A Bayesian Network



Pr(a,b,c,d,e) = Pr(a) Pr(b|a) Pr(c|a,b) Pr(d|a,b,c) Pr(e|a,b,c,d)= Pr(a) Pr(b|a) Pr(c|a) Pr(d|b,c) Pr(e|c)

Links Encode Conditional Probabilities



M: Pr($b = b_j | a = a_j$)



M: $Pr(b = b_j | a = a_i, c = c_k)$

Conditional Independence

Equivalent statements:

- b adds no useful information about a, given S
- Pr(a|b,s) = Pr(a| s)
- CI (a, S, b)
- CI (b, S, a)
- a and b "d-separated" by S in graph

Separation in Graphs: 1, 2

x blocks the path from a to b:



Separation in Graphs: 3

x unblocks the path from a to b:



D-Separation

<u>Defn</u>: Variables *a* and *b* are *d*-separated by S iff every undirected path from *a* to *b* is blocked by a variable in S and no path is unblocked.



a and b are d-separated by { w, x } but by no other subset of { w,x,y,z }

Direction Matters

- IF the sprinkler was on last night
- THEN there is suggestive evidence (0.9) that the grass will be wet this morning.
- IF the grass is wet this morning
- THEN there is suggestive evidence (0.8) that it rained last night.



Reasoning Patterns

Asymmetry of probabilistic dependence requires distinction between *predictive* and *diagnostic* inference.

predictive = causal

diagnostic = evidential

Intercausal relations specify interactions among causes of a common effect.



"Explaining Away"





Intercausal Reasoning



Schematic Action Model



- A is CI of both Q and R given S \cup B.
- Express effect as Pr(S | A, B), often simplifiable to [S | A] using:
 - canonical models
 - ceteris paribus clause