Chapter 10
Adaptive Intelligent Learning Environments

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Introduction

Adaptive Intelligent Learning Environments (AILE) are computer systems that help people to learn in a personalized manner. They build a model of the learner and use this model for selecting, scheduling or recommending relevant learning material, and for keeping the learner motivated and engaged. AILE has been an active research area since the 1970s, and is considered a major enabling technology for self-directed, collaborative and informal learning.

SCHOLAR (Carbonell, 1970) was one of the first intelligent teaching programs, which taught South American geography by engaging in a dialogue with the learner. The system remembered the concepts that had already been covered and tried to progress adaptively and gradually through the curriculum. SCHOLAR is considered the first ITS. Since then, the field has progressed significantly, embracing a range of intelligent techniques and covering a huge variety of domains and learning contexts.

Intelligent Tutoring Systems (ITS) and Adaptive Educational Hypermedia (AEH) are the two most significant types of learning systems that have evolved into the broader class of AILE. The ITS community focuses on the use of artificial intelligent techniques in tutoring applications. Initially, these applications were

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stand-alone, desktop applications, but nowadays most ITS systems are web-based. The AEH community emerged as a sub-area of the adaptive hypermedia community, which focuses on user modelling and personalization of web-based systems. Nowadays, both research streams have a significant overlap in the platforms, learning contexts and adaptation mechanisms that they develop.

This chapter will briefly outline ITSs and AEH systems, followed by a short description of the main concepts and technologies that they share. Further, we provide an overview of past and current trends and topics in the field, as identified in recent review articles.

ITS: Intelligent Tutoring Systems

ITSs are computer applications that support highly interactive, personalized, tutor-like instruction. The goal of an ITS is to simulate an individual tutor who closely follows students' progress, understands their current strengths and difficulties, and provides timely feedback in the form of hints and explanations.

In order to do so, ITSs rely on a range of technologies from the fields of Artificial Intelligence and Cognitive Psychology. ITSs maintain several rigorous models that represent the knowledge (or expertise) necessary for performing meaningful tutoring:

- a *domain model* defines a set of elementary knowledge components (e.g. concepts) that a student needs to master;
- a *learner model* (usually a subset—or an overlay—of the domain model) helps an ITS to keep track of what the learner knows;
- a *tutoring model* formalizes the necessary pedagogical principles and strategies to make intelligent decisions on how to best maintain the tutoring process.
- an *interface model* controls the interaction of a learner with an ITS.

Over the 40 years of ITS history, numerous systems implementing a multitude of techniques and approaches have been developed; notable examples include SHERLOCK (Lajoie & Lesgold, 1989), SQL-Tutor (Mitrovic & Ohlsson, 1999) and ActiveMath (Melis, Goguadze, Homik, Ullrich, & Winterstein, 2006).

As a representative example, the Andes system (Schulze, Shelby, Treacy, Wintersgill, Vanlehn, & Gertner, 2000) *(our first selected paper)* was designed to help students solve learning problems in the domain of classical physics. Every problem was represented as a Bayesian Network of rules that students had to master in order to solve it. As the students progressed through the problem, Andes traced their actions and updated the mastery probabilities of the corresponding rules. Andes provided students with instructional feedback and on-demand help, and selected the next problem based on the state of the learner model.

AEH: Adaptive Educational Hypermedia Systems

AILEs have been a major focus in the adaptive hypermedia community (Brusilovsky, 2001), which aims to provide alternatives for the 'one-size-fits-all' approach of traditional web-based systems. Early AEH systems mainly used hand-written rules and models for adaptive behaviour, but soon artificial intelligence techniques from the intelligent tutoring community and the user modelling community were adopted.

Traditional AEH personalization techniques are adaptive presentation and adaptive navigation (Brusilovsky, 2001). Adaptive presentation aims to provide relevant content by hiding, adding, annotating or modifying text fragments or by customizing multimedia material. Adaptive navigation aims to provide personalized guidance through learning material by suggesting next steps, offering personalized overviews and menus, or by hiding, adding, annotating or modifying links between the pages of an AEH system.

One of the earliest AEH systems is ELM-ART (Weber & Brusilovsky, 2001). Originally an interactive textbook, ELM-ART featured adaptive curriculum sequencing, tests and exercises. The 'traffic light' metaphor of ELM-ART—the color of a link indicates whether the learner is advised to follow it or not—has been adopted by many other systems. Another well-known AEH system is AHA! (De Bra, Aerts, Smits, & Stash, 2002) *(our second selected paper)*, which uses a dynamic overlay model where actions (e.g., reading about a concept) are propagated to related concepts: for example, reading about a particular Belgian beer also increases knowledge on Belgian beers in general.

Learner Modeling

A particular characteristic of any AILE is the techniques that it uses for eliciting, maintaining and using models of the learners and/or their contexts. In this section, we discuss various approaches towards learner and context modelling.

Modeling Knowledge, Cognition and Metacognition

Parameters defining the learner's cognitive state have always been the main factors influencing the adaptation of the learning process. Since the very beginning of AILEs, learner models included characteristics such as knowledge, background, goals and tasks. Early AEH systems like ELM-ART inferred learner knowledge by observing which pages learners have read and which exercises they have (or have not) solved. The ITS community used more theory-based approaches, such as the ACT-R cognitive architecture (Corbett & Anderson, 1995), which provides a computational framework for simulating how humans acquire, process and apply knowledge.

Besides domain knowledge and abilities, there exists another set of general and strategic skills that help us to regulate how we learn, process information and perform instructional tasks. This dimension of our cognitive apparatus is called *metacognition* (cognition about cognition). It includes components such as self-assessment and reflection, planning and monitoring, general problem-solving and help-seeking strategies, and the ability to self-explain your solution and self-regulate your learning. Several AILEs addressing the metacognitive traits of their users were designed. For example, Roll, Aleven, McLaren, and Koedinger (2007) presented an ITS that modelled students' help seeking behaviour and tried to teach them better strategies for soliciting instructional feedback from the system.

Beyond Cognition: Emotion, Affect and Context

Good human tutors adapt their teaching strategies not only to the learners' knowledge, but also to their emotional states and the context in which the learning takes place.

Most affective models are based on established theories from the field of psychology. But how does one measure emotion? Conati and Maclaren (2009) *(our third selected paper)* investigated two approaches. First, they created a probabilistic model that derives the learner's emotional state from the interaction with the system: does the learner 'have fun' or does the learner 'avoid failing'? Second, they used physiological sensors (heart rate, skin conductance, electromyogram) as a source for affective evidence. The approaches have been evaluated extensively, with both direct and indirect observational methods.

Emotion and affect are not (yet) part of a typical AILE's learner model. Measuring and modelling learner's emotional states is inherently difficult, and it is yet not clear how studies as described above can be generalized to other contexts.

Apart from the learner, the learner *context* is increasingly used as a basis for personalization. Adaptation to the learner's environment (such as time, location, velocity, noise level) and the device characteristics (like input devices, screen resolution, bandwidth) has been subject of various research projects.

Open Learner Modeling

Self (1988) suggested to 'make the contents of the student model open to the student, in order to provoke the student to reflect upon its contents and to remove all pretence that the ITS has a perfect understanding of the student.' An early, simple implementation of this idea was the 'skillometer' (Corbett, Anderson, Carver, & Brancolini, 1994), which showed a set of progress bars to inform the learners about the current learning state.

Since then, researchers identified several benefits of allowing learners to see their learner models, including raising awareness, promoting reflection, helping learners to plan and monitor their learning, facilitating collaboration and competition among the learners, aiding navigation through learning material, fostering independent learning, and—in some cases—improving the accuracy of leaner modelling. *Scrutable* learner models (Kay, 2006) form a specific category of open learner models that allow learners to inspect and edit the observations, inferences and assumptions that a system holds about them.

Emerging Trends in AILE

Currently, instead of hand-written rules and formal strategies, many systems use statistical models that rely on machine learning and data mining techniques for discovering learner knowledge and interests. This change started in the early 2000s (Brusilovsky, 2001), and later research on Recommender Systems and Web Usage Mining has strengthened the trend. Bayesian networks were one of the first machine learning techniques that were adopted (e.g. Conati & Maclaren 2009). Currently, many other techniques are used as well, including clustering, classification, collaborative filtering and association rule mining (Romero, Ventura, & Garca, 2008) *(our fourth selected paper)*.

Recommendation—the most popular commercial personalization technology—has found a rather limited use in e-learning thus far; in contrast to products in online stores, it is not sufficient to recommend material 'that other learners like'. As argued by Drachsler, Hummel, and Koper (2008), they should also take into account the current learning goal, prior knowledge and other learner characteristics. Therefore, it remains a challenge to design algorithms and interfaces that take these aspects into account.

The increasing importance of collaborative, self-directed and lifelong learning has led to a new type of adaptive systems: Personal Learning Environments (PLEs) (Gillet, Law, & Chatterjee, 2010). PLEs are aggregations (or mash-ups) of standard or dedicated (Web 2.0) tools for learning, collaboration and productivity. An important difference with traditional adaptive systems is the focus on personalized *functionality* rather than personalized content. Current research topics include the nature of self-regulated and community based learning, suitable recommendation techniques, inter-operability standards and in particular the usability of PLEs.

Concluding Remarks and Future Perspectives

The techniques and approaches for Adaptive Intelligent Learning Environments have changed considerably in the past few decades. Traditional ITSs provided adaptive sequencing of curricula and problem solving support through adaptive feedback and scaffolding. With the advent of the web, adaptive hypermedia techniques became increasingly popular as well.

The models and components constituting the 'intelligence' of AILEs used to be primarily based on formal rules and theories. Recently, adopting data-driven, empirical, and collaborative techniques has become a popular trend in AILE design. In addition, techniques for addressing the learners' metacognitive skills and affective states gain a lot of attention. Finally, the focus of AILEs shifts more and more from formal education contexts towards supporting self-regulated and informal learning.

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