

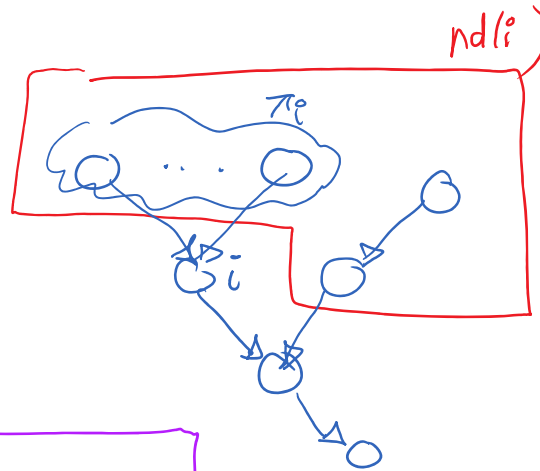
Lecture 12 - scribbles

Friday, October 12, 2018 13:34

today: finish DGM
start UGM

cond. indep. statements in DGM:

let $nd(i) \triangleq \{j : \text{no path } i \rightarrow j\}$
"non-descendants" of i



prop: $p \in \mathcal{L}(G) \iff X_i \perp\!\!\!\perp X_{nd(i)} \mid X_{\pi_i}$

(by decomposition $\Rightarrow X_i \perp\!\!\!\perp X_j \mid X_{\pi_i} \quad \forall j \in nd(i)$)

proof:

$\Rightarrow$) key point: let i be fixed,

then $\exists$ a tp. ordering s.t. $nd(i)$ are exactly before i

i.e. $(nd(i), i, \underbrace{descendant(i)})$

pick all these $\Rightarrow$

$$\Rightarrow p(x_i, x_{nd(i)}) = p(x_i \mid x_{\pi_i}) \prod_{j \in nd(i)} p(x_j \mid x_{\pi_j})$$

$p(x_1, \dots, x_n) = p(x_1 \mid x_{\pi_1}) \dots p(x_n \mid x_{\pi_n})$

$j \in nd(i)$

$$p(x_i | x_{nd(i)}) = \frac{p(x_i, x_{nd(i)})}{p(x_{nd(i)})} = p(x_i | x_{\pi_i}) \prod_{j \in nd(i)} \cancel{p(x_j | x_{\pi_j})} = p(x_i | x_{\pi_i})$$

$\left(\sum_{x_j} \cancel{p(x_j | x_{\pi_j})} \right) \prod_j \cancel{p(x_j | x_{\pi_j})}$
 $\downarrow$ no x_j here
 1 (because $j \in nd(i)$)
 $\Rightarrow i \notin \pi_j$

$\Leftarrow$) (suppose p satisfies cond. indep. statements)
 Let $1:n$ be a tp sort

then $1:i-1 \subseteq nd(i) \forall i$

[say $j < i$ is a descendant of i]
 $\Rightarrow$ back edge $\nexists$
 contradiction

$\Rightarrow X_i \perp\!\!\!\perp X_{1:i-1} | X_{\pi_i}$ (by decomposition)

$$p(x_i) = \prod_{i=1}^n p(x_i | x_{1:i-1}) \quad (\text{by chain rule})$$

$\xrightarrow{\text{this includes } \pi_i}$

$$= \prod_{i=1}^n p(x_i | x_{\pi_i}) \quad (\text{by C.I.})$$

$$\Rightarrow p \in \mathcal{J}(G)$$

$$p(x_i | x_{\pi_i}, x_{1:i-1}) \stackrel{\text{by cond. indep.}}{=} p(x_i | x_{\pi_i})$$

Other C.I. statements?

chain ... just any (undirected) path in graph from a to b

chain from a to b : just any (undirected) path in graph from a to b

d-separation : (intuition, is do not want this situation

def:

sets A & B are said to be d-separated by C

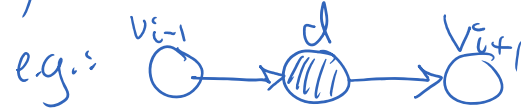
Set of observed R.V.
conditioned R.V.

iff all chains from $a \in A$ to $b \in B$ are "blocked" given C

where a chain from a to b is "blocked" at node d

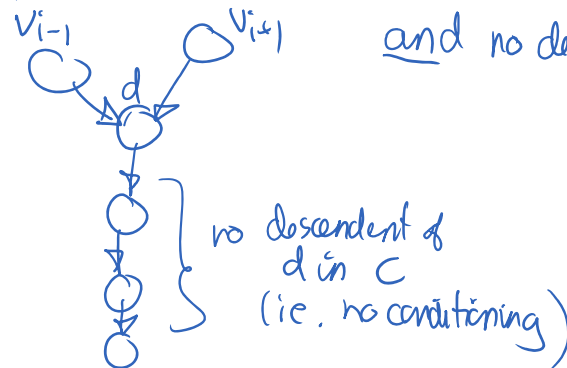
subpath of chain

if a) either $d \in C$ and (v_{i-1}, d, v_{i+1}) is not a v-structure



b) $d \notin C$ and (v_{i-1}, d, v_{i+1}) is a v-structure

and no descendant of d is in C



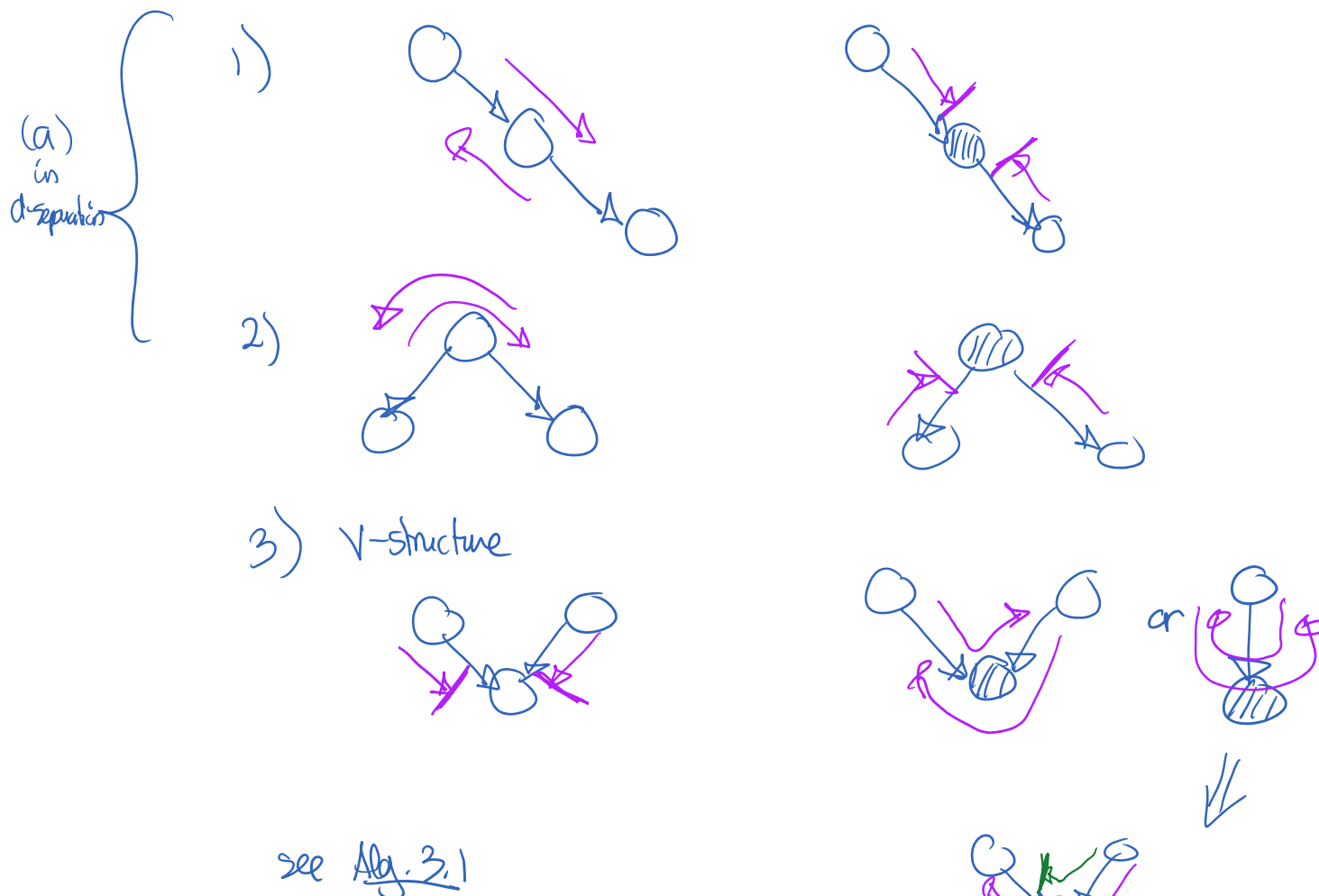
prop:

if $\phi \in \mathcal{I}(G) \Leftrightarrow X_A \perp\!\!\!\perp X_B \mid X_C$

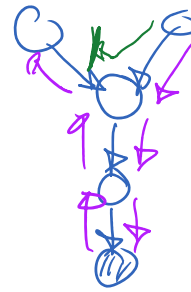
that is, if and only if ϕ is d-separated by C

prop. $\left| \begin{array}{l} \exists \rho \in \mathcal{J}(G) \Leftrightarrow X_A \perp\!\!\!\perp X_B \mid X_C \\ \forall A, B, C \text{ st. } A \text{ \& } B \text{ are } \underline{\text{d-separated by } C} \end{array} \right|$

"Bayes-Ball" alg. : "intuitive" alg. to check d-separation
rules for balls/chains being blocked



see Alg. 3.1
in L&F book



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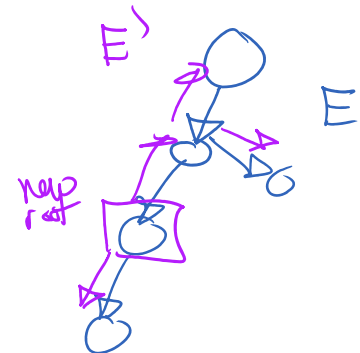
properties of DGM:

inclusion: $E \subseteq E' \Rightarrow \mathcal{I}(G) \subseteq \mathcal{I}(G')$
(adding edges increase # of distributions)

reversal: if G is a directed tree (or forest)
 $\hookrightarrow (|\pi_i| \leq 1$; i.e. there is no v-structure)

then let E' be another
directed tree by choosing
a different root
(reverse some edges, while keeping a directed tree)

$\Rightarrow \mathcal{I}(G) = \mathcal{I}(G')$
 $\hookrightarrow [G' = (V, E')]$



⊛ this is why direction of edges
are not causal

$$\hookrightarrow (G' = (V, E'))$$

⊗ this is why direction of edges are not causal

$$[\text{eg. } p(x, y) = p(x|y)p(y) = p(y|x)p(x)]$$



rephrasing: all directed trees from a undirected tree give same DGM

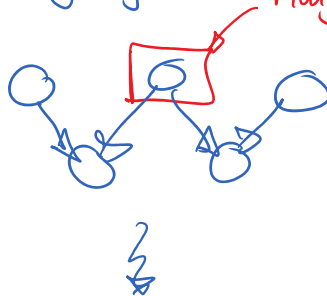
marginalizing:

- marginalizing a leaf node n gives us a smaller DGM

let $S = \{ q \text{ is dist on } x_{1:n-1} \text{ s.t. } q(x_{1:n-1}) = p(x_{1:n-1}) \text{ for } p \in \mathcal{S}(G) \}$
 then $S = \mathcal{S}(G')$ where G' is G with leaf n removed

- not true for all marginalization

eg-



marginalizing out this node

→ get a set of distributions $\neq$ to any $\mathcal{S}(G')$ for G'



ie. marginalization is not a "closed operation" on DGM

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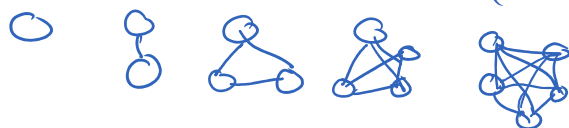
undirected GM (UGM) (also: Markov random field or Markov network)

Let $G=(V,E)$ be an undirected graph

Let $\mathcal{C}$ be the set of cliques of G

clique = fully connected set of nodes

(ie. $C \in \mathcal{C} \Leftrightarrow \forall i,j \in C, i \neq j, \{i,j\} \in E$)



UGM associated with G :

$$\mathcal{J}(G) \triangleq \left\{ p : p(x_v) = \frac{1}{Z} \prod_{C \in \mathcal{C}} \psi_C(x_C) \right\}$$

for some "potentials" ψ_C s.t.

$$\psi_C(x_C) \geq 0 \quad \forall x_C$$

$$\text{and } Z \triangleq \sum \left(\prod \psi_C(x_C) \right) \quad \text{"partition function"}$$

$$\text{and } Z \triangleq \sum_x \left(\prod_{C \in \mathcal{C}} \psi_C(x_C) \right) \quad \text{"partition function"}$$

notes: • unlike in a DGM (where we could think of C to be (i, π_i) , $\psi_C(x_C) = p(x_i | x_{\pi_i})$)

$\psi_C(x_C)$ is not directly related to $p(x_C)$

- can multiply any $\psi_C(\cdot)$ by a constant without changing p
- it is sufficient to consider only $\mathcal{C}_{\max}$, the set of maximal cliques

e.g. $C' \subseteq C$

redefine $\psi_C^{\text{new}}(x_C) = \psi_C^{\text{old}}(x_C) \psi_{C'}^{\text{old}}(x_{C'})$

(choose one C
when C' is included
in many C 's)

[we'll see later it is convenient to
consider 'overparameterization' of trees
using both $\psi_i(x_i)$ and
 $\psi_{ij}(x_i, x_j)$]



properties:

• as before, $E \subseteq E' \Rightarrow \mathcal{G}(G) \subseteq \mathcal{G}(G')$

$E = \emptyset \Rightarrow \mathcal{G}(G) = \text{fully factorized dist.}$

$E = \text{all pairs}$
(i.e. G is one
big clique)

$\Rightarrow$ all distributions

- If $\psi_c(x_c) > 0 \forall x_c$

can write $p(x_v) = \exp\left(\underbrace{\sum_{c \in \mathcal{C}_v} \log \psi_c(x_c)}_{\langle \Theta_{C_v}, T_C(x_c) \rangle} - \log Z\right)$

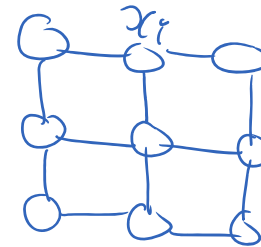
physics link: negative energy function

e.g. Ising model in physics:

$$x_i \in \{0, 1\}$$

node potentials $\rightarrow E_i$

edge potentials $\rightarrow E_{i,j}$



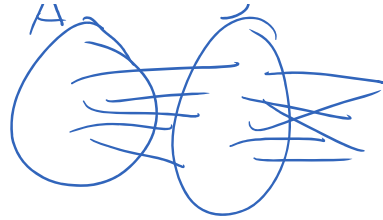
think also
social network modeling

conditional independence for UGM:

def: we say that p satisfies global Markov property (with respect to undirected graph G)

iff $\forall A, B, S \subseteq V$ s.t. S separates A from B in G
disjoin!





prop: $p \in \mathcal{I}(G) \Rightarrow p$ satisfies the global Markov property

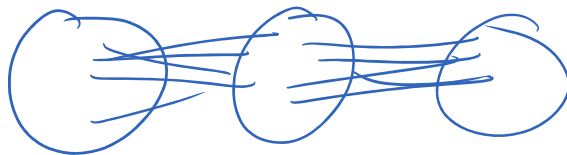
proof: WLOG, we assume $A \cup B \cup S = V$

[why? if not, let $\tilde{A} \triangleq A \cup \{a \in V : a \text{ and } A \text{ are not separated by } S\}$
 $\tilde{B} \triangleq V \setminus (S \cup \tilde{A})$]

then if have $X_A \perp\!\!\!\perp X_{\tilde{B}} \mid X_S \Rightarrow X_A \perp\!\!\!\perp X_B \mid X_S$

[exercise: show that $b \in \tilde{B}$
 $\Rightarrow b$ separated from A by S]

$$V = A \cup S \cup B$$



Let $C \in \mathcal{C}$

cannot have $C \cap A \neq \emptyset$ and $C \cap B \neq \emptyset$

$$\text{thus } p(x) = \frac{1}{Z} \prod_{\substack{C \in \mathcal{C} \\ C \subseteq A \cup S}} \psi_C(x_C) \prod_{\substack{C' \in \mathcal{C} \\ C' \subseteq A \cup S \\ \Rightarrow C' \subseteq B \cup S}} \psi_{C'}(x_{C'}) = f(x_{A \cup S}) g(x_{B \cup S})$$

$$p(x_A | x_S) \propto p(\underbrace{x_A, x_S}_{x_{AUS}}) = \sum_{x_B} p(x_v) \stackrel{\text{and } C' \notin S}{=} \sum_{x_B} f(x_{AUS}) g(x_{BUS})$$

$$= f(x_{AUS}) \underbrace{\sum_{x_B} g(x_{BUS})}_{\text{constant with respect to } x_A}$$

$$\Rightarrow p(x_A | x_S) = \frac{f(x_A, x_S)}{\sum_{x_A} f(x_A, x_S)}$$

$$\text{similarly, } p(x_B | x_S) = \frac{g(x_B, x_S)}{\sum_{x_B} g(x_B, x_S)}$$

$$p(x_A | x_S) p(x_B | x_S) = \frac{f(x_{AUS}) g(x_{BUS})}{\sum_{x_A} \sum_{x_B} f(x_A, x_S) g(x_B, x_S)} \} p(x_v) = p(x_A, x_B | x_S)$$

i.e. $X_A \perp\!\!\!\perp X_B | X_S$ //

thm: (Hammersley-Clifford) iff $p(x_v) > 0 \forall x_v$

then $p \in \mathcal{I}(G) \Leftrightarrow p$ satisfies global Markov property

then $p \in \mathcal{Z}(G) \Leftrightarrow p$ satisfies global Markov property
 $\stackrel{\text{Ch. 6}}{\Leftrightarrow}$

proof: see ch. 6 of Mike's book; use "Möbius inversion formula"

(as exclusion-inclusion principle
in prob)