Lab3

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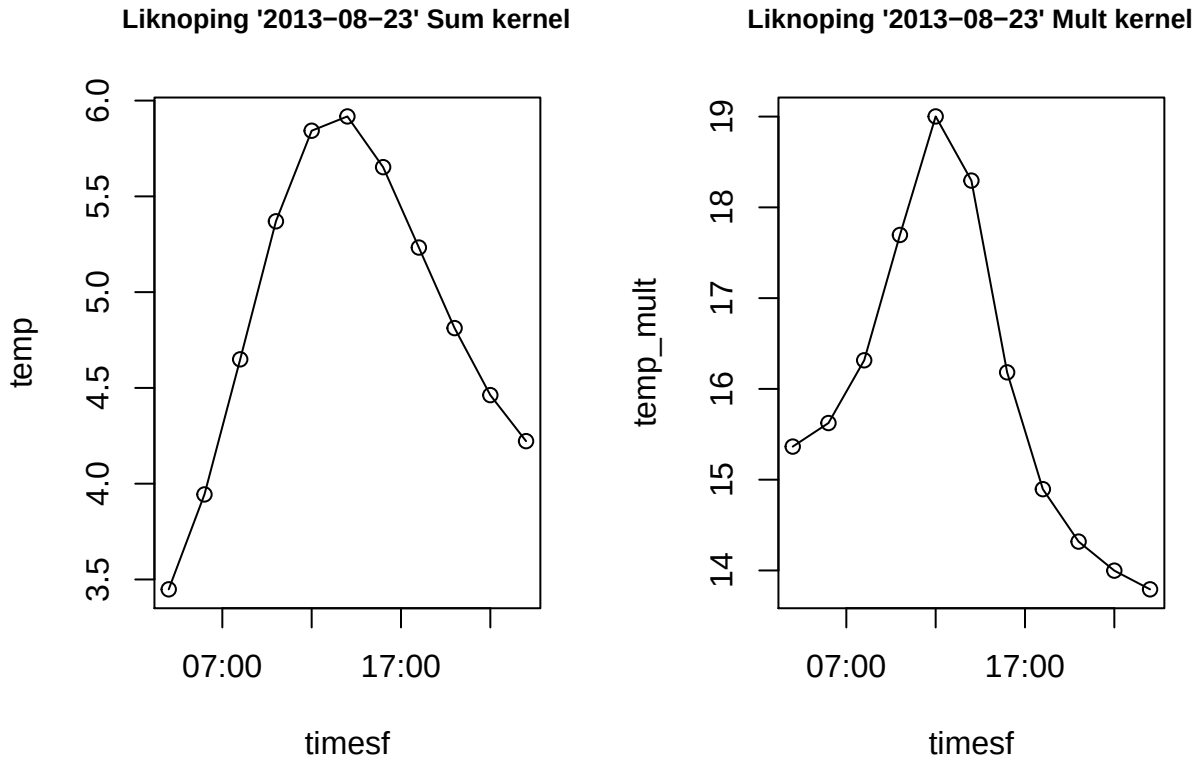
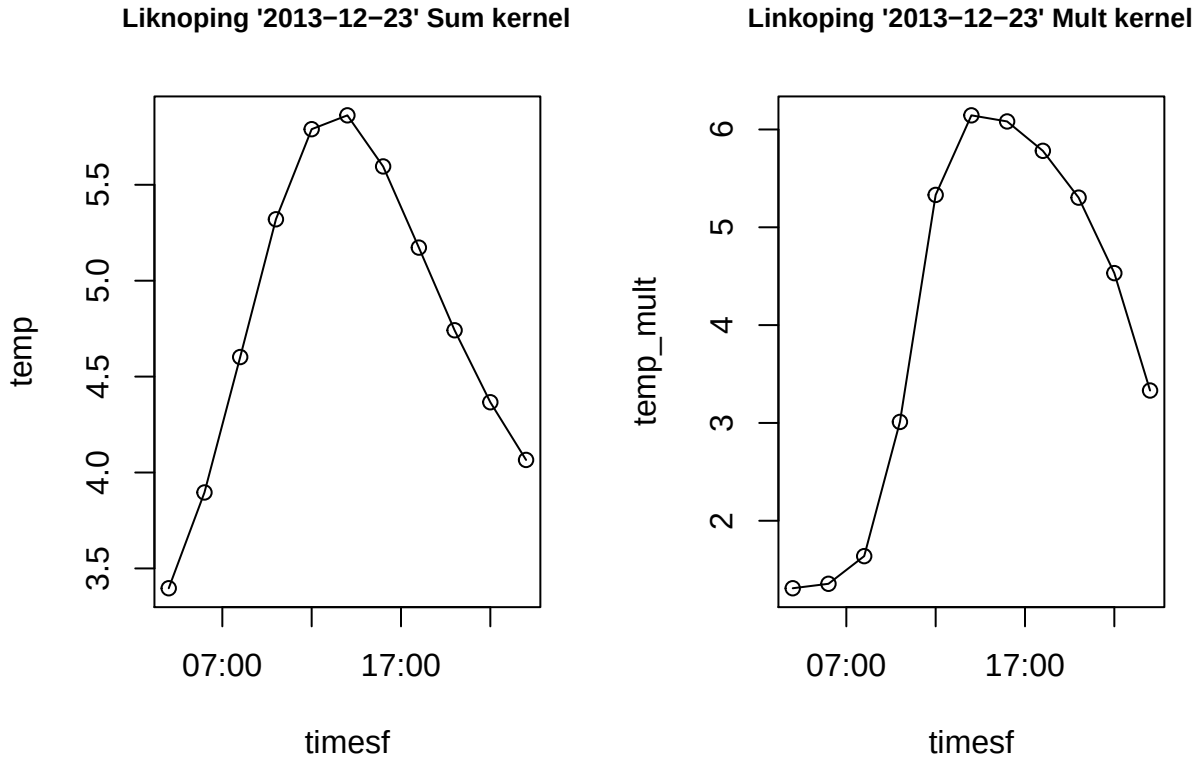
Contents

Assignment 1



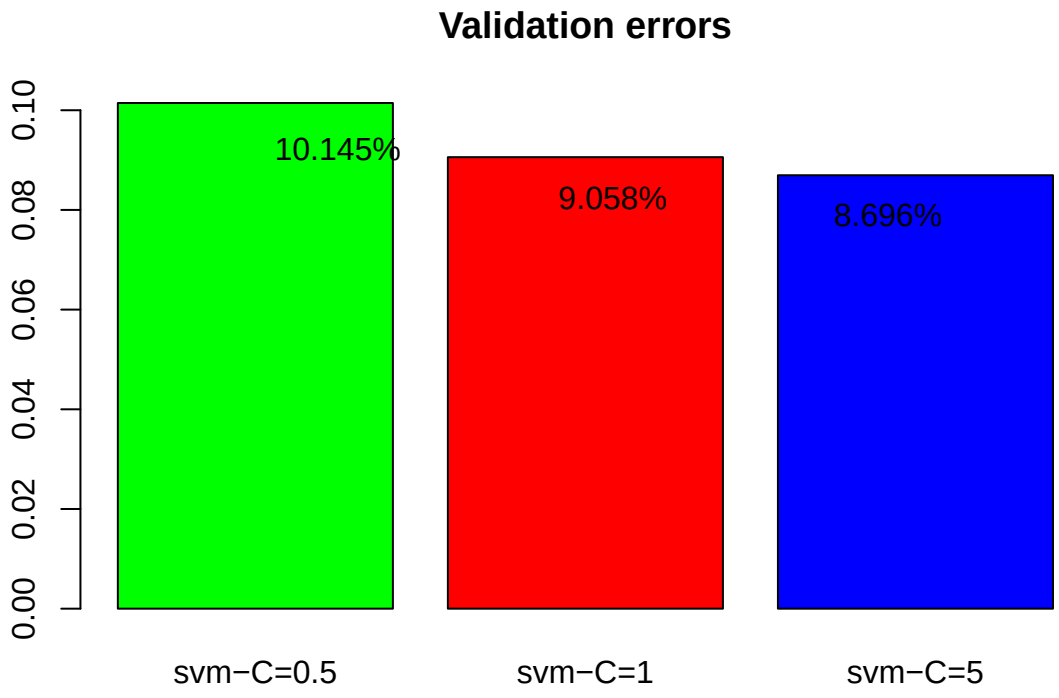
The above plot shows the temperature predictions for Linkoping for the date of '2013-08-23' with the summation and the multiplication kernel.



The above plot shows the temperature predictions for Linkoping for the date of '2013-12-23' with the summation and the multiplication kernel.

From the 2 plots we can see that the predictions of the multiplication kernel seem to be reasonable for the 2 dates but for the summation kernel only we can see that we basically achieve approximately the same predictions.The reason lies to the fact that in our implementation we choose to include the year information. The h values we used where :(20000,20,5) for (distance,days,time) respectfully.

Assignment 2



We choose the model with C=5 because it has the lowest misclassification error among the other values of C.Then we use the value of the parameter C in order to calculate the generalization error on a partion of the data we kept as test.

```
## ============================================================
##  The generalization error for the best C value is:  7.600434 %
```

The model that will be returned to the user is:

```
## ============================================================

## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 5
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  0.05
##
## Number of Support Vectors : 1547
##
## Objective Function Value : -2082.468
## Training error : 0.022169
```

Finally,the role of C is to control the regularization of the model.Once the C is large the model might have high variance. On the contrary a small C will lead to high bias for the model.

Apdendix

```
set.seed(1234567890)
library(geosphere)

stations <- read.csv("stations.csv",stringsAsFactors = F,fileEncoding = "latin1")
temps <- read.csv("temps50k.csv",stringsAsFactors = F)
st <- merge(stations,temps,by="station_number")
h_distance <- 20000        # These three values are up to the students
h_date <-20
h_time <-5
a <- 58.4274 #latitude # The point to predict (up to the students)
b <- 14.826  #logitude
date1 <- "2013-08-23" # The date to predict (up to the students)
times <- c("04:00:00", "06:00:00","08:00:00" ,"10:00:00","12:00:00","14:00:00",
           "16:00:00","18:00:00","20:00:00","22:00:00","24:00:00")


temp <- vector(length=length(times))
# Students' code here

timesf<-as.POSIXct(times,format="%H:%M:%S")
pred_date<-as.POSIXct( date1 , format = "%Y-%m-%d")

st$date<-as.POSIXct(st$date,format="%Y-%m-%d")
st$time<-as.POSIXct(st$time,format="%H:%M:%S")


st_filtered<-st[st$date< pred_date ,]



d1<-distm(st_filtered[,c("longitude","latitude")], c(b,a),fun=distHaversine)
d2<-as.numeric(difftime(pred_date ,st_filtered$date,units = "days"))


func <-function( time ,h){
  dist <- as.numeric(difftime(st_filtered$time,time , units="hours"))
  dist [dist >12] <- 24 - dist [dist >12]
  exp(-(dist/h)^2)
}


k1<-exp(-(d1/h_distance)^2)

k2<-exp(-(d2/h_date)^2)


for(i in 1:length(timesf)){
  k3<-func(timesf[i],h_time)
  K<-as.vector(k1)+as.vector(k2)+as.vector(k3)
  temp[i]<-sum(K*st_filtered$air_temperature)/sum(K)

}
```

```r
temp_mult<-vector(length=length(times))
for(i in 1:length(timesf)){
  k3<-func(timesf[i],h_time)
  K1<-as.vector(k1)*as.vector(k2)*as.vector(k3)
  temp_mult[i]<-sum(K1*st_filtered$air_temperature)/sum(K1)

}

par(mfrow=c(1,2))
plot(timesf,temp, type="o",main="Liknoping '2013-08-23' Sum kernel",cex.main=0.85)
plot(timesf,temp_mult,type="o",main="Liknoping '2013-08-23' Mult kernel",cex.main=0.85)

set.seed(1234567890)
library(geosphere)

stations <- read.csv("stations.csv",stringsAsFactors = F,fileEncoding = "latin1")
temps <- read.csv("temps50k.csv",stringsAsFactors = F)
st <- merge(stations,temps,by="station_number")
h_distance <- 20000        # These three values are up to the students
h_date <-20
h_time <-5
a <- 58.4274 #latitude # The point to predict (up to the students)
b <- 14.826  #logitude
date1 <- "2013-12-23" # The date to predict (up to the students)
times <- c("04:00:00", "06:00:00","08:00:00" ,"10:00:00","12:00:00","14:00:00",
           "16:00:00","18:00:00","20:00:00","22:00:00","24:00:00")


temp <- vector(length=length(times))
# Students' code here

timesf<-as.POSIXct(times,format="%H:%M:%S")
pred_date<-as.POSIXct( date1 , format = "%Y-%m-%d")

st$date<-as.POSIXct(st$date,format="%Y-%m-%d")
st$time<-as.POSIXct(st$time,format="%H:%M:%S")


st_filtered<-st[st$date< pred_date ,]



d1<-distm(st_filtered[,c("longitude","latitude")], c(b,a),fun=distHaversine)
d2<-as.numeric(difftime(pred_date ,st_filtered$date,units = "days"))


func <-function( time ,h){
  dist <- as.numeric(difftime(st_filtered$time,time , units="hours"))
  dist [dist >12] <- 24 - dist [dist >12]
  exp(-(dist/h)^2)
}
```

```r
k1<-exp(-(d1/h_distance)^2)

k2<-exp(-(d2/h_date)^2)


for(i in 1:length(timesf)){
  k3<-func(timesf[i],h_time)
  K<-as.vector(k1)+as.vector(k2)+as.vector(k3)
  temp[i]<-sum(K*st_filtered$air_temperature)/sum(K)

}

temp_mult<-vector(length=length(times))
for(i in 1:length(timesf)){
  k3<-func(timesf[i],h_time)
  K1<-as.vector(k1)*as.vector(k2)*as.vector(k3)
  temp_mult[i]<-sum(K1*st_filtered$air_temperature)/sum(K1)

}

par(mfrow=c(1,2))
plot(timesf,temp, type="o",main="Liknoping '2013-12-23' Sum kernel",cex.main=0.85)
plot(timesf,temp_mult,type="o",main="Linkoping '2013-12-23' Mult kernel",cex.main=0.85)

library(kernlab)

#load buid-in dataset from kernlab
data("spam")

#Split data to train,valid,test
n=dim(spam)[1]
set.seed(1234567890)
id=sample(1:n, floor(n*0.5))
train_spam=spam[id,]
id1=setdiff(1:n, id)
set.seed(1234567890)
id2=sample(id1, floor(n*0.3))
valid_spam=spam[id2,]
id3=setdiff(id1,id2)
test_spam=spam[id3,]

#fit svm models for every C value
svm1<-ksvm(type~.,data=train_spam,
           kernel = "rbfdot", kpar =list(sigma = 0.05),C = 0.5)

svm2<-ksvm(type~.,data=train_spam,
           kernel = "rbfdot", kpar =list(sigma = 0.05),C = 1)

svm3<-ksvm(type~.,data=train_spam,
           kernel = "rbfdot", kpar =list(sigma = 0.05),C = 5)


index_class_column<-which(names(spam)=="type") #index of the class column
```

```r
#make predictions on valid data with the 3 models
svm1_preds_valid<-predict(svm1,valid_spam[,-index_class_column],
                          type="response")

svm2_preds_valid<-predict(svm2,valid_spam[,-which(names(spam)=="type")],
                          type="response")

svm3_preds_valid<-predict(svm3,valid_spam[,-index_class_column],
                          type="response")
#calculate misclassification errors on valid data
error1<-mean(valid_spam$type!=svm1_preds_valid)
error2<-mean(valid_spam$type!=svm2_preds_valid)
error3<-mean(valid_spam$type!=svm3_preds_valid)
#combine data
errors_valid<-c(error1,error2,error3)
#plot the misclassification errors
barplot(errors_valid,names.arg=c("svm-C=0.5", "svm-C=1", "svm-C=5"),col=c("green","red","blue"),
        main = "Validation errors")
text((errors_valid/1.1),labels=paste0(round(errors_valid*100,digits=3),"%"))

#combine train and valid data
dt<-rbind(train_spam,valid_spam)
#fit svm with train and valid data
svm_best<-ksvm(type~.,data=dt,
               kernel = "rbfdot", kpar =list(sigma = 0.05),C = 5)
#predict on test data
svm3_preds_test<-predict(svm_best,test_spam[,-58],type="response")
#calculate misclassification error
error6<-mean(test_spam$type!=svm3_preds_test)
cat("================================================================\n",
  "The generalization error for the best C value is: ",error6*100,"%")

cat("============================================================\n")
svm_final<-ksvm(type~.,data=spam,
                kernel = "rbfdot", kpar =list(sigma = 0.05),C = 5)
svm_final
```