Course Logistics

- We're still working on MP1...
- Keep watching for it.

Five Boolean Random Variables:

B – a burglary is in progress

E – an earthquake is in progress

A – the alarm is sounding

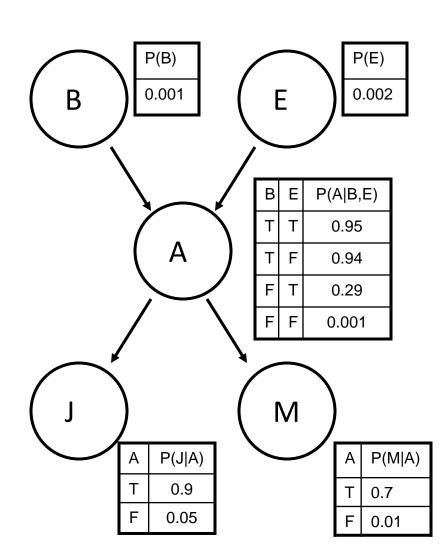
J – John calls

M – Mary calls

Are these numbers reasonable?

How would they be different if they were Joint entries?

We can compute Joint entries.



Form into Groups

- Get out a sheet of paper
- But DON'T put all your names on it
- It's just for any needed scratch work
- Now...

What's the probability of a burglary?

One in a thousand: 0.001

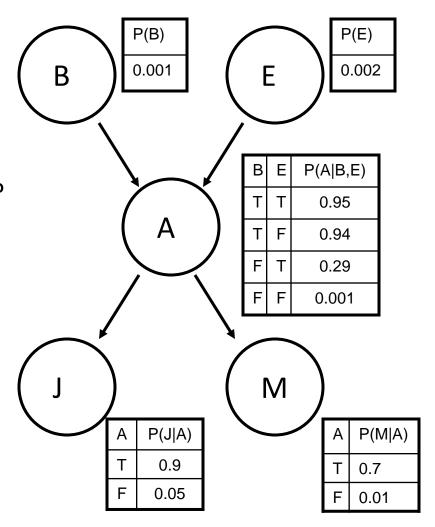
Are burglaries or earthquakes more likely?

Earthquakes are twice as likely

What's the probability of the alarm sounding when there is an earthquake but no burglary?

$$P(A|B=F,E=T)$$
 or $P(A|\neg b,e)$?

$$P(J|a, \neg b, e)$$
?
= $P(J|a) = 0.9$



$$P(A \mid \neg b)$$
?

blending of = $P(A|\neg b,e)$ and $P(A|\neg b,\neg e)$

blend how? By P(E)

 $0.29 \cdot 0.002 + 0.001 \cdot 0.998 = 0.01578$

This is just marginalizing over E

Why don't we marginalize over J? or M?

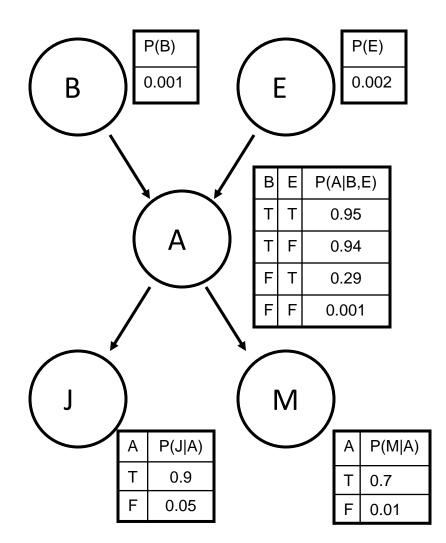
Can CPTs at J or M influence our opinion on A when B=F?

What if we know that John called?

We can ignore J & M when neither is an evidence or query variable; general rules?

John calling makes J an evidence variable

Variable elimination algorithm (fig 14.11)



$$P(A|J=T)$$
?

P(A=F) = 1 - P(A=T) so P(A=T) alone tells us the full distribution of A.

Bayes: $P(A|J) = P(J|A) \cdot P(A) / P(J)$

P(J|A) – from the BN; = 0.9

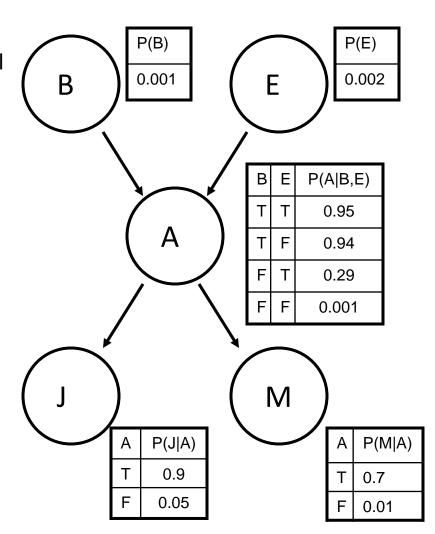
P(A) – marginalize over B and E; ~ 0.0025

P(J) – marginalize over A; ~ 0.052

Turns out P(A|J=T) is quite low ~ 0.043 Why?

Quite a few false positives 0.05

Alarm turns out to be unlikely $P(A) \sim 0.0025$



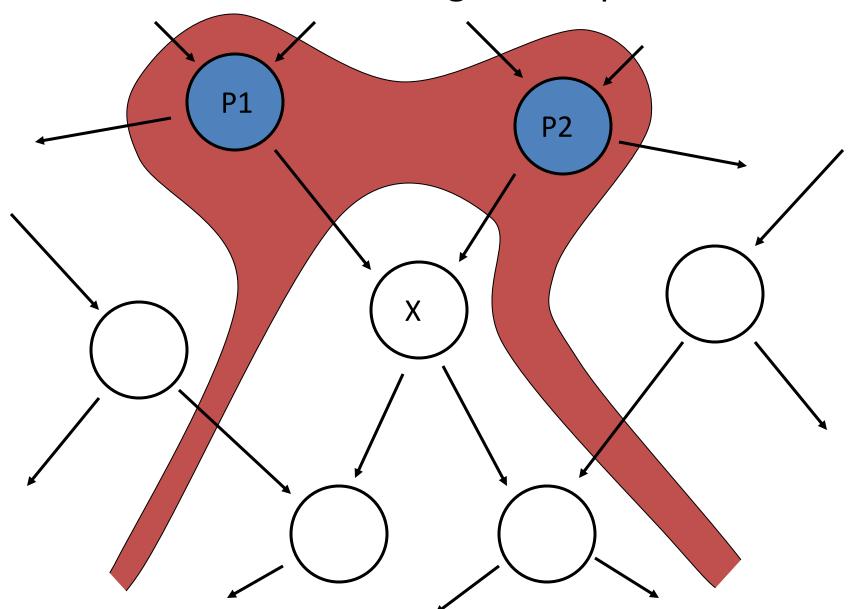
When are Variables Conditionally Independent from Evidence?

- A Variable is conditionally independent of its non-descendants given its parents.
- A Variable is conditionally independent of all other nodes in the network given its parents, children, and children's parents (coparents). This is its Markov blanket.

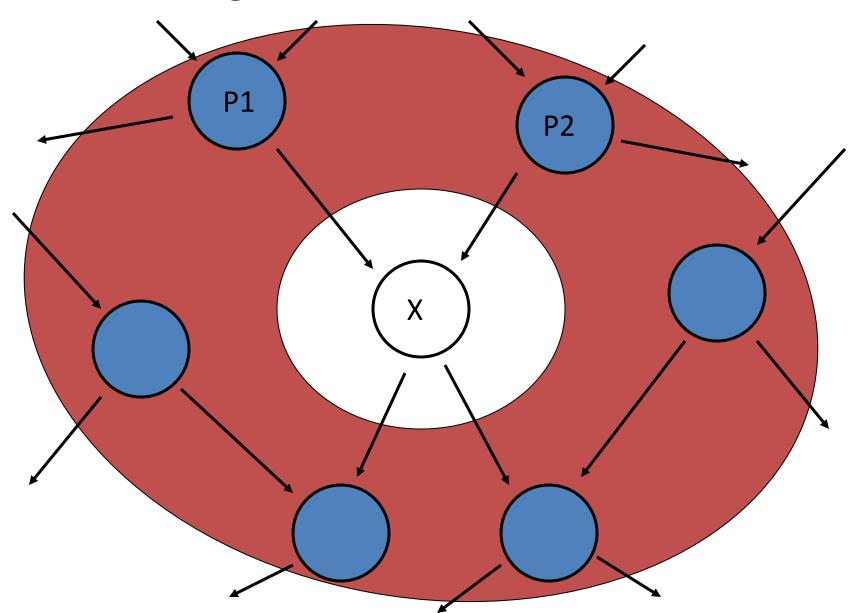
(See Figure 14.4 in text)

A set of Variables X is conditionally independent of a set of Variables Y given a set of Evidence Variables E if all paths connecting an x to a y are "d-separated"

X is conditionally independent of its non-descendants given its parents

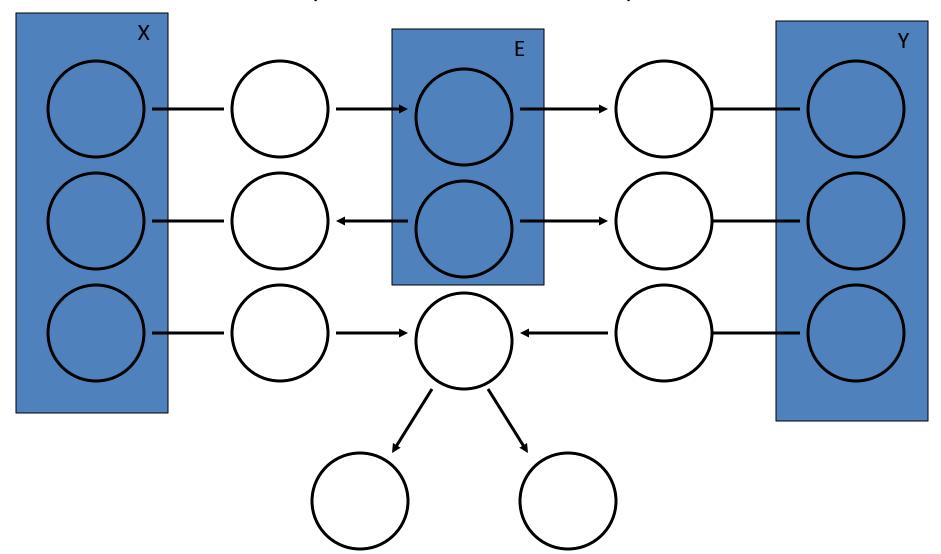


X is conditionally independent of everything else given its Markov blanket



d-separation

(standard but not in text)



Bayesian Belief Net

Five Boolean Random Variables:

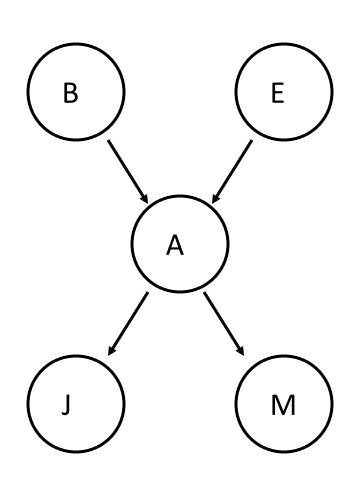
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BN Construction

- Identify variables
- Order them*
- While there are variables to add
 - Pick the next in the ordering
 - Identify its parents in the net
 - Hold all others constant (in every configuration)
 - If net variable influences it, net var is a parent
 - Draw all arcs and add CPT
- * order matters a lot

Heuristic

Usually the most compact representation results when belief causality mirrors physical causality

Dentist Example

3 Boolean Random Variables:

- C Patient has a cavity
- A Patient reports a toothache
- B Dentist's probe catches on tooth

