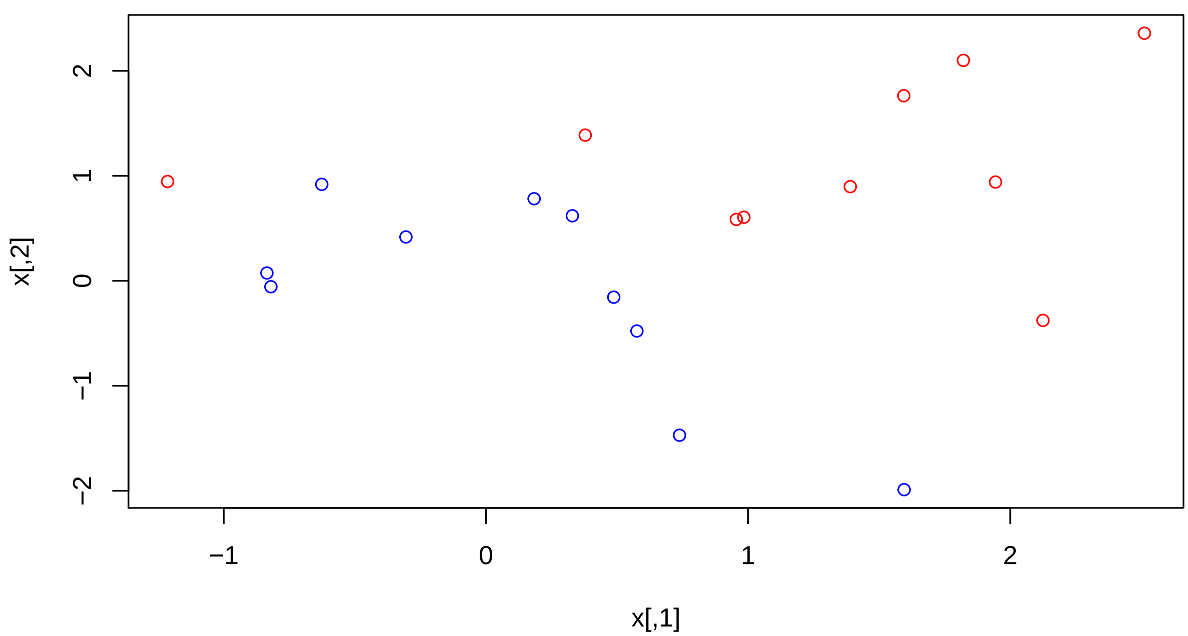
Lab: Support Vector Machines

Jonathan Bryan

August 21, 2018

9.6.1 Support Vector Classifier

```
#create simulated data
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))
```

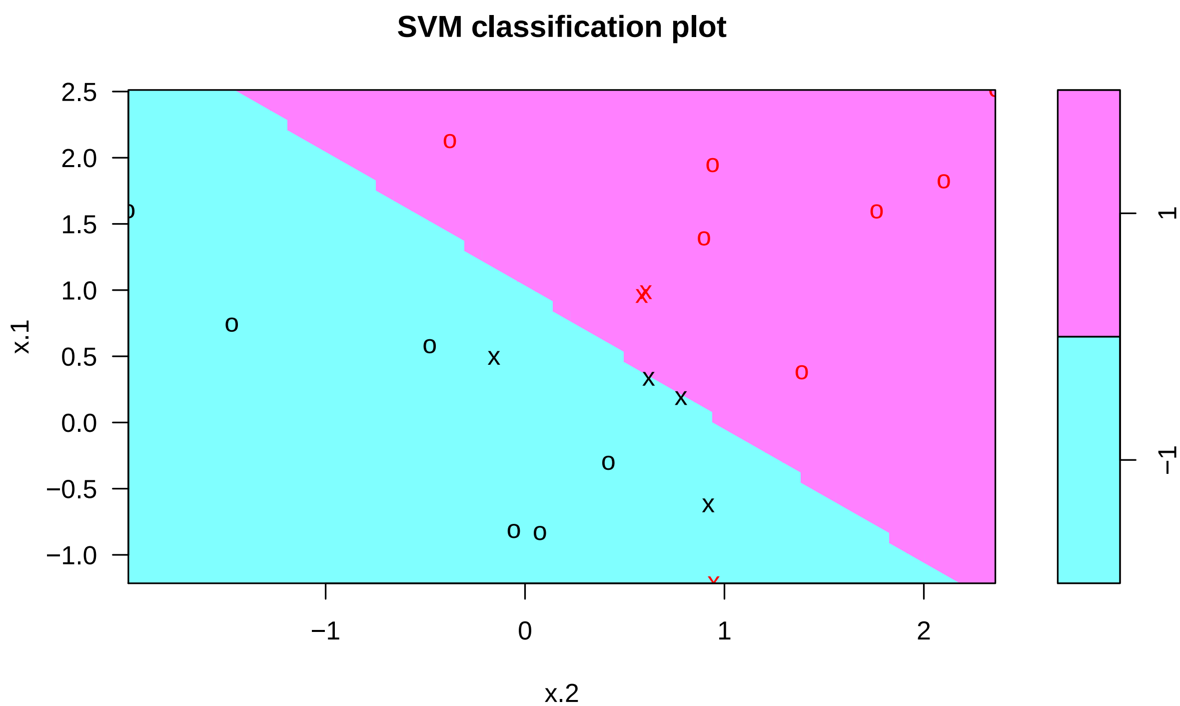



```
#encode response as a factor
dat = data.frame(x = x, y = as.factor(y))
library(e1071)
```

```
## Warning: package 'e1071' was built under R version 3.4.4
```

```
#model linear svm classfier
svmfit = svm(y~., data = dat,
                  kernel = "linear",
                  cost = 10,
                  scale = FALSE)

plot(svmfit,dat) #plot of linear support vector
```




```
svmfit$index #index of support vectors
```

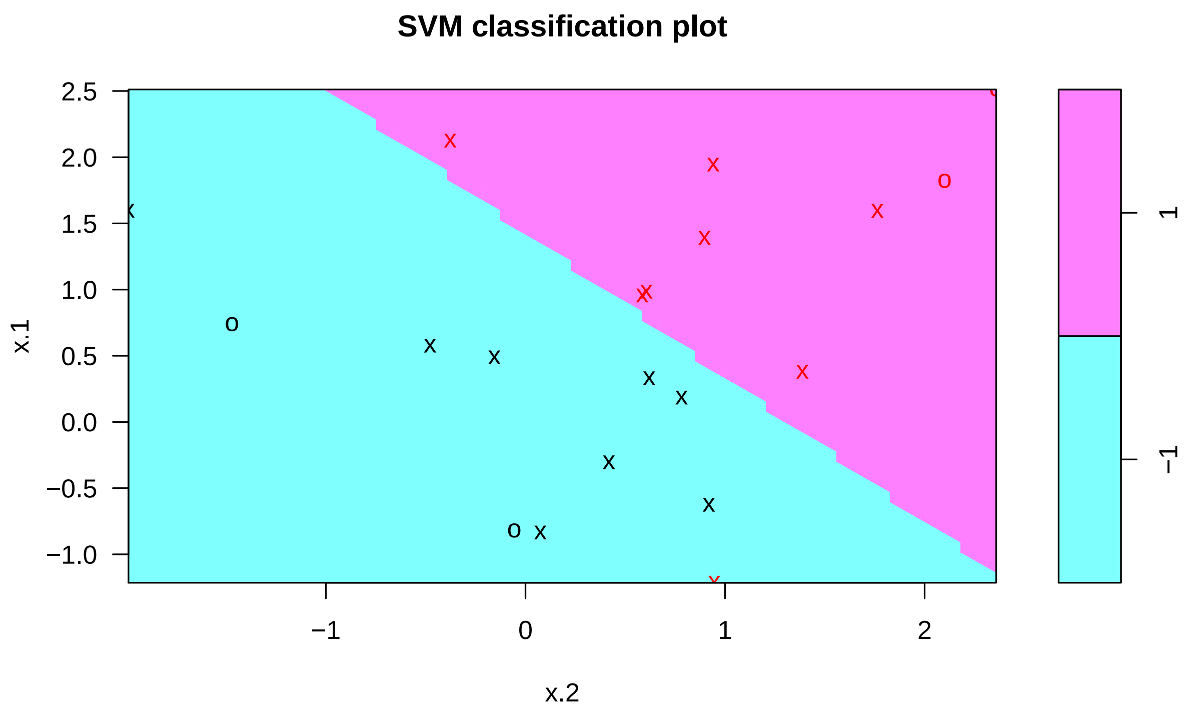
```
## [1]  1  2  5  7 14 16 17
```

```
summary(svmfit)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat, kernel = "linear", cost = 10,
##     scale = FALSE)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  10
##       gamma:  0.5
##
## Number of Support Vectors:  7
##
##  ( 4 3 )
##
##
## Number of Classes:  2
##
## Levels:
##  -1 1
```

```
#model linear svm classifier with smaller cost function
svmfit = svm(y ~., data = dat,
```

```
                    kernel = "linear",
                    cost = 0.1,
                    scale = FALSE)
plot(svmfit, dat)
```




```
svmfit$index
```

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

```
#svm cross-validation
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: 0.1
##
## - Detailed performance results:
```

```
##    cost error dispersion
## 1 1e-03  0.70  0.4216370
## 2 1e-02  0.70  0.4216370
## 3 1e-01  0.10  0.2108185
## 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
```

```
#access best cv model
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
##       gamma:  0.5
##
## Number of Support Vectors:  16
##
##  ( 8 8 )
##
##
## Number of Classes:  2
##
## Levels:
##  -1 1
```

```
#generate test observations
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))

#svm prediction with best cv model
ypred = predict(bestmod, testdat)
table(predict = ypred, truth = testdat$y)
```

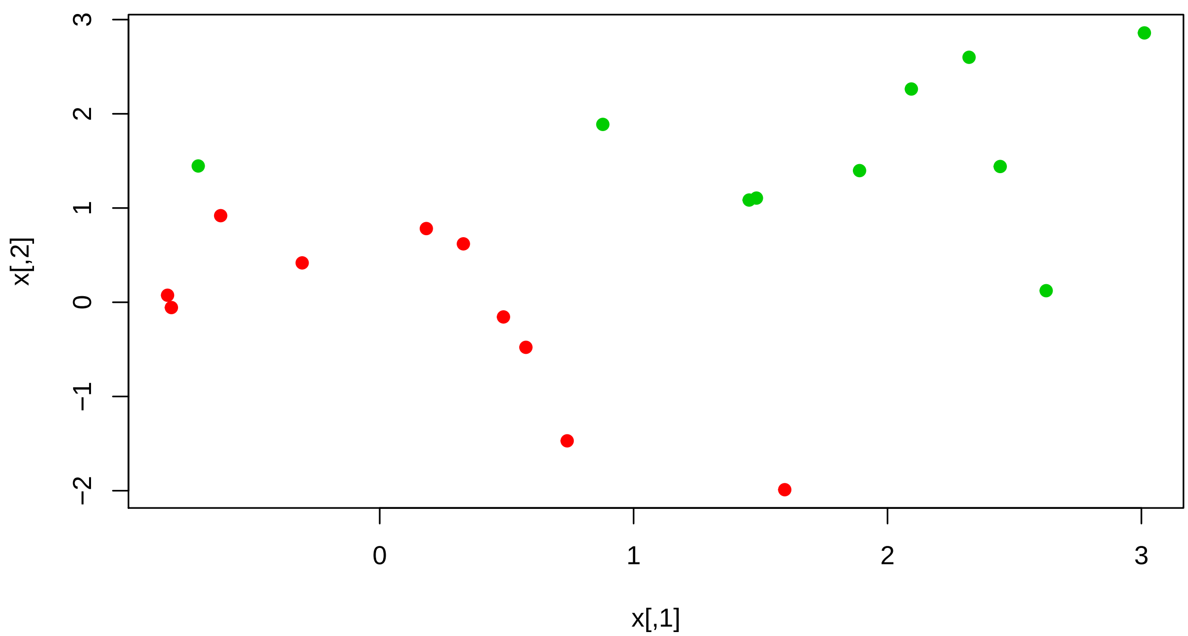
```
##        truth
## predict -1  1
##      -1 11  1
##      1   0  8
```

```
#svm prediction with smaller cost value
svmfit = svm(y~.,
             data=dat,
             kernel = "linear",
             cost = 0.01,
             scale = FALSE)
```

```r
ypred = predict(svmfit, testdat)
table(predict = ypred,
      truth = testdat$y)
```

```
##          truth
## predict -1  1
##      -1 11  2
##      1   0  7
```

```r
#modify training data to be linearly separable
x[y==1,]=x[y==1,] + 0.5
plot(x, col = (y+5)/2, pch =19)
```

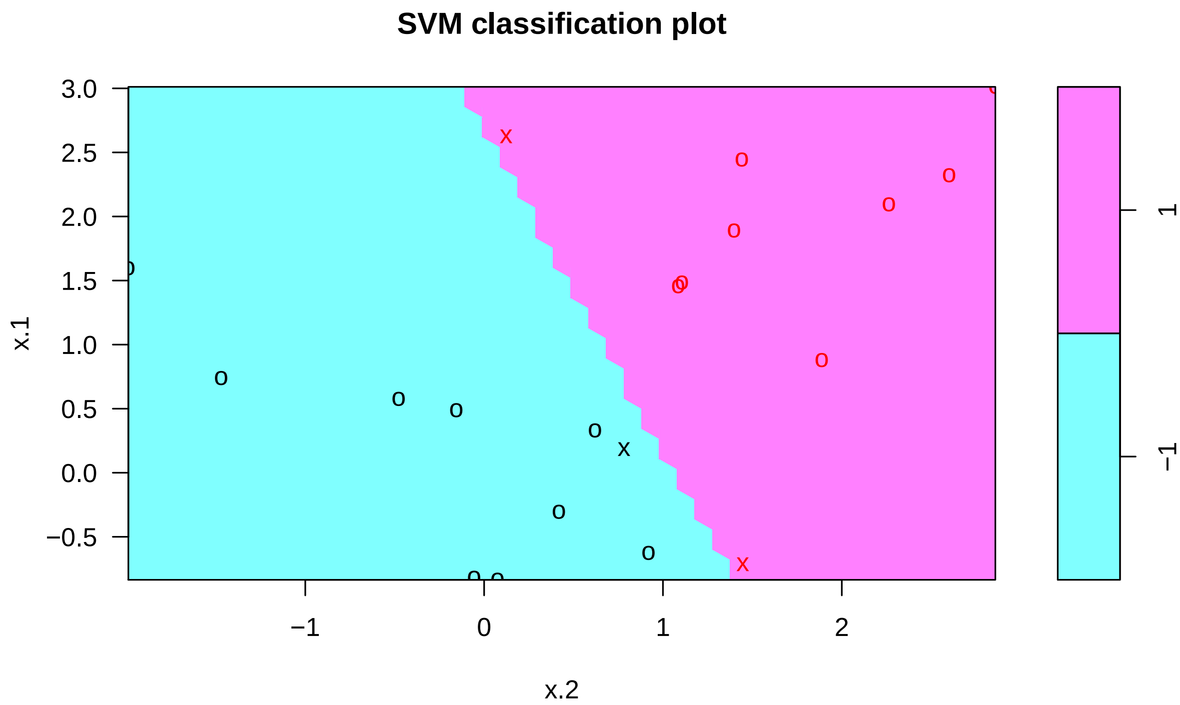



```r
#svm with high cost value to increase training accuracy
dat = data.frame(x=x,
                 y = as.factor(y))
svmfit = svm(y~.,
             data = dat,
             kernel = "linear",
             cost = 1e5)
summary(svmfit)
```

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

```
##        cost:  1e+05
##       gamma:  0.5
##
## Number of Support Vectors:  3
##
##  ( 1 2 )
##
##
## Number of Classes:  2
##
## Levels:
##  -1 1
```

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

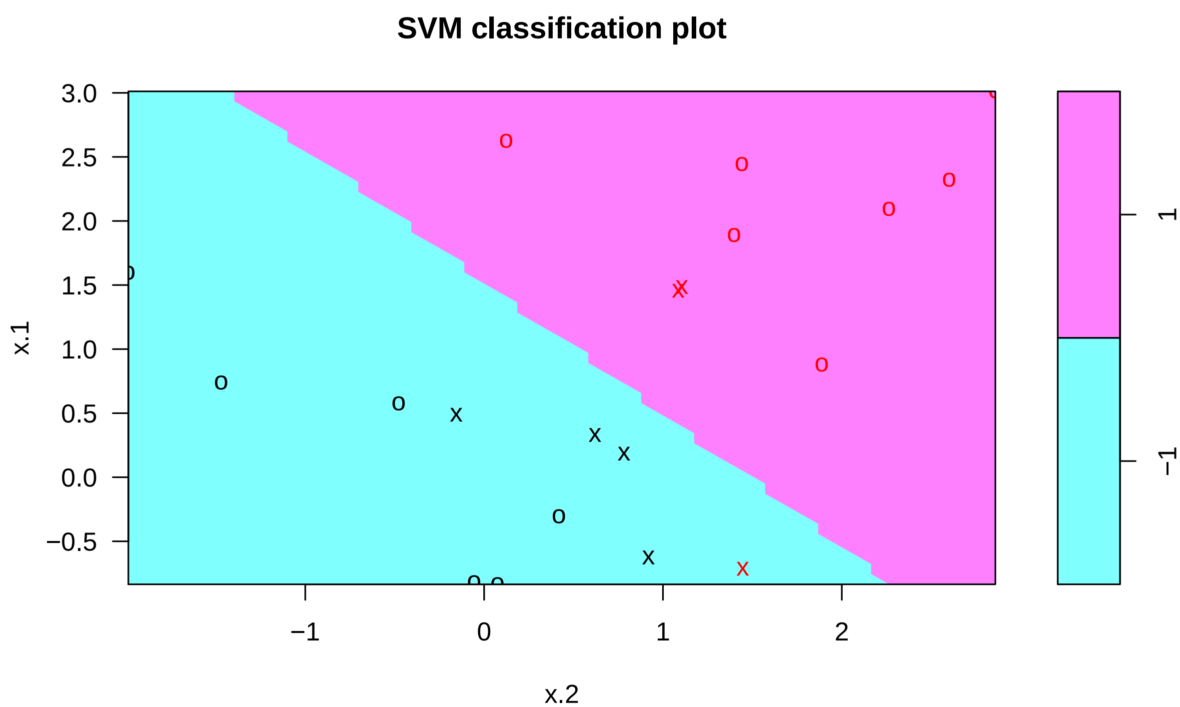



```r
#smaller cost value
svmfit = svm(y~.,
             data = dat,
             kernel = "linear",
             cost = 1)
summary(svmfit)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat, kernel = "linear", cost = 1)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
```

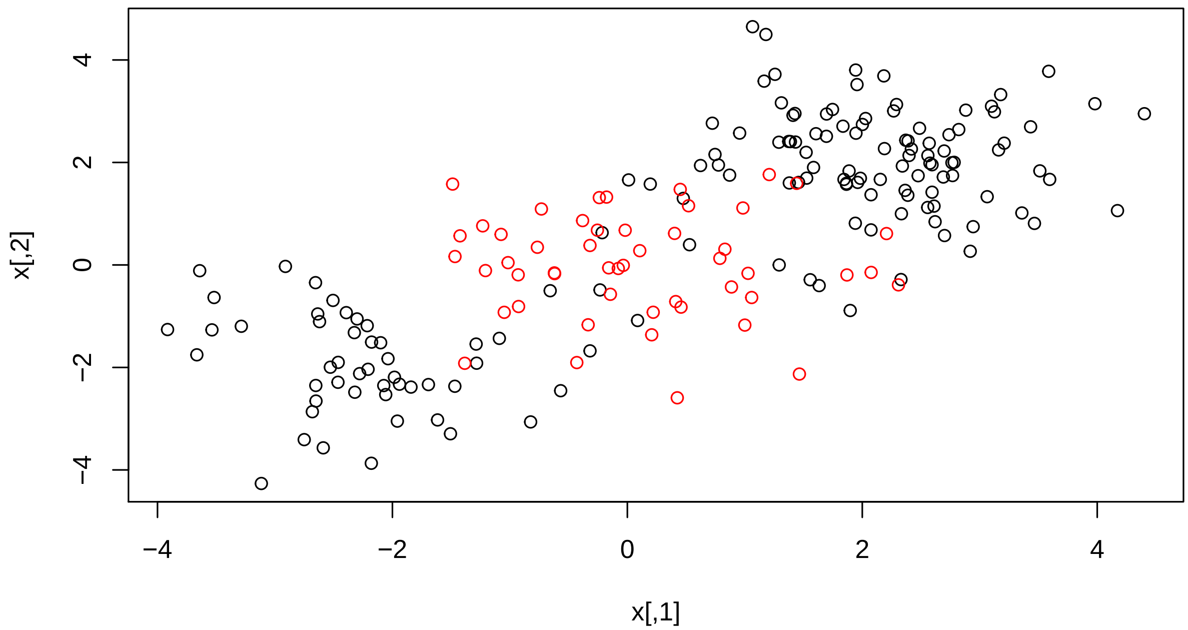
```
##        cost:  1
##       gamma:  0.5
##
## Number of Support Vectors:  7
##
##  ( 4 3 )
##
##
## Number of Classes:  2
##
## Levels:
##  -1 1
```

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

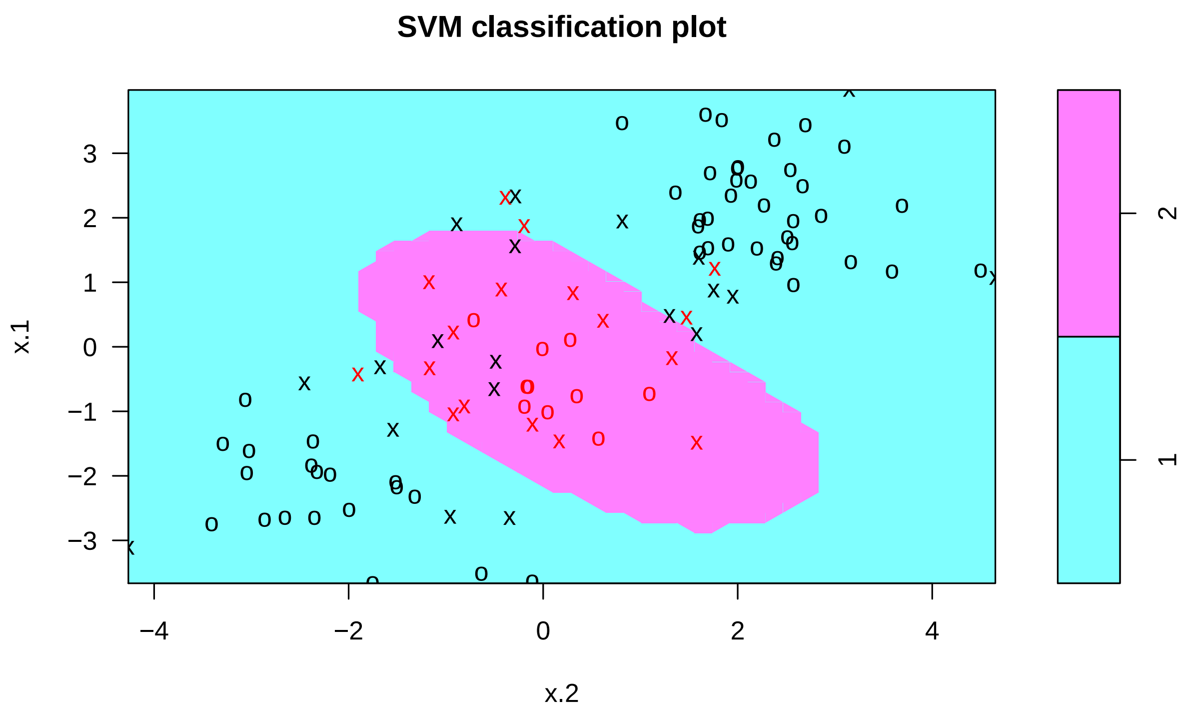


9.6.2 Support Vector Machine

```
#non-linear data generation
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))
dat = data.frame(x=x,
                 y=as.factor(y))
plot(x,col=y)
```




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

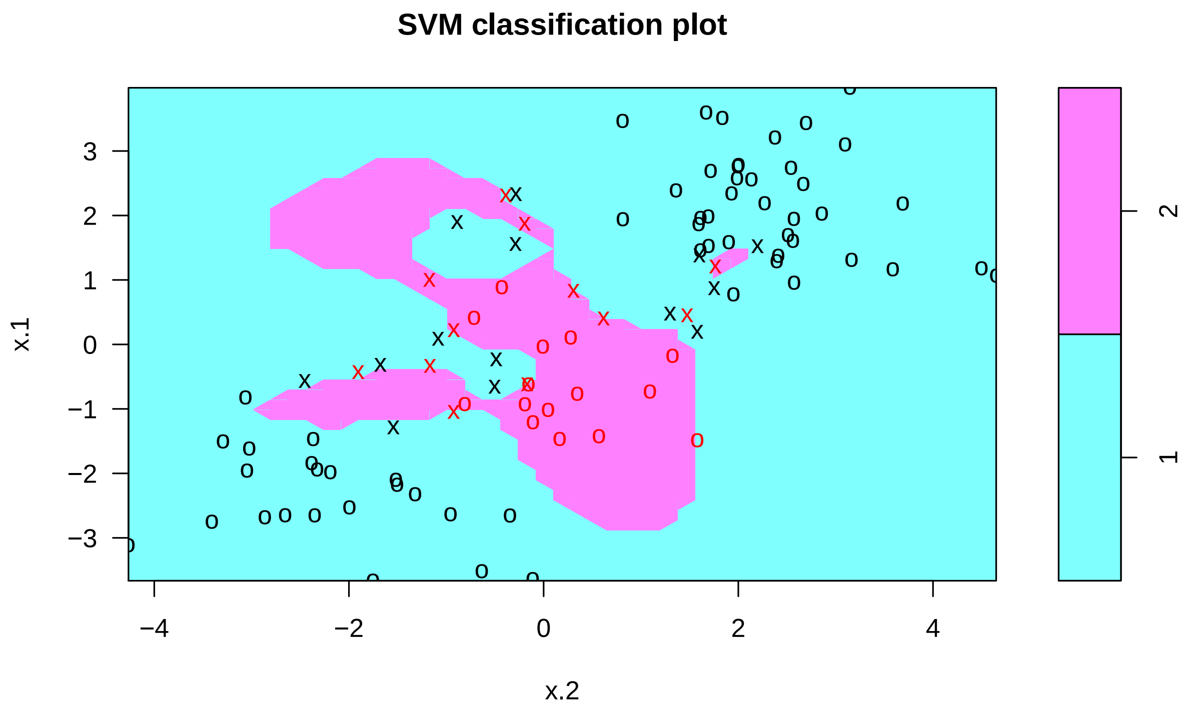



```
summary(svmfit)
```

```
##
## Call:
## svm(formula = y ~ ., data = dat[train, ], kernel = "radial",
##     gamma = 1, cost = 1)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  1
##       gamma:  1
##
## Number of Support Vectors:  37
##
##  ( 17 20 )
##
##
## Number of Classes:  2
##
## Levels:
##  1 2
```

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

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




```r
#radial svm cross-validation
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     2
##
## - best performance: 0.12
##
## - Detailed performance results:
##     cost gamma error dispersion
## 1  1e-01   0.5  0.27 0.11595018
## 2  1e+00   0.5  0.13 0.08232726
## 3  1e+01   0.5  0.15 0.07071068
## 4  1e+02   0.5  0.17 0.08232726
```

```
## 5   1e+03   0.5  0.21 0.09944289
## 6   1e-01   1.0  0.25 0.13540064
## 7   1e+00   1.0  0.13 0.08232726
## 8   1e+01   1.0  0.16 0.06992059
## 9   1e+02   1.0  0.20 0.09428090
## 10 1e+03   1.0  0.20 0.08164966
## 11 1e-01   2.0  0.25 0.12692955
## 12 1e+00   2.0  0.12 0.09189366
## 13 1e+01   2.0  0.17 0.09486833
## 14 1e+02   2.0  0.19 0.09944289
## 15 1e+03   2.0  0.20 0.09428090
## 16 1e-01   3.0  0.27 0.11595018
## 17 1e+00   3.0  0.13 0.09486833
## 18 1e+01   3.0  0.18 0.10327956
## 19 1e+02   3.0  0.21 0.08755950
## 20 1e+03   3.0  0.22 0.10327956
## 21 1e-01   4.0  0.27 0.11595018
## 22 1e+00   4.0  0.15 0.10801234
## 23 1e+01   4.0  0.18 0.11352924
## 24 1e+02   4.0  0.21 0.08755950
## 25 1e+03   4.0  0.24 0.10749677
```

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

```
##     pred
## true  1  2
##    1 74  3
##    2  7 16
```

9.6.3 ROC Curves

```
library(ROCR)
```

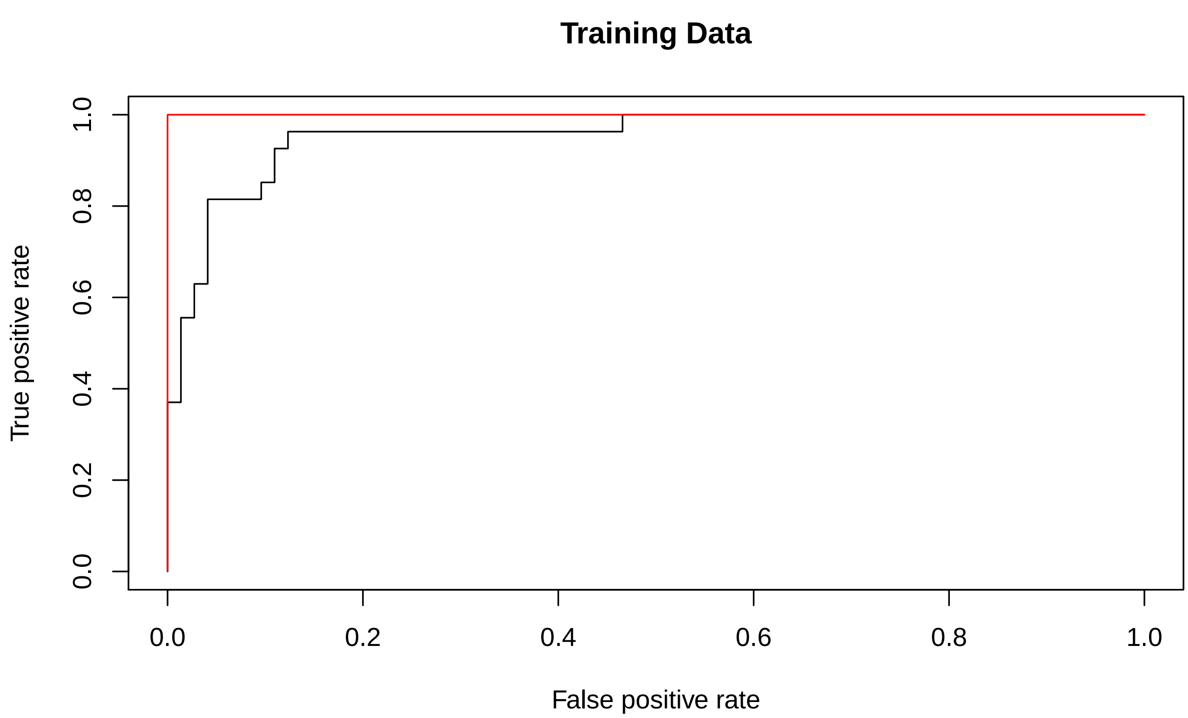
```
## Warning: package 'ROCR' was built under R version 3.4.4
## Loading required package: gplots
## Warning: package 'gplots' was built under R version 3.4.4
##
## Attaching package: 'gplots'
## The following object is masked from 'package:stats':
##
##     lowess
```

```
rocplot = function(pred, truth,...){
                  predob = prediction(pred, truth)
                  perf = performance(predob, "tpr", "fpr")
                  plot(perf,...)
}
```

```
#obtain fitted training set values for svm
svmfit.opt = svm(y~.,
```

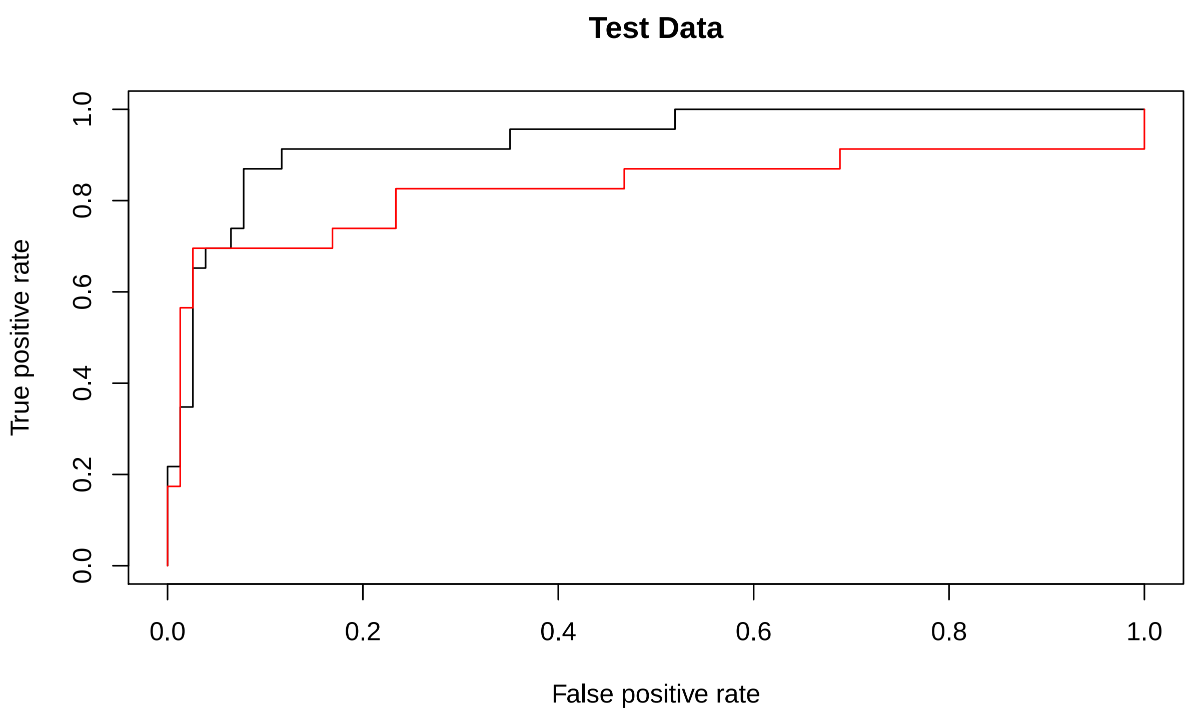
```
                 data = dat[train,],
                 kernel = "radial",
                 gamma = 2,
                 cost = 1,
                 decision.values = TRUE)
fitted = attributes(predict(svmfit.opt,
                           dat[train,],
                           decision.values = TRUE))$decision.values
rocplot(fitted,
        dat[train,"y"],
        main = "Training Data")

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



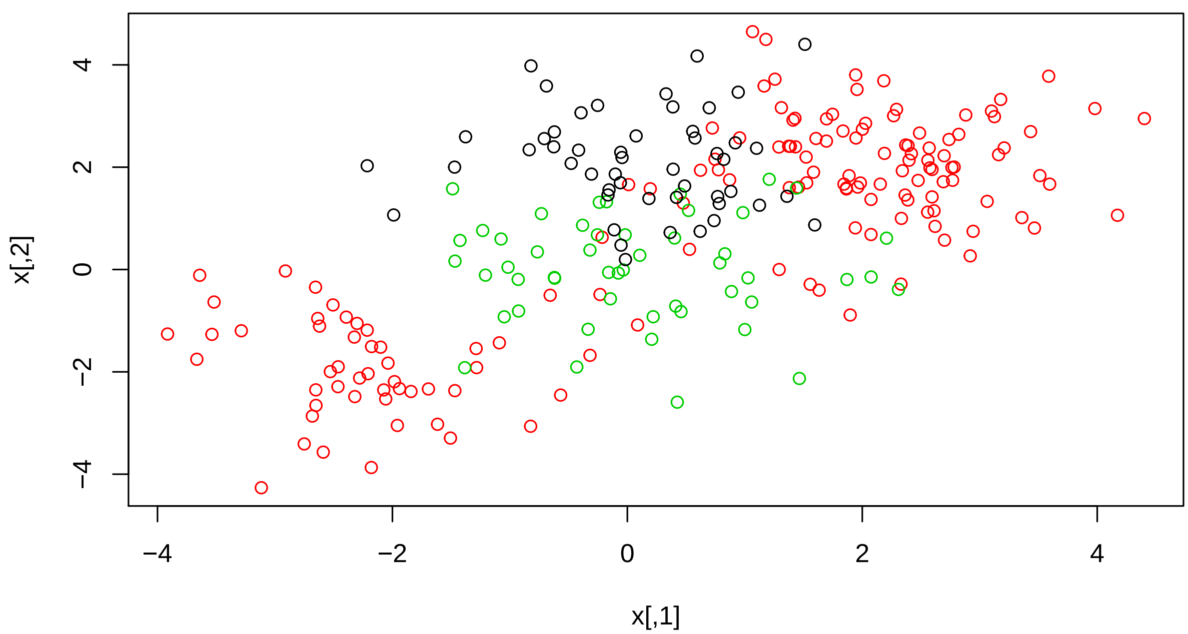

```
#obtain fitted values of radial svm on test data
fitted = attributes(predict(svmfit.opt,
                             dat[-train,],
```

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

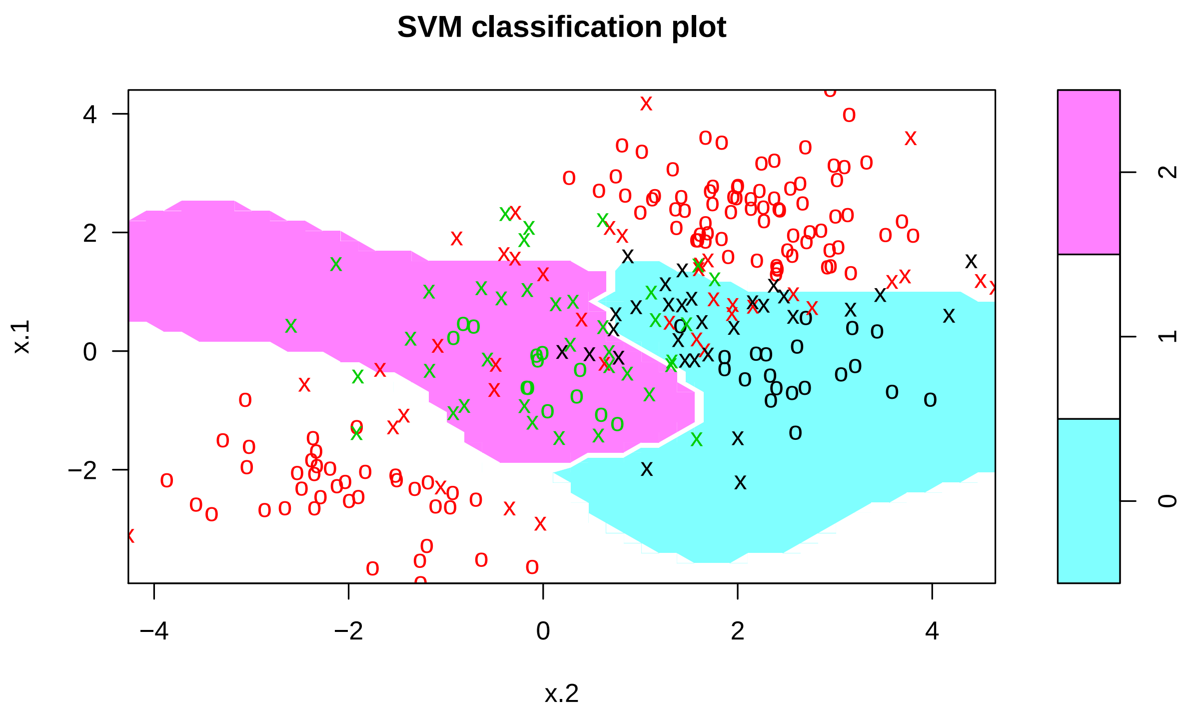


SVM with Multiple Classes

```
#multiple class data generation
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))
```




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



9.6.5 Application to Gene Expression Data

```
library(ISLR)

#EDA of gene expression data
names(Khan)
```

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

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

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

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

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

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

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

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

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

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

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

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

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

```r
#svm classifier with linear kernel
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
##       gamma:  0.0004332756
##
## Number of Support Vectors:  58
##
##  ( 20 20 11 7 )
##
##
## Number of Classes:  4
##
## Levels:
##  1 2 3 4
```

```r
#training prediction
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
```