Lab 3

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Contents

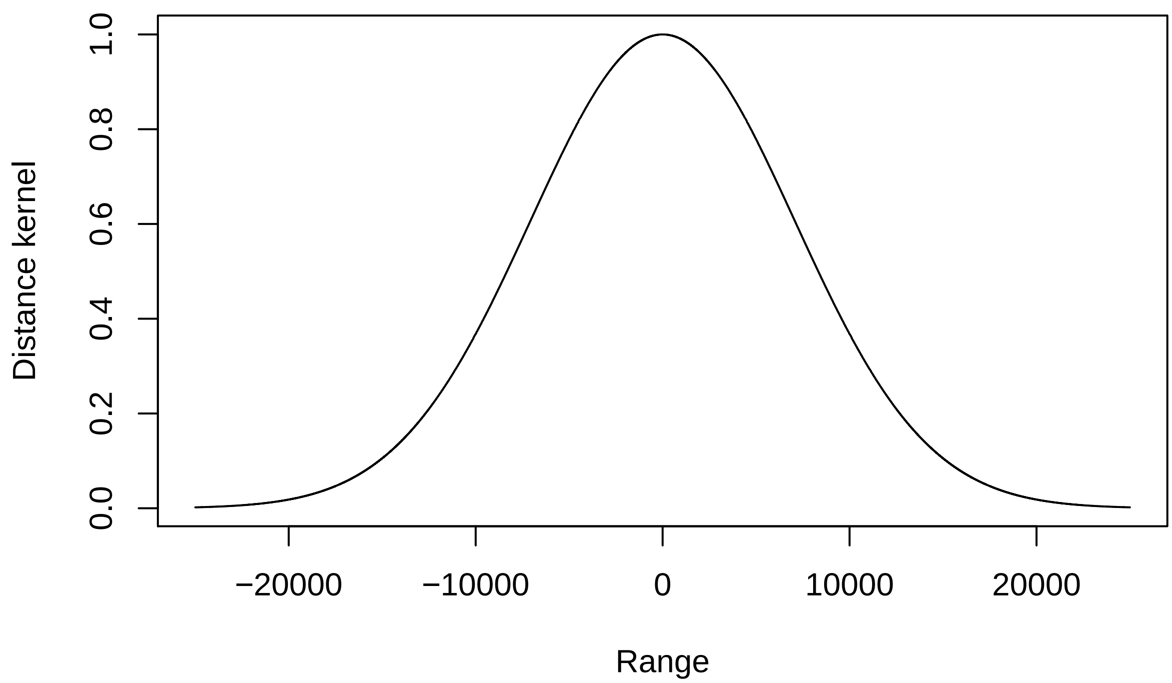
Assignment 1

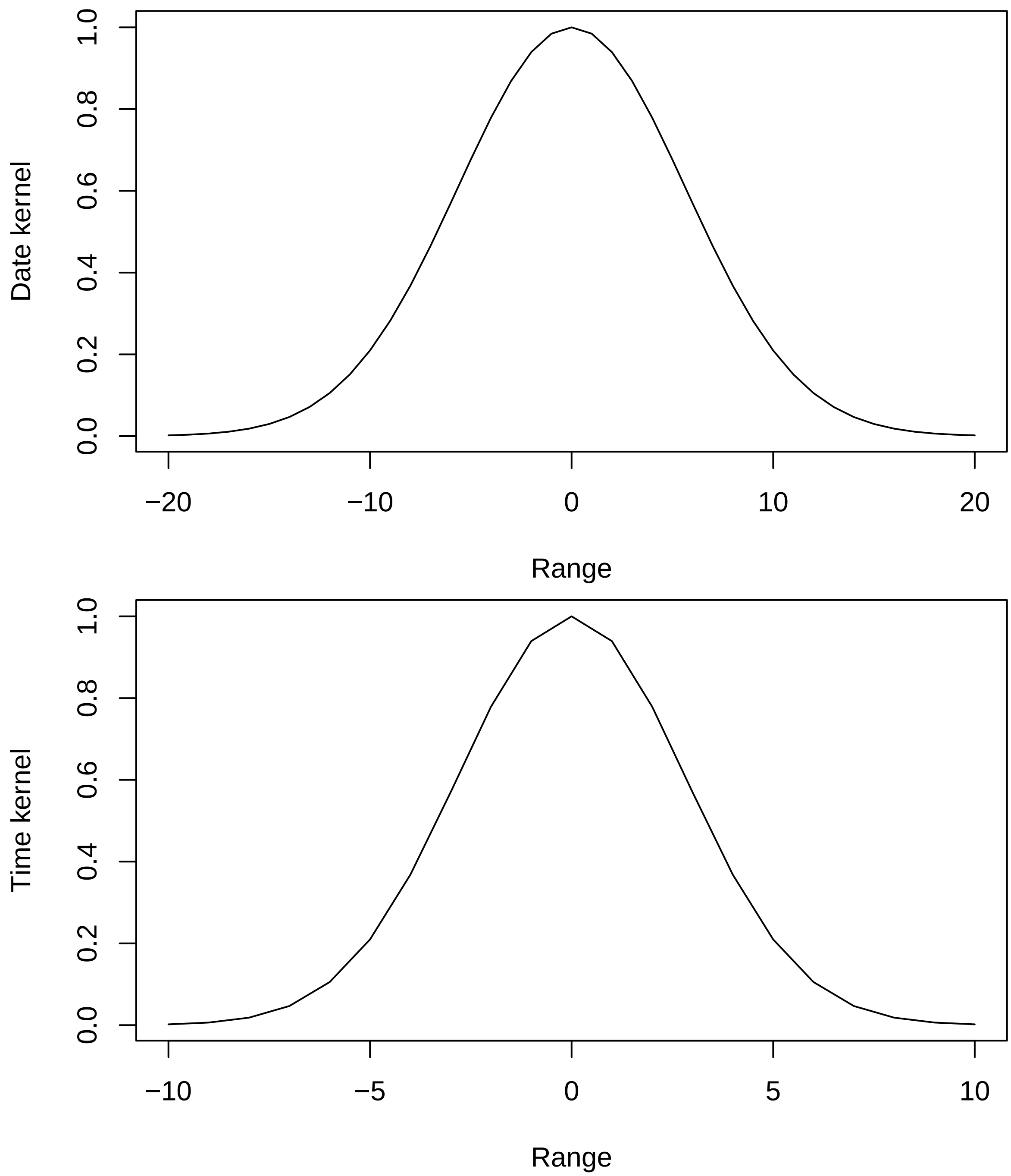
Part 1

The chosen width for each kernel is:

- h_distance: 10000 m
- h_date: 8 days
- h_time: 4 hours

The plots below show that the kernels gives more weight to closer points.





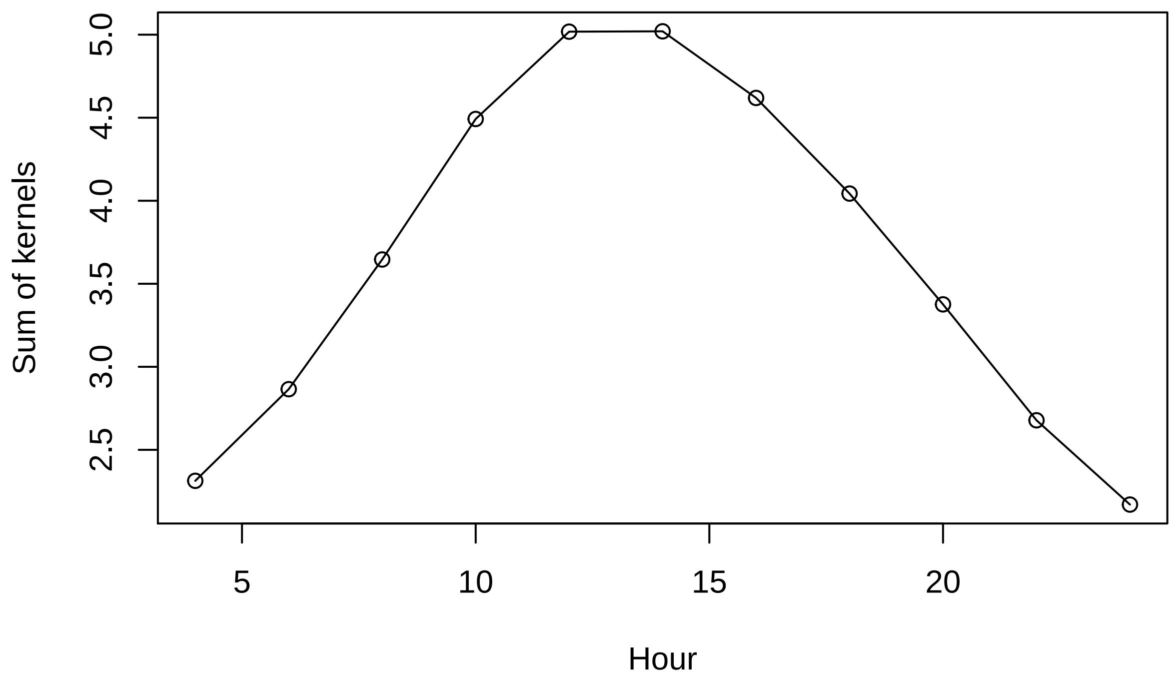
The values of widths were tested by changing them and evaluating predictions of temperature so that a plot of one day's temperature would look realistic. Each width defines where the amplification is e^{-1}, which gives some indication on where points starts to being cut away. The widths can be explained as:

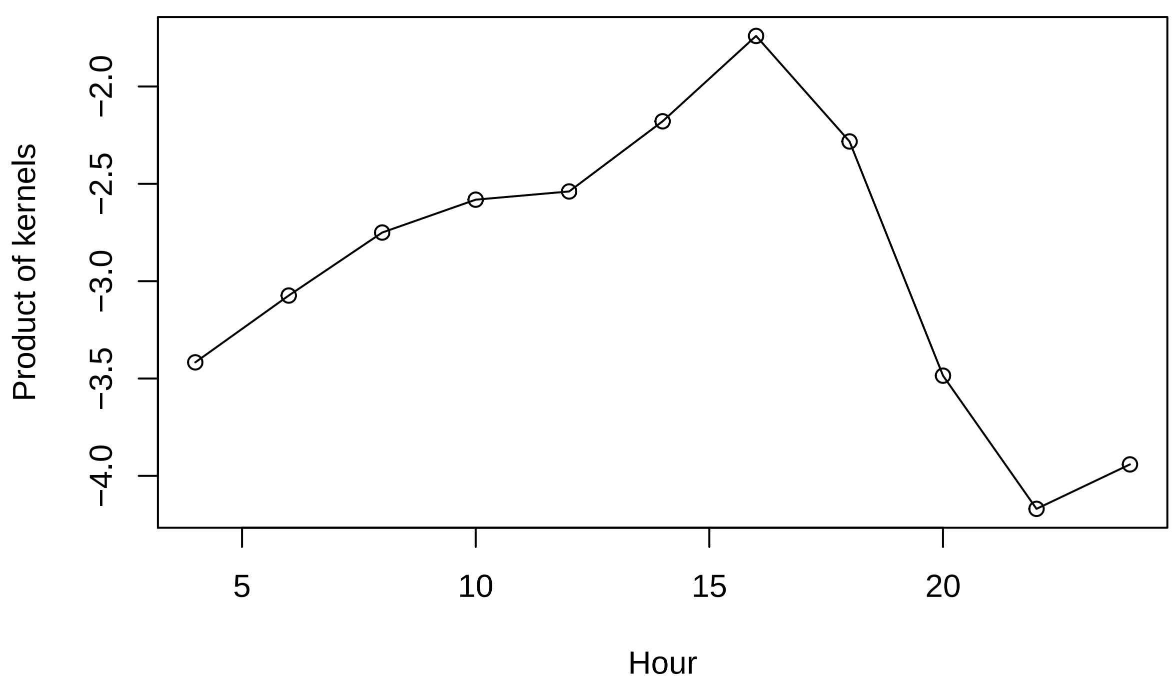
- Measurements within a distance of 10000 m are weighted greatest.
- The closest 8 days affect the temperature the most.
- A measurement within 4 h contributes to the prediction the most.

Of course, all of these kernels give the greatest amplification at zero distance. Since this model for predicting temperature is far from perfect, it's hard to tell what widths that are realistic. For instance, the model does not take into account what year a measurment was made, only the day of a year. With that in mind, the chosen widths can be assumed somewhat adequate for this case.

Part 2

The plots below show a temperature prediction on Christmas Eve. The first one summarizing each kernel, the other multiplying them.





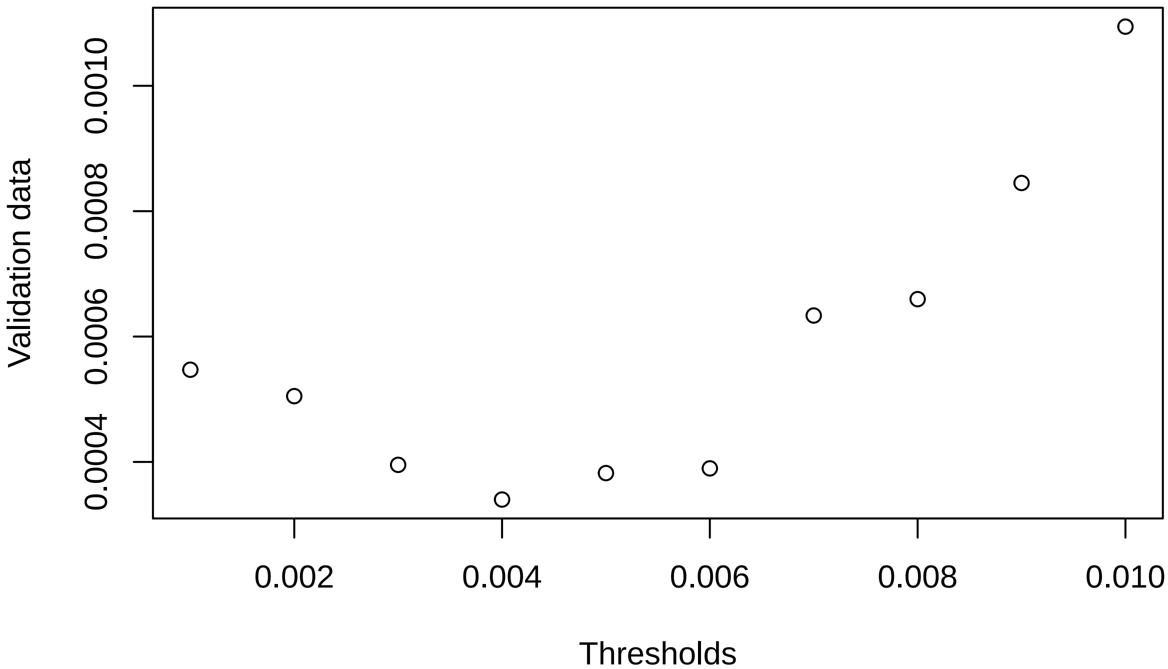
As can be seen, the product of the kernels give preffered results (since it's Christmas and I want snow). It is also more probable that it is minus degrees at the end of December.

A summation would not give a good result since then only one kernel need to have a good result to be counted in. Lets say a day is half a year away from target day, but at the exact same hour. That day should almost not count at all, but it still does with with the summation method. That way, the product gives a better result.

Assignment 3

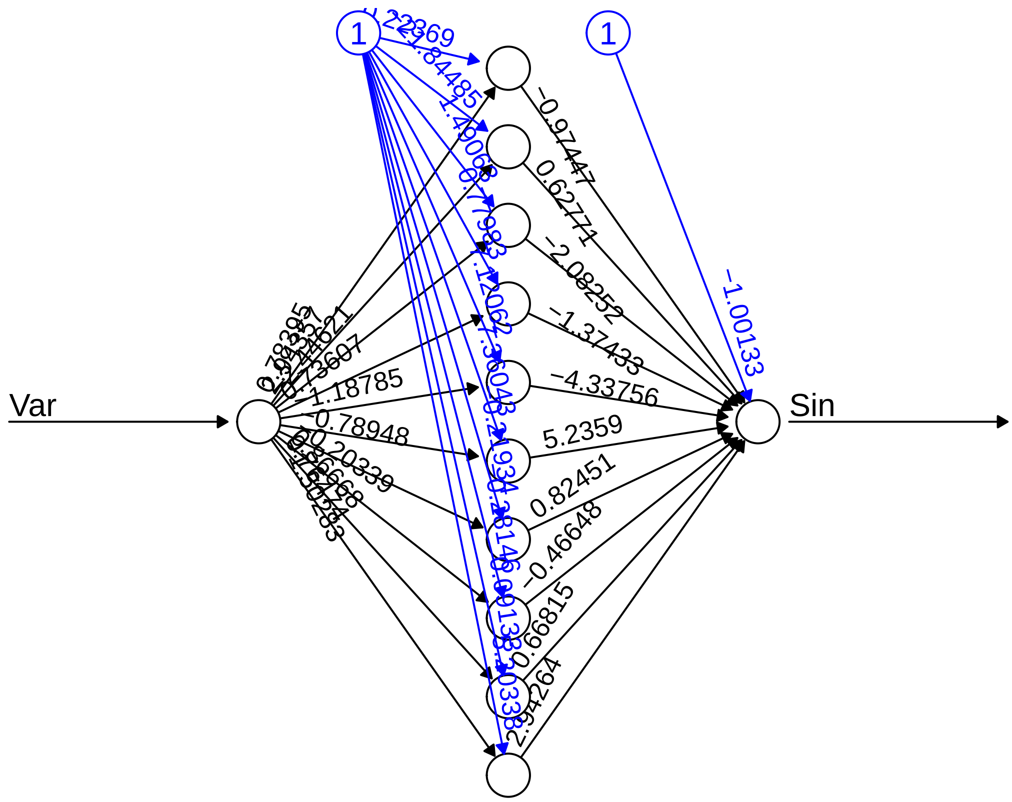
Validation

The threshold was chosen to the one that ended up resulting in the lowest mean square error when predicting the validation data. The MSE for thresholds in the interval [1/1000, 10/1000] are plotted below.



As seen here, the best threshold in this case is 4/1000.

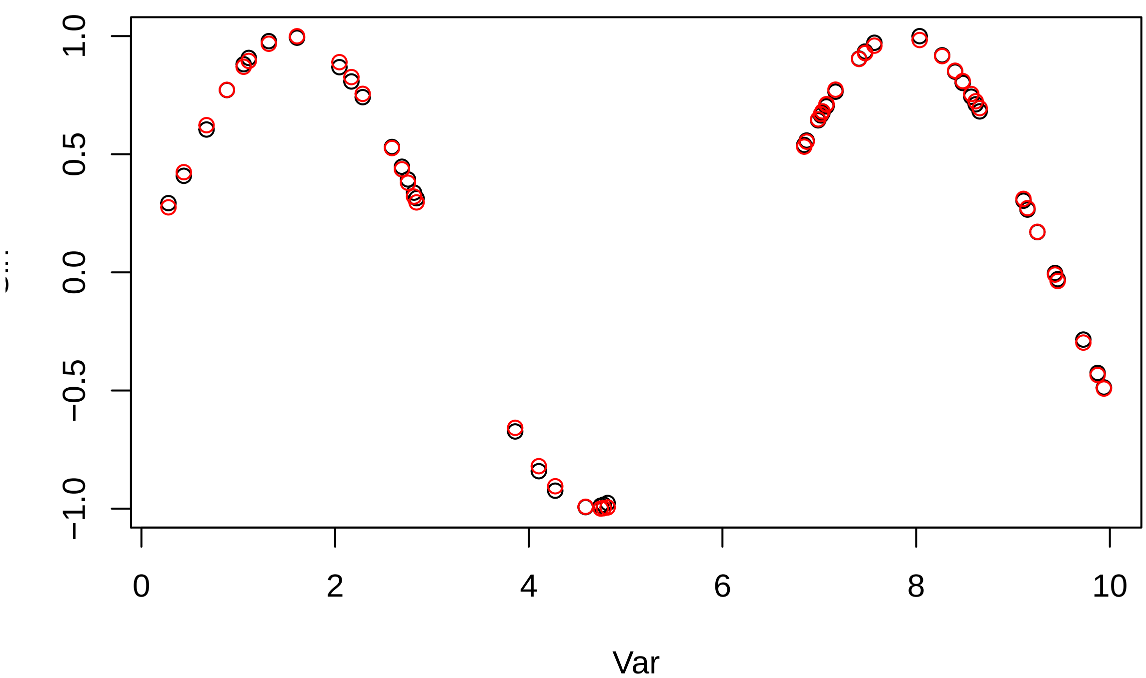
The final neural network



Prediction of Sin

Black dots are prediction, red ones are correct values.

```
## Data Error:  0;
```



Appendix

Assignment 1

```r
library("geosphere")

setwd("~/courses/tdde01/lab3/")

stations = read.csv("stations.csv", fileEncoding = "Latin1")
temps = read.csv("temps50k.csv")
st = merge(stations, temps, by="station_number")

gauss_kernel = function(u) {
    return (exp(-(u^2)))
}

h_distance = 10000
h_date = 8
h_time = 4

# Station is station number, interest is vector(long, lat)
kernel_distance = function(station, interest) {
    distance = distHaversine(station, interest)
    res = gauss_kernel(distance/h_distance)
    return (res)
}

# Calculates gaussian kernel provided with difference in days from day to interest
kernel_date = function(dates, interest) {
    dates = as.Date(dates)
    interest = as.Date(interest)
    distance = as.numeric(difftime(dates, interest, units=c("days")))
    leap_years = floor(floor(distance/365)/4)
    distance = (distance - leap_years) %% 365
    distance = sapply(distance, function(d) min(d, abs(365 - d)))
    res = gauss_kernel(distance/h_date)
    return (res)
}

# Calculates gaussian kernel provided with difference of hour and target hour
kernel_time = function(hour, interest) {
    h1 = as.numeric(substr(hour, 1, 2))
    h2 = as.numeric(substr(interest, 1, 2))
    distance = abs(((h2-h1) + 12) %% 24 - 12)
    return (gauss_kernel(distance/h_time))
}

# Plot kernels
width = 2.5
range = -(h_distance*width):(h_distance*width)
plot(x=range, y=gauss_kernel(range/h_distance), type="l", ylab = "Distance kernel", xlab="Range")

range = -(h_date*width):(h_date*width)
plot(x=range, y=gauss_kernel(range/h_date), type="l", ylab = "Date kernel", xlab="Range")
```

```r
range = -(h_time*width):(h_time*width)
plot(x=range, y=gauss_kernel(range/h_time), type="l", ylab = "Time kernel", xlab="Range")

# Summation of kernels. Passing product returns kernels multiplied
kernel_sum = function(long, lat, date, time, product=FALSE) {
    longlat = data.frame(st$longitude, st$latitude)
    distances = kernel_distance(longlat, c(long, lat))

    datediffs = kernel_date(st$date, date)

    timediffs = kernel_time(st$time, time)

    sum = sum((distances + datediffs + timediffs) * st$air_temperature)
    sum = sum / sum(distances + datediffs + timediffs)

    prod = sum((distances * datediffs * timediffs) * st$air_temperature)
    prod = prod / sum(distances * datediffs * timediffs)

    if (product) {
        return(prod)
    }
    else {
        return(sum)
    }
}

latitude = 58.4274 # The point to predict
longitude = 14.826
date = "2018-12-24" # The date to predict
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",
          "00:00:00")
# Remove posterior dates
st = st[as.Date(st$date) < as.Date(date),]

temp = lapply(times, function(t) kernel_sum(longitude, latitude, date, t, FALSE))

plot(temp, x=seq(4, 24, 2), type="o", ylab="Sum of kernels", xlab="Hour")

temp = lapply(times, function(t) kernel_sum(longitude, latitude, date, t, TRUE))

plot(temp, x=seq(4, 24, 2), type="o", ylab="Product of kernels", xlab="Hour")
```

Assignment 3

```r
library("neuralnet")
set.seed(1234567890)

# Random data from 0-10, uniformly distributed
Var = runif(50, 0, 10)
trva = data.frame(Var, Sin=sin(Var))
tr = trva[1:25,] # Training
```

```
va = trva[26:50,] # Validation

# Random initialization of the weights in the interval [-1, 1]
winit = runif(31, -1, 1)

# Loop over thresholds
validations = c()
for (i in 1:10) {
    nn = neuralnet(formula = Sin ~ Var, data = tr, hidden = 10, startweights = winit, threshold = i/1000
    comp = compute(nn, va$Var)

    mse = sum((comp$net.result - va$Sin)^2) / nrow(va)
    validations = c(validations, mse)
}
plot(x=seq(1/1000, 10/1000, 1/1000), y=validations, xlab="Thresholds", ylab="Validation data")
best_threshold = which.min(validations)/1000

# Optimal nn
nn = neuralnet(formula = Sin ~ Var, data = trva, hidden = 10, startweights = winit, threshold = best_thr

plot(nn, ylab="Neural network", rep="best")

# Plot of the predictions (black dots) and the data (red dots)
plot(prediction(nn)$rep1, ylim = c(-1, 1))
points(trva, col = "red")
```