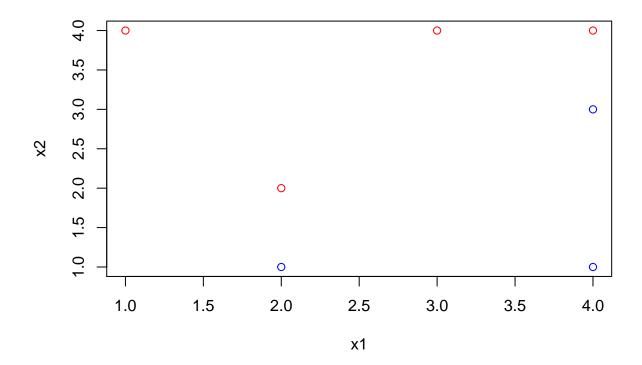
# HW10

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9.7 - 3

(a)

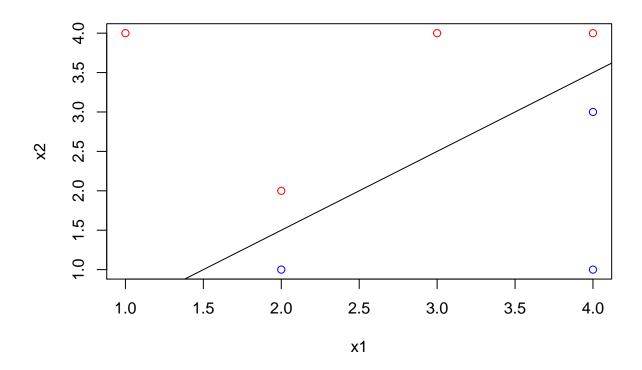
```
x1 <- c(3,2,4,1,2,4,4)
x2 <- c(4,2,4,4,1,3,1)
c <- c("red", "red", "red", "blue", "blue", "blue")
plot(x1, x2, col = c)</pre>
```



(b)

The optimal separating hyperplane must pass point (2, 1.5) and (4, 3.5). The equation for this hyperplane is  $-0.5 + x_1 - x_2 = 0$ .

```
plot(x1, x2, col = c)
abline(-0.5, 1)
```

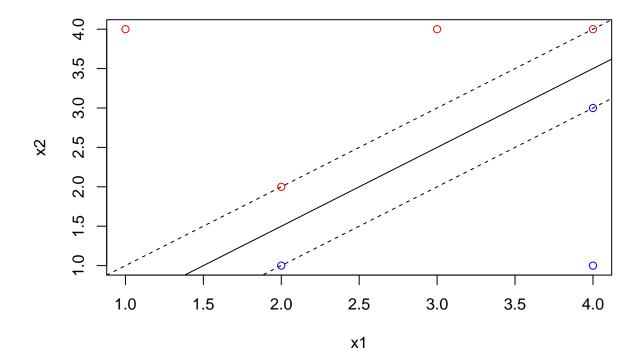


(c)

Classify to Red if  $-0.5 + x_1 - x_2 < 0$ , and classify to Blue otherwise.

(d)

```
plot(x1, x2, col = c)
abline(-0.5, 1)
abline(0, 1, lty = 2)
abline(-1, 1, lty = 2)
```



(e)

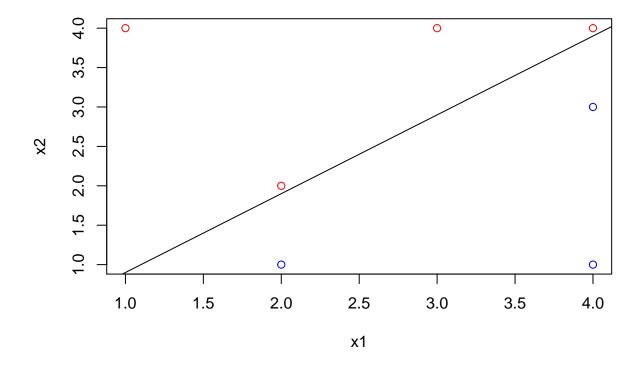
Support vectors are (2, 2), (4, 4), (2, 1) and (4, 3).

(f)

7th observation point is (4,1), which is away from blue margin. So, slight movement of this point does not change maximal margin hyperplane.

(g)

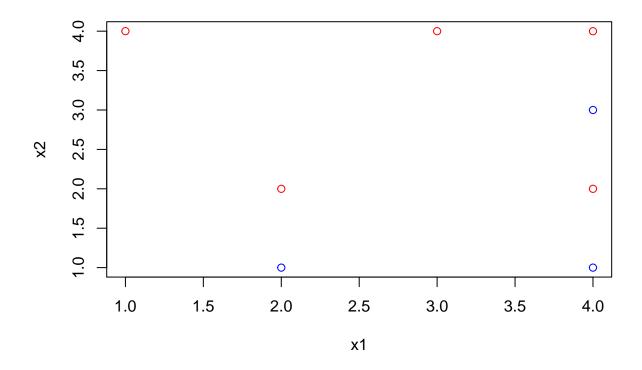
```
plot(x1, x2, col = c)
abline(-0.1, 1)
```



The equation for this hyperplane is  $-0.1 + x_1 - x_2 = 0$ .

## (h)

```
plot(x1, x2, col = c)
points(4,2,col = "red")
```



## 9.7 - 4

```
set.seed(1)
x <- runif(100, min = -1, max = 1)
y <- runif(100, min = -1, max = 1)
z <- as.numeric(y > 3*x^2+3*x)
plot(x, y, col = z+1)
```

```
00
                                                         0
                                                                          0
                                                       0
0.5
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    -1.0
                      -0.5
                                        0.0
                                                          0.5
                                                                            1.0
                                          Χ
```

```
library(e1071)
## Warning: package 'e1071' was built under R version 3.4.4
library(scatterplot3d)
## Warning: package 'scatterplot3d' was built under R version 3.4.4
set.seed(5322)
mydf <- data.frame(x,y,z)</pre>
train <- sample(100, 59)</pre>
test <- -train
traindf <- mydf[train,]</pre>
testdf <- mydf[test,]</pre>
svm.1 <- svm(factor(z) ~ ., data = traindf, scale = FALSE, kernel = "polynomial", d = 1, cost = 2)</pre>
trainpred <- predict(svm.1, traindf)</pre>
traintable <- table(traindf$z, trainpred)</pre>
traintable
##
      trainpred
##
        0 1
     0 33 2
##
     1 0 24
(traintable[2]+traintable[3])/59
```

## [1] 0.03389831

```
testpred <- predict(svm.1, testdf)
testtable <- table(testdf$z, testpred)
testtable

## testpred
## 0 1
## 0 23 1
## 1 1 16
(testtable[2]+testtable[3])/41</pre>
```

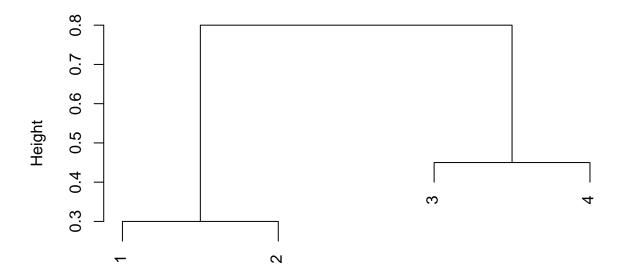
#### ## [1] 0.04878049

The best SVM option is actually the linear separation with cost 2. Evne though we separate the points with quadratic function, There are only 3 points at bottom left can be error points after classification. Training error rate is 3.39% and test error rate is 4.88%.

#### 10.7 - 2

(a)

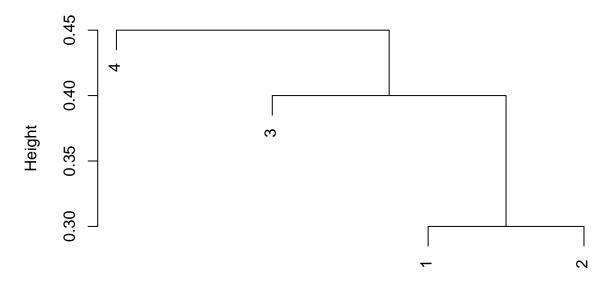
# **Cluster Dendrogram**



(b)

```
plot(hclust(diss, method = "single"))
```

## **Cluster Dendrogram**



### diss hclust (\*, "single")

(c)

Observation 1 and 2 are in a cluster and observation 3 and 4 are in the other cluster.

(d)

Observation 1, 2 and 3 are in a cluster and observation 4 is in the other cluster.

#### 10.7 - 11

(a)

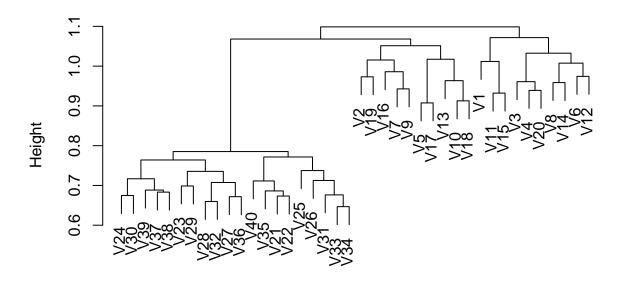
```
ch10ex11 <- read.csv("http://www-bcf.usc.edu/~gareth/ISL/Ch10Ex11.csv", header = FALSE)</pre>
```

(b)

```
dd <- as.dist(1-cor(ch10ex11))
hc.complete <- hclust(dd, method = "complete")
hc.average <- hclust(dd, method = "average")</pre>
```

```
hc.single <- hclust(dd, method = "single")
plot(hc.complete, main = "Complete Linkage with Correlation-Based Distance")</pre>
```

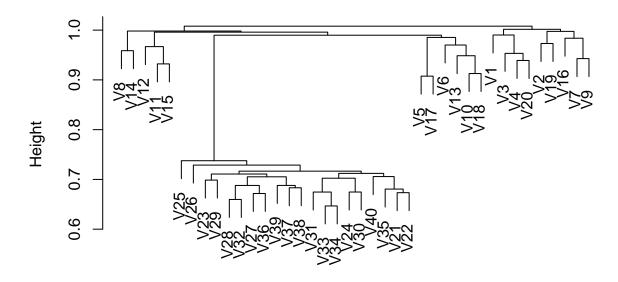
## **Complete Linkage with Correlation-Based Distance**



dd hclust (\*, "complete")

plot(hc.average, main = "Average Linkage with Correlation-Based Distance")

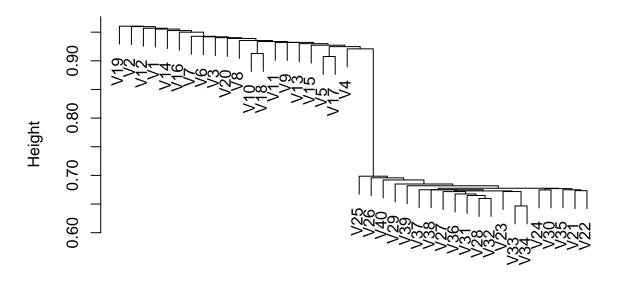
# **Average Linkage with Correlation–Based Distance**



dd hclust (\*, "average")

plot(hc.single, main = "Single Linkage with Correlation-Based Distance")

### Single Linkage with Correlation-Based Distance



dd hclust (\*, "single")

Yes, complete and average linkage can separate the samples into 2 groups with a gene.

(c)

```
index <- seq(1,20)
ch10ex11.1 <- ch10ex11[,index]
ch10ex11.2 <- ch10ex11[,-index]
mean.1 <- apply(ch10ex11.1, 1, mean)
mean.2 <- apply(ch10ex11.2, 1, mean)
abs.mean <- abs(mean.1 - mean.2)
which.max(abs.mean)

## [1] 600

n <- length(abs.mean)
which(abs.mean == sort(abs.mean,partial=n-1)[n-1])

## [1] 584
which(abs.mean == sort(abs.mean,partial=n-1)[n-2])

## [1] 513
which(abs.mean == sort(abs.mean,partial=n-1)[n-3])

## [1] 562</pre>
```

```
which(abs.mean == sort(abs.mean,partial=n-1)[n-4])
```

## [1] 549

To find which genes differ the most across the two groups, we look at their difference in means. The top 5 genes are Gene 593, 562, 568, 576, 502.