Chapter V

Using Bayesian Networks for Student Modeling

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ABSTRACT

This chapter purveys an account of Bayesian networks-related technologies for modeling students in intelligent tutoring systems. Uncertainty exists ubiquitously when we infer students’ internal status, for example, learning needs and emotion, from their external behavior, for example, responses to test items and explorative actions. Bayesian networks offer a mathematically sound mechanism for representing and reasoning about students under uncertainty. This chapter consists of five sections, and commences with a brief overview of intelligent tutoring systems, emphasizing the needs for uncertain reasoning. A succinct survey of Bayesian networks for student modeling is provided in Bayesian Networks, and we go through an example of applying Bayesian networks and mutual information to item selection in computerized adaptive testing in Applications to Student Models. We then touch upon influence diagrams and dynamic Bayesian networks for educational applications in More Graphical Models, and wrap up the chapter with an outlook and discussion for this research direction.

COMPUTER-ASSISTED LEARNING

In the past couple of decades, both the research literature and the real world have seen flourishing studies and applications of computer-assisted learning. (We use computer-assisted learning to refer to computer-assisted instruction as well.) The increasing capabilities and decreasing prices of personal computers have created an affordable environment for individualized computer-assisted learning. The explosive expansion of the Internet not only provides a rich source of information but also nourishes the studies and applications of Web-based learning systems. To give a few examples, Conati, Gertner, and VanLehn (2002) have studied computer-assisted learning of Newtonian Physics; Mislevy and Gitomer (1996) have investigated the techniques for computer-assisted learning.
of the troubleshooting of hydraulics systems in aircraft; Mitrovic, Martin, and Mayo (2002) have designed systems for teaching the SQL database language; Horvitz, Breese, Heckerman, Hovel, and Rommelse (1998) look into the possibilities of assisting users of Microsoft Excel with software agents; Anderson et al. have developed a system for learning LISP programming (Anderson, Boyle, Corbett, & Lewis, 1990) and high school mathematics (Anderson, Douglass, & Qin, 2004); Virvou, Maras, and Tsiriga (2000) construct systems for assisting the learning of the passive voice in English; and Brusilovsky et al. have discussed issues such as course sequencing (Brusilovsky & Vassileva, 2003) for Web-based education (Brusilovsky, Schwarz, & Weber, 1996).

**Student Modeling for Computer-Assisted Learning**

In order to build the software infrastructure that supports computer-assisted learning, researchers are employing techniques for modeling important participants in the learning process. Major participants in learning activities include students, instructors, and the targeted learning/teaching objects. Researchers have studied issues ranging from course material preparation to the eventual course material delivery to students, and have taken diverse approaches to modeling and decomposing the whole learning process. For instance, Virvou and Moundridou (2001) consider student and instructor models in their design of authoring tools; Mislevy, Steinberg, and Almond (2003) set up student, task, and evidence models for the assessment task; and Brusilovsky et al. (1996) places emphasis on making intelligent tutoring systems (ITSs) available on the Web.

Despite the differences in the ITS architectures, a significant portion of the literature focuses on student modeling. This is barely surprising. Students are the major, if not the most important, users of any computer-assisted learning systems, so inferring about the students for choosing appropriate learning activities is a key issue for system designers. Since learning is a cognitive process, modeling students’ learning process will have to explicitly or implicitly construct some artificially assembled images of the students’ cognition process (Anderson et al., 1990). For instance, Anderson et al. (1990, 1992, 2004) base much of their work on theories of cognition, and by working on computer-assisted learning systems, they examine and refine such cognitive theories as ACT* and ACT-R at the same time. They show how students apply and learn knowledge with performance and learning models, respectively. Their systems then apply the model and knowledge tracing techniques in monitoring students’ progresses in the problem domains. Similarly, Brusilovsky (1994) proposes overlay student, error, and genetic models for demonstrating different aspects of student performance. Overlay student models record students’ competence in different areas of the learning targets, error models provide an explanation of why students make mistakes, and genetic models capture student performances in executing procedural knowledge.

Besides comparing student models based on how theories of cognition are employed, we find previous approaches differ in how they link students’ external performance with their internal state of knowledge. On the one hand, we can assume that there is a one-to-one deterministic relationship, and build student models with either propositional or first-order logics. From here, it is natural to treat the problems of diagnosing students’ deficiency in knowledge as the problems of identifying buggy designs in electronic systems (de Kleer & Williams, 1987). For instance, Kono, Ikeda, and Mizoguchi (1994) build their work on de Kleer’s truth maintenance system (de Kleer, 1986). Such logic-based approaches face the challenges that students may not perform consistently over time and under different contexts, and researchers have to employ such techniques as nonmonotonic reasoning in their systems. On the other hand, we can accept that inconsistency is part of nature,