

Day 1, Lecture 2

Properly defining the target parameter

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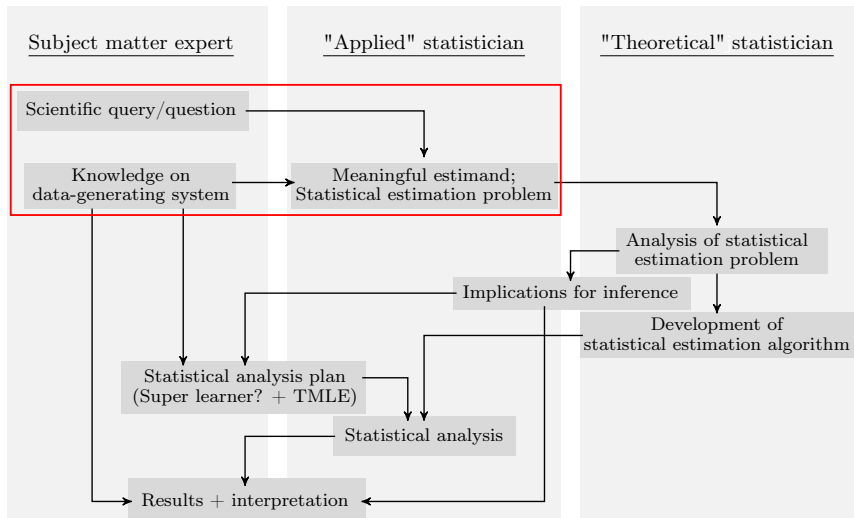
In this lecture, our goal is to:

1. Explain the utilization of causal inference tools to define nonparametric targets of estimation, highlighting the role of counterfactual reasoning and hypothetical interventions.
2. Differentiate between causal and statistical parameters, and list the assumptions necessary for the translation between them.

Properly defining the target parameter



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Properly defining the target parameter

- ▶ A clearly defined goal as a starting-point for any analysis
 - ▶ necessary to talk about estimator performance
 - ▶ semiparametric/nonparametric efficiency theory (and TMLE) requires a clearly defined goal
- ▶ Brief introduction to the setting of a typical causal inference problem
 - ▶ example: average treatment effect (ATE)
 - ▶ *model-free* and *estimator-free* definition of parameters

Moving targets with different logistic regression models

- ▶ $X \sim \text{Unif}(-2, 2)$
- ▶ $A \sim \text{Bernoulli}(0.5)$ (no confounding)
- ▶ $Y \in \{0, 1\}$

Say that the distribution of Y given X and A follows the parametric model:

$$\text{logit } \mathbb{E}[Y \mid A, X] = \beta_0 + \beta_A A + \beta_X^\top X^2$$

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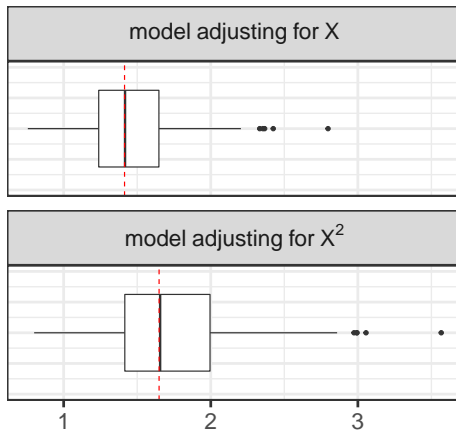
$$\text{logit } \mathbb{E}[Y \mid A, X] = \beta_0 + \beta_A A + \beta_X^\top X^2$$

The odds ratio $\exp(\beta_A)$ is a different parameter than $\exp(\alpha_A)$ in a different model:

$$\text{logit } \mathbb{E}[Y \mid A, X] = \alpha_0 + \alpha_A A + \alpha_X^\top X$$

Moving targets with different logistic regression models

- ▶ The variables X we include in the model to assess the effect of A on Y changes the parameter (conditional OR).
- ▶ Only one of the models can be true at a time.



The upper panel does not show a biased estimator, just an estimator targeting a different parameter (dashed red line).

Causal inference

What we obtain moving on to a causal inference setting: 1) An interpretable and relevant target of estimation, and 2) a model-free definition of a target parameter.

¹And, if you are already familiar, consider this a small repetition and introduction to the notation.

Causal inference

What we obtain moving on to a causal inference setting: 1) An interpretable and relevant target of estimation, and 2) a model-free definition of a target parameter.

- ▶ We are only going to go briefly over the "causal inference concepts",¹ but we need this part to be very clear about what we are estimating.
 - ▶ To start with, we consider just the simple example where the target of estimation is the average treatment effect (ATE).
- ▶ For the causal inference notation, we follow the book by Hernán and Robins (which, if you are interested, you can find here: https://cdn1.sph.harvard.edu/wp-content/uploads/sites/1268/2021/03/ciwhatif_hernanrobins_30mar21.pdf).
- ▶ I will leave out DAGs/SCMs.

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Steps of the roadmap

- Step 1 Go from scientific question to target causal estimand (stated in the language of counterfactuals)
- Step 2 Assess whether we can go from target causal estimand to target statistical estimand = assess "identifiability"

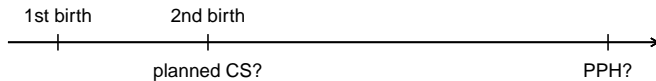
In a given data situation, we want to explicitly clarify:

1. Observed data
2. Causal model
3. Causal question and target causal estimand
4. Identifiability

An example we can have in the back of our minds

Scientific question:

Does having a planned cesarian section (intended cesarian section) among women who gave birth twice change the risk of postpartum haemorrhage (PPH) during the second delivery?



Goal: Translate this into a precise formulation of a statistical estimation problem.

Observed data

Observed data $O = (X, A, Y) \in \mathbb{R}^d \times \{0, 1\} \times \{0, 1\} = \mathcal{O}$

- * $X \in \mathbb{R}^d$ are covariates
ex: age at 2nd delivery, information of PPH at first delivery, ...
- * $A \in \{0, 1\}$ is a binary exposure variable (treatment decision)
ex: decision to have a planned cesarian section.
- * $Y \in \{0, 1\}$ is a binary outcome variable
ex: PPH (postpartum haemorrhage).

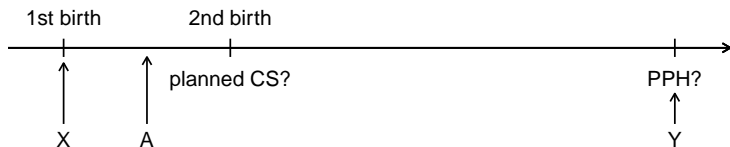
We observe a sample $O_1, \dots, O_n \stackrel{iid}{\sim} P_0 \in \mathcal{M}$, $n \in \mathbb{N}$.

\mathcal{M} is the set of all possible probability distributions for our data.

Observed data

Implicit assumptions for the data structure:²

- ▶ X are covariates known before the treatment decision A was made
- ▶ Outcome Y is observed after treatment decision was made



²This ordering could also be encoded in a structural causal model.

Observed data

Our statistical model \mathcal{M} for P_0 contains possible distributions P for the observed data O .

The density p of $P \in \mathcal{M}$ can be factorized into:

$$p(o) = \mu_Y(y \mid a, x) \pi(a \mid x) \mu_X(x),$$

- ▶ $\mu_Y(y \mid A, X) = P(Y = y \mid A, X)$
- ▶ $\pi(a \mid X) = P(A = a \mid X)$
- ▶ μ_X is the marginal density of X (with respect to an appropriate dominating measure)

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We assume that \mathcal{M} is a nonparametric model.

- * Throughout, we make *no parametric restrictions* on μ_Y, μ_X .
- * We could impose some parametric structure on π , but let us assume that we do not.

Operators on functions of the observed data³

For a function $h : \mathcal{O} \rightarrow \mathbb{R}$ and distribution P

$$Ph = \mathbb{E}_P[h(O)] = \int h dP = \int_{\mathcal{O}} h(o) dP(o)$$

where $\mathcal{O} = \mathbb{R}^d \times \{0, 1\} \times \{0, 1\}$ is the sample space of $O = (X, A, Y)$.

³van der Vaart, A. W. (2000). Asymptotic statistics (Vol. 3). Cambridge university press.

Confounding

How can we define a causal effect?

The contrast $\mathbb{E}_P[Y \mid A = 1] - \mathbb{E}_P[Y \mid A = 0]$ tells us about the risk difference between the two exposure groups.

Any such difference is likely due to other factors than the decision to initiate treatment or not

- * the exposure decision is **confounded**.

Counterfactuals

To answer a causal question, we ideally want to know

Scenario 1 What happened to a subject had they been exposed?

Scenario 2 What would have happened to the same subject had they not been exposed?

We imagine a model with two outcomes for each subject:

- ▷ a variable Y^1 corresponding to scenario 1, and
- ▷ a variable Y^0 corresponding to scenario 2

= the "counterfactuals" (aka **potential outcomes**).

Counterfactuals

- * Y^1 = outcome if exposed
- * Y^0 = outcome if not exposed

We use the counterfactual outcomes to define precisely what a causal effect is:

- on the individual level, $Y^1 = 1$ and $Y^0 = 0$ for a particular subject would tell us that this subject would experience outcome under exposure and not otherwise
- on the population level, $\mathbb{E}_P[Y^1] \neq \mathbb{E}_P[Y^0]$ tells us that the risk changes depending on whether exposed or not

Target causal estimand: Average causal effect (ATE)

The average causal effect⁴ (ATE/ACE) measures the average effect in the population

$$\text{ATE} = \mathbb{E}_P[Y^1] - \mathbb{E}_P[Y^0]$$

- It is interpreted as the difference in risk had everyone in the population been exposed and had everyone in the population been unexposed.

⁴or average treatment effect.

Identifiability (estimating the causal effect from observational data)

Can we estimate the causal effect from the observed data?

- ▷ only Y^1 or Y^0 is observed for each individual.

Identifying $\mathbb{E}_P[Y^1] - \mathbb{E}_P[Y^0]$

= write $\mathbb{E}_P[Y^1] - \mathbb{E}_P[Y^0]$ as a parameter of the observed data distribution.

requires three overall assumptions (identifiability assumptions).

Identifiability (estimating the causal effect from observational data)

1. Consistency: $Y^a = Y$ if $A = a$, $a = 0, 1$

- ▶ Requires that the "treatment intervention" is well-defined and no interference between subjects.
- ▶ Example of a violation: effect of vaccines (one subject's effect of a vaccine depends on whether other subjects are vaccinated or not).

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2. Exchangeability: $Y^a \perp\!\!\!\perp A \mid X$, for $a = 0, 1$

- ▶ Conditional on covariates, the exposed group tells us what would happen to the unexposed if they had been exposed and vice versa.
- ▶ Requires that there is **no unmeasured confounding**.

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- ▶ Requires that there is **no unmeasured confounding**.

3. Positivity: $P(A = a \mid X) > 0$ for $a = 0, 1$ and almost surely all X

- ▶ We cannot investigate the effect of an intervention that was never "tested" in the observed data (conditional on covariates X).

Identifiability (estimating the causal effect from observational data)

Under these assumptions:

$$\begin{aligned}\mathbb{E}_P[Y^1] - \mathbb{E}_P[Y^0] \\&= \mathbb{E}_P[\mathbb{E}_P[Y^1 | X] - \mathbb{E}_P[Y^0 | X]] \\&\stackrel{2.}{=} \mathbb{E}_P[\mathbb{E}_P[Y^1 | A = 1, X] - \mathbb{E}_P[Y^0 | A = 0, X]] \\&\stackrel{1.}{=} \mathbb{E}_P[\mathbb{E}_P[Y | A = 1, X] - \mathbb{E}_P[Y | A = 0, X]] \\&= \Psi(P)\end{aligned}$$

(3. (positivity) ensures that the conditional expectations are well-defined).

Goal achieved: Right hand side is expressed only in terms of observable quantities.

Identifiability (estimating the causal effect from observational data)

Under the assumptions:

$$\mathbb{E}_P[Y^1] - \mathbb{E}_P[Y^0] = \underbrace{\mathbb{E}_P[\mathbb{E}_P[Y \mid A = 1, X] - \mathbb{E}_P[Y \mid A = 0, X]]}_{(*)} = \Psi(P),$$

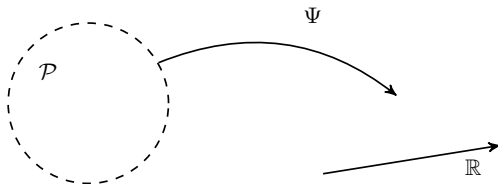
for any $P \in \mathcal{M}$.

In our statistical analysis, we proceed with (*).

"Causal inference part" is over.

Target statistical estimand

Now we are exactly in the situation we wanted:



Average treatment effect (ATE)

- ▶ $O = (X, A, Y) \in \mathbb{R}^d \times \{0, 1\} \times \{0, 1\}$
- ▶ The ATE is defined for $P \in \mathcal{M}$ as

$$\Psi(P) = \mathbb{E}_P[\mathbb{E}_P[Y \mid A = 1, X] - \mathbb{E}_P[Y \mid A = 0, X]]$$

Target statistical estimand: g-formula

We can write the target parameter as:

$$\begin{aligned}\Psi(P) &= \mathbb{E}_P[\mathbb{E}_P[Y \mid A = 1, X] - \mathbb{E}_P[Y \mid A = 0, X]] \\ &= \mathbb{E}_P[f(1, X) - f(0, X)] \\ &= \int_{\mathbb{R}^d} (f(1, x) - f(0, x)) d\mu_X(x) = \tilde{\Psi}(f, \mu_X) \quad (*)\end{aligned}$$

where

$$f(a, x) = \mathbb{E}[Y \mid A = a, X = x]$$

and μ_X is the marginal distribution of X .

We refer to this as the **g-formula**.

Target statistical estimand: IP-weighting

We can also rewrite the target parameter as:

$$\begin{aligned}\Psi(P) &= \int_{\mathbb{R}^d} (f(1, x) - f(0, x)) d\mu_X(x) & (*) \\ &= \int_{\mathbb{R}^d} \sum_{y=0,1} y (\mu_Y(y \mid 1, x) - \mu_Y(y \mid 0, x)) d\mu_X(x) \\ &= \int_{\mathbb{R}^d} \sum_{y=0,1} \sum_{a=0,1} y (a\mu_Y(y \mid a, x) - (1-a)\mu_Y(y \mid a, x)) d\mu_X(x) \\ &= \int_{\mathbb{R}^d} \sum_{y=0,1} \sum_{a=0,1} \left(\frac{ay}{\pi(a \mid x)} - \frac{(1-a)y}{\pi(a \mid x)} \right) \mu_Y(y \mid a, x) \pi(a \mid x) d\mu_X(x) \\ &= \tilde{\Psi}_{\text{ipw}}(\pi, p) \quad (**)\end{aligned}$$

where $\pi(a \mid x) = P(A = 1 \mid X = x)$.

Target statistical estimand

The **g-formula**:

$$\begin{aligned}\tilde{\Psi}(f, \mu_X) &= \int_{\mathbb{R}^d} (f(1, x) - f(0, x)) d\mu_X(x) \\ &= \mathbb{E}_P[f(1, X) - f(0, X)].\end{aligned}\quad (*)$$

The **IP-weighted formula**:

$$\begin{aligned}\tilde{\Psi}_{\text{ipw}}(\pi, p) &= \int_{\mathbb{R}^d} \sum_{a=0,1} \sum_{y=0,1} \left(\frac{ay}{\pi(a | x)} - \frac{(1-a)y}{\pi(a | x)} \right) dP(o) \\ &= \mathbb{E}_P \left[\frac{AY}{\pi(1 | X)} - \frac{(1-A)Y}{\pi(0 | X)} \right]\end{aligned}\quad (**)$$

- ▶ f and (the average over) μ_X are **nuisance parameters** for the g-formula.
- ▶ π and (the average over) p are **nuisance parameters** for the IP-weighted formula.

Target statistical estimand

Yet another representation of the target parameter is

$$\begin{aligned}\tilde{\Psi}_{\text{ee}}(f, \pi, p) &= \int_{\mathbb{R}^d} \sum_{a=0,1} \sum_{y=0,1} \left\{ \left(\frac{a}{\pi(a|x)} - \frac{1-a}{\pi(a|x)} \right) (y - f(a, x)) \right. \\ &\quad \left. + f(1, x) - f(0, x) \right\} p_Y(y | a, x) \pi(a | x) d\mu_X(x) \\ &= \mathbb{E}_P \left[\left(\frac{A}{\pi(A|X)} - \frac{1-A}{\pi(A|X)} \right) (Y - f(A, X)) + f(1, X) - f(0, X) \right]\end{aligned}$$

- f , π and (the average over) p are **nuisance parameters** for this parametrization.

Target statistical estimand

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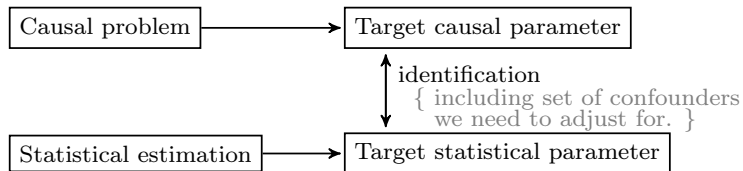
SMALL EXERCISE:

1. Note that $\tilde{\Psi}_{\text{ee}}(f, \pi, p) = \tilde{\Psi}(f, \mu_X) + [\text{an extra term}]_1$. Show that it can also be written as $\tilde{\Psi}_{\text{ee}}(f, \pi, p) = \tilde{\Psi}_{\text{ipw}}(\pi, p) + [\text{an extra term}]_2$.
2. Show that $\tilde{\Psi}_{\text{ee}}(f, \pi, p) = \mathbb{E}_P[Y^1] - \mathbb{E}_P[Y^0]$ under the identifiability assumptions (consistency, exchangeability and positivity).

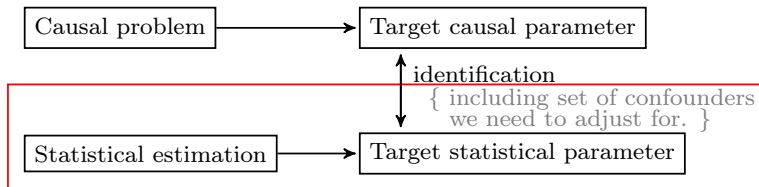
Summarizing comments on properly defining the target

- ▶ Causal parameter (now fixed).
- ▶ Causal model: How do the observed variables affect one another?
 - ▶ are the covariates we observe sufficient to remove confounding? which variables **do we need to adjust for** to make treatment groups comparable?
- ▶ Identifiability
 - ▶ identifiability assumptions allow us to write causal parameter as statistical parameter.
 - ▶ the assumptions may not hold, but we can state and discuss them.
- ▶ Statistical parameter
 - ▶ Statistical interpretation: The average effect in the population, standardized to the distribution of covariates.

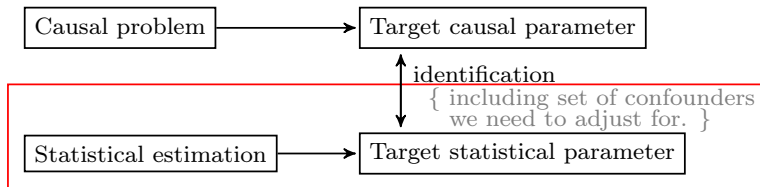
Summarizing comments on properly defining the target



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Summarizing comments on properly defining the target



- ▶ Estimands (target parameters) defined as statistical functionals $\psi : \mathcal{M} \rightarrow \Psi(\mathcal{M})$ are independent of the specific estimation method used.
- ▶ One estimator is not more causal than another.
- ▶ Different estimators are based on different nuisance parameters and have different statistical properties (bias/variance).
- ▶ Whether one type of estimator or algorithm best fit the data does not affect the estimand, only estimation performance.

On a sidenote: Other simple causal parameters

We focus on the ATE as an example of a causal parameter.

But note that other simple causal parameters can be constructed from $\mathbb{E}[Y^1]$ and $\mathbb{E}[Y^0]$.

Like:

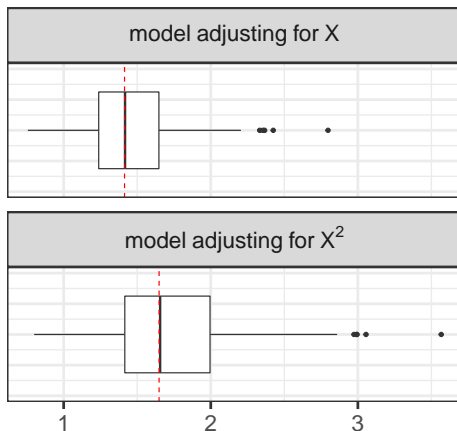
$$\psi^{\text{RR}}(P) = \frac{\mathbb{E}[Y^1]}{\mathbb{E}[Y^0]},$$

or,

$$\psi^{\text{OR}}(P) = \frac{\mathbb{E}[Y^1]/(1 - \mathbb{E}[Y^1])}{\mathbb{E}[Y^0]/(1 - \mathbb{E}[Y^0])}.$$

On a sidenote: Other simple causal parameters

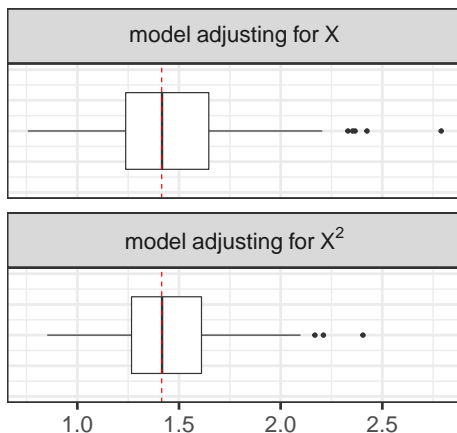
$\log(\text{OR})$ as a **regression coefficient** is a moving target in different logistic regression models:



The upper panel does not show a biased estimator, just an estimator targeting a different parameter (dashed red line).

On a sidenote: Other simple causal parameters

The corresponding **causal odds ratio** is a fixed target — and the target does not change depending on adjustment for X or X^2 :



... but these are different statistical estimators, and they have different statistical properties.