Statistica Sinica **32** (2022), 1563-1582
doi:https://doi.org/10.5705/ss.202020.0463

NONPARAMETRIC INTERACTION SELECTION

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Abstract: We consider the nonparametric two-way interaction model and propose a method to select important main effect and interaction effect terms simultaneously. Our method is based on backfitting local constant smoothing. Interaction selection is achieved by solving a constrained optimization problem to identify which main effect and interaction effect terms favor an infinity smoothing bandwidth. We establish the selection consistency for the proposed method. Simulation examples and a real-data example illustrate its competitive finite-sample performance.

Key words and phrases: Additive model, backfitting, local constant smoothing, variable selection.

1. Introduction

The ready availability of high-dimensional data owing to advances in technology has motivated the active research area of variable selection, resulting in numerous relevant methods having been proposed in the literature. In this study, we focus on a special kind of variable selection, namely interaction selection. More explicitly, we study how predictor variables contribute to the response via pairwise interaction, and how to select an important pairwise interaction.

We consider the nonparametric regression of a univariate response Y on multivariate predictors $\mathbf{X} = (X_1, X_2, \ldots, X_d)^T$, with $X_j \in \Omega_j \subset R$, for $j = 1, 2, \ldots, d$. The additive model $Y = \alpha + \sum_{j=1}^{d} m_j(X_j) + \epsilon$ is a simplification of the fully nonparametric regression model $Y = m(\mathbf{X}) + \epsilon$ by assuming the predictors' effects are additive. However, this additivity assumption may not be reasonable in many real applications. Note that the fully nonparametric regression model can be decomposed as $Y = \alpha + \sum_{j=1}^{d} m_j(X_j) + \sum_{1\le j<k\le d} m_{jk}(X_j, X_k) + \sum_{1\le j<k<l\le d} m_{jkl}(X_j, X_k, X_l) + \cdots + m_{12\ldots d}(X_1, X_2, \ldots, X_d) + \epsilon$ by separating the interaction effects at different orders. In this sense, the additive model is essentially an approximation of the fully nonparametric regression model in which we ignore all interaction effects.

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We focus on the nonparametric two-way interaction model

$$Y = \alpha + \sum_{j=1}^{d} m_j(X_j) + \sum_{1 \leq j < k \leq d} m_{jk}(X_j, X_k) + \epsilon, \tag{1.1}$$

and propose a new method to select important main effect and interaction effect terms simultaneously. However the main idea can be easily extended to more general cases with higher-order interactions. Model (1.1) is not identifiable itself. Additional identifiability conditions are required. There are different ways to formulate its identifiability conditions. To facilitate the implementation of our proposed nonparametric interaction selection method, we adopt the following fixed-point identifiability conditions (Gustafson (2000)):

$$m_j(x_{j,0}) = 0,\ j = 1, \ldots, d; \tag{1.2}$$

$$m_{jk}(x_{j,0}, \cdot) = 0,\ m_{jk}(\cdot, x_{k,0}) = 0 \text{ and } m_{jk}(x_{j,0}, x_{k,0}) = 0,\ 1 \leq j < k \leq d, \tag{1.3}$$

where $x_{j,0}$ is any fixed point in the domain Ω_j of X_j, for $j = 1, 2, \ldots, d$. Our goal is to estimate the sets of important main and interaction effects, denoted by $\mathcal{M} = \{j : m_j(\cdot) \neq 0\}$ and $\mathcal{I} = \{(j,k) : m_{jk}(\cdot, \cdot) \neq 0\}$, respectively.

Many attempts have been made to perform parametric interaction selection. The parametric two-way interaction model essentially assumes that $m_j(X_j) = \beta_j X_j$ and $m_{jk}(X_j, X_K) = \beta_{jk} X_j X_k$ in the above nonparametric two-way interaction model (1.1), and is also called a quadratic regression model. Zhao, Rocha and Yu (2009) proposed a composite absolute penalties family, and demonstrated that their method can perform parametric interaction selection for the parametric two-way interaction model. Yuan, Joseph and Zou (2009) proposed a structured variable selection and estimation procedure for the parametric two-way interaction model. Choi, Li and Zhu (2010) proposed a parametric interaction selection method under a strong heredity assumption. Here, strong heredity requires $j \in \mathcal{M}$ and $k \in \mathcal{M}$, as long as $(j,k) \in \mathcal{I}$. In comparison, weak heredity requires $j \in \mathcal{M}$ or $k \in \mathcal{M}$, or both, if $(j,k) \in \mathcal{I}$. Bien, Taylor and Tibshirani (2013) proposed a lasso for hierarchical interactions. Hao and Zhang (2014) and Niu, Hao and Zhang (2018) studied interaction screening. Hao, Feng and Zhang (2018) proposed a new regularization method, called the regularization algorithm under marginality principle (RAMP), to perform parametric interaction selection. Other related methods include those of Kong et al. (2017) and Wang, Jiang and Zhu (2021), among many others.

Our focus is on nonparametric interaction selection. Lin and Zhang (2006) proposed a component selection and smoothing operator based on a smoothing spline ANOVA that can be used to fit the above nonparametric two-way interaction model and perform interaction selection. Radchenko and James (2010) proposed a method, called variable selection using adaptive nonlinear interaction structures in high dimension (VANISH), for model (1.1). Their method represents each main effect and interaction effect term using a preselected set of univariate and bivariate orthonormal basis functions, respectively. In particular, the bivariate orthonormal basis function is chosen as the tensor product of the univariate basis functions in their implementation. This leads to some challenges in approximating the complex interaction effect component function.

In this paper, we propose a new nonparametric interaction selection method in a framework coupling backfitting with local constant smoothing. The essential idea is that if an infinity smoothing bandwidth is used in the local constant smoothing for each main effect or interaction effect component function, the corresponding component function estimate will be a constant function, implying that it is unimportant for the prediction of the response variable. Because we are backfitting local constant smoothing, our method is much more flexible in fitting any complex interaction component function. Furthermore, it can overcome the aforementioned limitation of using tensor products of univariate basis functions to approximate bivariate interaction component functions. In addition, our algorithm does not need the strong or the weak heredity assumption. However, it is possible to incorporate strong or weak heredity if such information is available, as discussed at the end of the paper.

For nonparametric variable selection, Wu and Stefanski (2015) studied the additive model

$$Y = \alpha + \sum_{j=1}^{d} m_j(X_j) + \epsilon$$

without interaction, and proposed a structure recovery scheme toward polynomial modeling. Their method is capable of identifying unimportant predictors, linear predictors, quadratic predictors, and so on. White, Stefanski and Wu (2017) proposed a variable selection method for the fully nonparametric model

$$Y = m(X_1, X_2, \ldots, X_d) + \epsilon.$$

The nonparametric two-way interaction model (1.1), which sits between the additive model and the fully nonparametric model, is the focus of the current study. The proposed method can estimate the sets of important main effects and two-way interaction effects. In addition, it can be readily extended to models with high-order interactions. With this new contribution, we now have a full spectrum of nonparametric variable selection methods.

The rest of the paper is organized as follows. Section 2 presents the basic backfitting local constant smoothing procedure for the two-way interaction model. Our new nonparametric interaction selection method is introduced in Section 3. Some implementation issues are discussed in Section 4, with a toy example to illustrate how it works. Selection consistency is established in Section 5. Simulation examples in Section 6 and a real-data example in Section 7 demonstrate of the proposed method's competitive finite-sample performance. Section 8 discusses how to incorporate strong or weak heredity information and possible future extensions.

2. Backfitting Estimation of the Two-way Interaction Model

Backfitting is a commonly used technique for the estimation of the additive model (Hastie and Tibshirani (1990)). It can also be used to fit the two-way interaction model (1.1) with both main and interaction effect terms. The backfitting algorithm is an iterative algorithm. In each iteration, it sequentially updates the estimate of one model component at a time. Each updating requires a univariate or bivariate smoothing, depending on whether we are updating a main effect or an interaction effect term. For the purpose of selecting important main and interaction effect terms, we couple backfitting with local constant smoothing (Fan and Gijbels (1996)).

2.1. Univariate local constant smoothing

Univariate local constant smoothing is used to update the estimate of the main effect terms. To estimate a univariate regression function $g(t) = E(Z|T = t)$ from a random sample $\{(T_i, Z_i) : i = 1, \ldots, n\}$, the univariate local constant smoothing approximates $g(t)$ by a constant a. A weighted least squares approach is used to estimate a, with weights specified by a kernel function $K(\cdot)$ and a smoothing bandwidth $h > 0$. More specifically, the univariate local constant smoothing estimate $\hat{g}(t)$ of $g(t)$ at any t is given by $\hat{a}$, the optimizer of $\hat{a} = \operatorname{argmin}_a \sum_{i=1}^{n}\{Z_i - a\}^2 K((T_i - t)/h)$. We denote such a univariate local constant smoothing by $S_{K,h}$.

2.2. Bivariate local constant smoothing

Bivariate local constant smoothing is used to estimate the interaction effect terms. It is based on the same idea as univariate local constant smoothing, but is used for the case with two predictors. Suppose we estimate a bivariate regression function $g(s,t) = E(Z|S = s, T = t)$ from a random sample $\{(S_i, T_i, Z_i) : i = 1, \ldots, n\}$. The bivariate local constant smoothing estimate $\hat{g}(s,t)$ of $g(s,t)$ at any s and t is given by $\hat{c}$, the optimizer of

$$\hat{c} = \operatorname*{argmin}_{c} \sum_{i=1}^{n} \{Z_i - c\}^2 K\left(\frac{S_i - s}{h}\right) K\left(\frac{T_i - t}{h}\right).$$

Note that potentially different smoothing bandwidths can be used for S and T. However, for simplicity, we use the same smoothing bandwidth. Denote this bivariate local constant smoothing by $S2_{K,h}$.

2.3. Backfitting algorithm

With the above univariate and bivariate local constant smoothings in place, we are ready to present the backfitting algorithm for the two-way interaction model (1.1). The backfitting algorithm is an iterative algorithm. The essential idea is to update the estimate of a single main or interaction effect term at every step, while keeping the estimates of all other terms fixed. The detailed backfitting algorithm for the two-way interaction model (1.1) is given in Algorithm 1, with given smoothing bandwidths $h_j > 0$ and $\tilde{h}_{jk} > 0$ for the main and interaction effect terms, respectively. Denote the estimates at the convergence by $\widehat{\alpha}^{BF}(\mathbf{h}, \tilde{\mathbf{h}})$, $\widehat{m}_j^{BF}(\cdot; \mathbf{h}, \tilde{\mathbf{h}})$, and $\widehat{m}_{jk}^{BF}(\cdot, \cdot; \mathbf{h}, \tilde{\mathbf{h}})$, with $\mathbf{h} = (h_1, h_2, \ldots, h_d)^T$ and $\tilde{\mathbf{h}} = (\tilde{h}_{1,2}, \tilde{h}_{1,3}, \ldots, \tilde{h}_{(d-1),d})^T$. Note that we use $\tilde{h}_{jk}$ and $\tilde{h}_{j,k}$ interchangeably to avoid potential confusion. Similarly, $m_{jk}(\cdot, \cdot)$ (resp. $\tilde{\lambda}_{jk}$ and $\widehat{\tilde{\lambda}}_{jk}$ to be defined) is the same as $m_{j,k}(\cdot, \cdot)$ (resp. $\tilde{\lambda}_{j,k}$ and $\widehat{\tilde{\lambda}}_{j,k}$).

In Algorithm 1, it is important to update the interaction effect terms before updating the main effect terms in each iteration, for the following reason. After applying a bivariate local constant smoothing to update the estimate of an interaction effect term in Step 2(a), the updated estimate of the interaction effect term may not satisfy the identifiability condition (1.3). To ensure the identifiability condition, a follow-up update in Step 2(b) is necessary in the interaction effect term that changes the estimates of the corresponding two main effect terms. This change may lead to suboptimal estimates of the main effect terms. However, it can be fixed automatically by the updating of the mean effect terms in Step 3.

3. Main and Interaction Effect Selection

Wu and Stefanski (2015) noted that when $h_j = \infty$, the univariate local constant smoothing in Step 3(a) approximates $m_j(\cdot)$ by a constant, leading to a

Algorithm 1 Backfitting algorithm for the two-way interaction model (1.1)

Step 1: Initialize by setting $\widehat{\alpha} = n^{-1} \sum_{i=1}^{n} Y_i$, $\widehat{m}_j(\cdot) \equiv 0$ for $j = 1, \ldots, d$ and $\widehat{m}_{jk}(\cdot) \equiv 0$, for $1 \leq j < k \leq d$.

Step 2: For $j = 1, \ldots, d-1$; $k = j+1, \ldots, d$:

(a) apply the bivariate local constant smoother $S2_{K,\tilde{h}_{jk}}$ to

$$\left[\left\{(X_{ij}, X_{ik}), Y_i - \widehat{\alpha} - \sum_{l=1}^{d} \widehat{m}_l(X_{il}) - \sum_{s<t\,:\,(s,t)\neq(j,k)} \widehat{m}_{st}(X_{is}, X_{it})\right\}; i = 1, \ldots, n\right]$$

and set the estimated function to be the updated estimate $\widehat{m}_{jk}(\cdot,\cdot)$ of $m_{jk}(\cdot,\cdot)$.

(b) update $\widehat{\alpha} \leftarrow \widehat{\alpha} + \widehat{m}_{jk}(x_{j,0}, x_{k,0})$, $\widehat{m}_j(\cdot) \leftarrow \widehat{m}_j(\cdot) + \widehat{m}_{jk}(\cdot, x_{k,0}) - \widehat{m}_{jk}(x_{j,0}, x_{k,0})$, $\widehat{m}_k(\cdot) \leftarrow \widehat{m}_k(\cdot) + \widehat{m}_{jk}(x_{j,0}, \cdot) - \widehat{m}_{jk}(x_{j,0}, x_{k,0})$ and $\widehat{m}_{jk}(\cdot,\cdot) \leftarrow \widehat{m}_{jk}(\cdot,\cdot) - \widehat{m}_{jk}(x_{j,0}, \cdot) - \widehat{m}_{jk}(\cdot, x_{k,0}) + \widehat{m}_{jk}(x_{j,0}, x_{k,0})$ to implement the identifiability conditions (1.2) and (1.3).

Step 3: for $j = 1, \ldots, d$:

(a) apply the univariate local constant smoother S_{K,h_j} to

$$\left[\left\{X_{ij}, Y_i - \widehat{\alpha} - \sum_{l\neq j} \widehat{m}_l(X_{il}) - \sum_{1\leq s<t\leq d} \widehat{m}_{st}(X_{is}, X_{it})\right\}; i = 1, \ldots, n\right]$$

and set the estimated function to be the updated estimate $\widehat{m}_j(\cdot)$ of $m_j(\cdot)$.

(b) update $\widehat{\alpha} \leftarrow \widehat{\alpha} + \widehat{m}_j(x_{j,0})$, $\widehat{m}_j(\cdot) \leftarrow \widehat{m}_j(\cdot) - \widehat{m}_j(x_{j,0})$ to implement the identifiability conditions (1.3).

Step 4: Update $\widehat{\alpha} \leftarrow (1/n) \sum_{i=1}^{n} \Big(Y_i - \sum_{j=1}^{d} \widehat{m}_j(X_{ij}) - \sum_{1\leq s<t\leq d} \widehat{m}_{st}(X_{is}, X_{it})\Big)$.

Step 5: Repeat Steps 2, 3, and 4 until the change in all $\widehat{m}_j(\cdot)$ for $j = 1, \ldots, d$ and $\widehat{m}_{jk}(\cdot)$ for $1 \leq j < k \leq d$ between successive iterations are less than a specified tolerance.

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constant function estimate. Then, Step 3(b) shifts the constant function estimate to a zero function $\widehat{m}_j(\cdot) = 0$ to satisfy the identifiability condition (1.2). As a result, an infinity smoothing bandwidth in the backfitting algorithm leads to the corresponding predictor's main effect being estimated as unimportant. Based on this finding, Wu and Stefanski (2015) proposed a variable selection method for the additive model.

By the same token, if $\tilde{h}_{jk} = \infty$ in Algorithm 1, the bivariate local constant smoothing in Step 2(a) leads to a bivariate constant function estimate. Then, Step 2(b) shifts it to a zero function estimate $\hat{m}_{jk}(\cdot,\cdot) = 0$ in the same way. A corresponding interpretation is that the interaction effect between X_j and X_k is estimated to be unimportant.

According to these findings, the selection of important main effect and interaction effect terms for the two-way interaction model (1.1) boils down to identifying which main effect and interaction effect terms favor an infinity smoothing bandwidth in Algorithm 1. Based on this, we now propose a new method to perform main effect and interaction effect selection simultaneously for the two-way interaction model (1.1).

It is not easy to estimate an infinity. We convert the estimation of an infinity to the estimation of a zero by reparametrizing $\lambda_j = 1/h_j$ and $\tilde{\lambda}_{jk} = 1/\tilde{h}_{jk}$, as in Wu and Stefanski (2015) and White, Stefanski and Wu (2017). Denote $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \ldots, \lambda_d)^T$ and $\tilde{\boldsymbol{\lambda}} = (\tilde{\lambda}_{12}, \tilde{\lambda}_{13}, \ldots, \tilde{\lambda}_{(d-1)d})^T$ as the vectors of the inverse smoothing bandwidths for the main and interaction effect terms, respectively. For a vector $\boldsymbol{\lambda}$, we denote $\boldsymbol{\lambda}^{-1} = (1/\lambda_1, 1/\lambda_2, \ldots, 1/\lambda_d)^T$.

Following Wu and Stefanski (2015) and White, Stefanski and Wu (2017), we propose estimating the favored smoothing bandwidth for each main effect or interaction effect term by solving the following constrained optimization problem

$$\begin{aligned}
&\min_{\boldsymbol{\lambda},\tilde{\boldsymbol{\lambda}}} \sum_{i=1}^{n} \Bigg\{ Y_i - \widehat{\alpha}^{BF}(\boldsymbol{\lambda}^{-1}, \tilde{\boldsymbol{\lambda}}^{-1}) - \sum_{j=1}^{d} \widehat{m}_j^{BF}(X_{ij}; \boldsymbol{\lambda}^{-1}, \tilde{\boldsymbol{\lambda}}^{-1}) \\
&- \sum_{j=1}^{d-1} \sum_{k=j+1}^{d} \widehat{m}_{jk}^{BF}(X_{ij}, X_{ik}; \boldsymbol{\lambda}^{-1}, \tilde{\boldsymbol{\lambda}}^{-1}) \Bigg\}^2, \qquad (3.1)\\
&\text{subject to } \ \lambda_j \geq 0, \quad j = 1, \ldots, d; \\
&\qquad\qquad\quad \tilde{\lambda}_{jk} \geq 0, \quad 1 \leq j < k \leq d; \\
&\qquad\qquad\quad \sum_{j=1}^{d} \lambda_j + \sum_{j=1}^{d-1} \sum_{k=j+1}^{d} \tilde{\lambda}_{jk} = \tau,
\end{aligned}$$

where $\tau \geq 0$ is a regularization parameter to be tuned. Denote the optimizer by $\widehat{\boldsymbol{\lambda}} \equiv \widehat{\boldsymbol{\lambda}}(\tau) = (\widehat{\lambda}_1(\tau), \widehat{\lambda}_2(\tau), \ldots, \widehat{\lambda}_d(\tau))^T$ and

$$\widehat{\tilde{\boldsymbol{\lambda}}} \equiv \widehat{\tilde{\boldsymbol{\lambda}}}(\tau) = (\widehat{\tilde{\lambda}}_{1,2}(\tau), \widehat{\tilde{\lambda}}_{1,3}(\tau), \ldots, \widehat{\tilde{\lambda}}_{(d-1)d}(\tau))^T.$$

For an appropriately tuned τ, some components of $\widehat{\boldsymbol{\lambda}}$ and $\widehat{\tilde{\boldsymbol{\lambda}}}$ will be exactly zero. Then, the estimated sets of important main and interaction effects are given by $\widehat{\mathcal{M}}(\tau) = \{j : \widehat{\lambda}_j(\tau) > 0\}$ and $\widehat{\mathcal{I}}(\tau) = \{(j,k) : \widehat{\tilde{\lambda}}_{jk}(\tau) > 0\}$, respectively. To match our asymptotic consistency, developed in Section 5, we can possibly use the alternative definitions $\widehat{\mathcal{M}}(\tau) = \{j : \widehat{\lambda}_j(\tau) > \varepsilon\}$ and $\widehat{\mathcal{I}}(\tau) = \{(j,k) : \widehat{\widetilde{\lambda}}_{jk}(\tau) > \varepsilon\}$, respectively, for some small $\varepsilon > 0$. For example, ε can be chosen to be twice the convergence tolerance adopted in the forthcoming modified coordinate descent algorithm. However, based on our limited numerical experience, we have observed that these two definitions always yield the same selection result, owing to the lasso-type constraint.

4. Implementation Issues and a Toy Example

4.1. Modified coordinate descent algorithm

Convexity is a highly desired property in optimization. However, owing to the complicated backfitting algorithm coupled with univariate and bivariate local constant smoothing, the objective function of the optimization problem (3.1) is not convex. We borrow the modified coordinate descent algorithm (Wu and Stefanski (2015)) to solve (3.1) for any given $\tau > 0$. We skip the details to save space.

4.2. Tuning

The AIC, the BIC, and cross-validation can be used to tune the hyperparameter τ in the constrained optimization problem (3.1). For the AIC and BIC, we need the sum of the squared errors and the degrees of freedom. The sum of the squared errors can be simply calculated by

$$\sum_{i=1}^{n}\Bigg\{Y_i - \widehat{\alpha}^{BF}(\widehat{\boldsymbol{\lambda}}^{-1}, \widehat{\widetilde{\boldsymbol{\lambda}}}^{-1}) - \sum_{j=1}^{d}\widehat{m}_j^{BF}(X_{ij}; \widehat{\boldsymbol{\lambda}}^{-1}, \widehat{\widetilde{\boldsymbol{\lambda}}}^{-1})$$
$$-\sum_{j=1}^{d-1}\sum_{k=j+1}^{d}\widehat{m}_{jk}^{BF}(X_{ij}, X_{ik}; \widehat{\boldsymbol{\lambda}}^{-1}, \widehat{\widetilde{\boldsymbol{\lambda}}}^{-1})\Bigg\}^2.$$

Note that the univariate and bivariate local constant smoothings are linear smoothers (Fan and Gijbels (1996)). The trace of the corresponding smoothing matrix can be used to gauge the degrees of freedom for the backfitting estimate of each model component of the two-way interaction model (1.1).

In particular, the degrees of freedom for the main effect estimate $\widehat{m}_j^{BF}(\cdot; \mathbf{h}, \tilde{\mathbf{h}})$ is given by $\mathrm{tr}\,(\boldsymbol{S_j} - \mathbf{1}(\mathbf{s}_j(x_{j,0}))^T)$. Here, $\mathbf{1}$ is a column vector of ones of an appropriate length and, in the current context, is of length n, and $\mathbf{S}_j = (\mathbf{s}_j(x_{1j}), \mathbf{s}_j(x_{2j}),$

$\ldots, \mathbf{s}_j(x_{nj}))^T$ is the smoothing matrix of the local constant smoothing, with

$$\mathbf{s}_j(x_j) = \left(K\left(\frac{X_{1j}-x_j}{h_j}\right), K\left(\frac{X_{2j}-x_j}{h_j}\right), \ldots, K\left(\frac{X_{nj}-x_j}{h_j}\right)\right)^T \Big/ \sum_{i=1}^{n} K\left(\frac{X_{ij}-x_j}{h_j}\right).$$

Note that the first and second terms of $\mathrm{tr}(\boldsymbol{S_j} - \mathbf{1}\,(\mathbf{s}_j(x_{j,0}))^T)$ correspond to Step 3(a) and 3(b), respectively. Because $\mathrm{tr}(\mathbf{1}\,(\mathbf{s}_j(x_{j,0}))^T) = \mathrm{tr}((\mathbf{s}_j(x_{j,0}))^T\,\mathbf{1}) = 1$, we have $\mathrm{tr}(\boldsymbol{S_j} - \mathbf{1}\,(\mathbf{s}_j(x_{j,0}))^T) = \mathrm{tr}(\boldsymbol{S_j}) - 1$, as in Wu and Stefanski (2015).

The process becomes more involved for the interaction effect term estimate $\widehat{m}_{jk}(\cdot,\cdot;\mathbf{h},\tilde{\mathbf{h}})$. Here are the details. Denote

$$\tilde{\mathbf{s}}_{jk}(x_j,x_k) = \frac{1}{\sum_{i=1}^{n} K((X_{ij}-x_j)/\tilde{h}_{jk})K((X_{ik}-x_k)/\tilde{h}_{jk})} \begin{pmatrix} K\left(\frac{X_{1j}-x_j}{\tilde{h}_{jk}}\right)K\left(\frac{X_{1k}-x_k}{\tilde{h}_{jk}}\right) \\ K\left(\frac{X_{2j}-x_j}{\tilde{h}_{jk}}\right)K\left(\frac{X_{2k}-x_k}{\tilde{h}_{jk}}\right) \\ \vdots \\ K\left(\frac{X_{nj}-x_j}{\tilde{h}_{jk}}\right)K\left(\frac{X_{nk}-x_k}{\tilde{h}_{jk}}\right) \end{pmatrix}.$$

Then, $\tilde{\mathbf{S}}_{jk} = (\tilde{\mathbf{s}}_{jk}(x_{1j},x_{1k}), \tilde{\mathbf{s}}_{jk}(x_{2j},x_{2k}), \ldots, \tilde{\mathbf{s}}_{jk}(x_{nj},x_{nk}))^T$ is the smoothing matrix for the bivariate local constant smoothing in Step 2(a) of Algorithm 1. For Step 2(b), we similarly denote

$$\tilde{\mathbf{S}}_{j0k} = (\tilde{\mathbf{s}}_{jk}(x_{j,0},x_{1k}), \tilde{\mathbf{s}}_{jk}(x_{j,0},x_{2k}), \ldots, \tilde{\mathbf{s}}_{jk}(x_{j,0},x_{nk}))^T$$

and

$$\tilde{\mathbf{S}}_{jk0} = (\tilde{\mathbf{s}}_{jk}(x_{1j},x_{k,0}), \tilde{\mathbf{s}}_{jk}(x_{2j},x_{k,0}), \ldots, \tilde{\mathbf{s}}_{jk}(x_{nj},x_{k,0}))^T.$$

Then, the degrees of freedom of the interaction effect estimate $\widehat{m}_{jk}(\cdot,\cdot;\mathbf{h},\tilde{\mathbf{h}})$ is given by

$$\mathrm{tr}\left\{\tilde{\mathbf{S}}_{jk} - \tilde{\mathbf{S}}_{j0k} - \tilde{\mathbf{S}}_{jk0} + \mathbf{1}\,(\tilde{\mathbf{s}}_{jk}(x_{j,0},x_{k,0}))^T\right\},$$

where the last three terms follow from Step 2(b), which makes the interaction effect estimate $\widehat{m}_{jk}(\cdot,\cdot;\mathbf{h},\tilde{\mathbf{h}})$ satisfy the identifiability condition (1.3).

Following Buja, Hastie and Tibshirani (1989) and putting all these together, the total degrees of freedom for the backfitting estimate for the two-way interaction model (1.1) is given by

$$1 + \sum_{j=1}^{d}(\mathrm{tr}(\mathbf{S}_j) - 1) + \sum_{1\le j<k\le d}\left[\mathrm{tr}\left\{\tilde{\mathbf{S}}_{jk} - \tilde{\mathbf{S}}_{j0k} - \tilde{\mathbf{S}}_{jk0}\right\} + 1\right]$$

by noting similarly that $\mathrm{tr}(\mathbf{1}\,(\tilde{\mathbf{s}}_{jk}(x_{j,0},x_{k,0}))^T) = \mathrm{tr}((\tilde{\mathbf{s}}_{jk}(x_{j,0},x_{k,0}))^T\,\mathbf{1}) = 1$. Here, the first term 1 is the degrees of freedom used to account for the intercept term estimated in Step 4 of Algorithm 1.

In our forthcoming numerical examples, we use the BIC to tune the regularization parameter τ.

4.3. Refitting

With the tuned optimal $\widehat{\tau}$, the final estimated sets of main and interaction effects are given by $\widehat{\mathcal{M}}(\widehat{\tau})$ and $\widehat{\mathcal{I}}(\widehat{\tau})$, respectively. If we want to estimate the overall regression function $m(\mathbf{x}) = \alpha + \sum_{j=1}^{d} m_j(x_j) + \sum_{1\le j<k\le d} m_{jk}(x_j,x_k)$ as well, a refitting step may be necessary to improve performance. Note that in the nonparametric main and interaction effect estimation method proposed above, we need to couple the backfitting algorithm with local constant smoothing to perform the selection. However, it is well known that local constant smoothing is suboptimal if one cares about estimating the regression function (Fan and Gijbels (1996)). In particular, Fan and Gijbels (1996) showed theoretically that local linear smoothing can do much better than local constant smoothing in terms of reducing the smoothing bias, while estimating the regression function. Consequently, a refitting step can be adopted to improve performance in terms of estimating the overall regression function $m(\mathbf{x})$.

For the selected final model

$$Y = \alpha + \sum_{j\in\widehat{\mathcal{M}}(\widehat{\tau})} m_j(X_j) + \sum_{(j,k)\in\widehat{\mathcal{I}}(\widehat{\tau})} m_{jk}(X_j,X_k) + \epsilon,$$

we couple the backfitting algorithm with univariate (resp. bivariate) local linear smoothing to update the main (resp. interaction) effect terms to obtain a final estimate of the overall regression function. An optimization problem similar to (3.1) can be used to determine optimal smoothing bandwidths for each term, in conjunction with using the AIC to tune the corresponding regularization parameter, because local linear smoothing is also a linear smoother (Fan and Gijbels (1996)).

4.4. A toy example

To get a better idea of how our proposed selection method works, we illustrate it using a toy example. A random sample of size $n = 200$ is generated from the following model, with five predictors in total, two important main effect terms

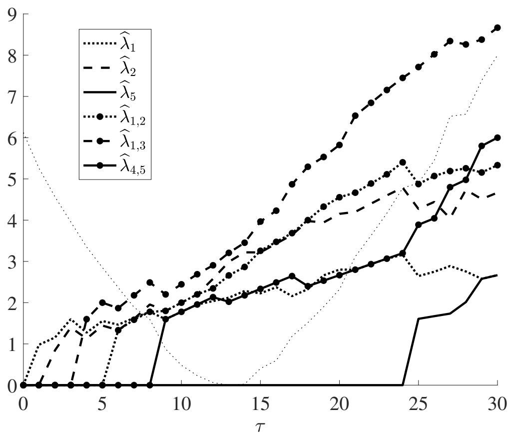

Figure 1. Solution path for the toy example.

and three important interaction effect terms:

$$Y = m_1(X_1) + m_2(X_2) + m_{1,2}(X_1, X_2) + m_{1,3}(X_1, X_3) + m_{4,5}(X_4, X_5) + \varepsilon,$$

where $m_1(t) = m_2(t) = 2\sin(\pi t)$, $m_{1,2}(s,t) = m_{1,3}(s,t) = m_{4,5}(s,t) = 2\sin(\pi st)$, $X_1, \ldots, X_5 \overset{i.i.d.}{\sim} Unif(-1,1)$, and independent $\varepsilon \sim N(0,1)$. The identifiability conditions (1.2) and (1.3) are satisfied with $x_{j,0} = 0$, for $j = 1, 2, \ldots, 5$. Note that there are five main effect terms and 10 interaction effect terms in total. We apply our proposed main and interaction effect selection algorithm. The solution path in Figure 1 plots $\widehat{\lambda}_j(\tau)$ and $\widehat{\widehat{\lambda}}_{jk}(\tau)$ versus the tuning parameter τ for the main and interaction effects. Note that we only plot up to $\tau = 30$ for the best visual effect.

In the beginning, with $\tau = 0$, all optimal inverse smoothing bandwidths are zero, because τ is the summation of all inverse smoothing bandwidths. As τ gradually increases, $\widehat{\lambda}_1(\tau)$, $\widehat{\lambda}_2(\tau)$, $\widehat{\widehat{\lambda}}_{1,3}(\tau)$, $\widehat{\widehat{\lambda}}_{1,2}(\tau)$, and $\widehat{\widehat{\lambda}}_{4,5}(\tau)$, corresponding to the important main and interaction effect terms, sequentially depart from zero before any unimportant term component does. Note that until $\tau = 25$, the optimal inverse smoothing bandwidth corresponding to one unimportant term becomes nonzero. Therefore, our proposed method can perform main and interaction effect selection perfectly, as long as τ is tuned in a large interval $[9, 24]$. After rescaling appropriately, we overlay the BIC in Figure 1, denoted by the thin black dotted line, showing that the BIC tuning leads to a perfect main and interaction effect selection.

5. Consistency

To establish the selection consistency for the proposed nonparametric main and interaction effect selection method, we prove the following asymptotic results for the optimizer of (3.1).

Theorem 1. *Under Conditions* 1–5 *in the Appendix, if* $\tau \to \infty$ *and* $\tau^4/n \to 0$ *as* $n \to \infty$*, the optimizer of* (3.1) *satisfies* $\widehat{h}_j(\tau) \xrightarrow{p} \infty$ *and* $\widehat{h}_{j'}(\tau) \xrightarrow{p} 0$ *for any* $j \in \mathcal{M}$ *and* $j' \notin \mathcal{M}$*, and* $\widehat{\widetilde{h}}_{jk}(\tau) \xrightarrow{p} \infty$ *and* $\widehat{\widetilde{h}}_{j'k'}(\tau) \xrightarrow{p} 0$ *for any* $(j,k) \in \mathcal{I}$ *and* $(j',k') \notin \mathcal{I}$.

Theorem 1 implies the selection consistency straightforwardly; that is, $P(\widehat{\mathcal{M}} = \mathcal{M}, \widehat{\mathcal{I}} = \mathcal{I}) \to 1$ as $n \to \infty$.

6. Simulation Studies

Predictors in our simulation examples are generated in two steps. We first generate multivariate Gaussian $(Z_1, Z_2, \ldots, Z_d)^T$ with $E(Z_j) = 0$ and $\mathrm{cov}(Z_j, Z_k) = \rho^{|j-k|}$, for $1 \leq j, k \leq d$. Here, ρ controls the correlation among the predictors, and we consider $\rho = 0.6$ in all of our simulation examples. Our predictors are generated by applying transformation the $X_j = 2\Phi(U_j) - 1$, with $\Phi(\cdot)$ being the cumulative distribution function of the standard normal distribution so that marginally $X_j \sim Unif(-1, 1)$, for $j = 1, 2, \ldots, d$. In our simulation studies, we fix $x_{j,0} = 0$, for $j = 1, 2, \ldots, d$, in the identifiability conditions (1.2) and (1.3). The dimension of the predictors d is either 10 or 20 for all simulation examples.

We compare our proposed method with two existing methods: the regularization algorithm under marginal principle (RAMP) method (Hao, Feng and Zhang (2018)), and the variable selection using adaptive nonlinear interaction structures in high dimensions (VANISH) method (Radchenko and James (2010)). We evaluate the performance of the methods in terms of two criteria: identifying important main and interaction effects, and the integrated squared error (ISE) of each estimate of the overall regression function $m(\cdot)$, defined as $ISE(\widehat{m}) = E_{\mathbf{X}}(m(\mathbf{X}) - \widehat{m}(\mathbf{X}))^2$, where $\widehat{m}(\cdot)$ denotes an estimate of $m(\cdot)$. The expectation $E_{\mathbf{X}}$ is replaced by an empirical expectation based on a big independent test set.

Note that the VANISH method is designed for a nonlinear two-way interaction model with strong heredity, and requires an extra validation set to tune its regularization parameter. Here, the strong heredity requires that if an interaction effect term is important, the two corresponding main effect terms must be important. The RAMP method is designed for a quadratic regression, essentially an extended linear model with interaction effect terms added, and uses the EBIC for tuning. In this sense, the RAMP is a linear method for main and interaction effect selection, and requires either strong or weak heredity. The weak heredity assumption requires that if an interaction effect term is important, at least one of the two corresponding main effect terms is important. Thus, to provide a fair comparison and a thorough investigation of our proposed method's finite-sample performance, we consider both linear and nonlinear two-way interaction models, with and without strong heredity. In total, we consider four simulation examples. For the models with strong heredity, the strong heredity version of RAMP is used, while for the models without strong heredity, the weak heredity version of RAMP is used. For all four examples, VANISH uses a Fourier basis.

6.1. Models with strong heredity

First, we consider models with strong heredity.

Example 1. (Linear two-way interaction model with strong heredity). Data are generated from the model

$$Y = 2.1X_1 + 2.1X_2 + 2.1X_3 + 2.1X_4 + 3.7X_1X_2 + 3.7X_1X_3 + \varepsilon,$$

where $\varepsilon \sim N(0,1)$ is independent of the predictors. In this model, there are four important main effect terms and two important interaction effect terms. Training sets of size 200 are used. An independent test set of size 1,000 is generated to evaluate the ISE for each final estimate of the overall regression function. The strong heredity version of RAMP is used for Examples 1 and 2. Because the tuning of VANISH requires a separate tuning set, we generate an independent tuning set the same size as the training sets. In this sense, VANISH uses more data than the other two methods being compared.

The results over 100 repetitions are summarized in the first block of Table 1. For all three methods, the columns M and NM are the average number of selected true and false main effect terms, respectively; the columns I and NI are the average number of selected true and false interaction effect terms, respectively; CM is the number of times recovering exactly the correct model (selecting all important terms and getting rid of all unimportant terms) among 100 repetitions; and ISE is the integrated squared error defined above. For our new method, there are two extra columns: OISE (oracle ISE), which reports the ISE corresponding to the oracle model with only true important main and interaction effect terms, and PC (path consistency), which is the number of times the solution path contains at least one exactly correct model. The OISE is essentially obtained by applying the refitting step of Section 4.3 with true sets of important main and interaction effect terms. It serves as a benchmark for the performance our method can achieve. The numbers in parentheses are the corresponding standard errors.

For main and interaction effect selection, our proposed method performs perfectly, selecting all important main and interaction effect terms, and excluding all unimportant terms. RAMP also performs well as a linear method. It selects all important main and interaction effect terms, but mistakenly includes a few unimportant interactions. In comparison, VANISH has trouble selecting all important terms, resulting in smaller number of correct models. RAMP has the smallest ISE because the true model is a linear two-way interaction model. The ISE of our proposed method is much smaller than that of VANISH.

Example 2. (Nonlinear two-way interaction model with strong heredity). Data are generated from the model

$$Y = m_1(X_1) + m_2(X_2) + m_3(X_3) + m_4(X_4) + m_{(1,2)}(X_1, X_2) + m_{(1,3)}(X_1, X_3) + \varepsilon,$$

where $m_1(X_1) = 2.1\exp(X_1)$, $m_2(X_2) = 2.1\exp(X_2)$, $m_3(X_3) = 1.9\cos(X_3\pi)$, $m_4(X_4) = 1.9\cos(X_4\pi)$, $m_{(1,2)}(X_1, X_2) = 1.9\cos((X_1 - X_2)\pi)$, and $m_{(1,3)}(X_1, X_3) = 6.8|X_1X_3| \cdot I_{\{X<0\}}(X_1X_3)$. The sample size of the training data is 250, and all other settings are as in the linear case.

The second block of Table 1 summarizes the corresponding simulation results in the same way. In terms of the main and interaction effect selection, our proposed method still performs perfectly. RAMP misses some important terms, especially when the shape of the nonlinear function is far from being linear, and adds some unimportant terms. VANISH also has trouble selecting some important main effect and interaction effect terms. As a result, both RAMP and VANISH have low numbers of correct models. Our proposed method has a significantly smaller ISE compared to the other two methods. Overall, our proposed method outperforms RAMP and VANISH in this nonlinear case.

6.2. Models without strong heredity

Although the strong heredity assumption is commonly used, weak heredity and no heredity constraints are possible in practice. Next, we consider more general models without strong heredity.

Example 3. Linear two-way interaction model without strong heredity:

$$Y = 2.5X_1 + 2.5X_2 + 4X_1X_2 + 4X_1X_3 + 4X_4X_5 + \varepsilon,$$

where $\varepsilon \sim N(0,1)$. In this model, there are two important main terms and three important interaction terms. Three different cases of important interaction terms are considered to evaluate the performance of the methods: interaction term (X_1, X_2), with both corresponding main effects being important; interaction term (X_1, X_3), with one of the corresponding main effects being important; interaction term (X_4, X_5), with none of the corresponding main effects being important. Training data sets of size 150 and an independent test set of size 1,000 are used. The third block of Table 1 shows the simulation results over 100 repetitions.

In terms of main and interaction effect selection, our proposed method still performs well, selecting important main and interaction effect terms perfectly (except missing one interaction term for one repetition) and unimportant terms at very low frequency. In comparison, both RAMP and VANISH suffer a little. RAMP, on average, selects several unimportant interaction terms, while VANISH fails to select some important main and interaction effects. Note that both RAMP and VANISH have either a weak or a strong heredity requirement. The interaction term (X_4, X_5) does not satisfy either weak or strong heredity, and thus cannot be chosen. RAMP tends to add some unimportant terms into the model to make up for it, resulting in a smaller number of correct models. Our proposed method has the smallest ISE. Although this is a linear model, our proposed method has better selection performance and leads to a smaller ISE compared with the linear method RAMP.

Example 4. Nonlinear two-way interaction model without strong heredity:

$$Y = m_1(X_1) + m_2(X_2) + m_{(1,2)}(X_1, X_2) + m_{(1,3)}(X_1, X_3) + m_{(4,5)}(X_4, X_5) + \varepsilon, \tag{6.1}$$

where $m_i(X_i) = 1.9\cos(X_i\pi)$ and $m_{(j,k)}(X_j, X_k) = 2.1sin(X_jX_k\pi)$. The sample size of the training data is 250, and all other settings are the same as in Example 3. The fourth block of Table 1 summarizes the corresponding simulation results over 100 repetitions.

The performance comparison is very similar to Example 3. In this case, our method achieves perfect main effect and interaction effect selection, while RAMP and VANISH exhibit some errors.

The path consistency (PC) of our new method is always 100 out of 100 repetitions for all four simulation examples, even though the correct model (CM) is not equal to 100 for Example 3. This could be improved by considering an alternative tuning method.

During the review process, one reviewer inquired about the computational

Table 1. Performance comparison for the simulation examples.

Example	d	New method							
		M	NM	I	NI	CM	PC	ISE	OISE
1	10	4.00	0.00	2.00	0.00	100	100	0.15(0.01)	0.15(0.01)
	20	4.00	0.00	2.00	0.00	100	100	0.15(0.01)	0.15(0.01)
2	10	4.00	0.00	2.00	0.00	100	100	0.70(0.01)	0.70(0.01)
	20	4.00	0.00	2.00	0.00	100	100	0.68(0.01)	0.68(0.01)
3	10	2.00	0.05	2.99	0.00	94	100	0.40(0.02)	0.38(0.02)
	20	2.00	0.07	3.00	0.00	93	100	0.42(0.02)	0.43(0.02)
4	10	2.00	0.00	3.00	0.00	100	100	0.98(0.03)	0.98(0.03)
	20	2.00	0.00	3.00	0.00	100	100	1.06(0.03)	1.06(0.03)
		RAMP							
		M	NM	I	NI	CM		ISE	
1	10	4.00	0.00	2.00	0.04	96		0.04(0.01)	
	20	4.00	0.02	2.00	0.04	94		0.04(0.01)	
2	10	2.62	0.79	1.23	3.08	0		3.89(0.16)	
	20	2.36	0.56	0.94	1.99	0		4.78(0.17)	
3	10	2.00	0.50	2.49	2.74	17		1.12(0.11)	
	20	2.00	0.44	2.25	2.02	7		1.86(0.11)	
4	10	0.34	0.80	1.26	3.58	0		6.00(0.23)	
	20	0.11	0.39	0.53	1.41	0		6.95(0.14)	
		VANISH							
		M	NM	I	NI	CM		ISE	
1	10	3.50	0.00	1.89	0.04	44		4.96(0.14)	
	20	3.64	0.00	1.93	0.07	56		4.91(0.16)	
2	10	3.89	0.00	1.38	0.91	8		3.15(0.08)	
	20	3.89	0.00	1.24	0.80	2		3.02(0.08)	
3	10	2.00	0.05	1.02	0.02	0		8.79(0.16)	
	20	1.98	0.02	0.96	0.03	0		8.52(0.28)	
4	10	2.00	1.20	2.04	0.92	0		3.17(0.06)	
	20	2.00	1.15	2.02	0.65	0		2.89(0.05)	

speed. On a MacBook equipped with an Intel Core i5 @2.3GHz processor, it takes, on average, 1.37 and 23.81 minutes to solve the optimization problem (3.1) for $p = 10$ and $p = 20$, respectively, in Example 3; it takes 3.60 and 59.81 minutes to solve the optimization problem (3.1) for $p = 10$ and $p = 20$, respectively, in Example 4.

Table 2. Performance comparison for the real-data example.

	New method	RAMP	VANISH
Main term size	3.1 (0.2)	2.9 (0.2)	1.0 (0.0)
Interaction term size	0.3 (0.1)	5.1 (0.6)	0.0 (0.0)
MSPE	76.03(2.58)	75.73(2.04)	170.85(3.71)

7. A real-data example

We apply our proposed method to analyze, the real estate valuation data reported in Yeh and Hsu (2018). The data set includes information on 414 properties for the period June 2012 to May 2013 from the Xindian districts in Taipei City. The response is the residential housing price per unit area, and there are six predictors: X_1=transaction date, X_2=house age, X_3=distance to the nearest MRT (Taipei mass rapid transit) station, X_4=number of convenience stores, X_5=latitude, and X_6=longitude. There are no missing values in this data set.

We randomly split the data into a training set of size $n = 210$ and a test set of size $\tilde{n} = 204$. We repeat this process with 30 random repetitions. We still compare our method with RAMP and VANISH in terms of the number of selected main and interaction effect terms. However, the ISE is replaced by the mean squared prediction error (MSPE) over the corresponding test set, namely $MSPE = (1/\tilde{n})\sum_{i=1}^{\tilde{n}}(\tilde{Y}_i - \hat{\tilde{Y}}_i)^2$, where $\tilde{Y}_i$ and $\hat{\tilde{Y}}_i$ are the observed response and the predicted response, respectively, for the ith observation in the test set for each repetition. RAMP uses its weak heredity version and the EBIC for tuning, VANISH uses 10-fold cross-validation for tuning, and our proposed method uses the BIC for tuning.

Table 2 summarizes the results for the three methods over 30 repetitions. VANISH only selects the third predictor in all repetitions, and the MSPE is larger than those of the other two methods. Our method is comparable with RAMP in terms of the MSPE. However, the model selected by our proposed method is more parsimonious and easier to interpret, because our method, in general, selects a model with fewer terms, especially for the interaction. Our method exhibits a good balance between model complexity and prediction performance.

For a random repetition, our proposed model selects the main effect of X_3 and the interaction effect of X_2 and X_3. The estimated main effect component function $\widehat{m}_3(X_3)$ and interaction effect component function $\widehat{m}_{2,3}(X_2, X_3)$ are plotted in Figures 2 and 3, respectively. The results show that X_2 (house age) and X_3 (distance to the nearest MRT station) show an interaction effect that cannot be explained by the additive model without the interaction.

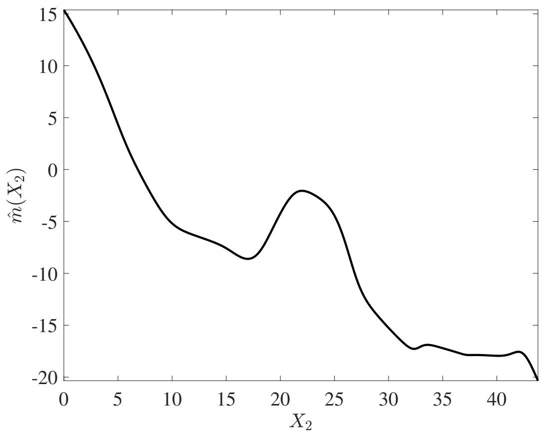

Figure 2. Plot of fitted main effect component function of X_3.

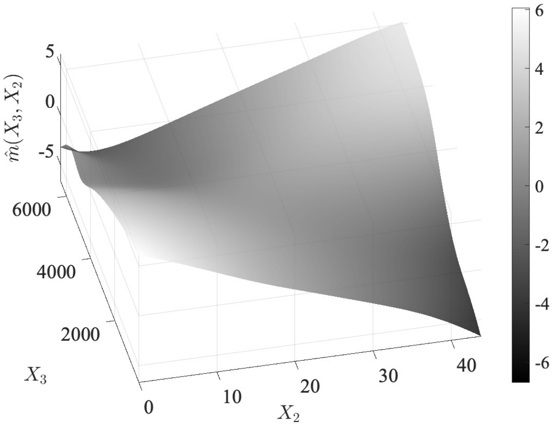

Figure 3. Plot of fitted interaction effect component function of X_2 and X_3.

8. Discussion

During the review process, one referee pointed out that it would be desirable to provide a version that achieves strong or weak heredity. In fact, this is possible. To achieve weak heredity, we can minimize (3.1) subject to the constraints

$$\begin{aligned} \lambda_j &\geq 0, \quad j = 1, 2, \ldots, d \\ \sum_{j=1}^{d} \lambda_j &= \tau \\ \tilde{\lambda}_{jk} &= \lambda_j + \lambda_k, \quad 1 \leq j < k \leq d. \end{aligned}$$

For strong heredity, we can minimize (3.1) subject to the constraints

$$\begin{aligned}
\delta_j &\geq 0, \quad j = 1, 2, \ldots, d, \\
\lambda_j &= \sum_{k \neq j} \tilde{\lambda}_{jk} + \delta_j, \quad j = 1, 2, \ldots, d, \\
\tilde{\lambda}_{jk} &\geq 0, \quad 1 \leq j < k \leq d, \\
\sum_{j=1}^{d} \delta_j + \sum_{j=1}^{d-1} \sum_{k=j+1}^{d} \tilde{\lambda}_{jk} &= \tau.
\end{aligned}$$

We admit that our algorithm is not fast. Our algorithm involves two layers of iterations: (modified) coordinate descent and backfitting algorithms, and the local constant smoothing. However, it is still manageable for a moderate dimensionality. For high-dimensional cases, we are working on an interaction screening procedure by extending the sure independence screening for nonparametric regression (Feng, Wu and Stefanski (2018)). Lastly, the selection consistency in Section 5 was established for the case with a fixed dimensionality. It would be of great interest to extend this to the case with a diverging dimensionality.

Supplementary Material

Supplementary material contains implementation codes, technical conditions, and proofs of theoretical results.

Acknowledgments

The authors would like to thank the two anonymous referees, associate editor, and co-editor Prof. Yazhen Wang for their constructive comments. This research was partially supported by NSF grants DMS-1821171 and CCF-1934915.

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(Received November 2020; accepted January 2021)