# Separation in Graphs

Bayesian Networks

## Simple Graph

A simple graph (or just: graph) is a tuple G = (V, E) where

 $V = \{A_1, \ldots, A_n\}$ 

represents a finite set of vertices (or nodes) and

$$E \subseteq (V \times V) \setminus \{(A, A) \mid A \in V\}$$

denotes the set of edges.

It is called simple since there are no self-loops and no multiple edges.

## Edge Types

Let  $\mathbf{G} = (V, E)$  be a graph. An edge e = (A, B) is called

directed if  $(A, B) \in E \Rightarrow (B, A) \notin E$ Notation:  $A \to B$ 

**undirected** if  $(A, B) \in E \Rightarrow (B, A) \in E$ Notation: A - B or B - A

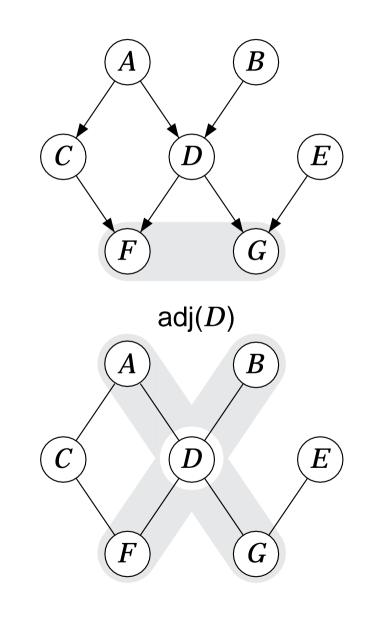
## (Un)directed Graph

A graph with only (un)directed edges is called an (un)directed graph.

### **Adjacency Set**

Let  $\mathbf{G} = (V, E)$  be a graph. The set of nodes that is accessible via a given node  $A \in V$  is called the **adjacency** set of A:

$$\operatorname{adj}(A) = \{ B \in V | (A, B) \in E \}$$



Paths

Let **G** = (*V*, *E*) be a graph. A series  $\rho$  of *r* pairwise different nodes

$$\rho = (A_{i_1}, \ldots, A_{i_r})$$

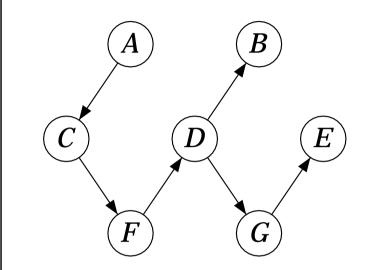
is called a **path** from  $A_i$  to  $A_j$  if  $A_{i_1} = A_i, \quad A_{i_r} = A_j$  $A_{i_{k+1}} \in \operatorname{adj}(A_{i_k}), \quad 1 \leq k < r$ 

A path with only undirected edges is called an undirected path

$$\rho = A_{i_1} - \cdots - A_{i_r}$$

whereas a path with only directed edges is referred to as a directed path

$$\rho = A_{i_1} \to \cdots \to A_{i_r}$$



If there is a directed path  $\rho$ from node A to node B in a directed graph **G** we write

$$\begin{array}{c} \mathbf{A} \xrightarrow{\rho}_{\mathcal{G}} \mathbf{B} \\ \text{If the path } \rho \text{ is undirected} \\ \text{we denote this with} \end{array}$$

 $A \leftrightarrow B$ 

we de

## Loop and Cycle

#### Loop

Let  $\mathbf{G} = (V, E)$  be an undirected graph. A path

$$\rho = X_1 - \cdots - X_k$$

with  $(X_k - X_1) \in E$  is called a loop.

### Cycle

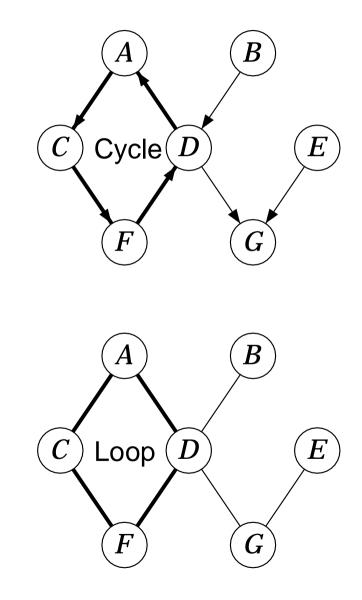
Let  $\mathbf{G} = (V, E)$  be a directed graph. A path

$$\rho = X_1 \rightarrow \cdots \rightarrow X_k$$

with  $(X_k \rightarrow X_1) \in E$  is called a cycle.

### **Directed Acyclic Graph (DAG)**

A directed graph  $\mathbf{G} = (V, E)$  is called acyclic if for every path  $X_1 \rightarrow \cdots \rightarrow X_k$  in  $\mathbf{G}$  the condition  $(X_k \rightarrow X_1) \notin E$  is satisfied, i. e. it contains no cycle.



Rudolf Kruse

Let  $\mathbf{G} = (V, E)$  be a directed graph. For every node  $A \in V$  we define the following sets:

Parents:

parents<sub>G</sub>(A) = { $B \in V | B \rightarrow A \in E$ }

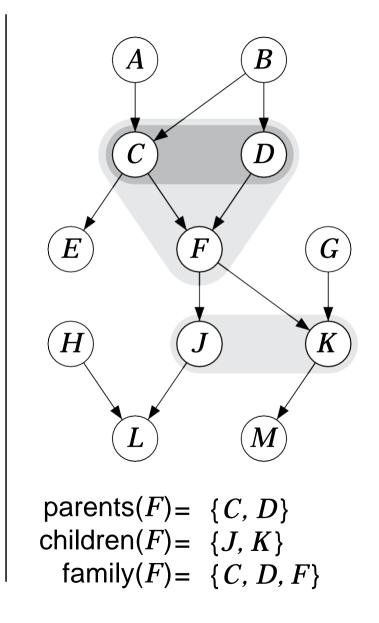
Children:

children<sub>G</sub>(A) = { $B \in V | A \rightarrow B \in E$ }

Family:

```
family<sub>G</sub>(A) = {A} Uparents<sub>G</sub>(A)
```

If the respective graph is clear from the context, the index **G** is omitted.



Let  $\mathbf{G} = (V, E)$  be a DAG. For every node  $A \in V$  we define the following sets:

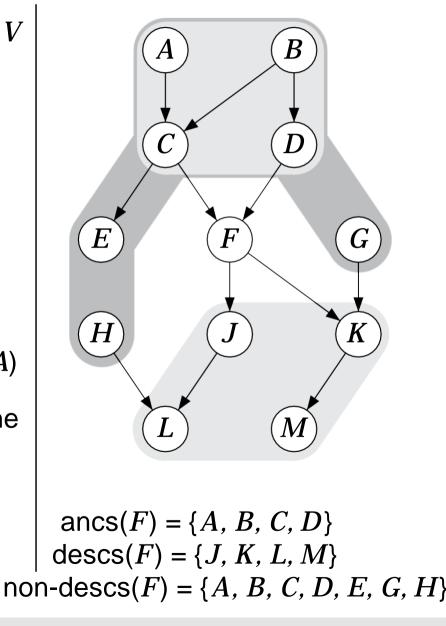
Ancestors:  
ancs(A) = 
$$\{B \in V \mid \exists \rho : B \xrightarrow{\rho}_{\mathcal{G}} A\}$$

**Descendants:**  $descs(A) = \{B \in V \mid \exists \rho : A \xrightarrow{\rho}{\mathcal{G}} B\}$ 

Non-Descendants:

non-descs<sub>G</sub>(A) =  $V \setminus \{A\} \setminus descs_{G}(A)$ 

If the respective graph is clear from the context, the index **G** is omitted.

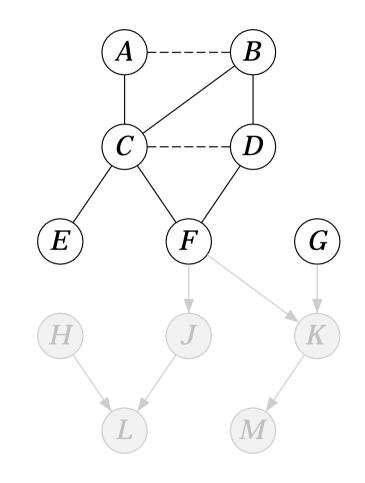


Let G = (V, E) be a DAG.

The Minimal Ancestral Subgraph of **G** given a set  $M \subseteq V$  of nodes is the smallest subgraph that contains M and all ancestors of all nodes in M.

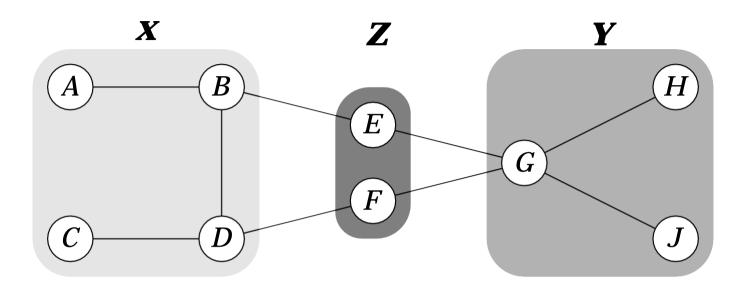
The Moral Graph of G is the undirected graph that is obtained by

- 1. connecting nodes that share a common child with an arbitrarily directed edge and,
- 2. converting all directed edges into undirected ones by dropping the arrow heads.



Moral graph of ancestral graph induced by the set  $\{E, F, G\}$ .

## u-Separation



Let  $\mathbf{G} = (V, E)$  be an undirected graph and  $X, Y, Z \subseteq V$  three disjoint subsets of nodes. We agree on the following separation criteria:

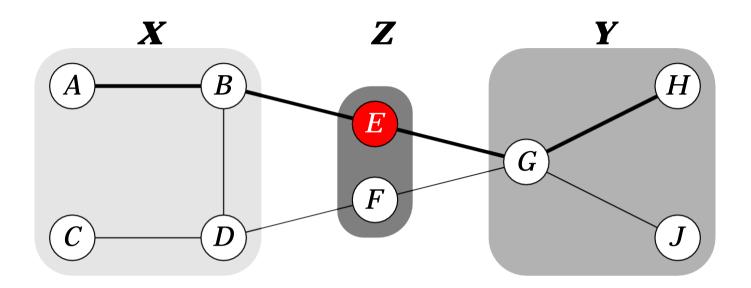
1. Z u-separates X from Y — written as

$$X \perp \square_{\mathsf{G}} Y \mid Z,$$

if every possible path from a node in X to a node in Y is blocked.

- 2. A path is blocked if it contains one (or more) blocking nodes.
- 3. A node is a blocking node if it lies in Z.

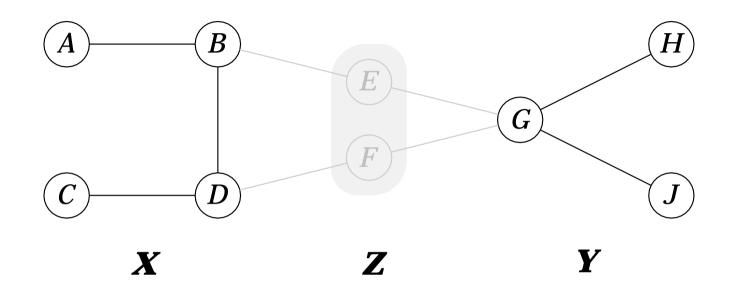
## u-Separation



e.g. path A - B - E - G - H is blocked by  $E \in Z$ . It can be easily verified, that every path from X to Y is blocked by Z. Hence we have:

 $\{A, B, C, D\} \sqcup \{G, H, J\} | \{E, F\}$ 

## u-Separation

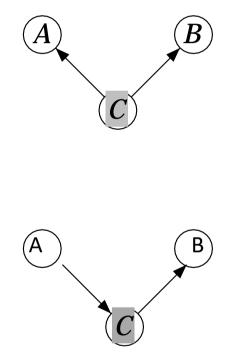


Another way to check for u-separation: Remove the nodes in Z from the graph (and all the edges adjacent to these nodes). X and Y are u-separated by Z if the remaining graph is disconnected with X and Y in two separate subgraphs.

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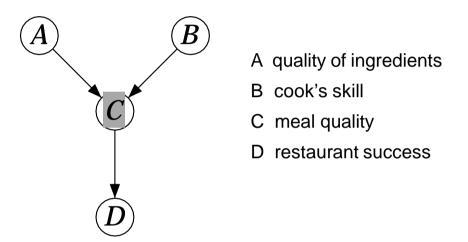
Bayesian Networks

Idea: Separation in Directed Graphs should fit to the concept of Conditional independence



If C is instantiated with c then A and B are conditional independent, i.e. P(A,BIC=c)=P(AIC=c)P(BIC=c)

C separates A and B C is a blocking node of the path A-B-C (walking against the direction of the arrows is allowed)



If C is instantiated with c then A and B are conditional dependent

If D is instantiated with d Then A and B are conditional dependent

C is no separator of A and B, C is no blocking node

D is no separator of A and B, C is no blocking node Separation criterion for directed graphs.

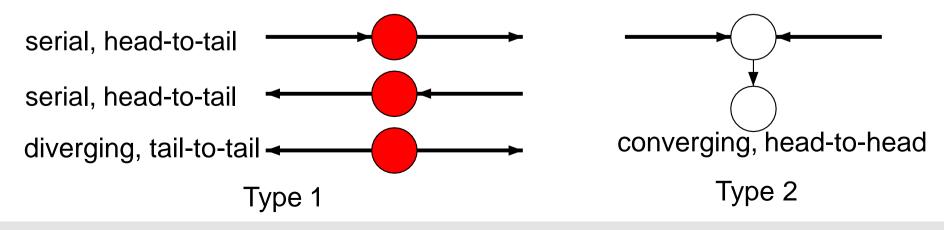
We use the same principles as for u-separation. Two modifications are necessary: Directed paths may lead also in reverse to the arrows. The blocking node condition is more sophisticated.

Blocking Node (in a directed path)

A node A is blocking if its edge directions along the path

are of type 1 and  $A \in \mathbf{Z}$ , or

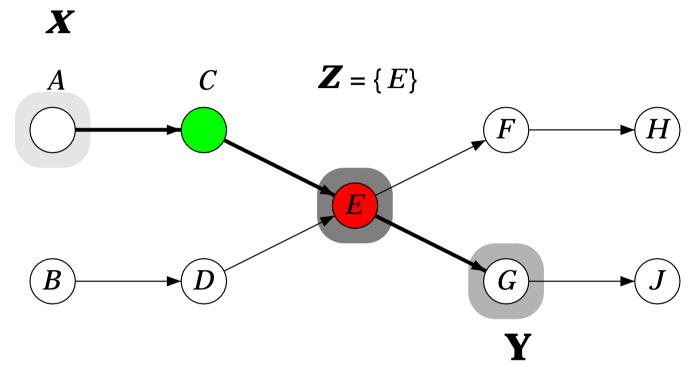
are of type 2 and neither A nor one of its descendants is in  $\mathbf{Z}$ .



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Bayesian Networks

## Examples for d-Separation $\mathbf{X} \perp \mathbf{Y} \mid \mathbf{Z}$



Checking path  $A \rightarrow C \rightarrow E \rightarrow G$ 

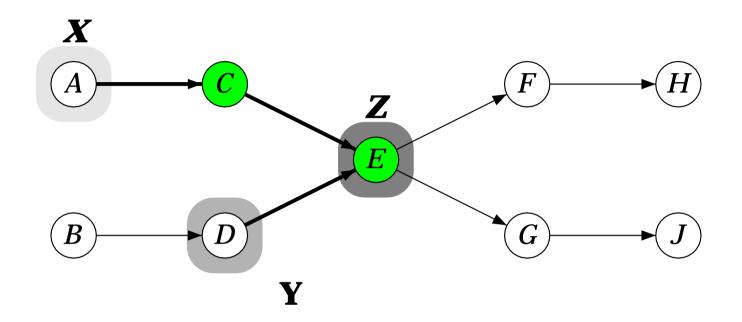
C is serial and not in Z: non-blocking

E is also serial but in Z: blocking

Path is blocked, no other paths between A and G are available

$$\Rightarrow \quad A \coprod G \mid E$$

# Examples for d-Separation $\mathbf{X} \not \perp \mathbf{Y} \mid \mathbf{Z}$



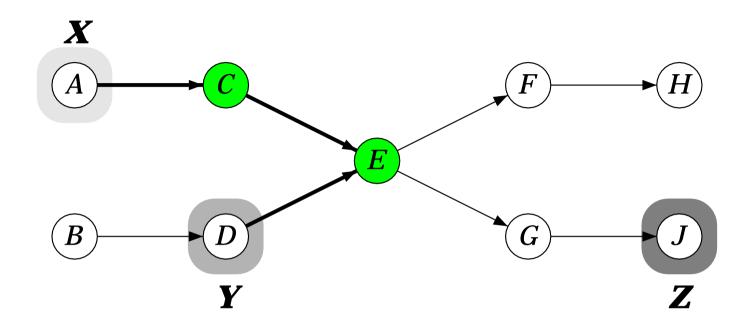
Checking path  $A \rightarrow C \rightarrow E \leftarrow D$ :

C is serial and not in Z: non-blocking

*E* is converging and in *Z*: non-blocking

 $\Rightarrow$  Path is not blocked

# Examples for d-Separation $\mathbf{X} \not\models \mathbf{Y} \mid \mathbf{Z}$



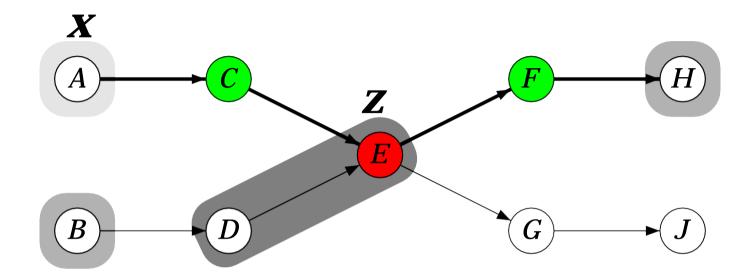
Checking path  $A \rightarrow C \rightarrow E \leftarrow D$ :

C is serial and not in Z: non-blocking

*E* is **converging** and not in *Z* but one of its descendants (J) is in *Z*: non-blocking

 $\Rightarrow$  Path is not blocked

## Examples for d-Separation $\mathbf{X} \perp \mathbf{Y} \mid \mathbf{Z}$



 $\boldsymbol{Y} = \{B, H\}$ 

Checking path  $A \rightarrow C \rightarrow E \rightarrow F \rightarrow H$ :

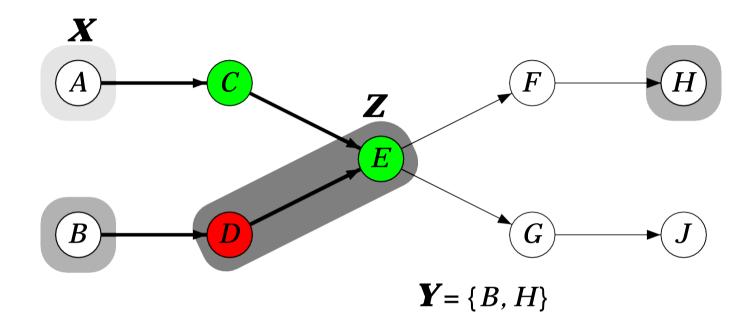
*C* is serial and not in *Z*: non-blocking

E is serial and in Z: blocking

F is serial and not in Z: non-blocking

 $\Rightarrow$  Path is blocked

## Examples for d-Separation $\mathbf{X} \perp \mathbf{Y} \mid \mathbf{Z}$



Checking path  $A \rightarrow C \rightarrow E \leftarrow D \rightarrow B$ :

*C* is serial and not in *Z*: non-blocking

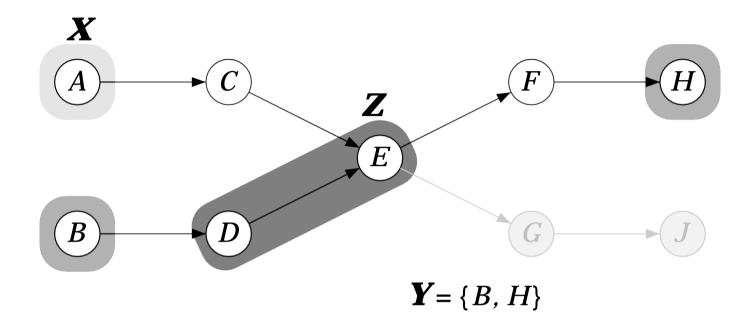
*E* is **converging** and in *Z*: non-blocking

D is serial and in Z: blocking

 $\Rightarrow$  Path is blocked

## $A \perp B, H \mid D, E$

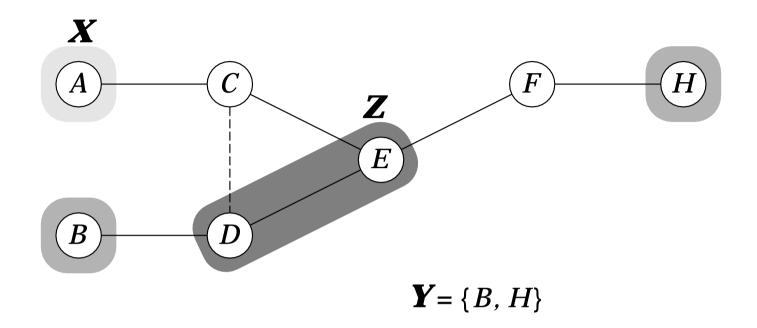
## d-Separation: Alternative Way for Checking



Steps

- Create the minimal ancestral subgraph induced by  $X \cup Y \cup Z$ 

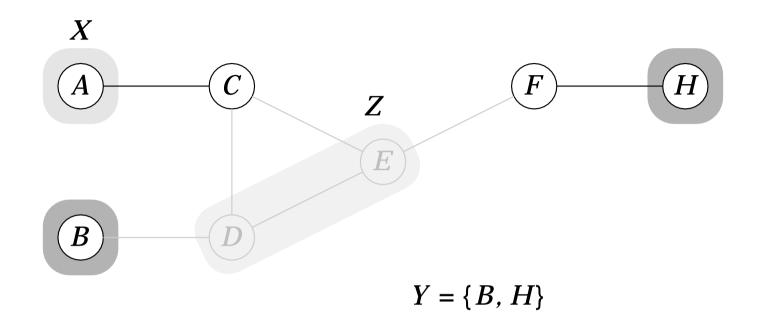
## d-Separation: Alternative Way for Checking



Steps

- Create the minimal ancestral subgraph induced by  $X \cup Y \cup Z$
- Moralize that subgraph

## d-Separation: Alternative Way for Checking



Steps:

- Create the minimal ancestral subgraph induced by  $X \cup Y \cup Z$
- Moralize that subgraph
- Check for u-Separation in that undirected graph

 $A \perp H, B \mid D, E$ 

Let G = (V, E) a DAG and  $X, Y, Z \in V$  three nodes.

- a) A set  $S \subseteq V \{X, Y\}$  *d-separates* X and Y, if S blocks all paths between X and Y. A path may also route in opposite edge direction.
- b) A path  $\pi$  is d-separated by *S* if at least one pair of consecutive edges along  $\pi$  is blocked. There are the following blocking conditions:
  - 1.  $X \leftarrow Y \rightarrow Z$ tail-to-tail2 $X \leftarrow Y \leftarrow Z$ head-to-tail3.  $X \rightarrow Y \leftarrow Z$ head-to-head
- c) Two edges that meet tail-to-tail or head-to-tail in node Yare blocked if  $Y \in S$ .
- d) Two edges meeting head-to-head in Y are blocked if neither Y nor its successors are in S.

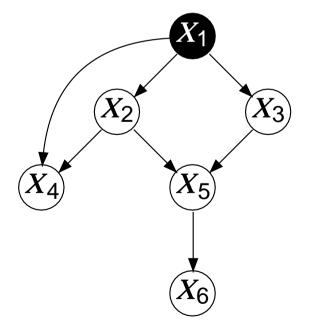
# d-Separation and Conditional Independence

#### Theorem

If  $S \subseteq V \{X, Y\}$  d-separates X and Y in a Bayesian network (V, E, P), then X and Y are conditionally independent given S:

$$P(X, Y \mid S) = P(X \mid S) \cdot P(Y \mid S)$$

Example



Paths: 
$$\pi_1 = (X_2 - X_1 - X_3), \ \pi_2 = (X_2 - X_5 - X_3), \ \pi_3 = (X_2 - X_4 - X_1 - X_3), \ S = \{X_1\}$$

$$\pi_1 \quad X_2 \leftarrow X_1 \rightarrow X_3 \text{ tail-to-tail} \\ X_1 \in S \Rightarrow \pi_1 \text{ is blocked by } S$$

$$\pi_2 \quad X_2 \to X_5 \leftarrow X_3 \text{ head-to-head} \\ X_5, X_6 \notin S \quad \Rightarrow \pi_2 \text{ is blocked by } S$$

 $\begin{array}{ll} \pi_3 & X_4 \leftarrow X_1 \rightarrow X_3 \text{ tail-to-tail } X_2 \rightarrow X_4 \leftarrow X_1 \\ \text{head-to-head both connections are} \\ \text{blocked} & \Rightarrow & \pi_3 \text{ is blocked} \end{array}$ 

X2 and X3 are d-separated via {X1}. X2 and X3 are therefore conditionally independent given X1 Conditional independence statements can be characterised qualitatively, e.g. without specifying the numerical values of probabilities.

Let  $(\Omega, \mathcal{E}, P)$  be a probability space and W, X, Y, Z disjoint subsets of variables. If X and Y are conditionally independent given Z we write:

## $X \amalg_P Y \mid Z$

Often, the following (equivalent) notation is used:

 $I_P(X \mid Z \mid Y)$  or  $I_P(X, Y \mid Z)$ 

If the underlying space is known the index P is omitted.

## (Semi-)Graphoid Axioms

**Definition:** Let V be a set of (mathematical) objects and  $(\cdot \bot \downarrow \cdot | \cdot)$  a three-place relation of subsets of V. Furthermore, let W, X, Y, and Z be four disjoint subsets of V. The four statements

symmetry:  $(X \perp\!\!\!\perp Y \mid Z) \Rightarrow (Y \perp\!\!\!\perp X \mid Z)$ 

decomposition:  $(W \cup X \perp Y \mid Z) \Rightarrow (W \perp Y \mid Z) \land (X \perp Y \mid Z)$ 

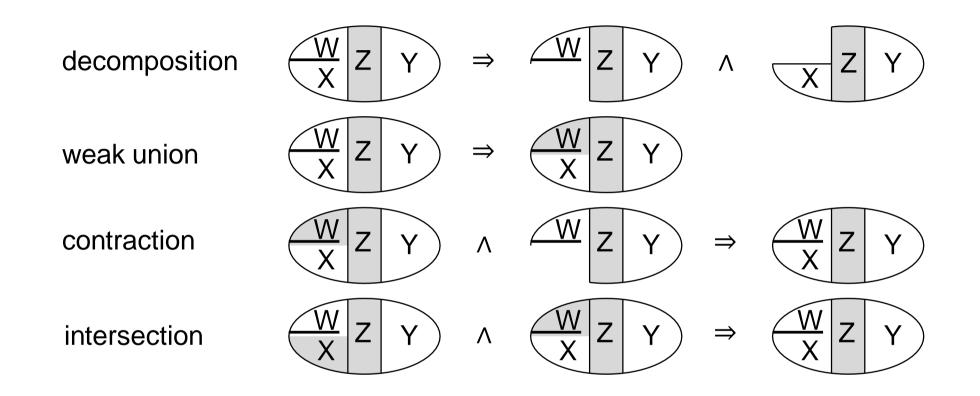
weak union:  $(W \cup X \perp Y \mid Z) \Rightarrow (X \perp Y \mid Z \cup W)$ 

contraction:  $(X \perp\!\!\!\perp Y \mid Z \cup W) \land (W \perp\!\!\!\perp Y \mid Z) \Rightarrow (W \cup X \perp\!\!\!\perp Y \mid Z)$ 

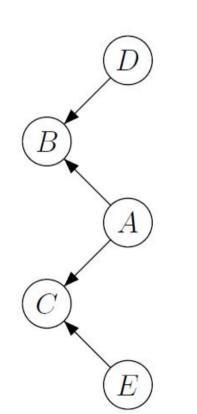
are called the **semi-graphoid axioms**. A three-place relation  $(\cdot \perp \!\!\!\perp \cdot \mid \cdot)$  that satisfies the semi-graphoid axioms for all W, X, Y, and Z is called a **semi-graphoid**.

Note: The probability calculus satisfies the four **semi-graphoid** axioms, but not the additional fifth intersection axiom of a **graphoid**.

## Illustration of the (Semi-)Graphoid Axioms



Example



	$D \amalg A, C \mid \emptyset  \land  B \amalg C \mid A, D$
$\stackrel{w. union}{\Longrightarrow}$	$D \perp\!\!\!\!\perp C \mid A  \wedge  B \perp\!\!\!\!\perp C \mid A, D$
$\underset{\longleftrightarrow}{\operatorname{symm.}}$	$C \perp\!\!\!\perp D \mid A  \wedge  C \perp\!\!\!\!\perp B \mid A, D$
$\stackrel{\text{contr.}}{\Longrightarrow}$	$C \!\perp\!\!\!\perp B, D \mid A$
$\stackrel{\text{decomp.}}{\Longrightarrow}$	$C \amalg B \mid A$
$\stackrel{\text{symm.}}{\iff}$	$B \perp\!\!\!\perp C \mid A$

Let  $(\cdot \perp \delta \cdot | \cdot)$  be a three-place relation representing the set of **conditional independence statements** that hold in a given distribution  $\delta$  over U.

A graph G=(U,E) over random variables U is called an **independence map (I-map)** for the joint probability space  $\delta$ , if for all disjoint subsets X,Y,Z of U the property

$$\langle X \mid Z \mid Y \rangle_G \Rightarrow X \perp _{\delta} Y \mid Z_{\bullet}$$

holds.

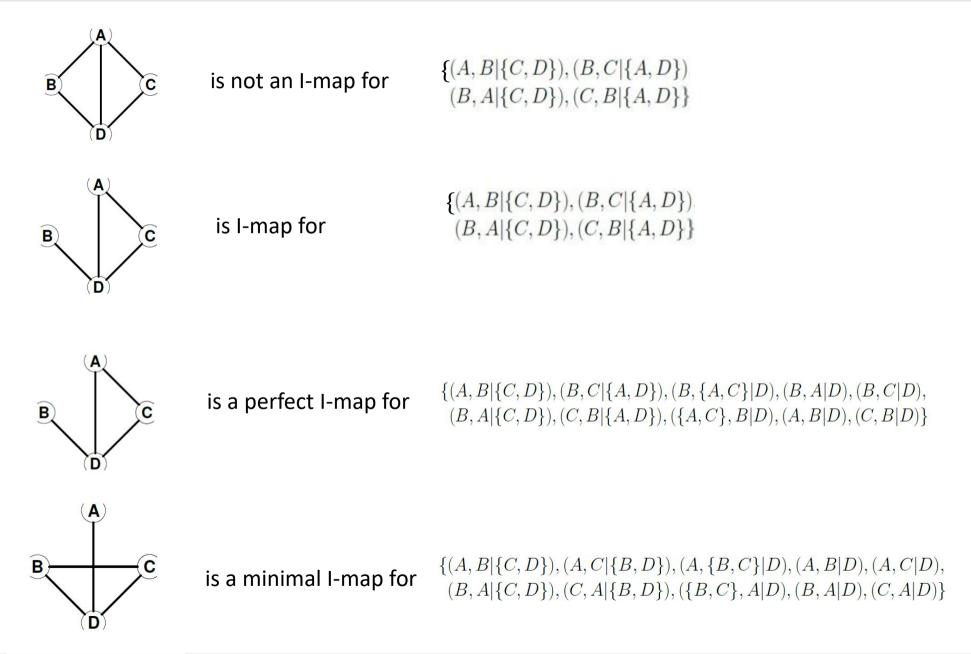
An I-map G for  $\delta$  captures **only** conditional independences that are valid in  $\delta$ .

An I-map G for  $\delta$  is called a **perfect map**, if G captures **all** valid conditional independences in  $\delta$ .

An I-map G for is called **minimal** iff no edge can be removed from G so that the resulting graph is still an I-map for  $\delta$ .

These definitions hold for directed as well as undirected graphs.

## Independence Maps: Examples for undirected graphs



## Independence Maps for Probability Spaces

If a probability P is given, then we can check for subsets X,Y,Z of random variables on P whether X and Y are conditionally independent with respect to Z. As the result we obtain a three-place relation representing a set of **conditional independence statements** 

$$X \amalg_P Y \mid Z$$

A directed graph G=(U,E) over U is called an **independence map (I-map)** for P, if for all disjoint subsets X,Y,Z of U the property

holds.

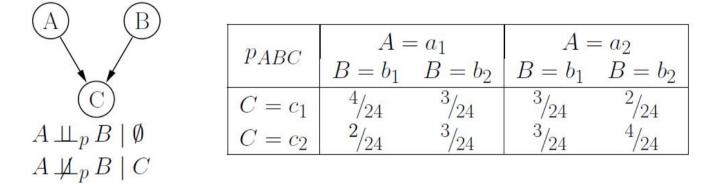
$$\langle X \mid Z \mid Y \rangle_G \Rightarrow X \amalg_P Y \mid Z$$

In an I-map every independence we can observe from G is encoded in P. In most cases the set of independencies we can see from the connectivity in the graph (via d-separation or useparation) is only a part of the independencies the joint distribution P has. The "ultimate" connection between probability distributions and graphs requires the other implication direction to hold, namely for every conditional independence in the probability distribution to correspond to a separation in the graph. This connection has been called **faithfulness** of the probability distribution and the graph.

# An I-map G for P is called a **perfect map**, if G captures **exactly the (**conditional) independences in P.

## Limitations of Graph Representations

Perfect directed map, no perfect undirected map:



Perfect undirected map, no perfect directed map:

	PABCD	$A = a_1$		$A = a_2$	
	PABCD	$B = b_1$	$B = b_2$	$B = b_1$	$B = b_2$
	$D = d_1$	1/47	$^{1}/_{47}$	$^{1}/_{47}$	$^{2}/_{47}$
(B)—(C)	$C = c_1$ $D = d_2$	$^{1}/_{47}$	$^{1}/_{47}$	$^{2}/_{47}$	$^{4}/_{47}$
$B \coprod_p D \mid \{A, C\}$	$D = d_1$	$^{1}/_{47}$	$^{2}/_{47}$	$^{1}/_{47}$	$^{4}/_{47}$
$A \perp p C \mid \{B, D\}$	$C = c_2 \qquad D = d_1$ $D = d_2$	$^{2}/_{47}$	4/47	4/47	16/47

## Limitations of Graph Representations

There are also probability distributions for which there exists neither a directed nor an undirected perfect map:

B C	$\begin{array}{c} A \amalg_p B \mid \emptyset \\ A \amalg_p C \mid \emptyset \\ B \amalg_p C \mid \emptyset \end{array}$	$p_{ABC}$		$\stackrel{=a_1}{B=b_2}$		$B^{= a_2} = b_2$
		$C = c_1$ $C = c_2$	$\frac{2}{12}$ $\frac{1}{12}$	$\frac{1}{12}$ $\frac{2}{12}$	$\frac{1}{12}$ $\frac{2}{12}$	$\frac{2}{12}$ $\frac{1}{12}$

In such cases either not all dependences or not all independences

can be captured by a graph representation.

In such a situation one usually decides to neglect some of the independence information, that is, to use only a (minimal) conditional independence graph.

This is sufficient for correct evidence propagation, the existence of a perfect map is not required.