machine learning(732A99) lab3

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Contents

Loading The Libraries

```
if (!require("pacman")) install.packages("pacman")
pacman::p_load(geosphere, kernlab, geosphere, ggplot2,caret)

set.seed(12345)
options("jtools-digits" = 2, scipen = 999)

# colours (colour blind friendly)
cbPalette <- c("#999999", "#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2",
               "#D55E00", "#CC79A7")
```

Assignment 1

1. Implement a kernel method to predict the hourly temperatures for a date and place in Sweden.To do so, you are provided with the files stations.csv and temps50k.csv. These files contain information about weather stations and temperature measurements in the stations at different days and times. The data have been kindly provided by the Swedish Meteorological and Hydrological Institute (SMHI).

```
rm(list=ls())
set.seed(1234567890)
stations <- read.csv("stations.csv")
temps <- read.csv("temps50k.csv")
st <- merge(stations,temps,by="station_number")
rm(temps, stations)
```

defining the function

```
kernel_method <- function(df, date, loc_long, loc_lat, h1, h2, h3) {

set.seed(1234567890)
start <- as.POSIXct(date)
interval <- 60
end <- start + as.difftime(1, units="days")
time_seq <- seq(from=start, by=interval*120, to=end)
time_seq <- as.data.frame(time_seq)
colnames(time_seq) <- "new_date_time"
time_seq$time_index <- rownames(time_seq)

df_new <- merge.data.frame(df,time_seq,all=TRUE)
rm(df)

df_new$new_date <- as.Date(df_new$new_date_time)
df_new$new_time <- format(df_new$new_date_time,"%H:%M:%S")
df_new$loc_long <- loc_long
df_new$loc_lat <-  loc_lat
```

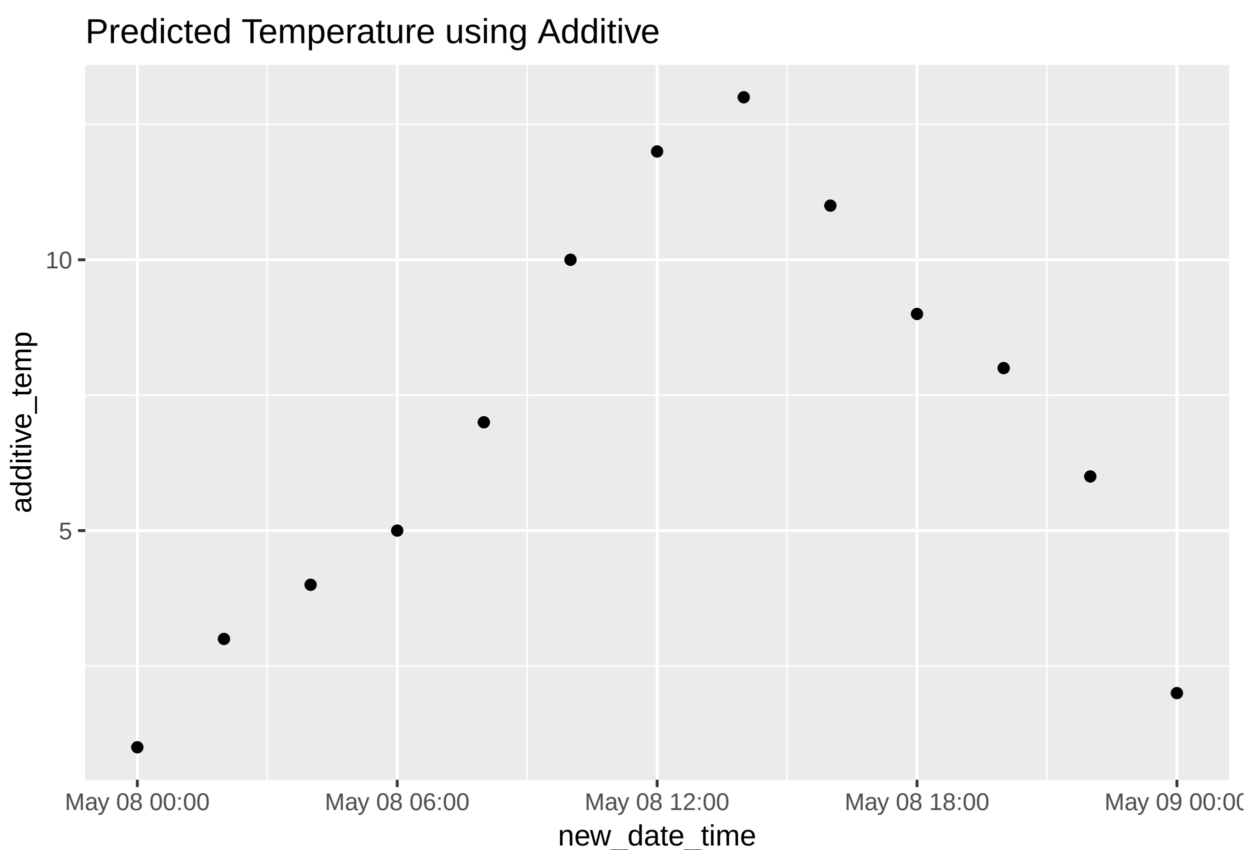
```r
df_new$h_distance <-  abs(distHaversine(p1 = df_new[,c("loc_long", "loc_lat")], p2 = df_new[,c("longitu

df_new$h_date <- as.numeric(abs(difftime(df_new$new_date, df_new$date, units = c("days"))))

df_new$h_time <- as.numeric(abs(difftime(strptime(paste(df_new$new_date,
                                                       df_new$new_time),"%Y-%m-%d%H:%M:%S"),
                                         strptime(paste(df_new$new_date, df_new$time),
                                   "%Y-%m-%d %H:%M:%S"),
                          units = c("hour"))))


df_new$date_time <- paste(df_new$date, df_new$time)
df_new$hd_dist <- as.numeric(difftime(df_new$new_date_time,
                          df_new$date_time,
                          units = c("hour")))

## removing any negative dates and time
df_new$posterior_flag <- as.factor(ifelse(df_new$h_distance > 0 & df_new$hd_dist > 0, "retain", "drop")


## calculating kernel distance and choosing guassian kernel
df_new$h_distance_kernel <- exp(-(df_new$h_distance/h1)^2)
df_new$h_date_kernel <- exp(-(df_new$h_date/h2)^2)
df_new$h_time_kernel <- exp(-(df_new$h_time/h3)^2)
df_new$total_additive_dist <- (df_new$h_distance_kernel + df_new$h_date_kernel + df_new$h_time_kernel)
df_new$total_mul_dist <- (df_new$h_distance_kernel * df_new$h_date_kernel * df_new$h_time_kernel)

df_new$additive_num <- ifelse(df_new$posterior_flag == "retain",
                              df_new$h_distance_kernel*df_new$air_temperature +
                                df_new$h_date_kernel*df_new$air_temperature +
                                df_new$h_time_kernel*df_new$air_temperature,0)

df_new$mul_num <- ifelse(df_new$posterior_flag == "retain",
                         (df_new$h_distance_kernel*df_new$air_temperature) *
                                (df_new$h_date_kernel*df_new$air_temperature) *
                                (df_new$h_time_kernel*df_new$air_temperature),0)

df_new$additive_den <- ifelse(df_new$posterior_flag == "retain", df_new$total_additive_dist, 0)
df_new$mul_den <- ifelse(df_new$posterior_flag == "retain", df_new$total_mul_dist, 0)

time = unique(time_seq$time_index)
result <- NULL

for(i in time){
temp <- df_new[df_new$time_index == i,]
additive_temp <- sum(temp$additive_num)/sum(temp$additive_den)
mult_temp <- sum(temp$mul_num)/sum(temp$mul_den)

temp <- cbind(additive_temp, mult_temp, i)
result <- rbind(temp,result)
}

result <- as.data.frame(result)
```

```r
result <- merge(x =result, y = time_seq, by.x = "i", by.y = "time_index", all.x = TRUE)
result$additive_temp <- as.numeric(result$additive_temp)
result$mult_temp <- as.numeric(result$mult_temp)

p1 <- ggplot(data=result, aes(x=new_date_time, y = additive_temp)) + geom_point() +
  ggtitle("Predicted Temperature using Additive")

p2 <- ggplot(data=result, aes(x=new_date_time, y = mult_temp)) + geom_point() +
  ggtitle("Predicted Temperature using Multiplicative")

final <- list(p1,p2)
return(final)
}
```

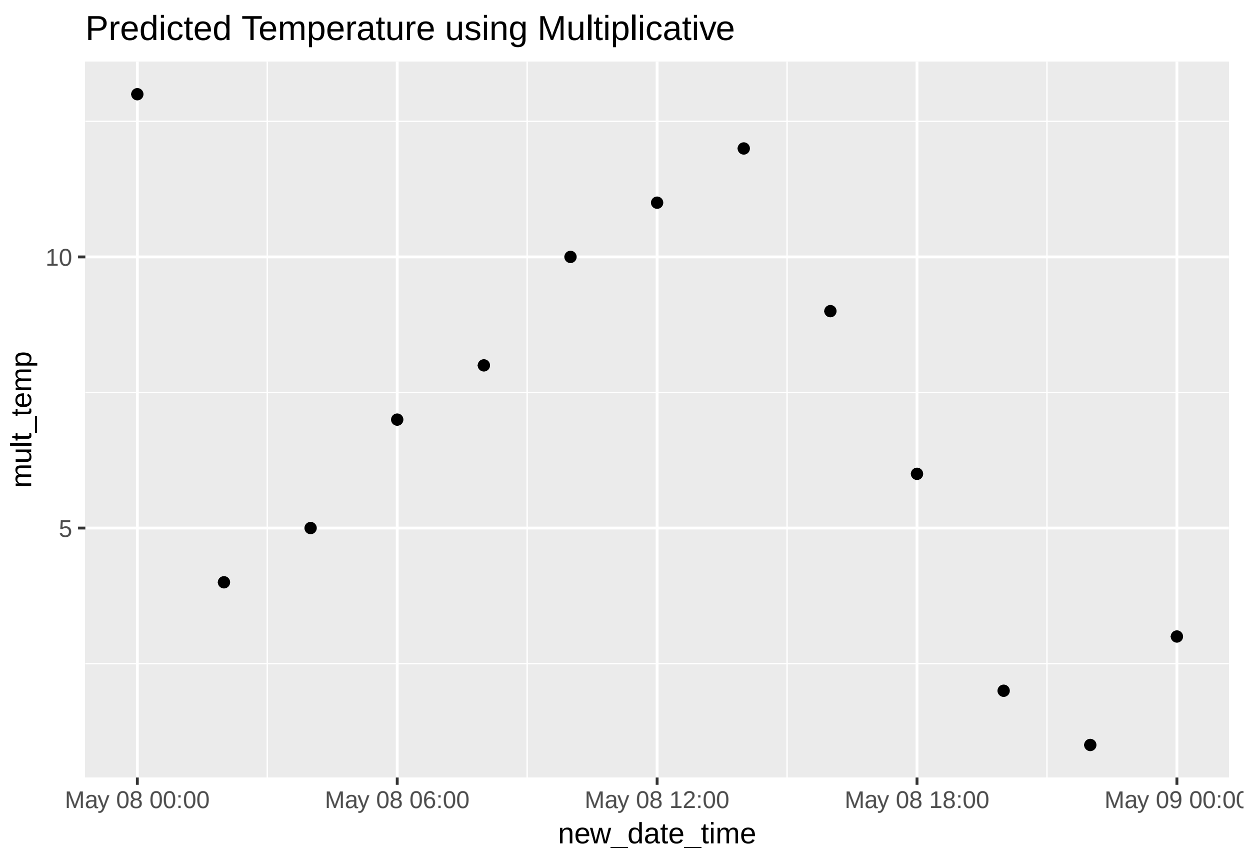
calling function

```r
kernel_method(df=st, date = "2000-05-08", loc_long = 17.6935,
              loc_lat = 59.9953, h1 = 30000, h2 = 2, h3 = 5)
```

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




```
##
## [[2]]
```



Analysis: A good width for the distance is 30Kms, the reasoning behind this is that temperature in Linkoping and Norrkoping tend to be similar but they vary by a few degree, given that sweden is way up north the temperature flucations will be less senstive to distance than compared to equator, thus 30Kms tend to be reasonable.

The width for the distance for day is 2, because I have personally experienced days where one days its freezing and next day I am sweating, thus 2 days is what I have choosen for my width.

For the width of time, considering the shorter winter days I do expect 3 hour of the time to be ideal window for temperature.

Assignment 2

Use the function ksvm from the R package kernlab to learn a SVM for classifying the spam dataset that is included with the package. Consider the radial basis function kernel (also known as Gaussian) with a width of 0.05. For the C parameter, consider values 0.5, 1 and 5. This implies that you have to consider three models.

```
rm(list=ls())
set.seed(1234567890)

data(spam)

## create test and training set
```

```r
index <- sample(1:dim(spam)[1])
spamtrain <- spam[index[1:floor(dim(spam)[1]/2)], ]
spamtest <- spam[index[((ceiling(dim(spam)[1]/2)) + 1):dim(spam)[1]], ]


## train a support vector machine
model_0.05 <- ksvm(type~., data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=0.05),
               C=0.5)

model_1.0 <- ksvm(type~.,data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=1.0),
               C=0.5)

model_5.0 <- ksvm(type~.,data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=5),
               C=0.5)

model_0.05
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 0.5
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  0.05
##
## Number of Support Vectors : 1063
##
## Objective Function Value : -304.0238
## Training error : 0.044783
```

```r
model_1.0
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 0.5
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  1
##
## Number of Support Vectors : 2098
##
## Objective Function Value : -615.9819
## Training error : 0.22913
```

```r
model_5.0
```

```
## Support Vector Machine object of class "ksvm"
##
```

```
## SV type: C-svc  (classification)
##  parameter : cost C = 0.5
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  5
##
## Number of Support Vectors : 2150
##
## Objective Function Value : -649.5897
## Training error : 0.274348
```

```
x <- as.matrix(spamtrain[,-58])


# confusion table

conf_model_0.05 <- table(spamtest[,58], predict(model_0.05,spamtest[,-58]))
names(dimnames(conf_model_0.05)) <- c("Actual Test", "P2redicted Test")
caret::confusionMatrix(conf_model_0.05)
```

```
## Confusion Matrix and Statistics
##
##            P2redicted Test
## Actual Test nonspam spam
##     nonspam    1345   56
##     spam        155  744
##
##                Accuracy : 0.9083
##                  95% CI : (0.8957, 0.9197)
##     No Information Rate : 0.6522
##     P-Value [Acc > NIR] : < 0.00000000000000022
##
##                   Kappa : 0.8035
##  Mcnemar's Test P-Value : 0.00000000001514
##
##             Sensitivity : 0.8967
##             Specificity : 0.9300
##          Pos Pred Value : 0.9600
##          Neg Pred Value : 0.8276
##              Prevalence : 0.6522
##          Detection Rate : 0.5848
##    Detection Prevalence : 0.6091
##       Balanced Accuracy : 0.9133
##
##        'Positive' Class : nonspam
##
```

```
conf_model_1.0 <- table(spamtest[,58], predict(model_1.0,spamtest[,-58]))
names(dimnames(conf_model_1.0)) <- c("Actual Test", "P2redicted Test")
caret::confusionMatrix(conf_model_1.0)
```

```
## Confusion Matrix and Statistics
##
##            P2redicted Test
## Actual Test nonspam spam
```

```
##     nonspam    1401    0
##     spam        685  214
##
##                Accuracy : 0.7022
##                  95% CI : (0.683, 0.7208)
##     No Information Rate : 0.907
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.2757
##  Mcnemar's Test P-Value : <0.0000000000000002
##
##             Sensitivity : 0.6716
##             Specificity : 1.0000
##          Pos Pred Value : 1.0000
##          Neg Pred Value : 0.2380
##              Prevalence : 0.9070
##          Detection Rate : 0.6091
##    Detection Prevalence : 0.6091
##       Balanced Accuracy : 0.8358
##
##        'Positive' Class : nonspam
##
```

```r
conf_model_0.05 <- table(spamtest[,58], predict(model_5.0,spamtest[,-58]))
names(dimnames(conf_model_0.05)) <- c("Actual Test", "P2redicted Test")
caret::confusionMatrix(conf_model_0.05)
```

```
## Confusion Matrix and Statistics
##
##            P2redicted Test
## Actual Test nonspam spam
##     nonspam    1401    0
##     spam        769  130
##
##                Accuracy : 0.6657
##                  95% CI : (0.646, 0.6849)
##     No Information Rate : 0.9435
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.1708
##  Mcnemar's Test P-Value : <0.0000000000000002
##
##             Sensitivity : 0.6456
##             Specificity : 1.0000
##          Pos Pred Value : 1.0000
##          Neg Pred Value : 0.1446
##              Prevalence : 0.9435
##          Detection Rate : 0.6091
##    Detection Prevalence : 0.6091
##       Balanced Accuracy : 0.8228
##
##        'Positive' Class : nonspam
##
```

Analysis:

From the summary of the three models build we can see that the accuracy of models are 90.83%, 70.22%, 66.57% respectively. Accuracy is only half the story, as a good spam detection should never classify a good mail has 'spam', which is something that model2 and model3 are doing. However in model 3 the accuracy is least thus, given a choice i would select model2 has the best model despite the lower accuracy.

Appendix

```
knitr::opts_chunk$set(echo = TRUE)
if (!require("pacman")) install.packages("pacman")
pacman::p_load(geosphere, kernlab, geosphere, ggplot2,caret)

set.seed(12345)
options("jtools-digits" = 2, scipen = 999)

# colours (colour blind friendly)
cbPalette <- c("#999999", "#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2",
               "#D55E00", "#CC79A7")

rm(list=ls())
set.seed(1234567890)
stations <- read.csv("stations.csv")
temps <- read.csv("temps50k.csv")
st <- merge(stations,temps,by="station_number")
rm(temps, stations)
kernel_method <- function(df, date, loc_long, loc_lat, h1, h2, h3) {

set.seed(1234567890)
start <- as.POSIXct(date)
interval <- 60
end <- start + as.difftime(1, units="days")
time_seq <- seq(from=start, by=interval*120, to=end)
time_seq <- as.data.frame(time_seq)
colnames(time_seq) <- "new_date_time"
time_seq$time_index <- rownames(time_seq)

df_new <- merge.data.frame(df,time_seq,all=TRUE)
rm(df)

df_new$new_date <- as.Date(df_new$new_date_time)
df_new$new_time <- format(df_new$new_date_time,"%H:%M:%S")
df_new$loc_long <- loc_long
df_new$loc_lat <-  loc_lat


df_new$h_distance <-  abs(distHaversine(p1 = df_new[,c("loc_long", "loc_lat")], p2 = df_new[,c("longitu

df_new$h_date <- as.numeric(abs(difftime(df_new$new_date, df_new$date, units = c("days"))))

df_new$h_time <- as.numeric(abs(difftime(strptime(paste(df_new$new_date,
                                                        df_new$new_time),"%Y-%m-%d%H:%M:%S"),
                                          strptime(paste(df_new$new_date, df_new$time),
                                    "%Y-%m-%d %H:%M:%S"),
```

```r
                          units = c("hour"))))


df_new$date_time <- paste(df_new$date, df_new$time)
df_new$hd_dist <- as.numeric(difftime(df_new$new_date_time,
                          df_new$date_time,
                          units = c("hour")))

## removing any negative dates and time
df_new$posterior_flag <- as.factor(ifelse(df_new$h_distance > 0 & df_new$hd_dist > 0, "retain", "drop"))


## calculating kernel distance and choosing guassian kernel
df_new$h_distance_kernel <- exp(-(df_new$h_distance/h1)^2)
df_new$h_date_kernel <- exp(-(df_new$h_date/h2)^2)
df_new$h_time_kernel <- exp(-(df_new$h_time/h3)^2)
df_new$total_additive_dist <- (df_new$h_distance_kernel + df_new$h_date_kernel + df_new$h_time_kernel)
df_new$total_mul_dist <- (df_new$h_distance_kernel * df_new$h_date_kernel * df_new$h_time_kernel)

df_new$additive_num <- ifelse(df_new$posterior_flag == "retain",
                              df_new$h_distance_kernel*df_new$air_temperature +
                                df_new$h_date_kernel*df_new$air_temperature +
                                df_new$h_time_kernel*df_new$air_temperature,0)

df_new$mul_num <- ifelse(df_new$posterior_flag == "retain",
                         (df_new$h_distance_kernel*df_new$air_temperature) *
                                (df_new$h_date_kernel*df_new$air_temperature) *
                                (df_new$h_time_kernel*df_new$air_temperature),0)

df_new$additive_den <- ifelse(df_new$posterior_flag == "retain", df_new$total_additive_dist, 0)
df_new$mul_den <- ifelse(df_new$posterior_flag == "retain", df_new$total_mul_dist, 0)

time = unique(time_seq$time_index)
result <- NULL

for(i in time){
temp <- df_new[df_new$time_index == i,]
additive_temp <- sum(temp$additive_num)/sum(temp$additive_den)
mult_temp <- sum(temp$mul_num)/sum(temp$mul_den)

temp <- cbind(additive_temp, mult_temp, i)
result <- rbind(temp,result)
}

result <- as.data.frame(result)
result <- merge(x =result, y = time_seq, by.x = "i", by.y = "time_index", all.x = TRUE)
result$additive_temp <- as.numeric(result$additive_temp)
result$mult_temp <- as.numeric(result$mult_temp)

p1 <- ggplot(data=result, aes(x=new_date_time, y = additive_temp)) + geom_point() +
  ggtitle("Predicted Temperature using Additive")

p2 <- ggplot(data=result, aes(x=new_date_time, y = mult_temp)) + geom_point() +
```

```r
  ggtitle("Predicted Temperature using Multiplicative")

final <- list(p1,p2)
return(final)
}

kernel_method(df=st, date = "2000-05-08", loc_long = 17.6935,
              loc_lat = 59.9953, h1 = 30000, h2 = 2, h3 = 5)
rm(list=ls())
set.seed(1234567890)

data(spam)

## create test and training set
index <- sample(1:dim(spam)[1])
spamtrain <- spam[index[1:floor(dim(spam)[1]/2)], ]
spamtest <- spam[index[((ceiling(dim(spam)[1]/2)) + 1):dim(spam)[1]], ]


## train a support vector machine
model_0.05 <- ksvm(type~., data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=0.05),
               C=0.5)

model_1.0 <- ksvm(type~.,data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=1.0),
               C=0.5)

model_5.0 <- ksvm(type~.,data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=5),
               C=0.5)

model_0.05
model_1.0
model_5.0

x <- as.matrix(spamtrain[,-58])


# confusion table

conf_model_0.05 <- table(spamtest[,58], predict(model_0.05,spamtest[,-58]))
names(dimnames(conf_model_0.05)) <- c("Actual Test", "P2redicted Test")
caret::confusionMatrix(conf_model_0.05)

conf_model_1.0 <- table(spamtest[,58], predict(model_1.0,spamtest[,-58]))
names(dimnames(conf_model_1.0)) <- c("Actual Test", "P2redicted Test")
caret::confusionMatrix(conf_model_1.0)

conf_model_0.05 <- table(spamtest[,58], predict(model_5.0,spamtest[,-58]))
```

```
names(dimnames(conf_model_0.05)) <- c("Actual Test", "P2redicted Test")
caret::confusionMatrix(conf_model_0.05)
```