What Does It Mean to Provide the Right Level of Support During Tutorial Dialogue?

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Abstract. We describe and illustrate factors that specify what it means for a tutor to provide different "levels of support", based on our analyses of models of the levels of support provided during human tutoring and teacher-led small group work. We then show how we used these factors to implement contingent scaffolding in a tutorial dialogue system for physics.

Keywords: Natural-language tutoring systems, Scaffolding, Student modeling.

1 Introduction

Studies of human tutoring and teacher guidance of small group work have shown that the extent to which support is contingent upon (i.e., tailored to) students' understanding and performance predicts achievement [e.g., 1, 2, 3]. These findings have prompted educators and educational psychologists to operationalize "contingent scaffolding" in order to effectively support students during classroom instruction, human tutoring, and interactions with an automated tutor in tutorial dialogue systems. Achieving this aim requires specifying what it means to provide the *right level of support* (LOS) to a student, at just the right time.

We addressed this question in the process of developing Rimac, a tutorial dialogue system designed to enhance students' conceptual understanding of physics [e.g., 4]. Rimac engages students in reflective dialogues after they have solved a physics problem on paper and have watched an annotated video of a correct solution. Rimac's dialogues are developed using an authoring framework called *Knowledge Construction Dialogues* (KCDs), which engage students in a series of carefully ordered questions known as a *Directed Line of Reasoning* (DLR) [5]. To our knowledge, Rimac is the only tutorial dialogue system that implements a student modeling engine that drives decisions about what content to address next during a dialogue and how to discuss focal content—that is, through which scaffolding strategies and at what level of support? These decisions depend on the student model's assessment of the student's understanding of the knowledge components associated with each step of a DLR.

Table 1. A Sample Level of Support Framework*

TDc1 *Lowest control—teacher:* • Provides no new content • Elicits an elaborate response • Asks a broad and open question	**TDc4** *High control—teacher:* • Provides new content • Elicits a response • Gives a hint or suggestive question
TDc2 *Low control—teacher:* • Provides no new content • Elicits an elaborate response, mostly for an elaboration or explanation • Asks a more detailed but still open question	**TDc5** *Highest control—teacher:* • Provides new content • Elicits no response • Gives an explanation or the answer to a question
TDc3 *Medium control—teacher:* • Provides new content • Elicits a short response (yes/no or choice)	*adapted from van de Pol (2012) TDc = degree of teacher control

In order to specify decision rules that can tailor the support provided at a particular step during a DLR to the student model's predictions, we examined prior research aimed at modeling the levels of support provided during tutoring and teacher-guided small group work [6]. This poster illustrates factors that operationalize "levels of support", shows how we incorporated these factors into rules to drive contingent scaffolding in Rimac, and describes an in-progress classroom study to evaluate the tutor.

2 Factors that Adjust Support in Questions and Feedback

Several frameworks have been developed to model the different levels of support provided in tutors' (and teachers') questions and feedback on students' responses. It is common for LOS framework developers to characterize their model in terms of broad dimensions like different "degrees of tutor control" and "degrees of cognitive complexity" [e.g., 2, 3, 7], such as the one posited by van de Pol et al. (2014) shown in Table 1. However, a closer look at the description of each level in a given framework revealed that tutor/teacher questions and feedback vary according to more specific factors, which can be incorporated within dialogue decision rules. For example, in van de Pol et al.'s LOS framework (Table 1), the "degree of teacher control" (TDc) depends on factors such as *response length* (e.g., yes/no or choice of options, versus elaborate response), *how much information the teacher provides* in a question or feedback, and a question's *level of abstraction*—for example, does the question provide a "hint or suggestive question" or more directive information?

Given the quantitative nature of our domain, we further specified *level of abstraction* in terms of factors such as *whether to refer to variables in abstract terms or in terms of the problem* (e.g., "velocity" vs. "velocity of the bicycle"), *whether to provide the name of a law or an equation* (e.g., $F_{net} = m * a$, vs. Newton's Second Law), and *whether to define the symbols in an equation* (e.g., v = velocity). We then used these factors to specify decision rules to adapt the tutor's support to students' knowledge level, according to their student model. For example, in Table 2, the rule for providing a high LOS (left column) would produce a question like, "Using Newton's Second Law ($F_{net} = m * a$) and knowing that the net force on the man in the elevator is zero, let me ask you about the man's acceleration. In which direction does the man's acceleration point"? In contrast, the rule for providing a low LOS (right column) would produce, "In which direction does the acceleration point?"

Table 2. Sample decision rules for question asking (differences *italicized*)

If the student's probability of answering the next question correctly is *low*:	**If the student's probability of answering the next question correctly is *high*:**
State quantities with reference to the problem	Reference quantities in *abstract terms*
Provide a hint or other type of support	*Do not provide* a hint or other type of support
Provide the name of the law/definition in equation form	*Do not provide* the name of the law or definition
Do not define symbols and/or variables	Do not define symbols and/or variables
Do not ask the question again if the response is incorrect	*Re-ask the question* if the response is incorrect

3 Conclusion

Our review of level of support frameworks revealed that broad dimensions such as "different degrees of tutor control" are too imprecise to guide the design of adaptive support in a tutorial dialogue system. We therefore dug deeper into these frameworks and uncovered factors that informed specification of decision rules to drive contingent scaffolding in Rimac. An in-progress evaluation of the tutor at several high schools in the Pittsburgh PA area, U.S.A., compares this dynamically updated, student model and decision rule-driven version of Rimac with a prior version that provides a static, less adaptive form of scaffolding based on students' pretest scores [4].

Acknowledgements. This research, which was supported by the Institute of Educational Sciences, U.S. Department of Education, through Grant R305A150155 to the University of Pittsburgh. The opinions expressed are those of the authors.

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