

Machine Learning: Probabilistic Graphical Models 1

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1. There are statistical independencies in probability distributions.
2. A graphical model is a compact representation of dependencies.
3. Statistical independencies can be reasoned on graphs.

Statistical independencies in probability distributions

- What are the statistical independencies in this distribution?

x	y	$p(x, y)$
0	0	12/21
0	1	2/21
1	0	6/21
1	1	1/21

- What are the statistical independencies in this distribution?

x	y	z	$p(x, y, z)$
0	0	0	3/16
0	1	0	6/16
1	0	0	1/16
1	1	0	2/16
0	0	1	4/60
0	1	1	1/60
1	0	1	8/60
1	1	1	2/60

- It's not at all obvious what statistical independencies there are even when we know the joint distribution.
- In this case,

$$p(x, y|z) = p(x|z)p(y|z), \quad (1)$$

or more succinctly

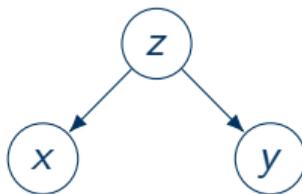
$$x \perp\!\!\!\perp y \mid z. \quad (2)$$

- How many possible independencies can we have for this distribution?

- A dumb algorithm for checking independencies in a distribution
 1. Compute $p(x|z)$, $p(y|z)$, and $p(x, y|z)$.
 2. Check if $p(x, y|z) = p(x|z)p(y|z)$.
 3. Repeat for all combination.
- This is inefficient, and we lack a language to talk about independencies.

Graphical models for encoding factorization

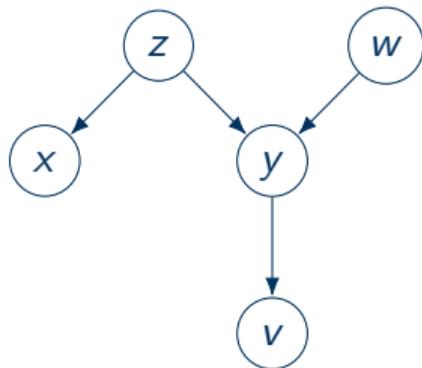
- The following graph



represents the distribution

$$p(x, y, z) = p(x|z)p(y|z)p(z). \quad (3)$$

- What factorization can we read off from this graph?



- The above graph represents the distribution

$$p(v, w, x, y, z) = p(v|y)p(x|z)p(y|z, w)p(z)p(w). \quad (4)$$

- **Definition.** A distribution p factorizes according to a directed graph G if

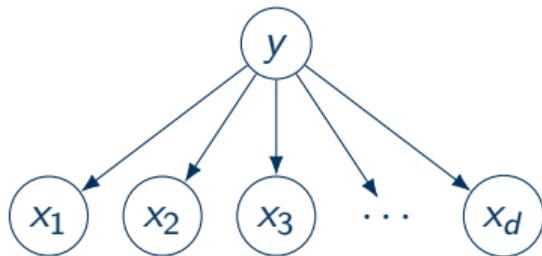
$$p(x_1, \dots, x_n) = \prod_{i=1}^n p(x_i | \text{Pa}_{x_i}) \quad (5)$$

where Pa_x is the set of parent vertices of x in G .

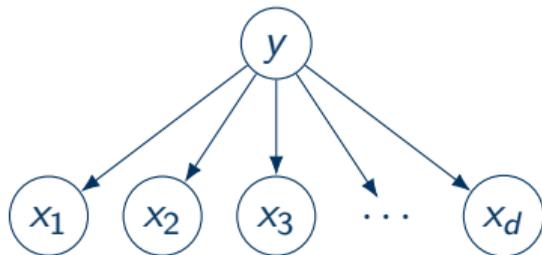
- Obviously, the graph G needs to have the same number of vertices as there are in the distribution p .
- The vertex u is one of v 's parent if there is an edge from u to v .



- What is the distribution that factorizes according to the following graph?



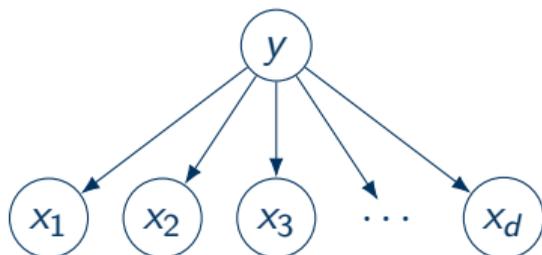
- What is the distribution that factorizes according to the following graph?



- The distribution that factorizes according to the graph has the form

$$p(x, y) = p(y)p(x_1|y)p(x_2|y)\cdots p(x_d|y) = p(y) \prod_{i=1}^d p(x_i|y). \quad (6)$$

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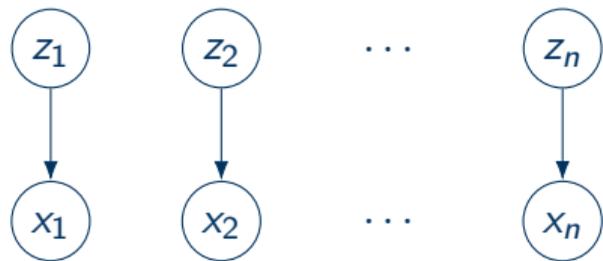


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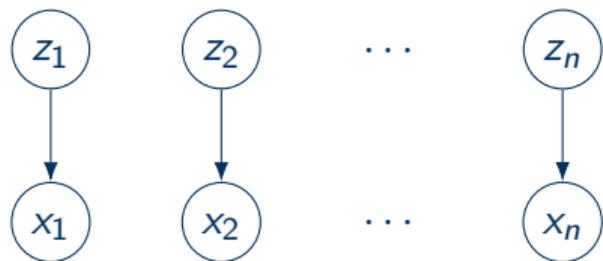
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- This is known as the naive Bayes model.

- What is the distribution that factorizes according to the following graph?



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- The distribution that factorizes according to the graph has the form

$$p(x_1, \dots, x_n, z_1, \dots, z_n) = \prod_{i=1}^n p(x_i | z_i) p(z_i) \quad (7)$$

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- What happens if we take

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$$p(x_i|z_i) = \frac{1}{(2\pi)^{d/2} |\Sigma_{z_i}|^{1/2}} \exp \left(-\frac{1}{2} (x_i - \mu_{z_i})^\top \Sigma_{z_i}^{-1} (x_i - \mu_{z_i}) \right) \tag{9}$$

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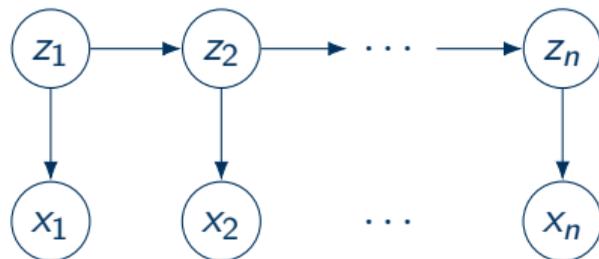
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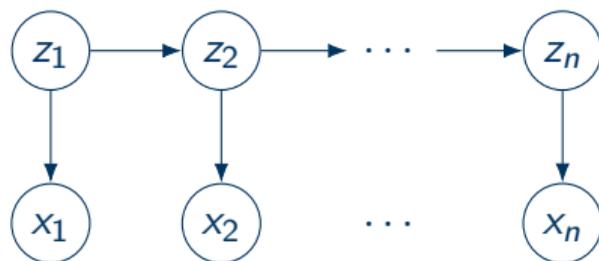
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- This is the Gaussian mixture model.

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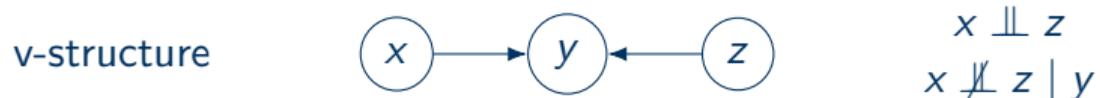
$$p(x_1, \dots, x_n, z_1, \dots, z_n) = p(z_1) \prod_{i=2}^n p(z_i | z_{i-1}) \prod_{i=1}^n p(x_i | z_i). \quad (10)$$

- This is known as the hidden Markov model.

- In general, a directed graph paired with a distribution that factorizes accordingly is called a **Bayesian network**.
- Can we read off statistical independencies from a graph?

Reading off statistical independencies from a directed graph

- There are three basic structures.

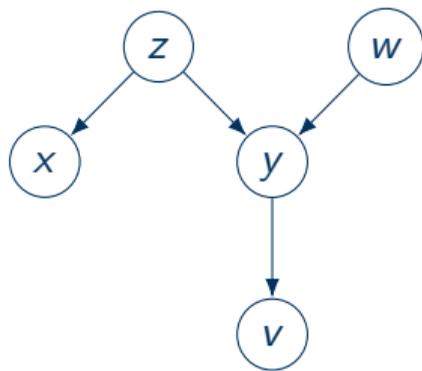


- The basic structure $x \rightarrow y \rightarrow z$ is blocked when y is given.
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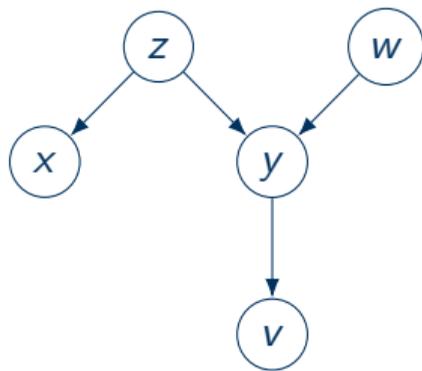
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- A path is blocked if any basic structure along the path is blocked.
- If all paths connecting two vertices are blocked, then they are **d-separated**.

- Let $I(p)$ be the set of all statistical independencies in a distribution p .
- Let $I(G)$ be the set of all d-separation in a directed graph G .
- **Theorem.** For almost all distributions that factorize over G , $I(p) = I(G)$.

- What is the set of d-separations in the following graph?



- What is the set of d-separations in the following graph?



- The list of basic structures includes

$$x \perp\!\!\!\perp y \mid z,$$

$$z \perp\!\!\!\perp w, z \not\perp\!\!\!\perp w \mid y, z \not\perp\!\!\!\perp w \mid v$$

$$z \perp\!\!\!\perp v \mid y, w \perp\!\!\!\perp v \mid y$$