Uncertainty management

Knowledge Engineering Course

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Knowledge and modeling

- Knowledge representation is a way to make models about the world to reason with
- Each model is different from the world: the map is not the land
- The difference between models and world causes “uncertainty”

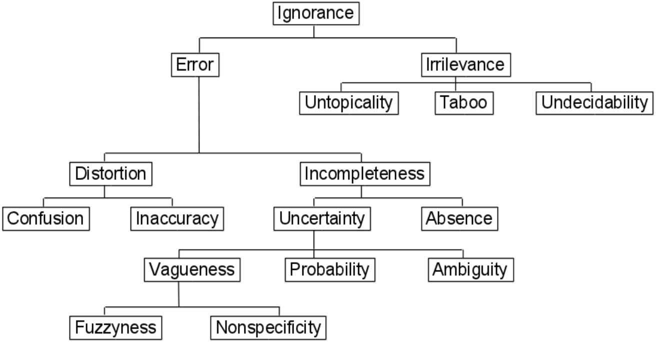
As written in Tao Te Ching..

Knowing ignorance is strength

Ignoring knowledge is sickness

What is uncertainty?

The term "uncertainty" may be related to different aspects, such as "ambiguity", "vagueness", "probability", "contradiction", ...



It is important to understand which aspects to represent in the application

What is truth?

We assume that something is true in a model, if there is enough evidence from the modeled entity to support it

Only defined concepts are always true
E.g.: A triangle has three angles, an elephant is a mammal, ...

For the others, it depends on collected evidence
E.g.: Elephant Jumbo is breast-feeding her son Dumbo
Is she Jumbo? Is he Dumbo? Is he her son? Is she really feeding him? ...

Uncertainty and Approximation

Uncertainty and approximation are different aspects, eventually related

E.g. "Dumbo weights 300 Kg."

- I've some doubts that Dumbo weights exactly 300 Kg
- I'm pretty sure that Dumbo weights$300Kg \pm 10Kg$

When should we represent uncertainty?

- When we know that the model is uncertain
- When we would like to obtain reasonable results even if the model is uncertain
- When we would like to have results naturally accepted by people

Two ways to manage uncertainty

- Modify reasoning according to uncertainty sources (e.g., different logics)
- Represent a measure of uncertainty (e.g., probability, possibility, ...)

Assumptions about models

- The model is a perfect representation of the modeled reality
  Two truth values: true and false
- The model is a perfect representation of the modeled reality, but not all reality is known
  Three truth values: true, false, and unknown
- Elements of the model are observed, deduced, or assumed
  Five truth values to distinguish situations
  Non-monotonic logic

The model is perfect

Any proposition is either true or false

- Problem 1: representation of absence of information
  Close world assumption: anything not true is false
- Problem 2: No quantification of the truth degree
- Problem 3: Management of contradiction and exceptions

Something is unknown

Another truth value is introduced: "unknown"
Problem 1 is partially solved.

Elements of the models observed or deduced

It is possible to treat in different ways the eventual contradictions in the model, thus reducing Problem 3.
Another pair of truth values are used to state that some proposition is true (or false) by default, until some evidence is collected on the opposite side.
Eventual conflicts are always solved in favour of observed evidence

Type of values and meaning

Let's distinguish between the type of values used to represent uncertainty measures and their meaning

- Type of values: numbers, linguistic labels, fuzzy numbers, ...
- Meaning of the measure: probability, possibility, subjective judgements, ...

Common elements

For all uncertainty measures, we have to define how uncertainty values of propositions combining propositions by logical operators are computed.

- **Negation**: not A
- **Conjunction**: A and B
- **Disjunction**: A or B
- **Aggregation**: how to aggregate knowledge coming from different sources
- **Detachment**: how to aggregate uncertainty on the antecedent of an inference with uncertainty associated to the inference itself

Bayesian approach

Numbers to represent **probability**
Given an exhaustive set of **mutual exclusive hypotheses**:

$$H = \{h_1, \ldots, h_n\}$$

and some evidence **e**, the posterior probability that a hypothesis is true is given by

$$P(h_i|e) = \frac{P(e|h_i)P(h_i)}{P(e)}$$

Bayes example

We have two alternative hypotheses:
h_1 = the lamp is broken
and
h_2 = the lamp is not broken
Given the evidence:
e= the lamp is off
we can deduce the probability for h_1 from:

$$P(h_1|e) = \frac{P(e|h_1)P(h_1)}{P(e)}$$

In this case $P(e|h_1) = 1$, $P(h_1)$ depends from the lamp and its life cycle, while $P(e)$ might depend on sensors producing the evidence: if we observe it directly we might assume it is $=1$

Bayesian networks

Bayesian networks implement chains of possible inferences based on the Bayes theorem

They are widely used to support decisions, by defining the probabilities of events and obtaining the probability of related events

Relationships (inference) and enough a priori probabilities are needed

Mycin: subjective evaluations

Numbers to represent **subjective evaluations**

Mycin was the first significant expert system. It provided diagnoses of blood diseases from exams and medical observations

Uncertainty was managed in expert systems from the beginning

Two measures are associated to each proposition: MB (Measure of increased Belief) and MD (Measure of increased Disbelief), which can be interpreted as:

$$MB = \frac{P(h_i|e)-P(h_i)}{1-P(h_i)} \text{ and } MD = \frac{P(h_i)-P(h_i|e)}{P(h_i)}$$

They are not probabilities, and are in principle independent from each other

A Certainty Factor (CF) is defined as $CF = MB - MD$

Mycin: pros and cons

Pros:

- it is possible to represent the effect of contradictory evidence
- MB and MD are acquired as subjective evaluations, and do not have to satisfy any particular property

Cons:

- the meaning of a number is not shared among different experts
- inappropriate feeling of precision

Linguistic labels

Linguistic labels to represent **subjective evaluations**

An ordered set of linguistic labels: certain, almost certain, uncertain, ...

E.g.: I'm almost certain that the patient risks some heart attack

This reduces the problem of agreement on labels, much easier and less biased than with numbers

Only a limited number of values is available, because of "The magic number 7"