

Topic 4

Representation and Reasoning with Uncertainty

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4.0 Representation and Reasoning with Uncertainty

Reasoning can be uncertain in several ways:

- Uncertainty in **data** (facts)
- Uncertainty in **inference processes** (rules)

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4.0 Representation and Reasoning with Uncertainty

Uncertainty in data (facts)

- **Data not available** (e.g., doctor does not know if patient has allergy to a drug.
- **Data unreliable**: data is available, but not trustworthy, e.g.,
 - **errors of measurement**, two measurements gave different results, etc.
 - The data is in an **imprecise representation**.
 - The data represents a **guess** by the expert,
 - e.g., Patient is in good health? True (0.9)
 - The data may be just a **default value**, and there may be exceptions to default values.

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4.0 Representation and Reasoning with Uncertainty

Uncertainty in knowledge (rules)

- Rule may represent just a statistical association observed by experts, e.g.,

```
IF      primary infection is bacteriacea
      AND site of infection is sterile
      AND entry point of infection
           is gastrointestinal tract
THEN organism is "bacteroid" (0.7)
```
- Rule may not be appropriate in all cases
 - e.g., rules designed for the average person may not be suitable for someone who is totally atypical

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4.0 Representation and Reasoning with Uncertainty

Issues in managing uncertainty

1. **How to represent uncertain data and knowledge.**
2. **How to combine two or more items of uncertain data** (e.g., if both premises to a rule are uncertain, how do we combine the uncertainty)
3. **How to draw inferences (conclusions) using uncertain data and knowledge** (e.g., how do we combine the uncertainty of premises and rules to estimate the uncertainty of the conclusion)

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4.0 Representation and Reasoning with Uncertainty

Some ways for representing uncertainty:

1. As **Probability** (Bayesian Logic): what is the probability of X being True
 - $P(x)=0$: X is false
 - $P(x)=1$: X is true
2. As a **Certainty Factor**: how certain are we that X is true or not true.
 - $CF(x)= 0$: I have no knowledge if x is true or false
 - $CF(x)= -1$: I believe x is not true
 - $CF(x)= 1$: I believe x is true
3. As **Fuzzy Logic**: to what degree x is in various sets.
 - a given cup of coffee can be member of cold-drink and hot-drink sets at the same time.

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Topic 4

Representation and Reasoning with Uncertainty

4.1 Probabilistic methods (Bayesian)

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4.1 Probabilistic methods (Bayesian)

Definitions

- **Random Variable:** an aspect of the problem for which a value is not initially known.
Examples: patient temperature, patient has viral infection?
- **Domain:** the range of possible values a variable can take. Can be boolean (true/false), discrete (black/red/green) or continuous values.
- **Atomic event (outcome):** A complete specification of the state of the world about which the agent is uncertain.
 - E.g., if the world consists of only two Boolean variables Cavity and Toothache, then there are 4 distinct atomic events:
 - Cavity = false & Toothache = false
 - Cavity = false & Toothache = true
 - Cavity = true & Toothache = false
 - Cavity = true & Toothache = true

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4.1 Probabilistic methods (Bayesian)

Example

Tossing a coin.

Random Variable X: the result of the toss

Domain: {head, tail}

Outcomes: {X=head, X=tail}

Two tosses of the same coin

Random Variable : X (result of the first toss),
 Y (result of the second toss)

Domain of both X and Y: {head, tail}

Outcomes: { {X=head, Y=head}, {X=head, Y=tail},
 {X=tail, Y=head}, {X=tail, Y=tail} }

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4.1 Probabilistic methods (Bayesian)

Example II

Patient being diagnosed with Flu base based on cough, temperature, age, fever .

Random Variables and their domains:

Cough:	{ yes, no}	(boolean)
Temperature	10-45°C	(discrete, if the thermometer has resolution of 0.5 °C)
Age:	0-100	(discrete)
Fever:	{yes, no}	(boolean)
Flu :	{yes, no}	(boolean)

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4.1 Probabilistic methods (Bayesian)

More definitions

- **Event:** set of zero, one or various atomic events.

It represents something that can happen .

Example : In the problem involving two tosses of the coin, the event "has at least one head" is the set :

$\{ \{X=\text{head}, Y=\text{head}\}, \{X=\text{head}, Y=\text{tail}\}, \{X=\text{tail}, Y=\text{head}\} \}$

The event "the second toss is different to the first" is:

$\{ \{X=\text{head}, Y=\text{tail}\}, \{X=\text{tail}, Y=\text{head}\} \}$.

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4.1 Probabilistic methods (Bayesian)

More definitions

- **Mutually exclusive events:** events that do not have any atomic event in common.
- This implies that they cannot happen simultaneously.
 - Example: The event "*the second toss is different to the first*" and the event "*the second toss is the same as the first*" are mutually exclusive.
 - The event "*there is at least one head*" and the event "*there is at least one tail*" are not mutually exclusive.
- **Exhaustive events:** a set of events which together cover all the atomic events of the problem.

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4.1 Probabilistic methods (Bayesian)

Probabilities

- The probability of event s_i is given as $p(s_i)$
- The probability of each event s_i is between 0 and 1 $0 < p(s_i) < 1.0$
- If \mathbf{s} is an event which must occur, $p(\mathbf{s}) = 1$.
If \mathbf{s} cannot occur, $p(\mathbf{s}) = 0$
- The sum of probabilities of all events is 1.0:

$$\sum_{i=1}^n p(s_i) = 1.0$$

- The probability of $\sim s$ is $1 - p(s)$:

$$p(\sim s_i) = 1 - p(s_i)$$

$$p(s_i) + p(\sim s_i) = 1$$

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4.1 Probabilistic methods (Bayesian)

Combined Probability

- If s_1 and s_2 are two outcomes ('U' = 'v' = 'or'; \cap = $\&$ = \wedge = 'and') :

$$p(s_1 \cup s_2) = p(s_1) + p(s_2) - p(s_1 \cap s_2)$$

e.g. $p(\text{dice} < 4) = 1/2$, $p(\text{dice} = \text{even}) = 1/2$,
 $p(\text{dice} < 4 \text{ or } \text{dice} = \text{even}) = 1/2 + 1/2 - 1/6 = 5/6$

- If s_1 and s_2 are **mutually exclusive**, this simplifies :

$$p(s_i \vee s_j) = p(s_i) + p(s_j)$$

e.g. $p(\text{dice} = 3) = 1/6$, $p(\text{dice} = 4) = 1/6$,
 $p(\text{dice} = 3 \text{ or } 4) = 2/6$

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4.1 Probabilistic methods (Bayesian)

Joint Probability

- If x_i and y_j are independent events:

$$p(x_i \& y_j) = p(x_i) p(y_j)$$

e.g. $p(\text{dice1}=3) = 1/6$, $p(\text{dice2}=4)=1/6$,
 $p(\text{dice1} = 3 \& \text{dice2}=4) = 1/36$

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4.1 Probabilistic methods (Bayesian)

Conditional Probability

- The probability of s_1 given outcome s_2 : $p(s_1 | s_2)$
- The conditional probability can be calculated

$$p(s_1 | s_2) \equiv \frac{p(s_1 \cap s_2)}{p(s_2)}$$

- E.g., $p(\text{dice}=4 | \text{dice}=\text{even}) = 1/6 / 1/2 = 1/3$
 - given we roll an even dice, we have 1/3 chance of rolling a 4.

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4.1 Probabilistic methods (Bayesian)

Conditional Probability with independent events

- If x and y are totally independent events:

$$p(x \& y) = p(x) \cdot p(y)$$

- Thus:

$$\begin{aligned} p(x | y) &= p(x \& y) / p(y) \\ &= p(x) \cdot p(y) / p(y) \\ &= p(x) \end{aligned}$$

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4.1 Probabilistic methods (Bayesian)

Conditional Probability: alternative formula

Given: $p(y | x) = p(y \& x) / p(x)$

Then: $p(y \& x) = p(y | x) * p(x)$

Substituting this into our prior formula:

$$p(x | y) = p(x \& y) / p(y)$$

Gives:

$$p(x | y) = p(y | x) * p(x) / p(y)$$

THIS IS CALLED BAYES THEOREM!!!

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4.1 Probabilistic methods (Bayesian)

Bayes Rule: example

Given that $p(\text{dice}=2|\text{dice}=\text{even}) = 1/3$

Calculate $p(\text{dice}=\text{even}|\text{dice}=2)$

$$\begin{aligned} p(\text{dice}=\text{even}|\text{dice}=2) &= \frac{p(\text{dice}=2|\text{dice}=\text{even}) * p(\text{dice}=\text{even})}{p(\text{dice}=2)} \\ &= \frac{1/3 * 1/2}{1/6} = \frac{1/6}{1/6} = 1 \end{aligned}$$