

Machine Learning – SVM

7.2

I use the R package 'e1071' for svm classification, which is the R interface of the LIBSVM. For details, I use linear kernel and set the cost coefficient to be 10.

```
library(e1071)
```

```
## Loading required package: class
```

```
data = data.frame(v1 = c(1, 2, 3, 2, 3), v2 = c(2, 3, 3, 1, 2), y =  
as.factor(c(1,  
  1, 1, -1, -1)))  
model = svm(y ~ ., data = data, kernel = "linear", cost = 10, scale =  
F)  
summary(model)
```

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

We can see the classification precision as below:

```
pred <- predict(model, data)  
table(pred, data$y)
```

```
##
## pred -1 1
##    -1  2 0
##     1  0 3
```

All training points are classified into the right class(their original class).

I calculate the coefficients for the classification's hyperplane using the returned values of the model.

```
(w = t(model$coefs) %*% model$SV)
```

```
##      v1 v2
## [1,] -1  2
```

```
(b = model$rho)
```

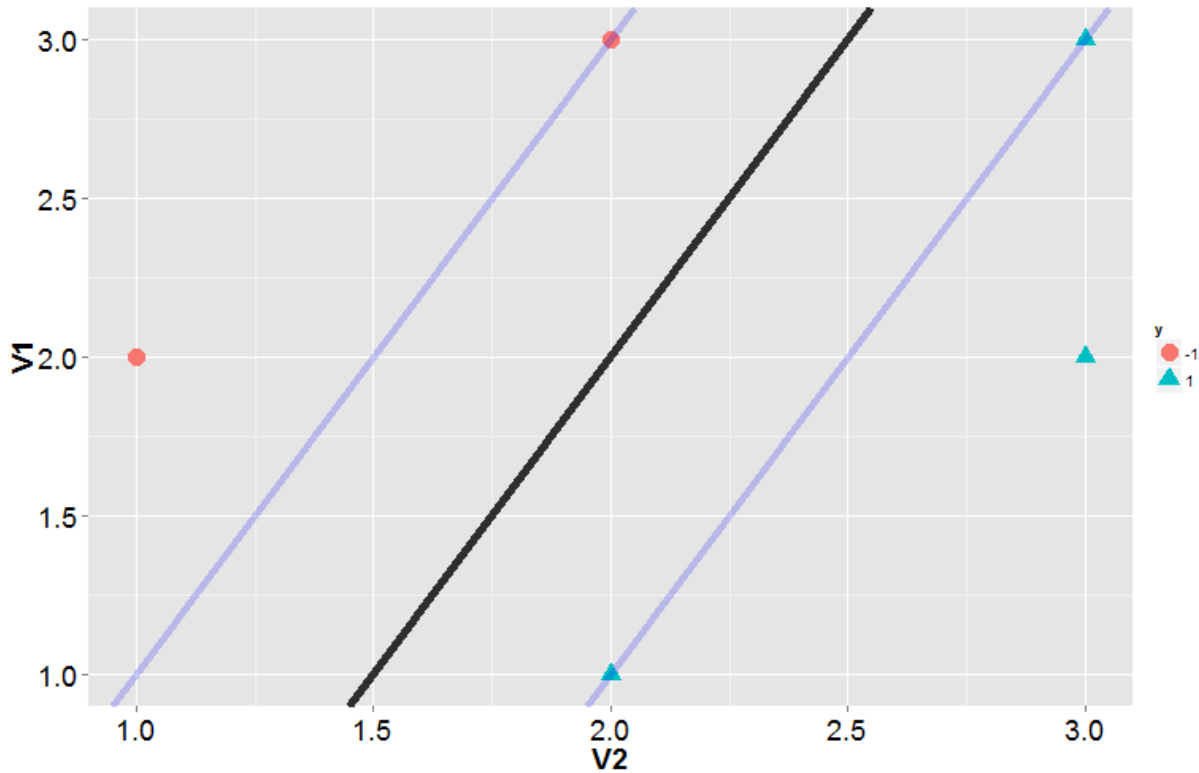
```
## [1] 2
```

The classification hyperplane is: $-X_1 + 2X_2 = 2$

The margin hyperplanes are: $-X_1 + 2X_2 = 2 + 1 = 3$ and $-X_1 + 2X_2 = 2 - 1 = 1$

Then we draw them on one picture:

```
library(ggplot2)
p <- ggplot(data, aes(v1, v2), group = y) + geom_point(aes(colour = y,
  shape = y),
  size = 5, xlim = c(0, 4))
p <- p + geom_abline(intercept = 2/2, slope = 1/2, colour = "black",
  size = 2,
  alpha = 0.8) + coord_flip()
p <- p + geom_abline(intercept = (2 + 1)/2, slope = 1/2, colour =
  "blue", size = 1.5,
  alpha = 0.2) + coord_flip()
p <- p + geom_abline(intercept = (2 - 1)/2, slope = 1/2, colour =
  "blue", size = 1.5,
  alpha = 0.2) + coord_flip()
p + theme(axis.text = element_text(size = rel(1.5), colour = "black"),
  axis.title.y = element_text(size = rel(1.5),
    angle = 90, face = "bold"), axis.title.x = element_text(size =
  rel(1.5),
    face = "bold"), plot.title = element_text(size = rel(1.8), face =
  "bold"),
  strip.text = element_text(size = 15, face = "bold", hjust = 0.5,
  vjust = 0.5))
```



7.3

Problem Description:

$$\begin{aligned} \min_{w,b,\xi} \quad & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i^2 \\ \text{s.t.} \quad & y_i(w \cdot x_i + b) \geq 1 - \xi_i, i = 1, 2, \dots, N \\ & \xi_i \geq 0, i = 1, 2, \dots, N \end{aligned}$$

First we write down the Lagrange Multiplier:

$$L = 1/2 \|w\|^2 + C \sum_{i=1}^N \xi_i^2 - \sum_{i=1}^N \alpha_i [y_i(w \cdot x_i + b) - 1 + \xi_i] + \sum_{i=1}^N \beta_i \xi_i$$

The dual problem is :

$$\max_{\alpha,\beta} \min_{w,b,\xi} L(w, b, \xi, \alpha, \beta)$$

We first solve the min problem. By using the first order condition, we have:

$$\nabla w = w - \sum_{i=1}^N \alpha_i y_i x_i = 0$$

$$\nabla b = \sum_{i=1}^N \alpha_i y_i = 0$$

$$\nabla \xi_i = 2C\xi_i - \alpha_i + \beta_i = 0$$

By substituting the condition into the L function, we get:

$$\begin{aligned} L &= 1/2 \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) - \sum_{i=1}^N \alpha_i y_i [(\sum_{j=1}^N \alpha_j y_j x_j) x_i + b] - \sum_{i=1}^N \alpha_i \\ &= -1/2 \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) - \sum_{i=1}^N \frac{(\alpha_i - \beta_i)^2}{2C} \end{aligned}$$

And it subjects to the restrictions:

$$\sum_{i=1}^N \alpha_i y_i = 0$$

$$\alpha_i \geq 0$$

$$\alpha_i \geq \beta_i \geq 0$$