Practical do-Shapley Explanations with Estimand-Agnostic Causal Inference

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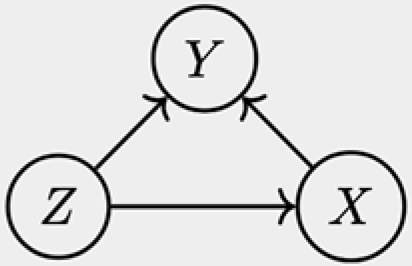
Introduction

- **Goal**: make causal explanations practical.
- **do-SHAP** (Jung et al. 2022): Shapley Values with *causal interventional* effects.

$$\phi_{\mathbf{x}}(X_k) = \sum_{\mathbf{S} \subseteq \mathbf{X} \setminus \{X_k\}} w(|\mathbf{S}|) \cdot (\nu_{\mathbf{x}}(\mathbf{S} \cup \{X_k\}) - \nu_{\mathbf{x}}(\mathbf{S})), \quad \nu_{\mathbf{x}}(\mathbf{S}) = \mathbb{E}[Y \mid do(\mathbf{S} = \mathbf{x}_{\mathbf{S}})]$$

- Two main **contributions**:
  1) A method to estimate $\nu_{\mathbf{x}}(\mathbf{S})$ in an automatable, practical way.
  2) A method to reduce the number of coalitions that need to be evaluated.

Jung, Y., Kasiviswanathan, S., Tian, J., Janzing, D., Blöbaum, P., & Bareinboim, E. (2022, June). On measuring causal contributions via do-interventions. In *International Conference on Machine Learning* (pp. 10476-10501). PMLR.

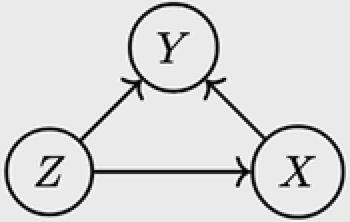


1) Why is do-SHAP impractical?

- By default, do-SHAP employs the **Estimand-Based approach**.
- Given a query (e.g., the effect of X on Y), compute an **estimand** of the query.

$$P_x(Y) = \mathbb{E}_Z\left[P(Y \mid x, Z)\right]$$

Estimand-Based approach



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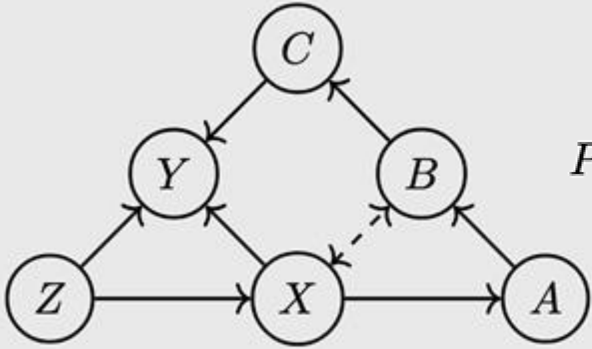
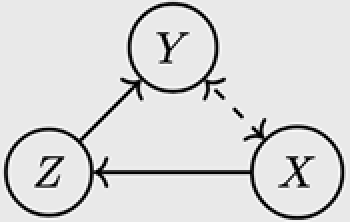




$$P_x(Y) = \mathbb{E}_{Z|x}\left[\mathbb{E}_X\left[P(Y \mid X, Z)\right]\right]$$

$$P_x(Y) = \mathbb{E}_{Z,C}\left[\frac{P(Y \mid x, Z, C)}{P(Z, C)} \cdot \mathbb{E}_{A|x}\left[\mathbb{E}_X\left[P(Z, C \mid X, A)\right]\right]\right]$$

Parafita, Á. (2022). *Causality without Estimands: from Causal Estimation to Black-Box Introspection* (Doctoral dissertation, Universitat de Barcelona (Spain)).

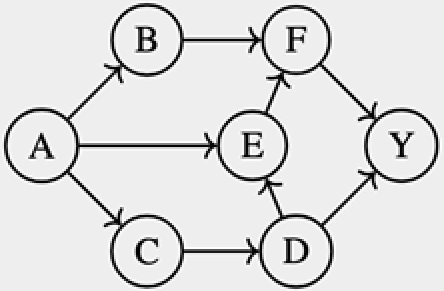
Estimands are impractical for do-SHAP

- **Problem**: do-SHAP needs to evaluate multiple queries, one per coalition:

$$\nu_{\mathbf{x}}(\mathbf{S}) = \mathbb{E}[Y \mid do(\mathbf{S} = \mathbf{x_S})]$$

- **Alternative:** Estimand-Agnostic Approach.
    - Train **a single Structural Causal Model**, following the known graph.
    - Use **general estimation procedures** to estimate any $\nu_{\mathbf{x}}(\mathbf{S})$.
- Guaranteed results as long as the queries are **identifiable.**

2) Reduce coalition evaluations



- Remove all **superfluous** nodes from any coalition.

$$\left.\begin{array}{l}\{A, B, C, E, F\},\ \{A, B, C, F\},\\ \{A, E, C, F\},\ \{B, E, C, F\},\\ \{A, C, F\},\ \{B, C, F\},\ \{E, C, F\}\end{array}\right\} = \{C, F\}$$

- **Cache**: only compute and store values for irreducible coalitions.

How to find the irreducible coalition?

Theorem. Given a topological order $<_{\mathcal{G}}$ in $\mathcal{G}$ and $\mathbf{S} \subseteq \mathbf{X}$, let $\mathbf{Z} := \{X \in \mathbf{S} \mid \mathbf{S}_{>_{\mathcal{G}} X} \in Fr_{\mathcal{G}}(X, Y)\}$, with $\mathbf{S}_{>_{\mathcal{G}} X} := \{Z \in \mathbf{S} \mid Z >_{\mathcal{G}} X\}$. Then $\nu(\mathbf{S}) = \nu(\mathbf{S} \setminus \mathbf{Z})$, and $\mathbf{S} \setminus \mathbf{Z}$ is irreducible.

Algorithm 1 Frontier-Reducibility Algorithm (FRA) – set version

Require: $\mathbf{S} \subseteq \mathbf{X}$, coalition.
Require: $\mathtt{Fr}$, a map: tuple[int] $\rightarrow$ bool.
Require: $\mathcal{G}$, causal graph.

procedure FRA($\mathbf{S}, \mathtt{Fr}; \mathcal{G}$)
  Sort($\mathbf{S}, <_{\mathcal{G}}$)
  $\mathbf{P} \leftarrow \varnothing$
  $\mathbf{Z} \leftarrow \varnothing$
  $k \leftarrow |\mathbf{S}|$
  while $k > 0$ **do**
    $X \leftarrow \mathbf{S}[k]$
    if $X \notin Pa_{\mathcal{G}}(Y)$ **then**
      $\mathbf{P'} \leftarrow \mathbf{P} \cap De_{\mathcal{G}}(X)$
      $\mathbf{T} \leftarrow (\mathbf{P'} \setminus \mathbf{Z}) \cup \{X\}$
      if $\mathbf{T} \notin \mathtt{Fr}$ **then**
        $\mathbf{C} \leftarrow \{X\}$
        while $\mathbf{C} \neq \varnothing$ and $Y \notin \mathbf{C}$ **do**
          $\mathbf{P'} \leftarrow \mathbf{P'} \cup \mathbf{C}$
          $\mathbf{C} \leftarrow \bigcup_{C \in \mathbf{C}} Ch_{\mathcal{G}}(C) \setminus \mathbf{P'}$
        end while
        $\mathtt{Fr}[\mathbf{T}] \leftarrow (C = \varnothing)$
      end if
      if $\mathtt{Fr}[\mathbf{T}]$ **then**
        $\mathbf{Z} \leftarrow \mathbf{Z} \cup \{X\}$
      end if
    end if
    $\mathbf{P} \leftarrow \mathbf{P} \cup \{X\}$
    $k \leftarrow k - 1$
  end while
  return $\mathbf{S} \setminus \mathbf{Z}$
end procedure

Conclusions

- **Estimand-Agnostic** Causal Inference as a **practical approach** for do-SHAP.
- **FRA** as an efficient algorithm to significantly **speed up do-SHAP**.

Questions?

- **Poster**: Wed 3 Dec, 11 a.m. – 2 p.m. PST
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