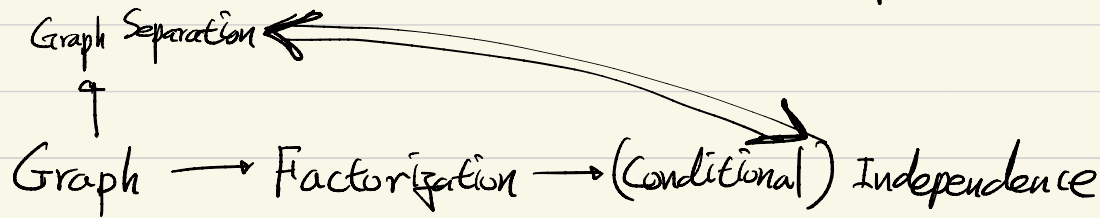
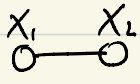


Probabilistic Graphical Model

- Bayesian Networks (Directed Graphical Models)
- Markov Random Fields (Undirected Graphical Models)
- Factor Graphs



ex) $X = [X_1, X_2]$

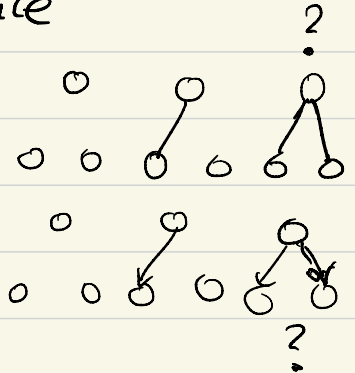


$$P(X_1, X_2)$$



$$P(X_1)P(X_2)$$

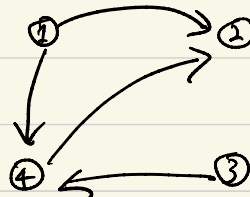
$$X_1 \perp\!\!\!\perp X_2$$



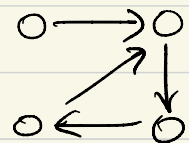
* Directed Graphical Models

Def. • Directed Acyclic Graph (DAG) $G = (V, E)$

- set of nodes $V = \{1, \dots, n\}$
- set of directed edges $E = \{(1,2), (4,2), (3,4), (1,4)\}$
 $(1,2) \neq (2,1)$



no cycle



cycle

- Parent set of i : $\pi_i = \{j \in V \mid (j,i) \in E\}$
- Directed Graphical Model on $G = (V, E)$ is a family of probability distributions on $X = [X_1, X_2, \dots, X_n]$ that factorizes as

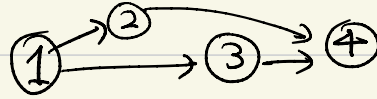
$$P(X_1, \dots, X_n) = \prod_{i=1}^n f_i(X_i, X_{\pi_i})$$

$$f_i: \mathcal{X}^{\pi_i+1} \rightarrow \mathbb{R}_+$$

$$\forall X_i \mid j \in \pi_i \text{ s.t. } \sum_{X_i} f_i(X_i, X_{\pi_i}) = 1.$$

Claim: $f_i(X_i, X_{\pi_i}) = P(X_i | X_{\pi_i})$ // ordering of nodes st $(i, j) \Rightarrow i < j$

without loss of generality, suppose topological ordering of DAG $G=(V, E)$ which is $(1, 2, \dots, n)$



$$P(X_1^n) = \prod_{i=1}^n f_i(X_i, X_{\pi_i})$$

$$X_i \triangleq [X_1 \dots X_i]$$

$$P(X_1^{n-1}) = \sum_{x_n} P(X_1^n) \stackrel{\text{Topological ordering}}{=} \prod_{i=1}^{n-1} f_i(X_i, X_{\pi_i}) \times \underbrace{\sum_{x_n} f_n(X_n, X_{\pi_n})}_{=1} = \prod_{i=1}^{n-1} f_i(X_i, X_{\pi_i})$$

$$f_n(X_n, X_{\pi_n}) = \frac{P(X_1^n)}{P(X_1^{n-1})} = P(X_n | X_1^{n-1}) \stackrel{\text{L.H.S is a function of only } (X_n, X_{\pi_n})}{\uparrow}$$

by induction, follows for all $i \in [n] \triangleq \{1, 2, \dots, n\}$

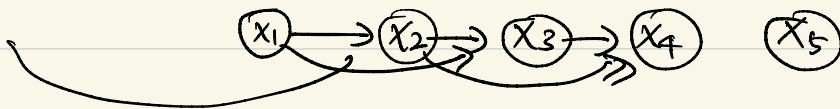
Directed Graphical Models encode Bayes rule (chain rule).

*chain rule: for any $P(x)$ and any ordering $(1, 2, \dots, n)$

$$P(x) = P(x_1) P(x_2 | x_1) P(x_3 | x_1, x_2) \dots P(x_n | x_1^n)$$

\Rightarrow can be represented by a complete DAG.

// all pairs connected



Q. What independence structure does general (incomplete) DAG encode?

ex)

$P(x_1) P(x_2 x_1) P(x_3 x_1, x_2)$	$P(x_1) P(x_2 x_1) P(x_3 x_1)$	$P(x_1) P(x_2 x_3) P(x_3)$	$P(x_2) P(x_3) P(x_1 x_2, x_3)$	$P(x_1) P(x_2 x_1) P(x_3 x_1)$	$P(x_1) P(x_2) P(x_3)$
\emptyset	$X_2 \perp\!\!\!\perp X_3 X_1$	$X_2 \perp\!\!\!\perp X_3$	$(X_1, X_2) \perp\!\!\!\perp X_3$	X_1, X_2, X_3 all independent of one another	

complex & unstructured \leftarrow
simple & structured \rightarrow

* Markov Property of Directed Graphical Models.

1. Directed ordered Markov Property

given a DAG $G=(V,E)$ with a topological ordering $(1, 2, \dots, n)$

$$X_i \perp\!\!\!\perp X_{Pr_i \setminus \pi_i} \mid X_{\pi_i}$$

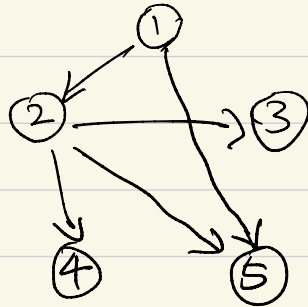
↑
set minus

$Pr_i \cong$ nodes before i
in the ordering.

proof \rightarrow chain rule \square

$(1, 2, 3, 4, 5)$ ordering

$(1, 2, 4, 5, 3)$ ordering



$$X_3 \perp\!\!\!\perp X_1 \mid X_2$$

$$X_3 \perp\!\!\!\perp (X_1, X_4, X_5) \mid X_2$$

2. Directed local Markov Property

$$X_i \perp\!\!\!\perp X_{ndr_i \setminus \pi_i} \mid X_{\pi_i}$$

X_1 no independence.

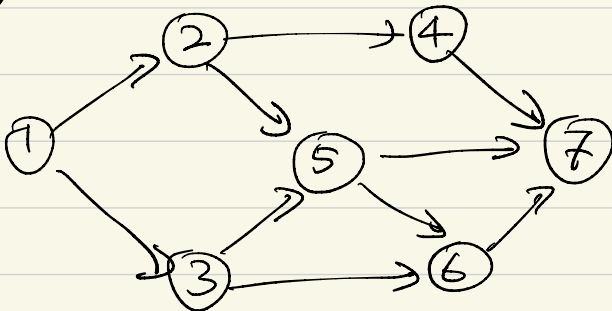
X_2 "

$$X_3 \perp\!\!\!\perp (X_1, X_4, X_5) \mid X_2$$

$$X_4 \perp\!\!\!\perp (X_1, X_3, X_5) \mid X_2$$

$$X_5 \perp\!\!\!\perp (X_3, X_4) \mid (X_1, X_2)$$

ex \rightarrow



more generally we want to answer if

$$A = \{4\}$$

$$B = \{3, 5\}$$

$$C = \{6\}$$

$$X_A \perp\!\!\!\perp X_C \mid X_B$$

3. Directed Global Markov Property.

$$X_A \perp\!\!\!\perp X_C \mid X_B \quad \text{for any } A, B, C \subseteq V$$

if A is d-separated from C w.r.t. B .

Def. $A \subseteq V$ is d-separated from $C \subseteq V$ w.r.t. $B \subseteq V$ if every path between any nodes $a \in A$ and $c \in C$ is blocked

- Path: $a - p_1 - p_2 - \dots - c$ that does not repeat nodes
- vs. walk: sequence of connected nodes that can repeat.
- a path is blocked if somewhere along the path

Intuition: consider $V = \{1, 2, 3\}$

$$\dots \textcircled{1} \rightarrow \textcircled{2} \rightarrow \textcircled{3} \dots \quad \& 2 \in B$$

$$1 \perp\!\!\!\perp 3 \mid 2$$

$$\dots \textcircled{1} \leftarrow \textcircled{2} \leftarrow \textcircled{3} \dots \quad \& 2 \in B$$

$$1 \perp\!\!\!\perp 3 \mid 2$$

$$1 \perp\!\!\!\perp 3 \mid 2$$

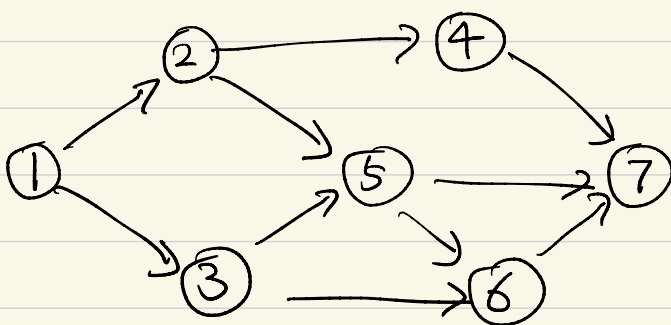
$$\dots \textcircled{1} \leftarrow \textcircled{2} \rightarrow \textcircled{3} \dots \quad \& 2 \in B$$

$$\dots \textcircled{1} \rightarrow \textcircled{2} \leftarrow \textcircled{3} \quad \& 2 \notin B$$

$$1 \perp\!\!\!\perp 3 \text{ but } 1 \not\perp\!\!\!\perp 3 \mid 2$$

* Bayes ball algorithm identifies conditional independence

$$X_A \perp\!\!\!\perp X_C \mid X_B$$



$$A = \{4\}$$

$$B = \{3, 5\}$$

$$C = \{6\}$$

Theorem. the following are equivalent.

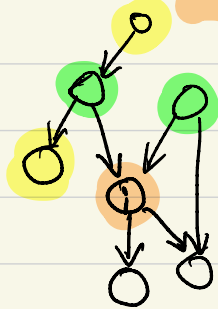
a) $P(x)$ factorizes according to a DAG $G=(V,E)$

b) $P(x)$ satisfies the directed global Markov property.

c) $P(x)$ satisfies the directed local Markov property

proof. b) \Rightarrow c)

set $A=i, B=\pi_i, C=nd_i \setminus \pi_i$



c) \Rightarrow a)

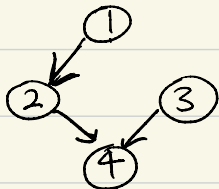
Consider any topological ordering, say $(1, 2, \dots, n)$

$$P(x) \stackrel{\text{chain rule}}{=} \prod_i P_i(x_i | x_{i-1}) \stackrel{\text{local Markov}}{=} \prod_i P_i(x_i | x_{\pi_i}) \underbrace{f_i(x_i, x_{\pi_i})}$$

a) \Rightarrow b) use induction (separate notes).

let $I(G)$ denote the set of C.I. relations implied by G .

ex)



$$I(G) = \{ X_3 \perp\!\!\!\perp (X_1, X_2), X_1 \perp\!\!\!\perp (X_3, X_4) | X_2 \}$$

let $I(P)$ denote the set of C.I. relations implied by $P(x)$

ex) Consider indep $Z_1, Z_2, \dots \sim \text{Bern}(1/3)$

let $X_1 = Z_1, X_3 = Z_3, X_2 = X_1, X_4 = X_2 \oplus X_3$

then $I(P) = \{ X_3 \perp\!\!\!\perp (X_1, X_2), X_1 \perp\!\!\!\perp (X_3, X_4) | X_2 \}$

remark 1. $\exists P$ s.t. there is no ^{DAG} G satisfying $I(P) = I(G)$

proof $\rightarrow P = \begin{cases} X_1 = X_2 \\ X_3 = X_1 + X_2 \end{cases} \quad I(P) = \begin{cases} X_1 \perp\!\!\!\perp X_3 \mid X_2 \\ X_2 \perp\!\!\!\perp X_3 \mid X_1 \end{cases}$

remark 2. $\forall G, \exists P$ s.t. $I(G) = I(P)$.

remark 3. $\exists G_1 \neq G_2$ s.t. $I(G_1) = I(G_2)$



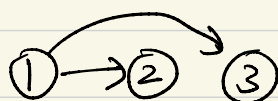
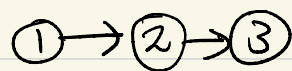
Def. DAG $G = (V, E)$ is a perfect map of P if $I(P) = I(G)$

Def. DAG $G = (V, E)$ is an I-map of P if $I(G) \subseteq I(P)$

Def. DAG $G = (V, E)$ is a minimal I-map of P if removing a single edge from G results in G no longer being an I-map.

Remark 4. minimal I-map is not unique.

- different ordering gives different I-maps.
- even with the same ordering, I-map is not unique



$P: \begin{cases} X_1 = X_2 \\ X_3 = X_1 + X_2 \end{cases}$

$I(P) = \{ X_3 \perp\!\!\!\perp X_1 \mid X_2, X_3 \perp\!\!\!\perp X_2 \mid X_1 \}$