Oracle properties of local adaptive grouped regularization

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1. Spatially varying coefficients regression

1.1. Model

Consider n data points, observed at sampling locations $\boldsymbol{s}_i = (s_{i,1} \;\; s_{i,2})^T$ for $i = 1, \dots, \boldsymbol{s}_n$, which are distributed in a spatial domain $D \subset \mathbb{R}^2$ according to a density $f(\boldsymbol{s})$. For $i = 1, \dots, n$, let $y(\boldsymbol{s}_i)$ and $\boldsymbol{x}(\boldsymbol{s}_i)$ denote the univariate response variable, and a $(p+1)$-variate vector of covariates measured at location $\boldsymbol{s}_i$, respectively. At each location $\boldsymbol{s}_i$, assume that the outcome is related to the covariates by a linear model where the coefficients $\boldsymbol{\beta}(\boldsymbol{s}_i)$ may be spatially-varying and $\varepsilon(\boldsymbol{s}_i)$ is random error at location $\boldsymbol{s}_i$. That is,

$$y(\boldsymbol{s}_i) = \boldsymbol{x}(\boldsymbol{s}_i)'\boldsymbol{\beta}(\boldsymbol{s}_i) + \varepsilon(\boldsymbol{s}_i). \tag{1}$$

Further assume that the error term $\varepsilon(\boldsymbol{s}_i)$ is normally distributed with zero mean and variance σ^2, and that $\varepsilon(\boldsymbol{s}_i)$, $i = 1, \dots, n$ are independent. That is,

$$\boldsymbol{\varepsilon} \overset{iid}{\sim} \mathcal{N}\left(0, \sigma^2\right). \tag{2}$$

In the context of nonparametric regression, the boundary-effect bias can be reduced by local polynomial modeling, usually in the form of a locally linear model (Fan and Gijbels, 1996). Here, locally linear coefficients are estimated by augmenting the local design matrix with covariate-by-location interactions in two dimensions as proposed by Wang et al. (2008). The augmented local design matrix at location $\boldsymbol{s}_i$ is

$$\boldsymbol{Z}(\boldsymbol{s}_i) = (\boldsymbol{X} \;\; L_i\boldsymbol{X} \;\; M_i\boldsymbol{X}) \tag{3}$$

where $\boldsymbol{X}$ is the unaugmented matrix of covariates, $L_i = \text{diag}\{s_{i'_1} - s_{i_1}\}$ and $M_i = \text{diag}\{s_{i'_2} - s_{i_2}\}$ for $i' = 1, \ldots, n$.

Now we have that $Y(\boldsymbol{s}_i) = \{\boldsymbol{Z}(\boldsymbol{s}_i)\}_i^T \boldsymbol{\zeta}(\boldsymbol{s}_i) + \varepsilon(\boldsymbol{s}_i)$, where $\{\boldsymbol{Z}(\boldsymbol{s}_i)\}_i^T$ is the ith row of the matrix $\boldsymbol{Z}(\boldsymbol{s}_i)$ as a row vector, and $\boldsymbol{\zeta}(\boldsymbol{s}_i)$ is the vector of local coefficients at location $\boldsymbol{s}_i$, augmented with the local gradients of the coefficient surfaces in the two spatial dimensions, indicated by ∇_u and ∇_v:

$$\boldsymbol{\zeta}(\boldsymbol{s}_i) = \left(\boldsymbol{\beta}(\boldsymbol{s}_i)^T \;\; \nabla_u\boldsymbol{\beta}(\boldsymbol{s}_i)^T \;\; \nabla_v\boldsymbol{\beta}(\boldsymbol{s}_i)^T\right)^T$$

1.2. Estimation

The values of the local coefficients $\boldsymbol{\zeta}(\boldsymbol{s})$ are estimated at location $\boldsymbol{s}$ by penalized weighted least squares. The weights are computed from a kernel function $K_h(\cdot)$ such as the Epanechnikov kernel:

$$\begin{aligned} K_h(\|\boldsymbol{s}_i - \boldsymbol{s}_{i'}\|) &= h^{-2}K\left(h^{-1}\|\boldsymbol{s}_i - \boldsymbol{s}_{i'}\|\right) \\ K(x) &= \begin{cases} (3/4)(1-x^2) & \text{if } x < 1, \\ 0 & \text{if } x \geqslant 1. \end{cases} \end{aligned} \tag{4}$$

Letting $\boldsymbol{W}(\boldsymbol{s})$ be a diagonal weight matrix where $W_{ii}(\boldsymbol{s}) = K_h(\|\boldsymbol{s} - \boldsymbol{s}_i\|)$, the weighted least squares objective and its minimizer are:

$$\mathcal{S}\left\{\boldsymbol{\zeta}(\boldsymbol{s})\right\} = (1/2)\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}^T \boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}^T$$

$$\therefore \tilde{\boldsymbol{\zeta}}(\boldsymbol{s}) = \left\{\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}(\boldsymbol{s})\right\}^{-1}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Y} \tag{5}$$

2. Local variable selection and parameter estimation

2.1. Local variable selection

Local adaptive grouped regularization (LAGR) is explored as a method of local variable selection and coefficient estimation in SVCR models. The proposed LAGR penalty is an adaptive ℓ_1 penalty akin to the adaptive group lasso (Wang and Leng, 2008; Zou, 2006).

Grouped variables are selected together for inclusion in the model. Each group in a LAGR model consists of one covariate and its interactions on the two dimensions of spatial location. That is, $\boldsymbol{\zeta}_j(\boldsymbol{s}) = \left(\beta_j(\boldsymbol{s}) \quad \nabla_u\beta_j(\boldsymbol{s}) \quad \nabla_v\beta_j(\boldsymbol{s})\right)^T$ for $j = 1, \dots, p$.

The objective function for the LAGR at location $\boldsymbol{s}$ is:

$$\begin{aligned} Q\{\boldsymbol{\zeta}(\boldsymbol{s})\} &= \mathcal{S}\left\{\boldsymbol{\zeta}(\boldsymbol{s})\right\} + \mathcal{J}\{\boldsymbol{\zeta}(\boldsymbol{s})\} \\ &= (1/2)\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}^T \boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}^T + \sum_{j=1}^{p}\phi_j(\boldsymbol{s})\|\zeta_j(\boldsymbol{s})\| \end{aligned} \tag{6}$$

which is the sum of the weighted sum of squares $\mathcal{S}\left\{\boldsymbol{\zeta}(\boldsymbol{s})\right\}$ and the LAGR penalty $\mathcal{J}\{\boldsymbol{\zeta}(\boldsymbol{s})\}$.

The LAGR penalty for the jth group of coefficients $\boldsymbol{\zeta}_j(\boldsymbol{s})$ at location $\boldsymbol{s}$ is $\phi_j(\boldsymbol{s}) = \lambda_n(\boldsymbol{s})\|\tilde{\boldsymbol{\zeta}}_j(\boldsymbol{s})\|^{-\gamma}$, where $\lambda_n(\boldsymbol{s}) > 0$ is a the local tuning parameter applied to all coefficients at location $\boldsymbol{s}$ and $\tilde{\boldsymbol{\zeta}}_j(\boldsymbol{s})$ is the vector of unpenalized local coefficients from (5).

2.2. Computation

2.2.1. Tuning parameter selection

3. Asymptotic properties

3.1. Notation and assumptions

Consider the local model at location $\boldsymbol{s}$ where there are $p_0 < p$ covariates with nonzero local regression coefficients. Without loss of generality, assume these are covariates $1, \ldots, p_0$.

Let $h = O(n^{-1/6})$.

Let $a_n = \max\{\phi_j(\boldsymbol{s}), j \leqslant p_0\}$ be the largest penalty applied to a covariate group whose true coefficient norm is nonzero, and $b_n = \min\{\phi_j(\boldsymbol{s}), j > p_0\}$ be the smallest penalty applied to a covariate group whose true coefficient norm is zero.

Let $\boldsymbol{Z}_k(\boldsymbol{s})$ be the design matrix for covariate group k, and $\boldsymbol{Z}_{-k}(\boldsymbol{s})$ be the design matrix for all the data except covariate group k, respectively. Similarly, let $\boldsymbol{\zeta}_k(\boldsymbol{s})$ be the coefficients for covariate group k and $\boldsymbol{\zeta}_{-k}(\boldsymbol{s})$ be the coefficients for all covariate groups except k.

Finally, let $\kappa_0 = \int_{R^2} K(\|\boldsymbol{s}\|)ds$ and $\kappa_2 = \int_{R^2} [(1,0)\boldsymbol{s}]^2 K(\|\boldsymbol{s}\|)ds = \int_{R^2} [(0,1)\boldsymbol{s}]^2 K(\|\boldsymbol{s}\|)ds$.

3.2. Results

Asymptotic normality.

Theorem 3.1. *If* $h^{-1}n^{-1/2}a_n \xrightarrow{p} 0$ *and* $hn^{-1/2}b_n \xrightarrow{p} \infty$ *then*

$$h\sqrt{n}\left[\hat{\boldsymbol{\zeta}}(\boldsymbol{s}) - \boldsymbol{\zeta}(\boldsymbol{s}) - \frac{\kappa_2 h^2}{2\kappa_0}\{\nabla^2_{uu}\boldsymbol{\zeta}(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}(\boldsymbol{s})\}\right] \xrightarrow{d} N(0, \cdot)$$

3.3. Selection

Theorem 3.2. *If $h^{-1}n^{-1/2}a_n \xrightarrow{p} \infty$ and $hn^{-1/2}b_n \xrightarrow{p} \infty$ then $P\left\{\hat{\boldsymbol{\zeta}}_j(\boldsymbol{s}) = 0\right\} \to 0$ if $j \leqslant p_0$ and $P\left\{\hat{\boldsymbol{\zeta}}_j(\boldsymbol{s}) = 0\right\} \to 1$ if $j > p_0$.*

3.4. A note on rates

To prove the oracle properties of LAGR, we assumed that $h^{-1}n^{-1/2}a_n \xrightarrow{p} 0$ and $hn^{-1/2}b_n \xrightarrow{p} \infty$. Therefore, $h^{-1}n^{-1/2}\lambda_n(\boldsymbol{s}) \to 0$ for $j \leqslant p_0$ and $hn^{-1/2}\lambda_n(\boldsymbol{s})\|\boldsymbol{\zeta}_j(\boldsymbol{s})\|^{-\gamma} \to \infty$ for $j > p_0$.

We require that $\lambda_n(\boldsymbol{s})$ can satisfy both assumptions. Suppose $\lambda_n(\boldsymbol{s}) = n^{\alpha}$, and recall that $h = O(n^{-1/6})$ and $\|\tilde{\boldsymbol{\zeta}}_p(\boldsymbol{s})\| = O(h^{-1}n^{-1/2})$. Then $h^{-1}n^{-1/2}\lambda_n(\boldsymbol{s}) = O(n^{-1/3+\alpha})$ and $hn^{-1/2}\lambda_n(\boldsymbol{s})\|\tilde{\boldsymbol{\zeta}}_p(\boldsymbol{s}\|^{-\gamma} = O(n^{-2/3+\alpha+\gamma/3})$.

So $(2-\gamma)/3 < \alpha < 1/3$, which can only be satisfied for $\gamma > 1$.

A. Proofs of theorems

Proof of theorem 3.1. Define $V_4^{(n)}(\boldsymbol{u})$ to be the

$$
\begin{aligned}
V_4^{(n)}(\boldsymbol{u}) &= Q\left\{\boldsymbol{\zeta}(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}\right\} - Q\left\{\boldsymbol{\zeta}(\boldsymbol{s})\right\} \\
&= (1/2)\left[\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\left\{\boldsymbol{\zeta}(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}\right\}\right]^T \boldsymbol{W}(\boldsymbol{s})\left[\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\left\{\boldsymbol{\zeta}(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}\right\}\right] \\
&\quad + \sum_{j=1}^{p} \phi_j(\boldsymbol{s})\|\boldsymbol{\zeta}_j(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}_j\| \\
&\quad - (1/2)\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}^T \boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\} - \sum_{j=1}^{p} \phi_j(\boldsymbol{s})\|\boldsymbol{\zeta}_j(\boldsymbol{s})\| \\
&= (1/2)\boldsymbol{u}^T\left\{h^{-2}n^{-1}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}(\boldsymbol{s})\right\}\boldsymbol{u} - \boldsymbol{u}^T\left[h^{-1}n^{-1/2}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}\right] \\
&\quad + \sum_{j=1}^{p} n^{-1/2}\phi_j(\boldsymbol{s})n^{1/2}\left\{\|\boldsymbol{\zeta}_j(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}_j\| - \|\boldsymbol{\zeta}_j(\boldsymbol{s})\|\right\} \qquad (7)
\end{aligned}
$$

Note the different limiting behavior of the third term between the cases $j \leqslant p_0$ and $j > p_0$:

Case $j \leqslant p_0$. If $j \leqslant p_0$ then $n^{-1/2}\phi_j(\boldsymbol{s}) \to n^{-1/2}\lambda_n(\boldsymbol{s})\|\boldsymbol{\zeta}_j(\boldsymbol{s})\|^{-\gamma}$ and $|\sqrt{n}\left\{\|\boldsymbol{\zeta}_j(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}_j\| - \|\boldsymbol{\zeta}_j(\boldsymbol{s})\|\right\}| \leqslant h^{-1}\|\boldsymbol{u}_j\|$ so

$$\lim_{n\to\infty} \phi_j(\boldsymbol{s})\left(\|\boldsymbol{\zeta}_j(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}_j\| - \|\boldsymbol{\zeta}_j(\boldsymbol{s})\|\right) \leqslant h^{-1}n^{-1/2}\phi_j(\boldsymbol{s})\|\boldsymbol{u}_j\| \leqslant h^{-1}n^{-1/2}a_n\|\boldsymbol{u}_j\| \to 0$$

Case $j > p_0$. If $j > p_0$ then $\phi_j(\boldsymbol{s})\left(\|\boldsymbol{\zeta}_j(\boldsymbol{s}) + h^{-1}n^{-1/2}\boldsymbol{u}_j\| - \|\boldsymbol{\zeta}_j(\boldsymbol{s})\|\right) = \phi_j(\boldsymbol{s})h^{-1}n^{-1/2}\|\boldsymbol{u}_j\|$.

And note that $h = O(n^{-1/6})$ so that if $hn^{-1/2}b_n \xrightarrow{p} \infty$ then $h^{-1}n^{-1/2}b_n \xrightarrow{p} \infty$.

Now, if $\|\boldsymbol{u}_j\| \neq 0$ then

$$h^{-1}n^{-1/2}\phi_j(\boldsymbol{s})\|\boldsymbol{u}_j\| \geqslant h^{-1}n^{-1/2}b_n\|\boldsymbol{u}_j\| \to \infty$$

. On the other hand, if $\|\boldsymbol{u}_j\| = 0$ then $h^{-1}n^{-1/2}\phi_j(\boldsymbol{s})\|\boldsymbol{u}_j\| = 0$.

Thus, the limit of $V_4^{(n)}(\boldsymbol{u})$ is the same as the limit of $V_4^{*(n)}(\boldsymbol{u})$ where

$$V_4^{*(n)}(\boldsymbol{u}) = \begin{cases} (1/2)\boldsymbol{u}^T\left\{h^{-2}n^{-1}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}(\boldsymbol{s})\right\}\boldsymbol{u} - \boldsymbol{u}^T\left[h^{-1}n^{-1/2}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}\right] & \text{if } \|\boldsymbol{u}_j\| = 0 \ \forall j > p_0 \\ \infty & \text{otherwise} \end{cases}.$$

From which it is clear that $V_4^{*(n)}(\boldsymbol{u})$ is convex and its unique minimizer is $\hat{\boldsymbol{u}}^{(n)}$:

$$0 = \left\{h^{-2}n^{-1}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}(\boldsymbol{s})\right\}\hat{\boldsymbol{u}}^{(n)} - \left[h^{-1}n^{-1/2}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}\right]$$

$$\therefore \hat{\boldsymbol{u}}^{(n)} = \left\{n^{-1}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}(\boldsymbol{s})\right\}^{-1}\left[hn^{-1/2}\boldsymbol{Z}^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s})\right\}\right] \tag{8}$$

By the epiconvergence results of Geyer (1994) and Knight and Fu (2000), the minimizer of the limiting function is the limit of the minimizers $\hat{\boldsymbol{u}}^{(n)}$. And since, by Lemma 2 of Sun et al. (2014),

$$\hat{\boldsymbol{u}}^{(n)} \xrightarrow{d} N\left(\frac{\kappa_2 h^2}{2\kappa_0}\{\nabla^2_{uu}\boldsymbol{\zeta}_j(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}_j(\boldsymbol{s})\}, f(\boldsymbol{s})\kappa_0^{-2}\nu_0\sigma^2\Psi^{-1}\right) \tag{9}$$

the result is proven. □

Proof of theorem 3.2. We showed in Theorem 3.1 that $\hat{\boldsymbol{\zeta}}_j(\boldsymbol{s}) \xrightarrow{p} \boldsymbol{\zeta}_j(\boldsymbol{s}) + \frac{\kappa_2 h^2}{2\kappa_0}\{\nabla^2_{uu}\boldsymbol{\zeta}_j(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}_j(\boldsymbol{s})\}$, so to complete the proof of selection consistency, it only remains to show that $P\left\{\hat{\boldsymbol{\zeta}}_j(\boldsymbol{s}) = 0\right\} \to 1$ if $j > p_0$.

The proof is by contradiction. Without loss of generality we consider only the case $j = p$.

Assume $\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s}) \neq 0$. Then $Q\{\boldsymbol{\zeta}(\boldsymbol{s})\}$ is differentiable w.r.t. $\boldsymbol{\zeta}_p(\boldsymbol{s})$ and is minimized where

$$\begin{aligned}
0 &= \boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\left\{\boldsymbol{Y} - \boldsymbol{Z}_{-p}(\boldsymbol{s})\hat{\boldsymbol{\zeta}}_{-p}(\boldsymbol{s}) - \boldsymbol{Z}_p(\boldsymbol{s})\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\right\} - \phi_p(\boldsymbol{s})\frac{\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})}{\|\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\|} \\
&= \boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\left[\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s}) - \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\boldsymbol{\zeta}(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}(\boldsymbol{s})\right\}\right] \\
&\quad + \boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}_{-p}(\boldsymbol{s})\left[\boldsymbol{\zeta}_{-p}(\boldsymbol{s}) + \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\boldsymbol{\zeta}_{-p}(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}_{-p}(\boldsymbol{s})\right\} - \hat{\boldsymbol{\zeta}}_{-p}(\boldsymbol{s})\right] \\
&\quad + \boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}_p(\boldsymbol{s})\left[\boldsymbol{\zeta}_p(\boldsymbol{s}) + \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\boldsymbol{\zeta}_p(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}_p(\boldsymbol{s})\right\} - \hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\right] \\
&\quad - \phi_p(\boldsymbol{s})\frac{\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})}{\|\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\|}
\end{aligned} \tag{10}$$

So

$$\begin{aligned}
\frac{h}{\sqrt{n}}\phi_p(\boldsymbol{s})\frac{\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})}{\|\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\|} &= \boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\frac{h}{\sqrt{n}}\left[\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s}) - \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\boldsymbol{\zeta}(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}(\boldsymbol{s})\right\}\right] \\
&\quad + \left\{n^{-1}\boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}_{-p}(\boldsymbol{s})\right\}h\sqrt{n}\left[\boldsymbol{\zeta}_{-p}(\boldsymbol{s}) + \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\boldsymbol{\zeta}_{-p}(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}_{-p}(\boldsymbol{s})\right\} - \hat{\boldsymbol{\zeta}}_{-p}(\boldsymbol{s})\right] \\
&\quad + \left\{n^{-1}\boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}_p(\boldsymbol{s})\right\}h\sqrt{n}\left[\boldsymbol{\zeta}_p(\boldsymbol{s}) + \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\boldsymbol{\zeta}_p(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}_p(\boldsymbol{s})\right\} - \hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\right]
\end{aligned} \tag{11}$$

From Lemma 2 of Sun et al. (2014), $\left\{n^{-1}\boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}_{-p}(\boldsymbol{s})\right\} = O_p(1)$ and $\left\{n^{-1}\boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\boldsymbol{Z}_p(\boldsymbol{s})\right\} = O_p(1)$.

From Theorem 3 of Sun et al. (2014), we have that $h\sqrt{n}\left[\hat{\boldsymbol{\zeta}}_{-p}(\boldsymbol{s}) - \boldsymbol{\zeta}_{-p}(\boldsymbol{s}) - \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\zeta_{-p}(\boldsymbol{s}) + \nabla^2_{vv}\zeta_{-p}(\boldsymbol{s})\right\}\right] = O_p(1)$ and $h\sqrt{n}\left[\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s}) - \boldsymbol{\zeta}_p(\boldsymbol{s}) - \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\zeta_p(\boldsymbol{s}) + \nabla^2_{vv}\zeta_p(\boldsymbol{s})\right\}\right] = O_p(1)$.

So the second and third terms of the sum in (11) are $O_p(1)$.

We showed in the proof of 3.1 that $h\sqrt{n}\boldsymbol{Z}_p^T(\boldsymbol{s})\boldsymbol{W}(\boldsymbol{s})\left[\boldsymbol{Y} - \boldsymbol{Z}(\boldsymbol{s})\boldsymbol{\zeta}(\boldsymbol{s}) - \frac{h^2\kappa_2}{2\kappa_0}\left\{\nabla^2_{uu}\boldsymbol{\zeta}(\boldsymbol{s}) + \nabla^2_{vv}\boldsymbol{\zeta}(\boldsymbol{s})\right\}\right] = O_p(1)$.

The three terms of the sum to the right of the equals sign in (11) are $O_p(1)$, so for $\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})$ to be a solution, we must have that $hn^{-1/2}\phi_p(\boldsymbol{s})\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})/\|\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\| = O_p(1)$.

But since by assumption $\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s}) \neq 0$, there must be some $k \in \{1, \dots, 3\}$ such that $|\hat{\zeta}_{p_k}(\boldsymbol{s})| = \max\{|\hat{\zeta}_{p_{k'}}(\boldsymbol{s})| : 1 \leqslant k' \leqslant 3\}$. And for this k, we have that $|\hat{\zeta}_{p_k}(\boldsymbol{s})|/\|\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\| \geqslant 1/\sqrt{3} > 0$.

Now since $hn^{-1/2}b_n \to \infty$, we have that $hn^{-1/2}\phi_p(\boldsymbol{s})\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})/\|\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s})\| \geqslant hb_n/\sqrt{3n} \to \infty$ and therefore the term to the left of the equals sign dominates the sum to the right of the equals sign in (11). So for large enough n, $\hat{\boldsymbol{\zeta}}_p(\boldsymbol{s}) \neq 0$ cannot maximize Q.

So $P\left\{\hat{\boldsymbol{\zeta}}_{(b)}(\boldsymbol{s}) = 0\right\} \to 1$. □

B. References

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