BIOS 7720: Applied Functional Data Analysis

Lecture 9: Function on Scalar Regression

Andrew Leroux

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- Thus far we've discussed regression models where you have a function as a predictor
- Now we'll discuss what changes when you have a function as your outcome

Consider our physical activity data

$$\mathsf{LAC}_i(t) = f_0(t) + f_1(t) \mathsf{Age}_i + \epsilon_i(t)$$

 $\epsilon_i(t) \stackrel{\mathsf{iid}}{\sim} \mathsf{N}(0, \sigma_\epsilon^2)$

- Recall from the lecture 4 in-class exercise that the assumptions of this model were violated (correlation within individuals)
- How to account for this correlation?

Consider our model

$$\begin{aligned} \mathsf{LAC}_i(s) &= f_0(s) + f_1(s) \mathsf{Age}_i + b_i(t) + \epsilon_i(s) \\ b_i(s) &\sim \mathsf{GP}(0, \Sigma_b) \\ \epsilon_i(s) &\stackrel{\mathsf{iid}}{\sim} \mathcal{N}(0, \sigma_\epsilon^2) \end{aligned}$$

ullet The assumption on b_i is the same as we used in fPCA

$$egin{aligned} \mathsf{LAC}_i(s) &= f_0(s) + f_1(s) \mathsf{Age}_i + \sum_{k=1}^K \xi_{ik} \phi_k(s) \xi_{ik} + \epsilon_i(s) \ b_i(t) &\sim \mathsf{GP}(0, \Sigma_b) \ \epsilon_i(s) \stackrel{\mathsf{iid}}{\sim} \mathcal{N}(0, \sigma_\epsilon^2) \end{aligned}$$

- How to estimate ϕ ?
- Iterative procedure

FoSR: Simulating Data

```
set.seed(19840)
# simulation settings
N <- 200 # number of functions to simulate
ns <- 100 # number of observations per function
sind <- seq(0,1,len=ns) # functional domain of observed functions
K <- 4 # number of true eigenfunctions
lambda <- 0.5<sup>(0:(K-1))</sup> # true egenfunctions
sig2 <- 2 # error variance
# set up true eigenfunctions
Phi <- sqrt(2)*cbind(sin(2*pi*sind), cos(2*pi*sind),
                     sin(4*pi*sind), cos(4*pi*sind))
# simulate coefficients
# first, simulate standard normals, then multiply by the
# standard deviation to get correct variance
xi_raw <- matrix(rnorm(N*K), N, K)
xi <- xi_raw %*% diag(sqrt(lambda))
# simulate b_i(s) as sum_k xi_ik phi_k(t)
bi <- xi %*% t(Phi)
```

FoSR: Simulating Data

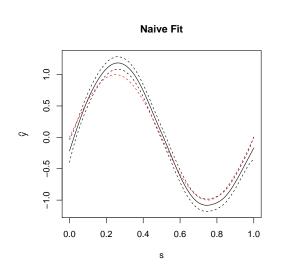
```
## define f(s)
f <- function(s) sin(2*pi*s)
## get f(s) for all i, s
## fS is an N x ns matrix with rows repeated
fS <- kronecker(matrix(f(sind), 1, ns), matrix(1, N, 1))
x <- rnorm(N)
## get f(s) *x for each individual
fX <- fS * kronecker(matrix(x, N, 1), matrix(1, 1, ns))
## simulate the outcome
y <- bi + fX + matrix(rnorm(N*ns, sd=2), N, ns)</pre>
```

FoSR: Ignore correlation

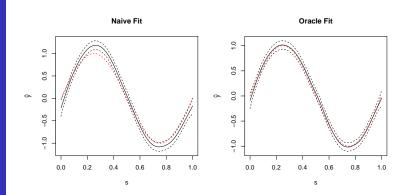
4 0.26764168 0.26764168

```
df fit <-
 data.frame(
   id = factor(rep(1:N,each=ns)),
   y = as.vector(t(y)),
   bi = as.vector(t(bi)),
   x = rep(x, each=ns),
   id = rep(1:N, each=ns),
   sind = rep(sind, N),
   phi1 = rep(Phi[.1], N).
   phi2 = rep(Phi[,1], N),
   phi3 = rep(Phi[,1], N),
   phi4 = rep(Phi[,1], N)
head(df fit)
    id
                         bi x id.1
                                                sind
                                                          phi1
                                                                     phi2
## 1 1 -0.4223359 0.8028229 -2.192767 1 0.00000000 0.00000000 0.00000000
## 2 1 -2.3254423 1.0359615 -2.192767 1 0.01010101 0.08969497 0.08969497
## 3 1 2.9544945 1.2651368 -2.192767
                                       1 0.02020202 0.17902876 0.17902876
## 4 1 3.2506201 1.4872519 -2.192767
                                        1 0.03030303 0.26764168 0.26764168
## 5 1 3.4911148 1.6992696 -2.192767
                                       1 0.04040404 0.35517689 0.35517689
## 6 1 3.1149040 1.8982600 -2.192767
                                        1 0.05050505 0.44128193 0.44128193
##
          phi3
                     phi4
## 1 0.00000000 0.00000000
## 2 0.08969497 0.08969497
## 3 0.17902876 0.17902876
```

FoSR: Ignore Correlation



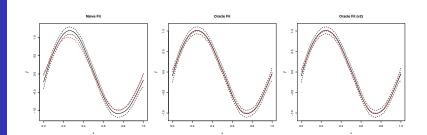
- What if we "knew" $b_i(s)$ for each person?
- We could treat this as an offset and consider it "fixed"



• In practice this is the same as defining

$$y_i^* = y_i - b_i(s)$$

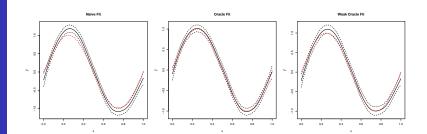
• And regressing y_i^* on x assuming iid normal errors



- In practice we never observe $b_i(s)$
- What if instead we knew ϕ_k ?
- Recall that under the fPCA framework ϕ_k are orthogonal
- And ξ_{ik} are independent

FoSR: "Weak" Oracle

FoSR: "Weak" Oracle



- In practice we also never observe $\phi_k(s)$
- How could we estimate them from the data?
- Iterative procedure:
 - Estimate the working model under independence
 - Fit fpca to the residuals
 - Extract the eigenfunctions
 - Fit the "weak" oracle model
 - Repeat 1-4 as necessary