

## Supporting Information for “Bayesian Functional Covariance Regression”

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## 1. Web Appendix A: Markov-chain monte carlo sampling algorithm

In this section we give a detailed Markov-Chain Monte Carlo (MCMC) algorithm to sample from the posterior. Let  $N$  be the number of independent functional responses and assume all response functions are observed on a common grid  $T = \{t_1, \dots, t_n\}$ . Let  $B$  be an  $n \times p$  matrix with  $B_{ij} = b_j(t_i)$ . Let  $X$  be an  $N \times r(d_1)$  matrix with row  $i$  equal to  $\mathbf{b}^x(\mathbf{x}_i)$ . Let  $Y$  be an  $N \times n$  matrix with  $Y_{ij} = y_i(t_j)$ , so that each row represents one discretized functional response. Let  $\Gamma_j$  be an  $N \times N$  diagonal matrix with  $r$ th diagonal element equal to  $\eta_{rj}$  for  $j = 1, \dots, k$ .

(1) Update  $\beta$ :

Let  $\Omega_r = \tau_{1xr}\tilde{K}_r + \tau_{1tr}\tilde{K}$  if  $p_r > 1$ . Otherwise set  $\Omega_r = \tau_{1tr}K$ . Construct

$$\Omega = \text{blkdiag}(\Omega_1, \dots, \Omega_R).$$

$$\text{Let } C = \sigma^{-2}X^\top X \otimes B^\top B + \Omega$$

$$\text{Let } A = \sigma^{-2}\text{vec}[\{B^\top Y^\top - B^\top B(\sum_{j=1}^k \Lambda_j X^\top \Gamma_j)\}X]$$

$$\text{Sample } \text{vec}(\beta) \sim N(C^{-1}A, C^{-1})$$

(2) Update  $\Lambda_j$ :

Let  $\Omega_r = \tau_{2xr}\tilde{K}_r + \tau_{2tr}\tilde{K} + \tau_{rj}^*\phi_{rj}$  if  $p_r > 1$ . Otherwise set  $\Omega_r = \tau_{2tr}K + \tau_{rj}^*\phi_{rj}$ .

$$\text{Construct } \Omega = \text{blkdiag}(\Omega_1, \dots, \Omega_R)$$

$$\text{Let } C = \sigma^{-2}X^\top \Gamma_j^2 X \otimes B^\top B + \Omega$$

$$\text{Let } A = \sigma^{-2}\text{vec}[\{B^\top Y^\top - B^\top B(\beta + \sum_{j' \neq j} \Lambda_{j'} X^\top \Gamma_{j'})\}\Gamma_j X]$$

$$\text{Sample } \Lambda_j \sim N(C^{-1}A, C^{-1})$$

(3) Update  $\eta_{ij}$ :

$$\text{Let } \boldsymbol{\eta}_i = (\eta_{i1}, \dots, \eta_{ik}).$$

$$\text{Let } \ddot{X}_i \text{ be a } p \times k \text{ matrix with column } j \text{ equal to } \Lambda_j \mathbf{b}^x(\mathbf{x}_i).$$

$$\text{Let } C = \sigma^{-2}\ddot{X}_i^\top B^\top B \ddot{X}_i + I_k, \text{ where } I_k \text{ is the } k \times k \text{ identity matrix.}$$

Let  $A = \sigma^{-2} \ddot{X}_i^\top \{B^\top Y_i - B^\top B \beta \mathbf{b}^x(\mathbf{x}_i)\}$

Sample  $\boldsymbol{\eta}_i \sim N(C^{-1}A, C^{-1})$

(4) Update  $\sigma^2$ :

Let  $A = Y^\top - B\beta X^\top + \sum_{j=1}^k B\Lambda_j X^\top \Gamma_j$

Sample  $\sigma^{-2} \sim \text{Gamma}(Nn/2 + a_\epsilon, A \odot A/2 + b_\epsilon)$ , where  $\odot$  denotes element-wise multiplication.

(5) Update  $\tau_{1tr}, \tau_{1xr}, \tau_{2tr}, \tau_{2xr}$ :

Sample  $\tau_{1tr} \sim \text{Gamma}\{\text{rank}(\tilde{K})/2 - 0.5, \text{vec}(\beta_r)^\top \tilde{K} \text{vec}(\beta_r)/2\}$

Sample  $\tau_{1xr} \sim \text{Gamma}\{\text{rank}(\tilde{K}_r)/2 - 0.5, \text{vec}(\beta_r^\top) \tilde{K}_r \text{vec}(\beta_r)/2\}$  (if  $p_r > 1$ )

Sample  $\tau_{2trj} \sim \text{Gamma}\{\text{rank}(\tilde{K})/2 - 0.5, \text{vec}(\Lambda_{rj})^\top \tilde{K} \text{vec}(\Lambda_{rj})/2\}$

Sample  $\tau_{2xrij} \sim \text{Gamma}\{\text{rank}(\tilde{K}_r)/2 - 0.5, \text{vec}(\Lambda_{rj}^\top) \tilde{K}_r \text{vec}(\Lambda_{rj})/2\}$  (if  $p_r > 1$ )

(6) Update  $\phi_{rj}$ :

Let  $\phi_{irj}$  denote the  $i$ th diagonal element of  $\phi_{rj}$ .

Let  $\lambda_{irj}$  be the  $i$ th element of  $\text{vec}(\Lambda_{rj})$ .

Sample  $\phi_{irj} \sim \text{Gamma}(a_\phi + 0.5, \tau_{rj}^* \lambda_{irj}^2/2 + b_\phi)$

(7) Update  $\delta_{r1}$ :

Let  $A = \text{vec}(\Lambda_{r1}^\top) \phi_{r1} \text{vec}(\Lambda_{r1})$

Let  $B = \sum_{j=2}^k \tau_{rj}^* \text{vec}(\Lambda_{rj})^\top \phi_{rj} \text{vec}(\Lambda_{rj})$

Sample  $\delta_{r1} \sim \text{Gamma}\{kp_r p/2 + a_{r0}, (A + B)/2 + 1\}$

(8) Update  $\delta_{rj}$ :

Let  $A = \sum_{j'=1}^k \tau_{rj'}^{*(j)} \text{vec}(\Lambda_{rj'})^\top \phi_{rj'} \text{vec}(\Lambda_{rj})$ , where  $\tau_{rj'}^{*(j)} = \tau_{rj'}$  if  $j \neq j'$  and 1 otherwise.

Sample  $\delta_{rj'} \sim \text{Gamma}\{p_r p(k - j' + 1)/2 + a_{r1}, A/2 + 1\}$

(9) Update  $a_{r0}$ :

Let  $\text{Gamma}^*(x, a, b)$  denote the Gamma density evaluated at  $x$  with shape  $a$  and rate  $b$ .

Let  $\phi(x)$  denote the standard normal cumulative distribution function evaluated at  $x$ .

Sample candidate  $a_{r0}^* \sim N(a_{r0}, 1)$  until  $a_{r0}^* > 0$ .

Compute  $A = \frac{\text{Gamma}^*(\delta_{r1}, a_{r0}^*, 1) \cdot \text{Gamma}^*(a_{r0}^*, 2, 1) \cdot \phi(a_{r0})}{\text{Gamma}^*(\delta_{r1}, a_{r0}, 1) \cdot \text{Gamma}^*(a_{r0}, 2, 1) \cdot \phi(a_{r0}^*)}$

Sample  $U \sim \text{Unif}(0, 1)$

If  $U \leq A$ , accept candidate  $a_{r0}^*$ .

(10) Update  $a_{r1}$ :

Let  $\delta_{r2}^* = \prod_{j=2}^k \delta_{rj}$

Let  $\text{Gamma}^*(x, a, b)$  denote the Gamma density evaluated at  $x$  with shape  $a$  and rate  $b$ .

Let  $\phi(x)$  denote the standard normal cumulative distribution function evaluated at  $x$ .

Sample candidate  $a_{r1}^* \sim N(a_{r1}, 1)$  until  $a_{r1}^* > 0$ .

Compute  $A = \frac{\text{Gamma}^*(\delta_{r2}^*, a_{r1}^*, 1) \cdot \text{Gamma}^*(a_{r1}^*, 2, 1) \cdot \phi(a_{r1})}{\text{Gamma}^*(\delta_{r2}^*, a_{r1}, 1) \cdot \text{Gamma}^*(a_{r1}, 2, 1) \cdot \phi(a_{r1}^*)}$

Sample  $U \sim \text{Unif}(0, 1)$

If  $U \leq A$ , accept candidate  $a_{r1}^*$ .

(11) Update missing values of  $Y$ :

Suppose  $y_i(t_j)$  is missing.

Let  $\mu = \mathbf{b}(t_j)\beta\mathbf{b}^x(\mathbf{x}_i) + \sum_{j=1}^k \mathbf{b}(t_j)\Lambda_j\mathbf{b}^x(\mathbf{x}_i)\eta_{ij}$

Sample  $y_i(t_j) \sim N(\mu, \sigma^2)$

For convenience, Table contains notation used in the main article and this document of supporting information.

[Table 1 about here.]

## 2. Web Appendix B: Additional details on posterior inference

## 3. Web Appendix C: Setting hyperparameters

## 4. Web Appendix D: Extended simulation results

## 5. Web Appendix E: Additional details on case studies

**Table 1***Notation used in the main article and document of supporting information.*

| Name                            | Description   | Dimension         |
|---------------------------------|---|-------------------|
| $\mathbf{x}_i$                  | Covariate vector for the $i$ th functional response   | $d_1 \times 1$    |
| $\mathbf{x}_{ir}$               | $r$ th group of covariates associated with the $i$ th functional response                         |                   |
| $\mathbf{b}^r(\mathbf{x}_{ir})$ | $r$ th group of covariates expanded into basis functions evaluated at $\mathbf{x}_{ir}$           | $p_r \times 1$    |
| $\mathbf{b}^x(\mathbf{x}_i)$    | Concatenated $\mathbf{b}^r(\mathbf{x}_{ir})$ , $r = 1, \dots, R$                                  | $r(d_1) \times 1$ |
| $p_r$                           | # of basis functions for $r$ th covariate group expansion   |                   |
| $r(d_1)$                        | Total number of covariate basis functions used equal to $\sum_{r=1}^R p_r$                        |                   |
| $\mathbf{b}(t)$                 | Basis functions for functional dimension evaluated at $t$   | $p \times 1$      |
| $\mu(t, \mathbf{x}_i)$          | Covariate-adjusted functional mean equal to $\mathbf{b}(t)^\top \beta \mathbf{b}^x(\mathbf{x}_i)$ |                   |
| $\beta$                         | Fixed effect parameter matrix equal to  |                   |