



UNIVERSITÄT ZU LÜBECK

# Finding minimal $d$ -separators in linear time and applications

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IM FOCUS DAS LEBEN



## Motivation and our Contribution

We investigate algorithmic aspects of the following problem:

### Problem

*For given nodes  $X, Y$  in a causal DAG, find a minimal  $d$ -separator between  $X$  and  $Y$ .*

- Minimal  $d$ -separators are an important graphical notion used in causality
- Many problems can be reduced to finding (minimal)  $d$ -separators
- The best previously known algorithm for minimal separators needs  $\mathcal{O}(n^2)$  time [Tian, Paz, and Pearl 1998]

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- Many problems can be reduced to finding (minimal)  $d$ -separators
- The best previously known algorithm for minimal separators needs  $\mathcal{O}(n^2)$  time [Tian, Paz, and Pearl 1998]

Our main result:

Finding minimal  $d$ -separators can be done in linear time

Our result also holds for classes beyond DAGs and minimal  $d$ -separators between node sets  $\mathbf{X}, \mathbf{Y}$ .

## Preliminaries: $d$ -separation in causal DAGs

Graph reveals conditional independences

A path is a sequence of adjacent nodes

A node  $V$  on a path is a *collider* if the adjacent edges are  $\rightarrow V \leftarrow$

A path is *blocked* if it contains a collider

(i.e., only edges  $\rightarrow V \rightarrow$ ,  $\leftarrow V \leftarrow$ , and  $\leftarrow V \rightarrow$  allowed)

Two nodes are  *$d$ -separated* if all paths between them are blocked

Two nodes are  *$d$ -connected* if they are not  $d$ -separated

(i.e., there exist any unblocked path between them)

$X$  and  $Y$  are correlated iff  $X$  and  $Y$  are  $d$ -connected

$X$  and  $Y$  are independent iff  $X$  and  $Y$  are  $d$ -separated

## Preliminaries: $d$ -separation in causal DAGs

Conditioning on a set  $\mathbf{Z}$  inverts the rules

	$V \notin \mathbf{Z}$	$V \in \mathbf{Z}$
$\rightarrow V \leftarrow$	blocked (unless a descendant is in $\mathbf{Z}$ )	allowed
$\rightarrow V \rightarrow$	allowed	blocked
$\leftarrow V \rightarrow$	allowed	blocked
$\leftarrow V \leftarrow$	allowed	blocked

A path is blocked, if any node on it is blocked

$X$  and  $Y$  are conditionally independent given  $\mathbf{Z}$  iff all paths between  $X$  and  $Y$  are blocked given  $\mathbf{Z}$

# Minimal $d$ -separators

## Definition

A given set  $\mathbf{Z}$  is a *minimal  $d$ -separator* between  $X$  and  $Y$  if

- $\mathbf{Z}$   $d$ -separates  $X$  and  $Y$
- No  $\mathbf{Z}' \subsetneq \mathbf{Z}$   $d$ -separates  $X$  and  $Y$

## Minimal $d$ -separators

Fact ([Tian, Paz, and Pearl, 1998])

*A given set  $\mathbf{Z}$  is a minimal  $d$ -separator between  $X$  and  $Y$  if*

- $\mathbf{Z}$   $d$ -separates  $X$  and  $Y$*
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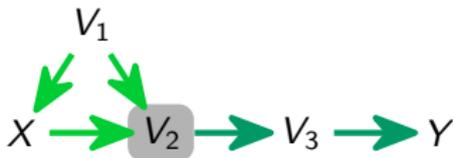
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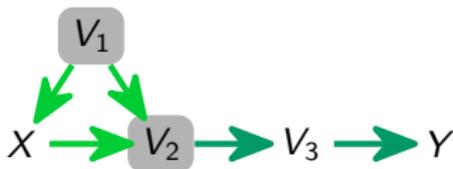
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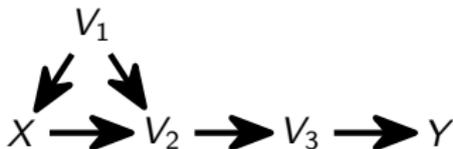
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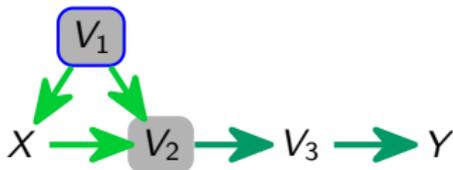
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## Minimal $d$ -separators: Collider examples



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## Minimal $d$ -separators in causal DAGs

$An(X, Y, \mathbf{I}) =$  ancestors of  $X$ ,  $Y$  and  $\mathbf{I}$

### Fact

*A given set  $\mathbf{Z}$  is a minimal  $d$ -separator between  $X$  and  $Y$  if*

- Every path in  $An(X, Y, \mathbf{I})$  between  $X$  and  $Y$  intersects  $\mathbf{Z}$  in a non-collider*
- For each  $Z \in \mathbf{Z} \setminus \mathbf{I}$  there are paths*
  - $\pi_{XZ}$  in  $An(X, Y, \mathbf{I})$  from  $X$  to  $Z$  and*
  - $\pi_{YZ}$  in  $An(X, Y, \mathbf{I})$  from  $Y$  to  $Z$**which contain no non-collider node of  $\mathbf{Z} \setminus Z$*

## Main Results

Let  $X^*$  be the nodes reachable from  $X$  through  $An(X, Y, \mathbf{I})$  by paths containing no non-collider in  $\mathbf{Z}$

Let  $Y^*$  be the nodes reachable from  $Y$  analogously

### Fact (Minimality Criterion)

*A given set  $\mathbf{Z}$  is a minimal  $d$ -separator between  $X$  and  $Y$  if*

- $Y \notin X^*$  (equivalently:  $X \notin Y^*$ )
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**Linear time algorithm to test if a given  $\mathbf{Z}$  is a minimal  $d$ -separator:**

- Calculate  $X^*$  and  $Y^*$
- Verify conditions of the minimality criterion

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### Linear time algorithm to find a minimal $d$ -separator $\mathbf{Z}$ :

- Start with non-minimal  $d$ -separator  $\mathbf{Z}_0 := An(X, Y, \mathbf{I}) \cap \mathbf{R}$
- Calculate  $X^*$  for  $\mathbf{Z}_0$
- Remove unnecessary nodes  $\mathbf{Z}_X := \mathbf{Z}_0 \cap X^* \cup \mathbf{I}$
- Calculate  $Y^*$  for  $\mathbf{Z}_X$
- Remove further unnecessary nodes and return  $\mathbf{Z} = \mathbf{Z}_X \cap Y^* \cup \mathbf{I}$

## Applications: Adjustment sets

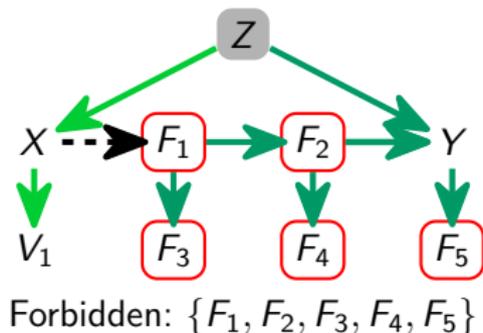
### Definition

A set  $\mathbf{Z}$  is an adjustment set relative to  $X$  and  $Y$  if the causal effect of  $X$  on  $Y$  is given by

$$P(Y \mid do(X)) = \sum_{\mathbf{Z}} P(Y \mid X, \mathbf{Z})P(\mathbf{Z})$$

### Theorem (van der Zander et al., UAI 2014)

A set  $\mathbf{Z}$  is an adjustment set relative to  $X$  and  $Y$  iff it contains no node of  $\text{Forbidden}(X, Y)$  and is a  $d$ -separator in the proper backdoor graph  $G_{XY}^{pbd}$



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### Proposition

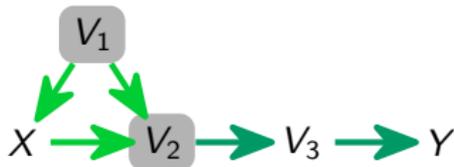
*Using our algorithms we can construct minimal adjustment sets in linear time*

## Applications: Nearest Separator

### Definition

A set  $\mathbf{Z} \subseteq \mathbf{R} \setminus \{X, Y\}$  is called a *nearest separator* relative to  $X$  and  $Y$  if

- (a)  $\mathbf{Z}$   $d$ -separates  $X$  and  $Y$ , and
- (b) for any  $Z \in \mathbf{Z}$  and any set  $\mathbf{W} \subseteq \mathbf{R} \setminus \{X, Y, Z\}$  that  $d$ -separates  $X$  and  $Y$ , it holds:  
 $\mathbf{W}$   $d$ -separates  $Z$  and  $Y$



Nearest separators:  $\mathbf{W} = \{V_2\}$  and  $\mathbf{W} = \{V_1, V_2\}$

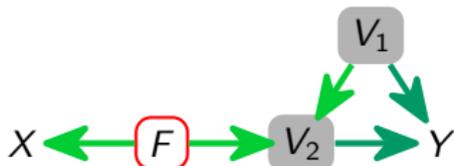
Not a nearest separator:  $\mathbf{W}' = \{V_3\}$

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Forbidden node  $F$ , i.e., constraint  $\mathbf{R} = \{V_1, V_2\}$

Nearest separator  $\mathbf{W} = \{V_1, V_2\}$

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Our algorithm always returns  $d$ -separators that are minimal and nearest separators

### Proposition

*In a linear graphical model (SEM) nearest separators ...*

*... used as adjustment sets have the optimal asymptotic variance among all adjustment sets that are subsets of  $An(Y, X, \mathbf{I})$*

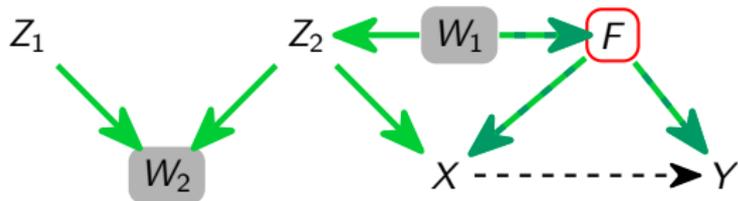
*... allow to find conditional instrumental variables (next slides)*

## Applications: Conditional Instrumental Variables

### Definition (Conditional instrumental variable)

Variable  $Z$  is a *conditional instrument* relative to edge  $X \rightarrow Y$ , if there exists a  $d$ -separator  $\mathbf{W} \subseteq \mathbf{R}$  such that

- $\mathbf{W}$  does not  $d$ -separate  $Z$  and  $X$ ,
- $\mathbf{W}$   $d$ -separates  $Z$  and  $Y$  after removal of the edge  $X \rightarrow Y$ ,
- $\mathbf{W}$  consists of non-descendants of  $Y$



Conditional instrument:  $Z = Z_1$ ,  $\mathbf{W} = \{W_1, W_2\}$

Conditional instrument with nearest separator:  $Z = Z_2$ ,  $\mathbf{W} = \{W_1\}$

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- (c)  $\mathbf{W}$  consists of non-descendants of  $Y$

Given a conditional instrument  $Z$  the direct causal effect of  $X \rightarrow Y$  is

$$\frac{\text{Cov}(Y, Z|\mathbf{W})}{\text{Cov}(X, Z|\mathbf{W})}$$

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### Theorem (van der Zander et al., IJCAI 2015)

- *Testing whether a given variable  $Z$  is a conditional instrumental variable is NP-complete, because finding the  $d$ -separator  $\mathbf{W}$  is NP-complete*
- *If any  $\mathbf{W} \subseteq \text{An}(Y, X)$  satisfies the definition, any nearest separator between  $Y$  and  $Z$  can be used as  $d$ -separator  $\mathbf{W}$*
- *If any conditional instrumental variable exists for given  $X, Y$ , then there exists one with its  $\mathbf{W} \subseteq \text{An}(Y, X)$*

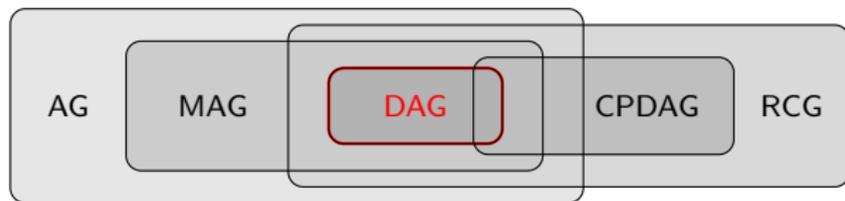
## Minimal separators in DAGs: Summary

We have improved the runtime of the following problems:

	Previously	Our Results
Verify a minimal $d$ -separator [Tian, Paz, and Pearl, 1998]	$\mathcal{O}(n^2)$	$\mathcal{O}(n + m)$
Find a minimal $d$ -separator [Tian, Paz, and Pearl, 1998]	$\mathcal{O}(n^2)$	$\mathcal{O}(n + m)$
Verify a minimal adjustment set [van der Zander, Textor, and Liśkiewicz, UAI 2014]	$\mathcal{O}(n^2)$	$\mathcal{O}(n + m)$
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Prune an adjustment set [Henckel, Perković, and Maathuis, 2019]	$\mathcal{O}(n(n + m))$	$\mathcal{O}(n + m)$
Find a nearest $d$ -separator [van der Zander, Textor, and Liśkiewicz, IJCAI 2015]	$\mathcal{O}(n(n + m))$	$\mathcal{O}(n + m)$
Find a conditional instrument [van der Zander, Textor, and Liśkiewicz, IJCAI 2015]	$\mathcal{O}(n^2(n + m))$	$\mathcal{O}(n(n + m))$

## Causal Models beyond DAGs

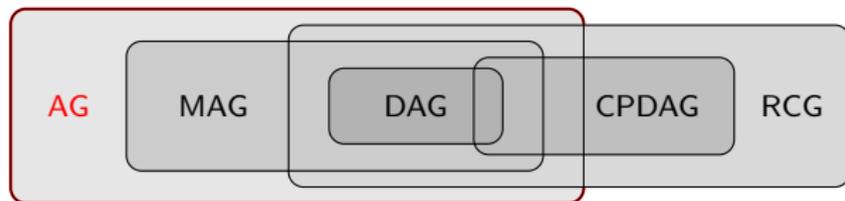
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**Directed acyclic graphs (DAGs)** the classic model

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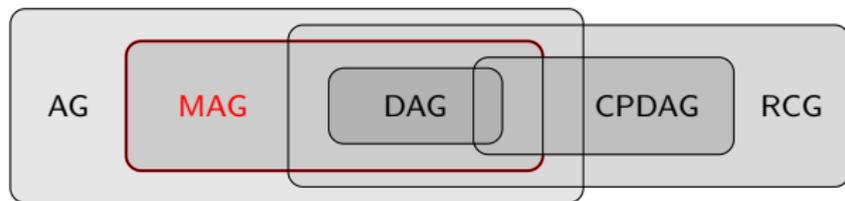


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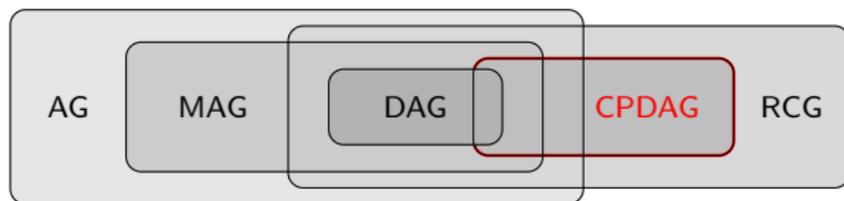
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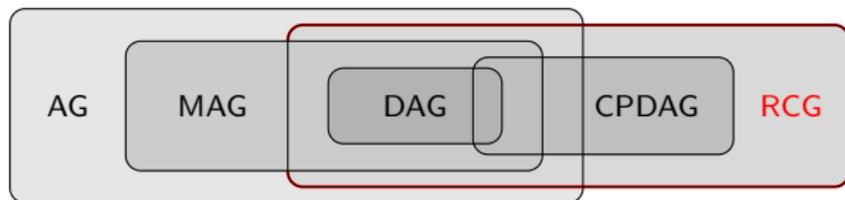
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**Completed Partially Directed Acyclic Graph (CPDAGs)**

represent entire class of Markov equivalent DAGs

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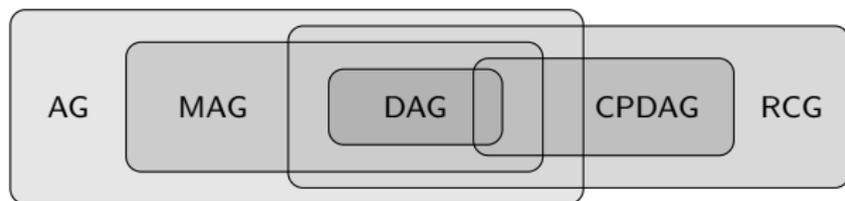
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**Restricted Chain Graphs (RCGs)** generalization of CPDAGs, represent a set of Markov equivalent DAGs

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*Thank you for your attention*