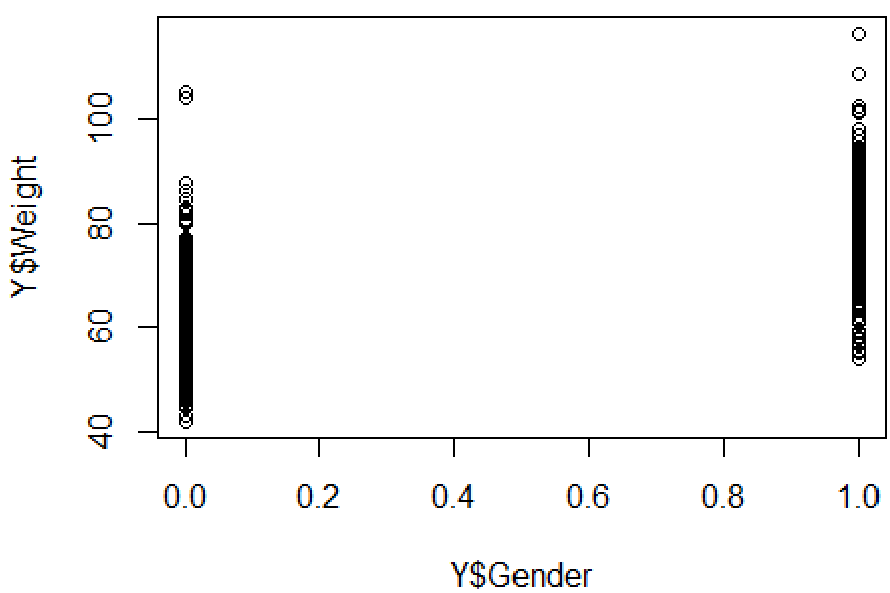
```
set.seed(1)
km.out=kmeans(scale(x),3,nstart=20)
table(y,km.out$cluster)

##
## y    1  2  3
##   1  7  2 11
##   2  3 13  4
##   3  4 10  6
```

  - There are more missclassifications compared to 3c; By scaling the points the distance between the points changes and hence it impacts the clustering results.

4. Q4

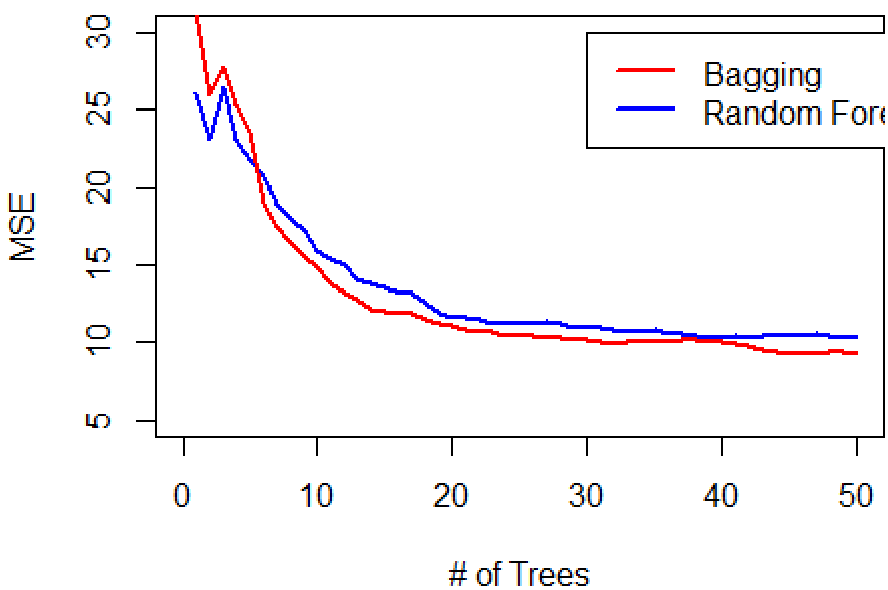
- 4a.

```
require(tree)

## Loading required package: tree

## Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
## logical.return = TRUE, : there is no package called 'tree'

require(randomForest)

## Loading required package: randomForest
## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.

bodyR=load("body.RData")
plot(Y$Gender,Y$Weight)
```



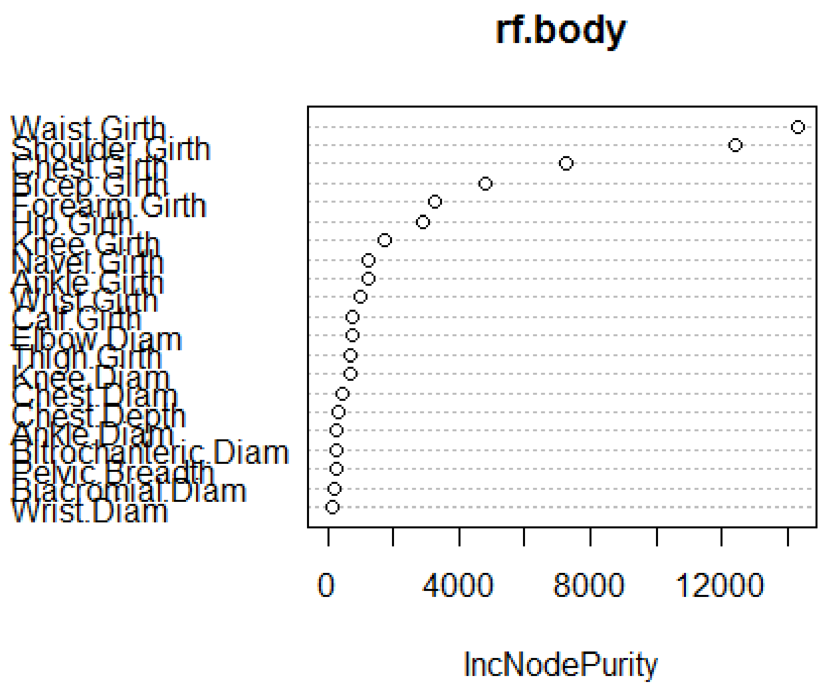

```
set.seed(1)
train=sample(507,307)
test=-train
X.train=X[train,]
X.test=X[test,]
Y.test=Y[test,"Weight"]
Y.train=Y[train,"Weight"]
```

```r
  bag.body=randomForest(Y.train~.,data=X.train,mtry=21,ntree=50)
  yhat.bag=predict(bag.body, newdata=X[-train,])
  mean((yhat.bag-Y$Weight[-train])^2)

## [1] 10.76931

  rf.body=randomForest(Y$Weight~.,data=X,subset=train,mtry=7,ntree=50)
  yhat.rf=predict(rf.body, newdata=X[-train,])
  mean((yhat.rf-Y$Weight[-train])^2)

## [1] 10.21739

  plot(c(0,50),c(5,30), type="n", xlab= "# of Trees", ylab="MSE")
  lines(rf.body$mse, col="blue", lwd=2.5)
  lines(bag.body$mse, col="red", lwd=2.5)
  legend(30,30,c("Bagging","Random Forest"))
  lwd=c(2.5,2,5)
  col=c("blue","red")
  legend(30,30,c("Bagging","Random Forest"),lty=c(1,1),lwd=c(2.5,2.5),col
=c("red","blue"))
```

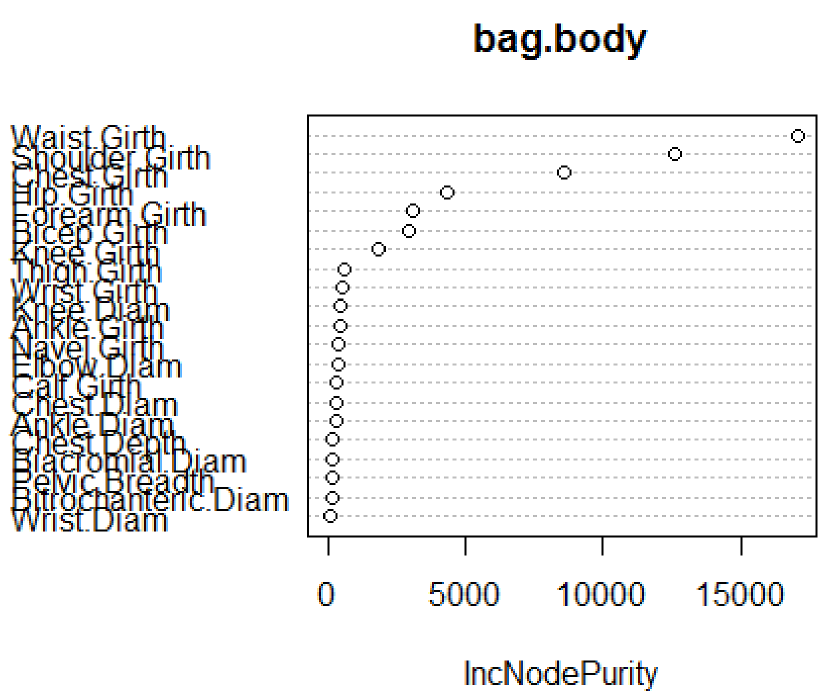


- 4b.

```r
  varImpPlot(rf.body)
```




```
varImpPlot(bag.body)
```



- Top 3 variables for randomForest: Waist.Girth, Shoulder.Girth, Chest.Girth

- Top 3 for bagging: Waist.Girth, Shoulder.Girth and Chest.Girth
- Same variables are chosen by both methods as most important.

- 4c.

```
set.seed(1)
rf.body=randomForest(Y$Weight~.,data=X,subset=train,mtry=7,ntree=500)
yhat.rf=predict(rf.body, newdata=X[-train,])
mean((yhat.rf-Y$Weight[-train])^2)

## [1] 9.904654
```

  - In the HW3 Solution, the PLS model had a test error of 8.65, PCR of 9.27, forward stepwise 8.63. The error here is a 9.9, that is bit higher than other methods.

- 4d.
  - The idea of using a smaller subet of 7 from 21 variables is so that we use trees from different variables and that they are uncorrelated, thus helping us to reduce the variance of the averaged trees.
  - Theorectically there are 21C7 ~116280 ways to select 7 variables from 21 variables. So theoretically adding more trees should give a better estimate.
  - Another practical way is to plot the test data error as a function of number of trees and see if the error improves.