

Exercise 1. Visualising and analysing Gibbs distributions via undirected graphs

We here consider the Gibbs distribution

 $p(x_1,\ldots,x_5) \propto \phi_{12}(x_1,x_2)\phi_{13}(x_1,x_3)\phi_{14}(x_1,x_4)\phi_{23}(x_2,x_3)\phi_{25}(x_2,x_5)\phi_{45}(x_4,x_5)$

(a) Visualise it as an undirected graph.

Solution. We draw a node for each random variable x_i . There is an edge between two nodes if the corresponding variables co-occur in a factor.



(b) What are the neighbours of x_3 in the graph?

Solution. The neighbours are all the nodes for which there is a single connecting edge. Thus: $ne(x_3) = \{x_1, x_2\}$. (Note that sometimes, we may denote $ne(x_3)$ by ne_3 .)

(c) Do we have $x_3 \perp \!\!\!\perp x_4 \mid x_1, x_2$?

Solution. Yes. The conditioning set $\{x_1, x_2\}$ equals ne₃, which is also the Markov blanket of x_3 . This means that x_3 is conditionally independent of all the other variables given $\{x_1, x_2\}$, i.e. $x_3 \perp x_4, x_5 \mid x_1, x_2$, which implies that $x_3 \perp x_4 \mid x_1, x_2$. (One can also use graph separation to answer the question.)

(d) What is the Markov blanket of x_4 ?

Solution. The Markov blanket of a node in a undirected graphical model equals the set of its neighbours: $MB(x_4) = ne(x_4) = ne_4 = \{x_1, x_5\}$. This implies, for example, that $x_4 \perp x_2, x_3 \mid x_1, x_5$.

(e) On which minimal set of variables A do we need to condition to have $x_1 \perp\!\!\!\perp x_5 \mid A$?

Solution. We first identify all trails from x_1 to x_5 . There are three such trails: (x_1, x_2, x_5) , (x_1, x_3, x_2, x_5) , and (x_1, x_4, x_5) . Conditioning on x_2 blocks the first two trails, conditioning on x_4 blocks the last. We thus have: $x_1 \perp x_5 \mid x_2, x_4$, so that $A = \{x_2, x_4\}$.

Exercise 2. Factorisation and independencies for undirected graphical models

We here consider the graph in Figure 1.

(a) What is the set of Gibbs distributions that are induced by the graph?



Figure 1: Graph for Exercise 2

Solution. The graph in Figure 1 has four maximal cliques:

 (x_1, x_2, x_4) (x_1, x_3, x_4) (x_3, x_4, x_5) (x_4, x_5, x_6)

The Gibbs distributions are thus

 $p(x_1,\ldots,x_6) \propto \phi_1(x_1,x_2,x_4)\phi_2(x_1,x_3,x_4)\phi_3(x_3,x_4,x_5)\phi_4(x_4,x_5,x_6)$

(b) Let p be a pdf that factorises according to the graph. Can we expect that $p(x_3|x_2, x_4) = p(x_3|x_4)$?

Solution. $p(x_3|x_2, x_4) = p(x_3|x_4)$ means that $x_3 \perp x_2 \mid x_4$. We can use the graph to check whether this generally holds for pdfs that factorise according to the graph. There are multiple trails from x_3 to x_2 , including the trail (x_3, x_1, x_2) , which is not blocked by x_4 . From the graph, we thus cannot conclude that $x_3 \perp x_2 \mid x_4$, and $p(x_3|x_2, x_4) = p(x_3|x_2)$ will generally not hold (the relation may hold for some carefully defined factors ϕ_i).

(c) Explain why $x_2 \perp \!\!\!\perp x_5 \mid x_1, x_3, x_4, x_6$ holds.

Solution. The distribution that factorises according to the graph satisfies the pairwise Markov property. Since x_2 and x_5 are not neighbours, and x_1, x_3, x_4, x_6 are the remaining nodes in the graph, the independence relation follows from the pairwise Markov property.

(d) Assume you would like to approximate $\mathbb{E}(x_1x_2x_5 \mid x_3, x_4)$, i.e. the expected value of the product of x_1, x_2 , and x_5 given x_3 and x_4 , with a sample average. Do you need to have joint observations for all five variables x_1, \ldots, x_5 ?

Solution. In the graph, all trails from $\{x_1, x_2\}$ to x_5 are blocked by $\{x_3, x_4\}$, so that $x_1, x_2 \perp x_5 \mid x_3, x_4$. We thus have

$$\mathbb{E}(x_1 x_2 x_5 \mid x_3, x_4) = \mathbb{E}(x_1 x_2 \mid x_3, x_4) \mathbb{E}(x_5 \mid x_3, x_4).$$

Hence, we only need joint observations of (x_1, x_2, x_3, x_4) and (x_3, x_4, x_5) . Variables (x_1, x_2) and x_5 do not need to be jointly measured.

Exercise 3. Undirected graphical model with pairwise potentials

We here consider Gibbs distributions where the factors only depend on two variables at a time. The probability density or mass functions over d random variables x_1, \ldots, x_d then take the form

$$p(x_1,\ldots,x_d) \propto \prod_{i \leq j} \phi_{ij}(x_i,x_j)$$

These models are typically called pairwise Markov networks.

(a) Let $p(x_1, \ldots, x_d) \propto \exp\left(-\frac{1}{2}\mathbf{x}^\top \mathbf{A}\mathbf{x} - \mathbf{b}^\top \mathbf{x}\right)$ where \mathbf{A} is symmetric and $\mathbf{x} = (x_1, \ldots, x_d)^\top$. What are the corresponding factors ϕ_{ij} for $i \leq j$?

Solution. Denote the (i, j)-th element of **A** by a_{ij} . We have

$$\mathbf{x}^{\top} \mathbf{A} \mathbf{x} = \sum_{ij} a_{ij} x_i x_j \tag{S.1}$$

$$=\sum_{i< j} 2a_{ij}x_ix_j + \sum_i a_{ii}x_i^2 \tag{S.2}$$

where the second line follows from $\mathbf{A}^{\top} = \mathbf{A}$. Hence,

$$-\frac{1}{2}\mathbf{x}^{\top}\mathbf{A}\mathbf{x} - \mathbf{b}^{\top}\mathbf{x} = -\frac{1}{2}\sum_{i < j} 2a_{ij}x_ix_j - \frac{1}{2}\sum_i a_{ii}x_i^2 - \sum_i b_ix_i$$
(S.3)

so that

$$\phi_{ij}(x_i, x_j) = \begin{cases} \exp(-a_{ij} x_i x_j) & \text{if } i < j \\ \exp\left(-\frac{1}{2} a_{ii} x_i^2 - b_i x_i\right) & \text{if } i = j \end{cases}$$
(S.4)

For $\mathbf{x} \in \mathbb{R}^d$, the distribution is a Gaussian with **A** equal to the inverse covariance matrix. For binary \mathbf{x} , the model is known as Ising model or Boltzmann machine. For $x_i \in \{-1, 1\}$, $x_i^2 = 1$ for all *i*, so that the a_{ii} are constants that can be absorbed into the normalisation constant. This means that for $x_i \in \{-1, 1\}$, we can work with matrices **A** that have zeros on the diagonal.

(b) For $p(x_1, \ldots, x_d) \propto \exp\left(-\frac{1}{2}\mathbf{x}^\top \mathbf{A}\mathbf{x} - \mathbf{b}^\top \mathbf{x}\right)$, show that $x_i \perp x_j \mid \{x_1, \ldots, x_d\} \setminus \{x_i, x_j\}$ if the (i, j)-th element of \mathbf{A} is zero.

Solution. The previous question showed that we can write $p(x_1, \ldots, x_d) \propto \prod_{i \leq j} \phi_{ij}(x_i, x_j)$ with potentials as in Equation (S.4). Consider two variables x_i and x_j for fixed (i, j). They only appear in the factorisation via the potential ϕ_{ij} . If $a_{ij} = 0$, the factor ϕ_{ij} becomes a constant, and no other factor contains x_i and x_j , which means that there is no edge between x_i and x_j if $a_{ij} = 0$. By the pairwise Markov property it then follows that $x_i \perp x_j \mid \{x_1, \ldots, x_d\} \setminus \{x_i, x_j\}$.