

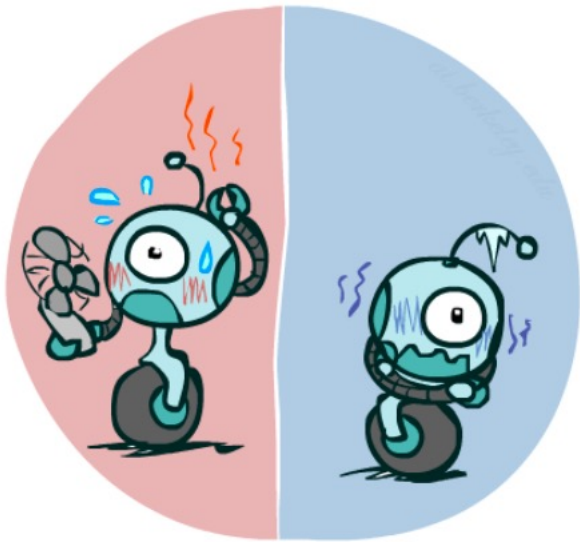
AIFA: Reasoning Under Uncertainty

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Koustav Rudra

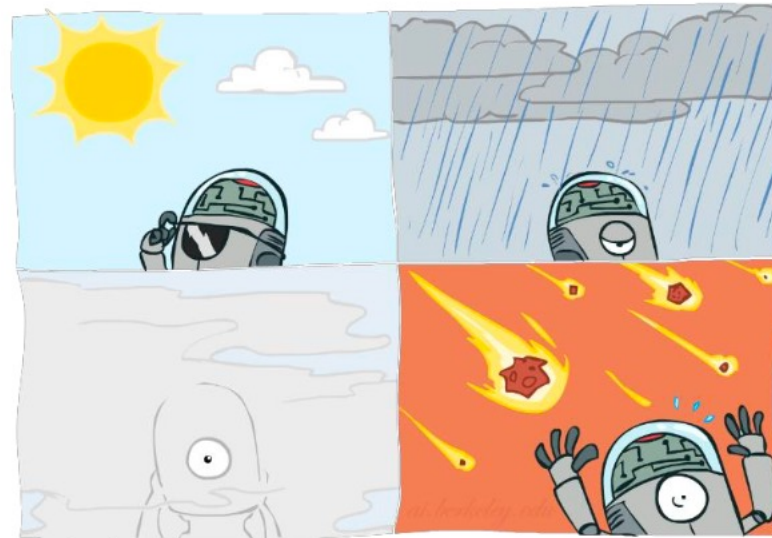
Probability Distributions

- A **probability distribution** is a description of how likely a random variable is to take on each of its possible states
- Notation: $P(X)$ is the probability distribution over the random variable X
- Associate a probability with each value



$P(T)$

T	P
hot	0.5
cold	0.5



$P(W)$

W	P
sun	0.6
rain	0.1
fog	0.3
meteor	0.0

- Unobserved random variables have distributions
- A distribution is a TABLE of probabilities of values

Axioms of Probability

- The probability of an event A in the given sample space \mathcal{S} , denoted as $P(A)$, must satisfy the following properties:
- Non-negativity
 - For any event $A \in \mathcal{S}$, $P(A) \geq 0$
- All possible outcomes
 - Probability of the entire sample space is 1, $P(\mathcal{S}) = 1$
- Additivity of disjoint events
 - For all events $A_1, A_2 \in \mathcal{S}$ that are mutually exclusive ($A_1 \cap A_2 = \emptyset$), the probability that both events happen is equal to the sum of their individual probabilities, $P(A_1 \cup A_2) = P(A_1) + P(A_2)$

Joint Distributions

- A joint distribution over a set of random variables: X_1, X_2, \dots, X_n
- Specifies a real number for each assignment (or outcome):
 - $P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n)$
 - $P(x_1, x_2, \dots, x_n)$
- Must satisfy
 - $P(x_1, x_2, \dots, x_n) \geq 0$
 - $\sum_{x_1, x_2, \dots, x_n} P(x_1, x_2, \dots, x_n) = 1$
- Size of distribution if n variables with domain sizes d ?

T	W	P
Hot	Sun	0.4
Hot	Run	0.1
Cold	Sun	0.2
Cold	Run	0.3

Probabilistic Models

- A probabilistic model is a joint distribution over a set of random variables
- Probabilistic models:
 - Random variables with domains
 - Assignments are called outcomes
 - Joint distributions: say whether
 - assignments (outcomes) are likely
 - Normalized: sum to 1.0
 - Ideally: only certain variables directly interact

T	W	P
Hot	Sun	0.4
Hot	Run	0.1
Cold	Sun	0.2
Cold	Run	0.3

Events

- An event is a set E of outcomes
- $P(E) = \sum_{x_1, x_2, \dots, x_n \in E} P(x_1, x_2, \dots, x_n)$
- From a joint distribution, we can calculate the probability of any event
 - Probability that it's hot AND sunny?
 - Probability that it's hot?
 - Probability that it's hot OR sunny?

T	W	P
Hot	Sun	0.4
Hot	Run	0.1
Cold	Sun	0.2
Cold	Run	0.3

Marginal Probability Distribution

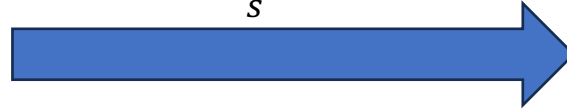
- **Marginal probability distribution** is the probability distribution of a single variable
- It is calculated based on the joint probability distribution $P(X,Y)$ using the **sum rule**:
- $P(X = x) = \sum_y P(X = x, Y = y)$

Marginal Distributions

- Marginal distributions are sub-tables which eliminate variables
- Marginalization (summing out): Combine collapsed rows by adding

T	W	P
Hot	Sun	0.4
Hot	Run	0.1
Cold	Sun	0.2
Cold	Run	0.3

$$P(t) = \sum_s P(t, s) = P(T)$$



T	P
Hot	0.5
Cold	0.5

$$P(s) = \sum_t P(t, s) = P(W)$$



W	P
Sun	0.6
Rain	0.4

$$P(X1 = x1) = \sum_{x2} P(X1 = x1, X2 = x2)$$

Conditional Probabilities

- $P(a|b) = \frac{P(a,b)}{P(b)}$
- $P(W = s|T = c) = \frac{P(W=s,T=c)}{P(T=c)}$
- $P(W = s|T = c) = \frac{0.2}{0.5}$

T	W	P
Hot	Sun	0.4
Hot	Run	0.1
Cold	Sun	0.2
Cold	Run	0.3

Conditional Distributions

- Conditional distributions are probability distributions over some variables given fixed values of others

Conditional Distributions

$P(W|T)$

$P(W T = \text{hot})$	
W	P
sun	0.8
rain	0.2

$P(W T = \text{cold})$	
W	P
sun	0.4
rain	0.6

Joint Distribution

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Normalization Trick

T	W	P
Hot	Sun	0.4
Hot	Run	0.1
Cold	Sun	0.2
Cold	Run	0.3

- SELECT the joint probabilities matching the evidence



$P(c, W)$

T	W	P
Cold	Sun	0.2
Cold	Rain	0.3

- Normalize the selection



$P(W|T = c)$

W	P
Sun	0.2
Rain	0.3

Product Rule

- Sometimes have conditional distributions but want the joint
- $P(y)P(x|y) = P(x, y)$

Bayesian Network

Conditional Independence

- Two events A and B are conditionally independent given another event C with $P(C) > 0$:
 - $P(A \wedge B|C) = P(A|C)P(B|C)$
- $P(A|B \wedge C) = \frac{P(A \wedge B|C)}{P(B|C)}$
- $P(A|B \wedge C) = \frac{P(A|C)P(B|C)}{P(B|C)}$
- $P(A|B \wedge C) = P(A|C)$

Conditional Independence and Chain Rule

Trivial decomposition:

$$P(\text{Traffic}, \text{Rain}, \text{Umbrella}) = \\ P(\text{Rain})P(\text{Traffic}|\text{Rain})P(\text{Umbrella}|\text{Rain}, \text{Traffic})$$

With assumption of conditional independence:

$$P(\text{Traffic}, \text{Rain}, \text{Umbrella}) = \\ P(\text{Rain})P(\text{Traffic}|\text{Rain})P(\text{Umbrella}|\text{Rain})$$

Bayes nets / graphical models help us express conditional independence assumptions



Conditional Independence

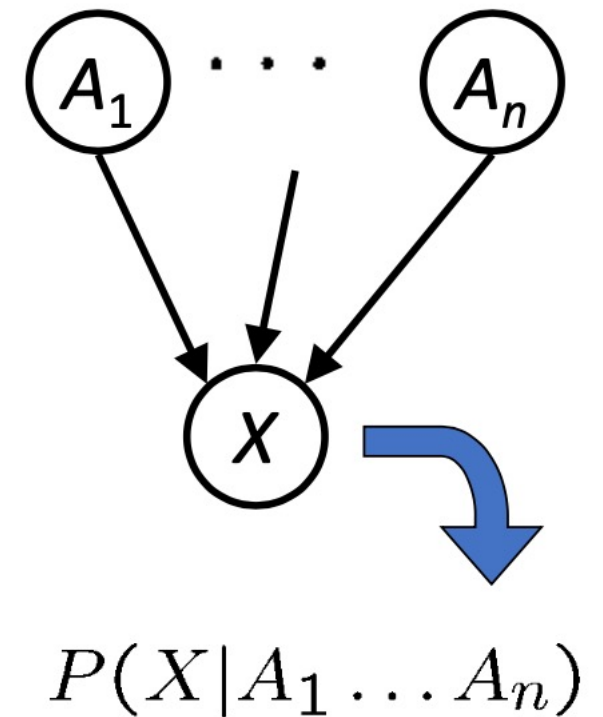
- $P(x_1, \dots, x_n) = P(x_n | x_{n-1}, \dots, x_1) P(x_{n-1}, \dots, x_1)$
 - $P(x_1, \dots, x_n) = P(x_n | x_{n-1}, \dots, x_1) P(x_{n-1} | x_{n-2}, \dots, x_1) \dots P(x_2 | x_1) P(x_1)$
 - $P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | x_{i-1}, \dots, x_1)$
-
- The belief network represents conditional independence:
 - $P(x_i | x_i, \dots, x_1) = P(x_i | \text{Parents}(x_i))$

Bayes Nets

- A Bayes' net is an efficient encoding of a probabilistic model of a domain
- Questions we can ask:
 - Inference: given a fixed BN, what is $P(X | e)$?
 - Representation: given a BN graph, what kinds of distributions can it encode?
 - Modeling: what BN is most appropriate for a given domain?

Bayes Net Semantics

- A set of nodes, one per variable X
- A directed, acyclic graph
- A conditional distribution for each node
 - A collection of distributions over X , one for each combination of parents' values
 - $P(X|a_1, a_2, \dots, a_n)$
- CPT: conditional probability table
- Description of a noisy “causal” process



A Bayes net = Topology (graph) + Local Conditional Probabilities

Probabilities in BN

- Bayes' nets **implicitly** encode joint distributions
 - As a product of local conditional distributions
 - $P(x_i | x_{i-1}, x_{i-2}, \dots, x_1) = P(x_i | \text{Parents}(x_i))$
- $\text{Parents}(x_i)$: minimal set of predecessors of X_i in the total ordering such that other predecessors are conditionally independent of X_i given $\text{Parent}(X_i)$

Bayesian Network

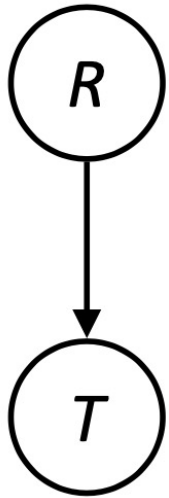
- What is the issue with joint probability distribution?
 - Become intractably large as the number of variables grows
 - Specifying probabilities for atomic events is really difficult
- How does Bayesian Network help?
 - Explore independence and conditional independence relationships among variables
 - To greatly reduce number of probabilities to be specified to define full joint distribution

Bayesian Network

- A set of random variables makes up the nodes of the network
 - Variables may be discrete or continuous
- A set of directed links or arrows connects pairs of nodes
 - Arrows represent probabilistic dependence among variables
- An arrow from $X \rightarrow Y$ indicates X is parent of Y
- Each node X_i has a conditional probability distribution $P(X_i | \text{Parents}(X_i))$
 - Quantifies the effect of the parents on the node
- The graph has no directed cycles (DAG)

Example1: Traffic

- Causal direction



$P(R)$

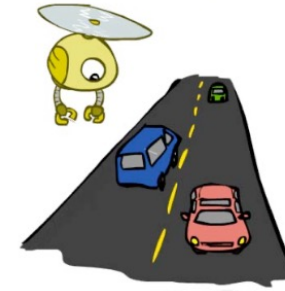
+r	1/4
-r	3/4

$P(T|R)$

+r	+t	3/4
	-t	1/4
-r	+t	1/2
	-t	1/2

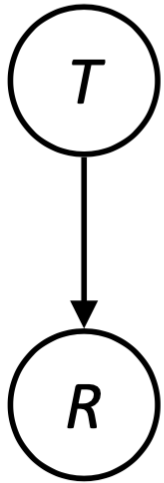
$P(T, R)$

+r	+t	3/16
+r	-t	1/16
-r	+t	6/16
-r	-t	6/16



Example2: Traffic

- Reverse causality?



$P(T)$

+t	9/16
-t	7/16

$P(R|T)$

+t	+r	1/3
	-r	2/3
-t	+r	1/7
	-r	6/7

$P(T, R)$

+r	+t	3/16
+r	-t	1/16
-r	+t	6/16
-r	-t	6/16



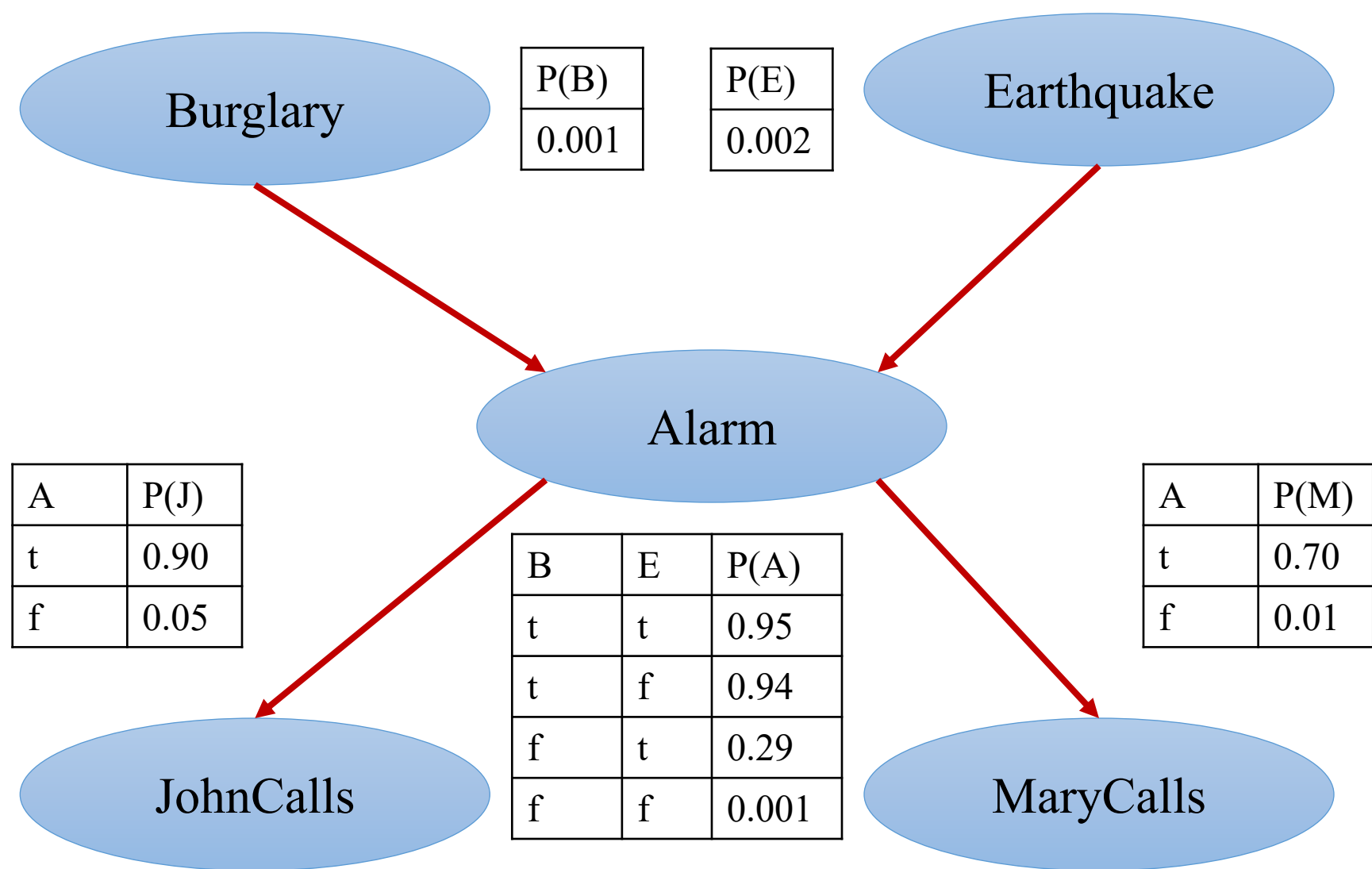
Causality?

- When Bayes' nets reflect the **true causal** patterns:
 - Often simpler (nodes have fewer parents)
 - Often easier to think about and to elicit from experts
- BNs need not actually be causal
 - Sometimes no causal net exists over the domain (especially if variables are missing)
 - End up with arrows that reflect correlation, not causation
- What do the arrows really mean?
 - Topology may happen to encode causal structure
 - **Topology really encodes conditional independence**

Example3: Home Alarm Network

- Burglar alarm at home
 - Fairly reliable at detecting a burglary
 - Responds at times to minor earthquakes
- Two neighbors, on hearing alarm, calls police
 - John always calls when he hears the alarm
 - But sometimes confuses the telephone ringing with the alarm and calls then too
- Mary likes loud music
 - But sometimes misses the alarm altogether

Belief Network



Joint probability distribution

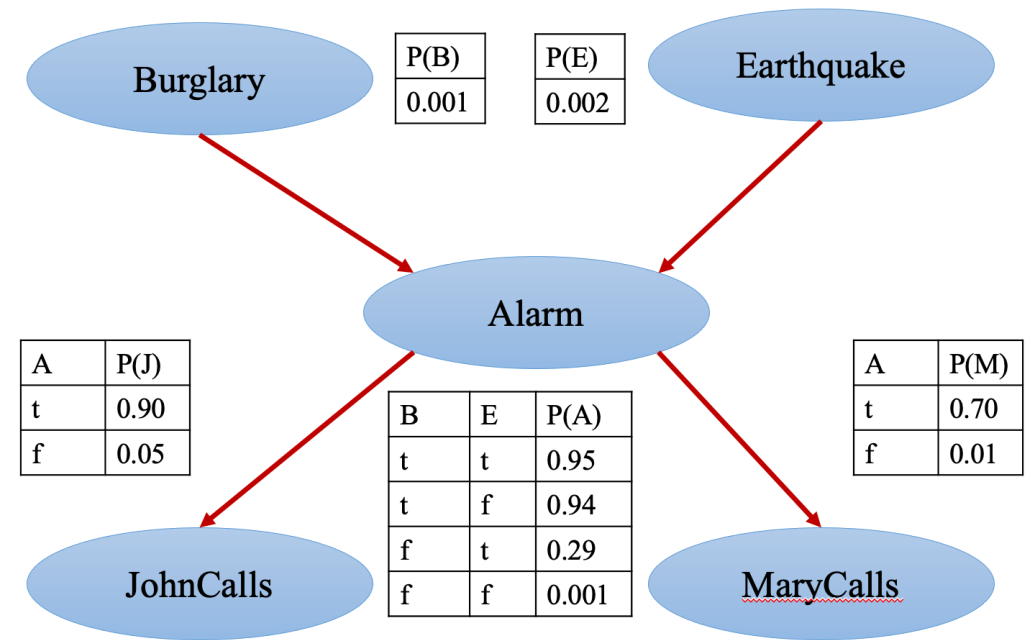
- $P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | \text{Parents}(x_i))$

- $P(J \wedge M \wedge A \wedge \sim B \wedge \sim E)$

- $P(J|A) *$
- $P(M|A) *$
- $P(A|\sim B \wedge \sim E) *$
- $P(\sim B) *$
- $P(\sim E)$

- $P(J \wedge M \wedge A \wedge \sim B \wedge \sim E) = 0.9 \times 0.7 \times 0.001 \times 0.999 \times 0.998 = 0.00062$

- $P(J) = ?$



Conditional Independence

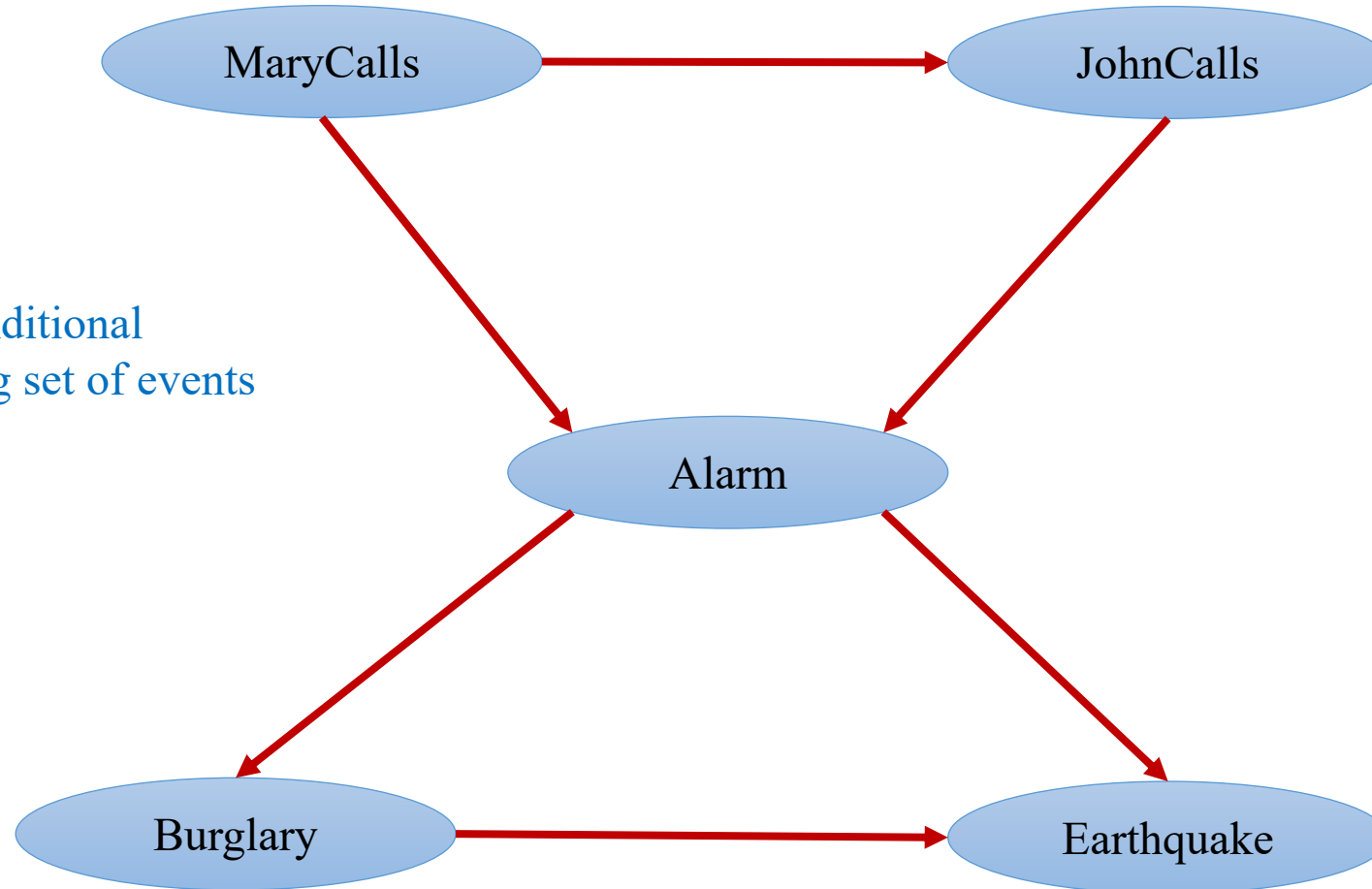
- $P(J, M, A, B, E) = P(J|M, A, B, E)P(M, A, B, E)$
- $P(J, M, A, B, E) = P(J|A)P(M|A, B, E)P(A, B, E)$
- $P(J, M, A, B, E) = P(J|A)P(M|A)P(A|B, E)P(B, E)$
- $P(J, M, A, B, E) = P(J|A)P(M|A)P(A|B, E)P(B)P(E)$

How does ordering matter?

Conditional Independence

- Earthquake, Burglary, Alarm, JohnCalls, MaryCalls
- $P(E|B,A,J,M)$

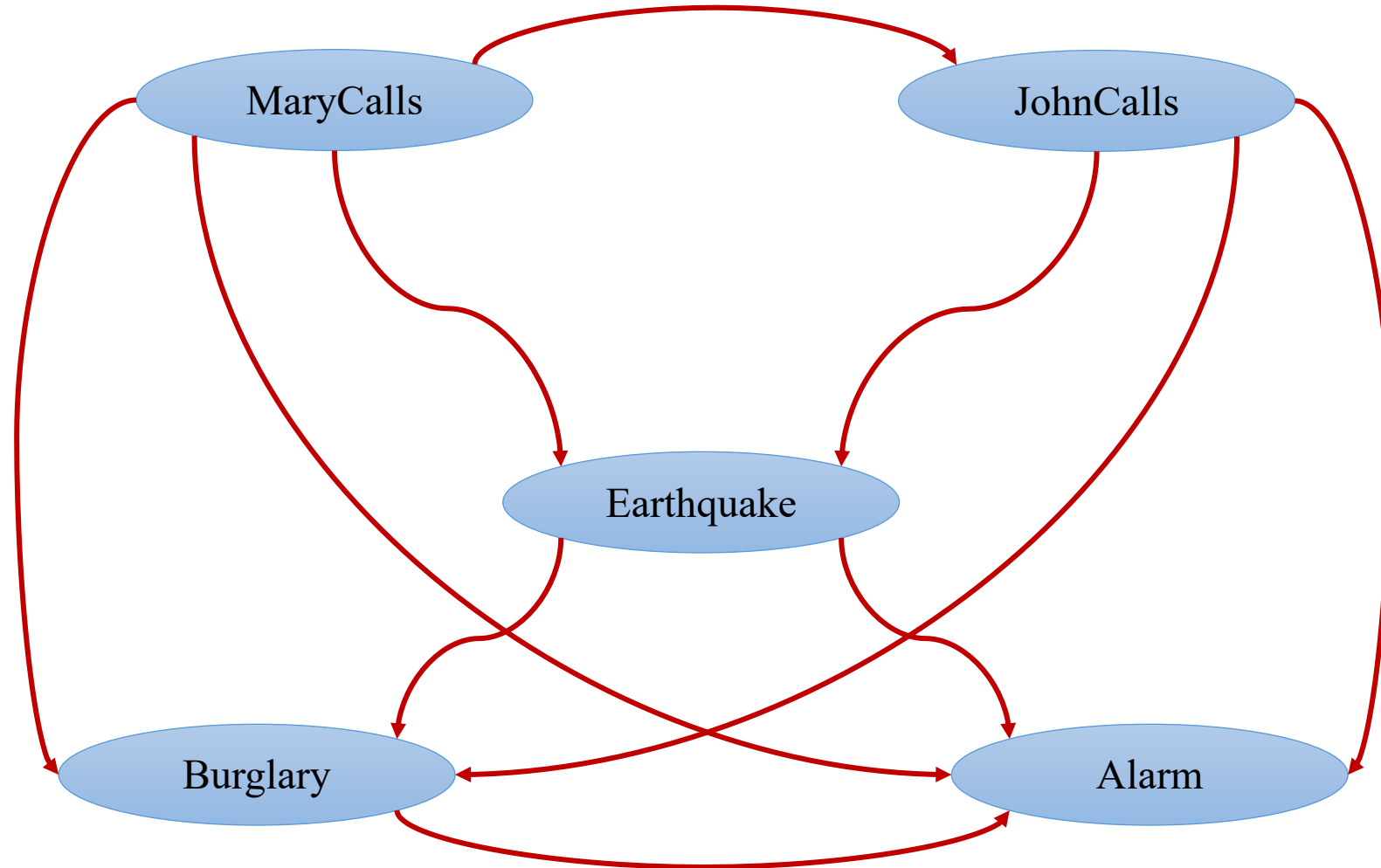
May have to define conditional probability of confusing set of events



Conditional Independence

- Alarm, Burglary, Earthquake, JohnCalls, MaryCalls

May have to construct
large probability tables



Incremental Network Construction

- Choose the set of relevant variables X_i , that describe the domain
- Choose an ordering for the variables [important step]
- While there are variables left:
 - Pick a variable X and add a node for it
 - Set $\text{Parents}(X)$ to some minimal set of existing nodes such that the conditional independence property is satisfied
 - Define conditional probability table for X

Why do we construct Bayes Network?

To answer queries related to joint probability distribution

Size of a Bayes Net

- How big is a joint distribution over N Boolean variables?
 - 2^N
- How big is an N -node net if nodes have up to k parents?
 - $O(N * 2^k)$
- Both give you the power to calculate
- BNs: Huge space savings!
- Also easier to elicit local CPTs
- Also faster to answer queries (coming)

Thank You