

二. 有向图一贝叶斯网络 (Bayesian Network)

2.1 基本知识

$$P(X_1, X_2, \dots, X_p) = P(X_1) \cdot \prod_{i=2}^p P(X_i | X_{1:i-1})$$

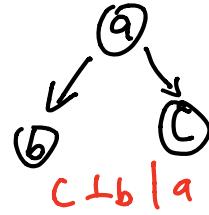
条件独立性: $X_A \perp X_C | X_B$

$$\text{因子分解: } P(X_1, X_2, \dots, X_p) = \prod_{i=1}^p P(X_i | X_{\text{parent}})$$

X_{parent} 是 X_i 的父集

如何从图中体现条件独立性?

① tail to tail 型图



若 a 被观测, 则路径被阻塞

$$\begin{aligned} P(a, b, c) &= P(a) \cdot P(b|a) \cdot P(c|a) \quad (\text{图 2.3}) \\ P(a, b, c) &= P(a) \cdot P(b|a) \cdot P(c|a, b) \quad (\text{chain rule}) \\ \text{关系 } ①, ②, \dots & \\ P(c|a) &= P(c|a, b) \\ \Rightarrow P(c|a) \cdot P(b|a) &= P(c|a, b) \cdot P(b|a) = P(b, c|a) \\ \Rightarrow P(c|a) \cdot P(b|a) &= P(b, c|a) \\ \text{即 } P_b \perp P_c | P_a \quad (\text{条件独立}) \end{aligned}$$

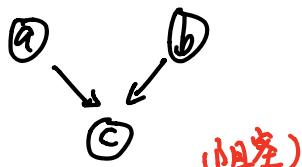
② head to tail 型图

$$a \rightarrow b \rightarrow c$$

$$a \perp c | b$$

若 b 被观测, 则路径被阻塞(独立)

③ head to head 型



$$\begin{aligned} P(a, b, c) &= P(a) \cdot P(b) \cdot P(c|a, b) \quad (\text{图 2.3}) \\ P(a, b, c) &= P(a) \cdot P(b|a) \cdot P(c|a, b) \quad (\text{chain rule}) \\ \Rightarrow P(b) &= P(b|a) \\ \Rightarrow a \perp b \end{aligned}$$

默认情况下, $a \perp b$. 若 c 被观测,

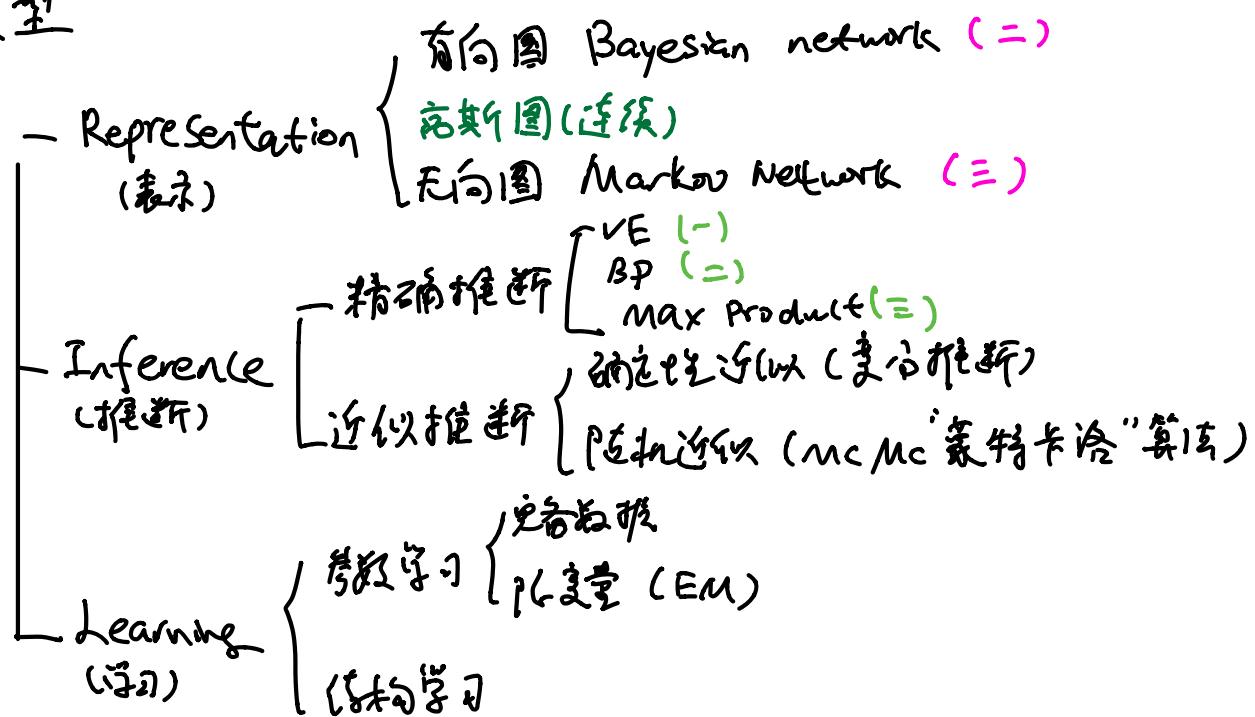
则 $a \not\perp b$ 不独立.

2.2. D 分割 (D-separation)

概率图模型

Outline

概 率 图



Representation

1. Background

- Some rules

$$\begin{cases} \text{边缘概率} & p(x_i) \\ \text{高维随机变量} & \text{条件概率} p(x_i | x_{-i}) \end{cases}$$

$$\text{Sum Rule: } p(x_1) = \int p(x_1, x_2) dx_2$$

$$\text{Product Rule: } p(x_1, x_2) = p(x_1) \cdot p(x_2 | x_1) = p(x_2) \cdot p(x_1 | x_2)$$

$$\text{Chain Rule: } p(x_1, x_2, \dots, x_p) = \prod_{i=1}^p p(x_i | x_1, x_2, \dots, x_{i-1})$$

$$\text{Bayesian Rule: } p(x_2 | x_1) = \frac{p(x_1, x_2)}{p(x_1)} = \frac{p(x_2) \cdot p(x_1 | x_2)}{\int p(x_1, x_2) dx_2}$$

- 困境: 维度高, 计算复杂. $p(x_1, x_2, \dots, x_p)$ 计算是过大

(从而更简化一些)

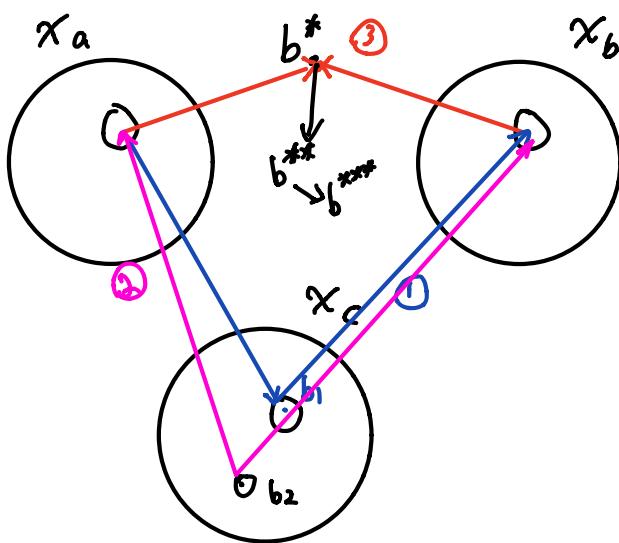
$$\downarrow$$

$$\text{简化, 相互独立} \rightarrow p(x_1, x_2, \dots, x_p) = \prod_{i=1}^p p(x_i) \xrightarrow{\text{Markov Property}} x_i \perp x_{i+1} | x_i, i < i$$

$$\therefore \text{Naive Bayes: } p(X|Y) = \prod_{i=1}^p p(X_i | Y)$$

\rightsquigarrow HMM假设
(齐次 Markov)
 $X_A \perp X_B | X_C$
 X_A, X_B, X_C 是集合且不相交

参见教材

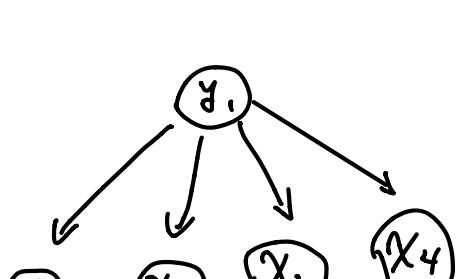
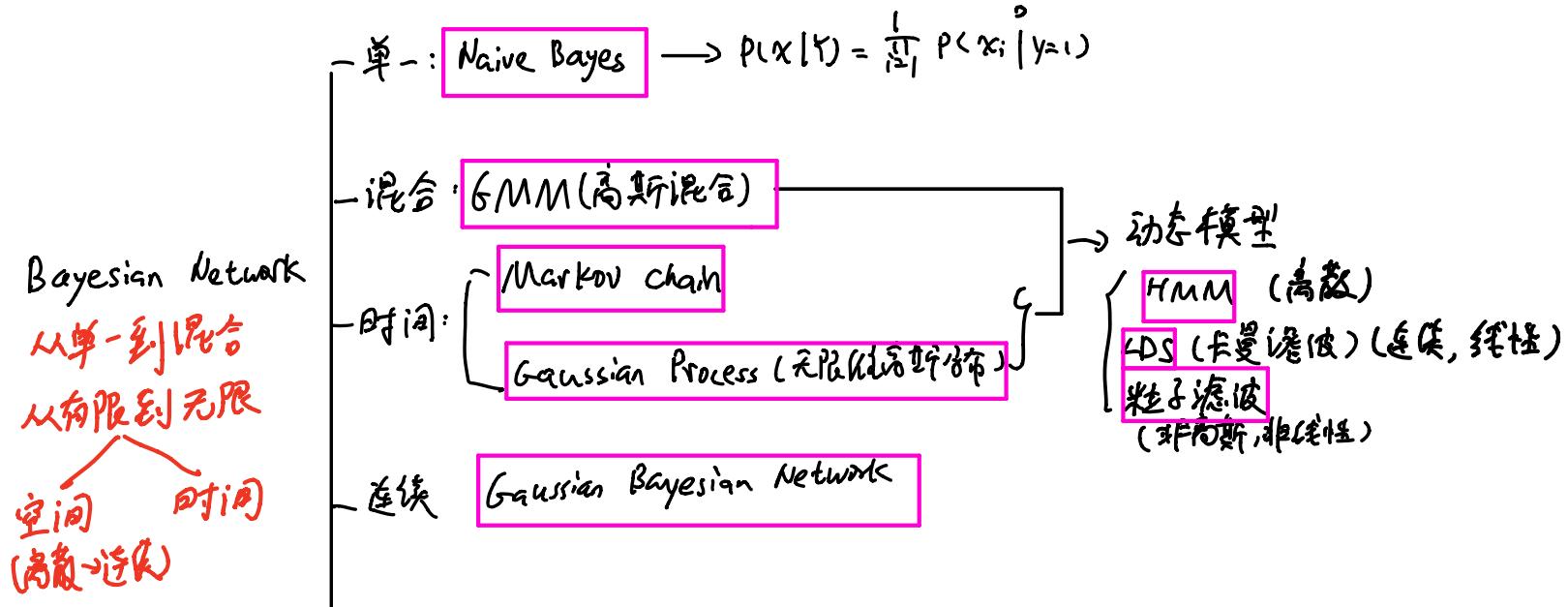


全局 Markov property

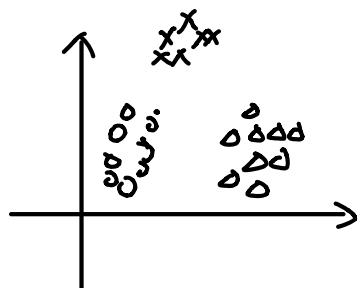
$$P(x_i | x_{-i}) = \frac{P(x_i, x_{-i})}{P(x_{-i})} = \frac{p(x)}{\int p(x) dx_i} = \frac{\prod_{j=1}^p P(x_j | x_{\text{parent}})}{\int \prod_{j=1}^p P(x_j | x_{\text{parent}}) dx_i}$$

Markov Blanket

2.3 具体模型



2. 2是高散的
 $x_1 | z \sim N(\mu, \Sigma)$



(x_1) (x_2) (x_3) (x_4)

Naive Bayes.

$$x_1 \perp x_2 \perp x_3 \perp x_4 \mid y_1$$

(x)

GMM

1

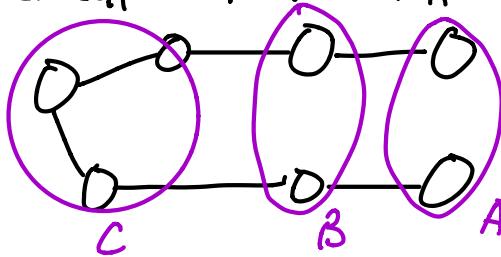
三. 无向图 - 马尔科夫网 / Markov Network (Markov Random Field)

一. 条件独立性

MRF $\Leftarrow\Rightarrow$ Gibbs Distribution

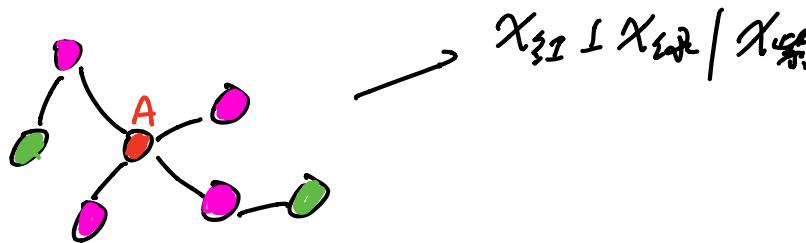
条件独立性可以体现在以下三个方面：

① Global Markov $x_A \perp x_C \mid x_B$. $P(x_A, x_C \mid x_B) = P(x_A \mid x_B) \cdot P(x_C \mid x_B)$



② Local Markov

$x_A \perp x_o \mid x_B$, 其中 A 是变量, B 是其邻居, O 为其余变量.



③ Pairwise Markov

$x_A \perp x_B \mid x_{-\{A,B\}}$, 即给定所有其他变量, 两个邻接变量条件独立.

二. 因子分解

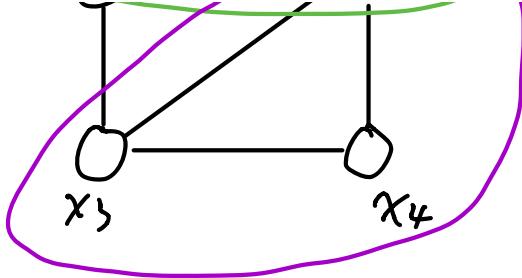
① 基本概念. 因

因：一个关于结点的集合. [集合内的结点之间相互连通]

最大因：若在一个因中加入其他任何节点都不再成因，则称该因为最大因。



绿圈为一个因, 紫圈为一个最大因.



两个相关簇之间定义势函数，在Markov Random Field中，多个变量的联合概率分布能表示为团分解为多个势函数的乘积，每一个团对应一个势函数。

$$p(x) = \frac{1}{Z} \prod_{i=1}^k \psi_i(x_{c_i})$$

C_i : 最大团

x_{c_i} : 最大团随机变量集合

$\psi(x_{c_i})$: 势函数，必须为正

$$Z: 归一化因子. Z = \sum \prod_{i=1}^k \psi(x_{c_i})$$

Explanation:

$$\sum_x p(x) = 1$$



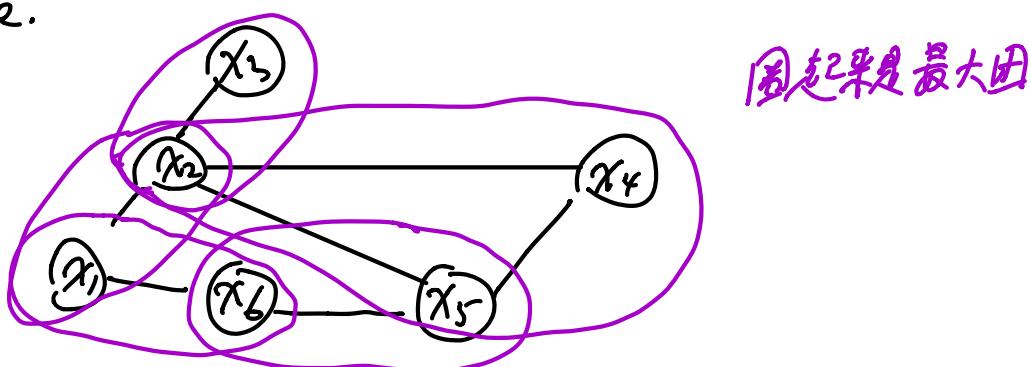
Gibbs Distribution

势函数可以记为 $\psi(x_{c_i}) = \exp(-E(x_{c_i}))$

于是可以记为 $p(x) = \frac{1}{Z} \exp\left(-\sum_{i=1}^k E(x_{c_i})\right)$ 指派族分布

分解与条件独立性等价 (Hammersley - Clifford 定理)

Example.



此图的团分解(联合概率密度)可写为：

$$p(x) = \frac{1}{Z} \psi_{12}(x_1, x_2) \psi_{16}(x_1, x_6) \psi_{23}(x_2, x_3) \psi_{5,6}(x_5, x_6) \psi_{2,4,5}(x_2, x_4, x_5)$$

四. 前向图与后向图的转换

看书，引入了逆向图和因子图

Inference

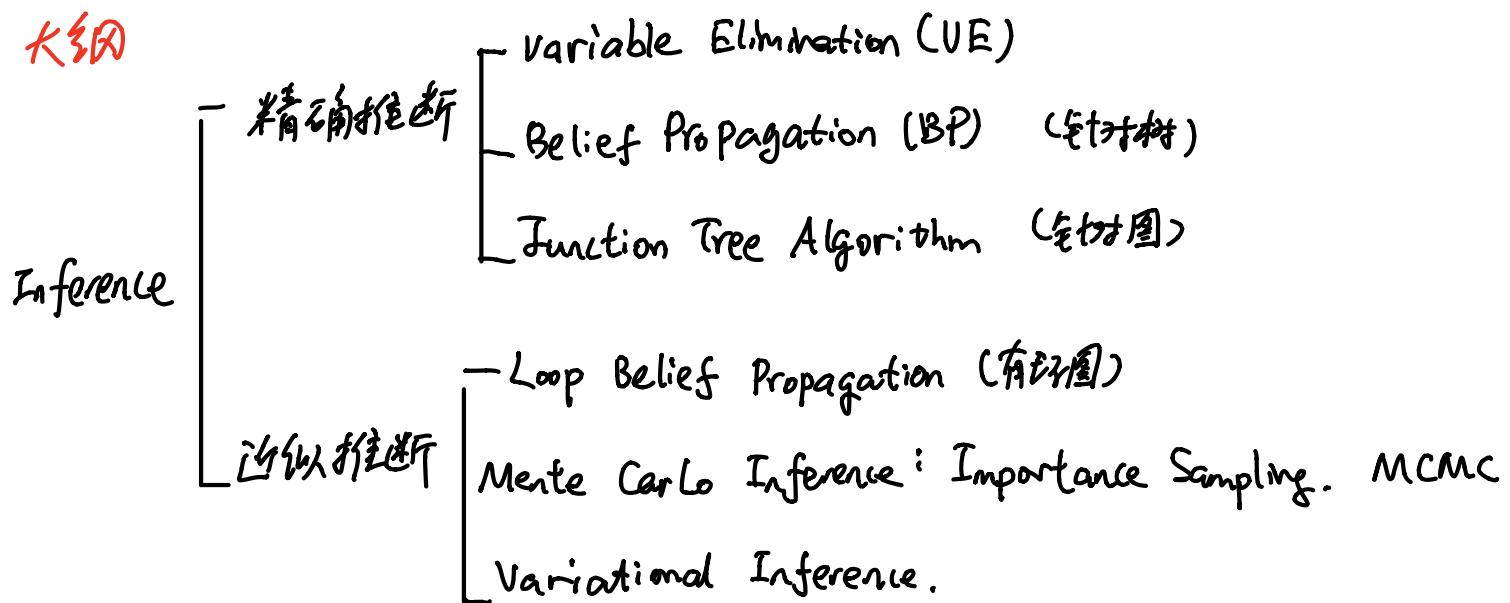
$$\text{联合概率} \quad P(x) = P(x_1, x_2, \dots, x_n)$$

$$\text{边缘概率} \quad P(x_i) = \sum_{x_1} \sum_{x_2} \dots \sum_{x_{i-1}} \sum_{x_{i+1}} \dots \sum_{x_n}$$

$$\text{条件概率} \quad P(x_A | x_B)$$

$$\text{MAP Inference: } \hat{x}_{\text{map}} = \underset{z}{\operatorname{argmax}} p(z|x) = \underset{z}{\operatorname{argmax}} p(x|z) \cdot p(z)$$

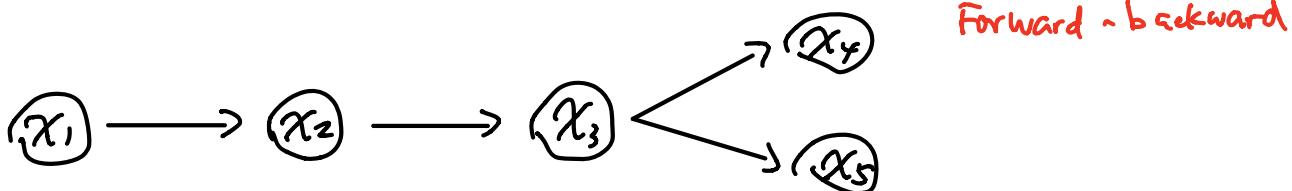
方法



一. Variable Elimination (VE)

思想：对联合概率不断求和消除其中的变量，最后得到边缘分布。

例子：

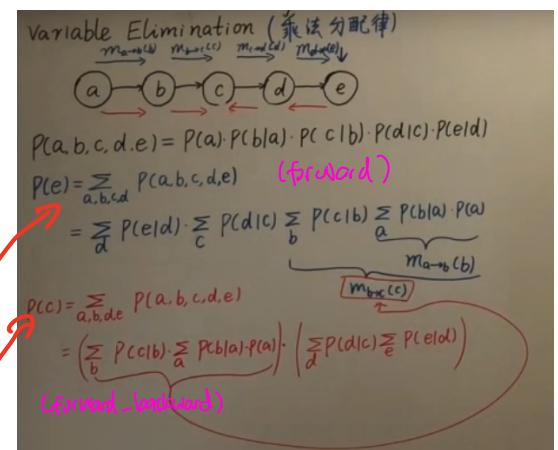


写出因子分解形式 因子分解: $P(x_1, x_2, \dots, x_p) = \prod_{i=1}^p P(x_i | x_{\text{parent}})$

$$P(x_5) = \sum_{x_4} \sum_{x_3} \sum_{x_2} \sum_{x_1} P(x_1, x_2, x_3, x_4, x_5) \quad (\text{边缘概率公式})$$

$$= \sum_{x_1} \sum_{x_2} \sum_{x_3} \sum_{x_4} P(x_1) P(x_2 | x_1) P(x_3 | x_2) P(x_4 | x_3) P(x_5 | x_4)$$

$$\begin{aligned}
 &= \sum_{x_3} p(x_5|x_3) \leq p(x_4|x_3) \frac{\leq p(x_3|x_2)}{x_2} \frac{\leq p(x_1)}{x_1} \\
 &= \sum_{x_3} p(x_5|x_3) \frac{\leq p(x_4|x_3)}{x_4} \frac{\leq p(x_3|x_2)}{x_2} \underline{M_{12}(x_2)} \\
 &= \sum_{x_3} p(x_5|x_3) \frac{\leq p(x_4|x_3)}{x_4} m_{23}(x_3) \\
 &= \sum_{x_3} p(x_5|x_3) m_{23}(x_3) \frac{\leq p(x_4|x_3)}{x_4} \\
 &= \sum_{x_3} p(x_5|x_3) m_{23}(x_3) \underline{x_{43}(x_3)} \\
 &= M_{35}(x_5)
 \end{aligned}$$

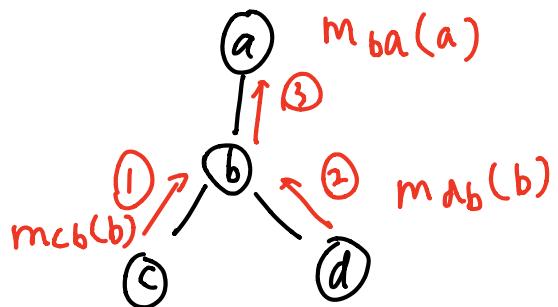


缺点：

- ① 消除的最优次序是一个 NP-Hard 问题
- ② 如果需要计算多于边缘分布，多次执行变量消除算法，但计算结果无法进行复用，导致效率低下。

二. Belief Propagation (BP)

· 解决了 VC 结果无法复用的问题



$$BP = VE + Cache (信息规划思想)$$

* 不直接求边缘概率 $p(a) p(b) p(c) p(d)$

只需求 $\underline{m_{i \rightarrow j}}$

Belief propagation

给定图7图。此图有四个结点和三条边。

$$P(a, b, c, d) = \frac{1}{2} \varphi_a(a) \varphi_b(b) \varphi_c(c) \varphi_d(d) \varphi_{ab}(a, b) \varphi_{bc}(c, b) \varphi_{bd}(d, b)$$

若想求边缘概率 $p(a)$ ，应沿着红色箭头传播。

$$\text{其中 } M_{cb}(b) = \sum_c \varphi(c) \cdot \varphi_{bc}(bc)$$

$$M_{db}(b) = \sum_d \varphi(d) \cdot \varphi_{ba}(bd)$$

$$M_{ba}(a) = \sum_b \varphi(b) \cdot \varphi_{ba}(ba) \cdot M_{cb}(b) \cdot M_{db}(b)$$

极点形式 -> (对所有结点 a, 最终 $P(a) = \varphi(a) \cdot M_{ba}(a)$)

写成一般的公式，对于结点 i, j

$$M_{ji}(i) = \sum_j \varphi_j(j) \phi_{ij}(ij) \prod_{k \in \text{neighbour}(j)-i} M_{kj}(j)$$

$$\text{belief}(b) = \varphi_b \cdot \text{children}$$

$$M_{ba} = \sum_b \varphi_{ab} \cdot \text{belief}$$

过程可以理解如下：

① 选取根节点 a

② 对根节点的邻居中的每一个节点收集入信息 ($M_{cb}, M_{db}, M_{ba}, \dots$)

③ 对根节点的邻居计算出信息 (M_{ba})

三. ~~MAP~~ (Max product)

max product algorithm

~~先看HMM~~

Target: 寻找 decoding 路径

$$\hat{x} = \arg \max_x P(X|E) \quad E = \{e_1, e_2, \dots, e_T\}$$

Review I. HMM for decoding: Viterbi algorithm

输入：模型 $\lambda = (A, B, \pi)$ 和观测 $O = (o_1, o_2, \dots, o_T)$;

输出：最优路径 $I^* = (i_1^*, i_2^*, \dots, i_T^*)$ 。

(1) 初始化

$$\delta_1(i) = \pi_i b_i(o_1), \quad i = 1, 2, \dots, N$$

$$\Psi_1(i) = 0, \quad i = 1, 2, \dots, N$$

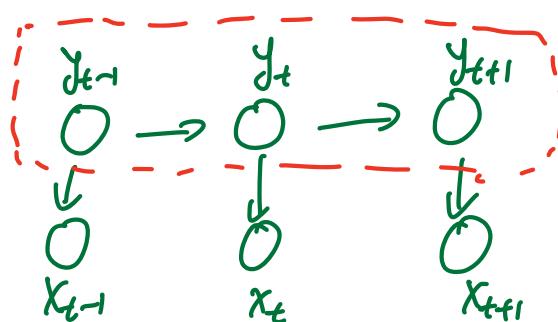
(2) 递推。对 $t = 2, 3, \dots, T$

$$\delta_t(i) = \max_{1 \leq j \leq N} [\delta_{t-1}(j) a_{ji}] b_i(o_t), \quad i = 1, 2, \dots, N$$

$$\Psi_t(i) = \arg \max_{1 \leq j \leq N} [\delta_{t-1}(j) a_{ji}], \quad i = 1, 2, \dots, N$$

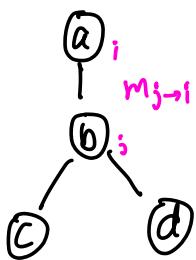
(3) 终止

$$P^* = \max_{1 \leq i \leq N} \delta_T(i)$$



Decoding: $\hat{i} = \arg \max_i P(Y|X)$

Review 2. Belief propagation [信念传播, BP]



$$m_{j \rightarrow i}(x_i) = \sum_{x_j} \psi_j(x_j) \psi_{ij}(x_i, x_j) \prod_{k \in NB(j)-i} m_{k \rightarrow j}(x_j)$$

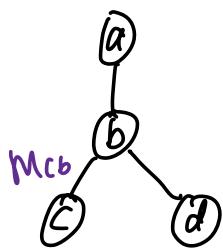
$$p(x_i) = \psi_i(x_i) \prod_{k \in NB(i)} m_{k \rightarrow i}(x_i)$$

Max Product:

① BP的改进

② Viterbi 算法

类似于 forward-backward 算法 Viterbi:



$$m_{j \rightarrow i} = \max_{x_j} \psi_j \psi_{ij} \prod_{k \in NB(j)-i} m_{k \rightarrow j}$$

$$\text{Target: } (x_a^*, x_b^*, x_c^*, x_d^*) = \arg \max_{x_a, x_b, x_c, x_d} p(x_a, x_b, x_c, x_d | E)$$

$$m_{cb}(x_c) = \max_{x_c} \psi_c \psi_{bc}$$

$$m_{db}(x_d) = \max_{x_d} \psi_d \psi_{db}$$

$$m_{ba} = \max_{x_b} \psi_b \psi_{ba} m_{cb} m_{db}$$

$$\max p(x_a, x_b, x_c, x_d) = \max_{x_a} \psi_a m_{ba}$$

4 : Exact Inference: Variable Elimination

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Scribes: Soumya Batra, Pradeep Dasigi, Manzil Zaheer

1 Probabilistic Inference

A probabilistic graphical model (PGM) M represents a unique probability distribution P over a set of random variables. Given such a representation, the following are some of the important tasks we can accomplish.

1. Querying: Computing the likelihood of certain variables, optionally conditioned on another set of variables. This is generally called *Probabilistic Inference*.
2. Estimation: When the model itself is unknown, estimating a plausible model M from data D . This process is called *Learning*.

Our current focus is on inference. Though learning is usually seen as a task different from inference, it is not always the case. Learning typically involves estimating parameters of the model M so that it explains or “fits” the data D . In Bayesian learning, we particularly seek $p(M|D)$, which is done by assigning prior distributions $p(M)$ over the parameters, and then estimating the parameters given the data $p(M|D)$, which is essentially inference. Sometimes learning has to be done from incomplete data. In such cases, we run inference to estimate hidden variables representing missing data.

There are three important kinds of queries given a distribution P_M represented by a graphical model M : likelihood, posterior belief and most probable assignment. We describe each of these in detail.

Likelihood This is the value of the marginal probability of a subset of variables E in the distribution. Likelihood is also calculated to get the conditional probability of a different subset of variables conditioned on E . In that case, E is called the evidence. Let us define a joint probability distribution P over variables $X_{1\dots n}$. Let $E = X_{k+1}, \dots, X_n$. To calculate $P(E)$, we do the following.

$$P(E) = \sum_{X_1} \dots \sum_{X_k} P(X_1 \dots X_n)$$

Posteriori Belief This is the conditional probability distribution of some query nodes conditioned on an evidence, $P(X|e)$.

$$P(X|e) = \frac{P(X, e)}{P(e)} = \frac{P(X, e)}{\sum_x P(X = x, e)}$$

In case there is a subset of X that we do not care about, that is if $X = Y, Z$ and we want to calculate $P(Y|e)$,

$$P(Y|e) = \sum_z P(Y, Z = z|e)$$

This process of summing out z is called marginalization. A generalization of the same idea is shown in Section ?? as variable elimination.

Posteriori belief has multiple applications in statistical analysis and learning. Given a causal trail, calculating the conditional probability of effects given causes is called prediction. In this case, the query node is a descendant of the evidence. Diagnosis is calculating the conditional probability of causes given effects, and this is useful in finding the probability of a disease given the symptoms. In this case, the query node is an ancestor of the evidence node in the trail. While learning under partial observation, posteriori belief of the unobserved variables given the observed ones is calculated.

Most Probable Assignment In this query, we are interested in finding only one set of values for the query variables that maximize the given conditional probability instead of finding the entire distribution.

$$MPA(Y|e) = \arg \max_{y \in Y} P(Y|e)$$

Calculating the posteriori belief is not a necessary pre-requisite for finding MPA as we can usually find some clever tricks to directly calculate the latter. MPA has direct applications in tasks like classification and explanation.

1.1 Complexity of Inference

Computing $P(X = x|e)$ in a GM is an NP-hard problem, which means that there is not generalized efficient algorithm for inference given an arbitrary PGM, query and evidence nodes. However, for some families of models, there are polynomial time algorithms for inference. Another solution to deal with the hardness of the problem is finding approximate solutions. The following is a list of some of the exact and approximate algorithms on graphical models.

Exact Inference

- Elimination algorithm
- Message passing algorithm
- Junction tree algorithms

Approximate Inference

- Stochastic simulation
- Markov chain Monte Carlo methods
- Variational algorithms

The current focus is on exact algorithms, and in particular we deal with the Elimination algorithm in detail. A key observation is that given query and evidence nodes in a PGM, calculating the posteriori belief does not involve some of the variables in the joint distribution. Hence the idea is to avoid the marginalization involving a naive summation over an exponential number of terms.

2 Marginalization and Elimination

2.1 Variable Elimination on a Chain

Let us consider a simple example of directed chain of 5 random variables A, B, C, D , and E , as in Figure ???. For simplicity suppose that each variable can take n number of values. A straightforward probabilistic description would require a full joint probability table containing n^5 entries. As we can see the size of this table is exponential in the number of variables. Now if we want to evaluate the probability that variable E takes on value e , i.e. $P(E = e)$ under this model description, we have to compute:

$$P(e) = \sum_{a,b,c,d} P(a, b, c, d, e)$$

However, this operation requires marginalizing/integrating/summing out the other 4 variables, which involves $O(n^4)$ addition operations, i.e. exponential number of operations in the number of variables.

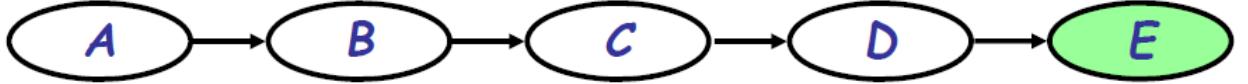


Figure 1: A simple directed probabilistic model with a chain structure

We can be smarter by exploiting the structure of the chain, i.e. factorize the joint probability according to the chain and rewrite as:

$$\begin{aligned} P(e) &= \sum_{a,b,c,d} P(a, b, c, d) \\ &= \sum_{a,b,c,d} P(a)P(b|a)P(c|b)P(d|c)P(e|d) \end{aligned}$$

Now in the factorized joint distribution, not all terms have a dependence on all variables. So if we want to sum over A , then $P(c|b)$, $P(d|c)$, and $P(e|d)$ are not affected by the value of a . So we can pull those three terms that don't depend on a out of this summation. Then we have to perform summation over the only terms that are affected, i.e. $P(a)$ and $P(b|a)$.

$$\begin{aligned} P(e) &= \sum_{a,b,c,d} P(a)P(b|a)P(c|b)P(d|c)P(e|d) \\ &= \sum_{b,c,d} P(c|b)P(d|c)P(e|d) \sum_a P(a)P(b|a) \\ &= \sum_{b,c,d} P(c|b)P(d|c)P(e|d)P(b) \end{aligned}$$

The result of the summation would marginal distribution of B which is a function that depends only on the value of B and no other variables. Next, we can repeat the same process using the summation over another variable, such as B . First we pull out all the terms in the joint distribution that don't depend on B , and

then we compute the value of the sum:

$$\begin{aligned} P(e) &= \sum_{b,c,d} P(c|b)P(d|c)P(e|d)P(b) \\ &= \sum_{c,d} P(d|c)P(e|d) \sum_b P(c|b)P(b) \\ &= \sum_{c,d} P(d|c)P(e|d)P(c) \end{aligned}$$

We can continue this process by performing the same steps for the remaining summations over C and D :

$$\begin{aligned} P(e) &= \sum_{c,d} P(d|c)P(e|d)P(c) \\ &= \sum_d P(e|d) \sum_c P(d|c)P(c) \\ &= \sum_d P(e|d)P(d) \end{aligned}$$

Using this procedure, we can eliminate one variable at a time. This reduces the amount of computation by performing the summations one at a time consisting of $O(n^2)$ operations (due to the number of values taken by the variable (node) being marginalized those taken by its child node). Then total elimination steps would be $O(kn^2)$ where k is the number of variables.

2.2 Variable Elimination on a HMM

A more realistic example would be to consider a Hidden Markov Model (HMM), as shown in Figure ???. Suppose we are interested in finding out the state the HMM is in when it emitted x_i , then we would like to evaluate $P(y_i|x_1, \dots, x_T)$. As in the chain, we begin by writing out the full joint distribution and marginalizing out all of the variables that we don't care about:

$$\begin{aligned} P(y_i|x_1, \dots, x_T) &\propto \sum_{y_1, \dots, y_{i-1}, y_{i+1}, \dots, y_T} p(x_1, x_2, \dots, x_T, y_1, y_2, \dots, y_T) \\ &= \sum_{y_1, \dots, y_{i-1}, y_{i+1}, \dots, y_T} p(y_1)p(x_1|y_1)p(y_2|y_1)p(x_2|y_2)\dots p(y_T|y_{T-1})p(x_T|y_T) \end{aligned}$$

Once again, we can reduce computational cost by exploiting the structure in the HMM or its graphical model. The procedure would be to move in any order through the variables being eliminated (all Y 's except Y_i), select only the terms in the factored joint distribution that depend on the current elimination variable Y_j , and calculate the summation over values y_j to generate a new factor that doesn't depend on Y_j . For example, suppose we start by eliminating Y_1 . Then the first summation we compute will be:

$$\sum_{y_1} P(y_1)P(x_1|y_1)P(y_2|y_1) = \alpha_1(x_1, y_2)$$

Next we eliminate Y_2 by performing the following summation:

$$\sum_{y_2} \alpha_1(x_1, y_2)P(x_2|y_2)P(y_3|y_2) = \alpha_2(x_1, x_2, y_3)$$

Then we eliminate each of Y_3, \dots, Y_{i-1} in turn. For the variables Y_{i+1}, \dots, Y_T we carry out similar procedure. Let us start by eliminating Y_T :

$$\sum_{y_T} P(x_T|y_T)P(y_T|y_{T-1}) = \beta_T(x_T, y_{T-1})$$

Next we eliminate y_{T-1} by performing the following summation:

$$\sum_{y_{T-1}} P(y_{T-1}|y_{T-2})P(x_{T-1}|y_{T-1})\beta_T(x_T, y_{T-1}) = \beta_{T-1}(x_{T-1}, x_T, y_{T-2})$$

After all the variables have been eliminated, we can calculate the conditional probability of y_i using final factor:

$$p(y_i|x_1, \dots, x_T) \propto P(x_i|y_i)\alpha_{i-1}(x_1, x_2, \dots, x_{i-1}, y_i)\beta_{i+1}(x_{i+1}, \dots, x_T, y_i)$$

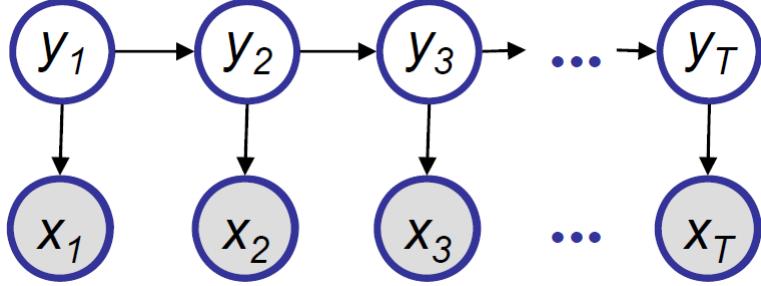


Figure 2: Hidden Markov Model

We next need to normalize to obtain a proper probability:

$$P(y_i|x_1, \dots, x_T) = \frac{P(x_i|y_i)\alpha_{i-1}(x_1, x_2, \dots, x_{i-1}, y_i)\beta_{i+1}(x_{i+1}, \dots, x_T, y_i)}{\sum_{y_i} P(x_i|y_i)\alpha_{i-1}(x_1, x_2, \dots, x_{i-1}, y_i)\beta_{i+1}(x_{i+1}, \dots, x_T, y_i)}$$

This procedure is same as the Forward Backward Algorithm for HMMs. Just as we saw in the chain example, the core operation is the marginalization of each variable, which takes $O(n^2)$ time. Since we perform T such steps, the total cost is again $O(Tn^2)$.

2.3 Variable Elimination on Undirected Chains

Now consider a simple example of undirected chain of 5 random variables A, B, C, D , and E , as in Figure ???. Now if we want to evaluate the probability that variable E takes on value e , i.e. $P(E = e)$ under this model description, we have to compute:

$$P(e) = \sum_{a,b,c,d} \frac{1}{Z} \phi(a, b)\phi(b, c)\phi(c, d)\phi(d, e)$$



Figure 3: A simple undirected probabilistic model with a chain structure

Like before we can see that not all terms have a dependence on all variables. So if we want to sum over A , then $\phi(b, c)$, $\phi(c, d)$, and $\phi(d, e)$ are not affected by the value of a . So we can pull those three terms that

don't depend on a out of this summation. Then we have to perform summation over the only $\phi(a, b)$. We keep repeating this procedure.

$$\begin{aligned}
P(e) &\propto \sum_{a,b,c,d} \phi(a, b)\phi(b, c)\phi(c, d)\phi(d, e) \\
&= \sum_{b,c,d} \phi(b, c)\phi(c, d)\phi(d, e) \sum_a \phi(a, b) \\
&= \sum_{b,c,d} \phi(b, c)\phi(c, d)\phi(d, e)m_a(b) \\
&= \sum_{c,d} \phi(c, d)\phi(d, e) \sum_b \phi(b, c)m_a(b) \\
&= \sum_{c,d} \phi(c, d)\phi(d, e)m_b(c) \\
&= \sum_d \phi(d, e) \sum_c \phi(c, d)m_b(c) \\
&= \sum_d \phi(d, e)m_c(d) \\
&= \sum_d \phi(d, e)m_c(d) \\
&= m_d(e)
\end{aligned}$$

Finally we normalize to obtain a proper probability:

$$P(e) = \frac{m_d(e)}{\sum_e m_d(e)}$$

Next we present a formal general algorithm to solve such problems.

2.4 The General Variable Elimination Algorithm

Suppose \mathcal{X} be set of all random variables involved in the graphical model. Let \mathfrak{F} denote the set of factors and then for each factor $\phi \in \mathfrak{F}$ denote by $\text{scope}[\phi] \subseteq \mathcal{X}$ the set of all variables involved in ϕ . Suppose $\mathcal{Y} \subset \mathcal{X}$ be the set of query variables, then $Z = \mathcal{X} - \mathcal{Y}$ would be the set of variables to be eliminated. Further we can have a set of observed variables, termed as evidence denoted by \mathcal{E} . We deal with evidence, i.e. observed variables by defining evidence potential:

$$\delta(\mathcal{E}_i, \bar{e}_i) = \begin{cases} 1 & \text{if } \mathcal{E}_i = \bar{e}_i \\ 0 & \text{if } \mathcal{E}_i \neq \bar{e}_i \end{cases}$$

and in turn the total evidence potential:

$$\delta(\mathcal{E}, \bar{e}) = \prod_{i \in \mathcal{I}} \delta(\mathcal{E}_i, \bar{e}_i)$$

This trick of evidence potential allows us to treat marginalization and conditioning as formally equivalent as the evidence potentials basically converts evaluations into sums.

The high level idea is to express any query in the following form:

$$P(\mathcal{Y}|\mathcal{E}) \propto \sum_{\mathcal{Z}} \prod_{\phi \in \mathfrak{F}} \phi(\text{scope}[\phi])\delta(\mathcal{E}, \bar{e})$$

Throughout the algorithm we maintain an active set of potential functions. The active list is initialized to hold all factors and the evidence potentials. Then iteratively we find all factors involving the next variable in the elimination ordering. These factors are removed from the active list and sum of their product with respect to current variable in the elimination order is carried out. In simple words we move all irrelevant terms outside of the innermost sum and compute the innermost sum. Thus obtaining a new intermediate factor, which we re-insert into the active list. We stop when all variables in \mathcal{Z} are eliminated in the ordering \mathcal{I} . Finally we wrap-up with normalization as:

$$P(\mathcal{Y}|\mathcal{E}) = \frac{\phi(\mathcal{Y}, \mathcal{E})}{\sum_{\mathcal{E}} \phi(\mathcal{Y}, \mathcal{E})}$$

2.5 Pseudocode

If G is the graphical model, the pseudocode for the algorithm can be given as

Eliminate($G, E, \mathcal{Z}, \mathcal{Y}$):

```
Initialize( $G, \mathcal{Y}$ )
Evidence( $\mathcal{E}$ )
Sum-Product-Variable-Elimination( $\mathcal{F}, \mathcal{Z}, \prec$ )
Normalization( $\mathcal{F}$ )
```

Let us see each of the sub-procedures in detail:

1. **Initialize(G, \mathcal{Z}):**

- (a) Choose an elimination ordering with the query variable at the end of the ordering. Also, if $\mathcal{Z}_1, \mathcal{Z}_2, \dots, \mathcal{Z}_k$ is the ordering then $\mathcal{Z}_i \prec \mathcal{Z}_j$ iff $i < j$.
- (b) Initialize the active list, which is essentially a stack \mathcal{F} with the full set of factors, ϕ_1, ϕ_2, \dots

2. **Evidence(E):**

- (a) Grow the stack \mathcal{F} further by loading all evidences

3. **Sum-Product-Variable-Elimination(F, \mathcal{Z}, \prec):**

- (a) For all variables in the ordering, $\mathcal{Z}_1, \mathcal{Z}_2, \dots, \mathcal{Z}_k$ call subroutine:

$$\mathcal{F} \leftarrow \text{Sum-Product-Eliminate-Var}(\mathcal{F}, Z_i); i = 1, \dots, k$$

Each iteration creates a new stack and overwrites the existing one. The subroutine sums over the product of all factors of the variable to be eliminated and returns a new stack with the variable eliminated.

- (b) After all iterations are complete, we get a stack of final potentials. We take product of all of these to get our query out.

$$\phi^* \leftarrow \prod_{\phi \in \mathcal{F}} \phi$$

4. **Normalization(F):**

- (a) Finally, we normalize the potential thus obtained ϕ^* .

$$P(X|E) \leftarrow \phi^*(X) / \sum_x \phi^*(X)$$

5. Sum-Product-Eliminate-Var (F, Z):

- (a) Define \mathcal{F}' as scope of Z , i.e., all terms in the stack \mathcal{F} having Z_i as an argument.

$$\mathcal{F}' \leftarrow \{\phi \in \mathcal{F} : Z \in \text{Scope}[\phi]\}$$

- (b) Define \mathcal{F}'' as the remaining stack.

$$\mathcal{F}'' \leftarrow \mathcal{F} - \mathcal{F}'$$

- (c) Take product of all factors in \mathcal{F}' . This is the product step of the Sum-Product operation.

$$\psi \leftarrow \prod_{\phi \in \mathcal{F}'} \phi$$

- (d) Take sum on these product factors over Z , so that Z is eliminated. A new factor τ is generated.

$$\tau \leftarrow \sum_Z \psi$$

- (e) Put τ on top of stack and return.

$$\text{return } \mathcal{F}'' \cup \tau$$

2.6 Variable Elimination on more complex network

Consider the a little more complicated directed graphical model as shown in figure 3. The complete set of random variables is $\mathcal{X} = A, B, C, D, E, F, G, H$. Suppose we need to evaluate the query $P(A|H = h)$, then $\mathcal{Y} = A$ and we need to eliminate $\mathcal{Z} = B, C, D, E, F, G, H$. The evidence set is simply $\mathcal{E} = H$ with the evidence potential being $\delta(\mathcal{E}, \bar{e}) = \delta(H, h)$.

So the initially with all factors we have

$$P(a)P(b)P(c|b)P(d|a)P(e|c, d)P(f|a)P(g|e)P(h|e, f)$$

and also push in the evidence potential $\delta(H, h)$. Suppose we choose an elimination order $\mathcal{I} = H, G, F, E, D, C, B$ (more on how to choose a good elimination order will follow). Then we follow the general variable elimination algorithm as follows:

- 1. Conditioning H:** As discussed earlier this step is isomorphic to a marginalization step wherein we fix the evidence node on its observed value:

$$m_h(e, f) = \sum_h p(h|e, f)\delta(h, \tilde{h})$$

Leaving the factors as

$$P(a)P(b)P(c|b)P(d|a)P(e|c, d)P(f|a)P(g|e)m_h(e, f)$$

- 2. Eliminate G:** We compute

$$m_g(e) = \sum_g P(g|e) = 1$$

to yield

$$P(a)P(b)P(c|b)P(d|a)P(e|c, d)P(f|a)m_h(e, f)$$

3. Eliminate F: We compute

$$m_f(e, a) = \sum_f p(f|a)m_h(e, f)$$

to yield

$$P(a)P(b)P(c|b)P(d|a)P(e|c, d)m_f(e, a)$$

4. Eliminate E: We compute

$$m_e(a, c, d) = \sum_e P(e|c, d)m_f(e, a)$$

to yield

$$P(a)P(b)P(c|b)P(d|a)m_e(a, c, d)$$

5. Eliminate D: We compute

$$m_d(a, c) = \sum_d P(d|a)m_e(a, c, d)$$

to yield

$$P(a)P(b)P(c|b)m_d(a, c)$$

6. Eliminate C: We compute

$$m_c(a, b) = \sum_c P(c|b)m_d(a, c)$$

to yield

$$P(a)P(b)m_c(a, b)$$

7. Eliminate B: We compute

$$m_b(a) = \sum_b P(b)m_c(a, b)$$

to yield

$$P(a)m_b(a)$$

8. Normalization: We wrap-up with normalization as

$$P(a|h = \tilde{h}) = \frac{P(a)m_b(a)}{\sum_a P(a)m_b(a)}$$

2.7 Complexity of Variable Elimination

For each variable x to be eliminated, the Sum-Product operation can be broken down into two parts:

1. Product:

$$m'_x(x, y_1, \dots, y_k) = \prod_{i=1}^k m_i(x, y_{c_i})$$

2. Sum:

$$m_x(y_1, \dots, y_k) = \sum_x m'_x(x, y_1, \dots, y_k)$$

Now, Total number of multiplications required = $k \times |Val(X)| \times \prod_i |Val(Y_{C_i})|$, where Y_{C_i} is the i^{th} configuration of the clique c defined on Y

Total number of additions = $|Val(X)| \times \prod_i |Val(Y_{C_i})|$

Following important points are made about the Sum-Product operation:

1. Both the above steps are polynomial, not exponential to the number of states in every random variable.
2. $Val(Y_{C_i})$ is the local exponential term, dependent on the size of the clique used to define intermediate term. However, outside the clique, this becomes multiplicative.
3. This is the major benefit of the Sum-Product operation. It reduced a globally exponential operation to one which is locally exponential but globally polynomial. The polynomial depends on the number of cliques used to define the model and the complexity depends on the local cliques produced.

3 Graph Elimination

3.1 Graph Elimination on Undirected and Directed Graphs

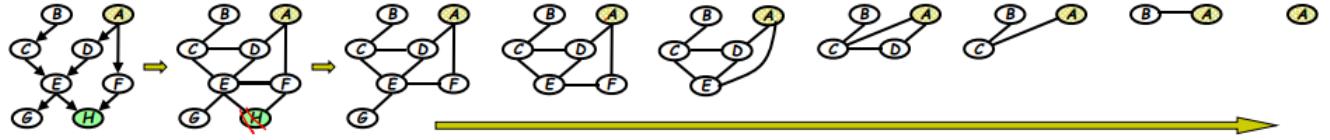


Figure 4: A Graph Elimination procedure

A graph elimination procedure for undirected graphs is as follows:

1. Begin with the graph and an elimination ordering.
2. For each variable in the ordering, connect all neighbors of the variable.
3. Eliminate the variable.

For a directed graph, first the graph is moralized. The remaining procedure stays the same as in undirected graphs. At each iteration, a sequence of subgraphs is obtained that includes the variable to be eliminated, remaining variables coupled with the variable to be eliminated and edges resultant from elimination. After each iteration, we record the elimination cliques of the graph, i.e., clique formed by the neighbors of the variable being eliminated and the variable itself. These cliques are equivalent to the sets of variables on which summations operate in probabilistic inference using Variable Elimination.

Graph Elimination presents two interesting intuitions:

1. The elimination ordering determines the intermediate terms being produced. Different subgraphs would be produced for different elimination orderings. The structure of the graph can give us intuition about how to structure our elimination ordering.

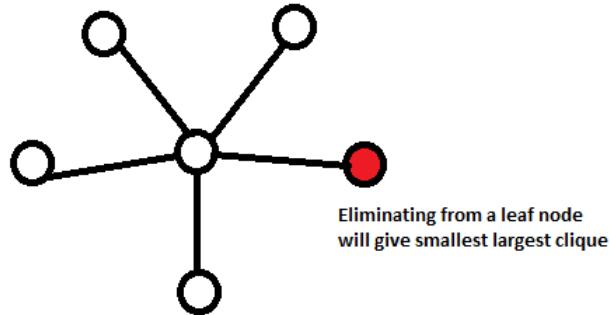


Figure 5: A Star Graph

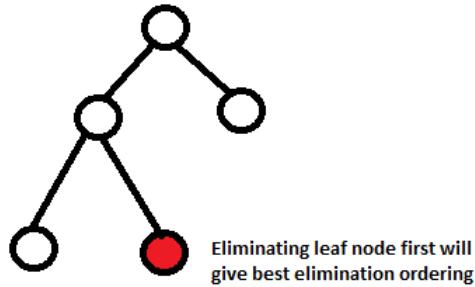


Figure 6: A Tree Graph

2. Intermediate terms can be viewed as different messages being passed from clique being eliminated to the next clique to be eliminated.

3.2 Complexity of Graph Elimination

The complexity for a Graph Elimination on a graph is proportional to the size of the largest intermediate message (intermediate term). The size of the largest intermediate clique would be the bottleneck of the algorithm. This is called the *tree-width* of the graph. Essentially, the problem of finding the largest intermediate clique would be NP-hard. However, we can use intuition from the structure of the graph to find a good ordering that will result in smallest largest intermediate clique. As an example, for a star graph, it is best to eliminate all the leaf nodes first. However, if we start from the middle node, it will result in one large clique consisting of all leaf nodes. Another example is of tree graphs like the one shown in Figure ???. Starting from the leaf nodes is the best elimination ordering.

Let us now consider the Ising Model as shown in Figure ???. The complexity or treewidth of this model is equal to the number of nodes in a single dimension of the grid. Such models can be used to represent images. However, in such a case memory requirements are too big. For a binary 255×255 image, we need 2^{255} bits. Hence, graph elimination is not practical in this case.

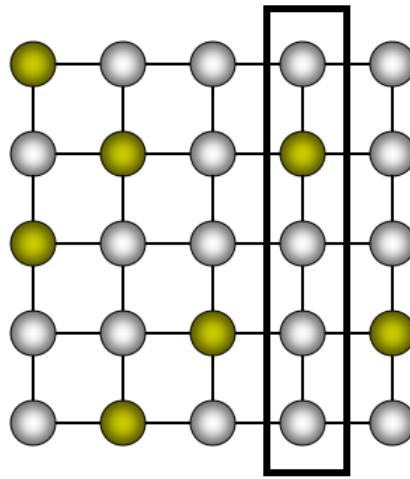


Figure 7: Graph Elimination on an Ising Model

3.3 Message Passing

A major limitation of the graph elimination algorithm is that the entire process needs to be carried for elimination of each query variable. An important observation is that most of the intermediate sums or messages computed for calculating one marginal can be reused for other marginals. This leads us to the *Message Passing* algorithm.