Exact Constraint-based Causal Discovery

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1 Introduction

- **2** Implicit Hitting Set Approach
- **3** Dseptor: Utilizing 3 Domain Specific Techniques

4 Experiments

5 Conclusion

Introduction

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- Good Accuracy, limited model space.
- **Exact**: Find the globally optimal graph(s).

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Constraint-based Methods: [Pearl, Spirtes,...]

- Deduce the graph structure from independence test results.
- General of the model space: Latent confounders, Cycles.
- Scale up by making **greedy** decision ⇒ poor accuracy.

INPUT: All weighted cond. (in)dependencies K among vars. **TASK:** Find G that minimizes $\sum_{k \in K : G \not\models k} w(k)$.

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- Often accurate. [Hyttinen et al. '14, Magliacane et al. '16, Borboudakis et al. '16]
- Several options for getting weighted independence constraints. [Margaritis et al. '09, Claassen et al. '12, Triantafillou et al. '15, Magliacane et al. '16]

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- Related Work: [Magliacane et al. '16, Claassen et al. '12, Triantafillou et al. '15]

Implicit Hitting Set Approach

SAT-solver:

- Is there a graph that satisfies constraints K?
- CNF-encoding of d-separation/connection: [Hyttinen et al. '14]

 $X \not \perp Y | C \quad \Leftrightarrow \quad X \to Y \quad \lor \quad Y \to X \quad \lor \quad X \leftrightarrow Y \quad \lor \quad \ldots$

- Returns SAT and a solution, or UNSAT and a core.
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Implementation:

• LMHS by [Saikko et al. '16] uses MiniSAT (backtracking depth first search) and CPLEX (simplex-based branch-and-cut).



Step 1 L = 0, U = 16

SAT solver

IP solver

Step 2 L = 0, U = 16





Step 3 L = 0, U = 16



SAT solver

IP solver

Step 4 L = 0, U = 16





Step 5 L = 1, U = 16

SAT solver

IP solver

Step 6 L = 1, U = 16



Step 7 L = 1, U = 16



SAT solver

IP solver

Step 8 L = 1, U = 16





Step 9 L = 1, U = 16

SAT solver

IP solver

Step 10 L = 1, U = 16











Dseptor: Utilizing 3 Domain Specific Techniques

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 - **Observe** which cores the solver uses, e.g.

$$\{X \perp Z; X \not\perp Z | Y; X \perp Y\}$$

• Generalize a core to a pattern, e.g.

 $\{X \perp\!\!\!\!\perp Z | C; \quad X \not\perp\!\!\!\!\perp Z | Y, C; \quad X \perp\!\!\!\!\perp Y | C\}, \quad \forall X, Y, Z, C$

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- We identified 7 cores patterns among 3-4 nodes and 3-5 constraints, each including independencies and dependencies.

Benefit: Thousands of small cores can be found in a fraction of the total solving time.

For all instantiations of nodes X, Y, Z, W and set C:

(i) $\{X \perp Z | C; X \perp Y | C; X \not\perp Z | Y, C\}$

- (ii) $\{X \not\perp Z | C; Y \not\perp Z | C; X \perp Y | C; X \perp Y | Z, C\}$
- (iii) { $X \not\perp Z | Y, C; Y \not\perp Z | X, C; X \perp Y | C; X \perp Y | Z, C$ }
- (iv) $\{Y \not\perp Z | C; X \not\perp Z | C; Z \perp W | X, Y, C;$
 - $X \perp Y | Z, C; \quad X \perp Y | W, C \}$
- (v) { $Y \not\perp Z | C; X \not\perp Z | C; Z \perp W | Y, C; X \perp Y | Z, C; X \perp Y | W, C$ }
- (vi) { $X \not\perp Y | Z, C; \quad Y \not\perp Z | X, W, C; \quad W \not\perp Y | Z, C; W \perp X | Y, Z, C; \quad X \perp Z | W, C$ }
- (vii) { $X \not\perp Y | Z, C; \quad Y \not\perp Z | X, W, C; \quad W \not\perp Y | C; \\ W \perp X | Y, C; \quad X \perp Z | W, C$ }

are minimal cores.

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Benefits: Smaller diverse cores, good upper bounds.

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Benefits: Less soft constraints, SAT-instances are tighter.



Example Run of Dseptor



Running Time Performance (1)



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 - 8 Bounds-based constraint hardening
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- Are further running time improvements possible?
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