Homework 1 - Ganapathy Raaman Balaji

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.

I am a Performance Analytics Engineer at Caterpillar. Performing exploratory analysis one high frequency engine and machine is my daily job. One of the projects I worked on was to classify gensets into different applications, based on the type of operation. I use Python for analysis, and used the Scikit Learn package in Python. I performed Regression Analysis on the following predictors to identify and classify the type of application based on a window of time of engine operation after ignition on.

Some of the factors are:

1. Engine RPM profile in this window (includes factors such as slope of change in a given time)
2. How much the engine is loaded in this window
3. Duration the genset engine was running
4. Generator Power Output
5. Fuel Consumption

```
In [ ]:
```

Question 2.2 (a):

Overall Best Solution: rbfdot seems to provide an accuracy of 99.54128% for cost value = 10000

Best vanilladot solution: Accuracy of 86.39144% for cost value = 1
Best anovadot solution: Accuracy of 90.82569% for cost value = 10000
Best polydot solution: Accuracy of 86.39144% for cost value = 1

We see different results if we split the data to train and test datasets. I have explained it in the following section.

I have also worked on this problem by splitting the data set to train-test (80-20) split.

Stepwise explanation to the problem approach:

In this problem, I have created vectors of different kernels and cost values. I am looping through each kernel list, and a nested loop to iterate over the different cost values. For each kernel and each cost value, I am appending the model accuracy, weights, bias, name of the kernel and the corresponding cost value to its own empty vectors. After this step, I am writing these vectors to a dataframe. Now, the weights are a one dimensional array of a1,a2..., am for each of the cost value and kernel. I am reshaping this array so the first row would contain columns of a1,...am for each C value. The data frame is also sorted by descending order of Model Accuracy.

The equation of the model, based on the highest model accuracy is:

Response, y = (-56.5077762 x A1) + (-90.32754705 x A2) + (-184.3305137 x A3) + (84.07522492 x A8) + (52.8714348 x A9) + (-108.9002671 x A10) + (94.62057917 x A11) + (-42.56268646 x A12) + (-100.3447438 x A14) + (94.97922712 x A15) - 0.88504516

In [25]:
```
options(scipen = 999)
library(kernlab)
library(e1071)
library(data.table)
library(dplyr)

data <- read.table("credit_card_data-headers.txt", header = TRUE)
cost_values = c(1, 10, 100, 1000, 10000, 0.1, 0.01, 0.001)
kernel_list = c("vanilladot", "rbfdot", "anovadot", "polydot")
accuracy_val <- c()
c_val <- c()
kernel_val <- c()
weights <- c()
bias <- c()

for (i in 1: length(kernel_list)){
    for (j in 1:length(cost_values)) {
      model <- ksvm(as.matrix(data[,1:10]), as.factor(data[,11]), type = "C-svc", kernel =  kernel_list[i], sc
aled = TRUE, C=cost_values[j])
      a<- colSums(model@xmatrix[[1]]*model@coef[[1]])
      a0 <- model@b
      pred <- predict(model,data[,1:10])
      accur = sum(pred == data[,11])/nrow(data)
      accuracy_val <- c(accuracy_val, accur)
      c_val <- c(c_val, cost_values[j])
      kernel_val <- c(kernel_val, kernel_list[i])
      weights <- c(weights, a)
      bias <- c(bias, a0)
    }
}
weights1 <- as.data.frame(matrix(weights, 32, 10, byrow = T))
df <- data.frame(kernel_val, c_val, accuracy_val*100, bias)
names(df) <- c("Kernel","Cost Value","Model Accuracy", "a0")
df1 <- merge(df, weights1, by=0)
drops <- c("Row.names")
df1[order(df1["Model Accuracy"], decreasing = TRUE),  !(names(df1) %in% drops)]
names(df1)[names(df1) == "V1"] <- "a1"
names(df1)[names(df1) == "V2"] <- "a2"
names(df1)[names(df1) == "V3"] <- "a3"
names(df1)[names(df1) == "V4"] <- "a8"
names(df1)[names(df1) == "V5"] <- "a9"
names(df1)[names(df1) == "V6"] <- "a10"
names(df1)[names(df1) == "V7"] <- "a11"
names(df1)[names(df1) == "V8"] <- "a12"
names(df1)[names(df1) == "V9"] <- "a14"
names(df1)[names(df1) == "V10"] <- "a15"
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	Kernel	Cost Value	Model Accuracy	a0	V1	V2	V3	V4	V5	
5	rbfdot	10000.000	99.23547	-0.63824146	-76.93709192106	-73.3619155041	-148.4894056079	126.5889917002	68.3144152	-135.9
4	rbfdot	1000.000	98.01223	-0.70466937	-58.53155010645	-12.6283069575	-40.4821556669	136.9102651836	83.0580193	-95.3
3	rbfdot	100.000	95.25994	-0.78805310	-19.19664569632	-37.2038168337	-8.6463593605	56.0607421094	50.0993321	-24.5
2	rbfdot	10.000	91.43731	-0.44146303	-3.01817583732	-17.8291518521	3.7185983605	26.3513848229	31.4942801	-12.4
14	anovadot	10000.000	90.82569	-21.79686445	0.11124018539	-104.1006008680	-199.0308606894	71.2938356661	2.7999202	-1.9
11	anovadot	100.000	90.67278	-1.17407433	0.01883723961	-22.4979970645	-28.0511250529	-2.3583891057	2.5358136	-1.1
13	anovadot	1000.000	90.67278	-8.83058576	0.13349017779	-29.4473951794	-69.1024744447	-21.9604353805	2.6573468	-1.6
10	anovadot	10.000	87.30887	-0.02852669	0.01108490367	-8.1314613538	-10.5797616103	3.7790032035	2.2218562	-0.3
32	rbfdot	1.000	87.00306	-0.42067564	0.58153076023	-1.6867985593	3.7221663922	12.6751302574	30.1475563	-6.2
1	vanilladot	1.000	86.39144	-0.08148382	-0.00110266416	-0.0008980539	-0.0016074557	0.0029041700	1.0047363	-0.0
9	anovadot	1.000	86.39144	-0.37489521	0.00190220241	-1.5386990249	-0.9004786939	0.6984353224	2.0504384	-0.0
12	vanilladot	10.000	86.39144	-0.08157559	-0.00090336713	-0.0007891036	-0.0016972133	0.0026113629	1.0050221	-0.0
18	polydot	1.000	86.39144	-0.08148471	-0.00117790293	-0.0007585829	-0.0015830018	0.0030741611	1.0045976	-0.0
19	polydot	10.000	86.39144	-0.08154590	-0.00096471814	-0.0010953376	-0.0015706841	0.0026559397	1.0050172	-0.0
20	polydot	100.000	86.39144	-0.08157716	-0.00109297047	-0.0012425741	-0.0015628157	0.0027739329	1.0051781	-0.0
23	vanilladot	100.000	86.39144	-0.08158492	-0.00100653481	-0.0011729048	-0.0016261967	0.0030064203	1.0049406	-0.0
24	polydot	0.100	86.39144	-0.08165418	-0.00121245690	-0.0006070979	-0.0013956063	0.0033049356	1.0040211	-0.0
25	polydot	0.010	86.39144	-0.08198853	-0.00015007085	-0.0014818363	0.0014082877	0.0072863924	0.9916470	-0.0
29	vanilladot	0.100	86.39144	-0.08155226	-0.00116089805	-0.0006366002	-0.0015209679	0.0032020638	1.0041339	-0.0
30	vanilladot	0.010	86.39144	-0.08198854	-0.00015007376	-0.0014818294	0.0014083130	0.0072863886	0.9916470	-0.0
15	anovadot	0.100	86.23853	-0.03920849	-0.00001012938	-0.1554799502	-0.0846437302	0.0708553124	2.0403653	-0.0
16	anovadot	0.010	86.23853	-0.14978982	-0.00795464422	0.0236412738	0.0247243307	0.2229233314	1.8114396	-0.0
21	polydot	1000.000	86.23853	-0.07044332	-0.00022971942	-0.0007721707	0.0003367117	0.0004066713	0.9983458	-0.0
22	polydot	10000.000	86.23853	-0.07188214	-0.00093819800	0.0026823497	0.0082815894	0.0052093978	1.0092086	-0.0
27	vanilladot	1000.000	86.23853	-0.07017871	-0.00021491854	0.0007097786	0.0011645166	0.0005673024	0.9987192	-0.0
28	vanilladot	10000.000	86.23853	-0.07046104	0.00089361671	0.0016125725	-0.0003415921	0.0042114213	1.0014528	0.0
6	rbfdot	0.100	85.93272	-0.49895859	0.44800542306	2.6930386158	2.9894344888	7.5262391844	18.2014277	-4.3
26	polydot	0.001	83.79205	0.22261555	-0.00215977831	0.0323381698	0.0466124485	0.1112231618	0.3753053	-0.2
31	vanilladot	0.001	83.79205	0.22261554	-0.00215977831	0.0323381696	0.0466124485	0.1112231617	0.3753053	-0.2
17	anovadot	0.001	58.86850	0.40814596	-0.00495820271	0.0732439801	0.0901967366	0.1794091425	0.4127070	-0.2
7	rbfdot	0.010	56.72783	0.37843714	0.19438004769	0.8585445702	0.9615202459	1.8307180198	4.1270703	-2.3
8	rbfdot	0.001	54.74006	0.94002520	0.01943800477	0.0867650055	0.0980760604	0.1828862979	0.4127070	-0.2

In [ ]:

Question 2.2(a) Alternate method

REPRODUCING THE ABOVE KSVM FUNCTION WITH 80-20 Train-Test Split for the best C-value for each of the above kernel methods.

Similar to the previous cell, I have created a dataframe of kernel, cost values, accuracy, wieghts and bias vectors. I have ordered the dataframe by accuracy in descending order.

The poor model accuracies could be simply a case of overfitting. In the previous cell, the model calculated predicted accuracy on data it was trained in, thus fit that data too well. But in this case, we are testing the model on a test dataset, leading to poorer model accuracy.

I used the split technique used in this stackoverflow link:

[https://stackoverflow.com/questions/17200114/how-to-split-data-into-training-testing-sets-using-sample-function (https://stackoverflow.com/questions/17200114/how-to-split-data-into-training-testing-sets-using-sample-function)](https://stackoverflow.com/questions/17200114/how-to-split-data-into-training-testing-sets-using-sample-function)

In [73]:
```
options(scipen = 999)
library(kernlab)
library(e1071)
library(data.table)
library(caTools)
require(caTools)
set.seed(101)

sample = sample.split(data$R1, SplitRatio = 0.80)
x_data_train <- subset(data[,1:10], sample == TRUE)
y_data_train <- subset(data[,11], sample == TRUE)
x_data_test <- subset(data[,1:10], sample == FALSE)
y_data_test <- subset(data[,11], sample == FALSE)

data <- read.table("credit_card_data-headers.txt", header = TRUE)
cost_values = c(1, 10, 100, 1000, 10000, 0.1, 0.01, 0.001)
kernel_list = c("vanilladot", "rbfdot", "anovadot", "polydot")
accuracy_val <- c()
c_val <- c()
kernel_val <- c()
weights <- c()
bias <- c()

for (i in 1: length(kernel_list)){
    for (j in 1:length(cost_values)) {
      model <- ksvm(as.matrix(x_data_train), as.factor(y_data_train), type = "C-svc", kernel =  kernel_list[i]
, scaled = TRUE, C=cost_values[j])
      a<- colSums(model@xmatrix[[1]]*model@coef[[1]])
      a0 <- model@b
      pred <- predict(model,x_data_test)
      accur = sum(pred == y_data_test)/length(y_data_test)

      accuracy_val <- c(accuracy_val, accur)
      c_val <- c(c_val, cost_values[j])
      kernel_val <- c(kernel_val, kernel_list[i])
      weights <- c(weights, a)
      bias <- c(bias, a0)
    }
}
weights1 <- as.data.frame(matrix(weights, 32, 10, byrow = T))
df <- data.frame(kernel_val, c_val, accuracy_val*100, bias)
names(df) <- c("Kernel","Cost Value","Model Accuracy", "Bias")
df1 <- merge(df, weights1, by=0)
drops <- c("Row.names")
df1[order(df1["Model Accuracy"], decreasing = TRUE),  !(names(df1) %in% drops)]
```

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	Kernel	Cost Value	Model Accuracy	Bias	V1	V2	V3	V4	V5	
11	anovadot	100.000	88.54962	-2.66983539	0.15681584311	-22.4787451448	-25.3143501802	0.0472051163	2.7056535	-1.2
13	anovadot	1000.000	87.78626	-7.73772115	0.20149114886	-62.3291855859	-54.5352431405	-12.7373786968	2.9827013	-2.0
10	anovadot	10.000	86.25954	-0.62600087	-0.01508102521	-8.2171063937	-10.3621450069	4.8201703856	2.3922116	-0.4
14	anovadot	10000.000	86.25954	-19.75539577	0.23603209871	-141.3793629830	-86.3276799089	-21.5872990256	2.9562049	-1.1
1	vanilladot	1.000	85.49618	-0.09739999	-0.00107433634	-0.0020990654	-0.0016807507	0.0042647148	1.0047152	-0.0
9	anovadot	1.000	85.49618	-0.58628080	-0.00106433194	-1.3151866751	-1.2742658817	1.1078581244	2.0630098	-0.0
12	vanilladot	10.000	85.49618	-0.09726800	-0.00117581013	-0.0021618342	-0.0020185757	0.0046171297	1.0049805	-0.0
15	anovadot	0.100	85.49618	-0.06077585	-0.00003832392	-0.1290328776	-0.1146214540	0.1085304610	2.0423360	-0.0
18	polydot	1.000	85.49618	-0.09729321	-0.00117728585	-0.0020144465	-0.0018992961	0.0045339600	1.0050025	-0.0
19	polydot	10.000	85.49618	-0.09740113	-0.00106567026	-0.0020013082	-0.0016111113	0.0040460833	1.0047940	-0.0
20	polydot	100.000	85.49618	-0.09710195	-0.00131673502	-0.0020654587	-0.0017846763	0.0043327819	1.0048605	-0.0
21	polydot	1000.000	85.49618	-0.08588901	0.00016348864	0.0005152847	-0.0002312576	0.0004359906	0.9981452	-0.0
22	polydot	10000.000	85.49618	-0.08526746	-0.00195078227	0.0038529897	0.0014114186	0.0064801281	0.9974943	-0.0
23	vanilladot	100.000	85.49618	-0.09721200	-0.00107671853	-0.0020602805	-0.0017033717	0.0039784939	1.0050680	-0.0
24	polydot	0.100	85.49618	-0.09834222	-0.00136258606	-0.0014045740	-0.0013012923	0.0035179549	1.0029793	-0.0
25	polydot	0.010	85.49618	-0.09754501	-0.00106415440	-0.0018193278	0.0039899832	0.0112262163	0.9845057	-0.0
27	vanilladot	1000.000	85.49618	-0.08606945	0.00019008636	0.0002998667	0.0002165888	0.0005074091	0.9974718	-0.0
28	vanilladot	10000.000	85.49618	-0.08871878	-0.00175092685	0.0036540001	-0.0045134983	0.0047415736	1.0014557	-0.0
29	vanilladot	0.100	85.49618	-0.09838218	-0.00129612346	-0.0013626013	-0.0013522761	0.0036024550	1.0029996	-0.0
30	vanilladot	0.010	85.49618	-0.09754502	-0.00106413518	-0.0018193307	0.0039899708	0.0112261930	0.9845058	-0.0
32	rbfdot	1.000	85.49618	-0.40957213	-2.04442860421	0.3866227893	2.0225476631	15.9647791351	28.5402266	-4.3
6	rbfdot	0.100	84.73282	-0.47822488	0.31827953404	2.4905123762	2.5146231116	7.0057362013	16.4593585	-3.6
26	polydot	0.001	83.96947	0.29164928	-0.00530297781	0.0338661041	0.0605962903	0.1069222905	0.3127378	-0.1
31	vanilladot	0.001	83.96947	0.29164928	-0.00530297871	0.0338661035	0.0605962901	0.1069222902	0.3127378	-0.1
2	rbfdot	10.000	81.67939	-0.44259458	-12.39184196070	-15.6758957448	4.5748748970	32.3394387855	28.2963105	-11.1
3	rbfdot	100.000	80.15267	-0.65145613	-10.20000313384	-27.7218582700	-5.6766002324	61.9698756554	56.4209665	-35.9
4	rbfdot	1000.000	79.38931	-1.23879027	-23.58541446144	-21.2492144343	-124.1571731667	93.6442944458	120.3203259	-98.8
5	rbfdot	10000.000	77.86260	-2.08644510	-14.95093912344	-79.1986580085	-236.4777338798	110.9654196790	123.6127404	-92.2
16	anovadot	0.010	74.04580	-0.19864180	-0.01535700189	0.0350049147	0.0463721843	0.2712795280	1.6279941	-0.1
17	anovadot	0.001	66.41221	0.50465689	-0.00444237055	0.0598649558	0.0879332478	0.1533199079	0.3329171	-0.1
7	rbfdot	0.010	54.96183	0.47706905	0.12963618386	0.7170428903	0.9166762262	1.5681187657	3.3291707	-1.8
8	rbfdot	0.001	54.96183	0.94854979	0.01512422145	0.0715753134	0.0920495128	0.1571744811	0.3329171	-0.1

Question 2.3:

Using the k-nearest-neighbors classification function kknn contained in the R kknn package, suggest a good value of k, and show how well it classifies that data points in the full data set. Don't forget to scale the data (scale=TRUE in kknn). Note that kknn will read the responses as continuous, and return the fraction of the k closest responses that are 1 (rather than the most common response, 1 or 0).

Stepwise explanation to the problem approach:

```
In this problem, I have created vectors of different kernels and k values. The logic is similar to train.kknn (leav
e-one-out cross validation). The method looks at all the data looks at all the data except for the i-th row of dat
a. To do this, I loop through the rows of data, over different values of k.

Since the predicted values have integers with decimal places, I round them to get predicted values of 0 or 1. For e
ach kernel and each k value, I am appending the model accuracy, k value and name of the kernel to its own empty vec
tors. After this step, I am joining these vectors to a dataframe (sorted by accuracy - descending).
```

Using this approach, 12 and 15 seem to be good values of k, and the model accuracy for both the values of k is 85.32110 %. I get the best possible accuracy when using "optimal" kernel.

In [43]:
```
library(kernlab)
library(kknn)

data <- read.table("credit_card_data-headers.txt", header = TRUE)

k_list <- c(1:50)
kernel_list <- c("rectangular" , "triangular", "inv", "gaussian", "rank", "optimal")

accuracy_val <- c()
k_val <- c()
kernel_val <- c()
pred <- rep(0, nrow(data))

for (m in 1:length(kernel_list)){
    for (i in 1:length(k_list)) {
        for (j in 1:nrow(data)) {
            kknn_model <- kknn(R1~., data[-j,1:11], data[j,1:11], k = k_list[i], distance = 2, scale = TRUE, k
ernel = kernel_list[m])
            pred[j] <- round(fitted(kknn_model))
        }
        accur = sum(pred == data[,11])/length(data[,11])
        accuracy_val <- c(accuracy_val, accur)
        k_val <- c(k_val, k_list[i])
        kernel_val <- c(kernel_val, kernel_list[m])
    }
}

df <- data.frame(kernel_val, k_val, accuracy_val*100)
names(df) <- c("Kernel","K Value","Model Accuracy")
df[order(df["Model Accuracy"], decreasing = TRUE), ]

# cat("Max Accuracy is:", max(accuracy[1:length(k_list)]), ",\nand the corresponding value of k is: ", k_list
[which.max(accuracy[1:length(k_list)])])
```

	Kernel	K Value	Model Accuracy
262	optimal	12	85.32110
265	optimal	15	85.32110
60	triangular	10	85.16820
255	optimal	5	85.16820
261	optimal	11	85.16820
263	optimal	13	85.16820
264	optimal	14	85.16820
266	optimal	16	85.16820
267	optimal	17	85.16820
268	optimal	18	85.16820
22	rectangular	22	85.01529
44	rectangular	44	85.01529
61	triangular	11	85.01529
62	triangular	12	85.01529
64	triangular	14	85.01529
142	inv	42	85.01529
158	gaussian	8	85.01529
222	rank	22	85.01529
244	rank	44	85.01529
260	optimal	10	85.01529
269	optimal	19	85.01529
270	optimal	20	85.01529
48	rectangular	48	84.86239
63	triangular	13	84.86239
65	triangular	15	84.86239
66	triangular	16	84.86239
67	triangular	17	84.86239
106	inv	6	84.86239
143	inv	43	84.86239
248	rank	48	84.86239
...	...	...	...
178	gaussian	28	82.72171
4	rectangular	4	82.56881
15	rectangular	15	82.56881
176	gaussian	26	82.56881
204	rank	4	82.56881
215	rank	15	82.56881
3	rectangular	3	82.26300
17	rectangular	17	82.26300
19	rectangular	19	82.26300
103	inv	3	82.26300
153	gaussian	3	82.26300
203	rank	3	82.26300
217	rank	17	82.26300
219	rank	19	82.26300
54	triangular	4	81.95719
1	rectangular	1	81.49847
51	triangular	1	81.49847

	Kernel	K Value	Model Accuracy
52	triangular	2	81.49847
101	inv	1	81.49847
102	inv	2	81.49847
151	gaussian	1	81.49847
152	gaussian	2	81.49847
201	rank	1	81.49847
251	optimal	1	81.49847
252	optimal	2	81.49847
253	optimal	3	81.49847
254	optimal	4	81.49847
53	triangular	3	80.88685
2	rectangular	2	78.59327
202	rank	2	78.59327

In [ ]:

Question 3.1 (a):

Problem:

```
Using the same data set (credit_card_data.txt or credit_card_data-headers.txt) as in Question 2.2, use the ksvm or
 kknn function to find a good classifier:
Using cross-validation (do this for the k-nearest-neighbors model; SVM is optional)
```

Solution:

```
Here I am using train.kknn and cv.kknn methods.
train.kknn - Training of kknn method via leave-one-out crossvalidation
cv.kknn - k-fold cross-validation, where k is the number number of data points (HERE I AM USING 10). Cross validate
s 1 row with k-1 rows.

I am also plotting all the "train.kknn" models in one plot. This shows mean squared error values vs. k-values. From
this plot visualization, it is not exactly possible to ascertain what the lowest MSE is, or what kernel has the low
est MSE. However, it can be seen that the lowest MSE seems to occur around k=22.

From the train.kknn approach, attributes(model) shows that the Minimal mean squared error is 10.61155 % for k = 22
 and for the "inv" Kernel.
```

Websites I referred to other than documentation, to work on this problem:

```
1. train.kknn - http://course1.winona.edu/bdeppa/Stat%20425/Handouts/Section%2013%20-%20Nearest%20Neighbor%20Classi
fication.docx
2. cv.kknn - https://www.kaggle.com/jaybee79/sf-crime-class-knn-s-only-benchmark
```

In [14]:
```
library(kernlab)
library(kknn)
library(data.table)
library(e1071)
library(caTools)
require(caTools)
set.seed(101)

data <- read.table("credit_card_data-headers.txt", header = TRUE)
kernels = c("rectangular", "triangular", "epanechnikov", "biweight", "triweight", "cos", "inv", "gaussian", "o
ptimal")

cat("-------------------------------------BEGIN train.kknn method ------------------------------------------
\n")
train_model <- train.kknn(R1~., data, kmax = 200, distance = 2, kernel = kernels, scale = TRUE)
train_model
plot(train_model)
title("Kernels using train.kknn")

best_train_kernel <- train_model$best.parameters$kernel
best_train_kval <- train_model$best.parameters$k
kknn_train_model <- train.kknn(R1~., data, ks=best_train_kval, distance = 2, kernel = best_train_kernel, scale
= TRUE)
pred <- round(predict(kknn_train_model, data[,1:10]))
train_model_accuracy <- sum(pred == data[,11])/length(data[,11])
cat("\nBest Kernel is:",best_train_kernel,", Best K Value is:",best_train_kval,", and the accuracy is:",train_
model_accuracy*100,"%\n")
cat("\n-------------------------------------END train.kknn method ------------------------------------------
\n\n")
cat("\n-------------------------------------BEGIN cv.kknn method ------------------------------------------
\n")
kvals <- c(1:100)
model_accuracy <- c()

for (i in 1:length(kernels)){
  for (j in 1:length(kvals)){
    cv_model <- cv.kknn(R1~., data= data, kcv = 10, scale = TRUE, kernel = kernels[i], k = kvals[j])
    cv_model <- data.table(cv_model[[1]])
    cv_model_accuracy <- sum(round(cv_model$yhat) == data$R1)/length(data$R1)
    model_accuracy <- c(model_accuracy, cv_model_accuracy)
  }
  cat("\nFor", kernels[i], "kernel, model accuracy is:", max(model_accuracy)*100,"% and corresponding k-value
 is:",kvals[which.max(model_accuracy[1:length(kvals)])])

}
cat("\n-------------------------------------END cv.kknn method ------------------------------------------\n")
```

```
Warning message:
"package 'data.table' was built under R version 3.5.3"

-------------------------------------BEGIN train.kknn method -------------------------------------------

Call:
train.kknn(formula = R1 ~ ., data = data, kmax = 200, distance = 2,     kernel = kernels, scale = TRUE)

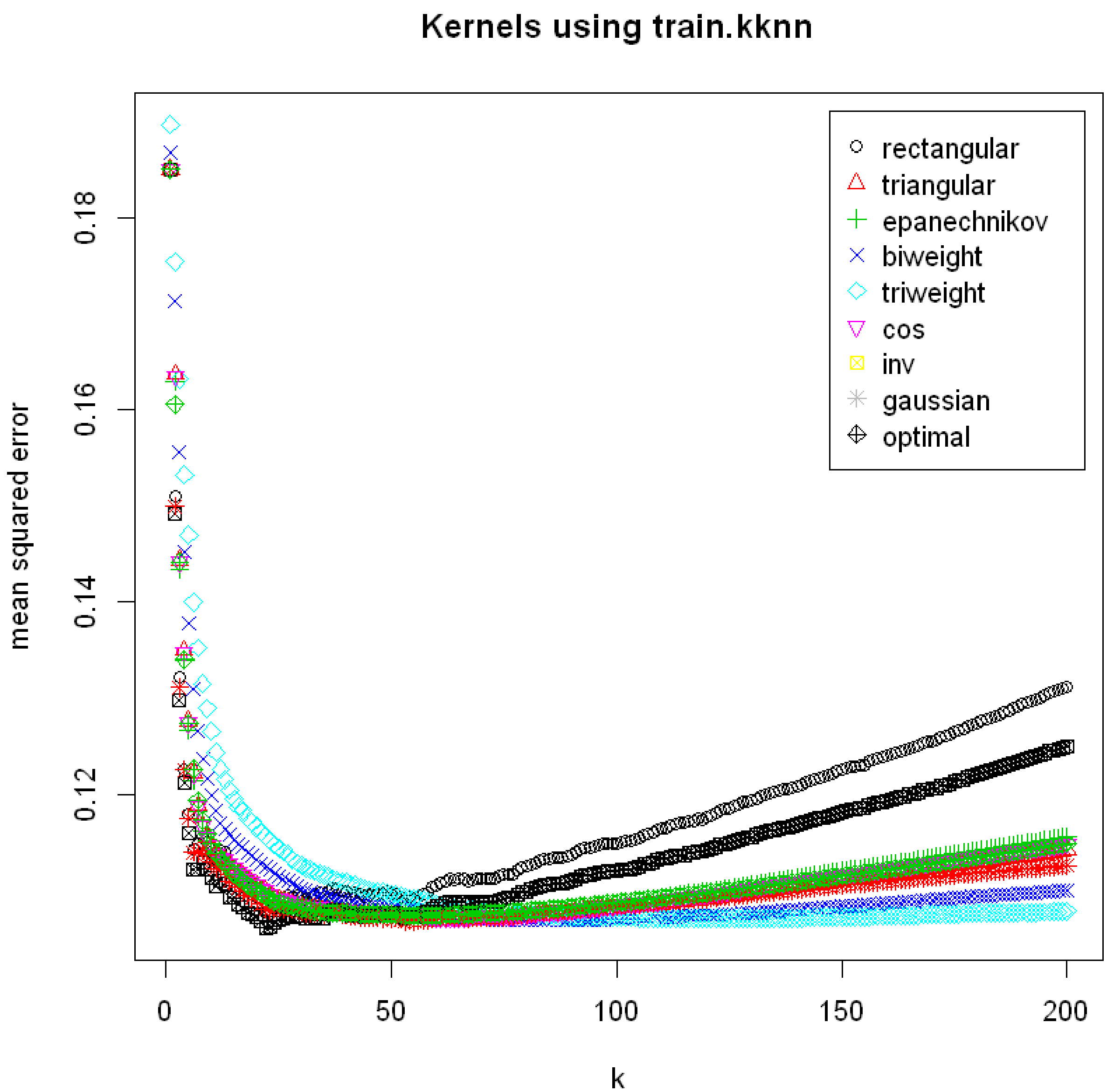
Type of response variable: continuous
minimal mean absolute error: 0.1850153
Minimal mean squared error: 0.1061155
Best kernel: inv
Best k: 22

Best Kernel is: inv , Best K Value is: 22 , and the accuracy is: 100 %

-------------------------------------END train.kknn method -------------------------------------------


-------------------------------------BEGIN cv.kknn method -------------------------------------------

For rectangular kernel, model accuracy is: 85.01529 % and corresponding k-value is: 38
For triangular kernel, model accuracy is: 85.3211 % and corresponding k-value is: 38
For epanechnikov kernel, model accuracy is: 85.47401 % and corresponding k-value is: 38
For biweight kernel, model accuracy is: 85.47401 % and corresponding k-value is: 38
For triweight kernel, model accuracy is: 85.77982 % and corresponding k-value is: 38
For cos kernel, model accuracy is: 85.93272 % and corresponding k-value is: 38
For inv kernel, model accuracy is: 85.93272 % and corresponding k-value is: 38
For gaussian kernel, model accuracy is: 85.93272 % and corresponding k-value is: 38
For optimal kernel, model accuracy is: 85.93272 % and corresponding k-value is: 38
-------------------------------------END cv.kknn method -------------------------------------------
```



Question 3.1 (b):

```
Here, I am splitting the data to train, validate and test. I am using 4 different ratios :
(50%,25%,25%), (60%,20%,20%),  (70%,15%,15%), and (80%,10%,10%).
I am going to run the ksvm model on the split datasets to predict the best model classifier.
I am not going to use Rotating method at this point.

For the different ratios, I am predicting model accuracies for four different kernels. Iterating over kernels and c
ost values for each ratio, the best TEST ACCURACY is 90.90909% (for polydot kernel and 80/10/10 split). However thi
s accuracy value is a lot higher compared to the training accuracy (85.27725%). "Anovadot" however, seems to be mor
e legit. For a split ratio of 60/20/20, Test Accuracy is 89.39394 %, validation accuracy is 83.07692 % and training
accuracy is 92.34694 %.

From Problem 2.1 (a) we concluded that rbfdot with C = 10000 had the best model accuracy. However, the accuracy for
that parameters on test data was considerably lower at 80.80808%.
```

Documentation on Stackoverflow showing examples to split data frame into train,validation and test datasets.

https://stackoverflow.com/questions/36068963/r-how-to-split-a-data-frame-into-training-validation-and-test-sets
(https://stackoverflow.com/questions/36068963/r-how-to-split-a-data-frame-into-training-validation-and-test-sets)

In [62]:
```
library(kernlab)
library(e1071)
library(caTools)
require(caTools)
set.seed(101)

data <- read.table("credit_card_data-headers.txt", header = TRUE)
kernel_list = c("vanilladot", "rbfdot", "anovadot", "polydot")

w <- c(0.5,0.25,0.25)
x <- c(0.6,0.2,0.2)
y <- c(0.7,0.15,0.15)
z <- c(0.8,0.1,0.1)
m <- list(w,x,y,z)

cost_value <- c()
kernel_val <- c()
train_frac_list <- c()
validate_frac_list <- c()
test_frac_list <- c()
Train_Accuracy  <- c()
Validation_Accuracy  <- c()
Test_Accuracy  <- c()

for (k1 in 1:length(kernel_list)){
    for (p in 1:length(m)){
        fractionTraining <- m[[p]][1]
        fractionValidation <- m[[p]][2]
        fractionTest <- m[[p]][3]

        sampleSizeTraining <- floor(fractionTraining * nrow(data))
        sampleSizeValidation <- floor(fractionValidation * nrow(data))
        sampleSizeTest <- floor(fractionTest * nrow(data))

        indicesTraining <- sort(sample(seq_len(nrow(data)), size=sampleSizeTraining))
        indicesNotTraining <- setdiff(seq_len(nrow(data)), indicesTraining)
        indicesValidation <- sort(sample(indicesNotTraining, size=sampleSizeValidation))
        indicesTest <- setdiff(indicesNotTraining, indicesValidation)

        dfTraining   <- data[indicesTraining, ]
        x_dfTraining <- dfTraining[,1:10]
        y_dfTraining <- dfTraining[,11]
        dfValidation <- data[indicesValidation, ]
        x_dfValidation <- dfValidation[,1:10]
        y_dfValidation <- dfValidation[,11]
        dfTest       <- data[indicesTest, ]
        x_dfTest <- dfTest[,1:10]
        y_dfTest <- dfTest[,11]

        cost_values = c(1, 10, 100, 1000, 10000, 0.1, 0.01, 0.001)
        train_accuracy <- c()
        prediction_train <- c()
        train_model <- c()

        for (i in 1:length(cost_values)){
          ksvm_model <- ksvm(as.matrix(x_dfTraining), as.factor(y_dfTraining), type = "C-svc", kernel = kernel
_list[k1], C = cost_values[i], scaled = TRUE)
          a <- colSums(ksvm_model@xmatrix[[1]]*ksvm_model@coef[[1]])
          a0 <- ksvm_model@b
          accuracy <- sum(predict(ksvm_model,x_dfTraining) == y_dfTraining)/length(y_dfTraining)
          train_accuracy <- c(train_accuracy,accuracy)
          train_model <- c(train_model, ksvm_model)
          prediction_train <- c(prediction_train, predict(ksvm_model,x_dfTraining))
        }

        model <- train_model[which.max(train_accuracy[1:length(cost_values)])]
        C_val = cost_values[which.max(train_accuracy[1:length(cost_values)])]
        train_accuracy <- max(train_accuracy[1:length(cost_values)])

        validation_predict <- predict(model[[1]],x_dfValidation)
        validation_accuracy <- sum(validation_predict == y_dfValidation)/length(y_dfValidation)

        test_predict <- predict(model[[1]],x_dfTest)
        test_accuracy <- sum(test_predict == y_dfTest)/length(y_dfTest)

        Train_Accuracy <- c(Train_Accuracy, train_accuracy)
```

```
        Validation_Accuracy <- c(Validation_Accuracy, validation_accuracy)
        Test_Accuracy <- c(Test_Accuracy, test_accuracy)
        cost_value <- c(cost_value, C_val)
        train_frac_list <- c(train_frac_list, fractionTraining*100)
        validate_frac_list <- c(validate_frac_list, fractionValidation*100)
        test_frac_list <- c(test_frac_list, fractionTest*100)
        kernel_val <- c(kernel_val, kernel_list[k1])
    }
}
df <- data.frame(kernel_val, cost_value, train_frac_list, validate_frac_list, test_frac_list, Train_Accuracy*1
00, Validation_Accuracy*100, Test_Accuracy*100)
names(df) <- c("Kernel","Cost Value","Train Split %","Validate Split %","Test Split %","Train Accuracy %","Val
idate Accuracy %","Test Accuracy %")
df[order(df["Test Accuracy %"], decreasing = TRUE), ]
```

```
Setting default kernel parameters
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```

	Kernel	Cost Value	Train Split %	Validate Split %	Test Split %	Train Accuracy %	Validate Accuracy %	Test Accuracy %
16	polydot	1	80	10	10	85.27725	90.76923	90.90909
14	polydot	1	60	20	20	85.96939	83.07692	90.15152
2	vanilladot	1	60	20	20	85.96939	84.61538	89.39394
10	anovadot	10000	60	20	20	92.34694	83.07692	89.39394
15	polydot	1	70	15	15	85.12035	89.79592	88.88889
11	anovadot	10000	70	15	15	89.71554	90.81633	86.86869
13	polydot	1	50	25	25	86.23853	87.11656	85.36585
4	vanilladot	1	80	10	10	86.61568	86.15385	84.84848
1	vanilladot	1	50	25	25	85.32110	90.18405	84.14634
9	anovadot	10000	50	25	25	94.80122	80.36810	84.14634
12	anovadot	10000	80	10	10	92.92543	81.53846	81.81818
3	vanilladot	1	70	15	15	87.52735	86.73469	80.80808
7	rbfdot	10000	70	15	15	99.34354	77.55102	80.80808
8	rbfdot	10000	80	10	10	99.42639	73.84615	78.78788
5	rbfdot	10000	50	25	25	100.00000	73.61963	76.82927
6	rbfdot	10000	60	20	20	99.23469	75.38462	76.51515

In [ ]: