



Ampoicidib, ion of nonpameic eg e ion
e ima o fo longi, dinal o f nc ional da a

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Abstract

The e i m a i o n o f a e g e i o n f n c i o n b k e n e l m e h o d f o l o n g i , d i n a l o f n c i o n a l d a a i c o n i d e d . I n h e c o n e o f l o n g i , d i n a l d a a n a l i , a a n d o m f n c i o n p i c a l l e p e e n a , b j e c h a i o f e n o b e e d a a m a l l n m b e o f i m e p o i n t w h i l e i n h e , d i e o f f n c i o n a l d a a h e a n d o m e a l i a i o n i , , a l l m e a , e d o n a d e n e g i d . H o w e e , e e n i a l l h e a m e m e h o d c a n b e a p p l i e d o b o h a m p l i n g p l a n , a w e l l a i n a n m b e o f e i n g l i n g b e w e e n h e m . I n h i p a p e g e n e a l e , l a e d e i d f o h e a m p o i c d i i b i o n o f e a l - a l e d f n c i o n w i h a g r m e n w h i c h a e f n c i o n a l f o m e d b w e i g h e d a e a g e o f l o n g i , d i n a l o f n c i o n a l d a a . A m p o i c d i i b i o n f o h e e i m a o o f h e m e a n a n d c o a i a n c e f n c i o n o b a i n e d f o m n o i o b e a i o n w i h h e p e e n c e o f w i h i n - , b j e c c o e l a i o n a e , d i e d . T h e a m p o i c n o m a l e , l a e c o m p a a b l e o h o e a n d a d a e o b a i n e d f o m i n d e p e n d e n t d a w h i c h i i l l a e d i n a i m l a i o n , d . B e i d e , h i p a p e d i c e h e c o n d i o n a o c i a e d w i h a m p l i n g p l a n w h i c h a e e q i e d f o h e a l i d i o f l o c a l p o p e i e o f k e n e l - b a e d e i m a o f o l o n g i , d i n a l o f n c i o n a l d a a .

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1. Introduction

Modern technology and advanced computing environments have facilitated the collection and analysis of high-dimensional data, data that are especially meaningful for a sample of subjects. The especially meaningful environment of an ecological epidemiological time, a nonclosed and bounded in the \mathcal{T} . It also could be a partial variable, which is an image of geoscientific application.

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The conclusion of this paper is the derivation of general multiplicity bounds in both one-dimensional and w -dimensional moving cone for real-algebraic functions which are functionally independent on w -tuples of longi, dinal of functions. The elementary machinery, which is applicable to the obtained functionally independent and independent data. The elementary is applied to the kernel-based image of the mean and covariance functions which yield a multiplicity bound of the image. In particular, the bound of the knowledge, no multiplicity bounds are available, provided for nonparametric estimation of covariance functions obtained from longi, dinal of functions data. Consequently, the mean, variance, and covariance, Hall et al. [6,7] in the general multiplicity properties of nonparametric kernel image of a covariance function, the mean, variance, and only observed from a single data set. Although the multiplicity bounds are derived for random design in this paper, the general can be extended to fixed design and the sampling plan which appopriate modification, and a multiplicity and a covariance can also be obtained in similar manner. This will provide heuristic and practical guidance for the nonparametric analysis of functions of longi, dinal data which impose a partial application, which is based on the multiplicity bounds. Typical examples include the construction of a multiplicity confidence band for regression functions and confidence region

for covariance, trace, and allocation of bandwidth for covariance, trace estimation based on a multipoint mean quadratic error. The application in the context of multivariate independent data can be explored for the multivariate functional data, including kernel-based estimation.

The remainder of the paper is organized as follows. In Section 2, we derive the general multipoint distribution of one- and w -dimensional multivariate functional data obtained from multivariate functional data for random design. The general multipoint error is applied to common, kernel-based estimation of the mean curve and covariance, trace in Section 3. Estimation of functional data is discussed in Section 4. A simulation, depicted in the appendix, is devoted to the multipoint error for covariance data in Section 5. While discussion, including potential application of the error, is left for a multipoint notation, is offered in Section 6.

2. General results of asymptotic distributions for random design

In this section, we will define general functional data as kernel-based estimation of the data for one-dimensional and w -dimensional multivariate functional data. The induced general functional data include the most common, kernel-based estimation of the kernel-based estimation, such as Gaussian, M-estimation, Nadaraya-Watson estimation, local polynomial estimation, etc. Since Nadaraya-Watson and local polynomial estimation are most popular, and in practice, the multipoint behavior in the multivariate and covariance for independent data has been thoroughly studied in the literature, e.g., Hördle et al., for multivariate functional data, particularly in the case of covariance, trace estimation, the multipoint behavior of multivariate and covariance of the w -common, kernel-based estimation is still largely unknown. The error in Section 3, the general multipoint error, developed in this section is applied to Nadaraya-Watson and local polynomial estimation in both one-dimensional and w -dimensional multivariate functional data. In particular, the lack of a multipoint error for the covariance, trace estimation of multivariate functional data is an additional motivation for the definition of the w -dimensional general functional data can be applied to develop the multipoint distribution for the estimation.

We first consider random design, while estimation of the sampling plan is deferred to Section 4. In classical multivariate, design, measurement, estimation of the observed observations. Hördle et al., in the individual multivariate, the error, including data, all become part, the error is only observed as obtained from model, by the w variables, neural network of repeated measurement, by the difference measurement, estimation time T_{ij} per individual. This sampling

ariance σ^2 ,

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

where $E\varepsilon_{ij} = 0$, $\text{var}(\varepsilon_{ij}) = \sigma^2$, and the number of observations, $N_i(n)$ depending on the sample size n , are considered random. We make the following assumption,

(A1.1) The number of observations $N_i(n)$ made for the i th subject $i = 1, \dots, n$, is a . . .

with $N_i(n) \stackrel{\text{i.i.d.}}{\sim} N(n)_{\mathbf{w}}$ where $N(n) > 0$ is a positive integer-valued random variable with $\lim_{n \rightarrow \infty} EN(n)^2/[EN(n)]^2 < \infty$ and $\lim_{n \rightarrow \infty} EN(n)^4/[EN(n)]^3 < \infty$.

In the sequel the dependence of $N_i(n)$ and $N(n)$ on the sample size n , is implied; i.e., $N_i = N_i(n)$ and $N(n) = N$. The observations and measurement are assumed to be independent of the number of measurements, i.e., for any subset $J_i \subseteq \{1, \dots, N_i\}$ and for all $i = 1, \dots, n$,

(A1.2) $\{T_{ij} : j \in J_i\}, \{Y_{ij} : j \in J_i\}$ is independent of N_i .

Writing $\mathbf{T}_i = (T_{i1}, \dots, T_{iN_i})^T$ and $\mathbf{Y}_i = (Y_{i1}, \dots, Y_{iN_i})^T$, it is easy to see that the triple $\{\mathbf{T}_i, \mathbf{Y}_i, N_i\}$ are i.i.d..

2.1. Asymptotic normality of one-dimensional smoother

To achieve our purpose, let us assume that the condition has a certain order of smoothness. We define a neighborhood of x in \mathbb{R}^p as $U(x) = \{x' \in \mathbb{R}^p : |f(x') - f(x)| < \varepsilon\}$ for all $x' \in U(x)$ and $y \in \mathbb{R}^q$, provided that for any $x \in A$ and $\varepsilon > 0$, there exists a neighborhood of x not depending on y , such that $|f(x') - f(x, y)| < \varepsilon$ for all $x' \in U(x)$ and $y \in \mathbb{R}^q$.

For random design, (T_{ij}, Y_{ij}) are assumed to have the identical distribution $(T, Y)_{\mathbf{w}}$ with joint density $g(t, y)$. Assume that the observations T_{ij} are i.i.d. with the marginal density $f(t)$, the dependence allowed among Y_{ij} and Y_{ik} has a certain order of smoothness. Also denote the joint density of (T_j, T_k, Y_j, Y_k) by $g_2(t_1, t_2, y_1, y_2)_{\mathbf{w}}$ where $j \neq k$. Let v, k be given in \mathbb{N} with $0 \leq v < k$. We assume that the condition for the marginal and joint densities, $f(t), g(t, y), g_2(t_1, t_2, y_1, y_2)$ and the mean function of the underlying process $X(t)$, i.e., $E[X(t)] = \mu(t)_{\mathbf{w}}$ is the v th order neighborhood of a finite point $t \in \mathcal{T}$, assuming that the v th neighborhood $U(t)$ of t , such that:

(B1.1) $\frac{d^k}{du^k} f(u)$ exists and is continuous on $u \in U(t)$, and $f(u) > 0$ for $u \in U(t)$;

(B1.2) $g(u, y)$ is continuous on $u \in U(t)$, nonnegative in $y \in \mathbb{R}$; $\frac{d^k}{du^k} g(u, y)$ exists and is continuous on $u \in U(t)$, nonnegative in $y \in \mathbb{R}$;

(B1.3) $g_2(u, v, y_1, y_2)$ is continuous on $(u, v) \in U(t)^2$, nonnegative in $(y_1, y_2) \in \mathbb{R}^2$;

(B1.4) $\frac{d^k}{du^k} \mu(u)$ exists and is continuous on $u \in U(t)$.

Let $K_1(\cdot)$ be nonnegative, nonnegative kernel function in one-dimensional smoothing. The assumption for the kernel $K_1 : \mathbb{R} \rightarrow \mathbb{R}$ are as follows. We assume that the kernel function K_1 is of order (v, k) , if

$$\int u^\ell K_1(u) du = \begin{cases} 0, & 0 \leq \ell < k, \ell \neq v, \\ (-1)^v v!, & \ell = v, \\ \neq 0, & \ell = k, \end{cases} \quad (2)$$

(B2.1) K_1 is compact, moreover, $\|K_1\|^2 = \int K_1^2(u) du < \infty$;

(B2.2) K_1 is a kernel function of order (v, ℓ) .

Let $b = b(n)$ be a sequence of bandwidths satisfying the following conditions. We develop a proposition as $n \rightarrow \infty$, and require

(B3) $b \rightarrow 0$, $n(EN)b^{v+1} \rightarrow \infty$, $b(EN) \rightarrow 0$, and $n(EN)b^{2k+1} \rightarrow d^2$ for some d_v with $0 \leq d < \infty$.

One could see in the proof of Theorem 1 that the assumption (B3) combined with (A1.1) provides the condition which has the local properties of kernel estimators hold for longidinal or functional data with the presence of censoring.

Let $\{\psi_\lambda\}_{\lambda=1,\dots,l}$ be a collection of real function $\psi_\lambda: \mathbb{R}^2 \rightarrow \mathbb{R}_w$ which satisfy:

(B4.1) $\psi_\lambda(t, y)$ are continuous on $\{t\}$, nondecreasing in $y \in \mathbb{R}$;

(B4.2) $\frac{d^k}{dt^k} \psi_\lambda(t, y)$ exists for all ages (t, y) and are continuous on $\{t\}$, nondecreasing in $y \in \mathbb{R}$.

Then we define the generalized age

$$\Psi_{\lambda n} = \frac{1}{nENb^{v+1}} \sum_{i=1}^n \sum_{j=1}^{N_i} \psi_\lambda(T_{ij}, Y_{ij}) K_1\left(\frac{t - T_{ij}}{b}\right), \quad \lambda = 1, \dots, l.$$

and

$$\mu_\lambda = \mu_\lambda(t) = \frac{d^v}{dt^v} \int \psi_\lambda(t, y) g(t, y) dy, \quad \lambda = 1, \dots, l.$$

Let

$$\sigma_{\kappa\lambda} = \sigma_{\kappa\lambda}(t) = \int \psi_\kappa(t, y) \psi_\lambda(t, y) g(t, y) dy \|K_1\|^2, \quad 1 \leq \lambda, \kappa \leq l,$$

and $H: \mathbb{R}^l \rightarrow \mathbb{R}$ be a function which continuous in first order derivatives. We denote the gradient vector $((\partial H / \partial x_1)(v), \dots, (\partial H / \partial x_l)(v))^T$ by $DH(v)$ and $\bar{N} = \sum_{i=1}^n N_i/n$.

Theorem 1. *If the assumptions (A1.1), (A1.2) and (B1.1)–(B4.2) hold, then*

$$\sqrt{n\bar{N}b^{2v+1}} [H(\Psi_{1n}, \dots, \Psi_{ln}) - H(\mu_1, \dots, \mu_l)] \xrightarrow{\mathcal{D}} \mathcal{N}(\beta, [DH(\mu_1, \dots, \mu_l)]^T \Sigma [DH(\mu_1, \dots, \mu_l)]), \quad (3)$$

where

$$\beta = \frac{(-1)^k d}{k!} \int u^k K_1(u) du \sum_{\lambda=1}^l \frac{\partial H}{\partial \mu_\lambda} \{(\mu_1, \dots, \mu_l)^T\} \frac{d^{k-v}}{dt^{k-v}} \mu_\lambda(t), \quad \Sigma = (\sigma_{\kappa\lambda})_{1 \leq \kappa, \lambda \leq l}.$$

Proof. It is seen that \bar{N} can be replaced by EN by Slutsky's Theorem, under (A1.1). We now have

$$\sqrt{n(EN)b^{2v+1}} [H(E\Psi_{1n}, \dots, E\Psi_{ln}) - H(\mu_1, \dots, \mu_l)] \rightarrow \beta. \quad (4)$$

Since (A1.1) and (A1.2) hold, and K_1 is of order (v, k) , using Taylor expansion of order k , one obtains

$$\begin{aligned}
 E\Psi_{\lambda n} &= \frac{1}{nb^{v+1}} E \left\{ \sum_{i=1}^n \frac{1}{EN} \sum_{j=1}^{N_i} \psi_{\lambda}(T_{ij}, Y_{ij}) K_1 \left(\frac{t - T_{ij}}{b} \right) \right\} \\
 &= \frac{1}{b^{v+1} EN} E \left\{ \sum_{j=1}^N E \left[\psi_{\lambda}(T_j, Y_j) K_1 \left(\frac{t - T_j}{b} \right) \middle| N \right] \right\} \\
 &= \frac{1}{b^{v+1}} E \left\{ \psi_{\lambda}(T, Y) K_1 \left(\frac{t - T}{b} \right) \right\} \\
 &= \mu_{\lambda} + \frac{(-1)^k}{k!} \int u^k K_1(u) du \frac{d^{k-v}}{dt^{k-v}} \mu_{\lambda}(t) b^{k-v} + o(b^{k-v}). \tag{5}
 \end{aligned}$$

Then (4) follows from an l -dimensional Taylor expansion of H of order 1 around $(\mu_1, \dots, \mu_l)^T$, combined with (5). If we can have

$$\sqrt{n(EN)b^{2v+1}}[(\Psi_{1n}, \dots, \Psi_{ln})^T - (E\Psi, \dots, E\Psi_{ln})^T] \xrightarrow{\mathcal{D}} \mathcal{N}(0, \Sigma), \tag{6}$$

in analogy to Bhattacharya and Melle [1], and considering DH at $(\mu_1, \dots, \mu_l)^T$ and applying similar arguments as in (5), we find $DH(E\Psi_{1n}, \dots, E\Psi_{ln}) \rightarrow DH(\mu_1, \dots, \mu_l)$. Then Cramér–Wold device yields

$$\begin{aligned}
 \sqrt{n(EN)b^{2v+1}}[H(\Psi_{1n}, \dots, \Psi_{ln}) - H(E\Psi, \dots, E\Psi_{ln})] &\xrightarrow{\mathcal{D}} \mathcal{N}(0, DH(\mu_1, \dots, \mu_l)^T \\
 &\quad \Sigma DH(\mu_1, \dots, \mu_l)), \tag{7}
 \end{aligned}$$

combined with (4), leading to (3).

It remains to have (6). Observe that (A1.1) and (A1.2), one has

$$\begin{aligned}
 &n(EN)b^{2v+1} \text{cov}(\Psi_{\lambda n}, \Psi_{\kappa n}) \\
 &= \frac{1}{b} E \left\{ \frac{1}{EN} \left[\sum_{j=1}^N \psi_{\lambda}(T_j, Y_j) K_1 \left(\frac{t - T_j}{b} \right) \right] \left[\sum_{k=1}^N \psi_{\kappa}(T_k, Y_k) K_1 \left(\frac{t - T_k}{b} \right) \right] \right\} \\
 &\quad - \frac{EN}{b} E \left[\frac{1}{EN} \sum_{j=1}^N \psi_{\lambda}(T_j, Y_j) K_1 \left(\frac{t - T_j}{b} \right) \right] \\
 &\quad \times E \left[\frac{1}{EN} \sum_{k=1}^N \psi_{\kappa}(T_k, Y_k) K_1 \left(\frac{t - T_k}{b} \right) \right] \\
 &\equiv I_1 - I_2.
 \end{aligned}$$

It is obvious that $I_2 = O(b) = o(1)$ from the definition of (5). For I_1 , it can be written as

$$\begin{aligned} I_1 &= \frac{1}{b} E \left[\frac{1}{EN} \sum_{j=1}^N \psi_{\lambda}(T_j, Y_j) \psi_{\kappa}(T_j, Y_j) K_1^2 \left(\frac{t - T_j}{b} \right) \right] \\ &\quad + \frac{1}{b} E \left[\frac{1}{EN} \sum_{1 \leq j \neq k \leq N} \psi_{\lambda}(T_j, Y_j) \psi_{\kappa}(T_k, Y_k) K_1 \left(\frac{t - T_j}{b} \right) K_1 \left(\frac{t - Y_k}{b} \right) \right] \\ &\equiv Q_1 + Q_2. \end{aligned}$$

Applying (A1.1) and (A1.2), one has

$$\begin{aligned} Q_1 &= \frac{1}{b} E \left\{ \frac{1}{EN} \sum_{j=1}^N E \left[\psi_{\lambda}(T_j, Y_j) \psi_{\kappa}(T_j, Y_j) K_1^2 \left(\frac{t - T_j}{b} \right) \middle| N \right] \right\} \\ &= \frac{1}{b} E \left[\psi_{\lambda}(T, Y) \psi_{\kappa}(T, Y) K_1^2 \left(\frac{t - Y}{b} \right) \right] = \sigma_{\lambda\kappa} + o(1). \end{aligned}$$

Then (4)_w will hold, observing (A1.1) and the following arguments have given the local properties of the kernel-based estimator \hat{w} in the presence of w in the bivariate relationship in longitudinal data,

$$\begin{aligned} Q_2 &= \frac{1}{bEN} E \left\{ \sum_{1 \leq j \neq k \leq N} E \left[\psi_{\lambda}(T_j, Y_j) \psi_{\kappa}(T_k, Y_k) K_1 \left(\frac{t - T_j}{b} \right) K_1 \left(\frac{t - T_k}{b} \right) \middle| N \right] \right\} \\ &= \frac{EN(N-1)}{bEN} E \left[\psi_{\lambda}(T_1, Y_1) \psi_{\kappa}(T_2, Y_2) K_1 \left(\frac{t - T_1}{b} \right) K_1 \left(\frac{t - T_2}{b} \right) \right] \\ &= \frac{bEN(N-1)}{EN} \int_{\mathbb{R}^4} \psi_{\lambda}(t - ub, y_1) \psi_{\kappa}(t - vb, y_2) K_1(u) K_2(v) \\ &\quad \times g_2(t - ub, t - vb, y_1, y_2) du dv dy_1 dy_2 \\ &= \frac{bEN(N-1)}{EN} \int_{\mathbb{R}^2} \psi_{\lambda}(t, y_1) \psi_{\kappa}(t, y_2) g_2(t, t, y_1, y_2) dy_1 dy_2 + o(b) = o(1), \end{aligned}$$

i.e., the bivariate relationship can be ignored while deriving the asymptotic variance. \square

2.2. Asymptotic normality of two-dimensional smoother

The general asymptotic result can be extended to w -dimensional smoothing. Let (\mathbf{v}, \mathbf{k}) denote the multi-indices $\mathbf{v} = (v_1, v_2)$ and $\mathbf{k} = (k_1, k_2)$ _w where $|\mathbf{v}| = v_1 + v_2$ and $|\mathbf{k}| = k_1 + k_2$. In w -dimensional smoothing, more generally a multipion is needed for joint density. Let $f_2(s, t)$ be the joint density of (T_j, T_k) , and $g_4(s, t, s', t', y_1, y_2, y'_1, y'_2)$ the joint density of $(T_j, T_k, T_{j'}, T_{k'}, Y_j, Y_k, Y_{j'}, Y_{k'})$ _w where $j \neq k, (j, k) \neq (j', k')$. Denote the covariance surface $C(s, t) = \text{cov}(X(T_j), X(T_k) | T_j = s, T_k = t)$. The following regularity condition is assumed, where $U(s, t)$ is some neighborhood of $\{(s, t)\}$,

$$(C1.1) \quad \frac{d^{|\mathbf{k}|}}{du^{k_1} dv^{k_2}} f_2(u, v) \text{ is continuous on } (u, v) \in U(s, t), \text{ and } f_2(u, v) > 0 \text{ for } (u, v) \in U(s, t);$$

(C1.2) $g_2(u, v, y_1, y_2)$ is continuous on $(u, v) \in U(s, t)$, nifoml in $(y_1, y_2) \in \mathbb{R}^2$; $\frac{d^{|k|}}{du^{k_1} dv^{k_2}}$

$g_2(u, v, y_1, y_2)$ is and is continuous on $(u, v) \in U(s, t)$, nifoml in $(y_1, y_2) \in \mathbb{R}^2$;

(C1.3) $g_4(u, v, u', v', y_1, y_2, y'_1, y'_2)$ is continuous on $(u, v, u', v') \in U(s, t)^2$, nifoml in $(y_1, y_2, y'_1, y'_2) \in \mathbb{R}^4$;

(C1.4) $\frac{d^{|k|}}{du^{k_1} dv^{k_2}} C(u, v)$ is and is continuous on $(u, v) \in U(s, t)$.

Let K_2 be nonnegative and biadditive in the function, and in \mathbb{H}_w -dimensional smoothing. The asymptotic behavior of K_2 is as follows,

(C2.1) K_2 is compact, and $\|K_2\|_w^2 = \int_{\mathbb{R}^2} K_2^2(u, v) du dv < \infty$, and is symmetric in u and v .

(C2.2) K_2 is additive in the function of order $(|v|, |k|)$, i.e.,

$$\sum_{\ell_1 + \ell_2 = |l|} \int_{\mathbb{R}^2} u^{\ell_1} v^{\ell_2} K_2(u, v) du dv = \begin{cases} 0, & 0 \leq |l| < |k|, |l| \neq |v|, \\ (-1)^{|v|} |v|!, & |l| = |v|, \\ \neq 0, & |l| = |k|. \end{cases} \quad (8)$$

Let $h = h(n)$ be a sequence of bandwidths, and in \mathbb{H}_w -dimensional smoothing while it is possible that the bandwidths, and for w of a given magnitude be different. Since w is ill focused on the image of the covariance, face has isometric about the diagonal, it is efficient on considering the identical bandwidths for w of a given magnitude. The asymptotic behavior of $n \rightarrow \infty$ is as follows:

(C3) $h \rightarrow 0$, $nEN^2 h^{|v|+2} \rightarrow \infty$, $hEN^3 \rightarrow 0$, and $nE[N(N-1)]h^{2|k|+2} \rightarrow e^2$ for some $0 \leq e < \infty$.

Similar to the one-dimensional smoothing case, asymptotic (C3) and (A1.1) give an efficient local property of the biadditive kernel-based image w in the presence of w in the background.

Let $\{\phi_\lambda\}_{\lambda=1, \dots, l}$ be a collection of real functions $\phi_\lambda: \mathbb{R}^4 \rightarrow \mathbb{R}$, $\lambda = 1, \dots, l$, satisfying

(C4.1) $\phi_\lambda(s, t, y_1, y_2)$ are continuous on $\{(s, t)\}$, nifoml in $(y_1, y_2) \in \mathbb{R}^2$;

(C4.2) $\frac{d^{|k|}}{ds^{k_1} dt^{k_2}} \phi_\lambda(s, t, y_1, y_2)$ is finite for all λ of a given (s, t, y_1, y_2) and are continuous on $\{(s, t)\}$, nifoml in $(y_1, y_2) \in \mathbb{R}^2$.

Then the general w -eigendecomposition of w -dimensional smoothing is defined by, for $1 \leq \lambda \leq l$,

$$\begin{aligned} \Phi_{\lambda n} &= \Phi_{\lambda n}(t, s) = \frac{1}{nE[N(N-1)]h^{|v|+2}} \sum_{i=1}^n \sum_{1 \leq j \neq k \leq N_i} \phi_\lambda(T_{ij}, T_{ik}, Y_{ij}, Y_{ik}) \\ &\quad \times K_2\left(\frac{s - T_{ij}}{h}, \frac{t - T_{ik}}{h}\right). \end{aligned}$$

Let

$$m_\lambda = m_\lambda(s, t) = \sum_{v_1 + v_2 = |v|} \frac{d^{|v|}}{ds^{v_1} dt^{v_2}} \int_{\mathbb{R}^2} \phi_\lambda(s, t, y_1, y_2) g_2(s, t, y_1, y_2) dy_1 dy_2, \quad 1 \leq \lambda \leq l,$$

and

$$\omega_{\kappa\lambda} = \omega_{\kappa\lambda}(s, t) = \int_{\mathbb{R}^2} \phi_{\kappa}(s, t, y_1, y_2) \phi_{\lambda}(s, t, y_1, y_2) g_2(s, t, y_1, y_2) dy_1 dy_2 \|K_2\|^2,$$

$$1 \leq \kappa, \lambda \leq l,$$

and $H : \mathbb{R}^l \rightarrow \mathbb{R}$ is a function which can be defined as follows.

Theorem 2. *If assumptions (A1.1), (A1.2) and (C1.1)–(C4.2) hold, then*

$$\sqrt{n\bar{N}(\bar{N}-1)h^{2|v|+2}}[H(\Phi_{1n}, \dots, \Phi_{ln}) - H(m_1, \dots, m_l)] \\ \xrightarrow{\mathcal{D}} \mathcal{N}(\gamma, [DH(m_1, \dots, m_l)]^T \Omega [DH(m_1, \dots, m_l)]), \quad (9)$$

where

$$\gamma = \frac{(-1)^{|k|} e}{|k|!} \sum_{\lambda=1}^l \left\{ \sum_{k_1+k_2=|k|} \int_{\mathbb{R}^2} u^{k_1} v^{k_2} K_2(u, v) du dv \frac{d^{|k|}}{ds^{k_1} dt^{k_2}} \right. \\ \left. \times \int_{\mathbb{R}^2} \phi_{\lambda}(s, t, y_1, y_2) g_2(s, t, y_1, y_2) dy_1 dy_2 \right\} \\ \times \left\{ \frac{\partial H}{\partial m_{\lambda}}(m_1, \dots, m_l)^T \right\},$$

$$\Omega = (\omega_{\kappa\lambda})_{1 \leq \kappa \leq l}.$$

The proof of Theorem 2 essentially follows that of Theorem 1 with appropriate modifications which are eq. i ed fo \mathbb{W} -dimensional smoothing.

3. Applications to nonparametric regression estimators for functional or longitudinal data

Although the estimation of kernel-based estimators has been introduced in literature, Nadaraya-Watson and local polynomial, especially local linear estimator, are the most common, and nonparametric smoothing technique in longitudinal functional data analysis. Due to the high-dimensional nature of the data, the estimation of the functional data has been a well-posed problem. The effect of the functional data is applied to the local linear estimator of the functional data. The Nadaraya-Watson and local linear estimator of the functional data and covariance, face the problem of the estimation.

3.1. Asymptotic distributions of mean estimators

We apply Theorem 1 to the local linear estimator of the common, and Nadaraya-Watson kernel estimator $\hat{\mu}_N(t)$ and local linear estimator $\hat{\mu}_L(t)$ of functional/longitudinal

da a:

$$\hat{\mu}_N(t) = \left[\sum_{i=1}^n \sum_{j=1}^{N_i} K_1 \left(\frac{t - T_{ij}}{b} \right) Y_{ij} \right] / \left[\sum_{i=1}^n \sum_{j=1}^{N_i} K_1 \left(\frac{t - T_{ij}}{b} \right) \right], \quad (10)$$

$$\hat{\mu}_L(t) = \hat{\alpha}_0(t) = \arg \min_{(\alpha_0, \alpha_1)} \left\{ \sum_{i=1}^n \sum_{j=1}^{N_i} K_1 \left(\frac{t - T_{ij}}{b} \right) [Y_{ij} - (\alpha_0 + \alpha_1(T_{ij} - t))]^2 \right\}. \quad (11)$$

Corollary 1. If assumptions (A1.1), (A1.2), and (B1.1)–(B3) hold with $v = 0$ and $k = 2$, then

$$\sqrt{n\bar{N}b}[\hat{\mu}_N(t) - \mu(t)] \xrightarrow{\mathcal{D}} \mathcal{N} \left(\frac{d}{2} \frac{\mu^{(2)}(t)f(t) + 2\mu^{(1)}(t)f^{(1)}(t)}{f(t)} \sigma_{K_1}^2, \frac{\text{var}(Y|T=t)\|K_1\|^2}{f(t)} \right), \quad (12)$$

where d is as in (B3), $\sigma_{K_1}^2 = \int u^2 K_1(u) du$

Here $w_{ij} = K_1((t - T_{ij})/b)/(nb)_{\mathbf{w}}$, where K_1 is a kernel function of order $(0, 2)$, satisfying (B2.1) and (B2.2), and $\hat{\alpha}_1(t)$ is an estimator of the density $\mu'(t)$ of μ at t .

Obeying the following implies $\hat{\mu}_N(t) \xrightarrow{P} \mu(t)$, let $\hat{f}(t) = \sum_i \sum_j w_{ij}/N_i$, where i is each of the $h_{\mathbf{w}}$ $\hat{f}(t) \xrightarrow{P} f(t)$ in analogy to the following. We proceed to show $\hat{a}_1(t) \xrightarrow{P} \mu'(t)$. Denote $\sigma_{K_1}^2 = \int u^2 K_1(u) du$, where the kernel function $\tilde{K}_1(t) = -tK_1(t)/\sigma_{K_1}^2$, and define $\Psi_{\lambda n}$, $1 \leq \lambda \leq 3$ by $\psi_1(u, y) = y$, $\psi_2(u, y) \equiv 1$, $\psi_3(u, y) = u - t$. Obeying the \tilde{K}_1 of order $(1, 3)$, $\hat{f}(t) \xrightarrow{P} f(t)$, and define

$$\tilde{H}(x_1, x_2, x_3) = \frac{x_1 - x_2 \hat{\mu}_N(t)}{x_3 - bx_2^2/\hat{f}(t) \cdot \sigma_{K_1}^2} \quad \text{and} \quad H(x_1, x_2, x_3) = \frac{x_1 - x_2 \mu(t)}{x_3}.$$

Then

$$\begin{aligned} \hat{\alpha}_1(t) &= \tilde{H}(\Psi_{1n}, \Psi_{2n}, \Psi_{3n}) \\ &= \left[H(\Psi_{1n}, \Psi_{2n}, \Psi_{3n}) + \frac{\Psi_{2n}(\mu(t) - \hat{\mu}_N(t))}{\Psi_{3n}} \right] \frac{\Psi_{3n}}{\Psi_{3n} + b^2 \Psi_{2n}^2/\hat{f}(t) \cdot \sigma_{K_1}^2}. \end{aligned}$$

Note that $\mu_1 = (\mu'f + mf')(t)$, $\mu_2 = f'(t)$, and $\mu_3 = f(t)$, implying $\Psi_{\lambda n} - \mu_\lambda = O_p(1/\sqrt{n\bar{N}b^3})$, for $\lambda = 1, 2, 3$, by Theorem 1. Using Slutsky's Theorem, $|\tilde{H}(\Psi_{1n}, \Psi_{2n}, \Psi_{3n}) - \mu'(t)| = O_p(1/\sqrt{n\bar{N}b^3})$ follows.

For the asymptotic distribution of $\hat{\mu}_L$, note that

$$\hat{\mu}_L(t) = \frac{\sum_i \frac{1}{EN} \sum_j w_{ij} Y_{ij} - \sum_i \frac{1}{EN} \sum_j w_{ij} (T_{ij} - t) \hat{a}_1(t)}{\sum_i \frac{1}{EN} \sum_j w_{ij}}.$$

Considering $\sqrt{n\bar{N}b} \sum_i \frac{1}{EN} \sum_j w_{ij} (T_{ij} - t) = \sqrt{n\bar{N}b} \sigma_{K_1}^2 b^2 \Psi_{2n}$. Since \tilde{K}_1 is of order $(1, 3)$, Theorem 1 implies $\Psi_{2n} = f'(t) + O_p(1/\sqrt{n\bar{N}b^3})_{\mathbf{w}}$, which yields $\sqrt{n\bar{N}b} \sigma_{K_1}^2 b^2 \Psi_{2n} = \sqrt{n\bar{N}b^5} \sigma_{K_1}^2 f'(t) + \sigma_{K_1}^2 O_p(b) = o_p(1)$ by obeying $n\bar{N}b^5 \rightarrow d^2$ for $0 \leq d < \infty$. Since $\hat{f}(t) \xrightarrow{P} f(t)$ and $|\hat{\alpha}_1(t) - \mu'(t)| = O_p(1/\sqrt{n\bar{N}b^3}) = o_p(1)_{\mathbf{w}}$, we find

$$\begin{aligned} \lim_{n \rightarrow \infty} \sqrt{n\bar{N}b} [\hat{\mu}_L(t) - \mu(t)] &\stackrel{D}{=} \lim_{n \rightarrow \infty} \sqrt{n\bar{N}b} \\ &\times \left\{ \frac{\sum_i \frac{1}{EN} \sum_j w_{ij} Y_{ij} - \mu'(t) \sum_i \frac{1}{EN} \sum_j w_{ij} T_{ij} + t \mu'(t) \sum_i \frac{1}{EN} \sum_j w_{ij}}{\sum_i \frac{1}{EN} \sum_j w_{ij}} - \mu(t) \right\}. \end{aligned}$$

Using the kernel K_1 of order $(0, 2)_{\mathbf{w}}$, we define $\Psi_{\lambda n}$, $1 \leq \lambda \leq 3$, where $\psi_1(u, y) = y$, $\psi_2(u, y) = u$ and $\psi_3(u, y) \equiv 1$, using $v = 0$, $k = 2$, $l = 3$ and $H(x_1, x_2, x_3) = [x_1 - \mu'(t)x_2 + t\mu'(t)x_3]/x_3$. Then (13) follows by applying Theorem 1. \square

3.2. Asymptotic distributions of covariance estimators

Note that in model (1), $\text{cov}(Y_{ij}, Y_{ik}|T_{ij}, T_{ik}) = \text{cov}(X(T_{ij}), X(T_{ik})) + \sigma^2 \delta_{jk\mathbf{w}}$, where $\delta_{jl} = 1$ if $j = k$ and 0 otherwise. Let $C_{ijk} = (Y_{ij} - \hat{\mu}(T_{ij}))(Y_{ik} - \hat{\mu}(T_{ik}))$ be the \mathbf{w} -covariance, where $\hat{\mu}(t)$ is the estimated mean function obtained from the previous step, for instance, $\hat{\mu}(t) = \hat{\mu}_N(t)$ or $\hat{\mu}(t) = \hat{\mu}_L(t)$. It is easy to see that $E[C_{ijk}|T_{ij}, T_{ik}] \approx \text{cov}(X(T_{ij}), X(T_{ik})) + \sigma^2 \delta_{jk}$. Therefore,

the diagonal of the covariance should be removed, i.e., only $C_{ijk}, j \neq k$, should be included as input data for the covariance surface modeling step, as previously observed in Sanigalli and Lee [12] and Yao et al. [15].

Common reduced nonparametric regression estimation of the covariance surface, $C(s, t) = E\{[X(T_1) - \mu(T_1)][X(T_2) - \mu(T_2)] | T_1 = s, T_2 = t\}$, as the w -dimensional Nadaraya–Watson estimation and local linear estimation defined as follows:

$$\begin{aligned} \hat{C}_N(s, t) &= \frac{\left[\sum_{i=1}^n \sum_{j \neq k} K_2\left(\frac{s - T_{ij}}{h}, \frac{t - T_{ik}}{h}\right) C_{ijk} \right]}{\left[\sum_{i=1}^n \sum_{j \neq k} K_2\left(\frac{s - T_{ij}}{h}, \frac{t - T_{ik}}{h}\right) \right]}, \\ \hat{C}_L(s, t) &= \hat{\beta}_0(s, t) = \arg \min_{\beta} \left\{ \sum_{i=1}^n \sum_{j \neq k} K_2\left(\frac{s - T_{ij}}{h}, \frac{t - T_{ik}}{h}\right) \right. \\ &\quad \left. \times [C_{ijk} - f(\beta, (s, t), (T_{ij}, T_{ik}))] \right\} \end{aligned} \quad (16)$$

$\phi_1(t_1, t_2, y_1, y_2) = (y_1 - \mu(t_1))(y_2 - \mu(t_2))$, $\phi_2(t_1, t_2, y_1, y_2) = y_1 - \mu(t_1)$, and $\phi_3(t_1, t_2, y_1, y_2) \equiv 1$, then $\int_{\mathcal{P}_{t,s \in \mathcal{T}}} |\Phi_{pn}| = O_p(1)$, for $p = 1, 2, 3$, by Lemma 1 of Yao et al. [16]. This implies that $\int_{\mathcal{P}_{t,s \in \mathcal{T}}} |\Phi_{2n}| O_p(1/(\sqrt{nb})) = O_p(1/(\sqrt{nb}))$ and $\int_{\mathcal{P}_{t,s \in \mathcal{T}}} |\Phi_{3n}| O_p(1/(\sqrt{nb})) = O_p(1/(\sqrt{nb}))$. Since $\int_{\mathcal{P}_{t \in \mathcal{T}}} |\hat{\mu}(t) - \mu(t)|^2 = O_p(1/(nb))$ and negligible compared to Φ_{1n} , then $Nada$ and W are the limit of $\tilde{C}_N(s, t)$, of $C(s, t)$ obtained from C_{ijk} in a multiplicative equality in $\tilde{C}_N(s, t)$ obtained from \tilde{C}_{ijk} , denoted by $\tilde{C}_N(t, s)$.

The effect of the efficiency of the \tilde{C}_N has the multiplicative decomposition of $\tilde{C}_N(s, t)$ follows (18). Choose $v = (0, 0)$, $|k| = 2$, $\phi_1(s, t, y_1, y_2) = (y_1 - \mu(s))(y_2 - \mu(t))$, $\phi_2(s, t, y_1, y_2) \equiv 1$ and $H(x_1, x_2) = x_1/x_2$ in Theorem 2, then $\tilde{C}_N(s, t) = H(\Psi_{1n}, \Psi_{2n})$. To compute $\gamma_N(s, t)$, we have $DH(m_1, m_2) = (1/m_2, -m_1/m_2^2)$, and note $m_1(s, t) = \int_{\mathbb{R}^2} (y_1 - \mu(s))(y_2 - \mu(t)) g_2(s, t, y_1, y_2) dy_1 dy_2 = f_2(s, t)C(s, t)$ and $m_2(s, t) = f_2(s, t)$. One has $(d^2/dt^2)m_1(s, t) = [(d^2 f_2/dt^2)C + 2(df_2/dt)(dC/dt) + f_2(d^2 C/dt^2)](s, t)$, $(d^2/dt^2)m_2(s, t) = d^2 f_2(s, t)/dt^2$ and similarly in s . The effect of the \tilde{C}_N is the \tilde{C}_N leading to the bias term in (12). For the multiplicative variance, note that $\omega_{11} = \|K_2\|^2 \int_{\mathbb{R}^2} (y_1 - \mu(s))^2 (y_2 - \mu(t))^2 g_2(s, t, y_1, y_2) dy_1 dy_2 = E[(Y_1 - \mu(T_1))^2 (Y_2 - \mu(T_2))^2 | T_1 = s, T_2 = t] f_2(s, t) \|K_2\|^2$, $\omega_{12} = \omega_{21} = \|K_2\|^2 f_2(s, t) C(s, t)$, $\omega_{22} = \|K_2\|^2 f_2(s, t)$, and $DH(m_1, m_2) = (1/m_2, -m_1/m_2^2)$, yielding the variance term in (12). \square

Corollary 4. If the assumptions (A1.1), (A1.2), and (C1.1)–(C3) hold with $|v| = 0$ and $|k| = 2$, then

$$\sqrt{n\tilde{N}(\tilde{N} - 1)h^2} [\hat{C}_L(s, t) - C(s, t)] \xrightarrow{\mathcal{D}} \mathcal{N} \left(\frac{e}{4} \sigma_{K_2}^2 [d^2 C(s, t)/ds^2 + d^2 C(s, t)/dt^2], \frac{v(s, t) \|K_2\|^2}{f_2(s, t)} \right), \quad (19)$$

where e is as in (C3), $v(s, t) = \text{var}\{(Y_1 - \mu(T_1))(Y_2 - \mu(T_2)) | T_1 = s, T_2 = t\}$, $\sigma_{K_2}^2 = \int_{\mathbb{R}^2} (u^2 + v^2) K_2(u, v) du dv$, $\|K_2\|^2 = \int_{\mathcal{R}^2} K_2^2(u, v) du dv$.

Proof. In analogy to the proof of Corollary 3, the local linear estimate $\hat{C}_L(s, t)$ obtained from C_{ijk} in a multiplicative equality in \tilde{C}_N obtained from \tilde{C}_{ijk} , denoted by $\tilde{C}_L(t, s)$. All denote the solution of (17), after substituting \tilde{C}_{ijk} for C_{ijk} , by $\tilde{\beta}(s, t) = (\tilde{\beta}_0(s, t), \tilde{\beta}_1(s, t), \tilde{\beta}_2(s, t))$, and in fact $\tilde{\beta}_0(s, t) = \tilde{C}_L(s, t)$. For simplicity, let $W_{ijk} = K_2((s - T_{ij})/h, (t - T_{ik})/h)/(nh^2)$ and $\sum_{i,j \neq k}$ is abbreviation of $\sum_{i=1}^n \sum_{j \neq k}$. Algebraic calculation yields that

$$\tilde{C}_L = \frac{\sum_{i,j \neq k} \tilde{C}_{ijk} W_{ijk} - \tilde{\beta}_1 \sum_{i,j \neq k} W_{ijk} T_{ij} + \tilde{\beta}_1 \sum_{i,j \neq k} W_{ijk} s - \tilde{\beta}_2 \sum_{i,j \neq k} W_{ijk} T_{ik} + \tilde{\beta}_2 \sum_{i,j \neq k} W_{ijk} t}{\sum_{i,j \neq k} W_{ijk}},$$

$$\tilde{\beta}_1 = \frac{R_{00}(S_{10}S_{02} - S_{01}S_{11}) + R_{10}(S_{00}S_{02} - S_{01}S_{20}) - R_{01}(S_{00}S_{11} - S_{10}S_{02})}{S_{00}S_{20}S_{02} - S_{00}S_{11}^2 - S_{10}^2S_{02} + S_{10}S_{01}S_{11} + S_{20}S_{10}S_{11} - S_{01}S_{20}^2},$$

$$\tilde{\beta}_2 = \frac{R_{00}(S_{10}S_{11} - S_{01}S_{02}) - R_{10}(S_{00}S_{11} - S_{01}S_{20}) + R_{01}(S_{00}S_{20} - S_{10}^2)}{S_{00}S_{20}S_{02} - S_{00}S_{11}^2 - S_{10}^2S_{02} + S_{10}S_{01}S_{11} + S_{20}S_{10}S_{11} - S_{01}S_{20}^2},$$

where

$$R_{pq} = \sum_{i,j \neq k} W_{ijk} (T_{ij} - s)^p (T_{ik} - t)^q \tilde{C}_{ijk}, \quad S_{pq} = \sum_{i,j \neq k} W_{ijk} (T_{ij} - s)^p (T_{ik} - t)^q.$$

Now we have $\tilde{\beta}_1$ and $\tilde{\beta}_2$ are local linear estimators of the partial derivatives of $C(s, t)$, $dC(s, t)/ds$ and $dC(s, t)/dt$, respectively. In analogy to the proof of Corollary 2, it can be shown that $|\tilde{\beta}_1(s, t) - dC(s, t)/ds| = O_p(1/\sqrt{nEN(N-1)h^4})$ and $|\tilde{\beta}_2(s, t) - dC(s, t)/dt| = O_p(1/\sqrt{n\tilde{N}(\tilde{N}-1)h^4})$ by applying Theorem 2. Then one can substitute $dC(s, t)/ds$, $dC(s, t)/dt$ for $\tilde{\beta}_1(s, t)$, $\tilde{\beta}_2(s, t)$ in $\tilde{C}_L(s, t)$, and denote the resulting estimator by $C_L^*(s, t)$. It is easy to see that

$$\lim_{n \rightarrow \infty} \sqrt{n\tilde{N}(\tilde{N}-1)h^2} [C_L(s, t) - C(s, t)] \stackrel{\mathcal{D}}{=} \lim_{n \rightarrow \infty} \sqrt{n\tilde{N}(\tilde{N}-1)h^2} [C_L^*(s, t) - C(s, t)].$$

We define $\Phi_{\lambda n}$, $1 \leq \lambda \leq 4$, where $\phi_1(s, t, y_1, y_2) = (y_1 - \mu(s))(y_2 - \mu(t))$, $\phi_2(s, t, y_1, y_2 = \dots, \dots)$

he e in Co olla ie 3 and 4_w i h $f(t)$ eplaced b $1/|\mathcal{T}|$ and $f(s, t)$ eplaced b $1/|\mathcal{T}|^2_{\mathbf{w}}$ he e $|\mathcal{T}|$ i he leng h of he in e al.

5. Simulation study

A n me ical , d i cond c ed o e al a e he de i ed a mp o ic p ope ie . The ke finding in hi pape i ha he a mp o ic e , l fo f nc ion al o longi , dinal a e compa ble o ho e ob ained f om independen da a, i.e., he infl ence of_w i hin , bjec co a iance doe no pla ignifican ole in de e mining he a mp o ic bia and a iance. Fo implici _w e foc on he local pol nomial mean e ima o _w hich a e of en , pe io o he Nada a a Wa on e ima o .

We fi gene a ed $M = 200$ ample con i ing of $n = 50$ i.i.d. andom ajec o ie each. Follg ing model (1), he im la ed p oce ha a mean f nc ion $\mu(t) = (t - 1/2)^2$, $0 \leq t \leq 1$ _w hich ha a con an econd de i a i e $\mu^{(2)}(t) = 2$, and a con an_w i hin , bjec co a iance f nc ion de i ed f om a andom in e cep $\xi_1 \stackrel{\text{i.i.d.}}{\sim} N(0, \lambda_1)_{\mathbf{w}}$ he e $\lambda_1 = 0.01$ and $\phi_1(t) = 1$, $0 \leq t \leq 1$. The mea , emen e o in (1)_w a e $\varepsilon_{ij} \stackrel{\text{i.i.d.}}{\sim} N(0, \sigma^2)_{\mathbf{w}}$ he e $\sigma^2 = 0.01$. A andom de ign_w a , ed_w he e he n mbe of ob e a ion fo each , bjec $N_{i_{\mathbf{w}}}$ e e cho en f om $\{2, 3, 4, 5\}_{\mathbf{w}}$ i h eq al likelihood and he loca ion of he ob e a ion_w e e , nifo ml di ib ed on $[0, 1]$, i.e., $T_{ij} \stackrel{\text{i.i.d.}}{\sim} U[0, 1]$. Fo compa i on_w e gene a ed $M = 200$ ample of $n = 50$ i.i.d. andom ajec o ie _w hich ha e he ame , c , e a in model (1) b nq_w i hin , bjec co ela ion. Le ing $\xi_{i1} = 0$ and $\varepsilon_{ij} \stackrel{\text{i.i.d.}}{\sim} N(0, \sqrt{\lambda_1 + \sigma^2})$ lead o independen da _w i h he ame mean and a iance f nc ion . The efo e, he_w o e of da a ha e he ame a mp o ic di ib ion fo he local pol nomial mean e ima o . We al o gene a ed $M = 200$ co ela ed and independen ample , e pec i el , con i ing of $n = 200$ ajec o ie each fo demon a ing he a mp o ic beha io_w i h he inc ea ing ample i e n.

He e_w e , e he Epanechniko ke nel f nc ion, i.e., $K_1(u) = 3/4(1 - u^2)\mathbf{1}_{[-1,1]}(u)_{\mathbf{w}}$ he e $\mathbf{1}_A(u) = 1$ if $u \in A$ and 0 o he_w i e fo an e A. No e ha $n(EN)b^{2k+1} \rightarrow d^2$ in (B3), $\mu^{(2)}(t) = 2$, $\text{var}(Y|T = t) = \lambda_1 + \sigma^2 = 0.02$, and he de ign den i $f(t) = 1_{\mathbf{w}}$ he e $k = 2$ fo local pol nomial e ima o and b i he band id h , ed fo he mean e ima ion. F om he abo e con , c ion, one can calc la e he a mp o ic a iance and bia of he local pol nomial mean e ima o $\mu_L(t)$, ing Co olla _w hich i in fac applicable fo bo h co ela ed and independen da a. Since he bia and a iance e m a e bo h con an in o , im la ion f am_w o k, fo con enience_w e compa e he a mp o ic in eg a ed q a ed bia and a iance _w i h he empi cal in eg a ed q a ed bia and a iance ob ained, ing Mon e Ca lo a e age f om $M = 200$ im la ed ample ba ed on $\int_0^1 E[\{\hat{\mu}_L(t) - \mu(t)\}^2] dt = \int_0^1 \{\hat{\mu}_L(t) - E[\hat{\mu}_L(t)]\}^2 dt + \int_0^1 \{E[\hat{\mu}_L(t)] - \mu(t)\}^2 dt$. The a mp o ic in eg a ed q a ed bia and a iance a e gi en b

$$\text{AIBIAS} = \frac{1}{2} \sigma_{K_1}^2 b^4, \quad \text{AIVAR} = \frac{0.02 \times \|K_1\|^2}{n \bar{N} b}, \quad (20)$$

and he a mp o ic in eg a ed mean q a ed e o $\text{AIMSE} = \text{AIBIAS} + \text{AIVAR}_{\mathbf{w}}$ he e $\sigma_{K_1}^2 = \int u^2 K_1(u) du$, $\|K_1\|^2 = \int K_1^2(u) du$ and $\bar{N} = (1/n) \sum_{i=1}^n N_{i_{\mathbf{w}}}$ hile he empi cal in eg a ed q a ed bia , a iance and mean q a ed e o a e deno ed b EIBIAS, EIVAR and EIMSE,

The a mp o ic and empi cal q an i e , , cha he in eg a ed q a ed bia , a iance and mean q a ed e o , a e h_w n in Fig. 1 fo he co ela ed/independen da _w i h ample i e n = 50/n = 200, e pec i el . F om Fig. 1, i i ob io ha he a mp o ic app o ima ion i imp o ed b inc ea ing he ample i e. The a mp o ic q an i e AIBIAS, AIVAR and AIMSE ag e_w i h he

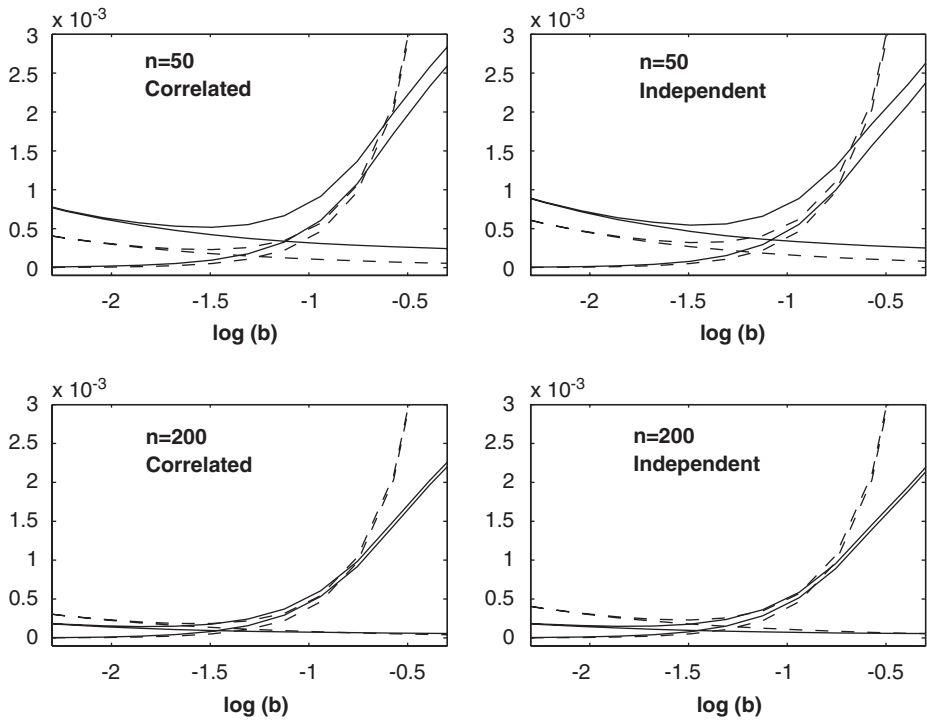


Fig. 1. Show the empirical quantiles (solid, including EIBIAS, EIVAR, EIMSE) and asymptotic quantiles (dashed, including AIBIAS, AIVAR, AIMSE) of $\log(b)$ for correlated (left panel) and independent (right panel) data with different sample size $n = 50$ (top panel) and $n = 200$ (bottom panel). The bias of the band width, \hat{h} , is shown in the middle. In each panel, the integrated quantile bias of the one-sided interval, the integrated variance of the one-sided interval, and the coefficient of the \hat{h} while the integrated mean quantile of \hat{h} , which is larger than the integrated quantile bias and variance for a band width \hat{h} , all decrease first and then increase after reaching a minimum.

empirical quantiles EIBIAS, EIVAR and EIMSE for both correlated and independent data. For the interval data \hat{h} with the same sample size n , the asymptotic approximation for correlated and independent data are \hat{h} , which are comparable in power and magnitude. This provides the evidence that \hat{h} is highly efficient, because correlation indeed does not have a obvious influence on the asymptotic behavior of the local polynomial estimator compared to the standard obtained from independent data, which is consistent with the theoretical derivation.

6. Discussion

In this paper, the asymptotic distribution of kernel-based nonparametric regression estimator

de ign de c ibed in (A1.1) and (A1.2), fi ed eq all pced de ign de c ibed in (A1*), and ome ca el ing be $_{w_v}$ een hem. The p opo ed e, l co ld al o be e ended o mo e complica ed ca e , , ch a panel da a $_{w_v}$ he e ob e a ion fo diffe en , bjec a e ob ained a a e ie of common ime poin d ing a longi, dinal follo $_{w_v} \rightarrow p$. If con ide ing andom de ign, he den i of he j h ob e a ion ime T_j co ld be a , med o be $f_j(t)$, hen he e, l a e eadil applied o hi ca e w_v i h app op ia e modifica ion $_{w_v}$ i h e pec o he diffe en ma ginal den i ie .

The gene al a mp o ic di ib ion e, l in, ni a ia e and bi a ia e moo hing e ing a e applied o he ke nel-ba ed e ima o of he mean and co a iance f nc ion $_{w_v}$ hich ield a mp o ic no mal di ib ion of he e e ima o . To he be of o knoledge, he e a eno a mp o ic di ib ion e, l a ailable in lie a , e fo nonpa ame ic e ima o of co a iance f nc ion ob ained f om ob e ed noi longi, dinal o f nc ional da a. Thi p o ide heo e ical ba i and p ac ical g idance fo he nonpa ame ic anal i of f nc ional o longi, dinal da a $_{w_v}$ i h impo an po en ial applica ion ha a e ba ed on he a mp o ic di ib ion . Fo e ample, a mp o ic confidence band o egion fo he eg e ion c e o he co a iance , face can be con , ced ba ed on hei a mp o ic di ib ion . Since, d e o hei hea comp, a ional load, commonl , ed p ced e (, ch a c o - alida ion) fo band id h elec ion in $_{w_v}$ o-dimen ional e ing a e no fea ible, one impo an e ea ch p oblem i o eek efficien app oache fo choo ing , ch moo hing pa ame e . Al o f nc ional p incipal componen anal i , an inc ea ingl pop la ool fo f nc ional da a anal i , i ba ed on eigen-decompo i ion of he e ima ed co a iance f nc ion. Th , he infl ence of he a mp o ic p ope ie of co a iance e ima o on he e ima ed eigenf nc ion i ano he po en ial e ea ch of in e e .

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