FUZZY COGNITIVE STRUCTURES FOR AUTOMATING HUMAN PROBLEM SOLVING SKILLS DIAGNOSIS

Bienvenido Jose A. Juliano, Jr.
Department of Computer Science and
Institute for Cognitive Sciences
The Florida State University
Tallahassee, Florida 32306-4019
U. S. A.
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Abstract

This paper presents the latest developments regarding a cognitive module of an intelligent system for diagnosing human problem solving skills. The module incorporates a *chain-of-thought analyzer* that establishes a model of the student. A *fuzzy cognitive map* [18], or *FCM*, formulation is proposed for this approach. It attempts to accomplish the necessary diagnostic task and it suggests effective tutoring capabilities as well. These FCMs represent approximations of a novice's concept manipulation and formation strategy in trying to solve a particular problem. They can be useful decision making tools in the instruction environment.

1 Introduction

The most accurate account for student intelligence is derived by direct interaction between the novice student and expert instructor. This is exemplified by a tutoring session. Perhaps the most important cognitive task performed by a tutor is the development and utilization of a *student model*. It is this model that provides an indicator of student knowledge. One can view this cognitive structure as a decision making tool. But traditional subjective grades are rather imprecise measures of one's intelligence. The instructor's teaching ability, the validity of the exam or quiz used to test student knowledge, and other factors limit the plausibility of these measures. Qualitative indicators such as *a very good student* or *a bright person* are more appropriate.

1.1 Decision Making in the Instruction Environment

A professor normally adheres to a specific curriculum or course outline when managing the instruction of a particular course. But as research advances in the field become available, coupled with the changing needs of society, this framework is modified. Such adjustments are made during the term as well, particularly to the course schedule. These decisions must be made based on information and assumptions regarding group and/or individual mastery of relevant topics.

Decision Support Systems, or DSSs, have normally been associated with the management sciences and operations research [12]. The primary function of DSS is to manage (possibly imprecise) information and quantify available data to aid corporate managers in reaching complex decisions [8]. Hence, DSS have been in use in industry, government, and the military [1]. In a smaller extent, the decisions faced by an instructor are similar to those made by a manager. Some examples of the queries an instructor may become interested in are "What suitable topics to concentrate on for today's lecture?", "Which areas have been appropriately mastered?", and tutoring questions like "When to interrupt and give information?", "What kind of and how much advice to give?" and more. The knowledge bases concerned are also different: pedagogical strategies, domain knowledge, student records, and others. Knowledge representation schemes are more complex since cognitive issues are involved [22].

1.2 IDSS for Instruction

The incorporation of cognitive modeling into the DSS framework is an attempt to make these systems more intelligent. Similarly to the shift from *Computer-Assisted Instruction* (CAI) to *Intelligent* CAI (ICAI) or *Intelligent Tutoring Systems* (ITS), these systems are refered to as *Intelligent* DSS or IDSS (see for example [7, 19, 28]). The general trend is to utilize human information processing models over or in conjunction with the network, control theory, decision theory, or queueing theory models [20]. These systems have also been refered to as *right-brained* DSS [29] in other literature. In contrast with former *left-brained* DSS that were limited to quantitative procedures, IDSS possess creative functions and use qualitative analyses. Such an approach is well-suited for instructional decision making tools. Some industrial and managerial IDSS may use such personal profiling as well.

These instruction-based decisions are dependent on possibly imprecise information. This makes Zadeh's *theory of fuzzy sets* [30] an ideal foundation since this imprecision does not stem from *randomness*, but from *fuzziness* [32]. As in [5], these decisions may be viewed as a set of alternatives resulting from what is permissible for the specified goals and constraints.

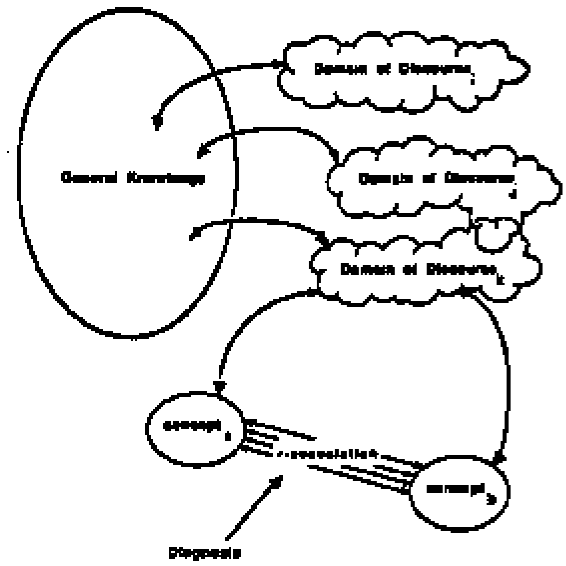

Figure 1: Preliminary notions

2 FCM Formulations

Portions of following mathematical formulations appear in detail in [13, 15]. Notations are consistent with these prior publications.

The conjectured interrelationship between knowledge, domains and concepts is depicted in Figure 1. Mathematically, we refer to general knowledge as a *universe*, X. The domains of discourse are also known as *concept spaces*, $\mathcal{C} \in \mathcal{P}(X)$. $\mathcal{P}(X)$ denotes an applicable formulation for the *power set* of X. Clearly, any concept $c \in X$ has the property that $c \in \mathcal{C}$, for at least one $\mathcal{C} \in \mathcal{P}(X)$.

2.1 The FCM

Define a *fuzzy cognitive map*, $\tilde{M} = (\mathcal{C}_{\tilde{M}}, \mathcal{R}_{\tilde{M}})$ over the universe X as a *fuzzy graph* [21] that is a 2-tuple of functions $\mu : \mathcal{C} \rightarrow [0,1]$ and $\rho : \mathcal{C} \times \mathcal{C} \rightarrow [0,1]$, for $\mathcal{C} \in [0,1]^X$:

- $\mathcal{C}_{\tilde{M}} \in [0,1]^X$ is a *fuzzy concept space* of X.
- $\mathcal{R}_{\tilde{M}}$ is a fuzzy relation on $\mathcal{C}_{\tilde{M}} \in [0,1]^X$, given by $\mathcal{R}_{\tilde{M}} : \mathcal{C}_{\tilde{M}} \times \mathcal{C}_{\tilde{M}} \rightarrow \Re$. The values of $\mathcal{R}_{\tilde{M}}$ are restricted by

$$\mathcal{R}_{\tilde{M}ij} \leq \mu_{\mathcal{C}_{\tilde{M}}} x_i \wedge \mu_{\mathcal{C}_{\tilde{M}}} x_j$$

for all $x_i, x_j \in \mathcal{C}_{\tilde{M}}$.

- The totally ordered *range set* $\Re = [0,1]$ establishes the *certainty* or *membership* values between concepts $C \in \mathcal{C}_{\tilde{M}}$.

2.2 FCM Operations

For arbitrary fuzzy cognitive maps $\tilde{M} = (\mathcal{C}_{\tilde{M}}, \mathcal{R}_{\tilde{M}})$ and $\tilde{N} = (\mathcal{C}_{\tilde{N}}, \mathcal{R}_{\tilde{N}})$ over the universe X:

- the *fuzzy join* of $\tilde{M}$ and $\tilde{N}$ is denoted by

$$\tilde{M} \oplus \tilde{N} = (\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}, \mathcal{R}_{\tilde{M}} \nearrow (\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}) \sqcup \mathcal{R}_{\tilde{N}} \nearrow (\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}})) \quad (1)$$

where $\cup$ is the *fuzzy set union* operator and $\sqcup$ is the *fuzzy relational union* operator, defined as

$$\forall x \in X, \; \mu_{\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}} x = \mu_{\mathcal{C}_{\tilde{M}}} x \vee \mu_{\mathcal{C}_{\tilde{N}}} x$$

$$(\mathcal{R}_{\tilde{M}} \nearrow (\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}) \sqcup \mathcal{R}_{\tilde{N}} \nearrow (\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}))_{ij} = (\mathcal{R}_{\tilde{M}} \nearrow (\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}))_{ij} \vee (\mathcal{R}_{\tilde{N}} \nearrow (\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}))_{ij}$$

respectively. The $\vee$ symbol denotes the *maximum* operator.

- the *fuzzy meet* of $\tilde{M}$ and $\tilde{N}$ is denoted by

$$\tilde{M} \otimes \tilde{N} = (\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}, \mathcal{R}_{\tilde{M}} \searrow (\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}) \sqcap \mathcal{R}_{\tilde{N}} \searrow (\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}})) \quad (2)$$

where $\cap$ is the *fuzzy set intersection* operator and $\sqcap$ the *fuzzy relational intersection* operator, defined as

$$\forall x \in X, \; \mu_{\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}} x = \mu_{\mathcal{C}_{\tilde{M}}} x \wedge \mu_{\mathcal{C}_{\tilde{N}}} x$$

$$(\mathcal{R}_{\tilde{M}} \searrow (\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}) \sqcap \mathcal{R}_{\tilde{N}} \searrow (\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}))_{ij} = (\mathcal{R}_{\tilde{M}} \searrow (\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}))_{ij} \wedge (\mathcal{R}_{\tilde{N}} \searrow (\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}))_{ij}$$

respectively. The $\wedge$ symbol denotes the *minimum* operator.

- the *fuzzy discrepancy* of $\tilde{M}$ over $\tilde{N}$ is denoted by

$$\tilde{M} \ominus \tilde{N} = (\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}, \mathcal{R}_{\tilde{M}} \searrow (\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}) \sqcap \neg(\mathcal{R}_{\tilde{N}} \searrow (\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}))) \quad (3)$$

where $\setminus$ is the *fuzzy set difference* operator and $\neg$ is the *fuzzy relational negation* operator, defined as

$$\forall x \in X, \; \mu_{\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}} x = \mu_{\mathcal{C}_{\tilde{M}}} x \wedge (1 - (\mu_{\mathcal{C}_{\tilde{N}}} x))$$

$$(\mathcal{R}_{\tilde{M}} \searrow (\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}) \sqcap \neg \mathcal{R}_{\tilde{N}} \searrow (\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}))_{ij} = (\mathcal{R}_{\tilde{M}} \searrow (\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}))_{ij} \wedge (1 - (\mathcal{R}_{\tilde{N}} \searrow (\mathcal{C}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{N}}))_{ij})$$

respectively.

The fuzzy join operation can be utilised to create and link cognitive maps. Truncation or pruning is accomplished by taking the fuzzy meet. Meanwhile, fault-detection is performed by taking the fuzzy discrepancy of the approximated chain-of-thought with a cognitive map supplied by the expert.

2.3 FCM Relations

The *degree of subsethood* of $\tilde{A}$ in $\tilde{B}$ for fuzzy subsets $\tilde{A}, \tilde{B} \in [0,1]^X$, written $\mu_{[0,1]\tilde{B}} \tilde{A}$, is a measure of uncertainty in terms of the possibility, π, defined as

$$\mu_{[0,1]\tilde{B}} \tilde{A} = \pi(\tilde{A} \subseteq \tilde{B}) \quad (4)$$

where $\mu_{[0,1]^X}\tilde{A}$ denotes the *membership function* that maps $\tilde{A}$ to the power set of $\tilde{B}$. The value returned by $\mu_{[0,1]^X}\tilde{A}$ would depend on the *fuzzy implication operator* utilized to embody the said mapping, since by definition

$$\pi(\tilde{A} \subseteq \tilde{B}) = \min_{x \in X} (\mu_{\tilde{A}}x \rightarrow \mu_{\tilde{B}}x). \tag{5}$$

For arbitrary fuzzy cognitive maps $\tilde{M} = (\mathcal{C}_{\tilde{M}}, \mathcal{R}_{\tilde{M}})$ and $\tilde{N} = (\mathcal{C}_{\tilde{N}}, \mathcal{R}_{\tilde{N}})$ over the universe X:

- the degree to which $\tilde{M}$ is a *fuzzy submap* of $\tilde{N}$, written $\pi(\tilde{M} \ll \tilde{N})$, is defined as

  $$\pi(\tilde{M} \ll \tilde{N}) = \begin{array}{l} \pi(\mathcal{C}_{\tilde{M}} \subseteq \mathcal{C}_{\tilde{N}}) \wedge \\ \pi(\mathcal{R}_{\tilde{M}}/\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}} \sqsubseteq \mathcal{R}_{\tilde{N}}/\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}}), \end{array} \tag{6}$$

  where $\pi(\mathcal{C}_{\tilde{M}} \subseteq \mathcal{C}_{\tilde{N}})$ is as defined in Equation (5), and similarly

  $$\pi\left(\begin{array}{l} \mathcal{R}_{\tilde{M}}/\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}} \\ \sqsubseteq \mathcal{R}_{\tilde{N}}/\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}} \end{array} \right) = \pi\left(\begin{array}{r} \wp\mathcal{R}_{\tilde{M}}/\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}} \subseteq \\ \wp\mathcal{R}_{\tilde{N}}/\mathcal{C}_{\tilde{M}} \cup \mathcal{C}_{\tilde{N}} \end{array} \right). \tag{7}$$

  A more harsh measure could be derived by utilizing the f-restriction of $\mathcal{R}_{\tilde{M}}$ and $\mathcal{R}_{\tilde{N}}$ on $\mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}$, which is given by the formula

  $$\pi(\tilde{M} \ll \tilde{N}) = \begin{array}{l} \pi(\mathcal{C}_{\tilde{M}} \subseteq \mathcal{C}_{\tilde{N}}) \wedge \\ \pi(\mathcal{R}_{\tilde{M}} \setminus \mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}} \sqsubseteq \mathcal{R}_{\tilde{N}} \setminus \mathcal{C}_{\tilde{M}} \cap \mathcal{C}_{\tilde{N}}). \end{array} \tag{8}$$

  Hence, $\tilde{M}$ is called a fuzzy submap of $\tilde{N}$ if and only if $\pi(\tilde{M} \ll \tilde{N}) \geq \alpha_{\ll}$. This preset threshold value is usually set at $\alpha_{\ll} \geq 0.50$.

- dually, denote the degree to which $\tilde{M}$ is a *fuzzy supermap* of $\tilde{N}$, written $\pi(\tilde{M} \gg \tilde{N})$, by

  $$\pi(\tilde{M} \gg \tilde{N}) = \pi(\tilde{N} \ll \tilde{M}). \tag{9}$$

  This is clear and has been shown in [13].

- $\tilde{M}$ is said to be *equal* to $\tilde{N}$, written $\tilde{M} = \tilde{N}$, when the following hold:

  $$\tilde{M} = \tilde{N} \Leftrightarrow \mathcal{C}_{\tilde{M}} = \mathcal{C}_{\tilde{N}} \text{ and } \mathcal{R}_{\tilde{M}} = \mathcal{R}_{\tilde{N}}. \tag{10}$$

  This means that

  $$\forall x \in X, \; \mu_{\mathcal{C}_{\tilde{M}}}x = \mu_{\mathcal{C}_{\tilde{N}}}x \tag{11}$$

  $$\text{and } \forall i,j \; \mathcal{R}_{\tilde{M}ij} = \mathcal{R}_{\tilde{N}ij}. \tag{12}$$

  Otherwise, $\tilde{M}$ is *not equal* to $\tilde{N}$, written $\tilde{M} \neq \tilde{N}$. The degree to which $\tilde{M}$ is *fuzzily equal* or *similar* to $\tilde{N}$ may be denoted by

  $$\pi(\tilde{M} = \tilde{N}) = \pi(\tilde{M} \ll \tilde{N}) \wedge \pi(\tilde{M} \gg \tilde{N}). \tag{13}$$

The cognitive map relations just presented could be utilised for comparing and analyzing approximated structures with idealized ones. Fuzzy orders [31] could provide interpretations of conceptual manipulation strategies employed by a particular novice. Other useful applications are also being investigated.

3 Tutorial Intervention and Performance Diagnosis

The tutor interupts a particular session when some form of fault is detected. This task entails an analogical mapping between the tutor's knowledge, $\tilde{T}$, and the approximated knowledge of the student, $\tilde{S}$. The former knowledge source is represented by a source FCM that may be selected and retrieved from an existing knowledge base or generated by a problem solving module. The formulations suggest that the discrepancy $\tilde{S} \ominus \tilde{T}$ captures these faults. Intervention may be triggered by the degree to which $\tilde{S}$ and $\tilde{T}$ are *fuzzily equal*. Although such a structural comparison merely demands a threshold value to determine the significance of a fault, semantic and pragmatic considerations should also be considered. These issues are more domain-dependent.

Performance diagnosis is achieved by backtracking along *negative nodes* resulting from the $\tilde{S} \ominus \tilde{T}$ operation. This also facilitates the generation of advisory data, which may be infered from the resulting analogical mapping. These are also domain-dependent.

4 Conclusions

FCMs are proposed to represent an approximation of the concept manipulation and formation strategy employed by a novice in attempting to solve a particular problem. Corresponding fuzzy formulations utilizing relations theory and the notion of restrictions and extensions were also presented. Interpretation of the resulting conceptual graph structures, which would be parallel to a conceived *solution path*, is derived by analogical mapping and back-tracking. Furthermore, this approach's applicability to other abductive systems requiring some fault detection or error diagnosis is being considered. Other plausible possibilistic formulations are currently being investigated. These provide sufficient initiative to continue extensive research on the subject area.

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