CSCI 3202: Intro to Artificial Intelligence
Lecture 23, 24: Bayesian Inference and Sampling

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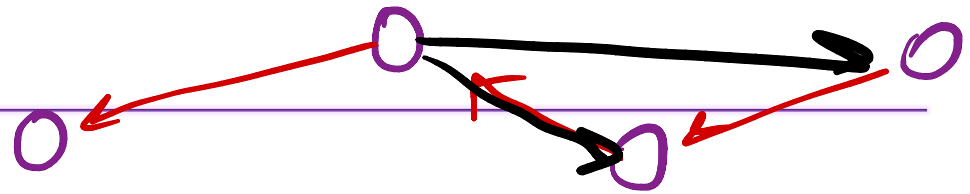
Bayes Net

→ directed acyclic graph

→ conditional probability tables

13.3, 13.4

Bayesian Networks



Bayes nets implicitly encode joint distributions as a product of the local conditional distributions:

$$P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid x_{i-1}, x_{i-2}, \ldots, x_2, x_1) = \ldots ?$$

Node ordering: write in such a way that

$$\text{parents}(X_i) \subseteq \{X_{i-1}, X_{i-2}, \ldots, X_2, X_1\}$$

$$\rightarrow \quad \prod_{i=1}^{n} P(x_i \mid x_{i-1}, x_{i-2}, \ldots, x_2, x_1) = \prod_{i=1}^{n} P(x_i \mid \text{parents}(X_i))$$

this is what encodes your joint distribution

This statement:

$$P(X_i \mid X_{i-1}, X_{i-2}, \ldots, X_2, X_1) = P(X_i \mid \text{parents}(X_i))$$

is key: **each node is conditionally independent of its other predecessors, given its parents**

.1

.7

H

H

T

T

H

H

H

p(data | Bias = .1)

p(data | bias = .7)

Bayesian Networks

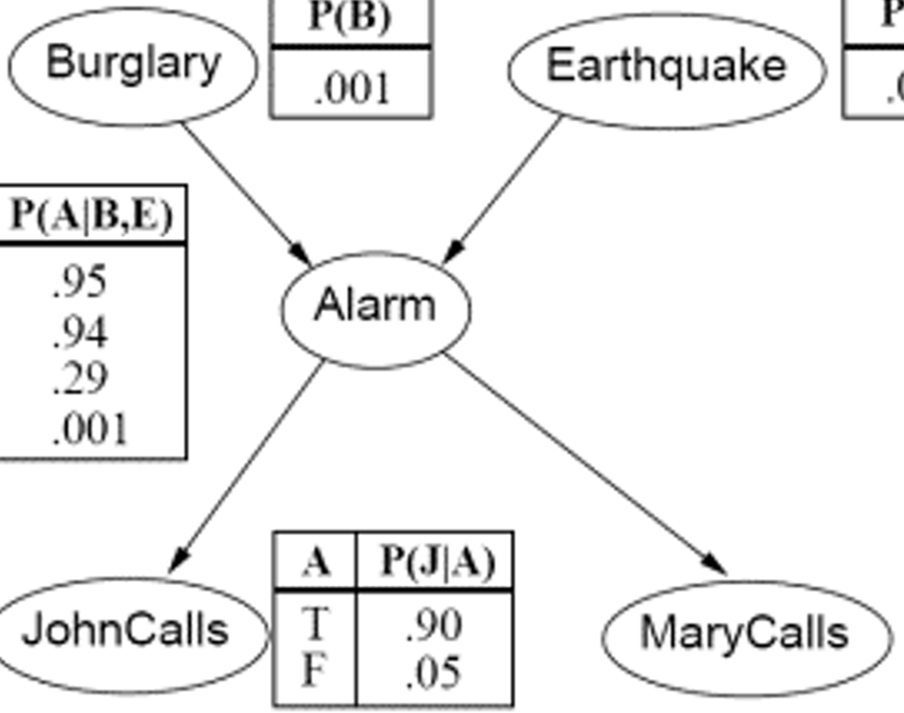
$B \begin{cases} \text{True} \\ \text{False} \end{cases}$

$P(+b) = .001$

$\Rightarrow P(\neg b) = 1 - .001$

$P(E = \text{True}) = .002$

$P(E = \text{False}) = 1 - .002$



P(B)
.001

P(E)
.002

B	E	P(A|B,E)
T	T	.95
T	F	.94
F	T	.29
F	F	.001

A	P(J|A)
T	.90
F	.05

A	P(M|A)
T	.70
F	.01

$P(\neg a \mid \neg b, \neg e)$

$= 1 - .001$

$P(\neg a \mid +b, +e)$

$= 1 - .95$

$\vdots$

etc.

Bayesian Networks

This is a joint distribution with 5 variables.

$\rightarrow P(B, E, A, J, M) = P(B \mid \text{parents}(B))\, P(E \mid \text{parents}(E)) \cdot P(A \mid \text{parents}(A)) \cdot p(J \mid \text{parents}(J)) \cdot p(M \mid \text{pare}$

Bayes nets implicitly encode joint distributions as a product of the local conditional distributions:

$$\boxed{P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i \mid \text{parents}(X_i))}$$

Example: Burglary or earthquake?

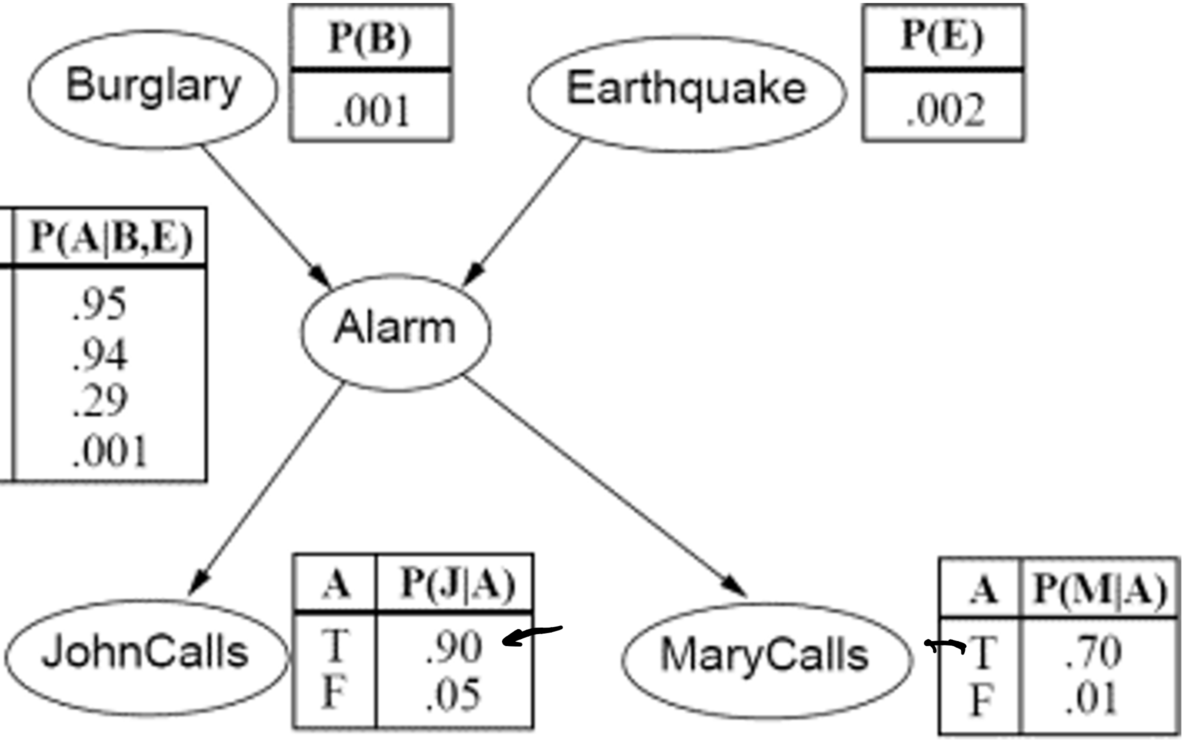
P(¬*j*, ¬*m*, +*a*, +*b*, +*e*) = ?

$= P(\neg j \mid +a)\, p(\neg m \mid +a)\, p(+a \mid +b, +e)\, p(+b)\, p(+e)$

$= (1 - .9)(1 - .7)(.95)(.001)(.002)$

$\boxed{= 0.00000057}$

B	E	P(A|B,E)
T	T	.95
T	F	.94
F	T	.29
F	F	.001



Bayesian Networks: Construction

Show a "flow" from cause to effect: **Pearl's Network Construction Algorithm**

Nodes: What is the set of variables we need to model?

Order them: $\{X_1, X_2, X_3, \ldots, X_n\}$

Best if ordered such that **causes precede effects**

Links: For each node X_i , do:

- Choose a minimal set of parents $\text{parents}(X_i) \subseteq \{X_{i-1}, X_{i-2}, \ldots, X_2, X_1\}$
  such that $P(x_i \mid x_{i-1}, x_{i-2}, \ldots, x_1) = P(x_i \mid \text{parents}(X_i))$
- For each parent, insert arcs (links) from parent to X_i
- Write down CPT $P(X_i \mid \text{parents}(X_i))$

Bayesian Networks: Construction

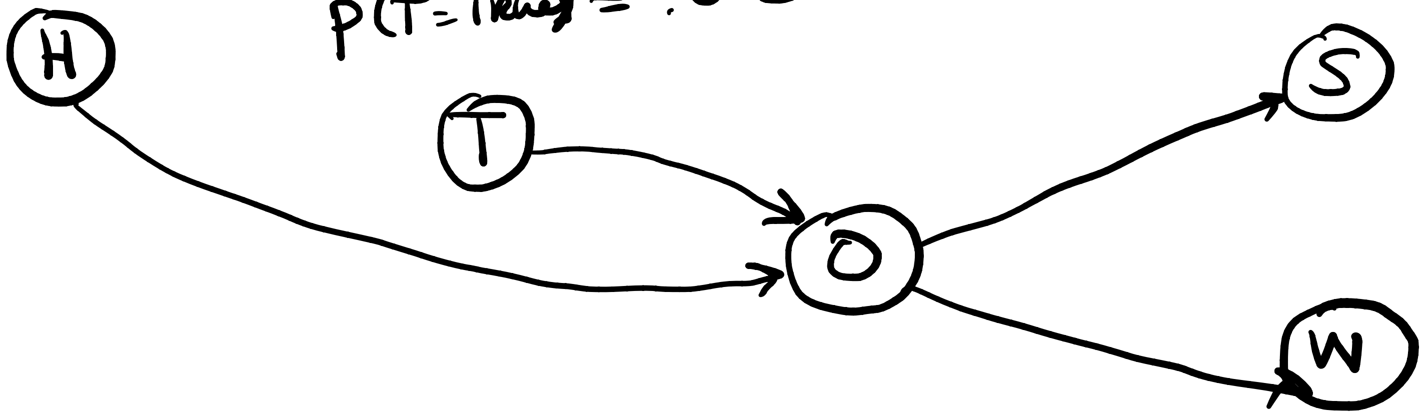
Example: Suppose we have an old motorcycle that might either blow a head gasket (H) or have a broken thermometer (T). Either one would cause the bike to overheat (O). If the bike overheats, then it might blow smoke (S) and/or run weak (W).

Construct a Bayesian network for this situation.

1. Node ordering: {H, T, O, W, S}
2. Insert arcs

$p(T = \text{True}) = .02$

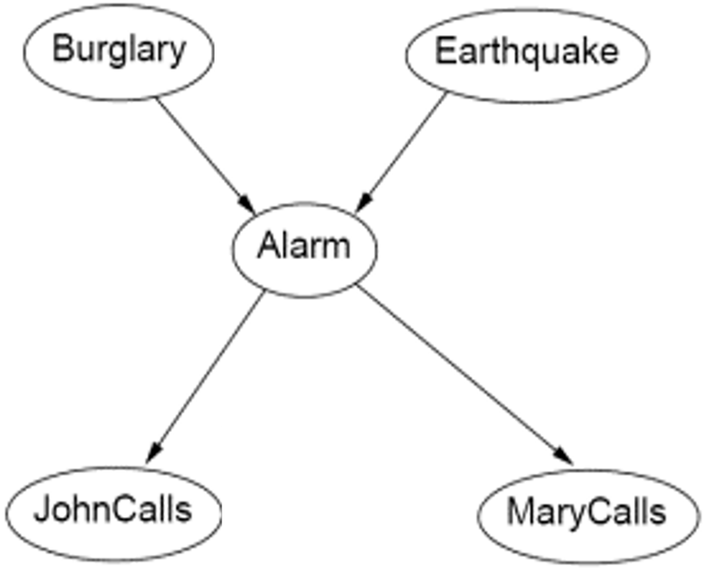
$p(H = \text{True}) = .01$



Bayesian Networks: Construction

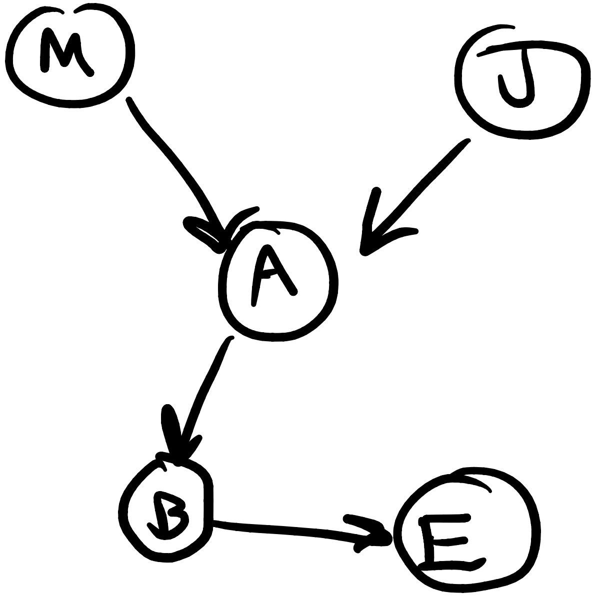
Here, we chose to put the causes before effects:

{Burglary, Earthquake, Alarm, JohnCalls, MaryCalls}



What if instead we did the following?

{MaryCalls, JohnCalls, Alarm,
Burglary, Earthquake}



$$P(B,E,A,J,M) = P(M)P(J)\,P(A \mid M,J)\,P(B \mid A)\,P(E \mid B)$$

- This network still encodes the joint prob distribution but its probably not as accurate.

Bayesian Networks: Construction with Python Example

What do we need to describe a Bayesian Network? Nodes, Arcs, Conditional Probability Tables (CPTs)

particular_bayes_net = BayesNet([list of nodes: (‘Name’, ‘Parents, [T, F], {dict cpt})

class BayesNet:
- generic “tree class” that will interact with a more specific Node class
- Read in the “Node Specifications”, like what’s listed above.
- Add Nodes using class BayesNode

class BayesNode:
- node = BayesNode(name=name, parents = parents, values = values, cpt = cpt)

We’ll have a **probability function** - calculates the probability of seeing a particular BayesNode variable when the parents’ values are given as “evidence”

We’ll have a **class PDF_discrete**

13.3, 13.4

Lastly, we’ll need a way to compute probabilities and ”ask” things of our Bayesian Network: **enumeration_ask**, **enumeration_all**

Bayesian Networks: Construction with Python Example

Example: Find $P(Burglary = T \mid JohnCalls = T, MaryCalls = T)$

Law of Total Probability

$$p(x) = \sum_{y \in Y} p(x \mid y)\, p(y)$$

$$= P(x \mid +y)\, p(+y) + P(x \mid -y)\, P(-y)$$

Entire Joint Probability Distribution:

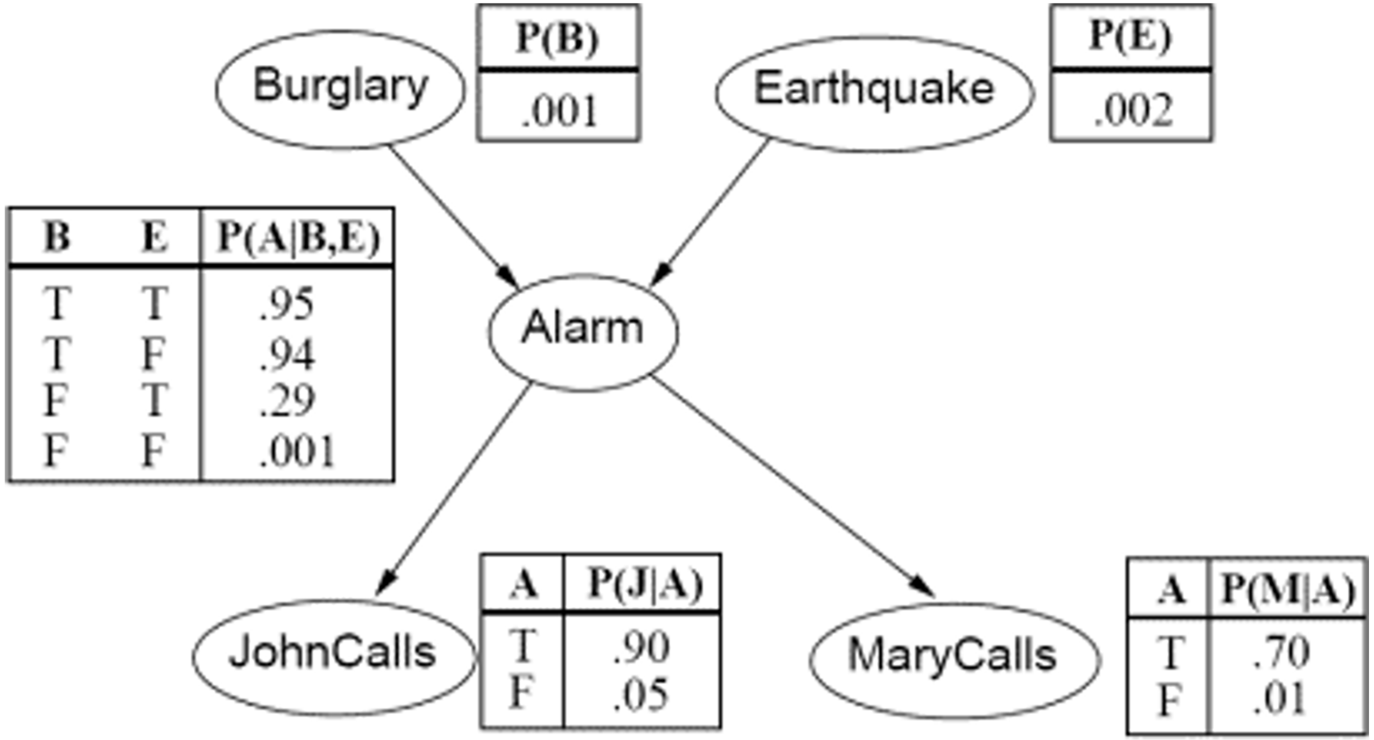
$P(B, E, A, J, M) = P(B)P(E)\ P(A \mid B, E)\ P(J \mid A)\ P(M \mid A)$

$$P(+b \mid +j, +m) = \frac{p(+j, +m \mid +b)\, p(+b)}{p(+j, +m)}$$

Bayes Rule

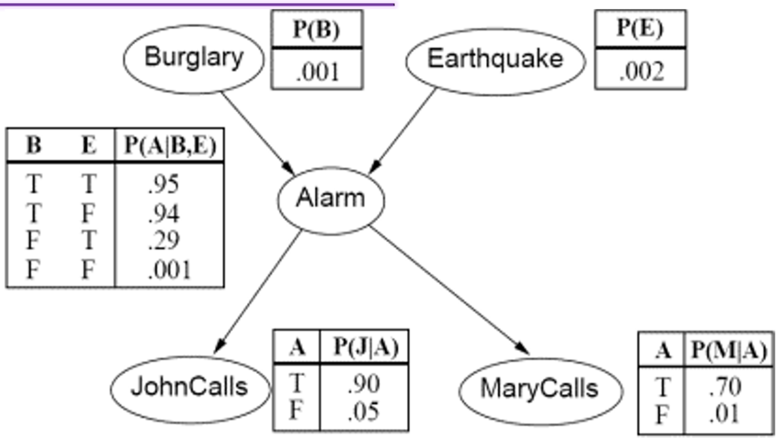
$$= \frac{P(+j, +m, +b)}{p(+j, +m)}$$

$=$



Bayesian Networks: Construction with Python Example

Example: Find $P(Burglary = T \mid JohnCalls = T, MaryCalls = T)$



Entire Joint Probability Distribution:

$$P(B,E,A,J,M) = P(B)P(E)\,P(A \mid B,E)\,P(J \mid A)\,P(M \mid A)$$

$$P(Burglary = T \mid JohnCalls = T, MaryCalls = T) = \frac{P(Burglary = T, JohnCalls = T, MaryCalls = T)}{P(JohnCalls = T, MaryCalls = T)}$$

$$= \frac{P(Burglary = T, \boldsymbol{Earthquake = T\ or\ F, Alarm = T\ or\ F}, JohnCalls = T, MaryCalls = T)}{P(\boldsymbol{Burglary = T\ or\ F, Earthquake = T\ or\ F, Alarm = T\ or\ F}, JohnCalls = T, MaryCalls = T)}$$

$$= \frac{P(+B,+E,+A,+J,+M) + P(+B,+E,-A,+J,+M) + P(+B,-E,+A,+J,+M) + P(+B,-E,-A,+J,+M)}{P(+B,+E,+A,+J,+M) + P(+B,+E,-A,+J,+M) + P(+B,-E,+A,+J,+M) + P(+B,-E,-A,+J,+M) + P(-B,+E,+A,+J,+M) + P(-B,+E,-A,+J,+M) + P(-B,-E,+A,+J,+M) + P(-B,-E,-A,+J,+M)}$$

$$= \frac{p(+B)p(+E)p(+A|+B,+E)p(+J|+A)p(+M|+A) + p(+B)p(+E)p(-A|+B,+E)p(+J|-A)p(+M|-A) + p(+B)p(-E)p(+A|+B,-E)p(+J|+A)p(+M|+A) + p(+B)p(-E)p(-A|+B,-E)p(+J|-A)p(+M|-A)}{\begin{array}{c} p(+B)p(+E)p(+A|+B,+E)p(+J|+A)p(+M|+A) + p(+B)p(+E)p(-A|+B,+E)p(+J|-A)p(+M|-A) + p(+B)p(-E)p(+A|+B,-E)p(+J|+A)p(+M|+A) + p(+B)p(-E)p(-A|+B,-E)p(+J|-A)p(+M|-A) \\ + p(-B)p(+E)p(+A|-B,+E)p(+J|+A)p(+M|+A) + p(-B)p(+E)p(-A|-B,+E)p(+J|-A)p(+M|-A) + p(-B)p(-E)p(+A|-B,-E)p(+J|+A)p(+M|+A) + p(-B)p(-E)p(-A|-B,-E)p(+J|-A)p(+M|-A) \end{array}}$$

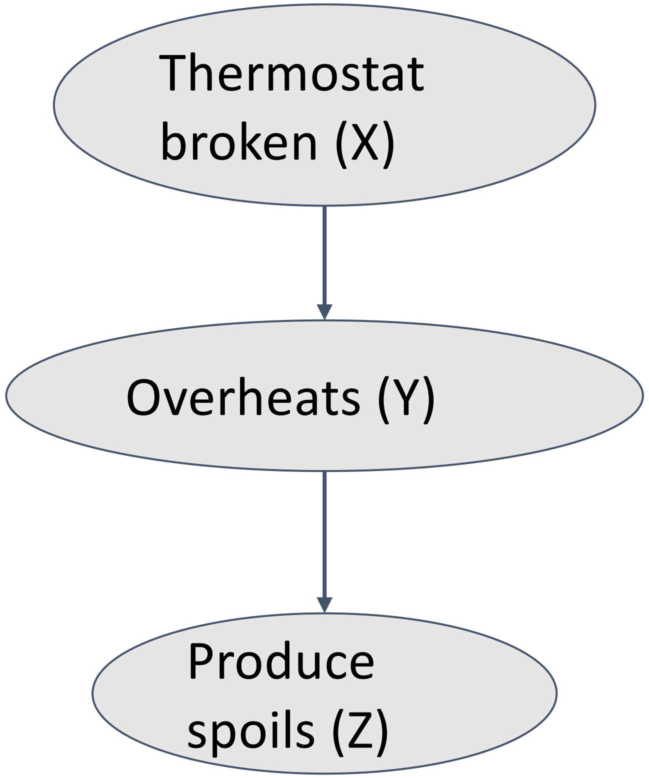
$$= \frac{(0.001)(0.002)(0.95)(0.90)(0.70) + (0.001)(0.002)(1-0.95)(0.05)(0.01) + (0.001)(1-0.002)(0.94)(0.90)(0.70) + (0.001)(1-0.002)(1-0.94)(0.05)(0.01)}{\begin{array}{c} (0.001)(0.002)(0.95)(0.90)(0.70) + (0.001)(0.002)(1-0.95)(0.05)(0.01) + (0.001)(1-0.002)(0.94)(0.90)(0.70) + (0.001)(1-0.002)(1-0.94)(0.05)(0.01) \\ + (1-0.001)(0.002)(0.29)(0.90)(0.70) + (1-0.001)(0.002)(1-0.29)(0.05)(0.01) + (1-0.001)(1-0.002)(0.001)(0.90)(0.70) + (1-0.001)(1-0.002)(1-0.001)(0.05)(0.01) \end{array}}$$

$$= \frac{0.0000012 + 0.000000001 + 0.0005910156 + 0.00000002994}{0.0000012 + 0.000000001 + 0.0005910156 + 0.00000002994 + 0.0003650346 + 0.00000070929 + 0.00062811126 + 0.000498002499} = \frac{0.00059224654}{0.002084104189} = \mathbf{0.284173}$$

Bayesian Networks: Canonical Cases

Important Bayes net question: Are two nodes independent *given* certain evidence?

- If yes -- can prove using algebra
- If no -- can prove using a counterexample



Example: Are X and Z necessarily independent?

no.

X is effecting Y.

Y is effecting Z.

So really X is effecting Z through Y.

Bayesian Networks: Canonical Cases

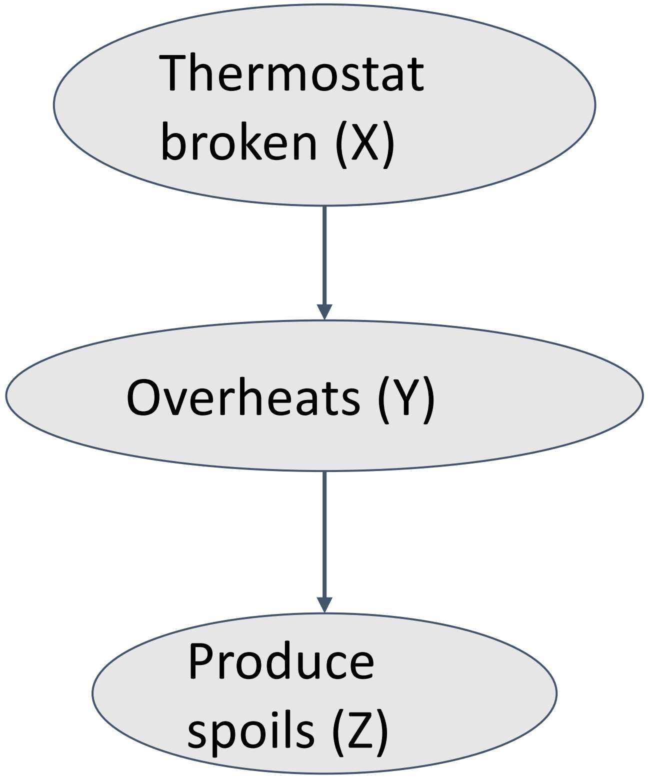
Important Bayes net question: Are two nodes independent *given* certain evidence?

- If yes -- can prove using algebra
- If no -- can prove using a counterexample

Example: Are X and Z necessarily independent?

No!

- X certainly influences Y, which influences Z
- Also, knowledge of Z influences beliefs about X (through Y)

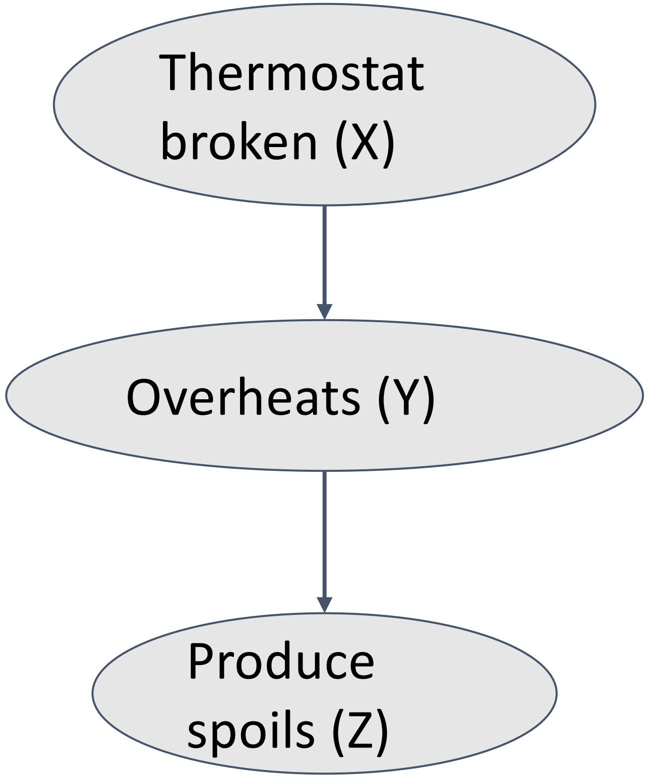


Bayesian Networks: Canonical Cases

Example, rebooted: What about X and Z, ***given*** Y?

This is a canonical case is called a **causal chain**

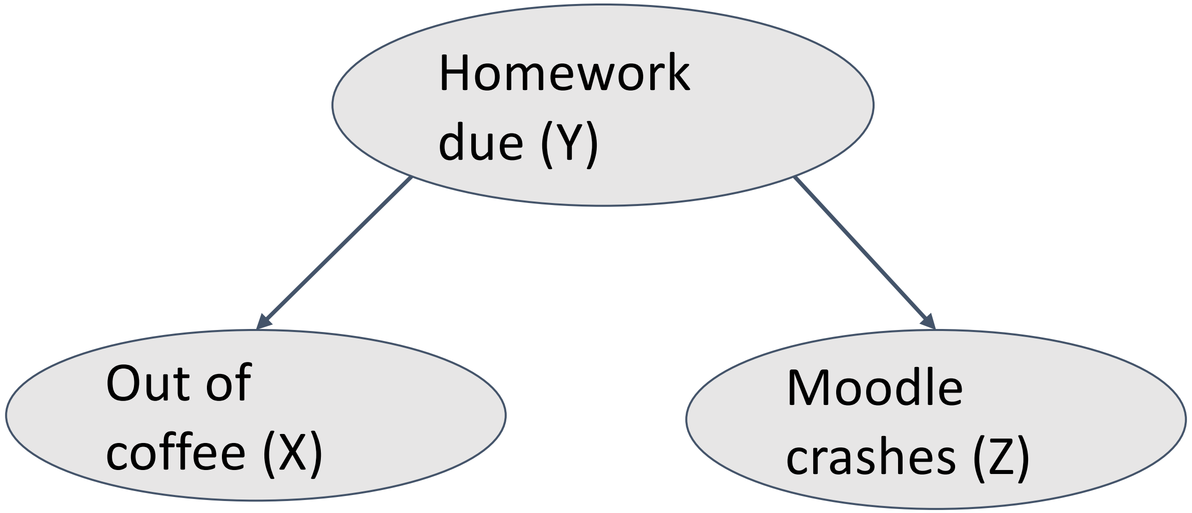
yes.



Bayesian Networks: Canonical Cases

Common cause is another canonical case.

→ Two effects, from the same cause



Example: Are X and Z independent?

Are X and Z independent ***given*** Y?

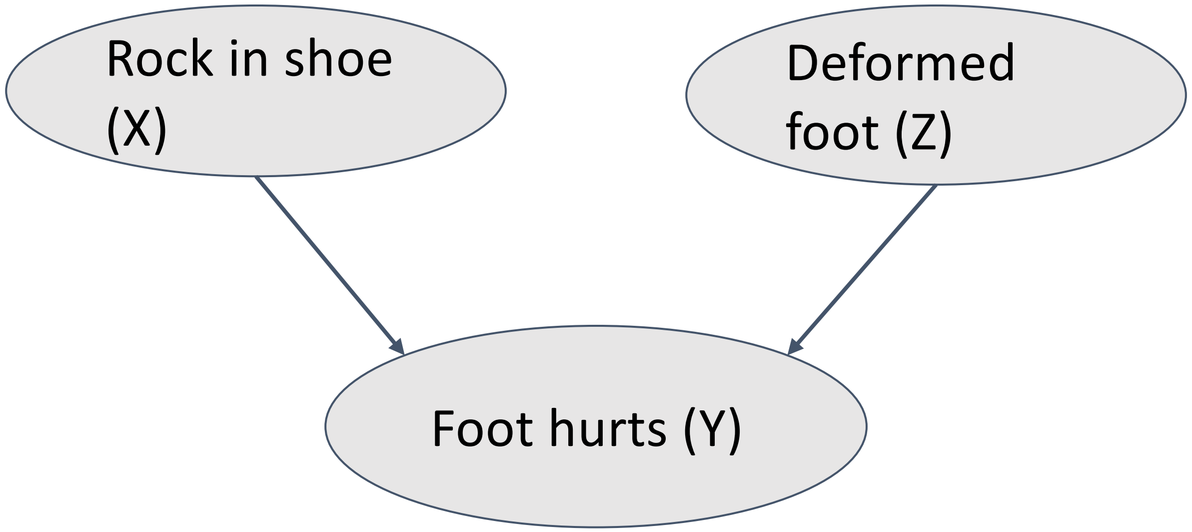
Bayesian Networks: Canonical Cases

Common effect is the third canonical case.

→ One effect, two possible causes

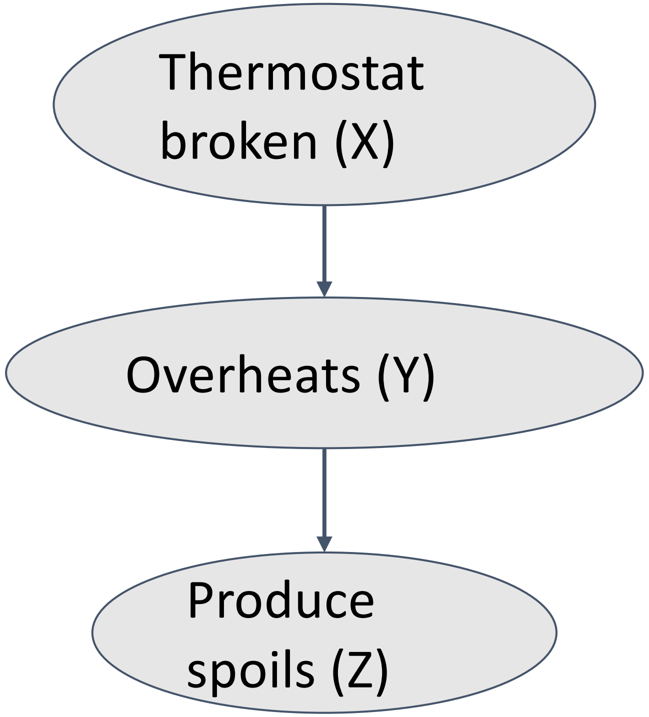
Example: Are X and Z independent?

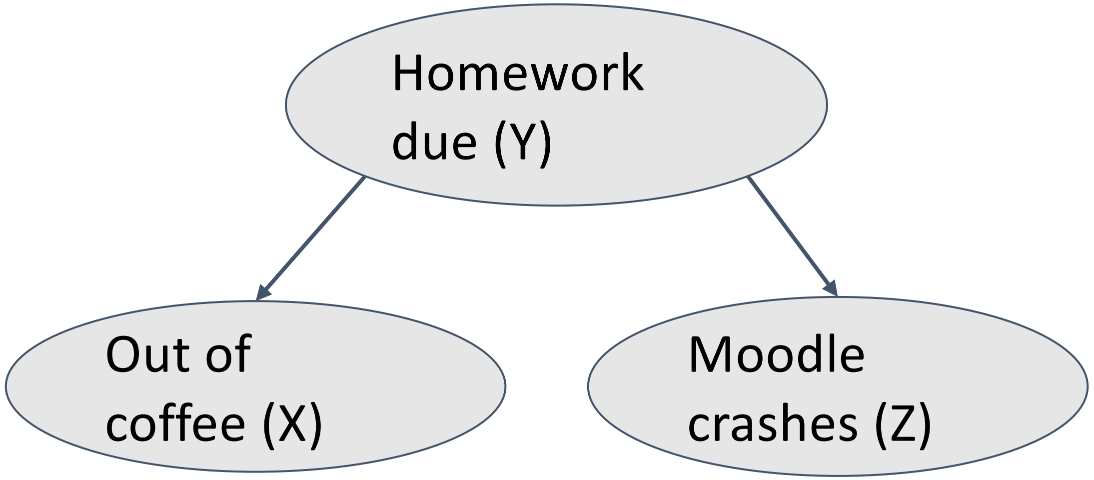
Are X and Z independent ***given*** Y?

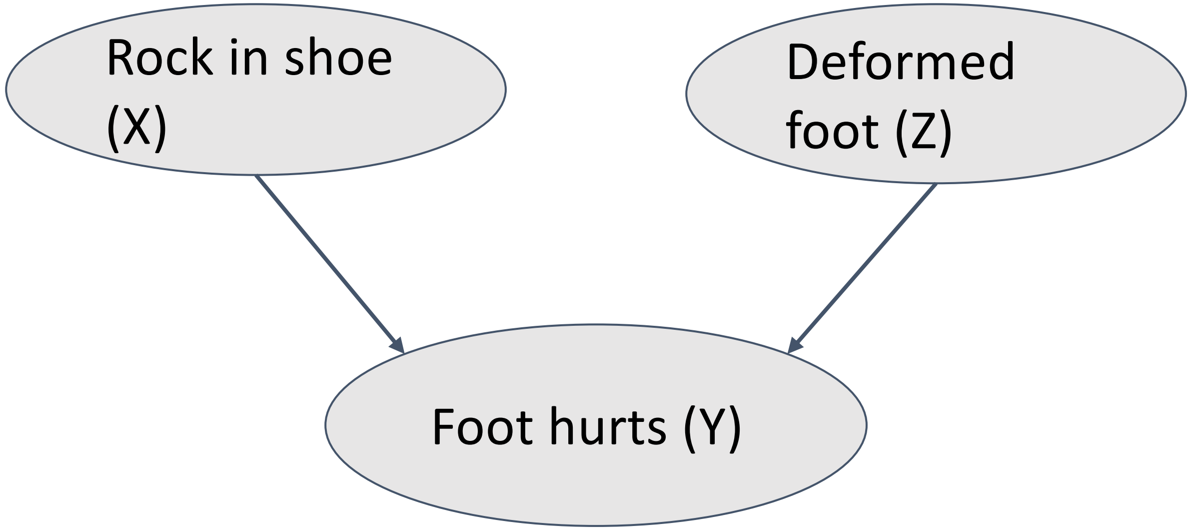


Causal vs Diagnostic Modeling

Causal:







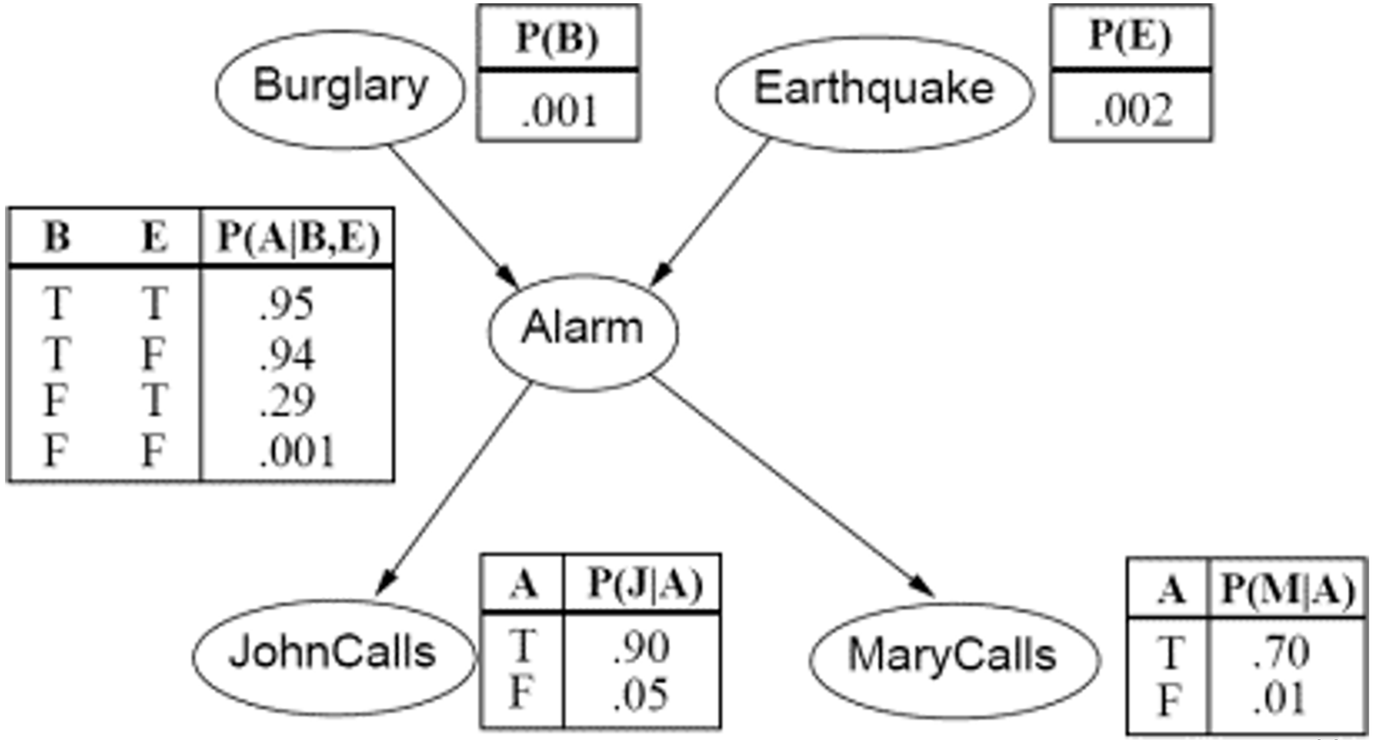
Diagnostic: observing an effect leads to competition between possible causes

→ *diagnose* which is most likely

Bayesian Networks: “Explaining Away”

Suppose we know that the alarm has gone off.

Suppose we find out later that we have been robbed



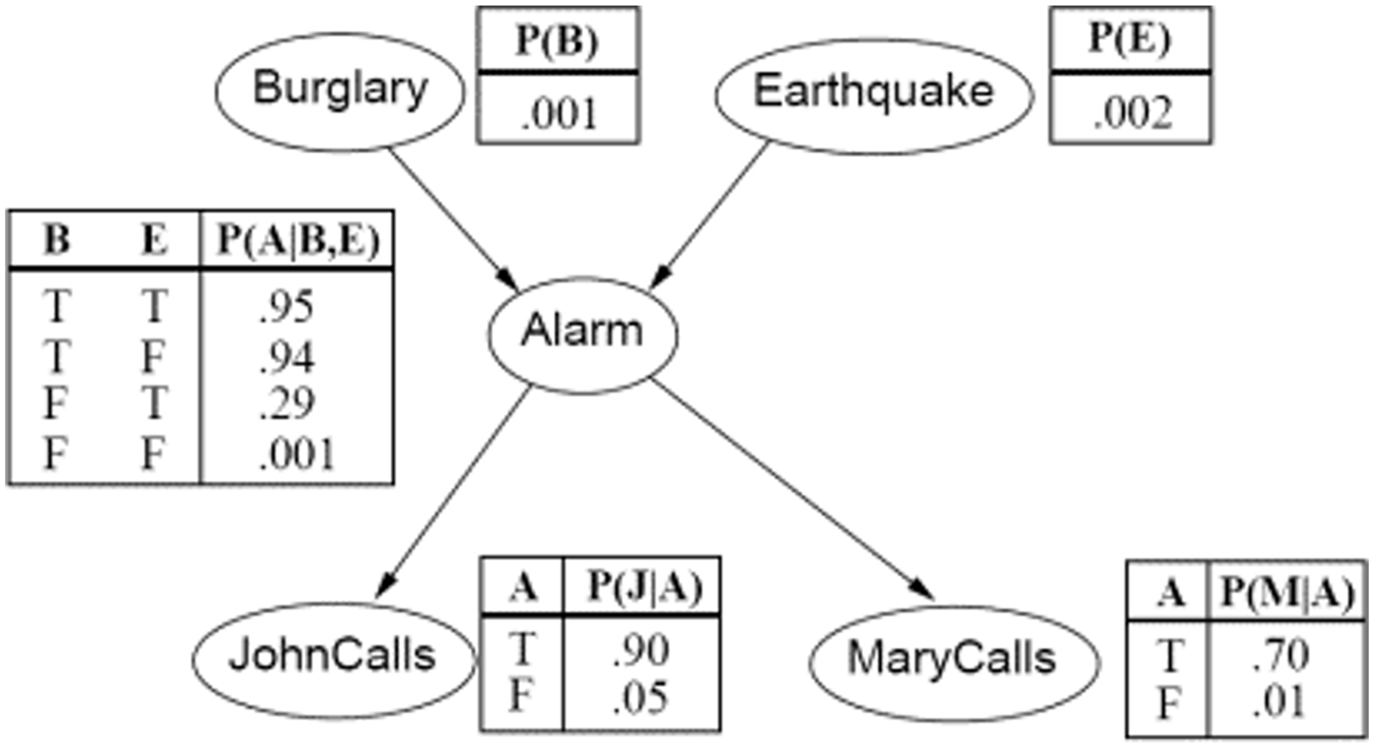
Bayesian Networks

The point of Bayes nets is to **represent full joint probability distributions**, *and*

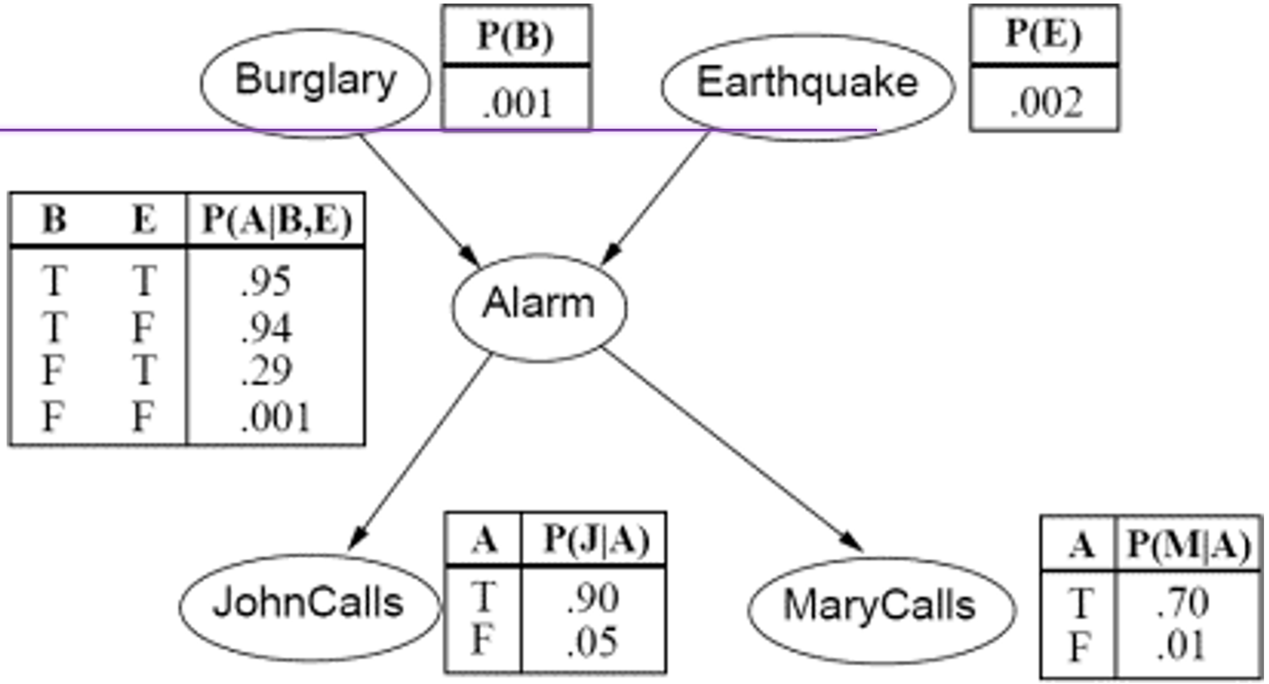
to encode an interrelated set of **conditional independence/probability statements**

- Consists of **nodes** (events), and
- **conditional probability tables (CPTs)**, relating those events

- Describe how variables interact **locally**
- Chain together local interactions to estimate **global**, **indirect** interactions



Bayesian Networks



Example: S'pose we know the alarm has gone off, and both John and Mary have called to warn us. What is the probability that we have been burgled?

→ $P(+b \mid +j, +m) = ?$

Query variables: what we want the **posterior** probability of, **given** some **evidence**

X = B

Evidence variables: the variables we are given an assignment of (the **data**)

E = [+j, +m]

Hidden variables: the non-evidence, non-query variables

y = [E, A]

Bayesian Networks

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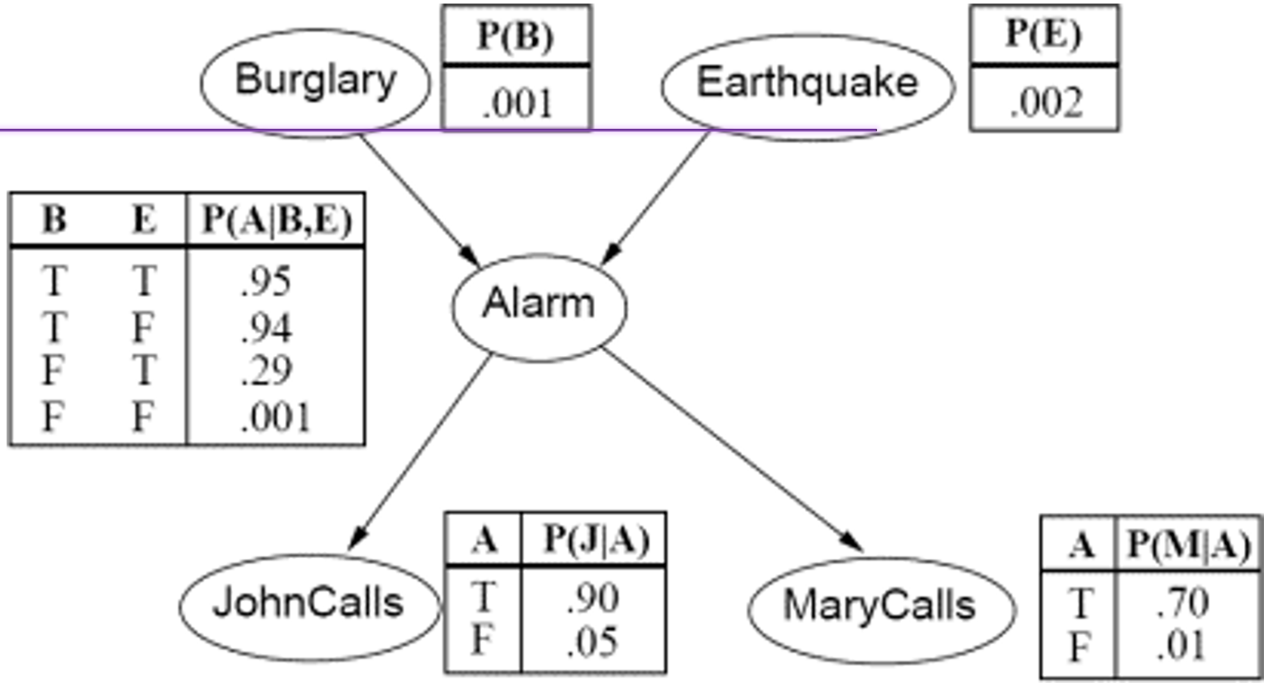
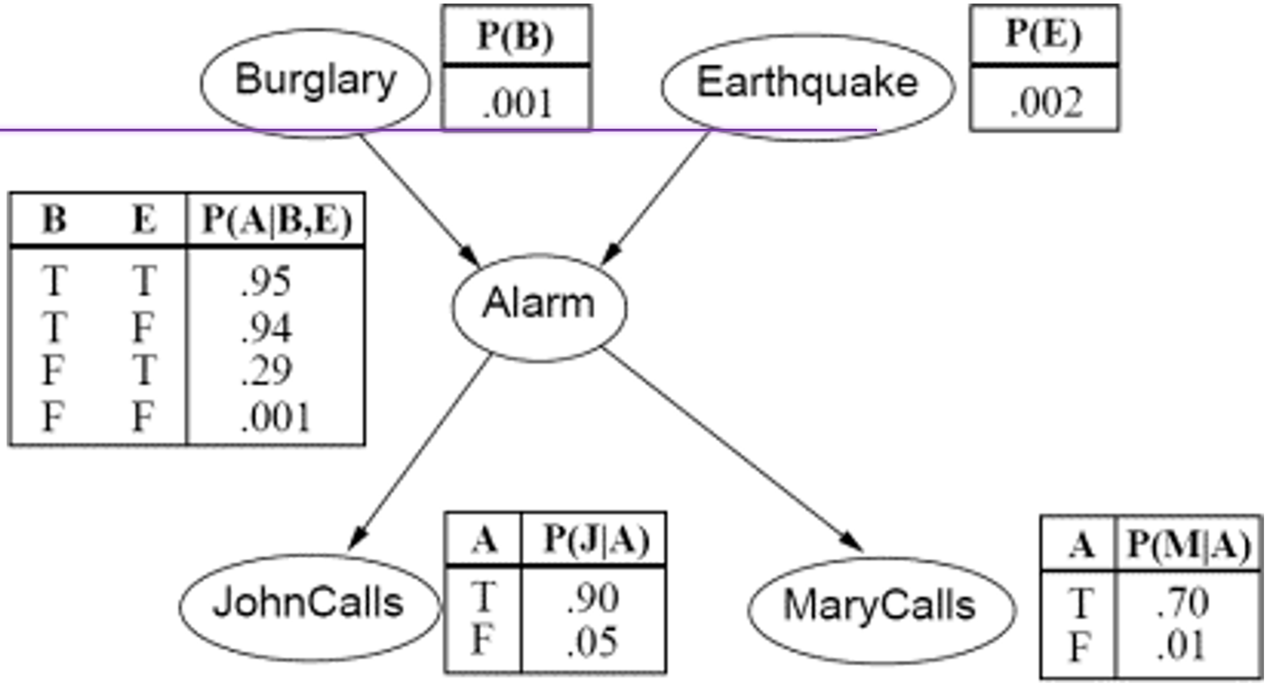


Calculation by **enumeration:**

Bayesian Networks



Example: S'pose we know the alarm has gone off, and both John and Mary have called to warn us. What is the probability that we have been burgled?

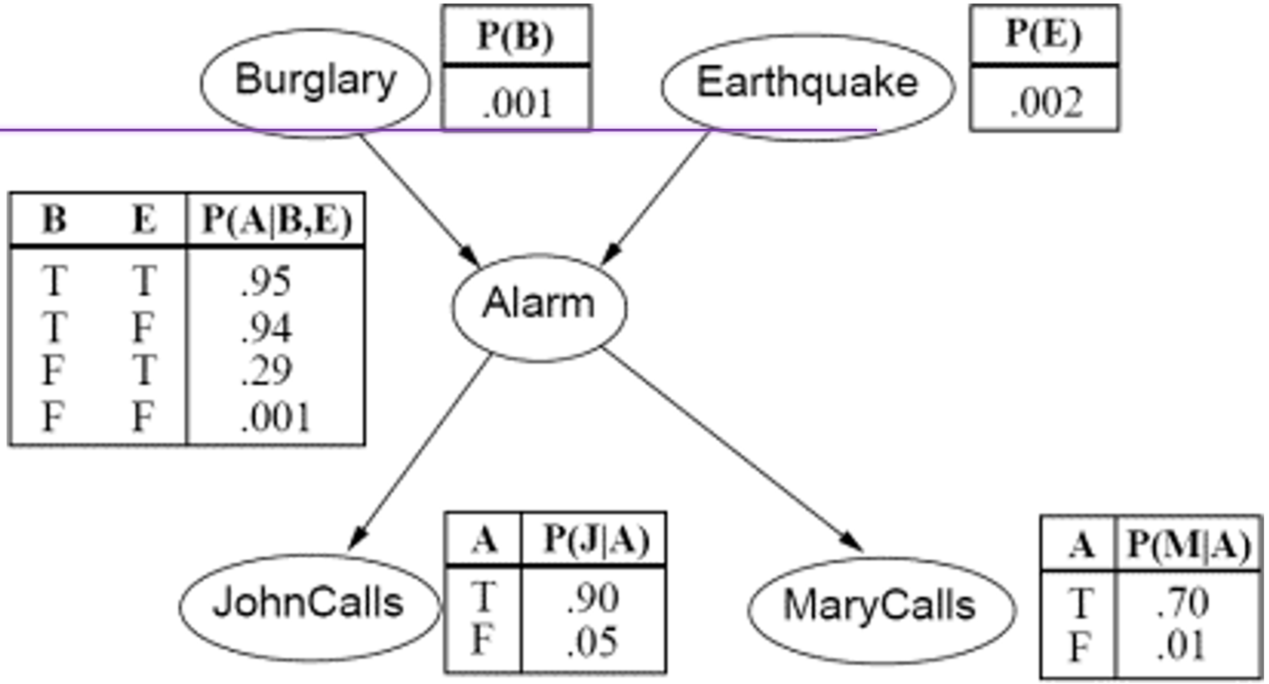
→ *P*(+b | +j, +m) = ?

Calculation by **enumeration:**

$$P(B \mid j, m) = \frac{P(B, j, m)}{P(j, m)} \quad \Rightarrow \quad \alpha = \frac{1}{P(j, m)} \quad \Rightarrow \quad P(B \mid j, m) = \alpha P(B, j, m)$$

We'll do our thing, then figure out the normalizing constant α later

Bayesian Networks



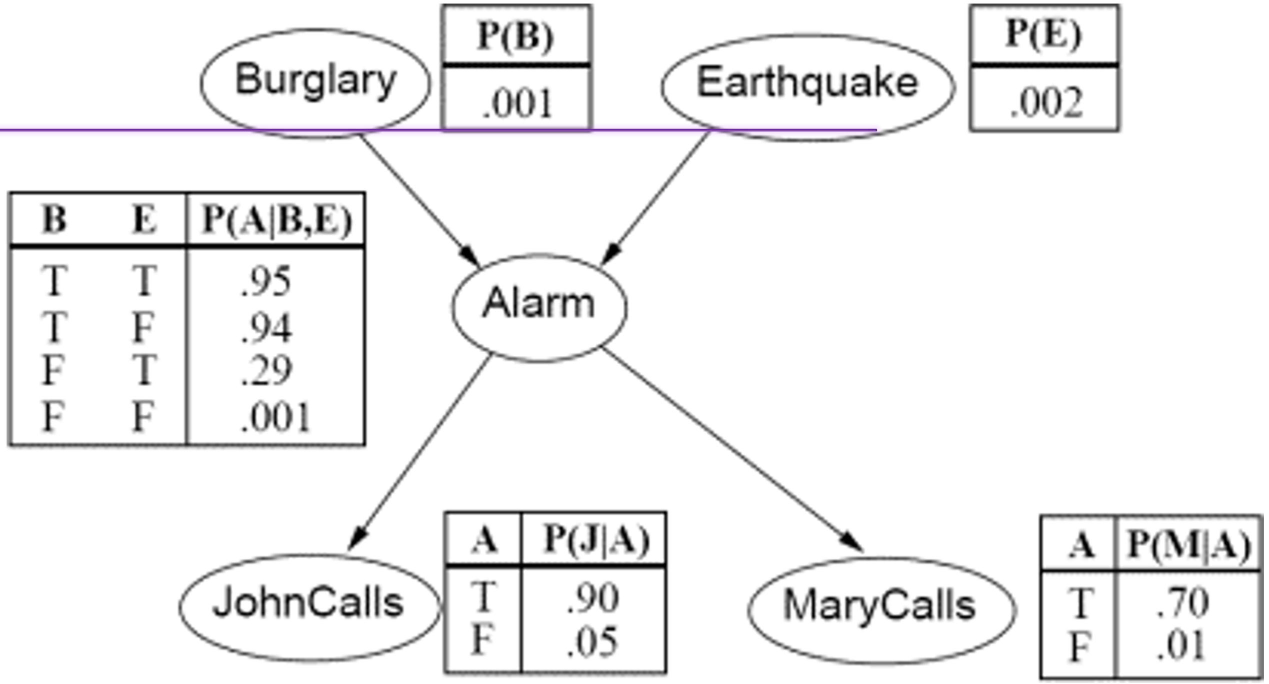
Example: Suppose we know the alarm has gone off, and both John and Mary have called to warn us. What is the probability that we have been burgled?

→ $P(+b \mid +j, +m) = ?$

Calculation by **enumeration:**

$$
\begin{aligned}
P(B \mid j, m) &= \alpha P(B, j, m) \\
&= \alpha \sum_a P(B, j, m \mid a) P(a) \\
&= \alpha \sum_a P(B, j, m, a)
\end{aligned}
$$

Bayesian Networks



P(B)
.001

P(E)
.002

B	E	P(A|B,E)
T	T	.95
T	F	.94
F	T	.29
F	F	.001

A	P(J|A)
T	.90
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Example: Suppose we know the alarm has gone off, and both John and Mary have called to warn us. What is the probability that we have been burgled?

→ $P(+b \mid +j, +m) = ?$

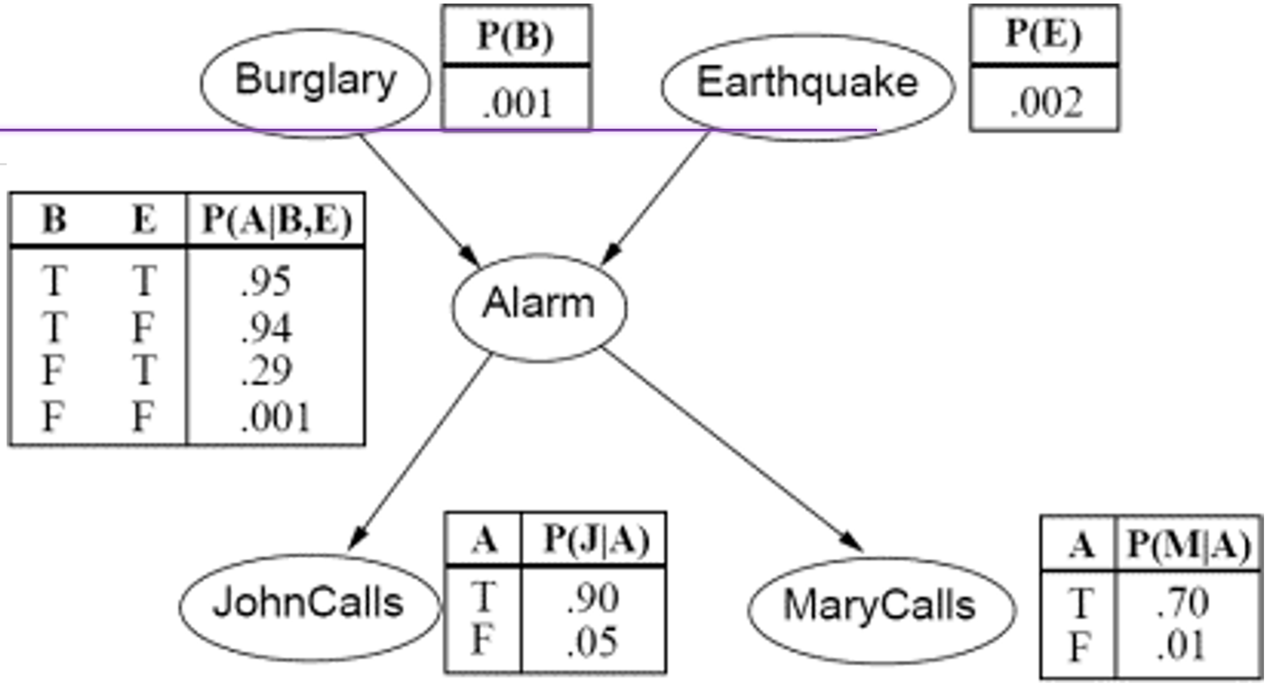
Calculation by **enumeration:**

$$P(B \mid j,m) = \alpha \sum_a P(B,j,m,a)$$

$$= \alpha \sum_e \sum_a P(B,j,m,a \mid e) P(e)$$

$$= \alpha \sum_e \sum_a P(B,j,m,a,e)$$

Bayesian Networks



Example: Suppose we know the alarm has gone off, and both John and Mary have called to warn us. What is the probability that we have been burgled?

→ $P(+b \mid +j, +m) = ?$

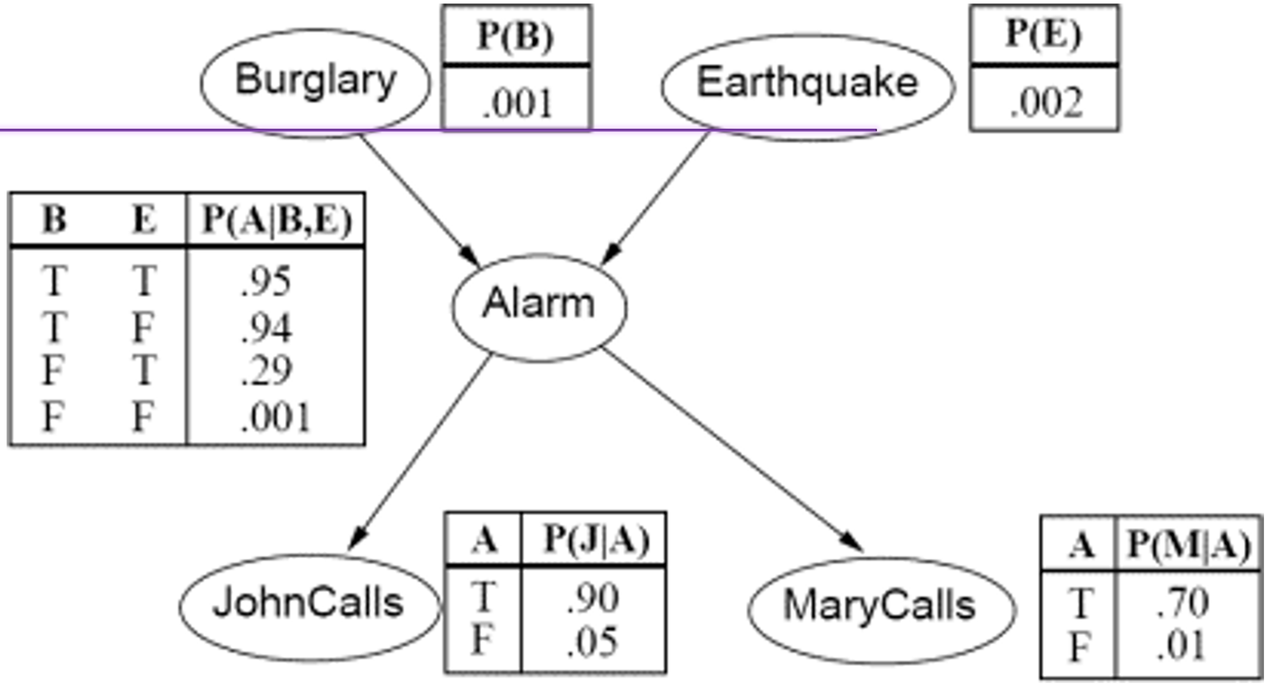
FINALLY we have:

$$P(B \mid j, m) = \alpha \sum_e \sum_a P(B, j, m, a, e)$$

From the conditional independence of the Bayes net:

$$P(B \mid j, m) = \alpha \sum_e \sum_a \prod_{i=1}^{n} P(x_i \mid \text{parents}(X_i))$$

Bayesian Networks



Example: Suppose we know the alarm has gone off, and both John and Mary have called to warn us. What is the probability that we have been burgled?

→ *P*(+b | +j, +m) = ?

So for this problem…

$$P(B \mid j, m) = \alpha \sum_e \sum_a \prod_{i=1}^{n} P(x_i \mid \text{parents}(X_i))$$

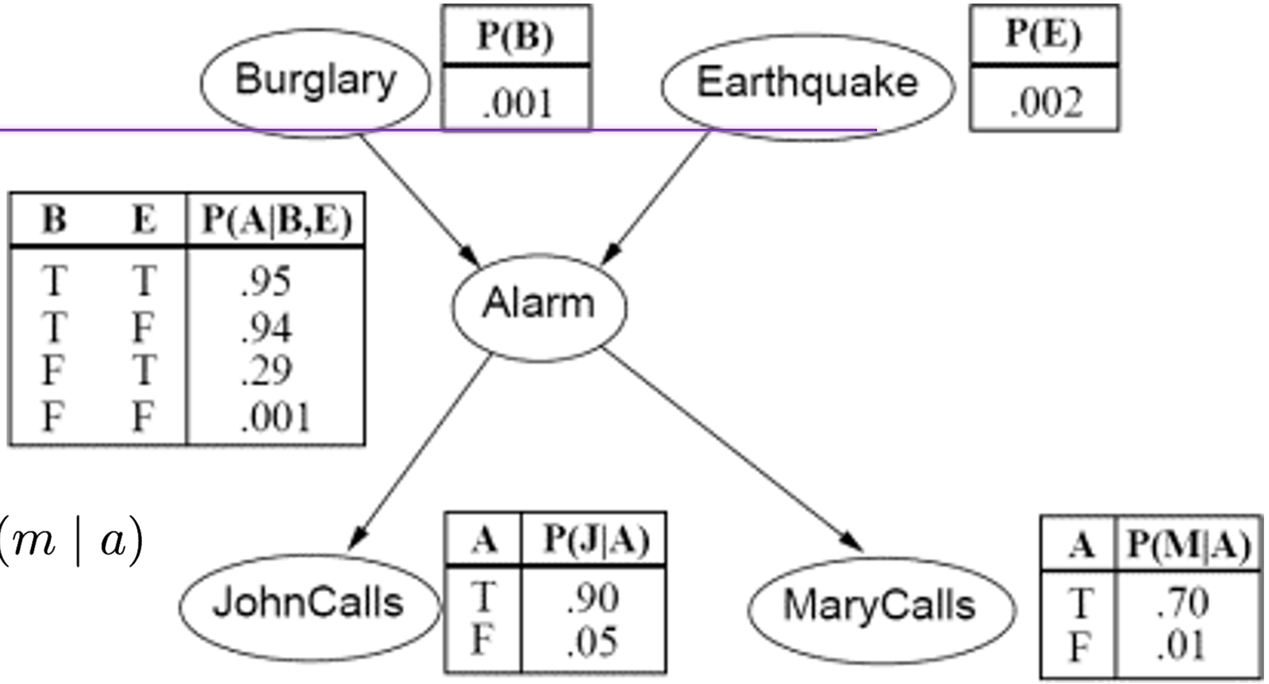
$$= \alpha \sum_e \sum_a P(B)P(e)P(a \mid B, e)P(j \mid a)P(m \mid a)$$

$$= \alpha P(B) \sum_e P(e) \sum_a P(a \mid B, e)P(j \mid a)P(m \mid a)$$

Bayesian Networks

Example: Are we ever going to actually calculate the probability that we have been burgled???

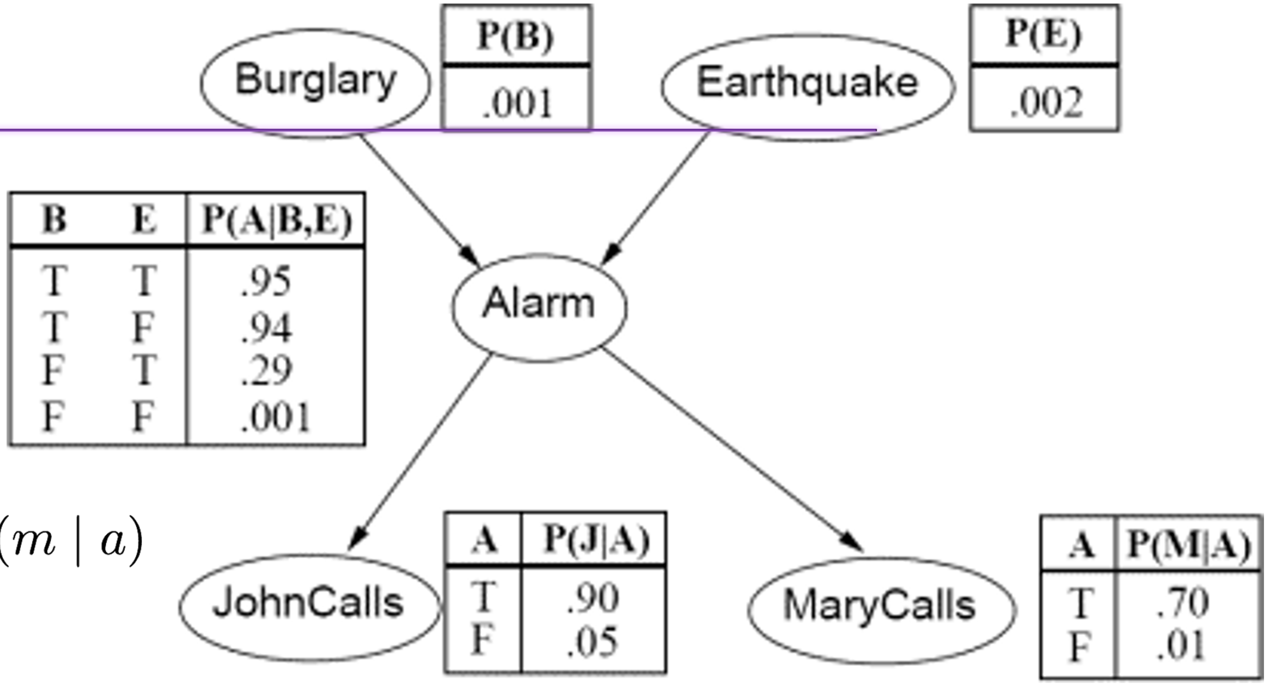
$$P(B \mid j, m) = \alpha P(B) \sum_{e} P(e) \sum_{a} P(a \mid B, e) P(j \mid a) P(m \mid a)$$



Bayesian Networks

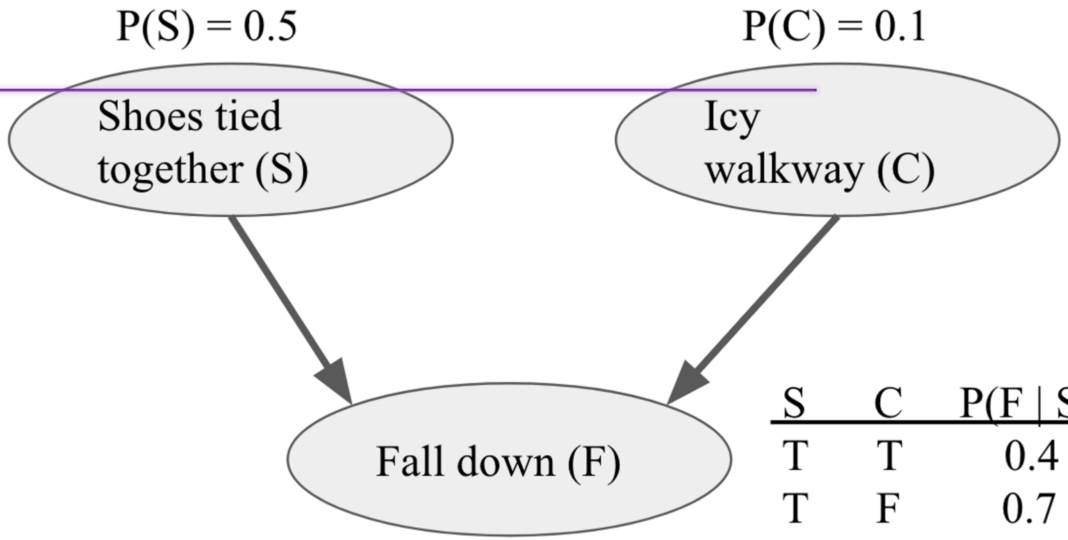
Example: Graphical representation

$$P(B \mid j, m) = \alpha P(B) \sum_{e} P(e) \sum_{a} P(a \mid B, e) P(j \mid a) P(m \mid a)$$



Prior Sampling

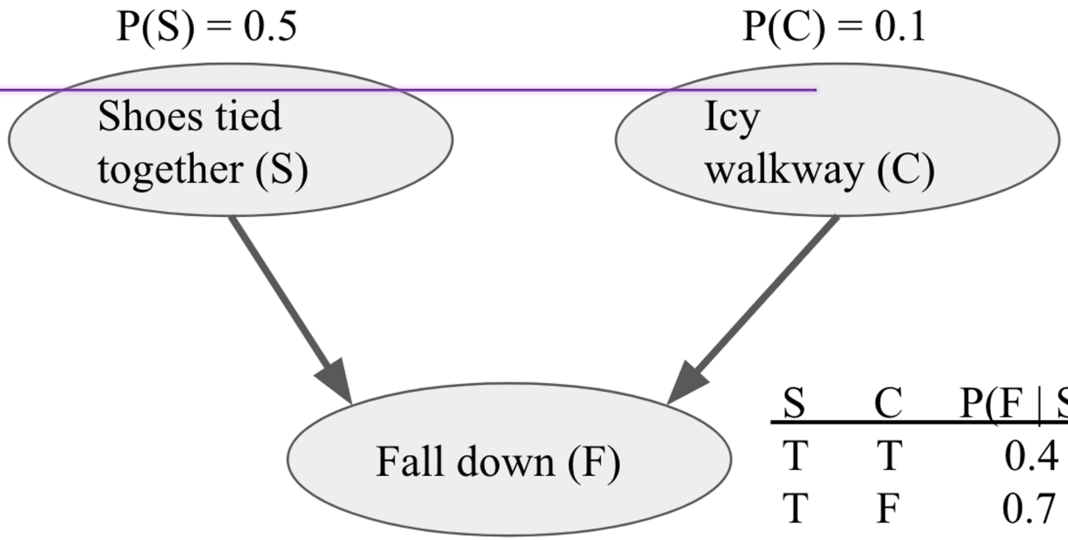
Calculation: P(+s, -f, -i) = ?



S	C	P(F | S, C)
T	T	0.4
T	F	0.7
F	T	0.1
F	F	0.01

Rejection Sampling

Calculation: P(+s | -f, -i) = ?



S	C	P(F | S, C)
T	T	0.4
T	F	0.7
F	T	0.1
F	F	0.01

Next Time

- *Bayesian Networks Notebook Day*