TDDE01 MACHINE LEARNING

Lab 3 - Report

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Assignment - 1

The objective of this assignment is to find the temperature readings between 4 AM to 24 PM in an interval of 2 hours with independent variables date and place in Sweden.

The following data are provided as input for forecasting the temperature

- **Date** : 2019-12-19
- **place**: **Longitude** :58.4108, **Latitude** :15.6214

The prediction is done using 3 kernels which are guassian kernels and given below

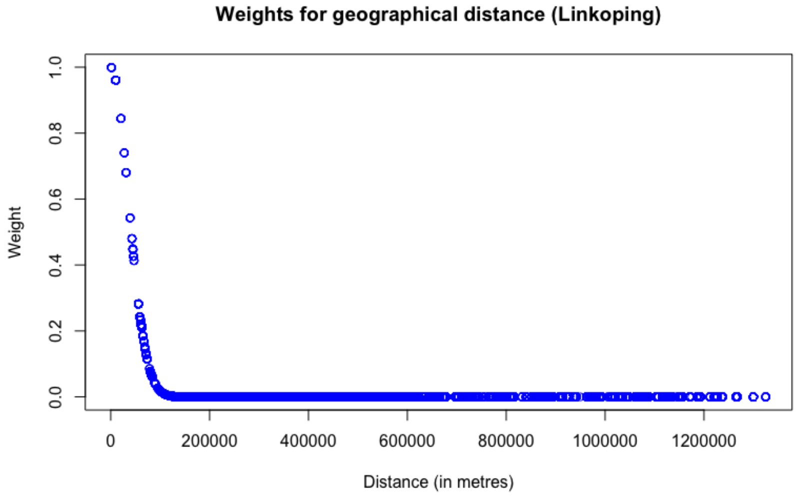
- The first to account for the distance from a station to the point of interest.
- The second to account for the distance between the day a temperature measurement was made and the day of interest.
- The third to account for the distance between the hour of the day a temperature measurement was made and the hour of interest.

3 Smoothing coefficients are selected for the above kernels

- h_distance = 50000 # m
- h_date = 7 # days
- h_time = 3 # hours

Geographical Kernel

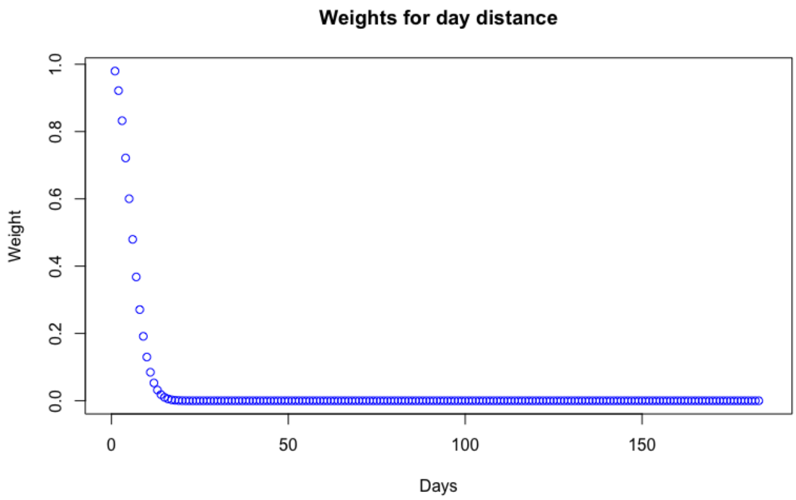
The plot below describe the weights which is provided by the 1st kernel for each of the data points based on the distance between two places



We can see from the above plot that as we move from the location we want to predict, the weights are getting reduced until they reach 0. This is the expected behaviour, as one moves away from a location, the temperature calculated becomes irrelavant for the prediction.

Day Kernel

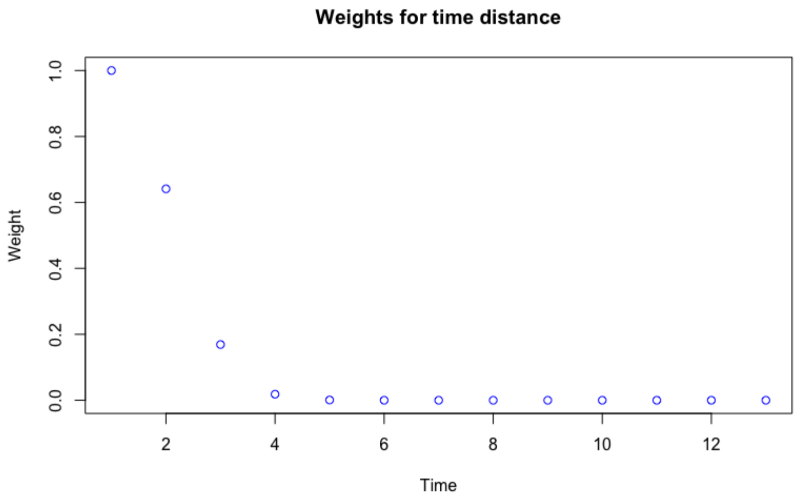
The plot below describe the weights which is provided by the 2^{nd} kernel for each of the data points based on the difference between prediction date and temperature measured dates (*in days*).



From the above plot, we could see that as we move away from the date to predict, the weights are getting reduced until they reach 0. This is the expected behaviour, as one moves away from a day, the temperature measured becomes irrelavant for the prediction

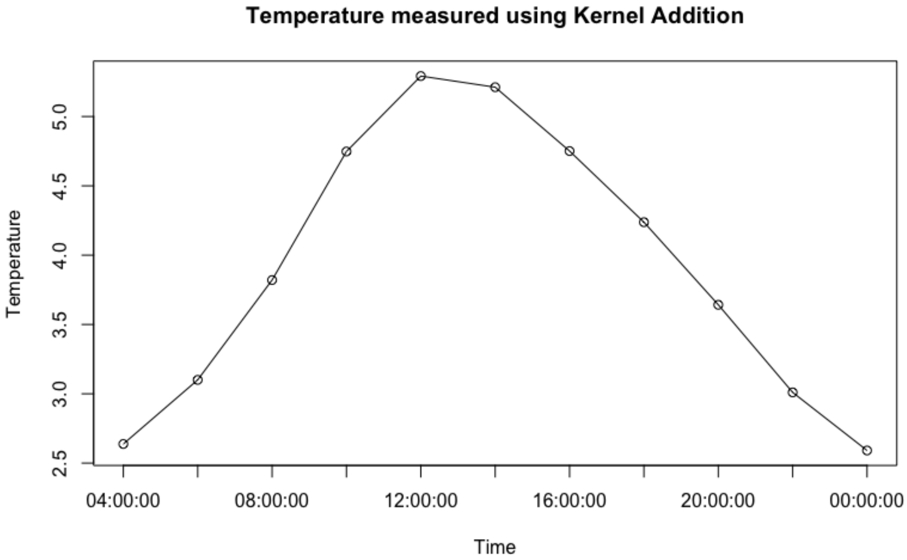
<u>Hour Kernel</u>

The plot below describe the weighs which is provided by the 3^{rd} kernel for each of the data points based on the time difference (*in hours*)

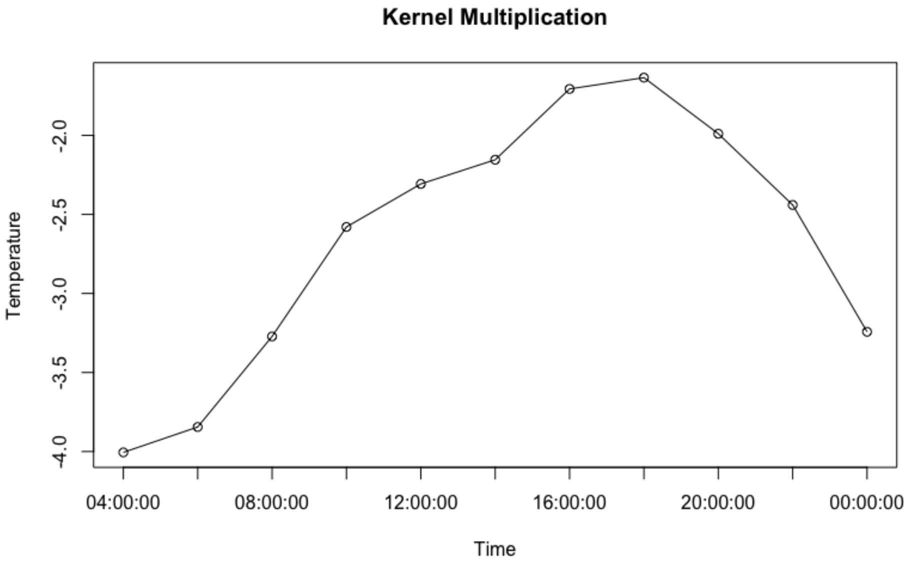


We can see from the above plot that, as we move away from the time we need to predict, the weights are reducing until they reach 0. This is the expected behaviour, as one moves away from a hour, the temperature measured becomes irrelvant for the prediction.

Temperature Prediction for 2019-12-19-Kernel Addition



Temperature Prediction for 2019-12-19-Kernel Multiplication



We predict the temperature by using the weighted mean of all observations temperatures. By looking the above two plots, we can see that multiplied kernel is better than summed kernel, because summed kernel provides higher MSE error rates when compared with multiplied kernel.

Assignment - 3

In this assignment, we were told to predict values of trignometric function *sin(x)* by using neural network. This can be achieved by using **Neuralnet** package in R.

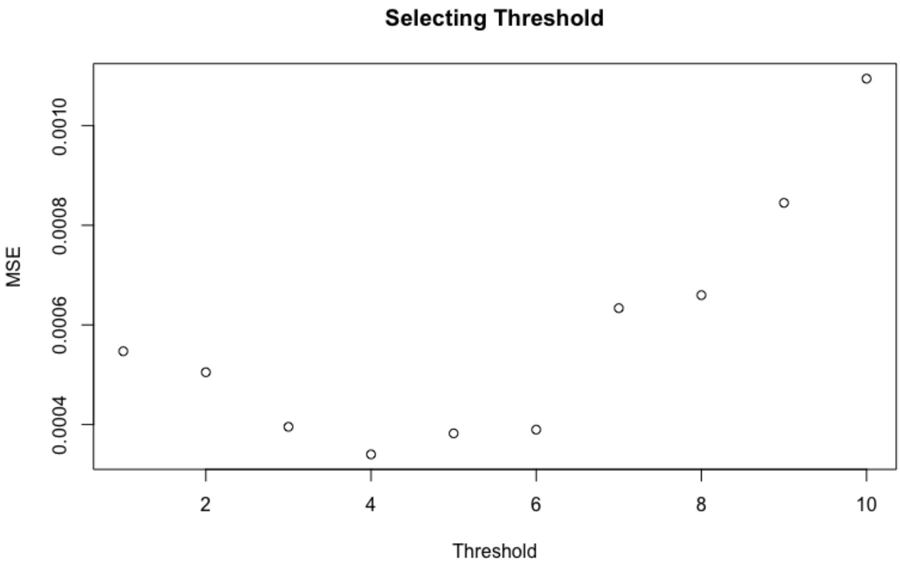
Initially, 50 data points (independent variable) are generated randomly between the interval [0,10] and *sin(x)* is applied which is dependent variable. The neural network is built with one input node, one hidden layer(10 hidden units of neurons) and one output node.

Next, weights has to be provided to the neural net in the interval [-1,+1]. So, the 31 (10 biases+10 intercepts for hidden layer) and (1 bias + 10 intercepts (from hidden layer) for output node) 31 weights has to be generated.

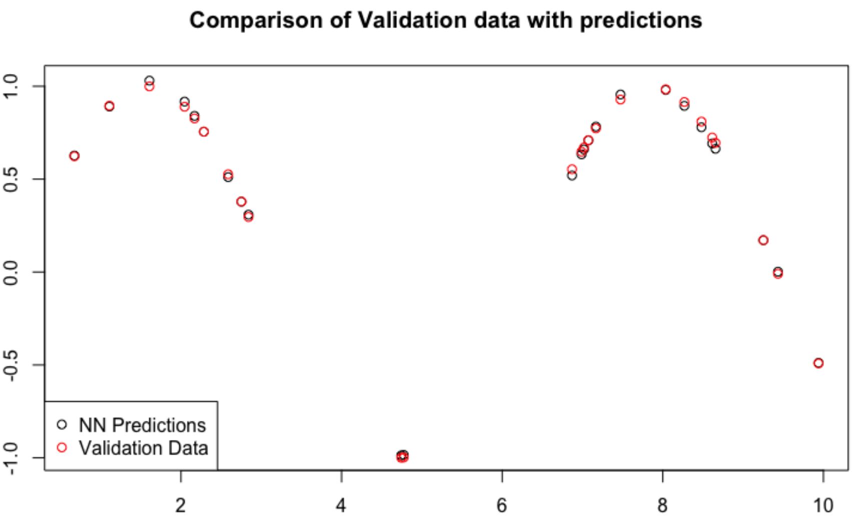
Implementing Neural net

Before executing neuralnet function, we need to choose optimal threshold. In order to select optimal threshold, we run the neural net function for 10 times and calculate the MSE for test data and select the MSE value which is less when compared with other values and there by selecting the optimal threshold corresponding to that MSE value.

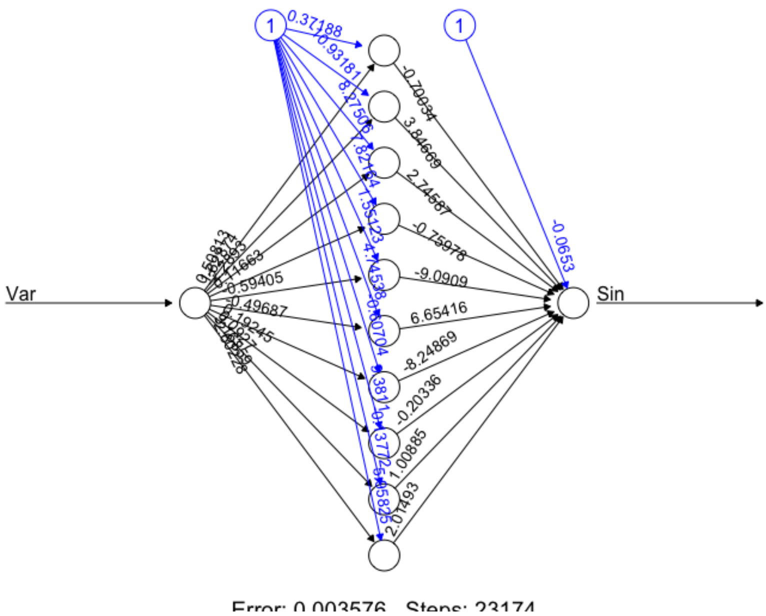
We choose **4/1000 = 0.004** as the optimal threshold from the plot below which has lower MSE value. The lower MSE value is **0.0003400358**



Once again, executing the neuralnet function with chosen optimal threshold and below is the result,



In order to visualize the network topology with weights and biases, we are plotting the nerual network and it is given below



Code Appendix

Assignment 1

```
options(scipen=999) #To avoid scientific notations
RNGversion('3.5.1')

set.seed(1234567890)
library(geosphere)
stations <- read.csv("stations.csv",stringsAsFactors=FALSE, fileEncoding="latin1")
temps <- read.csv("temps50k.csv")
st <- merge(stations,temps,by="station_number")
st$date = as.character(st$date)
st$time = as.character(st$time)

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")
h_distance <- 100000 # These three values are up to the students
h_date <- 7 #days
h_time <- 3 #hours
a <- 58.4108 # The point to predict (up to the students)
b <- 15.6214
latlong = data.frame(latitude = a,longitude = b)
pred_date <- "2019-12-19"
no_of_times = length(times)
latitude = rep(a,no_of_times)
longitude = rep(b,no_of_times)
dates = rep(pred_date,no_of_times)
data_Predict = data.frame(latitude=latitude,longitude=longitude,date=dates,time = times)

colSums(is.na(st))

st = st[as.Date(st$date)<as.Date(pred_date),]

gaussian_Kernel = function(u,h){
  return(exp(-abs(u/h)^2))
}

diff_distance_kernel = function(poi,stations)
{
  distance = distHaversine(poi,stations)
  return(gaussian_Kernel(distance,h_distance))
}

diff_date_kernel = function(doi,day)
{
  day_distance = abs(as.numeric(difftime(strptime(doi,format =
      "%Y-%m-%d"),strptime(day,format = "%Y-%m-%d"),units = "days")))
  day_distance = day_distance%%365
  day_distance[day_distance>182] = 365-day_distance[day_distance>182]
  return(gaussian_Kernel(day_distance,h_date))
```

```
}

diff_hour_kernel = function(hoi,hours)
{
  hour_difference = as.numeric(difftime(as.POSIXct(strptime(hoi, "%H:%M:%S")),
                                        as.POSIXct(strptime(hours, "%H:%M:%S")),
                                        units = "hour"))
  hour_difference = abs(hour_difference)
  hour_difference[hour_difference>12] = 24-hour_difference[hour_difference>12]
  return(gaussian_Kernel(hour_difference,h_time))
}

kernel_calculation_addition = function(toi)
{
  poi_distance = diff_distance_kernel(poi = latlong,stations = st[,4:5])
  doi_distance = diff_date_kernel(pred_date,st$date)
  toi_distance = diff_hour_kernel(toi,st$time)

  kernel_Sum = poi_distance + doi_distance + toi_distance

  kernel_Sum = (sum(kernel_Sum * st$air_temperature) / sum(kernel_Sum))

  return(kernel_Sum)
}

kernel_calculation_multiplication = function(toi)
{
  poi_distance = diff_distance_kernel(poi = latlong,stations = st[,4:5])
  doi_distance = diff_date_kernel(pred_date,st$date)
  toi_distance = diff_hour_kernel(toi,st$time)

  kernel_Multiplication = poi_distance * doi_distance * toi_distance

  kernel_Multiplication = (sum(kernel_Multiplication * st$air_temperature) /
      sum(kernel_Multiplication))

  return(kernel_Multiplication)
}

temp_1 = rep(0,length(times))
temp_2 = rep(0,length(times))
i = 0
for(i in 1:length(times)){
  temp_1[i] = kernel_calculation_addition(times[i])
  temp_2[i] = kernel_calculation_multiplication(times[i])
}

plot(temp_1, type="o", xaxt="n", xlab="Time", ylab="Temperature",main="Temperature
    measured using Kernel Addition")
axis(1, at=1:length(temp_1), labels=times)

plot(temp_2, type="o", xaxt="n", xlab="Time", ylab="Temperature",main="Kernel
```

```
    Multiplication")
axis(1, at=1:length(temp_1), labels=times)

plot(distHaversine(c(a,b),st[4:5]),gaussian_Kernel(distHaversine(c(a,b),st[4:5]),
h_distance),xlab = "Distance",
     ylab = "Weight",main = "Weights for geographical distance",col="blue")
plot(gaussian_Kernel(matrix(seq(1,183,1)),h_date),xlim=c(0,185),xlab="Days",
     ylab="Weight",main = "Weights for day distance",col="blue")
plot(gaussian_Kernel(matrix(seq(0,24,2)),h_time),main="Weights for time distance",
     xlab = "Time",ylab="Weight",col="blue")
```

Assignment 3

```
options(scipen=999) #To avoid scientific notations
RNGversion('3.5.1')
library(neuralnet)
library(ggplot2)

set.seed(1234567890)
Var <- runif(50, 0, 10)
trva <- data.frame(Var, Sin=sin(Var))
tr <- trva[1:25,] # Training
va <- trva[26:50,] # Validation
ggplot(trva,aes(x=Var,y=Sin))+geom_line()
# Random initialization of the weights in the interval [-1, 1]
winit <- runif(31,-1,1)
#Since we are dealing with regression, best way to choose the model is to use MSE
mse_test = rep(0,10)
mse_train = rep(0,10)

for(i in 1:10)
{
  nn = neuralnet(Sin~Var,data=tr,linear.output = TRUE,threshold = i/1000,hidden =
      10,startweights = winit)
  pred = predict(nn,va)
  mse_test[i] = sum((va$Sin-pred)^2)/nrow(va)
  mse_train[i] = sum((tr$Sin-pred)^2)/nrow(tr)
}

best_Threshold = which(mse_test == min(mse_test))
plot(1:10,mse_test,xlab="Threshold",ylab = "MSE",main="Selecting Threshold")
#1st model is having lowest test error when compared with other models.
nn = neuralnet(Sin~Var,data=tr,linear.output = TRUE,threshold =
     best_Threshold/1000,hidden = 10,startweights = winit)

plot(prediction(nn)$rep1,col="black",xlab = "",ylab = "")
points(tr,col="red")
legend(x="bottomleft",legend = c("NN Predictions","Train Data"),col=c("Black","Red"),pch
     = c(1,1))
```

```
plot(va$Var,predict(nn,va)[,1],col="black",xlab = "",ylab = "",main="Comparison of
    Validation data with predictions")
points(va,col="red")
legend(x="bottomleft",legend = c("NN Predictions","Validation
    Data"),col=c("Black","Red"),pch = c(1,1))

plot(nn,rep="best")
```