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Enhancing Directed Acyclic Graphs for Reliable Causal Discovery in Education

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Abstract: Discovering causal relationships in educational data is critical, yet traditional directed acyclic graph (DAG) construction methods often fail with noisy data. We propose the Causal Annotation Platform (CAP), which integrates teacher expertise into algorithmic causal discovery. CAP visualizes DAGs, simulates interventions via do-calculus, and incorporates expert annotations as weighted constraints in structure learning. Our prototype demonstrates how qualitative teacher judgments can be transformed into quantitative algorithmic inputs. By using expert input as algorithmic constraints, the system addresses limitations of conventional data-driven approaches. Future studies will evaluate the effectiveness of this method.

Keywords: DAG, causal discovery, Bayesian networks, human-in-the-loop

1. Introduction

Discovering causal relationships in educational data is increasingly recognized as a critical challenge (Kitto et al., 2023). A directed acyclic graph (DAG) visually represents a causal structure, offering intuitive feedback on complex variable relationships through directed edges. However, educational observational data often contain considerable noise, causing data-driven DAG construction to diverge from actual causal structures. Accepting such results without expert validation may lead to misguided educational interventions.

To address this issue, this study proposes a Causal Annotation Platform (CAP) that incorporates expert knowledge into DAG structural learning. This human-in-the-loop approach was inspired by the ideas presented in Flanagan et al. (2024), which highlights the benefits of collaboration between domain experts (such as teachers) and machine learning models. Therefore, the research question is:

RQ1: How can teacher insight be integrated into algorithms to reliably refine causal DAGs?

2. System Design and Prototype Interface for Proposed System

Bayesian networks generate DAGs representing conditional probability distributions based on conditional independence (Pearl, 2016). However, DAGs describe statistical relationships and do not necessarily represent true causal relationships (Pearl, 2009). In educational contexts, where observational data contain substantial noise and confounding factors, distinguishing between statistical associations and genuine causal mechanisms becomes particularly challenging. Expert knowledge from teachers, who possess a deep understanding of educational processes, can provide crucial insights to guide this distinction.

To address this challenge, our proposed system incorporates teacher annotations as structural constraints in the DAG learning process. Teachers evaluate potential causal relationships between variables, and their annotations are aggregated through a majority-voting mechanism. When multiple teachers assess each potential edge, those relationships deemed causally implausible by the majority are classified as "forbidden edges." The structure learning algorithm then optimizes the BIC score while ensuring the complete exclusion of these forbidden edges from the candidate graph space. This constraint-based approach ensures that educator consensus directly influences structural modifications, resulting in DAGs that align with the pedagogical understanding of causal mechanisms.

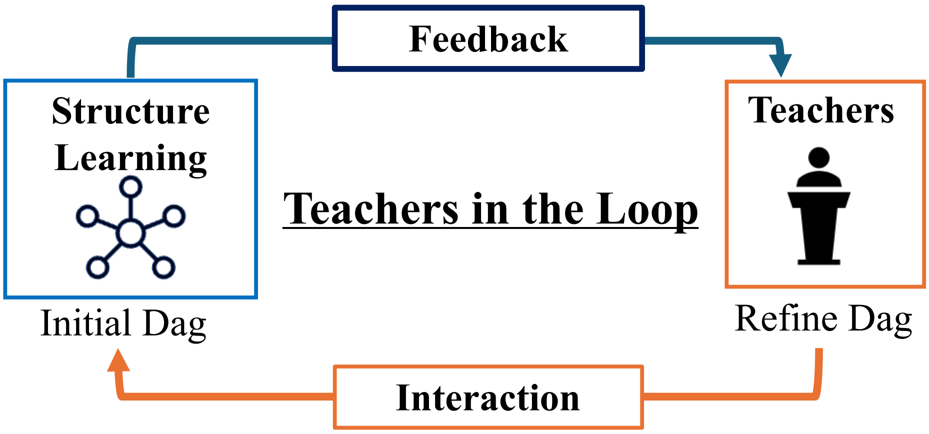

Figure 1. Teachers-in-the-loop DAG generation workflow

Figure 1 illustrates the iterative workflow of the teachers-in-the-loop approach. The process begins with a structure learning algorithm generating an initial DAG from observational educational data using standard statistical methods. While this initial DAG captures conditional dependencies, it may not accurately reflect true causal relationships due to the inherent limitations discussed above. Teachers then engage with the system through an interactive interface, examining the proposed DAG structure and providing causal interpretations based on their domain expertise.

The system aggregates these teacher inputs using a majority-voting mechanism. Edges deemed causally implausible by the majority of teachers are classified as forbidden edges and excluded from subsequent structure learning iterations. This cyclical process allows for the continuous improvement of causal structures through the systematic integration of educator consensus with statistical learning algorithms.

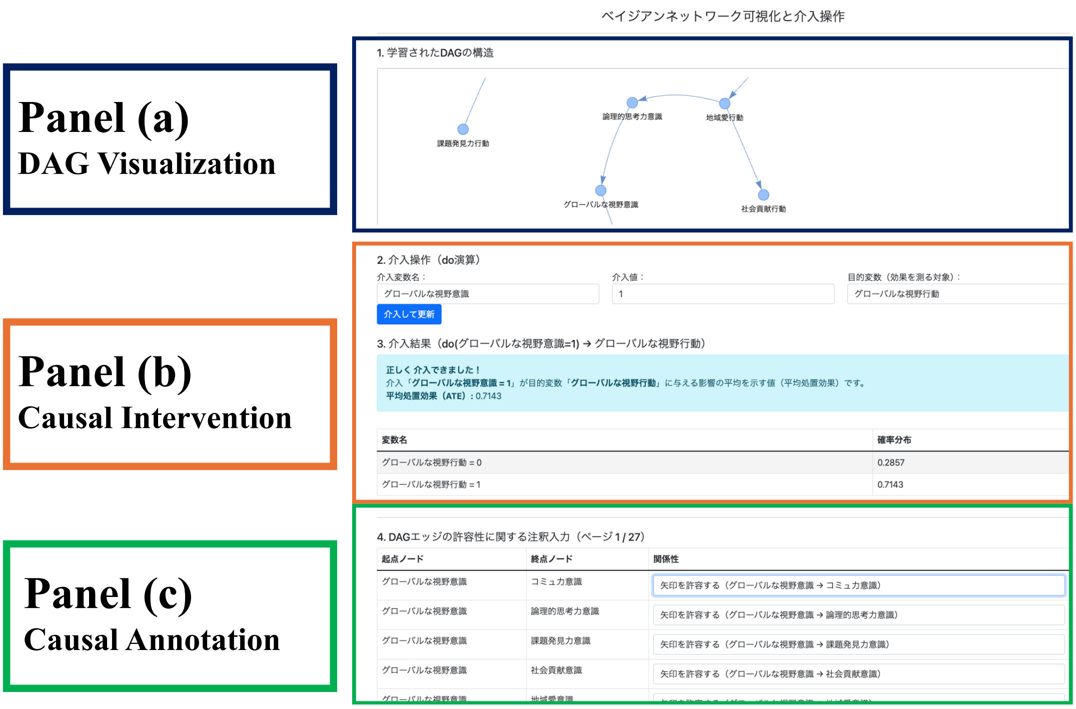

Figure 2. Prototype interface for causal annotation platform

Figure 2 illustrates the prototype interface implementing this workflow. The system comprises three main panels: (a) "DAG Visualization" displays the automatically generated

DAG structure and provides visual feedback on causal relationships; (b) "Causal Intervention" enables users to specify intervention variables, values, and targets to simulate hypothetical educational scenarios using do-calculus; and (c) "Causal Annotation" allows teachers to record their judgments on edge plausibility, classifying each potential causal relationship as either "plausible" or "implausible." These annotations are stored in a database and serve as input for the majority-voting mechanism and subsequent constraint-based DAG refinement. The system implementation utilizes *pgmpy*, a Python toolkit for probabilistic graphical models and Bayesian networks (Ankan & Textor, 2024).

3. Discussion and Future Work

This study presents a system design that facilitates the integration of human expertise into causal discovery. Although empirical evaluation is essential and planned for future work, the current contribution focuses on the algorithmic framework and interface design that enable this integration.

The proposed workflow incorporates domain experts' knowledge into algorithm-driven causal discovery, a particularly important consideration in education, where interpreting causal relationships requires professional judgment. By embedding Pearl's interventionist logic into the expert annotation workflow, the platform improves the stability of DAG structure estimation and transforms teachers' tacit knowledge into explicit, shareable intellectual assets.

Future work should explore extending the system to support more complex causal representations and implementing mechanisms to assess inter-annotator agreement among multiple experts. Furthermore, the system should be evaluated based on teacher feedback in real educational settings. By introducing this system into schools, we aim to develop a "causal knowledge commons" in education, where expert insights are systematically accumulated and refined.

4. Conclusion

This study proposed CAP, demonstrating how teacher annotations can be algorithmically integrated into DAG construction through a majority-voting mechanism. The system bridges data-driven discovery with pedagogical expertise via visualization, intervention simulation, and annotation interfaces. Although currently limited by the absence of empirical validation, the technical framework provides a foundation for future human-in-the-loop causal discovery systems. Immediate next steps include evaluating the system with educators and developing multi-expert consensus mechanisms.

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