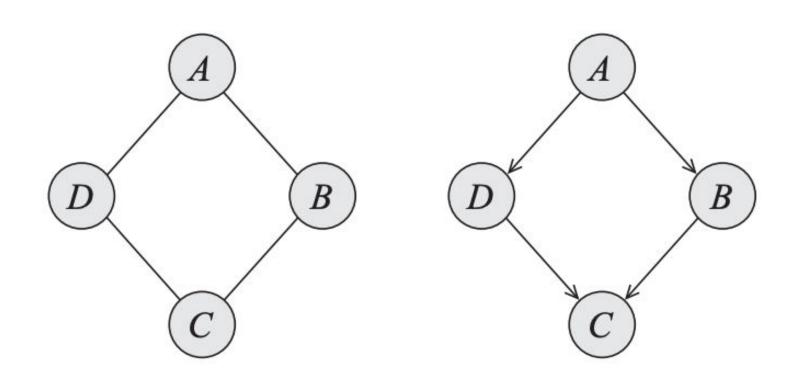
Advanced Machine Learning

Likhit Nayak

Undirected Graphs



Factors

Let D be a set of random variables. We define a factor ϕ to be a function from Val(D) to IR. A factor is nonnegative if all its entries are nonnegative. The set of variables D is called the scope of the factor and denoted $Scope[\phi]$.

| $\phi_1(A,B)$ | $\phi_2(B,C)$ | $\phi_3(C,D)$ | $\phi_4(D,A)$ | |
|---|--|--|--|--|
| $egin{array}{cccc} a^0 & b^0 & 30 \ a^0 & b^1 & 5 \ a^1 & b^0 & 1 \ a^1 & b^1 & 10 \ \end{array}$ | $ \begin{vmatrix} b^0 & c^0 & 100 \\ b^0 & c^1 & 1 \\ b^1 & c^0 & 1 \\ b^1 & c^1 & 100 \end{vmatrix} $ | $ \begin{vmatrix} c^0 & d^0 & 1 \\ c^0 & d^1 & 100 \\ c^1 & d^0 & 100 \\ c^1 & d^1 & 1 \end{vmatrix} $ | $ \begin{vmatrix} d^0 & a^0 & 100 \\ d^0 & a^1 & 1 \\ d^1 & a^0 & 1 \\ d^1 & a^1 & 100 \end{vmatrix} $ | |

Factors

A distribution P_{Φ} is a Gibbs distribution parameterized by a set of factors $\Phi = \{\phi_1(\mathbf{D}_1), \dots, \phi_K(\mathbf{D}_K)\}$ if it is defined as follows:

$$P_{\Phi}(X_1,\ldots,X_n)=rac{1}{Z} ilde{P}_{\Phi}(X_1,\ldots,X_n),$$

where

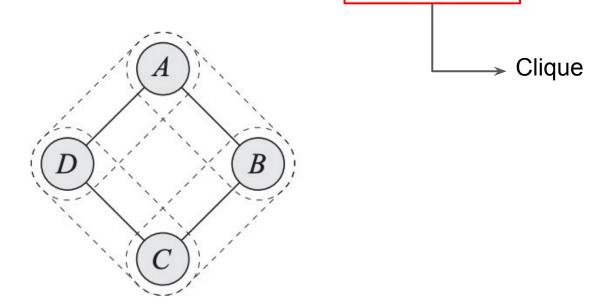
$$\tilde{P}_{\Phi}(X_1,\ldots,X_n) = \phi_1(\boldsymbol{D}_1) \times \phi_2(\boldsymbol{D}_2) \times \cdots \times \phi_m(\boldsymbol{D}_m)$$

$$Z = \sum_{X_1, \dots, X_n} \tilde{P}_{\Phi}(X_1, \dots, X_n)$$

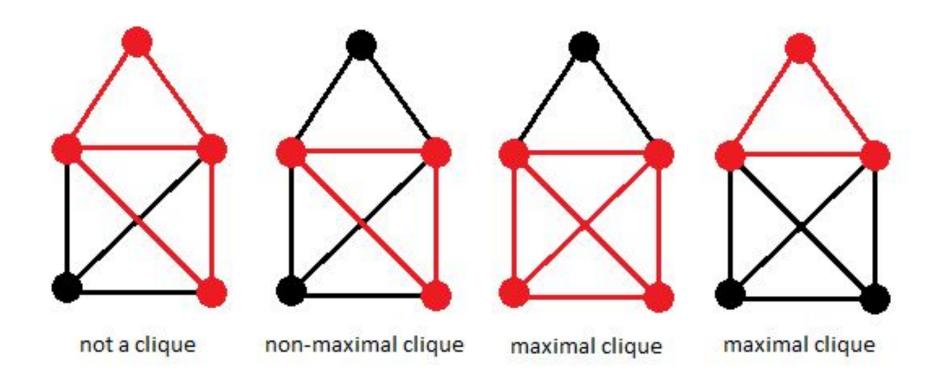
is a normalizing constant called the partition function.

Markov Network

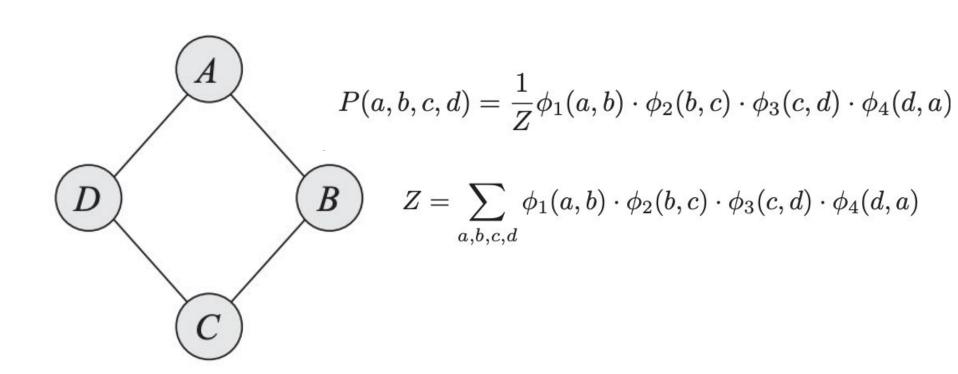
We say that a distribution P_{Φ} with $\Phi = \{\phi_1(\mathbf{D}_1), \dots, \phi_K(\mathbf{D}_K)\}$ factorizes over a Markov network \mathcal{H} if each \mathbf{D}_k $(k = 1, \dots, K)$ is a complete subgraph of \mathcal{H} .



Cliques and maximal cliques



Markov Network



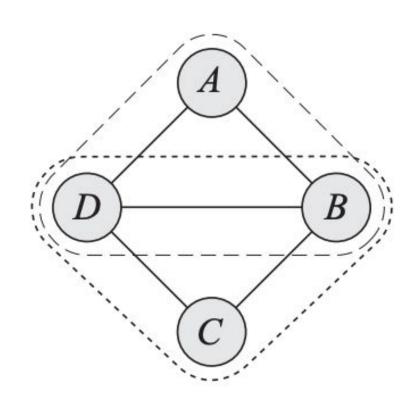
Factor Product

Let X, Y, and Z be three disjoint sets of variables, and let $\phi_1(X,Y)$ and $\phi_2(Y,Z)$ be two factors. We define the factor product $\phi_1 \times \phi_2$ to be a factor $\psi : Val(X,Y,Z) \mapsto \mathbb{R}$ as follows:

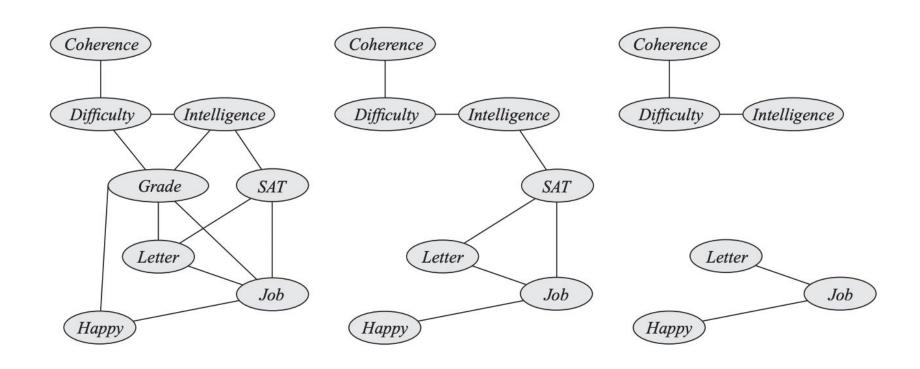
$$\psi(\boldsymbol{X}, \boldsymbol{Y}, \boldsymbol{Z}) = \phi_1(\boldsymbol{X}, \boldsymbol{Y}) \cdot \phi_2(\boldsymbol{Y}, \boldsymbol{Z}).$$

| a^1 | b^1 | 0.5 | | | | |
|-------|-------|-----|--------------------------------------|-------|-------|-----|
| a^1 | b^2 | 0.8 | | b^1 | c^1 | 0.5 |
| a^2 | b^1 | 0.1 | $\stackrel{\wedge}{\longrightarrow}$ | b^1 | c^2 | 0.7 |
| a^2 | b^2 | 0 | \longrightarrow | b^2 | c^1 | 0.1 |
| a^3 | b^1 | 0.3 | $V\gg$ | b^2 | c^2 | 0.2 |
| a^3 | b^2 | 0.9 | // ' | | | |

Markov Network



Reduced Markov Networks



Markov Networks - Image Segmentation







