

Bayesian Networks

2. Separation in Graphs

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Bayesian Networks



- 1. Separation in Undirected Graphs
- 2. Properties of Ternary Relations on Sets
- 3. Separation in Directed Graphs

Graphs



Definition 1. Let V be any set and

$$E \subseteq \mathcal{P}^2(V) := \{ \{x, y\} \mid x, y \in V \}$$

be a subset of sets of unordered pairs of V. Then G:=(V,E) is called an **undirected graph**. The elements of V are called **vertices** or **nodes**, the elements of E **edges**.

Let $e = \{x,y\} \in E$ be an edge, then we call the vertices x,y incident to the edge e. We call two vertices $x,y \in V$ adjacent, if there is an edge $\{x,y\} \in E$.

The set of all vertices adjacent with a given vertex $x \in V$ is called its **fan**:

$$fan(x) := \{ y \in V \mid \{x, y\} \in E \}$$

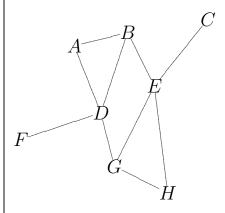


Figure 1: Example graph.

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Bayesian Networks / 1. Separation in Undirected Graphs



Paths on graphs

Definition 2. Let V be a set. We call $V^* := \bigcup_{i \in \mathbb{N}} V^i$ the **set of finite sequences in** V. The length of a sequence $s \in V^*$ is denoted by |s|.

Let G = (V, E) be a graph. We call

$$G^* := V_{|G}^* := \{ p \in V^* \mid \{ p_i, p_{i+1} \} \in E,$$

 $i = 1, \dots, |p| - 1 \}$

the **set of paths on** G.

Any contiguous subsequence of a path $p \in G^*$ is called a **subpath of** p, i.e. any path $(p_i, p_{i+1}, \ldots, p_j)$ with $1 \le i \le j \le n$. The subpath $(p_2, p_3, \ldots, p_{n-1})$ is called the **interior of** p. A path of length $|p| \ge 2$ is called **proper**.

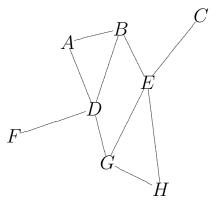


Figure 2: Example graph. The sequences

$$(A, D, G, H)$$
$$(C, E, B, D)$$
$$(F)$$

are paths on G, but the sequences

$$(A, D, E, C)$$
$$(A, H, C, F)$$

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Separation in graphs (u-separation)



Definition 3. Let G := (V, E) be a graph. | We write $I_G(X, Y|Z)$ for the statement, Let $Z \subseteq V$ be a subset of vertices. We say, two vertices $x,y \in V$ are **useparated by** Z **in** G, if every path from x to y contains some vertex of Z ($\forall p \in$ $G^*: p_1 = x, p_{|p|} = y \Rightarrow \exists i \in \{1, \dots, n\}:$ $p_i \in Z$).

Let $X, Y, Z \subseteq V$ be three disjoint subsets of vertices. We say, the vertices Xand Y are **u-separated by** Z **in** G, if every path from any vertex from X to any vertex from Y is separated by Z, i.e., contains some vertex of Z.

that X and Y are u-separated by Z in

 I_G is called **u-separation relation in** G.

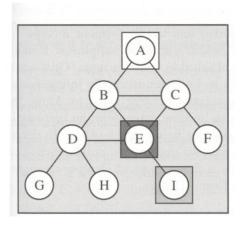
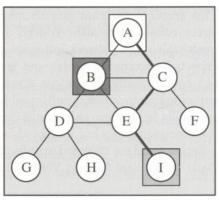


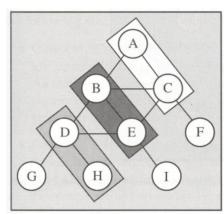
Figure 3: Example for u-separation [CGH97, p. 179].

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Bayesian Networks / 1. Separation in Undirected Graphs

Separation in graphs (u-separation)





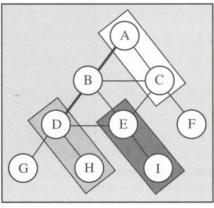


Figure 4: More examples for u-separation [CGH97, p. 179].

Properties of u-separation / no chardality



For u-separation the chordality property does not hold (in general).

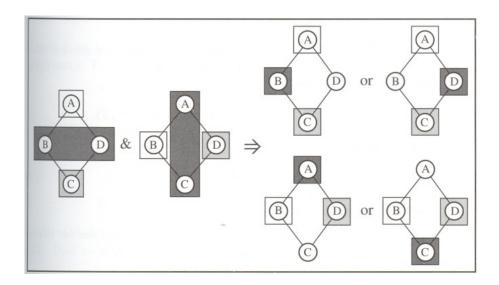


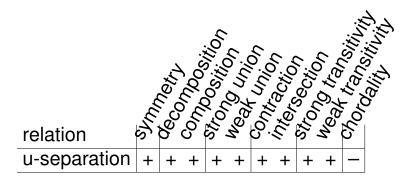
Figure 5: Counterexample for chordality in undirected graphs (u-separation) [CGH97, p. 189].

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Bayesian Networks / 1. Separation in Undirected Graphs



Properties of u-separation



Checking u-separation



To test, if for a given graph G=(V,E) two given sets $X,Y\subseteq V$ of vertices are u-separated by a third given set $Z\subseteq V$ of vertices, we may use standard breadth-first search to compute all vertices that can be reached from X (see, e.g., [OW02], [CLR90]).

```
breadth-first search(G, X):
border := X
reached := \emptyset

while border \neq \emptyset do
reached := reached \cup border
border := \operatorname{fan}_G(\operatorname{border}) \setminus \operatorname{reached}

defined
return reached
```

Figure 6: Breadth-first search algorithm for enumerating all vertices reachable from X.

For checking u-separation we have to tweak the algorithm

- 1. not to add vertices from ${\it Z}$ to the border and
- to stop if a vertex of Y has been reached.

```
check-u-separation(G, X, Y, Z):

border := X

reached := \emptyset

while border \neq \emptyset do

reached := reached \cup border

border := fan_G(border) \setminus reached \setminus Z

if border \cap Y \neq \emptyset

return false

find od

return true
```

Figure 7: Breadth-first search algorithm for checking u-separation of X and Y by Z.

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Bayesian Networks



- 1. Separation in Undirected Graphs
- 2. Properties of Ternary Relations on Sets
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Symmetry



Definition 4. Let V be any set and I a ternary relation on $\mathcal{P}(V)$, i.e., $I \subseteq (\mathcal{P}(V))^3$.

I is called **symmetric**, if

$$I(X,Y|Z) \Rightarrow I(Y,X|Z)$$

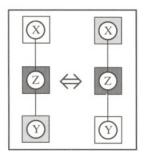


Figure 8: Examples for symmetry [CGH97, p. 186].

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Bayesian Networks / 2. Properties of Ternary Relations on Sets



Decomposition and Composition

Definition 5. *I* is called **(right-)decomposable**, if

$$I(X,Y|Z) \Rightarrow I(X,Y'|Z)$$
 for any $Y' \subseteq Y$

I is called (right-)composable, if

$$I(X,Y|Z)$$
 and $I(X,Y'|Z) \Rightarrow I(X,Y \cup Y'|Z)$

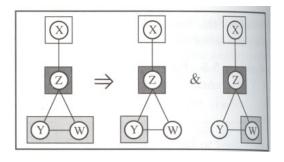


Figure 9: Examples for decomposition [CGH97, p. 186].

Union

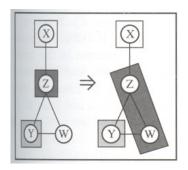


Definition 6. *I* is called **strongly unionable**, if

 $I(X,Y|Z) \Rightarrow I(X,Y|Z \cup Z')$ for all Z' disjunct with X,Y

I is called (right-)weakly unionable, if

$$I(X, Y|Z) \Rightarrow I(X, Y'|(Y \setminus Y') \cup Z)$$
 for any $Y' \subseteq Y$



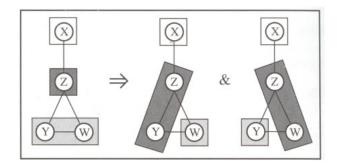


Figure 10: Examples for a) strong union and b) weak union [CGH97, p. 186,189].

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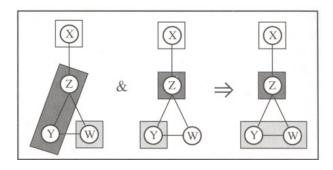


Definition 7. *I* is called **(right-)contractable**, if

$$I(X,Y|Z)$$
 and $I(X,Y'|Y\cup Z)\Rightarrow I(X,Y\cup Y'|Z)$

I is called (right-)intersectable, if

$$I(X,Y|Y'\cup Z)$$
 and $I(X,Y'|Y\cup Z)\Rightarrow I(X,Y\cup Y'|Z)$



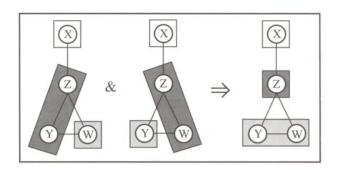


Figure 11: Examples for a) contraction and b) intersection [CGH97, p. 186].

Transitivity

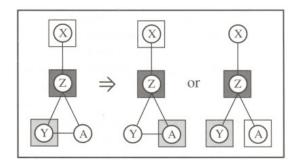


Definition 8. *I* is called **strongly transitive**, if

 $I(X,Y|Z) \Rightarrow I(X,\{v\}|Z) \text{ or } I(\{v\},Y|Z) \quad \forall v \in V \setminus Z$

I is called **weakly transitive**, if

I(X,Y|Z) and $I(X,Y|Z\cup\{v\}) \Rightarrow I(X,\{v\}|Z)$ or $I(\{v\},Y|Z) \quad \forall v \in V\setminus Z$



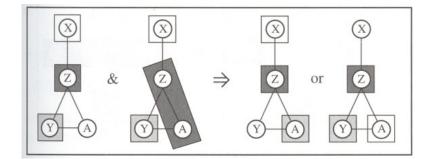


Figure 12: Examples for a) strong transitivity and b) weak transitivity. [CGH97, p. 189]

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Bayesian Networks / 2. Properties of Ternary Relations on Sets



Chordality

Definition 9. *I* is called **chordal**, if

 $I(\{a\},\{c\}|\{b,d\}) \text{ and } I(\{b\},\{d\}|\{a,c\}) \Rightarrow I(\{a\},\{c\}|\{b\}) \text{ or } I(\{a\},\{c\}|\{d\})$

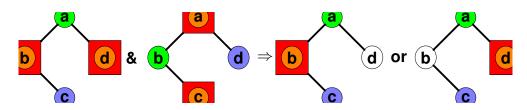


Figure 13: Example for chordality.



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Bayesian Networks / 3. Separation in Directed Graphs

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Directed graphs

Definition 10. Let V be any set and

$$E \subseteq V \times V$$

be a subset of sets of ordered pairs of V. Then G := (V, E) is called a **directed graph**. The elements of V are called **vertices** or **nodes**, the elements of E **edges**.

Let $e=(x,y)\in E$ be an edge, then we call the vertices x,y incident to the edge e. We call two vertices $x,y\in V$ adjacent, if there is an edge $(x,y)\in E$ or $(y,x)\in E$.

The set of all vertices with an edge from a given vertex $x \in V$ is called its **fanout**:

$$fanout(x) := \{ y \in V \, | \, (x, y) \in E \}$$

The set of all vertices with an edge to a given vertex $x \in V$ is called its **fanin**:

$$fanin(x) := \{ y \in V \mid (y, x) \in E \}$$

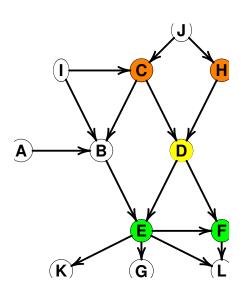


Figure 14: Fanin (orange) and fanout (green) of a node (blue).

Paths on directed graphs



Definition 11. Let G=(V,E) be a directed graph. We call

$$G^* := V_{|G}^* := \{ p \in V^* \mid (p_i, p_{i+1}) \in E,$$

 $i = 1, \dots, |p| - 1 \}$

the **set of paths on** G. For two vertices $x,y\in V$ we denote by

$$G_{[x,y]}^* := \{ p \in V_{|G}^* \mid p_1 = x, p_{|p|} = y \}$$

the set of paths from x to y.

The notions of **subpath**, **interior**, and **proper path** carry over to directed graphs.

A proper path $p=(p_1,\ldots,p_n)\in G^*$ with $p_1=p_n$ is called **cyclic**. A path without cyclic subpath is called a **simple path**. A graph without a cyclic path is called **directed acyclig graph (DAG)**.

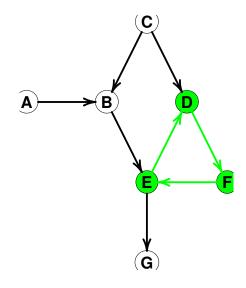


Figure 15: Example for a cycle.

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Bayesian Networks / 3. Separation in Directed Graphs



Paths on directed graphs (2/2)

Definition 12. For a DAG G vertices of the fanout are also called **children**

 $\operatorname{child}(x) := \operatorname{fanout}(x) := \{ y \in V \mid (x, y) \in E \}$ and the vertices of the fanin **parents**:

$$pa(x) := fanin(x) := \{ y \in V \mid (y, x) \in E \}$$

Vertices y with a proper path from y to x are called **ancestors of** x:

$$\operatorname{anc}(x) := \{ y \in V \mid \exists p \in G^* : |p| \ge 2, \\ p_1 = y, p_{|p|} = x \}$$

Vertices y with a proper path from x to y are called **descendents of** x:

$$\operatorname{desc}(x) := \{ y \in V \mid \exists p \in G^* : |p| \ge 2, \\ p_1 = x, p_{|p|} = y \}$$

Vertices that are not a descendent of x are called **nondescendents of** x.

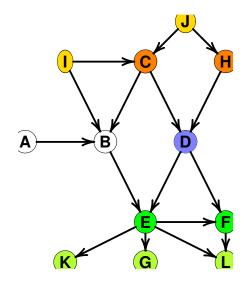


Figure 16: Parents/Fanin (orange) and additional ancestors (light orange), children/fanout (green) and additional descendants (light green) of a node (blue).

Chains



Definition 13. Let G:=(V,E) be a directed graph. We can construct an **undirected skeleton** u(G):=(V,u(E)) **of** G by dropping the directions of the edges:

$$u(E) := \{ \{x, y\} \mid (x, y) \in E \text{ or } (y, x) \in E \}$$

The paths on u(G) are called **chains of** G:

$$G^{\blacktriangle} := u(G)^*$$

i.e., a chain is a sequence of vertices that are linked by a forward or a backward edge. If we want to stress the directions of the linking edges, we denote a chain $p=(p_1,\ldots,p_n)\in G^\blacktriangle$ by

$$p_1 \leftarrow p_2 \rightarrow p_3 \leftarrow \cdots \leftarrow p_{n-1} \rightarrow p_n$$

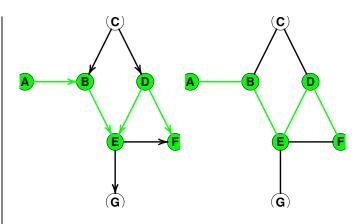


Figure 17: Chain (A, B, E, D, F) on directed graph and path on undirected skeleton.

The notions of length, subchain, interior and proper carry over from undi-

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Bayesian Networks / 3. Separation in Directed Graphs



Blocked chains

Definition 14. Let G := (V, E) be a directed graph. We call a chain

$$p_1 \rightarrow p_2 \leftarrow p_3$$

a head-to-head meeting.

Let $Z \subseteq V$ be a subset of vertices. Then a chain $p \in G^{\blacktriangle}$ is called **blocked** at **position** i by Z, if for its subchain (p_{i-1}, p_i, p_{i+1}) there is

$$\begin{cases} p_i \in Z, & \text{if not } p_{i-1} \to p_i \leftarrow p_{i+1} \\ p_i \not\in Z \cup \text{anc}(Z), & \text{else} \end{cases}$$

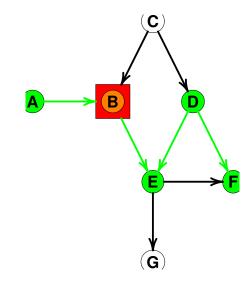


Figure 18: Chain (A,B,E,D,F) is blocked by $Z=\{B\}$ at 2.

Blocked chains / more examples



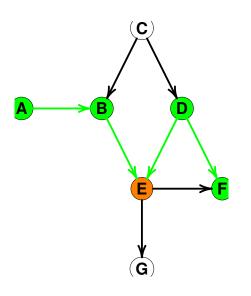


Figure 19: Chain (A,B,E,D,F) is blocked by $Z=\emptyset$ at 3.

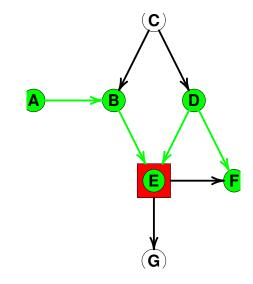


Figure 20: Chain (A,B,E,D,F) is **not** blocked by $Z=\{E\}$ at 3.

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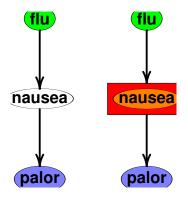
Bayesian Networks / 3. Separation in Directed Graphs

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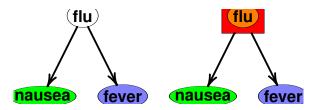
Blocked chains / rationale

The notion of blocking is choosen in a way so that chains model "flow of causal influence" through a causal network where the states of the vertices Z are already know.

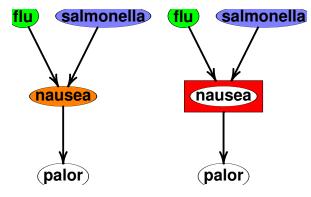
1) Serial connection / intermediate cause:



The notion of blocking is choosen in 2) Diverging connection / common a way so that chains model "flow of cause:



3) Converging connection / common effect:



Models "discounting" [Nea03, p. 51].

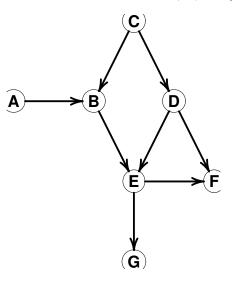
The moral graph

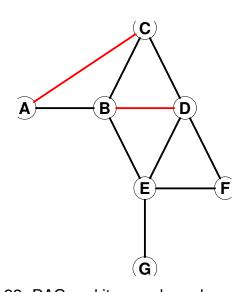


Definition 15. Let G := (V, E) be a DAG.

As the **moral graph of** G we denote the undirected skeleton graph of G plus additional edges between each two parents of a vertex, i.e. moral(G) := (V, E') with

$$E' := u(E) \cup \{ \{x, y\} \mid \exists z \in V : x, y \in pa(z) \}$$





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Bayesian Networks / 3. Separation in Directed Graphs



Separation in DAGs (d-separation)

Let G := (V, E) be a DAG.

Let $X, Y, Z \subseteq V$ be three disjoint subsets of vertices. We say, the vertices X and Y are **separated by** Z **in** G, if

- (i) every chain from any vertex from X to any vertex from Y is blocked by Z or equivalently
- (ii) X and Y are u-separated by Z in the moral graph of the ancestral hull of $X \cup Y \cup Z$.

We write $I_G(X,Y|Z)$ for the statement, that X and Y are separated by Z in G.

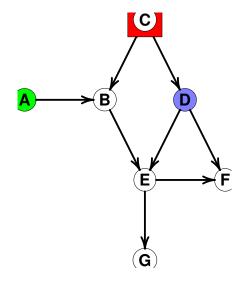


Figure 23: Are the vertices A and D separated by C in G?

Separation in DAGs (d-separation) / examples



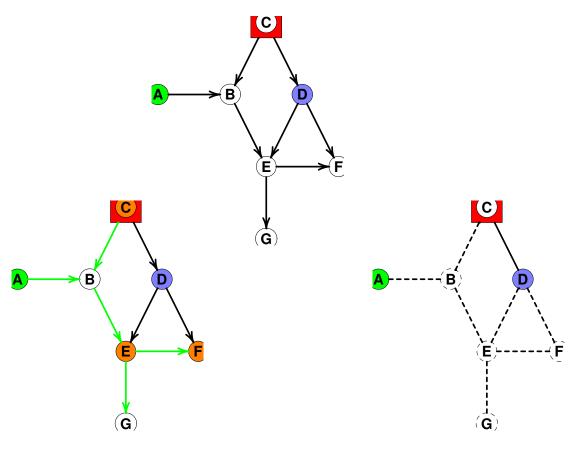


Figure 24: A and D are separated by C in G.

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Separation in DAGs (d-separation) / more examples

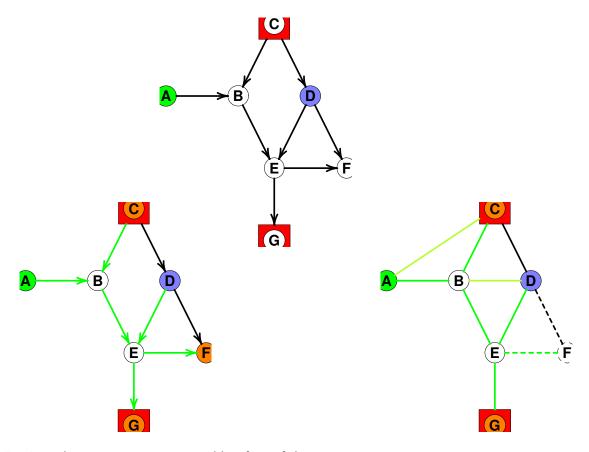


Figure 25: A and D are not separated by $\{C,G\}$ in G.

Checking d-separation



To test, if for a given graph G=(V,E) two given sets $X,Y\subseteq V$ of vertices are d-separated by a third given set $Z\subseteq V$ of vertices, we may

- build the moral graph of the ancestral hull and
- apply the u-separation criterion.

```
1 check-d-separation(G, X, Y, Z):
2 G' := \text{moral}(\text{anc}_G(X \cup Y \cup Z))
3 return check-u-separation(G', X, Y, Z)
```

Figure 26: Algorithm for checking d-separation via u-separation in the moral graph.

A drawback of this algorithm is that we have to rebuild the moral graph of the ancestral hull whenever X or Y changes.

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Bayesian Networks / 3. Separation in Directed Graphs

Checking d-separation



 $(z \in \text{fanout}(y))$

if $y \in Z \cup \operatorname{anc}(Z)$

Instead of constructing a moral graph, we can modify a breadth-first search for chains to find all vertices not d-separated from X by Z in G.

The breadth-first search must not hop over head-to-head meetings with the middle vertex not in \mathbb{Z} nor having an descendent in \mathbb{Z} .

```
I enumerate-d-separation(G = (V, E), X, Z):

borderForward := \emptyset

borderBackward := X \setminus Z

I reached := \emptyset

borderForward \neq \emptyset or borderBackward \neq \emptyset do

borderForward := reached \cup (borderForward \setminus Z) \cup borderBackward

borderForward := fanout_G(borderBackward \cup (borderForward \setminus Z)) \setminus reached

borderBackward := fanoin_G(borderBackward \cup (borderForward \cap (Z \cup anc(Z)))) \setminus Z \setminus reached

borderBackward := fanoin_G(borderBackward \cup (borderForward \cap (Z \cup anc(Z)))) \setminus Z \setminus reached

borderBackward := fanoin_G(borderBackward \cup (borderForward \cap (Z \cup anc(Z)))) \setminus Z \setminus reached

borderBackward := fanoin_G(borderBackward \cup (borderForward \cap (Z \cup anc(Z)))) \setminus Z \setminus reached
```

Figure 28: Algorithm for enumerating all vertices d-separated from X by Z in G via restricted breadth-first search (see [Nea03, p. 80–86] for another formulation).

Properties of d-separation / no strong union



For d-separation the strong union property does not hold.

I is called **strongly unionable**, if

 $I(X,Y|Z) \Rightarrow I(X,Y|Z \cup Z')$ for all Z' disjunct with X,Y

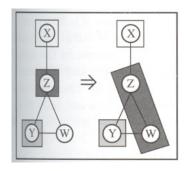


Figure 29: Example for strong union in undirected graphs (u-separation) [CGH97, p. 189].

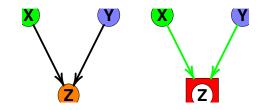


Figure 30: Counterexample for strong unions in DAGs (d-separation).

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Properties of d-separation / no strong transitivity

For d-separation the strong transitivity property does not hold.

I is called **strongly transitive**, if

$$I(X,Y|Z) \Rightarrow I(X,\{v\}|Z) \text{ or } I(\{v\},Y|Z) \quad \forall v \in V \setminus Z$$

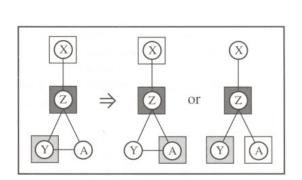


Figure 31: Example for strong transitivity in undirected graphs (u-separation) [CGH97, p. 189].

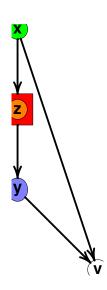


Figure 32: Counterexample for strong transitivity

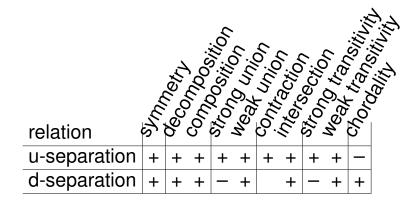
rected graphs (u-separation) [CGH97, p. 189]. in DAGs (d-separation).

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Properties of d-separation





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