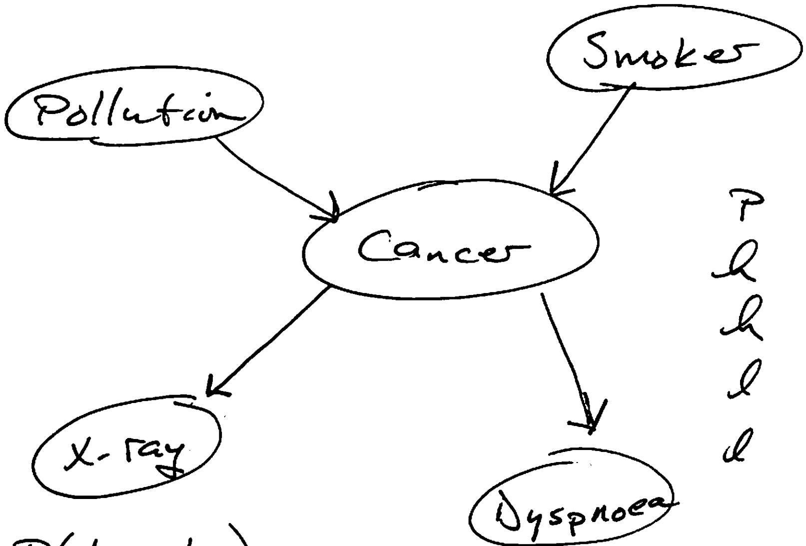
Bayes Nets

Types of reasoning - not just in direction of arcs.

New example

Dyspnoea: {T, F}
X-ray: {T, F}
Pollution: {low, high}
Smoker: {T, F}
Cancer: {T, F}



P(s=t)	P(s=f)
.30	.70

P(p=l)	P(p=h)
.90	.10

P	S	P(c | P, S)
h	t	.05
h	f	.02
l	t	.03
l	f	.001

C	P(X=pos | C)
t	.90
f	.20

C	P(D=t | C)
t	.65
f	.30

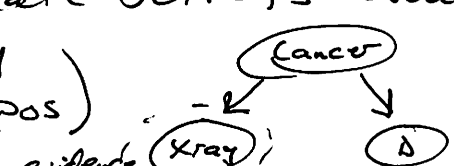
Probability of cancer is low even when pollution is high and patient is a smoker.

Positive X-ray is high probability when patient has cancer.

Diagnostic Reasoning

- reasoning from symptoms to cause, against the arcs ↑
- ex: observe the X-ray (this is evidence), then update beliefs about the cause, such as cancer or smoking

$P(C \mid Xray = pos)$ or $P(S \mid Xray = pos)$

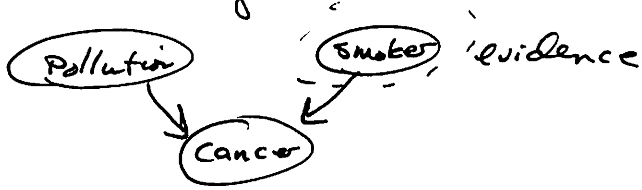


Predictive reasoning

Reason from new information about causes

ex: Patient tells doctor he is a smoker. Before any tests run or symptoms given.

Doctor knows this increases chances of patient having cancer



$P(C \mid S = \text{true})$

Still Don't know anything about pollution

Intercausal Reasoning

Reasoning about mutual causes of a common effect.

Causes are initially indep.

You learn patient has cancer, this increases probability of both causes

$P(P = \text{high} \mid C)$ or $P(S = \text{true} \mid C)$

$P(S = \text{true} \mid C) > P(S = \text{true})$

Then, you learn he is a smoker. This lowers probability that pollution caused the cancer.

Pollution as cause is explained away, even though they were initially independent.

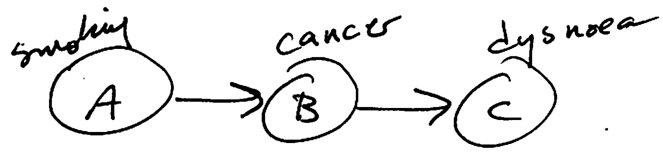
Bayes Net Structure

the point of a Bayes Net is to capture qualitative and quantitative relationships between variables. Ex: one variable is cause of another, variables are independent, variable has multiple effects

Conditional independence is important component, and shows up in different ways in a BN. Causal chains, common causes, common effects

Causal chain

Three nodes



Smoking causes cancer causes dysnoea : not independent

A not indep. of C

$P(C \mid A \wedge B) = P(C \mid B)$

$P(A,B,C) = P(A)\,P(B \mid A)\,P(C \mid B)$

A indep. of C given B $\quad A \perp\!\!\!\perp C \mid B$

$$P(C \mid A,B) = \frac{P(A,B,C)}{P(A,B)} = \frac{P(A)\,P(B \mid A)\,P(C \mid B)}{P(A)\,P(B \mid A)} = P(C \mid B)$$

A is removed

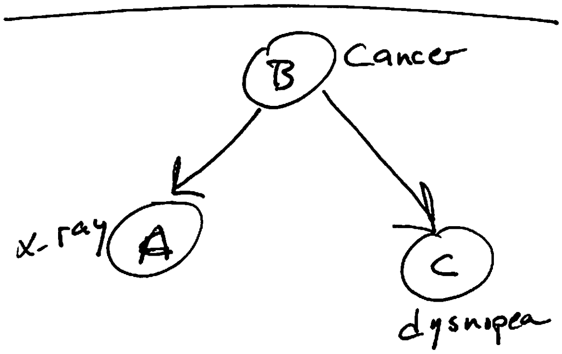
- Evidence along the chain "blocks" the influence

Causal chain

Probability of C given B is exactly the same as the probability of C given both B and A.

Ex: Probability of positive X-ray or dysn. depends ~~only~~ directly only on if person has cancer.
If we don't know anything about patient, but find out that he is smoker, this increases our believe that he has cancer, and that we will see positive x-ray and shortness of breath.
But, if we already know he has cancer, then smoking doesn't make any difference to probability of dysno.

Common causes



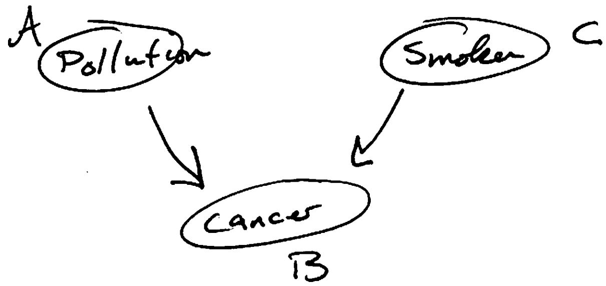
A and C have common cause B
ex: Cancer is cause of 2 symptoms

Same conditional indep. as causal chains. They're not independent.

$P(C \mid B, A) = P(C \mid B) \qquad A \perp\!\!\!\perp C \mid B$

Reasoning: Start w/ no knowledge, no evidence about cancer. Learn about one symptom, which increases probability of other symptom. However, if cancer known, positive x-ray gives no new information about breathing difficulty.

Common effects



Effect node has two causes.
ex: Cancer has causes pollution and smoking

Parents are marginally indep. $A \perp\!\!\!\perp C$
But become dependent given information about common effect
Conditional dependence
$P(A|C,B) \neq P(A|B) \equiv A \not\perp\!\!\!\perp C \mid B$

Back to explaining away reasoning:
If we observe the effect, then find out one of the causes is absent, this raises probability of other cause.

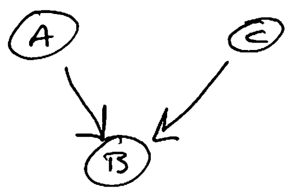
observe cancer and low pollution, then probability of smoker increases. Inverse of explaining away.

Markov blanket - conditional probabilities only examine one step away. Familiar? other

A node is conditionally indep. of all nodes in a network given its parents, children, children's parents. This is its Markov blanket.
ex: Smoker is indep. of X-ray given cancer.

d-seperation

Conditional indep. $A \perp\!\!\!\perp C \mid B$ means that knowing value of B blocks information about C being relevant to A.



Or, in this example lack of observing B blocks the relevance of C to A.

Learning B activates the relation between C and A.

Concept applies to sets of nodes

Given set of nodes X, can determine if set of nodes Y is indep. of X given set of evidence nodes E. Use rules of d-seperation (direction-dependent seperation). $X \perp\!\!\!\perp Y \mid E$

Def:

Undirected Path: A path between 2 sets of nodes X and Y is node sequence between member of X and member of Y s.t every adjacent pair is connected by an arc, no node appears twice in sequence.

Blocked Path: A path is blocked, given set of nodes E, if there is a node Z on path for which one of the following is true: see definitions in Moodle Bayes Nets Information., page 42.