# Comparison of Asymptotic Variance: MIPW vs IPW

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## 1 Introduction

**Proposition 1** (The Equivalent Estimating Equation for MIPW). Let  $(Y_i, Y_i^*, \mathbf{X}_i, \mathbf{X}_i^*, Z_i) \overset{i.i.d}{\sim} F, i = 1, \dots, N$ . Define the true parameter  $\theta_0 = (\beta_0, \pi_0, \mu_0(1), \mu_0(0)) \in \Theta \subset \mathbb{R}^{d+3}$  as  $E_F(\psi^*(\theta_0)) = 0$ . Then,  $\psi^{**}$  is an equivalent estimating equation of  $\psi^*$  where  $\psi^{**}$  is

$$\psi^{**}(\theta) = \begin{pmatrix} \left\{ \frac{1-\delta}{e^*(\mathbf{X};\beta)} Z + \left( \frac{\delta \pi}{(1-\pi)e^*(\mathbf{X};\beta)} - \frac{1}{1-e^*(\mathbf{X};\beta)} \right) (1-Z) \right\} \nabla_{\beta} e^*(\mathbf{X};\beta) \\ Z - \pi \\ ZY - Z\mu(1) \\ \frac{e(\mathbf{X};\beta)}{1-e(\mathbf{X};\beta)} (1-Z)Y - \frac{e(\mathbf{X};\beta)}{1-e(\mathbf{X};\beta)} (1-Z)\mu(0) \end{pmatrix}$$

This is the proposition that let us to calculate the MIPW estimator through only observed variance. By the M-estimation theory,  $\sqrt{n}^{-1}(\hat{\tau}-\tau) \stackrel{d}{\to} N(0,V_{MIPW})$  where

$$V_{MIPW} = V(\psi^{**}) = a^T A(\psi^{**}) B(\psi^{**}) A(\psi^{**})^T a$$
 (1)

$$A(\psi^{**}) = \left(E\left[-\frac{\partial}{\partial \theta}\psi^{**}\right]\right)^{-1} \tag{2}$$

$$B(\psi^{**}) = E\left[\psi^{**}(\psi^{**})^{T}\right] \tag{3}$$

$$a = \left(\mathbf{0}_d^T, 0, 1, -1\right)^T \tag{4}$$

We want to prove that  $V_{MIPW} < V_{IPW}$  when  $\delta$  is "bounded" away from 1. However, as we can observe from the simulation table 1 below, it is more likely that there is some range of  $\delta$  such inequality holds. The conducted simulation proceeded as so.

- 1. Set  $\delta=0.1$ . Generate 200 datasets with size n=500 from the "strong overlap" condition.
- 2. Calculate the sandwich variance estimator of IPW and MIPW for each datasets i.e.  $\hat{V}^1_{IPW},\dots,\hat{V}^{200}_{IPW}$  and  $\hat{V}^1_{MIPW},\dots,\hat{V}^{200}_{MIPW}$ .

- 3. Average the results and compare:  $\hat{V}_{IPW} = \sum_r \hat{V}_{IPW}^r$  vs  $\hat{V}_{MIPW} = \sum_r \hat{V}_{MIPW}^r$ .
- 4. Repeat 1, 2, 3 for  $\delta = 0.6$  and 0.9.
- 5. Repeat the whole process for n = 1000, 5000, 10000, 100000.

δ	N	500	$10^{3}$	$5 \times 10^3$	$10^{4}$	$10^{5}$
$\delta = 0.1$	$\hat{V}_{IPW}$	0.0487	0.0266	0.0051	0.0025	0.0003
	$\hat{V}_{MIPW}$	0.0385	0.0217	0.0042	0.0021	0.0002
$\delta = 0.6$	$\hat{V}_{IPW}$	0.0485	0.0237	0.0050	0.0025	0.0003
	$\hat{V}_{MIPW}$	0.0218	0.0106	0.0023	0.0011	0.0001
$\delta = 0.9$	$\hat{V}_{IPW}$	0.0509	0.0261	0.0050	0.0025	0.0003
	$\hat{V}_{MIPW}$	8.7025	1.9699	0.0108	0.0051	0.0005

Table 1: Simulation Result

This simulation result implies that  $V_{MIPW} < V_{IPW}$  does not hold for all  $\delta \in (0,1)$  but hopefully on certain  $(0,\tilde{\delta})$  for some constant  $\tilde{\delta} < 1$ .

## 2 Idea

#### 2.1 Notations

Recall the estimating equation for the IPW estimator.

$$\psi(\theta) = \psi(\theta; Y, \mathbf{X}, Z) = \begin{pmatrix} \frac{Z - e(\mathbf{X}; \beta)}{e(\mathbf{X}; \beta)(1 - e(\mathbf{X}; \beta))} \nabla_{\beta} e(\mathbf{X}; \beta) \\ ZY - Z\mu(1) \\ \frac{e(\mathbf{X}; \beta)}{1 - e(\mathbf{X}; \beta)} (1 - Z)Y - \frac{e(\mathbf{X}; \beta)}{1 - e(\mathbf{X}; \beta)} (1 - Z)\mu(0) \end{pmatrix}$$
(5)

Denote

$$\begin{split} e &:= e(\mathbf{X}; \beta), \quad e^* := e^*(\mathbf{X}; \beta) \\ \dot{e} &:= \frac{\partial}{\partial \beta} e(\mathbf{X}; \beta) = \nabla_{\beta} e(\mathbf{X}; \beta) \\ \dot{e}^* &:= \frac{\partial}{\partial \beta} e^*(\mathbf{X}; \beta) = \nabla_{\beta} e^*(\mathbf{X}; \beta) \end{split}$$

Note from Lemma 1 in the main paper,

$$e^* = \frac{\pi\delta + (1 - \pi - \delta)e}{1 - \pi + \pi\delta - \delta e} \tag{6}$$

$$\dot{e}^* = (1 - \delta) \left( \frac{1 - e^*}{1 - e} \right)^2 \dot{e} \tag{7}$$

Let

$$\mathbf{C}^* = \begin{bmatrix} c^* I_d & \mathbf{0}_{d \times 3} \\ \mathbf{0}_{3 \times d} & I_3 \end{bmatrix} \cdots c^* = \frac{e^* (1 - e)^2}{(1 - \delta)^2 (1 - e^*)^2 e}$$
(8)

#### 2.2 Discoveries

Some list of discoveries:

- (1)  $\psi = \mathbf{C}^* \psi^{**} \text{ for } 0 < \delta < 1$
- (2)  $B(\psi) \succeq B(\psi^{**})$  equality iff  $\delta = 0$

<u>Proof of (1)</u> Observe that  $\psi$  and  $\psi^{**}$  have the same form except for the first element. Let us examine the first elements of  $\psi$  and  $\psi^{**}$ ,  $\psi_1$  and  $\psi_1^{**}$ .

$$\psi_1 = \left(\frac{Z}{e} - \frac{1 - Z}{1 - e}\right) \dot{e}$$

$$\psi_1^{**} = \left(Z\frac{1 - \delta}{e^*} + (1 - Z)\frac{\delta\pi - (1 - \pi + \delta\pi)e^*}{(1 - \pi)e^*(1 - e^*)}\right) \dot{e}^*$$

Consider Z = 1. Then

$$\psi_1^{Z=1} = \frac{\dot{e}}{e} \tag{9}$$

$$\stackrel{e}{=} \frac{e^*(1-e)^2}{(1-\delta)^2(1-e^*)^2 e} (1-\delta) \frac{\dot{e}^*}{e^*}$$
 (10)

$$= \frac{e^*(1-e)^2}{(1-\delta)^2(1-e^*)^2e} (\psi_1^{**})^{Z=1}$$
(11)

Denote  $c^* = \frac{e^*(1-e)^2}{(1-\delta)^2(1-e^*)^2e}$  and note that  $c^* > 1$  a.s. We will use this later.

$$c^* \stackrel{(6)}{=} \frac{1 - \pi + \pi \delta - \delta e}{(1 - \pi)(1 - \delta)} \left( 1 + \frac{\delta}{1 - \delta} \frac{\pi}{1 - \pi} \frac{1 - e}{e} \right) > 1 \quad a.s$$
 (12)

$$(\because e < 1 \quad a.s) \tag{13}$$

Now consider Z = 0.

$$\psi_1^{Z=0} = -\frac{\dot{e}}{1 - e} \tag{14}$$

$$\stackrel{(7)}{=} -\frac{1-e}{(1-\delta)(1-e^*)^2} \dot{e}^* \tag{15}$$

$$\stackrel{(6)}{=} -\frac{1-\pi}{(1-\pi-\delta+\delta e^*)(1-e^*)}\dot{e}^*$$
 (16)

$$\stackrel{(6)}{=} \frac{(1-\pi)e^*(1-e)}{(1-\delta)(1-\pi-\delta+\delta e^*)(1-e^*)e} \frac{\delta \pi - (1-\pi+\delta \pi)e^*}{(1-\pi)e^*(1-e^*)} \dot{e}^*$$
(17)

$$= \frac{(1-\pi)e^*(1-e)}{(1-\delta)(1-\pi-\delta+\delta e^*)(1-e^*)e} (\psi_1^{**})^{Z=0}$$
(18)

However, note that  $\frac{(1-\pi)e^*(1-e)}{(1-\delta)(1-\pi-\delta+\delta e^*)(1-e^*)e}=c^*$ . Hence,  $\psi_1^{Z=0}=c^*(\psi_1^{**})^{Z=0}$ . Since Z is a binary variable, Z(1-Z)=0. Therefore,

$$\psi_1 = c^* Z \psi_1^{**} + c^* (1 - Z) \psi_1^{**} = c^* \psi_1^{**}$$
(19)

Then,

$$\psi = \mathbf{C}^* \psi^{**} \tag{20}$$

where

$$\mathbf{C}^* = \begin{bmatrix} c^* I_d & \mathbf{0}_{d \times 3} \\ \mathbf{0}_{3 \times d} & I_3 \end{bmatrix}$$
 (21)

Proof of (2)

$$B(\psi) \succeq B(\psi^{**}) \Leftarrow \psi \psi^T \succeq \psi^{**} (\psi^{**})^T \quad a.s \stackrel{(*)}{\Leftarrow} (1)$$
 (22)

Proof of (\*)

**Lemma 1.** Let  $x \in \mathbb{R}^d$  and diagonal  $D \in \mathbb{R}^{d \times d}$  s.t.  $D \succeq I$ . If y = Dx then  $yy^T \succeq xx^T$  where equality holds iff D = I.

*Proof.* WTS:  $yy^T = Dxx^TD \succeq xx^T$  which is equivalent to  $Dxx^TD - xx^T \succeq \mathbf{0}$  Note

$$(D-I)xx^{T}(D-I) \succeq \mathbf{0}$$
  
$$\Leftrightarrow Dxx^{T}D \succeq xx^{T}D + Dxx^{T} - xx^{T}$$

Hence,

ETS:  $xx^TD + Dxx^T - xx^T \succeq xx^T$  which is sufficed when  $Dxx^T \succeq xx^T$  since  $Dxx^T$  is symmetric. In other words, we need to show that  $(D-I)xx^T$  is a p.s.d. This is directly straightforward since  $rank((D-I)xx^T) \leq \min(rank(D-I)xx^T)$ 

This is directly straightforward since  $rank((D-I)xx^T) \leq \min(rank(D-I), rank(xx^T)) = 1$  and the unique pair of eigenvalue and eigenvector of  $(D-I)xx^T$  is  $x^T(D-I)x$  and (D-I)x, respectively.

If we can prove that  $A(\psi)^T = DA(\psi^{**})^T$  for some diagonal  $D \succeq I$  on  $0 \le \delta \le \tilde{\delta}$ , then  $V_{MIPW} > V_{IPW}$  on the same range by Lemma 2.

**Lemma 2.** Let  $x \in \mathbb{R}^d$  and diagonal  $D \in \mathbb{R}^{d \times d}$  s.t.  $D \succeq I$ . If y = Dx then  $x^T B x \leq y^T B y$  for a symmetric p.s.d B. The equality holds iff D = I.

*Proof.* To show  $x^TBx \leq x^TDBDx = y^TBy$ , note that since B is a p.s.d,  $\exists B^{1/2}: B = B^{1/2}(B^{1/2})^T$  and  $B^{1/2}$  is also symmetric (: spectral decomposition of B). Set  $v = (B^{1/2})^Tx$  then  $x^TBx = v^Tv \leq v^TD^2v = x^TDBDx$  where  $D^2 = DD$ . The equality holds iff D = I.

# **2.3** Simulation Study: Find D such that $A(\psi)^T = DA(\psi^{**})^T$

To see if  $A(\psi)^T (A(\psi^{**}))^{-T}$  is a diagonal matrix on a certain range of  $\delta$ , we conduct a simple simulation study.

- 1. Set  $\delta=0.1$ . Generate 200 datasets with size n=500 from the "strong overlap" condition.
- 2. Calculate the bread of the sandwich variance estimator of IPW and MIPW for each datasets i.e.  $\hat{A}(\psi)^1, \ldots, \hat{A}(\psi)^{200}$  and  $\hat{A}(\psi^{**})^1, \ldots, \hat{A}(\psi^{**})^{200}$ .
- 3. Compute  $\hat{D}^r = (\hat{A}(\psi)^r)^T (\hat{A}(\psi^{**})^r)^{-T}$
- 4. Extract the pair; minimum and the maximum value of the absolute diagonal and the non-diagonal elements from each  $\hat{D}^r, r = 1, \dots, 200$  i.e.  $\left(\min_i |\hat{D}^r_{ii}|, \max_i |\hat{D}^r_{ii}|\right)$  and  $\left(\min_{i \neq j} |\hat{D}^r_{ij}|, \max_{i \neq j} |\hat{D}^r_{ij}|\right)$ .
- 5. Average the pairs
- 6. Repeat 1 to 5 for  $\delta = 0.6$  and  $\delta = 0.9$ .
- 7. Repeat the whole process for n = 1000, 5000, 10000, 100000

We omit the result for n = 1000, 5000, 10000 for simplicity.

n		500		$10^{5}$		
		diag.	non-diag.	diag.	non-diag.	
$\delta = 0.1$	max	1.00064	1.00064	1.00013	0.05981	
	$\min$	0.74169	0.00000	0.77822	0.00000	
		diag.	non-diag.	diag.	non-diag.	
$\delta = 0.6$	max	1.00063	0.24343	1.00026	0.07236	
	$\min$	0.16752	0.00000	0.17835	0.00000	
		diag.	non-diag.	diag.	non-diag.	
$\delta = 0.9$	max	1.00029	0.55657	1.00118	0.01334	
	$\min$	0.01385	0.00000	0.01676	0.00000	

Table 2: Simulation Result

According to the simulation result, D is not a diagonal matrix. Thus, the conjecture made in this subsection is wrong.