

# Generalizing a causal effect: review, sensitivity analysis, and missing covariates

JSM 2021

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August, 12th

# Motivation

## Question of interest

Effect of acid tranexamic (TXA) on brain-injured related (TBI) deaths.

## Data at hand

*Randomized Controlled Trial - CRASH-3*

- 29 different countries
- 9202 patients

*Real World data - Traumabase*

- 23 French Trauma centers
- 8270 patients

*Is the RCT's estimate of the TXA effect the same for the Traumabase patients?*

## Outline for today's presentation

1. Review of the generalization estimators (<https://arxiv.org/abs/2011.08047>)
2. What if covariates from both data sets are different? (<https://arxiv.org/abs/2105.06435>)

# Context


- Randomized Controlled Trials (RCT) : gold standard to estimate a treatment effect.

For example any new drug or treatment that receives an authorization usually has been assessed through several trials. This is part of the *evidence-based medicine*.

- Observational data have a higher representativeness but they can lack of internal validity.

The unconfoundedness assumption is unverifiable!




- Our motivation on tranexamic acid is part of a wider issue called **Generalization** or **Transportability**.

Remember the discussion on the Oxford-AstraZeneca vaccine's efficacy 

*How can we leverage strengths of both type of data to gain information of a target population treatment efficacy?*

# Notations

Our notations take place in the Neyman-Rubin framework.

- $A$  treatment of interest, 
- $X$  covariates, 
- $Y$  the outcome, 

The target quantity is the average population treatment effect,

$$\tau = \mathbb{E}[Y(1) - Y(0)] = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)]$$

## External validity bias

We introduce  $s$  an indicator or eligibility in the trial ( $s = 1$  corresponds to eligibility)

The distribution of covariates  $x$  is not the same in the target population and in the RCT,

$$f_X \neq f_{X|S=1}.$$

# External validity

So that,

$$\tau_1 = \mathbb{E}[Y(1) - Y(0)|S = 1] \neq \mathbb{E}[Y(1) - Y(0)] = \tau.$$

Using two data sets?

	$S$	Set	Covariates			Treatment	Outcome
			$X_1$	$X_2$	$X_3$	$A$	$Y$
1	1	$\mathcal{R}$	1.1	20	F	1	1
	1	$\mathcal{R}$	-6	45	F	0	1
$n$	1	$\mathcal{R}$	0	15	M	1	0
$n+1$	0	$\mathcal{O}$		...		...	...
	0	$\mathcal{O}$	-2	52	M	-	-
	1	$\mathcal{O}$	-1	35	M	-	-
$n+m$	0	$\mathcal{O}$	-2	22	M	-	-

With our motivating example, the CRASH-3 trial corresponds to observations  $i = 1, \dots, n$ , and the Traumabase to observations  $i = n + 1, \dots, m + n$ .

# Identification

But **first**, an important step is to ensure the identifiability of  $\tau$ , and the two major assumptions are:

- **Ignorability assumption on trial participation**

$$Y(1) - Y(0) \perp S \mid X$$

💡  $X$  contains all covariates that are *treatment effect modifiers* and with a distributional shift.

- **Positivity of trial participation**

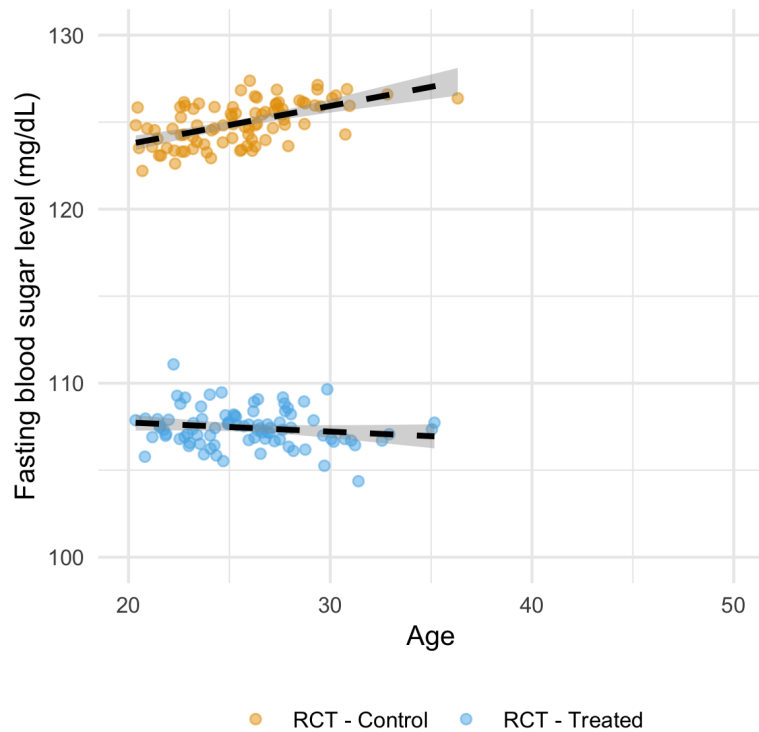
There exists a constant  $c$  such that for all  $x$  with probability  $\mathbf{1}$ ,  $\mathbb{P}(S = 1 \mid X = x) \geq c > 0$

💡 Each individual from the target population had a non-zero probability to be eligible in the trial.

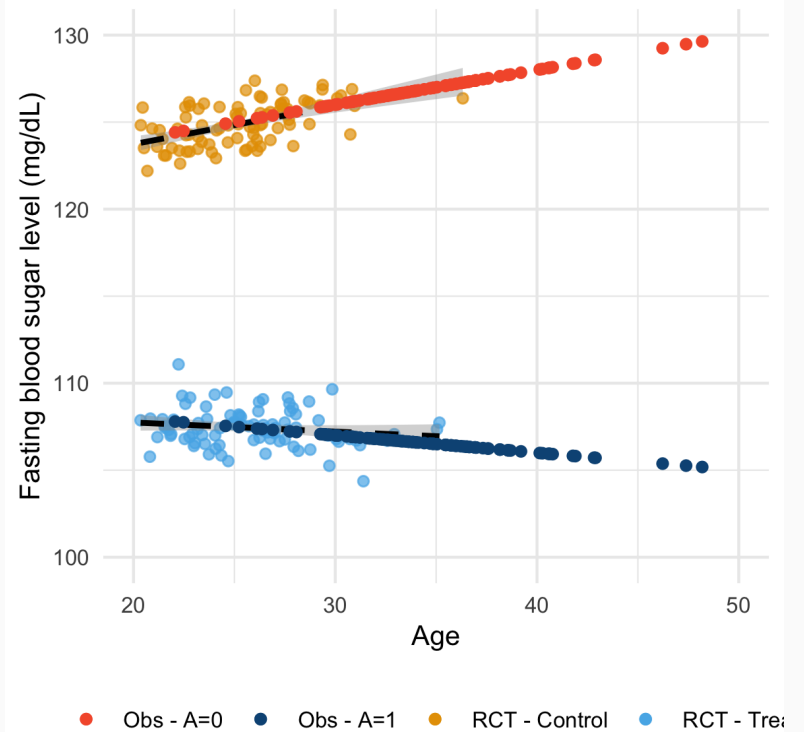
# Outcome regression (G-formula)

## Intuition

### Step 1



### Step 2



# Outcome regression (G-formula)

## Formalization

$$\hat{\tau}_{G,n,m} = \frac{1}{m} \sum_{i=n+1}^m \left( \hat{\mu}_{1,n}(X_i) - \hat{\mu}_{0,n}(X_i) \right),$$

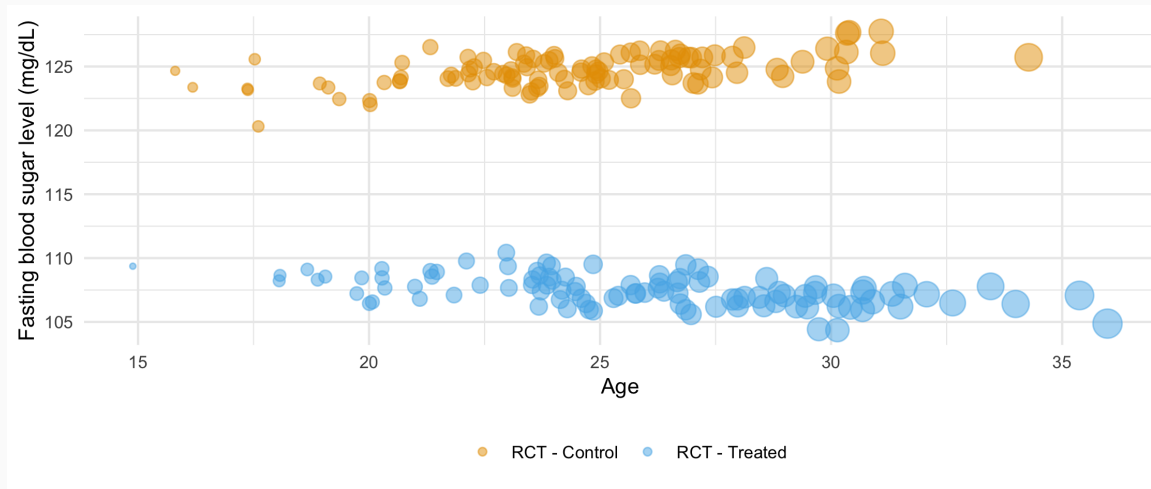
where,

- $\mu_a(\mathbf{x}) \triangleq \mathbb{E}[Y(\mathbf{w}) | \mathbf{X} = \mathbf{x}, \mathbf{A} = \mathbf{a}]$  are the response surfaces,
- $\hat{\mu}_{a,n}(X_i)$  are estimated on the RCT sample.



# Weighting (IPSW)

## Intuition



## Formalization

$$\hat{\tau}_{IPSW, n, m} = \frac{1}{m} \sum_{i=1}^n \frac{Y_i}{\hat{\alpha}_{n, m}(X_i)} \left( \frac{A_i}{e_1(X_i)} - \frac{1 - A_i}{1 - e_1(X_i)} \right),$$

where  $\hat{\alpha}_{n, m}$  is an estimate of the odd ratio of the indicatrix of being in the RCT, and  $e_1(X) = P(A = 1 \mid X = x, S = 1)$

# Toward sensitivity analysis

What if a covariate is missing?

Mathematically,  $\mathbf{X} = \mathbf{X}_{mis} \cup \mathbf{X}_{obs}$ , and

$$Y(1) - Y(0) \not\perp S \mid \mathbf{X}_{obs}$$

⚠️ Such a missing covariate breaks the identifiability assumption.

*What can we do?*

- 💡 The intuition is that *a poorly shifted missing covariate and/or a weak treatment effect missing covariate will lead to a small bias.*
- 🤔 Is there a way to link the bias to these two characteristics, so that domain expert can help assess whether or not the missing covariate breaks any conclusion?
- 📖 Such an approach is called a sensitivity analysis

# Key result - Model

## Model

We admit there exist  $\delta \in \mathbb{R}^p$ , and  $\sigma \in \mathbb{R}^+$  such that the semi-linear <sup>[1]</sup> model holds:

$$Y = g(X) + A\langle X, \delta \rangle + \varepsilon, \quad \text{where } \varepsilon \sim \mathcal{N}(0, \sigma^2).$$

## Assumption

The distribution of  $X$  is Gaussian, that is,  $X \sim \mathcal{N}(\mu, \Sigma)$ , and transportability of  $\Sigma$  is true, that is,  $X | S = 1 \sim \mathcal{N}(\mu_{S=1}, \Sigma)$ .

## Theorem in a sentence

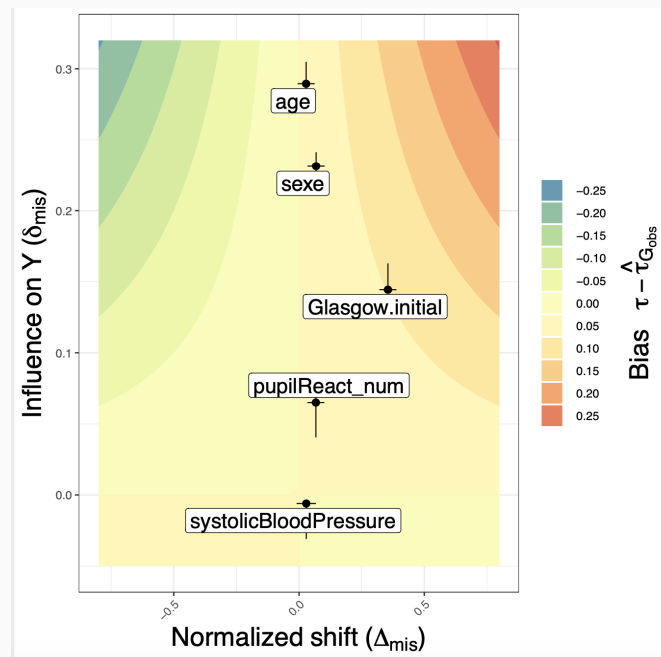
Under these assumptions, the bias of IPSW and G-formula are the same, that is:

$$B = \sum_{j \in mis} \delta_j \left( \mathbb{E}[X_j] - \mathbb{E}[X_j | S = 1] - \Sigma_{j,obs} \Sigma_{obs,obs}^{-1} (\mathbb{E}[X_{obs}] - \mathbb{E}[X_{obs} | S = 1]) \right).$$

# Sensitivity analysis in the real-world

⚠ We had to take a surrogate outcome that is continuous! --> Disability Rating Scale (DRS)

Target population ATE estimation with the G-formula on the set of observed covariate: 0.17 [95% CI -0.34 - 0.29]) with bootstrap.



Confidence intervals are done with bootstrap.

# Conclusion and perspectives

## **Contributions**

1. Handling all missing covariate patterns,
2. Lighten the usual independency condition,
3. Insist on interpretability.

## **Also present in the paper**

- Imputation?
- Proxy?

## **Place for improvement**

- Lighten the semi-parametric and Gaussian assumption?
- Binary outcome.

# Another related work



	Set	Covariates			Treatment	(Factual) Outcome
		$X_1^*$	$X_2^*$	$X_3^*$	$A$	$Y$
1	$\mathcal{R}$	1.1	20	NA	1	23.4
...	$\mathcal{R}$		...		...	...
$n-1$	$\mathcal{R}$	-6	NA	8.3	0	26.3
$n$	$\mathcal{R}$	0	15	6.2	1	28.1
$n+1$	$\mathcal{O}$	-2	52	NA	NA	NA
$n+2$	$\mathcal{O}$	-1	NA	2.4	NA	NA
...	$\mathcal{O}$		...		NA	NA
$n+m$	$\mathcal{O}$	NA	NA	3.4	NA	NA

Generalizing with missing attributes?  
(Mayer et al. 2021)

<https://arxiv.org/abs/2104.12639>

*Thank you for listening!*

Code: on Github [BenedicteColnet/unobserved-covariate](https://github.com/BenedicteColnet/unobserved-covariate)

? Questions / remarks / discussions / ideas are welcome : [benedicte.colnet@inria.fr](mailto:benedicte.colnet@inria.fr)