DAGs for Causal Inference

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Figure 1: Mediation

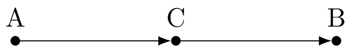


Figure 2: Mutual dependence

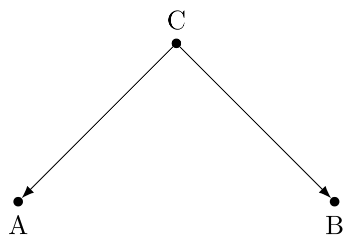


Figure 3: Mutual causation

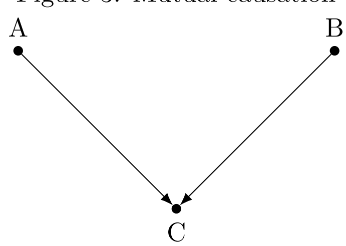
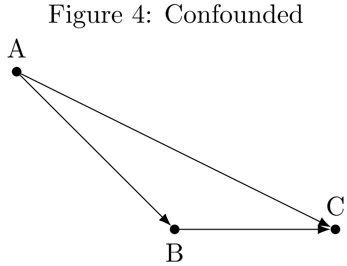


Figure 4: Confounded



Directed Acyclic Graphs (DAGs) are a foundational tool in causal inference, enabling researchers to formally represent and analyse causal relationships between variables. This short document lists key causal structures commonly depicted in DAGs, including mediation, confounding, mutual causation, and colliders. This document aims to clarify the role of DAGs in identifying causal pathways and disentangling different sources of association in empirical research.

Figure 1: Mediation. This figure shows a directed acyclic graph (DAG) with three nodes A, C, and B, where A and B are not directly connected, but there is a path from A to B through C. This type of graph represents mediation, where the effect of A on B is mediated by C.

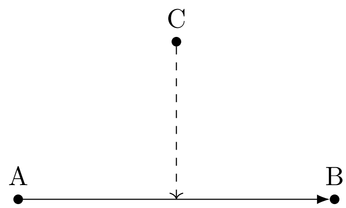
Figure 2 : Mutual dependence. This type of graph represents mutual dependence, where A and B both depend on C.

Figure 3 : Mutual causation (i.e. 'collider'). This figure shows a DAG with three nodes where A is directly connected to C and B is also directly connected to C. This type of graph represents mutual causation, where A and B both cause changes in C. In causal graphs, a collider is a variable influenced by two or more variables. The term "collider" comes from the graphical model, where the arrows from the influencing variables "collide" at the collider node. A collider blocks the direct association between its influencing variables, meaning there is no unconditional correlation between them.

Figure 4: Confounded. This is a DAG with three nodes A, B, and C, where A is directly connected to B, B is directly connected to C, and A is also directly connected to C. This type of graph represents confounding, where the effect of A on C is confounded by the effect of A on B and the effect of B on C.

Now we turn to a common issue when using DAGs as an aid for causal inference. Often, we conceptualize relationships between variables with statistical or mathematical models in mind. A common rela-

Figure 5: Moderated/Interaction



tionship used in regression models is an interaction effect.

Figure 5: This figure attempts to visually represent an interaction effect with three nodes: A, B, and C. Here, A has a direct causal effect on C, while B moderates this relationship, as indicated by the dashed line. In statistical models, this would correspond to an interaction term, meaning the effect of A on C depends on the value of B.

It is essential to distinguish between causal structures and statistical representations of interaction effects. While DAGs illustrate causal pathways, showing which variables influence others, they do not encode mathematical relationships such as additive, multiplicative, or interactive effects. Thus, Figures 1-4 represent causal factors typically analysed using a DAG, whereas Figure 5 visualises an interaction effect as used in a statistical modelling framework. In DAGs, effect moderation can sometimes be implied—for example, through a mediating process or other structural mechanisms.

Bibliography

Morgan, Stephen L, and Christopher Winship. 2007. Counterfactuals and Causal Inference: Methods and Principles for Social Research. Cambridge: Cambridge University Press.