Belief Networks

CMPUT 261: Introduction to Artificial Intelligence

P&M §8.3

Assignment #1

- Assignment #1 was due on Tuesday
- Late submissions will be accepted until **11:59pm TONIGHT**
  - 20% penalty

Recap: Chain Rule

Definition: chain rule

$$
\begin{aligned}
P(\alpha_1, \ldots, \alpha_n) &= P(\alpha_1) \times P(\alpha_2 \mid \alpha_1) \times \cdots \times P(\alpha_n \mid \alpha_1, \ldots, \alpha_{n-1}) \\
&= \Pi_{i=1}^{n} P(\alpha_i \mid \alpha_1, \ldots, \alpha_{i-1})
\end{aligned}
$$

$$
P(W, X, Y, Z) = \overbrace{\overbrace{\overbrace{P(W)P(X \mid W)}^{P(W,X)}P(Y \mid W, X)}^{P(W,X,Y)}P(Z \mid W, X, Y)}^{P(W,X,Y,Z)}
$$

Recap: Independence

Definition:
Random variables X and Y are **marginally independent** iff

$$P(X = x \mid Y = y) = P(X = x)$$

for all values of $x \in dom(X)$ and $y \in dom(Y)$.

Definition:
Random variables X and Y are **conditionally independent given Z** iff

$$P(X = x \mid Y = y, Z = z) = P(X = X \mid Z = z)$$

for all values of $x \in dom(X)$, $y \in dom(Y)$, and $z \in dom(Z)$.

Recap: Exploiting Independence

- Explicitly specifying an entire **unstructured joint distribution** is tedious and unnatural
- We can exploit **conditional independence**:
  - Conditional distributions are often more **natural** to write
  - Joint probabilities can be extracted from conditionally independent distributions by **multiplication**

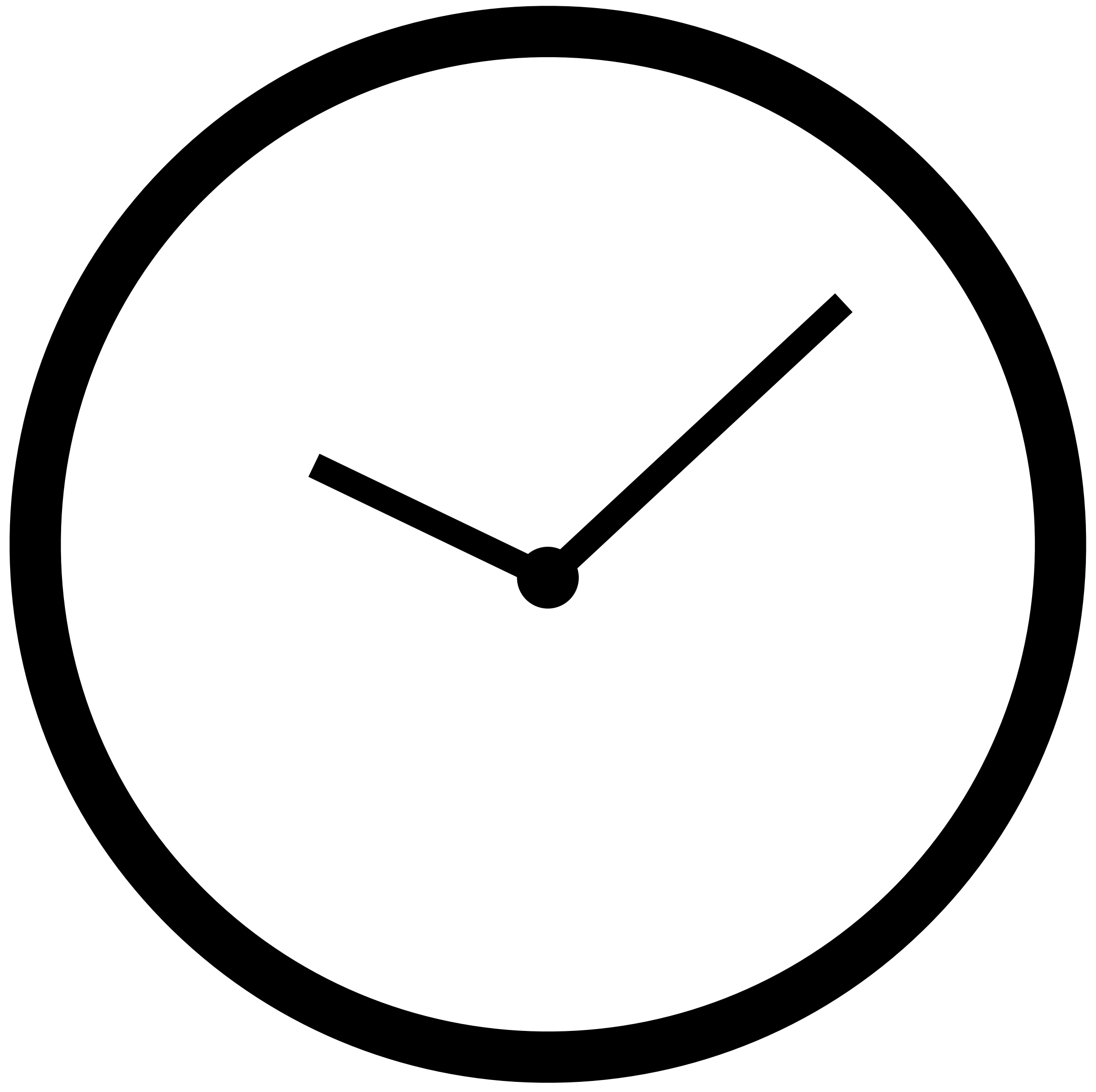
Lecture Outline

1. Recap & Logistics
2. Belief Networks as Factorings
3. Querying Joint Probabilities
4. Querying Independence

After this lecture, you should be able to:

- Define a belief network
- Construct a belief network that corresponds to a given factoring
- Recover a factoring that is consistent with a given belief network
- Compute joint probabilities using a belief network
- Identify independence relationships encoded by a given belief network

Factoring Joint Distributions



- We can **always** represent a joint distribution as a product of factors, even when there is **no** marginal or conditional independence (**why?**)

$$P(A, B, T) = P(T)P(A \mid T)\overset{= P(B \mid T)}{\boxed{P(B \mid A, T)}}$$

- **Question:** How much space do we save with this factored representation?

- When we do have independence, we can **simplify** some of these factors:

$$P(A, B, T) = P(T)P(A \mid T)P(B \mid T)$$

Random variables:

A - Time Alice thinks it is

B - Time Bob thinks it is

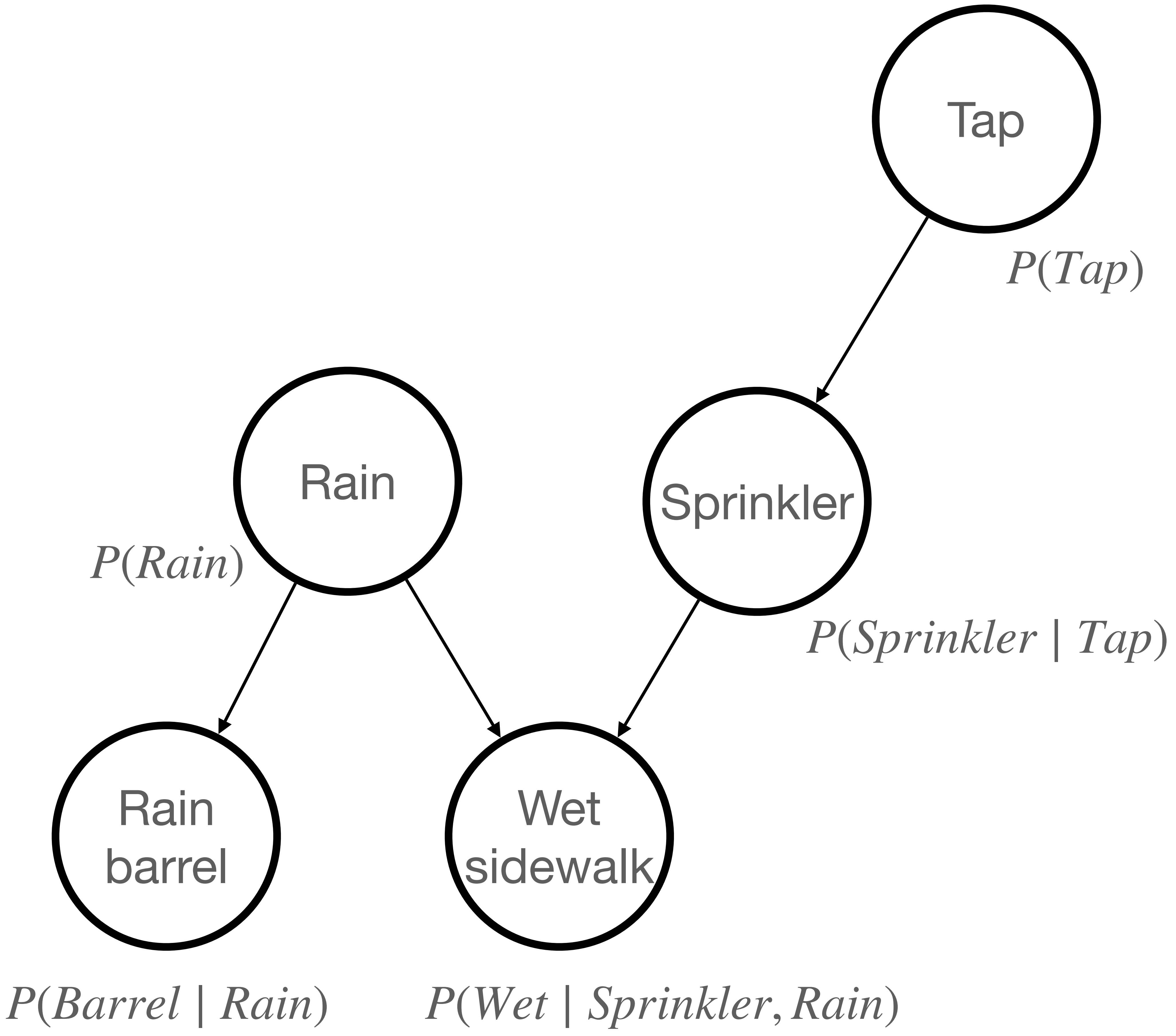
T - Actual time

Belief Networks, informally

We can represent a particular factoring of a joint distribution as a directed acyclic graph:

$$P(Tap, Rain, Sprinkler, Wet, Barrel) =$$
$$P(Tap)P(Rain)P(Sprinkler \mid Rain)P(Wet \mid Sprinkler, Rain)P(Barrel \mid Rain)$$

- **Nodes** are **random variables**
- Every variable has *exactly one* **factor** in the factoring
- The node's **parents** are the variables that its factor **conditions on**
  - (We'll sometimes say that the factor "depends on" its parents, but that is very imprecise)
- **More** independence means **fewer** arcs (**why?**)



Belief Networks

Definition:
A **belief network** (or **Bayesian network**) consists of:

1. A directed acyclic graph, with each node labelled by a **random variable**
2. A **domain** for each random variable
3. A **conditional probability table** for each variable given its **parents**

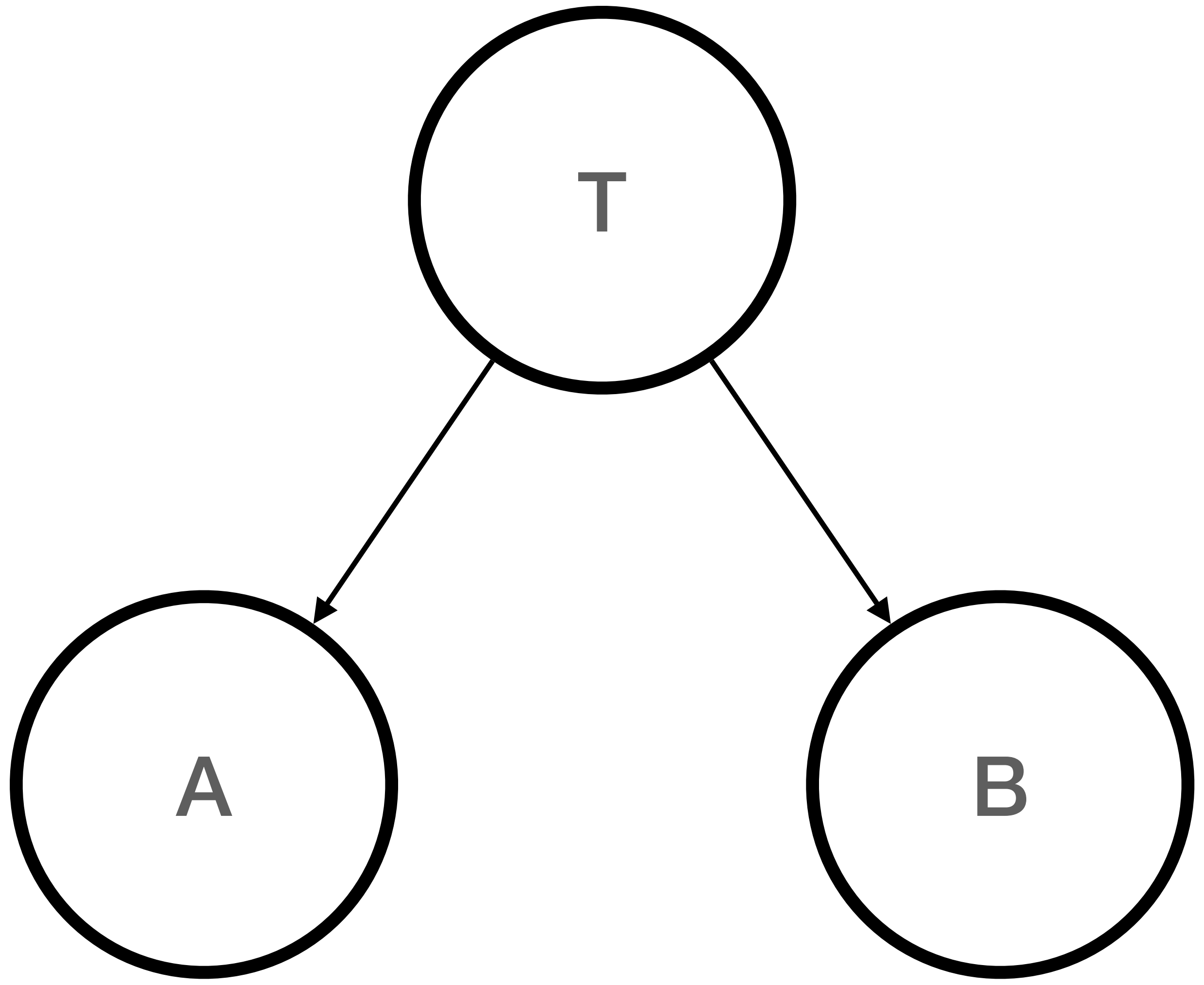
Why is the Graph Encoding Useful?

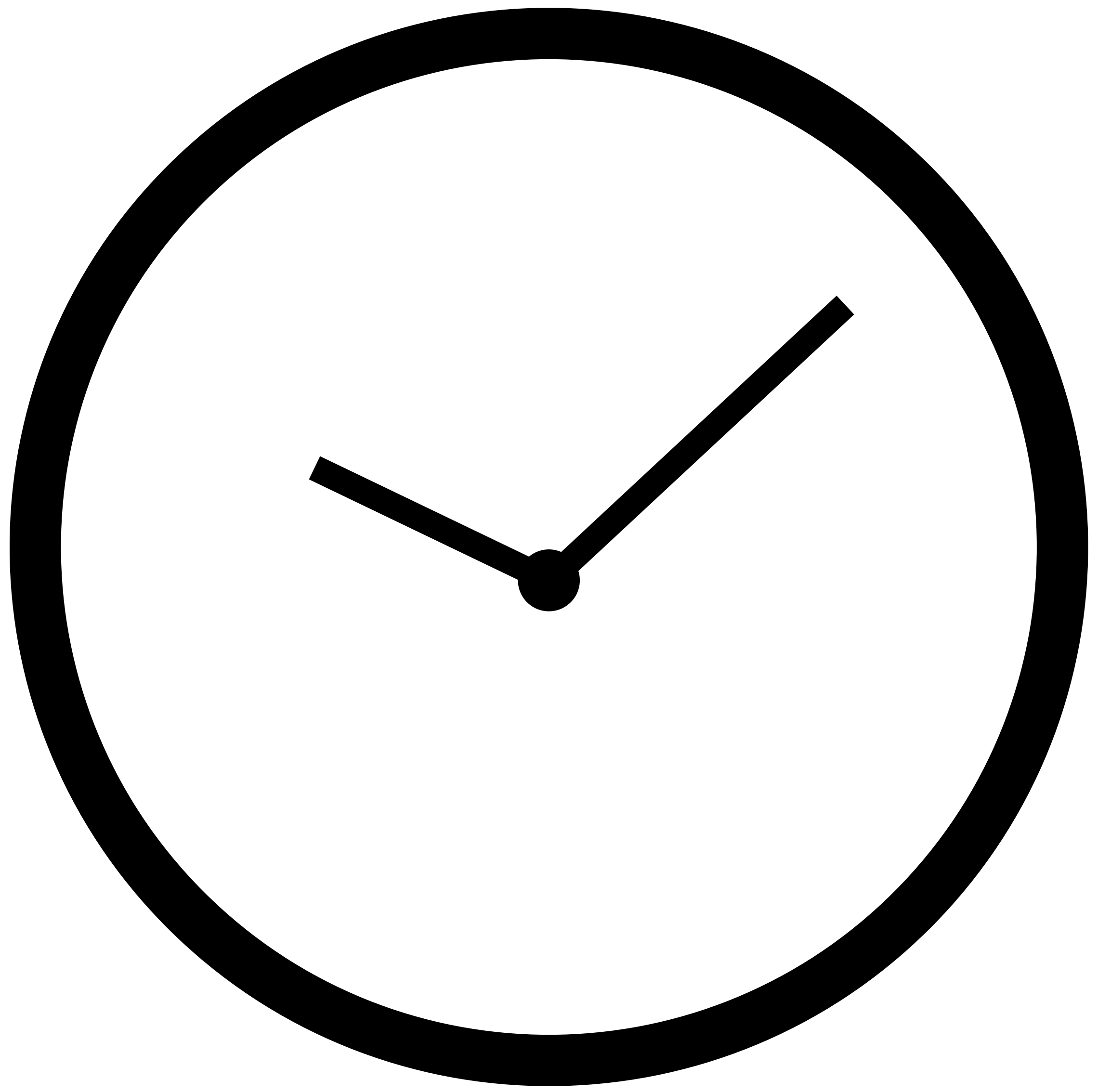
Encoding the distribution as a graph is useful for a number of reasons:

- Separates the **independence** structure (nodes, arcs) from the **quantitative** probabilities (conditional probability tables)
  - You can often reason about independence without reasoning about actual probability values
- Graph can be specified by reasoning **locally** about independence (i.e., what values fully determine a variable's distribution)
- **Complicated global** independence relationships can then be inferred based on graph structure
- Algorithms that exploit independence can be defined based on the graph structure alone

Clock Scenario

$$P(A, B, T) = P(\boxed{T})P(A \mid T)P(B \mid T)$$





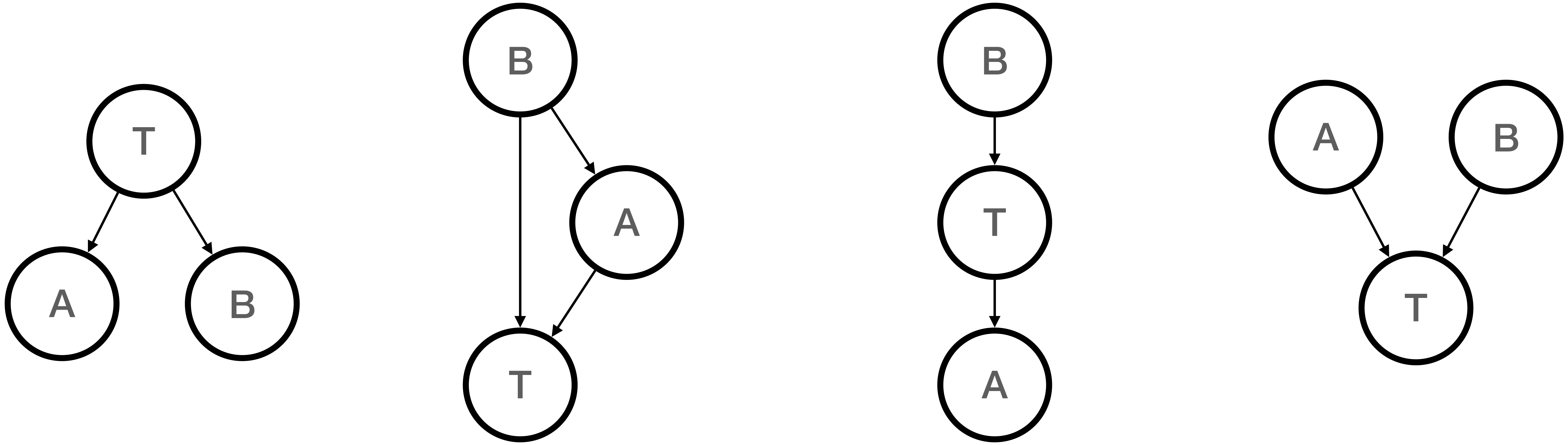
Random variables:

A - Time Alice thinks it is

B - Time Bob thinks it is

T - Actual time

Belief Networks as Factorings



- A joint distribution can be factored in **multiple** different ways
  - *Every* variable ordering induces at least one correct factoring (**Why?**)
- A belief network represents a **single** factoring
- *For a given joint distribution,*
  some factorings are correct, some are incorrect

Questions:

1. Does applying the **Chain Rule** to a given variable ordering give a **unique** factoring?
2. Does a given variable ordering correspond to a **unique Belief Network**?

Correct and Incorrect Factorings in the Clock Scenario

Definition:

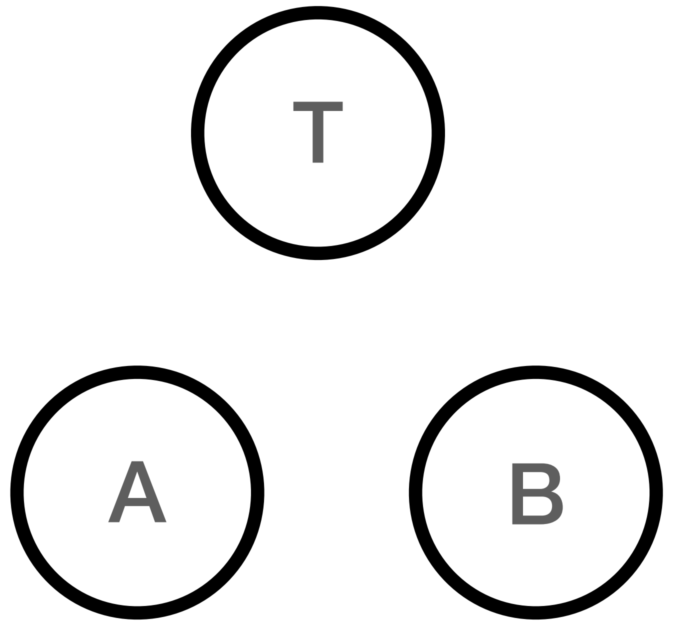
A **factoring** of a joint distribution is **correct** when every probability computed by the factoring gives the correct joint probability.

Which of the following are **correct** factorings of the joint distribution $P(A, B, T)$ in the Clock Scenario?

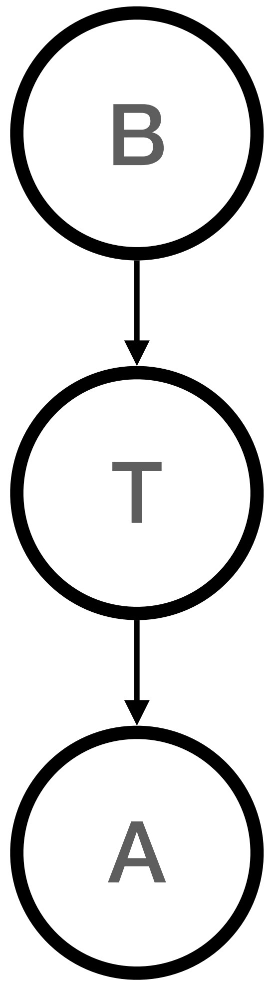
1. $P(A)P(B)P(T)$
2. $P(A)P(B \mid A)P(T \mid A, B)$ Chain rule(A,B,T): $P(A)P(B \mid A)P(T \mid A, B)$
3. $P(T)\boxed{P(B \mid T)}P(A \mid T)$ Chain rule(T,B,A): $P(T)\boxed{P(B \mid T, A)}P(A \mid T)$

Which of the above are a **good** factoring for the Clock Scenario? **Why?**

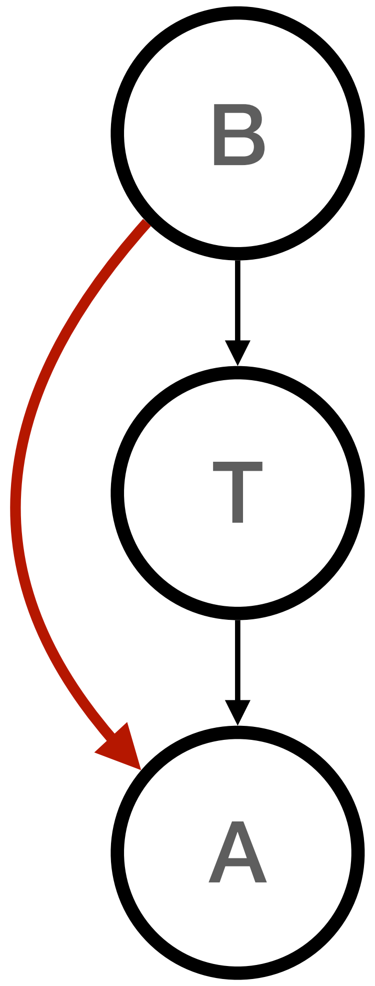
Belief Networks as Factorings



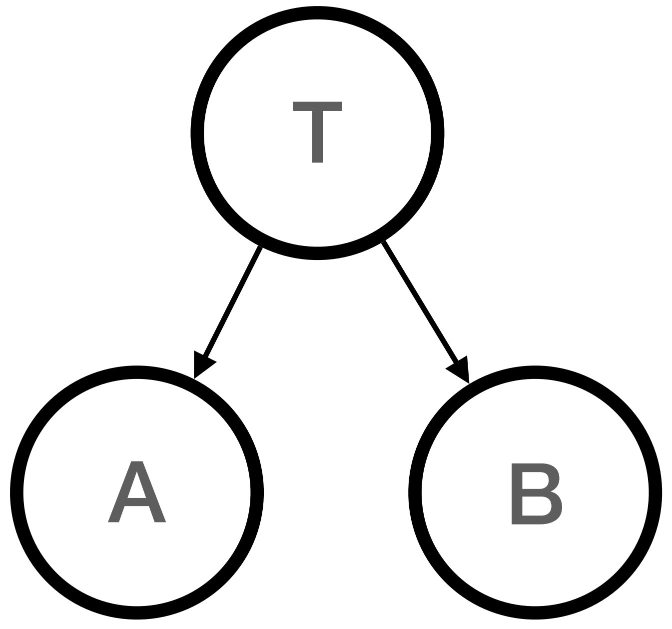
$P(A)P(B)P(T)$



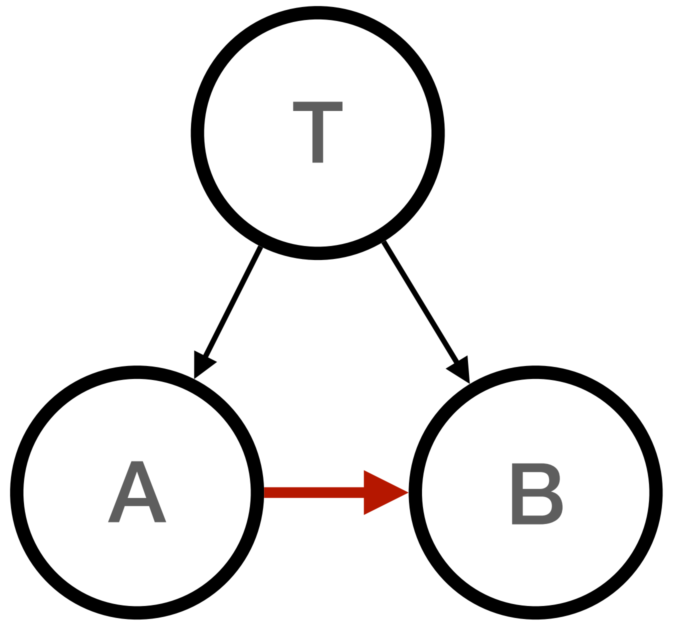
$P(B)P(T \mid B)P(A \mid T)$



$P(B)P(T \mid B)P(A \mid B, T)$

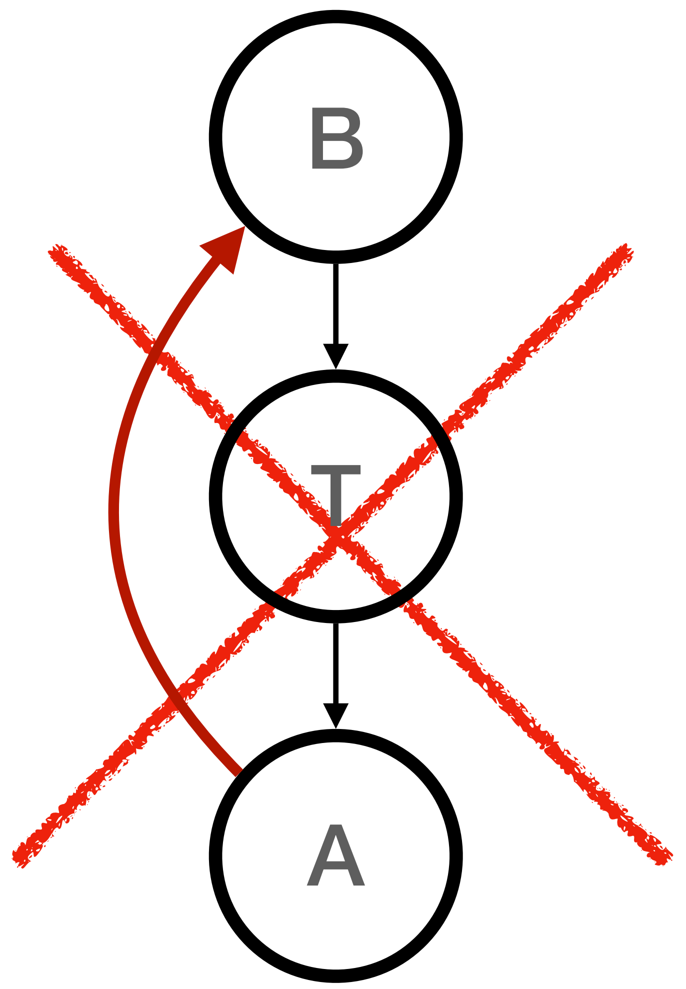


$P(T)P(A \mid T)P(B \mid T)$



$P(T)P(A \mid T)P(B \mid A, T)$

INVALID



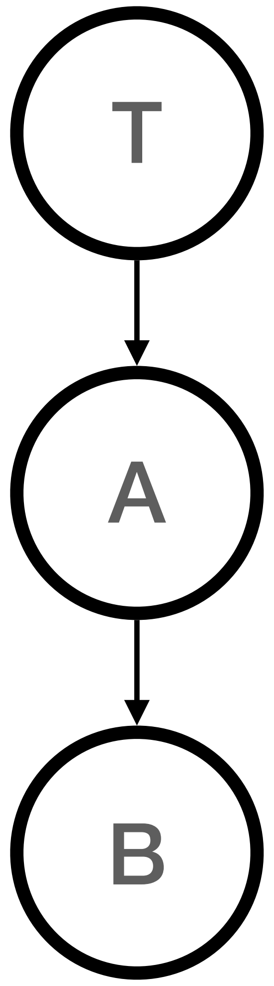
$\cancel{P(B \mid A)P(T \mid B)P(A \mid T)}$

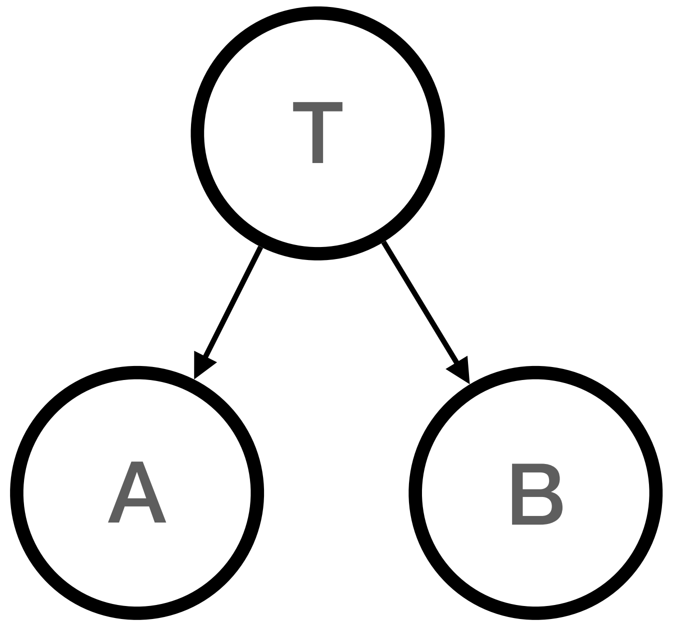
Question: What factoring is represented by each network?

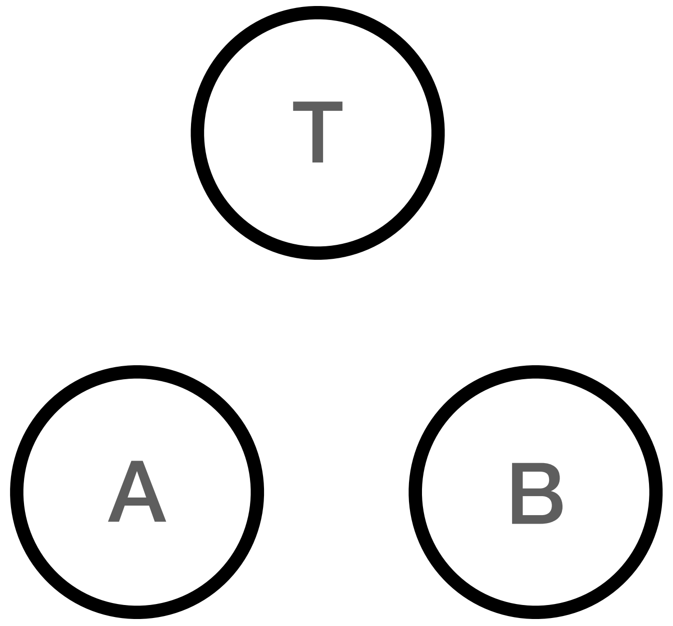
Conditional independence guarantees are represented in belief networks by the absence of edges.

Variations on the Clock Scenario

- A valid belief network is only "correct" or "incorrect" with respect to a given joint distribution
- A **single network** may be correct in one scenario and incorrect in another
- **Telephone Clock Scenario:** Alice looks at the clock, then tells Bob the time over a noisy phone connection
- **Desert Islands Clock Scenario:** Alice is on Island A. Bob is on Island B. The clock is on Island C. Alice and Bob cannot see or hear each other, or the clock.



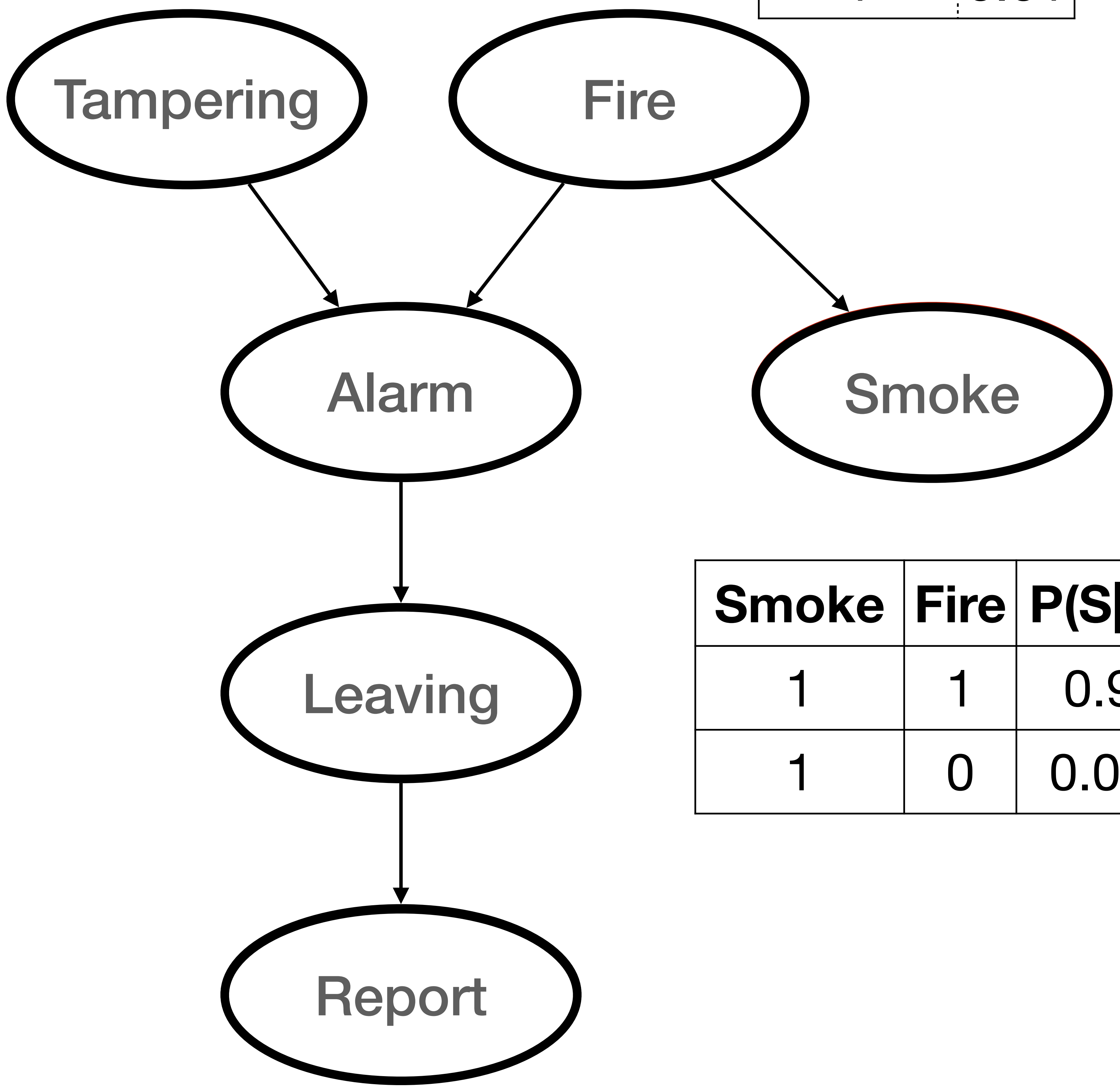




Queries

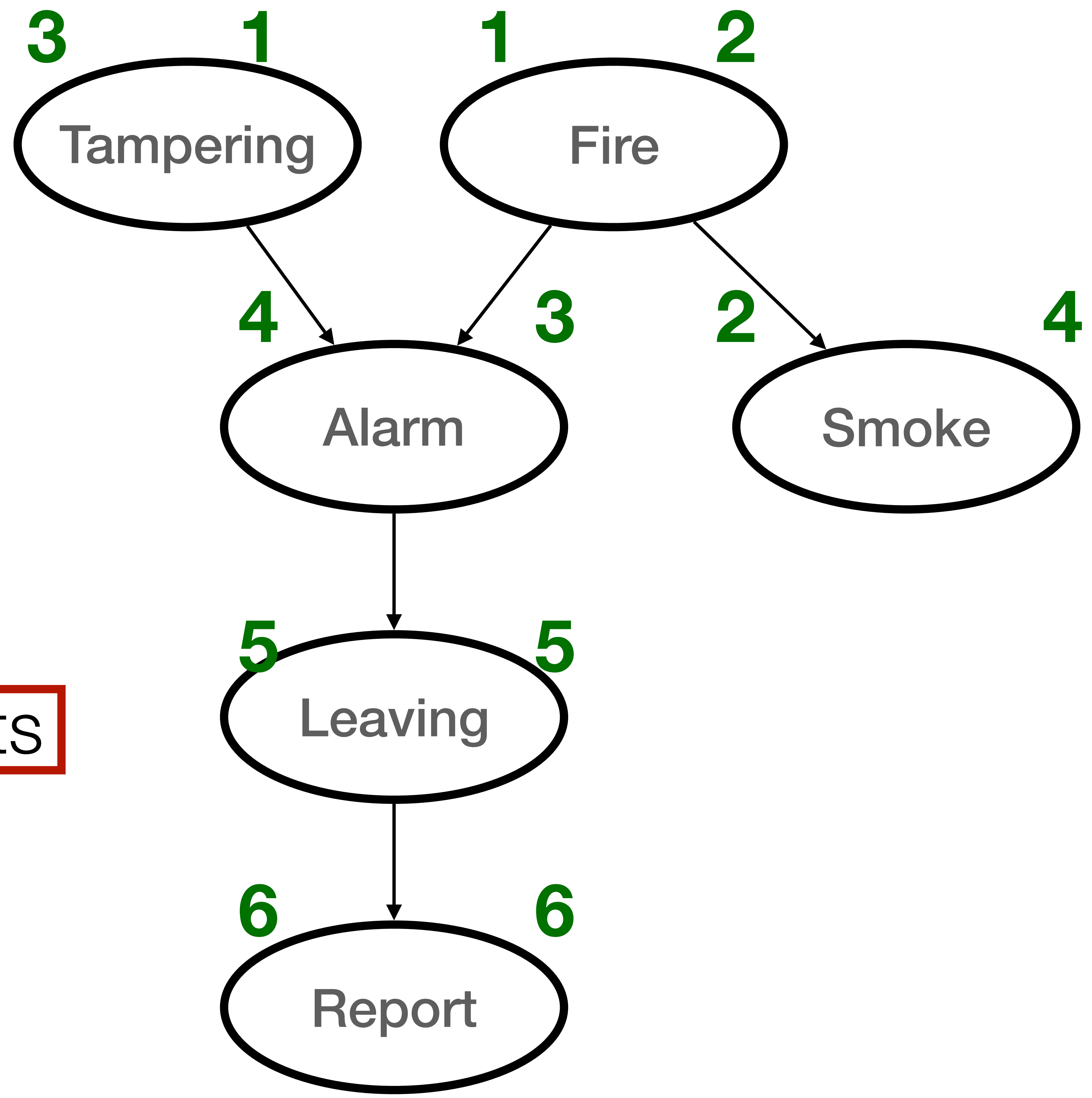
- The most common task for a belief network is to query **posterior probabilities** given some **observations**
- **Easy case:**
  - Observations are the **parents** of query target
- More **common** cases:
  - Observations are the **children** of query target
  - Observations have **no straightforward relationship** to the target

Fire	P(F)
1	0.01



Smoke	Fire	P(S|F)
1	1	0.9
1	0	0.01

Querying Joint Probabilities: Variable Ordering



To compute joint probability distribution, we need a variable **ordering** that is **consistent** with the graph

for i **from** 1 **to** n:

  select an unlabelled variable with no unlabelled parents

  label it as i

Question:

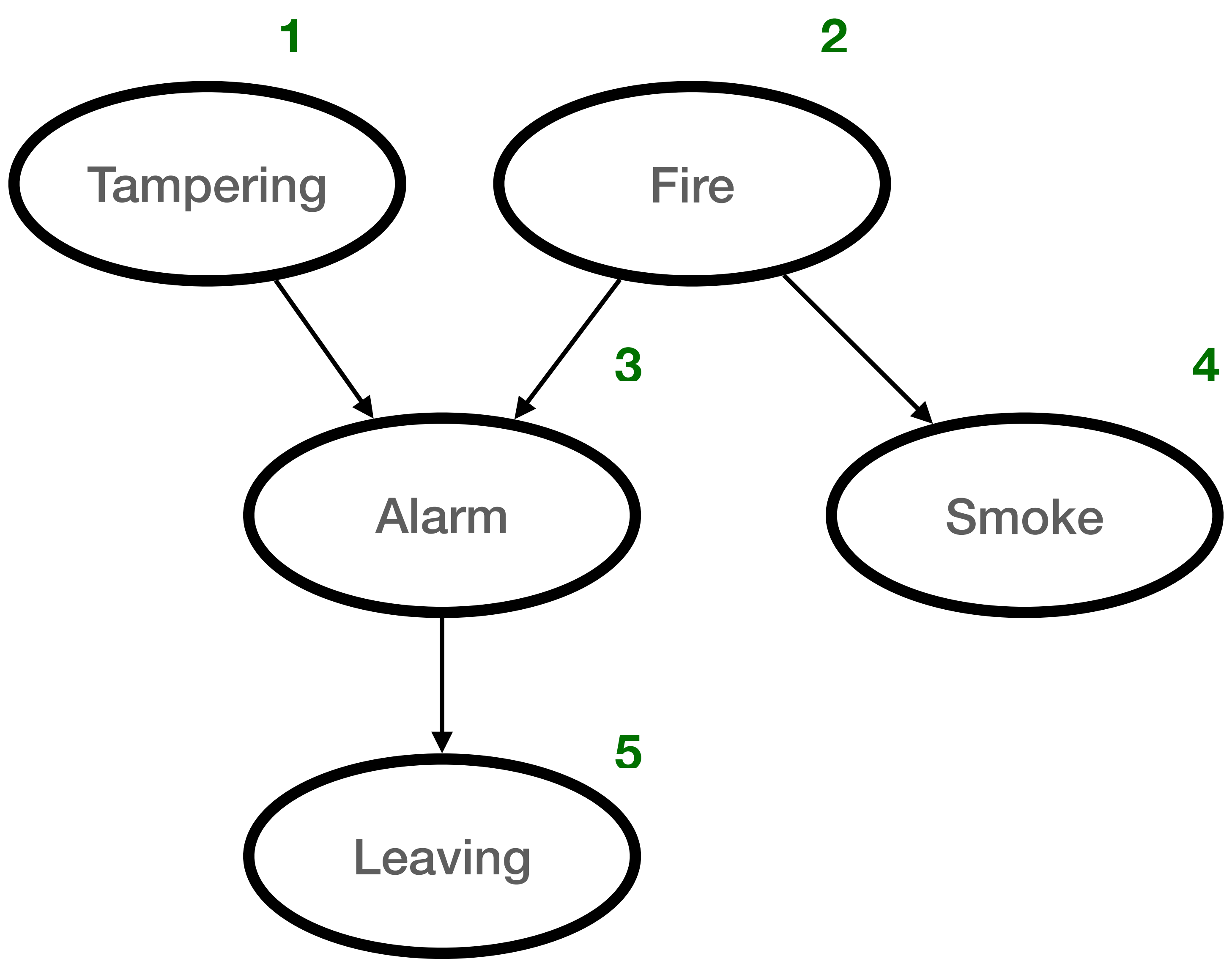
Is this **guaranteed** to exist **at every step**? **Why**?

Querying Joint Probabilities

- Multiply joint distributions in **variable order**
- **Example:** Given variable ordering
  Tampering, Fire, Alarm, Smoke, Leaving

Questions:

- Why $P(Fire)$ instead of $P(Fire \mid \cancel{Tampering})$?
- Why $P(Smoke \mid Fire)$ instead of $P(Smoke \mid \cancel{Tampering}, Fire, \cancel{Alarm})$?



$$P(Tampering) = P(Tampering)$$

$$P(Tampering, Fire) = P(Fire)P(Tampering)$$

$$P(Tampering, Fire, Alarm) =$$
$$P(Alarm \mid Tampering, Fire)P(Fire)P(Tampering)$$

$$P(Tampering, Fire, Alarm, Smoke) =$$
$$P(Smoke \mid Fire)P(Alarm \mid Tampering, Fire)P(Fire)P(Tampering)$$

$$P(Tampering, Fire, Alarm, Smoke, Leaving) =$$
$$P(Leaving \mid Alarm)Pr(Smoke \mid Fire)P(Alarm \mid Tampering, Fire)P(Fire)P(Tampering)$$

Independence in a Joint Distribution

Question: How can we answer questions about independence using the **full joint distribution**?

Examples using $P(A, B, T)$:

1. Is A independent of B?
   - $P(A = a \mid B = b) = P(A = a)$ **for all** $a \in \mathrm{dom}(A), b \in \mathrm{dom}(B)$?
2. Is T independent of A?
   - $P(T = t \mid A = a) = P(T = t)$ **for all** $a \in \mathrm{dom}(A), t \in \mathrm{dom}(T)$?
3. Is A independent of B given T?
   - $P(A = a \mid B = b, T = t) = P(A = a \mid T = t)$ **for all** $a \in \mathrm{dom}(A), b \in \mathrm{dom}(B), t \in \mathrm{dom}(T)$?

$$P(A, B) = \sum_{t \in T} P(A, B, T = t)$$

$$P(A, T) = \sum_{b \in B} P(A, B = b, T)$$

$$P(B, T) = \sum_{a \in A} P(A = a, B, T)$$

$$P(A) = \sum_{b \in B} P(A, B = b)$$

$$P(B) = \sum_{a \in A} P(A = a, B)$$

$$P(T) = \sum_{a \in A} P(A = a, T)$$

$$P(A \mid B, T) = \frac{P(A, B, T)}{P(B, T)}$$

$$P(A \mid B) = \frac{P(A, B)}{P(B)}$$

$$P(A \mid T) = \frac{P(A, T)}{P(T)}$$

$$P(T \mid A) = \frac{P(A, T)}{P(A)}$$

Independence in a Belief Network

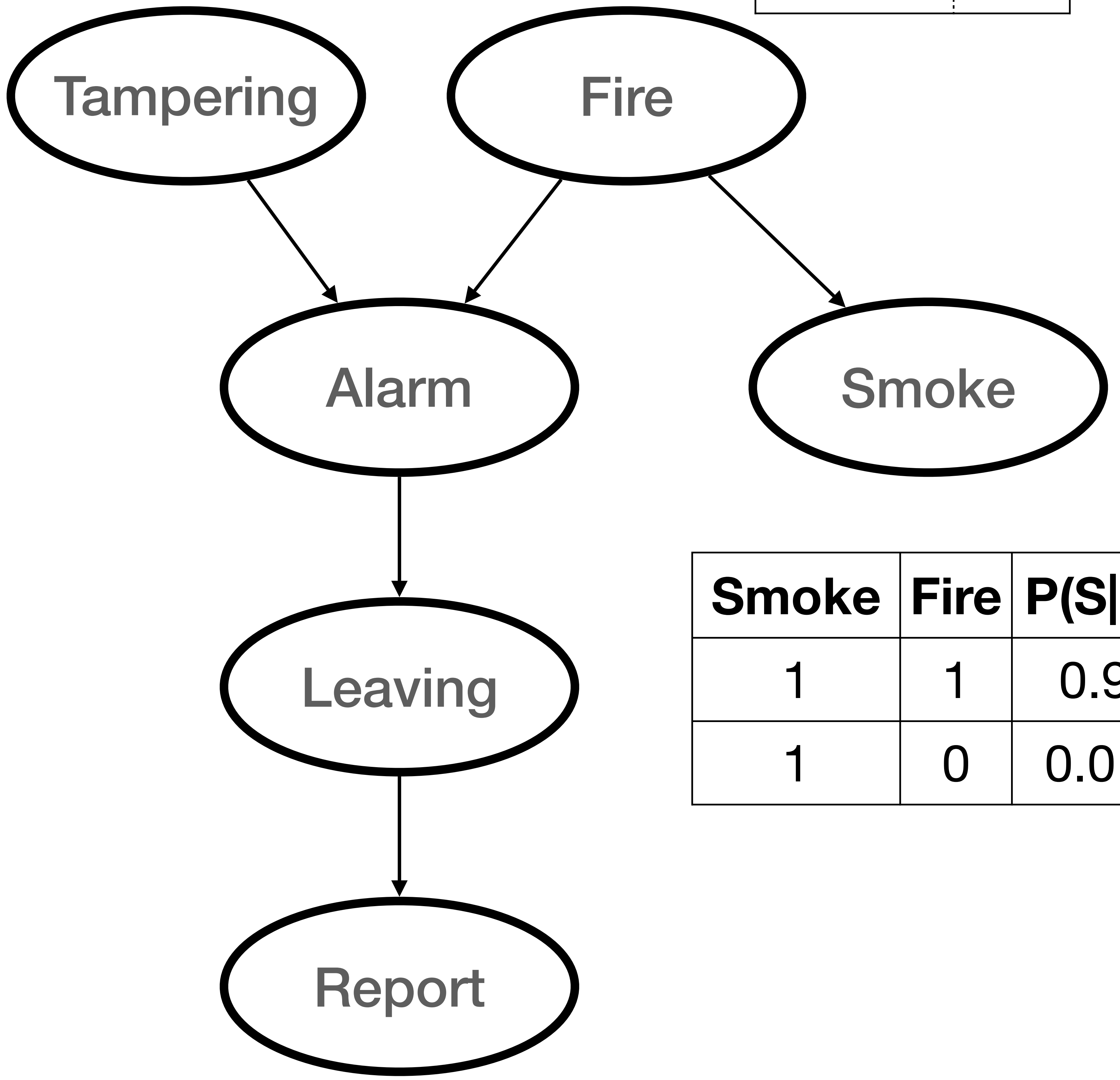
Definition:
A belief network represents a joint distribution that can be factored as

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid parents(X_i))$$

Theorem:
Every node is independent of its **non-descendants**, **conditional only** on its **parents:**

- Node u is a **parent** of v if a directed edge $u \rightarrow v$ exists
- Node v is a **descendant** of u if there exists a **directed path** from u to v
- Node v is a **non-descendant** of u if there **does not exist** a directed path from u to v

Fire	P(F)
1	0.01

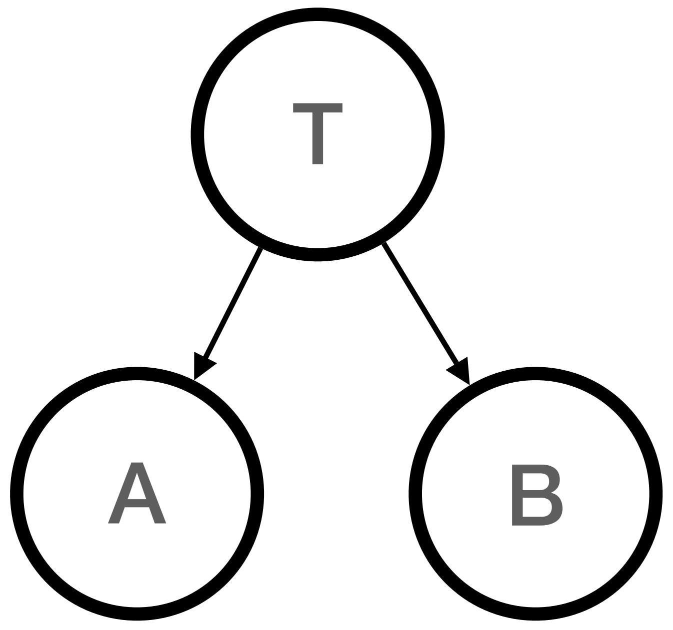


Smoke	Fire	P(S|F)
1	1	0.9
1	0	0.01

Querying Independence in a Belief Network

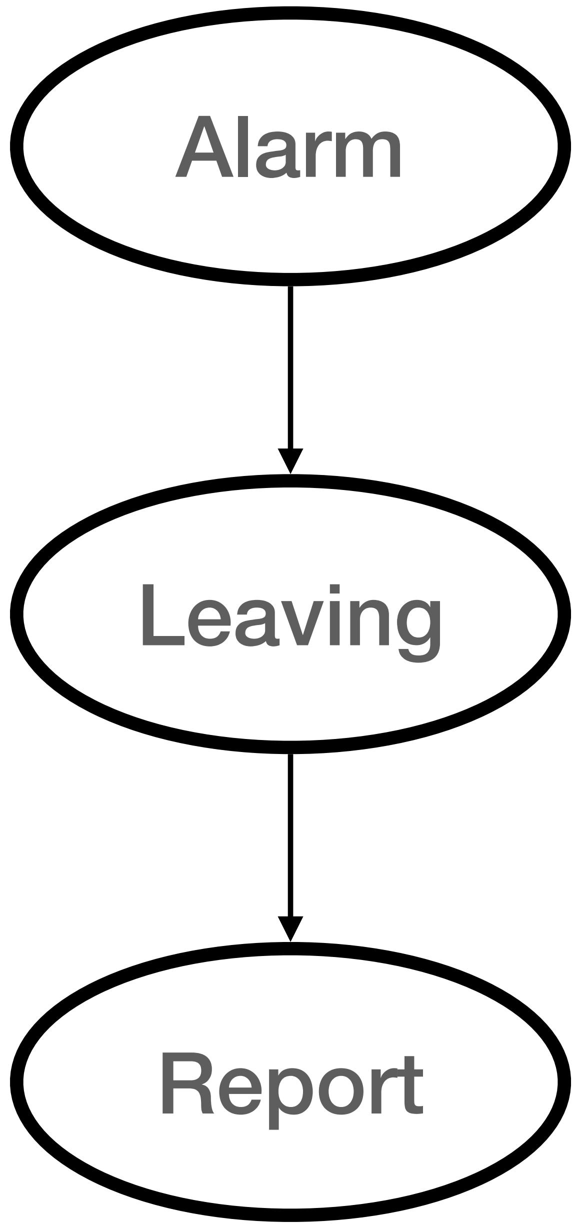
Belief Network Independence:
Every node is **independent** of its **non-descendants**, **conditional only** on its **parents**

- We can use a correct belief network to efficiently answer questions about independence without knowing any numbers
- Examples using the belief network at right:
  1. Is **T** independent of **A**?
  2. Is **A** independent of **B** given **T**?
  3. Is **A** independent of **B**?



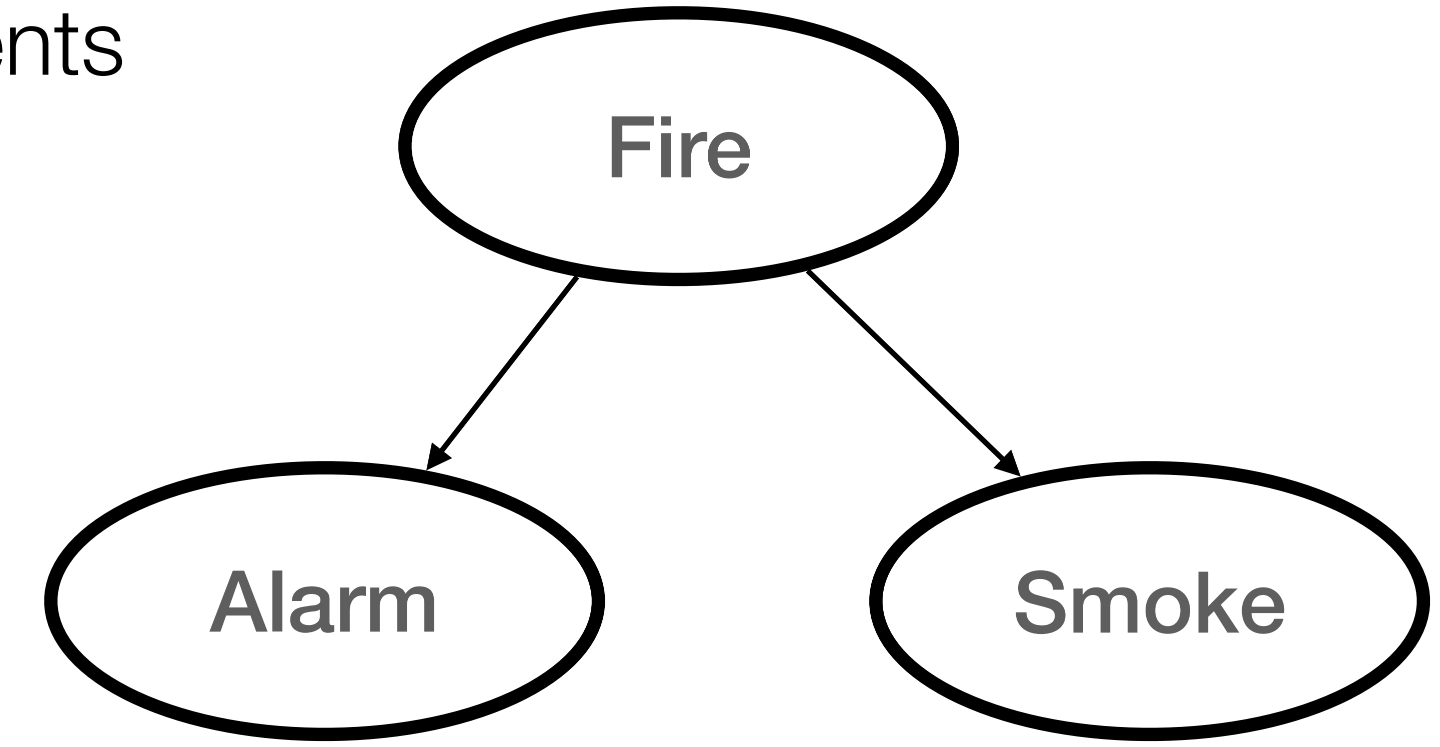
Chain

- **Question:** Is **Report** independent of **Alarm** given **Leaving**?
    - *Intuitively:* The only way learning **Report** tells us about **Alarm** is because it tells us about **Leaving**; but **Leaving** has already been observed
    - *Formally:* **Report** is independent of its non-descendants given only its parents
        - **Leaving** is **Report's** parent
        - **Alarm** is a non-descendant of **Report**
- **Question:** Is **Report** independent of **Alarm**?
    - *Intuitively:* Learning **Report** gives us information about **Leaving**, which gives us information about **Alarm**
    - *Formally:* **Report** is independent of **Alarm** given **Report's** parents; but the question is about **marginal** independence



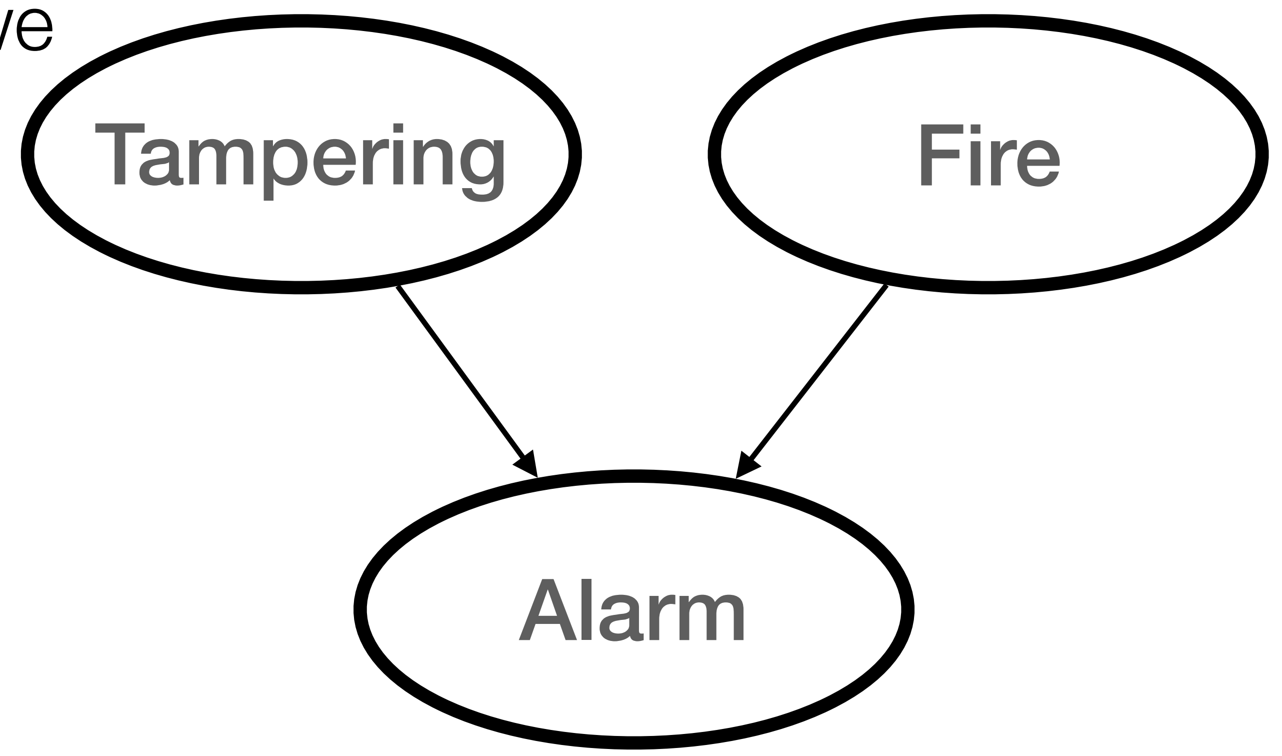
Common Ancestor

- **Question:** Is **Alarm** independent of **Smoke** given **Fire**?
  - *Intuitively:* The only way learning **Smoke** tells us about **Alarm** is because it tells us about **Fire**; but **Fire** has already been observed
  - *Formally:* **Alarm** is independent of its non-descendants given only its parents
    - **Fire** is **Alarm's** parent
    - **Smoke** is a non-descendant of **Alarm**
- **Question:** Is **Alarm** independent of **Smoke**?
  - *Intuitively:* Learning **Smoke** gives us information about **Fire**, which gives us information about **Alarm**
  - *Formally:* **Alarm** is independent of **Smoke** given only **Alarm's** parents; but the question is about **marginal independence**



Common Descendant ("collider")

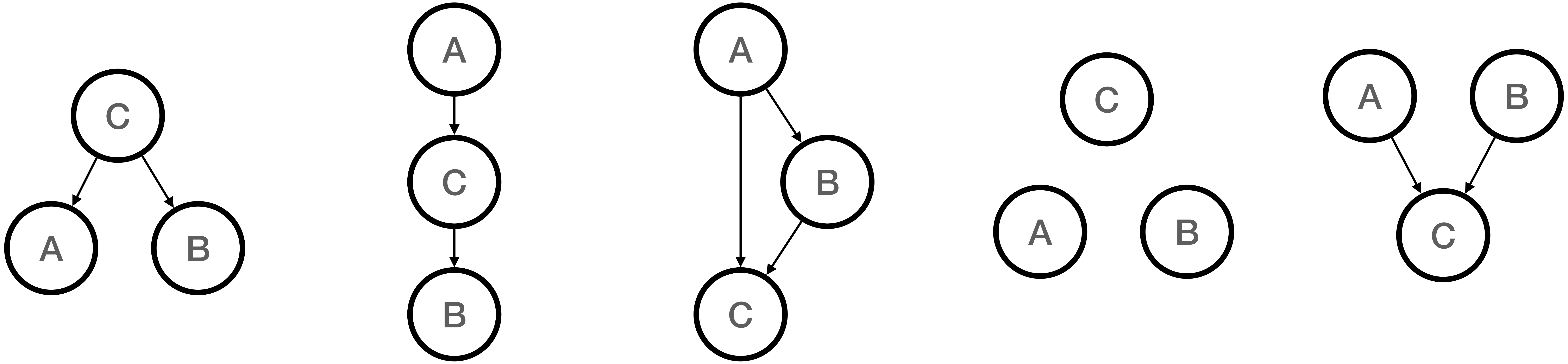
- **Question:** Is **Tampering** independent of **Fire** given **Alarm**?
  - *Intuitively:* If we know **Alarm** is ringing, then both **Tampering** and **Fire** are more likely. If we then learn that **Fire** is false, that makes it more likely that the **Alarm** is ringing because of **Tampering**.
  - *Formally:* **Tampering** is independent of **Fire** given **only** **Tampering's** parents; but we are conditioning on one of Tampering's **descendants**
    - Conditioning on a **common descendant** can make independent variables dependent through this **explaining away** effect
- **Question:** Is **Tampering** (marginally) independent of **Fire**?
  - *Intuitively:* Learning **Tampering** doesn't tell us anything about whether a **Fire** is happening
  - *Formally:* **Tampering** is independent of **Fire** given **Tampering's** parents
    - **Tampering** has no parents, so we are always conditioning on them
    - **Fire** is a non-descendant of **Tampering**



Correctness of a Belief Network

A belief network is a **correct** representation of a joint distribution when the factoring that it represents is a correct factoring of the joint distribution.

Equivalently: when the belief network answers "yes" to an independence question **only if** the **joint distribution** answers "yes" to the same question.

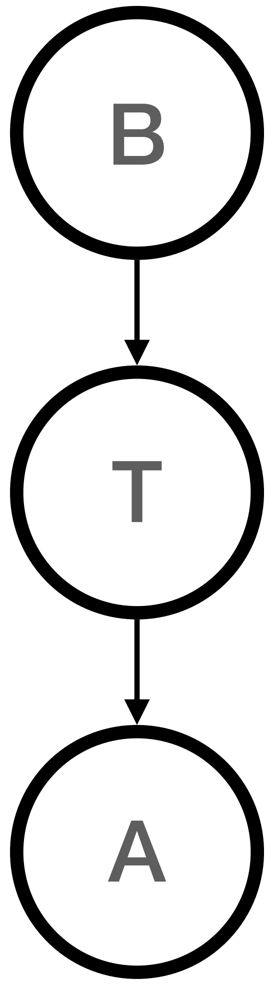


Questions:

1. Is A independent of B in the above belief networks?
2. Is A independent of B given C in the above belief networks?

Causal Network?

- The arcs in belief networks **do not**, in general, represent **causal** relationships!
  - $T \to A$ is a **causal** relationship if T **causes** the value of A
  - E.g., B doesn't cause T, but this is nevertheless a correct encoding of the joint distribution



- However, reasoning about causal relationships is often a good way to **construct** a **natural** encoding as a belief network
  - We can often reason about causal independence even when we don't know the full joint distribution

Summary

- A belief network represents a specific **factoring** of a joint distribution
    - **Graph structure** encodes conditional independence relationships
    - More than one belief network can correctly represent a joint distribution
    - A given belief network may be correct for one underlying joint distribution and incorrect for another
- A **good** belief network is one that encodes as many **true** conditional independence relationships as possible
- It is possible to read the conditional independence guarantees made by a belief network directly from its **graph structure**
- Arcs in a belief network **often** represent **causal** relationships
    - But they don't have to!