

Lecture Notes #6

d-seperation!

→ for sets of nodes x, y, E , when is

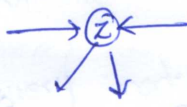
$$\left. \begin{aligned} P(y|E, x) &= P(y|E) \\ P(x|E, y) &= P(x|E) \\ P(x, y|E) &= P(x|E) P(y|E) \end{aligned} \right\} ?$$

→ True if all paths from x to y are "blocked"

→ A path is blocked if it has a node z that satisfies either

i) $z \in E \rightarrow (z) \rightarrow$ intervening Cause

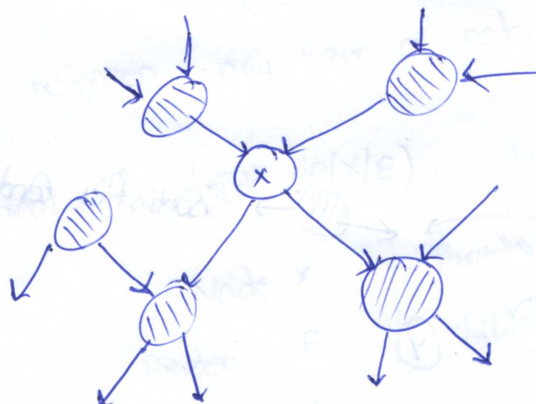
ii) $z \in E \leftarrow (z) \rightarrow$ Common Cause

OR) iii) $z \notin E$  no observed Common effect.
 $\text{descendants}(z) \not\subset E$

Markov Blanket!

Markov Blanket B_x of node x consists of parents, children and "spouses" (other parents of children).

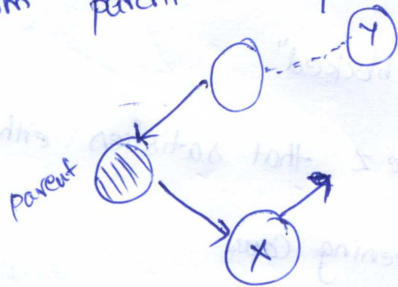
THEOREM! $P(x|B_x, y) = P(x|B_x)$ where $y \notin \{x, B_x\}$



All the other nodes, no matter wherever they appear, if ϕ will be independent of x , if Conditioned on B_x

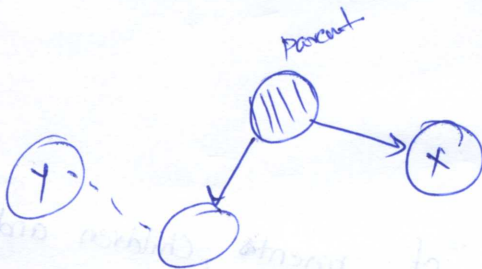
There are 5 different Cases to Consider. The path from x to y may pass

i) from parent of parent of x



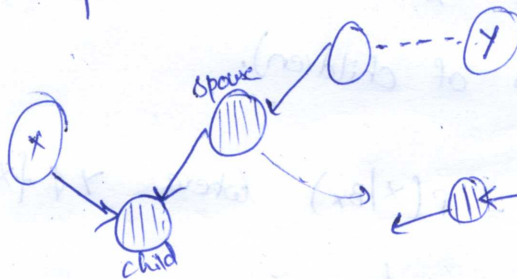
ϕ satisfies Condition ①

ii) from child of parent of x



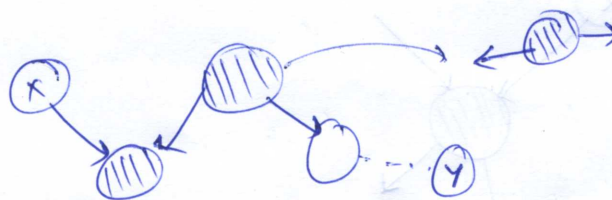
ϕ satisfies Condition ②

iii) from parent of spouse of x



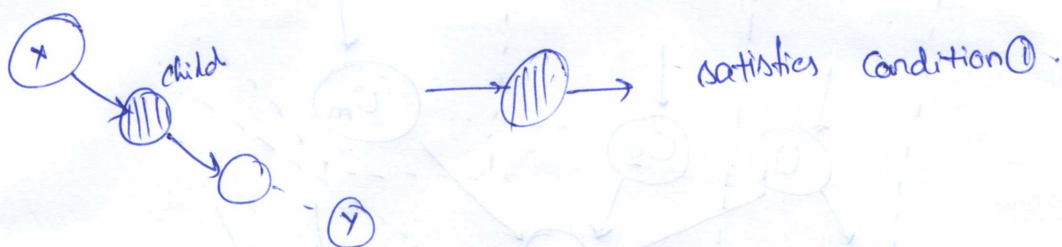
ϕ satisfies Condition ①

iv) from child of spouse of x



ϕ satisfies Condition ②

v) from child of child of x



Thus all paths from x to y are blocked.

$$\Rightarrow P(x/B_x, y) = P(x/B_x)$$

INFERENCE

→ Problem

E = Set of Evidence Nodes.

Q = Set of query nodes.

How to Compute posterior probabilities $P(Q/E)$

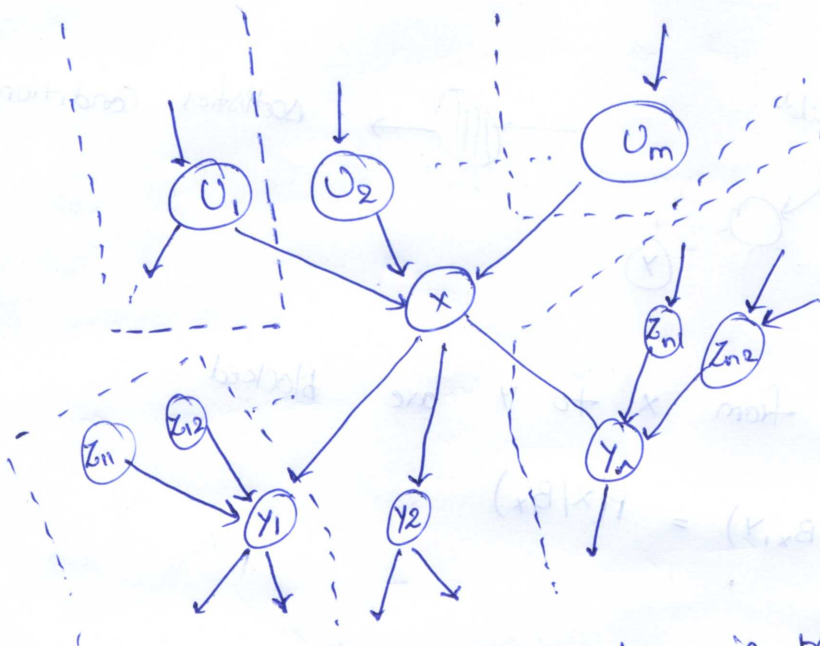
Q: When can we perform inference efficiently?

(polynomial time in size of DAG and CPTs)

A: Polytrees
 ↳ Singly Connected network; at most ^{one} undirected path between any pair of nodes; no loops.

→ Goal: To Compute $P(X/E)$

Node x	Parents u_i	spouses z_{jk}
Evidence E	children y_j	$\hookrightarrow$ kth parent of jth Child.



claim: Boxes don't overlap — no loops in polytree!

Type of evidence:

E_x^+ — upstream evidence "above" x
Connected to x through its parents.

E_x^- — downstream evidence "below" x ,
Connected to x through children

$E = E_x^+ \cup E_x^-$ (Assume $x \notin E$, otherwise trivial)

Inference in polytree:

$$P(x|E) = P(x|E_x^-, E_x^+) \quad [\because E = E_x^- \cup E_x^+]$$

$$= \frac{P(E_x^-|x, E_x^+) P(E_x^-|x)}{P(E_x^+|x)} \left[\begin{array}{l} \text{Conditional} \\ \text{Bayes Rule} \end{array} \right]$$

$$P(x|y, z) = \frac{P(y|x, z) P(x|z)}{P(y|z)}$$

$$= \frac{P(x, E_x^-|E_x^+)}{P(E_x^-|E_x^+)}$$

Conditionalized product rule

$$= \frac{P(x, E_x^-|E_x^+)}{\sum_x P(x, E_x^-|E_x^+)}$$

Marginalisation

→ Denominator is same Computation as numerator, but summed over x

→ So focus on numerator.

$$P(x, E_x^- / E_x^+) = \underbrace{P(x / E_x^+) P(E_x^- / x, E_x^+)}_{\text{conditionalised product rule}}$$

$$= \underbrace{P(x / E_x^+)}_{\text{upstream recursion}} \underbrace{P(E_x^- / x, E_x^+)}_{\text{downstream recursion}} \quad \left(\begin{array}{l} \text{d-separation Case 1} \\ E_x^-, E_x^+ \text{ are conditionally ind.} \\ \text{given } x \end{array} \right)$$

goal:

"upstream" Recursion:

$$P(x / E_x^+) = \sum_{\vec{u}} P(x, \vec{u} = \vec{a} / E_x^+) \quad \left\{ \begin{array}{l} \text{marginalisation} \\ \text{over parents} \end{array} \right.$$

$$= \sum_{\vec{u}} P(\vec{u} = \vec{u} / E_x^+) P(x / \vec{u} = \vec{u}, E_x^+) \quad \left\{ \begin{array}{l} \text{Conditionalised} \\ \text{product rule} \end{array} \right.$$

$$= \sum_{\vec{u}} P(\vec{u} = \vec{u} / E_x^+) P(x / \vec{u} = \vec{u}) \quad \left\{ \begin{array}{l} \text{d-separation Case ①} \\ \text{or ②} \end{array} \right.$$

$$= \sum_{\vec{u}} \left[P(x / \vec{u} = \vec{u}) \prod_{i=1}^m P(u_i / E_x^+) \right] \quad \left\{ \begin{array}{l} \text{d-separation Case ③} \\ \{x \text{ is the unobserved} \\ \text{common effect}\} \end{array} \right.$$

Let $E_{u_i} \setminus x$ denote evidence inside i th parent's box (connected to u_i via path that doesn't contain x)

$$P(x / E_x^+) = \sum_{\vec{u}} P(x / \vec{u} = \vec{u}) \prod_{i=1}^m P(u_i / E_{u_i} \setminus x)$$

→ Downstream recursion

How to compute $P(E_x/x)$?

possible but slightly more complicated

→ Termination Conditions

- root node (no parents)
- leaf node (no children)
- evidence node (trivial inference)

→ Running Time

- Linear in # nodes of BN

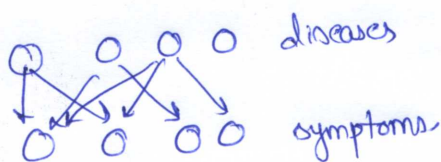
- Linear in size of CPTs because we must sum over parents

$$\sum P(\vec{O} = \vec{u}, \dots)$$

Loopy BNs, how to perform inference?

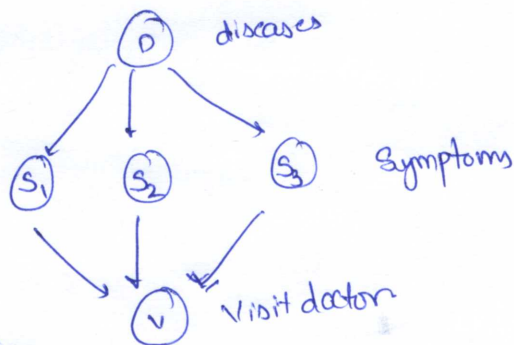
Ex: medical diagnosis.

2-layer network.



Ex: simpler example

Turn loopy-BN into polytree



→ one approach node clustering

→ Merge node S_1, S_2, S_3 to form polytree

→ How to merge? apply polytree algorithm

