

A Gentle Introduction into Structural Causal Models

Daniel Saggau • `daniel.saggau@campus.lmu.de`

Department of Statistics, Ludwig Maximilian University Munich, Germany

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Abstract

This paper provides a gentle introduction into causal inference, focusing on structural causal models and respective causal graphs. The first section provides introduces probabilities and will focus on clarifying the difference between observations and causal concepts. The second section discusses the hierarchy of causation. The third section discusses causal graphs.

Topic 1: Structural Causal Models (SCMs) Structural Causal Models are a general framework to describe data generating mechanisms. The values of variables are described as functions of exogenous and endogenous variables. These mechanisms can also be described with directed graphs. Typically one requires for the endogenous variables to fulfill causal sufficiency and the corresponding graph to be acyclic. Also, one requires mechanisms to be independent. The student should convey and explain the notation on a number of examples and explain the motivation and role of the aforementioned assumptions.

1 Introduction

1.1 Time in Causality

In causal research, we are interested in the relationship of our variables outside of a fixed time frame. We want to capture relationships that hold outside of an available dataset and results are intended to be generalizable to other time periods (other datasets).

1.2 SEM and Structural Causal Model

A lot of research ignores the distinction between structural equation models (SEM) and structural causal models (SCM). Essentially, the SCM builds on the SEM but there are some differences. Firstly, the structural equation model specification stems from disciplines like economics and psychology and is inherently a parametric specification. The SCM on the other hand is a non-parametric specification. Secondly, the SCM allows one to create causal graphs.¹

¹Note that we can also create causal graphs with other models like a bayesian causal network

Nevertheless, both models also have a lot in common.

There are a number of reasons why people are interested in structural causal models. We can specify exogenous and endogenous variables in our model specification. When all our variables are fully specified within our model specification (endogenous variables only) we have a deterministic SCM.

Note that while this is very unreasonable because we assume we can explain all exogenous error terms and further we assume that there are no unobserved variables. Henceforth, when applying these models, they are seldom fully deterministic.

Further, we are specifying the relationship in functional form.

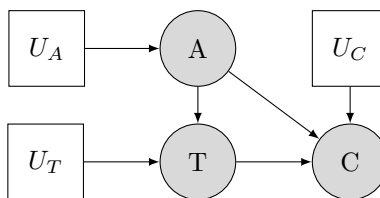


Figure 1: Structural Causal Model

2 Common Queries in Causal Models

Table 1: Pearl - Hierarchy of Causation

Method	Action	Example
Prediction	Observation/Co-occurrence	What happened...
Intervention	Do-manipulation	What happens if ...
Counterfactual	Hypothetical Realities	What would have happened if...

2.1 Prediction

2.2 Intervention

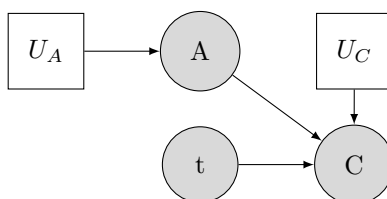


Figure 2: Atomic Intervention

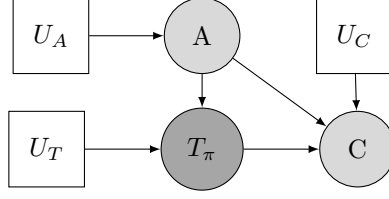


Figure 3: Policy Intervention

2.3 Counterfactuals

Process is described as follows:

- (a) Abduction: Cast probability $P(u)$ as conditional probability $P(u|\epsilon)$
- (b) Action: Exchange ($X = x$)
- (c) Prediction: Compute ($Y = y$)

2.4 Bayesian Models vs. SCM

2.5 Probabilistic Models vs SCMs

Method	CBN	SCM
Prediction	<ul style="list-style-type: none"> • Unstable • Volatile to parameter changes • Re-Estimate entire model 	<ul style="list-style-type: none"> • Stable • More Natural Specification • Only estimate Δ CM
Intervention	<ul style="list-style-type: none"> • Costly for Non-Markovian Models • Unstable(Nature CP) • Only generic estimates(Δ CP) 	<ul style="list-style-type: none"> • Pot. Cyclic Representation • Stable(Nature Eq.) • Context specific(Invariance of Eq.)
Counterfactuals	<ul style="list-style-type: none"> • Impossible • no information on latent factors(ϵ) 	<ul style="list-style-type: none"> • Possible • Inclusion of latent factors