Machine Learning - Lab03 - Group A2

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Contents

Contributions

For this report Thijs and Anubhav focused on assignment 1. Lennart focused on assignment 2. All code was written individually and independently.

Loading The Libraries

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

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 - Kernel Methods

```r
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)
```

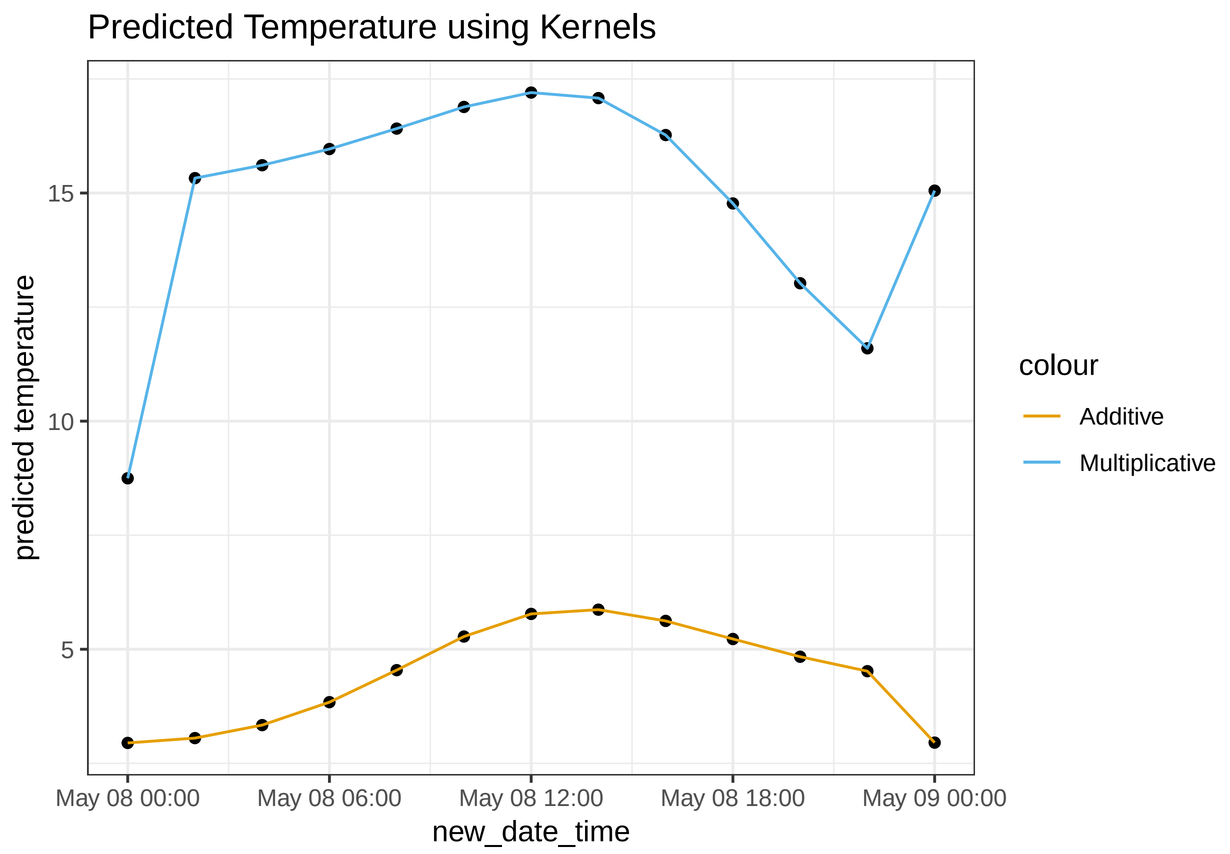
defining the function

```r
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("longitude", "latitude")]))

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$h_distance_kernel) *
                                (df_new$h_date_kernel) *
                                (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$additive_temp <- as.numeric(as.character(result$additive_temp))
result$mult_temp <- as.numeric(as.character(result$mult_temp))

p1 <- ggplot(data=result, aes(x=new_date_time)) +
  geom_point(aes(y = additive_temp)) +
  geom_point(aes(y = mult_temp)) +
  geom_line(aes(y = additive_temp, color = "Additive")) +
  geom_line(aes(y = mult_temp, color = "Multiplicative")) +
  scale_color_manual(values=c("#E69F00", "#56B4E9")) +
  ylab("predicted temperature") +
  theme_bw() +
  ggtitle("Predicted Temperature using Kernels")

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

calling function

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

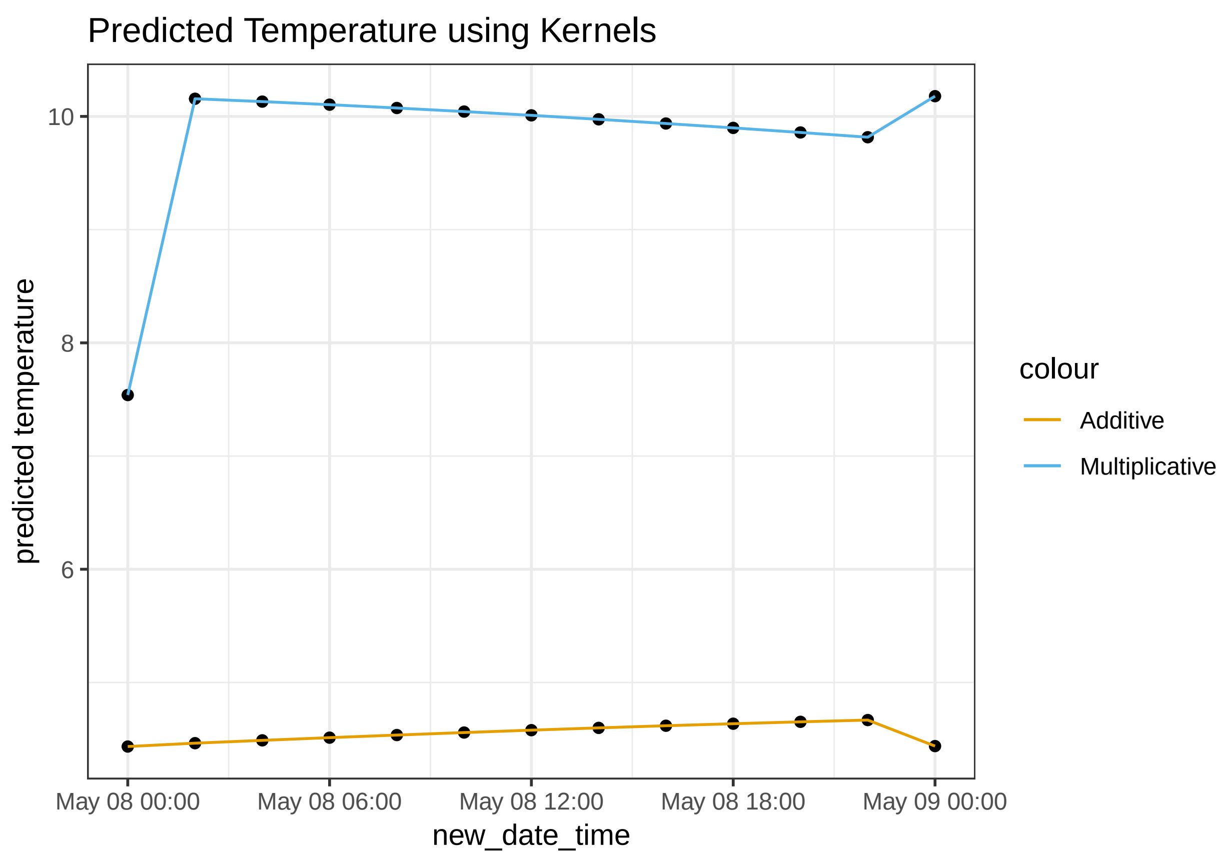
```
## [[1]]
```



### high values

```
kernel_method(df=st, date = "2000-05-08", loc_long = 17.6935,
              loc_lat = 59.9953, h1 = 30000, h2 = 100, h3 = 30)
```

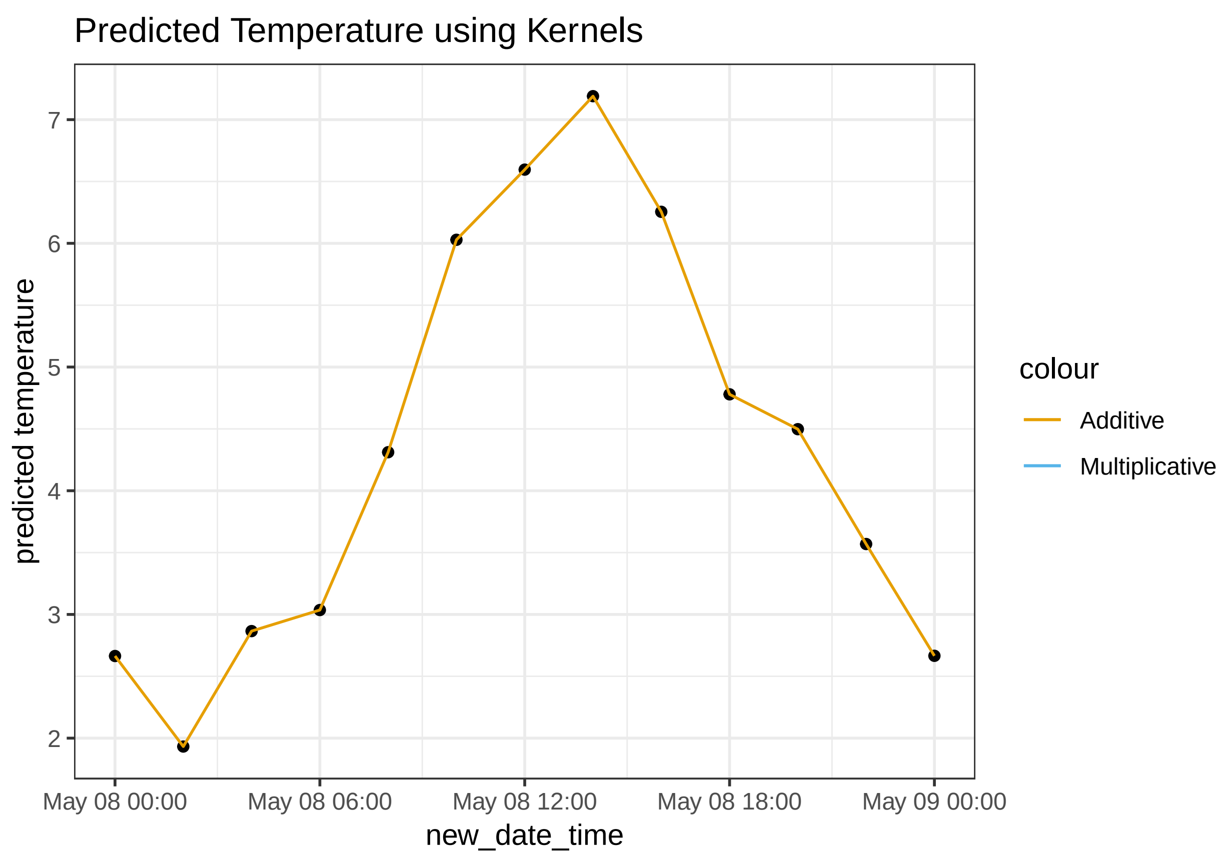
```
## [[1]]
```



low values

```
kernel_method(df=st, date = "2000-05-08", loc_long = 17.6935,
              loc_lat = 59.9953, h1 = 10, h2 = 0.05, h3 = 0.05)
```

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



Analysis:

For the kernel widths I have chosen the following values:

Distance: 30 kilometers

Date: 2 days

Time: 5 hours As evident from the plots using extreme values makes either multicative model or additive model (either terms tend to zero or all terms converge to one).When the widths are extremely large the values are saturated and there is no variations while when the values are really small the prediction by multiplicative effectively yields 0 while summation kernel predicted highly varying curve.

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 - Support Vector Machines

In this assignment, a Support Vector Machine (SVM), a supervised learning model, will be used to classify spam dataset that is included within the *kernlab*-package which will be used for this assignment.

```r
rm(list=ls())
set.seed(12345)

data(spam)

n = dim(spam)[1]
## create test and training set
id = sample(1:n, floor(n*0.7))
spamtrain = spam[id,]
spamtest = spam[-id,]

## 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=0.05),
               C=1.0)

model_5.0 <- ksvm(type~.,data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=0.05),
               C=5.0)

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

```
## Confusion Matrix and Statistics
##
##            Predicted Test
## Actual Test nonspam spam
##     nonspam     806   29
##     spam         86  460
##
##                Accuracy : 0.9167
##                  95% CI : (0.9009, 0.9308)
##     No Information Rate : 0.6459
##     P-Value [Acc > NIR] : < 0.0000000000000002
##
##                   Kappa : 0.8226
##  Mcnemar's Test P-Value : 0.000000177
##
##             Sensitivity : 0.9036
##             Specificity : 0.9407
##          Pos Pred Value : 0.9653
##          Neg Pred Value : 0.8425
##              Prevalence : 0.6459
##          Detection Rate : 0.5836
##    Detection Prevalence : 0.6046
##       Balanced Accuracy : 0.9221
##
##        '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", "Predicted Test")
caret::confusionMatrix(conf_model_1.0)
```

```
## Confusion Matrix and Statistics
##
##            Predicted Test
## Actual Test nonspam spam
##     nonspam     800   35
##     spam         68  478
##
##                Accuracy : 0.9254
##                  95% CI : (0.9103, 0.9387)
##     No Information Rate : 0.6285
##     P-Value [Acc > NIR] : < 0.00000000000000022
##
##                   Kappa : 0.8424
##  Mcnemar's Test P-Value : 0.001616
##
##             Sensitivity : 0.9217
##             Specificity : 0.9318
##          Pos Pred Value : 0.9581
##          Neg Pred Value : 0.8755
##              Prevalence : 0.6285
##          Detection Rate : 0.5793
##    Detection Prevalence : 0.6046
##       Balanced Accuracy : 0.9267
##
##        'Positive' Class : nonspam
##
```

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

```
## Confusion Matrix and Statistics
##
##            Predicted Test
## Actual Test nonspam spam
##     nonspam     798   37
##     spam         70  476
##
##                Accuracy : 0.9225
##                  95% CI : (0.9071, 0.9361)
##     No Information Rate : 0.6285
##     P-Value [Acc > NIR] : < 0.00000000000000022
##
##                   Kappa : 0.8362
##  Mcnemar's Test P-Value : 0.001978
##
```

```
##             Sensitivity : 0.9194
##             Specificity : 0.9279
##          Pos Pred Value : 0.9557
##          Neg Pred Value : 0.8718
##              Prevalence : 0.6285
##          Detection Rate : 0.5778
##    Detection Prevalence : 0.6046
##       Balanced Accuracy : 0.9236
##
##        'Positive' Class : nonspam
##
```

Analysis:

From the summary of the three models build we can see that the accuracy of models are 90.83%, 91.61%, 91.70% respectively. Accuracy is only half the story, as a good spam detection should never classify a good mail has 'spam', which is something that model1 is doing. However in model 1 also has the least accuracy however its marginally bad. Given a choice i would select model1 has the best model despite the lower accuracy.

Purpose of the 'C' parameter:- C is the cost parameter which penalizes large residuals. So a larger cost will result in a more flexible model with fewer misclassifications. In effect the cost parameter allows you to adjust the bias/variance trade-off. The greater the cost parameter, the more variance in the model and the less bias.The greater the cost, the fewer misclassifications are allowed. Note that here we penalize the residuals resulting in higher variance and lower bias.

Appendix

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

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"
```

```r
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("longitude", "latitude")]))

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$h_distance_kernel) *
                                (df_new$h_date_kernel) *
                                (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$additive_temp <- as.numeric(as.character(result$additive_temp))
result$mult_temp <- as.numeric(as.character(result$mult_temp))

p1 <- ggplot(data=result, aes(x=new_date_time)) +
  geom_point(aes(y = additive_temp)) +
  geom_point(aes(y = mult_temp)) +
  geom_line(aes(y = additive_temp, color = "Additive")) +
  geom_line(aes(y = mult_temp, color = "Multiplicative")) +
  scale_color_manual(values=c("#E69F00", "#56B4E9")) +
  ylab("predicted temperature") +
  theme_bw() +
  ggtitle("Predicted Temperature using Kernels")

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

kernel_method(df=st, date = "2000-05-08", loc_long = 17.6935,
              loc_lat = 59.9953, h1 = 30000, h2 = 2, h3 = 5)
kernel_method(df=st, date = "2000-05-08", loc_long = 17.6935,
              loc_lat = 59.9953, h1 = 30000, h2 = 100, h3 = 30)
kernel_method(df=st, date = "2000-05-08", loc_long = 17.6935,
              loc_lat = 59.9953, h1 = 10, h2 = 0.05, h3 = 0.05)
rm(list=ls())
set.seed(12345)

data(spam)

n = dim(spam)[1]
## create test and training set
id = sample(1:n, floor(n*0.7))
spamtrain = spam[id,]
spamtest = spam[-id,]

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

```r
model_1.0 <- ksvm(type~.,data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=0.05),
               C=1.0)

model_5.0 <- ksvm(type~.,data=spamtrain,
               kernel="rbfdot",
               kpar=list(sigma=0.05),
               C=5.0)

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