A PROCESS FOR EVALUATING TREE-CONSISTENCY

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ABSTRACT

General knowledge about conceptual classes represented in a concept hierarchy can provide a basis for various types of inferences about an individual. However the various sources of inference may not lead to a consistent set of conclusions about the individual. This paper provides a brief glimpse at how we represent beliefs about specific individuals and conceptual knowledge, discusses some of the sources of inference we have defined, and describes procedures and structures that can be used to evaluate agreement among sources whose conclusions can be viewed as advocating various values in a tree partition of alternate values. *

I. INTRODUCTION

Recent work by several investigators; [1], [3], [4] and [7]; has focused on the importance of augmenting deductive problem solvers with default knowledge. Their work provides some of the logical foundations for using such knowledge to make non-deductive inferences and for dealing with the side effects of such inferences. Currently, we are pursuing how conceptual knowledge about general classes of persons, locations, objects, and their corresponding properties can be represented and used by a planning process and a plan recognition process to make deductive and non-deductive inferences about particular persons, objects and locations in an incompletely specified situation (see [5] and [6]).

General knowledge about conceptual classes represented as a concept hierarchy provides a basis for various types of inferences about individuals. The definition of a conceptual class might be believed to hold for an individual, x!, that is believed to be a member of that class (Definitional Inference). The definitions of concept classes which include the class of which x! is a member might be believed to hold for x! (Inheritance Inference). The definition of some class that is a subset of the class to which x! belongs might be used as a source of potential inferences (a kind of Plausible Inference). Additionally, information might be stored directly about x! (Memory Inference) and there may be other inference types based on different strategies of deductive or plausible inference (for a more detailed discussion see [6]).

However, these <u>sources</u> of inference may not lead to a consistent set of conclusions about the individual. For default theories in general, Reiter [4] has shown that when a default theory is used to extend a set of beliefs, determining the consistency of the extensions is an intractable problem. In this paper we are concerned with a very local and focused subproblem involved in evaluating the agreement or consistency of a set of conclusions and with a strategy for dealing with belief inconsistency. The focus arises from considering these issues in the context of a concept class hierarchy where the classes form a tree partition. Before we discuss this restricted case of belief consistency, we provide a brief glimpse at how we represent beliefs about specific individuals and at several types of class hierarchies used to represent concepts.

II. REPRESENTATION OF BELIEFS AND CONCEPTS

Beliefs about specific objects, persons, etc. are represented as binary relations of the form ((x r y).[T F or Q]) where : r is a relation defined between two basic classes of entities X and Y; x is an instance of X; and y is either an instance of Y or is a concept that is part of the concept hierarchy with Y as its root. An example of the former relation is ((DON LOC NYC).F) where DON is an instance of PERSON and NYC is an instance of LOCATION. The latter form is exemplified by ((DON AGEIS YOUNG).T) where YOUNG is a concept that is part of an AGE hierarchy. T, F or Q represents the truth value in the current situation.

Concepts are organized into inclusion hierarchies which have as their root one of several basic classes, such as PERSON, AGE, LOCATION, OBJECT, which may have instances in a specific situation. A particular individual may be an instance of several basic classes, e.g. a person DON may be viewed as an OBJECT or a PERSON. Two simplified hierarchies are given below in graph form. Note that no claim is being made here about the adequacy or naturalness of the knowledge represented in these examples.

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              PERSON                             AGE
                 |                                |
        ------------------                     -------
        |                 |                    |     |
     STUDENT           ATHLETE               YOUNG  OLD
        |                 |                    |     |
   -----------       ----------              ----  ----
   |         |       |        |              |  |  |  |
HIGH SCHOOL COLLEGE BASEBALL FOOTBALL       15 25 40 80
  STUDENT   STUDENT PLAYER   PLAYER         YR YR YR YR
```

Hiearchies may contain subtree partitions as might be the case for the PERSON hierarchy shown above. A particular person may be a high school student and a football player. Some hierarchies, especially those representing properties, may form tree partitions, as is the case for the AGE hierarchy shown above.

There are several types of information that can be associated with a concept. One type, the concept definition, provides an intensional characterization of the elements of the conceptual class. A definition is a conjunctive set of descriptions of the form (<basic class> (r1 y1)(r2 z1)...) that are the necessary and sufficient conditions for an instance of the basic class to be considered an element of the conceptual class. The relation that represents the hierarchical structure among concepts is termed COVERS and appears in the above example as a line joining pairs of concepts. This relation implies that for each description in the higher level concept definition (e.g. (r1 y1)), there is a corresponding description (e.g. (r1 y2)) in the lower level concept definition and either y1=y2 or (y1 COVERS y2) in the Y (basic class) hierarchy and the lower or more specific concept definition must contain at least one description that is more specific (where (y1 COVERS y2)) than the corresponding description in the more general concept definition. As an example, consider these possible definitions for the concept ATHLETE and and a more specific concept, FOOTBALL-PLAYER.

```
 (ATHLETE DEF
     |  (PERSON (PHYSICALSTATE SOUND)
     |                (PLAYSON TEAM))
COVERS|
     |
 (FOOTBALL-PLAYER DEF
               (PERSON (PHYSICALSTATE SOUND)
                       (PLAYSON FOOTBALL-TEAM))
```

An example of a type of plausible inference can be given using these definitions. If the beliefs in memory about DON satisfy the descriptions in the definition of ATHLETE, then there is a basis for believing (DON PLAYSON FOOTBALL-TEAM) with truth value T. However, it is not the case that this inferred belief is consistent with those in memory. Thus two sources of information about DON, memory and plausible inference, may not agree.

III. CONSISTENCY OF INFERENCE SOURCES

We now consider structures that can be used to determine the consistency of a set of sources contributing beliefs relevant to a proposition about an individual. The following paradigm provides a more specific context in which to discuss the problems and mechanisms we have considered. Assume that the task specification is:

1) A goal proposition is given whose truth value is desired by a higher level process. The goal is a statement about a particular individual represented as a binary relation between the individual and a concept, called the goal-target. The goal-target is a member of a tree partition of concepts called the target-tree. This "family" of concepts is the set of potential targets defined for the relation occurring in the goal. It should be noted that there may be several trees rooted in the same basic class. For now we limit our consideration to the case where there is only one tree.

2) Several sources of inference are consulted for beliefs relevant to the goal, that is, beliefs relating the individual to concepts in the target-tree.

3) Since the target-tree is a partition, the "tree-consistency" of the beliefs can be evaluated and used to determine a truth value for the goal (one of T for true, F for false or Q for question, determinate T or F not assignable). This evaluation amounts to assessing the agreement among the sources on a truth value for the goal.

4) The structures created in 3 can be used to record the sources of inference drawn upon in the attempt to achieve a conclusion about the goal.

Many of the structures and procedures discussed in relation to this paradigm are implemented in the knowledge representation system AIMDS (see [8]).

The target-tree can be represented as a Truth Value Tree (TVT) where each node represents a concept in the target-tree. Each node has a slot, TV, for one of the determinate truth values, T or F, and slots for two lists, a true-list and a false-list. These lists consist of two inner lists. The true-list contains one list for recording the sources that support the truth value T and one for recording nodes that require the node to have the truth value T. The false-list has the same structure and records the information relevant to the truth value F. An example will serve to clarify how this structure is used to evaluate tree-consistency.

Assume that the goal is (DON AGEIS 40YR). The TVT for the goal represents the AGE tree presented in a previous example. Initially each node in the TVT has three empty slots shown below.

slots

```
  (TV    NIL)                   Truth Value
  (T     ()         ()      )   True-list
  (F     ()         ()      )   False-list

     supported    required
        by           by
```

If ((DON AGEIS YOUNG).T) is contributed by memory, the following cycle of actions takes place.

1) The truth value slot of each node is made NIL.

2) T is entered as the TV of the node representing YOUNG.

3) Tree-consistency rules propagate truth value requirements to other nodes. Note that these rules depend on interpreting the AGE hierarchy as a tree partition of a finite and closed set of values. One rule propagates T up the tree (to all ancestors), thus the AGE node receives the truth value T. Another rule gives the node OLD the truth value F since the relation AGEIS has been defined such that only one path (leaf to root) of targets in the tree can be true for an individual at any given time, and all others must be false. Finally, a third rule propagates F down the tree (to all descendents), thus the nodes 40YR and 80YR receive the truth value F. In the general case, these rules are looped through until no additional nodes can be given a truth value. Two other rules not applicable here are: propogate T from a parent to a daughter if all other siblings are F; and if all daughters are F, propogate F to the parent.

4) The source of the truth value T for the node YOUNG, i.e. Memory Inference (MI), is registered as support on its true-list. For each of the remaining nodes with a non-null TV, YOUNG is registered as a requirement on the true-list or false-list depending on the truth value required by YOUNG being T.

At the end of this cycle, the nodes in the AGE TVT have the following form.

```
                  AGE
                  TV T
                  (T ()(YOUNG))
                  (F ()())

  YOUNG                        OLD
  TV T                         TV F
  (T (MI)())                   (T ()())
  (F ()())                     (F ()(YOUNG))

15YR       25YR       40YR             80YR
TV NIL     TV NIL     TV F             TV F
(T ()())   (T ()())   (T ()())         (T ()())
(F ()())   (F ()())   (F ()(YOUNG))    (F ()(YOUNG))
```

This cycle can be repeated for each of the relevant beliefs that have been contributed. Note that a cycle generates the deductive consequences of a truth value assignment, T or F, to a single node. We are not concerned with the propagating changes to previously assigned truth values based on a new assignment from a second relevant belief. Such a mechanism would be required for updating a model and might utilize antecedent and consequent propagation proposed by London [2].

The TVT created by this cycle is inspected for a truth value for the goal. In our example, the node 40YR represents the goal-target and it has an entry for a single truth value, F. Thus F is returned as the truth value of the goal. However, the assignment of a truth value to the goal can be made contingent on the target-tree. Tree-consistency and thus agreement among the sources is easily determined. If any node has entries in both the true and false lists, then an inconsistency exists and the value Q (indeterminate truth value) should be returned even if a determinate truth value is indicated for the goal-target. Conversely, if no such node can be found, then the tree, and thus the set of beliefs contributed, are consistent and the truth value indicated for the goal-target may be returned.

One way to find a determinate truth value for the goal when the tree is inconsistent is to seek a subtree of TVT such that :

1) the subtree is rooted in the top node;

2) the subtree is tree-consistent;

3) the subtree contains the node representing the goal-target; and

4) this node has a true-list or false-list entry, then a determinate value can be assigned to the goal.

An intuitive example of this case is where you can be fairly sure that Don is young even though you have conflicting information about whether he is ten or fifteen years old. If the consistent subtree does not indicate a determinate truth value for the node representing the goal-target, the tree-consistency requirement can be relaxed in order to find a determinate truth value.

The consistent subtree can be extended such that the resulting subtree is tree-consistent, each node has a determinate truth value and the set of truth values is maximally supported by the sources contributing information. One extension procedure involves the following steps :

1) For each node in the consistent subtree assign the truth value indicated by its non-empty list.

2) From the set of nodes without a truth value (TV NIL), select the node with the maximum support for a truth value that is tree-consistent with the current subtree.

3) Assign this node the truth value indicated and apply the tree-consistency rules to further extend the consistent subtree.

4) Continue at 2 until all nodes have a truth value or the basis for deciding 2 does not exist (some

nodes may have empty support and cannot be assigned a determinate truth value by the rules).

Several issues must be addressed in carrying out step 2. First, since ties are possible, a decision procedure must be provided. Second, the degree to which a node is required to have a particular truth value might be taken as a measure of indirect support for that truth value. Since the set of nodes that could possibly require a node to have a truth value is partially dependent on its position in the tree, positional bias must be taken into account in deciding degree of indirect support.

This procedure can be applied even when a consistent subtree cannot be found. In this case the top node is given the truth value T to provide a trivial consistent subtree from which to extend. The staged relaxation of the tree-consistency constraint is particularly important when all of the beliefs relevant to a goal are drawn from default knowledge (arrived at through non-deductive inferences). There may be little basis for expecting this knowledge to be consistent yet it may be rich enough to suggest that one truth value is more plausible than the other.

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