Final Project

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Question1:

The original data has 10000 cases, and I choose 1200 cases from the data, and the data has 12 predictive attributes: tau1, tau2, tau3, tau4, p1, p2, p3, p4, g1, g2, g3, g4,

tau[] is the reaction time of participant

p[] is nominal power consumed(negative)/produced(positive)

g[] is the coefficient (gamma) proportional to price elasticity

They are all continuous.

We use these features to predict the stability of the Electrical Grid. If it is negative, then the electrical grid is unstable. If it's positive, then the electrical grid is stable.

The practical impact:

This data is to predict Electrical Grid Stability, and make sure that the ability of the electric grid to deliver electricity to customers without degradation or failure.

The mean of the features:

tau1	tau2	tau3	tau4	p1	p2	p3	p4	g1	g2	g3	g4
5.1264673	5.2347016	5.2547452	5.2058038	3.7480862	-1.2486064	-1.2446428	-1.2548370	0.5221146	0.5287688	0.5346838	0.5293942

The standard deviation of the features:

tau1	tau2	tau3	tau4	p1	p2	p3	p4	g1	g2	g3	g4
2.7302056	2.7496919	2.7724857	2.6920903	0.7598842	0.4309400	0.4344379	0.4353690	0.2730982	0.2756895	0.2729790	0.2784206

The mean of Y:

0.01560539

The standard deviation of Y:

0.0363883

the empirical correlations cor(X1, Y) ... cor(Xp,Y)

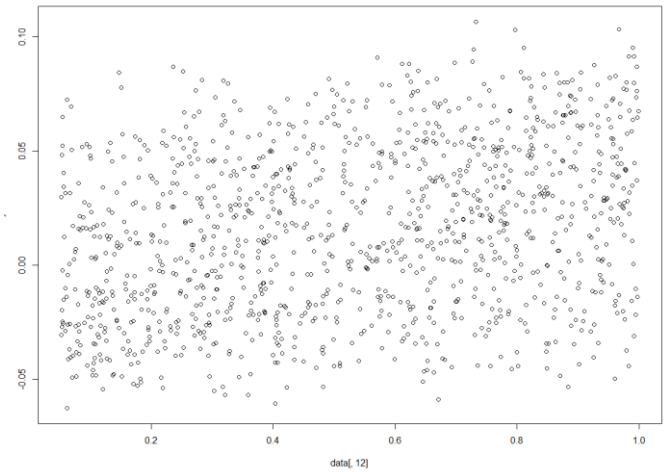
	corr
1	0.250988805
2	0.289904653
3	0.306817109
4	0.274249180
5	0.008602077
6	-0.016869099
7	0.020886938
8	-0.019158666
9	0.251188015
10	0.276306414
11	0.320215760
12	0.303189309

their absolute values C1 ... Cp

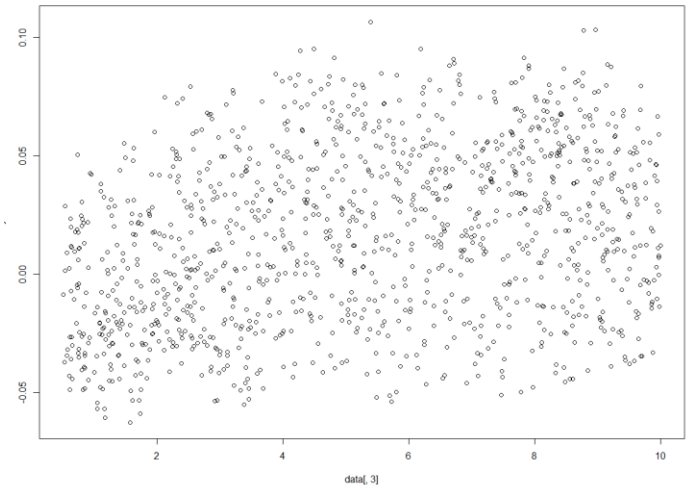
	abs.corr.
1	0.250988805
2	0.289904653
3	0.306817109
4	0.274249180
5	0.008602077
6	0.016869099
7	0.020886938
8	0.019158666
9	0.251188015
10	0.276306414
11	0.320215760
12	0.303189309

the 3 largest values among C1 ... Cp, to be denoted Cu > Cv > Cw which are display separately the 3 scatter plots:
C11=0.32>C3=0.31>C12=0.3

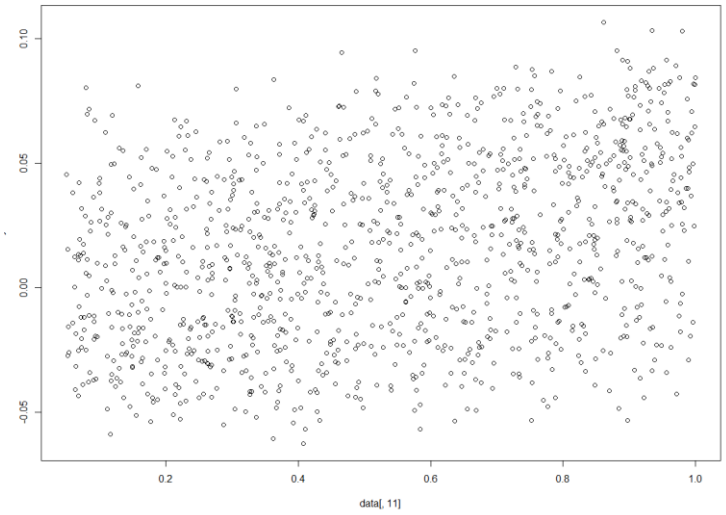
The scatter plot of (X12(j), Yj)



The scatter plot of (X3(j), Yj)



The scatter plot of (X11(j), Yj)

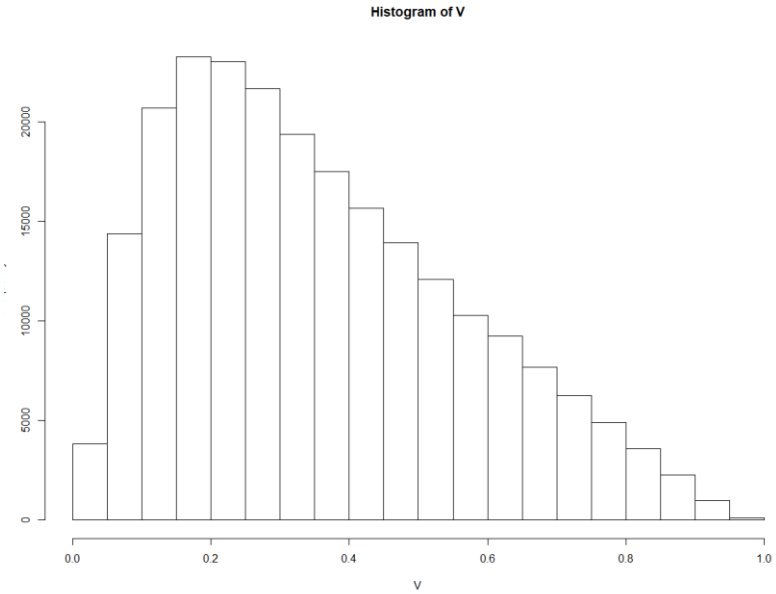


Interpretation:

The three largest correlation value is 0.32, 0.31, 0.3, they are all small, there is a weak correlation between these 3 features and Y. Based on the above scatter plot, we can see there are no linear correlation between each other.

Queation2:

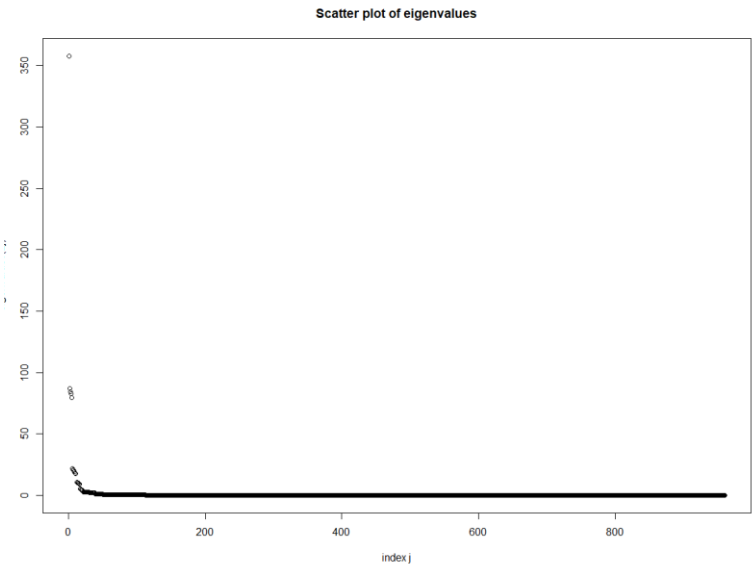
Plot the histogram of the 10000 numbers Dij:



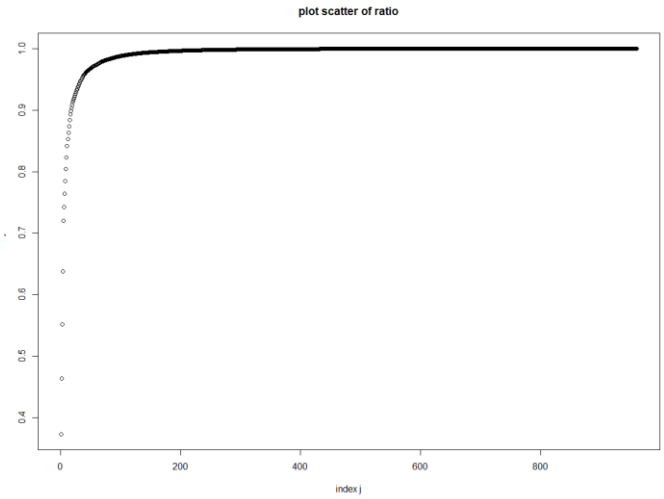
Compute q =10% quantile of the 10000 numbers Dij, q=51

Set gamma = 1/q=1/51

Plot Lj versus j



Plot the increasing ratios RATj= (L1 + ... + Lj)/(L1+ ... + Lm)



Identify the smallest j such that RATj ≥ 95% and set λ = Lj

j=35, λ= 2.008661

Compare these two RMSE values

RMSEtrain= 0.0202

RMSEtest= 0.02

compute their ratios RMSE/ avy

RMSEtrain/avy= 61.08%

RMSEtest/avy= 61.85%

Interpretation:

The KRR model with parameters (gamma=1/51, lambda=2) does not perform well. The ratio RMSEtrain/avy =61.08%, and the ratio of RMSEtest/avy= 61.85 %. They are both very high. Thus, we need to optimize the parameters.

Queation3:

First, I change only gamma:

gamma	lambda	RMSEtrain	RMSEtest	RMSEtrain/avy	RMSEtest/avy
0.001	1/55	0.033	0.031	98.34%	96.36%
0.01	1/55	0.019	0.022	58.53%	68.81%
0.05	1/55	0.019	0.02	58.01%	63.11%
0.02	1/55	0.02	0.02	60.95%	61.79%

then change lambda:

gamma	lambda	RMSEtrain	RMSEtest	RMSEtrain/avy	RMSEtest/avy
0.02	0.01	0.0056	0.0096	16.91%	29.88%
0.02	5	0.024	0.023	71.81%	71.61%
0.02	0.0001	0.0012	0.011	3.57%	34.13%
0.02	0.001	0.0032	0.0098	9.67%	30.47%

The best parameter gamma=0.02, lam=0.01

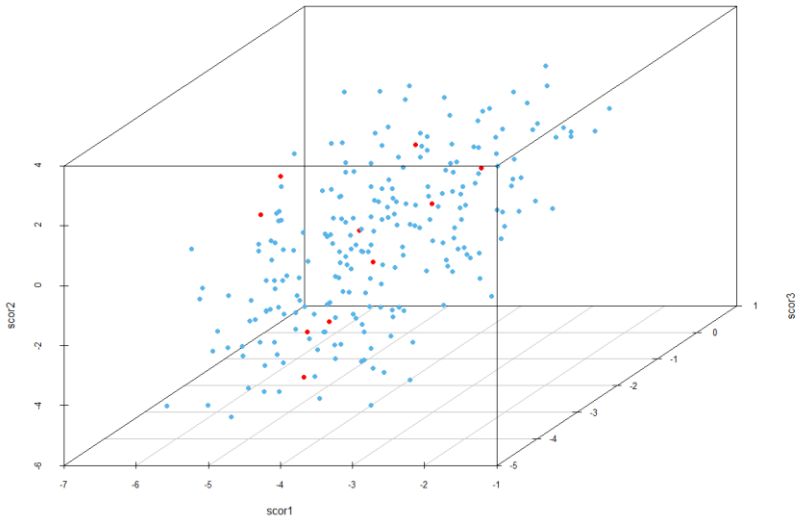
Compare to the other, this one has the smaller ratios of RMSE/avy and the RMSEtrain/avy and RMSEtest/avy are much closer than the others.

Compare to the result of question 2 that the ratios are more than 61%, the result after optimize the parameter is much better.

Identify the 10 cases in the TEST set for which the squared prediction error is the largest

```
Case: 214 208  18 169  22 171  37 101  96  34
```

Visualize the 10 cases by performing a PCA analysis and projecting all the TEST cases onto the first 3 principal eigenvectors of the PCA correlation matrix



The red dots represent the 10 cases, and blue bots represent all the TEST cases.
We cannot see the significant difference between the 10 cases and the other cases on the 3 dimensional plot.

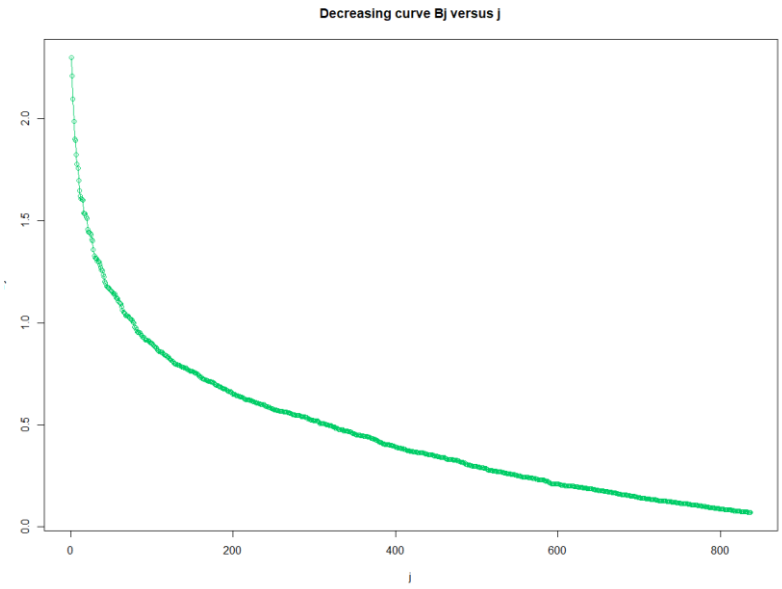
Interpretation:

The prediction does not do well, the RMSE is high, so we cannot accurately predict if the electrical grid is stable or not. So, we need to use other model to do the further research. Because the stability of the electrical grid is very important in our daily life, if it is not stable, then it may increase the frequency of outages and bring many problems.

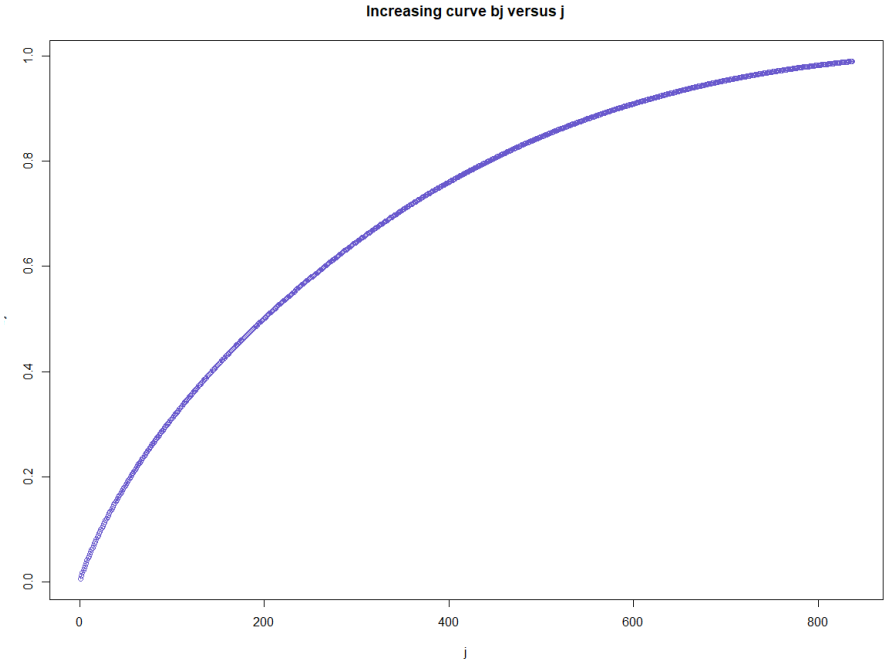
Question4:

The smallest j=837

plot the decreasing curve Bj versus j



plot the increasing curve bj versus j



THR = Bj =0.0711

The RMSE values

RMSEtrain= 0.104

RMSEtest= 0.106

The RMSE/ avy

RMSEtrain/avy= 3.145

RMSEtest/avy= 3.274

Interpretation:

We get RMSEtrain/avy=0.169, and RMSEtest/avy=0.299 from the original formula, and we get RMSEtrain/avy=3.145, and RMSEtest/avy=3.274 from the reduced formula. So, the reduced formula is not suitable.

Question5:

```
> krr.data <- constructData(as.matrix(TRAIN[,1:12]), TRAIN[,13])
> p <- list(kernel="rbfdot", sigma=0.02, lambda=0.01/getN(krr.data))
> krr <- constructKRRLearner()
>
> m <- krr$learn(krr.data, p)
> pred <- krr$predict(m, krr.data)
> krr_mse=mean((pred - krr.data$y)^2)
> krr_rmse=sqrt(krr_mse)
> krr_rmse
[1] 0.005595273
> krr_rrmse=krr_rmse/mean(abs(TRAIN[,13]))
> krr_rrmse
[1] 0.1690652
> krr.data_test <- constructData(as.matrix(TEST[,1:12]), TEST[,13])
> pred_test <- krr$predict(m, krr.data_test)
> krr_mse_t=mean((pred_test - krr.data_test$y)^2)
> krr_rmse_t=sqrt(krr_mse_t)
> krr_rmse_t
[1] 0.009646664
> krr_rrmse_t=krr_rmse_t/mean(abs(TEST[,13]))
> krr_rrmse_t
[1] 0.2988386
```

The result is same as Question 3 with the best parameter.

Code:

```
data=read.csv("C:/Users/yingy/Desktop/11 data mining/final project/data2.csv")
attach(data)
colnames(data)[1] <- "tau1"
y = data[,13]

#display its    mean and standard deviation
mean<- sapply(data[,1:12],mean)
mean
sd<- sapply(data[,1:12],sd)
sd

mean(data[,13])
sd(data[,13])
#Split the data set DS into a training set TRAIN and a test set TEST, with respective
proportions 80% ,    20%
n <- 1200
ntrain <- round(n*0.8)
```

```
set.seed(1)
tindex <- sample(n, ntrain)
TRAIN<- data[tindex,]
TEST<- data[-tindex,]

#Compute the empirical correlations cor(X1, Y) ... cor(Xp,Y) and their absolute values
C1 ... Cp
corr <- numeric(0)

for (i in 1:12){
   corr[i] =cor(data[,i],data[,13])
   print (corr)
   print(abs(corr))
}
data.frame(corr)
CORR=data.frame(abs(corr))
#compute    the 3 largest values among C1 ... Cp
order(CORR)

#display separately the 3 scatter plots (Xu(j), Yj)    ,    (Xv(j), Yj)    , (Xw(j), Yj)    where
j= 1...n
plot(data[,12],y)
plot(data[,3],y)
plot(data[,11],y)



#Q2
set.seed(100)
list1=sample(1:960, 100, replace=T)
list2=sample(1:960, 100, replace=T)

#For all i in List 1 and all j in List2    compute Dij = ||X(i) -X(j)||

D = matrix(nrow = length(list1), ncol = length(list2))
for (i in 1:length(list1)){
   for (j in 1:length(list2)){
      D[i,j]=list1[i]-list2[j]
   }
```

```
}
print(D)

V = abs(as.vector(t(D)))
print(V)
#Plot the histogram of the 10000 numbers Dij
hist(V)

#Compute q =10% quantile of the 10000 numbers Dij
quantile(V, probs = c(0.1))

#Set gamma = 1/q
gamma=1/51

#krr function
radial_k <- function (x, x.prime, g) {
   r <- apply(          x.prime
                       , 1
                       , function(a)
                          colSums(apply      (      x
                                                 ,   1
                                                 ,   function(b)
                                                     (b - a)^2)
                          )
   );
   return(exp(-g*r));
};
#G matrix

G <- radial_k(TRAIN[,1:12],TRAIN[,1:12],1/51)

#compute eigenvalues
eigenvalues.1 <- eigen(G,symmetric = TRUE,only.values = TRUE)
e_values.1 <- eigenvalues.1$values

plot(c(1:960),e_values.1,main="Scatter plot of eigenvalues",xlab="index
j",ylab="eigenvalues(Lj)")
#determine lambda
```

```
Rat=0
for (j in 1:960){
   Rat[j]<-sum(e_values.1[1:j])/sum(e_values.1)
}
#plot increasing
plot(c(1:960),Rat,main="plot scatter of ratio",xlab="index j",ylab="Ratj")
#identify smallest j
for (j in 1:960){
   if (Rat[j]>0.95){
      r=j
      break
   }
}

r
Rat[r]
lam=e_values.1[r]

M=G+(lam)*diag(960)
M_i=solve(M)

y=TRAIN[,13]
A=y%*%M_i
A
#train
Y.hat.train <- A%*%G
Y.hat.train


MSE.TRAIN <- mean((Y.hat.train-TRAIN[,13])^2)
RMSE.TRAIN <- sqrt(MSE.TRAIN)
RMSE.TRAIN
rRMSE.TRAIN <- RMSE.TRAIN/mean(abs(TRAIN[,13]))
rRMSE.TRAIN

#test
V <- radial_k(TRAIN[,1:12],TEST[,1:12],1/51)
Y.hat.TEST <- A%*%V
```

```
Y.hat.TEST


MSE.TEST <- mean((Y.hat.TEST-TEST[,13])^2)
RMSE.TEST <- sqrt(MSE.TEST)
RMSE.TEST
rRMSE.TEST <- RMSE.TEST/mean(abs(TEST[,13]))
rRMSE.TEST


#Q3
#set gamma=1000
gamma1=1000
G1 <- radial_k(TRAIN[,1:12],TRAIN[,1:12],gamma1)


M1=G1+(lam)*diag(960)
M1_i=solve(M1)

y=TRAIN[,13]
A1=y%*%M1_i
A1
#train
Y.hat.train1 <- A1%*%G1
Y.hat.train1


MSE.TRAIN1 <- mean((Y.hat.train1-TRAIN[,13])^2)
RMSE.TRAIN1 <- sqrt(MSE.TRAIN1)
RMSE.TRAIN1
rRMSE.TRAIN1 <- RMSE.TRAIN1/mean(abs(TRAIN[,13]))
rRMSE.TRAIN1

#test
V1 <- radial_k(TRAIN[,1:12],TEST[,1:12],gamma1)
Y.hat.TEST1 <- A1%*%V1
Y.hat.TEST1
```

```
MSE.TEST1 <- mean((Y.hat.TEST1-TEST[,13])^2)
RMSE.TEST1 <- sqrt(MSE.TEST1)
RMSE.TEST1
rRMSE.TEST1 <- RMSE.TEST1/mean(abs(TEST[,13]))
rRMSE.TEST1

#set gamma=0.001
gamma2=0.0001
G2 <- radial_k(TRAIN[,1:12],TRAIN[,1:12],gamma2)


M2=G2+(lam)*diag(960)
M2_i=solve(M2)

y=TRAIN[,13]
A2=y%*%M2_i
A2
#train
Y.hat.train2 <- A2%*%G2
Y.hat.train2


MSE.TRAIN2 <- mean((Y.hat.train2-TRAIN[,13])^2)
RMSE.TRAIN2 <- sqrt(MSE.TRAIN2)
RMSE.TRAIN2
rRMSE.TRAIN2 <- RMSE.TRAIN2/mean(abs(TRAIN[,13]))
rRMSE.TRAIN2

#test
V2 <- radial_k(TRAIN[,1:12],TEST[,1:12],gamma2)
Y.hat.TEST2 <- A2%*%V2
Y.hat.TEST2


MSE.TEST2 <- mean((Y.hat.TEST2-TEST[,13])^2)
RMSE.TEST2 <- sqrt(MSE.TEST2)
RMSE.TEST2
```

```
rRMSE.TEST2 <- RMSE.TEST2/mean(abs(TEST[,13]))
rRMSE.TEST2

#set gamma=0.1
gamma3=0.1
G3 <- radial_k(TRAIN[,1:12],TRAIN[,1:12],gamma3)


M3=G3+(lam)*diag(960)
M3_i=solve(M3)

y=TRAIN[,13]
A3=y%*%M3_i
#train
Y.hat.train3 <- A3%*%G3


MSE.TRAIN3 <- mean((Y.hat.train3-TRAIN[,13])^2)
RMSE.TRAIN3 <- sqrt(MSE.TRAIN3)
RMSE.TRAIN3
rRMSE.TRAIN3 <- RMSE.TRAIN3/mean(abs(TRAIN[,13]))
rRMSE.TRAIN3

#test
V3 <- radial_k(TRAIN[,1:12],TEST[,1:12],gamma3)
Y.hat.TEST3 <- A3%*%V3


MSE.TEST3 <- mean((Y.hat.TEST3-TEST[,13])^2)
RMSE.TEST3 <- sqrt(MSE.TEST3)
RMSE.TEST3
rRMSE.TEST3 <- RMSE.TEST3/mean(abs(TEST[,13]))
rRMSE.TEST3

#set gamma=0.05
gamma4=0.05
G4 <- radial_k(TRAIN[,1:12],TRAIN[,1:12],gamma4)
```

```
M4=G4+(lam)*diag(960)
M4_i=solve(M4)

y=TRAIN[,13]
A4=y%*%M4_i
#train
Y.hat.train4 <- A4%*%G4


MSE.TRAIN4 <- mean((Y.hat.train4-TRAIN[,13])^2)
RMSE.TRAIN4 <- sqrt(MSE.TRAIN4)
RMSE.TRAIN4
rRMSE.TRAIN4 <- RMSE.TRAIN4/mean(abs(TRAIN[,13]))
rRMSE.TRAIN4

#test
V4 <- radial_k(TRAIN[,1:12],TEST[,1:12],gamma4)
Y.hat.TEST4 <- A4%*%V4


MSE.TEST4 <- mean((Y.hat.TEST4-TEST[,13])^2)
RMSE.TEST4 <- sqrt(MSE.TEST4)
RMSE.TEST4
rRMSE.TEST4 <- RMSE.TEST4/mean(abs(TEST[,13]))
rRMSE.TEST4


#set gamma=0.02
gamma5=0.02
G5 <- radial_k(TRAIN[,1:12],TRAIN[,1:12],gamma5)


M5=G5+(lam)*diag(960)
M5_i=solve(M5)

y=TRAIN[,13]
A5=y%*%M5_i
```

```
#train
Y.hat.train5 <- A5%*%G5


MSE.TRAIN5 <- mean((Y.hat.train5-TRAIN[,13])^2)
RMSE.TRAIN5 <- sqrt(MSE.TRAIN5)
RMSE.TRAIN5
rRMSE.TRAIN5 <- RMSE.TRAIN5/mean(abs(TRAIN[,13]))
rRMSE.TRAIN5

#test
V5 <- radial_k(TRAIN[,1:12],TEST[,1:12],gamma5)
Y.hat.TEST5 <- A5%*%V5


MSE.TEST5 <- mean((Y.hat.TEST5-TEST[,13])^2)
RMSE.TEST5 <- sqrt(MSE.TEST5)
RMSE.TEST5
rRMSE.TEST5 <- RMSE.TEST5/mean(abs(TEST[,13]))
rRMSE.TEST5


##########################################################################
##
###set lam
lam1=0.01

M11=G5+(lam1)*diag(960)
M11_i=solve(M11)

y=TRAIN[,13]
A11=y%*%M11_i

#train
Y.hat.train11 <- A11%*%G5


MSE.TRAIN11 <- mean((Y.hat.train11-TRAIN[,13])^2)
```

```
RMSE.TRAIN11 <- sqrt(MSE.TRAIN11)
RMSE.TRAIN11
rRMSE.TRAIN11 <- RMSE.TRAIN11/mean(abs(TRAIN[,13]))
rRMSE.TRAIN11

#test
Y.hat.TEST11 <- A11%*%V5


MSE.TEST11 <- mean((Y.hat.TEST11-TEST[,13])^2)
RMSE.TEST11 <- sqrt(MSE.TEST11)
RMSE.TEST11
rRMSE.TEST11 <- RMSE.TEST11/mean(abs(TEST[,13]))
rRMSE.TEST11
#########################################################################3
###set lam2
lam2=5
M12=G5+(lam2)*diag(960)
M12_i=solve(M12)

y=TRAIN[,13]
A12=y%*%M12_i

#train
Y.hat.train12 <- A12%*%G5


MSE.TRAIN12 <- mean((Y.hat.train12-TRAIN[,13])^2)
RMSE.TRAIN12 <- sqrt(MSE.TRAIN12)
RMSE.TRAIN12
rRMSE.TRAIN12 <- RMSE.TRAIN12/mean(abs(TRAIN[,13]))
rRMSE.TRAIN12

#test
Y.hat.TEST12 <- A12%*%V5


MSE.TEST12 <- mean((Y.hat.TEST12-TEST[,13])^2)
```

```
RMSE.TEST12 <- sqrt(MSE.TEST12)
RMSE.TEST12
rRMSE.TEST12 <- RMSE.TEST12/mean(abs(TEST[,13]))
rRMSE.TEST12

#set lam3
lam3=0.0001
M13=G5+(lam3)*diag(960)
M13_i=solve(M13)

y=TRAIN[,13]
A13=y%*%M13_i

#train
Y.hat.train13 <- A13%*%G5


MSE.TRAIN13 <- mean((Y.hat.train13-TRAIN[,13])^2)
RMSE.TRAIN13 <- sqrt(MSE.TRAIN13)
RMSE.TRAIN13
rRMSE.TRAIN13 <- RMSE.TRAIN13/mean(abs(TRAIN[,13]))
rRMSE.TRAIN13

#test
Y.hat.TEST13 <- A13%*%V5


MSE.TEST13 <- mean((Y.hat.TEST13-TEST[,13])^2)
RMSE.TEST13 <- sqrt(MSE.TEST13)
RMSE.TEST13
rRMSE.TEST13 <- RMSE.TEST13/mean(abs(TEST[,13]))
rRMSE.TEST13

#set lam4
lam4=0.001
M14=G5+(lam4)*diag(960)
M14_i=solve(M14)
```

```
y=TRAIN[,13]
A14=y%*%M14_i

#train
Y.hat.train14 <- A14%*%G5


MSE.TRAIN14 <- mean((Y.hat.train14-TRAIN[,13])^2)
RMSE.TRAIN14 <- sqrt(MSE.TRAIN14)
RMSE.TRAIN14
rRMSE.TRAIN14 <- RMSE.TRAIN14/mean(abs(TRAIN[,13]))
rRMSE.TRAIN14

#test
Y.hat.TEST14 <- A14%*%V5


MSE.TEST14 <- mean((Y.hat.TEST14-TEST[,13])^2)
RMSE.TEST14 <- sqrt(MSE.TEST14)
RMSE.TEST14
rRMSE.TEST14 <- RMSE.TEST14/mean(abs(TEST[,13]))
rRMSE.TEST14


#######best    gamma5=0.02    lam1=0.01
lam1=0.01

M11=G5+(lam1)*diag(960)
M11_i=solve(M11)

y=TRAIN[,13]
A11=y%*%M11_i

#train
Y.hat.train11 <- A11%*%G5


MSE.TRAIN11 <- mean((Y.hat.train11-TRAIN[,13])^2)
```

```
RMSE.TRAIN11 <- sqrt(MSE.TRAIN11)
RMSE.TRAIN11
rRMSE.TRAIN11 <- RMSE.TRAIN11/mean(abs(TRAIN[,13]))
rRMSE.TRAIN11

#test
Y.hat.TEST11 <- A11%*%V5
#10 case
sse=(Y.hat.TEST11-TEST[,13])^2
order(sse,decreasing=TRUE)[1:10]
sse[order(sse,decreasing=TRUE)[1:10]]

#the first 3 principal eigenvectors
cor_test=cor(TEST[,1:12])
eigen_TEST <- eigen(cor_test)
eigenvectors_TEST <- eigen_TEST$vectors

pca_loading_set=eigen_TEST$vectors[,1:3]
pca_scores<-as.matrix(TEST[,1:12])%*%as.matrix(pca_loading_set)
scor1 <- pca_scores[,1]
scor2 <- pca_scores[,2]
scor3 <- pca_scores[,3]

########
pca = data.frame(pca_scores)
pca_scores
pca$col <- 2
pca$col[214]<-1
pca$col[208]<-1
pca$col[18]<-1
pca$col[169]<-1
pca$col[22]<-1
pca$col[171]<-1
pca$col[37]<-1
pca$col[101]<-1
pca$col[96]<-1
pca$col[34]<-1
```

```
#pca <- as.matrix(pca)
pc1<-pca[,1]
pc2<-pca[,2]
pc3<-pca[,3]

colors <- c("#FF0000", "#56B4E9")
colors <- colors[as.numeric(pca$col)]
install.packages("scatterplot3d")
library("scatterplot3d")
scatterplot3d(pc1, pc2, pc3, pch=16, grid=TRUE, box=TRUE,
                        color=colors, xlab="scor1", zlab="scor2", ylab="scor3")
###Q4


#reorder the |A1|, |A2|, ....|Am| in decreasing order , which gives a list B1 > B2 ... >
Bm    >0
A111=abs(A11)
B=A111[order(A111,decreasing=TRUE)]
B


#Compute the ratios bj = (B1 + ... + Bj)/(B1 + ...+Bm)and plot the increasing curve bj
versus j
b=0
for (j in 1:960){
   b[j]<-sum(B[1:j])/sum(B)
}
b
for (j in 1:960){
   if (b[j]>0.99){
      new_j=j
      break
   }
}
new_j
#j=837
```

```
#plot the decreasing curve Bj versus j
plot(B[1:837], type="o", col="springgreen3", ann="FALSE")
title(main="Decreasing curve Bj versus j", xlab="j", ylab="Bj")

#plot the increasing curve bj versus j

plot(b[1:837], type="o", col="slateblue3", ann="FALSE")
title(main="Increasing curve bj versus j", xlab="j", ylab="bj")

#threshold value THR = Bj
THR = B[837]

#For i =1... m, if |Ai|> THR set AAi = Ai      and otherwise set AAi = 0. This yields a
reduced formula
AA=0
for (i in 1:960){
   if(abs(A11[i])>THR){
      AA[i]=A11[i]
   }else{
      AA[i]=0
   }
   print(AA[i])
}
AA=t(as.matrix(AA))
#PRED(x)    = AA1 K(x, X(1)) + ... + AAm K(x,X(m))
pred_train=AA%*%G5

MSE.TRAIN_AA <- mean((pred_train-TRAIN[,13])^2)
RMSE.TRAIN_AA <- sqrt(MSE.TRAIN_AA)
RMSE.TRAIN_AA
rRMSE.TRAIN_AA <- RMSE.TRAIN_AA/mean(abs(TRAIN[,13]))
rRMSE.TRAIN_AA

#test
pred_test<-AA%*%V5

MSE.TEST_AA <- mean((pred_test-TEST[,13])^2)
RMSE.TEST_AA <- sqrt(MSE.TEST_AA)
```

```
RMSE.TEST_AA
rRMSE.TEST_AA <- RMSE.TEST_AA/mean(abs(TEST[,13]))
rRMSE.TEST_AA



#5

#5
install.packages('CVST')
library(CVST)



krr.data <- constructData(as.matrix(TRAIN[,1:12]), TRAIN[,13])
p <- list(kernel="rbfdot", sigma=0.02, lambda=0.01/getN(krr.data))
krr <- constructKRRLearner()

m <- krr$learn(krr.data, p)
pred <- krr$predict(m, krr.data)
krr_mse=mean((pred - krr.data$y)^2)
krr_rmse=sqrt(krr_mse)
krr_rmse
krr_rrmse=krr_rmse/mean(abs(TRAIN[,13]))
krr_rrmse



##test
krr.data_test <- constructData(as.matrix(TEST[,1:12]), TEST[,13])
pred_test <- krr$predict(m, krr.data_test)
krr_mse_t=mean((pred_test - krr.data_test$y)^2)
krr_rmse_t=sqrt(krr_mse_t)
krr_rmse_t
krr_rrmse_t=krr_rmse_t/mean(abs(TEST[,13]))
krr_rrmse_t
```