

# Causal Discovery in Non-Ideal Frameworks

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## **Abstract**

*A Causal Bayesian network (CBN) is a well-known technique to represent causal relations between variables. To learn the causal relations, experiments are needed in general because from observational data alone we can only learn up to Markov equivalence. The elicitation of this causal information from data provides useful insight in the system under study. Most existing algorithms for causal discovery implicitly assume a setting where all variables of the system under study are known and sufficient amount of data is present to perform reliable statistical tests. These assumptions provide an ideal framework, which facilitates the discovery task significantly. In this article we use existing techniques from this ideal setting as a starting point for new algorithms in non-ideal settings. We present two algorithms, UnCaDo and MyCaDo++, which can be used when insufficient data is present to perform statistical tests reliably and when there are latent variables respectively. Both techniques provide experimentation plans to recover the causal structure.*

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