Introduction

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Most undergraduate students that take a class in introductory statistics have heard the phrase 'correlation does not imply causation'. While correlation implies co-occurrence, people are frequently interesting a causal understanding of relationships between variables. One may argue that especially in a high stake predicament, algorithmic decision making based on co-occurrence is insufficient. Causal modelling has become a pivotal tool for interpretable modelling. There are different schools of thought on how to optimally model causal relationships. Structural Causal Models and Bayesian Causal Networks are two prominent causal models. Bayesian Causal Networks cast a model based on conditional probabilities. All relationships are defined in conditional probabilities, excluding exogenous variables.

Structural Causal Models (SCM) are a nonparametric modification of structural equations models. Structural equations models (SEM) are parametric causal models which are very popular in fields like economics, psychology and sociology. Here we differentiate between these two models because I focus on SCMs rather than SEMs. While both have a similar basis, they are some differences that I will further addressed in this essay. SCMs use assignment equations to specify an underlying data-generation-process, or in short DGP.[1]

Beyond the school of thought, there is also a hierarchy of causation which Pearl introduced in 2009. This hierarchy

Another important factor in causal research is the understanding of time. Causal models mostly disregard concise notions of time and make the strong assumption that relationships between variables hold beyond the confinement of time. Nevertheless, some research has also looked at causal models with a more concrete specification of time, treating time more like one would in a physical mechanism in hard sciences. In these specifications, we can use differental equations rather than assignment equations.

Understanding statistical models beyond black-box specifications sparked the wave of interpretable machine learning. One stream of research in interpretable machine learning is causal modelling. This paper addresses the linkage between standard machine learning approaches and causal machine learning.

[1] There is a lot of confusion around equations and what exactly they imply. Here we call them assignment equations rather than just equations to ensure that there is no misconception. I want to clarify that I mean equations as used in a computer science rather than an equation in mathematics.

Existing literature has provided an excellent introduction to structural causal models and bayesian causal networks. Judea Pearl (2009) provided a comprehensive and accessible introduction into this topic with his book on causality. Peters et al. (2017) added some elements, paying a lot of attention to the similarities and differences between causal modelling and physical sciences.

This paper brings together these contributions and attempts to provide a comprehensive summary of structural causal models. The insights in this paper are an abstraction of these pieces of work, offering the reading a basic understanding of the topic for future research and an overview of the current research.

The subsequent section examines central assumptions in causal modelling. The second section looks at the difference SCMs and BCNs. The section thereafter studies the hierachy of causation, looking at the different queries in the SCM and the BCN.