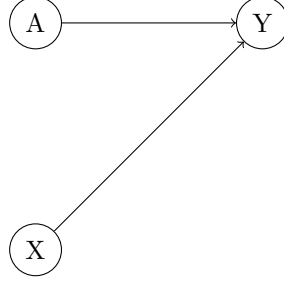


The data is modeled as:

$$(1) \quad \begin{aligned} (X_1, Y_1, A_1), \dots, (X_n, Y_n, A_n) &\stackrel{iid}{\sim} \mathcal{O} \\ A &\perp X \\ P(A = 1 \mid X) &= P(A = 1) = 1 - P(A = 0) = p \end{aligned}$$

for some law \mathcal{O} .



The estimand is

$$\psi_0 = E(Y \mid A = 1) - E(Y \mid A = 0).$$

An estimator is obtained as the solution in ψ of

$$\sum_{i=1}^n U(Y_i, A_i; \psi) = 0,$$

where

$$U(Y, A; \psi) = (Y - \psi A)(A - p).$$

Consistency and asymptotic normality of this estimator follow from:

Lemma 0.1. $E(U(Y, A; \psi_0)) = 0$.

Proof.

$$\begin{aligned} E(U(Y, A; \psi_0)) &= E[(Y - \psi_0 A)(A - p)] \\ &= E[(E(Y \mid A) - \psi_0 A)(A - p)] \\ &= (E(Y \mid A = 1) - \psi_0 A)(1 - p)p + E(Y \mid A = 0)(-p)(1 - p) \\ &= p(1 - p)[E(Y \mid A = 1) - E(Y \mid A = 0) - \psi_0] = 0. \end{aligned}$$

□

We consider estimators obtained as solutions in ψ to equations of the form

$$(2) \quad \sum_i U(Y_i, A_i; \psi) + (A_i - p)h(X_i) = 0$$

for [arbitrary] functions h . It follows from Lemma 0.1 and (1) that

$$E(U(Y, A; \psi_0) + (A - p)h(X)) = 0,$$

so these estimators are also consistent and asymptotically normal. An additional benefit is that the asymptotic variance of the resulting estimator may be minimized by varying h , perhaps improving on the efficiency of the estimator obtained from $\sum_i U(Y, A; \psi) = 0$. In fact, the minimizing choice of h is determined by the estimating equation given by

$$(3) \quad \begin{aligned} W(\psi) &= U(\psi) - E(U(\psi) \mid S_A) \\ &= U(\psi) - E(U(\psi) \mid A, X) + E(U(\psi) \mid X). \end{aligned}$$

A proof is given in Lemma 0.2, after rewriting (3). The first term on the rhs of (3) is

$$\begin{aligned} E(U(\psi) \mid A, X) &= (E(Y \mid A, X) - \psi A)(-1)^{1-A} \\ &= A[E(Y \mid A = 1, X) - \psi + E(Y \mid A = 0, X)] - E(Y \mid A = 0, X). \end{aligned}$$

For the second equality we use the identity $g(a, x) = a[g(1, x) - g(0, x)] + g(0, x)$, which holds for $a \in \{0, 1\}$ and arbitrary g, x , applied to the function $g : (a, x) \mapsto (E(Y \mid a, x) - \psi a)(-1)^{1-a}$. The second term on the rhs of (3) is

$$\begin{aligned} E(U(\psi) \mid X) &= (1/2)[E(U(\psi) \mid A = 1, X) + E(U(\psi) \mid A = 0, X)] \\ &= (1/2)[E(Y \mid A = 1, X) - \psi - E(Y \mid A = 0, X)], \end{aligned}$$

using in the first equality that A and X are independent under (1). Combining the last two displays,

$$\begin{aligned} W(\psi) &:= U(\psi) - E(U(\psi) \mid A, X) + E(U(\psi) \mid X) \\ &= U(\psi) - (A - 1/2)[E(Y \mid A = 1, X) + E(Y \mid A = 0, X) - \psi] \\ &= U(\psi) - (A - 1/2)[2E(Y \mid X) - \psi]. \end{aligned}$$

Lemma 0.2. *The asymptotic variance of the estimator obtained as the solution in ψ to*

$$(4) \quad \sum_i U(Y_i, A_i; \psi) + (A_i - 1/2)h(X_i) = 0$$

is minimized over arbitrary functions h of X at $h_0(X) = -(2E(Y \mid X) - \psi_0)$.

Proof. We give the $p = P(A = 1) = 1/2$ case. Under suitable regularity conditions, the asymptotic variance of the solution to the estimating equation (4) is given by the variance of the influence function,

$$- \left(E \frac{\partial}{\partial \psi} U(Y, A; \psi) \Big|_{\psi_0} \right)^{-1} (U(Y, A; \psi_0) + (A - 1/2)h(X)).$$

Thus we wish to show

$$\begin{aligned} \text{Var} \left[\left(E \frac{\partial}{\partial \psi} U(Y, A; \psi_0) \right)^{-1} (U(Y, A; \psi_0) + (A - 1/2)h(X)) \right] &\geq \\ \text{Var} \left[\left(E \frac{\partial}{\partial \psi} U(Y, A; \psi_0) \right)^{-1} (U(Y, A; \psi_0) + (A - 1/2)h_0(X)) \right] & \end{aligned}$$

or

$$(5) \quad \begin{aligned} E[(A - 1/2)^2 h^2(X)] + 2E[U(Y, A; \psi_0)(A - 1/2)h(X)] &\geq \\ E[(A - 1/2)^2 h_0^2(X)] + 2E[U(Y, A; \psi_0)(A - 1/2)h_0(X)]. & \end{aligned}$$

Since A, X are uncorrelated, and noting that $(A - 1/2)(-1)^{1-A} = 1/2$, the lhs is

$$\begin{aligned} &E[(A - 1/2)^2 h^2(X)] + 2E[U(Y, A; \psi_0)(A - 1/2)h(X)] \\ &= \text{Var}(A)Eh^2(X) + 2E[(A - 1/2)E(U(Y, A; \psi_0)h(X) \mid A)] \\ &= Eh^2(X)/4 + 2E[(A - 1/2)E((Y - \psi_0 A)(-1)^{1-A}h(X) \mid A)] \\ &= Eh^2(X)/4 + E[E((Y - \psi_0 A)h(X) \mid A)] \\ &= Eh^2(X)/4 + E((Y - \psi_0/2)h(X)). \end{aligned}$$

We obtain a corresponding expression for the rhs by substituting $h(X) := h_0(X) = -(2E(Y | X) - \psi_0)$,

$$\begin{aligned}
& E[(A - 1/2)^2 h_0^2(X)] + 2E[U(Y, A; \psi_0)(A - 1/2)h_0(X)] \\
&= Eh_0^2(X)/4 + E((Y - \psi_0/2)h_0(X)) \\
&= E[h_0(X)(h_0(X)/4 + Y - \psi_0/2)] \\
&= E[h_0(X)(-(2E(Y | X) - \psi_0)/4 + E(Y | X) - \psi_0/2)] \\
&= E[h_0(X)(E(Y | X)/2 - \psi_0/4)] \\
(6) \quad &= -Eh_0^2(X)/4 \\
&= -E[E(Y | X)^2] + \psi_0 EY - \psi_0^2/4.
\end{aligned}$$

Thus (5), which we wish to show, becomes

$$Eh^2(X)/4 + E((Y - \psi_0/2)h(X)) + E[E(Y | X)^2] - \psi_0 EY + \psi_0^2/4 \geq 0.$$

This inequality follows by an application of the Cauchy-Schwarz inequality,

$$\begin{aligned}
& Eh^2(X)/4 + E((Y - \psi_0/2)h(X)) + E[E(Y | X)^2] - \psi_0 EY + \psi_0^2/4 \\
&= (1/4)E[(h(X) - \psi_0)^2] + E(Yh(X)) + E[E(Y | X)^2] - \psi_0 EY \\
&= (1/4)E[(h(X) - \psi_0)^2] + E[E(Y | X)^2] + E[E(Y | X)(h(X) - \psi_0)] \\
&\geq (1/4)E[(h(X) - \psi_0)^2] + E[E(Y | X)^2] - E[(h(X) - \psi_0)^2]^{1/2} E[E(Y | X)^2]^{1/2} \\
&= \{(1/2)E[(h(X) - \psi_0)^2]^{1/2} - E[E(Y | X)^2]^{1/2}\}^2 \geq 0.
\end{aligned}$$

□

Remark. From (6), $Eh_0^2(X)/4$ is the reduction in the asymptotic variance gained by using (4) over (2).

From the identity $(-1)^{1-a} = (2a - 1) = 2(a - 1/2)$, $a \in \{0, 1\}$, we write

$$U(\psi) = (Y - \psi A)(-1)^{1-A} = 2(A - 1/2)(Y - \psi A),$$

obtaining

$$\begin{aligned}
W(\psi) &= U(\psi) - (A - 1/2)[2E(Y | X) - \psi] \\
&= (A - 1/2)[2(Y - E(Y | X)) - \psi(2A - 1)] \\
&= (A - 1/2)[2(Y - E(Y | X)) + (-1)^A \psi].
\end{aligned}$$

[[Extension to $P(A = 1 | X) = p \in (0, 1)$]]

$$V(\psi) = (Y - \psi A)(-1)^{1-A}, \quad \frac{\partial}{\partial \psi} V(\psi) = -A(-1)^{1-A}, \quad \mathbb{E}\left(\frac{\partial}{\partial \psi} V(\psi)\right) = -\frac{1}{2}$$

$$n^{1/2}(\hat{\psi}_n - \psi_0) = -\left(\mathbb{E}\frac{\partial V}{\partial \psi}\bigg|_{\psi_0}\right)^{-1} n^{1/2} \sum_i V(\psi_0) = 2n^{1/2} \sum_i (Y_i - \psi_0 A_i)(-1)^{1-A_i}$$

$$\tilde{Y}_i := Y_i - \mathbb{E}(Y|X_i)$$

$$\mathbb{E}(\tilde{Y}_i | A_i) = \alpha_0 + \beta_0 A_i + \varepsilon_i$$

$$\begin{cases} \mathbb{E}(\tilde{Y} | A=1) = \mathbb{E}(Y | A=1) - \mathbb{E}Y = \alpha_0 + \beta_0 \\ \mathbb{E}(\tilde{Y} | A=0) = \mathbb{E}(Y | A=0) - \mathbb{E}Y = \alpha_0 \\ \beta_0 = \alpha_1 = \mathbb{E}(Y | A=1) - \mathbb{E}(Y | A=0), \quad \alpha_0 = -\alpha_0/2 \end{cases}$$

$$0 = \sum_{i=1}^n \begin{pmatrix} 1 \\ A_i \end{pmatrix} (\tilde{Y}_i - \hat{\alpha} - A_i \hat{\beta}) = \sum_{i=1}^n \left\{ \begin{pmatrix} 1 \\ A_i \end{pmatrix} (\tilde{Y}_i - \alpha_0 - A_i \beta_0) + \begin{pmatrix} -1 & -A_i \\ -A_i & -A_i \end{pmatrix} \begin{pmatrix} \hat{\alpha} - \alpha_0 \\ \hat{\beta} - \beta_0 \end{pmatrix} \right\}$$

$$n^{1/2} \begin{pmatrix} \hat{\alpha} - \alpha_0 \\ \hat{\beta} - \beta_0 \end{pmatrix} = \left[\frac{1}{n} \sum \begin{pmatrix} 1 & A_i \\ A_i & A_i \end{pmatrix} \right]^{-1} n^{1/2} \sum \begin{pmatrix} 1 \\ A_i \end{pmatrix} (\tilde{Y}_i - \alpha_0 - A_i \beta_0)$$

$$= \begin{pmatrix} 1 & 1/2 \\ 1/2 & 1/2 \end{pmatrix}^{-1} n^{1/2} \sum \begin{pmatrix} 1 \\ A_i \end{pmatrix} (\tilde{Y}_i - \alpha_0 - A_i \beta_0) = 4 \begin{pmatrix} 1/2 & -1/2 \\ -1/2 & 1 \end{pmatrix} n^{1/2} \sum \begin{pmatrix} 1 \\ A_i \end{pmatrix} (\tilde{Y}_i - \alpha_0 - A_i \beta_0) \quad + o_p(1)$$

$$\begin{aligned} n^{1/2}(\hat{\beta}_n - \beta_0) &= n^{1/2} \sum \begin{pmatrix} 1 & -2 & 4 \end{pmatrix} \begin{pmatrix} 1 \\ A_i \end{pmatrix} (\tilde{Y}_i - \alpha_0 - A_i \beta_0) + o_p(1) = 2n^{1/2} \sum (2A_i - 1) (\tilde{Y}_i - \alpha_0 - A_i \beta_0) + o_p(1) \\ &= 2n^{1/2} \sum (-1)^{1-A_i} (\tilde{Y}_i - \alpha_0 - A_i \beta_0) + o_p(1) \end{aligned}$$

$$n^{1/2}(\hat{\psi}_n - \psi_0) = 2n^{1/2} \sum (-1)^{1-A_i} (Y_i - \psi_0 A_i - \tilde{Y}_i + \alpha_0 + A_i \beta_0) + o_p(1)$$

$$= 2n^{1/2} \sum (-1)^{1-A_i} (\varepsilon_i) + o_p(1) \rightsquigarrow N(0, \sigma^2), \quad \sigma^2 \neq 0$$