Uncertainty issues in Artificial Intelligence

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Artificial Intelligence aims at developing tools for representing pieces of knowledge and at providing inference mechanisms for elaborating conclusions of interest from stored information. The available knowledge is ususally far from being certain, complete and precise. The lack of certainty refers to the impossibility of considering a piece of information as definitely true or definitely false. Default rules where exceptions are not stated is an important example of incomplete knowledge. Besides, the contents of this knowledge may be imprecise with respect to some standard, or even vague due to the presence of vague predicates or quantifiers ; this vagueness may reflect the lack of precise information, or may be an attempt at stating that the piece of knowledge pertains to an ill-bounded class of situations, or is still a way of expressing flexibility and graduality.

The defects of the available knowledge have important consequences on the notion of truth. First a distinction should be made between degrees of (un)certainty and degrees of truth. Degrees of uncertainty are due to the lack of precise information and are estimates of the propensity for a proposition which is necessarily either true or false, to be true or to be false taking into account the available information. Degrees of truth are due to the presence of vague predicates in propositions which can then naturally receive intermediary degrees of truth even if the information is precise. Thus it is tempting to give a degree of truth intermediary between the total falsity and the complete truth to a proposition like "Peter is tall" knowing that Peter's height is 1,75 m. While it is impossible to have an extensional calculus of degrees of uncertainty (since there is no isomorphism between a Boolean algebra and a linearly ordered scale with more than two elements (like for instance the interval [0,1]), nothing a priori forbids to have a truth-functional calculus of degrees of truth (as soon as we consider that vague propositions no longer obey to all the laws of a Boolean algebra). Clearly the evaluation of vague propositions with respect to imprecise, uncertain or vague pieces of information leads to considering subsets of degrees of truth whose elements are graded with uncertainty (see Dubois and Prade (1988) for instance). The defects of the available knowledge imply that the truth is local (Bellman and Zadeh, 1976) in the sense that, as a measure of conformity between a proposition and what is known, it depends on the present state of the knowledge base and is provisional in nature since the modification of this base by adding or deleting information would lead to revise the evaluation of the truth of propositions of interest.

The mathematical models of uncertainty currently used in Artificial Intelligence, namely probability theory, Shafer's theory of evidence and Zadeh's possibility theory have various merits in the representation of uncertain pieces of knowledge. For instance, using probabilities, the total lack of belief in p ($\mathrm{Prob}(p) = 0$) entails that $\neg p$ should be considered as certain ($\mathrm{Prob}(\neg p) = 1$), while with the two other models the fact that p is not at all believed in does not entail that we should believe in $\neg p$ (only the converse is true : if we considered $\neg p$ as completely certain, it is not permitted to believe in p even to a small extent). Then states of complete or partial ignorance can be conveniently represented since nothing forbids to consider several mutually exclusive outcomes as simultaneously fully plausible or possible in Shafer's or Zadeh's theories. Probabilities are rather adapted to the estimation of the frequency with which an eventuality can be encountered. Another basic issue in the representation of uncertain knowledge is the modeling of conditionals : is the uncertainty of the rule "if p then q" correctly estimated in terms of $\mathrm{Prob}(p \rightarrow q)$ or in terms of $\mathrm{Prob}(q \mid p)$, if we are using a probabilistic view ?

The nature of the available information does not raise problems only at the representation level but has also consequences at the reasoning level. Indeed many approaches —non-numerical or numerical— have been proposed in the last ten years in Artificial Intelligence for reasoning from incomplete knowledge ; see (Léa Sombé, 1989) for an overview. We may deductively propagate the uncertainty attached to the premises onto the consequences, or we may introduce default assumptions or default information in order to obtain more precise conclusions which might be reconsidered if new information, invalidating previous default hypotheses, becomes available. Then a difficult problem is how to maintain the consistency of a knowledge base when new information is added which contradicts uncertain conclusions previously obtained or even information explicitly stored. Note that in the case of vague or uncertain information consistency may become a matter of degree. A way of revising a knowledge base is to question the less entrenched beliefs first (Gärdenfors, 1988). Interestingly enough the natural properties characterising this idea of entrenchment are equivalent to the axioms of possibility and necessity measures (Dubois and Prade, 1989).

The distinction between degrees of truth and degrees of uncertainty leads to two families of logics : logics of vagueness and logics of uncertainty. The latter can be subdivided into two classes : logics of incomplete information and probabilistic logics. In logics of incomplete information, propositions are assigned degrees of certainty and possibility, that quantify the extent to which the proposition of interest is respectively implied by and consistent with the available knowledge. In their simplest forms these logics aim at ordering propositions in terms of certainty as in epistemic entrenchment theory. Probabilistic logics are more or less equivalent to numerical quantifiers logics where degrees of probability play the role of numerical quantifiers : they are called Bayesian or non-Bayesian according to whether a set of numerically quantified statements determines a single probability measure over the models or constrains a family of probability measures. Probabilistic logics look very well-adapted to default reasoning when the amount of exceptions to universal statements can be quantified.

Logics of vagueness handle propositions where vague predicates (referring to fuzzy sets) appear. To-date fuzzy logic have essentially focused on the representation of linguistic descriptions of relationships between numerical variables, under the form of qualitative rules. There has been many applications to process control that take advantage of the possibility, offered by this type of model, to capture the ideas of similarity and interpolation in approximate reasoning. More recently, qualitative reasoning with fuzzily-described orders of magnitude has been formalized. These types of concern greatly depart both from classical deduction as well as probabilistic inference.

References

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