

Chapter 4

Graphical Models

4.1 Graphical Models

- GM for modelling
 - To describe how variables can interact, such as independence
 - Belief networks, Markov networks, chain graphs and influence diagrams
- GM for inference
 - To perform inference on a distribution
 - Factor graphs and junction trees

4.2 Markov Networks

- Definition 4.1 (Potential)
 - A **potential** $\phi(x)$ is a function with $\phi(x) \geq 0$
 - A **joint potential** $\phi(x_1, \dots, x_n)$ is a function with $\phi(x_1, \dots, x_n) \geq 0$
- A distribution is a potential satisfying normalization,
$$\sum_x \phi(x) = 1$$

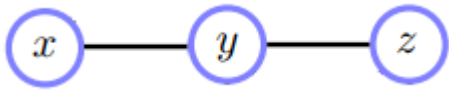
- Definition 4.2 (Markov Network).
 - For a set of variables $\mathcal{X} = \{x_1, \dots, x_n\}$
 - A **Markov network** is defined as a product of potentials on $\mathcal{X}_c \subseteq \mathcal{X}$:

$$p(x_1, \dots, x_n) = \frac{1}{Z} \prod_{c=1}^C \phi_c(\mathcal{X}_c)$$

where

$$Z = \sum_{x_1, \dots, x_n} \prod_{c=1}^C \phi_c(\mathcal{X}_c)$$

- Graphically this is represented by an undirected graph G with \mathcal{X}_c , $c = 1, \dots, C$ being the maximal cliques of G .

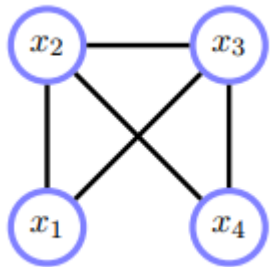


Maximal cliques: $\mathcal{X}_1 = \{x, y\}$, $\mathcal{X}_2 = \{y, z\}$

Potentials: $\phi(x, y)$, $\phi(y, z)$

Normalisation: $Z = \sum_{x,y,z} \phi(x, y), \phi(y, z)$

Distribution: $p(x, y, z) = \phi(x, y), \phi(y, z)/Z$



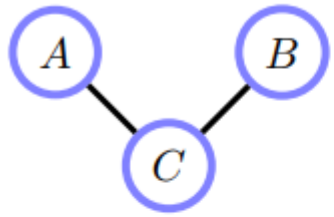
Maximal cliques: $\mathcal{X}_1 = \{x_1, x_2, x_3\}$, $\mathcal{X}_2 = \{x_2, x_3, x_4\}$

Potentials: $\phi(x_1, x_2, x_3)$, $\phi(x_2, x_3, x_4)$

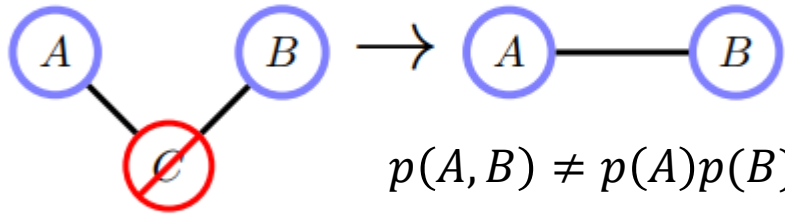
Normalisation: $Z = \sum_{x_1, x_2, x_3, x_4} \phi(x_1, x_2, x_3), \phi(x_2, x_3, x_4)$

Distribution: $p(x_1, x_2, x_3, x_4) = \phi(x_1, x_2, x_3), \phi(x_2, x_3, x_4)/Z$

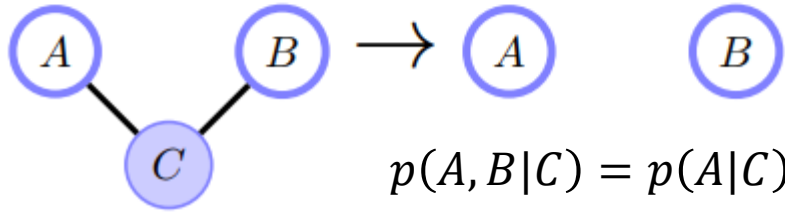
Definition 4.4 (Properties of Markov Networks).



$$p(A, B, C) = \phi_{AC}(A, C)\phi_{BC}(B, C)/Z$$



$$p(A, B) \neq p(A)p(B)$$



$$p(A, B|C) = p(A|C)p(B|C)$$

$$\begin{aligned} p(A, B|C) &= \frac{p(A, B, C)}{p(C)} \\ &= \frac{p(A, B, C)}{\sum_{A', B'} p(A', B', C)} \\ &= \frac{\frac{1}{Z}\phi(A, C)\phi(B, C)}{\sum_{A', B'} \frac{1}{Z}\phi(A', C)\phi(B', C)} \\ &= \frac{\phi(A, C)}{\sum_{A'} \phi(A', C)} \frac{\phi(B, C)}{\sum_{B'} \phi(B', C)} \end{aligned}$$

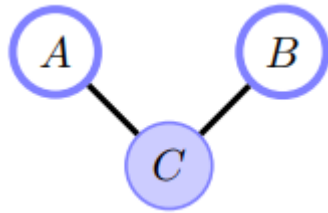
$$\begin{aligned} p(A|C) &= \frac{p(A, C)}{p(C)} \\ &= \frac{\sum_{B'} p(A, B', C)}{\sum_{A', B'} p(A', B', C)} \\ &= \frac{\sum_{B'} \frac{1}{Z}\phi(A, C)\phi(B', C)}{\sum_{A', B'} \frac{1}{Z}\phi(A', C)\phi(B', C)} \\ &= \frac{\phi(A, C)}{\sum_{A'} \phi(A', C)} \end{aligned}$$

$$p(A, B|C) = p(A|C)p(B|C)$$

- 4.2.1 Markov properties
 - properties of Markov networks, such as independence

- Definition 4.5 (Separation)

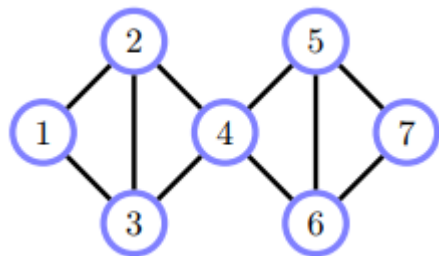
- A subset \mathcal{S} separates a subset \mathcal{A} from a subset \mathcal{B} if every path from any member of \mathcal{A} to any member of \mathcal{B} passes through \mathcal{S}



C separates A from B

- Definition 4.6 (Global Markov Property)

- If \mathcal{S} separates \mathcal{A} from \mathcal{B} , then \mathcal{A} and \mathcal{B} are independent given \mathcal{S} , i.e.
 $\mathcal{A} \perp\!\!\!\perp \mathcal{B} \mid \mathcal{S}$



$1 \amalg 7 \mid 4$

Computational description

$$\begin{aligned}
 p(1, 7|4) &\propto \sum_{2,3,5,6} p(1,2,3,4,5,6,7) \\
 &= \frac{1}{Z} \sum_{2,3,5,6} \phi(1,2,3)\phi(2,3,4)\phi(4,5,6)\phi(5,6,7) \\
 &= \frac{1}{Z} \sum_{2,3} \phi(1,2,3)\phi(2,3,4) \sum_{5,6} \phi(4,5,6)\phi(5,6,7)
 \end{aligned}$$

$$\begin{aligned}
 p(1|4) &\propto \sum_{2,3,5,6,7} p(1,2,3,4,5,6,7) \\
 &= \frac{1}{Z} \sum_{2,3,5,6,7} \phi(1,2,3)\phi(2,3,4)\phi(4,5,6)\phi(5,6,7) \\
 p(7|4) &\propto \frac{1}{Z} \sum_{2,3,5,6,7} \phi(1,2,3)\phi(2,3,4)\phi(4,5,6)\phi(5,6,7)
 \end{aligned}$$

using

$$p(4) = \frac{1}{Z} \sum_{1,2,3} \phi(1,2,3)\phi(2,3,4) \sum_{5,6,7} \phi(4,5,6)\phi(5,6,7)$$

we obtain

$$p(1, 7|4) = p(1|4)p(7|4)$$

- 4.2.2 Markov random fields

- Definition 4.7 (Markov Random Field)

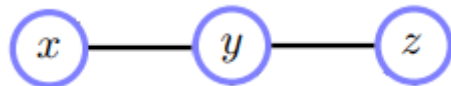
- A distribution is an MRF with respect to an undirected graph G if

$$p(x_i | x_{\setminus i}) = p(x_i | ne(x_i))$$

where $ne(x_i)$ are the neighbouring variables of variable x_i

- A Markov network is a MRF

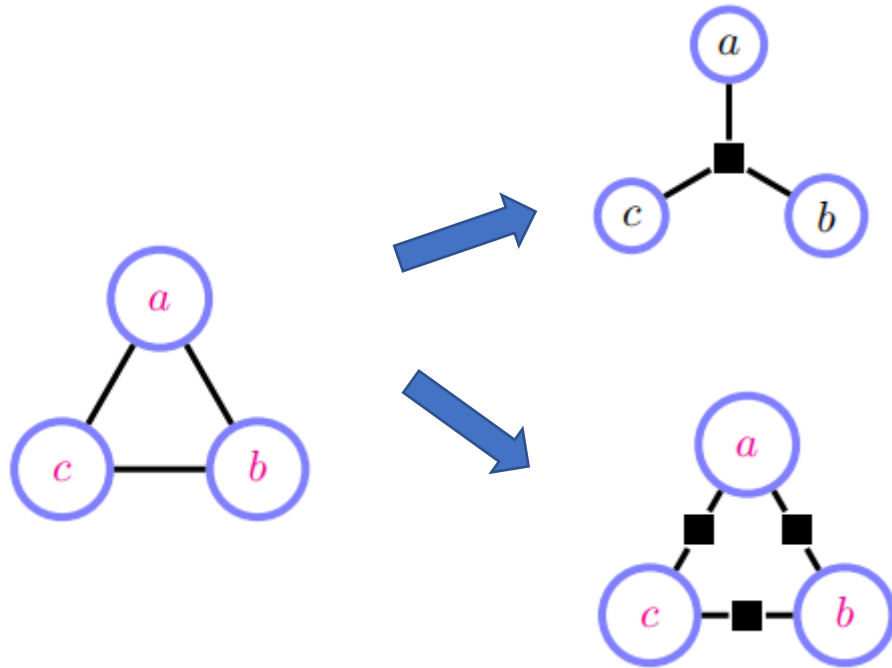
- Eg.



$$p(x|y, z) = p(x|y)$$

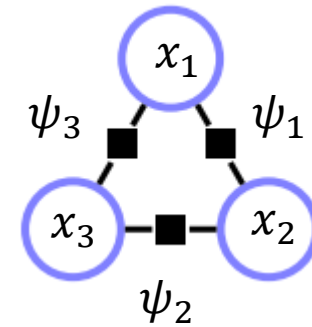
4.3 Chain Graphical Models

4.4 Factor Graphs



$$p(a, b, c) = \frac{1}{Z} \phi(a, b, c)$$

$$p(a, b, c) = \frac{1}{Z} \phi(a, b) \phi(b, c) \phi(c, a)$$

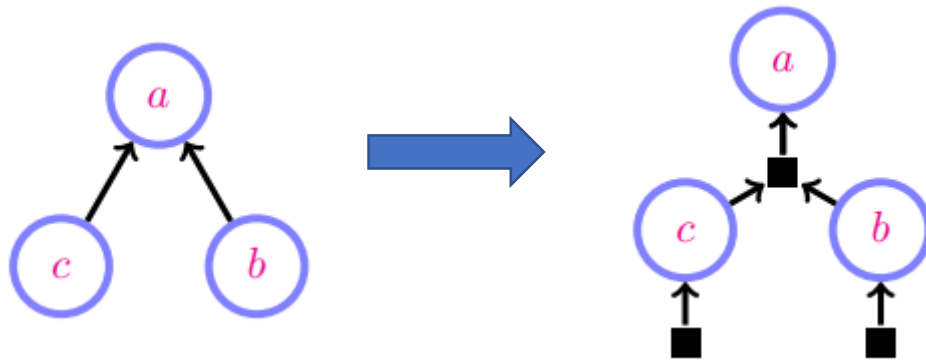


- Definition 4.10 (Factor Graph)

- The FG has a node (a square) for each factor ψ_i and a variable node (a circle) for each variable x_j
- For each $x_j \in \mathcal{X}_i$ an undirected link is made between factor ψ_i and variable x_j .
- When used to represent a distribution

$$p(x_1, \dots, x_n) = \frac{1}{Z} \prod_i \psi_i(x_i)$$

a normalisation constant $Z = \sum_{\mathcal{X}} \prod_i \psi_i(x_i)$ is assumed. Here \mathcal{X} represents all variables in the distribution.



$$\begin{aligned} p(a, b, c) &= p(c|a, b)p(a)p(b) \\ &= \frac{1}{Z} \phi(a, b, c)\phi(a)\phi(b) \end{aligned}$$