# GLMP for Automatic Assessment of DFS Algorithm Learning[1]


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## ABSTRACT

We describe how to use a Granular Linguistic Model of a Phenomenon (GLMP) to assess e-learning processes. We apply this technique to evaluate algorithm learning using the GRAPHs learning environment.



## Categories and Subject Descriptors

I.2.3 [**Artificial Intelligence**]: Deduction and Theorem Proving - *Answer/reason extraction; Deduction (e.g., natural, rule-based); Inference engines*. K.3.2 [**Computers and Education**]: Computer and Information Science Education – *computer science education.*

## General Terms

Design.

## Keywords

Granular Linguistic Model, Computing with Words and Perceptions, Automatic Assessment, Fuzzy Inference.


## 1. INTRODUCTION

Through the use of e-learning environments huge amounts of data can be output about a learning process. Nevertheless, this information has to be interpreted and represented in a practical way to arrive at a sound assessment that is not confined to merely counting mistakes. This includes establishing relationships between the available data and also providing instructive linguistic descriptions about learning evolution. Currently, only human experts are capable of making such assessments. Also, as e-learning sessions grow in complexity, it becomes more necessary, but also harder, to automate this assessment task. Our goal is to create a computational model that simulates the instructor's reasoning and generates an enlightening learning evolution report in natural language.

## 2. DESIGN OF A GLMP

Here, we have used a GLMP [2] to model the learning process of the depth-first search (DFS) algorithm. GLMPs are hierarchical structures used to organize and process data. In GLMPs, each of the elements in one level, which we call computational perceptions, will be a summary of a number of elements from lower levels. The information will be expressed in more or less detail depending on its position in the structure, where the bottom level will represent the finer-grained information. A GLMP aims to manage large quantities of information, which is grouped and summarized by means of computing with words techniques to extract the most important points.

In this GLMP, the input data are the correct and incorrect response rates in each algorithm step. These data are extracted from the interaction log generated by GRAPHs [1]. Figure 1 is a diagram of the GLMP that linguistically describes the proficiency level acquired by a student in the DFS algorithm learning process. This diagram shows the design of how information about the learning of key aspects of the algorithm is extracted from the available data. These partial summaries will be used to find out the final proficiency level acquired. The GLMP will output a numerical grade explained by a natural language report containing both the partial summaries and the final summary.

Each of the level-1 perceptions is composed of a numerical input variable and a linguistic output variable, represented by a vector that denotes the fuzzyfication of the input with respect to a number of linguistic labels.

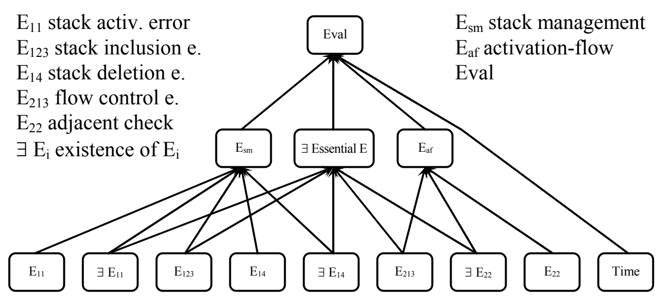


**Figure 1. GLMP of the level of proficiency acquired by the student**

Higher-level perceptions, output by a fuzzy inference engine, summarize the information from the lower levels. *Eval* perception is defuzzyfied using a weighted average to produce the numerical grade, and linguistic templates are enabled to express the summaries in natural language. For example, *in this simulation, the stack activation error is small..., the flow control error is acceptable..., the adjacent management error is low, the error in essential steps is not null... and the algorithm simulation time is adequate. Thus, the correctness level acquired by the student is very good and the grade attained is 7.4.*

## 3. CONCLUSION

Using computing with words and perceptions, the designed GLMP is able to emulate an expert instructor and automatically generates a natural language assessment report.


## 4. REFERENCES

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