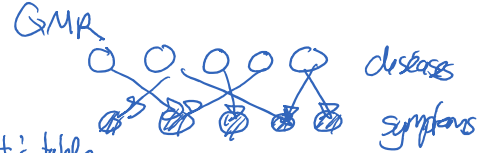


today : • graph theory
• DGM

Graphical model

graph. model $\leadsto$ prob. theory + C.S.
 $\downarrow$ $\downarrow$
 R.V. graph
 graph $\rightarrow$ efficient data structure

e.g. $X_1, \dots, X_n$ R.V. $n=100s$
 $X_i \in \{0,1\}$
 $\Rightarrow 2^{100}$ #s table $\leadsto$ intractable



graph theory review :

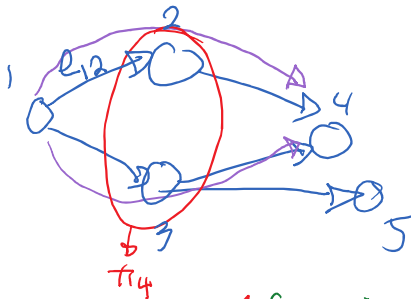
directed graph
 "digraph"

$$G = (V, E)$$

$V = \{1, \dots, n\}$ "nodes/vertices"

$E \subseteq V \times V$ "directed edges"

$$e_{1,2} = (1, 2)$$



directed path $1 \leadsto 4$

$(1,2), (2,4)$ seq. of compatible edges
 or
 $(1,3), (3,4)$

$$\pi_i \triangleq \{j \in V : \exists (j,i) \in E\}$$

set of parents of i

$$\text{children}(i) \triangleq \{j \in V : \exists (i,j) \in E\}$$

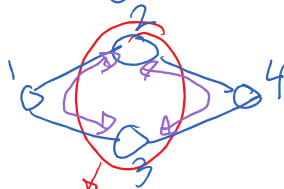
(Note: no self loop in this class
 i.e. $|e| = 2$)

undirected graph : $G = (V, E)$

where elements of E are 2-sets (sets of 2 elements)

thus we have $\{i,j\} = \{j,i\}$

Vs. $(i,j) \neq (j,i)$ [order matters]



"neighbors" of node 4 or 1

undirected path $2 \leadsto 3$

$N(i)$ for neighbors of i

$$= \{j \in V : \exists \{i,j\} \in E\}$$

⊗ neighbors replace the parent/children terminology from a digraph

def: DAG = directed acyclic graph = digraph with no cycles

def: an ordering $I: V \rightarrow \{1, \dots, |V|\}$ is said to be topological for digraph G

iff nodes in π_i appear before i in I $\forall i$



$$(j \in \pi_i \Rightarrow I(j) < I(i))$$

$\rightarrow$ if top. ordering $\Rightarrow$ all edges go from left to right
[no "back edge"]

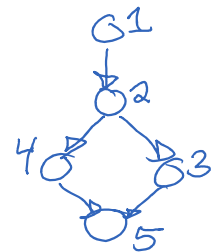
prop.: digraph G is a DAG $\Leftrightarrow \exists$ a topological ordering of G

proof: $\Leftarrow$) trivial: no back edge $\Rightarrow$ no cycle

$\Rightarrow$) use DFS algorithm to label nodes in decreasing order when have no children unlabeled
to construct a top. sort ordering

in $O(|E| + |V|)$

top. sort $\rightarrow$ finding a topological ordering of graph.



notation for graph models

n discrete R.V. $X_1, \dots, X_n$

$\hookrightarrow$ discrete R.V. for simplicity

(cond. distribution concept is tricky to formalize for dis. R.V.)

$V \rightarrow$ set of vertices
one R.V. per node

(see Borel-Kolmogorov paradox)

$$\begin{aligned} \text{joint } p(X_1=x_1, \dots, X_n=x_n) &= p(x_1, \dots, x_n) \quad \text{shorthand} \quad x = x_{1:n} \\ &= p(x_V) = p(x) \end{aligned}$$

for any $A \subseteq V$

$$p(x_A) = P\{x_i=x_i : i \in A\} = \sum_{x_{A^c}} p(x_A, x_{A^c})$$

subset of "subsets" summing over all possible values of x_{A^c} can take

i.e. $(x_i)_{i \in A^c} = v_{A^c}$

question: is $p(x_1, x_2, x_4) \stackrel{?}{=} p(x_2, x_1, x_4)$?

yes? usually in this class, we used "typed convention"

revisit cond. independence:

let $A, B, C \subseteq V$

⊗ $X_A \perp\!\!\!\perp X_B \mid X_C$

(F) $\Leftrightarrow p(x_A, x_B \mid x_C) = p(x_A \mid x_C) p(x_B \mid x_C)$ $\forall x_A, x_B, x_C$
 st. $p(x_C) > 0$

(C) $\Leftrightarrow p(x_A \mid x_B, x_C) = p(x_A \mid x_C)$ $\forall x_A, x_B, x_C$
 st. $p(x_B, x_C) > 0$

⊗ "marginal independence": $X_A \perp\!\!\!\perp X_B \mid \emptyset$
 or $X_\emptyset$
 $p(x_A, x_B) = p(x_A) p(x_B)$

2 facts about cond. indep.:

1) can repeat variables in statement (for convenience)

$X \perp\!\!\!\perp Y, Z \mid Z, W$ $\leftarrow$ is equivalent $X \perp\!\!\!\perp Y \mid Z, W$
 does not do anything $\leftarrow$ is fine to say

2) decomposition: $X \perp\!\!\!\perp (Y, Z) \mid W \Rightarrow X \perp\!\!\!\perp Y \mid W$
 and $X \perp\!\!\!\perp Z \mid W$

⊗ pairwise indep. $\nRightarrow$ mutual indep. $\rightarrow$ see lecture 3
 $Z = X \oplus Y$
 XOR

⊗ chain rule $p(x_v) = \prod_{i=1}^n p(x_i \mid x_{1:i-1})$
 always true

last conditional $p(x_n \mid x_{1:n-1})$
 $\leftarrow$ table with 2^n entries

assumption in DBM

$p(x_v) = \prod_{i=1}^n p(x_i \mid x_{\pi_i}) \rightarrow$ tables of $2^{\max_i |\pi_i| + 1}$

$X_i \perp\!\!\!\perp X_{1:i-1} \mid X_{\pi_i}$

16h08

Directed graph. model

let $G = (V, E)$ be a DAG

... direct ...

let $G = (V, E)$ be a DAG

a directed graphical model (DGM) (associated with G) (aka Bayesian network) is a family of distributions over X_V

$$\mathcal{L}(G) = \{ p \text{ is a dist. over } X_V : \exists \text{ legal factors } f_i \text{ s.t.} \}$$

$$p(x_V) = \prod_i f_i(x_i | x_{\pi_i}) \quad \forall x_V$$

$$\rightarrow \text{s.t. } f_i : \Omega_{X_i} \times \Omega_{X_{\pi_i}} \rightarrow [0, 1]$$

$$\text{s.t. } \sum_{x_i} f_i(x_i | x_{\pi_i}) = 1 \quad \forall x_{\pi_i}$$

$\rightarrow f_i$ is like a local CPT (conditional probability table)

terminology: if we can write $p(x_V) = \prod_i f_i(x_i | x_{\pi_i})$

then we say that " p factorizes according to G " $\rightarrow$ this defines G

one example:



$$p \in \mathcal{L}(G) \Leftrightarrow \exists f_X, f_Y, f_Z \text{ legal}$$

$$\text{s.t. } p(x, y, z) = f_X(x) f_Y(y) f_Z(z | x, y)$$

"leaf plucking" property (fundamental property of DGM)

let $p \in \mathcal{L}(G)$; let n be a leaf in G (i.e. n has no children)

$$a) \text{ then } p(x_{1:n-1}) \in \mathcal{L}(G - \{n\})$$

$\uparrow$ means remove node n from G

$$b) \text{ moreover if } p(x_{1:n}) = \prod_i f_i(x_i | x_{\pi_i}) \text{ then } p(x_{1:n-1}) = \prod_{i=1}^{n-1} f_i(x_i | x_{\pi_i})$$

$$\text{proof: } p(x_n, x_{1:n-1}) = f_n(x_n | x_{\pi_n}) \prod_{i=1}^{n-1} f_i(x_i | x_{\pi_i})$$

$\uparrow$ no n in any π_i

$$p(x_{1:n-1}) = \sum_{x_n} p(x_n, x_{1:n-1}) = \left(\sum_{x_n} f_n(x_n | x_{\pi_n}) \right) \left(\prod_{i=1}^{n-1} f_i(x_i | x_{\pi_i}) \right)$$

by def.

proposition: if $p \in \mathcal{L}(G)$

let $\{f_i\}$ be a factorization w.r. to G of p

$$\text{then } \forall i \quad p(x_i | x_{\pi_i}) = f_i(x_i | x_{\pi_i}) \quad \forall x_{\pi_i}$$

i.e. factors are correct conditionals of p (and are unique)

proof: wLOG, let $(1, \dots, n)$ be a top. sorting of G (possible since G is a DAG)
 let i be fixed; we want to show that $p(x_i | x_{\pi_i}) = f_i(x_i | x_{\pi_i})$

- n is a leaf $\rightarrow$ "pluck it" to get $p(x_{1:n-1}) = \prod_{j=1}^{n-1} f_j(x_j | x_{\pi_j})$
 justification for a DAG where x_{n-1} is now a leaf
- pluck $n-1$ as well? (as leaf, because of top. sort.)

- keep doing this [in reverse order $n-1, n-2, n-3, \dots, i+1$] to get
 $p(x_{1:i}) = f_i(x_i | x_{\pi_i}) \prod_{j=i}^{n-1} f_j(x_j | x_{\pi_j})$
 $\triangleq g(x_{1:i-1})$ no x_i in any π_j by top. sort property

partition: $1:i$ as $\{x_i\} \cup \{x_{\pi_i}\} \cup A$ [$A \triangleq 1:i-1 \setminus \pi_i$]
 $p(x_{1:i}) = p(x_i, x_{\pi_i}, x_A)$

$$p(x_i | x_{\pi_i}) = \frac{\sum_{x_A} p(x_i, x_{\pi_i}, x_A)}{\sum_{x_i} \sum_{x_A} p(x_i, x_{\pi_i}, x_A)} = \frac{f_i(x_i | x_{\pi_i}) \sum_{x_A} g(x_{1:i-1})}{\sum_{x_i} f_i(x_i | x_{\pi_i}) \sum_{x_A} g(x_{1:i-1})} = f_i(x_i | x_{\pi_i})$$

there is no x_i

$\oplus$ (now), we can safely write

$$\mathcal{L}(G) = \{ p : p(x_v) = \prod_{i=1}^n p(x_i | x_{\pi_i}) \}$$

properties of DGM:

adding edges $\Rightarrow$ more distributions

i.e. $G = (V, E)$ and $G' = (V, E')$ with $E' \supseteq E$
 then $\mathcal{L}(G) \subseteq \mathcal{L}(G')$

examples:

- $E = \emptyset$ $\Rightarrow \mathcal{L}(G)$ contains only fully independent distributions
 (trivial graph) i.e. $p(x_v) = \prod_i p(x_i)$
 $\uparrow$
 $p(x_i | \emptyset)$
- complete digraph (DAG)

- complete digraph (DAG)

for all $i \neq j$ either $(i, j) \in E$
or $(j, i) \in E$



$$p(x_i | \emptyset)$$

got WLOG

$$p(x_v) = \prod_i p(x_i | x_1 : x_{i-1})$$

(like chain rule)
 $\Rightarrow$ all dist. on X_V are in $\mathcal{G}(\text{complete})$

⊛ removing edges imposes more factorization constraints
(and thus more cond. indep. assumptions)