

Penalized functional principal component analysis

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Summary. We propose an iterative estimation procedure for performing functional principal component analysis. The procedure aims at functional or longitudinal data where the repeated measurements from the same subject are correlated. An increasingly popular smoothing approach, penalized spline regression, is used to represent the mean function. This allows straightforward incorporation of covariates and simple implementation of approximate inference procedures for coefficients. For the handling of the within-subject correlation, we develop an iterative procedure which reduces the dependence between the repeated measurements that are made for the same subject. The resulting data after iteration are theoretically shown to be asymptotically equivalent (in probability) to a set of independent data. This suggests that the general theory of penalized spline regression that has been developed for independent data can also be applied to functional data. The effectiveness of the proposed procedure is demonstrated via a simulation study and an application to yeast cell cycle gene expression data.

Keywords: Asymptotics; Functional data; Penalized spline regression; Principal components; Smoothing; Within-subject correlation

1. Introduction

Functional data analysis (FDA) has become an important area of research in recent years. The data are functions of a continuous variable, and the observations are curves or surfaces. The functional data are often correlated, and the correlation structure is often complex. In this paper, we propose a new method for analyzing functional data. The method is based on penalized spline regression and principal component analysis. The method is iterative, and it reduces the dependence between the repeated measurements that are made for the same subject. The resulting data after iteration are theoretically shown to be asymptotically equivalent (in probability) to a set of independent data. This suggests that the general theory of penalized spline regression that has been developed for independent data can also be applied to functional data. The effectiveness of the proposed procedure is demonstrated via a simulation study and an application to yeast cell cycle gene expression data.

A

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$$G(s, t) = \sum_{k=1}^{\infty} \lambda_k \phi_k(s) \phi_k(t) \quad t, s \in \mathcal{T}.$$

$$X_i(t) = \mu(t) + \sum_{k=1}^{\infty} \xi_{ik} \phi_k(t) \quad t \in \mathcal{T}$$

$$\xi_{ik} = \int_{\mathcal{T}} \{X_i(t) - \mu(t)\} \phi_k(t) dt$$

$$E(\xi_{ik}) = \lambda_k \quad \sum_k \lambda_k < \infty$$

$$\lambda_1 \geq \lambda_2 \geq \dots$$

$$Y_{ij} = X_i(t_{ij}) + \varepsilon_{ij} \quad t_{ij} \in \mathcal{T}$$

$$E(\varepsilon_{ij}) = 0 \quad E(\varepsilon_{ij}) = \sigma(t_{ij})$$

$$Y_{ij} = X_i(t_{ij}) + \varepsilon_{ij}$$

$$= \mu(t_{ij}) + \sum_{k=1}^{\infty} \xi_{ik} \phi_k(t_{ij}) + \varepsilon_{ij} \quad t_{ij} \in \mathcal{T} \quad (1)$$

$$E(\varepsilon_{ij}) = 0 \quad E(\varepsilon_{ij}) = \sigma(t_{ij})$$

2.2. Estimation of mean function using penalized spline regression

$$\mathbf{Y}_i = (Y_i(t_1), \dots, Y_i(t_{n_i})) \quad \mathbf{T}_i = (t_i, \dots, t_{i n_i}) \quad \mathbf{B}_q(t) = (B_q(t), \dots, B_{qk}(t))$$

$$\mathbf{B}_{qi} = (B_q(t_i), \dots, B_q(t_{i n_i})) \quad \mathbf{D} = \text{diag}(\lambda^*, \dots, \lambda^*)$$

$$\mathbf{Y}_i = \mathbf{B}_{qi} \boldsymbol{\beta} + \boldsymbol{\varepsilon}_i \quad \boldsymbol{\beta} = (\beta_1, \dots, \beta_k)$$

$$\sum_{i=1}^n \|\mathbf{Y}_i - \mathbf{B}_{qi} \boldsymbol{\beta}\|^2 + \lambda^* \boldsymbol{\beta}^T \mathbf{D} \boldsymbol{\beta} \quad (2)$$

$$\lambda^* \boldsymbol{\beta}^T \mathbf{D} \boldsymbol{\beta}$$

$$B_q(t) = \sum_{k=0}^p \binom{p}{k} (t - \kappa_k)_+^k \quad \kappa_0 = \dots = \kappa_k$$

$$\begin{array}{c}
 (x)_+ = \begin{pmatrix} x \\ 0 \end{pmatrix} \\
 \mathbf{I}_{k \times k} \quad \mathbf{0}_{p \times p} \quad \mathbf{I}_{p \times p} \\
 \mathbf{B}
 \end{array}
 \begin{array}{c}
 \mathbf{D} \\
 \mathbf{0}_{(p+) \times (p+)} \\
 \mathbf{I}_{p \times p} \\
 \mathbf{K}_j \\
 \mathbf{B} \\
 \mathbf{f}
 \end{array}$$

$$(x)_+ = \int_T G(s, t) \phi_k(s) ds = \lambda_k \phi_k(t) \quad (1)$$

$$\{\phi_k\}_{k \geq 1}$$

$$\xi_{ik} = \int \{X_i(t) - \mu_{g(i)}(t)\} \phi_k(t) dt$$

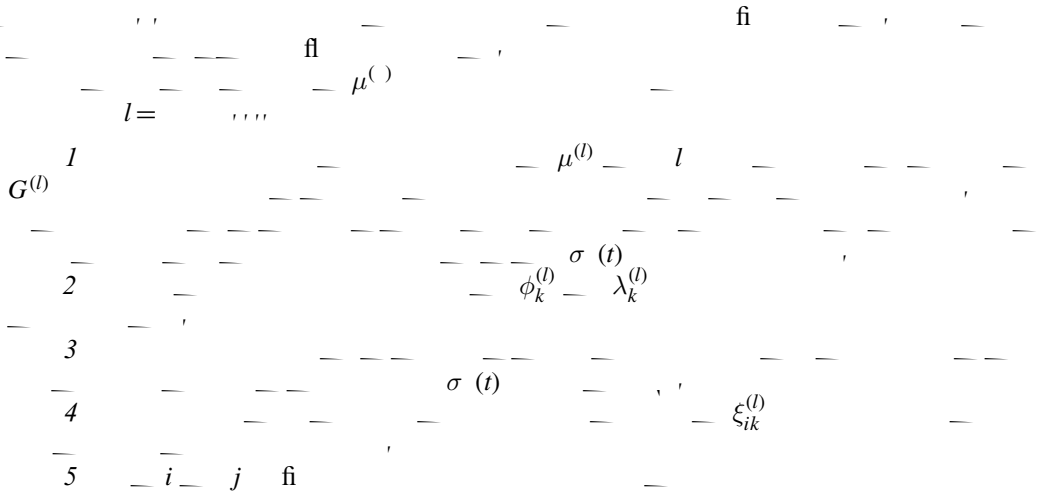
$$\xi_{ik} = \sum_{j=1}^{n_i} \{Y_{ij} - \mu(t_{ij})\} \phi_k(t_{ij}) (t_{ij} - t_{i, j-1}). \quad (2)$$

$$\mu_i = (\mu(t_{i1}), \dots, \mu(t_{in_i})) \quad \phi_{ik} = (\phi_k(t_{i1}), \dots, \phi_k(t_{in_i})) \quad \Sigma_i = \frac{1}{K} \{\sigma^2(t_{i1}), \dots, \sigma^2(t_{in_i})\}$$

$$(K) \propto \sum_{i=1}^n \left\{ - \left(\mathbf{Y}_i - \boldsymbol{\mu}_i - \sum_{k=1}^K \xi_{ik} \phi_{ik} \right) \Sigma_i^{-1} \left(\mathbf{Y}_i - \boldsymbol{\mu}_i - \sum_{k=1}^K \xi_{ik} \phi_{ik} \right) \right\} + K \quad (3)$$

3. Least squares estimation of the regression function

$$\mu_g(t)$$

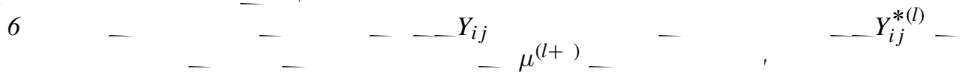


$$Y_{ij}^* = Y_{ij} - \sum_{i=1}^{\infty} \xi_{ik} \phi_k(t_{ij}).$$

Y_{ij}^*

$$Y_{ij}^{*(l)} = Y_{ij} - \sum_{k=1}^{K^{(l)}} \xi_{ik}^{(l)} \phi_k^{(l)}(t_{ij}) \quad ()$$

$K^{(l)}$



$$l = \int_T \{ \mu^{(l+)}(t) - \mu^{(l)}(t) \} t / \int_T \mu^{(l)}(t) t. \quad ()$$

$\mu^{(l)}$

1.

$$Y_i = \xi_{ik}^P \quad \xi_{ik}$$

2.

$$\mathbf{Y}_i = \mathbf{Y}_i^* = (Y_{i1}^*, \dots, Y_{in_i}^*) \quad \mathbf{a} \in \mathbb{R}^q$$

$$\boldsymbol{\beta} = \left(\sum_{i=1}^n \mathbf{B}_{qi} \mathbf{B}_{qi} + \lambda^* \mathbf{D} \right)^{-1} \sum_{i=1}^n \mathbf{B}_{qi} \mathbf{Y}_i^*$$

$$\delta_{kl} = \begin{matrix} (Y_{ij}^* Y_{il}^*) = \delta_{jl} \sigma(t_{ij}) \\ k=l \\ \delta_{kl} = \end{matrix} \quad \sigma(\cdot) \quad \mathbf{R}_i = \{ \sigma(t_i), \dots, \sigma(t_{in_i}) \}$$

$$\Sigma_{\boldsymbol{\beta}} = (\boldsymbol{\beta} \boldsymbol{\beta})$$

$$= \left(\sum_{i=1}^n \mathbf{B}_{qi} \mathbf{B}_{qi} + \lambda^* \mathbf{D} \right)^{-1} \left(\sum_{i=1}^n \mathbf{B}_{qi} \mathbf{R}_i \mathbf{B}_{qi} \right) \left(\sum_{i=1}^n \mathbf{B}_{qi} \mathbf{B}_{qi} + \lambda^* \mathbf{D} \right)^{-1}$$

$$\mathbf{a} \boldsymbol{\beta} \pm \Phi(-\alpha / \sqrt{\mathbf{a} \Sigma_{\boldsymbol{\beta}} \mathbf{a}})$$

$$\Sigma_{\boldsymbol{\beta}} \quad \Phi(\cdot) \quad \mathbf{B}_{qi}$$

3.2. Theoretical properties of iterative penalized splines

$$Y(t) = g(y, y, t, t) \quad g(x, t) \quad (Y(t), Y(t))$$

$$\mu^{(\cdot)}$$

$$\mu^{(\cdot)}$$

$$\mathbf{f}_i$$

$$X(t)$$

$$\xi_{ik}^{(\cdot)}$$

$$Y_{ij}^* \quad j$$

$$\{Y_{ij}^{*(\cdot)}\}$$

$$1. \quad g(x, t) - g(x, x, t, t)$$

$$\leq_{k \leq K} |\xi_{ik}^{(\cdot)} - \xi_{ik}| \rightarrow \quad ()$$

$$\leq_{j \leq n_i} |Y_{ij}^{*(\cdot)} - Y_{ij}^*| \rightarrow \quad ()$$

$$\theta_{in} \quad \text{fi} \quad \{Y_{ij}^*\} \quad \{Y_{ij}^{*(\cdot)}\} \quad |Y_{ij}^{*(\cdot)} - Y_{ij}^*| = O_p(\theta_{in})$$

$$i, \quad O_p(\cdot)$$

$$\{Y_{ij}^*\} \quad Y_{ij}^{*(\cdot)}$$

G

$$2. \quad g(x, t) - g(x, x, t, t)$$

$$t \in \mathcal{T} \quad |\mu(t) - \mu(t)| \rightarrow \quad ()$$

$$s, t \in \mathcal{T} \quad |G(s, t) - G(s, t)| \rightarrow \quad .$$

$$\mu \quad O_p(\cdot)$$

$$\begin{aligned}
 & \mathcal{N}(\lambda_k) \quad \xi_{ik} \\
 & \mathcal{N}\{-(\lambda_k/)\} / \lambda_k/ \} \\
 & \{c_1, \dots, c_p\} \\
 & c_i = s_i = s_i < e_i = s_i > \\
 & \{s_1, \dots, s_p\} \\
 & \{ \dots \}
 \end{aligned}$$

$$\begin{aligned}
 & \mu(t) \\
 & \mu(t) \\
 & \mu^{(1)} \\
 & \mu^{(2)}
 \end{aligned}$$

$$K(x) = -(-x) \mathbf{1}_{-}(x)$$

$$K(x, y) = -(-x)(-y) \mathbf{1}_{-}(x) \mathbf{1}_{-}(y)$$

$$\mathbf{1}_A(x) = \begin{cases} 1 & x \in A \\ 0 & \text{otherwise} \end{cases} \quad \mathbf{1}_A(x) = \dots, p = \dots, A$$

$$\begin{aligned}
 & \mu(t) \\
 & \int E\{\mu(t) - \mu(t)\} \cdot t = \int \mu(t) - E\{\mu(t)\} \cdot t + \int E\{\mu(t)\} - \mu(t) \cdot t
 \end{aligned}$$

$$\mu(t) + \sum_{k=1}^K \xi_{ik} \phi_k(t) \quad \xi_{ik} \quad K \quad X_i^K(t) =$$

X_i

$$= \sum_{i=1}^n \int \{X_i(t) - X_i^K(t)\}^2 dt/n$$

$$X_i^K(t) = \mu(t) + \sum_{k=1}^K \xi_{ik} \phi_k(t)$$

5. Application of the cell cycle gene expression data

α

β

β

β

β

$$\mu(t) \approx B_q(t)\beta$$

β

h_μ

λ^*

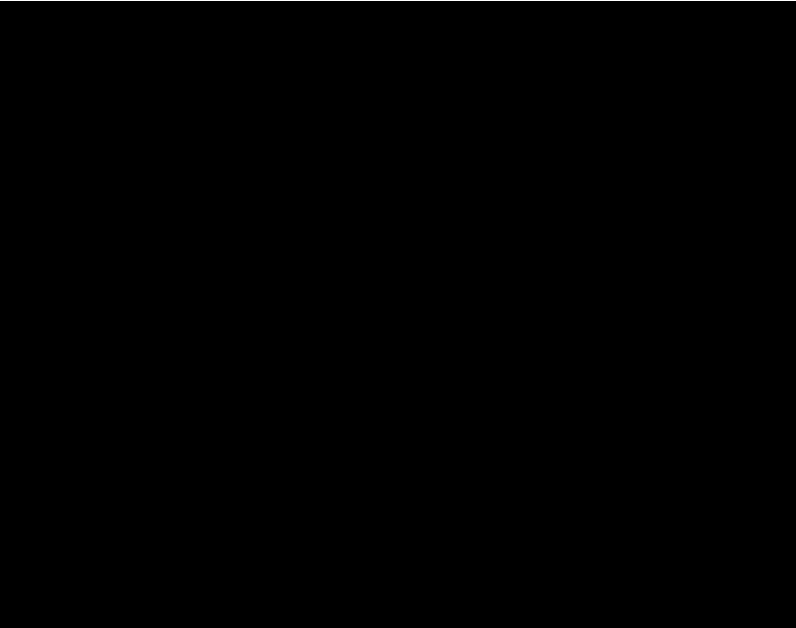
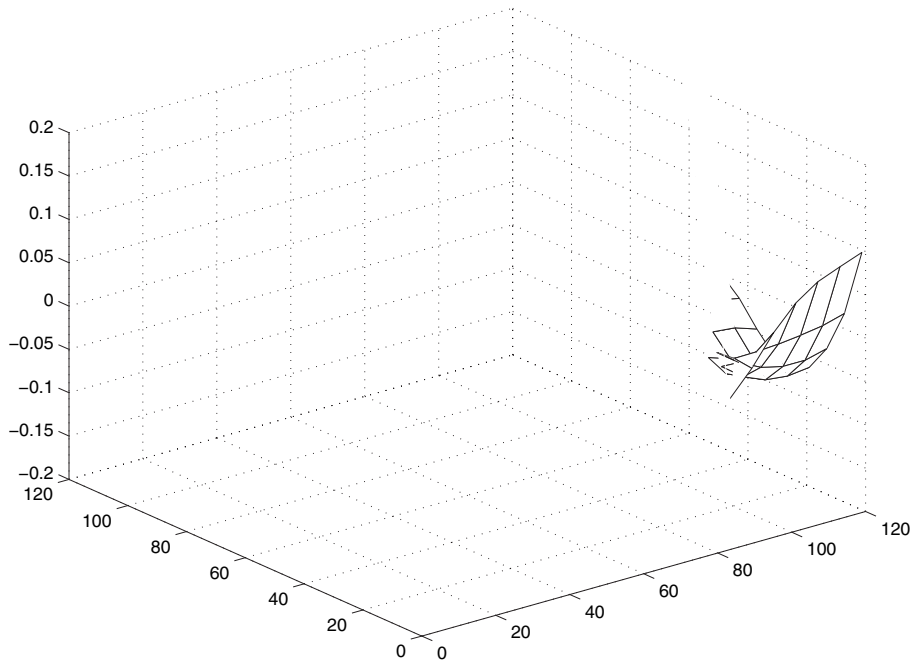


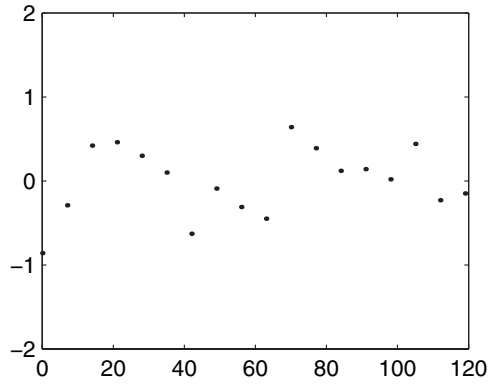
2
1.5
0.5
-1.5
-2
-2.5
0

20

0

120





$$X_i(t) = \mu(t) + \sum_{k=1}^K \xi_{ik} \phi_k(t)$$

ξ_{ik}

$$= \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^{n_i} \frac{\{Y_{ij} - Y_i(t_{ij})\}}{n_i}$$

6. Concluding remarks

Acknowledgements

Appendix A

A.1. Assumptions and notation

$$\sum_{i=1}^n \sum_{l=1}^{n_i} K \left(\frac{t_{ij} - t}{h_\mu} \right) \{Y_{ij} - \beta - \beta(t - t_{ij})\} \quad (A.1)$$

$$\beta^{(l)}(t) = \beta(t)$$

$$h_\mu = h_\mu(n) \quad h_G = h_G(n) \quad h_V = h_V(n) \quad \mu^{(l)} \quad G^{(l)} \quad g = \dots$$

$$V^{(\cdot)} \quad n \rightarrow \infty$$

$$\begin{aligned} h_\mu &\rightarrow h_V \rightarrow nh_\mu \rightarrow \infty \quad nh_V \rightarrow \infty \quad nh_\mu < \infty \quad nh_V < \infty \\ h_G &\rightarrow nh_G \rightarrow \infty \quad nh_G < \infty \end{aligned}$$

$$\begin{aligned} \mathcal{T} &= a_X b_X \quad t_{(\cdot)} = a_X \quad t_{(N+)} = b_X \quad \Delta_n = \{t_{(k)} - t_{(k-)} \mid k = \dots, N+ \} \quad N_n = \sum_{i=1}^n n_i \\ \Delta_{in} &= \{t_{ij} - t_{ij-} \mid j = \dots, n_i+ \} \quad \Delta_n^* = \{\Delta_{in} \mid i = \dots, n\} \\ t_i &= a_X \quad t_{i n_i+} = b_X \quad \bar{n} = n \quad \Sigma_{i=1}^n n_i \end{aligned}$$

$$\Delta_n = O\left(\frac{n^- / h_\mu^- \quad n^- / h_V^- \quad n^- / h_G^-}{\{n_i \mid i = \dots, n\} \leq C\bar{n}}\right) \quad C > \quad \Delta_n^* = O(1/\bar{n}) \quad n \rightarrow \infty$$

$$\int \{-(ut+vs)\} K(uv) u v \quad \kappa(t) = \int (-ut) K(u) u \quad \kappa(ts) =$$

$$\begin{aligned} \kappa(t) &= \int |\kappa(t)| \quad t < \infty \\ \kappa(ts) &= \int \int |\kappa(ts)| \quad t s < \infty \end{aligned}$$

$$Y(t) \quad t \in \mathcal{T} \dots$$

$$E\{Y(t)\} < \infty$$

$$\begin{aligned} \text{fi} \quad f \otimes g &= \langle f h \rangle y \quad f h \in H \\ H \quad F &\equiv \sigma(H) \quad \langle T T \rangle_F = \langle T T^* \rangle = \sum_j \langle T u_j T u_j \rangle_H \\ \|T\|_F &= \langle T T \rangle_F \quad T T \in F \quad \{u_j \mid j \geq 1\} \quad G = \int_{\mathcal{T}} G(s t) f(s) s \end{aligned}$$

$$\begin{aligned} \mathbf{G}(f) &= \int_{\mathcal{T}} G(s t) f(s) s \\ \mathcal{I}_i &= \{j \mid \lambda_j = \lambda_i\} \quad \mathcal{I}' = \{i \mid |\mathcal{I}_i| = 1\} \quad \mathcal{I}_i \quad \mathbf{P}_j = \\ \Sigma_{k \in \mathcal{I}_j} \phi_k \otimes \phi_k & \quad \mathbf{P}_j = \Sigma_{k \in \mathcal{I}_j} \phi_k \otimes \phi_k \quad \{\phi_k \mid k \in \mathcal{I}_j\} \quad \text{fi} \quad j \\ \delta_j &= \{|\lambda_l - \lambda_j| \mid l \notin \mathcal{I}_j\} \end{aligned}$$

$$\mathbf{G} \quad \mathbf{A}_{\delta_j} = \{z \in \mathcal{C} \mid |z - \lambda_j| = \delta_j\} \quad \mathcal{C} \quad \mathbf{R} \quad \mathbf{R}(z) = (\mathbf{G} - zI)^- \quad \mathbf{R}(z) = (\mathbf{G} - zI)^- \quad \mathbf{G}$$

$$A_{\delta_j} = \{\|\mathbf{R}(z)\|_F \mid z \in \mathbf{A}_{\delta_j}\} \quad (\quad)$$

$$K = K(n) \quad X(t)$$

$$X_i(t) = \mu^{(\cdot)}(t) + \sum_{k=1}^K \xi_{ik}^{(\cdot)} \phi_k^{(\cdot)}(t)$$

$$\begin{aligned} \text{fi} \quad \pi(\cdot) &= \frac{K}{n} \quad K = K^{(\cdot)} \quad \|\pi\|_\infty = \max_{t \in \mathcal{T}} \{|\pi(t)|\} \\ n &\rightarrow \infty \end{aligned}$$

$$\begin{aligned} K \rightarrow \infty \quad v_n &= \sum_{k=1}^K \delta_k A_{\delta_k} \|\phi_k\|_\infty / (n / h_G - A_{\delta_k}) \rightarrow \\ \Sigma_{k=1}^K \|\phi_k\|_\infty &= o\left(\frac{n / h_\mu}{\{n / h_\mu \bar{n}\}}\right) \quad \Sigma_{k=1}^K \|\phi_k\|_\infty \|\phi_k'\|_\infty = o(\bar{n}) \end{aligned}$$

$$\begin{aligned} \delta_k \quad \text{fi} \quad \mathbf{G} \quad \lambda_k \quad A_{\delta_k} \quad n \rightarrow \infty \\ K \quad n \dots n \gg K \end{aligned}$$

$$\begin{aligned} X \quad E(\|X\|_\infty + \|X'\|_\infty) < \infty \quad E\left\{\max_{t \in \mathcal{T}} |X(t) - X^K(t)|\right\} = o(n) \quad X^K(t) = \mu(t) + \sum_{k=1}^K \xi_{ik} \phi_k(t) \end{aligned}$$

$$\begin{aligned}
 & Y_{ij}^* = Y_{ij} - \sum_{k=1}^{\infty} \xi_{ik} \phi_k(t) \quad Y_{ij}^* = \mu(t) + \varepsilon_{ij} \\
 & \mu(t) = \sum_{l=1}^q \beta_l b_l(t) \quad b_l(t) = t^l \quad \leq l \leq p \quad b_l(t) = (t - \kappa_{l-p})_+^p \quad p+1 \leq l \leq k \quad q = p+k+1 \\
 & Y_{ij} \quad Y_{ij}^* \quad \tilde{\mu}(t) \quad \mu(t) \quad \text{fi} \\
 & \kappa \in \mathcal{T} \quad b_l(t) = b(t|\kappa_{l-p}) \quad l \geq p+1 \quad a(t) \quad b(t|\kappa) = (t - \kappa)_+^p \quad \kappa_j \\
 & j \leq q-p \quad \text{fi} \quad t \in \mathcal{T} \quad q \quad \tilde{\mu} \\
 & \infty \quad \mathcal{T} \quad \infty \quad \text{fi} \quad p \quad n \rightarrow \infty \quad a(t) \\
 & b(t|\kappa) \quad \text{fi} \quad \psi \\
 & \psi(u \ v) = \int_{\mathcal{T}} b(t|u) b(t|v) \ v \\
 & \alpha \quad \psi \alpha \quad \text{fi} \\
 & (\psi \alpha)(u) = \int_{\mathcal{T}} \psi(u \ v) \alpha(v) \ t. \\
 & \text{fi} \quad \beta^* \quad \mu^*(t) = \mu(t) - \sum_{l=1}^p \beta_l b_l(t) \\
 & \mu^*(t) = \int_{\mathcal{T}} \beta^*(s) b(t|s) a(s) \ s \\
 & t \in \mathcal{T}, \\
 & \int_{\mathcal{T}} \int_{\mathcal{T}} b(t|s) \ s < \infty \quad \psi \quad \beta^* \quad \int_{\mathcal{T}} \beta^*(t) \\
 & \int_{\mathcal{T}} \beta^*(t) \psi_j(t) \ t + \sum_{j=1}^{\infty} \sqrt{\{\rho_j \ (j)\}} < \infty \quad \lambda^* \rightarrow \text{fi} \quad n \rightarrow n \\
 & \int_{\mathcal{T}} \beta^*(t) \psi_j(t) \ t + \sum_{j=1}^{\infty} \sqrt{\{\rho_j \ (j)\}} / (\rho_j + \lambda^*) \rightarrow \lambda^* = \lambda^*(n) \\
 & \tilde{\mu}(t) \\
 & g(y \ t) \quad Y(t) = g(y \ y \ t \ t) \quad (Y(t) \ Y(t)), \\
 & \text{fi} \\
 & t_{ij} \\
 & \nu < l \\
 & (\ / \ t^l) g(y \ t) \quad \mathfrak{R} \times \mathcal{T} \\
 & q = l \quad K \quad (\nu \ l) \int u^q K(u) \ u \quad (-)^\nu \nu \quad q = \nu \quad K \quad \mathfrak{R} \rightarrow \mathfrak{R} \\
 & K \quad (\nu \ l) \quad \|K\| = \int K(u) \ u < \infty \\
 & \text{fi} \\
 & q \geq \quad (\psi_p)_p = \dots q \quad \psi_p \quad \mathfrak{R} \rightarrow \mathfrak{R}
 \end{aligned}$$

$$\psi_p = \int_{t \in \mathcal{T}} \psi_p(t; x) g(x; t) dx < \infty.$$

$$h_\mu = h_\mu(n)$$

$$nh_\mu^{\nu+} \rightarrow \infty, \Delta_n = O\{1/(nh_\mu^{\nu+})\} \rightarrow 0, \{n_i, i = 1, \dots, n\} \leq Cn, n \rightarrow \infty$$

fi

$$\Psi_{pn} = \Psi_{pn}(t) = \frac{1}{nh_\mu^{\nu+}} \sum_{i=1}^n \sum_{j=1}^{n_i} \psi_p(t_{ij}; Y_{ij}) K\left(\frac{t - t_{ij}}{h_\mu}\right), \quad p = 1, \dots, q$$

$$\mu_p = \mu_p(t) = \int \psi_p(t; x) g(x; t) dx, \quad p = 1, \dots, q.$$

A.2. Auxiliary results and proofs of main theorems

1. $\tau_{pn} = \sup_{t \in \mathcal{T}} |\Psi_{pn}(t) - \mu_p| = O_p\{1/(nh_\mu^{\nu+})\}$, fi

fi

2. $h_\mu, h_G, h_V, G^{(\cdot)}(s; t), V^{(\cdot)}(t), g(y; t), g(y; y; t; t)$

$$\begin{aligned} \sup_{t \in \mathcal{T}} |\mu^{(\cdot)}(t) - \mu(t)| &= O_p\left(\frac{1}{n/h_\mu}\right) \\ \sup_{s, t \in \mathcal{T}} |G^{(\cdot)}(s; t) - G(s; t)| &= O_p\left(\frac{1}{n/h_G}\right). \end{aligned} \quad ()$$

$$\begin{aligned} \lambda_k &= \phi_k \\ \sup_{t \in \mathcal{T}} |\phi_k^{(\cdot)}(t) - \phi_k(t)| &= O_p\left(\frac{\delta_k A_{\delta_k}}{n/h_G - A_{\delta_k}}\right) \\ \lambda_k^{(\cdot)} - \lambda_k &= O_p\left(\frac{\delta_k A_{\delta_k} \mathbb{1}_{\{0\}}}{\mathbb{G}_k}\right) \end{aligned}$$

3. λ^*

$\tilde{\mu}(t)$ $\overline{g(y, t)}$

$$\sup_{t \in \mathcal{T}} |\mu^*(t) - \mu(t)| = O_p(\omega_n)$$

$$\omega_n = \frac{1}{n} \sum_{j=1}^{\infty} \frac{\sqrt{\{\rho_j(j)\}}}{\rho_j + \lambda^*} + \sum_{j=1}^{\infty} \frac{\lambda^* |\int_{\mathcal{T}} \beta^*(t) \psi_j(t) dt|}{\rho_j + \lambda^*}. \quad ()$$

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$$\begin{aligned} \|X_i\|_L &= \left\{ \int_{\mathcal{T}} X_i(t) dt \right\}^{1/2} \\ &\leq \sum_{k \leq K} |\tilde{\tau}_{ik} - \xi_{ik}| \leq \sum_{k \leq K} \left\{ \|(X_i + \mu)' \phi_k + (X_i + \mu) \phi_k'\|_{\infty} \Delta_n^* \right\} \\ &\leq \sum_{k \leq K} (\|X_i\|_{\infty} \|\phi_k\|_{\infty} + \|X_i'\|_{\infty} \|\phi_k'\|_{\infty} + c \|\phi_k\|_{\infty} + c \|\phi_k'\|_{\infty}) \Delta_n^* \\ &\leq (c \|X_i\|_{\infty} + c \|X_i'\|_{\infty} + c) \sum_{k \leq K} (\|\phi_k'\|_{\infty} \Delta_n^*) \rightarrow \dots \end{aligned} \quad ()$$

$$|\tau_{ik}| \leq |\tilde{\tau}_{ik}| + \sum_{j=1}^{n_i} |\varepsilon_{ij}| |\phi_k^{(\cdot)}(t_{ij}) - \phi_k(t_{ij})| (t_{ij} - t_{i,j-1}).$$

$$\begin{aligned} E(\tilde{\tau}_{ik}) &= \dots \\ &= \sum_{j=1}^{n_i} \sigma(t_{ij}) \phi_k(t_{ij}) (t_{ij} - t_{i,j-1}) \\ &\leq \sum_{t \in \mathcal{T}} \{ \sigma(t) (\|\phi_k\|_{\infty} \|\phi_k'\|_{\infty} \Delta_n^*) \Delta_n^* \} \\ &\leq \sum_{t \in \mathcal{T}} \{ \sigma(t) \Delta_n^* \} \end{aligned}$$

$$\sum_{k=1}^K |\tilde{\tau}_{ik}| \|\phi_k\|_{\infty} \leq \sum_{t \in \mathcal{T}} \{ \sigma(t) \Delta_n^* \} \cdot \sum_{k=1}^K \|\phi_k\|_{\infty} \rightarrow \dots$$

$$\sum_{k=1}^K \sum_{j=1}^{n_i} |\varepsilon_{ij}| |\phi_k^{(\cdot)}(t_{ij}) - \phi_k(t_{ij})| (t_{ij} - t_{i,j-1}) \|\phi_k\|_{\infty} \leq v_n \sum_{j=1}^{n_i} |\varepsilon_{ij}| (t_{ij} - t_{i,j-1})$$

$$E \left\{ \sum_{j=1}^{n_i} |\varepsilon_{ij}| (t_{ij} - t_{i,j-1}) \right\} \leq |\mathcal{T}| \sum_{t \in \mathcal{T}} \{ \sigma(t) \}$$

$$\sum_{j=1}^{n_i} |\varepsilon_{ij}| (t_{ij} - t_{i,j-1}) = O_p(\dots)$$

$$\sum_{k=1}^K |\tau_{ik}| \|\phi_k\|_{\infty} \rightarrow \dots$$

fi

$$\left| \sum_{k=1}^K \xi_{ik}^{(\cdot)} \phi_k^{(\cdot)}(t) - \sum_{k=1}^{\infty} \xi_{ik} \phi_k(t) \right| \leq \left| \sum_{k=1}^K \{ \xi_{ik}^{(\cdot)} \phi_k^{(\cdot)}(t) - \xi_{ik} \phi_k(t) \} \right| + \left| \sum_{k=K+1}^{\infty} \xi_{ik} \phi_k(t) \right| \rightarrow \dots \quad ()$$

$K \rightarrow \infty, n \rightarrow \infty,$

fi

$$\begin{aligned} \left| \sum_{t \in \mathcal{T}} \left| \sum_{k=1}^K \{ \xi_{ik}^{(\cdot)} \phi_k^{(\cdot)}(t) - \xi_{ik} \phi_k(t) \} \right| \right| &\leq \sum_{k=1}^K |\xi_{ik}^{(\cdot)} - \xi_{ik}| (\|\phi_k\|_\infty + \tilde{v}_n) + \left| \sum_{k=1}^K \xi_{ik} \{ \phi_k^{(\cdot)}(t) - \phi_k(t) \} \right| \\ &\equiv Q(n) + \tilde{Q}(n). \end{aligned}$$

$$E|Q(n)| \leq \sum_{k=1}^K \delta_k A_{\delta_k} E|\xi_{ik}^{(\cdot)}| / (n' h_G - A_{\delta_k}) \leq \sum_{k=1}^K \delta_k A_{\delta_k} \lambda_k' / (n' h_G - A_{\delta_k})$$

$$\lambda_k \rightarrow E|Q(n)| = O(v_n), \quad Q(n) = O_p(v_n).$$

$$Q(n) \leq \sum_{k=1}^K |\xi_{ik}^{(\cdot)} - \xi_{ik}| \|\phi_k\|_\infty$$

n

$$\sum_{k=1}^K |\xi_{ik}^{(\cdot)} - \xi_{ik}| \|\phi_k\|_\infty \leq \sum_{k=1}^K |\eta_{ik} - \tilde{\eta}_{ik}| \|\phi_k\|_\infty + \sum_{k=1}^K |\tilde{\eta}_{ik} - \xi_{ik}| \|\phi_k\|_\infty + \sum_{k=1}^K |\tau_{ik}| \|\phi_k\|_\infty. \quad ()$$

fi

$$\{c (\|X_i\|_L + \|X_i\|_\infty \|X_i'\|_\infty \Delta_n^*) + c\} v_n + \left(+ \sum_{k=1}^K \|\phi_k\|_\infty \|\phi_k'\|_\infty \Delta_n^* \right) \frac{\sum_{k=1}^K \|\phi_k\|_\infty}{n' h_\mu} \rightarrow .$$

$$(c \|X_i\|_\infty + c \|X_i'\|_\infty + c) \sum_{k=1}^K \|\phi_k\|_\infty \|\phi_k'\|_\infty \Delta_n^* \rightarrow .$$

$$\sum_{k=1}^K |\tau_{ik}| \|\phi_k\|_\infty \rightarrow .$$

$$i \quad \theta_{in} \quad \text{fi} \quad \leq_{j \leq n_i} |Y_{ij}^* - Y_{ij}^{*(\cdot)}| = O_p(\theta_{in}) \quad O_p(\cdot) \\ \mu(t) \quad G(s, t) \quad G(s, t)$$

A.2.2.

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$$\begin{aligned} Y_{ij}^* \quad \mu(t) \quad Y_{ij}^{*(\cdot)} \quad \tilde{\mu}(t) \quad \tilde{G} \quad \text{fi} \\ \mu(t) \quad \mu(t) \quad \mu(t) \quad G \quad \text{fi} \\ \left| \sum_{t \in \mathcal{T}} |\mu(t) - \tilde{\mu}(t)| \right| = O_p(\tilde{\theta}_n) \quad \left| \sum_{s, t \in \mathcal{T}} |G(s, t) - \tilde{G}(s, t)| \right| = O_p(\tilde{\theta}_n) \quad O_p(\cdot) \\ \tilde{\theta}_n = \sum_{i=1}^n \theta_{in} \quad j \end{aligned}$$

$$E(\|X\|_\infty \|X'\|_\infty) \leq \{E(\|X\|_\infty) E(\|X'\|_\infty)\}' < \infty$$

$$E \left\{ \sum_{j=1}^{n_i} |\varepsilon_{ij}| (t_{ij} - t_{i, j-1}) \right\} \leq |\mathcal{T}| \{ \sigma(t) \} < \infty$$

$$E \left\{ \sum_{k=1}^K \delta_k A_{\delta_k} |\xi_{ik}^{(\cdot)}| / (n' h_G - A_{\delta_k}) \right\} \leq \sum_{k=1}^K \delta_k A_{\delta_k} \lambda_k' / (n' h_G - A_{\delta_k}) \leq v_n$$

$$\begin{aligned} \bar{\theta}_n &= O_p(\theta_n^*) \rightarrow \\ \theta_n^* & \text{ fi} \\ & \mu(t) - G(t) \\ & |\mu(t) - \mu(t)| = O_p(\omega_n + \theta_n^*) \\ & |G(s, t) - G(s, t)| = O_p\left(\omega_n + \theta_n^* + \frac{1}{n / h_G}\right) \\ \omega_n & \theta_n^* h_G \end{aligned} \quad ()$$

Reference.

..., B 47, ... 51, ... 55

