Causal Inference in Machine Learning: from prediction to decision making

Abstract

Causal questions are central to many areas of science. Does high salt intake increase the risk of heart attack? Does hormone replacement therapy reduce breast cancer risk? Would upping the minimum wage increase unemployment? These questions have in common that they require us to predict the consequences of an action. Traditionally machine learning solves problems of the form given some data, infer properties of the distribution that generated that data. These problems ask us to predict properties of the distribution after taking some action. Without experimentally testing the intervention or making assumptions that constrain how the action can change the distribution such inference is impossible.

The current approach to causal inference in fields such as economics and social science, where the variables of interest are subject to human experience, is to use expert knowledge to describe qualitatively how variables relate to one another and then fit the statistical aspects of the model. However there are problems, particularly in bioinformatics, where the number of variables is large, and we do not have sufficient direct human experience or prior theory to specify causal models. In these cases, automated causal structure learning provides the prospect of significant improvements relative to purely finding the strongest associations.

We present a survey of recent research on causality, focusing on the problems of inferring causal effects from observational data and causal structure learning. The first problem occurs when the structure of the relationship between variables is assumed to be at least partially given by theory or prior knowledge and has been addressed in some depth in statistics [5], social science [1], economics [2] and machine learning [3]. We describe how causal structural equation models unify the differing approaches to this problem and provide a complete framework to determine if and how causal queries can be inferred from observational data without parametric assumptions about the relationship between variables [6]. Causal structure learning attempts to infer causal structure from data based on more general assumptions. In particular, algorithms have been developed based on the assumption of faithfulness; that the distribution was generated by a directed acyclic graph over its variables and all the dependencies in the distribution are reflected by d-separation in that graph [7], and additive noise; effects are deterministic functions of their causes plus an additive noise term [4]. We summarise the application of these techniques on a range of practical problems and discuss their potential and limitations.

References

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