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**Chapter Five :Uncertain Knowledge and
Reasoning**

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Logic and Uncertainty

- Uncertainty is Bad for Agents based on Logic
- Example: Catching a Flight
- Let action A_t = leave for airport t minutes before flight
- Question: Will A_t get me there on time?
- Problems:
 - Partial observability (road state, other drivers' plans, etc.)
 - Noisy sensors (traffic reports)
 - Uncertainty in action outcomes (flat tire, etc.)
 - Complexity of modeling and predicting traffic
- A purely logical approach leads to conclusions that are too weak for effective decision making:
 - A_{25} will get me there on time if there is no accident on the bridge and it doesn't rain and my tires remain intact, etc., etc.
 - A_{Inf} guarantees to get there in time, but who lives forever?

Uncertainty

- 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.

Reasoning under Uncertainty

- A rational agent is one that makes rational decisions (in order to maximize its performance measure)
- A rational decision depends on:
 - the relative importance of various goals
 - the likelihood they will be achieved
 - the degree to which they will be achieved

Sources of Uncertainty

- Probabilistic assertions summarize effects of
- Laziness
 - facts, observability, etc. Ignorance
- Ignorance
 - lack of explicit theories, relevant facts, observability, etc.
- Randomness
 - Inherently random behavior
- Utility theory is used to represent and infer preferences.
- Decision theory = probability theory + utility theory

Probability Theory

- the set of all possible worlds is called the sample space.
- The possible worlds are mutually exclusive and exhaustive
 - two possible worlds cannot both be the case, and
 - one possible world must be the case.
- The Greek letter Ω (uppercase omega) is used to refer to the sample space, and
- ω (lowercase omega) refers to elements of the space, that is, particular possible worlds.
- A fully specified probability model associates a numerical probability with each possible world.
- The basic axioms of probability theory say that every possible world has a
 - probability between 0 and 1 and
 - that the total probability of the set of possible worlds is 1:

$$0 \leq P(\omega) \leq 1 \text{ for every } \omega \text{ and } \sum_{\omega \in \Omega} P(\omega) = 1.$$

- unconditional or prior refer to degrees of belief in propositions in the absence of any other information.
 - Probabilities such as $P(\text{doubles})$ and $P(\text{total} = 11)$
- conditional or posterior probability is a measure of the probability of an event given
 - that (by assumption, presumption, assertion or evidence) another event has already occurred.
 - This probability is written where $P(\text{doubles} | \text{Die} = 5)$ where the $|$ is pronounced "given".

- Frequentism (Empirical)

- Probabilities are relative frequencies determined by observation.
- For example, if we toss a coin many times, $p(\text{heads})$ is the proportion of the time the coin will come up heads
- But what if we are dealing with events that only happen once? E.g., what is the probability that a Republican will win the presidency in 2024?
- Reference class problem. E.g., how do we define comparable elections?

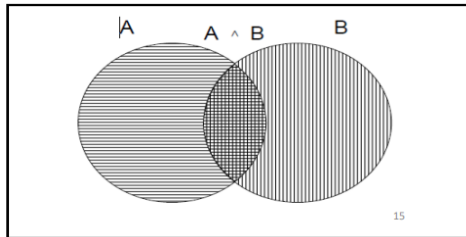
- Subjectivism (Bayesian Statistics)

- Probabilities are degrees of belief updated by evidence.
- How do we assign belief values to statements without evidence?
- How do we update our degrees of belief?
- What would make sure that agents hold consistent beliefs? E.g.,
- The coin will land heads up and tails up at the same time.

Axioms of Probability

- Probability Theory is governed by the following axioms:
 - All probabilities are real values between 0 and 1: for all φ , $0 \leq P(\varphi) \leq 1$
 - Valid propositions have probability 1 $P(\text{True}) = P(\alpha \vee \neg \alpha) = 1$
 - The probability of disjunction is defined as follows:

$$P(\alpha \vee \beta) = P(\alpha) + P(\beta) - P(\alpha \wedge \beta)$$



Cont...

- A random variable is a function that maps from the domain of possible worlds Ω (called sample space) to the real numbers written as $X: \Omega \rightarrow$
- Denoted by capital letters
 - R: Is it raining?
 - W: What's the weather?
 - Die: What is the outcome of rolling two dice?
 - V: What is the speed of a car (in MPH)?
- Names for values are always lowercase
 - A Boolean random variable has the range true, false .
 - the range of weather to be the set sun, cloud, rain, snow
- Domain values must be mutually exclusive and exhaustive
 - $R \in \text{True, False}$
 - $W \in \text{Sunny, Cloudy, Rainy, Snow}$
 - $\text{Die} \in (1,1), (1,2), \dots (6,6)$

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 $p(X)$.
- 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!).

Events and Propositions

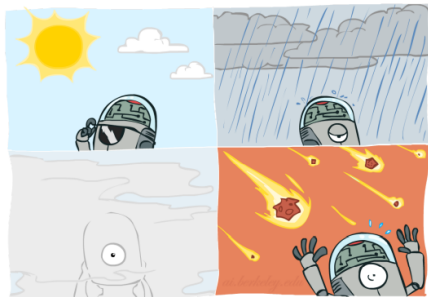
- Events
 - Probabilistic statements are defined over events, world states or sets of states
 - "It is raining"
 - "The weather is either cloudy or snowy"
 - "The sum of the two dice rolls is 11"
- Events are described using propositions:
 - $R = \text{True}$
 - $W = \text{"Cloudy"} \vee W = \text{"Snowy"}$
 - $D \in (5,6), (6,5)$

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.

$P(W)$

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 specifies the probability of each 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.

$P(T, W)$

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

$P(T)$

T	P
hot	0.5
cold	0.5

$P(W)$

W	P
sun	0.6
rain	0.4

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

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

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

Cont...

P(Cavity, Toothache)	
$Cavity = false \wedge Toothache = false$	0.8
$Cavity = false \wedge Toothache = true$	0.1
$Cavity = true \wedge Toothache = false$	0.05
$Cavity = true \wedge Toothache = true$	0.05

Marginal
Prob. Distr.

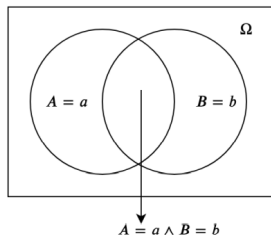
P(Cavity)	
$Cavity = false$	$0.8+0.1 = 0.9$
$Cavity = true$	$0.05+0.05=0.1$

P(Toothache)	
$Toothache = false$	$0.8+0.05= 0.85$
$Toothache = true$	$0.1+0.05= 0.15$

Conditional distributions

- $P(A)$ is the unconditional (or prior) probability of fact A
- An agent can use the unconditional probability of A to reason about A in the absence of further information
- If further evidence B becomes available, the agent must use the conditional (or posterior) probability:

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



Cont...

Joint Prob. Distr.

P(Cavity, Toothache)	
<i>Cavity = false</i> \wedge <i>Toothache = false</i>	0.8
<i>Cavity = false</i> \wedge <i>Toothache = true</i>	0.1
<i>Cavity = true</i> \wedge <i>Toothache = false</i>	0.05
<i>Cavity = true</i> \wedge <i>Toothache = true</i>	0.05

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

Marginal Prob. Distr.

P(Cavity)	
<i>Cavity = false</i>	0.9
<i>Cavity = true</i>	0.1

P(Toothache)	
<i>Toothache = false</i>	0.85
<i>Toothache = true</i>	0.15

What is $P(\text{Cavity} = \text{true} \mid \text{Toothache} = \text{false})$?

$$0.05 / 0.85 = 0.059$$

What is $P(\text{Cavity} = \text{false} \mid \text{Toothache} = \text{true})$?

$$0.1 / 0.15 = 0.667$$

Conditional distributions

P(Cavity, Toothache)	
<i>Cavity = false</i> \wedge <i>Toothache = false</i>	0.8
<i>Cavity = false</i> \wedge <i>Toothache = true</i>	0.1
<i>Cavity = true</i> \wedge <i>Toothache = false</i>	0.05
<i>Cavity = true</i> \wedge <i>Toothache = true</i>	0.05

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

A conditional distribution is a distribution over the values of one variable given fixed values of other variables

P(Cavity Toothache = true)	
<i>Cavity = false</i>	0.667
<i>Cavity = true</i>	0.333

P(Cavity Toothache = false)	
<i>Cavity = false</i>	0.941
<i>Cavity = true</i>	0.059

P(Toothache Cavity = true)	
<i>Toothache = false</i>	0.5
<i>Toothache = true</i>	0.5

P(Toothache Cavity = false)	
<i>Toothache = false</i>	0.889
<i>Toothache = true</i>	0.111

Normalization trick

- To get the whole conditional distribution $P(X|y)$ at once, select all entries in the joint distribution matching $Y = y$ and renormalize them to sum to one

$P(\text{Cavity}, \text{Toothache})$	
$\text{Cavity} = \text{false} \wedge \text{Toothache} = \text{false}$	0.8
$\text{Cavity} = \text{false} \wedge \text{Toothache} = \text{true}$	0.1
$\text{Cavity} = \text{true} \wedge \text{Toothache} = \text{false}$	0.05
$\text{Cavity} = \text{true} \wedge \text{Toothache} = \text{true}$	0.05



Select $P(X, y)$

$\text{Toothache}, \text{Cavity} = \text{false}$	
$\text{Toothache} = \text{false}$	0.8
$\text{Toothache} = \text{true}$	0.1

} Sum is $P(y) = 0.9$



Renormalize sum to 1 (= divide by $P(y)$)

$P(\text{Toothache} \mid \text{Cavity} = \text{false})$	
$\text{Toothache} = \text{false}$	0.889
$\text{Toothache} = \text{true}$	0.111

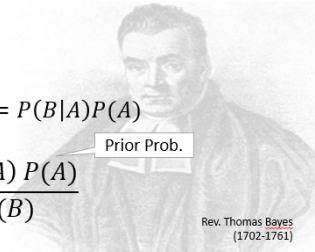
Equivalent to

$$P(X|y) = \alpha P(X, y)$$

with $\alpha = 1/P(y)$

Bayes' Rule

- The product rule gives us two ways to factor a joint distribution:


$$P(A, B) = P(A|B)P(B) = P(B|A)P(A)$$

Therefore

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

Posterior Prob.

Prior Prob.

Rev. Thomas Bayes
(1702-1761)

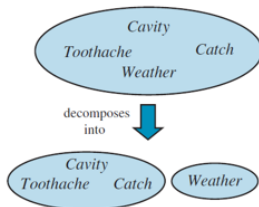
Independence

- Two events a and b are independent if and only if
 - $P(a \wedge b) = P(a) P(b)$
 - This is equivalent to $P(a | b) = P(a)$ and $P(b | a) = P(b)$
 - $P(a | b) = P(a)$
 - $P(b | a) = P(b)$
 - $P(a, b) = P(a)P(b)$
- Independence is denoted as $A \perp B$.

Cont...

- Independence is an important simplifying assumption for modeling,
- e.g., Cavity and Weather can be assumed to be independent

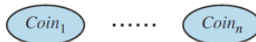
$$P(\text{Cavity} \mid \text{Weather}) = P(\text{Cavity})$$



$$P(\text{Cavity}, \text{Weather}) = P(\text{Cavity})P(\text{Weather})$$



decomposes
into



$$P(H, H, T, \dots, T) = P(H)P(H)P(T)\dots P(T)$$

Cont...

- Conditional independence: a and b are conditionally independent given c (i.e., if we know c) iff
- $P(a \wedge b | c) = P(a | c) P(b | c)$

$$P(a|b, c) = P(a|c), \text{ or}$$

$$P(b|a, c) = P(b|c), \text{ or}$$

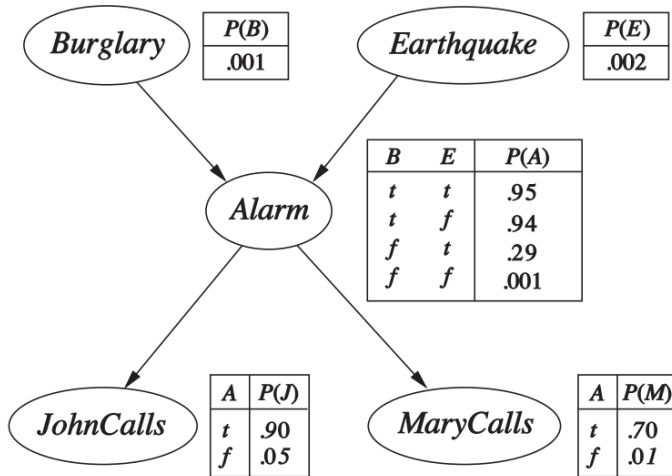
$$P(a, b|c) = P(a|c)P(b|c)$$

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

Bayesian network

- 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 to node , is said to be a parent of .
 - Each node is annotated with a conditional probability distribution

Cont...



Example

- 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

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 specify full joint distribution.
- They are often exponentially smaller than an explicitly enumerated joint distribution.