

CS 1675 Intro to Machine Learning  
Lecture 20

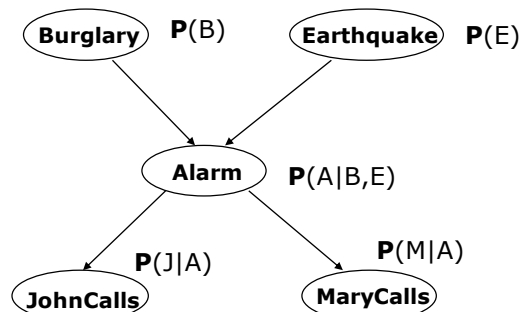
Bayesian belief networks IV  
(Monte Carlo inference)

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Bayesian belief network

Belief network structure:

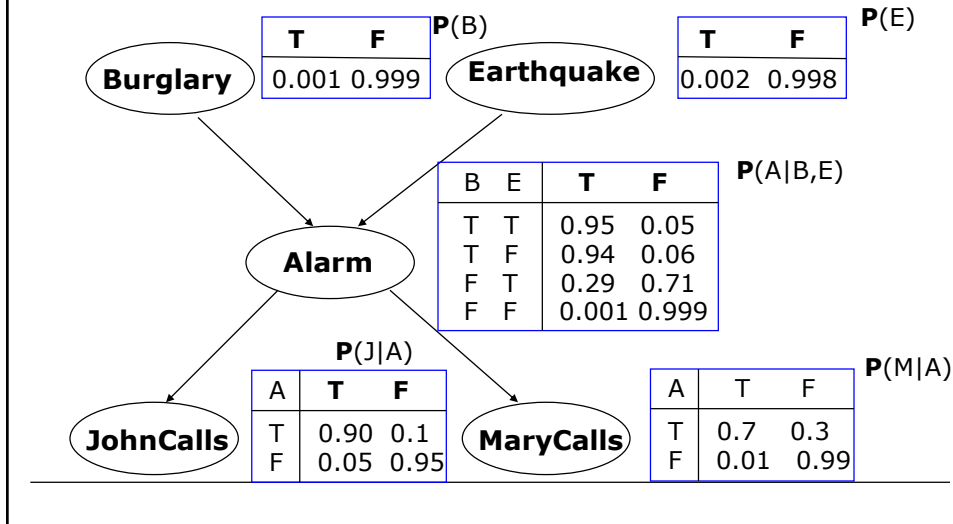
- **Nodes** = random variables  
Burglary, Earthquake, Alarm, Mary calls and John calls
- **Links** = direct (causal) dependencies between variables.  
The chance of Alarm being is influenced by Earthquake, The chance of John calling is affected by the Alarm



## Bayesian belief network

### 2. Local conditional distributions

- relating variables and their parents



## Inference in Bayesian network

- Exact inference algorithms:**
  - Variable elimination
  - Recursive decomposition (Cooper, Darwiche)
  - Symbolic inference (D'Ambrosio)
  - Belief propagation algorithm (Pearl)
  - Clustering and joint tree approach (Lauritzen, Spiegelhalter)
  - Arc reversal (Olmsted, Schachter)
- Approximate inference algorithms:**
  - Monte Carlo methods:**
    - Forward sampling, Likelihood sampling
  - Variational methods

## Monte Carlo approaches

- MC approximation:**

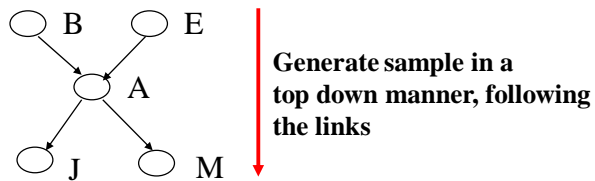
- The probability is approximated using sample frequencies

- **Example:**

$$\tilde{P}(B=T, J=T) = \frac{N_{B=T, J=T}}{N}$$

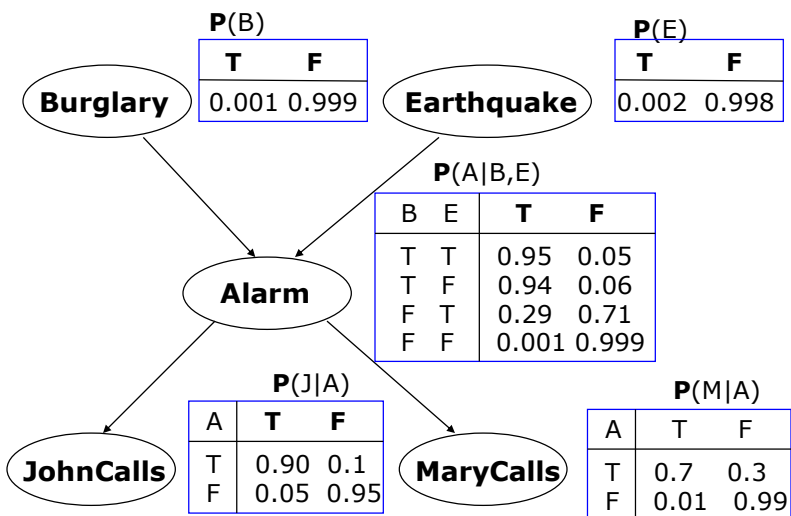
← # samples with  $B=T, J=T$ 
← total # samples

- Sample generation: BBN sampling of the joint is easy**

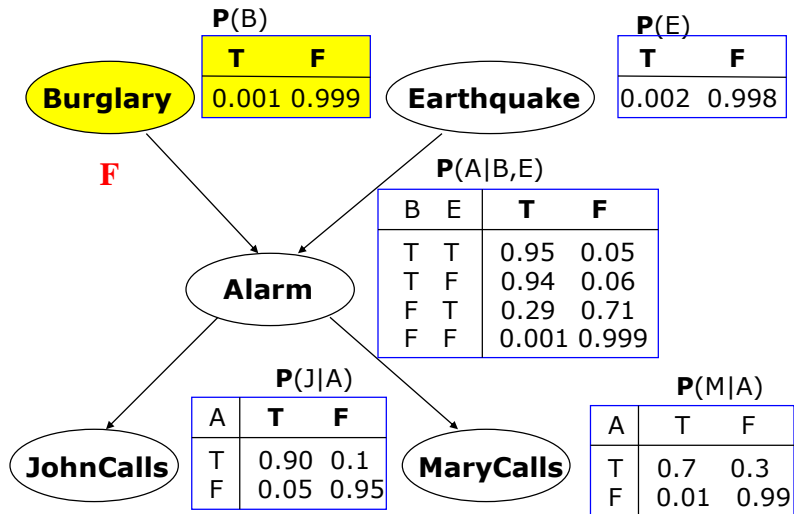


- One sample gives one assignment of values to all variables**

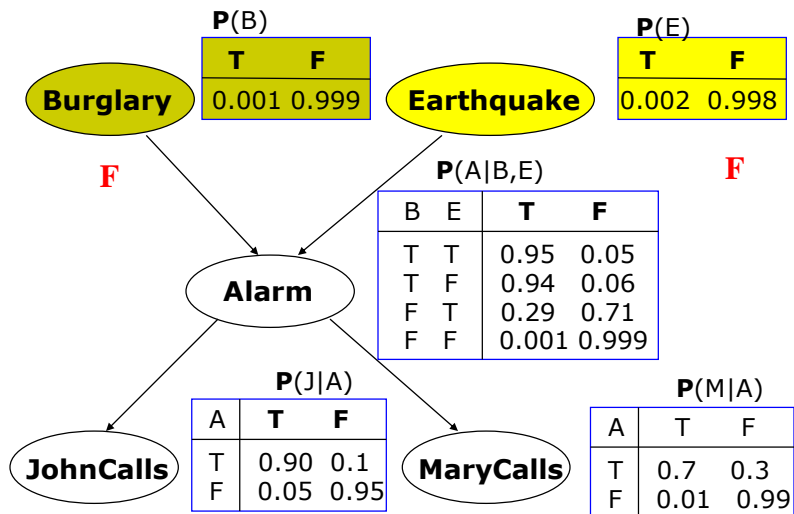
## BBN sampling example



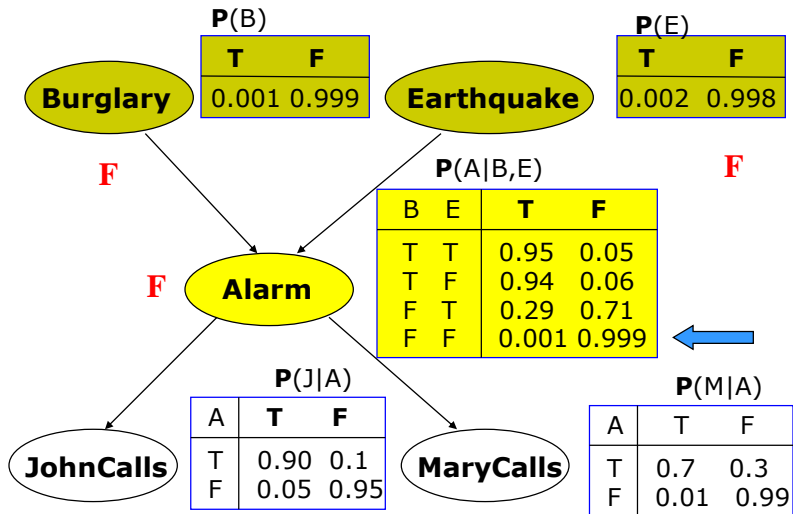
## BBN sampling example



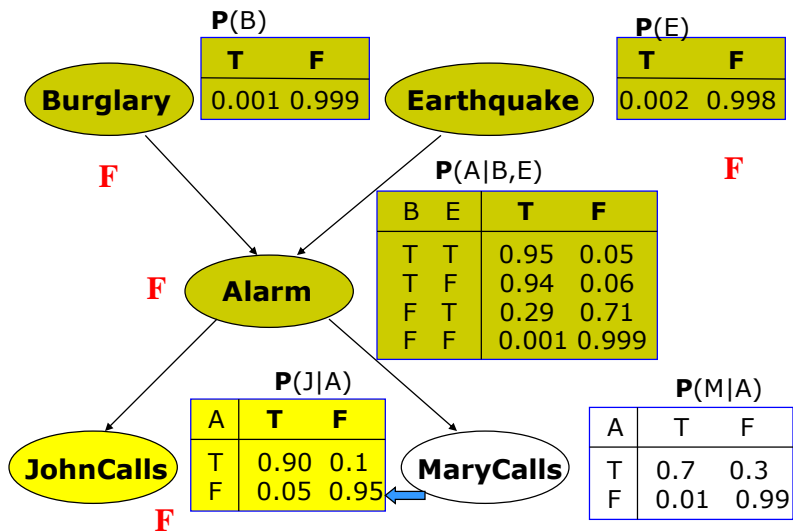
## BBN sampling example



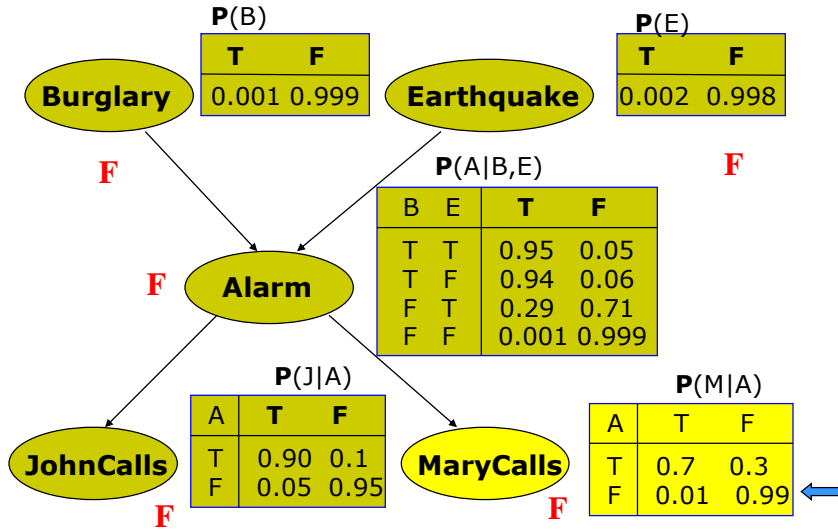
## BBN sampling example



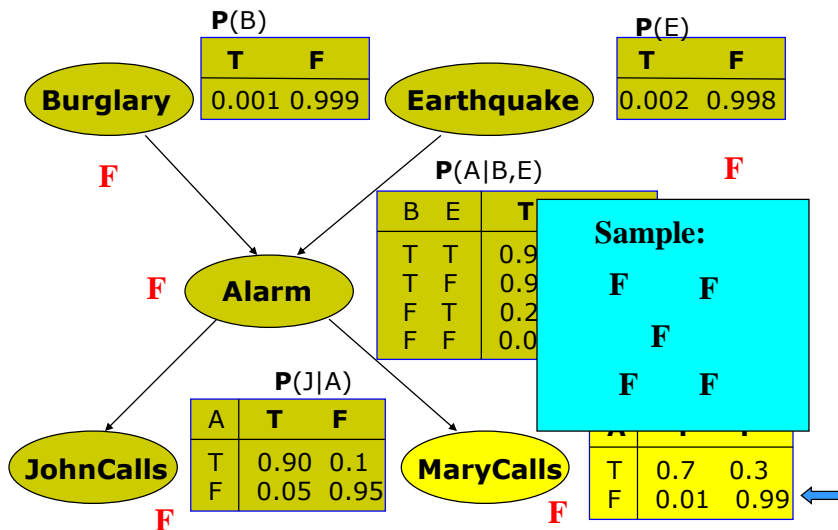
## BBN sampling example



## BBN sampling example



## BBN sampling example



## Monte Carlo approaches

- **MC approximation of conditional probabilities:**

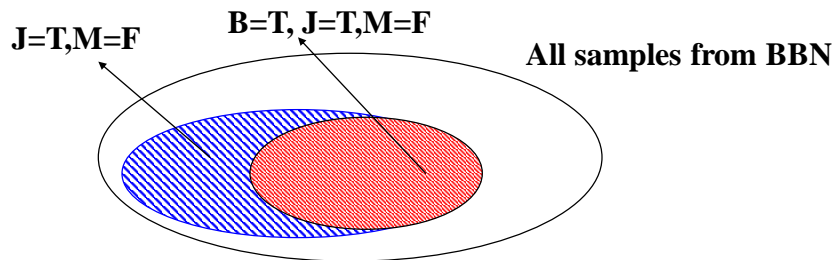
- The probability is approximated using sample frequencies

- **Example:**

$$\tilde{P}(B=T | J=T, M=F) = \frac{N_{B=T, J=T, M=F}}{N_{J=T, M=F}}$$

# samples with  $B=T, J=T, M=F$

# samples with  $J=T, M=F$



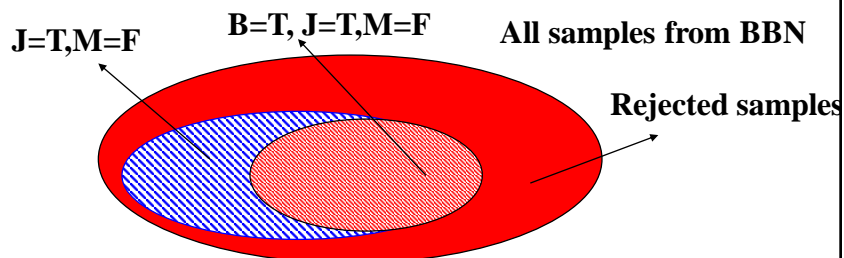
## Monte Carlo approaches

- **Rejection sampling**

- Generate samples from the full joint by sampling BBN

- Use only samples that agree with the condition, the remaining samples are rejected

- **Problem:** many samples can be rejected



## Likelihood weighting

**Idea:** generate only samples consistent with an evidence (or conditioning event)

- Benefit: Avoids inefficiencies of rejection sampling

**Problem:**

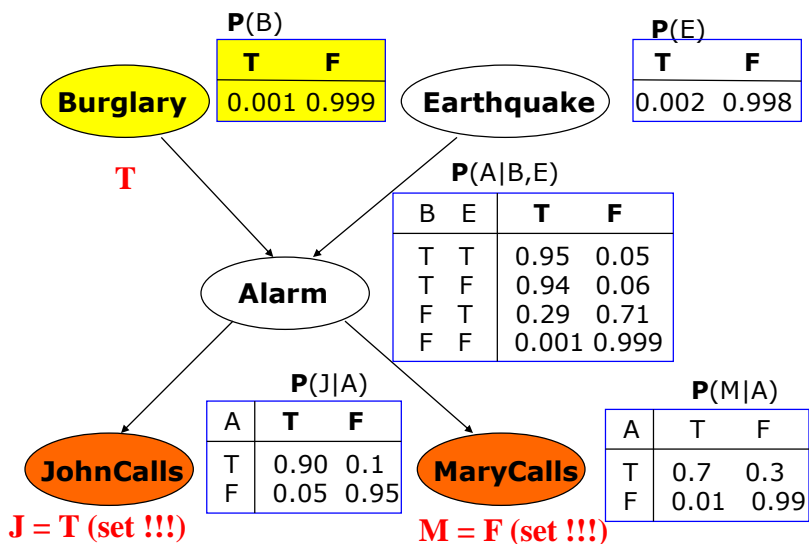
- the distribution generated by enforcing the conditioning variables to set values is biased
- simple counts are not sufficient to estimate the probabilities

**Solution:**

- With every sample keep a weight with which it should count towards the estimate

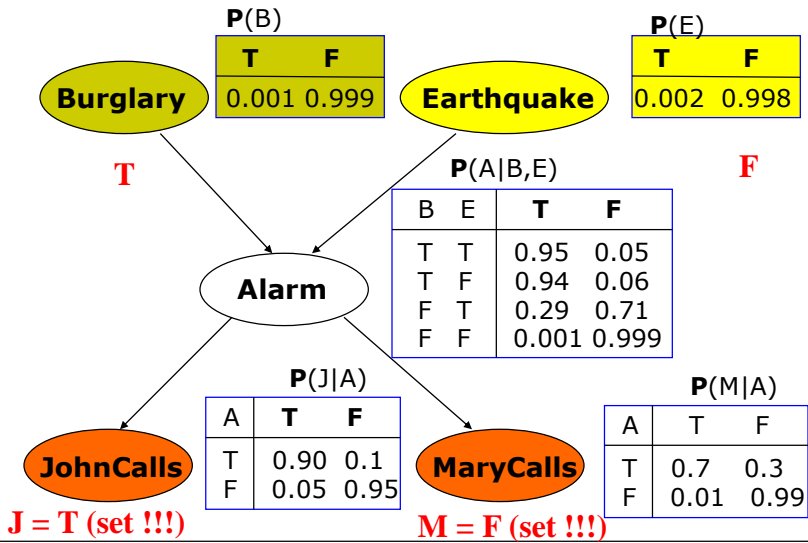
$$\tilde{P}(B = T \mid J = T, M = F) = \frac{\sum_{\text{samples with } B=T, M=F \text{ and } J=T} W_{B=T \mid J=T, M=F}}{\sum_{\text{samples with any value of } B \text{ and } J=T, M=F} W_{B=x \mid J=T, M=F}}$$

## BBN likelihood weighting example

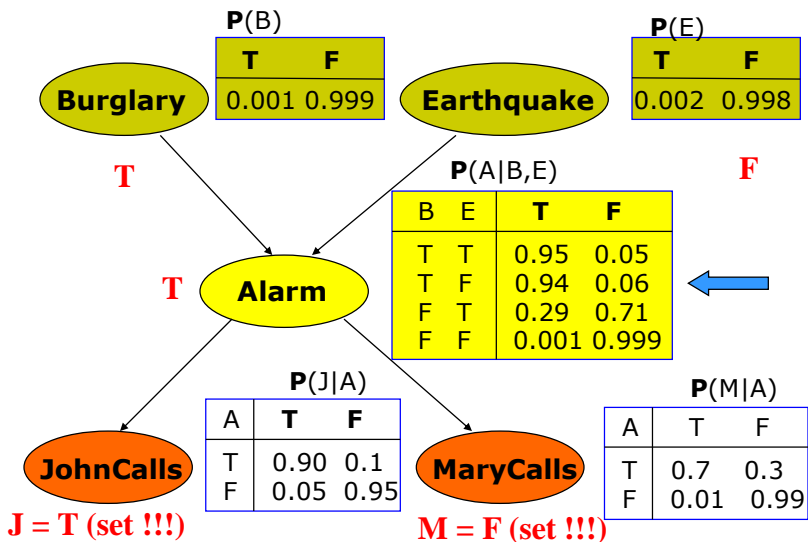




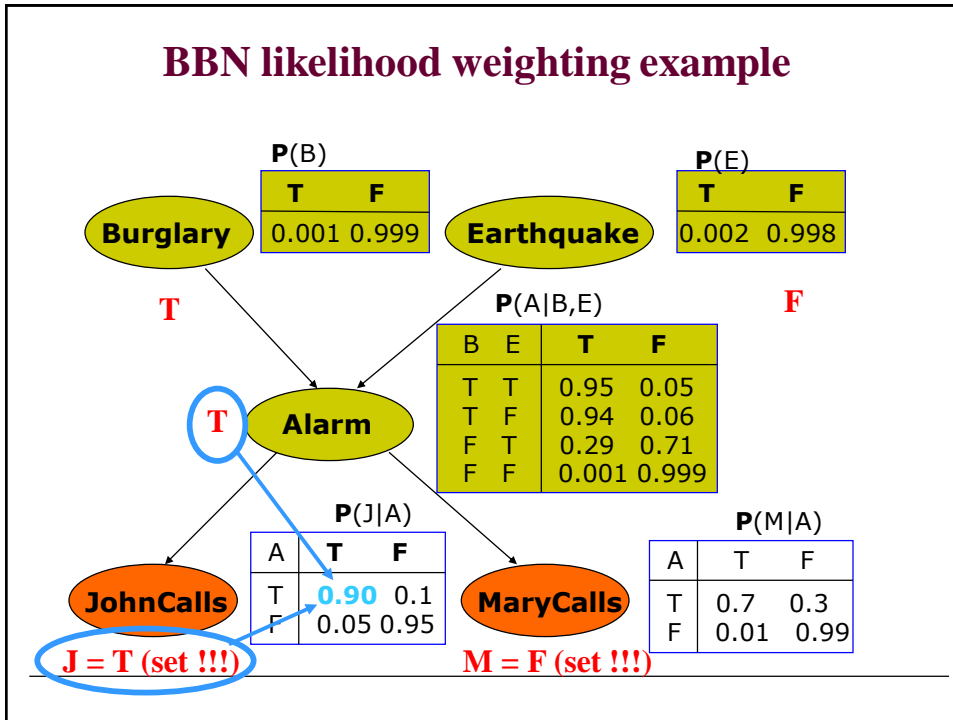
## BBN likelihood weighting example



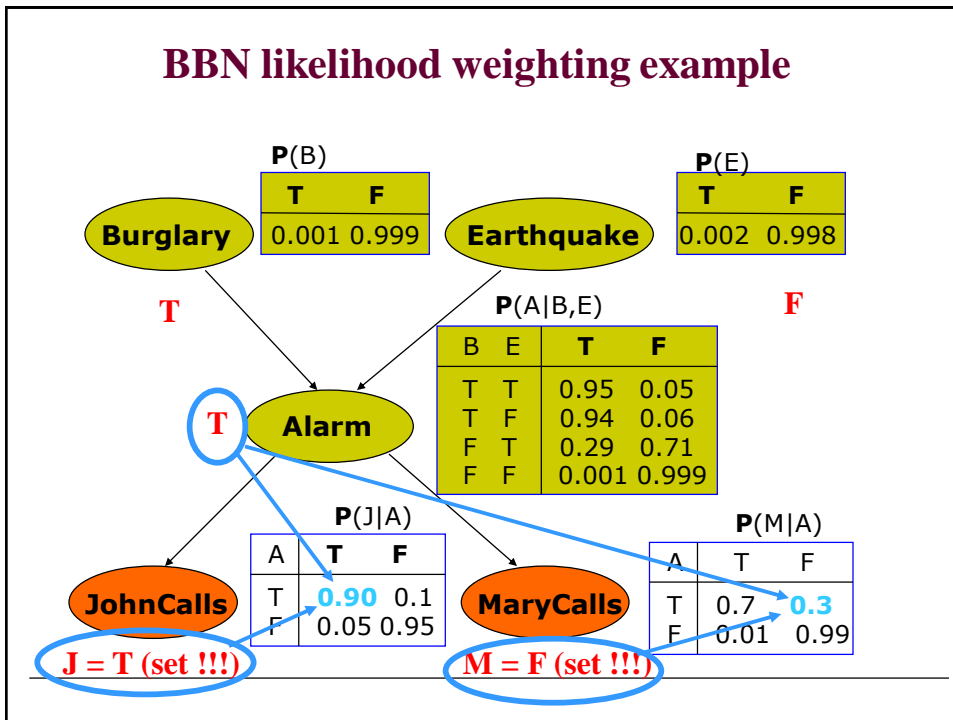
## BBN likelihood weighting example



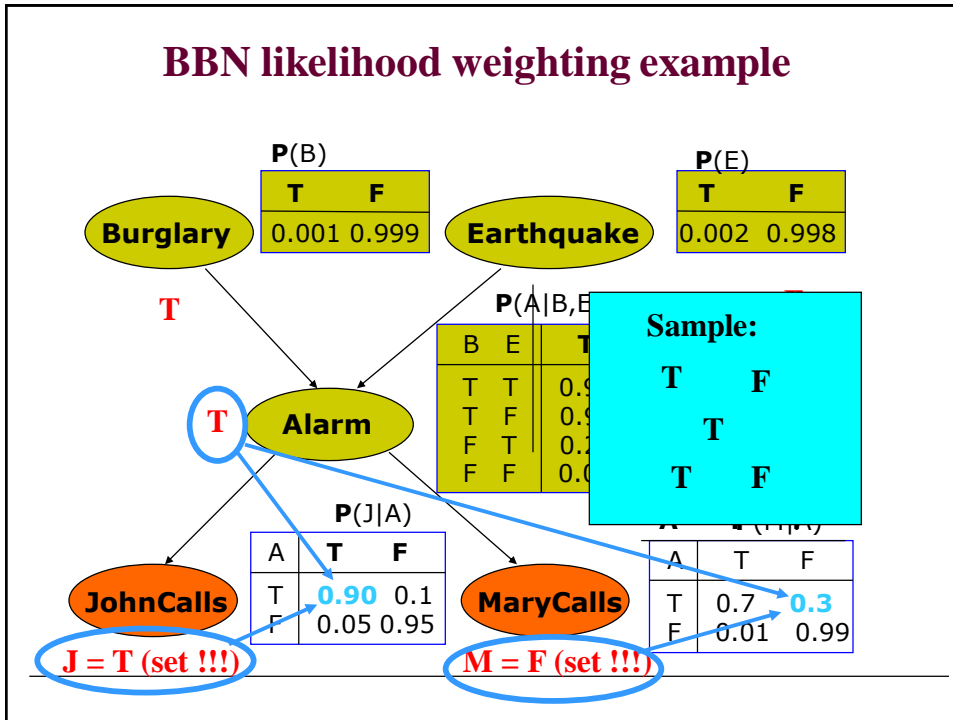
## BBN likelihood weighting example



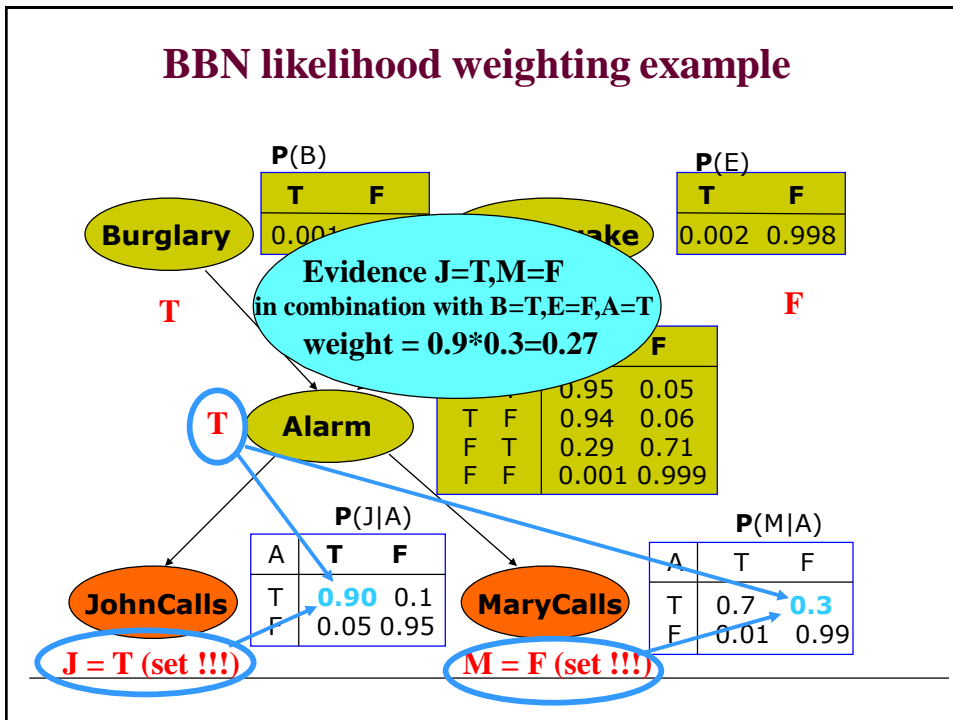
## BBN likelihood weighting example



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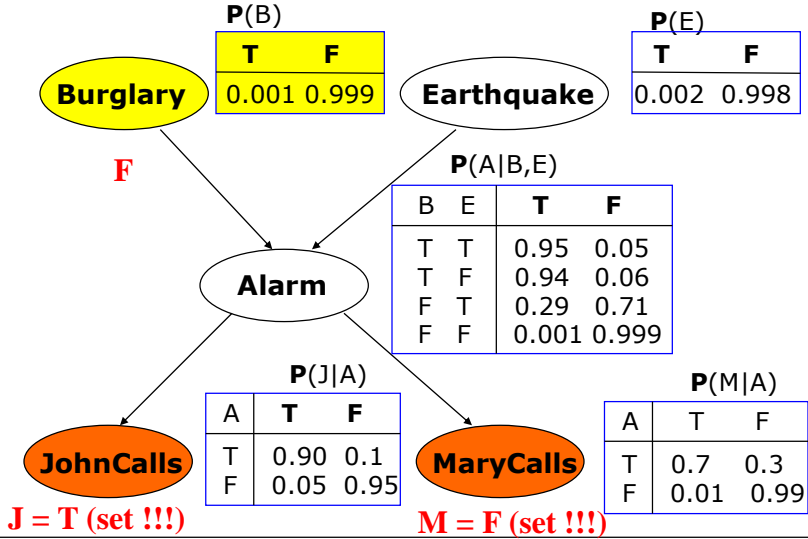


## BBN likelihood weighting example



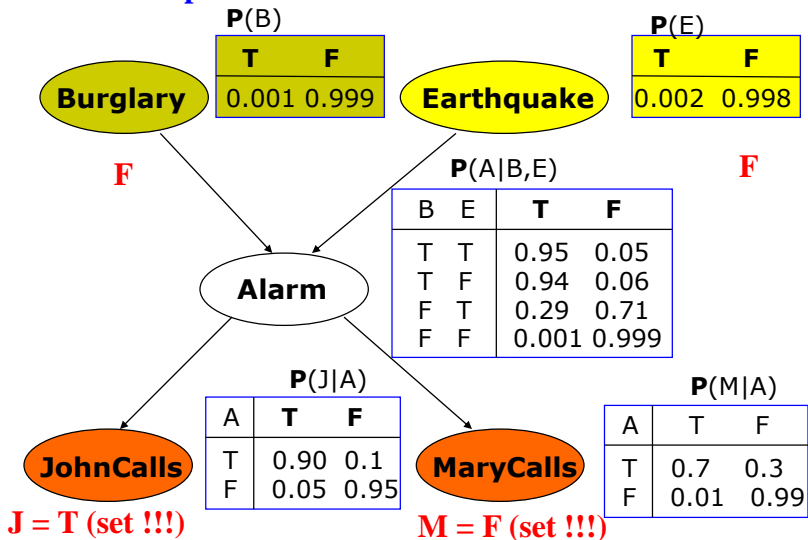
## BBN likelihood weighting example

Second sample



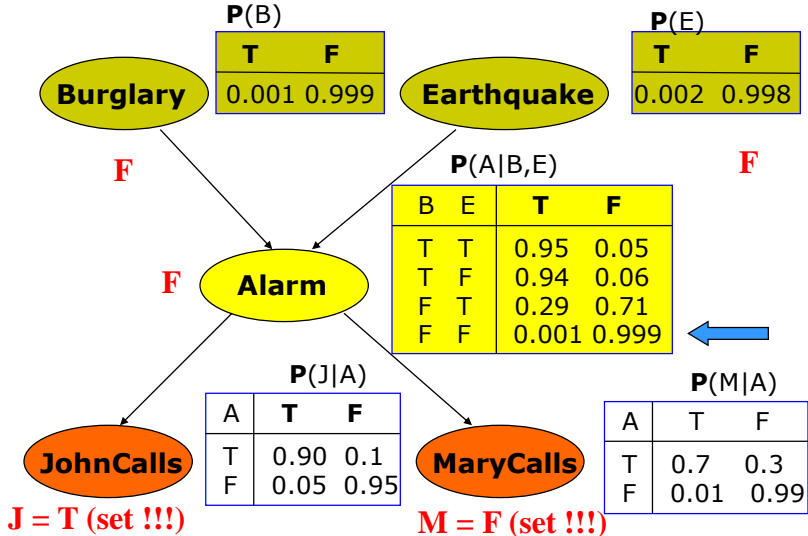
## BBN likelihood weighting example

Second sample



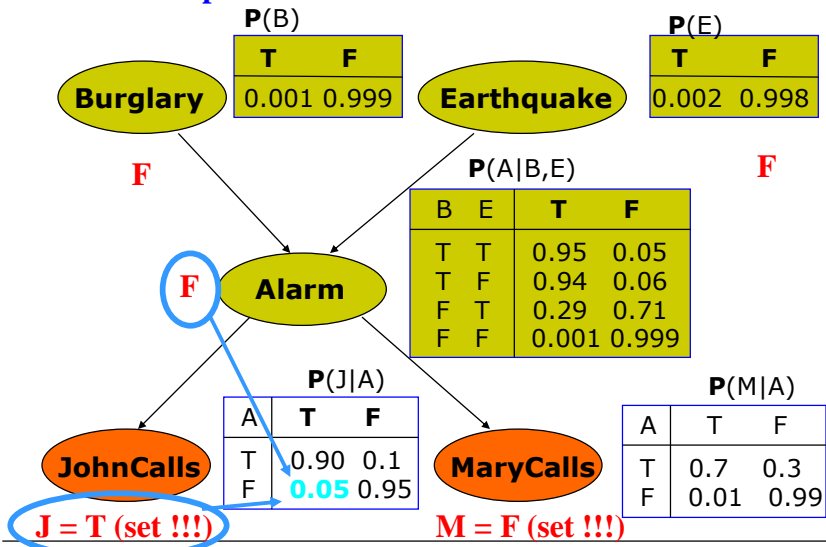
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Second sample



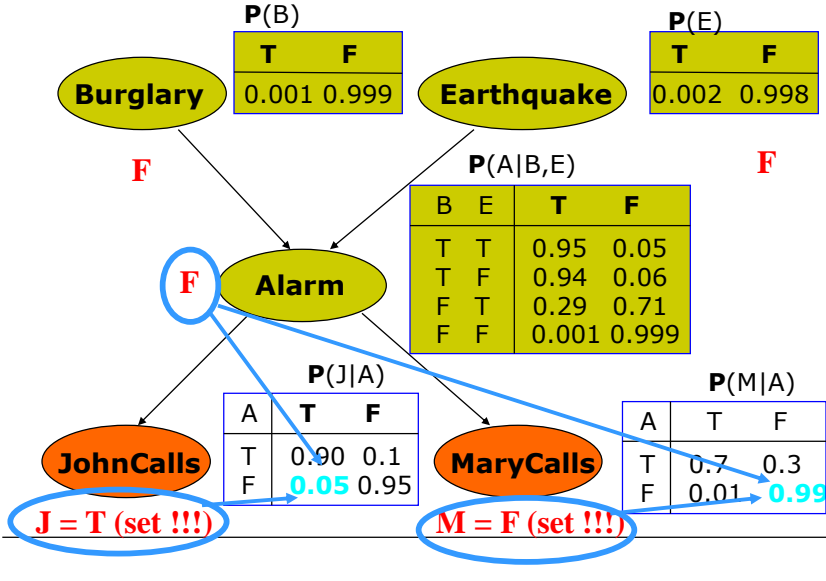
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Second sample



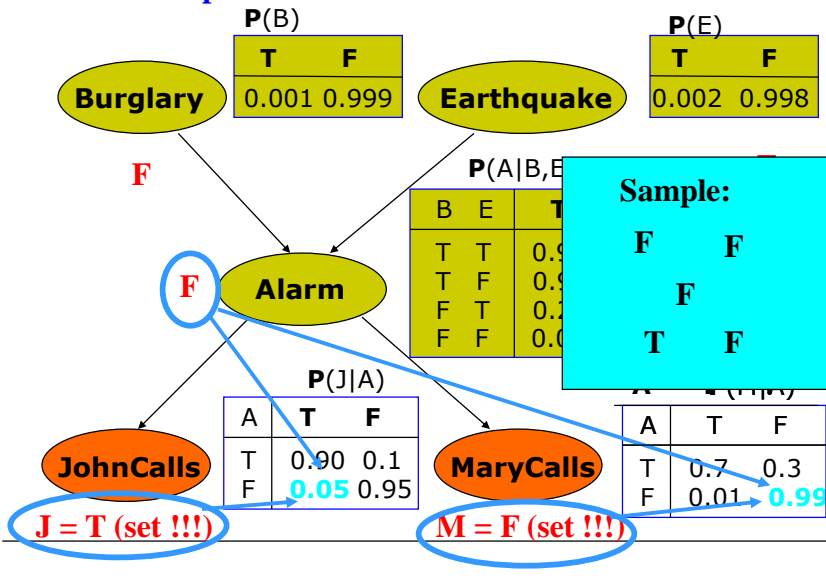
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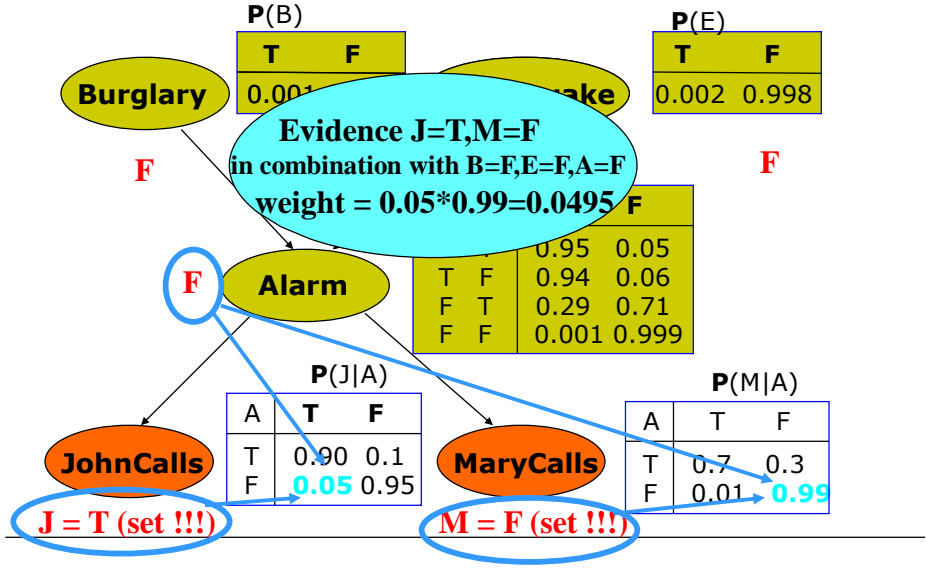
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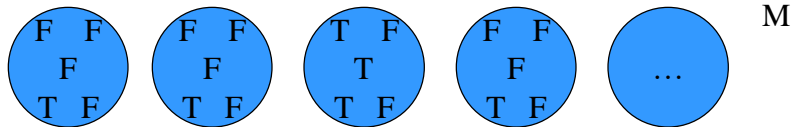
## BBN likelihood weighting example

Second sample



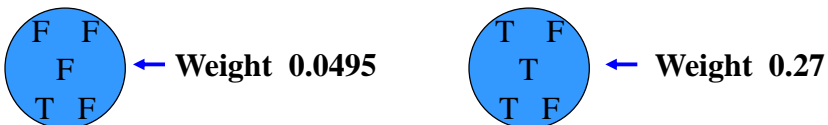
## Likelihood weighting

- Assume we have generated the following  $M$  samples:



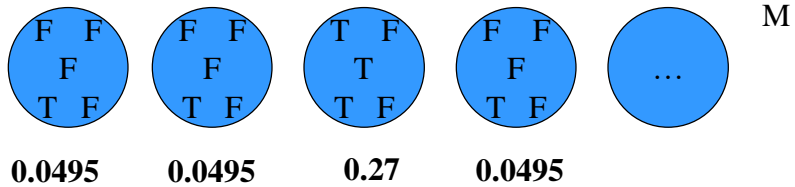
### How to make the samples consistent?

Weight each sample by probability with which it agrees with the conditioning evidence  $P(e)$ .



## Likelihood weighting

- Assume we have generated the following  $M$  samples:



$$\tilde{P}(B = T \mid J = T, M = F) = \frac{\sum_{\text{samples with } B=T, M=F \text{ and } J=T} w_{B=T \mid J=T, M=F}}{\sum_{\text{samples with any value of } B \text{ and } J=T, M=F} w_{B=x \mid J=T, M=F}}$$