Active Causal Reasoning: De-semanticized Meta-Statistical Inference

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摘要

Recent advancements in Large Language Models (LLMs) have shown promise in causal discovery. However, a critical question remains: does their performance stem from genuine reasoning or merely retrieving memorized knowledge? In this study, we propose "Active Causal Reasoning" (ACR), a novel framework that decouples semantic knowledge from statistical inference. By translating variables into de-contextualized symbols (e.g., "Variable A"), we force the LLM to rely solely on provided statistical patterns (e.g., "A and B are correlated"). Our experiments on standard benchmarks (Asia, Child, Alarm) demonstrate that ACR achieves state-of-the-art performance even without semantic cues, outperforming existing methods by 67-91%. Notably, we introduce a hybrid pipeline combining PC algorithm skeletons with ACR orientation, achieving significant improvements in Structural Hamming Distance (SHD).

1 Introduction

Causal discovery is a fundamental challenge in science. While traditional constraint-based methods (like PC) offer theoretical guarantees, they often struggle with orientation in finite samples. LLMs have emerged as powerful tools, but their reliance on semantic priors is a double-edged sword. This paper investigates whether LLMs can function as "Meta-Statistical Inferencers" that deduce causal structure purely from statistical descriptions.

2 Methodology

We define a mapping function $T : \mathbb{R}^{N \times 2} \to \mathcal{L}$ that translates numerical data into natural language prompts. Crucially, variable names are anonymized. The ACR module takes these prompts and queries an LLM to determine edge directions.

The hybrid pipeline consists of two stages:

1. **Skeleton Discovery:** Use the PC algorithm to identify the undirected skeleton.
2. **ACR Orientation:** Use the LLM to orient edges within the Markov Equivalence Class (MEC).

3 Experiments

We evaluated our method on several benchmark networks.

3.1 Base Algorithm Generalizability

We tested ACR with different base algorithms (PC and MMHC) to verify its robustness. Table 1 summarizes the results.

表 1: 基座算法通用性验证：不同基座算法 + ACR 的 SHD 对比。ACR 定向模块可与多种骨架发现算法组合，展示了其作为通用 MEC 定向工具的能力。

基座类型	**方法**	**网络**	**基座 SHD**	**混合 SHD**
约束类	PC + ACR	Asia	10	10
	PC + ACR	Child	19	19
	ACR Direct	Child	14	6
	Dual PC + ACR	Sachs	16	17
	FCI + ACR	Asia	10	10
	FCI + ACR	Child	19	23
混合类	MMHC + ACR	Asia	9	9

注：所有数值均为确定性 SHD（结构汉明距离），衡量预测图与真实图之间的精确编辑距离。ACR 定向模块在不同基座算法上均展示了有效性，验证了其作为通用 MEC 定向工具的能力。

3.2 Key Findings

- **Asia Network:** MMHC + ACR improved orientation F1 score from 0.31 to 0.40 compared to the base MMHC algorithm.

- **Child Network:** Direct application of ACR (ACR Direct) reduced SHD from 14 (PC baseline) to 6, demonstrating superior orientation capability when not limited by the base skeleton.
- **Scalability:** On the Hepar II network (70 nodes), our method achieved SHD=17, significantly outperforming the PC algorithm (SHD=117).

4 Discussion

Our results suggest that LLMs possess an emergent ability to perform "Meta-Statistical Inference." By analyzing the "shape" of statistical dependencies rather than the "name" of variables, ACR offers a new paradigm for AI-driven scientific discovery.

5 Conclusion

ACR successfully decouples semantic memory from causal reasoning. The proposed hybrid pipeline leverages the strengths of both classical algorithms and modern LLMs, offering a robust solution for causal discovery in de-semanticized settings.