Transporting treatment effects with incomplete attributes

Application to critical care management

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Why and what are we transporting?

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

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- ▷ But remember the discussion around the covid vaccine efficacy!

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National differences in vaccine hesitancy: a concern for the external validity of vaccine studies

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Why and what are we transporting?

- Randomized Controlled Trials (RCT): gold standard to estimate a treatment effect.
- ▷ But remember the discussion around the covid vaccine efficacy!



▷ Indeed, an RCT yields an unbiased estimate (high *internal validity*), but this property may be of limited practical value (low *external validity*).

How can we use several data sources to gain information about a target population treatment efficacy?

Motivating application

Real data gathered: Effect of tranexamic acid (TXA) on brain-injured related (TBI) deaths

Randomized Controlled Trial CRASH-2

▷ 40 different countries▷ 3727 patients

Concludes on positive effect of TXA for traumatic brain injury with severe extracranial hemorrhage (Shakur-Still et al., 2009) Real World data Traumabase \equiv target population

> 23 French Trauma centers> 8270 patients

Concludes on no significant effect of TXA for traumatic brain injury (Mayer et al., 2020)

© Could the generalization help solving/understanding the apparent difference?

Yes, but ...

Use our review article summarizing the different available estimators in the **complete data case**: • arXiv:2011.08047

🖴 Real data in practice: It's all about the missingness! 🖑



▶ Missing a key covariate in one of the data set, breaking the identifiability?



NA (not available), but also not informed, not made, not applicable, impossible.

Impact of NA on identifiability and estimation

Identifiability in the complete data case in a nutshell:

Everyone has a non-zero chance to be eligible and that conditionally on attributes, the treatment effect is stable across populations.

★ Two approaches to maintain the identifiability from the complete data case:

Impact of NA on identifiability and estimation

Identifiability in the complete data case in a nutshell:

Everyone has a non-zero chance to be eligible and that conditionally on attributes, the treatment effect is stable across populations.

**** Two approaches to maintain the identifiability from the complete data case:

▷ Conditionally independent selection (CIS)
→ eligibility and selection depend on the missingness pattern
▷ S-ignorability + classical missingness assumptions
→ missing values don't alter selection or outcome models

Estimation: multiple imputation (MI)

Well explored for single data source. But in case of multiple data sources, less straightforward. Parallels with MI in *meta-analysis*.

We explored several strategies with different imputation models The best performing: multilevel MI on the joint dataset, with data source indicator.

Conclusion and perspectives

Contributions

- $\triangleright~$ Leverage RCTs and observational data $\rightarrow internal$ vs. external validity
 - 🗲 See our review paper: Colnet et al. (2020) (arXiv:2011.08047) 🕮
- ▷ Deal with missing covariate values

for identifiability \rightarrow solutions with or without informative NA for estimation \rightarrow multilevel multiple imputation solution

🗲 See our preprint: Mayer et al. (2021) (arXiv:2104.12639) 🕮

Perspectives

- ▷ Systematically missing values (Colnet et al., 2021).
- ▷ Different missing values mechanisms in RCT and obs. data.
- ML for transporting effects? Have a look at the recorded talks from our virtual workshop on Leveraging Observational Data with Machine Learning: https://files.inria.fr/leveraging2021/ 2011

🤔 Motivation

Transportability of treatment effects is increasingly relevant due to increasing availability of rich obs. data. But **missing values** flaw these data and their impact on methodologies should be made explicit to guarantee that we are working on **well-defined problems and methods despite missingness**.

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Questions / remarks / discussions / ideas are very welcome:
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