

On Bootstrap Inconsistency and Its Repair via the Biased Bootstrap

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Outline

Weak Convergence of Random Distributions

Some Examples of Bootstrap Inconsistency

Repairing Inconsistency via the Biased Bootstrap

Examples Revisited

Simulations.

Some Old Friends . . .

Theorem (Slutsky)

$$\left. \begin{array}{l} X_n \xrightarrow{d} X \\ Y_n \xrightarrow{\text{Pr}} c \end{array} \right\} \implies (X_n, Y_n) \xrightarrow{d} (X, c)$$

Theorem (H. Rubin)

$$\left. \begin{array}{l} X_n \xrightarrow{d} X \\ g_n(x_n) \rightarrow g(x) \text{ for all}^* x_n \rightarrow x \end{array} \right\} \implies g_n(X_n) \xrightarrow{d} g(X)$$

* For all $x \in A$ and all sequences $x_n \rightarrow x$, where $\Pr(X \in A) = 1$.

... Applied to Random Distributions ...

Setup:

S_1 S_2 S_3 separable metric spaces

\mathcal{P}_1 \mathcal{P}_2 \mathcal{P}_3 spaces of probability measures on their Borel sets

$\rho_i =$ metric on \mathcal{P}_i metrizing weak convergence

$X_n =$ random elements of S_1

$Q_n =$ random elements of \mathcal{P}_2

$\psi_n =$ measurable mappings of $(S_1 \times \mathcal{P}_2)$ into \mathcal{P}_3

Assume:

$$X_n \xrightarrow{d} X$$

$$Q_n \xrightarrow{\text{Pr}} Q \text{ (nonrandom)}$$

$$\psi_n(x_n, Q_n) \rightarrow \psi(x, Q) \text{ for all}^* (x_n, Q_n) \rightarrow (x, Q)$$

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...

$$\left. \begin{array}{l} X_n \xrightarrow{d} X \\ Q_n \xrightarrow{\text{Pr}} Q \end{array} \right\} \xrightarrow{\text{Slutsky}} (X_n, Q_n) \xrightarrow{d} (X, Q)$$
$$\left. \begin{array}{l} \psi_n(x_n, Q_n) \rightarrow \psi(x, Q) \\ \text{for all}^* (x_n, Q_n) \rightarrow (x, Q) \end{array} \right\}$$

$$\xrightarrow{\text{H.Rubin}} \psi_n(X_n, Q_n) \xrightarrow{d} \psi(X, Q)$$

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Proposition

Assume:

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$$\psi_n(X_n, Q_n) \rightarrow \psi(X, Q) \text{ for all}^* (x_n, Q_n) \rightarrow (x, Q)$$

Then:

$$\psi_n(X_n, Q_n) \xrightarrow{d} \psi(X, Q)$$

X_n, Y_n random elements of S_1 and S_2 , resp.
 $g_n(x, y)$ S_3 -valued function on $S_1 \times S_2$
 \mathcal{A}_n sub- σ -algebra of underlying probability space

Corollary

Assume:

$$X_n \in \mathcal{A}_n \quad \text{and} \quad X_n \xrightarrow{d} X \sim P$$

$$\mathcal{L}(Y_n | \mathcal{A}_n) \xrightarrow{\text{Pr}} Q \text{ (nonrandom)}$$

$$g_n(x_n, y_n) \rightarrow g(x, y) \quad \text{for all}^* (x_n, y_n) \rightarrow (x, y)$$

Then:

$$\mathcal{L}(g_n(X_n, Y_n) | \mathcal{A}_n) \xrightarrow{d} \mathcal{L}(g(X, Y) | X), \quad X \sim P, \quad Y \sim Q, \quad X \perp\!\!\!\perp Y.$$

Examples: Generalities

Each of our examples follows the same pattern

- ▶ $X_{1:n} := X_1, \dots, X_n \sim \text{i.i.d.}$
- ▶ X_1^*, \dots, X_n^* a with-replacement random sample from $X_{1:n}$
- ▶ $S_n \in \sigma(X_{1:n})$ and $S_n \xrightarrow{d} Z \sim N(0, \Sigma)$
- ▶ $\mathcal{L}(S_n^* | X_{1:n}) \xrightarrow{\text{Pr}} N(0, \Sigma)$
- ▶ $T_n = g_n(0, S_n; \theta)$
- ▶ $T_n^* = g_n(S_n, S_n^*; \theta)$
- ▶ $g_n(x_n, y_n; \theta) \rightarrow g(x, y; \theta)$ for all* $(x_n, y_n) \rightarrow (x, y)$

Thus

- * $T_n \xrightarrow{d} g(0, Z; \theta) \quad Z \sim N(0, \Sigma)$
- * $\mathcal{L}(T_n^* | X_{1:n}) \xrightarrow{d} \mathcal{L}(g(Z, W; \theta) | Z) \quad Z, W \sim \text{i.i.d. } N(0, \Sigma)$

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- * $g_n(T_n, X_{1:n}) \xrightarrow{d} g(g(0, Z; \theta), Z)$ if $Z, W \stackrel{\text{i.i.d.}}{\sim} N(0, \Sigma)$

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- ▶ $T_n^* \xrightarrow{d} g(Z, Z; \theta) \in N(0, \Sigma)$ and $N(0, \Sigma)$

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For most values of θ :

$$g(x, y; \theta) = g(0, y; \theta)$$

so that

$$\begin{aligned} \mathcal{L}(g(Z, W; \theta) | Z) &= \mathcal{L}(g(0, W; \theta) | Z) \\ &= \mathcal{L}(g(0, W; \theta)) = \mathcal{L}(g(0, Z; \theta)) \quad \checkmark \end{aligned}$$

For other values of θ :

$g(x, y; \theta)$ depends on x and

$\mathcal{L}(g(Z, W; \theta) | Z)$ is random (varies with Z) ✗

Example: Hodges' Estimator

$$X_1, \dots, X_n \sim \text{i.i.d. } (\mu, 1)$$

$$0 \leq b < 1$$

$$\hat{\mu}_n = \begin{cases} \bar{X}_n & \text{if } |\bar{X}_n| > n^{-1/4} \\ b \bar{X}_n & \text{if } |\bar{X}_n| \leq n^{-1/4} \end{cases}$$

$$S_n = n^{1/2}(\bar{X}_n - \mu)$$

$$S_n^* = n^{1/2}(\bar{X}_n^* - \bar{X}_n)$$

$$S_n \xrightarrow{d} Z \sim N(0, 1)$$

$$\mathcal{L}(S_n^* | X_{1:n}) \xrightarrow{\text{Pr}} N(0, 1)$$

$$T_n = n^{1/2}(\hat{\mu}_n - \mu)$$

$$T_n^* = n^{1/2}(\hat{\mu}_n^* - \bar{X}_n)$$

$$g_n(x, y; \mu) = y - (1 - b)(x + y + n^{1/2}\mu) \mathbf{I}(|x + y + n^{1/2}\mu| \leq n^{1/4})$$

$$g(x, y; \mu) = \begin{cases} y, & \text{if } \mu \neq 0, \\ by + (1 - b)x, & \text{if } \mu = 0 \end{cases}$$

Example: Hodges' Estimator (p2)

$$g(x, y; \mu) = \begin{cases} y, & \text{if } \mu \neq 0, \\ by + (1 - b)x, & \text{if } \mu = 0 \end{cases}$$

$$T_n \xrightarrow{d} g(0, Z; \mu) = \begin{cases} Z & \text{if } \mu \neq 0 \\ bZ & \text{if } \mu = 0 \end{cases} \quad Z \sim N(0, 1)$$

$$\mathcal{L}(T_n^* | X_{1:n}) \xrightarrow{d} \mathcal{L}(g(Z, W; \mu) | Z) \quad Z, W \sim \text{i.i.d. } N(0, 1)$$

$$\mu \neq 0 : g(x, y; \mu) = g(0, y; \mu) = y$$

$$\mathcal{L}(g(Z, W; \mu) | Z) = \mathcal{L}(W | Z) = \mathcal{L}(W) = N(0, 1) \quad \checkmark$$

$$\mu = 0 : g(x, y; \mu) = by + (1 - b)x$$

$$\mathcal{L}(g(Z, W; 0) | Z) = \mathcal{L}(bW + (1 - b)Z | Z) = N((1 - b)Z, b^2) \quad \times$$

Example: Lindley's Estimator

$$X_1, \dots, X_n \sim \text{i.i.d. } (\mu, I_p) \quad (p \geq 4)$$

$$\hat{\mu}_n = m(\bar{X}_n)\mathbf{1}_p + \left\{ 1 - \frac{p-3}{n\|\bar{X}_n - m(\bar{X}_n)\mathbf{1}_p\|^2} \right\} \{\bar{X}_n - m(\bar{X}_n)\mathbf{1}_p\}$$

where

$$m(x) := \frac{1}{p} \sum_{i=1}^p x^{(i)}, \quad x \in \mathbb{R}^p$$

Example: Lindley's Estimator (p2)

$$S_n = n^{1/2}(\bar{X}_n - \mu)$$

$$S_n^* = n^{1/2}(\bar{X}_n^* - \bar{X}_n)$$

$$S_n \xrightarrow{d} Z \sim N(0, I_p)$$

$$\mathcal{L}(S_n^* | X_{1:n}) \xrightarrow{\text{Pr}} N(0, I_p)$$

$$T_n = n^{1/2}(\hat{\mu}_n - \mu)$$

$$T_n^* = n^{1/2}(\hat{\mu}_n^* - \bar{X}_n)$$

$$g_n(x, y; \mu) = y - \frac{(\rho - 3)[(x + y) - m(x + y)\mathbf{1}_\rho + n^{1/2}\{\mu - m(\mu)\mathbf{1}_\rho\}]}{\|(x + y) - m(x + y)\mathbf{1}_\rho + n^{1/2}\{\mu - m(\mu)\mathbf{1}_\rho\}\|^2}$$

$$g(x, y; \mu) = \begin{cases} y & \text{if } \mu \neq m(\mu)\mathbf{1}_\rho \\ y - \frac{(\rho - 3)[(x + y) - m(x + y)\mathbf{1}_\rho]}{\|(x + y) - m(x + y)\mathbf{1}_\rho\|^2} & \text{if } \mu = m(\mu)\mathbf{1}_\rho \end{cases}$$

Example: Lindley's Estimator (p3)

$$T_n \xrightarrow{d} g(0, Z; \mu) \quad Z \sim N(0, I_p)$$

$$\mathcal{L}(T_n^* | X_{1:n}) \xrightarrow{d} \mathcal{L}(g(Z, W; \mu) | Z) \quad Z, W \sim \text{i.i.d. } N(0, I_p)$$

$$\mu \neq m(\mu) \mathbf{1}_p : g(x, y; \mu) = g(0, y; \mu) = y$$

$$T_n \xrightarrow{d} Z \sim N(0, I_p)$$

$$\mathcal{L}(g(Z, W; \mu) | Z) = \mathcal{L}(W | Z) = \mathcal{L}(W) = N(0, I_p) \quad \checkmark$$

$$\mu = m(\mu) \mathbf{1}_p :$$

$$T_n \xrightarrow{d} Z - \frac{(p-3)\{Z - m(Z)\mathbf{1}_p\}}{\|Z - m(Z)\mathbf{1}_p\|^2}, \quad Z \sim N(0, I_p)$$

$$\mathcal{L}(g(Z, W; \mu) | Z) = \mathcal{L}\left(W - \frac{(p-3)[(Z+W) - m(Z+W)\mathbf{1}_p]}{\|(Z+W) - m(Z+W)\mathbf{1}_p\|^2} \middle| Z\right) \quad \times$$

Example: The LASSO (Correlation Model)

$$(X_1, Y_1), \dots, (X_n, Y_n) \text{ i.i.d.} \quad E[(Y_i - X_i^T \beta) X_i] = 0$$

$$\hat{\beta}_n = \operatorname{argmin}_b \left\{ \sum_{i=1}^n (Y_i - X_i^T b)^2 + \lambda_n \sum_{j=1}^p |b^{(j)}| \right\}$$

Assume: $E(\|(X_i, Y_i)\|^4) < \infty$

$$V := \operatorname{Var}[(Y_i - X_i^T \beta) X_i] \text{ positive definite}$$

$$C := E(X_i X_i^T) \text{ positive definite}$$

$$n^{-1/2} \lambda_n \rightarrow \lambda_0$$

Let: $\Sigma = C^{-1} V C^{-1}$

Bootstrapping Cases

$(X_1^*, Y_1^*), \dots, (X_n^*, Y_n^*)$ is a with-replacement random sample from $(X, Y)_{1:n} = \{(X_1, Y_1), \dots, (X_n, Y_n)\}$.

Example: LASSO (Correlation Model) (p2)

$$C_n = n^{-1} \sum_{i=1}^n X_i X_i^T$$

$$\bar{\beta}_n = C_n^{-1} n^{-1} \sum_{i=1}^n X_i Y_i \quad (\text{LSE})$$

$$S_n = n^{1/2}(\bar{\beta}_n - \beta)$$

$$T_n = n^{1/2}(\hat{\beta}_n - \beta)$$

$$C_n \xrightarrow{\text{Pr}} C$$

$$S_n \xrightarrow{d} Z \sim N(0, \Sigma)$$

$$C_n^* = n^{-1} \sum_{i=1}^n X_i^* X_i^{*T}$$

$$\bar{\beta}_n^* = C_n^{*-1} n^{-1} \sum_{i=1}^n X_i^* Y_i^*$$

$$S_n^* = n^{1/2}(\bar{\beta}_n^* - \bar{\beta}_n)$$

$$T_n^* = n^{1/2}(\hat{\beta}_n^* - \bar{\beta}_n)$$

$$C_n^* \xrightarrow{\text{Pr}} C$$

$$\mathcal{L}(S_n^* | X_{1:n}) \xrightarrow{\text{Pr}} N(0, \Sigma)$$

Example: LASSO (Correlation Model) (p3)

$$g_n(x, y, C; \beta) = y + \operatorname{argmin}_u \left\{ u^T C u + n^{-1/2} \lambda_n \sum_{j=1}^p \left(|n^{1/2} \beta^{(j)} + (x + y + u)^{(j)}| - |n^{1/2} \beta^{(j)}| \right) \right\}$$

$$g(x, y, C; \beta) = y + \operatorname{argmin}_u \left\{ u^T C u + \lambda_0 \sum_{j=1}^p \left(u^{(j)} \operatorname{sign}(\beta^{(j)}) + |(x + y + u)^{(j)}| \mathbb{1}(\beta^{(j)} = 0) \right) \right\}$$

Note: $\beta^{(j)} \neq 0$ for all $j = 1, \dots, p \implies g(x, y, C; \beta) = g(0, y, C; \beta)$

Example: LASSO (Correlation Model) (p4)

$$T_n \xrightarrow{d} g(0, Z, C; \beta), \quad Z \sim N(0, \Sigma)$$

$$\mathcal{L}(T_n^* | X_{1:n}) \xrightarrow{d} \mathcal{L}(g(Z, W, C; \beta) | Z) \quad Z, W \sim \text{i.i.d. } N(0, \Sigma)$$

$\beta^{(j)} \neq 0$ for all $j = 1, \dots, p$: $g(x, y, C; \beta) = g(0, y, C; \beta)$

$$\mathcal{L}(g(Z, W, C; \beta) | Z) = \mathcal{L}(g(0, W, C; \beta) | Z) = \mathcal{L}(g(0, W, C; \beta)) \quad \checkmark$$

$\beta^{(j)} = 0$ for at least one $j = 1, \dots, p$:

$$\mathcal{L}(g(Z, W, C; \beta) | Z) \text{ varies with } Z \text{ and is random } \times$$

A Way to Repair the Bootstrap

Why is the bootstrap inconsistent in these examples?

- ▶ Limiting distribution of T_n is discontinuous in μ .
- ▶ Resampling from empirical distribution with mean $\bar{X}_n \neq \mu$.

Idea

- ▶ Resample from a distribution with mean $\tilde{\mu}_n$ chosen to fix bootstrap inconsistency.

Candidate Family of Distributions

- ▶ Weighted empirical distribution with weight w_i on X_i , $i = 1, \dots, n$.
- ▶ For a given value of μ , choose the weights to
 - ▶ minimize Kullback-Leibler divergence from empirical distribution
 - ▶ subject to constraint $\sum_{i=1}^n w_i X_i = \mu$.
- ▶ Defines a pseudo-parametric family of distributions $\{\hat{P}_\mu\}$.

Theorem

Suppose:

- ▶ $\Theta = \uplus_{i \in \mathcal{I}} \Theta_i \subset \mathbb{R}^p$.
- ▶ $\mathcal{L}(\mathbf{S}_n^* | X_{1:n}) \xrightarrow{P_\theta^n} \mathbf{Q}_\theta$ for all $\theta \in \Theta$.
- ▶ $\mathbf{Q}_\theta(\mathbf{A}_\theta) = 1$ for all $\theta \in \Theta$.
- ▶ $\tilde{\theta}_n \xrightarrow{P_\theta^n} \theta$ and $P_\theta^n(\tilde{\theta}_n \in \Theta_i) \rightarrow 1$ for all $\theta \in \Theta_i$ and $i \in \mathcal{I}$.
- ▶ For all $i \in \mathcal{I}$ and all $\theta \in \Theta_i$, $g_n(x_n; \theta_n) \rightarrow g(x; \theta)$ for all sequences $x_n \rightarrow x \in \mathbf{A}_\theta$ and $\theta_n \rightarrow \theta$ with $\{\theta_n, n \geq 1\} \subset \Theta_i$.

Then for all $\theta \in \Theta$: $\mathcal{L}(g_n(\mathbf{S}_n^*, \tilde{\theta}_n) | X_{1:n}) \xrightarrow{P_\theta^n} \mathcal{L}(g(\mathbf{Z}, \theta))$, $\mathbf{Z} \sim \mathbf{Q}_\theta$.

Corollary

If $\mathcal{L}(\mathbf{S}_n) \xrightarrow{P_\theta^n} \mathbf{Q}_\theta$ for all $\theta \in \Theta$, then the conditional distribution of $T_n^* = g_n(\mathbf{S}_n^*, \tilde{\theta}_n)$ given $X_{1:n}$ consistently estimates the distribution of $T_n = g_n(\mathbf{S}_n, \theta)$ under all values of $\theta \in \Theta$.

Theorem

Suppose:

- ▶ $\Theta = \uplus_{i \in \mathcal{I}} \Theta_i \subset \mathbb{R}^p$.
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Theorem

Assume

$X_1, \dots, X_n \sim \text{i.i.d. } (\mu, \Sigma)$ (finite)

$\tilde{\mu}_n$ is \sqrt{n} -consistent for μ

Let

$X_1^*, \dots, X_n^* \sim \text{i.i.d. } \hat{P}_{\tilde{\mu}_n}$ conditional on $X_{1:n} = \{X_1, \dots, X_n\}$

Then

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Examples Revisited

Example (Hodges Estimator)

- ▶ $\theta_0 = \{0\}$, $\theta_1 = (-\infty, 0) \cup (0, \infty)$.
- ▶ $g_n(x; \mu) = x - (1 - b)(x + n^{1/2}\mu) I(|x + n^{1/2}\mu| \leq n^{1/4})$
- ▶ $g(x; \mu) = x - (1 - b)x I(\mu = 0) = \begin{cases} x & \text{if } \mu \neq 0 \\ bx & \text{if } \mu = 0 \end{cases}$
- ▶ $\tilde{\mu}_n = \bar{X}_n I(|\bar{X}_n| \geq a_n)$ with $a_n \rightarrow 0$ and $n^{1/2}a_n \rightarrow \infty$.

Examples Revisited

Example (Lindley's Estimator)

$$\blacktriangleright \Theta_0 = \{\mu \in \mathbb{R}^p : \mu = m(\mu)\mathbf{1}_p\}, \Theta_1 = \{\mu \in \mathbb{R}^p : \mu \neq m(\mu)\mathbf{1}_p\}.$$

$$\blacktriangleright g_n(x; \mu) = x - \frac{(\rho - 3)[(x) - m(x)\mathbf{1}_p + n^{1/2}\{\mu - m(\mu)\mathbf{1}_p\}]}{\|(x) - m(x)\mathbf{1}_p + n^{1/2}\{\mu - m(\mu)\mathbf{1}_p\}\|^2}$$

$$\blacktriangleright g(x; \mu) = \begin{cases} x, & \text{if } \mu \neq m(\mu)\mathbf{1}_p, \\ x - \frac{(\rho - 3)[(x) - m(x)\mathbf{1}_p]}{\|(x) - m(x)\mathbf{1}_p\|^2}, & \text{if } \mu = m(\mu)\mathbf{1}_p. \end{cases}$$

$$\blacktriangleright \tilde{\mu}_n = \begin{cases} \bar{X}_n & \text{if } \|\bar{X}_n - m(\bar{X}_n)\mathbf{1}_p\| > a_n \\ m(\bar{X}_n)\mathbf{1}_p & \text{if } \|\bar{X}_n - m(\bar{X}_n)\mathbf{1}_p\| \leq a_n \end{cases}$$

with $a_n \rightarrow 0$ and $n^{1/2}a_n \rightarrow \infty$.

Examples Revisited

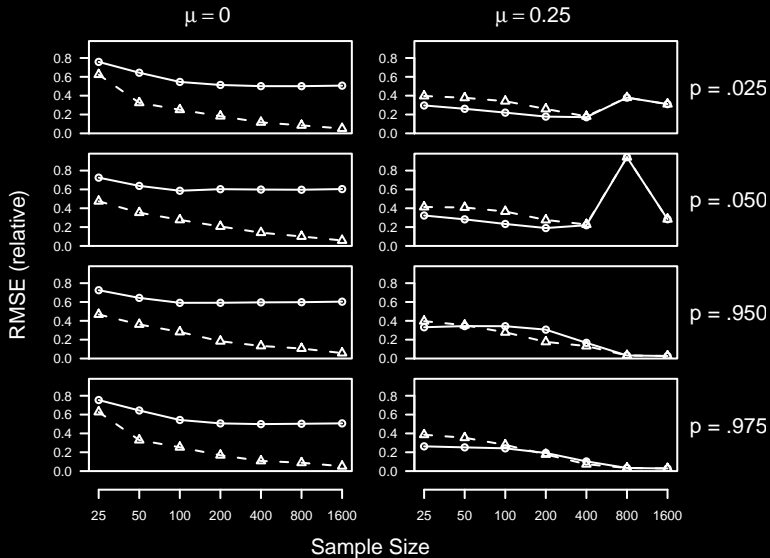
Example (LASSO)

- ▶ $\Theta = \mathbb{R}^p = \bigsqcup_{J \in \mathcal{I}} \Theta_J$ with $\mathcal{I} = \{J : J \subset \{1, \dots, p\}\}$ and

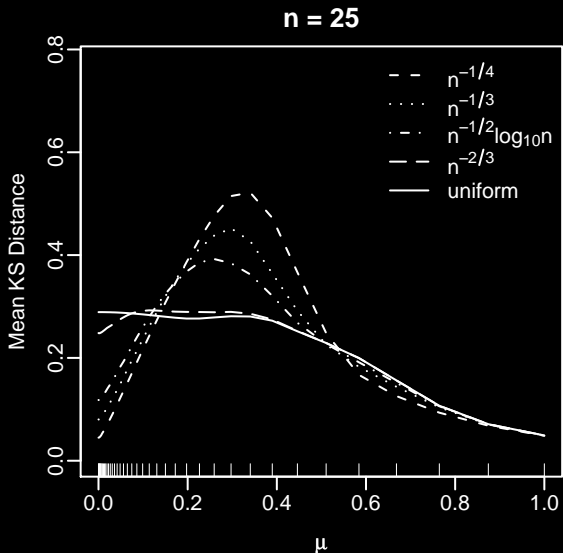
$$\Theta_J = \{\beta \in \mathbb{R}^p : \beta^{(j)} = 0 \text{ for all } j \in J, \beta^{(j)} \neq 0 \text{ for all } j \notin J\}$$

- ▶ $g_n(x, C; \beta) =$
 $x + \operatorname{argmin}_u \left\{ u^T C u + n^{-1/2} \lambda_n \sum_{j=1}^p \left(|n^{1/2} \beta^{(j)} + (x + u)^{(j)}| - |n^{1/2} \beta^{(j)}| \right) \right\}$
- ▶ $g(x, C; \beta) =$
 $x + \operatorname{argmin}_u \left\{ u^T C u + \lambda_0 \sum_{j=1}^p \left(u^{(j)} \operatorname{sign}(\beta^{(j)}) + |(x + u)^{(j)}| \mathbb{1}(\beta^{(j)} = 0) \right) \right\}$
- ▶ $\tilde{\beta}_n =$ an estimator with the “oracle” property, e.g., SCAD or adaptive-LASSO (but not the LASSO).

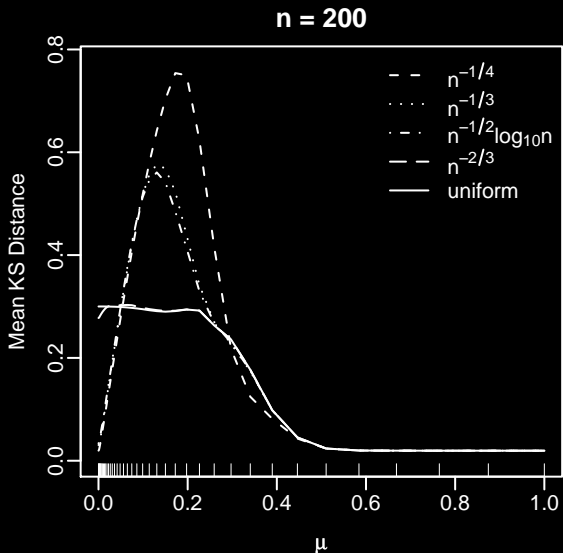
Simulations: Hodges' Estimator ($b = 0.5$), $a_n = n^{-1/2} \log_{10} n$



Simulations: Hodges Estimator ($b = 0.5$)



Simulations: Hodges Estimator ($b = 0.5$)



The End

No one will ever see this slide.

Proof of Corollary 1

Suppose $x_n \rightarrow x$ and $Y'_n \xrightarrow{d} Y \sim Q$.

Let $h_n(y) := g_n(x_n, y)$ and $h(y) := g(x, y)$.

$$\left. \begin{array}{l} Y'_n \xrightarrow{d} Y \\ h_n(y_n) \rightarrow h(y) \\ \text{for all}^* y_n \rightarrow y \end{array} \right\} \xrightarrow{\text{H.Rubin}} \begin{array}{l} h_n(Y'_n) \xrightarrow{d} h(Y) \\ g_n(x_n, Y'_n) \xrightarrow{d} g(x, Y) \end{array} \quad \Updownarrow$$

Translation: suppose $x_n \rightarrow x$ and $Q_n \rightarrow Q$. Then

$$\psi_n(x_n, Q_n) \rightarrow \psi(x, Q)$$

where

$$\begin{array}{l} \psi_n(x, Q') := \mathcal{L}(g_n(x, Y')) \\ \psi(x, Q') := \mathcal{L}(g(x, Y')) \end{array} \quad \text{when } Y' \sim Q'$$

Proof of Corollary (p2)

$$\begin{aligned}\psi_n(x, Q') &:= \mathcal{L}(g_n(x, Y')) \\ \psi(x, Q') &:= \mathcal{L}(g(x, Y'))\end{aligned} \quad Y' \sim Q'$$

$$\psi_n(x_n, Q_n) \rightarrow \psi(x, Q) \quad \text{for all}^* x_n \rightarrow x \text{ and } Q_n \rightarrow Q$$

Let $Q_n = \mathcal{L}(Y_n | \mathcal{A}_n)$. Then

$$\left. \begin{aligned}X_n &\xrightarrow{d} X \\ Q_n &\xrightarrow{\text{Pr}} Q \\ \psi_n(x_n, Q_n) &\rightarrow \psi(x, Q) \\ &\text{for all}^* (x_n, Q_n) \rightarrow (x, Q)\end{aligned} \right\} \xRightarrow{\text{Proposition}} \psi_n(X_n, Q_n) \xrightarrow{d} \psi(X, Q)$$

Proof of Corollary (p3)

$$\psi_n(x, Q') := \mathcal{L}(g_n(x, Y')) \quad Y' \sim Q'$$

$$\psi(x, Q') := \mathcal{L}(g(x, Y')) \quad Y' \sim Q'$$

$$Q_n := \mathcal{L}(Y_n | \mathcal{A}_n)$$

$$\psi_n(X_n, Q_n) \stackrel{d}{\rightarrow} \psi(X, Q) \quad X \sim P$$

But

$$\left. \begin{array}{l} X_n \in \mathcal{A}_n \\ Q_n := \mathcal{L}(Y_n | \mathcal{A}_n) \end{array} \right\} \implies \mathcal{L}(g_n(X_n, Y_n) | \mathcal{A}_n) = \psi_n(X_n, Q_n)$$

and

$$\psi(X, Q) = \mathcal{L}(g(X, Y) | X), \quad X \sim P, \quad Y \sim Q, \quad X \perp Y$$

so

$$\mathcal{L}(g_n(X_n, Y_n) | \mathcal{A}_n) \stackrel{d}{\rightarrow} \mathcal{L}(g(X, Y) | X), \quad X \sim P, \quad Y \sim Q, \quad X \perp Y$$

□