Machine learning II Master Data Science

Winter Semester 2023/24



Workshop 7 Support vector machines 2

with solutions

There is a written exercise at the end of this worksheet.

The required packages for The R-exercises are e1071, ISLR2, rpart, ROCR and MASS.

Exercise 1 Tutorial

A good website explaining the subject of SVMs with out too much maths can be found here: Support Vector Machines in R Click here 1

Included in this tutorial is a nicer plotting method than the default in the package e1071. If using more than 2 predictor variables then you need to take care defining the grid using the two variables you want to plot.

Read through this tutorial. **The second half includes R code which you should run yourself.** The data set can be downloaded directly from that web page; it originates from the more advanced course book for this course *Hastie*, *Tibshirani and Friedman*.

Exercise 2 Non-linear SVMs: using different kernels

Work through James Section 9.6.2 and 9.6.3 (pp. 392), which fits the the SVM algorithm using non-linear kernels. When you get to the svm command using the radial kernel function, fit SVM models with the following kernels:

· Linear kernel

```
> svmfit<-svm(y~., data=dat[train,], kernel="linear", scale=TRUE, cost=1)
> plot(svmfit, dat[train,])
```

No boundary in the data region is found, and all the red points are misclassified. Varying the cost does not help.

¹The link works in most PDF viewers but not all web browsers. If the link doesn't work, the URL is https://www.datacamp.com/community/tutorials/support-vector-machines-r

• Polynomial kernel with degree 2

```
> svmfit<-svm(y~., data=dat[train,], kernel="polynomial", degree=2,
+ scale=TRUE, coef0=1, cost=0.1)
> plot(svmfit, dat[train,])
```

With a quadratic polynomial kernel two distinct borders are possible. Try increasing the cost using a few values between 1 and 10, and look at the effect on the boundary.

Use tune () to find the best value for the cost parameter. and obtain the confusion matrix. This result is only very slightly worse than with the radial kernel in the book.

Remember that the parameter cost is the reverse of the parameter C in the lecture notes. A high value for cost penalises each support vector heavily. In the notes the parameter was similar to a budget and a high value allowed more support vectors.

• Try increasing the degree, and don't forget the arguments scale=T and coef0=1. The boundaries are slightly different but the results ar not any better.

Note: Last week you used the package pROC to obtain the ROC plots, which I prefer to ROCR. As James et al. uses ROCR this is the package used this week.

Exercise 3 SVM with multiple classes

Work through the short section 9.6.4. Which is a simple example of SVM with three classes. Although the support vector classifier algorithm is run 3 times, the code to do this is no more complex than for binary classification.

Exercise 4 Using SVMs on a practical data set

In Section 9.6.5 you will analyse the Khan *gene expression* data (in the ISLR package). This data set does not have many observations (63 in the training set) but 2308 variables each corresponding to a different gene. The value indicates how strongly each gene was "expressed". Many statistical learning methods have algorithmic problems when $p\gg n$, but this is not a problem with SVM.

Exercise to do at home

Work through Exercise 3 in James et al. Section 9.7 page 398. This could be typical of an exam question on this subject.

N.B. In Part (g) the task is to find a hyperplane which is separating but not optimal, rather than any non-optimal hyperplane.

- (b) $\beta_0 = -0.5$, $\beta_1 = 1$ and $\beta_2 = -1$, i.e. $-0.5 + x_1 x_2 = 0$ is one solution. Any multiple of these coefficients is sufficient.
- (c) classify blue if $-0.5 + x_1 x_2 \ge 0$ otherwise classify red. N.B. the direction of the inequality depends on the signs of β_1 and β_2 .
- (d) The value of M is $\frac{\sqrt{2}}{4}$ which is half the width of the margin.
- (e) Observations 2,3,5 and 6 are the support vectors.
- (f) As the seventh point is not a support vector, a small change will not move it into the margin and so will not change the maximal margin.
- (g) an easy solution is $\beta_0 = 0$, $\beta_1 = 1$ and $\beta_2 = -1$, i.e. $x_1 x_2 = 0$.
- (h) Any point on the wrong side will do, e.g. (1,3) Blue.