

Lecture 11 - DGM

Tuesday, October 10, 2023 2:28 PM

today: • graph theory
• DGM

graphical model

graph. model $\leadsto$ prob. theory + C.S.
 $\downarrow$ $\downarrow$
 R.V. graph

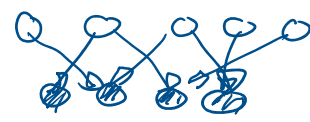
graph $\rightarrow$ efficient data structure

e.g. $X_1, X_2, \dots, X_n$ R.V.

GMR

$X_i \in \{0,1\}$ $n=1005$

$\Rightarrow 2^{1005}$ #'s table
 $\leadsto$ intractable



diseases
 symptoms

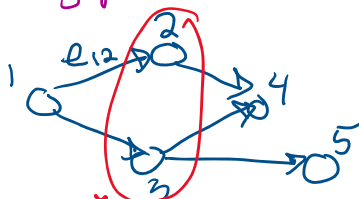
graph theory review

directed graph $G=(V,E)$

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

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

"digraph"



$e_{12} = (1,2)$

directed path

$1 \leadsto 4$

compatible req.
 of edges

or $(1,2), (2,4)$
 $(1,3), (3,4)$

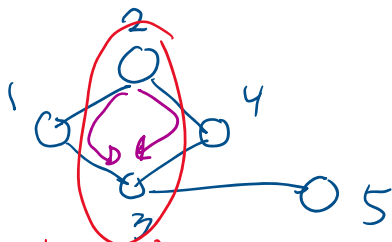
$\pi_i \triangleq \{j \in V : \exists (j,i) \in E\}$

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
 (set of 2 different elements of V)



"neighbors" of node 4 or 1

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

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

undirected path $2 \leadsto 3$

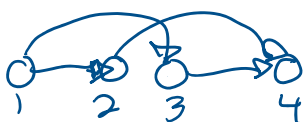
$N(i)$ for neighbors of i
 $\hat{=} \{j \in V : \exists \{i, j\} \in E\}$

⊗ neighbors replace the parents/children terminology from 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 $I \forall i$



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

→ 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

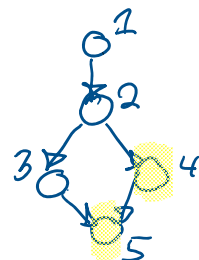
proof: $\Leftarrow$ trivial: no back edge $\Rightarrow$ no cycle

$\Rightarrow$) use DFS algorithm to label nodes in decreasing order when have no children

to construct a top. sort.

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

top. sort $\rightarrow$ finding a topological ordering



notation for graphical model

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

$\hookrightarrow$ discrete R.V. for simplicity

cond. dist. concept is tricky to formalize for $discrete$ R.V.
 (see Kalmogorov - Kalmogorov paradox)

$V \sim$ set of vertices
 can R.V. on nodes

threshold

V ~ set of vertices
one R.V. per node

perceptron

joint $p(X_1=x_1, X_2=x_2, \dots, X_n=x_n) \stackrel{\text{shorthand}}{=} p(x_1, \dots, x_n) \quad \mathcal{X} = \mathcal{X}_1 \times \dots \times \mathcal{X}_n$
 $= p(x_V) \stackrel{(\text{B})}{=} p(x)$

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 "subscripts" summing over all possible values of x_{A^c} i.e. $(x_i)_{i \in A^c} \subseteq V \setminus A$

question = is $p(x_1, x_2, x_4) \stackrel{?}{=} p(x_2, x_1, x_4)$?
 yes? usually in this class, we "typed conventions"

revisit cond. indep.

let $A, B, C \subseteq V$

⊕ $X_A \perp\!\!\!\perp X_B \mid X_C$

(F) $\Leftrightarrow p(x_A, x_B \mid x_C) = p(x_A \mid x_C) p(x_B \mid x_C) \quad \forall x_A, x_B, x_C$
 factorization s.t. $p(x_C) > 0$

(C) $p(x_A \mid x_B, x_C) = p(x_A \mid x_C) \quad \forall x_A, x_B, x_C$
 conditioning s.t. $p(x_B, x_C) > 0$

⊕ "marginal independence": $X_A \perp\!\!\!\perp X_B \quad (I \emptyset)$
 $p(x_A, x_B) = p(x_A) p(x_B)$

2 facts about cond. indep.:

1) can repeat variables in statement
 (for convenience)

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

2) decomposition: $X \perp\!\!\!\perp (Y, Z) \mid W \Rightarrow \begin{cases} X \perp\!\!\!\perp Y \mid W \\ X \perp\!\!\!\perp Z \mid W \end{cases}$

⊕ pairwise indep. $\nRightarrow$ mutual indep. $\rightarrow$ see lecture (3)?

⊗ chain rule (always true) $p(x_v) = \prod_{i=1}^n p(x_i | x_{1:i-1})$ $\leftarrow$ last cond. $p(x_n | x_{1:n-1})$
 table with 2^n entries

assumption in DBM

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

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

15h30

directed graph. model

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

a directed graphical model (DBM) (associated with G) (also a Bayesian network)

is a family of distributions over X_V

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

$$p(x_v) = \prod_{i=1}^n f_i(x_i | x_{\pi_i}) \quad \forall x$$

$$\left. \begin{aligned} &\text{st. } f_i : \Omega_{X_i} \times \Omega_{X_{\pi_i}} \rightarrow [0,1] \\ &\text{st. } \sum_{x_i} f_i(x_i | x_{\pi_i}) = 1 \quad \forall x_{\pi_i} \\ &\Rightarrow f_i \text{ is like a CPT (conditional prob. table)} \end{aligned} \right\}$$

fundamentally: if we can write $p(x_v) = \prod_i f_i(x_i | x_{\pi_i})$ $\rightarrow$ this determines G
 then we say that " p factorizes according to G "



$$p \in \mathcal{L}(G) \Leftrightarrow \exists f_x, f_y, f_z \text{ legal}$$

$$\text{st. } p(x,y,z) = f_x(x) f_y(y) f_z(z|x,y)$$

"leaf plucking" property (fundamental property of DBM)

"leaf plucking" property (fundamental property of DAG)

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

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

means remove node n from G

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

proof:

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

no n in any π_i

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

1 by defn

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

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

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

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

proof: wlog, let $(1, \dots, n)$ be a tp 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 $p(x_{1:n-1}) = \prod_{j=1}^{n-1} f_j(x_j | x_{\pi_j})$

factorization for a DAG
where x_{n-1} is now a leaf

• pluck $n-1$ as well? (as leaf, because of
tp-sort.)

• keep doing this [in reverse order $n-1, n-2, \dots, i+1$] to get

$$p(x_{1:i}) = f_i(x_i | x_{\pi_i}) \prod_{j=i}^{n-1} f_j(x_j | x_{\pi_j})$$

$\triangleq g(x_{1:i-1})$ i.e. there is no x_i
by tp-sort. property

partition $1:i$ as $\pi_i \cup \pi_i \cup A$ [$A \triangleq 1:i-1 \setminus \pi_i$]

$$p(x_{1:i}) = p(x_i, x_{\pi_i}, x_A)$$

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

(is there is no x_i ? there)

② (now), we can safely write

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

properties of DAG:

adding edges $\Rightarrow$ more distributions

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

examples:

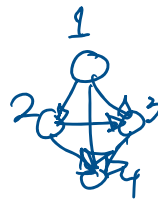
• $E = \emptyset$
(trivial graph)

$\Rightarrow \mathcal{J}(G)$ contains only fully independent distributions

$$\text{i.e. } p(x_V) = \prod_{i=1}^n p(x_i)$$

• complete DAG

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



get WLOG

$$p(x_V) = \prod_{i=1}^n p(x_i | x_{\pi_i})$$

(like chain rule)

$\Rightarrow$ all dist. on X_V
are in $\mathcal{J}(G_{\text{complete}})$

⊛ removing edges impose more factorization constraints

(and thus more cond. indep. assumptions)

"absence of edge" is meaningful in a DGM