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Belief as Summarization and Meta-Support

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A model of knowledge representation is described in which propositional facts and the relationships among them can be supported by other facts. The set of knowledge which can be supported is called the set of cognitive units, each having associated descriptions of their explicit and implicit support structures, summarizing belief and reliability of belief. This summary is precise enough to be useful in a computational model while remaining descriptive of the underlying symbolic support structure. When a fact supports another supportive relationship between facts we call this *meta-support*. This facilitates reasoning about both the propositional knowledge, and the support structures underlying it.

1. Introduction

The research described in this chapter pursues the problem of developing representational and inference mechanisms which are capable of dealing with incomplete and inaccurate knowledge about facts, and which can also be used to reason about the support structures which relate facts. The direction taken is based on the assumption that methods which deal effectively with uncertain knowledge and with supportive relationships must play an integral role in both models of human reasoning and flexible computational reasoning systems.

Network models of knowledge representation and belief maintenance typically distinguish between *factual knowledge* and *relational knowledge*. The factual knowledge, encoded as network nodes, represents propositions such as IT IS COLD INSIDE. Such propositions are labelled with parameters indicating probability [8, 12], possibility [18], plausibility [9, 4] or logical truth. In the simplest case, the existence of the proposition indicates a binary truth value. The relational knowledge, encoded as network connections, depicts relations and support among propositions, so for example, the proposition IT IS WINTER might support the proposition IT IS COLD OUTSIDE. In the most straightforward case, these relations may depict the origins of inferences in a belief maintenance system [6].

Recently, Cohen [3] has formulated a model of belief which does not rely on labels assigned to factual knowledge, but rather centralizes reasons for believing or disbelieving propositions (called *endorsements*) in order to establish a more clear indication of the

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status of the proposition. Our approach is similar, but we accomplish the representation of endorsements in a network of support. An individual node in the network is surrounded by a localized structure indicating endorsements for and against the proposition.

Within the network, nodes are assigned numeric labels which summarize their underlying support structure. Such numeric labels must be simple and precise enough to enable effective inferential reasoning, and yet remain descriptive of the local network of support. Most formal reasoning systems represent belief as a single value, whether binary or continuous-valued [3, 7, 18]. Craddock and Browse [5] suggest that the compression of a node's label into a single value, whether binary or continuous-valued, is justified in many cases, but there are many instances for which this simple summary is inadequate. Consider the proposition, RICK LIKES MATH. The extent of belief in this proposition may be high whether it is quite reliable (Rick has taken, and enjoyed a wide variety of math courses) or quite unreliable (Rick has only taken a single math course). As soon as we attempt to summarize the underlying support structure a single value becomes clearly inadequate. We have proposed instead that two values, belief and reliability of belief more precisely summarize the support structure.

We have incorporated a further extension by recognizing that the extent of support that one proposition offers another is itself subject to positive and negative endorsements, and should be permitted the same representational capabilities as the propositions themselves. For example, the proposition WINDOW IS OPEN may support the proposition IT IS COLD INSIDE, but the extent of this support is itself supported by the proposition IT IS WINTER. We propose that we must be able to reason about support for support (called *meta-support*), and that by doing so, there is a resultant increase in the expressive power of the network model of knowledge representation and belief.

The direction we have taken in developing representational and inference mechanisms to describe reasoning under conditions of uncertainty is based on the belief that methods which model the way people think under uncertainty may be used in the construction of flexible and more understandable computational reasoning systems. The model developed here involves collecting reasons for believing or disbelieving propositional knowledge [3] and relational knowledge, and then summarizing these reasons by a measure of belief and reliability of belief. The belief and reliability values can be used: (1) to determine how supportive a body of evidence for a particular hypothesis is and (2) to reason with evidential relationships such as conflicts among decisions [4].

2. The Network Model

We shall now illustrate how the languages of set theory, (eg. [13]) and graph theory, (eg. [2]), can be used to build a framework of precise definitions for a network model of knowledge representation. We shall demonstrate in the course of this section how the model is extended to represent meta-support and continuous belief summarization.

First, let a set of propositions $P = \{n_1 \ldots n_m, \mathrm{T}\}$ represent the set of factual knowledge, such as RICK LIKES MATH, where T , represents the source of the factual knowledge. T denotes the factual knowledge which is implicit in the knowledge model. We can then define $A = P \times P$ as the set of all possible relationships among elements of P.

P and A provide a framework for modelling behavior of many existing knowledge representations. Facts and relationships encountered in structures such as influence networks [10], and inference networks [7] can be depicted. Within this framework the propositions may be labelled with numeric or non-numeric quantifiers and qualifiers.

Similarly, the relationships in A can also be labelled, providing a model of inference or belief maintenance. However, the labels themselves are not subject to inference. As a result we can only reason about the factual knowledge P and not about the relationships which combine it to form more complex knowledge representations. We now introduce an extension to this framework called *meta-support* which will provide us with this facility.

Meta-support allows the model to reason about relationships by relating elements in P to facts in A. As a result, the set of knowledge which can be related to the set of facts P must be extended as the set C - known, for lack of a better word, as the set of cognitive units. C includes not only all the elements in P but also all the elements in A. Thus, C can be defined formally as the union of the arcs A, and the propositions P, $(A \cup P)$. The set of relationships A can then be extended using C to include the relationships between arcs and facts, as the set of supports S. S is formally defined as the set of relationships between elements in P and elements in C by $S = P \times C$.

Any support relationship s_{ij} in S is represented by the pair (p_i, c_j), where p_i is a particular member of P, and c_j is a particular member of C. If a particular p_i is the source of the knowledge model, $\top$, then we say that $s_{\top j}$ is equivalent to c_j. In a like fashion $s_{i\top}$ is equivalent to $\top$. We shall use this shorthand notation throughout the remainder of the paper. If c_j in the pair, $s_{ij} = (p_i, c_j)$ is a member of P, p_j, then p_i is said to support p_j. If, on the other hand, c_j is a member of A, (p_j, p_k), then p_i is said to *meta-support* the relationship c_j between two facts p_j and p_k. In the former case a fact is supported and in the latter a relationship is meta-supported. Only elements of A are subject to meta-support. The meta-supports, $\{(p_i, c_j) \mid c_j \in A\}$, are not subject to reasoning within the current model.

The meta-support and support relationships for a cognitive unit form the support structure of that unit. Any cognitive unit c_i with an underlying support structure can be labelled with a summarization of the structure called the *Rationale*. The Rationale labels a unit with two parameters, the *rationale belief* and the *rationale reliability*. The belief, $b \in [-1, 1]$, is a measure of the completeness and the strength of the supports for a cognitive unit. As b is a continuous value from -1 to 1 we may view cognitive units as statements in fuzzy logic [18] in which a belief of -1 indicates unbelievability and a belief of +1 indicates believability. The reliability, $r \in [0, 1]$, is the reliability of the evidence which was used to calculate the belief. A value of 0 represents complete unreliability and a value of 1 represents complete reliability.

The meta-supports and those cognitive units with no explicit support structure, and indeed any cognitive unit, are labelled with an Intuition. Labelling a structure with the Intuition provides an *Intuitive belief*, b', and an *Intuitive reliability*, r'. These structures appear much the same as those produced by the Rationale except that they are never computed, but remain available to take part in the computation of other beliefs. Intuitive values correspond to the usual direct assignment of belief and reliability to a cognitive unit from which other beliefs and reliabilities are to be determined. The application of the *Intuition* to $\top$, is such that $I(\top) = (1, 1)$. The external or *source knowledge* is thus assumed to be completely believable and this belief is completely reliable.

To illustrate the distinction between the belief and reliability of the Intuition and Rationale, consider the simple cognitive unit composed of the single proposition I LIKE MATH. This may have, for example $b_i = 0.4$ indicating moderately strong support for liking mathematics. On the other hand, the reliability, r_i, of this value might be high or low, depending on the person's exposure to mathematics. It is thus important to note that the measure of proposition's reliability is not closely related to its belief. A statement can be highly believable but still be very unreliable. In a similar fashion, a statement can be unbelievable but its incredibility may be very reliable [5] though there are cases in which these two summary aspects of support may be combined to provide a more concise belief estimate.

The supportive relationship between any two cognitive units is represented as a link and the strength of the relationship is specified by labelling the arc with the Intuition or Rationale. For example, in figure 1: I LIKE PSYCHOLOGY may support I LIKE COMPUTING. An Intuition may be assigned to the cognitive unit representing this relationship describing the strength of the support. However, the measure of this support may be contingent on the believability of the cognitive unit COMPUTATION MAY MODEL COGNITION. If COMPUTATION MAY MODEL COGNITION is unbelievable then the support relationship between I LIKE PSYCHOLOGY and I LIKE COMPUTING will be unsupported and will subsequently be labelled as unbelievable by the Rationale. In summary the model of knowledge representation described in this paper consists of a set of supportable knowledge, C, and a set of supports and meta-supports, S. We shall now go on to consider the mechanisms which permit the dynamic evaluations and maintenance of support based on the assigned values.

3. Computing Belief and Reliability values

While any cognitive unit, c_j, may simply be assigned values of belief and reliability of belief through the use of I_j, we wish to develop ways of computing the values of Rationale, R_j, for a cognitive unit c_j on the basis of the available supports. The strength of support between two cognitive units must be computed with consideration of the Rationale, R_i, of the supporting cognitive unit c_i, and the Rationale, R_k, of the supporting relationship, c_k. For example, given the support relation represented by the cognitive unit c_k in figure 2, the net endorsement of the cognitive unit c_j, I LIKE COMPUTER SCIENCE, must be dependent on the extent of our Rationale in the support, R_k, as well as in the Rationale of the supporting cognitive unit I LIKE WRITING.

We must first be able to calculate the strength of the support relationship, c_k, which is equal to R_k, or I_k if the rationale has not been defined. We can define the Rationale R_j of a cognitive unit, c_j, supported by c_i with the relationship c_k , as

$$R_j = (1, 1) \qquad \text{if } c_j = \mathrm{T}$$

$$R_j = Z(\{R_i, R_k \mid c_i \text{ supports } c_j \text{ with } c_k\})$$

If a person enjoys writing (see Figure 2), ie. $b_i = 0.8$, and they believe that enjoying writing is non-supportive of liking computing, ie. $b_j < 0$, then a net negative belief for the cognitive unit, I LIKE COMPUTER SCIENCE, results. If, on the other hand, they believe that enjoying writing is supportive of enjoying computer science, ie. $b_j > 0$, a net positive endorsement would result. The summarization function, Z, will therefore take a set of pairs of Rationales, (R_i, R_k), and compute a new Rationale. We shall now describe how Z can calculate the belief and reliability of the new Rationale.

Given a supported cognitive unit c_j we can define a measure of the relative reliability of each of its supports, c_i in $\{c_1 \ldots c_n\}$, as:

$$w_{r_i} = \frac{r_i}{r^*}$$

where r^* is the maximum reliability of all of its supports. We can also define a measure of the *relative belief of support*, $w_{b_{ij}}$, and *relative reliability of support*, $w_{r_{ij}}$, for each cognitive unit, s_{ij} representing a supportive relationship between an element c_i and an

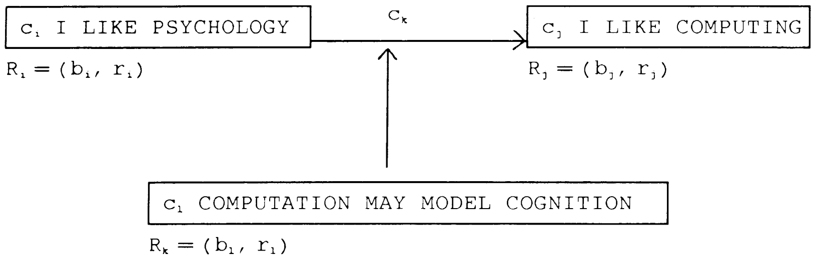

Figure 1. : An example of an endorsement c_k which influences the strength of support, R_l, between two other nodes.

element c_j , where b_{ij} and r_{ij} represent the belief and reliability of the supportive relationship.

$$w_{r_{ij}} = \frac{r_{ij}}{r^*}$$

$$w_{b_{ij}} = \frac{b_{ij}}{\sum_i b_{ij}}$$

Thus b_j, the *Rationale belief* of c_j, then becomes a function of the beliefs of each support and their relative reliabilities, w_{r_i}, and the relative beliefs and reliabilities for the supportive relationships:

$$b_j = \sum_i w_{r_i} \; b_i \; w_{b_{ij}} \; w_{r_{ij}}$$

The Rationale belief is a weighted measure of the beliefs of its supports. As its supports, beliefs, and relative reliabilities increase the aggregate belief will also increase. The reliability of this new belief may then be calculated as a function of the *agreement* between the beliefs of the supporting items and the newly calculated belief, b_j. Thus, belief must be calculated before reliability. The individual's agreement values are once again weighted by the relative reliability of the source support. This effect may be modelled in formula such as:

$$r_j = 1 - [\sum_i | b_i - b_j | \; w_{r_i} \; w_{r_{ij}}]$$

to provide r_j, the *Rationale reliability* of c_j , a measure of agreement among supports.

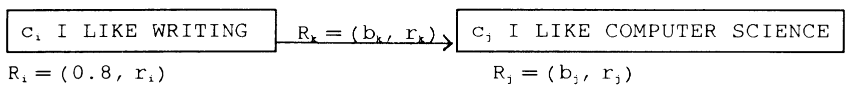

Figure 2. : An example of an endorsement which may have net positive or net negative support.

The formula for calculating belief and reliability provide a means of incorporating basic heuristics such as those described by Kahneman and Tversky [11] to evaluate supports and their underlying structure. The use of relative reliabilities and Rationales are a simple example of how we can allow a network model to utilize reasoning strategies which are satisfactory within constraints, but not necessarily optimal with respect to formal mathematical theory. Kahneman and Tversky [11] provide numerous examples in which subjects reach decisions which run counter to those reached by mathematical theories. It is important, therefore, that we be able to model not only the formal capabilities of mathematical reasoning but also the more human ones.

4. A Network of Cognitive Units

The model described so far is similar to many existing connectionist models, particularly the spreading activation models of Anderson [1], Rumelhart and McClelland [16], and McClelland and Rumelhart [14, 15]. The model which we have described can be used to represent the equivalent structures by restricting the set of cognitive units to those of solitary vertices and by labelling these units with the correct values. However, the model has several important differences which allow it to become a much more flexible form of knowledge representation.

- First, as discussed by Craddock & Browse [5] the uncertainty of a piece of information is represented numerically as the values of the Rationale, and non-numerically as the structure of supports.

- Second, once the supports have been collected, they are subject to reasoning and natural heuristics [4] to compute the belief and reliability values as depicted in section 3. In contrast most connectionist models ignore, or do not explicitly deal with the non-numeric representation of uncertainty, depending instead on numeric values which provide no evidence as to how they are calculated, what they represent, or how reliable they are [3]. Both non-numeric justifications and numeric summarizations are necessary to adequately describe knowledge.

- Third, is the ability to reason about the supportive relationships between facts, allows us to not only reason about an elements belief and reliability but also to reason about its underlying support structure. In this manner, we can represent such evidential relationships as disjunction, (that is, strong belief which may be propagated on the basis of only one of many supports [4]) without structures such as Rumelhart and Zipser's [17] "Inhibitory Clusters" which may incorrectly inhibit a nodes activation level instead of its support for another node.

- Finally, we can also represent *Contradictions* in supporting evidence. *Rationale contradictions* among endorsements are defined as follows: If c_i is compelling evidence against c_j but c_k is equally compelling evidence for c_j then the supports for c_j are inconsistent. In addition to a rationale contraction an *Intuition contradiction* can also be defined: If the intuitive belief, b'_i, of the Intuition is not equal to the rational belief, b_i, of the Rationale then the two beliefs are inconsistent. Intuitive contradictions are useful for recognizing changes in belief through a knowledge base when knowledge is added and removed and for controlling cycles which may force more global interpretations on input propositions. When cycles exist within a network $<C, S>$, belief and reliability values will only be calculated for nodes in a partial network $<C', S'>$, where $C' \subseteq C$, and $S' \subseteq S \cap (C \times C')$, where there exists a $c_i \in P - P'$ such that there is an elementary path from c_i to C' and $|I_i - R_i|$ is greater than some threshold T_i.

5.Conclusions

The model discussed in this paper describes the numeric parameters associated with a piece of knowledge, the cognitive unit, as the summarization of the explicit and implicit underlying support structures. Of major issue is the observation that a single numeric value is an inadequate representation of reasoning. Instead we propose that two values, belief and reliability, more adequately provide a summarization of, and a means of reasoning computationally with, the symbolic structures of support. In addition, the two numeric values can form both an *Intuition* and a *Rationale*. The Rationale provides a summary calculated form the explicit support structure while the Intuition is a summary of the implicit structure, that represented by the source T. The Rationale and the Intuition need not be identical for any cognitive unit and as a result can be used to diagnose evidential contradictions and to control the inference process.

Second, the model supports heuristics such as those proposed by Kahneman and Tversky [11]. The heuristics can be used not only to determine the relevance of information in an inference but also to summarize it in a manner supported by cognitive research.

Finally, a major issue is that both propositional and relational knowledge should be subject to inference. The inclusion of meta-support makes this possible. It is argued that meta-support both facilitates the control and representation of inference. Currently the model is restricted in two ways. First, the set of cognitive units is limited to propositions and arcs. Clearly C could be extended to include sub-graphs built form A and P, providing the model with the facility to reason with complex knowledge structures such as schema [15]. Second, only elements of C are subject to meta-support. The meta-supports themselves, $\{s_{ij} = (p_i, c_j) \mid c_j \in A\}$ are not. The effect of removing both these restrictions is currently being evaluated.

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