

PLSC 30600 — Homework 2

Due: Sun, February 1 (11:59pm)

General instructions

- **Show your work** for all hand calculations. A final numeric answer without intermediate steps, formulas, and/or justification is not sufficient.
 - For coding problems, submit a reproducible script (`.R/.rmd/.rnw`) along with the fully compiled pdf. Set a random seed and report it.
 - Include a brief note describing how you used AI tools (if at all), consistent with the course AI policy.
 - For each proof question, start with one sentence naming the technique you are using (e.g., direct proof, Law of Iterated Expectations, bounding, counterexample, construction, contradiction).
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Problem 0: Matrix algebra warm-up

For matrix *addition*, add corresponding entries. For matrix *multiplication*, use row-by-column dot products. For example, if

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}, \quad B = \begin{bmatrix} e & f \\ g & h \end{bmatrix},$$

then

$$A + B = \begin{bmatrix} a+e & b+f \\ c+g & d+h \end{bmatrix}, \quad AB = \begin{bmatrix} ae+bg & af+bh \\ ce+dg & cf+dh \end{bmatrix}.$$

Write out at least one entry (e.g., the (1, 2) entry) step-by-step, such as

$$(AB)_{12} = a \cdot f + b \cdot h.$$

0.a Commutative law of addition. Let

$$A = \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 1 \\ 2 & 3 \end{bmatrix}.$$

Compute $A + B$ and $B + A$ and verify that $A + B = B + A$.

0.b Multiplication is not commutative. Using the same A and B , compute AB and BA and show that $AB \neq BA$.

0.c Associative laws. Let

$$C = \begin{bmatrix} 1 & -1 \\ 4 & 0 \end{bmatrix}.$$

Verify $(A + B) + C = A + (B + C)$ and $(AB)C = A(BC)$.

0.d Distributive laws. Verify $A(B + C) = AB + AC$ and $(A + B)C = AC + BC$.

0.e Identity matrix. Let $I_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Verify $AI_2 = A$ and $I_2A = A$.

Problem 1: Weighting estimators

- 1.a IPW formula.** Let $p_D(X_i) \in (0, 1)$ be the propensity score for unit i . The IPW estimator for the ATE is:

$$\hat{\tau}_{\text{IPW}} = \frac{1}{n} \sum_{i=1}^n \left(\frac{D_i Y_i}{p_D(X_i)} - \frac{(1 - D_i) Y_i}{1 - p_D(X_i)} \right).$$

- 1.b Numerical check.** Suppose $n = 4$ with

$$\mathbf{D} = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \quad \mathbf{Y} = \begin{bmatrix} 5 \\ 3 \\ 2 \\ 1 \end{bmatrix}, \quad p_D(\mathbf{X}) = \begin{bmatrix} 0.6 \\ 0.6 \\ 0.4 \\ 0.4 \end{bmatrix}.$$

Compute $\hat{\tau}_{\text{IPW}}$.

- 1.c Compare to difference in means.** Using the same four observations, compute the unweighted difference in means $\bar{Y}_{D=1} - \bar{Y}_{D=0}$ and compare it to your IPW estimate.
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Problem 2: IPW proofs and identification

- 2.a Cell-balancing interpretation (discrete X).** Assume X takes finitely many values $x \in \mathcal{X}$. Let

$$\mu_1(x) = E[Y | D = 1, X = x], \quad \mu_0(x) = E[Y | D = 0, X = x], \quad p(x) = \Pr[D = 1 | X = x].$$

Show that

$$E\left[\frac{YD}{p(X)}\right] = \sum_{x \in \mathcal{X}} \Pr[X = x] \mu_1(x),$$

and

$$E\left[\frac{Y(1 - D)}{1 - p(X)}\right] = \sum_{x \in \mathcal{X}} \Pr[X = x] \mu_0(x).$$

Conclude that the IPW estimand equals

$$\sum_{x \in \mathcal{X}} \Pr[X = x] (\mu_1(x) - \mu_0(x)),$$

and explain briefly why this corresponds to reweighting so treated/control have the same X -distribution.
(You may cite the identity from Theorem 7.2.5 in Aronow-Miller.)

- 2.b Optional extension (ATT via weighting).** Derive an analogous identity for the ATT:

$$E[Y(1) - Y(0) | D = 1].$$

Using weighting, show how to express the ATT in terms of observable quantities. (The weights and normalization differ from the ATE case.)

- 2.c Where does it break?** Construct a simple data-generating process with binary $X \in \{0, 1\}$, binary D , and potential outcomes $Y(1), Y(0)$ such that:

- (i) positivity holds: $0 < p(X) < 1$ for both $X = 0, 1$,
- (ii) ignorability fails: $(Y(1), Y(0)) \not\perp\!\!\!\perp D | X$.

You may use a finite “science table” counterexample or a probability model.

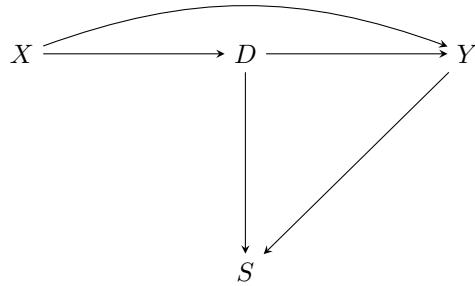
Compute both

$$E[\tau] = E[Y(1) - Y(0)], \quad E\left[\frac{YD}{p(X)} - \frac{Y(1-D)}{1-p(X)}\right],$$

and show they differ. Refer to where the proof of Theorem 7.2.5 fails under your DGP.

Problem 3: DAGs and post-treatment selection

Consider the DAG with observed pre-treatment covariates X , treatment D , outcome Y , and a post-treatment selection variable S :



3.a Conditioning on a post-treatment collider. Suppose you estimate

$$E[Y | D = 1, S = 1] - E[Y | D = 0, S = 1].$$

Does this identify the average treatment effect (ATE) $E[Y(1) - Y(0)]$? Answer *yes* or *no* and justify briefly using DAG language (e.g., d-separation / backdoor paths). If your answer is *no*, name the noncausal path(s) that become(s) open when conditioning on S .

3.b What estimand (if any) is being targeted? Let $S(d)$ denote the potential selection status under treatment $d \in \{0, 1\}$. Consider the “always-selected” principal stratum $\{S(1) = 1, S(0) = 1\}$. Is the quantity

$$E[Y | D = 1, S = 1] - E[Y | D = 0, S = 1]$$

equal to the principal-stratum causal effect

$$E[Y(1) - Y(0) | S(1) = 1, S(0) = 1] ?$$

Explain in 2–4 sentences. (If you think it can be given a causal interpretation only under additional assumptions, state one such assumption.)

Problem 4: LaLonde data

Data. Use the experimental LaLonde dataset: Download the file from github. \

<https://raw.githubusercontent.com/xuyiqing/lalonde/master/data/lalonde/nsw.dta>.

The experimental NSW sample provides a randomized benchmark before introducing additional adjustment methods. The outcome is `re78` and the treatment indicator is `treat`.

Variable	Description
treat	Treatment indicator (NSW program)
re78	Earnings in 1978 (outcome)
re75	Earnings in 1975 (pre-treatment)
age	Age
education	Years of education
black	Indicator for Black
hispanic	Indicator for Hispanic
married	Indicator for married
nodegree	Indicator for no high school degree

Packages you may need: haven, hot.deck, estimatr.

```
# You may need to run `install.packages(...)` first
library(haven) # to read in Stata .dta files
library(estimatr) # for lm_robust and lm_lin
library(hot.deck) # for hot-deck imputation

nsw_url <- "https://raw.githubusercontent.com/xuyiqing/lalonde/master/data/lalonde/nsw.dta"
nsw <- read_dta(nsw_url)
nsw <- as.data.frame(nsw)
```

4.a Read and inspect. Load the dataset and report:

- (i) the number of treated and control units,
- (ii) the mean of Y in each group.

4.b Difference in means. Compute the unadjusted difference-in-means estimate $\hat{\tau}_{\text{DM}} = \bar{Y}_{D=1} - \bar{Y}_{D=0}$.

4.c Propensity score estimation and overlap. Estimate the propensity score $\hat{p}_D(X_i) = \Pr[D_i = 1 | X_i]$ using a logit model with `glm(..., family = binomial())`. Use the covariates `age`, `education`, `black`, `hispanic`, `married`, `nodegree`, and `re75`. After fitting the model, use `predict(..., type = "response")` to get propensity scores. Then plot treated vs control distributions (histograms or density plots) with the same x-axis limits to assess overlap. Comment on overlap.

4.d IPW estimator. Using the estimated propensity scores, compute the IPW ATE:

$$\hat{\tau}_{\text{IPW}} = \frac{1}{n} \sum_{i=1}^n \left(\frac{D_i Y_i}{\hat{p}_D(X_i)} - \frac{(1 - D_i) Y_i}{1 - \hat{p}_D(X_i)} \right).$$

Compute an approximate 95% confidence interval using the nonparametric bootstrap. *Hint:* include propensity score estimation inside each bootstrap resample.

4.e Hot-deck matching (propensity score). Use the `hot.deck` package to impute counterfactual outcomes using the opposite treatment group as donors. Make sure to set a random seed. Use the estimated propensity score as the matching variable (instead of the full covariate set). One simple way is to set `re78` to NA for treated units (so controls are the only donors) and run hot-deck imputation, then repeat with `re78` set to NA for controls. Use the completed datasets to compute the ATE.

4.f Linear model with covariates. Fit a linear regression of Y on D and the covariates used in the propensity score model. Report the coefficient on D and interpret it as an adjusted ATE.

- 4.g Linear model with propensity score (estimatr).** Fit a linear regression of Y on D and $\hat{p}_D(X)$ using `estimatr::lm_robust`. Report the coefficient on D and compare it to your earlier estimates.
- 4.h Lin estimator vs. by-hand.** Use `estimatr::lm_lin` to compute the regression-adjusted ATE. Then demean the covariates, add treatment interactions, and estimate the same model using `lm_robust`. Compare the two estimates and confirm they match.
- 4.i Diagnostics.** Briefly summarize what you learned from comparing the estimators in this problem (2–4 sentences).