

Supplementary Material

Proofs

Proof of Theorem 1. Let us write SATT as

$$\text{SATT} = \frac{1}{n_1} \sum_{i \in \mathcal{T}_1} Y_i - \frac{1}{n_1} \sum_{i \in \mathcal{T}_1} Y_i(0).$$

It is then clear that SATT differs from $\hat{\tau}_W$ only in the second term, that is,

$$\begin{aligned} \hat{\tau} - \text{SATT} &= \frac{1}{n_1} \sum_{i \in \mathcal{T}_1} Y_i(0) - \sum_{i \in \mathcal{T}_0} W_i Y_i(0) \\ &= \sum_{i=1}^n (-1)^{T_i+1} W_i Y_i(0) \\ &= \sum_{i=1}^n (-1)^{T_i+1} W_i f_0(X_i) + \sum_{i=1}^n (-1)^{T_i+1} W_i \epsilon_i, \end{aligned}$$

where we recognize the last term as E_W . For each term of E_W we have

$$\begin{aligned} \mathbb{E}[(-1)^{T_i+1} W_i \epsilon_i | X, T] \\ &= (-1)^{T_i+1} W_i (\mathbb{E}[Y_i(0) | X, T] - f_0(X_i)) \\ &= (-1)^{T_i+1} W_i (\mathbb{E}[Y_i(0) | X] - f_0(X_i)) = 0, \end{aligned}$$

where the first equality is by definition of ϵ_i and the fact that $W_i = W_i(X, T)$ and the second is by Assumption 1. \square

Proof of Theorem 2. Let D be the distance matrix $D_{ii'} = \delta(X_i, X_{i'})$. For this choice of $(\mathcal{F}, \|\cdot\|)$, by linear optimization duality we get

$$\begin{aligned} \mathfrak{E}(W; \mathcal{F}) &= \frac{1}{n_1} \sup_{v_i - v_{i'} \leq D_{ii'} \forall i, i'} (\sum_{i \in \mathcal{T}_1} v_i - \sum_{i \in \mathcal{T}_0} n_1 W_i v_i) \\ &= \frac{1}{n_1} \min_S \sum_{i, i'} D_{ii'} S_{ii'} \\ &\quad \text{s.t. } S \in \mathbb{R}_+^{n \times n} \\ &\quad \sum_{i'=1}^n (S_{ii'} - S_{i'i}) = 1 \quad \forall i \in \mathcal{T}_1 \\ &\quad \sum_{i'=1}^n (S_{ii'} - S_{i'i}) = -n_1 W_i \quad \forall i \in \mathcal{T}_0. \end{aligned}$$

This describes a min-cost network flow problem with sources \mathcal{T}_1 with inputs 1, sinks \mathcal{T}_0 with outputs W_i , edges between every two nodes with costs $D_{ii'}$ and without capacities. Consider any source $i \in \mathcal{T}_1$ and any sink $i' \in \mathcal{T}_0$ and any path i, i_1, \dots, i_m, i' . By the triangle inequality, $D_{ii'} \leq D_{ii_1} + D_{i_1 i_2} + \dots + D_{i_m i'}$. Therefore, as there are no capacities, it is always preferable to send the flow from the sources to the sinks along the direct edges from \mathcal{T}_1 to \mathcal{T}_0 . That is, we can eliminate all other edges and write

$$\begin{aligned} \mathfrak{E}(W; \mathcal{F}) &= \frac{1}{n_1} \min_S \sum_{i \in \mathcal{T}_1, i' \in \mathcal{T}_0} D_{ii'} S_{ii'} \\ &\quad \text{s.t. } S \in \mathbb{R}_+^{\mathcal{T}_1 \times \mathcal{T}_0} \\ &\quad \sum_{i' \in \mathcal{T}_0} S_{ii'} = 1 \quad \forall i \in \mathcal{T}_1 \\ &\quad \sum_{i \in \mathcal{T}_1} S_{ii'} = n_1 W_i \quad \forall i' \in \mathcal{T}_0. \end{aligned}$$

In the case of with replacement and $\mathcal{W}_0 = \mathcal{W}_0^{\text{probability}}$,

using the transformation $W'_i = n_1 W_i$, we get

$$\begin{aligned} \min_{W \in \mathcal{W}} \mathfrak{E}(W; \mathcal{F}) \\ &= \frac{1}{n_1} \min_{S, W'} \sum_{i \in \mathcal{T}_1, i' \in \mathcal{T}_0} D_{ii'} S_{ii'} \\ &\quad \text{s.t. } S \in \mathbb{R}_+^{\mathcal{T}_1 \times \mathcal{T}_0} \\ &\quad W'_i \in \mathbb{R}_+^{\mathcal{T}_0} \\ &\quad \sum_{i \in \mathcal{T}_0} W'_i = n_1 \\ &\quad \sum_{i' \in \mathcal{T}_0} S_{ii'} = 1 \quad \forall i \in \mathcal{T}_1 \\ &\quad \sum_{i \in \mathcal{T}_1} S_{ii'} - W'_i = 0 \quad \forall i' \in \mathcal{T}_0. \end{aligned}$$

This describes a min-cost network flow problem with sources \mathcal{T}_1 with inputs 1; nodes \mathcal{T}_0 with 0 exogenous flow; one sink with output n_1 ; edges from each $i \in \mathcal{T}_1$ to each $i' \in \mathcal{T}_0$ with flow variable $S_{ii'}$, cost $D_{ii'}$, and without capacity; and edges from each $i \in \mathcal{T}_0$ to the sink with flow variable W'_i and without cost or capacity. Because all data is integer, the optimal solution of $W' = n_1 W$ is integer [1]. Hence, since $\mathcal{W}_0^{n_1\text{-multisubset}} \subseteq \mathbb{Z}/n_1$, the solution is the same when we restrict to $\mathcal{W}_0 = \mathcal{W}_0^{n_1\text{-multisubset}}$. This solution (in terms of W') is equal to sending the whole input 1 from each source in \mathcal{T}_1 to the node in \mathcal{T}_0 with smallest distance and from there routing this flow to the sink, which corresponds exactly to one-to-one matching with replacement.

In the case of no replacement and $\mathcal{W}_0 = \mathcal{W}_0^{n_1^{-1}\text{-bounded}}$, using the transformation $W'_i = n_1 W_i$, we get

$$\begin{aligned} \min_{W \in \mathcal{W}} \mathfrak{E}(W; \mathcal{F}) \\ &= \frac{1}{n_1} \min_{S, W'} \sum_{i \in \mathcal{T}_1, i' \in \mathcal{T}_0} D_{ii'} S_{ii'} \\ &\quad \text{s.t. } S \in \mathbb{R}_+^{\mathcal{T}_1 \times \mathcal{T}_0} \\ &\quad W'_i \in \mathbb{R}_+^{\mathcal{T}_0} \\ &\quad \sum_{i \in \mathcal{T}_0} W'_i = n_1 \\ &\quad W'_i \leq 1 \quad \forall i \in \mathcal{T}_0 \\ &\quad \sum_{i' \in \mathcal{T}_0} S_{ii'} = 1 \quad \forall i \in \mathcal{T}_1 \\ &\quad \sum_{i \in \mathcal{T}_1} S_{ii'} - W'_i = 0 \quad \forall i' \in \mathcal{T}_0. \end{aligned}$$

This describes the same min-cost network flow problem except that the edges from each $i \in \mathcal{T}_0$ to the sink have a capacity of 1. Because all data is integer, the optimal solution of S and $W' = n_1 W$ is integer [1]. Hence, since $\mathcal{W}_0^{n_1\text{-subset}} \subseteq \mathbb{Z}/n_1$, the solution is the same when we restrict to $\mathcal{W}_0 = \mathcal{W}_0^{n_1\text{-subset}}$. The optimal $S_{ii'}$ is integer and so, by $\sum_{i' \in \mathcal{T}_0} S_{ii'} = 1$, for each $i \in \mathcal{T}_1$ there is exactly one $i' \in \mathcal{T}_0$ with $S_{ii'} = 1$ and all others are zero. $S_{ii'} = 1$ denotes matching i with i' . The optimal W'_i is integral and so, by $W'_i \leq 1$, $W'_i \in \{0, 1\}$. Hence, for each $i \in \mathcal{T}_0$,

$\sum_{i' \in \mathcal{T}_1} S_{ii'} \in \{0, 1\}$ so we only use node i at most once. The cost of S is exactly the sum of pairwise distances in the match. Hence, the optimal solution corresponds exactly to one-to-one matching without replacement. \square

Proof of Corollary 3. Apply Theorem 2 with the metric

$$\delta'(x, x') = \mathbb{I}_{[x \neq x']} \max\{\delta(x, x'), \delta_0\}. \quad \square$$

Proof of Theorem 4. This choice of space leads to

$$\mathfrak{E}(W; \mathcal{F}) = \sum_{j=1}^M \left| \frac{1}{n_1} \sum_{i \in \mathcal{T}_1} \mathbb{I}_{[C(X_i)=j]} - \sum_{i \in \mathcal{T}_0} W_i \mathbb{I}_{[C(X_i)=j]} \right|.$$

That is, the worst-case f assigns ± 1 to each partition in order to make the difference of values in that partition be nonnegative. Then clearly the optimal choice of $W \in \mathbb{R}^{\mathcal{T}_0}$ is to make each of these absolute values equal zero. This happens exactly when, for each $i \in \mathcal{T}_0$,

$$\begin{aligned} W_i &= \frac{1}{n_1} \frac{|i' \in \mathcal{T}_1: C(X_{i'})=C(X_i)|}{|i' \in \mathcal{T}_0: C(X_{i'})=C(X_i)|} \\ &= \frac{1}{n_1} \frac{\text{num treatment subjects in same partition as } i}{\text{num control subjects in same partition as } i}, \end{aligned}$$

where $0/0 = 0$ and we never encounter dividing a positive integer by 0 due to the no-extrapolation assumption. Because the weight is nonnegative, the solution is unchanged when restricting to nonnegative weights. \square

Proof of Theorem 5. By duality of norms,

$$\begin{aligned} \mathfrak{E}(W; \mathcal{F}) &= \sup_{\beta^T V \beta \leq 1} \beta^T \left(\frac{1}{n_1} \sum_{i \in \mathcal{T}_1} X_i - \sum_{i \in \mathcal{T}_0} W_i X_i \right) \\ &= M_V(W). \end{aligned}$$

The optimal W minimizes this discrepancy over subsamples from control with the allowable size. \square

Proof of Theorem 6. We have

$$\begin{aligned} \mathfrak{E}^2(W; \mathcal{F}) &= \max_{\|f\| \leq 1} \left(\sum_{i=1}^n (-1)^{T_i+1} W_i f(X_i) \right)^2 \\ &= \left\langle \sum_{i=1}^n (-1)^{T_i+1} W_i \mathcal{K}(X_i, \cdot), \sum_{i=1}^n (-1)^{T_i+1} W_i \mathcal{K}(X_i, \cdot) \right\rangle \\ &= \sum_{i,j=1}^n (-1)^{T_i+T_j} W_i W_j K_{ij}, \end{aligned}$$

which when written in block form gives rise to the result. \square

Proof of Theorem 7. First we show $\mathfrak{E}_{\min}(\mathcal{F}) \rightarrow 0$ a.s. by showing that we can construct a feasible \tilde{W} such that $\mathfrak{E}(\tilde{W}; \mathcal{F}) \rightarrow 0$ a.s. Let $p(x) = \mathbb{P}(T=1|X=x)$. By Assumption 1, $0 < p(X) < 1$ a.s. So there exists $\alpha > 0$ such that $q(x) = \alpha p(x)/(1-p(x))$ is a.s. in $(0, 1)$. For each i , let $\tilde{W}'_i \in \{0, 1\}$ be Bernoulli with probability $q(X_i)$. Then we have that $X_i|T=0, \tilde{W}'_i=1$ is distributed as $X_i|T=1$. Let $n'_0 = \sum_{j \in \mathcal{T}_0} \tilde{W}'_j$ and

note that $n'_0 \geq n'_0$ eventually a.s. For each $i \in \mathcal{T}_0$, set $\tilde{W}_i = \tilde{W}'_i/n'_0$. Let $\zeta(f) = \mathbb{E}[f(X_1) | T=1]$, $\xi_i(f) = (T_i + \tilde{W}'_i)(f(X_i) - \zeta(f))$. Let $A_0 = \frac{1}{n_0} \sum_{i \in \mathcal{T}_0} \xi_i$ and $A_1 = \frac{1}{n_1} \sum_{i \in \mathcal{T}_1} \xi_i$. Adding and subtracting ζ , we see $\mathcal{E}(\tilde{W}; f) = A_1(f) - (n_0/n'_0)A_0(f)$. By construction of \tilde{W}'_i , we see that $\mathbb{E}[\xi_i] = 0$ (i.e., Bochner integral). By (5), $\|\xi\|_*$ has (a) second or (b) first moment. By (1), each ξ_i is independent. Therefore, by [2] for (5)(a) (since B -convexity of \mathcal{F} implies B -convexity of \mathcal{F}^* ; see [20]) or by [6] for (5)(b), a law of large numbers holds yielding, a.s., $\|A_0\|_* \rightarrow 0$ and $\|A_1\|_* \rightarrow 0$. Since $(n_0/n'_0) \rightarrow \alpha \mathbb{E}[p(X_1)] < \infty$ a.s., we have that $\|\mathcal{E}(\tilde{W}; \cdot)\|_* \rightarrow 0$ a.s. By (3) \tilde{W} is feasible, so, a.s.

$$\mathfrak{E}_{\min}(\mathcal{F}) = \mathfrak{E}(W; \mathcal{F}) \leq \mathfrak{E}(\tilde{W}; \mathcal{F}) = \|\mathcal{E}(\tilde{W}; \cdot)\|_* \rightarrow 0.$$

Fix $\epsilon > 0$. By (4), there is a $g_0 \in \mathcal{F}$ such that $\sup_x |f_0(x) - g_0(x)| \leq \epsilon/2$. Hence,

$$\begin{aligned} |\mathcal{E}(W; f_0)| &\leq |\mathcal{E}(W; g_0)| + 2 \sup_{i=1, \dots, n} |f_0(X_i) - g_0(X_i)| \\ &\leq \|g_0\| \mathfrak{E}(W; \mathcal{F}) + \epsilon = \|g_0\| \mathfrak{E}_{\min} + \epsilon \rightarrow \epsilon. \end{aligned}$$

Since true for any $\epsilon > 0$, $|\mathcal{E}(W; f_0)| \rightarrow 0$ a.s. \square