

# Lecture Notes for CS 726 - Spring 2022

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## Probabilistic Modeling

### Probability Theory

We will briefly review probability in a rigorous sense.

We define events considering we have a space of possible outcomes denoted by  $\Omega$ .  $\mathcal{S}$  is a set of measurable events, to which we assign probabilities, and each event  $\alpha \in \mathcal{S}$  is a subset of  $\Omega$ .

The event space necessarily satisfies three properties -

1. It contains the empty event  $\emptyset$  and the trivial event  $\Omega$ .
2. It is closed under union, i.e if  $\alpha, \beta \in \mathcal{S}$ , so is  $\alpha \cup \beta$ .
3. It is closed under complementation, i.e if  $\alpha \in \mathcal{S}$ , so is  $\Omega - \alpha$ .

**Definition 1** (Probability distribution). A probability distribution  $P$  over  $(\Omega, \mathcal{S})$  is a mapping of events in  $\mathcal{S}$  to real values satisfying

- ◇  $P(\alpha) \geq 0$  for all  $\alpha \in \mathcal{S}$
- ◇  $P(\Omega) = 1$
- ◇ If  $\alpha, \beta \in \mathcal{S}$  and  $\alpha \cap \beta = \emptyset$ , then  $P(\alpha \cup \beta) = P(\alpha) + P(\beta)$

Conditional probability answers the question - after learning that event  $\alpha$  is true, how does our belief about  $\beta$  change? Formally, we define

$$P(\beta|\alpha) = \frac{P(\alpha \cap \beta)}{P(\alpha)} \quad (1)$$

It can be checked that this satisfies Definition 1 and is a probability distribution. Noting that  $P(\alpha \cap \beta) = P(\alpha)P(\beta|\alpha)$ , we define the chain rule of conditional probabilities

$$P(\alpha_1 \cap \dots \cap \alpha_k) = P(\alpha_1)P(\alpha_2|\alpha_1) \dots P(\alpha_k|\alpha_1 \cap \dots \cap \alpha_{k-1}) \quad (2)$$

We further define the Bayes' rule

$$P(\alpha|\beta) = \frac{P(\beta|\alpha)P(\alpha)}{P(\beta)} \quad (3)$$

Here,  $P(\alpha|\beta)$  is called the *posterior*,  $P(\beta|\alpha)$  is the *likelihood*,  $P(\alpha)$  is the *prior* and  $P(\beta)$  is the *marginal probability* of the structure in context.

We can generalize Equation 3 as

$$P(\alpha|\beta \cap \gamma) = \frac{P(\beta|\alpha \cap \gamma)P(\alpha|\gamma)}{P(\beta|\gamma)} \quad (4)$$

Now, we formally define the notion of random variables, which intuitively can be considered to be attribute reporters.

In a single coin toss, we have

$$\Omega = \{H, T\}$$

A direct consequence of the properties is:

$$P(\emptyset) = 0$$

$$P(\alpha \cup \beta) = P(\alpha) + P(\beta) - P(\alpha \cap \beta)$$

**Definition 2** (Random Variable). A random variable  $X$  is a *measurable* function  $X : \Omega \rightarrow \mathcal{S}$ . The probability that  $X$  takes values in a set  $s \in \mathcal{S}$  is written as

$$\Pr(X \in s) = \Pr(\{\omega \in \Omega | X(\omega) \in s\}) \quad (5)$$

The marginal distribution over a random variable  $X$  is the distribution over events that can be described using  $X$ , and is denoted by  $P(X)$ . More generally, if we want to describe a distribution over a set of random variables  $\mathcal{X} = \{x_1, \dots, x_n\}$  called the *joint distribution* denoted as  $P(x_1, \dots, x_n)$ . The full assignment to the variables is denoted as  $\xi \in \text{Val}(\mathcal{X})$ . The space corresponding to the joint assignment in  $\mathcal{X}$  is called the *canonical outcome space*.

Now, we glance at independencies, a core component of Probabilistic Graphical Models.

**Definition 3** (Independence). An event  $\alpha$  is independent of an event  $\beta$  denoted by  $P \models (\alpha \perp\!\!\!\perp \beta)$ , if  $P(\alpha|\beta) = P(\alpha)$  or  $P(\beta) = 0$ .

**Proposition 4.** A distribution satisfies  $(\alpha \perp\!\!\!\perp \beta)$  if and only if

$$P(\alpha \cap \beta) = P(\alpha)P(\beta) \quad (6)$$

*Proof.* Skipped (hint: Use the definition of conditional probability).  $\square$

**Definition 5** (Conditional Independence). An event  $\alpha$  is conditionally independent of event  $\beta$  given  $\gamma$  in  $P$ , denoted by  $P \models (\alpha \perp\!\!\!\perp \beta | \gamma)$  if  $P(\alpha|\beta \cap \gamma) = P(\alpha|\gamma)$  or if  $P(\beta \cap \gamma) = 0$ .

**Proposition 6.**  $P$  satisfies  $(\alpha \perp\!\!\!\perp \beta | \gamma)$  if and only if

$$P(\alpha \cap \beta | \gamma) = P(\alpha | \gamma)P(\beta | \gamma) \quad (7)$$

**Definition 7.** Let  $\mathbf{X}, \mathbf{Y}, \mathbf{Z}$  be sets of random variables.  $\mathbf{X}$  is conditionally independent of  $\mathbf{Y}$  given  $\mathbf{Z}$  in a distribution  $P$  if  $P$  satisfies  $(\mathbf{X} = \mathbf{x} \perp\!\!\!\perp \mathbf{Y} = \mathbf{y} | \mathbf{Z} = \mathbf{z})$  for all values of  $\mathbf{x} \in \text{Val}(\mathbf{X})$ ,  $\mathbf{y} \in \text{Val}(\mathbf{Y})$  and  $\mathbf{z} \in \text{Val}(\mathbf{Z})$ . We say that the variables in  $\mathbf{Z}$  are *observed*. If  $\mathbf{Z}$  is empty, then we say that  $\mathbf{X}$  and  $\mathbf{Y}$  are marginally independent.

**Proposition 8.** The distribution  $P$  satisfies  $(\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z})$  if and only if

$$P(\mathbf{X}, \mathbf{Y} | \mathbf{Z}) = P(\mathbf{X} | \mathbf{Z})P(\mathbf{Y} | \mathbf{Z}) \quad (8)$$

The following properties hold for conditional independencies:

1. *Symmetry:*  $(\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}) \implies (\mathbf{Y} \perp\!\!\!\perp \mathbf{X} | \mathbf{Z})$
2. *Decomposition:*  $(\mathbf{X} \perp\!\!\!\perp \mathbf{Y}, \mathbf{W} | \mathbf{Z}) \implies (\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z})$
3. *Weak Union:*  $(\mathbf{X} \perp\!\!\!\perp \mathbf{Y}, \mathbf{W} | \mathbf{Z}) \implies (\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}, \mathbf{W})$

Decomposition can also be stated as

$$\mathbf{X} \perp\!\!\!\perp \{\mathbf{Y}, \mathbf{Z}\} \implies \mathbf{X} \perp\!\!\!\perp \mathbf{Y}, \mathbf{X} \perp\!\!\!\perp \mathbf{Z}$$

Weak Union can also be stated as

$$\mathbf{X} \perp\!\!\!\perp \{\mathbf{Y}, \mathbf{Z}\} \implies \mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}$$

But note that, if  $\mathbf{X} \perp\!\!\!\perp \mathbf{Y}$  and  $\mathbf{Z} \not\perp\!\!\!\perp \{\mathbf{X}, \mathbf{Y}\}$  then it is not necessary to have  $\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}$

4. *Contraction*:  $(\mathbf{X} \perp\!\!\!\perp \mathbf{W} | \mathbf{Z}, \mathbf{Y}) \ \& \ (\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}) \implies (\mathbf{X} \perp\!\!\!\perp \mathbf{Y}, \mathbf{W} | \mathbf{Z})$

If our distribution is positive (i.e, for all non-empty  $\alpha \in \mathcal{S}, P(\alpha) > 0$ ), we have another property

Contraction can also be stated as

$$\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}, \mathbf{X} \perp\!\!\!\perp \mathbf{Z} \implies \mathbf{X} \perp\!\!\!\perp \{\mathbf{Y}, \mathbf{Z}\}$$

◇ *Intersection*:  $(\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}, \mathbf{W}) \ \& \ (\mathbf{X} \perp\!\!\!\perp \mathbf{W} | \mathbf{Z}, \mathbf{Y}) \implies (\mathbf{X} \perp\!\!\!\perp \mathbf{Y}, \mathbf{W} | \mathbf{Z})$

**Theorem 9.** Consider  $\mathcal{X} = \{\mathbf{X}, \mathbf{Y}, \mathbf{Z}\}$ . Then  $P \models (\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z})$  if and only if we can write

$$P(\mathcal{X}) = \phi_1(\mathbf{X}, \mathbf{Z}) \phi_2(\mathbf{Y}, \mathbf{Z}) \quad (9)$$

*Proof.* Skipped. □

### Probabilistic Graphical Models

Given a set of  $n$  random variables  $\mathcal{X} = \{x_1, x_2, \dots, x_n\}$  where  $n$  is large, we want to build a joint probability distribution  $P$  over this set. Explicitly representing the joint distribution is computationally expensive, since just having binary values variables requires the joint distribution to specify  $2^n - 1$  numbers, and for more practical variables, the count is too large.

We want to efficiently represent, estimate and answer inference queries on the distribution.

An example of a query can be -  
Estimate the fraction of people  
with a bachelor's degree.

### Alternatives to explicit joint distributions

▷ Can we assume all columns are independent? **NO** - this is obviously a very bad assumption.

▷ Can we use data to detect highly correlated column pairs, and estimate their pairwise frequencies? **MAYBE** - but there might be too many correlated pairs, and the method is ad hoc.

To solve the above two not so good ways, we explore conditional independencies. It may be possible that  $\text{income} \not\perp\!\!\!\perp \text{age}$  but  $\text{income} \perp\!\!\!\perp \text{age} | \text{experience}$ .

Note that we write that a set  $X$  is conditionally independent of  $Y$  given  $Z$ , i.e  $X \perp\!\!\!\perp Y | Z$  if

$$\Pr(X|Y, Z) = \Pr(X|Z)$$

Probabilistic graphical models use a graph-based representation as the basis for compactly encoding a complex distribution over a high-dimensional space.

It is convenient to represent the independence assumption using a graph. The so called graphical model has nodes as the variables (continuous or discrete), and the edges represent direct interaction. If we consider directed edges, we talk about Bayesian Networks, and if we consider undirected edges, we talk about Markov Random Fields.

Essentially the graphical model is a combination of the graph and potentials.

**Definition 10** (Potentials). Potentials  $\psi_c(\mathbf{x}_c)$  are scores for assignment of values to subsets  $c$  of directly interacting variables. We factorize

the probability as a product of these potentials, i.e

$$\Pr(\mathbf{x} = x_1, \dots, x_n) \propto \prod \psi_s(\mathbf{x}_s) \quad (10)$$

## Bayesian Networks

Bayesian Networks, also referred to as *directed graphical models* are a family of probability distributions that has a compact parameterization representable using a directed graph.

It is known that

$$\Pr(x_1, x_2, \dots, x_n) = \Pr(x_1)\Pr(x_2|x_1)\Pr(x_3|x_2, x_1) \cdots \Pr(x_n|x_{n-1}, \dots, x_1) \quad (11)$$

A compact Bayesian Network is a distribution in which each factor in the above equation depends on the *parent* variables represented by  $\text{Pa}(x_i)$  for variable  $x_i$ . Thus, we have

$$\Pr(x_i|x_{i-1}, x_{i-2}, \dots, x_1) = \Pr(x_i|\text{Pa}(x_i)) \quad (12)$$

and the corresponding potentials at each node in terms of its parents are

$$\psi_i(x_i, \text{Pa}(x_i)) = \Pr(x_i|\text{Pa}(x_i)) \quad (13)$$

Thus,

$$\Pr(x_1, x_2, \dots, x_n) = \prod_{i=1}^n \Pr(x_i|\text{Pa}(x_i)) \quad (14)$$

Consider the situation when each variable can take  $d$  values. The naive approach gives us  $\mathcal{O}(d^n)$  parameters. If we think of the potentials as probability tables (with the rows corresponding to  $\text{Pa}(x_i)$ ) and columns corresponding to the values of  $x_i$ , with entries as  $\psi_i(x_i, \text{Pa}(x_i))$ , we can notice that if  $|\text{Pa}(x_i)| \leq k$ , then the number of parameters are  $\mathcal{O}(d^{k+1})$ , and for  $n$  variables, we have  $\mathcal{O}(nd^{k+1})$ , which provides us the compact representation.

### Definition

Now we formally define these -

**Definition 12** (Bayesian Network). A Bayesian Network is a directed graph  $G = (V, E)$  together with

- ◇ a random variable  $x_i$  for each node  $i \in V$
- ◇ a potential  $\psi_i(x_i, \text{Pa}(x_i))$  for each node  $i \in V$

For a variable  $x_i$  in our Bayesian Network  $\mathcal{G}$ , denote  $\text{ND}(x_i)$  as the non-descendants of  $x_i$ . The following local conditional independencies hold in  $\mathcal{G}$  -

$$x_i \perp\!\!\!\perp \text{ND}(x_i) | \text{Pa}(x_i) \quad (15)$$

Example 11 shows the independencies in a simple Bayesian Network.

### Example 11.

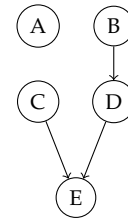


Figure 1: Sample BN

Consider the BN above. We will consider each variable at a time.

- ◇ A has no parent, and has no descendent. Thus,

$$A \perp\!\!\!\perp B, C, D, E$$

- ◇ B has no parent, but has D as a descendent. Thus,

$$B \perp\!\!\!\perp A, C$$

- ◇ C has no parent, but has E as a descendent. Thus,

$$C \perp\!\!\!\perp A, B, D$$

- ◇ D has B as a parent, and has E as the descendent. Thus,

$$D \perp\!\!\!\perp A, C | B$$

- ◇ E has C and D as parents, but has no descendent. Thus,

$$I \perp\!\!\!\perp A, B | C, D$$

**Definition 13** (Factorization). Let  $\mathcal{G}$  be a Bayesian Network graph over the variables  $\{X_i\}_{i=1}^n$ . We say that a distribution  $P$  over the same space factorizes according to  $\mathcal{G}$  if  $P$  can be expressed as a product described in Equation 14. Such factorization is also known as the chain rule for Bayesian Networks, and is denoted as  $\text{Factorize}(P, \mathcal{G})$ .

**Definition 14.** Let  $P$  be a distribution over  $\mathcal{X}$ . We define  $\mathcal{I}(P)$  to be the set of independent assertions of the form  $\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}$  that hold in  $P$ .

We can now write " $P$  satisfies the local independencies associated with  $\mathcal{G}$ " as  $\mathcal{I}_\ell(\mathcal{G}) \subseteq \mathcal{I}(P)$ .

**Definition 15** (Independency-Map). Let  $\mathcal{K}$  be any graph object associated with a set of independencies  $\mathcal{I}(\mathcal{K})$ . We call  $\mathcal{K}$  an I-map for a set of independencies  $\mathcal{I}$  if  $\mathcal{I}(\mathcal{K}) \subseteq \mathcal{I}$ .

Thus for  $\mathcal{G}$  to be an I-map for  $P$ , any independence that asserts in  $\mathcal{G}$  must also assert in  $P$ , but  $P$  can have additional independencies not reflected in  $\mathcal{G}$ .

*Remark 16* (Notation Alert). Note that we will use the following interchangeably -  $P$  satisfies the local conditional independencies satisfied by  $\mathcal{G}$  and  $\mathcal{G}$  is an I-map for  $P$ , i.e

$$\text{Local-CI}(P, \mathcal{G}) \equiv \mathcal{I}_\ell(\mathcal{G}) \subseteq \mathcal{I}(P) \quad (16)$$

**Definition 17** (I-equivalence). Two Bayesian Networks  $\mathcal{G}_1$  and  $\mathcal{G}_2$  are  $\mathcal{I}$ -equivalent, if they encode the same dependencies, i.e

$$\mathcal{I}(\mathcal{G}_1) = \mathcal{I}(\mathcal{G}_2) \quad (17)$$

**Theorem 18.** If  $\mathcal{G}_1$  and  $\mathcal{G}_2$  have the same skeleton, and the same  $v$ -structures (see *D-separation*), then they are  $\mathcal{I}$ -equivalent.

*Proof.* Skipped.  $\square$

**Theorem 19.** Given a distribution  $P(x_1, x_2, \dots, x_n)$  and a directed acyclic graph (DAG)  $\mathcal{G}$ ,

$$\text{Local-CI}(P, \mathcal{G}) \iff \text{Factorize}(P, \mathcal{G}) \quad (18)$$

*Proof.* (  $\implies$  ) We essentially need to show that if  $\mathcal{G}$  is an I-map for  $P$ , then  $P$  factorizes according to  $\mathcal{G}$ . Consider a topologically sorted order  $x_1, x_2, \dots, x_n$  in  $\mathcal{G}$ . Local-CI( $P, \mathcal{G}$ ) tells us that

$$\Pr(x_i | x_1, \dots, x_{i-1}) = \Pr(x_i | \text{Pa}(x_i))$$

We can write

$$P(x_1, x_2, \dots, x_n) = \prod_{i=1}^n P(x_i | x_1, \dots, x_{i-1})$$

Each term in the product can be simplified due to the notion of Local-CI stated above, and we reach Equation 14, proving factorization.

(  $\impliedby$  ) Proof has been skipped.  $\square$



### Minimal Construction

Our goal is to construct a minimal and correct BN  $\mathcal{G}$  to represent  $P$ . A DAG  $\mathcal{G}$  is correct if all Local-CIs that are implied in  $\mathcal{G}$  hold in  $P$ , and a DAG  $\mathcal{G}$  is minimal if we cannot remove any edge(s) from  $\mathcal{G}$  and still get a correct BN for  $P$ .

In the setting, we define our oracle  $\mathcal{O}$  to whom we can ask any query of the type "Is  $X \perp\!\!\!\perp Y|Z$ ?" pertaining to  $P$  and get a boolean answer. We will query the oracle several times to build up our BN. The following algorithm constructs such a BN -

```

1 Variables:  $x_1, x_2, \dots, x_n \leftarrow$  ordered variables in  $\mathcal{X}$ 
2 Independencies:  $\mathcal{I} \leftarrow$  set of independencies
3  $\mathcal{G} \leftarrow$  Empty graph over  $\mathcal{X}$ 
4 for  $i = 1$  to  $n$  do
5    $\mathbf{U} \leftarrow \{x_1, \dots, x_{i-1}\}$  // Set of candidate parents of  $x_i$ 
6   for  $U' \subseteq \{x_1, \dots, x_{i-1}\}$  do
7     if  $U' \subset \mathbf{U}$  and  $(x_i \perp\!\!\!\perp \{x_1, \dots, x_{i-1}\} - U' | U') \in \mathcal{I}$  then
8        $\mathbf{U} \leftarrow U'$ 
9     end
10  end
11  // Now we have the minimal set  $\mathbf{U}$  satisfying
     $(x_i \perp\!\!\!\perp \{x_1, \dots, x_{i-1}\} - \mathbf{U} | \mathbf{U})$ 
12  // Now we set  $\mathbf{U}$  to be the parents of  $x_i$ 
13  for  $x_j \in \mathbf{U}$  do
14    Add  $x_j \rightarrow x_i$  in  $\mathcal{G}$ 
15  end
16 end
17 return  $\mathcal{G}$ 

```

**Algorithm 1:** Minimal Bayesian Network Construction (I-Map)

We know sketch rough proofs for the claims of the algorithm.

**Theorem 20.** *The BN  $\mathcal{G}$  constructed by algorithm 1 is minimal, i.e we cannot remove any edge from the BN while maintaining the correctness of the BN for  $P$ .*

*Proof.* By construction. A subset of  $\text{ND}(x_i)$  were available when we chose parents of  $\mathbf{U}$  minimally.  $\square$

**Theorem 21.**  *$\mathcal{G}$  constructed by the above algorithm is correct, i.e, the local-CIs induced by  $\mathcal{G}$  hold in  $P$ .*

*Proof.* The construction is such that  $\text{Factorize}(P, \mathcal{G})$  holds everytime. Since  $\text{Factorize}(P, \mathcal{G}) \implies \text{Local-CI}(P, \mathcal{G})$ , the constructed BN satisfies the local-CIs of  $P$ .  $\square$

**Question 22** (Construction of BN). *Draw a Bayesian network over five variables  $x_1, \dots, x_5$  assuming the variable order  $x_1, x_2, x_3, x_4, x_5$ . For this*

ordering, assume that the following set of local CIs hold in the distribution:

$$x_1 \perp\!\!\!\perp x_2 \quad x_3 \perp\!\!\!\perp x_2 | x_1 \quad x_4 \perp\!\!\!\perp x_1, x_3 | x_2 \quad x_5 \perp\!\!\!\perp x_1, x_2 | x_3, x_4$$

*Answer 23.* Due to the ordering, we begin by inserting  $x_1$  into the BN. Then we follow Algorithm 1 as follows:

1.  $x_2$ : Predecessor -  $x_1$

- *Query 1* - Is  $x_2 \perp\!\!\!\perp x_1 | \emptyset$  ? : *Result 1* - True

Thus,  $x_2$  has no parents.

2.  $x_3$ : Predecessors -  $x_1, x_2$

- *Query 1* - Is  $x_3 \perp\!\!\!\perp \{x_1, x_2\} | \emptyset$  ? : *Result 1* - False
- *Query 2* - Is  $x_3 \perp\!\!\!\perp x_2 | x_1$  ? : *Result 2* - True

Thus,  $x_3$  has  $x_1$  as a parent, and  $x_2$  as a non-descendent.

3.  $x_4$ : Predecessors -  $x_1, x_2, x_3$

- *Query 1* - Is  $x_4 \perp\!\!\!\perp \{x_1, x_2, x_3\} | \emptyset$  ? : *Result 1* - False
- *Query 2* - Is  $x_4 \perp\!\!\!\perp \{x_2, x_3\} | x_1$  ? : *Result 2* - False
- *Query 3* - Is  $x_4 \perp\!\!\!\perp \{x_1, x_3\} | x_2$  ? : *Result 3* - True

Thus,  $x_4$  has  $x_2$  as a parent, and  $x_1, x_3$  as non-descendents.

4.  $x_5$ : Predecessors -  $x_1, x_2, x_3, x_4$

Check that it has  $x_3, x_4$  as parents and  $x_1, x_2$  as non-descendents.

Thus, finally we get the BN as in Figure 2

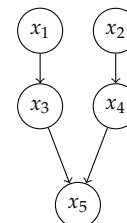


Figure 2: BN Example

*Remark 24* (Importance of ordering). It is possible that a different ordering in  $\mathcal{X}$  gives rise to a different BN, which although may be minimal, but may not be *optimal*. A minimal BN is defined for a given ordering, while an optimal BN is defined over all orderings. Example 25 shows such a case.

**Example 25.** Consider the BN shown in Figure 3, with the ordering  $x_1, x_2, x_3$ . We have  $x_1 \perp\!\!\!\perp x_2$  as the only CI holding. Now consider our order changes to  $x_3, x_2, x_1$ . We follow the procedure as before, first inserting  $x_3$  into the BN. Now

1.  $x_2$ : Predecessor -  $x_3$

- *Query 1* - Is  $x_2 \perp\!\!\!\perp x_3 | \emptyset$  ? : *Result 1* - False

Thus, we have  $x_3$  as a parent of  $x_2$ .

2.  $x_1$ : Predecessor -  $x_3, x_2$

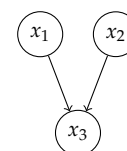


Figure 3: BN Ordering (optimal)

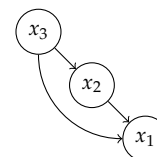


Figure 4: BN Ordering (non-optimal)

- Query 1 - Is  $x_1 \perp\!\!\!\perp \{x_2, x_3\} \mid \emptyset$  ? : Result 1 - False
- Query 2 - Is  $x_1 \perp\!\!\!\perp x_2 \mid x_3$  ? : Result 2 - False
- Query 3 - Is  $x_1 \perp\!\!\!\perp x_3 \mid x_2$  ? : Result 3 - False

Thus, we have both  $x_2$  and  $x_3$  as parents of  $x_1$ .

Thus we get the BN as in Figure 4, and see that the BN is minimal, but not optimal.

### D-Separation

Our goal is to know when we can guarantee  $\mathbf{X} \perp\!\!\!\perp \mathbf{Y} \mid \mathbf{Z}$  holds given a BN  $\mathcal{G}$ . The further discussion provides some cases where we can guarantee  $\mathbf{X} \not\perp\!\!\!\perp \mathbf{Y} \mid \mathbf{Z}$ .

1. **Direct Connection:** If there is an edge  $X \rightarrow Y$ , then regardless of any  $Z$ , we can find examples where they influence each other.
2. **Indirect Connection:** This means that there is a trail between the nodes in the graph. We consider the simple case when we have a 3-node graph and  $Z$  is between  $X$  and  $Y$ . Consider the 4 diagrams to the left for reference.
  - (a) *Indirect causal effect:*  $X$  cannot influence  $Y$  via  $Z$  if  $Z$  is observed.
  - (b) *Indirect evidential effect:* This is similar to the previous case as dependence is a symmetric notion. Thus,  $X$  can influence  $Y$  via  $Z$ , only if  $Z$  is not observed.
  - (c) *Common cause:* The conclusion is similar to (a) and (b).
  - (d) *Common effect:* (v-structure) This case is a bit tricky to understand, but the crux is that  $X$  can influence  $Y$  when either  $Z$  or one of  $Z$ 's descendants is observed.

If we have flow of influence from  $X$  to  $Y$  via  $Z$ , we say that the trail  $X \rightleftharpoons Y \rightleftharpoons Z$  is active.

$$\begin{aligned}
 & \left. \begin{array}{l} \text{Causal trail: } X \rightarrow Z \rightarrow Y \\ \text{Evidential trail: } Y \rightarrow Z \rightarrow X \\ \text{Common cause: } X \leftarrow Z \rightarrow Y \end{array} \right\} \text{Active if and only if } Z \text{ is observed} \\
 & \star \text{ Common effect: } X \rightarrow Z \leftarrow Y \} \\
 & \hookrightarrow \text{Active if and only if } Z \text{ or one of } Z\text{'s descendant is observed}
 \end{aligned} \tag{19}$$

Now, we can create a general notion of trails -

**Definition 26.** Let  $\mathcal{G}$  be a BN, and  $x_1 \rightleftharpoons \dots \rightleftharpoons x_n$  be a trail in  $\mathcal{G}$ . Let  $\mathbf{Z} \subset \{\text{observed variables}\}$ . The trail is active given  $\mathbf{Z}$  if

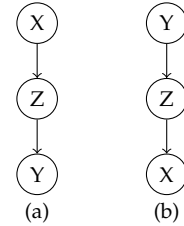


Figure 5: Causal and evidential effect

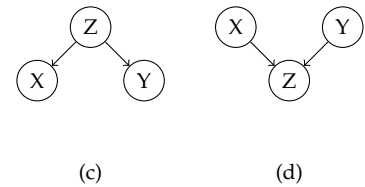


Figure 6: Common cause and common effect

- ◇ Whenever we have a v-structure  $x_{i-1} \rightarrow x_i \leftarrow x_{i+1}$ , then  $x_i$  or one of its descendants are in  $\mathbf{Z}$
- ◇ No other node along the trail is in  $\mathbf{Z}$ .

We can see that if  $x_1 \in \mathbf{Z}$  or  $x_n \in \mathbf{Z}$ , then the trail is inactive.

**Definition 27** (d-separation). Let  $\mathbf{X}, \mathbf{Y}, \mathbf{Z}$  be three sets of nodes in  $\mathcal{G}$ . We say that  $\mathbf{X}$  and  $\mathbf{Y}$  are d-separated given  $\mathbf{Z}$ , i.e  $\text{d-sep}_{\mathcal{G}}(\mathbf{X}; \mathbf{Y} | \mathbf{Z})$  if there is no active trail between any node  $x \in \mathbf{X}$  and  $y \in \mathbf{Y}$  given  $\mathbf{Z}$ .

**Definition 28** (Global Markov independencies). The set

$$\mathcal{I}(\mathcal{G}) \stackrel{\text{def}}{=} \{(\mathbf{X} \perp\!\!\!\perp \mathbf{Y} | \mathbf{Z}) : \text{d-sep}_{\mathcal{G}}(\mathbf{X}; \mathbf{Y} | \mathbf{Z})\} \quad (20)$$

denoting the set of independencies corresponding to d-separation is the set of global Markov independencies.

**Theorem 29.** *The d-separation test identifies the complete set of conditional independencies that hold in all distributions that conform to a given Bayesian Network.*

*Proof.* Skipped. □

Now, we look at another way to check d-separation over BNs, but first we define some terms.

**Definition 30** (Ancestral Graph). Given a graph  $G = (V, E)$  and a set of nodes to focus on, say  $V^* \subseteq V$ , the ancestral graph  $G^A$  is a subgraph induced by  $V^A = V^* \cup \mathcal{A}(V^*)$  where  $\mathcal{A}(V^*)$  denotes the ancestors of  $V^*$ . Thus,

$$G^A = G \langle V^A \rangle = (V^A, \{(u, v) | (u, v) \in E \text{ and } u, v \in V^A\}) \quad (21)$$

**Definition 31** (Markov Blanket). Given a random variable  $Y$  in a random variable set  $\mathcal{X} = X_1, X_2, \dots, X_n$ , its Markov Blanket is any subset  $\mathcal{S}$  of  $\mathcal{X}$ , conditioned on which other variables are independent with  $Y$ , i.e

$$Y \perp\!\!\!\perp \mathcal{X} \setminus \mathcal{S} | \mathcal{S} \quad (22)$$

Thus, we can infer  $Y$  from  $\mathcal{S}$  itself, and the rest of the elements are redundant in observation.

**Definition 33** (Moral graph). A moral graph of a directed acyclic graph  $G$  is an undirected graph in which each node of the original  $G$  is now connected to its *Markov Blanket*.

Essentially in a DAG,  $\mathbf{Z}$  d-separates  $\mathbf{X}$  from  $\mathbf{Y}$  if all paths  $\mathcal{P}$  from any  $\mathbf{X}$  to  $\mathbf{Y}$  is blocked by  $\mathbf{Z}$ .

A path  $\mathfrak{P}$  is *blocked* if it is inactive, i.e there is no flow of influence.

We use the same notation as  $\mathcal{I}(P)$  as we can show that the independencies in  $\mathcal{I}(\mathcal{G})$  are those guaranteed to hold for every distribution over  $\mathcal{G}$  (Theorem 29).

*Remark 32.* Essentially we are finding an equivalent undirected graph for a DAG. We find all pairs of non-adjacent nodes having a common child, and add an undirected edge between them. Then we transform all directed edges in the resulting graph to undirected edges.

```

1 Given: Bayesian Network  $\mathcal{G}$ , Condition to check  $\mathcal{C}$ :  $X \perp\!\!\!\perp Y | Z$ 
2  $\mathcal{C} \leftarrow \text{False}$ 
3  $G = (V, E) \leftarrow$  Underlying DAG in  $\mathcal{G}$ .
4  $G^A = (V^A, E^A) \leftarrow$  Ancestral graph of  $G$ 
5  $G_M^A = (V_M^A, E_M^A) \leftarrow$  Moral graph of  $G^A$  using Note 32
6 // Delete the nodes in  $Z$  and all its connections
7 for  $z \in Z$  do
8    $\Xi \leftarrow \{\}$ 
9   for  $u \in V$  such that  $\xi = (u, z) \in E_M^A$  do
10     $\Xi \leftarrow \Xi \cup \xi$ 
11  end
12   $E_M^A \leftarrow E_M^A \setminus \Xi$ 
13   $V_M^A \leftarrow V_M^A \setminus \{z\}$ 
14 end
15 if  $X$  and  $Y$  are disconnected in the resulting graph then
16    $\mathcal{C} \leftarrow \text{True}$ 
17 end

```

**Algorithm 2:** Checking for independence in a BN

**Definition 34** (Perfect map). A graph  $\mathcal{G}$  is a perfect map (P-map) for a set of independencies  $\mathcal{I}$  if  $\mathcal{I}(\mathcal{G}) = \mathcal{I}$ . Also,  $\mathcal{G}$  is P-map for a distribution  $P$  if  $\mathcal{I}(\mathcal{G}) = \mathcal{I}(P)$ .

### Limitations

Consider the following set of CIs

$$x \perp\!\!\!\perp y \quad y \perp\!\!\!\perp z \quad z \perp\!\!\!\perp x \quad x \not\perp\!\!\!\perp \{y, z\} \quad (23)$$

If you try to draw the BN for any ordering of the variables  $\{x, y, z\}$ , you can check that you get extraneous edges, and we fail to capture at least one of the conditions above. Thus, a symmetric dependency of this sort is not possible to be represented by Bayesian Networks. This, gives rise to a different field of graphical modeling using *Markov Networks*, which can represent some of these situations.

## Markov Random Fields

### Intuition

We saw previously that we cannot draw a *perfect* I-map such that  $\mathcal{I}(\mathcal{G}) = \mathcal{I}(P)$  for any distribution  $P$  using directed graphical models. Such too is the case with undirected graphical models, but they help us to represent some of these independencies which directed graphs couldn't.

To be added.

### Cliques

**Definition 35** (Complete Graph). A complete graph is a simple undirected graph in which every pair of distinct vertices is connected by a unique edge.

**Definition 36** (Clique). A clique  $C$  in an undirected graph  $G = (V, E)$  is a subset of vertices,  $C \subseteq V$  such that every two distinct vertices are adjacent. Thus, the subgraph induced by  $C$ , i.e  $G \langle C \rangle$ , is a complete graph.

**Definition 37** (Maximal Clique). A clique that cannot be extended by including one more adjacent vertex (i.e it does not exist exclusively within the vertex set of a larger clique) is a maximal clique.

**Definition 38** (Maximum Clique). A maximum clique of a graph  $G$ , is a clique such that there is no other clique with more vertices.

With each clique  $C$ , we associate a potential function  $\psi$ , which is a provisional function of its arguments that assigns a pre-probabilistic score of their joint distribution. It is to note that  $\psi$  must be non-negative, but it shouldn't be interpreted as probability.

### Gibbs Fields

A Gibbs Field is a representation of a set of random variables and their relationships. An example is in Figure 7. In this, the edges are undirected and imply some correlation between the connected nodes.

Consider clique potentials as  $\psi_i(c_i)$ . Then the joint probability for any set of random variables  $\mathcal{X} = \{x_1, \dots, x_n\}$  represented by a Gibbs Field can be written as a product of clique potentials

$$P(\mathcal{X}) = \frac{1}{Z} \prod_{c_i \in C} \psi_i(c_i) \quad (24)$$

$Z$  is a normalizing constant required to create a valid probability distribution, i.e

$$Z = \sum_{\mathcal{X}} \prod_{c_i \in C} \psi_i(c_i) \quad (25)$$

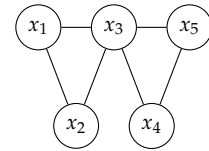


Figure 7: A Gibbs Field

*Remark 39.* For any Gibbs Field, there is a subset  $\hat{C}$  of  $C$  consisting of only maximal cliques, which are not proper subsets of any other cliques. We write the potentials for these maximal cliques as products of all potentials of their sub-cliques, and thus state the joint probability as

$$P(\mathcal{X}) = \frac{1}{Z} \prod_{c_i \in \hat{C}} \hat{\psi}_i(c_i) \quad (26)$$

### Formal Definition

**Definition 40** (Markov Random Field). A Markov Random Field (MRF) is a probability distribution  $P$  over variables  $x_1, \dots, x_n$  defined by an undirected graph  $G$  in which nodes correspond to variables  $x_i$  and has the form

$$P(x_1, x_2, \dots, x_n) = \frac{1}{Z} \prod_{c \in C} \psi_c(x_c) \quad (27)$$

where

$$Z = \sum_{x_1, \dots, x_n} \prod_{c \in C} \psi_c(x_c) \quad (28)$$

is the *partition function* which is the normalizing constant ensuring the distribution sums to 1.

As we saw earlier, if we have symmetric interactions, then UGMs become useful (such as labeling pixels in an image - see Figure 8). Define  $y_i = 1$  if the pixel is a part of the foreground, and 0 else. Taking cliques of size 1, we have the potential functions  $\psi_1(0)$  to  $\psi_9(0)$  and  $\psi_1(1)$  to  $\psi_9(1)$ . Now considering cliques of size 2, we have  $\psi(0,0)$ ,  $\psi(0,1)$ ,  $\psi(1,0)$  and  $\psi(1,1)$ . Thus we write

$$\Pr(y_1, \dots, y_9) \propto \prod_{k=1}^9 \psi_k(y_k) \prod_{(i,j) \in E(G)} \psi(y_i, y_j) \quad (29)$$

### Conditional Independencies

From now on, we will work on the UGM in Figure 8. Let

$$V = \{y_1, \dots, y_9\}$$

. We define three types of CIs in UGMs as follows

1. **Local CI:**  $y_i \perp\!\!\!\perp V - \mathcal{N}(y_i) - \{y_i\} | \mathcal{N}(y_i)$

$$y_1 \perp\!\!\!\perp y_3, y_5, y_6, y_7, y_8, y_9 | y_2, y_4$$

2. **Pairwise CI:**  $y_i \perp\!\!\!\perp y_j | V - \{y_i, y_j\}$  if  $(y_i, y_j) \notin E(G)$

$$y_1 \perp\!\!\!\perp y_3 | y_2, y_4, y_5, y_6, y_7, y_8, y_9$$

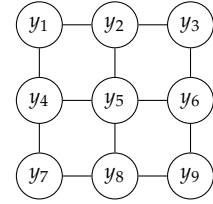


Figure 8: Relations in image pixels

In a graph  $G$  with vertices  $V = \{x_1, \dots, x_n\}$ ,  $\mathcal{N}(x_i)$  denotes the neighbors of  $x_i$  in the graph

### 3. Global CI: $X \perp\!\!\!\perp Y | Z$ if $Z$ separates $X$ and $Y$ in the graph

$$y_1, y_2, y_3 \perp\!\!\!\perp y_7, y_8, y_9 | y_4, y_5, y_6$$

Checking for CI in MRFs is much more easier than BNs. The way to check is through graph separability. Consider the example given in **Global CI**. If we remove  $y_4, y_5$  and  $y_6$  from the graph along with their edges, we see that the components  $y_1, y_2, y_3$  is disconnected from  $y_7, y_8, y_9$ , and hence the CI holds.

**Theorem 41.** Let  $G$  be an undirected graph of  $V = \{x_1, \dots, x_n\}$  nodes, and let  $P(x_1, \dots, x_n)$  be a distribution. If  $P$  is represented by  $G$ , that is, if it can be factorized as per the cliques of  $G$ , then  $P$  will also satisfy the global-CIs of  $G$ . Thus

$$\text{Factorize}(P, G) \implies \text{Global-CI}(P, G) \quad (30)$$

Note that for any arbitrary distribution, the converse doesn't hold, i.e in general for a distribution  $P$

$$\text{Factorize}(P, G) \not\Rightarrow \text{Global-CI}(P, G) \quad (31)$$

We see this through a counter example. Consider the UGM in Figure 9, for the probability distribution  $P(x_1, x_2, x_3, x_4)$  such that  $P(x_1, x_2, x_3, x_4) = \frac{1}{8}$  when  $x_1, x_2, x_3, x_4$  can take values from  $\{0000, 1000, 1100, 1110, 1111, 0111, 0011, 0001\}$  else 0. It can be manually checked that all 4 Global-CIs hold in the graph, for example  $x_1 \perp\!\!\!\perp x_3 | x_2, x_4$ . Now consider the factors in the edges as  $\psi(x_i, x_j)$ . These will be positive, but that cannot represent the probability for  $x_1, x_2, x_3, x_4 = 0101$ .

Also, it is trivial to see that

$$\text{Global-CI} \implies \text{Local-CI} \quad (32)$$

But again through a counter example, we will show that the converse doesn't hold, i.e

$$\text{Local-CI} \not\Rightarrow \text{Global-CI} \quad (33)$$

Consider a distribution over 5 binary variables  $P(x_1, \dots, x_5)$  where  $x_1 = x_2, x_4 = x_5$  and  $x_3 = x_2 \wedge x_4$ . Consider  $G$  as in Figure 10. Notice that all 5 Local-CIs hold in the graph, for example  $x_1 \perp\!\!\!\perp \{x_3, x_4, x_5\} | x_2$ . But notice that the graph also tells us that  $x_2 \perp\!\!\!\perp x_4 | x_3$ , but this is not present in the distribution  $P$ .

We also notice that

$$\text{Local-CI} \implies \text{Pairwise-CI} \quad (34)$$

But again through a counter example, we show that the converse doesn't hold, i.e

$$\text{Pairwise-CI} \not\Rightarrow \text{Local-CI} \quad (35)$$

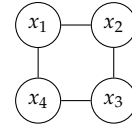


Figure 9: Sample UGM

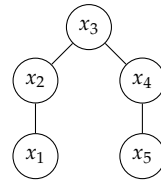


Figure 10: Sample UGM



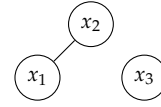


Figure 11: Sample UGM

Consider  $P(x_1, x_2, x_3)$  defined over 3 binary variables such that  $P(x_1, x_2, x_3) = \frac{1}{2}$  if  $x_1 = x_2 = x_3$  and 0 else. Let  $G$  be as in Figure 11. See that both the Pairwise-CIs, i.e  $x_1 \perp\!\!\!\perp x_3 | x_2$  and  $x_2 \perp\!\!\!\perp x_3 | x_1$  hold in the graph, but the local CI  $x_1 \perp\!\!\!\perp x_3$  doesn't hold.

We have made a lot of statements about converses not holding in arbitrary distributions, but the natural question to arise is, can we find distributions where all the relations hold? The answer is yes, and is shown by the following theorem, also called the *fundamental theorem of random fields* -

**Theorem 42** (Hammersley Clifford Theorem). *If a positive distribution  $P(x_1, \dots, x_n)$  confirms to the Pairwise-CIs of a UDGM  $G$ , then it can be factorized as per the cliques  $C$  of  $G$  as*

$$P(x_1, \dots, x_n) \propto \prod_{C \in G} \psi_C(\mathbf{y}_C) \quad (36)$$

A distribution  $P(\mathbf{x})$  is positive, if  $P(\mathbf{x}) > 0 \forall \mathbf{x}$ .

*Proof.* Skipped. □

Thus, in summary, for any arbitrary distribution  $P$  and UGM  $H$ ,

$$\begin{aligned} \text{Factorize}(P, H) &\implies \text{Global-CI}(P, H) \implies \\ \text{Local-CI}(P, H) &\implies \text{Pairwise-CI}(P, H) \end{aligned} \quad (37)$$

and if  $P$  is positive, then

$$\text{Pairwise-CI}(P, H) \implies \text{Factorize}(P, H) \quad (38)$$

Hence, for a positive distribution, all three types of CIs are *equivalent*.

### Minimal Construction

The question to answer is, given a positive distribution  $P(x_1, \dots, x_n)$  as an oracle  $\mathcal{O}$  to which we can ask the query - is  $X \perp\!\!\!\perp Y | Z$  and get a boolean answer, we need to draw a minimal and correct UGM  $G$  to represent  $P$ .

Denote  $V = \{x_1, x_2, \dots, x_n\}$  as the set of all variables. We see that there are two methods to draw the UGM -

1. *Using Pairwise-CIs:* For each pair of vertices  $(x_i, x_j)$ , if  $x_i \perp\!\!\!\perp x_j | V - \{x_i, x_j\}$  in  $P$ , add an edge between  $x_i$  and  $x_j$  in  $G$ .
2. *Using Local-CIs:* For each vector  $x_i$ , find the smallest subset  $U$  such that  $x_i \perp\!\!\!\perp V - U - \{x_i\} | U$  in  $P$ . Then, add  $U$  to  $\mathcal{N}(x_i)$  in  $P$ .

**Example 43.** To be added.

We had seen Markov Blankets before, but we re-define them in terms of a UGM.

**Definition 44** (Markov Blanket). The Markov Blanket (MB) of a variable  $x_i$  is the smallest subset of variables  $V$  that makes  $x_i$  conditionally independent of others given the MB, i.e

$$x_i \perp\!\!\!\perp V - MB(x_i) - \{x_i\} | MB(x_i) \quad (39)$$

**Theorem 45.** The MB of a variable is always unique for a positive distribution.

*Proof.* We will prove the following by contradiction. Let  $x_i \in V$  and  $M_1, M_2$  be two MBs. Let  $\alpha = M_1 - M_2$  and  $\beta = M_2 - M_1$ ,  $M = M_1 \cap M_2$ ,  $W = V - (M_1 \cup M_2)$ . Note that, by definition,  $x_i \perp\!\!\!\perp V - M_2 | M_2$  and  $x_i \perp\!\!\!\perp V - M_1 | M_1$ . Using this, we can write

$$x_i \perp\!\!\!\perp W, \alpha | M, \beta \quad x_i \perp\!\!\!\perp W, \beta | M, \alpha$$

For positive distributions, using intersection property, we can write

$$x_i \perp\!\!\!\perp W, \alpha, \beta | M$$

This implies that  $M$  is also a MB, but that is a contradiction since  $M_1$  and  $M_2$  were supposed to be minimal. Hence, the MB is unique.  $\square$

**Definition 46** (Immortality). In a directed acyclic graph, the structure of the form  $x \rightarrow y \leftarrow z$  is an immortality provided there is no edge between  $x$  and  $z$ .

With this, we can restate the equivalence of BNs -

Two BNs  $\mathcal{G}_1$  and  $\mathcal{G}_2$  are equivalent *iff* they have the same skeleton structure and the same set of immoralities.

Conversion to and from Bayesian Networks

**Theorem 47.** In a Bayesian Network  $\mathcal{G}$ , the Markov Blanket of a variable  $x_i$  is given as

$$MB(x_i) = Pa(x_i) \cup Ch(x_i) \cup Sp(x_i) \quad (40)$$

where  $Pa(x_i)$ ,  $Ch(x_i)$  and  $Sp(x_i)$  denote the parents, children and spouses (unmarried shared parent) of the children of  $x_i$  (if exists).

*Proof.* Only a flavor of the proof is provided. We have seen moralization of the Bayesian Network  $\mathcal{G}$ , and when we get  $\mathcal{G}^M$  (i.e the moralized graph), notice that removing the parents, children and spouses disconnects the node from the graph.  $\square$

For example, in Figure 12, the MB of  $x_2$  is given as

$$MB(x_2) = \{x_4\} \cup \{x_1\} \cup \{x_3\}$$

Interestingly, UGMs were initially used to model interactions of atoms in gases and solids in 1800. A few other places where they are used are in

1. Markov Random Fields - Image Segmentation
2. Conditional Random Fields - Information Extraction
3. Social Networks
4. Bio-informatics - Annotating active sites in proteins

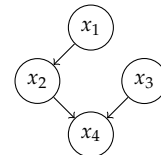


Figure 12: Sample BN

**Theorem 48.** *A Bayesian Network will have a perfect MRF if it has no immoralities.*

*Proof.* Skipped. □

We can ask the reverse question too. What condition should be posed on the MRF to have a perfect BN?

**Definition 49** (Chordal Graph). A chordal graph is a simple graph in which every graph cycle of length four or greater has a cycle chord.

With this, we can state that

**Theorem 50.** *An MRF can be perfectly converted to a BN if and only if it is chordal.*

*Proof.* Skipped. □

## Inference Queries

We have seen two major types of compact representations of joint probability distributions in terms of graphs. Summarizing the expressions of the joint distribution, we can write

$$\text{For UGM: } \Pr(x_1, \dots, x_n) = \frac{1}{Z} \prod_C \psi_C(x_C) \quad (41)$$

$$\text{For DGM: } \Pr(x_1, \dots, x_n) = \prod_i \Pr(x_i | \text{Pa}(x_i)) \quad (42)$$

We get a very compact representation if  $\text{Pa}(x_i)$  is small.

Given a probability distribution  $P$ , we can ask two major types of queries -

1. *Marginal probability queries over a sm'all subset of variables:* Given  $P$ , what is the marginal probability of  $x_1$ ?

$$\begin{aligned} \Pr(x_1) &= \sum_{x_2, \dots, x_n} \Pr(x_1, \dots, x_n) \\ &= \sum_{x_2=1}^m \dots \sum_{x_n=1}^m \Pr(x_1, \dots, x_n) \end{aligned} \quad (43)$$

We can see that if each variable takes  $m$  values, then the brute-force computation of the marginal probability will take  $\mathcal{O}(m^{n-1})$  time.

2. *Most likely labels of remaining variables (MAP queries):* Here, we ask questions of the form,

$$\mathbf{x}^* = \arg \max_{x_1, \dots, x_n} \Pr(x_1, \dots, x_n) \quad (44)$$

An example of such a query could be - find the most likely entity labels of all words in a sentence.

**Example 51** (Exact Inference). Say we have a probability distribution over three binary variables as

$$P(x_1, x_2, x_3) = \frac{1}{Z} \psi_{12}(x_1, x_2) \psi_{23}(x_2, x_3)$$

The UGM for this is shown in Figure 13. Say we have the potential tables (each entry being  $\psi_{ij}(a, b)$  representing the potential) as

		$x_2$				$x_3$	
		0	1			0	1
$x_1$	0	5	2	$x_2$	0	2	10
	1	1	4		1	5	3

For example, we see that  $\psi_{12}(0, 0) = 5$ . Let us find  $P(x_1)$ .

$$P(x_1) = \frac{1}{Z} \sum_{x_2 \in \{0,1\}} \sum_{x_3 \in \{0,1\}} \psi_{12}(x_1, x_2) \psi_{23}(x_2, x_3)$$

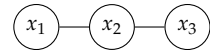


Figure 13: UGM for  $P(x_1, x_2, x_3)$

We multiply the above two tables to get an intermediate potential distribution  $\psi_{123}(x_1, x_2, x_3)$  and get a three dimensional table as follows (note that the columns denote  $x_2$  and the rows denote  $x_1$ )

		$x_3 = 0$				$x_3 = 1$	
		0	1			0	1
$x_1$	0	10	10	$x_1$	0	50	6
	1	2	20		1	10	12

For example,  $\psi_{12}(0,0)\psi_{23}(0,0) = 2 \times 5 = 10$ . The next computation is to sum over  $x_3$ .

$$P(x_1) = \frac{1}{Z} \sum_{x_2 \in \{0,1\}} \psi_{12}^*(x_1, x_2)$$

The table after sum denoting  $\psi_{12}^*(x_1, x_2)$  is

		$x_2$	
		0	1
$x_1$	0	60	16
	1	12	32

Now we eliminate  $x_2$  by summing over the row values, thus finally

$$\psi_1^*(x_1) = \frac{1}{Z} \begin{bmatrix} 76 \\ 44 \end{bmatrix}$$

Since this  $P(x_1) = \psi_1^*(x_1)$ , we immediately get to know that  $Z = 76 + 44 = 120$ .

Clearly, we see through the example that the calculation, even for three variables is cumbersome. Imagine doing this for thousands!

From the table in the above example, we can also calculate the assignment which gives the maximum probability. Note the  $\psi_{123}$  table made, and see that  $x_1 = 0, x_2 = 0, x_3 = 1$  has the score of 50 giving the highest probability. But let us write this in a more algorithmic way

$$\mathbf{x}^* = \arg \max_{x_2} \arg \max_{x_2} \arg \max_{x_3} \psi_{12}(x_1, x_2) \psi_{23}(x_2, x_3)$$

Let us construct the table  $\psi_{12}^{\max}(x_1, x_2)$  from the  $\psi_{123}$  table

		$x_2$	
		0	1
$x_1$	0	50 for $x_3 = 1$	10 for $x_3 = 0$
	1	10 for $x_3 = 0$	20 for $x_3 = 0$

Similarly,  $\psi_1^{\max}(x_1)$  will be

$$\begin{bmatrix} 50 \text{ for } x_2 = 0, x_3 = 1 \\ 20 \text{ for } x_2 = 1, x_3 = 0 \end{bmatrix}$$

At last, we can do an argmax over  $x_1$  to get the assignment  $x_1 = 0, x_2 = 0, x_3 = 1$  for the score of 50.

Clearly, after the example, it is clear that we want to avoid the exponential overhead that brute-force approach applies.

### Exact Inference on Chains

Consider the chain show in Figure 14.

We see that in the graph we would have potentials of the form  $\psi_i(y_i, y_{i+1})$ , and

$$\Pr(y_1, \dots, y_n) = \prod_i \psi_i(y_i, y_{i+1}) \quad (45)$$

*Note:* Since we don't have immoralities, the MRF is equivalent to the undirected version of the graph. Say we want to calculate

$$\Pr(y_5 = 1) = \sum_{y_1, \dots, y_4} \Pr(y_1, y_2, y_3, y_4, 1) \quad (46)$$

The key idea to reducing computations is to push summations past the multiplications, i.e

$$\begin{aligned} \Pr(y_5 = 1) &= \sum_{y_1, \dots, y_4} \Pr(y_1, y_2, y_3, y_4, 1) \\ &= \sum_{y_1} \sum_{y_2} \sum_{y_3} \sum_{y_4} \psi_1(y_1, y_2) \psi_2(y_2, y_3) \psi_3(y_3, y_4) \psi_4(y_4, 1) \\ &= \sum_{y_1} \sum_{y_2} \psi_1(y_1, y_2) \sum_{y_3} \psi_2(y_2, y_3) \sum_{y_4} \psi_3(y_3, y_4) \psi_4(y_4, 1) \\ &= \sum_{y_1} \sum_{y_2} \psi_1(y_1, y_2) \sum_{y_3} \psi_2(y_2, y_3) \mathcal{B}_3(y_3) \\ &= \sum_{y_1} \sum_{y_2} \psi_1(y_1, y_2) \mathcal{B}_2(y_2) \\ &= \sum_{y_1} \mathcal{B}_1(y_1) \end{aligned} \quad (47)$$

We denote  $\mathcal{B}_i(y_i)$  as the *belief* which flows from node  $i + 1$  to  $i$ . This is an efficient computation. In general, if we have a chain with  $n$  variables and each can take  $m$  values, the above algorithm (breaking into beliefs) takes time in order of  $\mathcal{O}(nm^2)$ .

Notice that we did the efficient computation for chains, the natural question is, for what other graphs can this be done?

Another one is shown in Figure 15. We define potential over each triangle (say  $\psi_{123}$ ). If we follow a similar idea as the algorithm above, the time required for this computation will be  $\mathcal{O}(nm^3)$ .

### Hardness of Inference and 3-SAT

The above discussion might lead to the thought that any graph  $G$  which can be factorized into small clique sizes might have an efficient

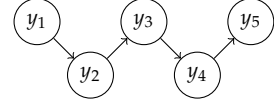


Figure 14: Chain graph

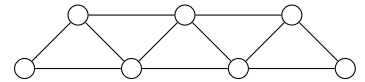


Figure 15: Triangular graph

computation method (i.e polynomial time) of calculating the marginal probability.

The answer sadly is no, and a counter example is the grid graph shown in Figure 16.

We will now reduce the 3-SAT to inference in Bayesian Networks.

**Definition 52** (3-SAT Problem). Given  $n$  boolean variables  $x_1, \dots, x_n$  such that  $x_i \in \{T, F\}$ . We define a literal  $\ell$  to be the variable  $x_i$  or its negation  $\neg x_i$  or  $\bar{x}_i$ . Given a set of  $K$  clauses  $C_1, C_2, \dots, C_K$  with each clause being

$$C_j = \ell_{j_1} \vee \ell_{j_2} \vee \ell_{j_3} \quad (48)$$

The 3-SAT problem is to decide if there exists an assignment of values to the  $n$  variables such that

$$C_1 \wedge C_2 \wedge \dots \wedge C_K = T \quad (49)$$

**Example 53.** Consider  $n = 4, K = 3$  and

$$C_1 = x_1 \vee \bar{x}_2 \vee \bar{x}_3$$

$$C_2 = x_2 \vee x_3 \vee \bar{x}_4$$

$$C_3 = x_4 \vee \bar{x}_1 \vee \bar{x}_2$$

In this case, having all  $x_i = T$  for  $i = \{1, 2, 3, 4\}$  solves the problem.

In the above example, we by chance got lucky and solved the problem, but in general for a large number of variables, it is not possible to go over all possible combinations of values, since it requires an exponential amount of time.

Now we represent 3-SAT as a Bayesian Network.

Let us do that in a *layer* sense. Let the first layer have all the variables as nodes and the next layer have all the clauses. Each clause will have 3 parents due to Equation 48. Finally, the third layer would have  $S$ , which is the satisfiability (Equation 49), and its parents would be all the clauses. Figure 17 shows the BN of Example 53.

Coming back to the general setting, for each variable  $x_i$ , we denote

$$\Pr(x_i) = \begin{cases} \frac{1}{2} & x_i = F \\ \frac{1}{2} & x_i = T \end{cases} \quad (50)$$

We also need to define  $\Pr(C_j | \ell_{j_1}, \ell_{j_2}, \ell_{j_3})$ . To do this, we assign a non-zero probability to only those which make  $C_j = T$ . This can be done uniformly (say out of the 8 assignments, 5 give a non-zero value, then 1 for each of those assignments, and 0 to rest - this is done because each  $C_j$  is a deterministic function of the literals). Finally, we write the last probability  $\Pr(S | C_1, \dots, C_K)$  as 1 if  $C_1, \dots, C_K = T$ , i.e all are true, and in the rest of the cases, we assign it as zero (note the

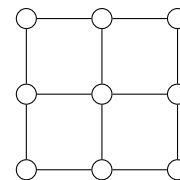


Figure 16: Grid graph

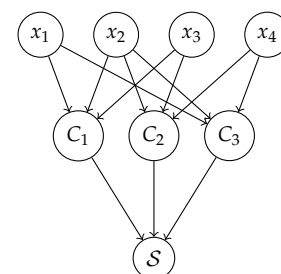


Figure 17: 3-SAT as BN

difference here - the table for each  $C_i$  had 8 rows, and the table for  $S$  has  $2^K$  rows). The  $2^K$  shows that it is not polynomial. This is again, not efficient.

One small change we can do is that instead of having a single  $S$  in the last layer, have  $K - 1$ , such that each  $S_i$  is connected to  $C_{i-1}$  and  $C_i$  as parents, and each  $S_i$  is a parent of  $S_{i+1}$ . This allows us to create the probability table as  $\Pr(S_j | S_{j-1}, C_{j-1}, C_j)$  which represents the logic

$$S_j = S_{j-1} \wedge C_{j-1} \wedge C_j \quad (51)$$

This allows each  $S_j$  with 8 variables, bringing in the needed efficiency. More specifically, the space required now is polynomial, since each  $S_j$  requires only  $2^4$  space, each  $C_j$  requires  $2^5$  space and each  $x_j$  requires just constant (2) space. Thus overall the space required is  $\mathcal{O}((K - 1) \cdot 2^4 + K \cdot 2^5 + 2)$

Finally, if we can answer  $\Pr(S_j = 1) > 0$  positively, then we know that a 3-SAT assignment exists, else it does not.

### Variable Elimination on General Graphs

We saw that using brute-force (i.e an exponential number of operations), we could calculate the normalizer  $Z$ . This is impractical, and hence we need a more efficient way to do so. Let's define the problem again -

Given an arbitrary set of potentials  $\psi_C(x_C)$  in a graph  $G$  where  $C$  are the cliques in  $G$ , we need to find

$$Z = \sum_{x_1, \dots, x_n} \prod_C \psi_C(x_C)$$

The algorithm to do so is as follows:

```

1 Input: Graph  $G$ 
2 Variables:  $x_1, x_2, \dots, x_n$  present in a good ordering
3  $\mathcal{F} \leftarrow \{\psi_C(x_C) \text{ where } C = \text{cliques in } G\}$ 
4 for  $i = 1$  to  $n$  do
5    $\mathcal{F}_i \leftarrow$  factors in  $\mathcal{F}$  containing  $x_i$ 
6    $\mathcal{M}_i \leftarrow$  product of factors in  $\mathcal{F}_i$ 
7    $m_i \leftarrow \sum_{x_i} \mathcal{M}_i$ 
8    $\mathcal{F} \leftarrow (\mathcal{F} - \mathcal{F}_i) \cup \{m_i\}$ 
9 end

```

#### Algorithm 3: Variable Elimination

At the end,  $\mathcal{F}$  consists of only a constant. Note that the product of factors isn't trivial, i.e we would need to multiply probability tables. To understand Algorithm 3, let's see an example.

**Example 54.** Say we have been given 5 variables, and the cliques are

$$\psi_{12}(x_1, x_2), \psi_{24}(x_2, x_4), \psi_{23}(x_2, x_3), \psi_{45}(x_4, x_5), \psi_{35}(x_3, x_5)$$



The corresponding graph is in Figure 18. We can see that

$$Z = \sum_{x_1 \cdots x_5} \psi_{12}(x_1 x_2) \psi_{24}(x_2 x_4) \psi_{23}(x_2 x_3) \psi_{45}(x_4 x_5) \psi_{35}(x_3 x_5)$$

Say our good ordering is  $x_1, x_2, x_3, x_4, x_5$ . So we start

◇ First variable  $x_1$  -

$$\begin{aligned} \mathcal{F}_1 &= \{\psi_{12}(x_1, x_2)\} \\ \mathcal{M}_1(x_1, x_2) &= \psi_{12}(x_1, x_2) \\ m_1(x_2) &= \sum_{x_1} \mathcal{M}_1 \\ \mathcal{F} &= \{\psi_{24}(x_2, x_4), \psi_{23}(x_2, x_3), \psi_{45}(x_4, x_5), \psi_{35}(x_3, x_5), m_1(x_2)\} \end{aligned}$$

◇ Second variable  $x_2$  -

$$\begin{aligned} \mathcal{F}_2 &= \{\psi_{24}(x_2, x_4), \psi_{23}(x_2, x_3), m_1(x_2)\} \\ \mathcal{M}_2(x_2, x_3, x_4) &= \psi_{12}(x_2, x_4) \psi_{23}(x_2, x_3) m_1(x_2) \\ m_2(x_3, x_4) &= \sum_{x_2} \mathcal{M}_2 \\ \mathcal{F} &= \{\psi_{45}(x_4, x_5), \psi_{35}(x_3, x_5), m_2(x_3, x_4)\} \end{aligned}$$

◇ Third variable  $x_3$  -

$$\begin{aligned} \mathcal{F}_3 &= \{\psi_{35}(x_3, x_5), m_2(x_3, x_4)\} \\ \mathcal{M}_3(x_3, x_4, x_5) &= \psi_{35}(x_3, x_5) m_2(x_3, x_4) \\ m_3(x_4, x_5) &= \sum_{x_3} \mathcal{M}_3 \\ \mathcal{F} &= \{\psi_{45}(x_4, x_5), m_3(x_4, x_5)\} \end{aligned}$$

◇ Fourth variable  $x_4$  -

$$\begin{aligned} \mathcal{F}_4 &= \{\psi_{45}(x_4, x_5), m_3(x_4, x_5)\} \\ \mathcal{M}_4(x_4, x_5) &= \psi_{45}(x_4, x_5) m_3(x_4, x_5) \\ m_4(x_5) &= \sum_{x_4} \mathcal{M}_4 \\ \mathcal{F} &= \{m_4(x_5)\} \end{aligned}$$

The above example showed how  $\mathcal{F}$  is a singleton set at the end. We can also modify Algorithm 3 to get  $\Pr(x_i)$  as follows -

- ◇ In line 1 of Algorithm 3, we choose a good ordering such that  $x_i$  is last
- ◇ The for loop in line 3 runs only for  $n - 1$  iterations

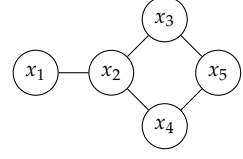


Figure 18: UGM for Example

- ◇ After this, at the end,  $\mathcal{F}$  will consist of unnormalized values, sum of which will give  $Z$ , and each term divided by  $Z$  will give the required probability.

What if we want to compute the MAP query? For that, we do the following -

- ◇ In line 6, we have  $\hat{m}_i = \max_{x_i} \mathcal{M}_i$  and we have to keep around the maximizing assignment
- ◇ In the end  $\mathcal{F}$  consists of the required argmax.

**Theorem 55.** *The complexity of the Variable Elimination algorithm is  $\mathcal{O}(nm^w)$  where  $w$  is the maximum number of variables in any factor.*

*Sketch of proof.* The bottleneck step in the algorithm's for loop is computing the product of factors, and in general if the factor has  $\kappa$  variables, then the time to do the product will be  $\mathcal{O}(m^\kappa)$ .  $\square$

In Example 54, we see that the time complexity is  $\mathcal{O}(nm^3)$ . If we started with  $x_2$ , our time complexity would've been  $\mathcal{O}(nm^4)$ .

More interestingly, if we have a star graph (Figure 19), and if we start with the centre node first, we encounter a very severe penalty in terms of time complexity. This elimination order will give you  $\mathcal{O}(m^n)$  running time, while removing the non-central nodes first gives you just  $\mathcal{O}(nm^2)$  running time.

Unfortunately, choosing the optimal elimination order is NP hard in general. But for chordal (triangulated) graphs, the algorithm is polynomial time. But another problem we stumble upon is that if our graph is not triangular, optimal triangulation is NP hard (but there exist many heuristics to do this in polynomial time).

**Definition 56** (Simplicial). A vertex in a graph  $G$  is simplicial if its neighbors form a complete set.

**Theorem 57.** *Every triangulated graph is either complete or has at least two non-adjacent simplicial vertices.*

*Proof.* To be added.  $\square$

The goal is to find an optimal ordering for inferring  $\Pr(x_1)$ , which means  $x_1$  should be last.

```

1 Input: Graph  $G$ ,  $n$  = number of vertices in  $G$ 
2 for  $i = 1$  to  $n$  do
3    $\pi_i \leftarrow$  any simplicial vertex in  $G$  except 1
4   Remove  $\pi_i$  from  $G$ 
5 end
6 return ordering  $\pi_1, \dots, \pi_{n-1}$ 

```

**Algorithm 4:** Optimal ordering for triangulated graph

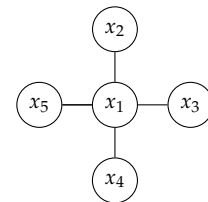


Figure 19: Star Graph

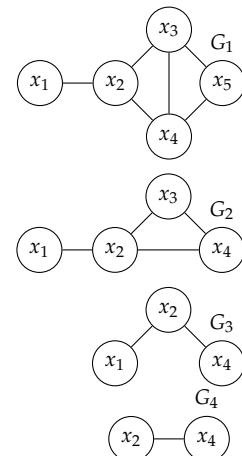


Figure 20: Sequence of graphs

**Example 58.** Consider the triangulated graph  $G_1$  given on the right for which we have to find the optimal ordering. We go over the iterations as follows

1. In  $G_1$ , we have  $x_1$  and  $x_5$  as simplicial vertices. Say we remove  $x_5$  first, to get  $G_2$ .
2. In  $G_2$ , we have  $x_1, x_3$  and  $x_4$  as the simplicial vertices. Say we remove  $x_3$  to get  $G_3$ .
3. In  $G_3$ , we have  $x_1$  and  $x_4$  as simplicial vertices. Say we remove  $x_1$  to get  $G_4$ .
4. In  $G_4$  we have  $x_2$  and  $x_4$  as simplicial vertices. Say we remove  $x_2$ .

The sequence of graphs is shown in Figure 20.

Thus, finally we get the ordering  $x_5, x_3, x_1, x_4, x_2$  as an optimal ordering.

### Multiple Inference Queries

The above subsection showed how we can calculate the optimal ordering and a single inference query. But say, we have been given a chain graph with potentials as  $\psi_{i,i+1}(x_i, x_{i+1})$ , say we need all  $\Pr(x_1), \dots, \Pr(x_n)$ , can we do that faster? A no-brain method would be to use variable elimination  $n$  times to get  $\mathcal{O}(n^2 m^2)$ .

Say I have the chain graph in Figure 21. If we need to calculate  $\Pr(x_1)$ , we first remove  $x_5$ . This is followed by removing  $x_4, x_3$  and  $x_2$ .

Now if we want to calculate  $\Pr(x_2)$ . We can reuse the computation done in removing  $x_5, x_4$  and  $x_3$ .

We will see that if we skillfully reuse such computation, if each variable elimination run takes time  $\mathfrak{T}$ , the time for  $n$  inference queries will take just  $2\mathfrak{T}$ .

**Remark 59.** Refer to Example 54. In this notice that the arguments of  $\mathcal{M}_i(\cdot)$  are cliques with *induced* edges. For example, we have  $\mathcal{M}_1(x_1, x_2)$  and clearly  $\{x_1, x_2\}$  forms a clique. Second, we have  $\mathcal{M}_2(x_2, x_3, x_4)$  and notice that when we add or *induce* an edge between  $x_2$  and  $x_3$ ,  $\{x_2, x_3, x_4\}$  forms a clique. This can be extended to all  $\mathcal{M}_i(\cdot)$ . For our notion of reusing, we are interested in the maximal cliques formed, and you can check that they refer to the cliques formed by the arguments of  $\mathcal{M}_1, \mathcal{M}_2$  and  $\mathcal{M}_3$ .

### Junction Trees

The junction tree algorithm is an optimal general-purpose algorithm for **exact** marginal or MAP queries, and can simultaneously compute many such queries. It utilizes efficient data structures and overall has

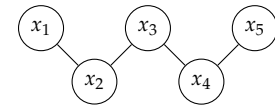


Figure 21: Chain graph

a complexity of  $\mathcal{O}(m^w N)$  where  $w$  is the size of the largest clique in the triangulated graph and each variable can take  $m$  values. It is to note that

- ◇ Viterbi algorithm of Hidden Markov Models
- ◇ Forward-backward algorithm of Kalman Filters

are special cases of junction trees.

**Definition 60** (Junction Tree). Junction tree JT of a triangulated graph  $G$  with nodes  $x_1, \dots, x_n$  is a tree where the nodes are the maximal cliques of  $G$  and the edges obey the *running intersection property*. This property states that if any two nodes contain variable  $x_i$ , then  $x_i$  is present in every node in the unique path between them.

**Example 61.** For the graph given in Figure 22, we have the maximal cliques as  $\{x_1, x_2, x_3\}$ ,  $\{x_3, x_4\}$ ,  $\{x_4, x_5\}$ . Thus, the junction tree for the graph is given in Figure 23

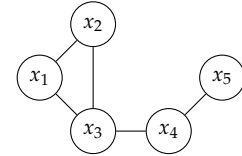


Figure 22: Sample graph for JT

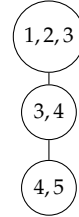


Figure 23: Junction Tree example

**Theorem 62.** A graph will have a junction tree if and only if it is chordal.

*Proof.* Skipped. □

### Construction of a junction tree

If our graph is chordal, we have efficient polynomial time algorithms to create a JT. We first enumerate a set of maximal cliques covering our graph  $G$ , then we connect the cliques to get a tree satisfying the *running intersection property*. Note that if our graph is non-triangulated, we need to triangulate it first using heuristics, since optimal triangulation is NP-hard.

**Definition 63** (Optimal triangulation). A triangulation which gives rise to a JT where the size of the largest clique is smallest is called the optimal triangulation.

A general method for finding heuristics is -

```
for i = 1 to n
  choose the vertex for which some score is minimum
  connect all neighbors of chosen vertex
  remove the chosen vertex from the graph
```

Some heuristics of triangulation are

1. Choose the vertex with smallest degree and connect all its neighbors
2. Chose the vertex which will require the smallest number of edges to connect neighbors

**Example 64.** Creation of a JT from a UGM:

1. Consider the graph in Figure 24 as our starting graph.
2. We triangulate the graph to get the graph in Figure 25. Notice that the maximal cliques are  $C_1 = \{x_1, x_2\}$ ,  $C_2 = \{x_2, x_3, x_4\}$  and  $C_3 = \{x_3, x_4, x_5\}$ .
3. These cliques act as nodes in our junction tree, and we connect the three cliques such that they satisfy the running intersection property. I have dropped the  $x$  and just written the indices to avoid clutter. Note in Figure 26 that now we have two types of nodes - in circle we have the cliques, and in rectangles we have the *separators*. Separators are variables present in the intersection of the nodes, thus

$$\text{Separator}(C_i, C_j) = C_i \cap C_j \quad (52)$$

4. Now we assign potentials to all cliques. Note that from Example 54, we had potentials  $\psi_{12}, \psi_{23}, \psi_{24}, \psi_{35}, \psi_{45}$ . Thus here we can assign  $\psi_{12}$  to  $C_1$ ,  $\psi_{23}, \psi_{24}$  to  $C_2$  and  $\psi_{35}, \psi_{45}$  to  $C_3$ .

*Remark 65.* If we encounter any ambiguity in assigning potentials, i.e we can assign potentials to more than once clique-node, then we can arbitrarily assign it to any one.

**Theorem 66.** Every triangulated graph has a simplicial vertex.

*Proof.* Skipped.  $\square$

We now state the algorithm to find the maximal cliques in a triangulated graph

```

1 Input: Triangulated graph  $G$ ,  $n$  = number of vertices in  $G$ 
2 for  $i = 1$  to  $n$  do
3    $\pi_i \leftarrow$  any simplicial vertex in  $G$ 
4    $C_i \leftarrow \{\pi_i\} \cup \mathcal{N}(\pi_i)$ 
5   Remove  $\pi_i$  from  $G$ 
6 end
7 return the maximal cliques from  $C_1, \dots, C_n$ 

```

**Algorithm 5:** Finding maximal cliques in a chordal graph

**Theorem 67.** A clique tree that satisfies the running intersection property maximized the number of separator variables.

*Proof.* To be added.  $\square$

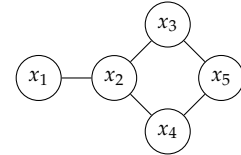


Figure 24: Non-chordal graph

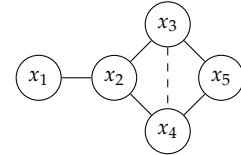


Figure 25: Chordal graph

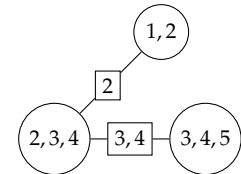


Figure 26: Clique-node graph

```

1 Input: Cliques  $C_1, \dots, C_k$ 
2 Form a complete weighted graph  $H$  with cliques as nodes and
  edge weights = size of the intersection of the two cliques it
  connects
3  $T \leftarrow$  maximum weight spanning tree of  $H$ 
4 return  $T$  as the junction tree

```

**Algorithm 6:** Forming a junction tree from a clique-node graph

Note that once we have the clique graph, we can make a weighted clique graph from that by adding  $|\mathcal{S}|$  as the weight for each edge between  $C_i$  and  $C_j$  where  $\mathcal{S} = C_i \cap C_j$ , and the problem of finding the junction tree boils down to finding the maximum weight spanning tree of the weighted graph.

**Example 68.** Consider the undirected graph  $H$  in Figure 27. Say the potentials are defined over cliques of size 2.

To triangulate, say we pick a heuristic - smallest degree first. Start with  $x_6$  and notice that its neighbors  $x_2$  and  $x_5$  are connected. Next we choose  $x_3$  and connect  $x_1$  and  $x_5$ . You can go on further, but notice that the graph is already triangulated (since on removing  $x_1$  the graph becomes complete). Thus an ordering we can have is

$$x_6, x_3, x_1, x_2, x_5, x_4$$

Next we choose the maximal cliques. This can be done using Algorithm 5. This gives the set of maximal cliques as

$$\begin{aligned} C_1 &= \{x_3, x_1, x_5\} \\ C_2 &= \{x_6, x_2, x_5\} \\ C_3 &= \{x_1, x_2, x_4, x_5\} \end{aligned}$$

We then make the complete weighted graph as in Figure 28. Clearly by removing the edge  $C_1 - C_2$ , we get the maximum spanning tree, and that gives the junction tree as shown in Figure 29.

To assign the potentials, we can assign  $\psi_{13}, \psi_{35}$  to  $C_1$ ,  $\psi_{14}, \psi_{12}, \psi_{45}, \psi_{24}$  to  $C_3$  and finally  $\psi_{25}, \psi_{26}$  to  $C_2$ . The potential of a clique is the product of the potentials assigned to it.

### Message Passing

Say each node  $c$ , which is a clique in the JT, sends a message  $m_{c \rightarrow c'}(\cdot)$  to its neighbors  $c'$  once it has messages from every other neighbor  $\mathcal{N}(c) - \{c'\}$ .

$$m_{c \rightarrow c'}(\mathbf{x}_s) = \sum_{\mathbf{x}_{c-s}} \psi_c(\mathbf{x}_c) \prod_{d \in \mathcal{N}(c) - \{c'\}} m_{d \rightarrow c}(\mathbf{x}_{d \cap c}) \quad (53)$$

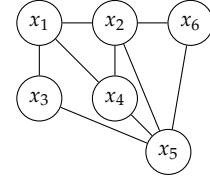


Figure 27: Undirected graph

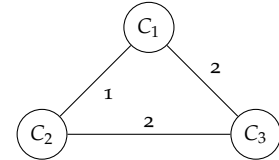


Figure 28: Complete Weighted Graph

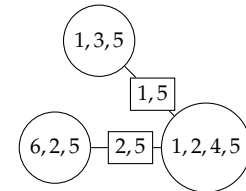


Figure 29: Junction Tree

For a MAP query, we can replace the  $\sum$  with max. Note that the  $\sum$  sums over all the variables present in clique but not in separator.

We can write

$$\Pr(\mathbf{x}_c) \propto \psi_c(\mathbf{x}_c) \prod_{d \in \mathcal{N}(c)} m_{d \rightarrow c}(\mathbf{x}_{d \cap c}) \quad (54)$$

And to get the marginal probability of any  $x_i$ , we can just sum over the rest, i.e

$$\Pr(x_i) = \sum_{\mathbf{x}_c - x_i} \Pr(\mathbf{x}_c) \quad (55)$$

**Example 69.** Consider the JT shown in Figure 30. Note that we have edge potentials, and each clique has the product of such potentials present. Each node can send a message once it has messages from neighbors.

Initially,  $C_1 = \{y_1, y_2\}$  or  $C_3 = \{y_3, y_4, y_5\}$  can initiate the message passing since they have single neighbors. Thus, we have

1.  $C_1$  initiates message  $m_{12 \rightarrow 234}(y_2) = \sum_{y_1} \psi_{12}(y_{12})$  to  $C_2 = \{y_2, y_3, y_4\}$ .
2.  $C_3$  sends message  $m_{345 \rightarrow 234}(y_3) = \sum_{y_5} \psi_{345}(y_{345})$  to  $C_2$
3.  $C_2$  sends message  $m_{234 \rightarrow 345} = \sum_{y_2} \psi_{234}(y_{234}) m_{12 \rightarrow 234}(y_2)$  to  $C_3$
4.  $C_2$  sends message  $m_{234 \rightarrow 12}(y_2) = \sum_{y_3, y_4} \psi_{234}(y_{234}) m_{345 \rightarrow 234}(y_{34})$  to  $C_1$

We also write that  $\Pr(y_1) \propto \sum_{y_2} m_{234 \rightarrow 12}(y_2)$ .

*Remark 70 (Intuition behind message passing).* Message from  $c$  to  $c'$  denotes the result of VE of potentials on the side of the tree that contains the clique  $c$  but not  $c'$  leaving only the separator variables  $s = c \cap c'$ .

### Addition of Evidence

In such queries, we have an evidence or conditioning set  $\mathbf{x}_e$ , and we need to find similar types of sub-queries shown before, i.e

1.  $\Pr(x_1 | \mathbf{x}_e) = \sum_{x_2, \dots, x_m} \Pr(x_1, \dots, x_n | \mathbf{x}_e)$
2.  $\mathbf{x}^* | \mathbf{x}_e = \arg \max_{x_1, \dots, x_m} \Pr(x_1, \dots, x_n | \mathbf{x}_e)$

where  $\{x_2, \dots, x_m\} = V - \mathbf{x}_e - \{x_1\}$ . The trick to add evidence is to change the potentials.

**Example 71 (Viterbi Algorithm).** Consider the Hidden Markov Model shown in Figure 31. Define edge potentials as  $\Pr(y_i | y_{i-1})$  and  $\Pr(x_i | y_i)$ . Also, let the evidence variables be  $\mathbf{x} = x_1, \dots, x_n =$

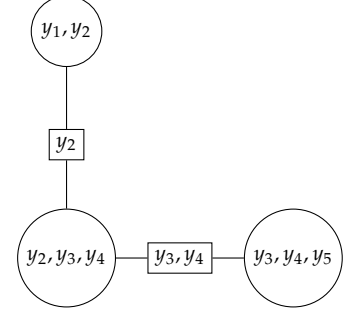


Figure 30: Junction Tree

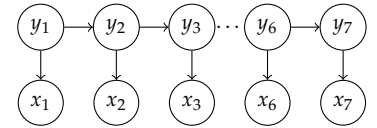


Figure 31: Sample HMM

$o_1, \dots, o_n$ . We need to find the most likely values of the hidden state variables  $\mathbf{y} = y_1, \dots, y_n$ , i.e

$$\arg \max_{\mathbf{y}} \Pr(\mathbf{y} | \mathbf{x} = \mathbf{o})$$

We redefine the potentials as

$$\psi_i(y_{i-1}, y_i) = \Pr(y_i | y_{i-1}) \Pr(x_i = o_i | y_i)$$

Since we have fixed the observations of  $x_i = o_i$ , we have a 1D table instead of a 2D potential table. This gives the reduced chain graph as in Figure 32. Now we use the message passing algorithm shown earlier, just replacing sum with max. For ease of calculation, only consider a three node chain, with the following probabilities:

$$\Pr(y_i = 0 | y_{i-1}) = \begin{cases} 0.9 & \text{if } y_{i-1} = 0 \\ 0.2 & \text{if } y_{i-1} = 1 \end{cases}$$

$$\Pr(x_i = 0 | y_i) = \begin{cases} 0.7 & \text{if } y_i = 0 \\ 0.6 & \text{if } y_i = 1 \end{cases}$$

Also,  $\Pr(y_1 = 1) = 0.5$ . Say our observations are

$$[x_1, x_2, x_3] = [0, 0, 0]$$

We want to calculate

$$\arg \max \Pr(y_1, y_2, y_3 | x_1, x_2, x_3 = [0, 0, 0])$$

Now, we calculate the potential

$$\psi_{12}(y_1, y_2) = \Pr(y_2 | y_1) \Pr(x_1 = 0 | y_1) \Pr(y_1)$$

	$\psi_{12}(y_1, y_2)$	
	0	1
0	$0.9 \times 0.7 \times 0.5$	$0.1 \times 0.7 \times 0.5$
1	$0.2 \times 0.6 \times 0.5$	$0.8 \times 0.6 \times 0.5$

Note that when we calculate

$$\psi_{23}(y_2, y_3) = \Pr(y_3 | y_2) \Pr(x_2 = 0 | y_2) \Pr(x_3 = 0 | y_3)$$

*Remark 72* (Approximate Inference). Note the followings points:

- ◇ Exact inference is NP hard. First define the tree width  $w$  of a triangulated graph as one less than the size of the maximal clique. The complexity of exact inference is  $\mathcal{O}(m^w)$ .
- ◇ It is seen that real-life graphs produce large cliques on triangulation. For example, an  $n \times n$  grid has a tree width of  $n$ . A Kalman filter on  $K$  parallel state variables influencing a common observation variable has a tree width of size  $K + 1$ .

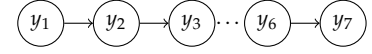


Figure 32: Sample HMM



### Generalized Belief Propagation

Here, we try to run some kind of message passing algorithms on graphs which look like junction trees. Instead of creating an exact JT which satisfies the running intersection property, we try to create a cluster graph with two relaxations -

1. The nodes are arbitrary clusters instead of cliques in the chordal graph. We only ensure that all potentials are subsumed.
2. Instead of adding separator nodes, we add a subset of intersecting variables so as to satisfy the running intersection property.

**Example 73.** Consider the JT creation in Example 64. For that graph, we see that we get maximal clique size of 3. Suppose we want to maintain a clique size of 2.

We create a *factor graph* such that the nodes of the factor graph correspond to the edge potentials given. The cluster/factor graph will be as shown in Figure 33. Note that factor graphs are special kinds of cluster graphs.

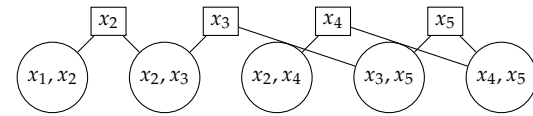


Figure 33: Factor Graph

Belief propagation algorithms are approximate message passing algorithms, and differ in the order of sending of messages. Note that in general graph can have loops and thus we can't apply tree-based two phase methods.

Variants of scheduling order of propagating beliefs are -

1. Simple loopy belief propagation
2. Tree-reweighted message passing
3. Residual belief propagation

There are other classes too, which are

1. Sampling
2. Combinatorial Algorithms
3. Greedy algorithms: relaxation labeling
4. Variational methods - mean-field & structured mean-field
5. Linear and Quadratic Programming based approaches

## *Learning from Data*

Each graphical model consists of two major components - the graph structure, and the potentials given the graph structure.

### *Graph Structure*

There are two major methods to learn the graph:

1. **Manual:** A domain expert manually designs the graphs. This is popular in applications where we are well-versed with the underlying dependency structure. For example - Quick Medical Reference (QMR) systems for disease-symptoms matching, Kalman Filters, Grid graphs in Computer Vision, Hidden Markov Models (HMM) in speech recognition/information extraction.
2. **Learning from Examples:** It can be shown that recovering the graph structure is NP hard. Usually learning methods are branch and bound search problems, which are particularly useful in dynamic situations.

### *Parameters in Potentials*

As before, there are the two same methods for learning:

1. **Manual:** Done by a domain expert usually for infrequently constructed graphs (QMR systems), or where the potentials are a trivial function of the attributes of the connected graphs (grid graphs). This is a relevant method for Bayesian Networks, as potentials correspond to conditional probabilities. Thus in data-starved regions, with priors we can use Bayesian Networks.
2. **Learning from Examples:** A popular method where humans cannot make objective assignments. Two major subdomains are table potentials, where each entry is a parameter (HMMs), and potentials with shared parameters and data attributed (CRFs).

Given a sample of data  $\mathcal{D}$  generated from a distribution  $P$ , being represented by a known graphical model  $G$ , our aim is to learn the potentials. There can be many scenarios to consider -

#### 1. **Variables:**

- (a) In each training instance, we have observed all the variables  $\mathcal{X}$ . Such a setting is called fully supervised setting.
- (b) In each training instance, we have observed a subset of variables  $\mathcal{X} \subset \mathcal{X}$ . Such a setting is called partially observed setting.

## 2. Potentials:

3. In BNs, we don't have a log-partition function  $\log Z$ , and thus in most cases, we'd be able to find closed form solutions for potentials.
4. In UGMs,  $\log Z$  causes a lot of trouble. Since potentials are attached to arbitrary overlapping subset of variables, we require gradient descent kind of iterative algorithms.

Representation of potentials as parameters includes -

1. **Generative:**  $P(\mathbf{x}) = P(x_1, \dots, x_n)$  is represented as our  $G$ . The training samples are  $\mathcal{D} = \{\mathbf{x}^1, \dots, \mathbf{x}^N\}$  where  $\mathbf{x}^i = \{x_1^i, x_2^i, \dots, x_n^i\}$ , and we finally learn the potentials  $\psi_C(\mathbf{x}_C)$ .
2. **Conditional:** We work with  $P(\mathbf{y}|\mathbf{x}) = P(y_1, \dots, y_n|\mathbf{x})$  represented by our  $G$  over  $\mathbf{y}$  variables. Our training instances in this case would be 2-tuples  $\mathcal{D} = \{(\mathbf{x}^1, \mathbf{y}^1), \dots, (\mathbf{x}^N, \mathbf{y}^N)\}$  and we learn the potentials  $\psi_C(\mathbf{y}_C, \mathbf{x})$ .

### *Learning under Conditional Representation*

We now focus on the conditional representation of potentials, and provide a general framework for parameter learning.

Consider the conditional distribution  $\Pr(\mathbf{y}|\mathbf{x}, \theta)$ , potentials are function of  $\mathbf{x}$ , and we want to learn  $\theta$ . Say  $\mathbf{y} = y_1, \dots, y_n$  forms a graphical model  $G$ .

Say  $G$  is undirected, then

$$\begin{aligned} \Pr(y_1, \dots, y_n|\mathbf{x}, \theta) &= \frac{\prod_C \psi_C(\mathbf{y}_C, \mathbf{x}, \theta)}{Z_\theta(\mathbf{x})} \\ &= \frac{1}{Z_\theta(\mathbf{x})} \exp \left( \sum_C F_\theta(\mathbf{y}_C, C, \mathbf{x}) \right) \end{aligned} \quad (56)$$

where  $F_\theta(\mathbf{y}_C, C, \mathbf{x}) = \log \psi_C(\mathbf{y}_C, \mathbf{x}, \theta)$ ,  $Z_\theta(\mathbf{x}) = \sum_{\mathbf{y}'} \exp \left( \sum_C F_\theta(\mathbf{y}'_C, C, \mathbf{x}) \right)$ .

Now, we can think of  $F_\theta(\mathbf{y}_C, C, \mathbf{x})$  in many ways

1. **Log-linear model** over features defined by the user (eg. in CRFs, Maxent models). Say we gave  $K$  features, and each feature is represented as  $f_k(\mathbf{y}_C, C, \mathbf{x})$ . Thus,

$$F_\theta(\mathbf{y}_C, C, \mathbf{x}) = \sum_{k=1}^K \theta_k f_k(\mathbf{y}_C, C, \mathbf{x}) \quad (57)$$

2. **Neural Network** which takes in  $\mathbf{y}_C, C, \mathbf{x}$  and transforms them non-linearly into  $\mathcal{Y} \in \mathbb{R}$ , and  $\theta$  are the parameters of the neural network.

**Example 74** (Named Entity Recognition). Consider the task of NER, where  $y_i$  can take 3 values, and the structure is represented as a chain graph. Thus essentially, the user enforces that only adjacent words in the sentence affect the labels taken. Since we have a chain graph, we take the cliques as edges, and we take our templated functions as  $\mathbf{f}(y_i, y_{i-1}, i, \mathbf{x})$ , where  $C = i$  is a short hand for  $C = (i-1, i)$ . Defining the features  $f_i(y_i, y_{i-1}, i, \mathbf{x})$ . We can manually write heuristics, or in something like BERT, we can have  $\mathbf{f}(y_i, y_{i-1}, i, \mathbf{x}) = \mathbf{e}_i \in \mathbb{R}^K$  where  $e_i$  is the embedding generated by BERT.

Now, for training, we have been given  $N$  input pairs represented by  $\mathcal{D} = \{(\mathbf{x}^1, \mathbf{y}^1), \dots, (\mathbf{x}^N, \mathbf{y}^N)\}$ , and the form of  $F_\theta$ . We learn  $\theta$  through maximum likelihood, i.e

$$\max_{\theta} LL(\theta, \mathcal{D}) = \max_{\theta} \sum_{i=1}^N \log \Pr(\mathbf{y}^i | \mathbf{x}^i, \theta) \quad (58)$$

We can write

$$\begin{aligned} LL(\theta, \mathcal{D}) &= \sum_{i=1}^N \log \Pr(\mathbf{y}^i | \mathbf{x}^i, \theta) \\ &= \sum_{i=1}^N \log \left( \frac{1}{Z_\theta(\mathbf{x}^i)} \exp \left( \sum_C F_\theta(\mathbf{y}_C^i, C, \mathbf{x}^i) \right) \right) \\ &= \sum_{i=1}^N \left[ \sum_C F_\theta(\mathbf{y}_C^i, C, \mathbf{x}^i) - \log Z_\theta(\mathbf{x}^i) \right] \end{aligned} \quad (59)$$

Note that computing  $F_\theta$  is not difficult, but to calculate  $Z_\theta$  for each  $i$  requires invoking an inference algorithm.

For training, we can use gradient descent. For now, let us assume a log-linear model as  $F_\theta(\mathbf{y}_C^i, C, \mathbf{x}) = \theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}_C^i, C)$ , and denote  $\mathbf{f}(\mathbf{x}^i, \mathbf{y}^i) = \sum_C \mathbf{f}(\mathbf{x}^i, \mathbf{y}_C^i, C)$ . Thus,

$$LL(\theta) = \sum_i \left( \theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}^i) - \log Z_\theta(\mathbf{x}^i) \right) \quad (60)$$

We can add a regularizer to prevent over-fitting. Thus, our objective becomes

$$\max_{\theta} \sum_i \left( \theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}^i) - \log Z_\theta(\mathbf{x}^i) \right) - \frac{\|\theta\|^2}{C} \quad (61)$$

The objective function is concave in  $\theta$ , and thus we can reach the globally optimal value of  $\theta$  using gradient descent. The gradient of the objective  $L(\theta)$  is

$$\begin{aligned} \nabla L(\theta) &= \sum_i \left( \theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}^i) - \frac{\sum_{\mathbf{y}'} \mathbf{f}(\mathbf{y}', \mathbf{x}^i) \exp(\theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}'))}{Z_\theta(\mathbf{x}^i)} \right) - \frac{2\theta}{C} \\ &= \sum_i \left( \theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}^i) - \sum_{\mathbf{y}'} \mathbf{f}(\mathbf{x}^i, \mathbf{y}') \Pr(\mathbf{y}' | \theta, \mathbf{x}^i) \right) - \frac{2\theta}{C} \\ &= \sum_i \left( \theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}^i) - \mathbb{E}_{\Pr(\mathbf{y}' | \theta, \mathbf{x}^i)} \mathbf{f}(\mathbf{x}^i, \mathbf{y}') \right) - \frac{2\theta}{C} \end{aligned} \quad (62)$$

where

$$\begin{aligned}
 \mathbb{E}_{\Pr(\mathbf{y}'|\theta, \mathbf{x}')} f_k(\mathbf{x}^i, \mathbf{y}') &= \sum_{\mathbf{y}'} f_k(\mathbf{x}^i, \mathbf{y}') \Pr(\mathbf{y}'|\theta, \mathbf{x}^i) \\
 &= \sum_{\mathbf{y}'} \sum_C f_k(\mathbf{x}^i, \mathbf{y}'_C, C) \Pr(\mathbf{y}'|\theta, \mathbf{x}^i) \\
 &= \sum_C \sum_{\mathbf{y}'_C} f_k(\mathbf{x}^i, \mathbf{y}'_C, C) \Pr(\mathbf{y}'_C|\theta, \mathbf{x}^i)
 \end{aligned} \tag{63}$$

**Example 75.** Consider an undirected graphical model on 3 binary variables  $\{y_1, y_2, y_3\}$  represented as  $\mathbf{y}$ , and are forming a chain. We define two features for the model as

$$\begin{aligned}
 f_1(\mathbf{x}, y_j, j) &= x_j y_j \quad \text{where } x_j \text{ is the intensity of pixel } j \\
 f_2(\mathbf{x}, (y_k, y_j), (k, j)) &= \llbracket y_k \neq y_j \rrbracket \quad \text{where } \llbracket \alpha \rrbracket = 1 \text{ if } \alpha = \text{true}
 \end{aligned}$$

Consider the initial parameters as  $\theta = [\theta_1, \theta_2] = [3, -2]$ , and consider  $\mathbf{x}^1 = [0.1, 0.7, 0.3]$  and  $\mathbf{y}^1 = [1, 1, 0]$ .

◇ The log-node potentials  $F_\theta(y_j, C = j, \mathbf{x})$  are given as

$$y_j = \theta \cdot \mathbf{f}(\mathbf{x}, y_j, j) = \theta_1 x_j y_j$$

For  $y_1$ , we have the value as  $[0, 0.3]$ ,  $y_2$  will have the value  $[0, 2.1]$  and  $y_3$  will have  $[0, 0.09]$ .

◇ The log-edge potentials  $F_\theta((y_1, y_2), C = (1, 2), \mathbf{x})$  are given as

$$\theta_2 f_2(\mathbf{x}, (y_1, y_2), (1, 2))$$

For  $(1, 2)$  we have the value as  $[0, -2, 0, -2]$  corresponding to  $y_1 y_2 = \{00, 01, 10, 11\}$  (can consider it to be a matrix for ease of understanding). Since our edge potentials don't depend on  $x$ ,  $F_\theta((y_2, y_3), C = (2, 3), \mathbf{x}) = [0, -2, 0, -2]$ .

**Example 76.** Consider parameter learning for  $\mathbf{y} = \{y_1, \dots, y_6\}$ , where  $y_j = \pm 1$ . Let us define 8 features for the variables as

$$\begin{aligned}
 f_1(y_j, y_{j+1}) &= \llbracket y_j + y_{j+1} > 1 \rrbracket, \quad 1 \leq j \leq 5 \\
 f_2(y_1, y_3) &= -2y_1 y_3 \\
 f_3(y_2, y_3) &= y_2 y_3 \\
 f_4(y_3, y_4) &= y_3 y_4 \\
 f_5(y_2, y_4) &= \llbracket y_2 y_4 < 0 \rrbracket \\
 f_6(y_4, y_5) &= 2y_4 y_5 \\
 f_7(y_3, y_5) &= -y_3 y_5 \\
 f_8(y_5, y_6) &= \llbracket y_5 + y_6 > 0 \rrbracket
 \end{aligned}$$

Consider

$$\mathbf{f}(\mathbf{y}) = [f_1, \dots, f_8] \text{ and } \theta = [1 \ 1 \ 1 \ 2 \ 2 \ 1 \ -1 \ 1]^\top$$

The underlying graphical model is given in Figure 34. For the above graph, we can draw the junction tree to find

$$Z = \sum_{\mathbf{y}} \exp(\theta^\top \mathbf{f}(\mathbf{x}, \mathbf{y}))$$

For clique  $C$ , we have  $\psi_C(\mathbf{y}_C) = \exp(\theta \cdot \mathbf{f}_C(\mathbf{x}, \mathbf{y}_C))$ .

The junction tree for the above graph is given in Figure 35. Say from left to right in the JT, we call the cliques  $\mathcal{C}_1$  to  $\mathcal{C}_4$ . For  $\mathcal{C}_2$ , the log-potential will be  $2 \cdot f_5(y_2, y_4) + 1 \cdot f_1(y_3, y_4) + 2 \cdot f_4(y_3, y_4)$ . We can easily find for others too.

Now, coming back to the expectation, we need to compute

$\mathbb{E}_{\Pr(\mathbf{y}|\theta^\top, \mathbf{x}^i)} f_k(\mathbf{x}^i, \mathbf{y})$ . To do this, we can proceed as follows:

1. Represent the probability  $\Pr(\mathbf{y}|\theta^\top, \mathbf{x}^i)$  as UGM where nodes are  $y_1, \dots, y_n$  and the potential  $\psi_C(\mathbf{y}_C, \mathbf{x}, \theta)$  for clique  $C$  is  $\exp(\theta^\top \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}_C^i, C))$ .
2. Run a sum-product inference algorithm on the above UGM and compute for each  $C$ ,  $\mathbf{y}_C$  the marginal probability  $\mu(\mathbf{y}_C, C, \mathbf{x}^i)$ .
3. Using these nodes, compute

$$\mathbb{E}_{\Pr(\mathbf{y}|\theta^\top, \mathbf{x}^i)} f_k(\mathbf{x}^i, \mathbf{y}) = \sum_C \sum_{\mathbf{y}_C} \mu(\mathbf{y}_C, C, \mathbf{x}^i) f_k(\mathbf{x}^i, C, \mathbf{y}_C)$$

Having done this, we continue Example 75. We can calculate marginals  $\mu(y_j, j)$  and  $\mu(y_k, y_j, (k, j))$ , and write

$$\begin{aligned} \mathbb{E}[f_1(\mathbf{x}^1, \mathbf{y})] &= \sum_j \sum_{y'_j} \mu_j(y'_j, j) x_j y'_j = \sum_j y_j x_j \mu_j(1, j) \\ &= 0.1\mu(1, 1) + 0.7\mu(1, 2) + 0.3\mu(1, 3) \\ \mathbb{E}[f_2(\mathbf{x}^2, \mathbf{y})] &= \sum_C \sum_{y'_C} \mu_j(y'_C, C) f_2(y'_C, C, x) \\ &= \mu(1, 0, (1, 2)) + \mu(0, 1, (1, 2)) + \mu(1, 0, (2, 3)) + \mu(0, 1, (2, 3)) \end{aligned}$$

Now, value of

$$\begin{aligned} f_1(\mathbf{x}^1, \mathbf{y}^1) &= \sum_C f_1(\mathbf{x}^1, \mathbf{y}_C^1, C) = \sum_{j=1}^3 f_1(\mathbf{x}^1, y_j^1, j) = \sum_{j=1}^3 x_j y_j \\ &= 0.1 \times 1 + 0.7 \times 1 + 0.3 \times 0 = 0.8 \\ f_2(\mathbf{x}^1, \mathbf{y}^1) &= \llbracket y_1^1 \neq y_2^1 \rrbracket + \llbracket y_2^1 \neq y_3^1 \rrbracket = 1 \end{aligned}$$

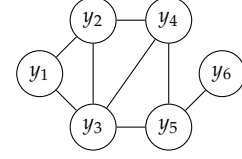


Figure 34: UGM for example

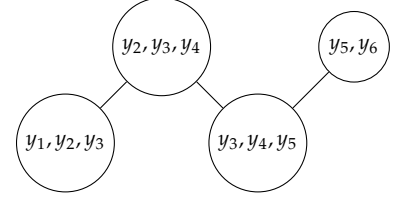


Figure 35: JT for above UGM

Thus we can write the gradients for each parameter as

$$\begin{aligned}\nabla L(\theta_1) &= 0.8 - \mathbb{E}(f_1(\mathbf{x}^1, \mathbf{y})) - 2 \cdot \frac{3}{C} \\ \nabla L(\theta_2) &= 1 - \mathbb{E}(f_2(\mathbf{x}^1, \mathbf{y})) + 2 \cdot \frac{2}{C}\end{aligned}$$

### Training Algorithm

```

1 Input:  $\mathcal{D} = \{(\mathbf{x}^i, \mathbf{y}^i)\}_{i=1}^N$ ,  $\mathbf{f} : f_1, \dots, f_K$ 
2 Output:  $\theta = \arg \max \sum_{i=1}^N (\theta \cdot \mathbf{f}(\mathbf{x}^i, \mathbf{y}^i) - \log Z_\theta(\mathbf{x}^i)) - \frac{\|\theta\|^2}{C}$ 
3 Initialize:  $\theta^0 = \mathbf{0}$ 
4 for  $t = 1$  to  $T$  do
5   for  $i = 1$  to  $N$  do
6      $g_{k,i} = f_k(\mathbf{x}^i, \mathbf{y}^i) - \mathbb{E}_{\Pr(\mathbf{y}'|\theta^t, \mathbf{x}^i)} f_k(\mathbf{x}^i, \mathbf{y}')$  for  $k = 1, \dots, K$ 
7   end
8    $g_k = \sum_i g_{k,i}$  for  $k = 1, \dots, K$ 
9    $\theta_k^t = \theta_k^{t-1} + \gamma_t (g_k - 2 \frac{\theta_k^{t-1}}{C})$ 
10  Exit: if  $\|\mathbf{g}\| \approx 0$ 
11 end

```

#### Algorithm 7: Training Algorithm for Parameter Learning

The running time for Algorithm 7 in case of chain graph is  $\mathcal{O}(INn(m^2 + K))$  where  $I$  is the total number of iterations. But in general, for a graph with tree-width of  $w$ , the running time has  $m^{w+1}$  instead of  $m^2$ .

The above algorithm is a generalized framework, and we can see its use in Bayesian Networks now.

### Local Conditional Probability for Bayesian Networks

For a Bayesian Network

$$\begin{aligned}\Pr(y_1, \dots, y_n | \mathbf{x}, \theta) &= \prod_j \Pr(y_j | \mathbf{y}_{\text{Pa}(j)}, \mathbf{x}, \theta) \\ &= \prod_j \frac{\exp(F_\theta(\mathbf{y}_{\text{Pa}(j)}, y_j, j, \mathbf{x}))}{\sum_{y'_j=1}^m \exp(F_\theta(\mathbf{y}_{\text{Pa}(j)}, y'_j, j, \mathbf{x}))}\end{aligned}\tag{64}$$

The potentials above are locally normalized. Now, we can write the likelihood as

$$\begin{aligned}
 LL(\theta, \mathcal{D}) &= \sum_{i=1}^N \log \Pr(\mathbf{y}^i | \mathbf{x}^i, \theta) \\
 &= \sum_{i=1}^N \log \left( \prod_j \Pr(y_j^i | \mathbf{y}_{\text{Pa}(j)}^i, \mathbf{x}^i, \theta) \right) \\
 &= \sum_i \sum_j \log \Pr(y_j^i | \mathbf{y}_{\text{Pa}(j)}^i, \mathbf{x}^i, \theta) \\
 &= \sum_i \sum_j F_\theta(\mathbf{y}_{\text{Pa}(j)}^i, y_j^i, j, \mathbf{x}^i) - \log \sum_{y'=1}^m \exp(F_\theta(\mathbf{y}_{\text{Pa}(j)}^i, y', j, \mathbf{x}^i))
 \end{aligned} \tag{65}$$

We can notice that we are essentially doing a softmax over  $F_\theta(\cdot)$ , and thus we are doing a normal classification task.

### Table Potentials in Feature Framework

Consider a generative model (i.e  $\mathbf{x}^i$  does not exist) - such as an Hidden Markov Model.

- ◇  $F_\theta(\mathbf{y}_{\text{Pa}(j)}^i, y_j^i, j) = \log P(y_j^i | \mathbf{y}_{\text{Pa}(j)}^i)$ , and the normalizer vanishes.
- ◇  $\Pr(y_j | \mathbf{y}_{\text{Pa}(j)})$  is a table of real values denoting the probability of each value of  $x_j$  corresponding to each combination of values of the parents ( $\theta^j$ ).
- If each variable takes  $m$  values, and has  $k$  parents, then each  $\Pr(y_j | \mathbf{y}_{\text{Pa}(j)})$  will require  $m^{k+1}$  parameters in  $\theta^j$ .

$$\theta_{vu_1, \dots, u_k}^j = \Pr(y_j = v | \mathbf{y}_{\text{Pa}(j)} = [u_1, \dots, u_k]) \tag{66}$$

**Example 77** (HMM Parameter Learning). Consider the HMM shown in Figure 36. Say  $y_j \in \{1, 2, 3\}$  and  $x_j \in \{A, B, C, D\}$ . The above table

$(y_1, x_1)$	$(y_2, x_2)$	$(y_3, x_3)$	$(y_4, x_4)$
1, A	1, B	2, A	3, C
2, B	1, A	3, A	3, D
1, B	1, B	2, C	3, D

contains the values for  $\mathcal{D} = (N = 3, n = 4)$ . We need to calculate the probability of variable given its parent. Since  $y_1$  has no parent, we can write

$$P(y_1) = \begin{array}{|c|c|c|} \hline 1 & 2 & 3 \\ \hline \frac{2}{3} & \frac{1}{3} & 0 \\ \hline \end{array}$$

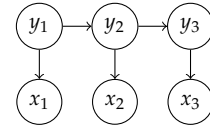


Figure 36: Sample HMM



The values from left to right denote  $\theta_1^1, \theta_2^1, \theta_3^1$ . For  $y_2$  we need to find  $\theta_{v:u}^2 = P(y_2 = v | y_1 = u)$  and this will have 9 values.

	$y = 1$	$y = 2$	$y = 3$
1	$\frac{2}{5}$	$\frac{2}{5}$	$\frac{1}{5}$
2	$\frac{1}{3}$	0	$\frac{2}{3}$
3	0	0	1

Now, to find  $\theta_{u:v}^{x_1} = P(x_1 = u, y_1 = v)$ , we will have 12 values.