Understanding Causal Inference with Causal Statistical Decision Theory

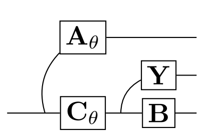
Abstract

We develop *causal statistical decison theory* (CSDT) a novel theory of causal inference which we derive by introducing the idea that "decisions have consequences" to statistical decision theory. CSDT features *causal theories* as the central object of study. We show that causal Bayesian networks have a natural representation as a causal theory and that potential outcomes models may arguably be represented as causal theories as well. In both cases the resulting theories feature unreasonably rich sets of decisions, which we suggest is because both approaches aim to produce reusable causal models. Using causal theories, we investigate reusability – when can knowledge gained using one causal theory be applied to another – and show that this is possible when the theories are related by a *coarsening*.

1 Invariance and Capital C Causality

CSDT features *consequences* - that is, probabilistic relations between decisions and results - but it does not feature *causal effects*, which seem to be probabilistic relations between random variables on the observation space E that are not necessarily disintegrations of a joint distribution. Here is a provisional account of how causal effects might arise in CSDT.

Suppose $\mathbf{C} : D \times \Theta \to \Delta(\mathcal{E})$ is the consequence of interest, and furthermore that given some $\theta \in \Theta$, the observations are distributed according to



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References

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Appendix: