The Design Rationale of Logic-Muse, an ITS for Logical Reasoning in Multiple Contexts

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Abstract. This paper describes the design and implementation of Logic-Muse, an Intelligent Tutoring System (ITS) that helps learners develop reasoning skills on various contents. The study was conducted jointly with the active participation of logicians and reasoning psychologists. Logic-Muse's current version was internally validated. It is focused on propositional logic and supports learners reasoning in a wide range of situations.

Keywords: Reasoning skills · Cognitive diagnosis · ITS

1 Introduction

Many experiments in cognitive science have shown that systematic errors are common in human logical reasoning (Evans et al. 1993). A number of questions are raised when looking for solutions to improve human skills in this domain: What are the phenomena involved in learning logical reasoning skills? Does modeling allow to elicit them? What are the strategies to foster the development of reasoning skills? What are the characteristics of an ITS to support this learning?

Answers cannot be brought to these questions without an appropriate elicitation and understanding of the knowledge behind logical reasoning and errors made by humans. An active involvement of stakeholder experts is required including ITS experts, logicians, psychologists of reasoning, and educational professionals in logic.

The goal is to study the fundamentals of learning logical reasoning skills, to understand the difficulties in such learning and to build an ITS that can detect, diagnose and correct reasoning errors in various situations.

2 Logical Reasoning and ITS: Theoretical Background

Motivations: Logical reasoning plays an important role in our reasoning mechanisms. As a cognitive machine struggling to survive, humans tend to make systematic errors in their logical reasoning. Learning to think logically is to learn the valid laws and procedures of logical reasoning inseparably.

C. Conati et al. (Eds.): AIED 2015, LNAI 9112, pp. 738–742, 2015.
DOI: 10.1007/978-3-319-19773-9_105

Need of Technological Support: Although many ITSs have been developed since the early 70s, few dealt with logic as a learning domain (Lesta & Yacef 2002, Barnes & Stamper 2010, Tchetagni et al. 2007). Existing systems are limited in terms of strong semantic grounding in explicit reasoning knowledge structures or lack of metacognitive support in reasoning skills learning. Some eLearning tools for logic also exist but fail to explicitly encode the reasoning knowledge.

Multiple Standpoints on Reasoning Learning: It is worth noting that none of the systems previously mentioned uses the standpoint of dual processes, nor our correctionist theory of learning. In fact, the theoretical standpoint used in the development of Logic-Muse is correctionist in the sense that learning to reason is learning to correct creative inferences, so that our capacity for the prediction of events improves (Robert, 2009). Integrating an explicit catalog of reasoning errors in Logic-Muse and developing effective services to detect and address errors patterns in learner reasoning is our way to support this standpoint. Moreover, dual processes of inference (Stanovich 2011) is another standpoint of Logic-Muse from which, to learn logic and to become logically more competent is to recognize type 1 processes (spontaneous) and their fallacies, to learn how to inhibit them and to learn the type 2 processes that should be used instead. This standpoint is implemented in Logic-Muse through its capability to demarcate type 1 from type 2 processes.

3 Participatory Design and Implementation of Logic-Muse

Specifying Propositional Logic Semantics and Procedural Memories. The participatory design of each component of the expert module was carefully carried out in the team. First, we studied the propositional logic domain and came up with a thorough specification of all concepts related to it, which led to a formal ontology model. The ontology was then validated in another round with the logician experts.

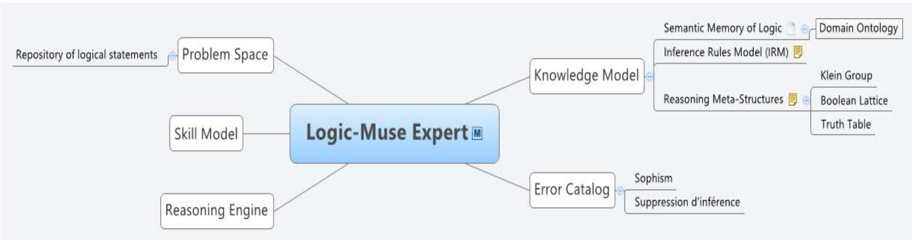

Fig. 1. Logic-Muse Expert Component

Multiple Reasoning Situations. Reasoning is not an absolute process. Many studies have shown that reasoners give different conclusions for formally identical inferences that only differ in premise content. For example, drawing the *modus ponendo ponens* (*MPP*) inference rule– to conclude "Q is true" from the premises "If P then Q, P is true"- in a given situation doesn't mean that it will be drawn in another. Our experts identified three main classes of reasoning situations, given the nature of the content:

Concrete, Contrary-to-fact and Abstract. Each class was refined into two sub-classes (e.g. *Concrete with Few Alternatives* (CFA); *Concrete with Many Alternatives* (CMA), *Formal, Abstract*). Therefore, one can clearly be evaluated as skilled on MPP in a CFA content but fails to be in CMA. This claim is supported by the results of many studies carried out by our team members (Brisson et al, 2014).

This reasoning content categorization not only provides a framework for classifying reasoning skills, but also a way to organized reasoning learning activities (or items). Because we focused on three reasoning mode (disjunction, implication and incompatibility) each having four inference rules, Logic-Muse for the propositional logic is made of 3x4x6 (72) reasoning skills. This includes 36 valid inferences rules (making the Inference Rule Model) as depicted in figure 1, and 36 invalid inferences (the error catalog). Our experts defined two types of reasoning errors: fallacies and suppressions of valid inferences. Fallacies are clear logical reasoning errors in which the reasoner fails to recognise the uncertainty of a conclusion. For example, the affirmation of the consequent inference – to conclude "P is true" from the premises "If P then Q, Q is true" is a fallacious one, while the logical answer is to be uncertain about this conclusion. Suppressions of valid inferences occur when the reasoner is incorrectly uncertain about a logical conclusion.

The Learner Model. The learner model has several dimensions including an episodic memory which keeps track of all the exercises performed by the learner. The cognitive model basically represents the state of the learner's knowledge. It is a Bayesian network where influence relationships between nodes (reasoning skills) as well as prior probabilities are provided by the experts. Some nodes are directly connected to the reasoning activities (items) while others refer to reasoning errors. The model can be opened on many perspectives (e.g. Mastered level of reasoning skills, etc.).

Tutoring Feedback. Together with the experts, we specified the tutor interventions when errors are detected and the way the tutor will help to correct it. For instance, in a simple syllogism problem in causal concrete situation with many alternatives (CMA content), if the learner decides not to conclude, the system should check if this is because he or she didn't considered other possible alternatives of the subject mentioned in the premises. Then, the tutor can ask for the reason of that inference suppression. If it appears that it is clearly due to that fact, the tutor will tackle the learner by making him/her aware about the existence of other alternatives that can hold. Here is an example of intervention rule (see its execution in figure 2):

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IF ReasoningSituation is CMA
And Reasoning problem is Simple Syllogism
And the Inference type is the Affirming the Consequent fallacy
And the Learner Abstain
  Prompt the learner on the reasons of his abstain
  IF the reason is not link to the existence of possible alternative,
      It is a fallacy; Prompt the learner and Suggest the alternatives
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The experts described such an intervention rule for each possible error in respect to the situation in which the reasoning is carrying out. Furthermore, one of our goals was to set up some metacognitive support to the learner. We carefully examine logical meta-structures (e.g. Boolean lattice) and analyse how they could be used to provide visual feedback to the learner so that she/he can reflect on her/his reasoning errors.

The Learning Environment. Logic-Muse tutoring system provides four levels of learning activity to the learner organized into four groups of learning services (figure 2): 1) Domain exploration service using the domain ontology; 2) General exercises on basic logic concepts including well-formed formulas (wff) checking, truth table building, etc. 3) Reasoning procedural learning service (e.g. syllogism and polysyllogism problem solving), which includes an automatic problem generator; some questions allow a limited answering time of just a few seconds, so that the spontaneous character of type 1 answers will be more easily determined while others invite the participants to briefly describe the procedure used to answer, so that it can help for the interpretation of the results and can reveal procedural differences between type 1 and type 2 answers; 4) Metacognitive support through logical meta-structure visualization.

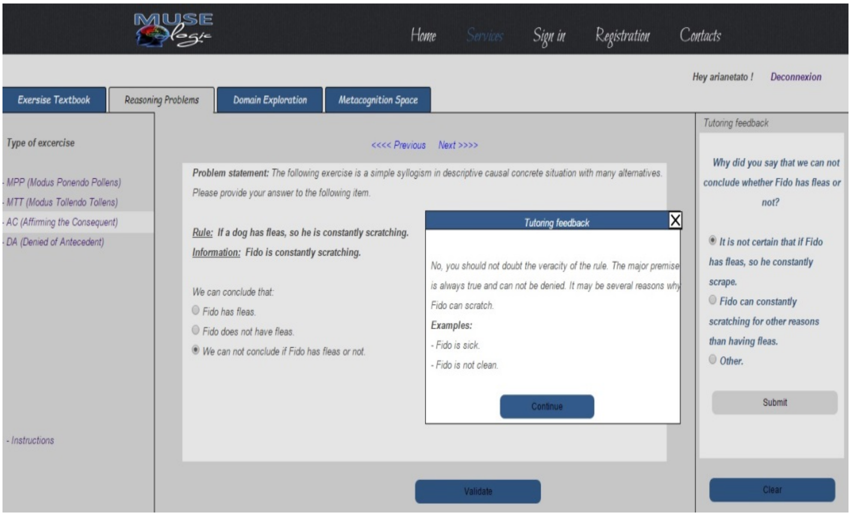

Fig. 2. Logic-Muse Reasoning Service

4 Conclusion

The Logic-Muse development is a multidisciplinary initiative which enabled us to enroll in a perspective of participatory design that has led to a set of valid components of logical reasoning implemented within an ITS. This paper was intended to share this unique experience with the reader. We presented the process undertaken to define and explained the reference components used in Logic-Muse. The system has been implemented for propositional logic with a fully functional and valid (internal) Expert module (which demonstrates all valid reasoning skills and detects and explains reasoning errors) plus a Tutor that integrates a reasoning problem generator in various contexts. The next step is the external evaluation of this first version of Logic-Muse in a logic course offered to first year students at the University of Quebec at Montreal.

Acknowledgement. We'd like to thank all Logic-Muse team members (J. Bourdeau, P. Kissok, A. Tato, M. Bélanger, A. Cloutier, J-B. Plouhinec, H. Markovits & M. Sainte-Marie) for their contributions.

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