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Learning Causal Models via Algebraic Constraints

Abstract: One of the main tasks of causal inference is to learn direct causal relationships among observed random variables. These relationships are usually depicted via a directed graph whose vertices are the variables of interest and whose edges represent direct causal effects. In this talk we will discuss the problem of learning such a directed graph for a linear causal model. We will specifically address the case where the graph may have directed cycles. In general, the causal graph cannot be learned uniquely from observational data. However, in the special case of linear non-Gaussian acyclic causal models, the directed graph can be found uniquely. When cycles are allowed the graph can be learned up to an equivalence class. We characterize the equivalence classes of such cyclic graphs and we propose algorithms for causal discovery. Our methods are based on using specific polynomial relationships which hold among the second and higher order moments of the random vector and which can help identify the graph.