

DOTE 6635: Artificial Intelligence for Business Research

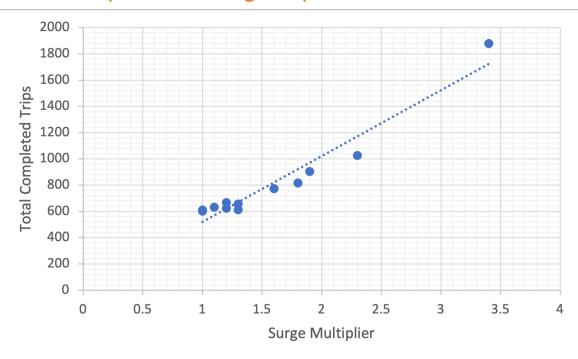
Causal Inference Fundamentals

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From Philosophy to Science

- Causality has been an important philosophical question throughout human civilization (https://grok.com/share/bGVnYWN5_fabab87f-004e-4711-83bf-47e9cb4ba195).
- Neyman (1923) and Rubin (1974) make causality a scientific field of study.
- Causal inference** is the process of determining the independent, actual **effect** of a particular phenomenon that is part of a larger system.



Treatment	Condition		Mortality Rate
	Mild	Severe	
A	15% (210/1400)	30% (30/100)	16% (240/1500)
B	10% (5/50)	20% (100/500)	19% (105/550)

Estimating causal effects of treatments in randomized and nonrandomized studies.

[DB Rubin - Journal of educational Psychology, 1974 - psychnet.apa.org](#)

... use of carefully controlled nonrandomized data to estimate causal effects is a reasonable ... of the use of nonrandomized studies to estimate causal effects of treatments (eg, Campbell & ...

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Agenda

- Potential Outcomes Model, RCT and Difference-in-Mean Estimator
- Linear Regression
- Unconfoundedness and Inverse Propensity Weighting
- Augmented Inverse Propensity Weighting and Double Robustness

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Potential Outcomes Model

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- In total n subjects, each subject is assigned a binary treatment $W_i = 0, 1$ and an outcome $Y_i(W_i)$.

The individual causal effect of the treatment on the i -th unit is then^[2]

$$\Delta_i = Y_i(1) - Y_i(0). \quad (1.1)$$

- Fundamental challenge of causal inference: Only one of $Y_i(1)$ and $Y_i(0)$ is observable, so we take average:

$$\bar{\Delta} = \frac{1}{n} \sum_{i=1}^n (Y_i(1) - Y_i(0)) \qquad \qquad \tau = \mathbb{E}_P [Y_i(1) - Y_i(0)]$$

Sample Average Treatment Effect

Average Treatment Effect

$$\hat{\tau}_{DM} := \frac{1}{n_1} \sum_{W_i=1} Y_i - \frac{1}{n_0} \sum_{W_i=0} Y_i, \quad n_w = |\{i : W_i = w\}|$$

Difference-in-Mean (DM) Estimator

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RCT & SUTVA

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- Under randomized controlled trials, we impose two additional assumptions:

$$\begin{aligned} Y_i &= Y_i(W_i) & (1.5) \\ W_i &\perp\!\!\!\perp \{Y_i(0), Y_i(1)\} & (\text{random treatment assignment}) \end{aligned}$$

- Stable Unit Treatment Value Assumption (SUTVA) = Consistency + No Interference.
- Usually, we need unbiasedness and statistical consistency first.

Suppose furthermore that the treatment is in fact randomized, i.e., that conditionally all the potential outcomes $\{Y_i(0), Y_i(1)\}_{i=1}^n$ and the number of treated units n_1 , all units are treated with the same probability:^[3]

$$\mathbb{P}[W_i = 1 \mid \{Y_i(0), Y_i(1)\}_{i=1}^n, n_1] = \frac{n_1}{n}, \quad i = 1, \dots, n. \quad (1.6)$$

Then $\hat{\tau}_{DM}$ is finite-sample unbiased for the SATE as defined in (1.2).

Theorem 1.1. Under assumptions (1.5) and (1.6),

$$\mathbb{E}[\hat{\tau}_{DM} \mid \{Y_i(0), Y_i(1)\}_{i=1}^n, n_0 > 0, n_1 > 0] = \bar{\Delta}. \quad (1.7)$$

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Statistical Inference with RCT

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- If the treatment assignment is randomized as a Bernoulli trial,

$$W_i \mid \{Y_i(0), Y_i(1)\} \stackrel{\text{iid}}{\sim} \text{Bernoulli}(\pi), \quad 0 < \pi < 1. \quad (1.8)$$

- Then we have a central limit theorem (CLT), or root-n consistency:

Theorem 1.2. Under the assumptions of Theorem 1.2, suppose furthermore that the potential outcomes are drawn as $\{Y_i(0), Y_i(1)\} \stackrel{\text{iid}}{\sim} P$ from a distribution P with bounded second moments and that we run a Bernoulli trial as in (1.8). Then,

$$\sqrt{n}(\hat{\tau}_{DM} - \tau) \Rightarrow \mathcal{N}(0, V_{DM}), \quad V_{DM} = \frac{\text{Var}[Y_i(0)]}{1 - \pi} + \frac{\text{Var}[Y_i(1)]}{\pi}. \quad (1.9)$$

Furthermore, the plug-in variance estimate

$$\hat{V}_{DM} := \frac{n}{n_0^2} \sum_{W_i=0} \left(Y_i - \frac{1}{n_0} \sum_{W_i=0} Y_i \right)^2 + \frac{n}{n_1^2} \sum_{W_i=1} \left(Y_i - \frac{1}{n_1} \sum_{W_i=1} Y_i \right)^2 \quad (1.10)$$

is consistent, $\hat{V}_{DM} \rightarrow_p V_{DM}$.

$$\lim_{n \rightarrow \infty} \mathbb{P}\left[\tau \in \left(\hat{\tau}_{DM} \pm \Phi^{-1}(1 - \alpha/2) \sqrt{\hat{V}_{DM}/n}\right)\right] = 1 - \alpha$$

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RCT as the Gold Standard for Causal Inference

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- We usually say that RCTs are the **gold standard for causal inference**. Why?
- The estimator (DM) is very **simple**.
- It achieves root-n consistency, so we can have valid inference.
- It is unbiased for finite samples (Theorem 1.1 above).

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Back to Our Original Causal Inference Problem

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- We have made **three essential assumptions** that make our problem of inferring **ATE** super easy.
 1. Identical and independently distributed (**IID**) samples
 2. Random treatment assignment (**RCT**)
 3. **SUTVA**
- Next, we try to **relax them** one by one.

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Power of Covariates

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- We now assume that there are some control variables X in the (linear) data generating process (DGP).

Linear DGP

$$Y_i(w) = \alpha_{(w)} + X_i \cdot \beta_{(w)} + \varepsilon_i(w),$$

$$\mathbb{E} [\varepsilon_i(w) | X_i] = 0, \quad \text{Var} [\varepsilon_i(w) | X_i] = \sigma^2$$

$$\mathbb{P} [W_i = 0] = \mathbb{P} [W_i = 1] = \frac{1}{2} \quad \mathbb{E} [X] = 0, \quad \text{and define} \quad A = \text{Var} [X]$$

Linear Regressions under Different Treatment Assignments

Estimator
for ATE

$$Y_i \sim \alpha_{(0)} + X_i \cdot \beta_{(0)} \text{ for all } i \text{ with } W_i = 0,$$

$$Y_i \sim \alpha_{(1)} + X_i \cdot \beta_{(1)} \text{ for all } i \text{ with } W_i = 1,$$

$$\hat{\tau}_{IREG} = \hat{\alpha}_{(1)} - \hat{\alpha}_{(0)} + \bar{X} (\hat{\beta}_{(1)} - \hat{\beta}_{(0)}).$$

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Power of Covariates

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- We now assume that the DGP is linear in some control variables X.

CLT for OLS

$$\sqrt{n_w} \left(\begin{pmatrix} \hat{\alpha}_{(w)} \\ \hat{\beta}_{(w)} \end{pmatrix} - \begin{pmatrix} \alpha_{(w)} \\ \beta_{(w)} \end{pmatrix} \right) \Rightarrow \mathcal{N} \left(0, \sigma^2 \begin{pmatrix} 1 & 0 \\ 0 & A^{-1} \end{pmatrix} \right)$$

CLT for IREG

$$\hat{\tau}_{IREG} - \tau = \underbrace{\hat{\alpha}_{(1)} - \alpha_{(1)}}_{\approx \mathcal{N}(0, \sigma^2/n_1)} - \underbrace{\hat{\alpha}_{(0)} - \alpha_{(0)}}_{\approx \mathcal{N}(0, \sigma^2/n_0)} + \underbrace{\bar{X} (\beta_{(1)} - \beta_{(0)})}_{\approx \mathcal{N}(0, \|\beta_{(1)} - \beta_{(0)}\|_A^2/n)}$$

$$+ \underbrace{\bar{X} (\hat{\beta}_{(1)} - \hat{\beta}_{(0)} - \beta_{(1)} + \beta_{(0)})}_{\mathcal{O}_P(1/n)},$$

$$\sqrt{n} (\hat{\tau}_{IREG} - \tau) \Rightarrow \mathcal{N} (0, V_{IREG}), \quad V_{IREG} = 4\sigma^2 + \|\beta_{(0)} - \beta_{(1)}\|_A^2$$

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Power of Covariates

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- We now assume that the DGP is linear in some control variables X.

Variance for DM

$$\begin{aligned} V_{DM} &= \frac{\text{Var}[Y_i(0)]}{0.5} + \frac{\text{Var}[Y_i(1)]}{0.5} \\ &= 2(\text{Var}[X_i\beta_{(0)}] + \sigma^2) + 2(\text{Var}[X_i\beta_{(1)}] + \sigma^2) \\ &= 4\sigma^2 + 2\|\beta_{(0)}\|_A^2 + 2\|\beta_{(1)}\|_A^2 \\ &= 4\sigma^2 + \|\beta_{(0)} + \beta_{(1)}\|_A^2 + \|\beta_{(0)} - \beta_{(1)}\|_A^2, \end{aligned}$$

IREG More Efficient Than DM

$$V_{IREG} = V_{DM} - \|\beta_{(0)} + \beta_{(1)}\|_A^2 \leq V_{DM}$$

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Non-linear DGPs

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- Consider a model where the DGP is non-linear (still random treatment assignment).

Non-linear DGP

$$\mu_{(w)}(x) = \mathbb{E} [Y_i(w) \mid X_i = x], \quad \sigma_{(w)}^2(x) = \text{Var} [Y_i(w) \mid X_i = x]$$

$$\mathbb{P}[W_i = 1] = \pi \quad \mathbb{E}[X] = 0, \quad \text{and define } A = \text{Var}[X]$$

Variance of DM

$$\sqrt{n}(\hat{\tau}_{DM} - \tau) \Rightarrow \mathcal{N}(0, V_{DM}) = 4\sigma^2 + 2\text{Var}[\mu_{(0)}(X_i)] + 2\text{Var}[\mu_{(1)}(X_i)]$$

Same Estimator for ATE

$$Y_i \sim \alpha_{(0)} + X_i \cdot \beta_{(0)} \text{ for all } i \text{ with } W_i = 0,$$

$$Y_i \sim \alpha_{(1)} + X_i \cdot \beta_{(1)} \text{ for all } i \text{ with } W_i = 1,$$

$$\hat{\tau}_{IREG} = \hat{\alpha}_{(1)} - \hat{\alpha}_{(0)} + \bar{X} (\hat{\beta}_{(1)} - \hat{\beta}_{(0)}).$$

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Non-linear DGPs

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- Consider a model where the DGP is non-linear (still random treatment assignment).

Best Linear Projection Coefficients

$$(\alpha_{(w)}^*, \beta_{(w)}^*) = \underset{\alpha, \beta}{\operatorname{argmin}} \left\{ \mathbb{E} [(Y_i(w) - \alpha - X_i \cdot \beta)^2] \right\}$$

CLT for IREG

Theorem 1.3. Under the conditions of Theorem 1.2, assume furthermore that $\mathbb{E}[X'X]$ is invertible. Then,

$$\begin{aligned} \sqrt{n}(\hat{\tau}_{IREG} - \tau) &\Rightarrow \mathcal{N}(0, V_{IREG}), \\ V_{IREG} &= \text{Var}[X_i \cdot (\beta_{(1)}^* - \beta_{(0)}^*)] + \frac{1}{\pi} \mathbb{E} [(Y_i(1) - \alpha_{(1)}^* - X_i \cdot \beta_{(1)}^*)^2] \\ &\quad + \frac{1}{1-\pi} \mathbb{E} [(Y_i(0) - \alpha_{(0)}^* - X_i \cdot \beta_{(0)}^*)^2]. \end{aligned} \quad (1.23)$$

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Where Amazing Happens

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- Consider a model where the DGP is **non-linear** (still random treatment assignment).

IREG is more efficient than DM even for nonlinear DGP!

$$\begin{aligned}
 V_{IREG} &= 2MSE_{(0)}^* + 2MSE_{(1)}^* + \|\beta_{(1)}^* - \beta_{(0)}^*\|_A^2 & \hat{\tau}_{IREG} &= \frac{1}{n} \sum_{i=1}^n \left(\underbrace{(\hat{\alpha}_{(1)} + X_i \hat{\beta}_{(1)})}_{\hat{\mu}_{(1)}(X_i)} - \underbrace{(\hat{\alpha}_{(0)} + X_i \hat{\beta}_{(0)})}_{\hat{\mu}_{(0)}(X_i)} \right) \\
 &= 4\sigma^2 + 2 \text{Var} [\mu_{(0)}(X) - X\beta_{(0)}^*] && \text{Another Perspective:} \\
 &\quad + 2 \text{Var} [\mu_{(1)}(X) - X\beta_{(1)}^*] + \|\beta_{(1)}^* - \beta_{(0)}^*\|_A^2 && \text{Difference in Predictions} \\
 &= 4\sigma^2 + 2 (\text{Var} [\mu_{(0)}(X)] - \text{Var} [X\beta_{(0)}^*]) && \\
 &\quad + 2 (\text{Var} [\mu_{(1)}(X)] - \text{Var} [X\beta_{(1)}^*]) + \|\beta_{(1)}^* - \beta_{(0)}^*\|_A^2 && \pi = 0.5 \\
 &= 4\sigma^2 + 2 (\text{Var} [\mu_{(0)}(X)] + \text{Var} [\mu_{(1)}(X)]) && \sigma_{(1)}^2(x) = \sigma_{(0)}^2(x) = \sigma^2 \text{ for all } x \\
 &\quad + \|\beta_{(1)}^* - \beta_{(0)}^*\|_A^2 - 2 \|\beta_{(0)}^*\|_A^2 - 2 \|\beta_{(1)}^*\|_A^2 && \\
 &= 4\sigma^2 + 2 (\text{Var} [\mu_{(0)}(X)] + \text{Var} [\mu_{(1)}(X)]) - \|\beta_{(0)}^* + \beta_{(1)}^*\|_A^2 && \\
 &= V_{DM} - \|\beta_{(0)}^* + \beta_{(1)}^*\|_A^2.
 \end{aligned}$$

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RCT Recap

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- Causal inference is to infer about a parallel world, so it must rely on taking averages.
- RCT is the gold standard for causal inference, thanks to 3 important assumptions.
 - IID
 - RCT
 - SUTVA
- DM estimator in RCT is root-n consistent and unbiased.
- With informative covariates, IREG estimator based on OLS is more efficient than DM estimator, even when the model is mis-specified.

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What if We Have No Randomized Assignment

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 Simpson's Paradox: https://en.wikipedia.org/wiki/Simpson%27s_paradox

- **Simpson's Paradox** is a notorious example where RCT is violated.
- Solution: Aggregate DM estimates from different groups by sample size weights.
- **Unconfoundedness**: Conditional independence assumption (**CIA**, the most common, but also very strong, assumption in observational studies):

Treatment Stone size	Treatment A	Treatment B
Small stones	Group 1 93% (81/87)	Group 2 87% (234/270)
Large stones	Group 3 73% (192/263)	Group 4 69% (55/80)
Both	78% (273/350)	83% (289/350)

$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp W_i \mid X_i = x$, for all $x \in \mathcal{X}$  You observe all potential confounders.

- Conditional Average Treatment Effect (CATE): $\tau(x) = \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x]$
- Stratified estimator: $\hat{\tau}_{STRAT} = \sum_{x \in \mathcal{X}} \frac{n_x}{n} \hat{\tau}(x)$, $\hat{\tau}(x) = \frac{1}{n_{x1}} \sum_{\{X_i=x, W_i=1\}} Y_i - \frac{1}{n_{x0}} \sum_{\{X_i=x, W_i=0\}} Y_i$.
 where $n_x = |\{i : X_i = x\}|$ and $n_{xw} = |\{i : X_i = x, W_i = w\}|$

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Stratified Estimator

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- Is the **Stratified Estimator** convergent?
 - CLT for each stratum:

$$\sqrt{n_x} (\hat{\tau}(x) - \tau(x)) \Rightarrow \mathcal{N} \left(0, \frac{\sigma_{(1)}^2}{e(x)} + \frac{\sigma_{(0)}^2(x)}{1 - e(x)} \right)$$

$\sigma_{(w)}^2(x) = \text{Var}[Y_i(w) | X_i = x]$
 $e(x) = \mathbb{P}[W_i = 1 | X_i = x]$
 $\tau(x) = \mathbb{E}[Y_i(1) - Y_i(0) | X_i = x]$
Propensity Score (PS)

Stratified Estimator is **root-n consistent**:

Theorem 2.1. Suppose that $\{X_i, Y_i(0), Y_i(1), W_i\} \stackrel{\text{iid}}{\sim} P$ for some distribution P where X_i takes values in a finite cardinality set \mathcal{X} and potential outcomes have bounded second moments conditionally on X_i . Suppose furthermore that both (2.1) and SUTVA hold, and that there is non-trivial treatment variation for each $x \in \mathcal{X}$, i.e., writing $e(x) = \mathbb{P}[W_i = 1 | X_i = x]$, we have $0 < e(x) < 1$ for all x . Then, using notation as in (1.21),

(2.1): Unconfoundedness

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp W_i | X_i = x, \quad \text{for all } x \in \mathcal{X} \quad \sqrt{n}(\hat{\tau}_{\text{STRAT}} - \tau) \Rightarrow \mathcal{N}(0, V_{\text{STRAT}})$$

$$V_{\text{STRAT}} = \text{Var}[\tau(X_i)] + \mathbb{E} \left[\frac{\sigma_{(1)}^2(X_i)}{e(X_i)} + \frac{\sigma_{(0)}^2(X_i)}{1 - e(X_i)} \right]. \quad (2.4)$$

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Stratified Estimator & Propensity Score

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- Stratified estimator is just **propensity score estimation on a discrete set**.
 - What if the covariates are **continuous**?
- Unconfoundedness: $\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp W_i | X_i,$ (2.5)

Statistically, a key property of the propensity score is that it is a balancing score: If (2.5) holds, then in fact

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp W_i | e(X_i), \quad (2.7)$$

i.e., it actually suffices to control for $e(X)$ rather than X to remove biases associated with a non-random treatment assignment. We can verify this claim as follows:

$$\begin{aligned} & \mathbb{P}[W_i = w | \{Y_i(0), Y_i(1)\}, e(X_i)] \\ &= \int_{\mathcal{X}} \mathbb{P}[W_i = w | \{Y_i(w)\}, X_i = x] \mathbb{P}[X_i = x | \{Y_i(w)\}, e(X_i)] dx \\ &= \int_{\mathcal{X}} \mathbb{P}[W_i = w | X_i = x] \mathbb{P}[X_i = x | \{Y_i(w)\}, e(X_i)] dx \quad (\text{unconf.}) \\ &= \begin{cases} e(X_i) & \text{if } w = 1, \\ 1 - e(X_i) & \text{else.} \end{cases} \end{aligned}$$

- Overlapping assumption: $\eta \leq e(x) \leq 1 - \eta$ for all $x \in \mathcal{X}$

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Propensity Stratification

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Imbens, G.W. and Rubin, D.B., 2015. *Causal inference in statistics, social, and biomedical sciences*.

Rosenbaum, P.R. and Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), pp.41-55.

Propensity stratification One instantiation of this idea is propensity stratification, which proceeds as follows. First obtain an estimate $\hat{e}(x)$ of the propensity score via non-parametric regression, and choose a number of strata J . Then:

- Sort the observations according to their propensity scores, such that

$$\hat{e}(X_{i_1}) \leq \hat{e}(X_{i_2}) \leq \dots \leq \hat{e}(X_{i_n}). \quad (2.8)$$

- Split the sample into J evenly size strata using the sorted propensity score and, in each stratum $j = 1, \dots, J$, compute the simple difference-in-means treatment effect estimator for the stratum:

$$\hat{\tau}_j = \frac{\sum_{i=\lfloor(j-1)n/J\rfloor+1}^{\lfloor jn/J\rfloor} W_i Y_i}{\sum_{i=\lfloor(j-1)n/J\rfloor+1}^{\lfloor jn/J\rfloor} W_i} - \frac{\sum_{i=\lfloor(j-1)n/J\rfloor+1}^{\lfloor jn/J\rfloor} (1 - W_i) Y_i}{\sum_{i=\lfloor(j-1)n/J\rfloor+1}^{\lfloor jn/J\rfloor} (1 - W_i)}. \quad (2.9)$$

- Estimate the average treatment by applying the idea of (2.3) across strata:

$$\hat{\tau}_{PSTRAT} = \frac{1}{J} \sum_{j=1}^J \hat{\tau}_j. \quad (2.10)$$

Propensity Stratification is consistent when the propensity score estimator is uniformly consistent and the number of strata J grows appropriately with n .

Another more popular approach:
Propensity Score Matching (PSM)

- Chapter 15 of Imbens and Rubin (2015)

See Rosenbaum and Rubin (1983) for comprehensive discussions on these two methods which rely on similar assumptions.

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Inverse Propensity Weighting (IPW)

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- Another common way of using propensity score is the IPW estimator:

$$\hat{\tau}_{IPW} = \frac{1}{n} \sum_{i=1}^n \left(\frac{W_i Y_i}{\hat{e}(X_i)} - \frac{(1 - W_i) Y_i}{1 - \hat{e}(X_i)} \right)$$

- To analyze this estimator, it is convenient to compare it to an oracle where the actual propensity score is known, because these two estimators' difference can be bounded by the performance of PS estimator:

$$\hat{\tau}_{IPW}^* = \frac{1}{n} \sum_{i=1}^n \left(\frac{W_i Y_i}{e(X_i)} - \frac{(1 - W_i) Y_i}{1 - e(X_i)} \right)$$

- A related concept, Horvitz-Thompson estimator: https://grok.com/share/bGVnYWN5_2e4d6004-5e65-4cb4-82d8-8c5aa6bc3218

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Performance of IPW

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Theorem 2.2. Suppose that $\{X_i, Y_i(0), Y_i(1), W_i\} \stackrel{iid}{\sim} P$, that both (2.5) and SUTVA hold, and that all moments used in the expression for V_{IPW^*} below are finite. Then, the oracle IPW estimator is unbiased, $\mathbb{E}[\hat{\tau}_{IPW}^*] = \tau$, and

$$\sqrt{n}(\hat{\tau}_{IPW}^* - \tau) \Rightarrow \mathcal{N}(0, V_{IPW^*})$$

$$V_{IPW^*} = \text{Var}[\tau(X_i)] + \mathbb{E}\left[\frac{(\mu_{(0)}(X_i) + (1 - e(X_i))\tau(X_i))^2}{e(X_i)(1 - e(X_i))}\right] + \mathbb{E}\left[\frac{\sigma_{(1)}^2(X_i)}{e(X_i)} + \frac{\sigma_{(0)}^2(X_i)}{1 - e(X_i)}\right]. \quad (2.13)$$

Unconfoundedness:

$$\{Y_i(0), Y_i(1)\} \perp\!\!\!\perp W_i \mid X_i, \quad (2.5)$$

Overlapping:

$$\eta \leq e(x) \leq 1 - \eta \text{ for all } x \in \mathcal{X}$$

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IPW vs. STRAT

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 Applied Causal Inference Powered by ML and AI: https://chapters.causalmi-book.org/CausalML_book_2022.pdf

- Stratified estimator is a special case of IPW:

$$\hat{\tau}_{STRAT} = \frac{1}{n} \sum_{i=1}^n \left(\frac{W_i Y_i}{\hat{e}(X_i)} - \frac{(1 - W_i) Y_i}{1 - \hat{e}(X_i)} \right), \quad \hat{e}(x) = \frac{n_{x1}}{n_x}$$

- What is interesting is that STRAT is more efficient than IPW:

$$V_{IPW^*} = V_{STRAT} + \mathbb{E}\left[\frac{(\mu_{(0)}(X_i) + (1 - e(X_i))\tau(X_i))^2}{e(X_i)(1 - e(X_i))}\right]$$

- When X is discrete with a natural but specific propensity model, one feasible IPW can outperform the oracle IPW.
 - This result should not be over-generalized.

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What's Wrong with IPW?

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- If the propensity score $e(\cdot)$ is unknown, does IPW converge sufficiently fast to ensure semi-parametric efficiency, i.e., root-n consistency or the gap between oracle IPW and general IPW is of order $o(\sqrt{n})$?

$$\hat{\tau}_{IPW} = \underbrace{\hat{\tau}_{IPW}^*}_{\text{a good estimator}} + \underbrace{\hat{\tau}_{IPW} - \hat{\tau}_{IPW}^*}_{\text{due to errors in } \hat{e}(\cdot)}.$$

Let's try to bound the error using Cauchy-Schwarz:

$$\begin{aligned} \hat{\tau}_{IPW} - \hat{\tau}_{IPW}^* &= \frac{1}{n} \sum_{i=1}^n \left(\left(\frac{W_i}{\hat{e}(X_i)} - \frac{(1-W_i)}{1-\hat{e}(X_i)} \right) - \left(\frac{W_i}{e(X_i)} - \frac{(1-W_i)}{1-e(X_i)} \right) \right) Y_i \\ &\leq \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\left(\frac{W_i}{\hat{e}(X_i)} - \frac{(1-W_i)}{1-\hat{e}(X_i)} \right) - \left(\frac{W_i}{e(X_i)} - \frac{(1-W_i)}{1-e(X_i)} \right) \right)^2} \\ &\quad \times \sqrt{\frac{1}{n} \sum_{i=1}^n Y_i^2} \\ &\approx \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{e}(X_i) - e(X_i))^2}. \end{aligned}$$

- Not good enough!
- For most ML algorithms, $RMSE \gg \sqrt{1/n}$.
- So the second term is non-negligible in finite samples.
- This naïve plug-in IPW will generally produce invalid confidence intervals.

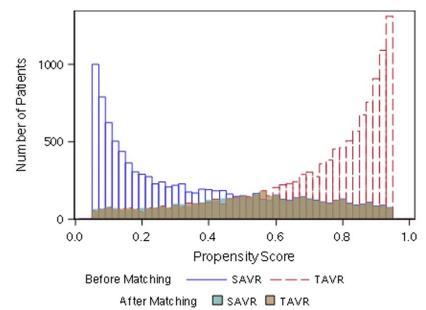
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Overlapping Assumption $\eta \leq e(x) \leq 1 - \eta$ for all $x \in \mathcal{X}$

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 Imbens, G.W. and Rubin, D.B., 2015. *Causal inference in statistics, social, and biomedical sciences*.
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- Overlapping assumption is important, both theoretically and practically, but we often do not have overlapping.
 - Severe weights in extreme cases, which lead to biases in estimates.
 - Estimating ATE becomes impossible, but only the ATE on overlapping samples (i.e., conditional ATE).
- Adjustments methods
 - Regression: Model sensitive to extreme data
 - Matching: Many samples are excluded
 - Stratification: Adds bias due to residual imbalance within strata
- Trimming
 - Remove data samples with PS outside $[a, 1-a]$, $a=0.1$ as a baseline.
 - Further remove data samples whose PS is below q -quantile of treated units.
 - Further remove data samples whose PS is above $(1-q)$ -quantile of control units.
 - Winsorize all PS below a to a and above $1-a$ to $1-a$.



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Balancing Weights

Duke STA640 Causal Inference: <https://www2.stat.duke.edu/~fl35/CausalInferenceClass.html>
 Balancing covariates via propensity score weighting: <https://arxiv.org/abs/1404.1785>

- IPW is a special case of balancing weights.
 - ▶ Assume density of the observed covariates, $f(x)$, exists wrt a measure μ
 - ▶ Consider a target population, denoted by a density $g(x)$, possibly different from $f(x)$
 - ▶ The ratio $h(x) = g(x)/f(x)$ is called a *tilting function*, which re-weights the observed sample to represent the target population
 - ▶ A new class of estimands: the ATE over the target population g

$$\tau_h \equiv \mathbb{E}_g [Y_i(1) - Y_i(0)] = \frac{\int \tau(x) f(x) h(x) \mu(dx)}{\int f(x) h(x) \mu(dx)} = \frac{\mathbb{E}\{h(x)\tau(x)\}}{\mathbb{E}\{h(x)\}}$$

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Balancing Weights

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 Balancing covariates via propensity score weighting: <https://arxiv.org/abs/1404.1785>

- Different weighting schemes:

target population	$h(x)$	estimand	weight (w_1, w_0)
combined	1	ATE	$\left(\frac{1}{e(x)}, \frac{1}{1-e(x)}\right)$ [HT]
treated	$e(x)$	ATT	$\left(1, \frac{e(x)}{1-e(x)}\right)$
control	$1 - e(x)$	ATC	$\left(\frac{1-e(x)}{e(x)}, 1\right)$
overlap	$e(x)(1 - e(x))$	ATO	$(1 - e(x), e(x))$
truncated combined	$\mathbf{1}(\alpha < e(x) < 1 - \alpha)$		$\left(\frac{\mathbf{1}(\alpha < e(x) < 1 - \alpha)}{e(x)}, \frac{\mathbf{1}(\alpha < e(x) < 1 - \alpha)}{1 - e(x)}\right)$
matching	$\min\{e(x), 1 - e(x)\}$		$\left(\frac{\min\{e(x), 1 - e(x)\}}{e(x)}, \frac{\min\{e(x), 1 - e(x)\}}{1 - e(x)}\right)$

$$\hat{\tau}_h = \frac{\sum_i w_1(x_i) Z_i Y_i}{\sum_i w_1(x_i) Z_i} - \frac{\sum_i w_0(x_i) (1 - Z_i) Y_i}{\sum_i w_0(x_i) (1 - Z_i)}$$

Table 1: Examples of balancing weights and corresponding target population and estimand under different h .

Theorem 1. $\hat{\tau}_h$ is a consistent estimator of τ_h .

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Agenda

- Potential Outcomes Model, RCT and Difference-in-Mean Estimator
- Linear Regression
- Unconfoundedness and Inverse Propensity Weighting
- Augmented Inverse Propensity Weighting and Double Robustness

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Augmented Inverse Propensity Weighting (AIPW)

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- The performance of IPW estimators depend on:
 - The performance of PS estimator
 - The weighting mechanisms (regression, matching, stratification, etc.)
- Can we improve IPW with machine learning?
- Yes, with new doubly robust estimators: Augmented Inverse Propensity Weighting.
- Two consistent characterizations of ATE: IPW and nonparametric regression.

Nonparametric Regression

$$\begin{aligned}\tau(x) &:= \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x] \\ &= \mathbb{E}[Y_i(1) \mid X_i = x] - \mathbb{E}[Y_i(0) \mid X_i = x] \\ &= \mathbb{E}[Y_i(1) \mid X_i = x, W_i = 1] - \mathbb{E}[Y_i(0) \mid X_i = x, W_i = 0] \quad (\text{unconf}) \\ &= \mathbb{E}[Y_i \mid X_i = x, W_i = 1] - \mathbb{E}[Y_i \mid X_i = x, W_i = 0] \quad (\text{SUTVA}) \\ &= \mu_{(1)}(x) - \mu_{(0)}(x),\end{aligned}$$

$$\begin{aligned}\tau &= \mathbb{E}[\mu_{(1)}(X_i) - \mu_{(0)}(X_i)] \\ \hat{\tau}_{REG} &= n^{-1} \sum_{i=1}^n (\hat{\mu}_{(1)}(X_i) - \hat{\mu}_{(0)}(X_i))\end{aligned}$$

IPW

$$\tau = \mathbb{E}[\hat{\tau}_{IPW}^*], \quad \hat{\tau}_{IPW}^* = \frac{1}{n} \sum_{i=1}^n \left(\frac{W_i Y_i}{e(X_i)} - \frac{(1 - W_i) Y_i}{1 - e(X_i)} \right)$$

Estimation of regression coefficients when some regressors are not always observed

JM Robins, A Rotnitzky, LP Zhao - Journal of the American ... , 1994 - Taylor & Francis
 ... each previous estimator is asymptotically equivalent to some, usually inefficient, estimator in our ... that every regular asymptotic linear estimator of α_0 is asymptotically equivalent to some ...
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Double Robustness of AIPW

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$$\hat{\tau}_{AIPW} = \frac{1}{n} \sum_{i=1}^n \left(\hat{\mu}_{(1)}(X_i) - \hat{\mu}_{(0)}(X_i) + W_i \frac{Y_i - \hat{\mu}_{(1)}(X_i)}{\hat{e}(X_i)} - (1 - W_i) \frac{Y_i - \hat{\mu}_{(0)}(X_i)}{1 - \hat{e}(X_i)} \right)$$

- Weak double robustness: If either $\hat{\mu}_{(w)}(x) \approx \mu_{(w)}(x)$ or $\hat{e}(x) \approx e(x)$, AIPW is consistent.

$$\begin{aligned} \hat{\tau}_{AIPW} &= \underbrace{\frac{1}{n} \sum_{i=1}^n (\hat{\mu}_{(1)}(X_i) - \hat{\mu}_{(0)}(X_i))}_{\text{the regression estimator}} + \underbrace{\frac{1}{n} \sum_{i=1}^n \left(\frac{W_i}{\hat{e}(X_i)} (Y_i - \hat{\mu}_{(1)}(X_i)) - \frac{1 - W_i}{1 - \hat{e}(X_i)} (Y_i - \hat{\mu}_{(0)}(X_i)) \right)}_{\approx \text{mean-zero noise}} \\ &\quad + \underbrace{\frac{1}{n} \sum_{i=1}^n \left(\hat{\mu}_{(1)}(X_i) \left(1 - \frac{W_i}{\hat{e}(X_i)} \right) - \hat{\mu}_{(0)}(X_i) \left(1 - \frac{1 - W_i}{1 - \hat{e}(X_i)} \right) \right)}_{\approx \text{mean-zero noise}} \end{aligned}$$

- Strong double robustness: root-n consistency and CLT.

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Strong Double Robustness of AIPW

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- More interesting and useful strong double robustness: If the black-box predictors of mean and propensity score are reasonably good (i.e., converge to the ground-truth reasonably fast), AIPW is root-n consistent.

consistency statement given above. At a high level, strong double robustness is a claim that results of the following type exist: If we use estimators $\hat{\mu}_{(w)}(x)$ and $\hat{e}(x)$ that are both consistent with root-mean squared error (RMSE) decaying faster than $n^{-\alpha_\mu}$ and $n^{-\alpha_e}$ respectively, and if furthermore $\alpha_\mu + \alpha_e \geq 1/2$, then

$$\begin{aligned} \sqrt{n}(\hat{\tau}_{AIPW} - \tau) &\Rightarrow \mathcal{N}(0, V_{AIPW}), \\ V_{AIPW} &= \text{Var}[\tau(X_i)] + \mathbb{E}\left[\frac{\sigma_0^2(X_i)}{1 - e(X_i)}\right] + \mathbb{E}\left[\frac{\sigma_1^2(X_i)}{e(X_i)}\right]. \end{aligned} \quad (3.5)$$

The reason this meta-result holds is that, in general, if the RMSE of $\hat{\mu}_{(w)}(x)$ decays faster than $n^{-\alpha_\mu}$ and the RMSE of $\hat{e}(x)$ decays faster than $n^{-\alpha_e}$, then the bias of AIPW decays faster than $n^{-(\alpha_\mu + \alpha_e)}$; and, in particular, if $\alpha_\mu + \alpha_e \geq 1/2$ then the bias is lower-order on the $1/\sqrt{n}$ -scale. What's remarkable about this result is that, under the same conditions, the bias of the regression estimator would in general only be bounded to order $n^{-\alpha_\mu}$ and that of IPW to order $n^{-\alpha_e}$; and so the AIPW construction succeeds in making bias substantially smaller than what either the regression or IPW estimators could achieve on their own.^[17]

$$\mathbb{E}[(\hat{\mu}_{(w)}(X) - \mu_{(w)}(X))^2]^{\frac{1}{2}}, \mathbb{E}[(\hat{e}(X) - e(X))^2]^{\frac{1}{2}} \ll \frac{1}{\sqrt[4]{n}}$$

Can be generalized to order $n^{-\alpha_\mu}$ and $n^{-\alpha_e}$

Then the error of AIPW will be of order $n^{-(\alpha_\mu + \alpha_e)}$

As long as $\alpha_\mu + \alpha_e \geq 1/2$, the error of AIPW is smaller than $o(n^{-1/2})$, establishing the desired root-n consistency.

This is the core idea of double machine learning (DML).

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AIPW vs. IPW

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- If we need naïve plug-in IPW to be root-n consistent and produce invalid confidence intervals, the underlying ML PS estimates should have $o(n^{-1/2})$ L2-norm error (sometimes called parametric rate), which is too optimistic in most real-world applications.
- For AIPW, it suffices for conditional mean and PS estimates to achieve $o(n^{-1/4})$ L2-norm error (sometimes called semiparametric efficient), which is realistic and pretty accurate for complex ML methods.
- AIPW translates natural and realistic assumptions on ML estimates accuracy into valid inference.
- For AIPW, we only need one moment condition to be true, and the convergency speed of the final estimator is the product of convergence speed of both estimators.

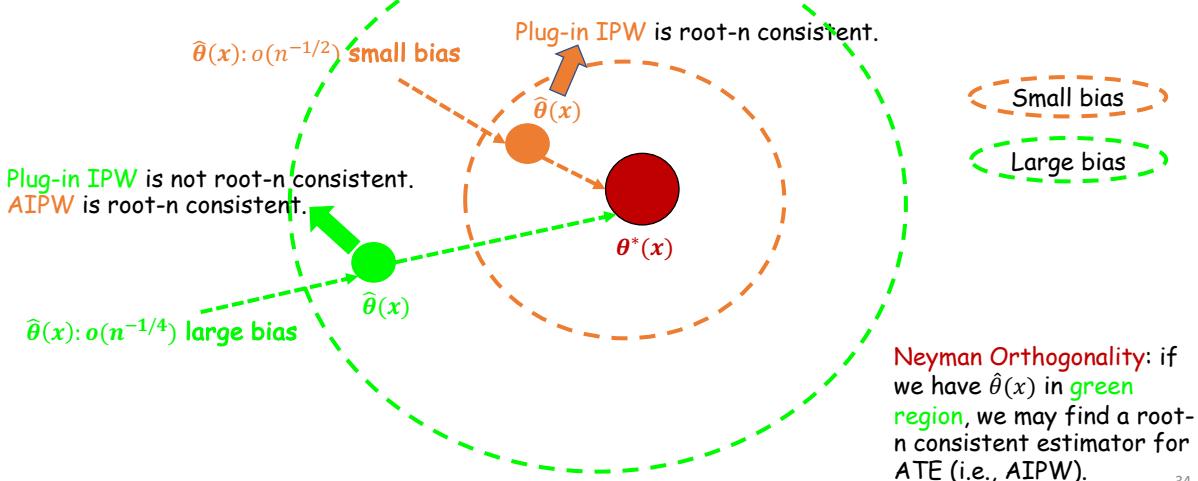
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AIPW vs. IPW

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$\hat{\theta}(x)$: estimators for conditional mean and propensity score.



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AIPW Asymptotic Normality

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- Like IPW, we first establish the root-n consistency of **oracle AIPW**, who has access to the ground-truth conditional mean and propensity score.

$$\hat{\tau}_{AIPW}^* = \frac{1}{n} \sum_{i=1}^n \Gamma_i$$

$$\Gamma_i = \mu_{(1)}(X_i) - \mu_{(0)}(X_i) + W_i \frac{Y_i - \mu_{(1)}(X_i)}{e(X_i)} - (1 - W_i) \frac{Y_i - \mu_{(0)}(X_i)}{1 - e(X_i)}$$

Proposition 3.1. Under the basic setting with SUTVA, unconfoundedness and strong overlap given at the beginning of this chapter, the oracle AIPW estimator has the limit distribution given in (3.5), i.e.,

$$\sqrt{n} (\hat{\tau}_{AIPW}^* - \tau) \Rightarrow \mathcal{N}(0, V_{AIPW}). \quad (3.7)$$

$$V_{AIPW} = \text{Var}[\tau(X_i)] + \mathbb{E}\left[\frac{\sigma_0^2(X_i)}{1 - e(X_i)}\right] + \mathbb{E}\left[\frac{\sigma_1^2(X_i)}{e(X_i)}\right]. \quad (3.5)$$

- Hence, it suffices to show that if $\hat{\mu}_{(w)}(\cdot)$ and $\hat{e}(\cdot)$ converge to the ground-truth fast enough:

$$\sqrt{n} (\hat{\tau}_{AIPW} - \hat{\tau}_{AIPW}^*) \rightarrow_p 0$$

- To this root-n equivalence between AIPW and oracle AIPW, we leverage the idea of **cross-fitting**.

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Cross Fitting

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- For AIPW, we typically have two steps of estimation:
 - First, we predict the mean responses and propensity scores using ML.
 - Then, we use these predictions to estimate the ATE via AIPW.
- Cross-fitting** is a common strategy for AIPW:
 - Split the data into two samples: One sample for ML prediction and the other sample to use ML predictions and data to construct AIPW estimators.

Train	Infer	
-------	-------	--

$$\hat{\tau}_{AIPW} = \frac{|\mathcal{I}_1|}{n} \hat{\tau}^{\mathcal{I}_1} + \frac{|\mathcal{I}_2|}{n} \hat{\tau}^{\mathcal{I}_2}, \quad \hat{\tau}^{\mathcal{I}_1} = \frac{1}{|\mathcal{I}_1|} \sum_{i \in \mathcal{I}_1} \left(\hat{\mu}_{(1)}^{\mathcal{I}_2}(X_i) - \hat{\mu}_{(0)}^{\mathcal{I}_2}(X_i) \right. \\ \left. + W_i \frac{Y_i - \hat{\mu}_{(1)}^{\mathcal{I}_2}(X_i)}{\hat{e}^{\mathcal{I}_2}(X_i)} - (1 - W_i) \frac{Y_i - \hat{\mu}_{(0)}^{\mathcal{I}_2}(X_i)}{1 - \hat{e}^{\mathcal{I}_2}(X_i)} \right), \quad (3.9)$$

Infer	Train	
-------	-------	--

where the $\hat{\mu}_{(w)}^{\mathcal{I}_2}(\cdot)$ and $\hat{e}^{\mathcal{I}_2}(\cdot)$ are estimates of $\mu_{(w)}(\cdot)$ and $e(\cdot)$ obtained using only the half-sample \mathcal{I}_2 , and $\hat{\tau}^{\mathcal{I}_2}$ is defined analogously (with the roles of \mathcal{I}_1 and \mathcal{I}_2 swapped). In other words, $\hat{\tau}^{\mathcal{I}_1}$ is a treatment effect estimator on \mathcal{I}_1 that uses \mathcal{I}_2 to estimate its nuisance components, and vice-versa.

- The "honest" regression residual (different training and inference data) cannot be artificially shrunk by overfitting.

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Back to AIPW Asymptotic Normality

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- Under cross-fitting and $\hat{\mu}_{(w)}(\cdot)$ and $\hat{e}(\cdot)$ converging to ground-truth sufficiently fast, we have the root-n equivalence between between AIPW and oracle AIPW.

Theorem 3.2. Given our basic setting with SUTVA, unconfoundedness and strong overlap, suppose that we construct $\hat{\tau}_{AIPW}$ using cross-fitting with estimators satisfying, for $w \in \{0, 1\}$ and also with the roles of \mathcal{I}_1 and \mathcal{I}_2 swapped,

$$\begin{aligned} o(n^{-\alpha_\mu}) \text{ RMSE/L}^2\text{-norm error} &\rightsquigarrow n^{-2\alpha_\mu} \frac{1}{|\mathcal{I}_1|} \sum_{i \in \mathcal{I}_1} \left(\hat{\mu}_{(w)}^{\mathcal{I}_2}(X_i) - \mu_{(w)}(X_i) \right)^2 \rightarrow_p 0, \\ o(n^{-\alpha_e}) \text{ RMSE/L}^2\text{-norm error} &\rightsquigarrow n^{-2\alpha_e} \frac{1}{|\mathcal{I}_1|} \sum_{i \in \mathcal{I}_1} \left(\frac{1}{\hat{e}^{\mathcal{I}_2}(X_i)} - \frac{1}{e(X_i)} \right)^2 \rightarrow_p 0, \end{aligned} \quad (3.11)$$

for some constants with $\alpha_\mu, \alpha_e \geq 0$ and $\alpha_\mu + \alpha_e \geq 1/2$. Then (3.9) and thus also (3.5) hold.

$$\sqrt{n} (\hat{\tau}_{AIPW} - \tau) \Rightarrow \mathcal{N}(0, V_{AIPW}), \quad \sqrt{n} (\hat{\tau}_{AIPW} - \hat{\tau}_{AIPW}^*) \rightarrow_p 0$$

$$V_{AIPW} = \text{Var} [\tau(X_i)] + \mathbb{E} \left[\frac{\sigma_0^2(X_i)}{1 - e(X_i)} \right] + \mathbb{E} \left[\frac{\sigma_1^2(X_i)}{e(X_i)} \right]$$

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Estimation and Inference with AIPW

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- Generalize into K-fold cross-fitting:

We define the data into K folds (above, $K = 2$), and compute estimators $\hat{\mu}_{(w)}^{(-k)}(x)$, etc., excluding the k -th fold. Then, writing $k(i)$ as the mapping that takes an observation and puts it into one of the k folds, we can write

$$\begin{aligned} \hat{\tau}_{AIPW} &= \frac{1}{n} \sum_{i=1}^n \left(\hat{\mu}_{(1)}^{(-k(i))}(X_i) - \hat{\mu}_{(0)}^{(-k(i))}(X_i) \right. \\ &\quad \left. + W_i \frac{Y_i - \hat{\mu}_{(1)}^{(-k(i))}(X_i)}{\hat{e}^{(-k(i))}(X_i)} - (1 - W_i) \frac{Y_i - \hat{\mu}_{(0)}^{(-k(i))}(X_i)}{1 - \hat{e}^{(-k(i))}(X_i)} \right). \end{aligned} \quad (3.16)$$

Train	Train	Infer
Train	Infer	Train
Infer	Train	Train

K = 3

(1 - α)-Confidence Level:

$$\tau \in \left(\hat{\tau}_{AIPW} \pm \Phi^{-1} \left(1 - \frac{\alpha}{2} \right) \frac{1}{\sqrt{n}} \sqrt{\hat{V}_{AIPW}} \right)$$

Inverse CDF of standard normal.

$$\begin{aligned} \hat{\Gamma}_i &= \hat{\mu}_{(1)}^{(-k(i))}(X_i) - \hat{\mu}_{(0)}^{(-k(i))}(X_i) \\ &\quad + W_i \frac{Y_i - \hat{\mu}_{(1)}^{(-k(i))}(X_i)}{\hat{e}^{(-k(i))}(X_i)} - (1 - W_i) \frac{Y_i - \hat{\mu}_{(0)}^{(-k(i))}(X_i)}{1 - \hat{e}^{(-k(i))}(X_i)}. \end{aligned}$$

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(Optimal) Efficiency of AIPW

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- AIPW achieves the same efficiency as the stratify-by-X method, which is actually optimal.

$$\hat{\tau}_{STRAT} = \sum_{x \in \mathcal{X}} \frac{n_x}{n} \hat{\tau}(x), \quad \hat{\tau}(x) = \frac{1}{n_{x1}} \sum_{\{X_i=x, W_i=1\}} Y_i - \frac{1}{n_{x0}} \sum_{\{X_i=x, W_i=0\}} Y_i \text{ where } n_x = |\{i : X_i = x\}| \text{ and } n_{xw} = |\{i : X_i = x, W_i = w\}|$$

Theorem 3.4. Under basic setting with SUTVA, unconfoundedness and strong overlap, V^* is the efficient variance for estimating the average treatment effect.

$$\sqrt{n} (\hat{\tau} - \tau^*) \Rightarrow \mathcal{N}(0, V^*)$$

$$V^* = \text{Var} [\tau(X_i)] + \mathbb{E} \left[\frac{\sigma_0^2(X_i)}{1 - e(X_i)} \right] + \mathbb{E} \left[\frac{\sigma_1^2(X_i)}{e(X_i)} \right]$$

- For a long time, (optimal) efficiency is not a good criterion for designing practical estimators for ATE.
 - Efficient estimators were considered fragile, complicated and/or impractical.
 - Econometric practice largely focused on methods under parametric assumptions (e.g., linear regression), or non-efficiently but conceptually simple (e.g., matching).
- The AIPW method (more generally, DML), however, makes use of efficient treatment effect estimators practical. See also: <https://rphilipzhang.github.io/rphilipzhang/DeDL-nonblind.pdf>.

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