PAPER IN PRESS AT *NATURE REVIEWS PSYCHOLOGY*

Rethinking Graphical Causal Models

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Psychologists are often interested in causal questions. For example, a researcher might want to know the consequences of childhood adversities on mental health in adulthood. However, psychology researchers rarely use frameworks that are appropriate to inform inferences about causality, particularly if randomized manipulation is impossible due to ethical or practical concerns.

On the one hand, researchers might carefully avoid causal language, even when the underlying question is causal in nature. On the other hand, researchers might attempt to control for as many variables as possible to isolate an effect. Neither of these options is ideal: The former often creates disconnects between aims, results, and purported implications, and the latter can render estimates biased or uninterpretable.

In her 2018 paper, Julia Rohrer used illustrative examples to highlight the potential for directed acyclic graphs to facilitate causal analysis in psychology. Directed acyclic graphs are a form of graphical causal model developed years earlier by computer scientist Judea Pearl. A directed acyclic graph is composed of nodes (variables) and edges (arrows) that depict known and potential causal relations. Unlike other box-and-arrow diagrams, the approach allows only for single-headed arrows and encourages researchers to develop the assumed structure of both measured and unmeasured variables. One particular example in Rohrer's paper shaped my academic interests in the application of causal-inference tools to misinformation research.

Rohrer described a hypothetical study that found a negative association between the methodological rigour of studies and their innovativeness, after controlling for publication status. That is, the researcher stratified the analysis and found that published studies that were higher in rigour were less innovative. The researcher also found that the relationship held when examining only studies that were not published. It might be tempting to conclude on the basis of this finding that rigour limits innovativeness. However, this conclusion is not warranted, not due to any confound, but because of collider bias. To illustrate, consider two variables X and Y. Whereas confounds are variables that impact both X and Y (common causes), colliders are variables that both X and Y impact (common outcomes).

Controlling for colliders, such as via regression models or stratification, can induce spurious associations between X and Y. For instance, within the published research literature, the probability that a study is innovative increases if the study is not rigorous because a study can reach the publication threshold through either rigour or innovativeness. This relationship holds even without a causal link between innovativeness and rigour. In this situation, the collider is publication status and the researcher's use of stratification on this variable undermined any inference of causality between rigour and innovativeness.

In general, the probability of alternative causes for a given outcome changes whenever one potential cause is ruled out or fixed. Although researchers should control for confounds to rule out alternative explanations, colliders should not be included in the set of control variables. Thus, including more control variables is not always better. Rather, a directed acyclic graph can help researchers determine the appropriate analysis plan.

The greater the complexity of a causal network, the more the benefits to researchers to adopt a graphical, transparent approach to causal analysis. Directed acyclic graphs help researchers better plan and communicate their analyses and help readers better gauge the credibility of the researchers' claims. Alongside the continued development of empirical strategies (such as synthetic control and instrumental variable analyses), my hope is that the wider adoption of this approach will take psychology a step further in addressing the difficult problem of causal inference with non-experimental data.

References

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