

Unified Covariate Adjustment for Causal Inference

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Motivation

Causal effects are often identified as *various forms of covariate adjustments* (which is a summation of products of conditional distributions).

Back-door adjustment	$\mathbb{E}[Y \text{do}(x)] = \sum_z \mathbb{E}[Y x, z]P(z)$
Front-door adjustment	$\mathbb{E}[Y \text{do}(x)] = \sum_{x', z, c} \mathbb{E}[Y x', z, c]P(z x, c)P(x', c)$
Verma's equation	$\mathbb{E}[Y \text{do}(x)] = \sum_{a, b, x'} \mathbb{E}[Y a, b, x]P(b a, x')P(a x)P(x')$
Domain Generalization	$\mathbb{E}[Y \text{do}(x), S = 0] = \sum_z \mathbb{E}[Y x, z, S = 1]P(z S = 0)$
Policy Intervention	$\mathbb{E}[Y_{\sigma_X}] = \sum_{z, x'} \mathbb{E}[Y x', z]\sigma_X(x' z)P(z)$
Effect of Treatment on the Treated	$\mathbb{E}[Y_{X=1} X = 0] = \sum_z \mathbb{E}[Y X = 1, z]P(z X = 0)$

However, no *unified* estimators for those various covariate adjustments with (1) *computational efficiency* and (2) *statistical robustness* exists.

United Covariate Adjustment (UCA)

The **UCA** is $\sum_{c_1, \dots, c_m} \mathbb{E}_{P_{m+1}}[Y | c^{(m)}, r^{(m)}] \prod_{i=1}^m P^i(c_i | c^{(i-1)}, r^{(i-1)}) \sigma_{R_i}^i(r_i | c^{(i)}, r^{(i-1)})$, where P^i is an arbitrary distribution and $\sigma_{R_i}^i$ is an intervention policy.

 *Various forms of covariate adjustment, beyond the back-door adjustment, can be represented as **UCA**.*

Example: UCA for expressing the front-door adjustment

The **UCA** reduces to $\sum_{x', z, c} \mathbb{E}[Y | x', z, c]P(z | x, c)P(x', c)$, with

$(R_1, R_2) = \emptyset, (C_1, C_2, Y) = (X, Z, Y), P^1(C_1) = P(X), P^2(C_2 | C_1) := P(Z | x), P^3(Y | C_1, C_2) = P(Y | Z, X)$.

DML-UCA: Estimator for UCA

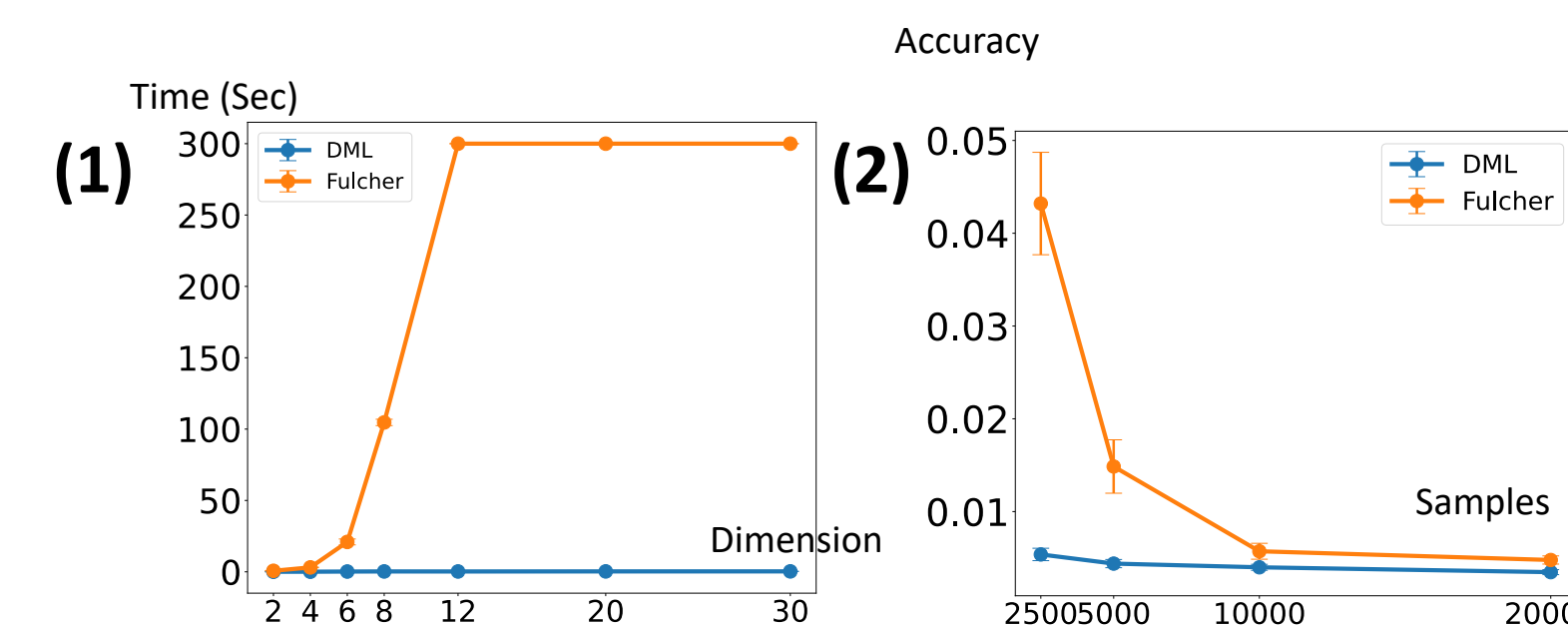
DML-UCA($\{\hat{\mu}^i, \hat{\pi}^i\}, \{D^i\}$) = $\sum_{i=1}^m \mathbb{E}_{D^{i+1}}[\hat{\pi}^i \{\check{\mu}^{i+1} - \hat{\mu}^i\}] + \mathbb{E}_{D^1}[\check{\mu}^1]$ (where $\{\hat{\mu}^i, \hat{\pi}^i\}$ are nuisance estimates and $D^i \sim P^i$ are samples) satisfies the following:

-  1. *Computational Efficiency* (evaluable in polynomial time); and
- 2. *Doubly Robustness* (If $\hat{\mu}^i, \hat{\pi}^i$ converges to μ_0^i, π_0^i at $n^{-1/4}$ rate, DML-UCA converges at $n^{-1/2}$ rate).

Example: DML-UCA for the front-door adjustment

DML-UCA evaluates $\mathbb{E}_P[\pi_0^2(Z, X, C)\{Y - \mu_0^2(Z, X, C)\} + \mathbb{E}_P[\pi^1(C)\{\mu^2(Z, X', C) - \mu^1(X', C)\} | x] + \mathbb{E}_P[\mu_0^1(X, C)]$,

- $\mu^2 = \mathbb{E}[Y | Z, X, C], \mu_0^1 = \mathbb{E}[\mu_0^2(Z, X', C) | x, C, X']$, and X' is an independent copy of X .
- $\pi_0^2 = P(Z | x, C)/P(Z | X, C), \pi^1 = P(x)/P(x | C)$.



- (1) *Computational Efficiency*: The estimator can be estimable in a polynomial time.
- (2) *Doubly Robustness*: The estimator converges fast even when $\{\pi^i\}$ and $\{\mu^i\}$ converges slow.

Conclusion

- Unified Covariate Adjustment (UCA)* unifies various covariate adjustments in a form of a summation of products of conditional distributions.
- We develop **DML-UCA** that is *computationally efficient* and *doubly robust* and provide its finite sample guarantee.