

Web Appendix

Lemma 1: $c(z, e) = E[c^*(z, X) | e(X) = e]$ for $z \in \{0, 1\}$

Proof: By definition, $c^*(z, X) = E[Y_z | Z = 1, X] - E[Y_z | Z = 0, X]$. For $z \in \{0, 1\}$, let $f(X | Z = z, e(X) = e)$ denote the conditional distribution of the confounder vector X given the treatment group $Z = z$ and the PS $e(X) = e$, and $f(X | e(X) = e)$ denote the conditional distribution of X given $e(X) = e$ only. By the definition of the propensity score, $\Pr(Z = 1 | X, e(X) = e) = e = \Pr(Z = 1 | e(X) = e)$, i.e., $Z \perp\!\!\!\perp X | e(X) = e$. Then, $f(X | Z = z, e(X) = e) = f(X | e(X) = e)$. Moreover,

$$\begin{aligned} & E[E(Y_z | Z = 1, X) | e(X) = e] \\ &= \int E(Y_z | Z = 1, X) f(X | e(X) = e) dX \\ &= \int E(Y_z | Z = 1, X, e(X) = e) f(X | Z = 1, e(X) = e) dX \\ &= E[Y_z | Z = 1, e(X) = e] \end{aligned}$$

Following similar argument, it can be shown that

$$E[E(Y_z | Z = 0, X) | e(X) = e] = E[Y_z | Z = 0, e(X) = e].$$

As a direct consequence, we have proved that $c(z, e) = E[c^*(z, X) | e(X) = e]$.

Lemma 2: Suppose the sensitivity function $c(z, e)$ is correctly specified, then the bias correction term in the SF-corrected estimator will remove the bias due to uncontrolled confounding.

Proof: By definition,

$$\begin{aligned} Y^{SF} &\equiv Y - (E[Y_Z | Z, e(X)] - E[Y_Z | e(X)]) \\ &= \begin{cases} Y - (1 - e(X))c(1, e) & \text{if } Z = 1 \\ Y + e(X)c(0, e) & \text{if } Z = 0 \end{cases} \end{aligned} \quad (1)$$

We first consider the daily users with $Z_i = 1$, then $Y_i = Y_{1,i}$,

$$Y_i^{SF} = Y_i - (E[Y_{1,i} | Z_i = 1, e(X_i)] - E[Y_{1,i} | e(X_i)]),$$

and

$$\begin{aligned} E\left[\frac{Z_i}{e(X_i)} Y_i^{SF}\right] &= E\left[\frac{Z_i}{e(X_i)} E(Y_i^{SF} | Z_i = 1, e(X_i))\right] \\ &= E\left[\frac{Z_i}{e(X_i)} \left\{ E(Y_i | Z_i = 1, e(X_i)) \right. \right. \\ &\quad \left. \left. - (E[Y_{1,i} | Z_i = 1, e(X_i)] - E[Y_{1,i} | e(X_i)]) \right\}\right] \\ &= E\left[\frac{Z_i}{e(X_i)} E[Y_{1,i} | e(X_i)]\right] = E\left[\frac{E[Z_i | e(X_i)]}{e(X_i)} E[Y_{1,i} | e(X_i)]\right] \\ &= E(E[Y_1 | e(X)]) = E[Y_1] \end{aligned}$$

Similarly, it can be proved that for the periodic users ($Z_i = 0$), $Y_i = Y_{0,i}$ and

$$E\left[\frac{1-Z_i}{1-e(X_i)}Y_i^{SF}\right] = E[Y_0].$$

Apparently, the bias correction term ($E[Y_Z | Z, e(X)] - E[Y_Z | e(X)]$)

removes the bias due to uncontrolled confounding.

In addition, for $z \in \{0,1\}$, by the definition of conditional expectation,

$$\begin{aligned} E[Y_z | e(X)] &= E[Y_z | Z = 1, e(X)]\Pr(Z = 1 | e(X)) + E[Y_z | Z = 0, e(X)]\Pr(Z = 0 | e(X)) \quad . \\ &= E[Y_z | Z = 1, e(X)]e(X) + E[Y_z | Z = 0, e(X)](1 - e(X)) \end{aligned}$$

Then, after simple algebra, it can be shown that,

$$\begin{aligned} E[Y_1 | Z = 1, e(X)] - E[Y_1 | e(X)] &= (1 - e(X))c(1, e) \\ E[Y_0 | Z = 0, e(X)] - E[Y_0 | e(X)] &= -e(X)c(0, e) \quad . \end{aligned}$$

Furthermore, for any given sensitivity function $c(z, e)$, $\hat{\psi}^{SF}$ can be easily obtained by replacing the unknown PS using $\{\hat{e}(X_i), i = 1, \dots, n\}$.