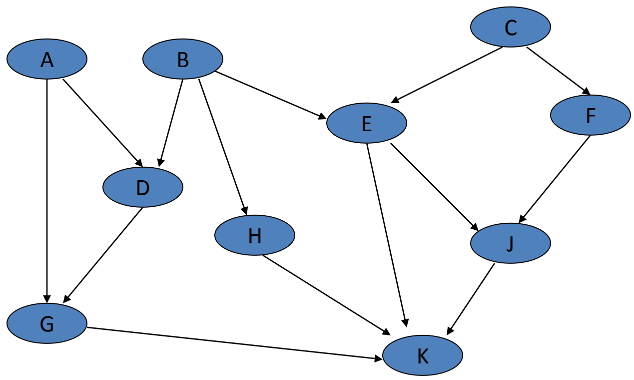
Probabilistic Reasoning

Unit # 4

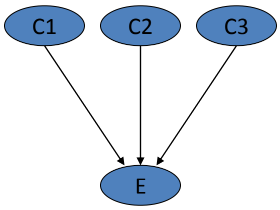
Intractability of Knowledge Acquisition



- # of parameters required to completely specify the joint distribution?
- # of parameters required for the given BN?
- # of parameters required to specify conditional probability table (CPT) for node K?

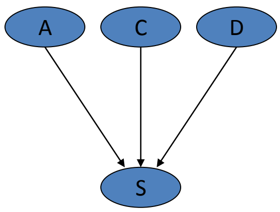
Noisy-Or

- In the Noisy-Or model, an expert is asked to assign only n conditional probabilities for a node, where n is the number of parents.
- The model makes the following assumptions.
  - **Causal Inhibition:** This assumption entails that there is some mechanism which inhibits a cause from bringing about its effect, and the presence of the cause results in the presence of the effect if and only if this mechanism is disabled (turned off).
  - **Exception independence:** This assumption entails that the mechanism that inhibits one cause is independent of the mechanism that inhibits other causes.
  - **Accountability:** This assumption entails that an effect can happen only if at least one of its causes is present and is not being inhibited.



Example (Laskey)

- Sneezing can be caused by an allergy (A), a cold (C), or dust (D) in the air
  - Allergy triggers sneezing with probability pA = .6
  - Cold triggers sneezing with probability pC = .9
  - Dust triggers sneezing with probability pD = .3



Noisy-Or Equations

- If A_1, A_2,………, A_n are the causes of a variable B, then the probability of each A_i causing B is p_i.
- The probability of Ai inhibiting B is q_i or $(1- p_i)$.
- Assuming that the inhibiting variables are independent, the combined probability becomes one minus the product of the probability of inhibitors.

$$P (B \mid A_1, A_2,\ldots, A_n) = 1 – (1- p_1)(1- p_2)\ldots(1- p_n)$$

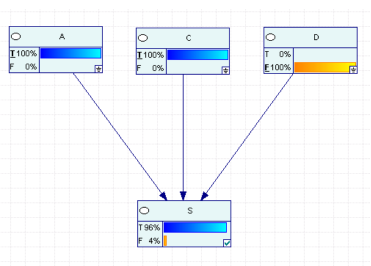
Noisy-Or Computation

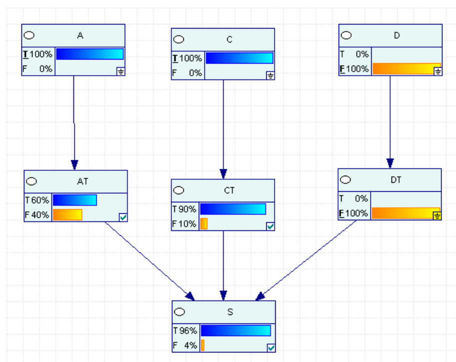
- P(Sneezing | Allergy) = 0.6
- P(Sneezing | Cold) = 0.9
- P(Sneezing | Dust) = 0.3

A	C	D	P(S)
F	F	F	
F	F	T	
F	T	F	
F	T	T	
T	F	F	
T	F	T	
T	T	F	
T	T	T	

Noisy-Or Modeling using Genie

Noisy-Or: Alternative Representations





Leak Probability

- BN2O can be extended to incorporate the probability that the effect can be produced by some un-modeled cause.
- This requires the elicitation of one more probability, called "leak" probability, from the expert.
- To include the leak probability, the equation can be modified as

  $P(B \mid A_1, A_2, \ldots\ldots, A_n) = 1 - (1- p_0)((1- p_1)(1- p_2)\ldots\ldots(1- p_n)$

  where p0 is the probability that B will be true even if none of the A_i are true.

Leak Probability

- If none of "known" causes are present, a person could still have sneezing.
- $P(S \mid \neg A, \neg C, \neg D) = 0.01$

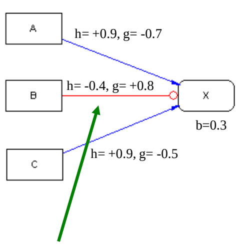
A	C	D	P(S)
F	F	F	
F	F	T	
F	T	F	
F	T	T	
T	F	F	
T	F	T	
T	T	F	
T	T	T	

CAST Logic

- CAusal STrength logic was developed at George Mason University in 1994 to elicit the large number of conditional probabilities from a small set of user-defined parameters.
- The logic has its roots in Noisy-Or.
- The logic requires only a pair of parameters for each dependency relationship between any two nodes.
- Each parameter can take values in the range of (-1, 1).
  - Positive values on arcs are causal influences that cause a node to occur with some probability,
  - Negative values are influences that cause the negation of a node to occur with some probability.
- All non-root nodes are assigned a baseline probability, same as the leak probability in Noisy-Or.

Computation of CAST Logic

- There are four major steps:
  - Aggregate positive causal strengths
  - Aggregate negative causal strengths
  - Combine the positive and negative causal strengths, and
  - Derive conditional probabilities



The first value, referred to as h, states that if B is true, then this will cause X to be false with probability 0.4, while the second value, referred to as g, states that if B is false, then this will cause X to be true with probability 0.8.

Aggregate Positive Strengths

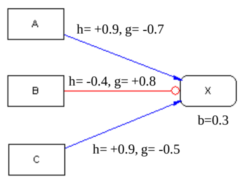
- In this step, the set of causal strengths with positive influence are combined. They are aggregated using the equation

$$PI = 1 - \prod_i (1 - S_i) \qquad \forall S_i > 0$$

where *Si* is the corresponding h or g value having positive influence and *PI* is the combined positive causal strength.

- To compute P(X | A, B, ¬C), we have {0.9, -0.4, -0.5}

PI = 1 – (1 – 0.9) = 0.9



Aggregate Negative Strengths

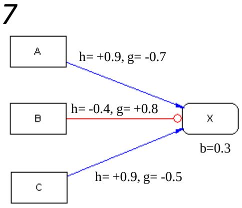
- In this step, the causal strengths with negative values are combined. The equation used for aggregation is

$$NI = 1 - \prod_i (1 - |S_i|) \qquad \forall S_i < 0$$

where *Si* is the corresponding h or g value having negative influence and NI is the combined negative causal strength.

- For our example,

NI = 1 – (1 – 0.4) (1 – 0.5) = 0.7



Combine Positive and Negative Strengths

- In this step, aggregated positive and negative influences are combined to obtain an overall net influence.

If PI > NI

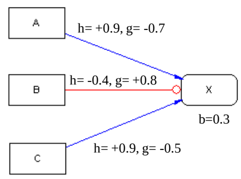
$$AI = \frac{PI - NI}{1 - NI}$$

If NI > PI

$$AI = \frac{NI - PI}{1 - PI}$$

If PI = NI

AI = 0



- For our example

AI = (0.9 – 0.7) / (1 – 0.7) = .66

Derive Conditional Probabilities

- In the final step, the overall influence is used to compute the conditional probability value of a child for the given combination of parents.

P(child | jth state of parent states)

= baseline + (1 – baseline) x AI *when PI > NI*

= baseline – baseline x AI *when PI < NI*

= baseline *when PI = NI*

- For our example,

*P (X | A, B, ¬C) = 0.3 + 0.7 * 0.66 = .762*

- Practice Assignment: Compute the rest of the conditional probabilities

CAST logic Modeling Using GeNIe and IBAYes