Adaptive Literacy-Aware Integration of Learning Material

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ABSTRACT

The growing amount of available learning material nowadays requires a significant filtering effort by students for problem solving tasks. In addition, the choice of the appropriate type of learning material differs depending on the individual learner's preferences. In this work, we suggest to move from a material-centered to a student- and task-centered approach by integrating and suggesting learning material based on the user's literacy and the context of the task to be completed. Data from social networking platforms may both enrich the available learning material and give insights on the user's preferences, to adequately match material and learner in the given context. Finally, computer-based assessment may give insights on the learner's progress and the proposed study material.

Keywords

Adaptive learning; recommender systems; social media; 21st century literacies; computer-based assessment.

1. INTRODUCTION

Students are often confronted with the challenge of organizing and retrieving documents from a vast collection of learning material, which needs a significant amount of time and which ultimately may lead to an information overload [4]. High-quality resources might even remain undiscovered [19]. As these resources are not limited anymore to static, local files but to the dynamic and widespread content on the Web, including social platforms, high-quality information extraction is increasingly complex [4]. Therefore, multiple, simultaneous and multidirectional information channels need to be consolidated while allowing a fast and more accurate retrieval. In addition, if students are confronted with a problem solving task and need to retrieve related information from learning material, context switches are often needed, which again interrupts their line of thought [10].

We propose to move from a material-centered approach to a student- and task-centered vision. A literacy- and context-aware recommender system would be able to adaptively integrate and suggest cross-curricular learning material to students in problem solving environments. This way, we could avoid cognitive overload caused by context switches and information overload caused by vast resource collections from different sources. Corresponding to the individual user's learning preferences and the context of the task to be realized, data from social platforms could be used to enrich her profile. Finally, computer-based assessment of the use of the suggested learning material for a certain user in a given context may improve the suggestions and provide interesting insights about her learning process and the material itself. Apart from proposing concepts relying on strong, interdisciplinary literature and closely collaborating with the Faculty of Humanities of the University of Luxembourg, this research would be evaluated through field tests and usability studies. As a main use case, we wish to integrate computer programming-related material in Integrated Development Environments (IDE) for development projects.

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2. BACKGROUND & RELATED WORK

Learning management systems (LMS) can provide learning modules, such as SCORM packages, which are usually composed of a static, predefined and finite set of learning material. While permitting dynamic content such as quizzes, they do not adaptively suggest learning material, based on the individual user's learning preferences, from the dynamic and vast set of resources available online. The realization of these intentions requires us to consider many different aspects, which we will now further describe.

Information overload can be reduced, e.g., through recommender systems. Collaborative filtering (CF) may help to predict appropriate, cross-contextual and high-quality learning material based on the experiences of learners with similar interests and behavior [19]. Data sparsity and the cold start problem are inherent limitations of CF, as the quality of recommendations heavily depends on the quality and quantity of the information on user behavior. However, user profiles may sometimes be incoherent, due to a natural variability in their ratings [2]. This increases the lower bound of the recommendation error. Even user profiles with a huge data set can be uninformative, if the data is not reliable [19]. While traditional recommender systems rely on user preferences retrieved explicitly (e.g. through ratings) or implicitly (e.g. by mining behavioral data), hybrid approaches include auxiliary data such as the user's age, gender or cultural background, the item's metadata or the context of use [19]. In addition, user profiles can be enriched through data originating from social platforms [6]. For instance, recommender systems could benefit from likes, friendship relations and tags on Facebook. Even better personalized search results can be achieved when taking into account the evolution of the user profile [9]. Not only the content of social web interactions, but also their freshness is important. This temporal reliability thus relies on both recent and persistent preferences.

Social networks do not only provide information on user preferences, but they are also heavily used by students as a learning support, either for communication (chatting, brainstorming, giving feedback) with peers or sharing and seeking of learning resources. This social literacy may provide students emotional support and foster their creativity [7]. Some rankings even list social platforms like Twitter, YouTube and Facebook significantly higher with respect to popularity as learning tools than traditional LMS like Moodle [15]. In a recent study, while 75% of the students perceived social networks as a useful learning support, almost half of the teachers would not respond to this question, which shows their uncertainty [18].

Targeting individuals through an adaptive learning support may lead to a better performance. Learners' needs, skills, prior experience, pace and literacy should be taken into account [3]. In their seminal 1988 paper, Felder and Silverman identified 32 different learning styles based on 5 dimensions [5]. The UNESCO[1] coined the term *Media & Information Literacy* (MIL), a higher-order thinking skill which encompasses a set of sub-skills to access, utilize and create information and media to improve reflective learning strategies for digital natives through the use of ICT [20]. Active learning can be fostered through learning support that enables experimentation, but current study material often consists of static content [11]. In addition, Adaptive Educational Hypermedia Systems (AEHS) are often seen as an overhead by teachers. Lopez distinguished two types of students [12]. On one hand, there are students who look at the material in a periodic and uniform way to enrich their knowledge and generally do not have issues with the subject. On the other hand, there are students who only look at learning material under pressure before a project deadline, which inherently leads to difficulties in most cases.

An efficient recommender system for learning material should also aggregate interdependent relevance dimensions, such as personal preferences and contextual factors (e.g. timing, task peculiarities) [16]. It is impossible to separate the learner, the learning material and the context [13]. Learning should be holistic rather than fragmented into disciplines [1]. Integrated curricula with connected subjects better represent real world situations, which usually require the whole *frame of reference*. In problem-based learning (PBL), where students learn knowledge through experiences in problem solving tasks, the artificial boundaries between different disciplines, as well as theory and practice, are blurred and higher-order skills are stimulated [1]. This way, interconnections and patterns between learning aspects are better understood by the human brain. However, *domain-general* problem-solving skills are still neglected in many educational systems, although tasks at work are increasingly cross-curricular [8].

Computer-based assessment methods may be used to evaluate these cognitive abilities. For instance, log-file analysis can bring more insights than classical paper-and-pencil assessment, such as time spent on a task, which can be an indicator for student's investment and achievement. Log-file analysis has also been used to detect, for instance, developers' behavior [17] based on interaction data to enhance programming workflows through an adaptive UI [14].

[1] http://www.unesco.org/new/en/communication-and-information/media-development/media-literacy/mil-as-composite-concept/

3. RESEARCH GOALS

The following research questions try to holistically address the main objective of moving from a material-centered to a student- and task-centered vision.

RQ1 How can fine-grained and cross-curricular relations between learning aspects in tasks and the corresponding learning material be established?

The material may come from different sources (e.g., lecture notes, slides, Web 2.0 platforms) and traverse different disciplines. The cross-curricular facet may be beneficial for students who have not seen a certain topic from a basic course considered as a requirement in a more advanced course. For instance, concurrent access on data structures would require basic understanding of multithreading. Integrating learning material at a fine-grained level could foster the divide-and-conquer approach to fully explain a piece of code, from low-level programming language constructs to high-level API interconnections or programming patterns. Different approaches for the relation building could be considered, such as manual, explicitly created annotations by the teacher, semantic metadata (e.g. tags on Stack Overflow questions), hyperlinks and linked data graphs. While this research question is not the most central one, the described aspects are still needed as a framework for the remainder of this project. Already existing approaches will be evaluated and adapted if needed.

RQ2 How can learning material be suggested in a personalized literacy- and context-aware way?

We intend to build a recommender system into a popular IDE to suggest related learning material in development tasks. This way, we want to minimize both the time students spend in resource retrieval and the risk of them overseeing critical material during the browsing process. The recommendations shall be adaptive and aware of the individual user's literacy, learning needs, skills and personal characteristics. For instance, while student A might prefer "classical" learning resources such as books, student B goes for online tutorials or Stack Overflow questions, and student C might fancy YouTube videos. These 21st century literacies shall be taken into account. Collaborative filtering could also be beneficial to predict material suggestions based on users with similar preferences. Those users could already have gone through a curation process of proposed learning material and could thus accelerate and improve the filtering for a new user, indicating how useful a certain resource was to understand a given aspect. Also, past searches from an established user can be reused in different contexts. For instance, a programming language issue could arise again in a more advanced development project, leading the user back to helpful material from former experiences. This however would also need to take user profile evolution into account, as short- and long-term preferences might vary. However, local optima in recommendations should be avoided. From a computer science point of view, going too far into one dimension of learning material could lead into a dead end, if combinations of different learning material types are not considered. From a psychological point of view, a certain, not too disruptive ”surprise effect” could be beneficial, such that the learner discovers new directions and possibilities by thinking outside the box. In addition, the learning process would be less monotonic. Finally, the way the suggested resources are embedded and visualized is also very important, as the material shall be helpful without causing distractions from the task at hand.

RQ3 How may data from social networks be beneficial for the establishment of an accurate user profile?

Social media platforms are widely and frequently used, and the *social login* mechanism allows to authenticate users and authorize the handling of their social networking data on third-party platforms. Depending on the activities and preferences a user states on his profiles, conclusions might be drawn on the user's literacy preferences. For instance, if a user expressed more ”likes” for books than for movies, he might prefer ”traditional” material over Web 2.0 resources. This assumption however would need to be verified. Social data could help our recommender system in the cold start problem. Of course, this is only possible for the subset of users who is reliably active on social media. Otherwise, a questionnaire assessing a user's preferences could inform about an initial user profile.

RQ4 How can the system benefit from computer-based assessment?

Recommender systems are usually improved through machine learning techniques. Assessing how individual or groups of users use the suggested material can give insights about themselves and the learning material in the given context. The frequency of accesses might indicate issues with a certain aspect. The learning material considered helpful by a group of users might eventually indicate to the teacher whether her own lecture notes were appropriate or not. The students' behavior within the system could indicate whether they are *gaming the system* by frequently retrieving material on recurring aspects to see how it works without caring to really learn its functioning, or whether they only occasionally retrieve material to check whether they are on the right track, even though they actually understood the aspect. It is critical to understand what needs to be assessed (user's performance, learning efficiency, workload and frustration, material appropriateness, contextual factors, ...) and how (implicit vs. explicit measures). How can individual assessments be weighted with respect to group-based insights? Shall the assessment be shown to the user, and if so, how can this visualization be achieved in a non-negative way? Shall repetitive accesses for learning material on the same aspect be shown to the user to identify learning issues?

In summary, the main question is to find the right resource at the right time in the right context for the right user, visualized in the right way.

4. PLANNED CONTRIBUTION

The overall objective is to integrate learning material in problem solving environments. In particular, resources related to programming should be suggested within an IDE to improve user experience and learning processes when confronted with a development project. The underlying recommender system shall be literacy- and context-aware, tailored to the user's particular needs and skills. It needs to rely on the relations between learning material as well as the creation and evolution of user profiles based on, among others, social networking preferences. Furthermore, the user experience should be enhanced by allowing the learner to discover different approaches and by visualizing the suggested material in an appropriate way. In addition, computer-based assessment techniques shall enrich the recommender system and give insights both on the learner's progress and on the quality of the available learning material within the given context. We aim at reducing both cognitive and information overload for development projects while improving the learning process in programming-based computer science classes. By providing productive support during the development instead of relying on receptive or reproductive instructions, we want to maximize the learning output. While our main use case focuses on computer programming due to our background, we aim at finding generalizable results with potentially beneficial outcomes for other domains, such as writing poetry or solving math exercises. Analyzing the transferability and applicability of our approach will show the limitations which could appear in ill-structured problem solving tasks.

We are currently still at the initial stages of this project, discovering the opportunities from both a computer science and educational psychology point of view. We aim at providing high quality findings for this interdisciplinary field, based on a thorough literature review, a strong conceptual framework and insightful data from usability studies. As the different research questions described above are holistically interconnected,, it could be beneficial to base the development on agile principles, allowing short development cycles with progressive evaluation. In order to assess the usability of the developed system, it is likely that several empirical studies will need to be carried out, at different stages of our agile development, focussing on different facets as defined by our research questions. We expect that finding the right balance between providing a sufficiently developed prototype at each stage and evaluating its use could indicate early enough whether the conceptual framework is practically useful. These usability studies could be realized in two different settings. On one hand, using our system in class at the University of Luxembourg could demonstrate the performance of our system when used by computer science students which already had their first experiences in development projects and programming in general. On the other hand, using the system at high-school level (*lycée classique*) in Luxembourg would show how helpful it could be when mainly used by novices in programming. However, this would require an introduction to a selected programming language, to give traditional learning material a fair chance in comparison to online tutorials. The Faculty of Humanities of the University of Luxembourg maintains a *Usability Laboratory*[2], supporting interdisciplinary research activities

[2] http://wwwen.uni.lu/recherche/flshase/education_culture_

through state-of-the-art facilities and expert knowledge. Experiments would assess how good the overall recommendations of learning material for individual students and groups of students are, how quickly the system adapts towards the user's literacy and how insightful the computer-based assessment results are with respect to the machine learning of the recommender system and the learning material given by the teacher. The recommender system can benefit from social networking preferences and activities of the users, if they are willing to share this information. In addition, they need to agree that their utilization behavior within the system gets captured and analyzed.

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