

# Probabilistic Graphical Models

Tianyu Du

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## 1 Graphical Representations

### 1.1 Factors

**Definition 1.1.** Let  $X_1, X_2, \dots, X_k$  be a set of random variables, then a **factor**  $\phi$  is a mapping from values of these random variables to  $\mathbb{R}$ .

$$\phi : Val(X_1, X_2, \dots, X_k) \rightarrow \mathbb{R} \quad (1)$$

The set of random variables  $\{X_1, X_2, \dots, X_k\}$  is defined as the **scope** of  $\phi$ .

**Definition 1.2.** Let  $\phi_1$  and  $\phi_2$  be two factors with scopes  $\{A, B\}$  and  $\{B, C\}$ . Then the **factor product**  $\phi_1 \times \phi_2$  is a factor with scope  $\{A, B, C\}$  defined as

$$\phi_1 \cdot \phi_2(a, b, c) = \phi_1(a, b) \cdot \phi_2(b, c) \quad (2)$$

**Definition 1.3.** Let  $\phi$  be a factor with scope  $\{A, B, C\}$ , then **marginalizing  $C$  from  $\phi$**  results in a factor  $\phi'$  with scope  $\{A, B\}$  defined as the following:

$$\phi'(a, b) = \sum_{c \in Val(C)} \phi(a, b, c) \quad (3)$$

**Definition 1.4.** The **factor reduction** operation restricts  $\phi(A, B, C)$  to take only a specific value of  $C = c$ , and results in a factor  $\phi'$  with scope  $\{A, B\}$ .

$$\phi'(a, b) = \phi(a, b, c) \quad (4)$$

### 1.2 Semantics and Factorization

**Definition 1.5.** A **Bayesian network** consists of (i) a directed acyclic graph (DAG)  $G$  whose nodes correspond to random variables  $X_1, \dots, X_n$  (ii) and a conditional probability distribution  $P(X_i | Par_G(X_i))$  for each node  $X_i$ . The joint distribution is defined as the factorization

$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i | Par_G(X_i)) \quad (5)$$

**Definition 1.6.** Let  $G$  be a graph over  $X_1, \dots, X_n$ , then the joint probability  $P$  **factorizes** over  $G$  if and only if

$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i | Par_G(X_i)) \quad (6)$$

### 1.3 Pass of Influences in Bayesian Networks

**Definition 1.7.** A path  $X_1 - \dots - X_k$  in Bayesian network  $G$  is **active** if there is no explaining-away structure  $X_{i-1} \rightarrow X_i \leftarrow X_{i+1}$  in it.

**Definition 1.8.** Let  $Z \subseteq V_G$  be a set of random variables in the Bayesian network, then a path  $X_1 - \dots - X_k$  in  $G$  is **active conditioned on  $Z$**  if

1. for all explaining-away structure  $X_{i-1} \rightarrow X_i \leftarrow X_{i+1}$  in the path,  $X_i$  or some decedents of  $X_i$  are in  $Z$ ,
2. and no other node in the path is in  $Z$ .

**Definition 1.9.** Let  $X, Y, Z \subseteq V_G$ , if there is no path from  $X$  to  $Y$  is active conditioned on  $Z$ , then  $X$  and  $Y$  are **d-separated** by  $Z$  in graph  $G$  denoted as  $X \perp_G Y | Z$ .