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## **Bayesian Networks**

# II. Probabilistic Independence and Separation in Graphs (part 2)

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- **1. Basic Probability Calculus**
- 2. Separation in undirected graphs
- **3. Separation in directed graphs**

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### Directed graphs

**Definition 1.** 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**:

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

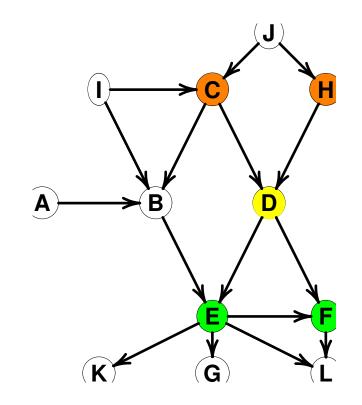


Figure 1: Fanin (orange) and fanout (green) of a node (blue).

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## Paths on directed graphs

**Definition 2.** 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)**.

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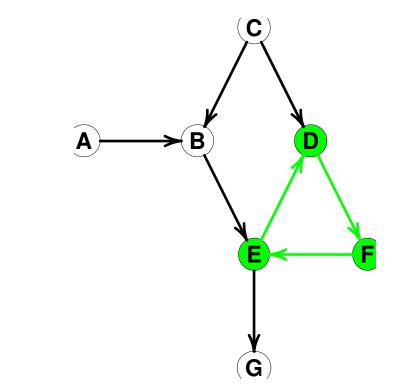


Figure 2: Example for a cycle.



Paths on directed graphs (2/2)

**Definition 3.** 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 xare called **ancestors of** x:

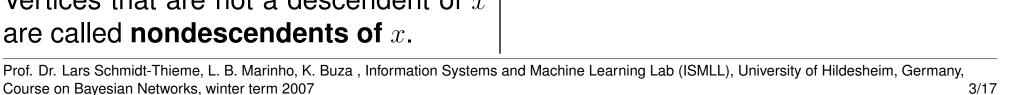
anc(x) := {
$$y \in V | \exists p \in G^* : |p| \ge 2$$
,  
 $p_1 = y, p_{|p|} = x$ }

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

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

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

Figure 3: Parents/Fanin (orange) and additional ancestors (light orange), children/fanout (green) and additional descendants (light green) of a node (blue).





## Chains

**Definition 4.** Let G := (V, E) be a directed graph. We can construct an **undirected pendant** u(G) := (V, u(E)) of *G* by dropping the directions of the edges:

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

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

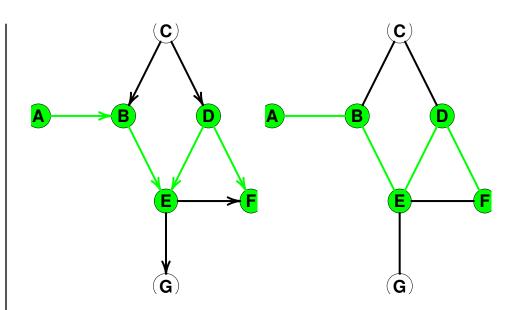
$$G^{\blacktriangle} := u(G)^*$$

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

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

#### The notions of length, subchain, interior and proper carry over from undi-Prof. Dr. Lars Schmidt-Thieme, L. B. Marinho, K. Buza, Information Systems and Machine Learning Lab (ISMLL), University of Hildesheim, Germany, Correction Bayesian Networks, Winter Item, 2007

Figure 4: Chain (A, B, E, D, F) on directed graph and path on undirected pendant.







**Blocked chains** 

**Definition 5.** 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

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

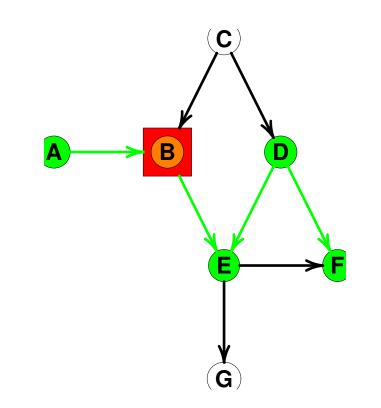
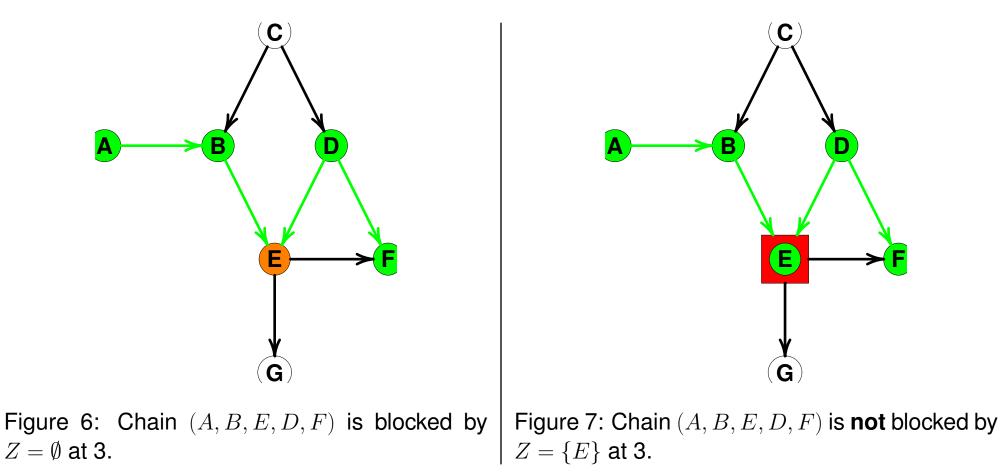


Figure 5: Chain (A, B, E, D, F) is blocked by  $Z = \{B\}$  at 2.

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### Blocked chains / more examples





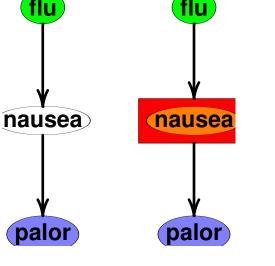
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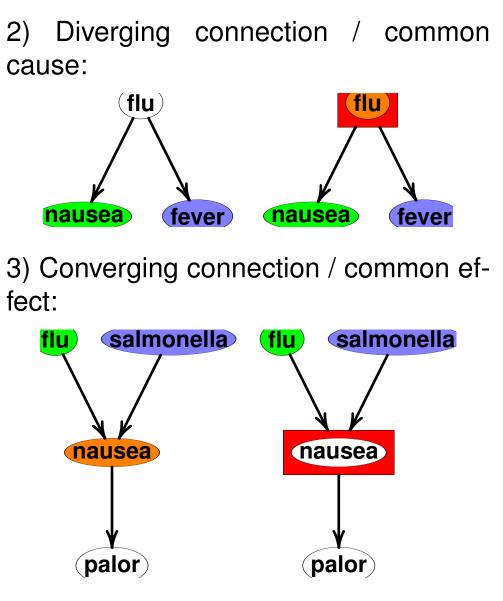
### Blocked chains / rationale

The notion of blocking is choosen in 2) Diverging connection a way so that chains model "flow of cause: causal influence" through a causal network where the states of the vertices Z are already know.

1) Serial connection / intermediate cause:

enal connection / intermed ; flu flu





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

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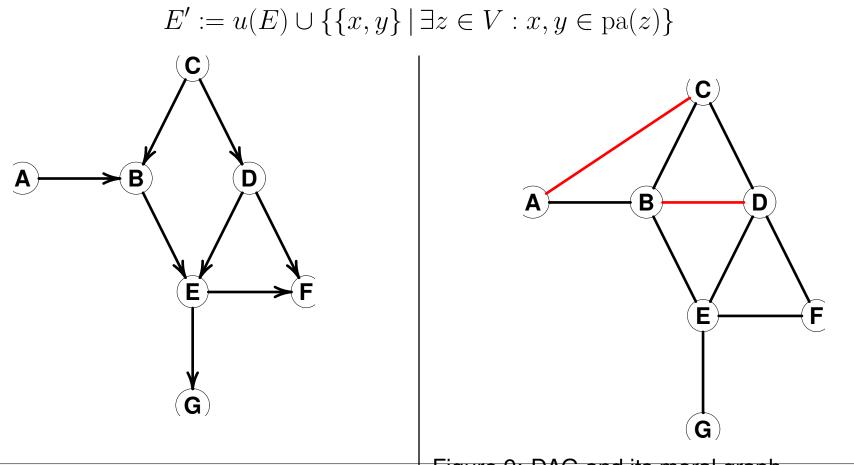




The moral graph

**Definition 6.** 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



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## 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 Xto any vertex from Y is blocked by Zor 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.

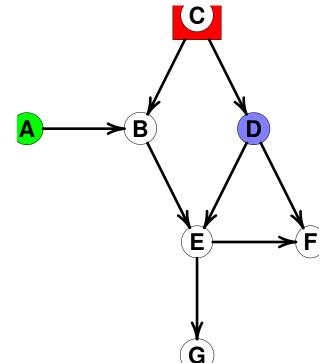
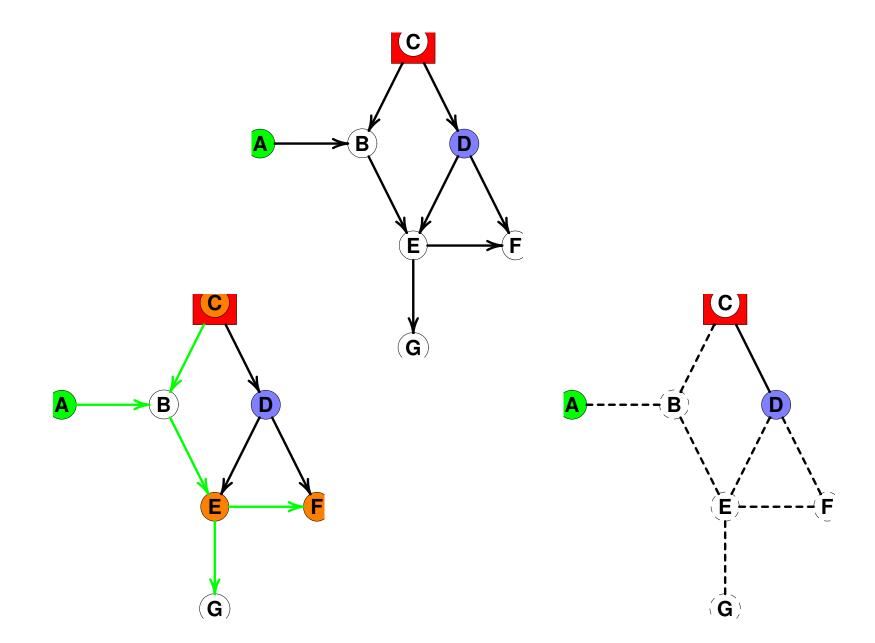


Figure 10: Are the vertices A and D separated by C in G?

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#### Separation in DAGs (d-separation) / examples

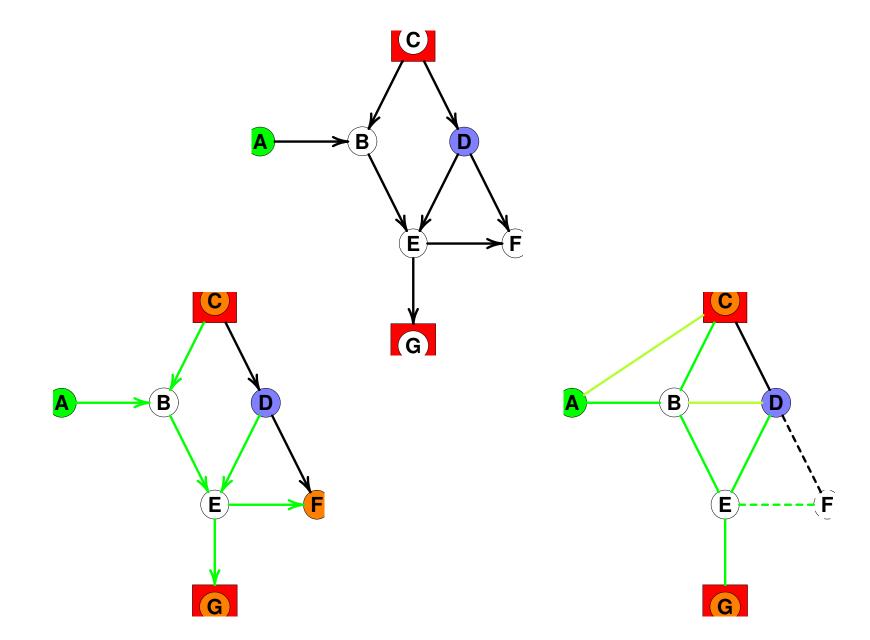


#### Figure 11: A and D are separated by C in G.

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#### Separation in DAGs (d-separation) / more examples



#### Figure 12: A and D are not separated by $\{C, G\}$ in G.

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## 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.

- *i* check-d-separation(G, X, Y, Z):
- $2 \ G' := \operatorname{moral}(\operatorname{anc}_G(X \cup Y \cup Z))$
- <sup>3</sup> <u>return</u> check-u-separation(G', X, Y, Z)

Figure 13: 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.



#### Checking d-separation

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 Z nor having an descendent in Z.

*i* enumerate-d-separation(G = (V, E), X, Z):

```
<sup>2</sup> borderForward := \emptyset
```

```
<sup>3</sup> borderBackward := X \setminus Z
```

```
4 reached := \emptyset
```

```
<sup>5</sup> <u>while</u> borderForward \neq \emptyset or borderBackward \neq \emptyset <u>do</u>
```

- 6 reached := reached  $\cup$  (borderForward  $\setminus Z$ )  $\cup$  borderBackward
- *p* borderForward := fanout<sub>G</sub>(borderBackward  $\cup$  (borderForward  $\setminus Z$ ))  $\setminus$  reached
- 8 borderBackward :=  $fanin_G(borderBackward \cup (borderForward \cap (Z \cup anc(Z)))) \setminus Z \setminus reached$
- 9 <u>od</u>

```
10 <u>return</u> V \setminus reached
```

Figure 15: 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).

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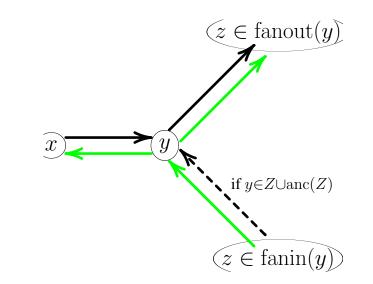


Figure 14: Restricted breadth-first search of non-blocked chains.

Bayesian Networks / 3. Separation in directed graphs

Properties of d-separation / no strong union

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

I is called **strongly unionable**, if

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

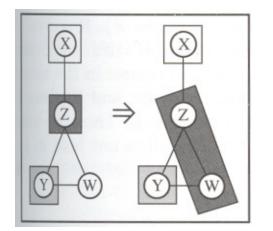


Figure 16: Example for strong union in undirected graphs (u-separation) [CGH97, p. 189].

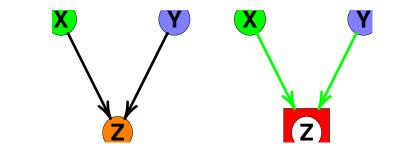


Figure 17: Counterexample for strong unions in DAGs (d-separation).



Bayesian Networks / 3. Separation in directed graphs



Properties of d-separation / no strong transitivity

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

I is called **strongly transitive**, if

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

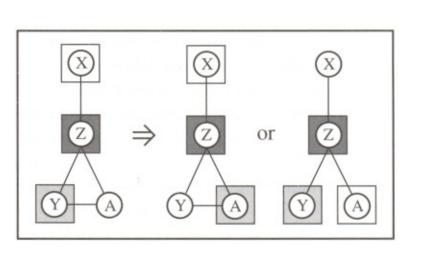


Figure 18: Example for strong transitivity in undirected graphs (u-separation) [CGH97, p. 189].

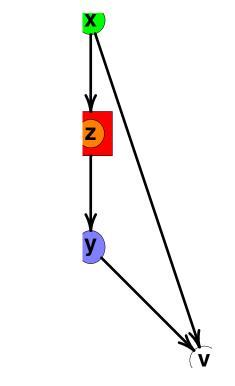


Figure 19: Counterexample for strong transitivity in DAGs (d-separation).

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## Properties of d-separation



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u-separation	+	+	+	+	+	+	+	+	+	_	
d-separation	+	+	+	_	+		+	_	+	+	

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#### References



[CGH97] Enrique Castillo, José Manuel Gutiérrez, and Ali S. Hadi. *Expert Systems and Probabilistic Network Models*. Springer, New York, 1997.

[Nea03] Richard E. Neapolitan. *Learning Bayesian Networks*. Prentice Hall, 2003.

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