Robustness to Missing Data: Breakdown Point Analysis

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Introduction

- Missing data is common, as are the selection concerns it raises
- Common solution: assume data are Missing (Completely) At Random
  - Impute or ignore incomplete observations, use standard methods
  - Convenient solution, often implausible justification
- This paper proposes an interpretable measure of selection, and estimates how much selection is needed to overturn a conclusion

Missing Data

- Bollinger et al. (2019) "Trouble in the Tails? What We Know about Earnings Nonresponse 30 Years after Lillard, Smith, and Welch"
  - CPS ASEC 2015 item and whole nonresponse rate: 43%
  - By linking data with SSA tax records, show missing earnings data is not MAR
- Finkelstein et al. (2012), "The Oregon Health Insurance Experiment: Evidence From the First Year"
  - Survey data shows Medicaid improved self-reported physical/mental health
  - Only 50% of survey recipients responded.
  - When Lee (2009) sample selection bounds were applied, this conclusion could no longer be supported.

Related literature

- Missing data without MAR
  - Point identification: Heckman (1979), Das et al. (2003)
  - Partial identification: Manski (2005), Lee (2009)
  - Robustness/sensitivity analysis: Kline and Santos (2013)
- Robustness/Sensitivity analysis
  - Missing data: Kline and Santos (2013)
  - Potential outcomes: Masten and Poirier (2020)
  - Omitted variable bias: Diegert et al. (2022)

$\Rightarrow$ This paper contributes a robustness exercise that

i. allows for any number of variables to be missing
ii. directly uses the researcher's GMM model
iii. requires no additional data or modeling (no exclusion restriction)
iv. gives results that are succinct and interpretable

Overview

Overview

Setting

- Data is i.i.d. sample $\{D_i, D_i Y_i, X_i\}_{i=1}^n$, where $D_i = \mathbb{1}\{Y_i \text{ is observed}\}$.
  - Variables of interest are $(Y, X) \in \mathbb{R}^{d_y} \times \mathbb{R}^{d_x}$.
  - Y may be a vector. If present, X_i is assumed finitely supported
  - Example: $Y_i = (Y_i^{(1)}, Y_i^{(2)}) \in \mathbb{R}^2$ collected through survey, X_i is administrative data (age, occupation, etc.).

- Parameter $\beta \in \mathbf{B} \subseteq \mathbb{R}^{d_b}$ is identified through moment conditions

$$E_P[g(Y, X, b)] = 0 \text{ if and only if } b = \beta$$

where P is the unconditional distribution of (Y, X).

  - Example: OLS coefficients $g(Y, X, b) = \begin{pmatrix} Y^{(2)} \\ X \end{pmatrix} (Y^{(1)} - (Y^{(2)}, X^\intercal)b)$

- Conclusion to be investigated is that β is outside $\mathbf{B}_0$

$$H_0 : \beta \in \mathbf{B}_0 \qquad \text{vs} \qquad H_1 : \beta \in \mathbf{B} \setminus \mathbf{B}_0$$

  - Example: first OLS coefficient is positive. $\mathbf{B}_0 = \{b \in \mathbf{B} \, ; \; b^{(1)} \leq 0\}$

Setting

- Let $p_D = P(D = 1)$, $X \mid D = 0 \sim P_{0X}$, and

$$(Y, X) \mid D = 1 \sim P_1, \qquad (Y, X) \mid D = 0 \sim P_0,$$
$$P = p_D P_1 + (1 - p_D) P_0$$

  - The sample $\{D_i, D_i Y_i, X_i\}_{i=1}^n$, identifies p_D, P_1, and P_{0X}...
  - ...but not P_0, P, or β solving $E_P[g(Y, X, \beta)] = 0$

- Common solution: estimate β_1 instead

$$E_{P_1}[g(Y, X, \beta_1)] = 0$$

  MCAR is the assumption $P_0 = P_1$. Implies $P = P_1$ and $\beta = \beta_1$.

- Suppose preliminary analysis suggests $\beta_1 \in \mathbf{B} \setminus \mathbf{B}_0$, but MCAR is doubtful. MAR?
  - Hope to defend $\beta \in \mathbf{B} \setminus \mathbf{B}_0$
  - So $P_0 \neq P_1$... but *how* different could they plausibly be?
  - A quantitative measure of selection will allow meaningful discussion.

Quantifying selection: predictive power of (Y, X)

Sample is $\{D_i, D_i Y_i, X_i\}_{i=1}^n$, i.i.d.. $p_D = P(D = 1)$,

$$(Y, X) \mid D = 1 \sim P_1, \qquad (Y, X) \mid D = 0 \sim P_0,$$
$$P = p_D P_1 + (1 - p_D) P_0$$

- Selection is a greater concern when context suggests (Y, X) would predict D well
  - Example: survey asking about arrest record, vs. survey asking about TV preferences
- See this formally with densities. Let f_1, f_0 be densities of P_1, P_0 wrt P. Then

  $$f_1(y, x) = \frac{p_D(y, x)}{p_D} \qquad f_0(y, x) = \frac{1 - p_D(y, x)}{1 - p_D}$$

  where $p_D(y, x) = P(D = 1 \mid Y = y, X = x)$.
  - Optimistic: D is independent of (Y, X).
    $\implies p_D(y, x) = p_D$, so $f_1 = f_0$ (data is MCAR)
  - Pessimistic: D is almost a function of (Y, X).
    $\implies p_D(y, x) \approx 1$ or 0; f_1 and f_0 look quite different

Quantifying selection with squared Hellinger

- Measure **selection** as the **squared Hellinger distance** between P_0 and P_1:

$$H^2(P_0, P_1) = \frac{1}{2} E_P \left[(\sqrt{f_0(Y,X)} - \sqrt{f_1(Y,X)})^2 \right]$$

  where $f_0(y,x)$ and $f_1(y,x)$ are densities of P_0 and P_1 wrt P.

- $f_1(y,x) = p_D(y,x)/p_D$ and $f_0(y,x) = (1 - p_D(y,x))/p_D$ implies

$$H^2(P_0, P_1) = 1 - \frac{E_P\left[\sqrt{\mathrm{Var}(D \mid Y, X)}\right]}{\sqrt{\mathrm{Var}(D)}}$$

  - Interpretation: expected percent standard deviation of D "explained" by (Y, X)
  - Captures intuition: more predictive power, higher selection
  - Range is $[0,1]$. Equals $0 \Leftrightarrow \mathrm{Var}(D \mid Y, X) = \mathrm{Var}(D)$, equals $1 \Leftrightarrow \mathrm{Var}(D \mid Y, X) = 0$

- Assumption: P_0 is dominated by P_1. Domination
  - Rules out selection mechanisms that "truncate" data; e.g. $D_i = \mathbb{1}\{Y_i \leq c\}$.

Other Selection Measures

Recap

- Setting:
  - Model: $E_P[g(Y, X, \beta)] = 0$
  - Hypothesis test: $H_0 : \beta \in \mathbf{B}_0$ vs $H_1 : \beta \in \mathbf{B} \setminus \mathbf{B}_0$
  - Data: $\{D_i, D_i Y_i, X_i\}_{i=1}^n$ i.i.d.. with $D_i = \mathbb{1}\{Y_i \text{ is observed}\}$.
  - Identified: p_D, P_1, P_{0X}. Not identified: $P = p_D P_1 + (1 - p_D) P_0$
  - Measure of selection: $H^2(P_0, P_1) = 1 - E_P[\sqrt{\text{Var}(D \mid Y, X)}]/\sqrt{\text{Var}(D)}$
- β_1 solves $E_{P_1}[g(Y, X, \beta_1)] = 0$; preliminary analysis suggests $\beta_1 \in \mathbf{B} \setminus \mathbf{B}_0$
- How much selection is needed to overturn the conclusion?
  - Given p_D, P_1, and P_{0X} how large must $H^2(P_0, P_1)$ be to rationalize $\beta \in \mathbf{B}_0$?

Overview

Breakdown point

- Let $\mathbf{P}^b$ be the set of distributions Q dominated by P_1 with marginal $Q_X = P_{0X}$ and

$$0 = p_D E_{P_1}[g(Y, X, b)] + (1 - p_D) E_Q[g(Y, X, b)]$$

  say Q **rationalizes** b.

- The **breakdown point** is the minimum selection needed to rationalize $\beta \in \mathbf{B}_0$:

$$\delta^{BP} = \inf_{b \in \mathbf{B}_0} \inf_{Q \in \mathbf{P}^b} H^2(Q, P_1)$$

- Large values of δ^{BP} assuage selection concerns
  - The claim $\beta \in \mathbf{B}_0$ implies $\delta^{BP} \leq \frac{1}{2} H^2(P_0, P_1) = 1 - E_P\left[\sqrt{\mathrm{Var}(D \mid Y, X)}\right] / \sqrt{\mathrm{Var}(D)}$
  - If the claim (Y, X) predicts D this well is implausible, then $\beta \in \mathbf{B}_0$ is implausible.
  - Context matters! Example: Survey about arrest record vs. survey about TV

- δ^{BP} is point identified
  - Reporting estimates $\hat{\delta}_n^{BP}$ can facilitate selection concern discussions
  - Worries that $\hat{\delta}_n^{BP} > \delta^{BP}$ (due to sample noise) can be addressed with lower confidence intervals

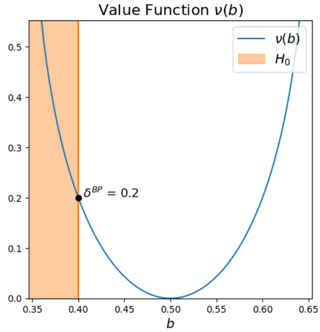
Breakdown point: uniform expectation

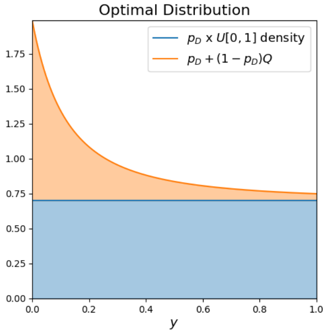
$$\delta^{BP} = \inf_{b \in \mathbf{B}_0} \underbrace{\inf_{Q \in \mathbf{P}^b} H^2(Q, P_1)}_{\nu(b)}$$

- Example: The sample is $\{D_i, D_i Y_i\}_{i=1}^n$, and $\beta = E[Y] \in \mathbb{R}$.

$$Y \mid D = 1 \sim \mathcal{U}[0,1], \qquad p_D = P(D=1) = 0.7$$

The claim to be supported is $H_1 : \beta > 0.4$.





Simulations

Overview

Estimation overview

- The breakdown point:

$$\delta^{BP} = \inf_{b \in \mathbf{B}_0} \underbrace{\inf_{Q \in \mathbf{P}^b} \; H^2(Q, P_1)}_{\nu(b)}$$

is estimated with a two-step procedure:

1. $\hat{\nu}_n(b)$ estimates $\nu(b) = \inf_{Q \in \mathbf{P}^b} \; H^2(Q, P_1)$
2. Plug-in second step $\hat{\delta}^{BP} = \inf_{b \in \mathbf{B}_0} \nu(b)$

- $\hat{\nu}_n(b)$ based on finite dimensional, well-behaved dual problem
- Second stage estimator analyzed using functional delta method
- Lower confidence intervals constructed using bootstrap procedure

Skip to Simulations

Duality

- The **primal problem** is

$$\nu(b) = \inf_{Q \in \mathbf{P}^b} H^2(Q, P_1) \tag{1}$$

- The **dual problem** is

$$V(b) = \sup_{\lambda \in \mathbb{R}^{d_g + K}} E\left[\frac{\lambda^\intercal J(D) h(DY, X, b)}{1 - p_D} - \frac{D f^*(\lambda^\intercal h(DY, X, b))}{p_D}\right] \tag{2}$$

  a finite dimensional convex optimization problem.
  - f^*, J and h are known functions,
  - the expectation is wrt the distribution of (D, DY, X), and
  - K is the cardinality of $\text{Supp}(X)$.

- Under regularity conditions, **strong duality** holds:

$$V(b) = \nu(b)$$

  - Assume this holds for all $b \in B \subseteq \mathbf{B}$, with $\inf_{b \in \mathbf{B}_0} \nu(b) = \inf_{b \in B \cap \mathbf{B}_0} \nu(b)$
  - $\implies$ we can focus on the dual problem.

Dual problem detail   Strong duality assumptions

Estimators

- With strong duality, the breakdown point is $\delta^{BP} = \inf_{b \in B \cap \mathbf{B}_0} \nu(b)$, where

$$\nu(b) = \sup_{\lambda \in \mathbb{R}^{d_g + K}} E\left[\underbrace{\frac{\lambda^\intercal J(D) h(DY, X, b)}{1 - p_D} - \frac{D f^*(\lambda^\intercal h(DY, X, b))}{p_D}}_{:= \varphi(D, DY, X, b, \lambda, p)} \right]$$

- Straightforward sample analogue estimators: $\hat{\delta}_n^{BP} = \inf_{b \in \mathbf{B}_0} \hat{\nu}_n(b)$, where

$$\hat{\nu}_n^*(b) = \sup_{\lambda \in \mathbb{R}^{d_g + K}} \frac{1}{n} \sum_{i=1}^{n} \varphi(D_i, D_i Y_i, X_i, b, \lambda, \hat{p}_{D,n})$$

- Under additional regularity conditions, estimators are consistent:

$$\hat{\nu}_n \xrightarrow{p} \nu \quad \text{in } \ell^\infty(B), \qquad\qquad \hat{\delta}_n^{BP} \xrightarrow{p} \delta^{BP}$$

Consistency Assumptions

Inference: asymptotic distributions

Theorem Under assumptions discussed in the paper,

$$\sqrt{n}(\hat{\nu}_n - \nu) \xrightarrow{L} \mathbb{G}_\nu \qquad \text{in } \ell^\infty(B)$$

- Intuition: for a fixed b, view estimation as GMM:

$$\frac{1}{n}\sum_{i=1}^{n}\begin{pmatrix} \varphi(D_i, D_iY_i, X_i, b, \hat{\lambda}_n(b), \hat{p}_{D,n}) - \hat{\nu}_n(b) \\ \nabla_\lambda \varphi(D_i, D_iY_i, X_i, b, \hat{\lambda}_n(b), \hat{p}_{D,n}) \\ D_i - \hat{p}_{D,n} \end{pmatrix} = 0$$

which is asymptotically linear. This linearization is shown to hold uniformly over $b \in B$.

Theorem Suppose the same assumptions hold. Then $\mathbf{m}(\nu) = \arg\min_{b \in B \cap \mathbf{B}_0} \nu(b)$ is nonempty and

$$\sqrt{n}(\hat{\delta}_n^{BP} - \delta^{BP}) \xrightarrow{L} \inf_{b \in \mathbf{m}(\nu)} \mathbb{G}_\nu(b)$$

- Follows from Hadamard directional differentiability of $\nu \mapsto \inf_{b \in B \cap \mathbf{B}_0} \nu(b)$ and the functional delta method (Fang and Santos (2019)).
- $\mathbf{m}(\nu)$ is plausibly a singleton: $\{b^i\}$. If so, $\sqrt{n}(\hat{\delta}_n^{BP} - \delta^{BP})$ is asymptotically normal.

Inference: lower confidence intervals

- A large δ^{BP} assuages selection concerns
- Skeptical readers may worry $\hat{\delta}_n^{BP} > \delta^{BP}$ due to sample noise
  - The argument is only strengthened if $\hat{\delta}_n^{BP} < \delta^{BP}$
- Reporting a **lower confidence interval** addresses this concern:

$$\lim_{n\to\infty} P\left(\underbrace{\hat{\delta}_n^{BP} - \frac{1}{\sqrt{n}}\hat{c}_{1-\alpha,n}}_{\widehat{CI}_{L,n}} \leq \delta^{BP}\right) = 1-\alpha$$

- $\hat{c}_{1-\alpha,n}$ is estimated with the score bootstrap
  - Assuming $\mathbf{m}(\nu) = \arg\min_{b\in B\cap \mathbf{B}_0} \nu(b)$ is the singleton $\{b^i\}$, $\hat{c}_{1-\alpha,n}$ is computed with a computationally convenient procedure

Score Bootstrap

Overview

Simulations: uniform expectation

- Example: The sample is $\{D_i, D_i Y_i\}_{i=1}^n$, and $\beta = E[Y] \in \mathbb{R}$.

$$Y \mid D = 1 \sim \mathcal{U}[0,1], \qquad p_D = P(D = 1) = 0.7$$

  The claim to be supported is $H_1 : \beta > 0.4$.

- 250 simulations with $P(D = 1) = 0.7$, and $\delta^{BP} \approx 0.2$:

Table: Simulations, Squared Hellinger, Uniform, Mean

n	RMSE	Emp. Bias	Emp. CI Coverage	Ave. CI Length
1000	0.060	0.008	98.4	0.091
2000	0.040	0.005	97.6	0.063
3000	0.032	0.001	96.8	0.051
5000	0.024	0.003	96.4	0.040

Illustration

Simulations: OLS

- Consider a linear model

$$Y_1 = \beta_0 + \beta_1 X_1 + \beta_2 Y_2 + \beta_3 X_2 + \varepsilon = W^\intercal \beta + \varepsilon, \qquad E[W\varepsilon] = 0$$

where X_1, X_2 are discrete and Y_1, Y_2 are continuous.

- The conclusion to be investigated is $H_1 : \beta_1 > 0$. The observed data is $\{D_i, D_i Y_{i1}, D_i Y_{i2}, X_{i1}, X_{i2}\}_{i=1}^n$.

- 250 simulations from a DGP with $P(D = 1) \approx 0.7$, and $\delta^{BP} \approx 0.2$:

Table: Simulations, Squared Hellinger, OLS

n	RMSE	Emp. Bias	Emp. CI Coverage	Ave. CI Length
1000	0.043	0.009	100.0	0.078
2000	0.033	0.005	98.0	0.052
3000	0.026	0.007	98.0	0.043
5000	0.017	0.002	98.0	0.032

- Empirical coverage suggests inference is conservative.

Conclusion

- Breakdown point analysis is a tractable approach to assessing how robust a conclusion is to relaxing common missing data assumptions.

- For the conclusion $\beta \in \mathbf{B} \setminus \mathbf{B}_0$, the claim $\beta \in \mathbf{B}_0$ implies

$$\delta^{BP} \leq 1 - \frac{E_P[\sqrt{\mathrm{Var}(D \mid Y, X)}]}{\sqrt{\mathrm{Var}(D)}}$$

  If it is implausible (Y, X) predicts D this well, then $\beta \in \mathbf{B}_0$ is similarly implausible.

- The breakdown point δ^{BP} is $\sqrt{n}$-estimable, and lower confidence intervals can be constructed with simple bootstrap procedures.

- Reporting $\hat{\delta}_n^{BP}$ and the lower confidence interval $\widehat{CI}_L$ is a succinct summary of a conclusion's robustness.

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Missing (completely) at random

- With i.i.d. sample $\{D_i, D_i Y_i, X_i\}_{i=1}^n$, where $D_i = \mathbb{1}\{Y_i \text{ is observed}\}$

$$(Y, X) \mid D = 1 \sim P_1, \qquad (Y, X) \mid D = 0 \sim P_0,$$
$$P = p_D P_1 + (1 - p_D) P_0$$

  two common assumptions restore point identification of P

- **Missing completely at random** (MCAR) assumes $P_0 = P_1$
  - Testable: do distributions of X match? $P_{0X} = P_{1X}$?
  - Justifies dropping observations where $D_i = 0$

- **Missing at random** (MAR) assumes $Y \mid X = x, D = 0$ follows the same distribution as $Y \mid X = x, D = 1$
  - Not testable
  - Justifies imputating $Y \mid X = x, D = 0$ based on distribution of $Y \mid X = x, D = 1$

- Preliminary analysis may be based on either assumption.

Setting

Assumption: P_0 is dominated by P_1

- **Assumption:** P_0 is dominated by P_1, i.e. $P_0 \ll P_1$.
  - For any set A with $P_1((X, Y) \in A) = 0$, then $P_0((X, Y) \in A) = 0$.
  - Simplifies analysis considerably; set of possible P_0 characterized by densities wrt P_1
  - Allows squared Hellinger to be written as an f-divergence

- Some support assumption is typically necessary for an interesting exercise.
  - Example: $\beta = E[Y]$. P_1 and P_0 given by

$$\begin{array}{lll} P_1(Y = -1) = 0.5 & P_1(Y = 1) = 0.5 & \\ P_0(Y = -1) = 0.5 & P_0(Y = 1) = 0.5 - \alpha & P_0(Y = y) = \alpha \end{array}$$

Then

$$H^2(P_0, P_1) = (\sqrt{0.5 - \alpha} - \sqrt{0.5} + \sqrt{\alpha})^2$$

can be made **arbitrarily close to zero** by choice of $\alpha > 0$. For any $\alpha > 0$,

$$E_P[Y] = (1 - p_D)E_{P_0}[Y] = (1 - p_D)\alpha(y - 1)$$

can be made **any number** by choice of $y \in \mathbb{R}$.

f-divergence Squared Hellinger

Other selection measures: f-divergences

- Given a convex function $f : \mathbb{R} \to [0, \infty]$ satisfying $f(t) = \infty$ for $t < 0$ and taking a unique minimum of $f(1) = 0$, the corresponding f-**divergence** is the function given by

$$d_f(Q\|P) = \begin{cases} \int f\left(\frac{dQ}{dP}\right) dP & \text{if } Q \ll P \\ \infty & \text{otherwise} \end{cases} \tag{3}$$

- Many popular divergences can be written as f-divergences (when $Q \ll P$):

Name	Common formula	$f(t)$ when $t \geq 0$
Squared Hellinger	$H^2(Q,P) = \frac{1}{2}\int\left(\sqrt{\frac{dQ}{dP}(z)} - 1\right)^2 dP(z)$	$f(t) = \frac{1}{2}(\sqrt{t}-1)^2$
Kullback-Leibler (KL)	$KL(Q\|P) = \int \log\left(\frac{dQ}{dP}(z)\right) dQ(z)$	$f(t) = t\log(t) - t + 1$
"Reverse" KL	$KL(P\|Q) = \int \log\left(\frac{dP}{dQ}(z)\right) dP(z)$	$f(x) = -\log(t) + t - 1$
Cressie-Read	–	$f_\gamma(t) = \frac{t^\gamma - \gamma t + \gamma - 1}{\gamma(\gamma-1)}$, $\gamma < 1$

Table: Common f-divergences

- Results in the paper allow any f-divergence (satisfying certain regularity conditions) to be used to measure selection

Squared Hellinger

Breakdown Point through Partial Identification

- Breakdown point analysis can be framed as an exercise in partial identification, as in Kline and Santos (2013), Masten and Poirier (2020), and Diegert et al. (2022).
- In this framing, consider assumptions of the form $H^2(P_0, P_1) \leq \delta$ for some $\delta > 0$.
- The *nominal* identified set $\mathbf{B}_{ID}(\delta)$ for β grows with δ. As long as $\mathbf{B}_{ID}(\delta) \subseteq \mathbf{B} \setminus \mathbf{B}_0$, it is clear the conclusion holds.
- The **breakdown point** δ^{BP} can then be defined as either:
  1. the largest δ for which $\mathbf{B}_{ID}(\delta) \subseteq \mathbf{B} \setminus \mathbf{B}_0$, or
  2. the smallest δ for which $\mathbf{B}_{ID}(\delta) \cap \mathbf{B}_0 \neq \varnothing$

Breakdown Point

Dual problem (detailed)

- The **dual problem** using squared Hellinger is

$$V(b) = \sup_{\lambda \in \mathbb{R}^{d_g+K}} E\left[\frac{\lambda^\intercal J(D)h(DY,X,b)}{1-p_D} - \frac{Df^*(\lambda^\intercal h(DY,X,b))}{p_D}\right]$$

  where

$$J(D) = \begin{bmatrix} -DI_{d_g} & 0 \\ 0 & (1-D)I_K \end{bmatrix}, \qquad h(DY,X,b) = \begin{pmatrix} g(DY,X,b) \\ \mathbb{1}\{X = x_1\} \\ \vdots \\ \mathbb{1}\{X = x_K\} \end{pmatrix},$$

$$f^*(r) = \begin{cases} \frac{1}{2}\left(\frac{1}{1-2r} - 1\right) & \text{if } r < 1/2 \\ \infty & \text{o.w.} \end{cases}$$

  and $\{x_1, \dots, x_K\}$ is the support of X.

- $f^*(r) = \sup_{t \in \mathbb{R}}\{rt - f(t)\}$ is the **convex conjugate** of $f(t)$, the function defining the f-divergence used to measure selection.

Duality f-divergences

Formal assumptions: setting and strong duality

Assumption 1 (Setting) $\{D_i, D_i Y_i, X_i\}_{i=1}^n$ is an i.i.d. sample from a distribution satisfying

(i) $p_D = P(D = 1) \in (0, 1)$

(ii) $X \mid D = 1$ and $X \mid D = 0$ have the same finite support $\{x_1, \ldots, x_K\}$

(iii) $E[\sup_{b \in \mathbf{B}} \|g(Y, X, b)\| \mid D = 1] < \infty$

Assumption 2 (Strong duality) $B \subseteq \mathbf{B}$ is such that $\inf_{b \in \mathbf{B}_0} \nu(b) = \inf_{b \in B \cap \mathbf{B}_0} \nu(b)$. Furthermore, for each $b \in B$,

(i) there exists $Q^b \in \mathbf{P}^b$ such that $0 < \frac{\partial Q^b}{\partial P_1}(y, x) < \infty$, almost-surely P_1.

(ii) $\lambda(b)$ solving the dual problem is in the interior of $\{\lambda \,;\, E[|f^*(\lambda^\intercal h(Y, X, b))| \mid D = 1] < \infty$.

Duality

Formal assumptions: consistency

Assumption 3 (Consistency)

(i) B is compact

(ii) $g(y, x, b)$ is continuous in b for all (y, x)

(iii) For each $b \in B$, $\{h_j(y, x, b)\}_{j=1}^{d_g+K}$ are linearly independent in the sense that for any $\lambda \neq 0 \in \mathbb{R}^{d_g+K}$,

$$P(\lambda^{\intercal} h(Y, X, b) \neq 0 \mid D = 1) > 0$$

(iv) For each $b \in B$, there exists a closed convex $\bar{\Lambda}^b$ with $\lambda(b) \in \text{int}(\bar{\Lambda}^b)$ such that $\bar{\Lambda}^B = \left\{(b, \lambda)\ ;\ b \in B,\ \lambda \in \bar{\Lambda}^b\right\}$ is copmact, and for some open $\mathcal{N} \subset \mathbb{R}$ containing p_D,

$$E\left[\sup_{p \in \mathcal{N}} \sup_{(b,\lambda) \in \bar{\Lambda}^B} |\varphi(D, DY, X, b, \lambda, p)|\right] < \infty,$$

$$E\left[\sup_{(b,\lambda) \in \bar{\Lambda}^B} \|\nabla_{\lambda}\varphi(D, DY, X, b, \lambda, p_D)\|\right] < \infty, \quad E\left[\sup_{(b,\lambda) \in \bar{\Lambda}^B} \|\nabla^2_{\lambda}\varphi(D, DY, X, b, \lambda, p_D)\|\right] < \infty$$

If assumptions 1, 2, and 3 hold, then $\hat{\nu}_n \xrightarrow{p} \nu$ in $\ell^{\infty}(B)$ and $\hat{\delta}_n^{BP} \xrightarrow{p} \delta^{BP}$.

Estimators

Formal assumptions: inference

Let $\theta(b) = (\nu(b), \lambda(b), p_D)$, $\theta = (v, \lambda, p)$,

$$\phi(D, DY, X, b, \theta) = \phi(D, DY, X, b, v, \lambda, p) = \begin{pmatrix} \varphi(D, DY, X, b, \lambda, p) - v \\ \nabla_\lambda \varphi(D, DY, X, b, \lambda, p) \\ D - p \end{pmatrix},$$

$\Theta^b = \left\{\theta = (v, \lambda, p) \; ; \; v \in [0, \mathcal{V}], \; \lambda \in \bar{\Lambda}^b, p \in [\underline{p}, \overline{p}]\right\}$, and $\theta^B = \left\{(b, \theta) \; ; \; b \in B, \theta \in \Theta^b\right\}$.

Assumption 4 (Inference) Suppose that

(i) $\mathbf{B}_0$ is closed

(ii) B is convex

(iii) $g(z, b)$ is continuously differentiable with respect to b

(iv) $\hat{\theta}_n(b) = (\hat{\nu}_n(b), \hat{\lambda}_n(b), \hat{p}_{D,n}) \in \Theta^b$ for each b

(v) There exists $F(d, dy, x)$ such that

$$\sup_{b \in B} \sup_{\theta \in \Theta^b} \|\nabla_{(b,\theta)} \phi(d, dy, x, b, \theta)\| \leq F(d, dy, x)$$

and $E[F(D, DY, X)^2] < \infty$.

If assumptions 1, 2, 3, and 4 hold, then

$$\sqrt{n}(\hat{\nu}_n - \nu) \xrightarrow{L} \mathbb{G}_\nu \text{ in } \ell^\infty(B), \qquad \text{and} \qquad \sqrt{n}(\hat{\delta}_n^{BP} - \delta^{BP}) \xrightarrow{L} \inf_{b \in \mathbf{m}(\nu)} \mathbb{G}_\nu(b) \text{ in } \mathbb{R}$$

Asymptotic Distributions

Score bootstrap

- Let $\{W_i\}_{i=1}^n$ be i.i.d. scalars, independent of $\{D_i, D_i Y_i, X_i\}_{i=1}^n$, satisfying
  (i) $E[W] = 0$,
  (ii) $E[W^2] = 1$, and
  (iii) $E[|W|^{2+a}] < \infty$ for some $a > 0$.

- Let $\hat{\Phi}_n(b) = \frac{1}{n}\sum_{i=1}^n \nabla_\theta \phi(D_i, D_i Y_i, X_i, b, \hat{\theta}_n(b))$,

$$\hat{G}_n^*(b) = \hat{\Phi}_n(b)^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n W_i \phi(D_i, D_i Y_i, X_i, b, \hat{\theta}_n(b))$$

  and $\hat{G}_n^*(b, 1)$ be the first coordinate of the vector $\hat{G}_n^*(b)$.

Bootstrap procedure

1. Compute $\hat{b}_n^i = \arg\min_{b \in B \cap \mathbf{B}_0} \hat{\nu}_n(b)$,
2. Generate N bootstrap samples $\{W_i\}_{i=1}^n$ from a distribution with moments described above, and compute $\hat{G}_n^*(\hat{b}_n^i, 1)$ for each of the N bootstrap samples,
3. Let $\hat{c}_{1-\alpha,n}$ be the $1-\alpha$ quantile of $\{\hat{G}_{n,k}^*(\hat{b}_n^i, 1)\}_{k=1}^N$.

If assumptions 1, 2, 3, and 4 hold, and $\mathbf{m}(\nu) = \arg\min_{b \in B \cap \mathbf{B}_0} \nu(b)$ is the singleton $\{b^i\}$, then $\lim_{n\to\infty} P\left(\hat{\delta}_n^{BP} - \frac{1}{\sqrt{n}}\hat{c}_{1-\alpha,n} \leq \delta^{BP}\right) = 1 - \alpha$.

Inference: lower confidence intervals