

# Functional Additive Models

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 2. 在下列各数中，哪些是质数？哪些是合数？  
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$\mathcal{E} = \{E_1, E_2, \dots, E_n\}$  is a set of events,  $\mathcal{P} = \{P_1, P_2, \dots, P_m\}$  is a set of processes,  $\mathcal{C} = \{C_1, C_2, \dots, C_k\}$  is a set of channels,  $\mathcal{S} = \{S_1, S_2, \dots, S_l\}$  is a set of signals,  $\mathcal{M} = \{M_1, M_2, \dots, M_p\}$  is a set of messages,  $\mathcal{D} = \{D_1, D_2, \dots, D_q\}$  is a set of data,  $\mathcal{R} = \{R_1, R_2, \dots, R_r\}$  is a set of resources,  $\mathcal{V} = \{V_1, V_2, \dots, V_s\}$  is a set of variables,  $\mathcal{F} = \{F_1, F_2, \dots, F_t\}$  is a set of functions,  $\mathcal{G} = \{G_1, G_2, \dots, G_u\}$  is a set of graphs,  $\mathcal{H} = \{H_1, H_2, \dots, H_v\}$  is a set of hypotheses,  $\mathcal{I} = \{I_1, I_2, \dots, I_w\}$  is a set of instances,  $\mathcal{J} = \{J_1, J_2, \dots, J_x\}$  is a set of jobs,  $\mathcal{K} = \{K_1, K_2, \dots, K_y\}$  is a set of keys,  $\mathcal{L} = \{L_1, L_2, \dots, L_z\}$  is a set of languages,  $\mathcal{N} = \{N_1, N_2, \dots, N_a\}$  is a set of networks,  $\mathcal{O} = \{O_1, O_2, \dots, O_b\}$  is a set of operations,  $\mathcal{Q} = \{Q_1, Q_2, \dots, Q_c\}$  is a set of queries,  $\mathcal{R} = \{R_1, R_2, \dots, R_d\}$  is a set of relations,  $\mathcal{S} = \{S_1, S_2, \dots, S_e\}$  is a set of sets,  $\mathcal{T} = \{T_1, T_2, \dots, T_f\}$  is a set of trees,  $\mathcal{U} = \{U_1, U_2, \dots, U_g\}$  is a set of units,  $\mathcal{V} = \{V_1, V_2, \dots, V_h\}$  is a set of values,  $\mathcal{W} = \{W_1, W_2, \dots, W_i\}$  is a set of weights,  $\mathcal{X} = \{X_1, X_2, \dots, X_j\}$  is a set of variables,  $\mathcal{Y} = \{Y_1, Y_2, \dots, Y_k\}$  is a set of variables,  $\mathcal{Z} = \{Z_1, Z_2, \dots, Z_l\}$  is a set of variables.

additive model ( $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$ ),

where  $Y$  is the response variable,  $m$  is the number of covariates,  $K$  is the number of clusters, and  $M$  is the number of subjects in each cluster.

### 3. Model Assumptions

Assumption 1. The response variable  $Y$  is continuous and the covariates  $X$  are discrete. The joint distribution of  $Y$  and  $X$  is bivariate normal.

$$E(Y - \mu_Y | X) = b_k(X) \quad E(X | Y) = b_{km}(Y) \quad (1)$$

where  $b_k(X)$  and  $b_{km}(Y)$  are the conditional expectation functions of  $Y$  given  $X$  and  $X$  given  $Y$ , respectively.

Assumption 2. The joint distribution of  $Y$  and  $X$  is bivariate normal.

Assumption 3. The joint distribution of  $Y$  and  $X$  is bivariate normal.

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Assumption 19. The joint distribution of  $Y$  and  $X$  is bivariate normal.

Assumption 20. The joint distribution of  $Y$  and  $X$  is bivariate normal.

Assumption 21. The joint distribution of  $Y$  and  $X$  is bivariate normal.

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Assumption 24. The joint distribution of  $Y$  and  $X$  is bivariate normal.

Assumption 25. The joint distribution of  $Y$  and  $X$  is bivariate normal.

Assumption 26. The joint distribution of  $Y$  and  $X$  is bivariate normal.

Assumption 27. The joint distribution of  $Y$  and  $X$  is bivariate normal.

$$E(X | Y) = E\{E(X | Y) | Y\} \\ = E\left\{\sum_{j=1}^{\infty} f_{jm}(j) | Y\right\} = f_{km}(Y). \quad (2)$$

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$$\{\hat{y}_{ik}, \hat{y}_{im}\}_{i=1, \dots, n} \text{ and } \hat{y}_{ik} = \hat{y}_{im} = (x - \hat{y}_{ik}) \quad (1)$$

$$\hat{f}_{mk}(x) = \hat{f}_k(x) \quad (2)$$

$$\hat{E}(Y|X) = \bar{Y} + \sum_{k=1}^K \hat{f}_k(x) \quad (3)$$

$$R = - \frac{\sum_{i=1}^n \{Y_i - E(Y_i|X_i)\}}{\sum_{i=1}^n (Y_i - \mu_Y)} \quad (4)$$

$$\hat{R} = - \frac{\sum_{i=1}^n \{Y_i - \hat{E}(Y_i|X_i)\}}{\sum_{i=1}^n (Y_i - \bar{Y})} \quad (5)$$

$$\hat{E}(Y(t)|X) = \hat{\mu}_Y(t) + \sum_{m=1}^M \sum_{k=1}^K \hat{f}_{mk}(x) \hat{g}_m(t), \quad t \in \mathcal{T} \quad (6)$$

$$R = - \frac{\sum_{i=1}^n \int [Y_i(t) - E\{Y_i(t)|X_i\}] dt}{\sum_{i=1}^n \int \{Y_i(t) - \mu_Y(t)\} dt} \quad (7)$$

$$\hat{R} = - \frac{\sum_{i=1}^n \sum_{l=1}^{m_l} [V_{il} - \hat{E}\{Y_i(t_{il})|X_i\}] (t_{il} - t_{i,l-})}{\sum_{i=1}^n \sum_{l=1}^{m_l} \{V_{il} - \mu_Y(t_{il})\} (t_{il} - t_{i,l-})} \quad (8)$$

$$\hat{E}(Y_i(t)|X_i) = \hat{E}\{Y_i(t)|X_i\} \quad (9)$$

## 5. A

$$\begin{aligned} & \hat{y}_{ik}, \hat{y}_{im} = \hat{y}_{im}, k = 1, \dots, K, m = 1, \dots, M, \\ & \hat{f}_k = \hat{f}_{km} \end{aligned} \quad (10)$$

$$\{\hat{y}_{ik}, Y_i\} = \{\hat{y}_{ik}, \hat{y}_{im}\} \quad i = 1, \dots, n \quad (11)$$

$$K(n) \rightarrow \infty, \quad M = M(n) \rightarrow \infty \quad (12)$$

$$Theorem 1. \quad (13)$$

$$\hat{f}_k(x) - f_k(x) \xrightarrow{P} 0 \quad (14)$$

$$k \geq j, j \leq k \quad (15)$$

$$\hat{f}_{km}(x) - f_{km}(x) \xrightarrow{P} 0 \quad (16)$$

$$\hat{f}_k(x) - f_k(x) \xrightarrow{P} 0 \quad (17)$$

$$\hat{f}_{mk}(x) - f_{mk}(x) \xrightarrow{P} 0 \quad (18)$$

$$Theorem 2. \quad (19)$$

$$\hat{E}(Y|X) - E(Y|X) \xrightarrow{P} 0 \quad (20)$$

$$\hat{E}(Y|X) = \bar{Y} + \sum_{k=1}^K \hat{f}_k(x) \quad (21)$$

$$\hat{E}\{Y(t)|X\} - E\{Y(t)|X\} \xrightarrow{P} 0 \quad (22)$$

$$\hat{E}\{Y(t)|X\} = \hat{\mu}_Y(t) + \sum_{k=1}^K \sum_{m=1}^M \hat{f}_{mk}(x) \hat{g}_m(t) \quad (23)$$

$$|\hat{E}(Y|X) - E(Y|X)| \xrightarrow{n} 0 \quad (24)$$

## 6. A

$$\begin{aligned} & X_i = \mu_X(s) + \epsilon_i(s), \quad s \leq s \leq \\ & \epsilon_i(s) = -(\epsilon_i(s)/\sqrt{\epsilon_i(s)}) \quad \epsilon_i(s) = (\epsilon_i(s)/\sqrt{\epsilon_i(s)}) \leq \\ & s \leq \epsilon_i(s) = k \geq \epsilon_i(s) \quad (25) \\ & ij \sim (\epsilon_i(s)) \quad (26) \\ & ik \sim \mathcal{N}(\epsilon_i(s), k) \quad (27) \\ & k = \epsilon_i(s) \quad (28) \end{aligned}$$

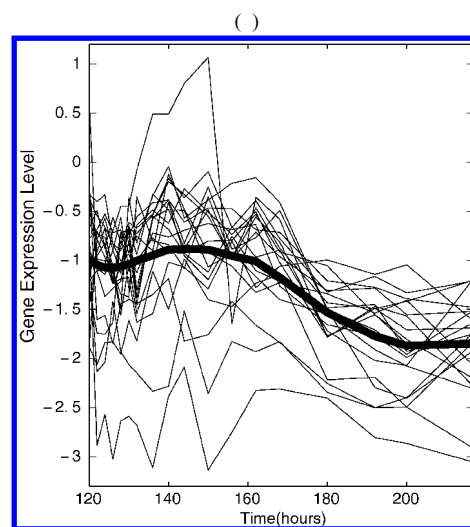
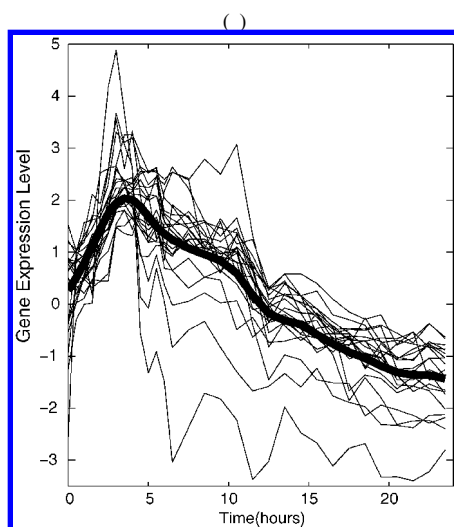


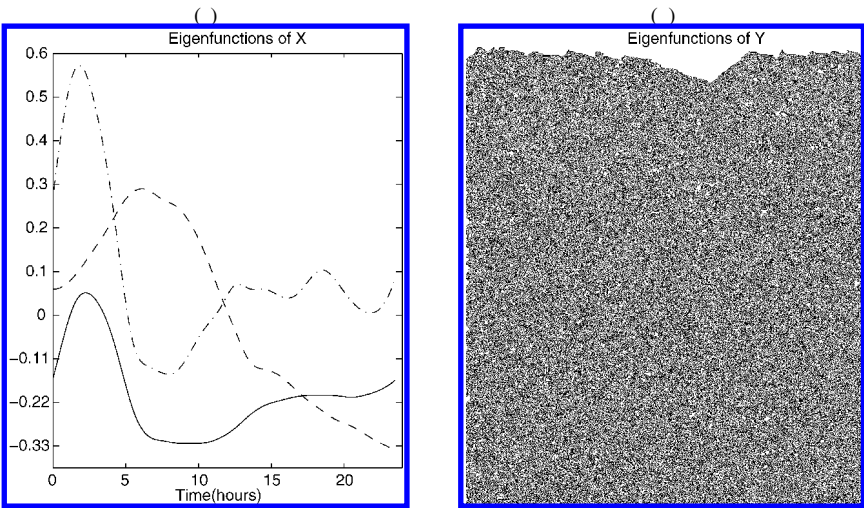
$$f(x) = \frac{1}{2} \left( \frac{1}{2} + \frac{1}{2} \right) = \frac{1}{2} \quad \text{for } x = \frac{1}{2}.$$
[illegible]
$$y_E = y - \frac{1}{n} \sum_{j=1}^n y_j = y - \bar{y}$$

7. A A X  
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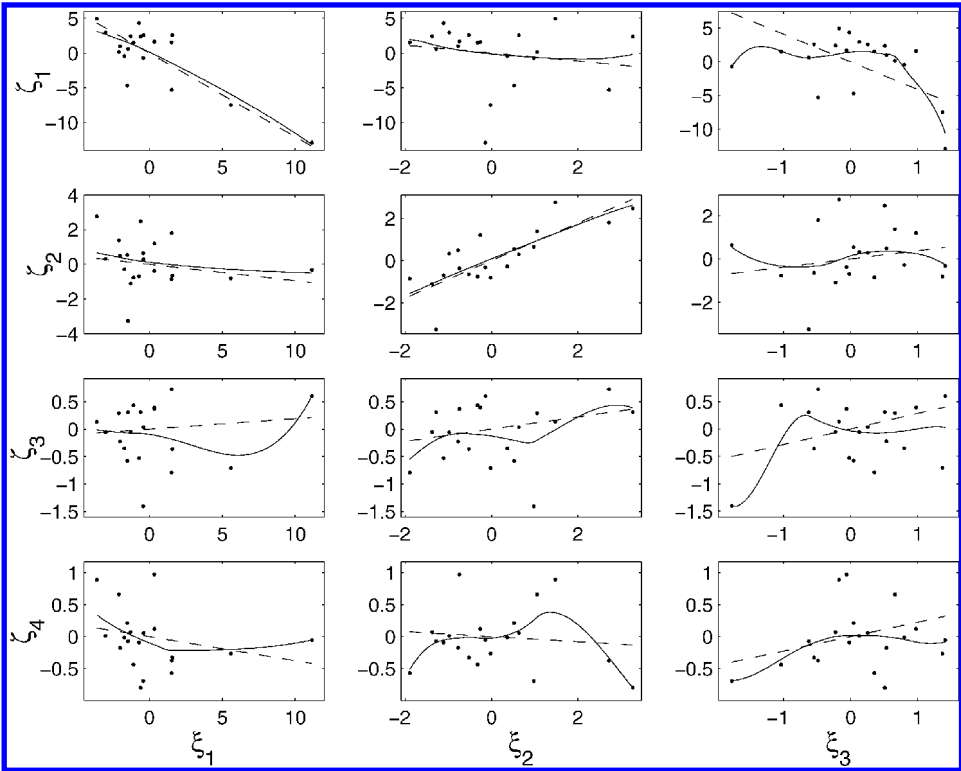
$n =$

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... ( ) ...  $\hat{y}$  ...  $K =$  ...  $M =$  ...

...  $\hat{y}$  ...  $y$  ...  $y$  ...



... ( ) ...  $y$  ...  $\hat{y}$  ...  $(m, m = , , , )$  ...







$$h_X^* \quad a = \{s \mid s \in \mathcal{S}\}, b = \{s \mid s \in \mathcal{S}\}, \\ |\mathcal{S}| = b - a, \quad \mathcal{S} = [a + |\mathcal{S}|/2, b - |\mathcal{S}|/2] \quad X$$

$$\hat{X} = \int \{ \widehat{V}_X(s) - \widetilde{G}_X(s) \} ds / |\mathcal{S}| \quad (3.1)$$

$$\hat{X} > \hat{X} = \mathbb{E} \left[ \sum_{k \geq 1} \left( \hat{k}, \hat{k} \right) \right]$$



# Supplement for “Functional Additive Models”

## 1. NOTATIONS AND AUXILIARY RESULTS

Consequently, we denote by  $G_{\mathbf{X}}, \widehat{G}_{\mathbf{X}}$ , respectively by  $G_{\mathbf{Y}}, \widehat{G}_{\mathbf{Y}}$  the  
 $G_{\mathbf{X}}(s) = \int_{\mathcal{T}} G_{\mathbf{X}}(s, t) f(t) ds, \widehat{G}_{\mathbf{X}}(s) = \int_{\mathcal{T}} \widehat{G}_{\mathbf{X}}(s, t) f(t) ds$  for any  $f \in L^2(\mathcal{T})$  where  
 $D_{\mathbf{X}} = \int_{\mathcal{T}^2} \{\widehat{G}_{\mathbf{X}}(s, t) - G_{\mathbf{X}}(s, t)\}^2 ds dt, \quad \delta_{\mathbf{k}}^{\mathbf{x}} = \max_{1 \leq j \leq K} |\lambda_j - \lambda_{j+1}|,$   
 $K_0 = \inf\{j \geq 1 : \lambda_j - \lambda_{j+1} \leq D_{\mathbf{X}}\} - 1, \quad \pi_{\mathbf{k}}^{\mathbf{x}} = \lambda_{\mathbf{k}} - \lambda_{\mathbf{k}+1} / \lambda_{\mathbf{k}} - \lambda_{\mathbf{k}+1} / \delta_{\mathbf{k}}^{\mathbf{x}}.$

Let  $K = K_n$  denote the number of eigenfunctions needed to approximate  $X$  in the  $L^2$  norm; i.e.,  $\widehat{X}_i(s) = \mu_{\mathbf{X}}(s) + \sum_{k=1}^K \xi_{ik} \phi_k(s)$ . Analogously, define the eigenfunctions  $G_{\mathbf{Y}}, \widehat{G}_{\mathbf{Y}}, D_{\mathbf{Y}}, \delta_{\mathbf{m}}^{\mathbf{y}}, \pi_{\mathbf{m}}^{\mathbf{y}}, M_0$  and  $M$  for the process  $Y$ , for the case of functional responses where  $n$  is the number of observations. In the following, we develop the proof of the

**Lemma 1** Under  $A_1, A_2, C_1, C_2$  and  $C_3$

$\sup_{t \in \mathcal{S}} |\mu_{\mathbf{X}}(s) - \mu_{\mathbf{X}}(s)| = O_p(\frac{1}{\sqrt{nb_{\mathbf{X}}}}), \sup_{s_1, s_2 \in \mathcal{S}} |\widehat{G}_{\mathbf{X}}(s_1, s_2) - G_{\mathbf{X}}(s_1, s_2)| = O_p(\frac{1}{\sqrt{nh_{\mathbf{X}}^2}}),$   
and as a consequence  $\sigma_{\mathbf{X}}^2 - \sigma_{\mathbf{X}}^2 = O_p(n^{-1/2} h_{\mathbf{X}}^{-2}) = n^{-1/2} h_{\mathbf{X}}^*.$  Considering eigenvalues  $\lambda_{\mathbf{k}}$  of, typically one  $\phi_{\mathbf{k}}$  can be chosen such that

$P(\sup_{1 \leq k \leq K_0} |\lambda_{\mathbf{k}} - \lambda_{\mathbf{k}}| \leq D_{\mathbf{X}}) \rightarrow 1, \sup_{s \in \mathcal{S}} |\phi_{\mathbf{k}}(s) - \phi_{\mathbf{k}}(s)| = O_p(\frac{\pi_{\mathbf{k}}^{\mathbf{x}}}{\sqrt{nh_{\mathbf{X}}^2}}), k = 1, \dots, K_0,$   
here  $D_{\mathbf{X}} = \pi_{\mathbf{k}}^{\mathbf{x}}$  and  $K_0$  are defined in (1).

Analogously under  $B_1, B_2, C_1, C_2$  and  $C_3$

$\sup_{t \in \mathcal{T}} |\mu_{\mathbf{Y}}(t) - \mu_{\mathbf{Y}}(t)| = O_p(\frac{1}{\sqrt{nb_{\mathbf{Y}}}}), \sup_{t_1, t_2 \in \mathcal{T}} |\widehat{G}_{\mathbf{Y}}(t_1, t_2) - G_{\mathbf{Y}}(t_1, t_2)| = O_p(\frac{1}{\sqrt{nh_{\mathbf{Y}}^2}}),$   
and as a consequence  $\sigma_{\mathbf{Y}}^2 - \sigma_{\mathbf{Y}}^2 = O_p(n^{-1/2} h_{\mathbf{Y}}^{-2}) = n^{-1/2} h_{\mathbf{Y}}^*.$  Considering eigenvalues  $\rho_{\mathbf{m}}$  of, typically one  $\psi_{\mathbf{m}}$  can be chosen such that

$P(\sup_{1 \leq m \leq M_0} |\rho_{\mathbf{m}} - \rho_{\mathbf{m}}| \leq D_{\mathbf{Y}}) \rightarrow 1, \sup_{t \in \mathcal{T}} |\psi_{\mathbf{m}}(t) - \psi_{\mathbf{m}}(t)| = O_p(\frac{\pi_{\mathbf{m}}^{\mathbf{y}}}{\sqrt{nh_{\mathbf{Y}}^2}}), m = 1, \dots, M_0,$

here  $D_{\mathbf{Y}} = \pi_{\mathbf{k}}^{\mathbf{Y}}$  and  $M_0$  are denoted analogous to  $\mathcal{M}$  for process  $Y$

and  $\|f\|_{\infty} = \sup_{\mathbf{x} \in \mathcal{A}} |f(\mathbf{x})|$  for any function  $f$  on  $\mathcal{A}$ , and  $\|g\| = \sqrt{\int_{\mathcal{A}} g^2 dt}$  for any  $g \in L^2(\mathcal{A})$  and define

$$\begin{aligned} \theta_{\mathbf{ik}}^{(1)} &= c_1 \|X_{\mathbf{i}}\| + c_2 \|X_{\mathbf{i}} X'_{\mathbf{i}}\|_{\infty}^* + c_3, & Z_{\mathbf{k}}^{(1)} &= \sup_{\mathbf{s} \in \mathcal{S}} |\phi_{\mathbf{k}}(\mathbf{s}) - \phi_{\mathbf{k}}(\mathbf{s}')|, \\ \theta_{\mathbf{ik}}^{(2)} &= \|\phi_{\mathbf{k}} \phi'_{\mathbf{k}}\|_{\infty}^*, & Z_{\mathbf{k}}^{(2)} &= \sup_{\mathbf{s} \in \mathcal{S}} |\mu_{\mathbf{X}}(\mathbf{s}) - \mu_{\mathbf{X}}(\mathbf{s}')|, \\ \theta_{\mathbf{ik}}^{(3)} &= c_4 \|X_{\mathbf{i}}\|_{\infty} + c_5 \|X'_{\mathbf{i}}\|_{\infty} + c_6, & Z_{\mathbf{k}}^{(3)} &= \|\phi'_{\mathbf{k}}\|_{\infty}^*, \\ \theta_{\mathbf{ik}}^{(4)} &= |\sum_{j=2}^{n_i} \epsilon_{ij} \phi_{\mathbf{k}}(s_{ij}) - s_{i,j-1}|, & Z_{\mathbf{k}}^{(4)} &= \mathbb{E}, \\ \theta_{\mathbf{ik}}^{(5)} &= \sum_{j=2}^{n_i} |\epsilon_{ij}| |s_{ij} - s_{i,j-1}|, & k & \end{aligned}$$

**Lemma 2** For  $\theta_{\mathbf{ik}}^{()}$ ,  $Z_{\mathbf{k}}^{()}$ ,  $v_{\mathbf{im}}^{()}$  and  $Q_{\mathbf{m}}^{()}$  as defined in (1) and (2)

$$|\xi_{\mathbf{ik}}^{\mathbf{l}} - \xi_{\mathbf{ik}}| \leq \sum_{=1}^5 \theta_{\mathbf{ik}}^{(\cdot)} Z_{\mathbf{k}}^{(\cdot)}, \quad |\zeta_{\mathbf{im}}^{\mathbf{l}} - \zeta_{\mathbf{im}}| \leq \sum_{=1}^5 \vartheta_{\mathbf{im}}^{(\cdot)} Q_{\mathbf{m}}^{(\cdot)}.$$

The proof is on the one hand by the steps in the C  
e,  $\xi_{ik}$  and  $\zeta_{im}$

and the dependence of  $\mathbf{A}$  and  $\mathbf{d}$  on  $h_{\mathbf{k}}$  and  $h_{\mathbf{mk}}$  are played on  $\mathbf{A}$  and  $\mathbf{d}$  as  $f_{\mathbf{k}}$  and  $f_{\mathbf{mk}}$  for the reason on  $f_{\mathbf{k}}$  and  $f_{\mathbf{mk}}$ , and the density of  $\xi_{\mathbf{k}}$  is denoted by  $p_{\mathbf{k}}$  as the

$$\begin{aligned} \theta_{\mathbf{k}} & p_{\mathbf{k}} \left\{ \frac{\pi_{\mathbf{k}}^{\mathbf{x}}}{\sqrt{nh_{\mathbf{x}}^2}} \right\} \frac{\sqrt{\mathbf{x}}}{\sqrt{nb_{\mathbf{x}}}} \sqrt{\mathbf{x}^*}, \\ \vartheta_{\mathbf{mk}} & p_{\mathbf{k}} \left\{ \frac{\pi_{\mathbf{m}}^{\mathbf{y}}}{\sqrt{nh_{\mathbf{y}}^2}} \right\} \frac{\sqrt{\mathbf{y}}}{\sqrt{nb_{\mathbf{y}}}} \sqrt{\mathbf{y}^*}. \end{aligned}$$

The convergence  $\|u_{\theta_k} - u_{\theta_{k+1}}\|_{\mathcal{H}} \rightarrow 0$  and  $\|u_{\theta_k} - u_{\theta_{k+1}}\|_{\mathcal{H}} \rightarrow 0$  of the sequence  $\{u_{\theta_k}\}_{k=0}^{\infty}$  and  $\{f_{\theta_k}\}_{k=0}^{\infty}$  follows from the fact that  $\{u_{\theta_k}\}_{k=0}^{\infty}$  and  $\{f_{\theta_k}\}_{k=0}^{\infty}$  are bounded in  $\mathcal{H}$  and  $\mathcal{F}$  respectively.

$$\begin{aligned} & \theta_{\mathbf{k}} \frac{\partial}{\partial h_{\mathbf{k}}} - |f''_{\mathbf{k}}| h_{\mathbf{k}}^2 \sqrt{\frac{4|Y[x]| \|K_1\|^2}{p_{\mathbf{k}} n h_{\mathbf{k}}}}, \\ & \vartheta_{\mathbf{mk}} \frac{\partial}{\partial h_{\mathbf{mk}}} - |f''_{\mathbf{mk}}| h_{\mathbf{mk}}^2 \sqrt{\frac{4|\zeta_{\mathbf{m}}[x]| \|K_1\|^2}{p_{\mathbf{k}} n h_{\mathbf{mk}}}}. \end{aligned}$$

Consider the prediction  $\hat{E}[Y|X]$  for the sample  $\mathcal{S}$  and  $\hat{E}\{Y^*|X\}$  for the function response, where  $\mathcal{S}$  is of size  $n$  and  $M$  is used for approximation. We need to process  $X$  and  $Y$  independently. As the size  $n$  increases, we have  $K \leq K_0$  and  $M \leq M_0$  in  $\mathcal{A}$  since for  $\mathcal{S}$  of size  $K_0 \rightarrow \infty$ ,  $\mathcal{S}$  contains  $\lambda_j$  of  $\mathcal{P}$  and  $\mathcal{M}$  of  $\mathcal{S}$  for  $M_0$ ,  $\mathcal{S}$  contains  $\mathcal{C}$  and  $\mathcal{E}$  of  $\mathcal{P}$  and  $\mathcal{N}$  and  $\mathcal{N}_k = \{1, \dots, k\}$ . Consequently,  $\theta_n^*$  and  $\vartheta_n^*$  for the prediction and

$$\mathbf{r}_k^* = \mathbf{e}_k^* f_0$$

$$\theta_{\mathbf{n}}^* = \sum_{\mathbf{k}=1}^{\mathbf{K}} \left\{ \frac{\theta_{\mathbf{k}} \xi_{\mathbf{k}}}{h_{\mathbf{k}}} - |f''_{\mathbf{k}} \xi_{\mathbf{k}}| h_{\mathbf{k}}^2 \sqrt{\frac{\zeta_{\mathbf{Y}} |\xi_{\mathbf{k}}| \|K_1\|^2}{p_{\mathbf{k}} \xi_{\mathbf{k}} n h_{\mathbf{k}}}} \right\} + \left| \sum_{\mathbf{k} \geq \mathbf{K}+1} f_{\mathbf{k}} \xi_{\mathbf{k}} \right|,$$

$$\vartheta_{\mathbf{n}}^* = \sum_{\mathbf{k}=1}^{\mathbf{K}} \sum_{\mathbf{m}=1}^{\mathbf{M}} \left\{ \frac{\theta_{\mathbf{k}} \xi_{\mathbf{k}}}{h_{\mathbf{mk}}} \vartheta_{\mathbf{mk}} \xi_{\mathbf{k}} |\psi_{\mathbf{m}}| - |f''_{\mathbf{mk}} \xi_{\mathbf{k}}| \psi_{\mathbf{m}} | h_{\mathbf{mk}}^2 \sqrt{\frac{\zeta_{\mathbf{m}} |\xi_{\mathbf{k}}| \|K_1\|^2}{p_{\mathbf{k}} \xi_{\mathbf{k}} n h_{\mathbf{k}}}} |\psi_{\mathbf{m}}| \right. \\ \left. \frac{\pi_{\mathbf{y}}^{\mathbf{y}} |f_{\mathbf{mk}} \xi_{\mathbf{k}}|}{\pi_{\mathbf{y}}^{\mathbf{y}} |f_{\mathbf{mk}} \xi_{\mathbf{k}}|} \right\}$$

Now in  $\xi_{ik} - \eta_{ik} - \tau_{ik}$ , one find

$$|\xi_{ik} - \xi_{ik}| \leq \{|\eta_{ik} - \eta_{ik}| + |\eta_{ik} - \xi_{ik}| + |\tau_{ik}|\}.$$

Moreover, since  $\|\phi_k\|_\infty \geq r$ ,  $\|\phi'_k\|_\infty \geq r$ ,  $\|X_i\|_\infty \geq r$  and  $\|X'_i\|_\infty \geq r$ ,  $\theta_{ik}^{(1)}$  and  $Z_k^{(1)}$ ,  $\ell = 1, \dots, p$ , the first term on the RHS of (2.10) is bounded by

$$\begin{aligned} & \left\{ \sum_{j=2}^{n_i} |X_i(s_{ij}) - \mu(s_{ij})| \cdot |\phi_k(s_{ij}) - \phi_k(s_{ij})| + |\mu(s_{ij}) - \mu(s_{ij})| \cdot |\phi_k(s_{ij})| |s_{ij} - s_{i,j-1}| \right\} \\ & \leq \left\{ \sum_{j=1}^{n_i} |X_i(s_{ij})| + |\mu(s_{ij})| r^2 |s_{ij} - s_{i,j-1}| \right\}^{1/2} \left\{ \sum_{j=2}^{n_i} \phi_k(s_{ij}) - \phi_k(s_{ij})^2 |s_{ij} - s_{i,j-1}| \right\}^{1/2} \\ & \quad \left\{ \sum_{j=1}^{n_i} \mu(s_{ij}) - \mu(s_{ij})^2 |s_{ij} - s_{i,j-1}| \right\}^{1/2} \left\{ \sum_{j=2}^{n_i} \phi_k^2(s_{ij}) |s_{ij} - s_{i,j-1}| \right\}^{1/2} \\ & \leq \theta_{ik}^{(1)} Z_k^{(1)} + \theta_{ik}^{(2)} Z_k^{(2)}. \end{aligned}$$

The second term on the RHS of (2.10) is of the type

$$|\eta_{ij} - \xi_{ik}| \leq \|X_i - \mu' \phi_k - X_i - \mu' \phi_k\|_\infty \leq \theta_{ik}^{(3)} Z_k^{(3)}.$$

Moreover, the third term on the RHS of (2.10) is bounded by  $\theta_{ik}^{(4)} Z_k^{(4)} + \theta_{ik}^{(5)} Z_k^{(5)}$ .

□

*Proof of Theorem 2.1.* For simplicity, denote  $\sum_{i=1}^n Y_i = \sum_i Y_i$ ,  $w_i = K_1\{(x - \xi_{ik})/h_k\}/nh_k$ ,  $w_i = K_1\{(x - \xi_{ik})/h_k\}/nh_k$ , and let  $\theta_k = \theta_k(x)$  denote the local density of  $f_k(x)$  of the data on which  $f_k(x)$  can be predicted.

$$f_k(x) = \frac{\sum_i w_i Y_i}{\sum_i w_i} - \frac{\sum_i w_i \xi_{ik} - x}{\sum_i w_i} f'_k(x),$$

where

$$f'_k(x) = \frac{\sum_i w_i \xi_{ik} - x Y_i - \{\sum_i w_i \xi_{ik} - x \sum_i w_i Y_i\} / \sum_i w_i}{\sum_i w_i \xi_{ik} - x^2 - \{\sum_i w_i \xi_{ik} - x\}^2 / \sum_i w_i}.$$

Let  $f_k(x)$  be a positive density, so, of course,  $w_i$  and  $\xi_{ik}$  for  $w_i$ ,  $\xi_{ik}$  in (2.11) and (2.12) are all the  $|f_k(x) - f_k(x)|$ , one can find the



o de  $s$  of the de  $s$  ence  $s$

$$\begin{aligned} D_1 &= \sum_i w_i - \hat{w}_i, & D_2 &= \sum_i w_i - \hat{w}_i Y_i, \\ D_3 &= \sum_i w_i \xi_{ik} - w_i \hat{\xi}_{ik}, & D_4 &= \sum_i w_i \xi_{ik}^2 - w_i \hat{\xi}_{ik}^2. \end{aligned}$$

Consequence of Lemma 4.1, the following proposition holds.

$$D_1 \leq \frac{c}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} |\xi_{\mathbf{i}\mathbf{k}} - \xi_{\mathbf{i}\mathbf{k}}| \{I_{\sqrt{\cdot}} |x - \xi_{\mathbf{i}\mathbf{k}}| \leq h_{\mathbf{k}}^{\frac{1}{2}}\} \quad I_{\sqrt{\cdot}} |x - \xi_{\mathbf{i}\mathbf{k}}| \leq h_{\mathbf{k}}^{\frac{1}{2}}\},$$

for  $\sigma \in c >$ , the  $I$ - $\Delta$ - and  $\Delta$ - $\Gamma$ -conclusion Lemma 4.1 precludes the  $\Gamma$ - $\Delta$ -conclusion Lemma 4.2 of  $\Delta$ .

$$\frac{1}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} |\xi_{\mathbf{i}\mathbf{k}} - \xi_{\mathbf{i}\mathbf{k}}| I_{\mathbf{k}} |x - \xi_{\mathbf{i}\mathbf{k}}| \leq h_{\mathbf{k}} \leq \sum_{i=1}^5 Z_{\mathbf{k}}^{(i)} \frac{1}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} \theta_{\mathbf{i}\mathbf{k}}^{(i)} I_{\mathbf{k}} |x - \xi_{\mathbf{i}\mathbf{k}}| \leq h_{\mathbf{k}}.$$

Applying the central limit theorem for the  $\mathbf{S}_n$  and  $\mathbf{B}_n$  say, (99), we obtain

$$\frac{1}{nh_{\mathbf{k}}} \sum_{\mathbf{i}} \theta_{\mathbf{i}\mathbf{k}}^{(\cdot)} I_{\mathbf{k}} |x - \xi_{\mathbf{i}\mathbf{k}}| \leq h_{\mathbf{k}} \xrightarrow{p} p_{\mathbf{k}} E \theta_{\mathbf{i}\mathbf{k}}^{(\cdot)},$$

Proofed by Lemma A.1,  $E\theta_{ik}^{(\ell)} < \infty$  for  $\ell = 1, \dots, 5$ . Note that  $E\theta_{ik}^{(1)} < \infty$ ,  $E\theta_{ik}^{(3)} < \infty$  by Assumption 1,  $E\theta_{ik}^{(4)} \leq \sigma_X \sqrt{\kappa^*}$  and  $E\theta_{ik}^{(5)} \leq |\mathcal{S}| \sigma_X$  by the Cauchy-Schwarz inequality when

$$\begin{aligned} Z_{\mathbf{k}}^{(1)} \frac{\sqrt{\cdot}}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} \theta_{\mathbf{i}\mathbf{k}}^{(1)} I_{\sqrt{\cdot}} |x - \xi_{\mathbf{i}\mathbf{k}}| &\leq h_{\mathbf{k}}^{\frac{1}{2} + \frac{\alpha}{2}}, \\ Z_{\mathbf{k}}^{(2)} \frac{\sqrt{\cdot}}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} \theta_{\mathbf{i}\mathbf{k}}^{(2)} I_{\sqrt{\cdot}} |x - \xi_{\mathbf{i}\mathbf{k}}| &\leq h_{\mathbf{k}}^{\frac{1}{2} + \frac{\alpha}{2}}, \\ Z_{\mathbf{k}}^{(3)} \frac{\sqrt{\cdot}}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} \theta_{\mathbf{i}\mathbf{k}}^{(3)} I_{\sqrt{\cdot}} |x - \xi_{\mathbf{i}\mathbf{k}}| &\leq h_{\mathbf{k}}^{\frac{1}{2} + \frac{\alpha}{2}}, \\ Z_{\mathbf{k}}^{(4)} \frac{\sqrt{\cdot}}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} \theta_{\mathbf{i}\mathbf{k}}^{(4)} I_{\sqrt{\cdot}} |x - \xi_{\mathbf{i}\mathbf{k}}| &\leq h_{\mathbf{k}}^{\frac{1}{2} + \frac{\alpha}{2}}, \\ Z_{\mathbf{k}}^{(5)} \frac{\sqrt{\cdot}}{nh_{\mathbf{k}}^2} \sum_{\mathbf{i}} \theta_{\mathbf{i}\mathbf{k}}^{(5)} I_{\sqrt{\cdot}} |x - \xi_{\mathbf{i}\mathbf{k}}| &\leq h_{\mathbf{k}}^{\frac{1}{2} + \frac{\alpha}{2}}, \end{aligned}$$

it follows from  $n h_k^{-1} \sum_i |\xi_{ik} - \xi_{ik}| I_{|x - \xi_{ik}| \leq h_k} = O_p(\theta_k h_k^{-1})$  and by Proposition 4.1 of the second part, we deduce that for any  $\epsilon > 0$ ,

$$\frac{1}{n h_k} \sum_i I_{|x - \xi_{ik}| \leq h_k} \leq \frac{1}{n h_k} \sum_i \{I_{|x - \xi_{ik}| \leq h_k} I_{\sum_{i=1}^5 \theta_{ik}^{(\cdot)} Z_k^{(\cdot)} > h_k}\} \xrightarrow{p} p_k,$$

and from  $n h_k^{-1} \sum_i |\xi_{ik} - \xi_{ik}| I_{|x - \xi_{ik}| \leq h_k} = O_p(\theta_k h_k^{-1})$  we get  $D_1 = O_p(\theta_k h_k^{-1})$  from (5).

And similarly, one has  $D_2 = O_p(\theta_k h_k^{-1})$ , applying the Cauchy-Schwarz inequality for  $\theta_{ik}^{(\cdot)}$ ,  $\ell = 1, \dots, p$ , and using the independence between  $Y_i$  and  $\theta_{ik}^{(\cdot)}$  for  $\ell = 1, \dots, p$ , then the conclusion on  $D_3$  follows.

$$D_3 = \sum_i \{w_i - \hat{w}_i \xi_{ik} - (w_i - \hat{w}_i) \xi_{ik} - \xi_{ik}\} \equiv D_{31} + D_{32} + D_{33}.$$

From  $D_{31} = O_p(\theta_k h_k^{-1})$ , and by Proposition 4.1, it follows that  $D_{32} = o_p(D_{31})$ . Since  $D_{33} \leq c \sum_{i=1}^5 Z_k^{(\cdot)} n h_k^{-1} \sum_i \theta_{ik}^{(\cdot)} I_{|x - \xi_{ik}| \leq h_k}$  for some  $c > 0$ , one obtains  $D_{33} = o_p(D_{31})$  as soon as  $D_3 = O_p(\theta_k h_k^{-1})$ . On the other hand,  $|\xi_{ik}^2 - \xi_{ik}^2| \leq |\xi_{ik} - \xi_{ik}| \cdot |\xi_{ik}| + |\xi_{ik} - \xi_{ik}|^2$ , one can show  $D_4 = O_p(\theta_k h_k^{-1})$ , then  $D_3 = O_p(\theta_k h_k^{-1})$  and  $E \xi_{ik}^4 < \infty$  follows. Consequently, we have for  $D$ ,  $\ell = 1, \dots, p$ , and applying the Cauchy-Schwarz inequality, we deduce that  $|f_k(x) - \hat{f}_k(x)| = O_p(\theta_k h_k^{-1})$  and applying the dominated convergence theorem for every point  $x$  outside  $\text{supp}(f_k)$  completes the proof of (9).

Moreover, it is only necessary to consider  $\sum_i w_i \zeta_{im} - w_i \zeta_{im} = \sum_i \{w_i - \hat{w}_i \zeta_{im} - (w_i - \hat{w}_i) \zeta_{im} - \zeta_{im}\}$ , where we have used the fact that  $\zeta_{im} = \theta_{im}^{(\cdot)} \vartheta_{im}^{(\cdot)}$  and  $\theta_{im}^{(\cdot)} = O_p(\vartheta_{im}^{(\cdot)})$  for any  $m$ .

$$\left| \sum_i w_i \zeta_{im} - \zeta_{im} \right| \leq \sum_{i=1}^5 Q_m^{(\cdot)} \sum_i w_i \vartheta_{im}^{(\cdot)} \leq \frac{1}{n h_{mk}} \sum_{i=1}^5 Q_m^{(\cdot)} \sum_i \vartheta_{im}^{(\cdot)} I_{|x - \xi_{ik}| \leq h_{mk}}$$

It follows that  $D_5 = o_p(D_3)$  and the conclusion follows.  $\square$

*Proof of Theorem 3.* In  $A_n$ , we deduce from the definition of  $\theta_n^*$  that for any  $\epsilon > 0$ ,

for all  $n$  we have  $\varphi_n \rightarrow \varphi$  in  $\mathcal{S}$  so  $\varphi$  is in  $\mathcal{S}$ , no problem.

$$\begin{aligned} & \widehat{E}\{Y_{\mathbf{t}}|X\} - E\{Y_{\mathbf{t}}|X\} \\ \leq & \sum_{\mathbf{k}=1}^{\mathbf{K}} \sum_{\mathbf{m}=1}^{\mathbf{M}} |f_{\mathbf{mk}}(\xi_{\mathbf{k}})\psi_{\mathbf{m}}(\mathbf{t}) - f_{\mathbf{mk}}(\xi_{\mathbf{k}})\psi_{\mathbf{m}}(\mathbf{t})| + \sum_{\mathbf{k}\geq \mathbf{K}+1} \sum_{\mathbf{m}\geq \mathbf{M}+1} |f_{\mathbf{mk}}(\xi_{\mathbf{k}})\psi_{\mathbf{m}}(\mathbf{t})| \\ \leq & \sum_{\mathbf{k}=1}^{\mathbf{K}} \sum_{\mathbf{m}=1}^{\mathbf{M}} |f_{\mathbf{mk}}(\xi_{\mathbf{k}}) - f_{\mathbf{mk}}(\xi_{\mathbf{k}})|\{|\psi_{\mathbf{m}}(\mathbf{t})| + |\psi_{\mathbf{m}}(\mathbf{t}) - \psi_{\mathbf{m}}(\mathbf{t})|\} + |f_{\mathbf{mk}}(\xi_{\mathbf{k}})| \cdot |\psi_{\mathbf{m}}(\mathbf{t}) - \psi_{\mathbf{m}}(\mathbf{t})| \\ & + \left| \sum_{(\mathbf{k},\mathbf{m})\in \mathcal{N}^2\setminus \mathcal{N}_K\times \mathcal{N}_M} f_{\mathbf{mk}}(\xi_{\mathbf{k}})\psi_{\mathbf{m}}(\mathbf{t}) \right|. \end{aligned}$$

$\varphi_n \rightarrow \varphi$  in  $\mathcal{S}$  is consequence of  $\varphi$  is  $\vartheta_n^*$  in  $\mathcal{S}$ .