Causal Inference in Multi-Agent Causal Models

Sam Maes, Stijn Meganck, Bernard Manderick

Computational Modeling Lab,
Vrije Universiteit Brussel,
Pleinlaan 2 - 1050 Brussel,
sammaes, smeganck, bmanderi@vub.ac.be,
http ://como.vub.ac.be

1 Introduction

This paper treats the calculation of the effect of an intervention (also called causal effect) on a variable from a combination of observational data and some theoretical assumptions. Observational data implies that the modeler has no way to do experiments to assess the effect of one variable on some others, instead he possesses data collected by observing variables in the domain he is investigating.

The theoretical assumptions are represented by a semi-Markovian causal model (SMCM), containing both arrows and bi-directed arcs. An arrow indicates a direct causal relationship between the corresponding variables from cause to effect, meaning that in the underlying domain there is a stochastic process *P(effect|cause)* specifying how the effect is determined by its cause. Furthermore this stochastic process must be autonomous, i.e., changes or interventions in *P(effect|cause)* may not influence the assignment of other stochastic processes in the domain. A bi-directed arc represents a spurious dependency between two variables due to an unmeasured common cause (Tian and Pearl, 2002), this is also called a confounding factor between the corresponding variables.

Deciding if a causal effect is identifiable (i.e. can be computed) in a SMCM amounts to assessing whether the assumptions of a diagram are sufficient to calculate the effect of the desired intervention from observational data. When all variables of a domain can be observed, all causal effects are identifiable. In the presence of unmeasured confounders, identifiability becomes an issue (e.g. the causal effect of X on Y is not identifiable in the causal diagram of Figure 1, since we can not distinguish causal influence from X to Y form the influence via the unobserved confounder (Pearl, 2000).

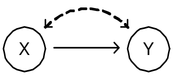

FIG. 1 – *The causal effect of X on Y is not identifiable in this SMCM.*

In this paper we introduce an algorithm for the identification of causal effects in a context where no agent has complete access to the overall domain. Instead we consider a multi-agent approach where several agents each observe only a subset of the variables. The main advantages of the multi-agent solution is that the identification of causal