

Lecture 5

Oct. 10th

Review

* $P(X, Y | E) = P(X | E)P(Y | E)$ when all path from X to Y are d-separated by E .

* A path π is d-separated if there exists a node ~~$z \in E$~~ $z \in \pi$ for which

1) $z \in E$: $\rightarrow \textcircled{z} \rightarrow$ (causal chain)

2) $z \in E$: $\leftarrow \textcircled{z} \rightarrow$ (common cause)

3) $z \notin E$, descendant (z) $\notin E$.

(not necessarily immediate) $\rightarrow \textcircled{z} \leftarrow$ (unobserved common effect).
child/grand children/

Inference

Query nodes Q

Evidence nodes E

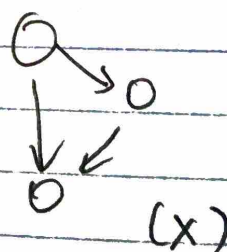
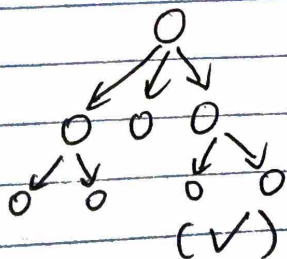
How to compute $P(Q | E)$?

More precisely, how to express $P(Q | E)$, in terms of CPTs $P(x_i | \text{pa}(x_i))$?

Assumed to be given.

Question : * When can inference be done efficiently ?

Answer : In polytree (- a graph w/o loops
- singly connect network
- between $\forall z$ nodes there's at most one path



* Strategies:

- 1) Bayes Rule
- 2) Product Rule
- 3) Marginal / conditional indep
- 4) Combination of 1) & 3)

- 1) express $P(Q|E)$ in terms of conditional probs that repeat order of DAG
- 2) express joint predictions in terms of individual predictions.
- 3) introduce nodes to predict children from parents (using OPTs)
- 4) remove non-parent ancestors from RHTs of conditional bar.

Goal = Compute $P(X=x|E)$

Node X

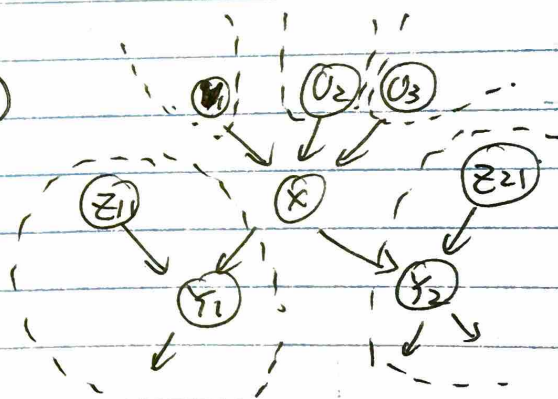
Evidence E

Assume $X \notin E$.

Parents: U_1, U_2, U_3, \dots

Children: Y_1, Y_2, \dots

Spouses: Z_{jk} (parents of j th child excluding X).



Draw one box for each parent & child.

claim: boxes don't overlap for polytree.

Types of Evidence: E_x^+ - evidence connected to X thro parents.

E_x^- - ---- children

$$E = E_x^+ \cup E_x^-$$

General Strategy — recursion

$$\begin{aligned} P(X=x|E) &= P(X=x|E_x^-, E_x^+) \\ &= \frac{P(E_x^-|X=x, E_x^+) P(X=x|E_x^+)}{P(E_x^-|E_x^+)} \end{aligned}$$

Bayes Rule

$$= P(E_x^-|X=x) P(X=x|E_x^+) / P(E_x^-|E_x^+).$$

CI + d-sep rule 1).

- Plan of attack =
- compute terms in numerator
 - compute denominator via

Since : $\sum_x P(X=x|E) = 1 = \frac{\sum_x P(E_x^-|X=x) P(X=x|E_x^+)}{P(E_x^-|E_x^+)}$

$$\Rightarrow P(E_x^-|E_x^+) = \sum_x P(E_x^-|X=x) P(X=x|E_x^+)$$

* Recursion through parents :

$$\begin{aligned} P(X=x|E_x^+) &= \sum_{\vec{u}} P(E_x^+|X=x, \vec{u}) \\ &= \sum_{\vec{u}} P(X=x, \vec{u}|E_x^+) \end{aligned}$$

where $\vec{u} = (u_1, u_2, \dots)$

$$\begin{aligned} &= \sum_{\vec{u}} P(\vec{u}|E_x^+) P(X=x|\vec{u}, E_x^+) \\ &= \sum_{\vec{u}} P(\vec{u}|E_x^+) P(X=x|\vec{u}) \end{aligned}$$

(CI)

$$= \sum_{\vec{u}} P(X=x | U=\vec{u}) \left\{ \prod_{i=1}^n P(U_i=u_i | E_x^+) \right\}$$

[CI thru d-sep ③]

Let $E_{U_i \setminus X}$ = evidence connected to U_i not thru X .

$$E_x^+ = E_{U_1 \setminus X} \cup E_{U_2 \setminus X} \cup \dots$$

$$= \sum_{\vec{u}} \underbrace{P(X=x | U=\vec{u})}_{\text{CPT given}} \left\{ \prod_{i=1}^n \underbrace{P(U_i=u_i | E_{U_i \setminus X})}_{\text{recursive instance.}} \right\} \quad \boxed{\text{CI}} \text{ d-sep ③}$$

* Recursion through children.

$$P(E_x^- | X=x) = \prod_{j=1}^n P(E_{X_j \setminus X} | X=x) \quad \text{can be computed recursively} \quad \boxed{\text{CI}} \text{ d-sep ③}$$

Next steps: introduce children Y_j 's, spouses, Z_j 's.

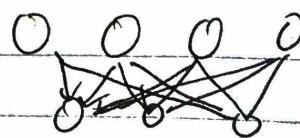
* Termination Conditions:

- 1) Root node (no parent)
- 2) leaf node (no children)
- 3) Evidence node (trivial)

* Runtime Analysis:

linear in # nodes and size of CPTs.

Q: What about BNs?



(bipartite)