

**MATH-449 - Biostatistics**  
**EPFL, Spring 2022**  
**Problem Set 1**

1. Determine whether each of these questions are phrased as causal questions or not (yes or no).
  - a) Does the Moderna vaccine reduce the risk of severe COVID-19 infection? *Yes - this is a question about the (causal) explanatory power of the vaccine in regards to COVID-19.*
  - b) Do women with breast cancer survive longer than men with prostate cancer? *No, this is simply a descriptive comparison of the factual survival distributions under different conditioning events.*
  - c) Is the life expectancy in Switzerland longer than the life expectancy in Italy? *No (see above).*
  - d) Does drinking 0.5 L beer compared to 0.5 L Coca Cola at 19h00 affect the quality of sleep? *Yes, see the word \*affect\*, implying a counterfactual comparison of sleep quality under interventions on beer vs Coca Cola.*
  - e) Would drinking a cup of coffee 2 hours before your exam improve your performance? *Yes - this is a question about outcomes under a hypothetical intervention (or lack thereof).*
2. Based on the definition of a causal effects in the lecture slides, argue whether the following statements about a covariate  $L \in \mathbb{R}$ , a treatment  $A = 0, 1$  and an outcome  $Y \in \mathbb{R}$  are right or wrong (there is no guarantee that  $A$  is randomly assigned).
  - a)  $\mathbb{E}(Y^{a=1} | L = l) - \mathbb{E}(Y^{a=0} | L = l)$  is a causal effect. *Yes, by linearity of expectations, we re-express as  $\mathbb{E}(Y^{a=1} - Y^{a=0} | L = l)$ , which is the expected individual causal effect among units with  $L = l$ .*
  - b)  $\mathbb{E}(Y | A = 1, L = l) - \mathbb{E}(Y | A = 0, L = l)$  is a causal effect. *No. without additional assumptions, this is simply a contrast of conditional outcome means, representing the association between  $A$  and  $Y$  given  $L = l$ .*
  - c)  $\mathbb{E}(Y^{a=1} | A = 1, L = l) - \mathbb{E}(Y^{a=0} | A = 1, L = l)$  is a causal effect. *Yes (see part a)).*
  - d)  $\frac{\mathbb{E}(Y^{a=1})}{\mathbb{E}(Y^{a=0})}$  is an average over individual level (additive) causal effects. *By counter-example: we know that an individual-level additive causal effect is the random variable  $Z = Y^{a=1} - Y^{a=0}$  which has support in  $\mathbb{R}$ , and thus the parameter space for its expectation is also  $\mathbb{R}$ . However,  $X = \frac{Y^{a=1}}{Y^{a=0}}$  is undefined whenever  $Y^{a=0} = 0$  and also  $\frac{\mathbb{E}(Y^{a=1})}{\mathbb{E}(Y^{a=0})}$  is undefined whenever  $\mathbb{E}(Y^{a=0}) = 0$ .*
3. Translate these English sentences to mathematical (counterfactual) statements.
  - a) The average causal effect of receiving a COVID-19 vaccine ( $A = 1$ ) vs placebo ( $A = 0$ ) on mortality after one year ( $Y = 1$  is death,  $Y = 0$  is alive) in the entire population of interest. **Answer:**  $\mathbb{E}[Y^{a=1} - Y^{a=0}]$ .
  - b) The average causal effect of receiving a COVID-19 vaccine ( $A = 1$ ) vs placebo ( $A = 0$ ) on mortality after one year ( $Y = 1$  is death,  $Y = 0$  is alive) among those who received placebo in the observed (factual) data. **Answer:**  $\mathbb{E}[Y^{a=1} - Y^{a=0} | A = 0]$ .
  - c) The average causal effect of receiving a COVID-19 vaccine ( $A = 1$ ) vs placebo ( $A = 0$ ) on mortality after one year ( $Y = 1$  is death,  $Y = 0$  is alive) among those who received treatment in the observed (factual) data. **Answer:**  $\mathbb{E}[Y^{a=1} - Y^{a=0} | A = 1]$ .
  - d) The average causal effect of receiving a COVID-19 vaccine ( $A = 1$ ) vs placebo ( $A = 0$ ) on mortality after one year ( $Y = 1$  is death,  $Y = 0$  is alive) in men ( $X = 1$ ). **Answer:**  $\mathbb{E}[Y^{a=1} - Y^{a=0} | X = 1]$ .

- e) Are your answers in a)-d) estimands, estimators or estimates? **Estimands**.
4. Suppose investigators had access to data from a study in which they observed for each patient a binary outcome  $Y$ , a binary treatment  $A$  and a 4-level baseline covariate  $L$ . The parameters of the joint density of  $(L, A, Y)$  were computed from the data and summarized in Table 1 (where we suppose that the sample size was so large, that sampling variability is not a concern).

- a) From the parameters in Table 1, compute  $\mathbb{E}[Y]$ .

$$\mathbb{E}[Y] = \sum_{l,a} P(Y = 1 | A = a, L = l)P(A = a | L = l)P(L = l) = 0.5$$

- b) Suppose now that the data did not in fact arise from a regular observational study, but had instead come from a special trial. Upon recruitment into the study, each patient's covariate  $L$  is measured and then they are sorted into groups based on that covariate's value. In each group, the investigators conduct a separate experiment, which are identical except they use a special coin to randomize patients to either treatment ( $a = 1$ ) or control ( $a = 0$ ), with "heads" corresponding to treatment and "tails" corresponding to control. The probabilities for heads for each of these sub-trials is given by the column labeled  $P(A = 1 | L = l)$ . Assume consistency holds ( $Y^A = Y$ ), and that patients perfectly complied with their assignments. With the information in the table, compute the effect of treatment  $\mathbb{E}[Y^{a=1} - Y^{a=0} | L = l]$  for each subgroup  $L = l$  that was targeted in each of the sub-trials. What additional assumptions did you use along the way, that was justified given the source of the data?

$$\mathbb{E}[Y^a | L = l] = P(Y = 1 | A = a, L = l)$$

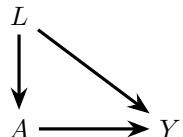
*By consistency and by the exchangeability  $Y^a \perp\!\!\!\perp A = a | L = l$  justified by the conditional randomization in the trial for which, by design,  $(Y^{a=0}, Y^{a=1}) \perp\!\!\!\perp A | L$ .*

|         | $E(Y^{a=1}   L = l)$ | $E(Y^{a=0}   L = l)$ | $E(Y^{a=1} - Y^{a=0}   L = l)$ |
|---------|----------------------|----------------------|--------------------------------|
| $l = 1$ | .1                   | .8                   | -.7                            |
| $l = 2$ | .2                   | .7                   | -.5                            |
| $l = 3$ | .3                   | .6                   | -.3                            |
| $l = 4$ | .4                   | .5                   | -.1                            |

- c) From the quantities computed in part a), use laws of probability to compute the average treatment effect, among the whole population,  $\mathbb{E}[Y^{a=1} - Y^{a=0}]$ .

$$\mathbb{E}[Y^a | L = l] = \sum_l \mathbb{E}[Y^a | L = l]P(L = l) = -0.4$$

- d) Draw a directed acyclic graph (DAG) that could depict the mechanism that generated the observed data.



- e)

- f) The data analyst for the study approaches you and said they made a terrible mistake: when preparing the column  $P(A = 1 | L = l)$  in Table 1, they reverse coded the treatment variable, so in fact the true values of the treatment propensities are 1 minus those listed in the table. What will be the values of the previously computed parameters, and explain in words why these changes did (or did not occur).

*Only the factual marginal expectation of  $Y$  will change - the other parameters are not functions of the propensities.*

|         | $P(Y = 1   A = a, L = l)$ |         | $P(A = 1   L = l)$ | $P(L = l)$ |
|---------|---------------------------|---------|--------------------|------------|
|         | $a = 1$                   | $a = 0$ |                    |            |
| $l = 1$ | .1                        | .8      | .2                 | .2         |
| $l = 2$ | .2                        | .7      | .4                 | .4         |
| $l = 3$ | .3                        | .6      | .6                 | .1         |
| $l = 4$ | .4                        | .5      | .8                 | .3         |

Table 1: Parameters of  $P_{L,A,Y}$  observed in the conditionally randomized trial.

5. Consider a covariate  $L \in \mathbb{R}$ , a treatment  $A = 0, 1$  and an outcome  $Y \in \mathbb{R}$ .

- a) Investigator 1 claims that  $A \perp\!\!\!\perp Y \implies A \perp\!\!\!\perp Y | L$ . Show that the statement is wrong.

*Consider the following joint distribution with binary  $L, A, Y$ :*

|         | $P(Y = 1   A = a)$ |         | $P(Y = 1   A = a, L = l)$ |         | $P(L = l   A = a)$ |         |
|---------|--------------------|---------|---------------------------|---------|--------------------|---------|
|         | $a = 1$            | $a = 0$ | $a = 1$                   | $a = 0$ | $a = 1$            | $a = 0$ |
| $l = 1$ | .5                 | .5      | .25                       | .75     | .5                 | .5      |
| $l = 2$ | .75                | .25     | .75                       | .25     | .5                 | .5      |

- b) Investigator 2 claims that  $A \perp\!\!\!\perp Y | L \implies A \perp\!\!\!\perp Y$ . Show that the statement is wrong.

*Consider the following joint distribution with binary  $L, A, Y$ :*

|         | $P(Y = 1   A = a)$ |         | $P(Y = 1   A = a, L = l)$ |         | $P(L = l   A = a)$ |         |
|---------|--------------------|---------|---------------------------|---------|--------------------|---------|
|         | $a = 1$            | $a = 0$ | $a = 1$                   | $a = 0$ | $a = 1$            | $a = 0$ |
| $l = 1$ | .65                | .5      | .2                        | .2      | .25                | .5      |
| $l = 2$ | .8                 | .2      | .8                        | .2      | .75                | .5      |