# lab3\_kernel\_2

Zhixuan\_Duan(zhidu838) and zahra jalilpour(zahja096)

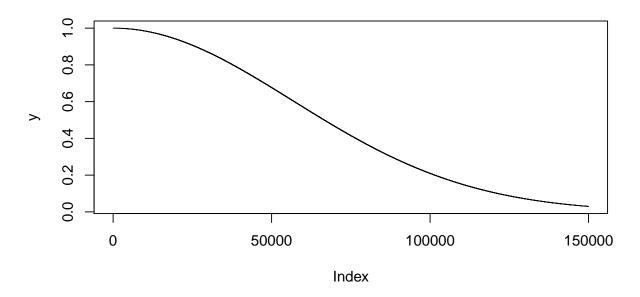
```
# load package
library(ggplot2)
```

Test h\_distance, h\_date and h\_time.

```
h_distance <- 80000
h_date <- 10
h_time <- 6

dist = seq(0,150000, 1)
y = exp(-(dist/h_distance)^2)
plot(y, type="l", main = "Distance kernel")</pre>
```

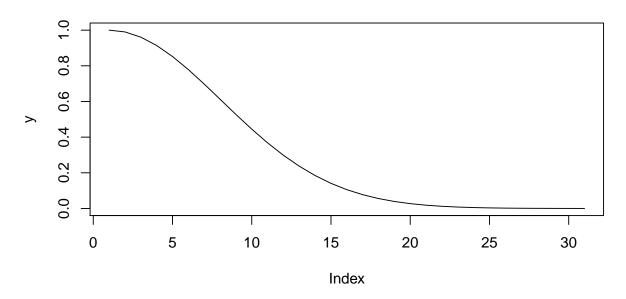
## **Distance kernel**



```
# the haversine function outputs kms, so we define h_{distance} = 80
dat = seq(0,30, 1)
```

```
y = exp(-(dat/h_date)^2)
plot(y, type="l", main = "Date kernel")
```

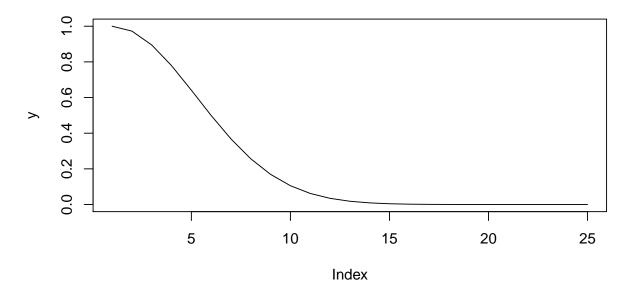
# **Date kernel**



```
# h_date = 10

tim = seq(0, 24, 1)
y = exp(-(tim/h_time)^2)
plot(y, type="l", main = "Time kernel")
```

## Time kernel



```
# h_time = 6
```

## pyspark code

```
from __future__ import division
from math import radians, cos, sin, asin, sqrt, exp
from datetime import datetime
from pyspark import SparkContext
sc = SparkContext(appName="lab_kernel_2")
def haversine(lon1, lat1, lon2, lat2):
    Calculate the great circle distance between two points
    on the earth (specified in decimal degrees)
    # convert decimal degrees to radians
    lon1, lat1, lon2, lat2 = map(radians, [lon1, lat1, lon2, lat2])
    # haversine formula
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = \sin(dlat/2)**2 + \cos(lat1) * \cos(lat2) * \sin(dlon/2)**2
    c = 2 * asin(sqrt(a))
    km = 6367 * c
    return km
h_distance = 80
h_{date} = 10
```

```
h_{time} = 6
a = 58.40 \# latitude
b = 15.62 \# longitude
date = "2013-11-04"
## date
def d_date(date1, date2):
    date1 = datetime.strptime(date1, "%Y-%m-%d")
    date2 = datetime.strptime(date2, "%Y-%m-%d")
    output = abs((date2 - date1).days)
    return output
## time
def d_time(time1,time2):
    time1 = datetime.strptime(time1, '%H:%M:%S')
    time2 = datetime.strptime(time2, '%H:%M:%S')
    output = abs((time1-time2))
    return output
def add kernels(d1, d2, d3):
    k1 = \exp(-d1**2 / (2*(h_distance**2)))
    k2 = \exp(-d2**2 / (2*(h_date**2)))
    k3 = exp(-d3**2 / (2*(h_time**2)))
    output = k1 + k2 + k3
    return output
def mul_kernels(d1, d2, d3):
    k1 = \exp(-d1**2 / (2*(h_distance**2)))
    k2 = \exp(-d2**2 / (2*(h_date**2)))
    k3 = exp(-d3**2 / (2*(h_time**2)))
    output = k1 * k2 * k3
    return output
stations = sc.textFile("/Users/darin/Desktop/stations.csv")
temp = sc.textFile("/Users/darin/Desktop/temperature-readings-small.csv")
##########
stations = stations.map(lambda x: x.split(";"))
stations = stations.map(lambda x: (x[0],haversine(b,a,float(x[4]),float(x[3]))))
m=sc.parallelize(stations.collect()).collectAsMap()
stations=sc.broadcast(m)
##########
temp = temp.map(lambda x: x.split(";"))
temp = temp.map(lambda x: (stations.value[str(x[0])],x[1],x[2],float(x[3])))
filter_temp = temp.filter(lambda x: x[1] <= date)</pre>
filter_temp = filter_temp.map(lambda x: (x[0], d_date(date,x[1]), d_time(time,x[2]), x[3]))
```

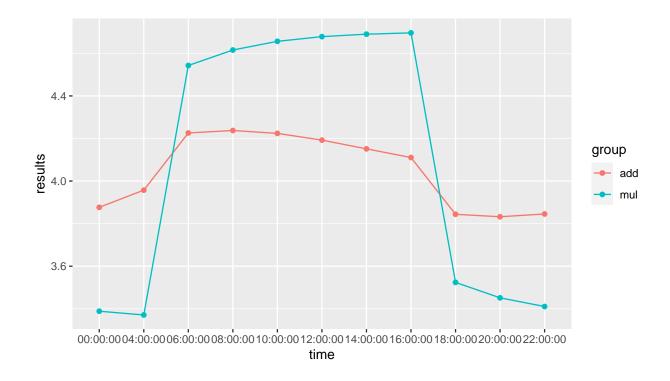
```
#########
predicted_add=[]
predicted_mul=[]

for time in ["00:00:00", "22:00:00", "20:00:00", "18:00:00", "16:00:00", "14:00:00",
"12:00:00", "10:00:00", "08:00:00", "06:00:00", "04:00:00"]:
    add_allkernels = filter_temp.map(lambda x:(add_kernels(x[0],x[1],x[2]),x[3])).map(lambda x:(x[0],x[
    predicted_add.append(add_allkernels[1] / add_allkernels[0])

    mul_allkernels = filter_temp.map(lambda x:(mul_kernels(x[0],x[1],x[2]),x[3])).map(lambda x:(x[0],x[
    predicted_mul.append(mul_allkernels[1] / mul_allkernels[0])

print(predicted_add)
print('\n')
print(predicted_mul)
sc.parallelize(predicted_add).saveAsTextFile("add_kernel_predictions")
sc.parallelize(predicted_mul).saveAsTextFile("mul_kernel_predictions")
sc.stop()
```

#### Prediction



# Analysis

The predicted temperature is not much different in the additive model, but the multiplicative model shows a clear upward and downward trend.

We think this is because when the three kernels are all very small and close to 0, the multiplication model will be smaller(approaching 0), and the addition model will be relatively large. And when the three kernels are large, the multiplication model will have a greater impact on the predicted value compared to additive model.