A Schema-Associative Model of Memory

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This paper[*] describes an innovative model of long term memory (SALT -- Schema-Associative Long Term memory). It also presents an implementation of the SALT model, a specification of an agent, and some scenarios of interactions with the agent. The model presented has its roots in two of the most important general theories of human memory, namely the associative network theory and the schema-based theory. The main advantage of the SALT model is its capability of generating context-dependent cognition. The examples selected for illustrating the functioning of the implementation were chosen from the field of personnel evaluation.

1 - Introduction

Much work has been done in Artificial Intelligence aimed at solving several problems concerned with the construction of autonomous agents. Part of this work has to do with the architecture of artificial reactive agents but adopts an engineering point of view (e.g., [3], [8], [15]). Some of it is more concerned with the definition of formal logics suited to represent the mental states of the agents and their reasoning capabilities (e.g., [4], [9], [17]). Only a few exceptions try to learn useful guidelines from theories and experiments of cognitive psychology and cognitive social psychology and apply them to the construction of artificial intelligence agents (e.g., [6], [12]). In the present paper, the authors present a model of memory based in two well documented theories of human memory in psychology and artificial intelligence: the associative network memory (e.g., [1], [5], [13]) and the schema-based memory (e.g., [2], [14], [19]). The innovative character of the model described consists of the unification in a single framework of the fundamental concepts of these two traditionally separate and somewhat opposed theories. Its main advantage is its

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context-dependent cognition. This is an important feature since it enables an agent to react differently to the same problem, in different contexts.

Section 2 presents the problem addressed by the SALT model; section 3 describes the model; section 4 discusses implementation issues; finally, section 5 compares SALT with other approaches and presents some conclusions.

2 - Context-Dependent Cognition

The SALT model was proposed to address the problem of context-dependent cognition. In this section we present some situations in which the context interacts with the cognitive process of an individual conditioning his or her decision making. We also describe the cognitive mechanisms that mediate that interaction - direct and indirect cognitive priming. The discussion refers to a situation in which a specific student (i.e., the rater) has to evaluate the performance of a given professor (i.e., the ratee). When the model is tested (section 4) the artificial agent plays the role of the student.

According to [11] and [18], the evaluation of the ratee will be based on several dimensions of evaluation only if an information structure containing those dimensions is highly accessible in the rater's memory. Otherwise, the evaluation will be based on the general impression the rater has about the ratee. This phenomenon can be understood in terms of the interaction between the context and the organization of information in long-term memory. It is widely accepted that the context enhances the accessibility of some information structures stored in long term memory - those more related to the context. Besides, in absence of a strong motivation, the information more accessible in memory will be used to handle the situation the person is in ([7], [10]). Hence, the context determines the information used to handle a given situation.

There are two ways in which the accessibility of a particular information structure may be enhanced in

memory. First, by direct exposure to a stimulus that matches that information structure. Second, by the activation of another information structure associated to that particular information structure. Both of these processes are termed "priming processes" because they lead to the preparation (i.e., priming) of information in memory. We refer to the first process as direct priming, and to the second as indirect priming. A particular information structure is more likely to be used in a certain situation if it has been previously primed.

With the purpose of testing our model with respect to these two kinds of priming we created two scenarios (fig 2.1 a and b) in which we predicted the answers a rater would give to several evaluation problems[1].

Scenario 1: Indirect Priming   2.1 (a)
Q1: What is your general impression about the professor (1-5)?
A1: 5
Q2: How do you rate the professor's performance (1-5)?
A2: 5
Q3: What are the dimensions used in evaluating a professor?
A3: Knowledge of the domain, pedagogic capabilities and interpersonal relationship.
Q4: How do you rate the professor's performance (1-5)?
A4: 4

Scenario 2: Direct Priming   2.1 (b)
Q5: How do you rate the professor's performance (1-5)?
A5: 4

Scenario 3: Conformity   2.1 (c)
Q6: How do you rate the professor's performance, considering the general impression you make of him (1-5)?
A6: 5

Figure 2.1 - Context-Dependent Cognition

In scenario 1 (fig 2.1 a - indirect priming), the answers (A2 and A4) given by the rater to the same problem are based in different information structures. In A2, a particular information structure is used because the information structure used in A1 is associated to it, in the rater's memory. Therefore when A1 is produced, the accessibility of the information structure used in A2 is enhanced. A similar effect is responsible for generating answer A4. These are examples of indirect priming.

The interaction imagined in scenario 2 (fig 2.1 b) is an instance of direct priming. This time the information structure used to answer a given question (Q4 of scenario 1) is used to answer the question immediately following it (Q5), just because it is more accessible.

The information used by an individual to handle a particular situation is not always the most accessible information structure found in memory - it must conform to the processing objectives of the individual, [19]. We created a third scenario (fig 2.1 c) for testing our model against this hypothesis. In this last scenario, although a particular information structure is made more accessible, it is not used because it doesn't conform to the processing objectives adopted by the rater. We assume that the rater adopts processing objectives implicit in question Q6, i.e., the processing objective of using an information structure that represents the evaluation in terms of the general impression. Therefore, in answer A6, in spite the most accessible representation concerned with the evaluation is based on a set of specific dimensions of evaluation (used in A5), the rater uses another representation - the one compatible with his processing objectives.

3 - The SALT Model

In this section we present a description of the SALT model (Schema-Associative Long Term memory), and we show that it explains the context-dependent phenomena illustrated in section 2.

SALT is concerned with the organization of information in long-term memory and the corresponding access methods. The basic notion of the model is the notion of an associative network which may be represented by a directed labeled graph. However, our network is different from other associative and semantic networks (e.g., [1], [5], [16]) in three aspects: the contents of nodes, the meaning and labels of arcs, and the inference made in the network.

contents of the nodes

A node is equivalent to a scheme in many schema-based representation systems. It contains a set of propositions expressed in the language of first order predicate calculus[2]. Besides the set of propositions, a node is characterized by an activation value that represents its accessibility in long term memory. Like bins in the bin storage model, [19], a node also contains a header describing the concepts involved by the set of propositions represented in the node.

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[1]Scenarios depicted in figure 2.1 represent an imagined situation inspired on the study reported in [28].

[2]The use of predicate calculus or any other representation system is not a personal stance of the authors. Actually, a node may also contain a set of procedures expressed in any procedural representation language.

In its present form, the model doesn't specify the exact structure and contents of the headers of the nodes. When memory is searched for a node suited to handle a particular situation, the features of the situation are matched against the header of the searched nodes. The node selected is the first one that matches the situation. The model postulates a search procedure that samples nodes in descending order of activation - nodes more activated are sampled first.

information and labels of arcs

A directed arc from node x to node y represents an asymmetric association between the two nodes: if one thinks about concepts in node x, then it is likely that concepts represented in node y may come to one's mind, but the converse is not necessarily true. The labels in the arcs represent the strength of the correspondent association. The strengths of associations may vary between but excluding 0 (no association at all) and 1 (strongest association possible). The sum of the strengths of all associations of a given node must be less than or equal to 1.

inference in the network

The inference mechanisms of our associative network are activation and inheritance.

Activation corresponds to the same concept introduced in theories of spreading activation (e.g., [1], [5]). Each node is characterized by an activation that represents its accessibility in the network. Each time a node is selected to handle a situation it becomes highly activated. Whenever a node's activation increases, the increment of activation spreads to the network (almost) instantaneously, [1], through the arcs getting out of the activated node. The proportion of the activation's increment that spreads through a particular arc is determined by the product of that increment by the strength of the association: the stronger the association, the greater the activation that spreads through it. Just like [1], our model postulates that activation decays exponentially with time.

If node N_1 is associated to node N_2, then inheritance is the property that the concepts in N_2 become available to reasoning performed over the concepts of N_1. Stated more formally, suppose node N_1 contains the set of propositions Δ_1, and nodes N_2, ..., N_n represent the theories T_2, ..., T_n. Suppose also that there are $n-1$ directed arcs from node N_1 to all nodes N_2, ..., N_n. Then, the theory represented by node N_1 is the closure of $\Delta_1 \cup T_2 \cup ... \cup T_n$ under logical implication.

priming and conformity to processing objectives

In section 2, we presented three scenarios illustrating three patterns of behavior due to three cognitive phenomena: direct priming, indirect priming and conformity to processing objectives. Here we show how the SALT model explains all those phenomena.

Direct priming occurs when the presentation of a stimulus to an individual enhances the accessibility of a certain information structure in its long-term memory. As a result, when the individual has to handle a subsequent situation, the enhanced information structure is more likely to be used. In the SALT model, information structures are encapsulated in nodes. According to SALT, when a situation is presented to an individual, the node selected to handle it gets highly activated. On one hand, as the search procedure samples nodes in descending order of activation, the presentation of a situation to an individual also enhances the accessibility of the node used to handle it. On the other hand, as the activation decays exponentially with time, the effects of the enhanced accessibility persist over (a certain interval of) time.

Indirect priming occurs when an information structure associated to another information structure gets activated, enhancing the activation of the other information structure. According to SALT, if node x is associated to node y with association strength s, and the activation of x increases by i, then the activation of y increases by $j=i\times s$. Therefore, as the SALT model explains the direct priming phenomena, it also explains the indirect priming.

Finally, the conformity to the processing objectives of the individual, are captured by SALT through the implicit assumption that a situation presented to an agent is not fully described by a simple question, but also by a set of restrictions embedded in the text of the question (or otherwise present in the context). In this way, the search procedure is not just seeking any answer for a given problem. It seeks an answer that conforms to certain restrictions -- the processing objectives adopted by the individual.

4 - Implementation and Testing

We wrote a Prolog program and an agent specification for testing the model described in section 3. As exemplified in figure 4.1, the specification of the contents of the agent's long term memory is made in a declarative fashion, using Prolog.

```
/* Node4                           */
evaluation(E) :-
    knowledge(Wk, Vk),
    pedagogy(Wp, Vp),
    interpersonal(Wi, Vi),
    X is (Wk * Vk)+(Wp * Vp)+(Wi * Vi),
    Y is Wk + Wp + Wi,
    E is X/Y.
knowledge(3, 3).
pedagogy(4, 4).
interpersonal(3, 5).
```

4.1 Partial Model of the Agent

We ran the agent through the interactions corresponding to scenarios 1, 2 and 3 presented in section 2 (fig 2.1), and it behaved as expected in all cases. This constitutes an encouraging piece of evidence in favor of our model. Figure 4.2 depicts a sequence of the interactions corresponding to scenarios 2 and 3 (fig 2.1 b and c). In the second question, the user compels the agent to consider its general impression about the professor. This is done using the special operator ←. This operator specifies a list of concepts to be used in answering a given question *(How do you rate the professor's performance, <u>considering the general impression?</u>).*

```
Q: evaluation(E).
A: evaluation(4).              (node4)
Q: evaluation(E)←[generalImpression(_)].
A: evaluation(5).              (node3)
```

4.2 Interaction Sequence

The SALT model doesn't specify the structure and exact contents of the header of a node, nor does it say anything concrete about the nature of the process that matches the features of the current situation with the headers of the nodes. In the present implementation, the header represents all concepts contained in the node. For each concept, it represents the set of concepts on which it depends. An empty dependence set indicates that the concept doesn't depend on anything - it is a fact.

```
{<evaluation(_), {knowledge(_,_), pedagogy(_,_),
                      interpersonal(_,_)}>,
  <knowledge(_,_),    {}>,
  <pedagogy(_,_),     {}>,
  <interpersonal(_,_), {}>}
```

4.3 Header of Node4

Figure 4.3 shows the header of Node4 (fig 4.1) built by the program. It has the following reading: Node4 represents the evaluation in terms of the knowledge, the pedagogic qualities and the interpersonal relationship; and represents the knowledge, the pedagogic qualities, and the interpersonal relationship as basic facts.

5 - Conclusions

Through out this paper we have presented SALT, a model of long term memory. SALT is capable of explaining and generating context-dependent cognition phenomena like those presented in section 2. In this section we draw some comments about the model and present some advantages over schema-based models, spreading activation models and semantic network representations.

The SALT model postulates that activation spreads instantaneously from an activated node to the rest of the network through the arcs beginning in that node. There are two aspects that deserve further consideration about this postulate. In the first place, if there are cyclic paths in the network, an exact implementation of the model would lead to a non stopping process of spreading activation. In the second place, the instantaneous nature of the spreading activation, [1], is impossible to achieve, specially if the agent has a memory with many nodes. Notice that, after the activation spreads to the network, all the nodes must be sorted in descending order of activation, so that their accessibility is changed accordingly. For solving these two problems, the present implementation adopted a slightly modified version of the model: the spreading of activation stops when the activation to be propagated is less then a small percentage of the fixed amount of activation received by the node selected[3]. We think differences between the theoretic model and the concrete implementation arise because the nature of the physical system modeled (the physical human memory) is very different from that of an electronic von Neuman computer.

SALT is better than a schema-based model of human memory, like [2], [14] and [19], because it predicts that the accessibility of information structures stored in memory changes dynamically as a consequence of spreading activation. The model described in [19] also provides for changes in accessibility, but only due to the frequency and recency of the selection of information structures, and at the expense of a continuing replication of information structures in memory. Besides avoiding the replication of information in memory, SALT explains changes in accessibility also due to associations between information structures.

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[3]Presently we adopt a threshold equal to 1% of the activation received by the node selected. However, this is quite arbitrary and needs further tuning.

SALT is superior to a pure spreading activation model ([1], [5], [13]) in that it permits the simultaneous activation of a full set of propositions needed to handle a particular situation, while in typical spreading activation models nodes represent only simple concepts like classes, instances and qualities, but not relations between concepts, nor full sets of propositions. With a distinct purpose from ours (i.e., retrieving and representing episodes in memory) the REMIND model, [12], also integrates schema and spreading activation. However, REMIND presents significant differences to our model. First, REMIND is a connectionist model, while ours is a symbolic model. Second, when a situation is presented to REMIND, all nodes sharing features with the situation get highly activated. Then the activation spreads to the network. After the activation of the network settles, the most activated node is selected to interpret it. By contrast, when a situation is presented to the SALT model, the node selected is the first found in long-term memory that matches the situation. Although the experimentation performed (section 4) is not conclusive in this respect, it seems the SALT model yields a more reactive system than REMIND. Which is better depends probably on the specific application of the model.

Finally, our model is also superior to semantic networks like the SNePS, [16], in that it encompasses the notion of spreading activation which, as argued before, is responsible for changes in the accessibility of information structures in memory due both to the frequency and recency of activation, and to associations between nodes.

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