Towards Requirements for Intelligent Mentoring Systems

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ABSTRACT

The raising demands on qualification increase the importance of technology as a facilitator in the educational process on the side of both receivers and providers. Beside the cognitive aspects, also metacognitive, emotional and motivational ones play a crucial role in learning. A challenge is to recognize the affective status of participants and react to them accordingly, in order to make the learning experience effective and efficient. Various approaches were investigated and reported in the literature. In order to develop mentoring support at the university level in concrete settings, we researched them and tried to identify the key requirements for our solution. Based on these requirements, we plan to design intelligent knowledge services for scalable mentoring processes.

CCS CONCEPTS

• Applied computing • Education • E-learning

KEYWORDS

Intelligent mentoring systems; Requirements

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1 Introduction

Research and technological progress enables new approaches to the crucial issue: How can we design educational concepts that enable a scalable individual mentoring in the development of competences? Interdisciplinary orientation of such endeavours is a natural demand and was also incorporated in the tech4comp project (tech4comp.de), which focuses on the university study, especially in the areas of mathematics, informatics and educational sciences.

To achieve a common understanding, we use the following description of the concept *mentoring*: "Manifestations of mentoring are very diverse, and they are often associated and confused with other forms of guidance such as coaching and tutoring. While these tend to be quite structured and focused on performance, in mentoring the process is more spontaneous, holistic, and directed by the mentee's needs and interests. The mentee sets the pace of the relationship and thus, the relationship is more complex, reciprocal and oriented to emotions. Mentoring is consistently associated with the idea of a close and safe relationship underpinned by empathy and mutual trust, free of power relationships, where benefits are bidirectional and mutual. Thus, psychosocial and emotional support and mutual understanding are at the core of the mentoring relationship." [18] Our aim is the development of knowledge services for the automatic realization of parts of the individualized mentoring process. This should make the work of mentors more efficient, getting rid of routine tasks and focusing on the essential ones. On the other hand, the mentees should benefit as well, receiving prompt responses to their issues more often. To start with, we review the existing research and try to specify requirements for our intelligent mentoring system.

In the following, we first introduce the related work that we found most relevant in this field. Afterwards, we consider several factors that are typical for mentoring. Based on them and the previous work, we identify various requirements for intelligent mentoring systems that we want to consider for implementation.

2 Related Work

Traditionally, intelligent tutoring systems focused mainly on the cognitive aspects of learning. More recently, also metacognitive, emotional and motivational factors, which are typical for intelligent mentoring systems, were taken into account. Here we introduce several relevant approaches.

2.1 Affect Detection

Efforts to incorporate mentoring features into existing systems build on research on affect detection. Approaches to affect detection can broadly be distinguished into sensor-based and sensor-free affect detection. Sensor-based affect detection relies on sensors to provide data about facial expressions, body posture or physiological features, from which the user's affective state can

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be inferred. Sensor-free affect detection on the other hand uses self-reports or log data about the user's interaction with the system to draw conclusions about learner emotions [12]. Sensor-based systems are more difficult to deploy on a large scale in real-world settings, because not all sensors are affordable and universally available. An exception from this rule are web cameras and microphones, which nowadays are embedded in most mobile computers. Furthermore, sensors may be perceived as intrusive by students and could in the worst case lead to a sense of surveillance.

Fermat, a social educational network that includes an affect-sensitive intelligent tutoring system, uses data captured by the web camera to infer student emotions from facial features. The system does not focus on learning-centered emotions, but detects basic emotions such as joy or anger. Its responses to student's affect are based on the expertise of human teachers, but do not consider specific theories on the relationship between learning and affective states [6]. Other systems (e.g. [2, 11]) have based their affective and motivational intelligence on the control-value theory of achievement emotions [17] or the flow theory [16]. Research on affect detection has also led to new models of the dynamics of learning-centered emotions, like the cognitive disequilibrium framework [7, 9, 19].

MathSpring uses effort-based tutoring to act in a cognitively, metacognitively and motivationally intelligent way. It tracks student behavior such as the time spent on previous tasks, the number of errors made and hints requested, and from this data estimates the student's cognitive and metacognitive skills as well as their current affective state. Accordingly, the system offers metacognitive and motivational scaffolds: for example, it may display progress charts that encourage students to reflect on their learning progress, or it may have an animated learning companion praise the student's effort, independent of their success [2]. MathSpring has experimented with both sensor-based and sensor-free methods for affect detection, opting for the latter due to its scalability [2, 21].

AutoTutor, an intelligent tutoring system, in which learners interact in natural language with a virtual agent, has also developed an affect-sensitive version. Affective AutoTutor detects whether a student is bored, confused, frustrated or in a neutral affective state from a combination of facial features, body posture and discourse features. The system reacts to the detected affective state with empathic and motivational feedback and automatically adapts the agent's facial expression and speech prosody to match the feedback. This sensitivity to the students' affect improved the learning for students with lower prior knowledge [8].

2.2 Metacognitive Support

The metacognitive intelligence of machines is generally too limited to allow them to detect high-level cognitive processes and provide direct feedback and advice. Systems that aim to support the learner's metacognitive skills therefore typically adopt a different strategy: they seek to leverage human intelligence via metacognitive prompts [15]. One example is the use of open learner models to prompt students to reflect on their learning progress. MathSpring features such an open learner model in the form of the Student Progress Page, which visualizes students' progress according to topics. The Student Progress Page does not only encourage self-reflection, but also allows students to actively guide the learning process: they can choose between different topics and decide whether they would like to continue where they left off, review what they have done so far or challenge themselves with more difficult problems [2].

MetaTutor is a hypermedia learning environment that tracks and supports self-regulated learning (SRL). It involves setting goals, monitoring the learning progress, evaluating and possibly adapting learning strategies, and requires metacognitive knowledge and skills [22]. MetaTutor allows students to define their own subgoals for a learning session and encourages them to choose between different SRL processes, such as evaluating their knowledge or the relevance of the content to their current subgoal. This allows the system to monitor the student's SRL and increases the student's awareness of these processes. Additionally, virtual agents can adaptively prompt students to perform SRL processes and provide direct feedback on SRL [3]. Studies have found that when learning with MetaTutor, students increasingly engaged in SRL processes of their own accord, even as prompts from virtual agents decreased [5].

2.3 Lifelong Mentoring

Another challenge is to provide mentoring for lifelong learning. Lifelong virtual mentors extend their support beyond a single course, accompanying learners throughout their academic career and beyond. This commitment brings with it new challenges, such as collecting and integrating information from different sources in order to build a lifelong learner model. Systems that are oriented towards long-term career goals often need to assess and promote soft skills like problem-solving and communication [14].

PAL3 aims to guide learners throughout their entire career. It uses long-term learner modeling, also addressing issues such as forgetting. Rather than providing direct tutoring, the platform recommends learning resources to close the learner's skill gaps, and is designed to increase learner motivation and engagement [19]. PAL3 incorporates a variety of learning resources from different sources and provides personalized recommendations based on the learner's career goals and current skill level. This approach is shared by other systems that work towards lifelong mentoring, like the platform MARi [14].

2.4 Prediction

While the previous systems seek to automate the tasks of a mentor, other approaches use artificial intelligence to augment human intelligence and to support human mentors in their work. Models are trained to predict the probability of students failing a course or abandoning their studies. The systems report to students or staff, allowing them to intervene early-on [4]. Depending on the system, the model's predictions may be based on data related to academic performance and engagement as well as demographic data. Predictive models have become part of many learning analytics services, an example being the open-source solution developed by the Open Academic Analytics Initiative [13]. Building on previous work with Course Signals [1], the system prompts staff to contact students at risk and encourages them to join an online support site, thus facilitating the exchange between mentors and mentees. Apart from alerting mentors to students in need of mentoring, the data provided by the system can also serve as a "dialogic tool" [20]: it "act[s] as a 'third-voice' in the conversation", providing additional input, and requires both parties to negotiate a shared understanding of the data.

3 Mentoring Aspects

Various aspects of mentoring have been identified. Here we look at them and consider how they can be supported by technology. During the *consultation*, the mentor listens, reflects problems, questions and thoughts of the mentee and gives recommendations for the further course of action. The advice seekers should make informed decisions. The related requirements include predictions about learning success, recommendations in form of hints and reflection on progress. During the *instruction*, the mentor, as an expert in the specific domain, can explain concepts, clarify contexts and set tasks. In *training*, the mentees exercise what they learned, with the mentor referring to helpful strategies. These activities include requirements like personalized and adaptive explanations, as well as interactive exercises. *Activation* here means arousing interest in further topics. The mentor makes the mentee's strengths visible and encourages him to set goals. *Motivation* can also be stimulated by a reward system. Required are such functionalities as goal setting, planning, reflection (openly viewable learning models), self-evaluation, comments from virtual agents (considering experiences of similar users) and rewards for active behavior. The mentor provides *socio-emotional support* to help with problems affecting the learning process and the personal wellbeing of the mentee, e.g. with even more personal help. Features like affect detection, positive feedback from an animated learning partner and self-reflection are to be considered. *Networking* means that the mentor proposes further learning resources (also experts) to the mentee and points out career prospects. Model solutions would be an *example*. This requires recommendations to close relevant competence gaps and for lifelong learning.

4 Requirements of Intelligent Mentoring Systems

Finally, we summarize the requirements for AI-based knowledge services to support mentoring. We differentiate three phases – preparation, learning process and follow-up, as well as more general requirements. Preparation includes activities like goal setting, self-evaluation, recommendations (to close relevant competence gaps, also from lifelong learning perspective), and planning (to actively shape one's own learning process). The learning process itself can be supported by personalized and adaptive explanations, recommendation of suitable resources, interactive exercises, affect detection, and an animated learning partner (giving positive feedback and affective support). The follow-up phase includes reflection (e.g. openly viewable learning models) and predictions about the learning success. The other requirements refer to adaptations (based on ethnic diversity, cultural self-perception, preferences), communication style (polite and positive, suggestions as questions), experiences of similar users, virtual agents (possible role changes), and rewards (benefits for active behavior).

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