# Cost-effectively Identifying Causal Effects When Only Response Variable is Observable


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Learning And Mining from DatA

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## Problem setting

- **Goal:**

In this paper, we aim to identify the **causal effects** of each variable $X_i$ (covariates) on the **response variable** Y (target/outcome/reward) in Pearl's causal framework.

- **Basic assumptions:**

  **Causal sufficiency** + **Faithfulness**.

- **Input:**

  observational data of full variables (X and Y).

- **By:**

Discovering related **causal relations** by introducing **interventions** (causal discovery with both observational and interventional data) and estimate the causal effects by **back-door (adjustment) criterion**.

- **Main difference between ours and previous methods:**

In real tasks, it is hard to observe full variables under intervention. We consider such a setting, that **only response variable** is observed under intervention.

- **Mission:**

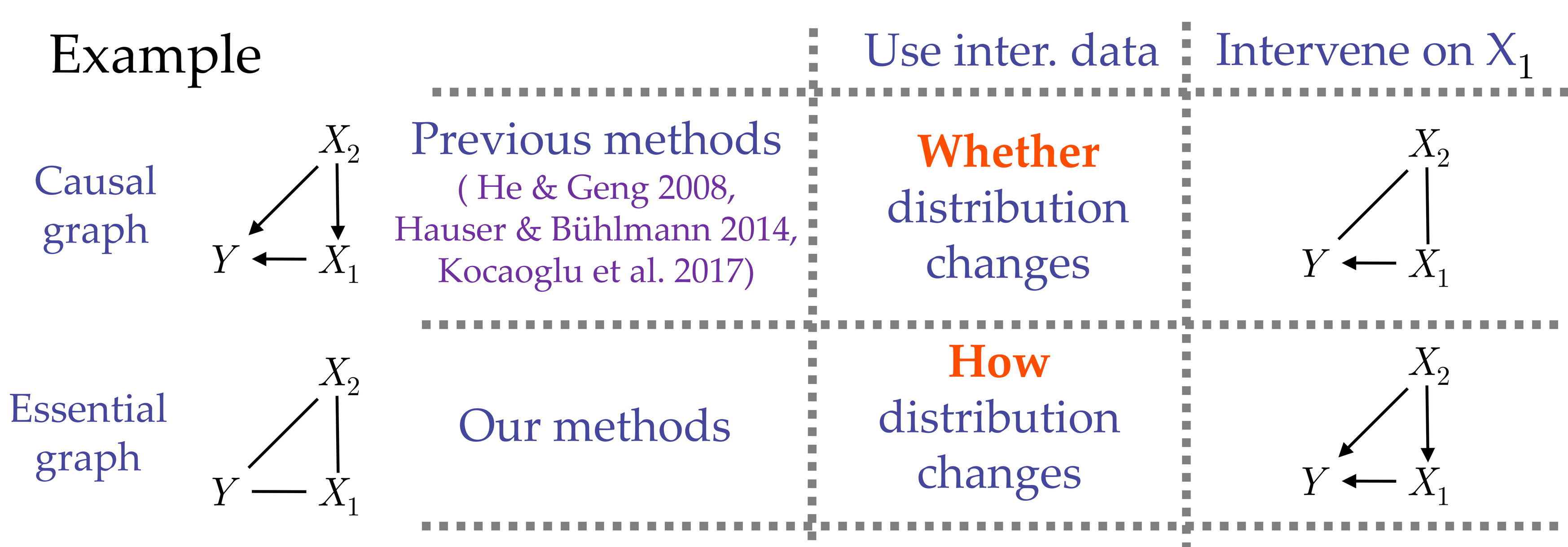
Observational data of full variables

Interventional data of Y

→ Causal effect identification of each $X_i$ on Y

## Main innovation

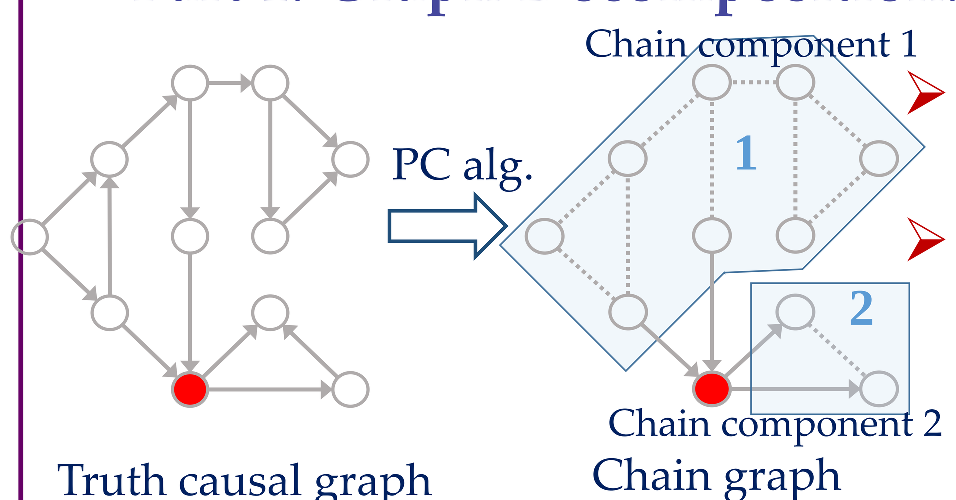
- **How to use the interventional data:**




- **An active intervention strategy to identify causal effects:**

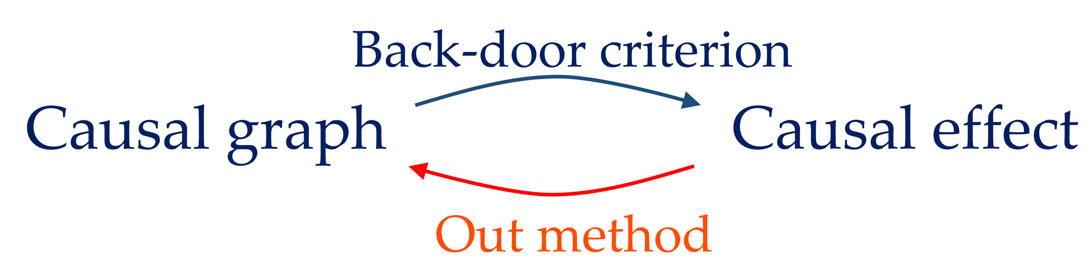
## The ACI Algorithm

- **Begin from Essential graph obtained by observational data.**
- **Part 1: Graph Decomposition.**

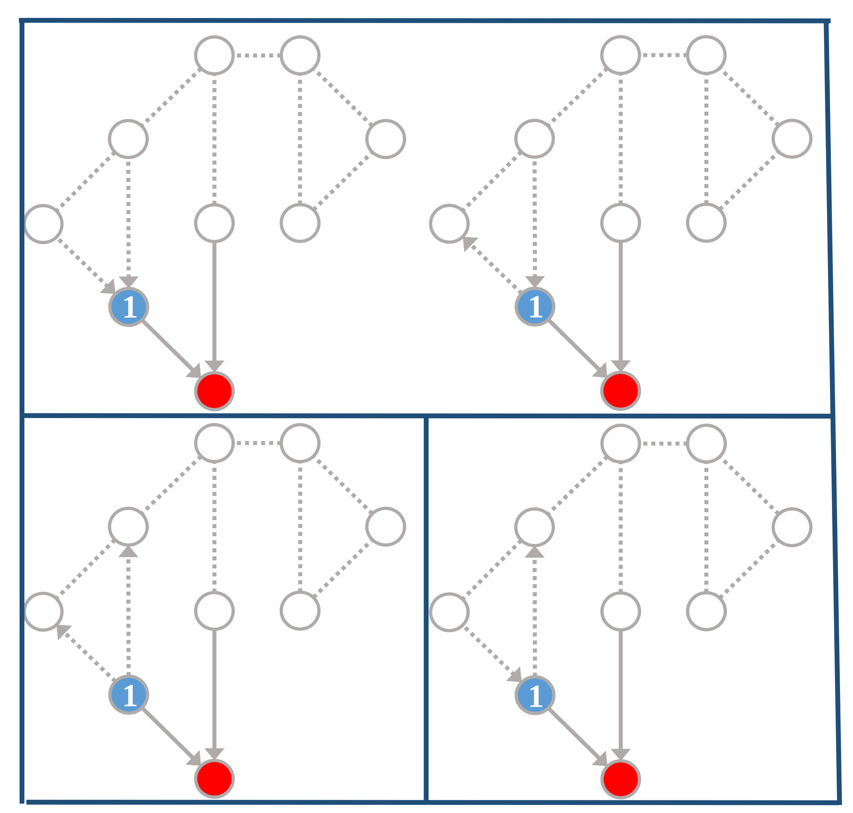



- Causal discovery in each chain component is independent;
- Ignore the chain component which has no directed path to Y in the chain graph.

- **Part 2: Structure Inference.**




Idea: use back-door criterion reversely

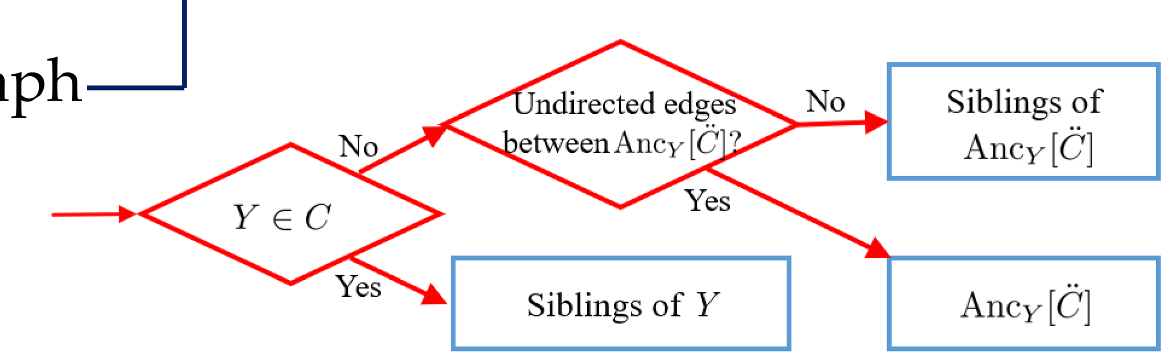


1. Orient undirect edges of the intervened variable ;
2. Find Minimal parental back-door admissible set for each oriented graph and classify them by the set;
3. Estimate the causal effects on Y in each class and compare them to interventional data of Y.

- **Part 3: Intervention Variable Selection.**
  - **Goal:**
    - At least one ancestor edges can be identified;
    - Discover more undirected edges.
  - **Step 1:**

    Select a set as the graph
  - **Step 2:**

    Select the variable with the maximum sibling in the set




## Theoretical analysis

- **Identifiability**

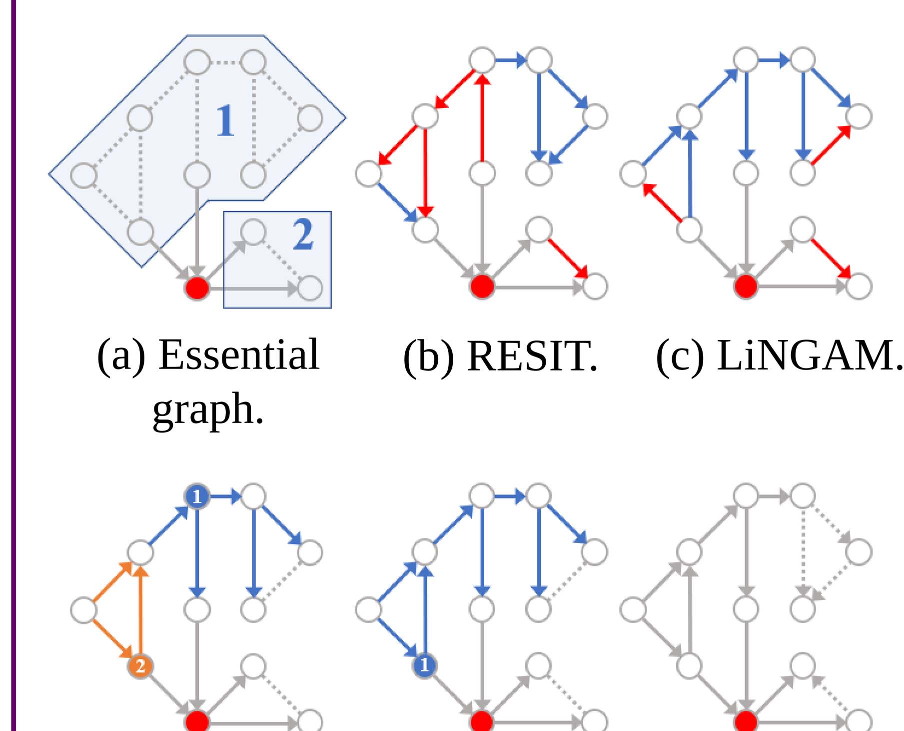
Under the interventional-faithfulness assumption, the ancestor causal structure is identifiable, which leads to the identifiability of the causal effect of each variable on Y.

- **Intervention times analysis**

| | Ratio of Inter. times | Ours | Eberhardt (2007) |
|---|---|---|---|
| Complete causal graph | Y is at the last position | 2/3 | 2/3 |
| | Y is in random position | 5/6 | 1/3 |

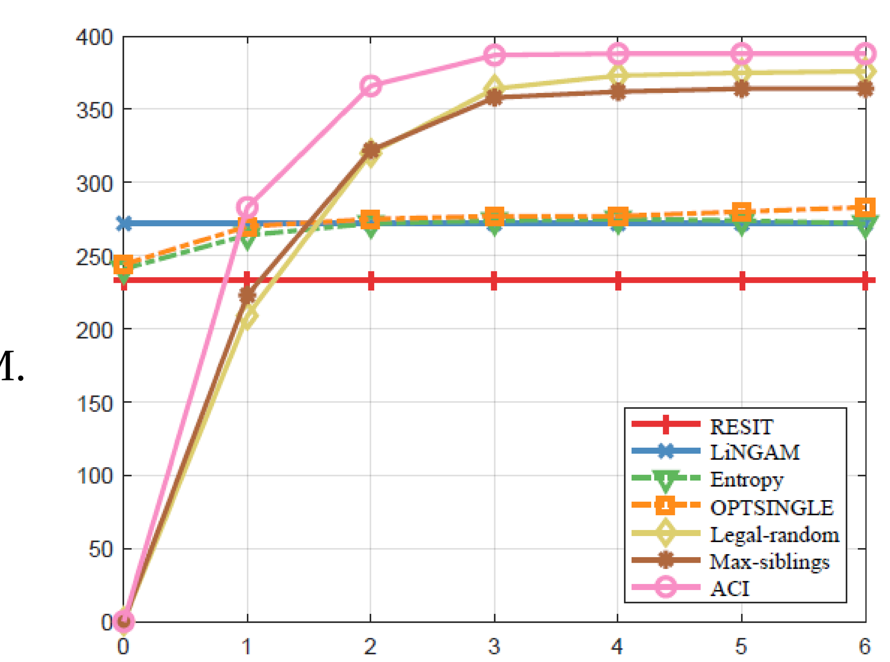
## Experiments

**Experimental process:**




(a) Essential graph. (b) RESIT. (c) LiNGAM. (d) Entropy-full & OPTSINGLE-full (e) ACI. (f) Causal graph.

**Simulation**




The number of newly identified ancestor edges as the intervention times grow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