

Lab3

Group8-lab3

12/14/2017

LAB 3 BLOCK 1: KERNEL METHODS AND NEURAL NETWORKS

1. KERNEL METHODS

In this assignment forecast consist of temperature from 4:00 to 24:00 in interval of 2 hours. We have implemented the three kernels to calculate

1. station point(lat,lng) from point of interest(lat,lng)
2. date distance from point of interest date
3. hour distance

we have make this three kernels function by setting the smoothing coefficient or width for each kernel which involve most of the point to consider

- Distacne kernel (h_distance = 1000000)
- Date kernel (h_date = 12)
- Time kernel (h_time = 7)

The all these three kernels were built on Gaussian kernel which is expressed as

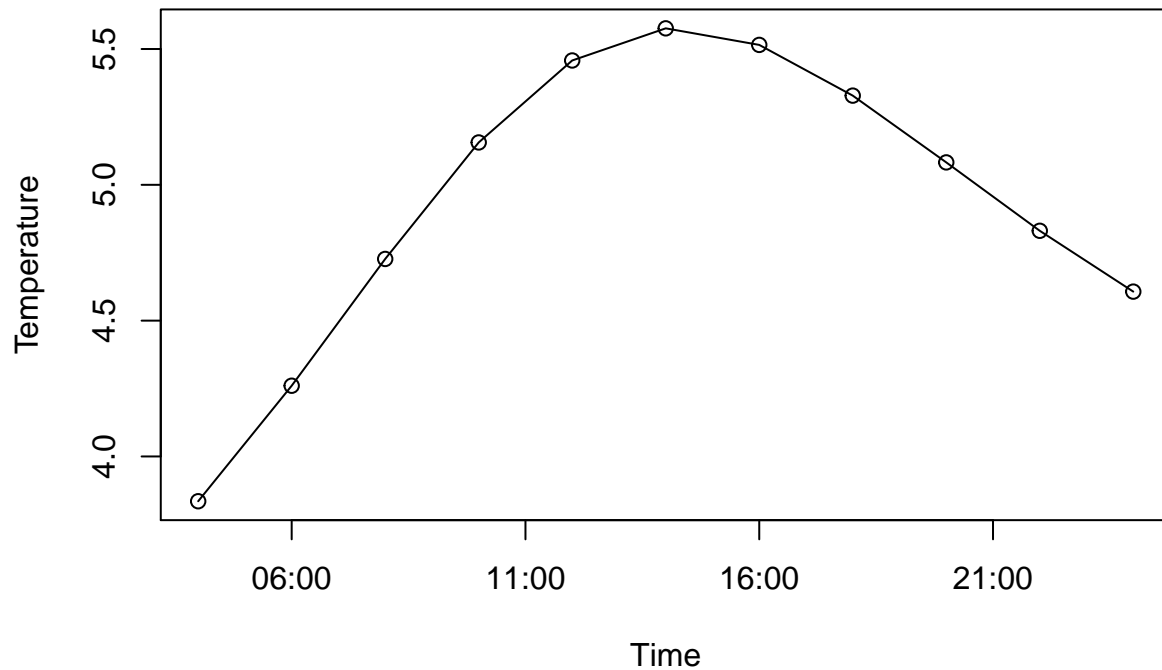
$$kernel = \exp^{-\frac{(x-\bar{x})}{h}}$$

```
#temperature values after added a sum of kernel weights  
temp
```

```
## [1] 3.835112 4.260383 4.727093 5.156020 5.457799 5.576042 5.515154  
## [8] 5.328433 5.082580 4.830791 4.606805
```

```
#plot of additive kernel  
plot(x=times,y=temp, type = "o" ,  
      main = "Temperature using Additive kernels" ,  
      xlab = "Time" ,  
      ylab = "Temperature")
```

Temperature using Additive kernels



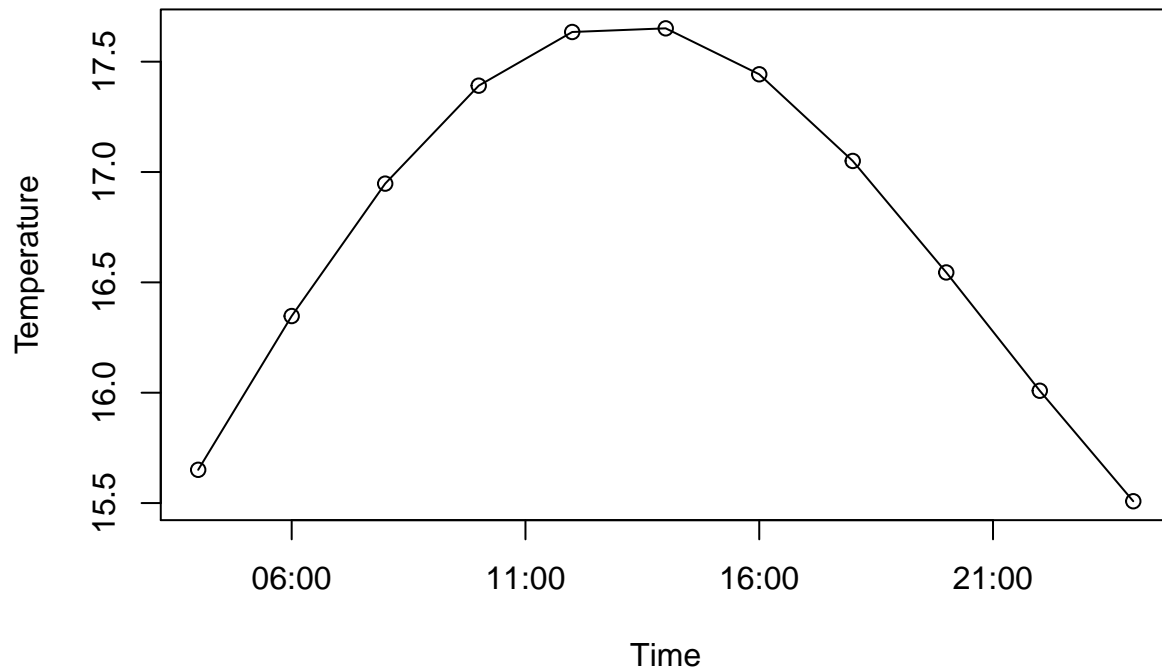
From plot we can see that X-axis has time and Y-axis is the additive temperature values and it can be observed that maximum temperature will be at time 15:00 and temperature is 5.8 degree and minimum temperature is at some what 5:00 having a temperature 3.0 degree

```
#temperature values after added a sum of kernel weights  
temp2
```

```
## [1] 15.65067 16.34742 16.94738 17.39124 17.63451 17.65100 17.44289  
## [8] 17.05014 16.54490 16.00891 15.50823
```

```
# plot of multiplicative kernels  
#par(mar=c(3,3,3,3))  
plot(x=times,y=temp2, type = "o",  
     main = "Temperature using Multiplicative kernels" ,  
     xlab = "Time" ,  
     ylab = "Temperature")
```

Temperature using Multiplicative kernels



From plot we can see the that X-axis has times and Y-axis is the Multiplicative temperature values and it can be observed that maximum temperature will be at time 15:00 and temperature is 17.7 degree and minimum temperature is at some what 5:00 having a temperature 15.53 degree

2. NEURAL NETWORKS

Most Appropriate Threshold

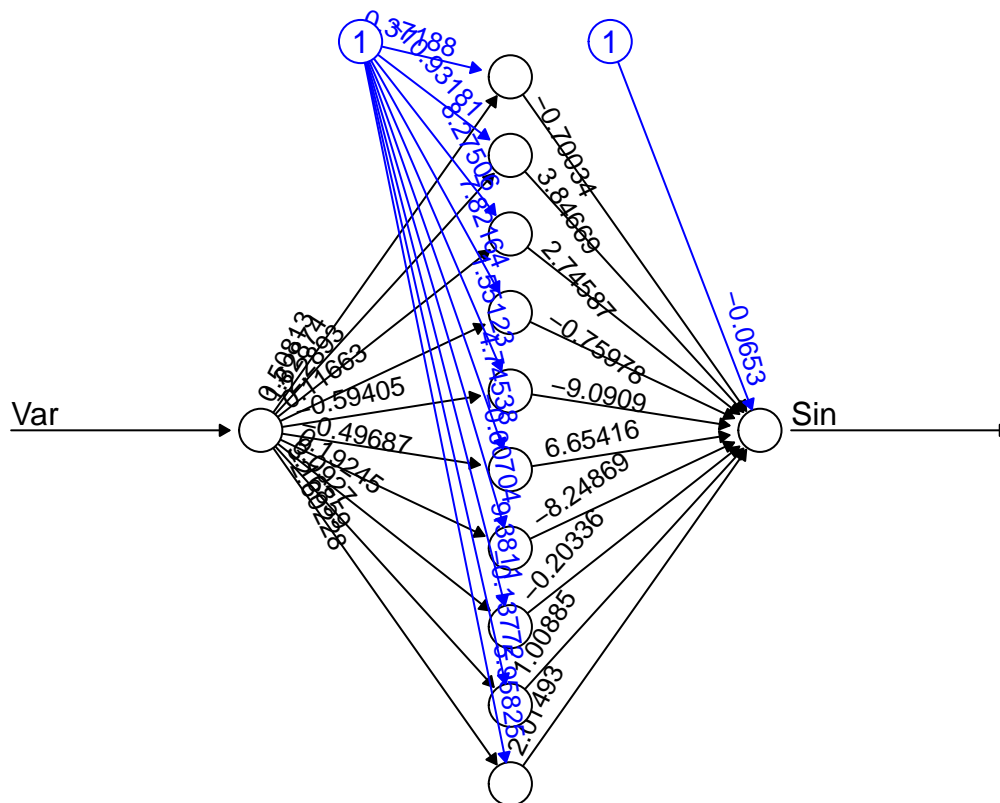
```
#threshold value for best
stopping_thresshold <- (which.min(va_MSE)) / 1000
stopping_thresshold

## [1] 0.004

the most appropriate value for threshold is 0.0004

nn <- neuralnet(formula = Sin~Var ,data = tr,
                 hidden=c(10), threshold = stopping_thresshold,
                 startweights= winit)

#par(mar=c(2,2,2,2))
plot(nn, rep="best")
```



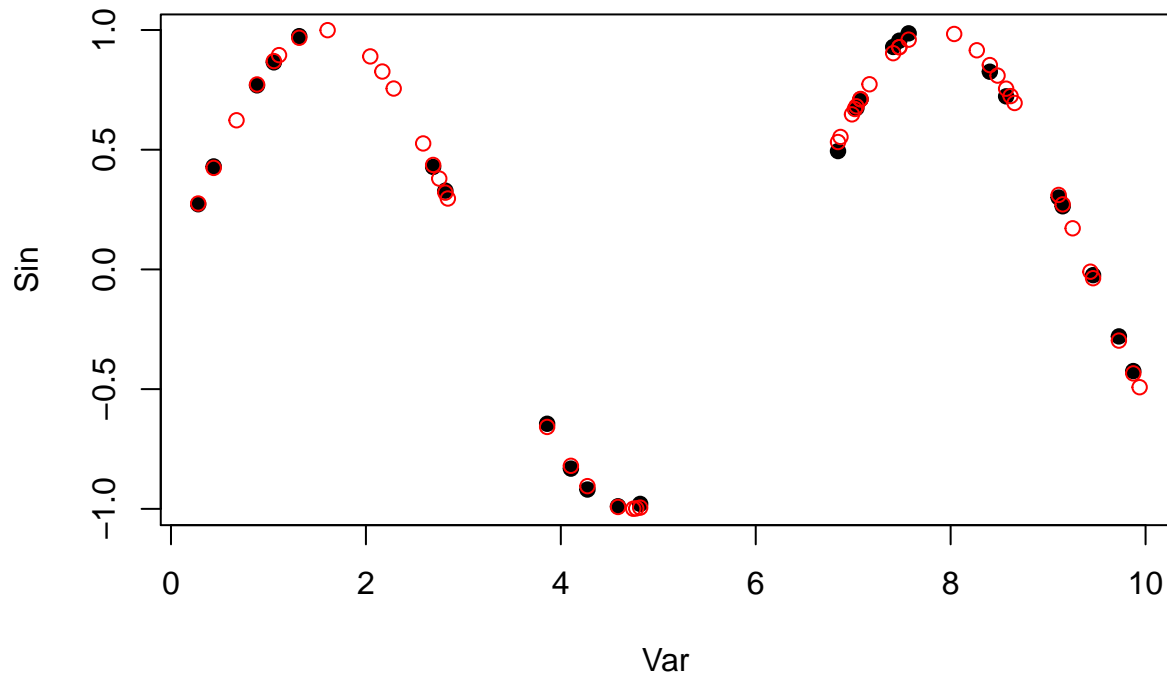
Error: 0.003576 Steps: 23174

The final neural network for trigonometric sine function learned at threshold 4/1000 which is 0.0004. Plot implies that the model fitted well, there is not much deviation.

```
plot(prediction(nn)$rep1, pch=19, cex=1)
```

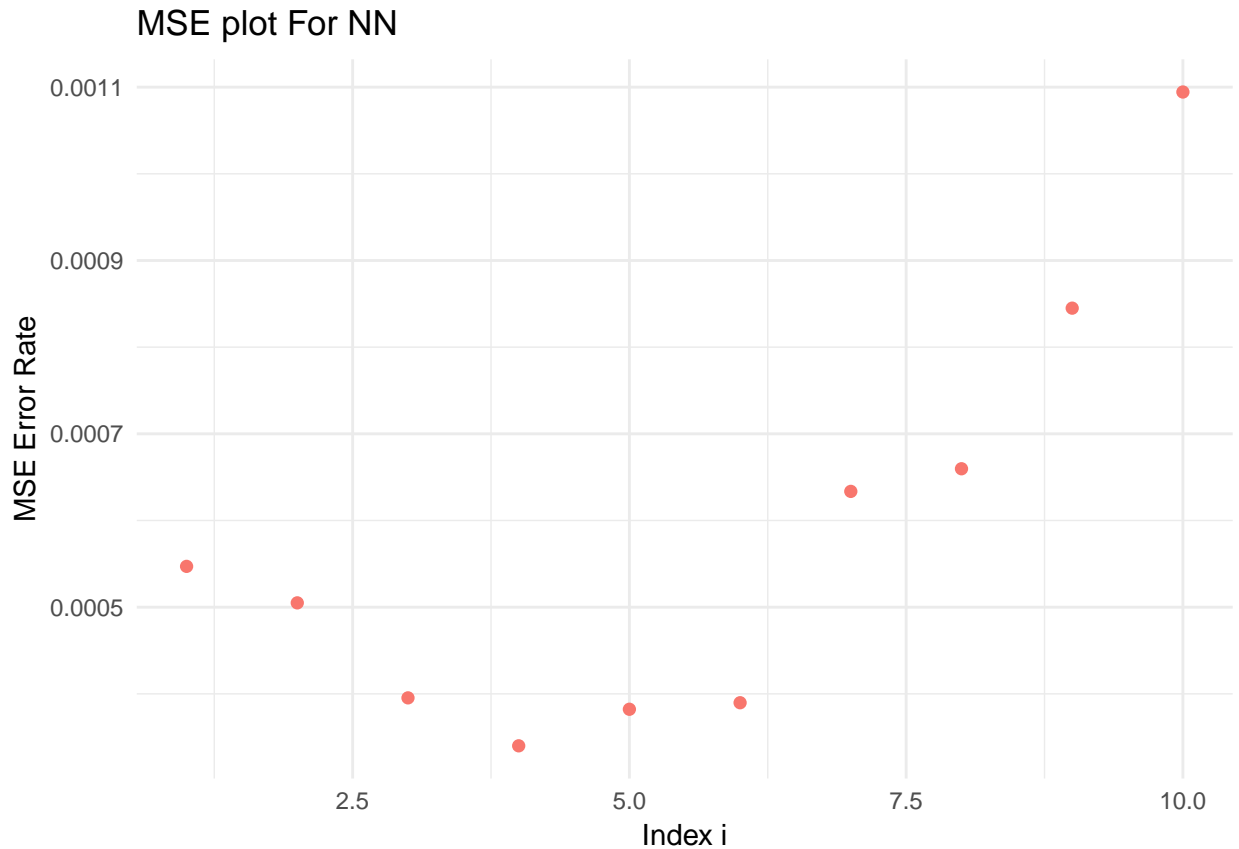
```
## Data Error: 0;
```

```
points(trva, col = "red")
```



This plot show the sinosedial sin waves with Sin function on Y-axis and Var on x-axis and the red dotted points curve show the original sinosedial sin waves and black dotted points curve show the predicted sin wave which is similar to the original one.

```
result <- data.frame(MSE=va_MSE, x=c(1:10))
ggplot(result, aes(x=x, y=MSE, color = "red")) +
  geom_point(shape = 16, size = 2, show.legend = FALSE) +
  theme_minimal() + ggtitle("MSE plot For NN") + xlab("Index i") +
  ylab("MSE Error Rate")
```



MSE plot show's that MSE error rate (Y-axis) on each $threshold = i/1000$ (X-axis) from plot it is clearly see that at index $i = 4$ the error rate is minimum so which give the optimal Neural Network

Appendix

1. KERNEL METHODS

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

stations <- read.csv("stations.csv",fileEncoding = "Latin1")
temps <- read.csv("temps50k.csv",fileEncoding = "Latin1")

st <- merge(stations,temps,by="station_number")
h_distance <- 1000000 # These three values are up to the students
h_date <- 12
h_time <- 7
a <- 59.8586 # The point to predict (up to the students)
b <- 17.6253
date <- "2015-07-12" # 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

#distance kernel
gaussion_distance <- function(db_point, point_intreset)
{
  #distance to the other point
  dist <- distHaversine(db_point, point_intreset)
  return (exp(-(dist / h_distance)^2)) #gaussian kernel
}

#gaussian date kernel
gaussion_date <- function(db_date, point_of_intreset_date)
{
  #date difference to other point
  diff_date <- as.numeric(difftime(point_of_intreset_date,db_date,unit = "days"))
  return (exp(-(diff_date / h_date)^2))
}

#gaussian time kernel
gaussion_hours <- function(db_time, point_of_intreset_date)
{
  #hours difference to other point
  diff_date <- as.numeric(difftime(point_of_intreset_date,db_time,unit = "hours"))
  return (exp(-(diff_date / h_time)^2))
}

point_intreset <- c(a,b) #point fo intreset
data_dist = st[,c("longitude", "latitude")]

#calculate gaussian distance
gaussion_distacne_v<- gaussion_distance(data_dist, point_intreset)

#calculate gaussian date distance
gaussion_date_v <- gaussion_date(st$date,date)

time_conv <- data.frame(time=as.POSIXct(paste(Sys.Date(), st$time),
                                             format="%Y-%m-%d %H:%M:%S"))
times <- strptime( paste( Sys.Date(),times), "%Y-%m-%d %H:%M:%S")

temp2 <- vector(length=length(times))
# temp_type <- vector(length=length(times))
# temp2_type <- vector(length=length(times))

for (i in 1:length(times))
{
  gaussian_hours <- gaussion_hours(time_conv$time, times[i])
  #sum of all kernels
  sum_of_k <- (gaussion_distacne_v + gaussion_date_v + gaussian_hours)
  temp[i] <- sum((st$air_temperature * sum_of_k)) / sum(sum_of_k)
  # temp_type[i] <- "kernel_sum"

  #multiplication of kernels
  multiply_of_k <- (gaussion_distacne_v * gaussion_date_v * gaussian_hours)

```

```

temp2[i] <- sum((st$air_temperature * multiply_of_k)) / sum(multiply_of_k)
# temp2_type[i] <- "kernel_mul"
}

#plot of additive kernels
plot(x=times,y=temp, type = "o" ,
     main = "Temperature using Additive kernels" ,
     xlab = "Time" ,
     ylab = "Temperature")

#plot of multiplicative kernels
plot(x=times,y=temp2, type = "o",
     main = "Temperature using Multiplicative kernels" ,
     xlab = "Time" ,
     ylab = "Temperature")

# result <- data.frame(kernel=c(temp,temp2) , type=c(temp_type,temp2_type), x=times)
#
# library(ggplot2)
# ggplot(data=result, aes(x=x, y=kernel, colour=type)) + geom_line() + geom_point()

```

2. NEURAL NETWORKS

```

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

# Random initialization of the weights in the interval [-1, 1]
va_MSE <- c()
tr_MSE <- c()

winit <- runif(31, -1, 1)
for(i in 1:10) {
  nn <- neuralnet(formula = Sin~Var ,data = tr ,hidden = c(10),
                  threshold = i/1000, startweights= winit)
  va_predict <- compute(nn,va$Var)
  tr_predict <- compute(nn,tr$Var)
  va_MSE[i] <- sum( (va$Sin - va_predict$net.result[,1])^2) / nrow(tr)
  tr_MSE[i] <- sum( (va$Sin - tr_predict$net.result[,1])^2) / nrow(tr)
}

#comment
#by visualizing the graph the thresshold value is 4/1000 which the stoping creteria
#so NN model for such a thresshold is below

#thresshold for stoping NN

stopping_threshold <- which.min(va_MSE)/1000

```



```

nn <- neuralnet(formula = Sin~Var ,data = tr ,hidden = c(10),
                threshold = stoping_thresshold,
                startweights= winit)
plot(nn, rep="best" , main="Neural Network Plot")

#another plot
plot(prediction(nn)$rep1)
points(trva, col = "red")

#MSE plot
result <- data.frame(MSE=va_MSE, x=c(1:10))
ggplot(result, aes(x=x, y=MSE, color = "red")) +
  geom_point(shape = 16, size = 2, show.legend = FALSE) +
  theme_minimal() + ggtitle("MSE plot For NN") + xlab("Index i") +
  ylab("MSE Error Rate")

```