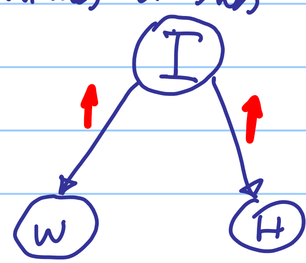
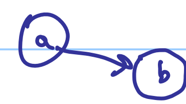
582 2014-01-21 (includes 01-14 & 01-16)

Note Title 2014-01-14

Icy roads example. Three variables with states yes, no:

I, icy roads; W, Watson crashes;
H, Holmes crashes





"a may cause b"
"a influences b"
indicates the direction of impact on certainty (belief).

So, the graph tells us that an increased belief in the roads being icy increases inspector Smith's belief that both Holmes and Watson have crashed.

Smith starts from some initial belief on I, W, H. When he hears that W = yes (Watson has crashed), he reasons in the evidential direction (against the arrow of causality

and his belief (certainty) in I increases.
This is reasoning from effect to cause;
the presence of the effect justifies the cause
(or makes us believe more strongly in the cause).

Inspector Smith's increased belief in Icy Roads
increases his belief in Holmes having crashed.
This is an example of causal reasoning;
increased belief in a cause makes its effect
more credible.

When Smith's belief in I is changed ($I = no$), then the state of W has no longer an effect on H, because the information that Watson has crashed can no longer change the belief in I, and therefore the belief in H.

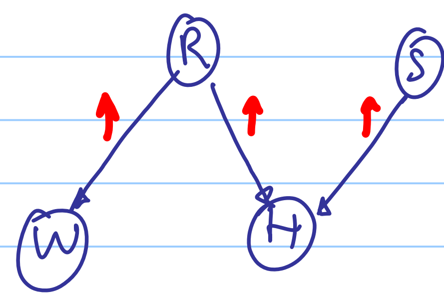
Here we see that dependence / independence changes with evidence: In the absence of

evidence on I, W and H are dependent,
but in the presence of evidence on I,
W and H are independent.

2nd example. Wet grass

H: Holmes' lawn is wet, W: Watson's lawn is wet

R: it rained ; S: Holmes's sprinkler was on

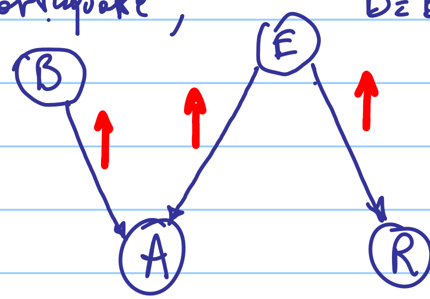


"Explaining away" is a kind of intercausal reasoning that occurs when the common effect of two or more causes holds.

2014-01-16

Earthquake or burglary example

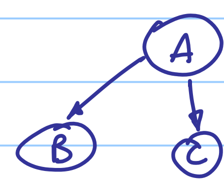
A = Holmes's alarm, R = radio report of earthquake,
E = small earthquake, B = burglary



The reasoning in this example is very similar to that of the wet lawn example

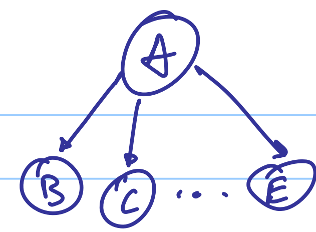
From these examples, we can distinguish different kinds of transmission of evidence:

2. Diverging influence

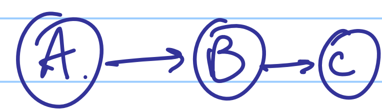


B may pass influence to C (influence may pass between B and C) if A is not known; if A is known, no influence passes between B and C.

This may be generalized to

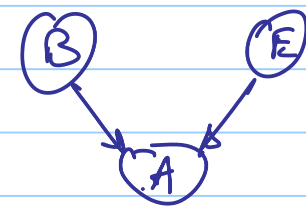


1. Pipelined (serial) influence



If B is not known, influence may pass between A and C. If B is known, no influence passes between A and C.

3. Converging influence



If A is not known,
influence does not pass between B and E.

If A is known, influence may pass between B and E.

Need: defn. of causal graph. (Directed graph as in the stories.) network (directional)

Definition 2.1 [J] (d-separation) (p. 30)

Two distinct variables A and B in a causal network are <u>d-separated</u> if for all paths between A and B there is an intermediate variable V [Note: therefore two adjacent variables may not be d-separated.]

such that either

- the connection is serial or diverging and V is instantiated ("is known") or

- the connection is converging and neither V nor any of V's descendants has received evidence ("is known").

If A and B are not d-separated, we call them d-connected.

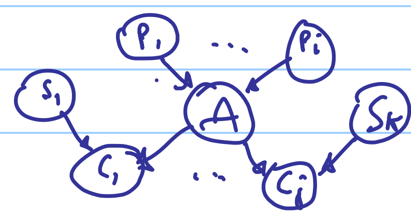
D-separation is taken to be a requirement for transmission of evidence.

Claim (p. 30 [J]): If A and B are d-separated, then changes in the certainty of A have no impact on the certainty of B.

Defn. The Markov blanket of a variable A is the set consisting of the parents of A, the children of A, and the variables sharing a child with A.

Claim (will be an exercise) HW 1: exercise 2.8 due Tuesday, 9/21

Let A be a variable in a causal network. Assume that all variables in A's Markov blanket are instantiated. Then, A is d-separated from the remaining uninstantiated variables.



Prove by cases. List each type of path starting at A.

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D-separation algorithms based on the definition are too slow, b/c they require enumerating paths.
Efficient algorithms are based on the following theorem, due to Lauritzen.

Thm. Let A, B, S be mutually exclusive sets of variables (nodes) in a causal network. Then, A and B are d-separated by S whenever A and B are separated (in the undirected graph sense) by S in the graph $\left(\mathcal{G}_{An(A \cup B \cup S)}\right)^m$, the moral graph of the smallest ancestral set containing $A \cup B \cup S$.

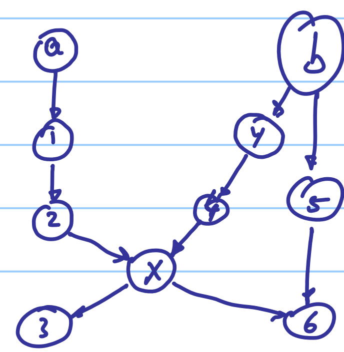
$An(U)$ is the smallest ancestral set of U, i.e. the smallest set containing U and all its ancestors.

$\mathcal{G}_W$ is the induced subgraph of $\mathcal{G}$ that includes the vertices of W.

$\mathcal{G}^m$, where $\mathcal{G}$ is a directed graph, is an undirected graph with the same nodes as $\mathcal{G}$, edges for each direct edge as $\mathcal{G}$, and additional edges that join ("marry") nodes in $\mathcal{G}$ that have a common child.

<u>Example</u>.

$\mathcal{G}$:



$A = \{a\}$

$B = \{b\}$

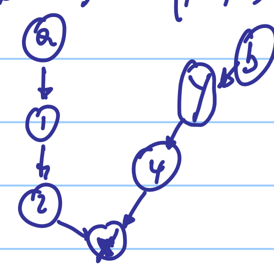
$S = \{x, y\}$

Are A and B d-separated by S?

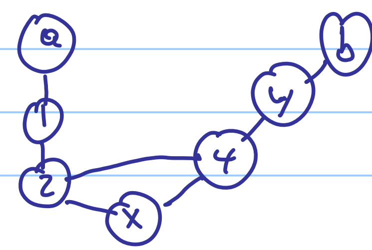
$A \cup B \cup S = \{a, b, x, y\}$, $An(A \cup B \cup S) = An(\{a, b, x, y\}) =$

$= \{a, b, x, y, 1, 2, 4\}$

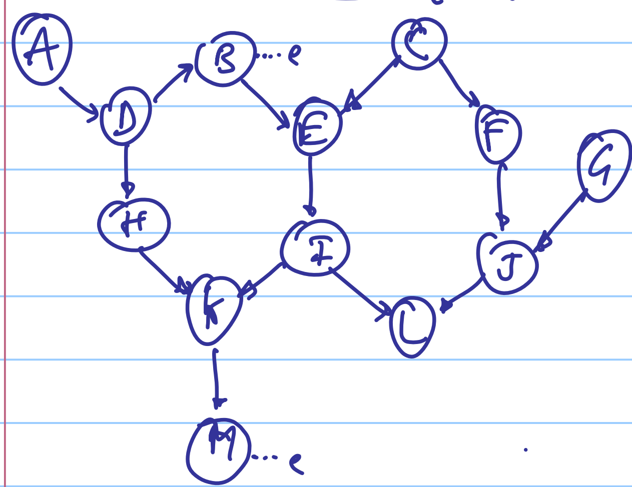
$\mathcal{G}_{An(A \cup B \cup S)} = \mathcal{G}_{\{a,b,x,y,1,2,4\}} =$



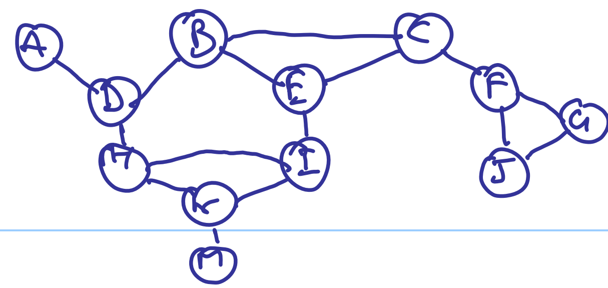
$\left(\mathcal{G}_{An(A \cup B \cup S)}\right)^m =$



Another example (fig. 2.10 in [J07])



Is A d-sep. from J by {B, M} ?



no