



## Too Long; Didn't Read

We extend causal reasoning to arbitrary partitions of the variables in a causal graph.

## Cluster-DAG Framework

In many domains, the full causal diagram is **unknown**. **Cluster DAGs (C-DAGs)** provide a **coarser abstraction**:

- Variables are grouped into **clusters**.
- Only **inter-cluster relations** are shown.
- Each C-DAG represents a **collection of compatible graphs**.

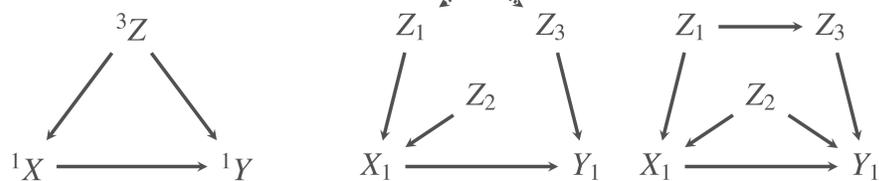


Figure 1. A C-DAG (left) and two compatible graphs (middle and right).

**Key result.** The original calculus is shown to be **sound and complete for causal effect identification** in the original setting.

**Limitation.** The partition had to be **admissible**, i.e., the resulting C-DAG had to be **acyclic**.

**Our contribution.** We **remove the acyclicity constraint**, allowing reasoning with **any partition** of variables.

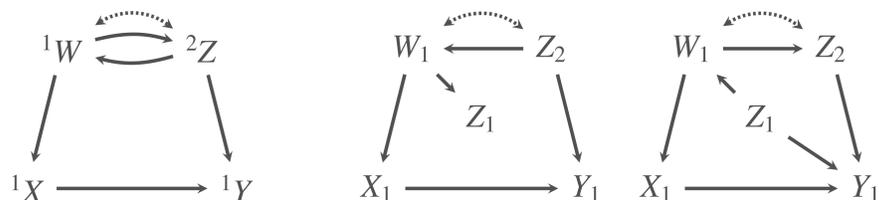


Figure 2. A cyclic C-DAG (left) and two compatible graphs (middle and right).

## D-separation via Structures of Interest

**Definition.** A **structure of interest**  $\sigma$  is an ADMG, with a single connected component, in which each node  $V$  satisfies the following property:

- $V$  has at most one outgoing arrow, or,
- $V$  has two outgoing arrows but no incoming arrow.

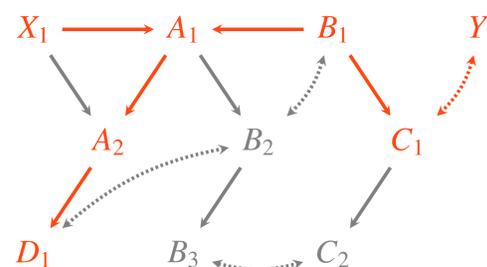


Figure 3. A causal graph containing a structure of interest in orange, that connects  $X_1$  and  $Y_1$  under  $\{D_1, C_1\}$ .

**Theorem (D-connection with structures of interest).** Let  $\mathcal{G}$  be an ADMG. Let  $\mathcal{X}, \mathcal{Y}, \mathcal{Z}$  be pairwise disjoint subsets of nodes of  $\mathcal{G}$ . The following properties are equivalent:

- $\mathcal{X} \perp_{\mathcal{G}} \mathcal{Y} \mid \mathcal{Z}$ ,
- $\mathcal{G}$  contains a structure of interest  $\sigma$  such that  $\mathcal{X} \perp_{\sigma} \mathcal{Y} \mid \mathcal{Z}$ .

**Structures of interest:**

- Encode all the **information required for d-connection**,
- Allow **efficient reasoning** over compatible ADMGs by avoiding an explicit path search.

## Example of causal reasoning

In Figure 2, the following identities hold for all compatible graphs:

$$P(y_1 \mid \text{do}(x_1)) = \sum_{w_1, z_1, z_2} P(y_1 \mid x_1, w_1, z_1, z_2) P(w_1, z_1, z_2)$$

$$P(x_1 \mid \text{do}(w_1)) = P(x_1 \mid w_1)$$

## A Sound and Complete Calculus

**Key result.** For each **do-calculus rule**, we can test whether it holds for **all compatible graphs** without having to enumerate them.

The calculus provides **three rules** (R1, R2, R3) that mirror Pearl's do-calculus:

- Each rule checks for the **absence of certain structures of interest** in modified versions of the C-DAG,
- If no such structure exists, the corresponding causal manipulation is valid,
- This avoids explicit enumeration of **infinitely many** compatible ADMGs.

**Theorem.** The calculus is **sound and atomically complete** for causal reasoning over C-DAGs.

## Computational Efficiency

Reasoning over C-DAGs with large clusters can be computationally expensive.

**Theorem (Infinity is at most 3).** For any C-DAG  $\mathcal{C}$  and any do-calculus rule  $R$ , the following are equivalent:

- There exists an ADMG compatible with  $\mathcal{C}$  in which  $R$  does not hold.
- There exists such an ADMG, using only **clusters of size at most 3**, in which  $R$  does not hold.

**Implication.** Large clusters can be safely **reduced to size 3**, preserving causal validity while **drastically simplifying computation**.

This makes the calculus **practically efficient** even for complex abstractions.