Importing Human Tutor's Conversation Strategy into Dialog Systems for Language Learning using Fuzzy Logic

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Abstract. Foreign language tutors have some conversation strategies to help learners to successfully finish a learning session. But these strategies are generally described by vague linguistic terms so that they cannot be easily transformed to a computational model. Therefore, this study presents a fuzzy logic-based method that considers learner's proficiency level and difficulty of system responses together to determine the best desirable system response. By modeling and utilizing human tutor's conversation strategy, our system is better able to fulfill its role as a conversational agent for language tutoring.

Keywords: language learning; spoken dialog system; fuzzy logic

1 Introduction

We have been developing Dialog-Based Computer-Assisted Language Learning (DB-CALL) systems in which the system plays the role of a language tutor [1] [2] [3] [4]. As foreign language tutors take into account learners' proficiency level in order to induce learners' uptake effectively, DB-CALL systems should also take such tutoring strategies [5]. For example, let's say that there are two available system responses that can follow the dialog in the upper box in Fig. 1. Undoubtedly, veteran teachers would speak the easier utterance (1) to beginner level students and the more difficult utterance (2) to advanced level students.

However, the words like "beginner level", "advanced level", "easy", and "difficult" do not have sharp, well-defined boundaries and when we attempt to describe them in a computational model the result often looks clumsy and artificial. For instance, we might encode the descriptive term "proficiency level" as the set of intervals:

- Beginner = the test score is between 0 and 50 points
- Intermediate = the test score is between 50 and 80 points
- Advanced = the test score is between 80 and 100 points

But what if the score is 51? Using these intervals to represent proficiency level, a computer will put the student in the "intermediate level", even though the subtraction of a couple more points will transform it to being the beginner level. It is not hard to see that when manipulating data presented in such a way any AI's reasoning is going to be fundamentally flawed. Compare this to a human reasons. When considering linguistic terms such as "beginner level", "advanced level", "easy", and "difficult", a human being is able to place vague boundaries on those terms and allow a value to be associated with a term to a matter of degree. When the score is 51 points, a human will regard it to be partly associated with the term "intermediate level" and partly with the term "beginner level." In this way humans perceive the score quality gradually shifting between linguistic terms instead of changing abruptly, allowing us to reason about linguistic rules.

Fuzzy logic is known as a well-suited method to such problems [6]. It enables a computer to reason about linguistic terms and rules in a way similar to humans. Therefore, this study presents a fuzzy logic based method for incorporating human tutors' strategies to determine the best desirable system response.

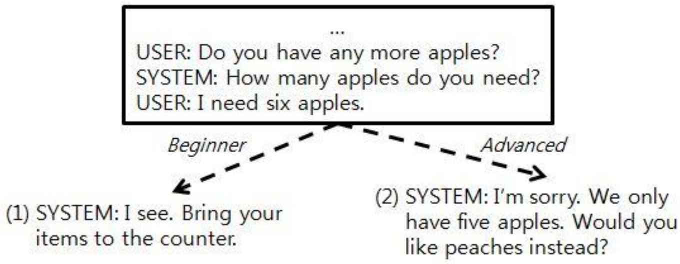

Fig. 1. Proficiency level sensitive system responses

2 Fuzzy linguistic variables for language tutoring

The desirability of selecting a particular system response is dependent on two factors: the leaner's proficiency level and the difficulty of the response. Therefore we define three *Fuzzy Linguistic Variables* (FLVs): Proficiency Level, Difficulty (antecedents), and Desirability (consequent) and rules pertinent to human tutors' conversation strategy. The rules infer how desirable a system response is for each possible response under a given dialog context, enabling the system to select the response with the highest desirability score.

For Desirability, we have chosen to use three member sets: a left-shouldered set, a triangular set, and a right-shouldered set, representing the linguistic terms Undesirable, Desirable, and VeryDesirable. Next, we will consider the antecedent: Proficiency Level. Once again the FLV is comprised of three sets, named Beginner, Intermediate, and Advanced. The shape of fuzzy sets follows the general criteria of communicative ability test used in Korean high schools. The Difficulty also consists of three sets: Easy, Normal, Difficult. We have measured the degree of difficulty of a system response by interpolating syntactic difficulty and discourse difficulty (Eq. 1).

$$\text{Difficulty} = \left(\alpha \cdot \frac{\text{\# of nodes}}{\text{MAX \# of nodes}} + (1-\alpha) \cdot \frac{\text{\# of slots}}{\text{MAX \# of slots}}\right) \times 100 \quad (1)$$

The syntactic features aim to reflect the structural complexity of a response utterance based on the number of the non-leaf nodes in the phrase structure tree. The discourse features are designed to take into account how difficult to reply to the system's request based on the number of slots expected by the system's utterance (Fig. 2).

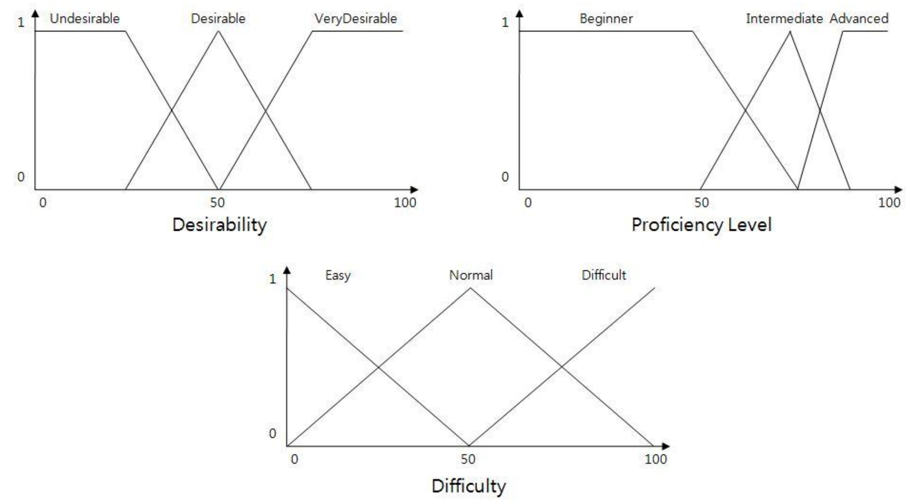

Fig. 2. Fuzzy Linguistic Variables

3 Fuzzy Rules

Unlike conventional rules where the consequent either fires or not, in fuzzy systems the consequent can fire to a matter of degree. The degree of membership (DOM) of the antecedent defines the degree to which the consequent fires. Each time a fuzzy system iterates through its rule set it combines the consequents that have fired and defuzzifies the result to give a crisp value. To cover all the possibilities, a rule must be created for each possible combination of antecedent sets:

- Rule 1. IF Beginner AND Easy THEN VeryDesirable
- Rule 2. IF Beginner AND Normal THEN Undesirable
- Rule 3. IF Beginner AND Difficult THEN Undesirable
- Rule 4. IF Intermediate AND Easy THEN Desirable
- Rule 5. IF Intermediate AND Normal THEN VeryDesirable
- Rule 6. IF Intermediate AND Difficult THEN Undesirable
- Rule 7. IF Advanced AND Easy THEN Undesirable
- Rule 8. IF Advanced AND Normal THEN Desirable
- Rule 9. IF Advanced AND Difficult THEN VeryDesirable

4 Fuzzy Inference

Fuzzy inference follows these steps:

1. For each rule,
    a. For each antecedent, calculate the DOM of the input data.
    b. Calculate the rule's inferred conclusion based upon the values determined in 1a.
2. Combine all the inferred conclusions into a single conclusion (a fuzzy set).
3. For crisp values, the conclusion from 2 must be defuzzified.

To facilitate comprehension, let's now work through these steps using the rules we have created for some crisp input values. Let's say the proficiency level is 80 and the difficulty of a system response is 90. The DOM of the value 80 to the set Advanced is 0.33. The DOM of the value 90 in the set Difficult is 0.8. The AND operator results in the minimum of these values so the inferred conclusion for Rule 9 is VeryDesirable = 0.33. To spare a lot of repetition the inferred results for all the rules are summarized by the matrix shown in Fig. 3. Note that VeryDesirable has fired twice with the degrees 0.2 and 0.33. Desirable has fired once to a degree of 0.2, and Undesirable has fired once to a degree of 0.67. One way to think of these values is as confidence levels. But what conclusion can be inferred for VeryDesirable, which has fired twice? The two most popular are bounded sum and maximum value. We prefer to OR the values together, which in this example results in a confidence for VeryDesirable of 0.33. These results are then used to clip the membership function of Desirability.

	Beginner	Intermediate	Advanced
Easy	VeryDesirable 0	Desirable 0	Undesirable 0
Normal	Undesirable 0	VeryDesirable 0.2	Desirable 0.2
Difficult	Undesirable 0	Undesirable 0.67	VeryDesirable 0.33

Fig. 3. Fuzzy associative matrix (FAM) for proficiency level = 80 and difficulty = difficult. The shaded cells highlight rules that have fired

Now that we have a composite fuzzy set representing the inferred conclusion of all the rules in the rule base, it is time to convert this output set into a single crisp value. This is achieved by a process called defuzzification. Among many techniques for doing this, we use the average of maxima (MaxAv) method. The MaxAv defuzzification method scales the average of maxima of each consequent by its confidence and takes the average, like so:

$$\text{Crisp value} = \frac{\sum \text{average of maxima} \times \text{confidence}}{\sum \text{confidence}} \quad (2)$$

The values of the average of maxima of the sets are summarized in Table 1.

Table 1. The average of maxima

Set	Average of maxima	Confidence
Undesirable	12.5	0.67
Desirable	50	0.2
VeryDesirable	87.5	0.33

Plugging these values into the equation gives the desirability as a crisp value:

$$\text{Desirability} = \frac{12.5 \times 0.67 + 50 \times 0.2 + 87.5 \times 0.33}{0.67 + 0.2 + 0.33} = 39.375 \quad (3)$$

If this process is repeated for each possible system responses, it is a simple matter to select the one with the highest desirability score to be the best system response.

5 Conclusion

This paper presents the ongoing research on the fuzzy logic-based approach to modeling foreign language tutors' conversation strategies that help learners to achieve communicative ability effectively. By modeling and utilizing human tutor's conversation strategy, our system is better able to select the most appropriate system response in accordance with the learner's proficiency level. Our future work includes adding more expert knowledge to incrementally improve the performance and conducting experiments to measure the real effectiveness.

Acknowledgement

This research was supported by the Web-Scale NLP Theme Program funded by Microsoft Research Asia.

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