

ATE & Variance Estimators for the Case with Multiple Treatments and Linear Adjustments

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February 28, 2024

1 CAR without Clusters

Notation

Let us introduce some additional notations besides the notation used in (Juang et al., 2017).

$$\begin{aligned}
 N_a &:= \sum_{i \in [N]} \mathbb{I}\{A_i = a\}, \quad \forall a \in \mathcal{A} \\
 N_0 &:= \sum_{i \in [N]} \mathbb{I}\{A_i = 0\} \\
 I_{\{a,0\}} &:= \{i \in [N] : A_i = a\} \cup \{i \in [N] : A_i = 0\}, \quad \forall a \in \mathcal{A} \\
 \hat{\pi}_a(s) &:= \frac{N_a(s)}{N(s)}, \quad \hat{\pi}_0(s) := \frac{N_0(s)}{N(s)}, \quad \forall a \in \mathcal{A} \text{ and } \forall s \in \mathcal{S} \\
 \tilde{A}_i &= \begin{cases} 1, & \text{if } A_i = a, \quad \forall a \in \mathcal{A} \\ 0, & \text{if } A_i = 0. \end{cases}
 \end{aligned}$$

ATE Estimator

Let us recall the version for a binary treatment case:

$$\hat{\tau} \equiv \frac{1}{N} \sum_{i=1}^N \left[\frac{A_i(Y_i - \hat{\mu}(1, S_i, X_i))}{\hat{\pi}(S_i)} - \frac{(1 - A_i)(Y_i - \hat{\mu}(0, S_i, X_i))}{1 - \hat{\pi}(S_i)} + \hat{\mu}(1, S_i, X_i) - \hat{\mu}(0, S_i, X_i) \right].$$

Since in the case with multiple treatments $\hat{\pi}_a(s) + \hat{\pi}_0(s) \neq 1$, we should make the following corrections to the expression. First, instead of $1 - \hat{\pi}(s)$ we should directly use $\hat{\pi}_0 = \frac{n_0(s)}{n(s)}$. Second, instead of a binary treatment variable A_i , we should use an indicator variable $\tilde{A}_i = \mathbb{I}\{A_i = 1\}$. Thus, the estimator for any treatment $a \in \mathcal{A}$ (relative to control) becomes:

$$\hat{\tau}_a \equiv \frac{1}{N} \sum_{i=1}^N \left[\frac{\tilde{A}_i(Y_i - \hat{\mu}(a, S_i, X_i))}{\hat{\pi}_a(S_i)} - \frac{(1 - \tilde{A}_i)(Y_i - \hat{\mu}(0, S_i, X_i))}{\hat{\pi}_0(S_i)} + \hat{\mu}(a, S_i, X_i) - \hat{\mu}(0, S_i, X_i) \right],$$

where

$$\tilde{A}_i = \begin{cases} 1, & \text{if } A_i = a, \quad \forall a \in \mathcal{A} \\ 0, & \text{if } A_i = 0. \end{cases}$$

Variance Estimator

Recall that the expression of the variance estimator for the binary treatment case has the following form:

$$\hat{\sigma}^2 = \frac{1}{N} \sum_{i=1}^N \left[A_i \hat{\Xi}_1^2(\mathcal{D}_i, S_i) + (1 - A_i) \hat{\Xi}_0^2(\mathcal{D}_i, S_i) + \hat{\Xi}_2^2(\mathcal{D}_i, S_i) \right],$$

where

$$\begin{aligned} \hat{\Xi}_1(\mathcal{D}_i, s) &= \tilde{\Xi}_1(s) - \frac{1}{N_1(s)} \sum_{j \in I_1(s)} \tilde{\Xi}_{1,j}(\mathcal{D}_i, s), \\ \hat{\Xi}_0(\mathcal{D}_i, s) &= \tilde{\Xi}_0(s) - \frac{1}{N_0(s)} \sum_{j \in I_0(s)} \tilde{\Xi}_{0,j}(\mathcal{D}_i, s), \\ \hat{\Xi}_2 &= \left(\frac{1}{N_1(s)} \sum_{j \in I_1(s)} (Y_j - \hat{\tau} A_j) \right) - \left(\frac{1}{N_0(s)} \sum_{j \in I_0(s)} (Y_j - \hat{\tau} A_j) \right) \\ \tilde{\Xi}_1(\mathcal{D}_i, s) &= \left(1 - \frac{1}{\hat{\pi}(s)} \right) \hat{\mu}(1, s, X_i) - \hat{\mu}(0, s, X_i) + \frac{Y_i}{\hat{\pi}(s)}, \\ \tilde{\Xi}_0(\mathcal{D}_i, s) &= \left(\frac{1}{1 - \hat{\pi}(s)} - 1 \right) \hat{\mu}(0, s, X_i) + \hat{\mu}(1, s, X_i) - \frac{Y_i}{1 - \hat{\pi}(s)}. \end{aligned}$$

Following the same reasoning as for the ATE estimator, we need to make the following corrections to get the expression for the multiple treatments case.

First, notice that we can rewrite $\tilde{\Xi}_1(\mathcal{D}_i, s)$ and $\tilde{\Xi}_0(\mathcal{D}_i, s)$ as follows:

$$\begin{aligned} \tilde{\Xi}_1(\mathcal{D}_i, s) &= \hat{\mu}(1, s, X_i) - \hat{\mu}(0, s, X_i) + \frac{Y_i - \hat{\mu}(1, s, X_i)}{\hat{\pi}(s)}, \\ \tilde{\Xi}_0(\mathcal{D}_i, s) &= \hat{\mu}(1, s, X_i) - \hat{\mu}(0, s, X_i) - \frac{Y_i - \hat{\mu}(0, s, X_i)}{1 - \hat{\pi}(s)}. \end{aligned}$$

For the same reasoning as before, to generalize these terms for the multiple treatments scenario we need to substitute $\hat{\pi}_a(s)$ and $\hat{\pi}_0(s)$ for $\hat{\pi}(s)$ and $1 - \hat{\pi}(s)$ respectively.

Combining the corrections, we get the following expression of the variance estimator for every treatment $a \in \mathcal{A}$:

$$\hat{\sigma}_a^2 = \frac{1}{N} \sum_{i=1}^N \left[\tilde{A}_i \hat{\Xi}_a^2(\mathcal{D}_i, S_i) + (1 - \tilde{A}_i) \hat{\Xi}_0^2(\mathcal{D}_i, S_i) + \hat{\Xi}_2^2(\mathcal{D}_i, S_i) \right],$$

where

$$\begin{aligned} \hat{\Xi}_a(\mathcal{D}_i, s) &= \tilde{\Xi}_a(s) - \frac{1}{N_a(s)} \sum_{j \in I_a(s)} \tilde{\Xi}_{a,j}(\mathcal{D}_i, s), \\ \hat{\Xi}_0(\mathcal{D}_i, s) &= \tilde{\Xi}_0(s) - \frac{1}{N_0(s)} \sum_{j \in I_0(s)} \tilde{\Xi}_{0,j}(\mathcal{D}_i, s), \\ \hat{\Xi}_2 &= \left(\frac{1}{N_a(s)} \sum_{j \in I_a(s)} (Y_j - \hat{\tau}_a \tilde{A}_j) \right) - \left(\frac{1}{N_0(s)} \sum_{j \in I_0(s)} (Y_j - \hat{\tau}_a \tilde{A}_j) \right), \\ \tilde{\Xi}_a(\mathcal{D}_i, s) &= \hat{\mu}(a, s, X_i) - \hat{\mu}(0, s, X_i) + \frac{Y_i - \hat{\mu}(a, s, X_i)}{\hat{\pi}_a(s)}, \\ \tilde{\Xi}_0(\mathcal{D}_i, s) &= \hat{\mu}(a, s, X_i) - \hat{\mu}(0, s, X_i) - \frac{Y_i - \hat{\mu}(0, s, X_i)}{\hat{\pi}_0(s)}. \end{aligned}$$

2 CAR with Clusters

Using the same reasoning as before, we can generalize the ATE and variance estimators for the case with clusters and multiple treatments as follows.

ATE Estimator

$$\begin{aligned}\hat{\tau}_a &= \frac{\sum_{g=1}^G \hat{\Xi}_g}{\sum_{g=1}^G N_g}, \\ \hat{\Xi}_g &= \frac{\tilde{A}_g (N_g \bar{Y}_g - \hat{\mu}(a, S_g, X_g, N_g))}{\hat{\pi}_a(S_g)} - \frac{(1 - \tilde{A}_g) (N_g \bar{Y}_g - \hat{\mu}(0, S_g, X_g, N_g))}{\hat{\pi}_0(S_g)} \\ &\quad + \hat{\mu}(a, S_g, X_g, N_g) - \hat{\mu}(0, S_g, X_g, N_g),\end{aligned}$$

where

$$\tilde{A}_i = \begin{cases} 1, & \text{if } A_i = a, \forall a \in \mathcal{A} \\ 0, & \text{if } A_i = 0. \end{cases}$$

Variance Estimator

$$\hat{\sigma}_a^2 = \frac{\frac{1}{G} \sum_{g=1}^G \left[\tilde{A}_g \hat{\Xi}_a^2(\mathcal{D}_g, S_g) + (1 - \tilde{A}_g) \hat{\Xi}_0^2(\mathcal{D}_g, S_g) + \hat{\Xi}_2^2(\mathcal{D}_g, S_g) \right]}{\left(\frac{1}{G} \sum_{g=1}^G N_g \right)^2},$$

where

$$\begin{aligned}\hat{\Xi}_a(\mathcal{D}_g, s) &= \tilde{\Xi}_a(s) - \frac{1}{G_1(s)} \sum_{j \in I_1(s)} \tilde{\Xi}_{1,j}(s) - \hat{\tau}_a \left(N_g - \frac{1}{G(s)} \sum_{j \in I(s)} N_j \right), \\ \hat{\Xi}_0(\mathcal{D}_g, s) &= \tilde{\Xi}_0(s) - \frac{1}{G_0(s)} \sum_{j \in I_0(s)} \tilde{\Xi}_{0,j}(s) - \hat{\tau}_a \left(N_g - \frac{1}{G(s)} \sum_{j \in I(s)} N_j \right), \\ \hat{\Xi}_2(s) &= \left(\frac{1}{G_1(s)} \sum_{j \in I_1(s)} N_j \bar{Y}_j \right) - \left(\frac{1}{G_0(s)} \sum_{j \in I_0(s)} N_j \bar{Y}_j \right) - \hat{\tau}_a \times \left(\frac{1}{G(s)} \sum_{j \in I(s)} N_j \right), \\ \tilde{\Xi}_a(\mathcal{D}_g, s) &= \hat{\mu}(a, s, X_g, N_g) - \hat{\mu}(0, s, X_g, N_g) + \frac{N_g \bar{Y}_g - \hat{\mu}(a, s, X_g, N_g)}{\hat{\pi}_a(s)}, \\ \tilde{\Xi}_0(\mathcal{D}_g, s) &= \hat{\mu}(a, s, X_g, N_g) - \hat{\mu}(0, s, X_g, N_g) - \frac{N_g \bar{Y}_g - \hat{\mu}(0, s, X_g, N_g)}{\hat{\pi}_0(s)}.\end{aligned}$$