

Question 2.1

Describe a situation or problem from your job, everyday life, current events, etc., for which a classification model would be appropriate. List some (up to 5) predictors that you might use.

1. Classifying candidates, who apply for a job, after interview as “No hire”, “Leaning No hire”, “Leaning Hire”, “Hire”, “Strong Hire”
 - a. Predictors: no. of questions, no. of correct, no. of incorrect, experience of the candidate
2. After grocery shopping classify items as perishable vs non-perishable and store them either in the refrigerator or outside on the shelf
 - a. Predictors: type of item, vegetables, packed goods, frozen or not
3. While Playing lego blocks with my daughter, helping her classify the blocks by color, shapes and sizes
 - a. Predictors: colors, shape, size
4. Classifying good vs bad apples when buying them
 - a. Predictors: color, shape, firmness
5. Classifying weekend hikes by intensity and time before deciding on the hike to take
 - a. Predictors: distance, location from home, elevation

Question 2.2

Import Libraries

```
library(kernlab)
library(rmarkdown)
require(data.table)
```

```
## Loading required package: data.table
```

Read data

```
data<-read.table("/Assignments/ISYE-6501/week1/data\ 2.2/credit_card_data-headers.txt", header=TRUE)
datamatrix <- as.matrix(data)
```

Train Model

trainLoop function to loop through different values of C for a given svm kernel. Return the best performing model

```
trainLoop <- function(k) {
  results=list()
```


Setting default kernel parameters

Top Results for each Kernal

```
## [[1]]
##   kernal_    a0_      a_ C_ accuracy_
## 1: vanilladot 0.08159128 -0.0009884196 25 0.8639144
## 2: vanilladot 0.08159128 -0.0008760683 25 0.8639144
## 3: vanilladot 0.08159128 -0.0016321668 25 0.8639144
## 4: vanilladot 0.08159128  0.0026042255 25 0.8639144
## 5: vanilladot 0.08159128  1.0052357680 25 0.8639144
## 6: vanilladot 0.08159128 -0.0025888253 25 0.8639144
## 7: vanilladot 0.08159128 -0.0001812252 25 0.8639144
## 8: vanilladot 0.08159128 -0.0003848578 25 0.8639144
## 9: vanilladot 0.08159128 -0.0012054701 25 0.8639144
## 10: vanilladot 0.08159128  0.1064407684 25 0.8639144
##
## [[2]]
##   kernal_    a0_      a_ C_ accuracy_
## 1: rbfdot 0.7059756 -58.31781 1000 0.9801223
## 2: rbfdot 0.7059756 -13.54450 1000 0.9801223
## 3: rbfdot 0.7059756 -41.33221 1000 0.9801223
## 4: rbfdot 0.7059756 135.03942 1000 0.9801223
## 5: rbfdot 0.7059756  83.16611 1000 0.9801223
## 6: rbfdot 0.7059756 -95.43087 1000 0.9801223
## 7: rbfdot 0.7059756 110.28435 1000 0.9801223
## 8: rbfdot 0.7059756 -70.23276 1000 0.9801223
## 9: rbfdot 0.7059756 -81.11027 1000 0.9801223
## 10: rbfdot 0.7059756 100.73060 1000 0.9801223
##
## [[3]]
##   kernal_    a0_      a_ C_ accuracy_
## 1: polydot 0.08155816 -0.0010504747 25 0.8639144
## 2: polydot 0.08155816 -0.0012724073 25 0.8639144
## 3: polydot 0.08155816 -0.0015648400 25 0.8639144
## 4: polydot 0.08155816  0.0024923798 25 0.8639144
## 5: polydot 0.08155816  1.0053108361 25 0.8639144
## 6: polydot 0.08155816 -0.0027017651 25 0.8639144
## 7: polydot 0.08155816 -0.0002493278 25 0.8639144
## 8: polydot 0.08155816 -0.0003655242 25 0.8639144
## 9: polydot 0.08155816 -0.0013374678 25 0.8639144
## 10: polydot 0.08155816  0.1063986013 25 0.8639144
```

For the given kernels, rbfdot seems to perform the best.

Equations

Kernel=rbfdot

a0

[1] **0.7059756**

$$(-58.31781 \cdot A_1 + -13.54450 \cdot A_2 + -41.33221 \cdot A_3 + 135.03942 \cdot A_8 + 83.16611 \cdot A_9 + -95.43087 \cdot A_{10} + 110.28435 \cdot A_{11} + -70.23276 \cdot A_{12} + -81.11027 \cdot A_{14} + 100.73060 \cdot A_{15} + \mathbf{0.7059756}) \cdot R_1 \geq 1$$

Kernel=vanilladot

a0

[1] **0.08159128**

$$(-0.0009884196 \cdot A_1 + -0.0008760683 \cdot A_2 + -0.0016321668 \cdot A_3 + 0.0026042255 \cdot A_8 + 1.0052357680 \cdot A_9 + -0.0025888253 \cdot A_{10} + -0.0001812252 \cdot A_{11} + -0.0003848578 \cdot A_{12} + -0.0012054701 \cdot A_{14} + 0.1064407684 \cdot A_{15} + \mathbf{0.08159128}) \cdot R_1 \geq 1$$

KKNN

```
library(kknn)
library(data.table)
```

Load data

```
data<-read.table("/Assignments/ISYE-6501/week1/data\ 2.2/credit_card_data-headers.txt",
header=TRUE)
```

Looping Method

Train function to loop for every value of K for a given kernel, for each i

```
trainkknloop <- function(kknn_kernel){  
  
  predicted <- rep(0,(nrow(data)))  
  kvalues = seq(2,3)  
  results = list()  
  count=0;  
  m = dim(data)[1]  
  for (kval in kvalues){  
  
    for(i in 1:m){  
      kknnmodel_2 <-NULL  
      kknnmodel_2 <- kknn(R1~.,data[-i,],data[i,], k=kval, kernel=kknn_kernel, scale=TRUE)  
      fit <- fitted(kknnmodel_2)  
      predicted[i] = fit  
    }  
    count = count +1  
    results[[count]] = data.table(accuracy=sum(predicted == data[,11])/m, kval=kval, kernel=kknn_kernel)  
  }  
  return(rbindlist(results)[order(-accuracy)][1])  
}
```

Call Training function for each kernel and try different K values from 2 to 10

```
kkcount <-0  
  
accuracy_list= list()  
kknn_kernels = c("rectangular", "triangular","gaussian")  
for (kknn_kernel in kknn_kernels) {  
  
  kkcount = kkcount+1  
  accuracy_list[[kkcount]] = trainkknloop(kknn_kernel)  
}
```

Top K value for each kernel

```
## [[1]]  
## accuracy kval kernel  
## 1: 0.6865443 2 rectangular  
##  
## [[2]]  
## accuracy kval kernel  
## 1: 0.6865443 2 triangular  
##
```

```
## [[3]]  
## accuracy kval kernel  
## 1: 0.6865443 2 gaussian
```

Method 2 using train.knn function

Sample data and break them into train and validation sets

```
m <- dim(data)[1]  
test_sample <- sample(1:m, size = round(m/3), replace = FALSE, prob = rep(1/m, m))
```

```
testing <- data[test_sample, ]  
learning <- data[-test_sample, ]
```

```
dim(learning)
```

```
## [1] 436 11
```

```
dim(testing)
```

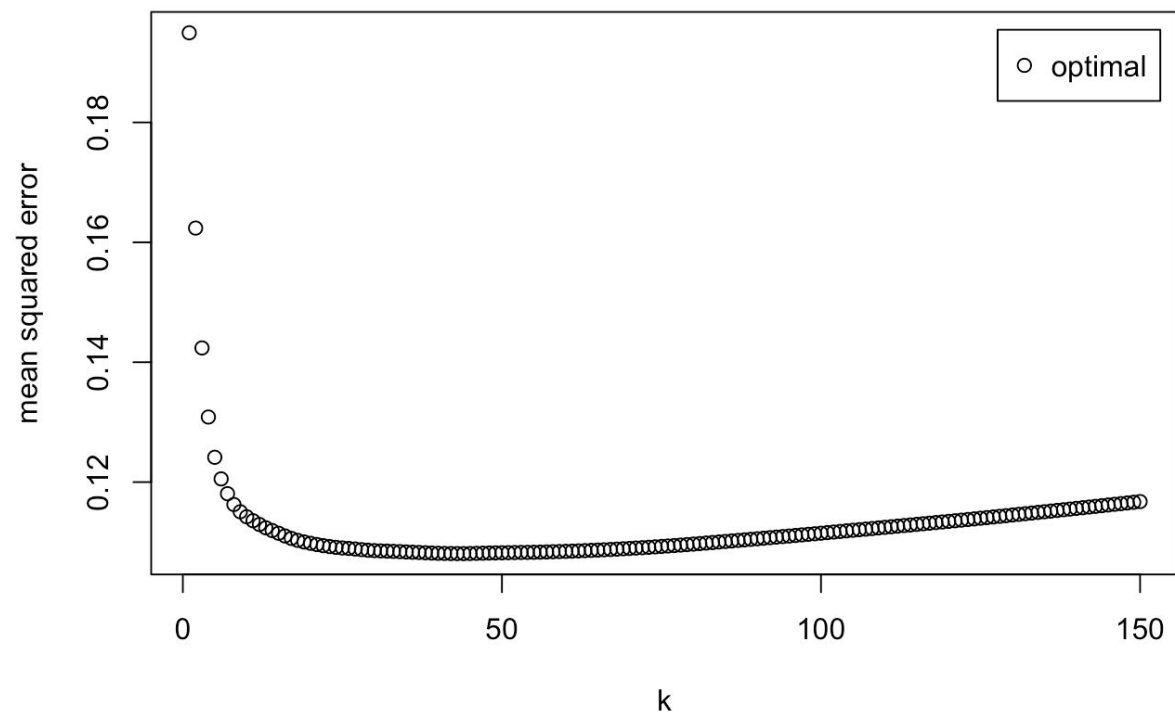
```
## [1] 218 11
```

Train the model on the training set

```
kknnmodel <- train.kknn(R1 ~ ., data = learning, kmax = 150, scale=TRUE)
```

Optimal K value

```
## [1] 43
```



Accuracy

```
prediction <- predict(kknnmodel, testing[, -11])  
pred<-round(prediction)  
pred_accuracy<-table(pred,testing$R1)  
pred_accuracy
```

```
##  
## pred  0  1  
##    0 103 15  
##    1  17 83
```

```
sum(pred==testing$R1)/length(testing$R1)
```

```
## [1] 0.853211
```