

Probabilistic Machine Learning:

8. Belief Networks: Independence

Tomasz Kajdanowicz

Department of Computational Intelligence
Wrocław University of Technology

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HR EXCELLENCE IN RESEARCH



Wrocław University
of Science and Technology

The presentation was inspired by Chapter 3 of D. Koller and N. Friedman book "Probabilistic Graphical Models - Principles and Techniques", 2009.



Conditional Independence

For sets of random variables X, Y, Z , $P \models (X \perp Y|Z)$ if:

- ▶ $P(X, Y|Z) = P(X|Z)P(Y|Z)$ or
- ▶ $P(X|Y, Z) = P(X|Z)$ or
- ▶ $P(Y|X, Z) = P(Y|Z)$

How to determine the Conditional Independence?

d-separation

Conditional Independence

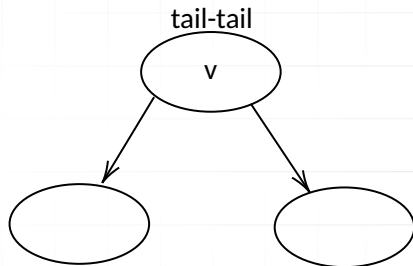
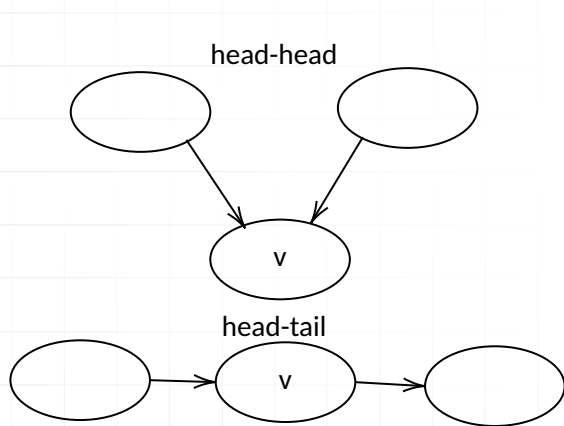
For random variables X, Y, Z if X and Y are ***d-separated*** by Z then $(X \perp Y|Z)$

d-separation

X and Y are d-separated by Z if all paths from a vertex of X to a vertex of Y are **blocked** with respect to v .

Types of connection on the path

with respect to Z

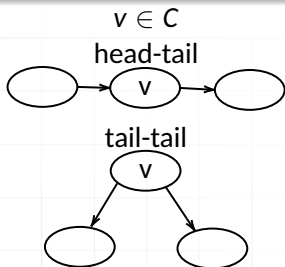


Blocked path

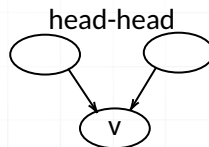
Blocked path

A path (not necessary directed) between two vertices is **blocked** with respect to C (even set of vertices) if it passes through a vertex v s.t. either:

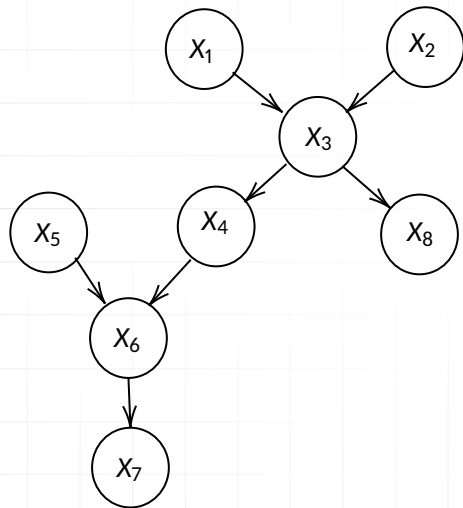
- ▶ the connections are head-tail or tail-tail and $v \in C$
- ▶ the connections are head-head and $v \notin C$ and none of descendants of v are in C



$v \notin C$ and none of descendants of v are in C



Example

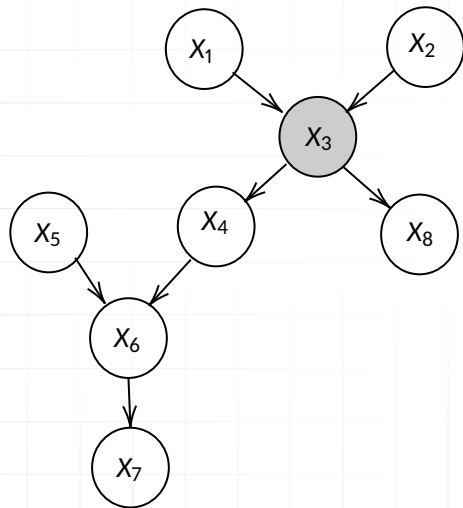


► taking e.g.:

► $C = \{X_3\}$

► $(X_i \perp X_j) | X_C$???

Example



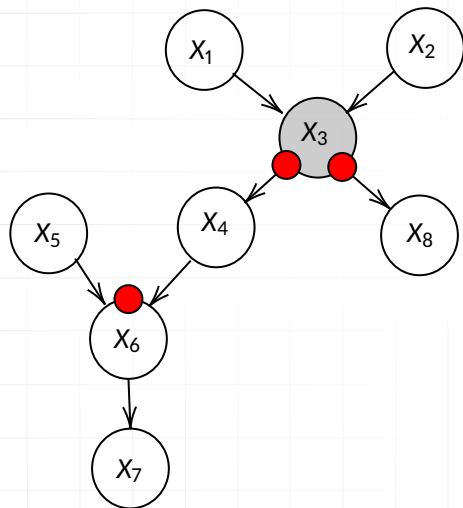
► taking e.g.:

► $C = \{X_3\}$

► $(X_i \perp X_j) | X_C$???

i	j	d-separated
1	4	yes
1	2	no
4	5	yes

Example



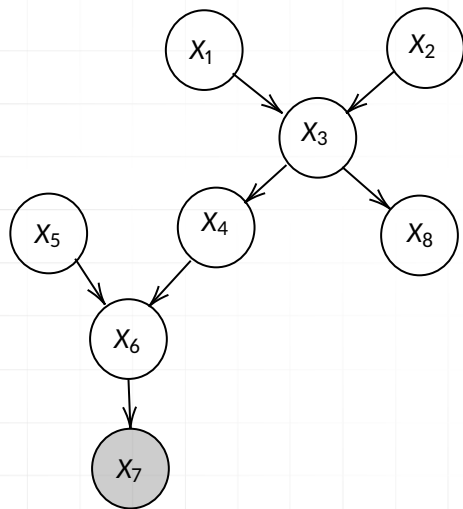
► taking e.g.:

► $C = \{X_3\}$

► $(X_i \perp X_j) | X_C$???

i	j	d-separated
1	4	yes
1	2	no
4	5	yes
4	7	no
4	8	yes
4	6	no
2	7	yes
2	5	yes
5	8	yes

Example 2



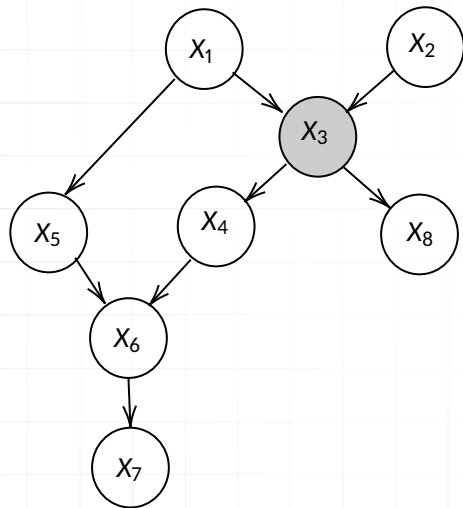
► taking e.g.:

► $C = \{X_7\}$

► $(X_i \perp X_j) | X_C$???

$i \quad j \quad \text{d-separated}$

Example 3



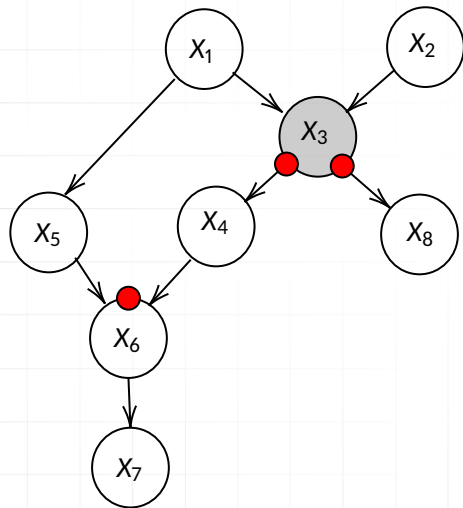
► taking e.g.:

► $C = \{X_3\}$

► $(X_i \perp X_j) | X_C$???

$i \quad j \quad \text{d-separated}$

Example 3



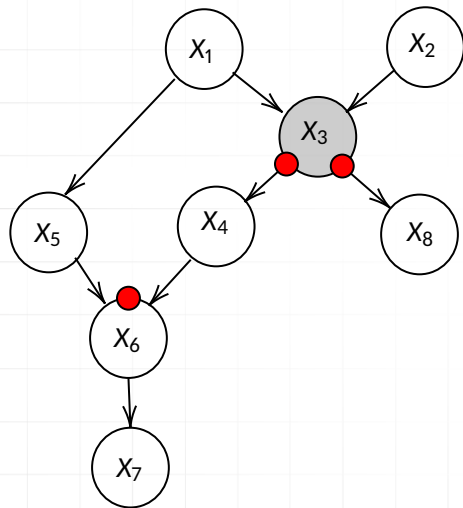
► taking e.g.:

► $C = \{X_3\}$

► $(X_i \perp X_j) | X_C$???

$i \quad j \quad \text{d-separated}$

Example 3



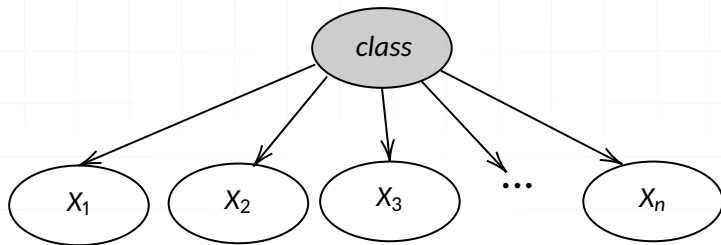
► taking e.g.:

► $C = \{X_3\}$

► $(X_i \perp X_j) | X_C$???

i	j	d-separated
2	5	no
2	7	no
2	4	yes
7	8	yes

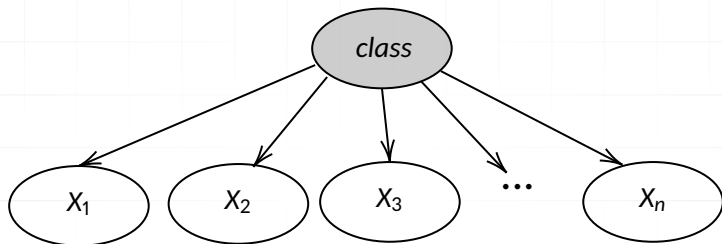
Naive Bayes



- ▶ we infer *class*
- ▶ based on features $X_1, X_2, X_3, \dots, X_n$
- ▶ model accomplishes: $(X_i \perp X_j) | X_C$ for all X_i, X_j

$$P(C, X_1, \dots, X_n) = P(C) \prod_{i=1}^n P(X_i | C)$$

Naive Bayes



$$\frac{P(C = c^1 | x_1, \dots, x_n)}{P(C = c^2 | x_1, \dots, x_n)} = \frac{P(C = c^1)}{P(C = c^2)} \prod_{i=1}^n \frac{P(x_i | C = c^1)}{P(x_i | C = c^2)}$$