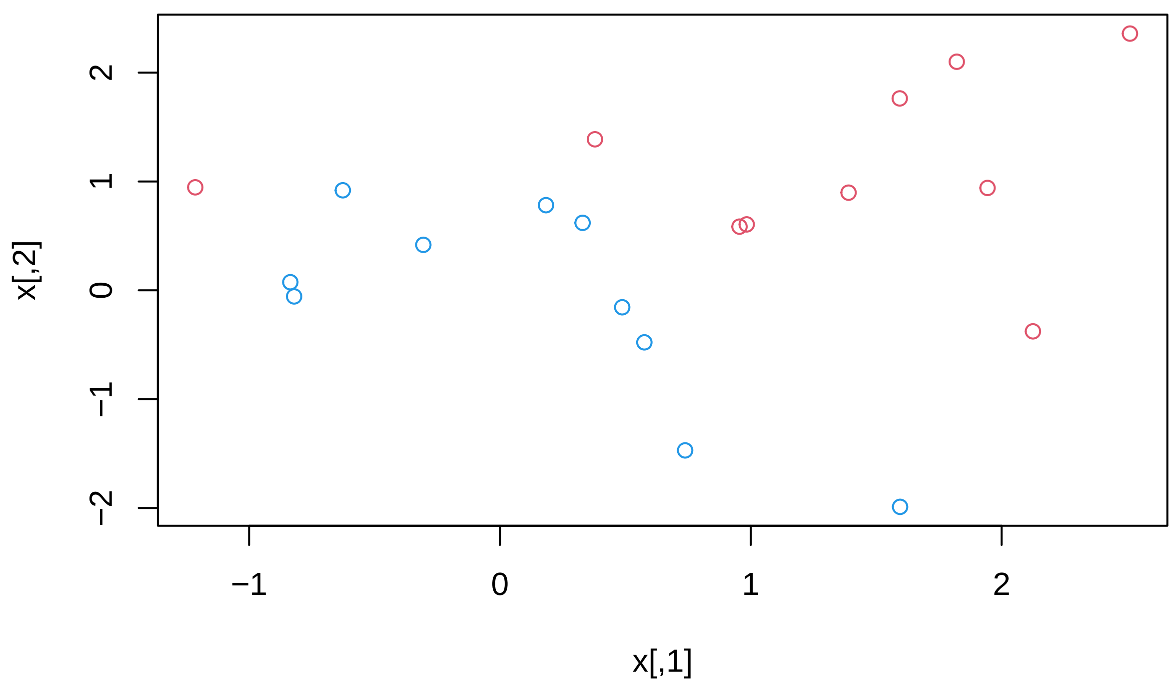
Lab 9.6

Jacob Thielemier

16 April 2024

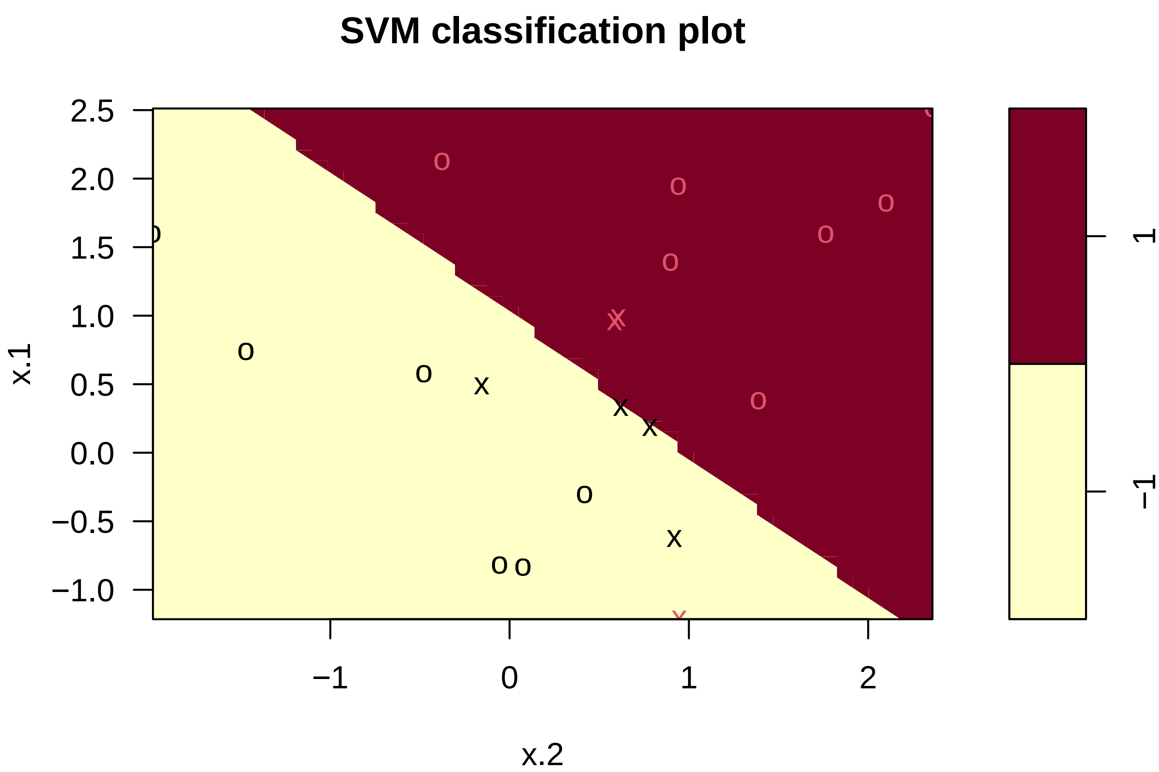
9.6.1

```
set.seed(1)
x <- matrix(rnorm(20 * 2), ncol = 2)
y <- c(rep(-1, 10), rep(1, 10))
x[y == 1, ] <- x[y == 1, ] + 1
plot(x, col = (3 - y))
```




```
dat <- data.frame(x = x, y = as.factor(y))
library(e1071)
svmfit <- svm(y ~ ., data = dat , kernel = "linear",
  cost = 10, scale = FALSE)
```

```r
plot(svmfit , dat)
```




```r
svmfit$index
```

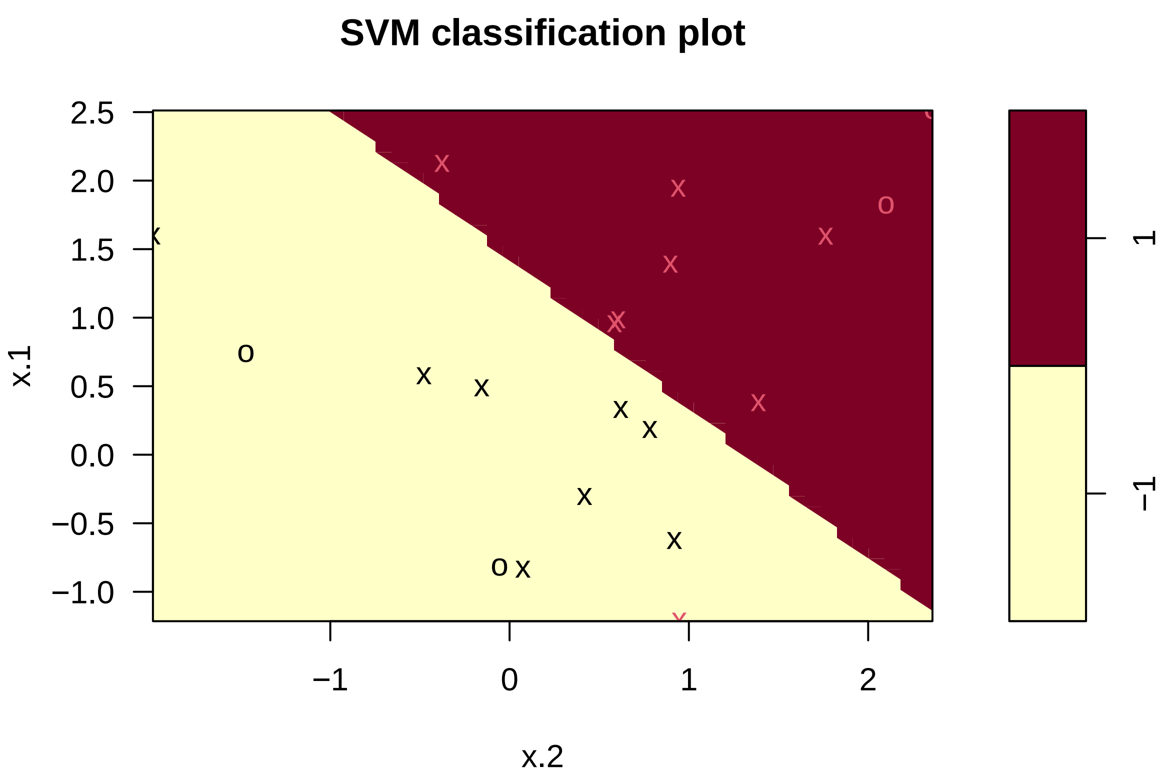
```
## [1]  1  2  5  7 14 16 17
```

```r
summary(svmfit)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat, kernel = "linear", cost = 10, scale = FALSE)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  10
##
## Number of Support Vectors:  7
##
##  ( 4 3 )
##
##
```

```
## Number of Classes:  2
##
## Levels:
##  -1 1
```

```r
svmfit <- svm(y ~ ., data = dat , kernel = "linear",
  cost = 0.1, scale = FALSE)
plot(svmfit , dat)
```




```r
svmfit$index
```

```
##  [1]  1  2  3  4  5  7  9 10 12 13 14 15 16 17 18 20
```

```r
set.seed(1)
tune.out <- tune(svm , y ~ ., data = dat , kernel = "linear",
  ranges = list(cost = c(0.001, 0.01, 0.1, 1, 5, 10, 100)))
summary(tune.out)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
```

```
##  cost
##   0.1
##
## - best performance: 0.05
##
## - Detailed performance results:
##    cost error dispersion
## 1 1e-03  0.55  0.4377975
## 2 1e-02  0.55  0.4377975
## 3 1e-01  0.05  0.1581139
## 4 1e+00  0.15  0.2415229
## 5 5e+00  0.15  0.2415229
## 6 1e+01  0.15  0.2415229
## 7 1e+02  0.15  0.2415229
```

```r
bestmod <- tune.out$best.model
summary(bestmod)
```

```
##
## Call:
## best.tune(METHOD = svm, train.x = y ~ ., data = dat, ranges = list(cost = c(0.001,
##     0.01, 0.1, 1, 5, 10, 100)), kernel = "linear")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.1
##
## Number of Support Vectors:  16
##
##  ( 8 8 )
##
##
## Number of Classes:  2
##
## Levels:
##  -1 1
```

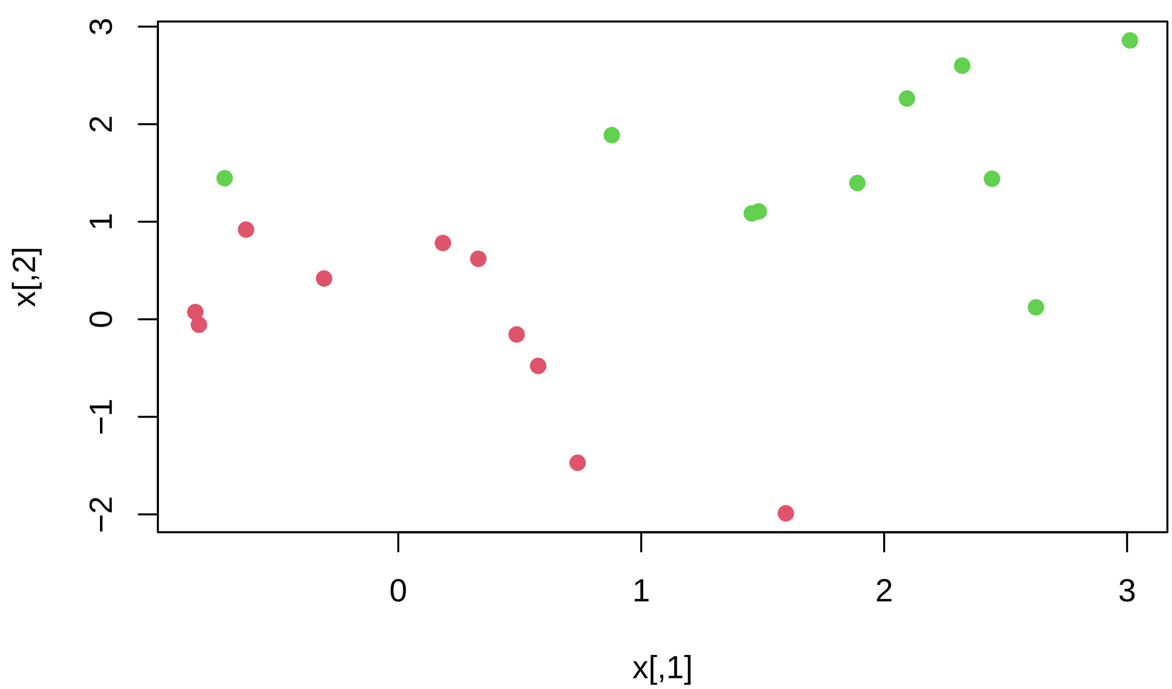
```r
xtest <- matrix(rnorm(20 * 2), ncol = 2)
ytest <- sample(c(-1, 1), 20, rep = TRUE)
xtest[ytest == 1, ] <- xtest[ytest == 1, ] + 1
testdat <- data.frame(x = xtest , y = as.factor(ytest))

ypred <- predict(bestmod , testdat)
table(predict = ypred , truth = testdat$y)
```

```
##        truth
## predict -1 1
##      -1  9 1
##      1   2 8
```

```
svmfit <- svm(y ~ ., data = dat , kernel = "linear",
  cost = .01, scale = FALSE)
ypred <- predict(svmfit , testdat)
table(predict = ypred , truth = testdat$y)
```

```
##        truth
## predict -1  1
##      -1 11  6
##      1   0  3
```

```
x[y == 1, ] <- x[y == 1, ] + 0.5
plot(x, col = (y + 5) / 2, pch = 19)
```

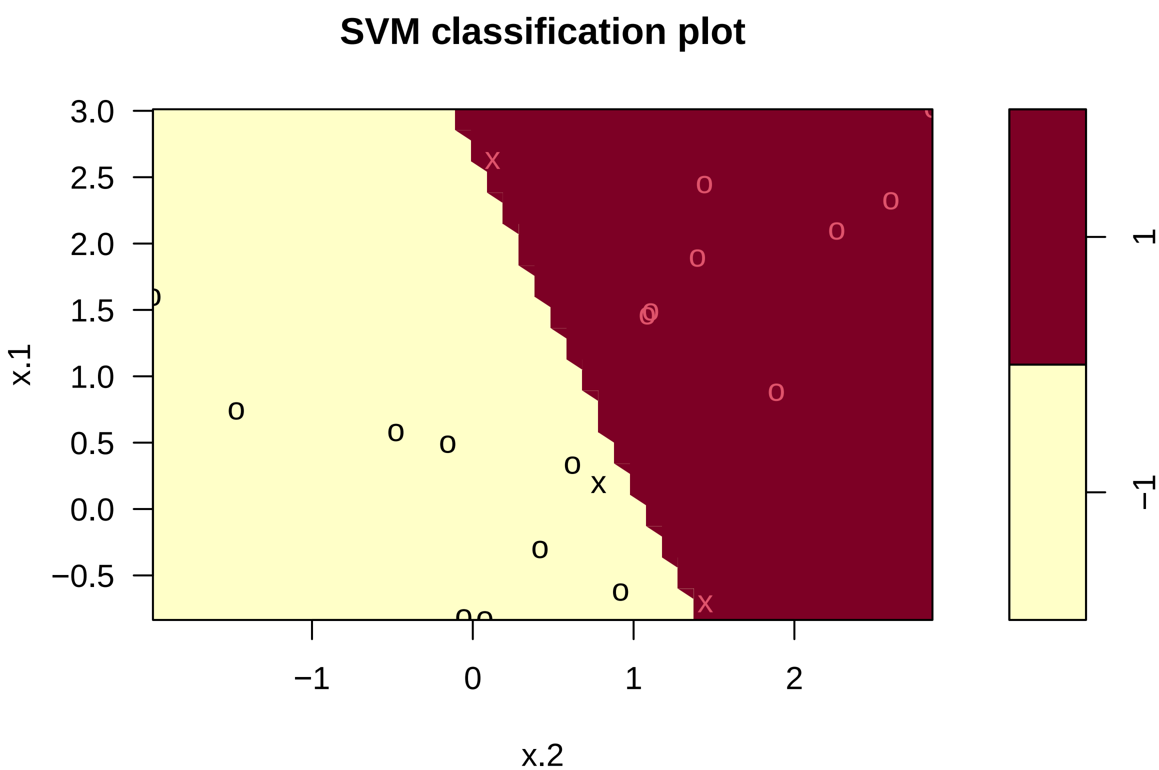



```
dat <- data.frame(x = x, y = as.factor(y))
svmfit <- svm(y ~ ., data = dat , kernel = "linear",
  cost = 1e5)
summary(svmfit)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat, kernel = "linear", cost = 1e+05)
##
##
## Parameters:
```

```
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1e+05
##
## Number of Support Vectors:  3
##
##  ( 1 2 )
##
##
## Number of Classes:  2
##
## Levels:
##  -1 1
```

```r
plot(svmfit , dat)
```

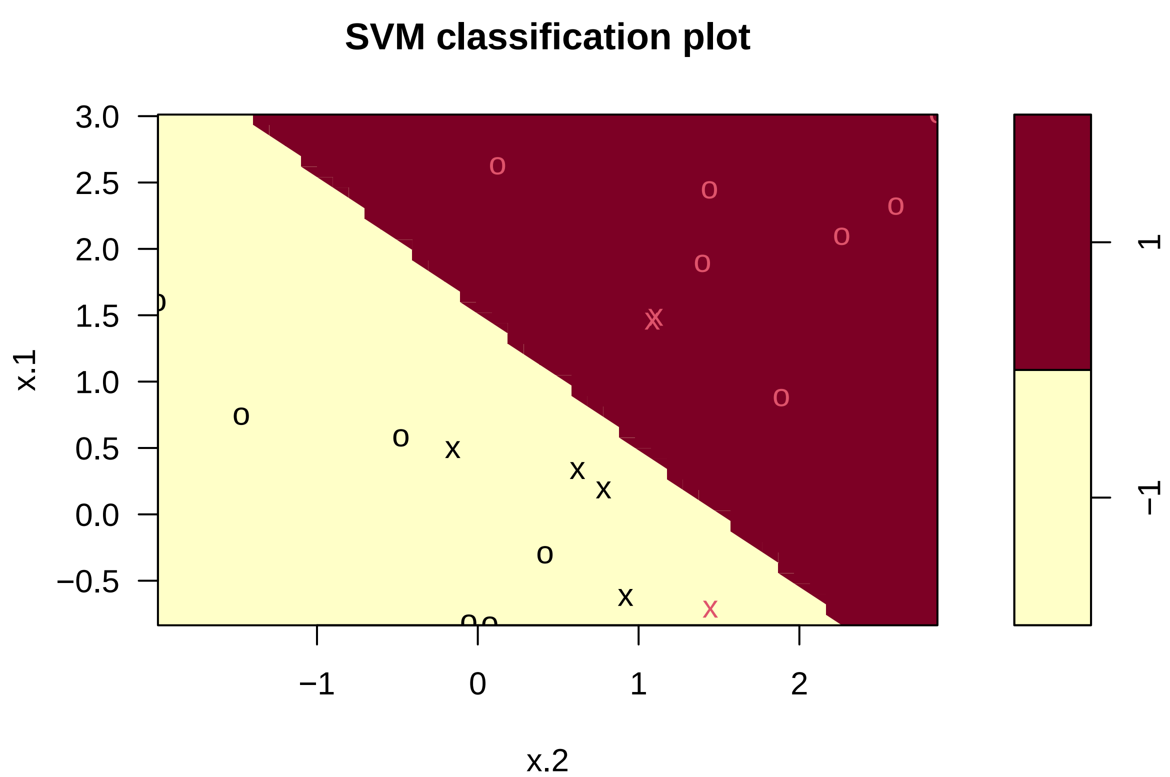



```r
svmfit <- svm(y ~ ., data = dat , kernel = "linear", cost = 1)
summary(svmfit)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat, kernel = "linear", cost = 1)
##
##
## Parameters:
```

```
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1
##
## Number of Support Vectors:  7
##
##  ( 4 3 )
##
##
## Number of Classes:  2
##
## Levels:
##  -1 1
```

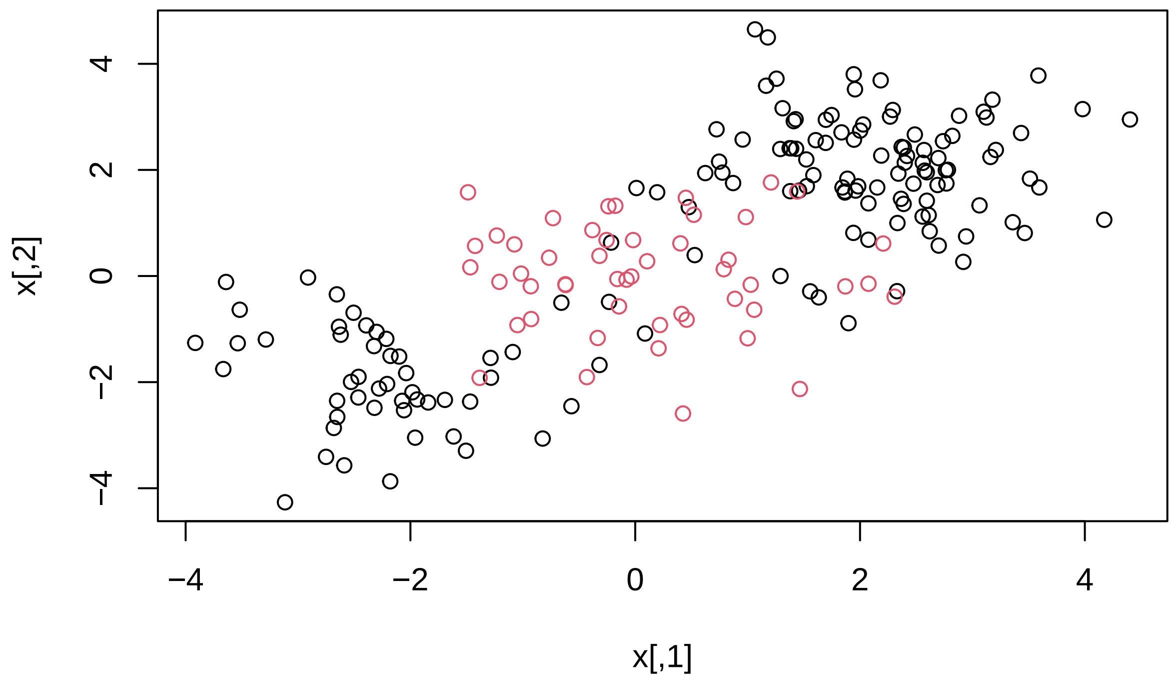
```r
plot(svmfit , dat)
```



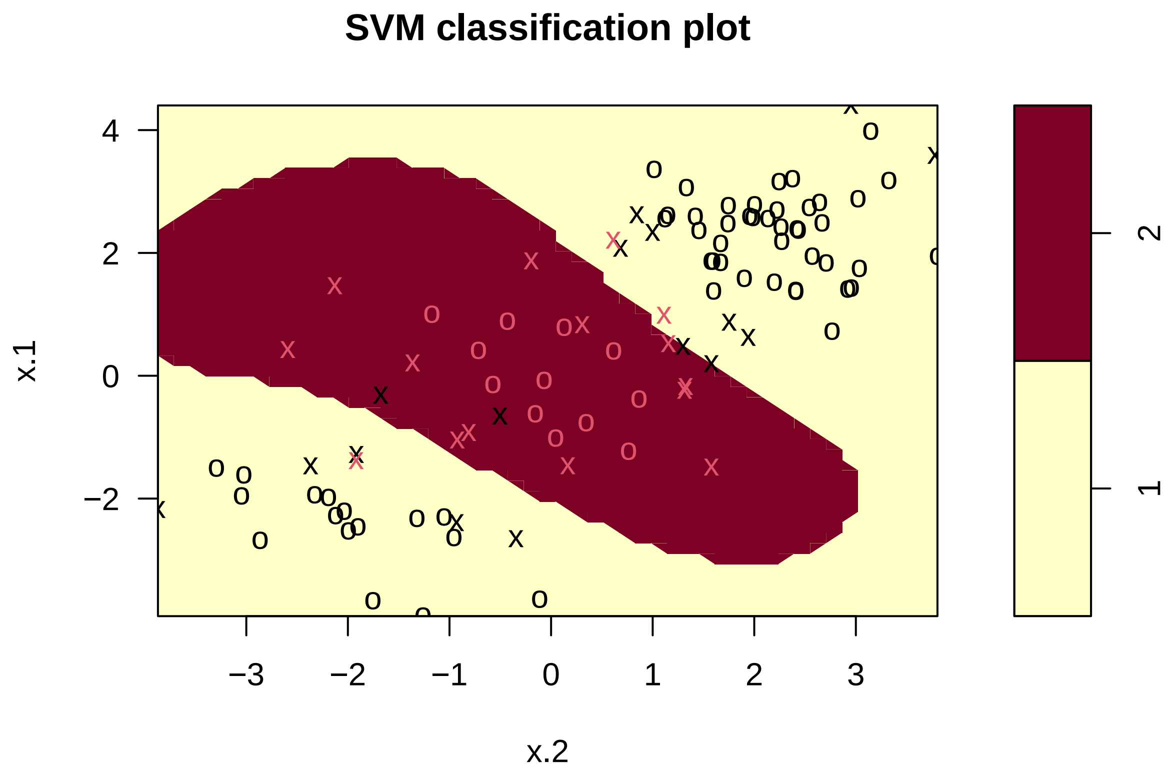
9.6.2

```r
set.seed(1)
x <- matrix(rnorm(200 * 2), ncol = 2)
x[1:100, ] <- x[1:100, ] + 2
x[101:150, ] <- x[101:150, ] - 2
y <- c(rep(1, 150), rep(2, 50))
```

```r
dat <- data.frame(x = x, y = as.factor(y))

plot(x, col = y)
```




```r
train <- sample(200, 100)
svmfit <- svm(y ~ ., data = dat[train , ], kernel = "radial",
  gamma = 1, cost = 1)
plot(svmfit , dat[train , ])
```

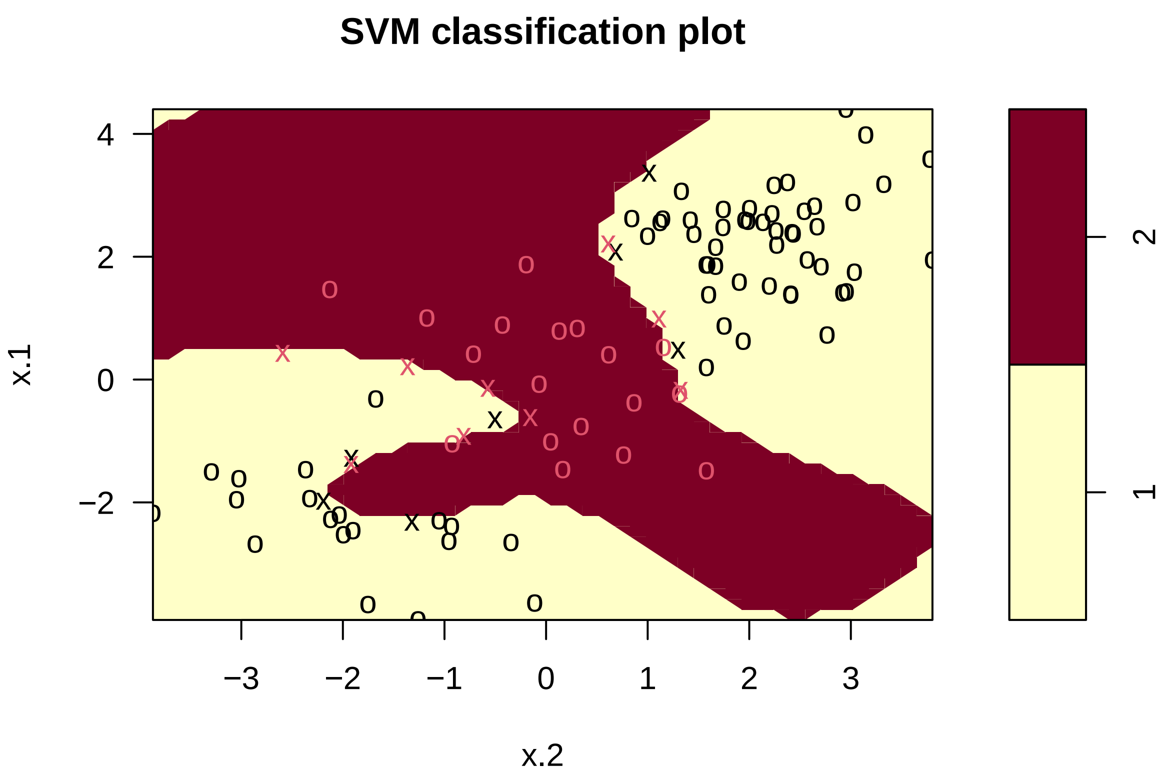



```r
summary(svmfit)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat[train, ], kernel = "radial", gamma = 1,
##     cost = 1)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  1
##
## Number of Support Vectors:  31
##
##  ( 16 15 )
##
##
## Number of Classes:  2
##
## Levels:
##  1 2
```

```r
svmfit <- svm(y ~ ., data = dat[train , ], kernel = "radial",
  gamma = 1, cost = 1e5)
```

```r
plot(svmfit , dat[train , ])
```




```r
set.seed(1)
tune.out <- tune(svm , y ~ ., data = dat[train , ],
  kernel = "radial",
  ranges = list(
  cost = c(0.1, 1, 10, 100, 1000),
  gamma = c(0.5, 1, 2, 3, 4)
    )
  )
summary(tune.out)
```

```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost gamma
##     1   0.5
##
## - best performance: 0.07
##
## - Detailed performance results:
##     cost gamma error dispersion
```

```
## 1  1e-01   0.5  0.26 0.15776213
## 2  1e+00   0.5  0.07 0.08232726
## 3  1e+01   0.5  0.07 0.08232726
## 4  1e+02   0.5  0.14 0.15055453
## 5  1e+03   0.5  0.11 0.07378648
## 6  1e-01   1.0  0.22 0.16193277
## 7  1e+00   1.0  0.07 0.08232726
## 8  1e+01   1.0  0.09 0.07378648
## 9  1e+02   1.0  0.12 0.12292726
## 10 1e+03   1.0  0.11 0.11005049
## 11 1e-01   2.0  0.27 0.15670212
## 12 1e+00   2.0  0.07 0.08232726
## 13 1e+01   2.0  0.11 0.07378648
## 14 1e+02   2.0  0.12 0.13165612
## 15 1e+03   2.0  0.16 0.13498971
## 16 1e-01   3.0  0.27 0.15670212
## 17 1e+00   3.0  0.07 0.08232726
## 18 1e+01   3.0  0.08 0.07888106
## 19 1e+02   3.0  0.13 0.14181365
## 20 1e+03   3.0  0.15 0.13540064
## 21 1e-01   4.0  0.27 0.15670212
## 22 1e+00   4.0  0.07 0.08232726
## 23 1e+01   4.0  0.09 0.07378648
## 24 1e+02   4.0  0.13 0.14181365
## 25 1e+03   4.0  0.15 0.13540064
```

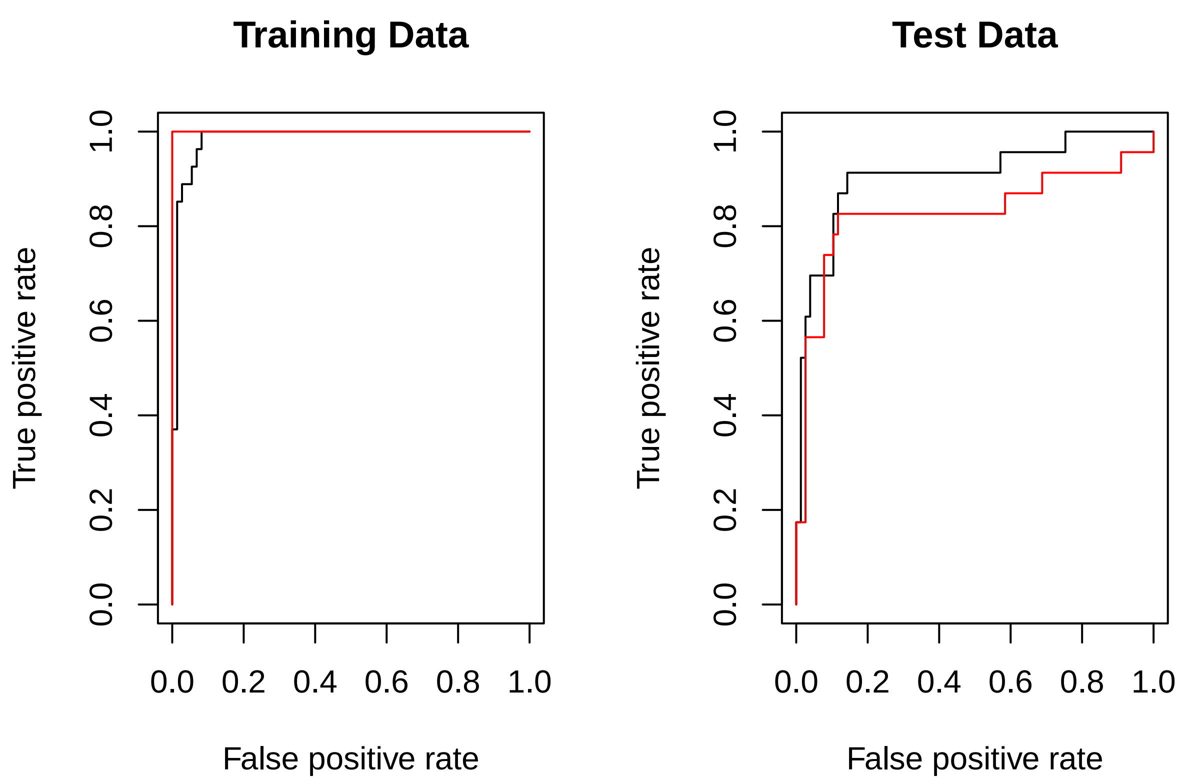
```r
table(
  true = dat[-train , "y"],
  pred = predict(
  tune.out$best.model, newdata = dat[-train, ]
    )
  )
```

```
##     pred
## true  1  2
##    1 67 10
##    2  2 21
```

9.6.3

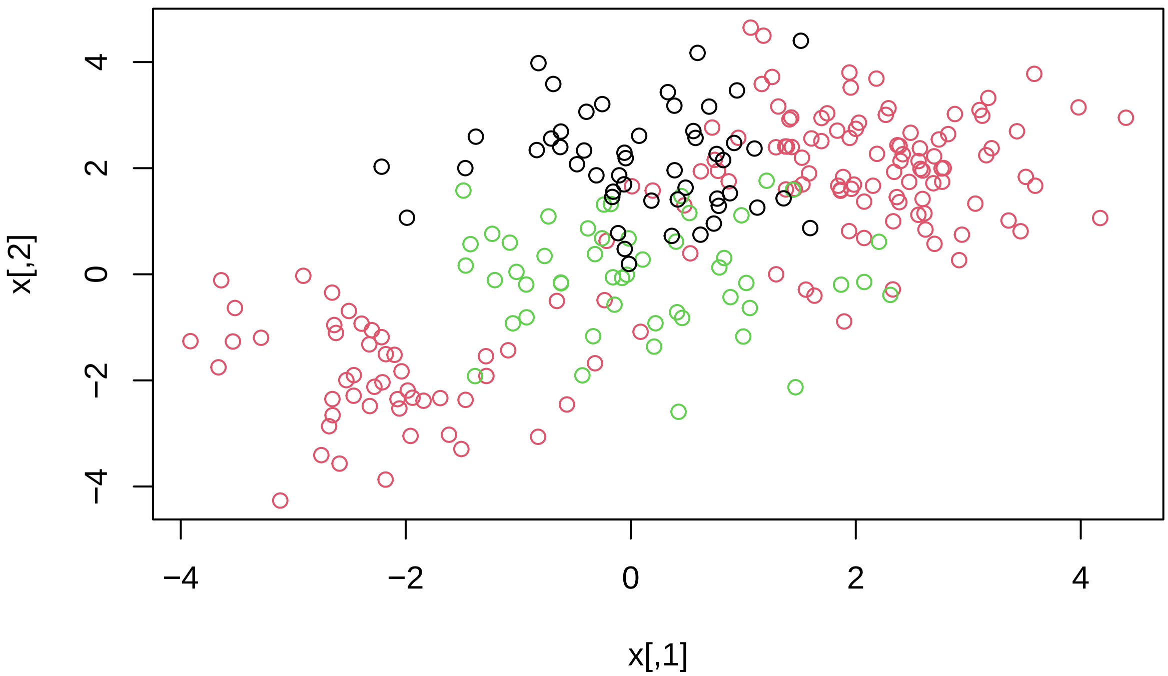
```r
library(ROCR)
rocplot <- function(pred , truth , ...) {
  predob <- prediction(pred , truth)
  perf <- performance(predob , "tpr", "fpr")
  plot(perf , ...)
}

svmfit.opt <- svm(y ~ ., data = dat[train , ],
  kernel = "radial", gamma = 2, cost = 1,
  decision.values = T)
fitted <- attributes(
```

```r
  predict(svmfit.opt , dat[train , ], decision.values = TRUE)
  )$decision.values

par(mfrow = c(1, 2))
rocplot(-fitted, dat[train, "y"], main = "Training Data")

svmfit.flex <- svm(y ~ ., data = dat[train , ],
  kernel = "radial", gamma = 50, cost = 1,
  decision.values = T)
fitted <- attributes(
  predict(svmfit.flex , dat[train , ], decision.values = T)
  )$decision.values
rocplot(-fitted, dat[train, "y"], add = T, col = "red")

fitted <- attributes(
  predict(svmfit.opt , dat[-train , ], decision.values = T)
  )$decision.values
rocplot(-fitted, dat[-train, "y"], main = "Test Data")
fitted <- attributes(
  predict(svmfit.flex , dat[-train , ], decision.values = T)
  )$decision.values
rocplot(-fitted, dat[-train, "y"], add = T, col = "red")
```

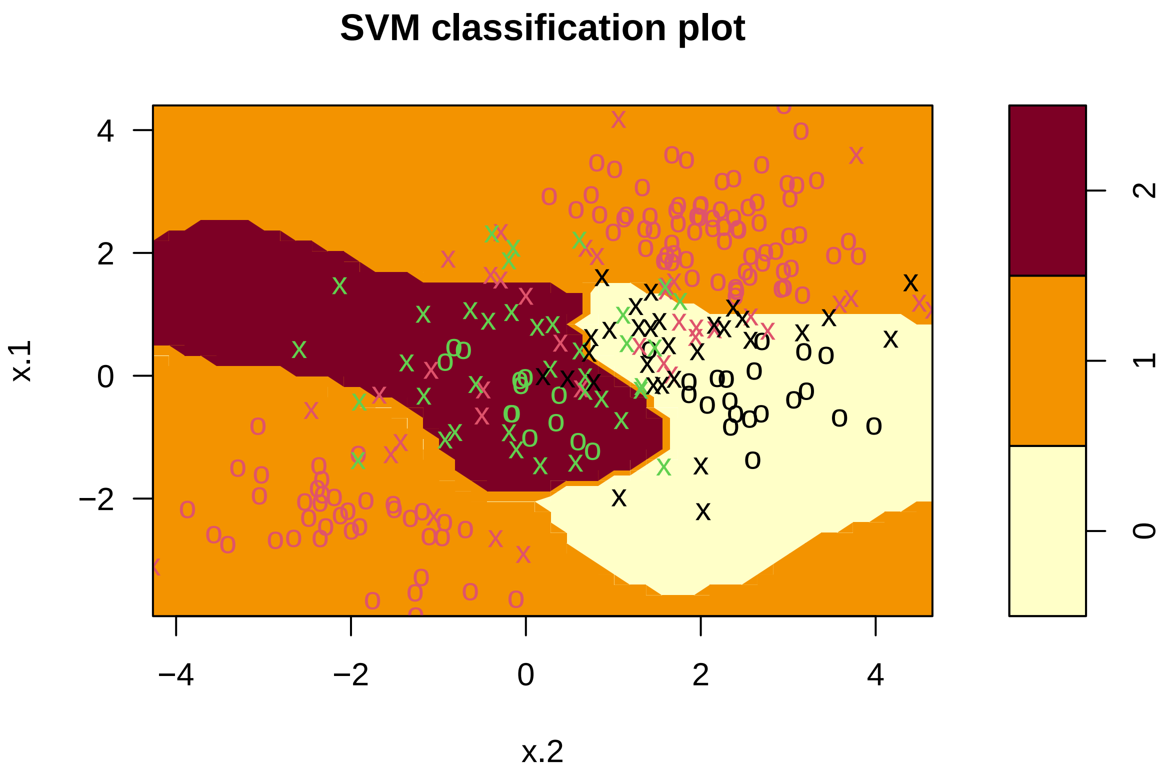


9.6.4

```
set.seed(1)
x <- rbind(x, matrix(rnorm(50 * 2), ncol = 2))
y <- c(y, rep(0, 50))
x[y == 0, 2] <- x[y == 0, 2] + 2
dat <- data.frame(x = x, y = as.factor(y))
par(mfrow = c(1, 1))
plot(x, col = (y + 1))
```




```
svmfit <- svm(y ~ ., data = dat , kernel = "radial",
  cost = 10, gamma = 1)
plot(svmfit , dat)
```



9.6.5

```
library(ISLR2)
names(Khan)
```

```
## [1] "xtrain" "xtest"  "ytrain" "ytest"
```

```
dim(Khan$xtrain)
```

```
## [1]   63 2308
```

```
dim(Khan$xtest)
```

```
## [1]   20 2308
```

```
length(Khan$ytrain)
```

```
## [1] 63
```

```r
length(Khan$ytest)
```

```
## [1] 20
```

```r
table(Khan$ytrain)
```

```
##
##  1  2  3  4
##  8 23 12 20
```

```r
table(Khan$ytest)
```

```
##
## 1 2 3 4
## 3 6 6 5
```

```r
dat <- data.frame(
  x = Khan$xtrain,
  y = as.factor(Khan$ytrain)
  )
out <- svm(y ~ ., data = dat , kernel = "linear",
  cost = 10)
summary(out)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat, kernel = "linear", cost = 10)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  10
##
## Number of Support Vectors:  58
##
##  ( 20 20 11 7 )
##
##
## Number of Classes:  4
##
## Levels:
##  1 2 3 4
```

```r
table(out$fitted, dat$y)
```

```
##
##      1  2  3  4
##   1  8  0  0  0
##   2  0 23  0  0
##   3  0  0 12  0
##   4  0  0  0 20
```

```r
dat.te <- data.frame(
  x = Khan$xtest,
  y = as.factor(Khan$ytest))
pred.te <- predict(out , newdata = dat.te)
table(pred.te, dat.te$y)
```

```
##
## pred.te 1 2 3 4
##       1 3 0 0 0
##       2 0 6 2 0
##       3 0 0 4 0
##       4 0 0 0 5
```