A Symbolic Representation of Misconceptions

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ABSTRACT

An intelligent system must process information as human beings do. A framework is presented wherein dynamic cognitive structures called chains of thought are used to embody the dynamic aspects of the intentions of intelligent agents. These chains of thought are represented as fuzzy cognitive structures. In this particular framework, structure mapping plays an important role in the notion of misconceptions. An expert agent has to deduce the "private" symbolic constructs of a novice agent in order to correctly guide the novice through a particular task. These "private" constructs are derived from (partially) corresponding "public" symbolic constructs that are a result of intelligent symbolic communication between the expert agent and novice agent. This whole process embodies what the author refers to as cognitive diagnosis.

Chains of thought, the "private" symbolic constructs, are the main focus of the current paper. Its applications in designing intelligent systems and cognitive diagnosis are emphasized. The resulting framework is also an important step towards developing a method for evaluating degrees of intelligence and possible comparison between (groups of) intelligent systems.

I. INTRODUCTION

For an artificial system to be considered intelligent, it must process information as human beings do. The theoretical work presented in this paper has two major goals. First, it investigates and describes what types of cognitive structures are used when intelligent agents communicate with each other. Secondly, it attempts to capture the dynamics of these cognitive structures during symbolic communication between intelligent agents.

Intelligent agents express their intentions when they communicate with one another. In order for this communication to take place, a common vocabulary has to be used. These "public" symbolic constructs make up speech, be it spoken or otherwise. In addition to this common vocabulary, there needs to be a correspondence between the syntax of the language used by each participant. As noted by Kohout [2], there must also be semantic agreement if the conversation is to be successful. Unfortunately, the transition from "private" intentions to "public" symbolic constructs is not always clear. This is true not just to agents actively involved in the conversation (we shall call these participants), but also to those agents not really involved in the conversation: spectators (correspondingly, non-participants) just observing the interaction.

Dynamic cognitive structures must be used by intelligent agents to deduce and make decisions. These must also be used to express themselves. The whole process of trying to determine what one agent is thinking, or attempting to express, based on a dialogue, their behavior, their actions, etc. is what initiated the work presented in this paper.

This work has relatively close ties to the field of semiotics, a discipline of combining the theory of signs, symbols, and meaning extraction. In the next few sections, we explore the area of intelligent tutoring systems as a foundation for the work by Juliano and Bandler [1]. Next, the dynamic cognitive structures that Juliano and Bandler call chains of thought [1] are introduced. A brief discussion of the implications of this work is presented and further work is also proposed.

II. TUTORING SYSTEMS AND DEDUCING MISCONCEPTIONS

Intelligent tutoring systems

Intelligent tutoring systems (or ITSs) provide, perhaps, the best ground work for investigating the cognitive structures of interest in this study. ITSs are systems designed to aid in tutoring students on a particular subject matter. These systems are supposed to possess some form of intelligence by having

1. some form of model of the student; and
2. some reasoning capabilities based on this model

The most common approach in the design of an ITS is to get a better understanding of possibly how we as humans perform in a tutoring role. In particular, we need to investigate how we represent and process information based on the two items listed above. This entails an approximation of the thinking process using some knowledge structure based on a system's "own" expert knowledge structure. The process of "thinking about thinking" is what Juliano and Bandler [1] have referred to as cognitive diagnosis, which includes any method of confirming the relative position of the novice student's thinking pattern based on a corresponding idealized pattern.

The approach we take is based on cognitive diagnosis during problem solving. In this scenario, the student is given several problems to solve and the tutor may intervene whenever appropriate in directing the student to understanding the concepts involved. It is during this problems solving session that a model of the student's understanding has to be formulated and used in determining when to intervene and how to control the direction of the session (do we present a simpler problem or do we go with one that is a little bit more challenging?).

The process of deducing misconceptions

Perhaps the most important factor in successful tutoring is how to correctly deduce student misconceptions. This is based on information gathered during a tutoring session, most likely consisting of partial or incomplete solutions to the problem at hand. This information may also contain a lot of noise. The student may indicate varying degrees of uncertainty (or confidence) to their solutions. Furthermore, under most normal situations, the information is usually available in various forms: verbal, visual cues, scribbled computations, diagrams or doodles, etc. Clearly, all this complicates approximating this in an artificial system.

To simplify the process, the following main assumptions are made for an underlying theory of knowledge states, which can be conveniently represented in a computer:

1. The knowledge of the expert agent and the knowledge of the novice agent overlap one another.
2. A knowledge state describes a set of concepts and the set of relations among these concepts.
3. When an expert agent approximates the knowledge state of a novice agent, this information is used to generate "lines of reasoning", which we call *chains of thought*, to account for each observed action.

The first assumption is important because it implies the view that expertise is decomposable into independent components that may be used to define various dimensions of knowledge. It also implies that "subsets" inherit essential characteristics of the "full" model; hence, the novice agent's mastery of a particular component can somewhat be deduced.

The second assumption indicates an associative representation. Fuzzy cognitive maps are used to account for the inherent vagueness and imprecision in most natural tutoring environments where decisions are based on imprecise, qualitative data. The third assumption adds an important level of detail in the dynamics of the process of cognitive diagnosis.

This subsethood assumption between the knowledge of the expert agent and novice agent somewhat parallels Kohout's [2] note that semantic agreement is required if a conversation between two agents is to be successful. In his statement, he indicates that there must be some form of overlap for this to proceed.

The process by which tutoring systems deduce misconceptions by novice agents is also similar to the way intelligent agents perceive their surrounding environment. In the tutoring scenario, the environment is replaced by a particular novice. The expert agent has to adjust to each novice agent and base its actions on its current model of that agent. Similarly, intelligent agents must adapt to changes in their environment.

III. Approximating Chains of Thought

Fuzzy cognitive maps

As indicated in the previous section, one of the assumptions we have is that knowledge states describe a set of concepts and the set of relations among these concepts. The dynamic cognitive structures we use to represent knowledge states are fuzzy cognitive maps (or FCMs). Mathematically [1], a FCM $M = (C_M, R_M)$ over a finite universe of discourse, X, is a *fuzzy graph* that is a 2-tuple where:

$$C_M \in [0,1]^X \text{ is a } \textit{fuzzy concept space} \text{ of } X \tag{1}$$

and

$$R_M = \left(R_M^1, R_M^2, \ldots, R_M^{r_M}\right) \text{ is a } \textit{fuzzy multirelation} \tag{2}$$

Each R^k (where $1 \le k \le r_M$) is a *fuzzy relation* on the fuzzy concept space C_M. For more details on the mathematics, operations, etc. on FCMs, refer to [1].

FCMs are ideal representations of knowledge states not just because they capture the essence of the first two assumptions listed in the previous section. They are ideal also because they can be encoded from the communication between two intelligent agents. This gives us a means of possibly representing "private" symbolic constructs to correspond to an agent's expertise or knowledge, or as an approximation of what another agent is trying to say.

Chains of thought

Knowledge states alone are not sufficient in capturing the three assumptions we laid out. To represent lines of reasoning, there has to be a way to move or transform from one knowledge state to another. This requires a formal representation of chains of thought. Mathematically [1], we can define a chain-of-thought structure on a universe of discourse, X, to be a 5-tuple $T = \left(C, R, \Psi, \Phi, \delta\right)$ where the pair C and R define a FCM structure based on (1) and (2), respectively, and

$$\Psi \in [0,1]^X \text{ is a } \textit{knowledge state space} \tag{3}$$

$$\Phi \in [0,1]^X \text{ is a } \textit{valid input space} \tag{5}$$

$$\delta : \Psi \times \Phi \to \Psi \text{ is a } \textit{transition function} \tag{6}$$

Notice that these definitions have some similarities to the formal definition of a finite-state sequential machine. For more details on the mathematics, operations, etc. on chains of thought, refer to [1].

Knowledge communication and cognitive diagnosis

What are the distinct processes involved in approximating chains of thought? We shall consider two intelligent agents, *A* and *B*, although this could be extended to more than two agents. Without loss of generality, let us assume that *A* is the expert agent and *B* is the novice agent in a tutoring environment. Initially, we start off with the arrangement given in Figure 1 below.

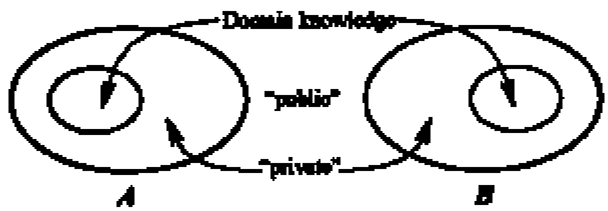

Figure 1 Initial phase of the interaction

The shaded region in each agent denotes domain knowledge. Recall that in our first assumption, the overlay principle (subsethood property) actually holds between agents.

Agent *B*'s knowledge is then communicated to agent *A* in some manner, possibly during a problem solving task. This is depicted in Figure 2.

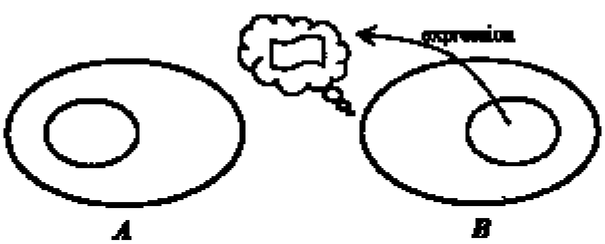

Figure 2 Communication from the novice agent

Whatever was expressed by novice Agent *B* now has to be encoded by expert Agent *A*. This is done by Agent *A* to either develop or update a model of what Agent *B* is thinking. This is illustrated in Figure 3.

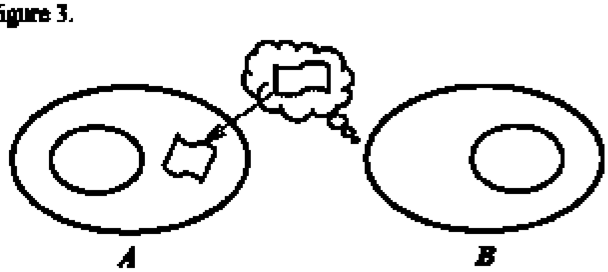

Figure 3 Encoding and model generation/updating by the expert agent

After expert Agent *A* has generated and/or updated its model of what Agent *B* is expressing (or thinking), the next step is model interpretation. In [1], Juliano and Bandler propose the use of a discrepancy operator to identify misconceptions, if any, indicated by the model of the novice. Whatever type of operator is used, this is applied to the expert's domain knowledge and the current model of the novice. This is depicted in Figure 4.

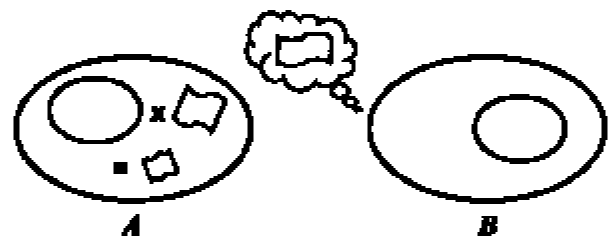

Figure 4 Model interpretation by the expert agent

Whatever interpretation is derived by expert Agent *A*, this has to be conveyed back to novice Agent *B* in some form. This is illustrated in Figure 5. Hopefully this information will direct Agent *B* to the ideal chain of thought.

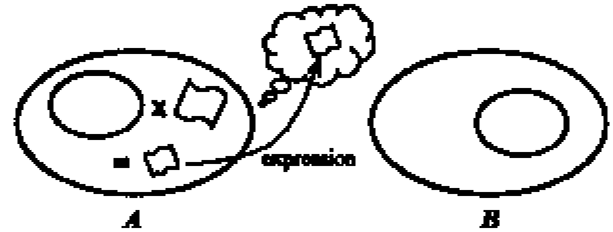

Figure 5 Expressing misconceptions identified by the expert agent

Next, notice that the novice Agent *B* now undergoes a process similar to that depicted in Figures 3 and 4. Communication from expert Agent *A* has to be encoded and this information interpreted and possibly assimilated into Agent *B*'s current knowledge structure. Thus, this model has a fairly general application for intelligent agents and the modeling of some underlying cognitive processes.

IV. Discussion

The model for cognitive diagnosis outlined in the previous section warrants elaboration. Firstly, the appropriateness of using FCMs to represent knowledge states is emphasized by two factors in the model. Knowledge communication, the act of expressing one's knowledge (see Figures 2 and 5), is primarily fuzzy in nature. One can observe how to express most everyday reasoning and common sense knowledge - these are conveyed imprecisely. When it comes to approximating this in a machine, this is where the expressiveness of fuzzy set theory steps in. Furthermore, the transformation of spoken (or otherwise) language into an internal, "private" model as in Figure 3 is inherently noisy and imprecise as well. Again, fuzzy set theory can capture this imprecision.

The use of fuzzy graphs, called FCMs, also facilitates modeling of the operation(s) depicted in Figure 4. In [1], operations for *fuzzy difference* and *fuzzy discrepancy* between two