Algorithmic Syntactic Causal Identification

Causal identification in causal Bayes nets (CBNs) is an important tool in causal inference allowing the derivation of interventional distributions from observational distributions where this is possible in principle. However, most existing formulations of causal identification using techniques such as d-separation and do-calculus are expressed within the mathematical language of classical probability theory on CBNs. However, there are many causal settings where probability theory and hence current causal identification techniques are inapplicable such as relational databases, dataflow programs such as hardware description languages, distrib-uted systems and most modern machine learning algorithms. We show that this restriction can be lifted by replacing the use of classical probability theory with the alternative axiomatic foundation of symmetric monoidal categories. In this alternative axiomatization, we show how an unambiguous and clean distinction can be drawn between the general syntax of causal models and any specific semantic implementation of that causal model. This allows a purely syntactic algorithmic description of general causal identification by a translation of recent formulations of the general ID algorithm through fixing. Our description is given entirely in terms of the non-parametric ADMG structure specifying a causal model and the algebraic signature of the corresponding monoidal category, to which a sequence of manipulations is then applied so as to arrive at a modified monoidal category in which the desired, purely syntactic interventional causal model, is obtained. We use this idea to derive purely syntactic analogues of classical back-door and front-door causal adjustment, and illustrate an application to a more complex causal model.