

Problem Set 3

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```
library(dplyr)
```

```
##  
## Attaching package: 'dplyr'
```

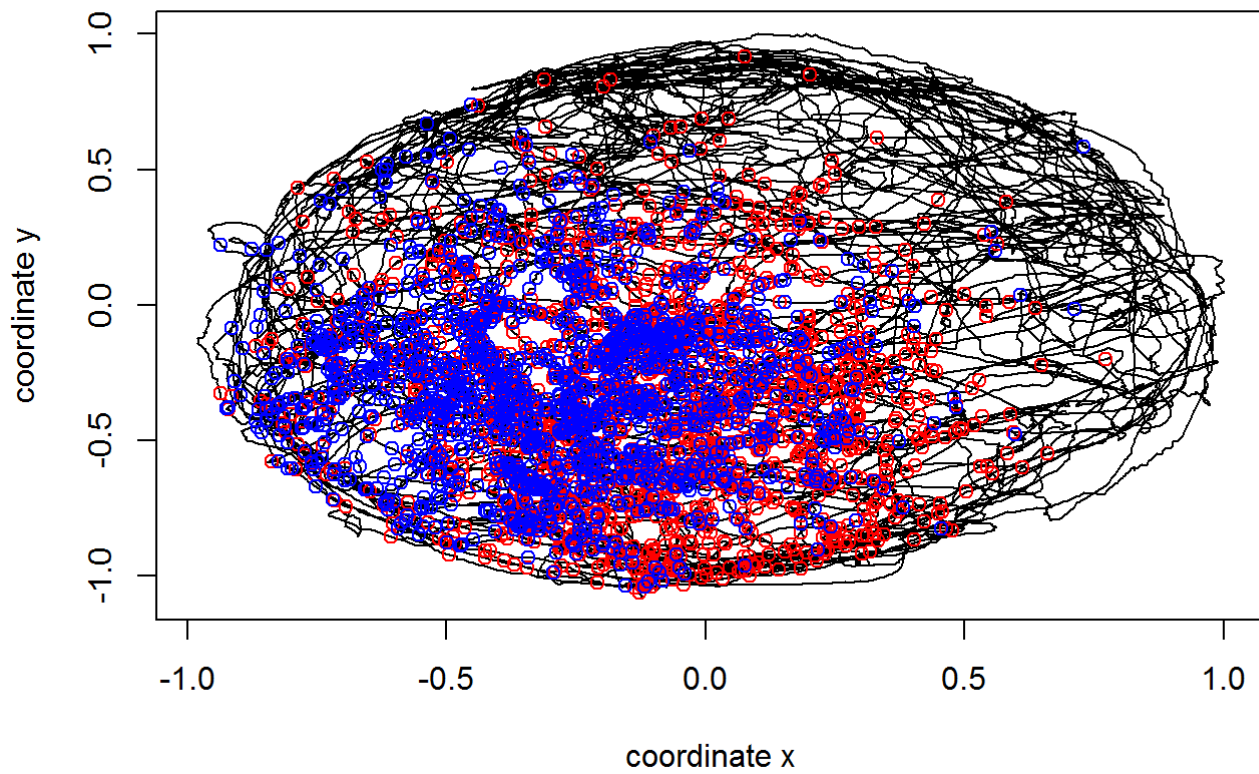
```
## The following objects are masked from 'package:stats':  
##  
##   filter, lag
```

```
## The following objects are masked from 'package:base':  
##  
##   intersect, setdiff, setequal, union
```

```
hipp_data <- read.csv("C:/YUKIHO/BU/MA 615/Classes/9.12.2016/class 9.12.2016/ma_568/Homework 3/hipp_data.csv")
```

Problem 1

```
plot(hipp_data$xN, hipp_data$yN, type='l', xlab="coordinate x", ylab="coordinate y")  
  
hipp1_data <- subset(hipp_data, spikes==1)  
points(hipp1_data$xN, hipp1_data$yN, col='red')  
  
hipp2_data <- subset(hipp_data, spikes2==1)  
points(hipp2_data$xN, hipp2_data$yN, col='blue')
```



The plot shows that, both neuron's spikes are gathered in the left-bottom of the graph; thus we could say they are probably correlated.

Problem 2

```
m1 <- glm(spikes ~ xN + yN, poisson, hipp_data)
summary(m1)
```

```
##
## Call:
## glm(formula = spikes ~ xN + yN, family = poisson, data = hipp_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -0.5501  -0.3718  -0.2621  -0.1928   2.6004
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.24918    0.02760 -117.74  <2e-16 ***
## xN          -0.50623    0.04724  -10.72  <2e-16 ***
## yN          -1.18010    0.04477  -26.36  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 12311  on 41327  degrees of freedom
## Residual deviance: 11388  on 41325  degrees of freedom
## AIC: 15492
##
## Number of Fisher Scoring iterations: 6
```

All parameters are significant.

```
lambda <- function(x, y) {
  exp(m1$coefficients[1] + m1$coefficients[2] * x + m1$coefficients[3] * y)
}

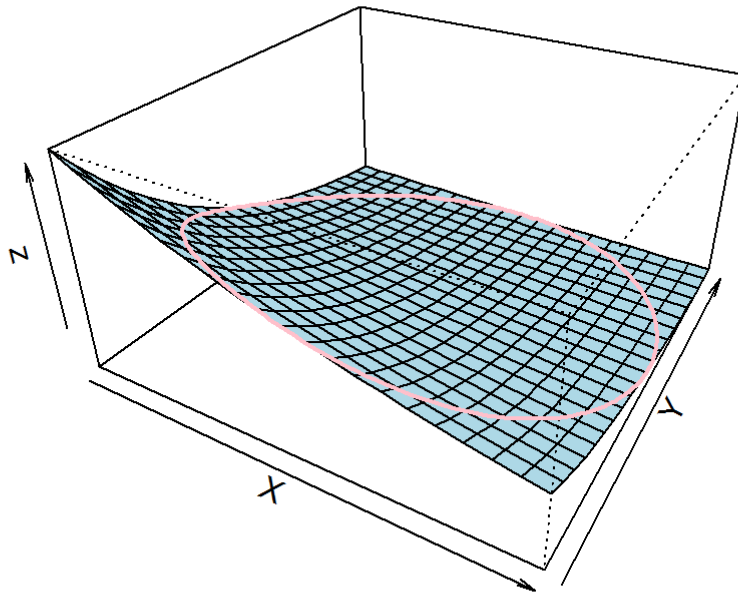
x2 <- y2 <- seq(-1, 1, .1)
?outer
```

```
## starting httpd help server ...
```

```
## done
```

```
z<- outer(x2, y2, lambda)
persp(x2, y2, z, theta = 30, phi = 30, expand = 0.5, col = "lightblue", xlab="X", ylab = "Y", mai
n="Maximum Likelihood Model Indensity") -> res
phi <- seq(0, 2 * pi, len = 201)
xr <- cos(phi)
yr <- sin(phi)
lines(trans3d(xr, yr, lambda(xr, yr), res), col = "pink", lwd = 2)
```

Maximum Likelihood Model Indensity



Due to the graph shows, the spatial firing properties are well captured.

Problem 3

```
hipp_data$xN2 <- (hipp_data$xN)^2  
hipp_data$yN2 <- (hipp_data$yN)^2  
m2 <- glm(spikes ~ xN2 + yN2 + xN + yN, poisson, hipp_data)  
summary(m2)
```

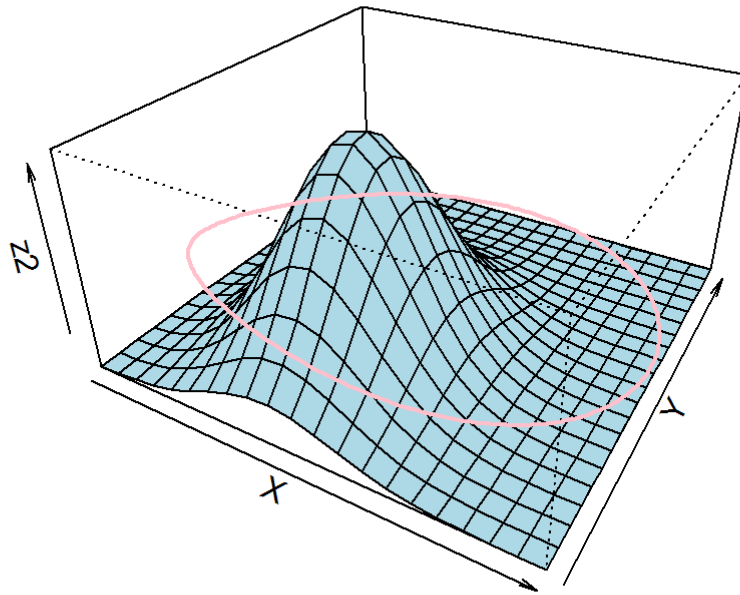
```
##
## Call:
## glm(formula = spikes ~ xN2 + yN2 + xN + yN, family = poisson,
##      data = hipp_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7260  -0.3359  -0.1564  -0.0580   3.5332
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.82026    0.03723  -48.89  <2e-16 ***
## xN2          -5.81075    0.19772  -29.39  <2e-16 ***
## yN2          -3.66241    0.13449  -27.23  <2e-16 ***
## xN           -1.45219    0.09165  -15.85  <2e-16 ***
## yN           -2.40928    0.09536  -25.27  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 12311.2  on 41327  degrees of freedom
## Residual deviance:  9141.5  on 41323  degrees of freedom
## AIC: 13249
##
## Number of Fisher Scoring iterations: 7
```

All significant.

```
lambda2 <- function(x, y) {
  exp(m2$coefficients[1] + m2$coefficients[2] * (x^2) + m2$coefficients[3] * (y^2) + m2$coefficients[4]
* x + m2$coefficients[5] * y)
}

x2 <- y2 <- seq(-1, 1, .1)
z2<- outer(x2, y2, lambda2)
persp(x2, y2, z2, theta = 30, phi = 30, expand = 0.5, col = "lightblue", xlab="X", ylab = "Y", ma
in="Maximum Likelihood Model Indensity") -> res
phi <- seq(0, 2 * pi, len = 201)
xr <- cos(phi)
yr <- sin(phi)
lines(trans3d(xr, yr, lambda(xr, yr), res), col = "pink", lwd = 2)
```

Maximum Likelihood Model Indensity



```
m1$aic
```

```
## [1] 15492.16
```

```
m2$aic
```

```
## [1] 13249.46
```

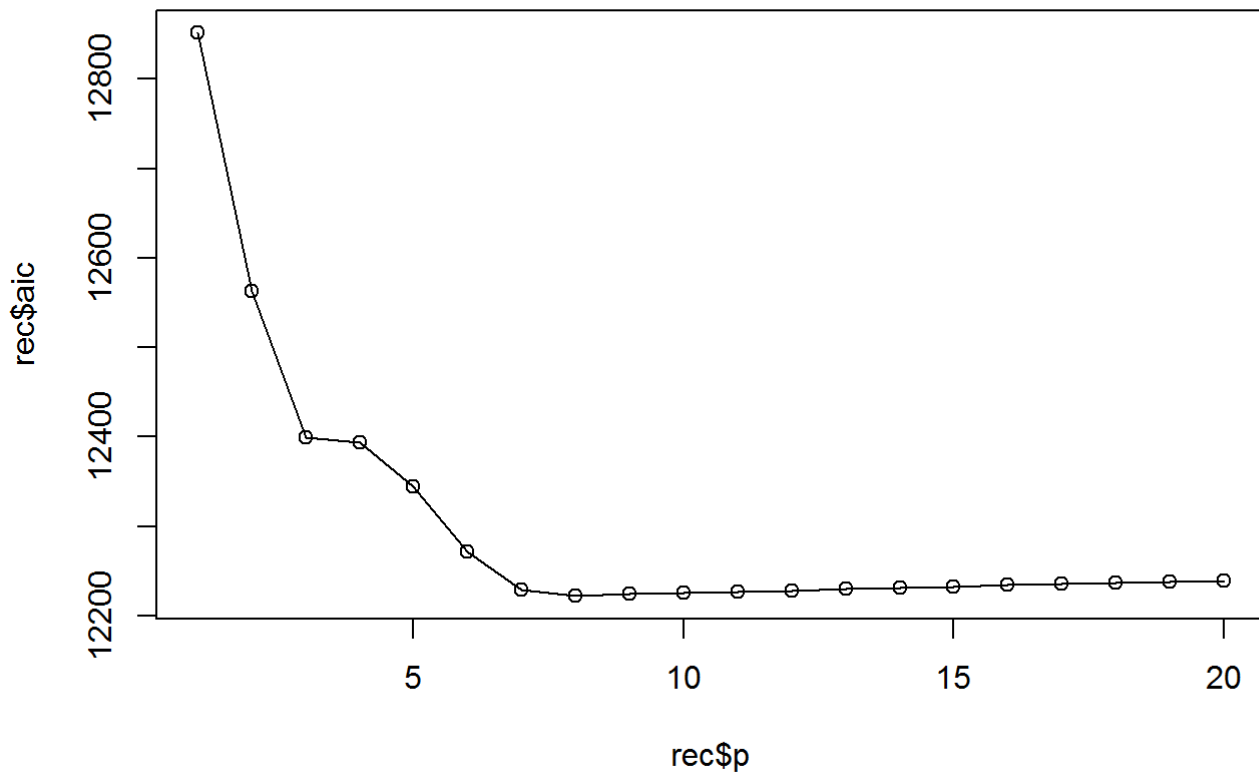
Problem 4

```

hipp_data_n <- hipp_data[, c("spikes", "xN", "yN", "xN2", "yN2", "spikes_hist1", "spikes_hist2", "spikes_hist3", "spikes_hist4", "spikes_hist5", "spikes_hist6", "spikes_hist7", "spikes_hist8", "spikes_hist9", "spikes_hist10", "spikes_hist11", "spikes_hist12", "spikes_hist13", "spikes_hist14", "spikes_hist15", "spikes_hist16", "spikes_hist17", "spikes_hist18", "spikes_hist19", "spikes_hist20")]
p <- aic <- c()
for (i in 6:25) {
  hipp_data_a <- hipp_data_n[, 1:i]
  m3 <- glm(spikes ~ ., poisson, hipp_data_a)
  aic <- c(aic, m3$aic)
  p <- c(p, i-5)
}

rec <- data.frame("p"=p, "aic"=aic)
plot(rec$p, rec$aic, type="l")
points(rec$p, rec$aic)

```



```
subset(rec, aic==min(aic))
```

```
## p aic
## 8 8 12222.27
```

Problem 5

```

hipp_data_n2 <- hipp_data[, c("spikes", "xN", "yN", "xN2", "yN2", "spikes_hist1", "spikes_hist2", "spikes_hist3", "spikes_hist4", "spikes_hist5", "spikes_hist6", "spikes_hist7", "spikes_hist8", "spikes2_hist1", "spikes2_hist2", "spikes2_hist3", "spikes2_hist4", "spikes2_hist5", "spikes2_hist6", "spikes2_hist7", "spikes2_hist8", "spikes2_hist9", "spikes2_hist10", "spikes2_hist11", "spikes2_hist12", "spikes2_hist13", "spikes2_hist14", "spikes2_hist15", "spikes2_hist16", "spikes2_hist17", "spikes2_hist18", "spikes2_hist19", "spikes2_hist20")]

p2 <- aic2 <- c()

for (i in 14:33) {
  hipp_data_a <- hipp_data_n2[, 1:i]
  m3 <- glm(spikes ~ ., poisson, hipp_data_a)
  aic2 <- c(aic2, m3$aic)
  p2 <- c(p2, i-13)
}

rec2 <- data.frame("p1"=8, "p2"=p2, "aic2"=aic2)

subset(rec2, aic2==min(aic2))

```

```

##    p1 p2    aic2
## 1  8  1 12224.16

```

Problem 6

```

hipp_data_n3 <- select(hipp_data, spikes, xN, yN, xN2, yN2, spikes_hist1:spikes_hist20, spikes2_hist1:spikes2_hist20)
p41 <- p42 <- aic4 <- c()

for (k in 6:25){
  hipp_data_a <- hipp_data_n3[, 1:k] %>% select(-xN, -yN, -xN2, -yN2)
  m3 <- glm(spikes ~ ., poisson, hipp_data_a)
  aic4 <- c(aic4, m3$aic)
  p41 <- c(p41, k-5)
  p42 <- c(p42, 0)
  for (i in 26:45){
    hipp_data_a <- hipp_data_n3[, c(1:k, 26:i)] %>% select(-xN, -yN, -xN2, -yN2)
    m3 <- glm(spikes ~ ., poisson, hipp_data_a)
    aic4 <- c(aic4, m3$aic)
    p41 <- c(p41, k-5)
    p42 <- c(p42, i-25)
  }
}

rec4 <- data.frame("p1"=p41, "p2"=p42, "aic"=aic4)
subset(rec4, aic==min(aic))

```

```

##    p1 p2    aic
## 420 20 20 13534.88

```


This does have a minimum aic. Almost every parameters are significant. The reason for why only when we fail to model the spatial component of the firing activiety is that, in spatial component, the correlation between history and network interaction is more significant.

Problem 7

```
m0 <- glm(spikes ~ xN2 + yN2 + xN + yN + spikes_hist1 + spikes_hist2 + spikes_hist3 + spikes_hist4 + spikes_hist5 + spikes_hist6 + spikes_hist7 + spikes_hist8, poisson, hipp_data)
hipp_data[, "num"] <- 1:nrow(hipp_data)
hipp_data_zz <- subset(hipp_data, spikes==1)
Xi <- hipp_data_zz[, "num"]
```