

Default Reasoning Using Monotonic Logic: Nutter's modest proposal revisited, revised and implemented

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Abstract

It is sometimes necessary to reason non-monotonically, to withdraw previously held beliefs. Default rules and defeasible reasoning have been frequently used to handle such situations. Some years ago, J. Terry Nutter proposed a form of defeasible reasoning involving additional truth-values that would avoid non-monotonicity in many situations. We adopt and implement much of Nutter's underlying concept, but use a structure of case frames in our knowledge representation to avoid the need for more than the standard truth values. Our implementation captures most of the advantages of the original proposal and in some cases allows more flexibility.

Introduction

As part of an ongoing project in constructing an artificially intelligent cognitive agent known as Cassie, that (among other skills) reads and comprehends narrative text [Shapiro 1989], we are developing a system that builds definitions for unknown words from their linguistic context combined with background knowledge [Ehrlich 1995, Ehrlich & Rapaport 1997, Rapaport & Ehrlich 2000, Rapaport & Kibby 2002].

While reading, one may encounter information that appears to contradict one's previous understanding. In some cases, it is clear that the original understanding was in error. In those cases, we must withdraw previous belief; we must have recourse to non-monotonic reasoning. However, we can often avoid the need for non-monotonicity by expressing our beliefs in less than absolute terms. Defeasible rules are one way to do this: a rule may be blocked in some cases, but is assumed to apply if not specifically blocked.

In a classic example, we have the rule that, by default, birds fly. On reading that Tweetie is a bird, and knowing no contradictory information, the rule would, by default, lead to the conclusion that Tweetie flies. If Tweetie is a healthy young canary, the rule *should* apply, and all is well. If one knows that penguins are flightless birds, and reads of Opus, a penguin, one would not conclude that Opus flies. One would infer that Opus is a bird, but the defeasible rule would not be applied, because we have specific information blocking its application in this case. We know that the rule does not apply to Opus, and all is

again well. So long as one has all relevant information before attempting to deduce whether a particular bird flies, there should be no trouble. However, if one must make a decision in advance of potentially relevant data, the fact that a defeasible rule was used will have no effect on the conclusion drawn, or the need to revise it.

For example, if we read of Elmer the emu, and all we know of emus is that they are birds, we will conclude that Elmer flies. If we later learn that emus are no more flight-capable than penguins, we'll need to retract the conclusion, just as if it were based on an indefeasible rule that all birds fly.

Rather than use defeasible rules that rely on knowing in advance whether they are applicable in certain cases, we employ a method, based largely on theoretical work by Nutter [1983a,b], in which some rules have consequents marked as presumably true. Frequently, this avoids the need for non-monotonicity. In our example from above, we would have the rule that, if something is a bird, then presumably it flies. Opus, the penguin, and Elmer the emu, being both birds, would fit the antecedent, and we would conclude that presumably each flies. Learning (for example) that emus do not fly does not, then, produce a contradiction, but rather the concatenation that Elmer could be presumed to fly though in fact he does not.

Underlying Software: SNePS

Our system is built on SNePS, a semantic-network-based knowledge representation and reasoning system developed by Stuart C. Shapiro and the SNePS Research Group [1996, 1999], which has facilities both for parsing and generating English and for belief revision [Shapiro 1979; Shapiro 1982; Shapiro & Rapaport 1987; Martins & Shapiro 1988; Shapiro & Rapaport 1992; Cravo & Martins 1993; Shapiro & the SNePS Implementation Group 1999].

SNePS has been and is being used for several research projects in natural language understanding and generation including Rapaport [1986], Almeida [1987], Peters & Shapiro [1987a,b], Peters, Shapiro & Rapaport [1988], Rapaport [1988a,b], Peters & Rapaport [1990], Wyatt [1990], Shapiro & Rapaport [1991], Yuhon [1991], Ali [1993], Ali & Shapiro [1993], Kumar [1993], Shapiro [1993], Chalupsky & Shapiro [1994], Wiebe [1994], Almeida [1995], Rapaport & Shapiro [1995], Yuhon & Shapiro [1995], Chalupsky & Shapiro [1996], Wiebe &

Rapaport [1996], Johnson & Shapiro [1999a,b], Shapiro, Ismail & Santore [2000], Shapiro & Johnson [2000], and Shapiro & Ismail 2003.

The Nature Of SNePS Networks. Each node in a SNePS network is a term in a language of thought that represents a mental object (possibly built of other mental objects). Labeled arcs link the nodes to one another.

[A]ll information, including propositions, “facts”, etc., is represented by nodes [and] propositions about propositions can be represented with no limit.

Arcs merely form the underlying syntactic structure of SNePS. [O]ne cannot add an arc between two existing nodes. That would be tantamount to telling SNePS a proposition that is not represented by a node. [Shapiro & Rapaport 1987: 266-267]

Anything about which one can think is represented as a node. Nodes represent the concepts embodied by the nouns, pronouns, verbs, adjectives, and adverbs of natural language. Base nodes (those that have no arcs emerging from them) typically represent a cognitive agent’s concepts of particular objects or entities, or they represent individual words or sensory inputs. Molecular nodes represent structured concepts, including those that might be expressed in natural language phrases and sentences [Maida & Shapiro 1982, Shapiro & Rapaport 1987]. A special variety of molecular node is the pattern node,

which has arcs to variable nodes. These pattern nodes and variable nodes are used in the construction of rules, as we shall see below.

Certain propositions may be asserted in SNePS, but it is possible to represent propositions without asserting them. Thus, a cognitive agent whose mental state is represented as a SNePS network can consider a proposition without necessarily believing it. Typically, a proposition embedded within another proposition is not asserted (although it can be; see Wiebe & Rapaport [1986], Rapaport [1986], Rapaport, Shapiro, & Wiebe [1997], Rapaport [1998]).

Rule-Based Inference In SNePS. SNePS allows the creation of universally quantified rules such as: (For all v_1, v_2, v_3) [(Before (v_1, v_2) & Before (v_2, v_3)) => Before (v_1, v_3)]. In SNePS list-representation such a rule could be represented as:

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(M1! (FORALL V1 V2 V3)
  (&ANT (P1 (BEFORE V1 AFTER V2))
    (P2 (BEFORE V2 AFTER V3)))
  (CQ (P3 (BEFORE V1 AFTER V3))))
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In this representation, a node is described as a list, the first element of which is its name, and subsequent elements of which describe the arcs leading from it. Each of these descriptions is a list whose first element is the arc-name and whose second element is a list of all the nodes at the

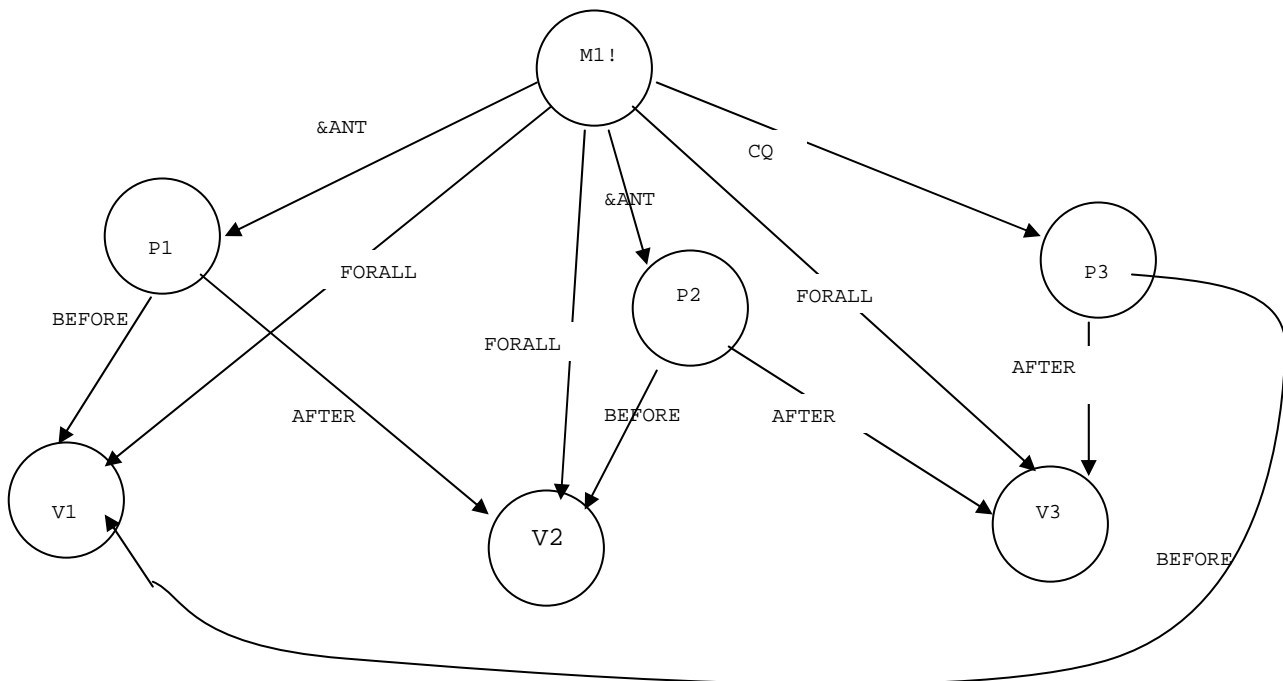


fig.1 Rule (M1) describing the transitivity of “before” and “after”

heads of those arcs. A typical SNePS rule node has one or more of each of the following arcs: FORALL pointing to the variable node(s) of the rule, ANT or &ANT pointing to the antecedent pattern(s), and CQ pointing to the consequent pattern(s) of the rule. If the antecedent is a single proposition, or if there is a choice among possible antecedents, we use the ANT arc. If the rule requires that multiple antecedents be matched, we use the &ANT arc. So, in rule M1!, both patterns P1 and P2, must be satisfied by matching against other propositions (by substituting for the variables V1, V2, and V3) in order to allow the rule to fire and create a new asserted proposition that matches the consequent pattern P3. A graphical representation of M1! is depicted in *figure 1*.

Assertion is indicated by an exclamation mark following the name of the node (e.g., M1!) If we think of the

network as Cassie's mind, an asserted proposition is one that believed to be true and an unasserted node represents a concept that has been entertained but not necessarily believed. Coming to believe a previously considered idea, then, involves the assertion of a pre-existing propositional node. Ceasing to hold a previous belief entails "un-asserting" an asserted node. The antecedents of the above rule will be satisfied if there exist a pair of asserted nodes with "before" and "after" arcs, and the "before" arc from one points to the same node as does the "after" arc from the other, for example:

- (M14! (BEFORE B23) (AFTER B24))
- (M19! (BEFORE B24) (AFTER B28))

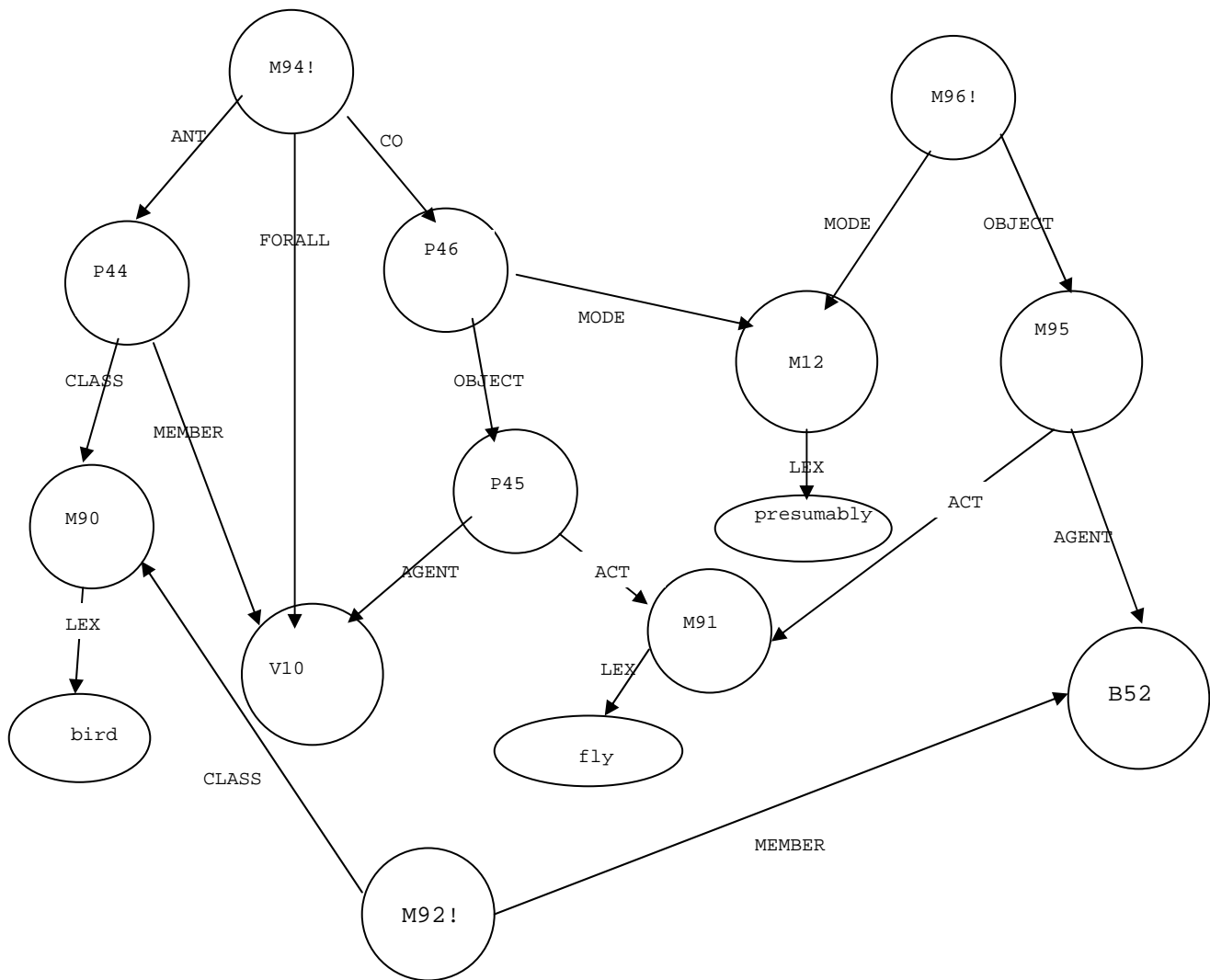


fig. 2 Rule(M94) that if V10 is a bird, then presumably it flies and derived assertion (M96) that a particular bird, B52, flies.

Here, the asserted propositions M14! and M19! match the pattern nodes P1 and P2, so that, when the rule M1! fires, it will build a new asserted proposition (M20!) to the effect that the time represented by B23 is before the time represented by B28.

(M20! (BEFORE B23) (AFTER B28))

Case Frames for “Modal Logic”

In our implementation, rules with consequents that are presumably true differ from ordinary rules only in that the consequent takes the form of a (MODE OBJECT) case frame. For example, node M94! (see *figure 2*) is the rule that, for all V10, if V10 is a bird then presumably V10 flies.

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(M94! (FORALL V10)
  (ANT (P44 (CLASS (M90 (LEX bird)))
        (MEMBER V10)))
  (CQ (P46 (MODE (M12 (LEX presumably)))
          (OBJECT (P45 (ACT (M91 (LEX fly)))
                    (AGENT V10))))))

(M96! (MODE (M12 (LEX presumably)))
  (OBJECT (M95 (ACT (M91 (LEX fly)))
            (AGENT B52))))
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B52 is Cassie’s concept of a particular bird, and node M96! is the belief (created by the firing of M94!) that presumably B52 flies. Notice that node M95, the proposition that B52 flies, is not asserted. At this point Cassie does not believe either that B52 flies or that it doesn’t. New information could cause either M95 or its negation to be asserted, *without* contradicting M96!

Note that, as used here, “presumably” is just a word representing a concept in the Cassie’s knowledge base. It is not a logical operator. Nutter originally proposed the use of “presumably” as an operator, and suggested expanding the number of truth values to four: “true”, “presumably true”, “false”, and “presumably false”. This is different from the five truth values (“monotonically true”, “default true”, “unknown”, “default false”, “monotonically false”) employed in the Cyc KB. In Cyc, a “monotonically true” assertion is true in all circumstances, whereas a “default true” assertion is an assertion (often a rule) to which there may be exceptions [Cycorp 2002]. Nutter’s theory allows a proposition to be both “presumably true” and “false” without there being a contradiction. The gloss (as in the case of Elmer or Opus flying) would be something like: “there is reason to believe that *P*, but not *P*”. Our system uses only the standard SNePS truth values: assertions are believed to be true; assertions of negation mean that the negated proposition is false; unasserted propositions have no real truth value as far as the system is concerned. It might be interesting to one day implement a “presumably” operator, expand of the number of possible truth-values, and compare such an approach with our case-frame

approach. Currently, however, we believe that the case-frame approach captures the important elements of Nutter’s proposal without the need for additional truth-values.

Using a case-frame approach also allows us a greater degree of flexibility in the construction of rules than would be the case if we used a logical operator and the revised truth-values. Nutter suggested that, if a presumably true assertion matched the antecedent of a rule, the assertion built as a result of the rule’s firing would also be presumably true. When this is what we want, we can write our rule this way, with the (MODE presumably OBJECT <pattern>) case-frame appearing in both the antecedent and the consequent: If presumably *P*, then presumably *Q*. But our approach also allows us to have a rule with a “presumable” antecedent and a consequent that is baldly asserted, e.g.: “If, presumably, *x* purrs, then *x* is feline.” We would be unlikely to presume *x* purred, *unless* it were feline.

So, our case-frame approach allows us to write the same sort of default rules (If *P*, then presumably *Q*) as would the operator and truth-values approach, and it allows us the flexibility to write rules of the form “If presumably *P* then *Q*”. The trade-off we make is that, in some cases we may need two rules, where using the operator and expanded set of truth-values would require only one. Under Nutter’s proposed implementation, the antecedent of a rule such as “If *x* purrs, then *x* is feline” could match the belief that “Presumably, Tom purrs” and lead to the conclusion that “Presumably, Tom is feline”. Our approach does not allow that match. If we wanted a rule that would fire when it was found that Tom purrs *or* that presumably he purrs, we would need to write that rule with a disjunction of two antecedents: “If *x* purrs, or if presumably *x* purrs, then *x* is feline”. If we wanted the unqualified assertion to lead to an unqualified conclusion, and a presumably true assertion to lead to a conclusion marked as presumably true, then we would need two rules.

It seems probable that some such implicit qualification is part of most humans’ understanding, though it is not generally expressed. People are apt to state their rules of thumb without qualification unless the exceptions are explicitly drawn to their attention, but they maintain those rules even when well aware that there are exceptions. When exceptions are pointed out, a typical reaction is something on the order of “well, of course, but in general...”. There is not usually any sense that one’s belief was in error, or in need of modification.

As mentioned at the beginning of this article, the case frame implementation of presumably true propositions is being currently being used in a project on contextual vocabulary acquisition. Much background knowledge is

encapsulated in rules that employ this case frame. When asked for a definition of a word, Cassie selects relevant aspects of her knowledge and experience with that word to report. Just which aspects are chosen depends upon the type and quantity of her exposure to the word, and the contexts in which it occurs, as well as what background knowledge she has. If she has information about the presumable actions, functions, structure, etc., of objects named by a certain noun, she will report those in preference to the observed actions, functions, structure of individual instances of that noun, but lacking such information, she relies on what she knows of individuals. On the other hand, if she has hard and fast rules (really *definitional* rules) such information takes precedence over the “presumably true” behaviors, etc. Similarly in defining verbs, Cassie employs a hierarchy in analyzing the effects of actions. Those effects known to follow from certain actions are reported preferentially, but the known probable effects of actions are usually reported as well, if available. If no such knowledge is to be had, Cassie may hypothesize as to the possible effects of the action described by certain verb, based on observation of changes described in the narrative in which she encounters the word knowledge [Ehrlich 1995, Ehrlich & Rapaport 1997, Rapaport & Ehrlich 2000, Rapaport & Kibby 2002].

Conclusion

While neither traditional defeasible rules nor rules whose consequents are marked as presumably true can entirely relieve us of the need for non-monotonic reasoning, both (and especially the latter) can reduce the frequency of such a need. Either is probably a more accurate representation of the knowledge with which we reason (although they are usually less accurate representations of how we report our knowledge) than classical, indefeasible, non-modal logic is. We have used case-frames in our knowledge representation and reasoning system to implement a variant of Nutter’s proposed modal logic, marking certain propositions as “presumably true”, and allowing that a proposition may be both “presumably true” and “false” at the same time without contradiction. This approach allows us to reason monotonically wherever possible (reserving the need for non-monotonic reasoning to those situations in which previous beliefs are actually shown to be erroneous), but does not require the implementation of more than the classical truth values.

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