Causal identification with Y_0

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Summary

Researchers often want to know whether one thing causes another—for example, does a new medication reduce symptoms, or does education improve income? While randomized controlled experiments provide the most direct evidence for causal relationships, they are often impossible, unethical, or prohibitively expensive to conduct for the specific questions researchers want to answer. Causal inference provides statistical methods to answer cause-and-effect questions using whatever data is available—whether observational data (collected by observing the world as it naturally occurs), experimental data from controlled studies, or a combination of both. However, determining causation is challenging because correlation does not imply causation, and many confounding factors can create misleading associations.

A key step in any causal analysis is **causal identification**—determining whether it's theoretically possible to estimate a causal effect from available data, given assumptions about relationships between variables. Causal questions exist at different levels: **interventional queries** ask "What would happen if we intervene?" (e.g., "What would be the average effect if everyone received treatment?"), while **counterfactual queries** ask "What would have happened to specific individuals in an alternative scenario?" (e.g., "Would this patient who recovered have recovered anyway without treatment?"). Modern causal identification also addresses **transportability**—determining when causal findings from one population can be validly applied to another, and how to combine evidence from multiple studies or populations to draw conclusions about a target group of interest.

The Y_0 Python package addresses a gap in the current software ecosystem by providing causal identification algorithms that handle interventional queries, counterfactual queries, and transportability challenges across different types of data. While several excellent packages exist for estimating causal effects once identification is established, Y_0 focuses specifically on the identification step—helping researchers determine *whether* a causal relationship can be estimated from their available data (observational, experimental, or mixed) before attempting to estimate *how strong* that relationship is. Y_0 provides a domain-specific language for expressing causal queries, tools for representing graphical causal models that incorporate various data types from single or multiple populations, and implementations of numerous identification algorithms from the causal inference literature.

State of the Field

Several open source packages in the Python programming language have implemented the most simple identification algorithm (`ID`) from Shpitser & Pearl (2006) including Ananke (J. J. R. Lee et al., 2023), pgmpy (Ankan & Panda, 2015), DoWhy (Sharma & Kiciman, 2020), and causaleffect-py (Pedemonte et al., 2021). Further, Ananke and DoWhy implement algorithms that consume the estimand returned by `ID` and observational data in order to estimate the average causal effect of an intervention on the outcome. However, these methods are limited in their generalization when causal queries include multiple interventions, multiple outcomes, conditionals, or interventions.

In the R programming language, the causaleffect package (Tikka & Karvanen, 2017a) implements ID, IDC (Shpitser & Pearl, 2008), surrogate outcomes (TRSO) (Tikka & Karvanen, 2019), and transport (S. Lee et al., 2020). The cfid package from the same authors (Tikka, 2023) implements ID* (Shpitser & Pearl, 2012) and IDC* (Shpitser & Pearl, 2012). However, these packages are challenging to use and extend.

Finally, CausalFusion is a web application that implements many identification and estimation algorithms, but is neither open source, available for registration of new users, nor provides documentation.

Causal inference remains an active research area where new identification algorithms are regularly published (see the recent review from Tikka et al. (2021)), but often without a reference implementation. This motivates the implementation of a modular framework with reusable data structures and workflows to support the implementation of both previously published and future algorithms and workflows.

Implementation

Probabilistic Expressions Y_0 implements an internal domain-specific language that can capture variables, counterfactual variables, population variables, and probabilistic expressions in which they appear. It covers the three levels of Pearl's Causal Hierarchy (Bareinboim et al., 2022), including the probability of sufficient causation $P(Y_X \mid X^*, Y^*)$, necessary causation $P(Y_{X^*}^* \mid X, Y)$, and necessary and sufficient causation $P(Y_X, Y_{X^*}^*)$. Expressions can be converted to SymPy (Meurer et al., 2017), LaTeX expressions, and be rendered in Jupyter notebooks.

Data Structure Y_0 builds on NetworkX (Hagberg et al., 2008) to implement an (acyclic) directed mixed graph data structure, used in many identification algorithms, and the latent variable graph structure described by Evans (2016). It includes a suite of generic graph operations, graph simplification workflows such as the one proposed by Evans, and conversion utilities for Ananke, CausalFusion, pgmpy, and causaleffect.

Falsification Y_0 implements several workflows for checking the consistency of graphical models against observational data. First, it implements D-separation (Pearl, 2009), M-separation (Drton & Richardson, 2004), σ-separation (Forré & Mooij, 2018) that are applicable to increasingly more generic mixed graphs. Then, it implements a workflow for identifying conditional independencies (Pearl et al., 1989) and falsification (Eulig et al., 2023). Finally, it provides a wrapper around causaleffect through rpy2 for calculating Verma constraints (Tian & Pearl, 2012).

Identification Y_0 has the most complete suite of identification algorithms of any causal inference package. It implements ID (Shpitser & Pearl, 2006), IDC (Shpitser & Pearl, 2008), ID* (Shpitser & Pearl, 2012), IDC* (Shpitser & Pearl, 2012), surrogate outcomes (TRSO) (Tikka & Karvanen, 2019), tian-ID (Tian & Shpitser, 2010), transport (S. Lee et al., 2020), counterfactual transport (Correa et al., 2022), and identification for causal queries over hierarchical causal models (Weinstein & Blei, 2024).

Case Study

We present a case study regarding the effect of how smoking relates to cancer. First, we construct a graphical model (Figure 1A) representing the following prior knowledge:

1. Smoking causes an accumulation of tar in the lungs
2. Accumulation of tar in the lungs increase the risk of cancer
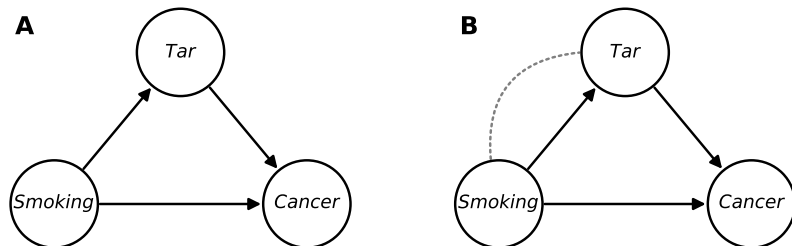3. Smoking itself also increases the risk of cancer

Figure 1: A) A simplified acyclic directed graph model representing prior knowledge on smoking and cancer and **B**) a more complex acyclic directed mixed graph that explicitly represents confounding variables.

The identification algorithm (`ID`) (Shpitser & Pearl, 2006) estimates the effect of smoking on the risk of cancer in Figure 1A as $\sum_{Tar} P(Cancer|Smoking, Tar)P(Tar|Smoking)$. However, the model in Figure 1A is inaccurate because it does not represent confounders between smoking and tar accumulation, such as the choice to smoke tar-free cigarettes. Therefore, we add a *bidirected* edge in Figure 1B. Unfortunately, `ID` can not produce an estimand for Figure 1B, which motivates the usage of an alternative algorithm that incorporates observational and/or interventional data. For example, if data from an observational study (π^*) and data from an interventional trial on smoking (π_1) are available, the TRSO algorithm (Tikka & Karvanen, 2019) estimates the effect of smoking on the risk of cancer in Figure 1B as $\sum_{Tar} P^{\pi^*}(Cancer|Smoking, Tar)P_{\text{Smoking}}^{\pi_1}(Tar)$. Code and a more detailed description of this case study can be found in the following Jupyter notebook.

We provide a second case study demonstrating the transport (S. Lee et al., 2020) and counterfactual transport (Correa et al., 2022) algorithms for epidemiological studies in COVID-19 in this Jupyter notebook.

We highlight several which used (and motivated further development of) Y_0:

- Mohammad-Taheri et al. (2022) used Y_0 to develop an automated experimental design workflow.
- Mohammad-Taheri et al. (2023) used Y_0 for falsification against experimental and simulated data for several biological signaling pathways.
- Mohammad-Taheri et al. (2024) used Y_0 and Ananke to implement an automated causal workflow for simple causal queries compatible with `ID`.
- Ness (2024) used Y_0 as a teaching tool for identification and the causal hierarchy

Future Directions

There remain several high value identification algorithms to include in Y_0 in the future. For example, the cyclic identification algorithm (`ioID`) (Forré & Mooij, 2019) is important to work with more realistic graphs that contain cycles, such as how biomolecular signaling pathways often contain feedback loops. Further, missing data identification algorithms can account for data that is missing not at random (MNAR) by modeling the underlying missingness

mechanism (Mohan & Pearl, 2021). Several algorithms noted in the review by Tikka et al. (2021), such as generalized identification (gID) (S. Lee et al., 2019) and generalized counterfactual identification (gID*) (Correa et al., 2021), can be formulated as special cases of counterfactual transportability. Therefore, we plan to improve the user experience by exposing more powerful algorithms like counterfactual transport through a simplified APIs corresponding to special cases like gID and gID*. Similarly, we plan to implement probabilistic expression simplification (Tikka & Karvanen, 2017b) to improve the consistency of the estimands output from identification algorithms.

It remains an open research question on how to estimate the causal effect for an arbitrary estimand produced by an algorithm more sophisticated than ID. Two potential avenues for overcoming this might be a combination of the Pyro probabilistic programming langauge (Bingham et al., 2018) and its causal inference extension ChiRho. Tractable circuits (Darwiche, 2022) also present a new paradigm for generic estimation. Such a generalization would be a lofty achievement and enable the automation of downstream applications in experimental design.

Availability and Usage

y0 is available as a package on PyPI with the source code available at https://github.com/y0-causal-inference/y0, archived to Zenodo at doi:10.5281/zenodo.4432901, and documentation available at https://y0.readthedocs.io. The repository also contains an interactive Jupyter notebook tutorial and notebooks for the case studies described above.

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