

Introduction to Artificial Intelligence

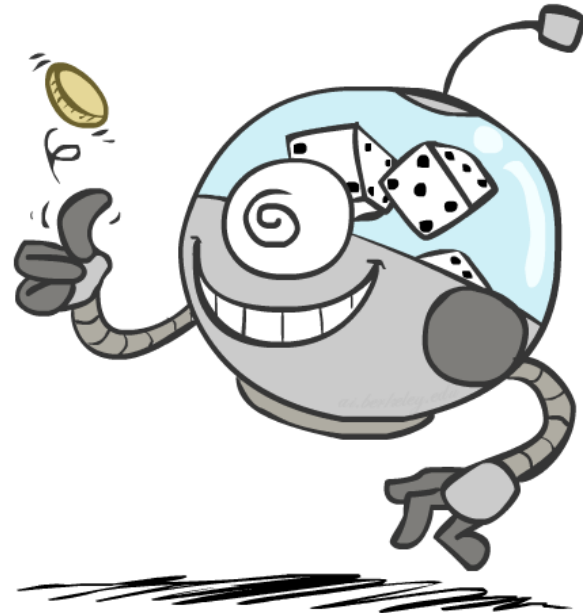
Lecture 4: Representing uncertain knowledge

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Today

- Probability:
 - Random variables
 - Joint and marginal distributions
 - Conditional distributions
 - Product rule, Chain rule, Bayes' rule
 - Inference
- Bayesian networks:
 - Representing uncertain knowledge
 - Semantics
 - Construction



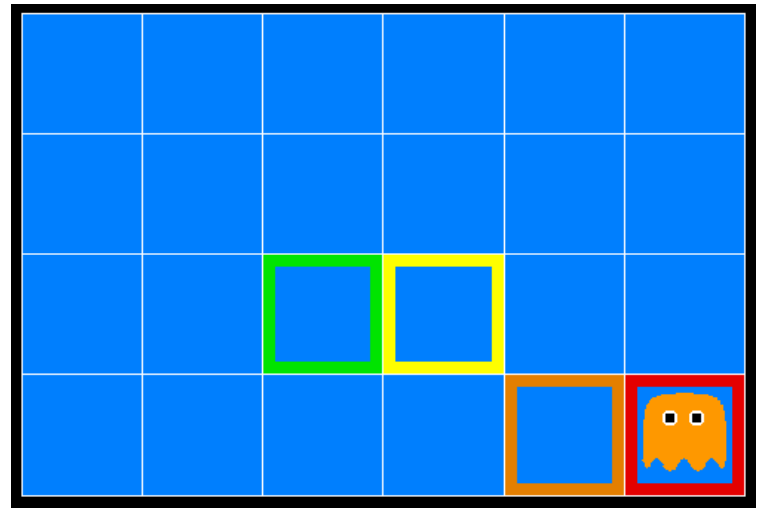
Do not overlook this lecture!

Quantifying uncertainty

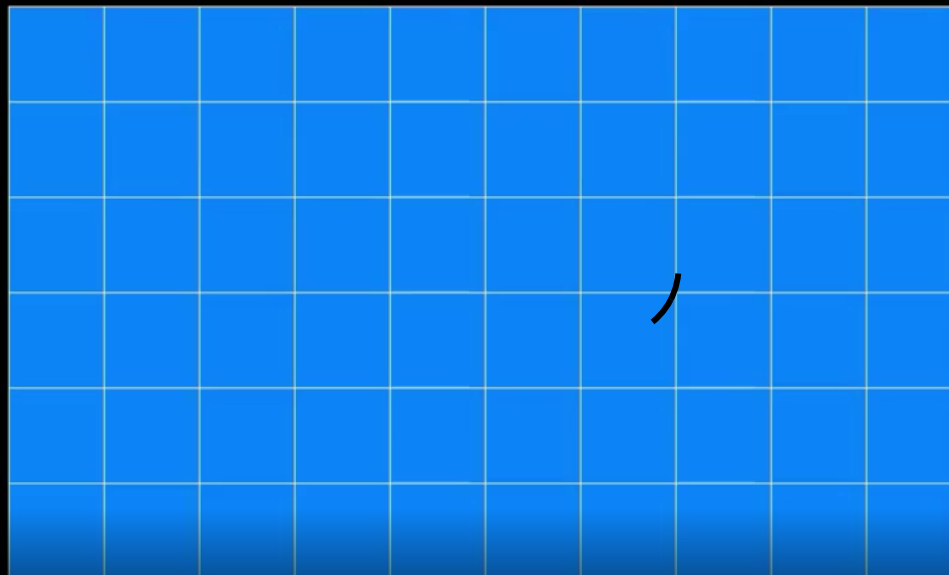
A ghost is **hidden** in the grid somewhere.

Sensor readings tell how close a square is to the ghost:

- On the ghost: red
- 1 or 2 away: orange
- 3 away: yellow
- 4+ away green



Sensors are **noisy**, but we know the probability values $P(\text{color}|\text{distance})$, for all colors and all distances.



GHOSTS REMAINING: 1
BUSTS REMAINING: 1
SCORE: 0

MESSAGES:

BUST

TIME+1

▶ 0:00 / 1:26



Uncertainty

General setup:

- **Observed** variables or evidence: agent knows certain things about the state of the world (e.g., sensor readings).
- **Unobserved** variables: agent needs to reason about other aspects that are uncertain (e.g., where the ghost is).
- (Probabilistic) **model**: agent knows or believes something about how the known variables relate to the unknown variables.

How to handle uncertainty?

- A purely logical approach either risks falsehood, or leads to conclusions that are too weak for decision making.
- **Probabilistic reasoning** provides a framework for managing our knowledge and beliefs.

Probabilistic assertions

Probabilistic assertions express the agent's inability to reach a definite decision regarding the truth of a proposition.

- Probability values **summarize** effects of
 - **laziness** (failure to enumerate all world states)
 - **ignorance** (lack of relevant facts, initial conditions, correct model, etc).
- Probabilities relate propositions to one's own state of knowledge (or lack thereof).
 - e.g., $P(\text{ghost in cell } [3, 2]) = 0.02$

Frequentism vs. Bayesianism

What do probability values represent?

- The objectivist **frequentist** view is that probabilities are real aspects of the universe.
 - i.e., propensities of objects to behave in certain ways.
 - e.g., the fact that a fair coin comes up heads with probability **0.5** is a propensity of the coin itself.
- The subjectivist **Bayesian** view is that probabilities are a way of characterizing an agent's beliefs or uncertainty.
 - i.e., probabilities do not have external physical significance.
 - This is the interpretation of probabilities that we will use!

Kolmogorov's probability theory

Begin with a set Ω , the **sample space**.

$\omega \in \Omega$ is a **sample point** or possible world.

A **probability space** is a sample space equipped with a probability function, i.e. an assignment $P : \mathcal{P}(\Omega) \rightarrow \mathbb{R}$ such that:

- 1st axiom: $P(\omega) \in \mathbb{R}, 0 \leq P(\omega)$ for all $\omega \in \Omega$
- 2nd axiom: $P(\Omega) = 1$
- 3rd axiom: $P(\{\omega_1, \dots, \omega_n\}) = \sum_{i=1}^n P(\omega_i)$ for any set of samples

where $\mathcal{P}(\Omega)$ the power set of Ω .

Example

- Ω = the 6 possible rolls of a die.
- ω_i (for $i = 1, \dots, 6$) are the sample points, each corresponding to an outcome of the die.
- Assignment P for a fair die:

$$P(1) = P(2) = P(3) = P(4) = P(5) = P(6) = \frac{1}{6}$$

Random variables

- A **random variable** is a function $X : \Omega \rightarrow D_X$ from the sample space to some domain defining its outcomes.
 - e.g., $\text{Odd} : \Omega \rightarrow \{\text{true}, \text{false}\}$ such that $\text{Odd}(\omega) = (\omega \bmod 2 = 1)$.
- P induces a **probability distribution** for any random variable X .
 - $P(X = x_i) = \sum_{\{\omega: X(\omega)=x_i\}} P(\omega)$
 - e.g., $P(\text{Odd} = \text{true}) = P(1) + P(3) + P(5) = \frac{1}{2}$.
- An **event** E is a set of outcomes $\{(x_1, \dots, x_n)_i\}$ of the variables X_1, \dots, X_n , such that

$$P(E) = \sum_{(x_1, \dots, x_n) \in E} P(X_1 = x_1, \dots, X_n = x_n).$$

Notations

- Random variables are written in upper roman letters: X, Y , etc.
- Realizations of a random variable are written in corresponding lower case letters. E.g., x_1, x_2, \dots, x_n could be of outcomes of the random variable X .
- The probability value of the realization x is written as $P(X = x)$.
- When clear from context, this will be abbreviated as $P(x)$.
- The probability distribution of the (discrete) random variable X is denoted as $\mathbf{P}(X)$. This corresponds e.g. to a vector of numbers, one for each of the probability values $P(X = x_i)$ (and not to a single scalar value!).

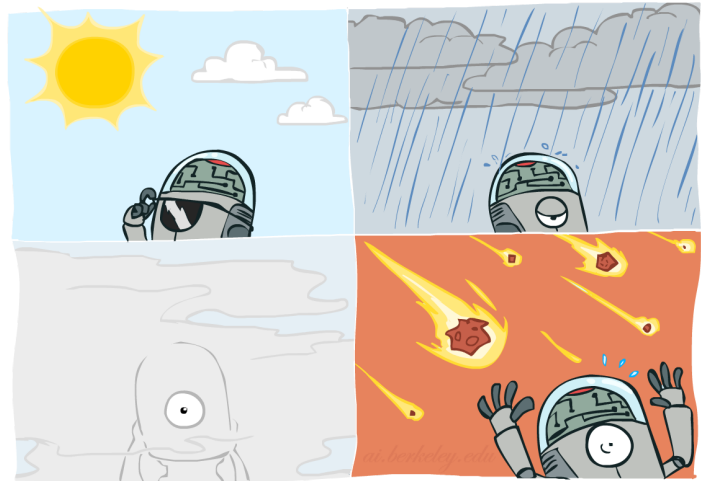
Probability distributions

For discrete variables, the **probability distribution** can be encoded by a discrete list of the probabilities of the outcomes, known as the **probability mass function**.

One can think of the probability distribution as a **table** that associates a probability value to each **outcome** of the variable.

$P(W)$

W	P
sun	0.6
rain	0.1
fog	0.3
meteor	0.0



Joint distributions

A **joint** probability distribution over a set of random variables X_1, \dots, X_n specifies the probability of each (combined) outcome:

$$P(X_1 = x_1, \dots, X_n = x_n) = \sum_{\{\omega: X_1(\omega)=x_1, \dots, X_n(\omega)=x_n\}} P(\omega)$$

$$\mathbf{P}(T, W)$$

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

From a joint distribution, the probability of any event can be calculated.

- Probability that it is hot and sunny?
- Probability that it is hot?
- Probability that it is hot or sunny?

Interesting events often correspond to **partial assignments**, e.g. $P(\text{hot})$.

Marginal distributions

The **marginal distribution** of a subset of a collection of random variables is the joint probability distribution of the variables contained in the subset.

$$\mathbf{P}(T, W)$$

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

$$\mathbf{P}(T)$$

T	P
hot	0.5
cold	0.5

$$\mathbf{P}(W)$$

W	P
sun	0.6
rain	0.4

$$P(t) = \sum_w P(t, w) \qquad P(w) = \sum_t P(t, w)$$

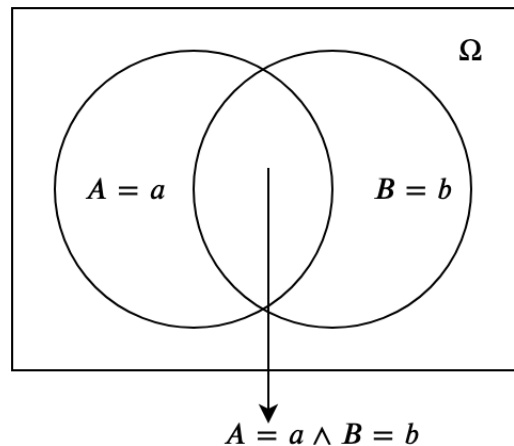
Intuitively, marginal distributions are sub-tables which eliminate variables.

Conditional distributions

The **conditional probability** of a realization a given the realization b is defined as the ratio of the probability of the joint realization a and b , and the probability of b :

$$P(a|b) = \frac{P(a, b)}{P(b)}.$$

Indeed, observing $B = b$ rules out all those possible worlds where $B \neq b$, leaving a set whose total probability is just $P(b)$. Within that set, the worlds for which $A = a$ satisfy $A = a \wedge B = b$ and constitute a fraction $P(a, b)/P(b)$.



Conditional distributions are probability distributions over some variables, given **fixed** values for others.

$$\mathbf{P}(T, W)$$

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

$$\mathbf{P}(W|T = \text{hot})$$

T	P
sun	0.8
rain	0.2

$$\mathbf{P}(W|T = \text{cold})$$

W	P
sun	0.4
rain	0.6

Normalization trick

$$\mathbf{P}(T, W)$$

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

$$\rightarrow \mathbf{P}(T = \text{cold}, W)$$

T	W	P
cold	sun	0.2
cold	rain	0.3

Select the joint probabilities matching the evidence $T = \text{cold}$.

$$\rightarrow \mathbf{P}(W|T = \text{cold})$$

W	P
sun	0.4
rain	0.6

Normalize the selection (make it sum to **1**).

Probabilistic inference

Probabilistic **inference** is the problem of computing a desired probability from other known probabilities (e.g., conditional from joint).

- We generally compute conditional probabilities.
 - e.g., $P(\text{on time} | \text{no reported accidents}) = 0.9$
 - These represent the agent's **beliefs** given the evidence.
- Probabilities change with new evidence:
 - e.g., $P(\text{on time} | \text{no reported accidents, 5AM}) = 0.95$
 - e.g., $P(\text{on time} | \text{no reported accidents, rain}) = 0.8$
 - e.g., $P(\text{ghost in } [3, 2] | \text{red in } [3, 2]) = 0.99$
 - Observing new evidence causes **beliefs to be updated**.

General case

- Evidence variables: $E_1, \dots, E_k = e_1, \dots, e_k$
- Query variables: Q
- Hidden variables: H_1, \dots, H_r
- $(Q \cup E_1, \dots, E_k \cup H_1, \dots, H_r)$ = all variables X_1, \dots, X_n

Inference is the problem of computing $\mathbf{P}(Q|e_1, \dots, e_k)$.

Inference by enumeration

Start from the joint distribution $\mathbf{P}(Q, E_1, \dots, E_k, H_1, \dots, H_r)$.

1. Select the entries consistent with the evidence $E_1, \dots, E_k = e_1, \dots, e_k$.
2. Marginalize out the hidden variables to obtain the joint of the query and the evidence variables:

$$\mathbf{P}(Q, e_1, \dots, e_k) = \sum_{h_1, \dots, h_r} \mathbf{P}(Q, h_1, \dots, h_r, e_1, \dots, e_k).$$

3. Normalize:

$$Z = \sum_q P(q, e_1, \dots, e_k)$$
$$\mathbf{P}(Q|e_1, \dots, e_k) = \frac{1}{Z} \mathbf{P}(Q, e_1, \dots, e_k)$$

Example

- $P(W)$?
- $P(W|\text{winter})$?
- $P(W|\text{winter, hot})$?

S	T	W	P
summer	hot	sun	0.3
summer	hot	rain	0.05
summer	cold	sun	0.1
summer	cold	rain	0.05
winter	hot	sun	0.1
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.2

Complexity

- Inference by enumeration can be used to answer probabilistic queries for **discrete variables** (i.e., with a finite number of values).
- However, enumeration **does not scale!**
 - Assume a domain described by n variables taking at most d values.
 - Space complexity: $O(d^n)$
 - Time complexity: $O(d^n)$

Exercise

Can we reduce the size of the representation of the joint distribution?

Product rule

$$P(a, b) = P(b)P(a|b)$$

Example

$P(W)$

W	P
sun	0.8
rain	0.2

$P(D|W)$

D	W	P
wet	sun	0.1
dry	sun	0.9
wet	rain	0.7
dry	rain	0.3

$P(D, W)$

D	W	P
wet	sun	?
dry	sun	?
wet	rain	?
dry	rain	?

Chain rule

More generally, any joint distribution can always be written as an incremental product of conditional distributions:

$$P(x_1, x_2, x_3) = P(x_1)P(x_2|x_1)P(x_3|x_1, x_2)$$

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

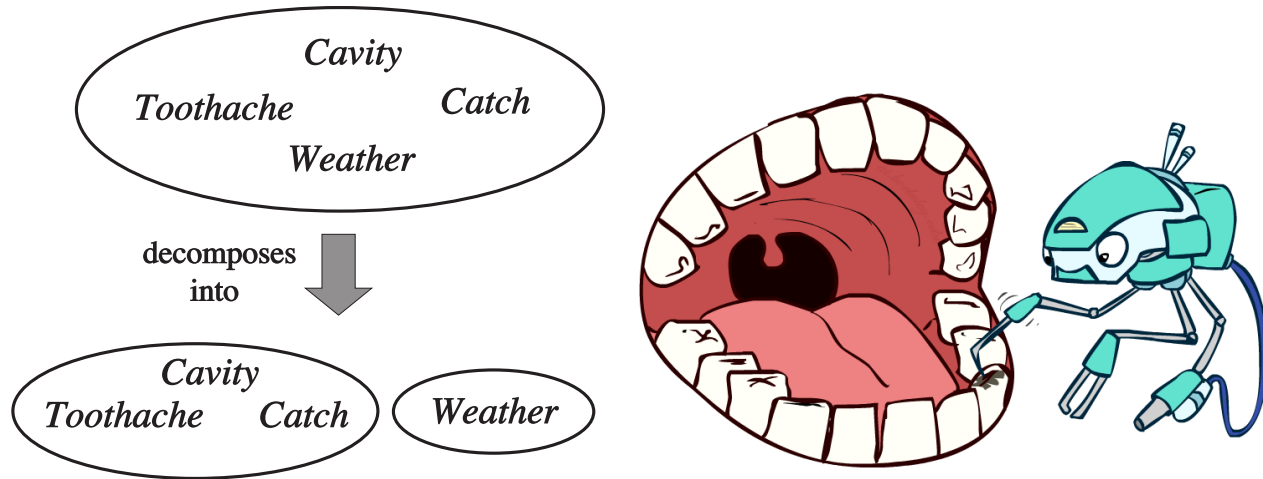
Independence

A and B are **independent** iff, for all $a \in D_A$ and $b \in D_B$,

- $P(a|b) = P(a)$, or
- $P(b|a) = P(b)$, or
- $P(a, b) = P(a)P(b)$

Independence is denoted as $A \perp B$.

Example 1



$$\begin{aligned} &P(\text{toothache}, \text{catch}, \text{cavity}, \text{weather}) \\ &= P(\text{toothache}, \text{catch}, \text{cavity})P(\text{weather}) \end{aligned}$$

The original 32-entry table reduces to one 8-entry and one 4-entry table (assuming 4 values for **Weather** and boolean values otherwise).

Example 2

For n independent coin flips, the joint distribution can be fully **factored** and represented as the product of n 1-entry tables.

- $2^n \rightarrow n$

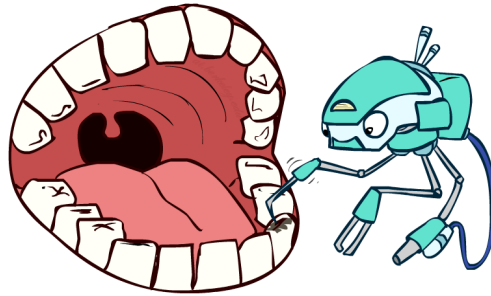
Conditional independence

A and B are **conditionally independent** given C iff, for all $a \in D_A, b \in D_B$ and $c \in D_C$,

- $P(a|b, c) = P(a|c)$, or
- $P(b|a, c) = P(b|c)$, or
- $P(a, b|c) = P(a|c)P(b|c)$

Conditional independence is denoted as $A \perp B|C$.

- Using the chain rule, the join distribution can be factored as a product of conditional distributions.
- Each conditional distribution may potentially be **simplified by conditional independence**.
- Conditional independence assertions allow probabilistic models to **scale up**.



Example 1

Assume three random variables **Toothache**, **Catch** and **Cavity**.

Catch is conditionally independent of **Toothache**, given **Cavity**. Therefore, we can write:

$$\begin{aligned} P(\text{toothache}, \text{catch}, \text{cavity}) \\ &= P(\text{toothache} | \text{catch}, \text{cavity}) P(\text{catch} | \text{cavity}) P(\text{cavity}) \\ &= P(\text{toothache} | \text{cavity}) P(\text{catch} | \text{cavity}) P(\text{cavity}) \end{aligned}$$

In this case, the representation of the joint distribution reduces to $2 + 2 + 1$ independent numbers (instead of $2^n - 1$).

Example 2 (Naive Bayes)

More generally, from the product rule, we have

$$P(\text{cause}, \text{effect}_1, \dots, \text{effect}_n) = P(\text{effect}_1, \dots, \text{effect}_n | \text{cause}) P(\text{cause})$$

Assuming **pairwise conditional independence** between the effects given the cause, it comes:

$$P(\text{cause}, \text{effect}_1, \dots, \text{effect}_n) = P(\text{cause}) \prod_i P(\text{effect}_i | \text{cause})$$

This probabilistic model is called a **naive Bayes** model.

- The complexity of this model is $O(n)$ instead of $O(2^n)$ without the conditional independence assumptions.
- Naive Bayes can work surprisingly well in practice, even when the assumptions are wrong.

Study the next slide. **Twice.**

The Bayes' rule

The product rule defines two ways to factor the joint distribution of two random variables.

$$P(a, b) = P(a|b)P(b) = P(b|a)P(a)$$

Therefore,

$$P(a|b) = \frac{P(b|a)P(a)}{P(b)}.$$



- $P(a)$ is the prior belief on a .
- $P(b)$ is the probability of the evidence b .
- $P(a|b)$ is the posterior belief on a , given the evidence b .
- $P(b|a)$ is the conditional probability of b given a . Depending on the context, this term is called the likelihood.

$$P(a|b) = \frac{P(b|a)P(a)}{P(b)}$$



The Bayes' rule is the **foundation** of many AI systems.

Example 1: diagnostic probability from causal probability.

$$P(\text{cause}|\text{effect}) = \frac{P(\text{effect}|\text{cause})P(\text{cause})}{P(\text{effect})}$$

where

- $P(\text{effect}|\text{cause})$ quantifies the relationship in the **causal** direction.
- $P(\text{cause}|\text{effect})$ describes the **diagnostic** direction.

Let S =stiff neck and M =meningitis. Given $P(s|m) = 0.7$, $P(m) = 1/50000$, $P(s) = 0.01$, it comes

$$P(m|s) = \frac{P(s|m)P(m)}{P(s)} = \frac{0.7 \times 1/50000}{0.01} = 0.0014.$$

Example 2: Ghostbusters, revisited

- Let us assume a random variable G for the ghost location and a set of random variables $R_{i,j}$ for the individual readings.
- We start with a uniform **prior distribution** $\mathbf{P}(G)$ over ghost locations.
- We assume a sensor **reading model** $\mathbf{P}(R_{i,j} | G)$.
 - That is, we know what the sensors do.
 - $R_{i,j}$ = reading color measured at $[i, j]$
 - e.g., $P(R_{1,1} = \text{yellow} | G = [1, 1]) = 0.1$
 - Two readings are conditionally independent, given the ghost position.

- We can calculate the **posterior distribution** $\mathbf{P}(G|R_{i,j})$ using Bayes' rule:

$$\mathbf{P}(G|R_{i,j}) = \frac{\mathbf{P}(R_{i,j}|G)\mathbf{P}(G)}{\mathbf{P}(R_{i,j})}.$$

- For the next reading $R_{i',j'}$, this posterior distribution becomes the prior distribution over ghost locations, which we update similarly.

0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

GHOSTS REMAINING: 1
 BUSTS REMAINING: 1
 SCORE: 0

MESSAGES:

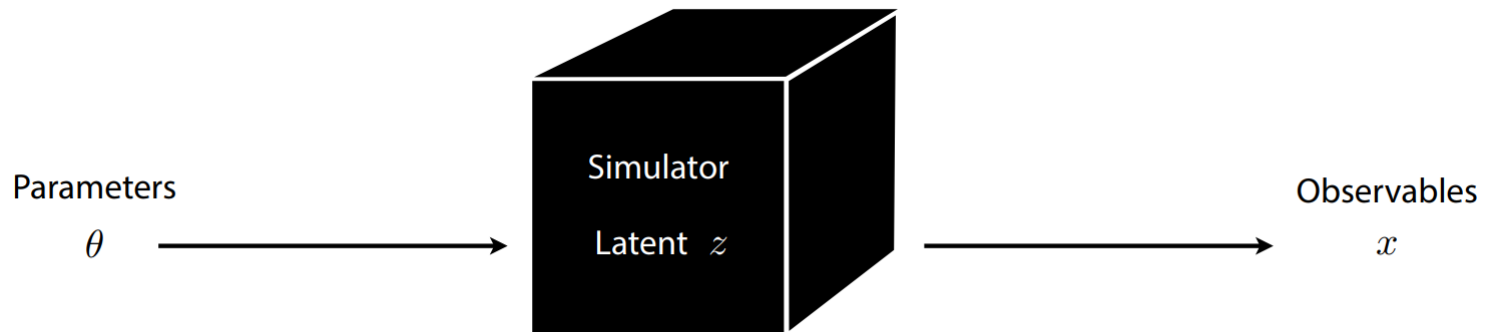
BUST

TIME+1

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Example 3: AI for Science





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Given some observation x and prior beliefs $p(\theta)$, science is about updating one's knowledge, which may be framed as computing

$$p(\theta|x) = \frac{p(x|\theta)p(\theta)}{p(x)}.$$

Probabilistic reasoning

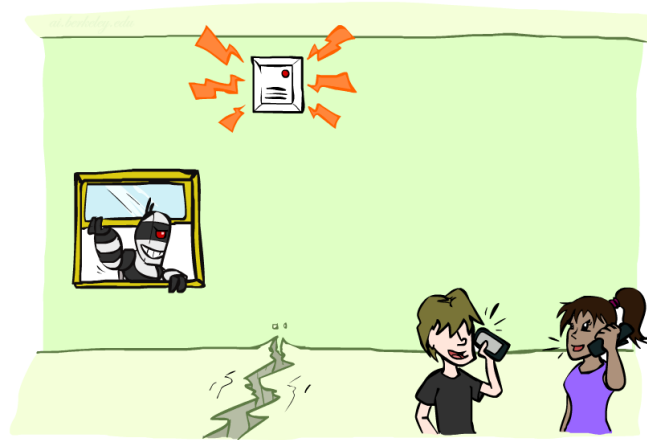
Representing knowledge

- The joint probability distribution can answer any question about the domain.
- However, its representation can become **intractably large** as the number of variable grows.
- **Independence** and **conditional independence** reduce the number of probabilities that need to be specified in order to define the full joint distribution.
- These relationships can be represented explicitly in the form of a **Bayesian network**.

Bayesian networks

A **Bayesian network** is a **directed acyclic graph** (DAG) in which:

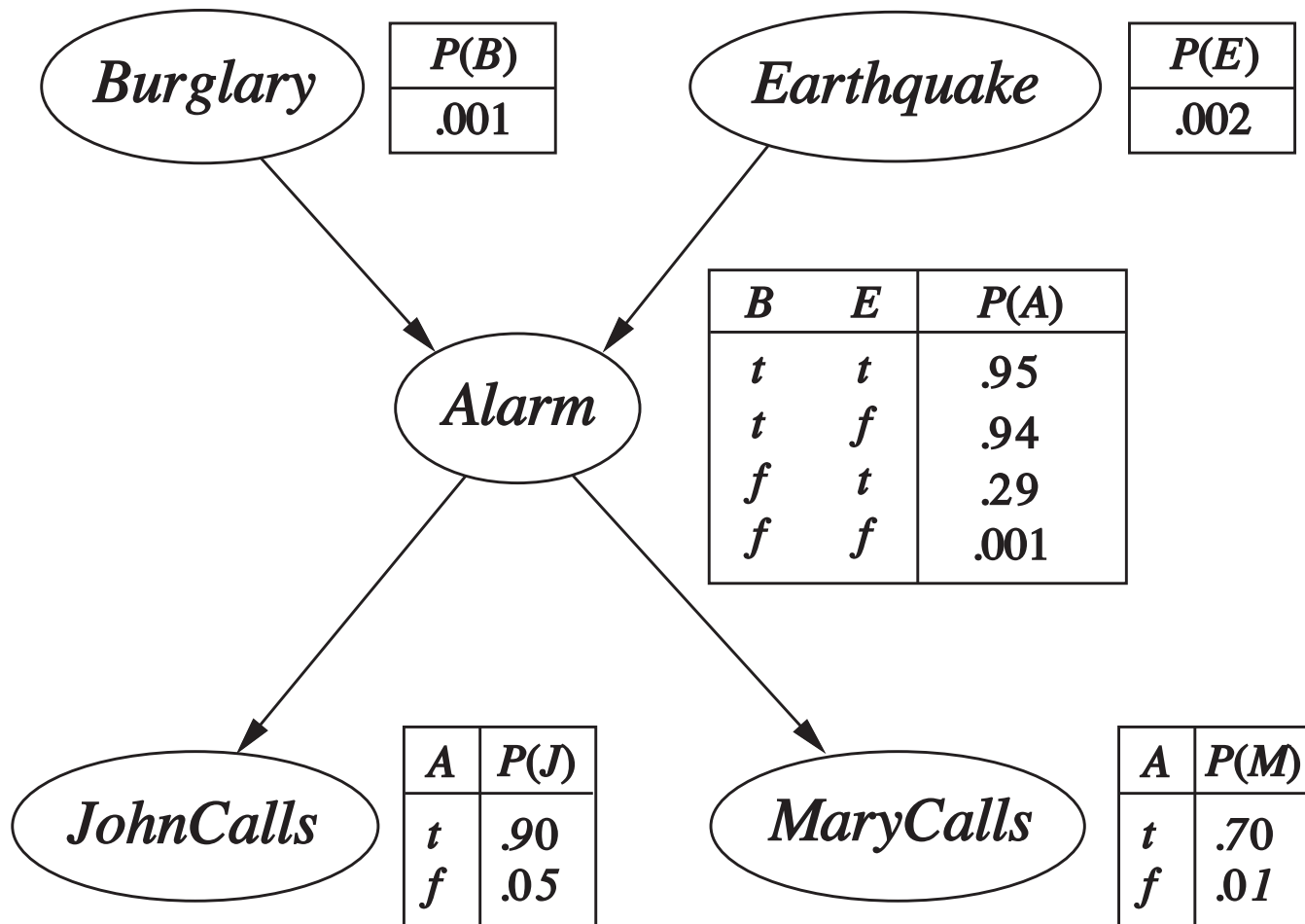
- Each **node** corresponds to a **random variable**.
 - Can be observed or unobserved.
 - Can be discrete or continuous.
- Each **edge** indicates dependency relationships.
 - If there is an arrow from node X to node Y , X is said to be a **parent** of Y .
- Each node X_i is annotated with a **conditional probability distribution** $\mathbf{P}(X_i | \text{parents}(X_i))$ that quantifies the effect of the parents on the node.



Example 1

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

- Variables: **Burglar**, **Earthquake**, **Alarm**, **JohnCalls**, **MaryCalls**.
- Network topology from "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



Semantics

A Bayesian network implicitly **encodes** the full joint distribution as the product of the local distributions:

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

Example

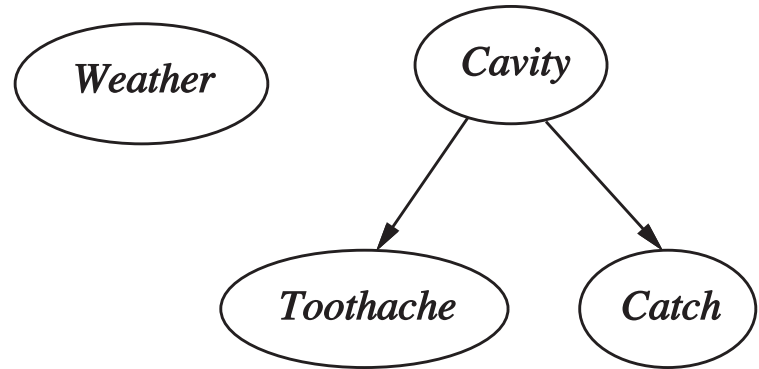
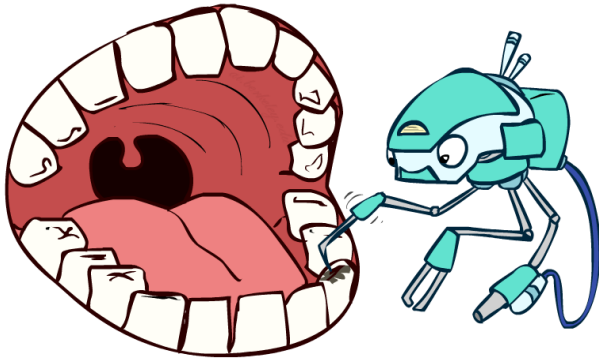
$$\begin{aligned} P(j, m, a, \neg b, \neg e) &= P(j|a)P(m|a)P(a|\neg b, \neg e)P(\neg b)P(\neg e) \\ &= 0.9 \times 0.7 \times 0.001 \times 0.999 \times 0.998 \\ &\approx 0.00063 \end{aligned}$$

Why does $\prod_{i=1}^n P(x_i | \text{parents}(X_i))$ result in the proper joint probability?

- By the **chain rule**, $P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | x_1, \dots, x_{i-1})$.
- Provided that we assume **conditional independence** of X_i with its predecessors in the ordering given the parents, and provided $\text{parents}(X_i) \subseteq \{X_1, \dots, X_{i-1}\}$:

$$P(x_i | x_1, \dots, x_{i-1}) = P(x_i | \text{parents}(X_i))$$

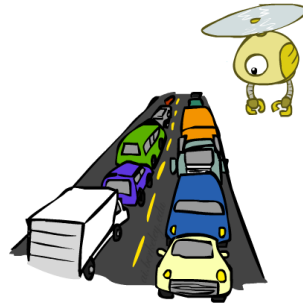
- Therefore $P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | \text{parents}(X_i))$.



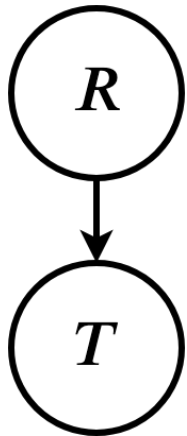
Example 2

The topology of the network encodes conditional independence assertions:

- *Weather* is independent of the other variables.
- *Toothache* and *Catch* are conditionally independent given *Cavity*.



Example 3



$P(R)$

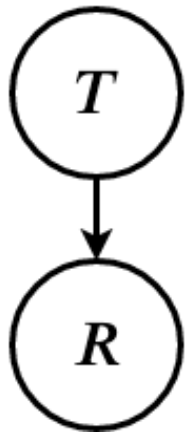
R	P
r	0.25
$\neg r$	0.75

$P(T|R)$

R	T	P
r	t	0.75
r	$\neg t$	0.25
$\neg r$	t	0.5
$\neg r$	$\neg t$	0.5



Example 3 (bis)



$P(T)$

T	P
r	9/16
$\neg r$	7/16

$P(R|T)$

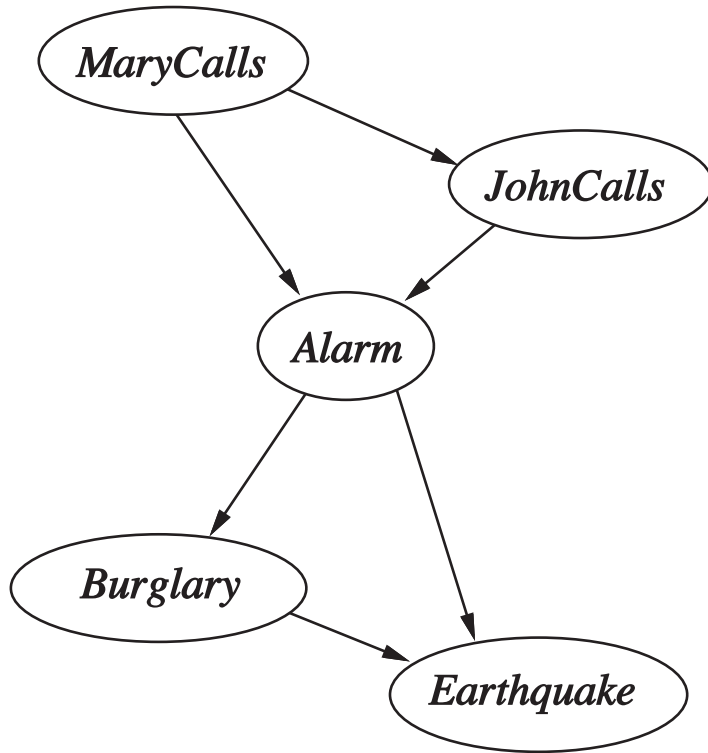
T	R	P
t	r	1/3
t	$\neg r$	2/3
$\neg t$	r	1/7
$\neg t$	$\neg r$	6/7

Construction

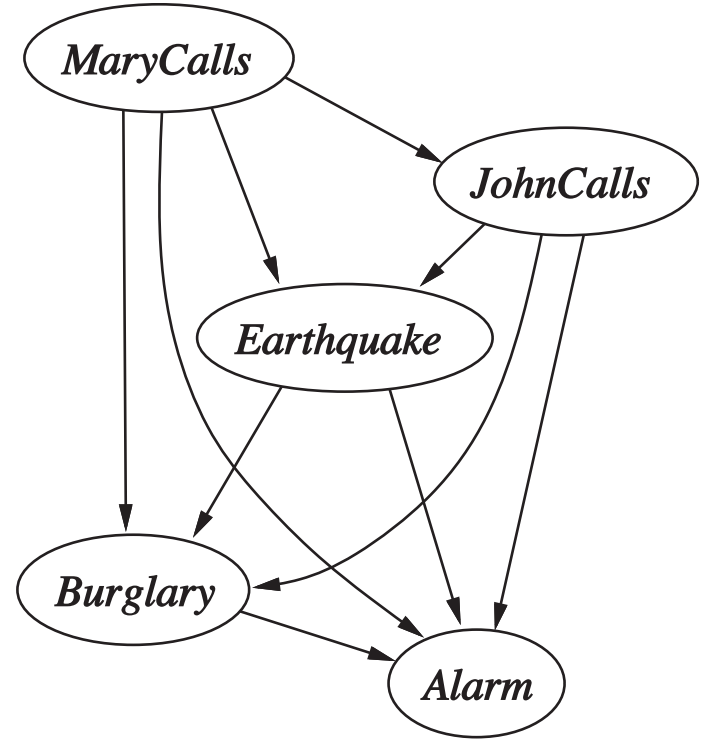
Bayesian networks are correct representations of the domain only if each node is conditionally independent of its other predecessors in the node ordering, given its parents.

Construction algorithm

1. Choose some **ordering** of the variables X_1, \dots, X_n .
2. For $i = 1$ to n :
 1. Add X_i to the network.
 2. Select a minimal set of parents from X_1, \dots, X_{i-1} such that $P(x_i | x_1, \dots, x_{i-1}) = P(x_i | \text{parents}(X_i))$.
 3. For each parent, insert a link from the parent to X_i .
 4. Write down the CPT.



(a)



(b)

Exercise

Do these networks represent the same distribution?

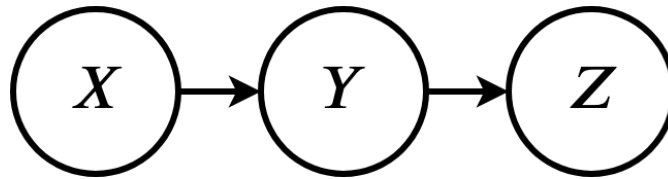
Compactness

- A CPT for boolean X_i with k boolean parents has 2^k rows for the combinations of parent values.
- Each row requires one number p for $X_i = \text{true}$.
 - The number for $X_i = \text{false}$ is just $1 - p$.
- If each variable has no more than k parents, the complete network requires $O(n \times 2^k)$ numbers.
 - i.e., grows linearly with n , vs. $O(2^n)$ for the full joint distribution.
- For the burglary net, we need $1 + 1 + 4 + 2 + 2 = 10$ numbers (vs. $2^5 - 1 = 31$).
- Compactness depends on the node ordering.

Independence

Important question: Are two nodes independent given certain evidence?

- If yes, this can be proved using algebra (tedious).
- If no, this can be proved with a counter example.



Example: Are X and Z necessarily independent?

Cascades

Is X independent of Z ? No.

Counter-example:

- Low pressure causes rain causes traffic, high pressure causes no rain causes no traffic.
- In numbers:
 - $P(y|x) = 1$,
 - $P(z|y) = 1$,
 - $P(\neg y|\neg x) = 1$,
 - $P(\neg z|\neg y) = 1$



X : low pressure, Y : rain, Z : traffic.

$$P(x, y, z) = P(x)P(y|x)P(z|y)$$

Is X independent of Z , given Y ? Yes.

$$\begin{aligned} P(z|x, y) &= \frac{P(x, y, z)}{P(x, y)} \\ &= \frac{P(x)P(y|x)P(z|y)}{P(x)P(y|x)} \\ &= P(z|y) \end{aligned}$$

We say that the evidence along the cascade "**blocks**" the influence.



X : low pressure, Y : rain, Z : traffic.

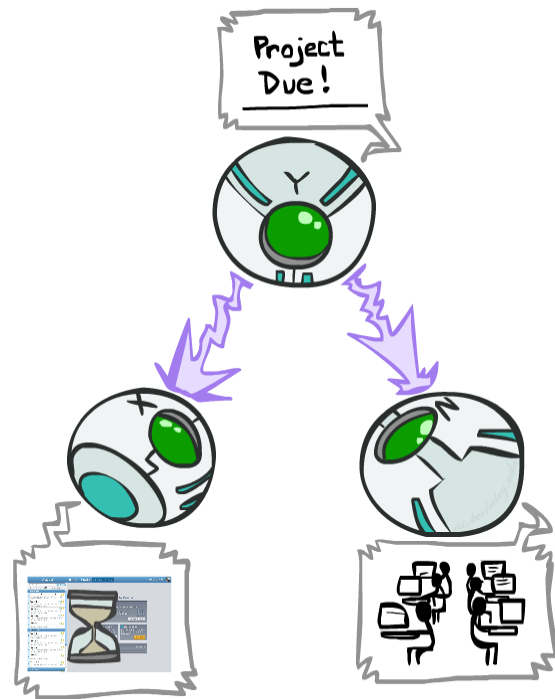
$$P(x, y, z) = P(x)P(y|x)P(z|y)$$

Common parent

Is X independent of Z ? No.

Counter-example:

- Project due causes both forums busy and lab full.
- In numbers:
 - $P(x|y) = 1$,
 - $P(\neg x|\neg y) = 1$,
 - $P(z|y) = 1$,
 - $P(\neg z|\neg y) = 1$



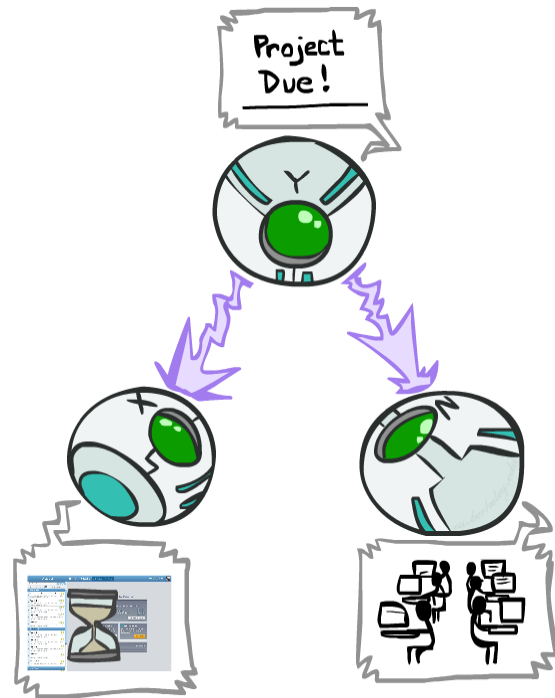
X : forum busy, Y : project due, Z : lab full.

$$P(x, y, z) = P(y)P(x|y)P(z|y)$$

Is X independent of Z , given Y ? Yes

$$\begin{aligned} P(z|x, y) &= \frac{P(x, y, z)}{P(x, y)} \\ &= \frac{P(y)P(x|y)P(z|y)}{P(y)P(x|y)} \\ &= P(z|y) \end{aligned}$$

Observing the parent blocks the influence between the children.



X : forum busy, Y : project due, Z : lab full.

$$P(x, y, z) = P(y)P(x|y)P(z|y)$$

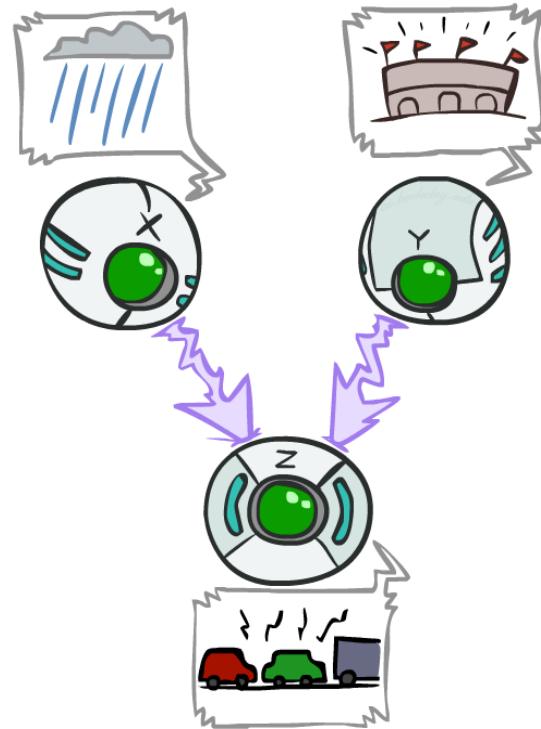
v-structures

Are X and Y independent? Yes.

- The ballgame and the rain cause traffic, but they are not correlated.
- (Prove it!)

Are X and Y independent given Z ?
No!

- Seeing traffic puts the rain and the ballgame in competition as explanation.
- This is **backwards** from the previous cases. Observing a child node **activates** influence between parents.



X : rain, Y : ballgame, Z : traffic.

$$P(x, y, z) = P(x)P(y)P(z|x, y)$$

d-separation

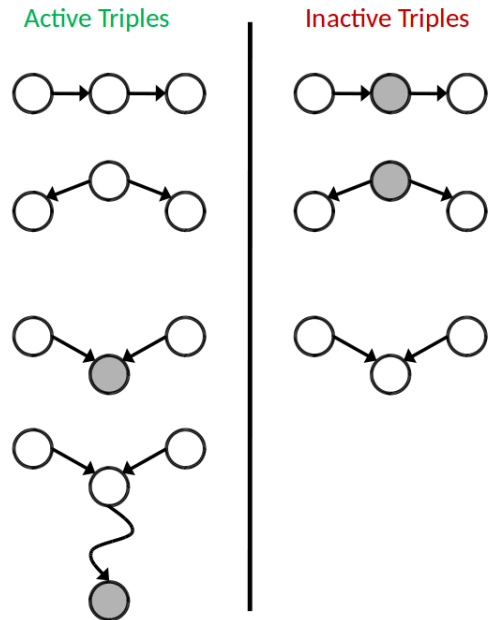
Let us assume a complete Bayesian network. Are X_i and X_j conditionally independent given evidence $Z_1 = z_1, \dots, Z_m = z_m$?

Consider all (undirected) paths from X_i to X_j :

- If one or more active path, then independence is not guaranteed.
- Otherwise (i.e., all paths are inactive), then independence is guaranteed.

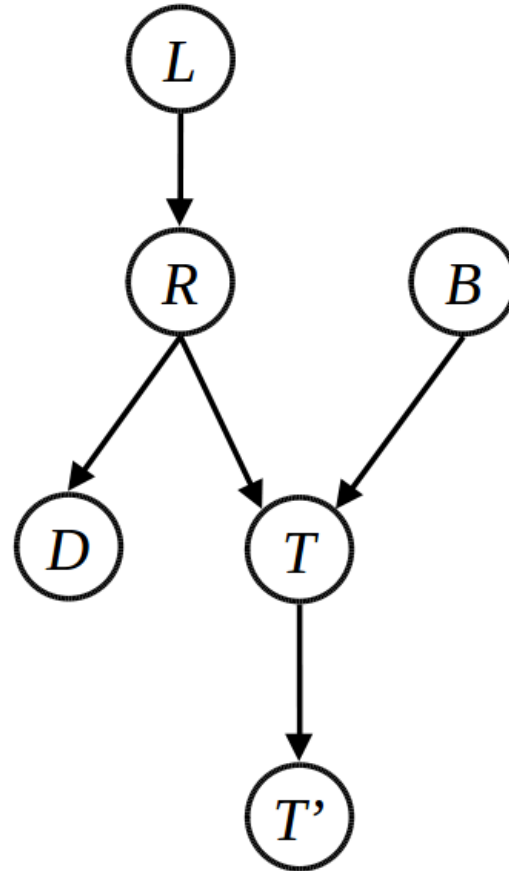
A path is **active** if each triple is active:

- Cascade $A \rightarrow B \rightarrow C$ where B is unobserved (either direction).
- Common parent $A \leftarrow B \rightarrow C$ where B is unobserved.
- v-structure $A \rightarrow B \leftarrow C$ where B or one of its descendants is observed.



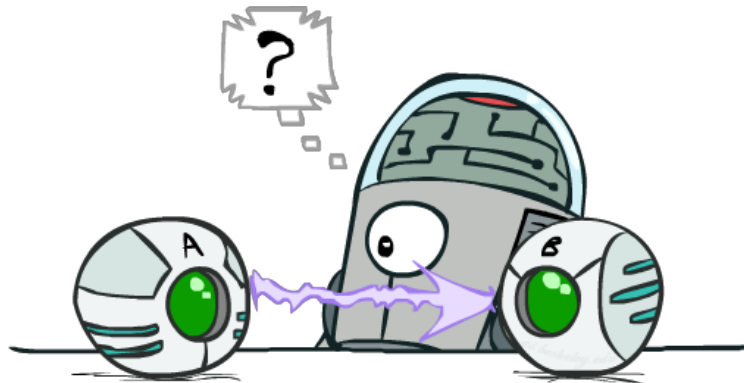
Example

- $L \perp T' | T?$
- $L \perp B?$
- $L \perp B | T?$
- $L \perp B | T'?$
- $L \perp B | T, R?$



Causality?

- When the network reflects the true causal patterns:
 - Often more compact (nodes have fewer parents).
 - Often easier to think about.
 - Often easier to elicit from experts.
- But, Bayesian networks **need not be causal**.
 - Sometimes no causal network exists over the domain (e.g., if variables are missing).
 - Edges reflect **correlation**, not causation.
- What do the edges really mean then?
 - Topology **may** happen to encode causal structure.
 - **Topology really encodes conditional independence**.



- Correlation does not imply causation.
- Causes cannot be expressed in the language of probability theory.



Judea Pearl

Philosophers have tried to define causation in terms of probability: $X = x$ causes $Y = y$ if $X = x$ raises the probability of $Y = y$.

However, the inequality

$$P(y|x) > P(y)$$

fails to capture the intuition behind "probability raising", which is fundamentally a causal concept connoting a causal influence of $X = x$ over $Y = y$.

The correct formulation should read

$$P(y|\text{do}(X = x)) > P(y),$$

where $\text{do}(X = x)$ stands for an external intervention where X is set to the value x instead of being observed.

Observing vs. intervening

- The reading in barometer is useful to predict rain.

$$P(\text{rain} | \text{Barometer} = \text{high}) > P(\text{rain} | \text{Barometer} = \text{low})$$

- But hacking a barometer will not cause rain!

$$P(\text{rain} | \text{Barometer hacked to high}) = P(\text{rain} | \text{Barometer hacked to low})$$

Summary

- Uncertainty arises because of laziness and ignorance. It is **inescapable** in complex non-deterministic or partially observable environments.
- Probabilistic reasoning provides a framework for managing our knowledge and **beliefs**, with the Bayes' rule acting as the workhorse for inference.
- A **Bayesian Network** specifies a full joint distribution. They are often exponentially smaller than an explicitly enumerated joint distribution.
- The structure of a Bayesian network encodes conditional independence assumptions between random variables.

The end.