

Types of graphical causal models

A graphical causal model (GCM) comprises a graphical structure of causal relationships (e.g., $X \rightarrow Y$) and causal mechanisms (i.e., $P(Y|X)$) that describe the (conditional) distribution of each node. In other words, a GCM aims at representing the true data generation process. For a given set of variables X_0, \dots, X_n , a GCM models the joint distribution that can be factorized as $P(X_0, \dots, X_n) = \prod_i P(X_i|PA_i)$ where PA_i are the parents of X_i , which could be an empty set in the case of root nodes. The causal mechanism $P(X_i|PA_i)$ may require additional constraints depending on the type of causal questions.

Pearl identifies three levels on the ladder of causality:

1. Association: Evaluate and reason using observational data $P(X_0, \dots, X_n)$. This level is common for machine learning prediction problems.
2. Intervention: Execute interventions and estimate causal effects. This level is most relevant for causal effect estimation questions, where we obtain interventional distributions in the form $P(Y|do(X = \dots))$.
3. Counterfactuals: Estimate counterfactual outcomes of observed events. The main difference between interventions and counterfactuals is that interventions focus on “forward-looking” questions like “What will happen if we change X?”, while counterfactuals examine hypothetical scenarios that deviate from the actual observed event, such as “What if X had taken a different value, how would our observation have been?”.

Estimating counterfactuals in Pearl’s framework demands stronger assumptions on causal mechanisms compared to those needed for estimating interventions. DoWhy offers three different classes with varying degrees of causal mechanism flexibility:

ProbabilisticCausalModel (PCM): A PCM provides the greatest flexibility in modeling causal mechanisms, as it only requires generating samples conditioned on a node’s parents. Any model that can handle conditional distributions, such as a wide array of Bayesian models, can be

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StructuralCausalModel (SCM): An SCM limits mechanisms to a deterministic functional causal model (FCM) of parents and unobserved noise, represented as $X_i = f_i(PA_i, N_i)$, where N_i denotes unobserved noise. When fitting the FCM, the model needs to be capable of accounting for the assumption that N_i is unobserved, but can be used as an input when provided. A SCM generally allows modeling rungs 1 and 2, but additional constraints on the FCM are necessary to model rung 3.

InvertibleStructuralCausalModel (ISCM): An ISCM is an SCM that further requires the underlying FCMs of nodes to be invertible with respect to noise, meaning the noise can be reconstructed from the observed data. This additional constraint reduces model flexibility but is required for modeling rung 3. With invertible models, we can address (sample-specific) counterfactual questions. A typical example of an invertible FCM for continuous variables is an additive noise model (ANM) of the form $X_i = f_i(PA_i, N_i) = f'_i(PA_i) + N_i$, which can be learned using standard regression models. The noise then becomes simply the residual.

For causal questions like treatment effect estimation, modeling rung 2 is sufficient. On the other hand, to determine root causes by asking “Would the target have been an outlier if node X behaved differently?”, rung 3 is required. The following provides an overview of available types of causal mechanisms that are supported out-of-the box:

Available Causal Mechanisms

To support causal mechanisms that can be used for any of the types of causal models above, we have simple interfaces that a causal mechanism needs to implement. For instance, to use a causal mechanism in a PCM, one only needs to implement a method that expects samples from the parent nodes and returns samples from the conditional distribution. Having these lightweight interfaces allows easily using your own and customized types of causal mechanisms for different use cases. However, DoWhy also has different types of mechanisms, specifically functional causal models, implemented natively supporting different types of data:

- [Additive Noise Models](#) (continuous data) of the form $X_i = f_i(PA_i) + N_i$, where f_i can be any kind of regression function (e.g., from scikit-learn) and the noise N_i is unobserved noise. When fitting an ANM, this then boils down to fitting the f_i model (e.g., via least squares) and fitting N_i based on the residuals $N_i = X_i - f_i(PA_i)$. As mentioned throughout the user guide, ANMs are the most commonly used types of causal models due to their simplicity and ability to answer counterfactual questions.

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- [Post-nonlinear Models](#) (continuous data) of the form $X_i = g_i(f_i(PA_i) + N_i)$, where g_i is assumed to be invertible. These are a generalization of ANMs, allowing more complex relationships between N_i and PA_i .
- [Discrete Additive Noise Models](#) (discrete data), which have a similar definition as ANMs but are restricted to discrete values.
- [Classifier-based Functional Causal Models](#) (categorical data) of the form $X_i = f_i(PA_i, N_i)$, which cannot be used for rung 3 queries, since f_i is typically not invertible here with respect to N_i , but can be used for algorithms relying only on interventional queries (rung 2). Here, f_i can be based on any classification model (e.g., from scikit-learn) and N_i is by definition a uniform distribution on $[0, 1]$ used to sample from the conditional class probabilities.

In all mechanisms, causal sufficiency is assumed, i.e., N_i is assumed to be independent of PA_i . More details and justification of these types of causal mechanisms can be found in the correspondingly linked papers. Note that when using the auto assignment function, DoWhy tries to use invertible FCMs, such as ANMs, due to their flexibility in addressing rung 3 queries. For categorical data, make sure to represent them as strings.

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