732A99/732A68/ TDDE01 Machine Learning

Computer lab 3 block 1

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Contents

1 Contribution of work

Mikael did assignment 1, Siddhesh did assignment 3, Johannes did assignment 2.

2 Assignment 1 - Kernels

3 Assignment 2 - SVM

The code in the file Lab3Block1 2021 SVMs St.R performs SVM model selection to classify the spam dataset. To do so, the code uses the function ksvm from the R package kernlab, which also includes the spam dataset. All the SVM models to select from use the radial basis function kernel (also known as Gaussian) with a width of 0.05. The C parameter varies between the models. Run the code in the file Lab3Block1 2021 SVMs St.R and answer the following questions.

3.1 1

Which filter do you return to the user ? filter0, filter1, filter2 or filter3? Why?

```
## [1] 0.0675
```

```
## [1] 0.08489388
```

```
## [1] 0.082397
```

```
## [1] 0.02122347
```

Filter2 is trained on training and validation data, and gets a lower score on the test data than filter0/1(they are the same filter, the error is calculated on on different data). And as filter3 is trained on all data then tested on a part of it, its not the generalized or validation error that's calculated. So we could chose filter2 as it got the lowest error on the test data 0.082397 vs filter0/1 with 0.08489388. So one could think in this case it was better to just use the train / test split as filter0 underfitted the model a bit when only using the training data and with more data, filter 2 was able to improve the predictions on the test data. But as the c parameter is validated from testing different c values on the training data and validated on the validation data, which also includes in the training in filter2, a bias is included. Therefore filter1(same as filter0) should be returned to the user.

3.2 2

What is the estimate of the generalization error of the filter returned to the user? err0, err1, err2 or err3? Why?

Table 1: Generalization error of the returned filter(1)

x
0.0848939

As filter1 is the returned to the user and err1 is for the testdata, its the Generalized error for the returned filter.

3.3 3

Once a SVM has been fitted to the training data, a new point is essentially classified according to the sign of a linear combination of the kernel function values between the support vectors and the new point. You are asked to implement this linear combination for filter3. You should make use of the functions alphaindex, coef and b that return the indexes of the support vectors, the linear coefficients for the support vectors, and the negative intercept of the linear combination. See the help file of the kernlab package for more information. You can check if your results are correct by comparing them with the output of the function predict where you set type = "decision". Do so for the first 10 points in the spam dataset. Feel free to use the template provided in the Lab3Block1 2021 SVMs St.R file.

$$\hat{\alpha} = \begin{bmatrix} \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \vdots \\ \hat{\alpha}_n \end{bmatrix}$$

$$\hat{y}(x_\star) = \hat{\alpha}^T K(X, x_\star)$$

Where $K()$ is the radial basis function kernel.

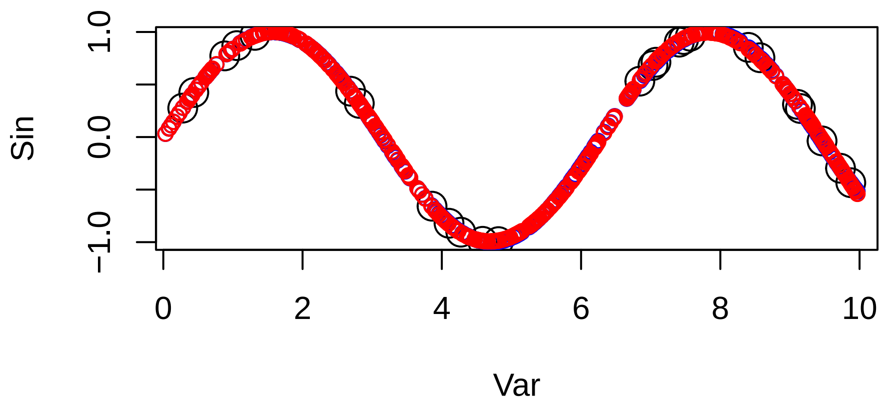
```
##  [1] -1.998999  1.560584  1.000278 -1.756815 -2.669577  1.291312 -1.068444
##  [8] -1.312493  1.000184 -2.208639
```

```
##            [,1]
##  [1,] -1.998999
##  [2,]  1.560584
##  [3,]  1.000278
##  [4,] -1.756815
##  [5,] -2.669577
##  [6,]  1.291312
##  [7,] -1.068444
##  [8,] -1.312493
##  [9,]  1.000184
## [10,] -2.208639
```

We get the same results as the predicted values from filter3

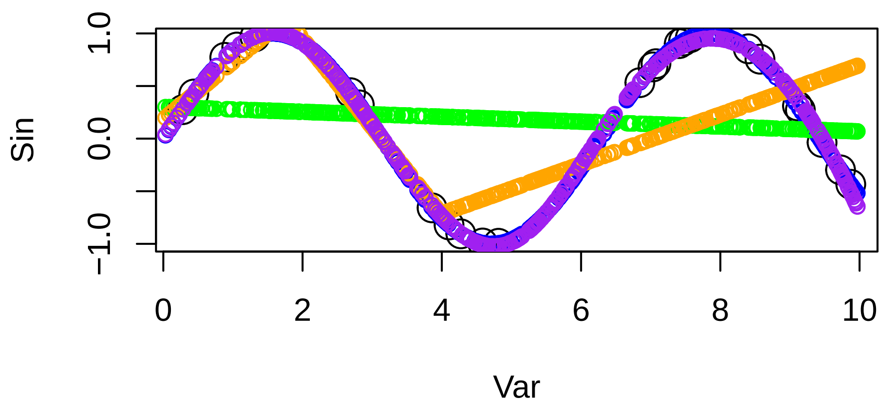
4 Assignment 3 - NN

4.1 1)



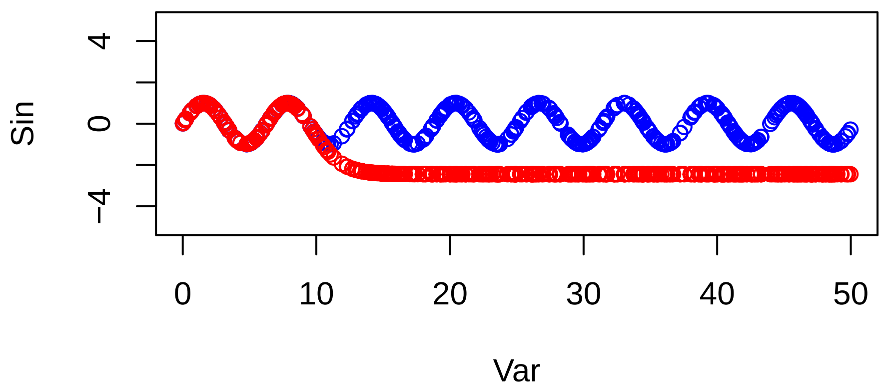
As we can see from the plot, we get very good results, the test data points and predicted sin value for the test data points using the neural network overlap each other suggesting that the model makes good prediction.

4.2 2)



Based on the 3 activation functions, we can see that the softplus activation function does the best and the linear activation function does the worst.

4.3 3)

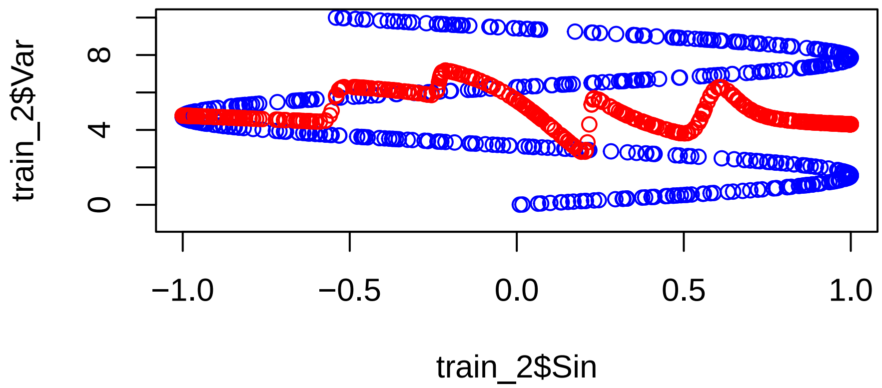


We can see from the plot that the model does well for input values between 0 and 10, and after that it doesnt get any prediction right. The neural network model that we trained was only trained for input values between 0 and 10. While the test data that we fed to this model has input values ranging from 0 and 50 as a result of this we can see that the model doesnt do well.

4.4 4)

We can see after input values of 10, the model predictions becomes a constant value. This is because for that model, the sigmoid activation function would always be close to 1 since the input values for it will be very large for the model. As a result, the in the final layer the prediction will gradually lead to a constant value.

4.5 5)



As we can see, the model doesn't do well to make good predictions. This is because when we take the inverse of the sine function, for a particular input value, we can get multiple possible output values and as a result of this, the model makes bad predictions.

5 Appendix

```
knitr::opts_chunk$set(echo = FALSE, message = FALSE, warning=FALSE, fig.width = 5, fig.height = 3, fig.a
set.seed(12345)
# packages
library(glmnet)
library(caret)
library(dplyr)
library(ggplot2)

# Lab 3 block 1 of 732A99/TDDE01/732A68 Machine Learning
# Author: jose.m.pena@liu.se
# Made for teaching purposes

library(kernlab)
set.seed(1234567890)

data(spam)
foo <- sample(nrow(spam))
spam <- spam[foo,]
spam[,-58]<-scale(spam[,-58])
```

```r
tr <- spam[1:3000, ]
va <- spam[3001:3800, ]
trva <- spam[1:3800, ]
te <- spam[3801:4601, ]

by <- 0.3
err_va <- NULL
for(i in seq(by,5,by)){
  filter <- ksvm(type~.,data=tr,kernel="rbfdot",kpar=list(sigma=0.05),C=i,scaled=FALSE)
  mailtype <- predict(filter,va[,-58])
  t <- table(mailtype,va[,58])
  err_va <-c(err_va,(t[1,2]+t[2,1])/sum(t))
}

filter0 <- ksvm(type~.,data=tr,kernel="rbfdot",kpar=list(sigma=0.05),C=which.min(err_va)*by,scaled=FALSE
mailtype <- predict(filter0,va[,-58])
t <- table(mailtype,va[,58])
err0 <- (t[1,2]+t[2,1])/sum(t)
err0

filter1 <- ksvm(type~.,data=tr,kernel="rbfdot",kpar=list(sigma=0.05),C=which.min(err_va)*by,scaled=FALSE
mailtype <- predict(filter1,te[,-58])
t <- table(mailtype,te[,58])
err1 <- (t[1,2]+t[2,1])/sum(t)
err1

filter2 <- ksvm(type~.,data=trva,kernel="rbfdot",kpar=list(sigma=0.05),C=which.min(err_va)*by,scaled=FAL
mailtype <- predict(filter2,te[,-58])
t <- table(mailtype,te[,58])
err2 <- (t[1,2]+t[2,1])/sum(t)
err2

filter3 <- ksvm(type~.,data=spam,kernel="rbfdot",kpar=list(sigma=0.05),C=which.min(err_va)*by,scaled=FAL
mailtype <- predict(filter3,te[,-58])
t <- table(mailtype,te[,58])
err3 <- (t[1,2]+t[2,1])/sum(t)
err3

knitr::kable(err1, caption = "Generalization error of the returned filter(1)")

sv<-alphaindex(filter3)[[1]]
co<-coef(filter3)[[1]]
inte<- - b(filter3)
k<-NULL
rbf <- rbfdot(0.05) # the used kernel

for(i in 1:10){ # We produce predictions for just the first 10 points in the dataset.
  k2<-NULL
  for(j in 1:length(sv)){
```

```
    # go through every obs in the supportvector and doing the multiplication of the coefficient and kern
    k2 <- c(k2,co[j] * kernelMatrix(as.matrix(spam[sv[j],-58]),as.matrix(spam[i,-58]), kernel = rbf))
  }
  k <-c(k, sum(k2) +inte) # adding the intercept to the predicted k2
}
k
predict(filter3,spam[1:10,-58], type = "decision")


library(neuralnet)
library(sigmoid)
set.seed(1234567890)
Var <- runif(500, 0, 10)
mydata <- data.frame(Var, Sin=sin(Var))
train <- mydata[1:25,] # Training
test <- mydata[26:500,] # Test

#Plotting train and test data
plot(train, cex=2)
points(test, col = "blue", cex=1)



model1<-neuralnet(Sin~Var,data = mydata,hidden = 10)


points(test[,1],predict(model1,test), col="red", cex=1)

plot(train, cex=2)
points(test, col = "blue", cex=1)
linear<-function(x){
  x
}


model2<-neuralnet(Sin~Var,data = mydata,hidden = 10,act.fct = linear)
points(test[,1],predict(model2,test), col="green", cex=1)



model3<-neuralnet(Sin~Var,data = mydata,hidden = 10,act.fct = relu)
points(test[,1],predict(model3,test), col="orange", cex=1)

# https://stackoverflow.com/questions/34532878/package-neuralnet-in-r-rectified-linear-unit-relu-activat

# We can see that directly using a function and feeding max(0,x) will not work as in the neuralnet() it
# activation function should be differentiable so go around this problem by using the "sigmoid" package.
```

```r
softplus<-function(x){
  log(1+exp(x))
}
model4<-neuralnet(Sin~Var,data = mydata,hidden = 10,act.fct = softplus,threshold = 0.1,stepmax = 1e7)
points(test[,1],predict(model4,test), col="purple", cex=1)

# We had to increase the threshold and stepmax values since the neural network required more time to con

# https://stackoverflow.com/questions/16631065/r-neuralnet-does-not-converge-within-stepmax-for-time-ser

Var<- runif(500, 0, 50)
newdata <- data.frame(Var, Sin=sin(Var))

plot(newdata, col = "blue", cex=1, xlim= c(0,50), ylim= c(-5,5))
points(newdata[,1],predict(model1,newdata), col="red", cex=1)

Var<- runif(500, 0, 10)
train_2 <- data.frame(Var, Sin=sin(Var))

model5<-neuralnet(Var~Sin,data = train_2,hidden = 10,threshold = 0.1)

plot(train_2$Sin,train_2$Var, col = "blue", cex=1,ylim=c(-1,10))
points(train_2[,2],predict(model5,train_2), col="red", cex=1)
```