

## CHAPTER 14.1-3

### BAYESIAN NETWORKS

A simple, graphical notation for conditional independence assertions and hence for compact specification of full joint distributions

In the simplest case, conditional distribution represented as

a directed, acyclic graph (link  $\approx$  "directly influences")

a set of nodes, one per variable

a conditional distribution for each node given its parents:

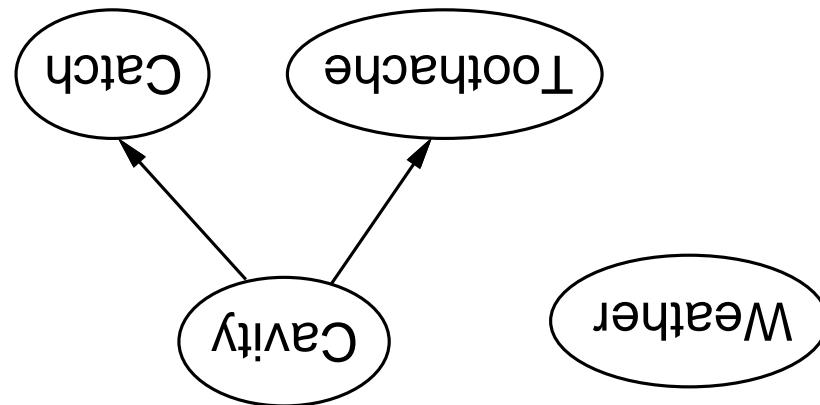
$P(X_i | \text{Parents}(X_i))$

In the simplest case, conditional distribution over  $X^i$  for each combination of parent values giving the

## Bayesian networks

*Toothache* and *Catch* are conditionally independent given *Cavity*

*Weather* is independent of the other variables



Topology of network encodes conditional independence assertions:

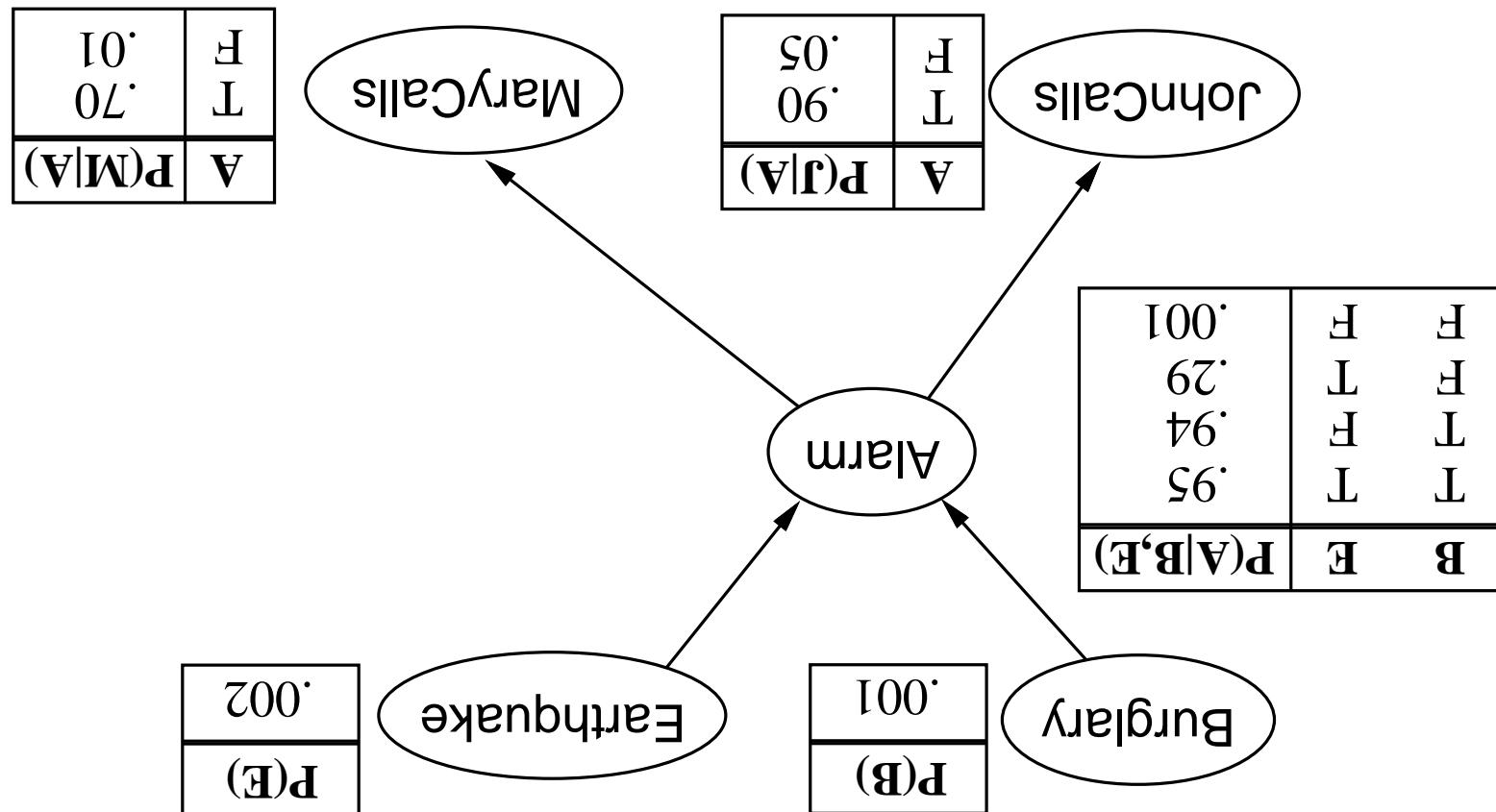
Example

I'm at work, neighbor John calls to say my alarm is ringing, but neighbor Mary doesn't call. Sometimes it's set off by minor earthquakes. Is there a burglar?

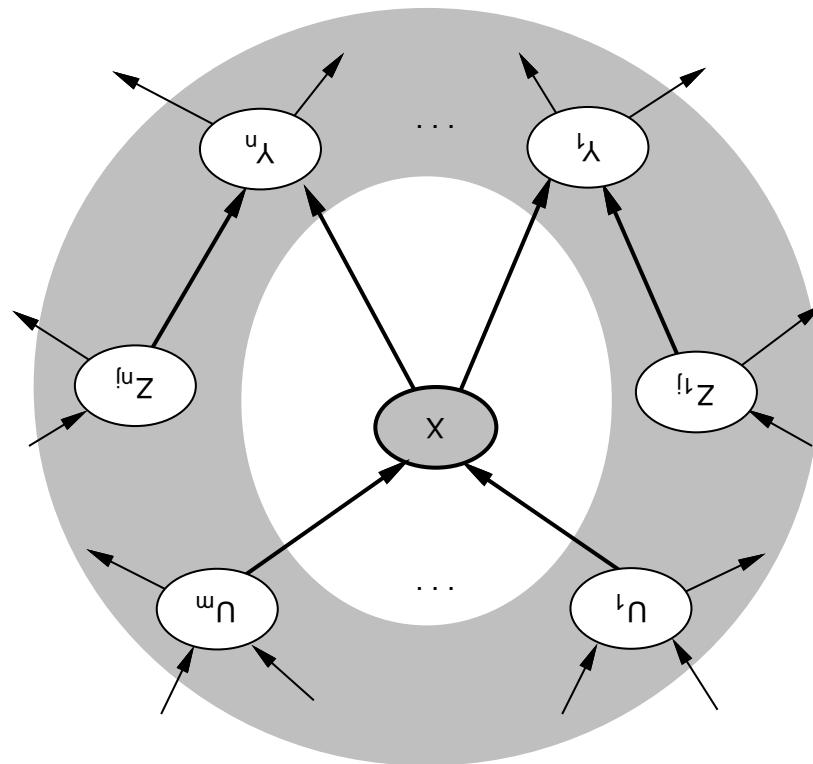
Variables: *Burglar*, *Earthquake*, *Alarm*, *JohnCalls*, *MaryCalls*

Network topology reflects "causal" knowledge:

- A burglar can set the alarm off
- An earthquake can set the alarm off
- The alarm can cause Mary to call
- The alarm can cause John to call

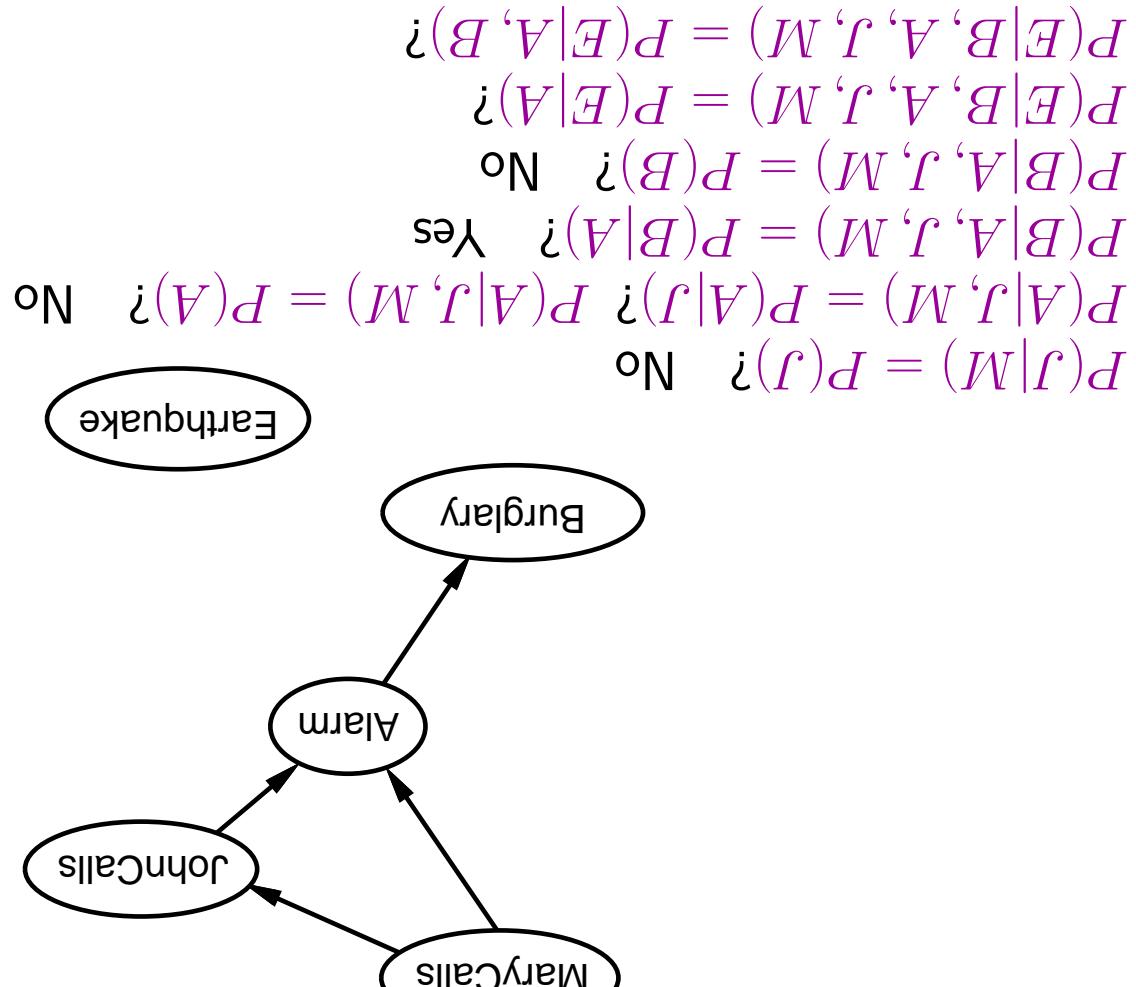


Example cont'd.



Each node is conditionally independent of all others given its  
Markov blanket: parents + children + children's parents

Markov blanket



Suppose we choose the ordering  $M, J, A, B, E$

## Example

Bayes nets provide a natural representation for (causally induced) conditional independence

Topology + CPTs = compact representation of joint distribution

Generally easy for (non)experts to construct

Canonical distributions (e.g., noisy-OR) = compact representation of CPTs  
Continuous variables  $\Rightarrow$  parameterized distributions (e.g., linear Gaussian)

## Summary