QR WITH LDP

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1. Reference

Koul and Mukherjee (1994), JMA

2. Notations

| 1. X | the $n \times p$ design matrix of known constants |
|---------------------------------------|---|
| 2. x_{ni} | <i>i</i> th row of \boldsymbol{X} , $(1 \times p)$ -matrix |
| $3. \ F$ | the common d.f. of $\{\epsilon_i\}$ |
| 4. $\psi = (c, d) \subset \mathbb{R}$ | $= \{x \in \mathbb{R}; 0 < F(x) < 1\}$ |
| 5. G | a measurable function from \mathbb{R} to \mathbb{R} |
| 6. D_c | $= (C'C)^{1/2}$, where C is of the full rank. |
| 7. $\ X_n\ _a$ | $= \sup\{\ \boldsymbol{X}_n(\alpha)\ , a \le \alpha \le 1 - a\}$ |
| 8. $X_n = O_P^*(1)$ | $\equiv \ \boldsymbol{X}_n\ _a = O_P(1) \text{ for every } a \in (0, 1/2].$ |

3. Concepts and definitions

3.1. model. η_1, η_2, \ldots stationary mean zero unit variance Gaussian process with

$$\rho(k) = E\eta_1\eta_{k+1}.$$

The response variable $\{Y_{ni}\}$ satisfying

$$Y_{ni} = \boldsymbol{x}'_{ni}\boldsymbol{\beta} + \epsilon_i, \quad 1 \le i \le n, \quad \boldsymbol{\beta} \in \mathbb{R}^p,$$

with $\epsilon_i = G(\eta_i)$.

3.2. long range dependence.

$$\rho(k) = k^{-\theta} L(k), \text{ for some } 0 < \theta < 1, \forall k \ge 1,$$

where L(k) is positive for large k and is slowly varying at infinity.

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3.3. exponent. m is the Hermite rank of the class of functions.

$$J_q(x) = E\{\mathbb{1}(G(\eta) \ge x) - F(x)\}H_q(\eta)$$

Also, suppose $m(x) = \min\{q \ge 1; J_q \neq 0\}$, then

$$m = \inf\{m(x); x \in \psi\}$$

Also, define $J_m^+(x)$ as

$$J_m^+(x) = E\mathbb{1}(G(\eta) \le x)|H_m(\eta)|.$$

3.4. normalizing order. Assume $0 < \theta < 1/m$,

$$\tau_n = n^{(1-m\theta)/2} L^{m/2}(n), \quad n \ge 1.$$

3.5. regression transform.

$$\boldsymbol{\beta}(\alpha) = \boldsymbol{\beta} + F^{-1}(\alpha)\boldsymbol{e}_1, \quad \boldsymbol{e}_1 = (1, 0, \dots, 0)',$$

and

$$q(\alpha) = f(F^{-1}(\alpha)), \quad 0 \le \alpha \le 1.$$

3.6. minimum-distance type estimator of β .

$$\hat{\boldsymbol{\beta}}_{md}(\alpha) = \arg\min_{t} \|D_x^{-1}T(\boldsymbol{t},\alpha)\|^2,$$

where

$$T(\boldsymbol{t}, lpha) = \sum_{i} \boldsymbol{x}_{ni} \{ \mathbbm{1}(Y_{ni} - \boldsymbol{x}'_{ni} \boldsymbol{t} \le 0) - lpha \}, 0 \le lpha \le 1, \quad \boldsymbol{t} \in \mathbb{R}^{d}$$

3.7. α th regression quantile.

$$\hat{\boldsymbol{\beta}}_n(\alpha) = \hat{\boldsymbol{B}}(\alpha) = \left\{ \boldsymbol{b} \in \mathbb{R}^p : \sum_{i=1}^n h_\alpha(Y_{ni} - \boldsymbol{x}'_{ni}\boldsymbol{b}) = \text{minimum} \right\},\$$

where $h_{\alpha}(u) = \alpha u \mathbb{1}(u > 0) - (1 - \alpha) u \mathbb{1}(u \le 0), u \in \mathbb{R}, 0 \le \alpha \le 1.$

4. Assumptions

- 4.1. Assumptions on γ_{ni} and ξ_{ni} . (GX0-1) $\sum_{i=1}^{n} \gamma_{ni}^2 = 1, \forall n \ge 1$
- (GX0-2) $\max_{1 \le i \le n} n^{1/2} |\gamma_{ni}| = O(1)$
- (GX1-1) $\sum_{i=1}^{n} \gamma_{ni}^2 = 1, \forall n \ge 1$
- (GX1-2) $\max_{1 \le i \le n} n^{1/2} |\gamma_{ni}| = O(1)$
- (GX1-3) $\max_{1 \le i \le n} |\xi_i| = o(1)$

(GX2-1) F has a continuous density f.

(GX2-2)
$$\tau_n^{-1} \sum_{i=1}^n |\gamma_{ni}\xi_{ni}| = O(1).$$

- (GX3-1) F has a continuous and positive density f.
- (GX3-2) The functions $J_m(x)$ and $J_m^+(x)$ are continuously differentiable with derivatives equal to $\dot{J}_m(x)$ and $\dot{J}_m^+(x)$.
- (GX3-3) $\tau_n^{-1} \sum_{i=1}^n |\gamma_{ni}\xi_{ni}| = O(1).$
- (GX4-1) F has a continuous and positive density f.
- (GX4-2) f is uniformly continuous.
- (GX4-3) The functions $J_m(x)$ and $J_m^+(x)$ are continuously differentiable with derivatives equal to $\dot{J}_m(x)$ and $\dot{J}_m^+(x)$.
- (GX4-4) $|\dot{J}_m(x)| \lor \dot{J}_m^+(x) \to 0$ as $|x| \to |c| \lor |d|$.
- (GX4-5) $\tau_n^{-1} \sum_{i=1}^n |\gamma_{ni}\xi_{ni}| = O(1).$

4.2. Assumptions on X.

- (X.1) The first column of X is **1**.
- (X.2) $(\mathbf{X}'\mathbf{X})^{-1}$ exists for all $n \ge p$.
- (X.3) $n^{1/2} \max_{i} \| \boldsymbol{x}'_{ni} \boldsymbol{D}_{\boldsymbol{x}}^{-1} \| = O(1).$

5. Formulae

6. Results

Lemma 6.1 (km1994). Under Assumption GX0, we have $\forall x \in \psi$,

$$\sup_{x\in\bar{\psi}} \left| \tau_n^{-1} \sum_i \gamma_{ni} \{ \mathbb{1}(\epsilon_i \le x) - F(x) \} - \frac{J_m(x)}{m!} \tau_n^{-1} \sum_i \gamma_{ni} H_m(\eta_i) \right| = o_P(1).$$

Under Assumption GX1, we have $\forall x \in \psi$,

$$\left|\tau_n^{-1}\sum_i \gamma_{ni} \{\mathbb{1}(\epsilon_i \le x + \xi_{ni})\} - F(x + \xi_{ni}) - \mathbb{1}(\epsilon_i \le x) + F(x)\}\right| = o_P(1).$$

Under Assumptions GX1 and GX2, then

$$\left|\tau_n^{-1}\sum_i \gamma_{ni} \{\mathbb{1}(\epsilon_i \le x + \xi_{ni})\} - \mathbb{1}(\epsilon_i \le x)\} - \tau_n^{-1}\sum_i \gamma_{ni}\xi_{ni}f(x)\right| = o_P(1).$$

Under Assumptions GX1 and GX3, then for any $0 < \kappa < \infty$ with $K = \{x \in \psi; |x| \le \kappa\}$,

$$\sup_{x\in K} \left| \tau_n^{-1} \sum_i \gamma_{ni} \{ \mathbb{1}(\epsilon_i \le x + \xi_{ni}) \} - \mathbb{1}(\epsilon_i \le x) \} - \tau_n^{-1} \sum_i \gamma_{ni} \xi_{ni} f(x) \right| = o_P(1).$$

Under Assumptions Assumptions GX1 and GX4, for $\bar{\psi} = [c, d]$,

$$\sup_{x\in\bar{\psi}} \left| \tau_n^{-1} \sum_i \gamma_{ni} \{ \mathbb{1}(\epsilon_i \le x + \xi_{ni}) \} - \mathbb{1}(\epsilon_i \le x) \} - \tau_n^{-1} \sum_i \gamma_{ni} \xi_{ni} f(x) \right| = o_P(1).$$

Lemma 6.2 (km1994). Under Assumption X, we have

$$\sup_{0 \le \alpha \le 1} \left\| B_x^{-1} T(\boldsymbol{\beta}(\alpha), \alpha) - S_x \frac{J_m(F^{-1}(\alpha))}{m!} \right\| = o_P(1).$$

and

$$\|S_x\| = O_P(1).$$

Under Assumptions X and GX3-1, we have for every $0 < K < \infty$ and $0 < \alpha < 1$,

$$\sup_{\|s\| \le K} \left\| B_x^{-1} \left[T(\boldsymbol{\beta}(\alpha) + A_x^{-1} \boldsymbol{s}, \alpha) - T(\boldsymbol{\beta}(\alpha), \alpha) \right] - sq(\alpha) \right\| = o_P(1).$$

Also, for every $0 < \alpha < 1$,

$$A_x(\hat{\beta}_{md}(\alpha) - \beta(\alpha)) = -\{q(\alpha)\}^{-1} B_x^{-1} T(\beta)(\alpha), \alpha) + o_P(1)$$

= $-\{q(\alpha)\}^{-1} S_x \frac{J_m(F^{-1}(\alpha))}{m!} + o_P(1),$

and

$$A_x\{\hat{\boldsymbol{\beta}}_n(\alpha) - \hat{\boldsymbol{\beta}}_{md}(\alpha)\} = o_P(1).$$

Under Assumptions X and GX4, we have for every $0 < K < \infty$ and $0 < \alpha < 1$,

$$\sup_{0 \le \alpha \le 1, \|s\| \le K} \left\| B_x^{-1} [T(\boldsymbol{\beta}(\alpha) + A_x^{-1} \boldsymbol{s}, \alpha) - T(\boldsymbol{\beta}(\alpha), \alpha)] - sq(\alpha) \right\| = o_P(1).$$

Theorem 6.3. Under Assumptions X and GX3-1, we have for any $0 < \alpha < 1$,

$$A_x(\hat{\beta}_n(\alpha) - \beta(\alpha)) = -\{q(\alpha)\}^{-1} B_x^{-1} T(\beta)(\alpha), \alpha) + o_P(1)$$

= $-\{q(\alpha)\}^{-1} S_x \frac{J_m(F^{-1}(\alpha))}{m!} + o_P(1).$

Consequently, for any $0 < \alpha_1 < \alpha_2 < \cdots < \alpha_k < 1$,

$$[A_x(\hat{\beta}_n(\alpha_1) - \beta(\alpha_1)), \dots, A_x(\hat{\beta}_n(\alpha_k) - \beta(\alpha_k))] = -(m!)^{-1}[\{q(\alpha_1)\}^{-1}J_m(F^{-1}(\alpha_1)), \dots, \{q(\alpha_k)\}^{-1}J_m(F^{-1}(\alpha_k))] \otimes S_x + o_P(1).$$

Under Assumptions X and GX3-1 and GX3-2, then

$$A_x(\hat{\boldsymbol{\beta}}_n(\alpha) - \boldsymbol{\beta}(\alpha)) = O_P^*(1).$$