Testing compatibility of causal models with (historical) data under missingness not at random

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Abstract

Missingness graphs (m-graphs) are directed acyclic graphs (DAGs) designed to represent the causal relationships between (and internally among) (1) a set of variables of interest, and (2) a process that causes some or all of those variables to be only partially observed (i.e. to be missing some but not all of their values). They do so by decomposing the (possibly very complex) process that accounts for missing observations into a set of atomic missingness mechanisms, one acting on each partially observed variable. These mechanisms are themselves represented by variables and causal influences in the natural way of causal DAGs.

Missingness graphs are a powerful and transparent formalism for reasoning about missing data problems, and they give an intuitive characterization of the three fundamentally different forms of missingness described by Rubin in his seminal 1976 paper: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). The question of whether a given parameter of interest (e.g. a causal effect) can, in theory, be *recovered (identified)* from observed data under various forms of missingness has been studied extensively, as has the question of how to empirically *estimate* recoverable parameters from finite samples. Both questions take for granted the correctness (compatibility with data) of their m-graphs, and in both cases it turns out that a surprising amount of information can be recovered using the right method, even if data are missing not at random (MNAR). But when is it possible to check the correctness of a missingness graph? This is the question of *testability* under missingness, and it has received much less study than questions of recoverability and estimation. Several basic questions about testability under missingness remain open, particularly for MNAR data.

In my talk I propose to briefly introduce missingness graphs in terms of Rubin's MAR/MCAR/MNAR taxonomy (5 min); distill the current state of knowledge about testability under missingness and state the key open questions (5 min); and give a simple example, from my dissertation research on Ancient Greek demography, of how m-graphs can be applied in a discipline like history, where essentially all data is MNAR, to clarify and resolve questions that were thought to be intractable (4 min + 1 min buffer).

References

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