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Educational Recommender Systems: An Overview and Guidelines for Further Research and Development

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Abstract

Educational Recommender Systems (ERS) are increasingly used as tools to help students and teachers during the implementation of the learning process. The main difference between ERS and their commercial counterparts is in the pedagogical principles appropriate for the learning and teaching process. The differences in the educational methods used in a variety of educational situations, and their dependence on the field of study, set initial guidelines for ERS design. This paper reviews the evolution of ERS up to the currently achieved level of development and presents the basic techniques used in ERS design and the common problems they encounter in their work. Examples of classification of different ERS, according to their specific characteristics and basic approaches in their work, are presented. Based on this analysis, along with the training and upgrading of the existing algorithms, five specific areas in which future research and development can be expected are defined: construction of universal ERS, ERS intended primarily for teachers, ERS that links student achievements across different courses, ERS which take into account physical distance between students and use of ERS to motivate students to work continuously.

Key words: *educational environment; e-learning; learning outcomes; Web 2.0 tools.*

Introduction

Using recommendations during the analysis of the available facts in the decision-making process is one of the fundamental elements that people apply when making decisions (Jamil & Megias, 2008; Prem & Vikas, 2010). The development of computers and the World Wide Web in the past decades coupled with the consequential increase of the available integrated information has logically imposed the need for designing systems whose main purpose would be to determine the most accurate and meaningful recommendations that would facilitate orientation and enable finding relevant information. In order to satisfy these needs Recommender systems have evolved over the last two decades (Cremones et al., 2011; Gediminas & Tuzhilin, 2005).

A large number of different recommender systems are in operation today. They are based on different approaches and techniques, and the development of new and the improvement of existing systems is a very active area of scientific research (Manouselis et al., 2012). This development is based on the continuing evolution of statistical methods, machine learning, artificial intelligence, data mining, and information retrieval, among others (Prem & Vikas, 2010).

The aim of this paper is to present the evolution of recommender systems with a particular focus on the systems used in education, their currently achieved level of development through examples of ERS that are in active use today, and to give guidelines for future research and development.

Firstly, the evolution of ERS up to the currently achieved level of development is presented. This is followed by a detailed description of the basic techniques of recommendation upon which the operation of ERS is based. Next, common problems ERS encounter in their work (Automatic information retrieval, Cold-start (New User/Item) problem, Content overspecialization and non-diversity, Sparsity and Gray Sheep problem and Fraud problem) are discussed, after which examples of currently used ERS are grouped according to the basic characteristics of their design and their application. Based on the presented material, the following five potential areas in which we can expect future scientific research and development are examined: construction of universal ERS, ERS intended primarily for teachers, ERS that link student achievements across different courses, ERS which take into account the physical distance between students and use of ERS to motivate students to work continuously. Finally, the paper closes with some concluding remarks.

The Evolution of Educational Recommender Systems

With the emergence of the World Wide Web, a large amount of information has become available to a large number of users. This situation has brought about the problem of orientation, and finding the relevant information in the vast amounts of information available. In order to address this problem, information-filtering systems were developed and today, in their various forms, they are the main solution for information overload (De Gemmis et al., 1999).

The first recommender systems that were developed were intended for commercial use. The main objective of these systems was to recommend products to potential customers in on-line shops. However, the beginning of the World Wide Web opened up the possibility of using these new technologies in the education.

At first, these new technologies were used in education only to deliver traditionally prepared learning materials for learners. These materials were mostly digitized versions of classic textbooks and learners were just passive recipients of the submitted materials. They were not able to use these materials in a different order, or in a different way from that envisaged when they were originally prepared.

To solve this problem and to achieve a personalized distribution of prepared learning materials, different approaches have been developed. Based on intelligent and adaptive algorithms *Intelligent Tutoring Systems* (ITS), *Adaptive Hypermedia Systems* (AHS) and *Recommender Systems* (RS) were developed (Brusilovsky, 2008). These systems introduced interactivity and were enhanced by incorporating communication capabilities, evaluation and monitoring of learners' progress (Kamal et al., 2014). In addition, these systems introduced personalization features with adaptive navigation through learning materials and/or adaptive presentation of learning materials.

At this stage of development, one of the basic obstacles to the implementation of new technologies in the educational process was the teaching staff's lack of technical skills, especially those whose main field of work was not computer science. The practical application of developed *Information and Communication Technologies* (ICT) and e-learning advances required that teachers possess advanced knowledge in computer science, which was not the case.

In order to solve this problem a uniform system that is easily implemented without much need for further training of teaching staff was developed. These systems were designed as closed systems for e-learning with a top-down approach in organizing learning materials and learning courses. They are called *Learning Management Systems* (LMS) and today they are commonly used at all levels of education (Martinez et al., 2009).

The majority of LMS are designed and used as closed learning environments (Sikka et al., 2012). Preparation and organization of learning materials, as well as their use is entirely based on a centralized organization of the learning content by teachers. These systems are used with the aim of supplementing the usual face-to-face teaching experiences in the classroom, and to facilitate distance learning (Kroop et al., 2015). This combination of traditional teaching methods and the use of LMS to complement the teaching process enabled the rise of the hybrid model of teaching and learning.

Over the last ten years, a change in the method of organization, production and presentation of content called Web 2.0 has happened on the World Wide Web. The main change is that the emphasis on the authors of materials shifted towards the user of materials in a way that the users are given the opportunity to actively participate in the preparation and organization of the available materials. This progress inevitably influenced the future development of Educational Recommender Systems and e-learning approaches (Aini Abd Majid, 2014; Colvin & Mayer, 2008).

The consequence of the implementation of Web 2.0 approaches in education has resulted in shifting focus from e-learning systems as supporting tools for e-learning to the users of these systems as a starting point for organizing e-learning. Different styles of teaching and learning (El-Bishouty et al., 2014; Felder & Silverman, 1988) as well as new learning tools that arose with the development of Web 2.0 technologies (such as YouTube, Diigo, SlideShare etc.) generated a need for individualization of the learning process in accordance with the needs of individual learners. During the learning process, today's learners combine learning materials organized within the closed LMS with freely available learning materials, as well as Web 2.0 tools. In this fashion, learners develop their own *Personal Learning Environments* (PLE) inside which, apart from learning from the existing materials, they can create new learning materials that will also become available to other learners (Anido-Rifon et al., 2015; Drachsler et al., 2009).

The continuous increase in the number of available learning materials, both within the closed LMS and especially among freely available materials on the World Wide Web, emphasizes the problem of finding the right materials to fit the needs of each learner. Because of this, there is a significant difference between the traditional top-down approach (within the formal educational structures) and the open bottom-up approach (present outside the formal educational structures), as well as a combination of these two approaches.

The described evolution of the different approaches and techniques on the World Wide Web inevitably influenced the design and methods of operation of the ERS. However, it is important to emphasize that the foundations of the ERS are based around the basic techniques presented in the next section.

Basic Techniques for Generating Recommendations

The algorithms used in the Educational Recommender Systems are based on the following basic techniques (Anandakumar et al., 2014; Drachsler et al., 2015; Gediminas & Tuzhilin, 2005): Collaborative Filtering (CF), Content-based recommending (CB), Knowledge-based recommending (KB) and Hybrid approaches (HA).

Collaborative filtering is based on collecting user feedback (in the form of ratings of items that the user has used and rated) and finding similarities in the ratings between different users of the system. Based on the observed similarities between different users, the algorithm recommends items that are similarly rated by other users (Chatti et al., 2013; Lee Vee, 2001). Collaborative filtering can be further divided into two main approaches (Cremones et al., 2011; Drachsler et al., 2007; Prem & Vikas, 2010): the neighborhood-based approach and the model-based approach.

In the neighborhood-based approach users of the system are grouped into subsets based on the similarities between them, and on the basis of the weighted combination of their ratings recommendations are predicted for the targeted user (this approach also encompasses *Item-based CF*, *User-based CF* and *Stereotype-based CF*),

In the model-based approach, users and items of recommendation are represented by vectors in the low-dimensional 'latent factor' space where they are directly comparable, so the unknown ratings can be estimated as the proximity between these two vectors (Cremones et al., 2011).

Content-based recommending is based on comparing the content of the items of recommendation with contents that are of interest to the user (Lops et al., 2011). While the interest of users for certain content can be collected explicitly (by users ratings) or implicitly (by tracking users' activities), the description of items of recommendation depends on the available data that can be used for describing items content (Cremonesi et al., 2011; De Gemmis et al., 1999).

Knowledge-based recommending is used in cases where the item ratings provided by users are not sufficient input for the system's prediction algorithm. In that case, the system is built around a predefined expert system in which if-then rules are used to represent knowledge for the items of recommendation and their usefulness in relation to the potential user's interests.

The use of this type of algorithm is limited to specific areas in which the knowledge base does not significantly change with time. Making changes in the expert system can be extremely difficult and time consuming, because of the need for a formal expression of knowledge of human experts in charge of creating and maintaining a database on which the whole system is built (Negnevitsky, 2005).

Hybrid approaches are based on a combination of various individual techniques used in the Recommender system algorithms (Anandakumar et al., 2014). The basic idea is that the combination of complementary techniques would result in a system that will take advantage of the strengths while minimizing the impact of the limits of each technique.

The success of hybrid approaches depends on the ability to combine individual techniques, provided that in some cases there are still gaps that may significantly affect the quality of the generated recommendations.

Common Problems in Educational Recommender Systems

There are a few common problems in ERS. The algorithms used to make recommendations have to deal with them, and they show more or less successful results in finding adequate solutions. Today, the most prominent problems in ERS are: Automatic information retrieval, Cold-start (New User/Item) problem, Content overspecialization and non-diversity, Sparsity and Gray Sheep problem and Fraud problem.

In the *Automatic information retrieval problem,* the main issue is that today's algorithms have limited ability to automatically analyze the content of items that are recommended. Items with associated textual content (such as books, web pages, etc.) are usually easily described (using different approaches for Information retrieval from texts). The most developed algorithms are tailored for the analysis of textual content (Santos & Boticario, 2011). They use keywords and phrases that are found in the text and compare them with search parameters. With the higher correlation between these data, likelihood that a particular text can be recommended to the designated user is greater (Gediminas & Tuzhilin, 2005).

However, the problem occurs in items that are not textual (such as video or audio content, multimedia educational materials, etc.). In recommending audio or video content, the existing algorithms rely on the textual version of audio data and the basic tags set by the creator of the content or subsequent users. Unfortunately, based on this information only, a satisfactory understanding of the audio and video content cannot be achieved, certainly not at the necessary level for successful recommending. Although algorithms which aim to identify the content of these types of materials were developed (Jie et al., 2009), it is still often the case that appropriate item description can be obtained only through direct entry of data by the creator of the content.

Regardless of the kind of content that needs to be described through automatically collected information, there is the problem of categorization of different content related to the same topic. In fact, if two different documents are presented by the same parameters collected automatically by the system, they cannot be mutually distinguishable. The consequence of this problem is that, in these cases, the system is not able to differentiate between the quality of the content of documents that are recommended. This problem is dominant in content-based (CB) ERS (Cremonesi et al., 2011; Van Meteren & Van Someren, 2000).

The Cold-start (New User/Item) problem appears in situations when ERS encounters a user or an item that could be recommended for the first time. In such cases, the system does not have enough information about this user or the item to be able to prepare a meaningful recommendation (Al Mamunur et al., 2008). Consequently, the system depends on the manually entered initial parameters about the user or the items of recommendation provided by the user or system administrator.

A New user may be asked by the system to add some information to their profile that can be used to determine the initial recommendations (usually by reviewing certain items or fulfilling basic data when logging into the system like first and last name, age, personal preferences, etc.). This is an explicit approach to data collection which requires cooperation from the users. If the user decides not to cooperate with the system (does not want to give correct information or enters false or incomplete information), the system will not be able to determine appropriate recommendations.

On the other hand, implicitly gathered information about the user, which does not require the user's cooperation, will give the system more accurate information about the user's interest, how the user uses the system or what contents are recommended, etc. (Reddy, 2016). However, for implicit data collection, the user must use the system for a certain period of time. During this period, the system should make recommendations with which the user will be satisfied. If, due to lack of data on the user system, the wrong recommendations are given, there is a risk that the user will withdraw from further use of the system, believing that the system is inefficient.

In formal education, the problem of the new user can be partly solved through information about the user that is collected throughout previous educational activities (preferably related to the content of course). However, in the aforementioned data collection, there is the problem of privacy and the risk of marking users based on previous achievements (good or bad), which does not necessarily correspond to the possibilities and achievements of the other users on the course during which ERS is used.

In addition to the problem of determining the new user's profile, another difficulty lies in determining the parameters of the new items that are recommended. If the new recommended items are added to the system, they should be treated equally by the systems as the existing items on which the system has already collected additional information. In formal education, the teacher can provide the necessary information to address this problem. However, in open education surroundings there is a danger that, due to the lack of information about the new items, they will not be treated like that by the system. In these cases, ERS rely only on the available information about items that are in some cases dependent on the other users of the system (through ratings, etc.). This problem is dominant in ERS that are built on content-based (CB) and collaborative filtering (CF) techniques (Al Mamunur et al., 2008; Gediminas & Tuzhilin, 2005).

Content overspecialization and non-diversity problem is pronounced in cases where the ERS only recommends items that score highly with the user's profile. In these cases, there is a risk that the user will only be recommended very similar items. Consequently, the user stays within a limited area in the content which is recommended, and the system does not offer content that would be of interest to the user but is not highly evaluated in relation to the user's profile.

In ERS, this issue is more pronounced in open educational environments that usually determine recommendations based on matching the user's profile and items that are recommended (Sunil & Saini, 2013). In formal education environments, teachers could rectify the system in a way to ensure that diverse items are recommended (in accordance with the objectives of the course).

On the other hand, in open education environments, the most common approach for solving this problem is the introduction of a random selection of content that will be recommended, taking into account that there is a proper correlation between this content and the content the user is interested in (Cremones et al., 2011; Gediminas & Tuzhilin, 2005). This problem is dominant in ERS that are built on content-based (CB) and collaborative filtering (CF) techniques (Al Mamunur et al., 2008; Gediminas & Tuzhilin, 2005).

The Sparsity and Gray Sheep problem usually appears when ERS depends on the ratings of items by the users of the system or when the recommendation is done based on grouping and comparing similar users. If some items that the system can recommend have been evaluated by a small number of users of these items, regardless of their quality, they will not be widely recommended to other users. In addition to the items' content, the problem of sparsity could appear among system users. The user who does not fit well in any of the groups will not get good recommendations.

In the formal educational environments, these problems can be solved through interventions done by teachers. However, in open education environments, there is a risk that they will remain unresolved, thus preventing satisfactory use of the system for all users (Gediminas & Tuzhilin, 2005). This problem is dominant in ERS that are built on the collaborative filtering (CF) technique.

Fraud problem in ERS is related to the data entered by the user. These data could be basic data on/about the user's profile or the data collected through tests used for monitoring user advancement through the course. Although fraud problems make no sense in open education environments, in formal education environments where achievement in an assignment may have consequences for the overall success of the user, there is a possibility of fraud. This can happen when the user is not monitored during the use of the ERS (test questions are answered with the unauthorized assistance of a colleague, the use of unauthorized materials, etc.).

This problem is a relatively unexplored area, in particular, in the context of ERS especially in formal education environments, and is dominant in ERS that are built on collaborative filtering (CF) and content-based (CB) techniques.

Examples of Educational Recommender Systems

Today, a large number of different ERS are in active use. Their aims are to facilitate the modernization of the educational process, whether in a formal or open education environment. Usually, these systems, hybrid in design and behavior, combine various techniques and approaches to generate recommendations. ERS can be divided into systems that recommend learning materials or learning objects, colleagues for joint implementation of activities or for tutoring work, different educational paths through learning materials that correspond to individualized users preferences, or help in building one's personalized learning path (PLP).

In addition, learning materials that ERS recommend to users can be divided into materials within the formal educational environments and freely available materials on the World Wide Web. Given the widespread use of Web 2.0 tools for e-learning, most ERS recommend a combination of those materials. Furthermore, some ERS help teachers by taking over part of the monitoring of students (Tejeda-Lorente et al., 2015) or finding materials for the development of learning objects (Gallego et al., 2013).

Jamil & Megias (2008) explored the use of ERS within the LMS with the aim to recommend learning objects within formal courses, as well as expand the recommendations to learning objects freely available outside the LMS. Sunita and Lobo (2012) have developed the ERS which recommends courses available in LMS to students, taking into account the best combination of available courses and the interests of the individual user.

Personalized Learning Object Recommender System (PLORS) (Imran et al., 2016) is an ERS within the LMS that recommends different learning objects, with the aim of personalizing the formal educational process, based on monitoring of previous student activities and comparing them with other students and their activities. Imran and Aniza (2011) have developed ERS that associate learning objects with previous good learners' ratings and recommend learning objects to future generations of students based on their similarities with previous generations and the collected ratings.

When building a user profile to determine the recommendations, one of the fundamental elements are learning styles. Customizing learning objects to suit different learning styles can greatly improve the results of the educational process (Balaraman et al., 1996; Bernhard, 1997; Felder et al., 2000; Felder & Silverman, 1988; Swart, 2016), both in the formal and open educational environments. Thus, El-Bishouty et al. (2014) proposed ERS that would help teachers expand the material for e-learning in a way to adapt them to their students' different learning styles. Also, E-learning Activities Recommender System (ELARS) (Hoic-Bozic et al., 2016) uses visual, aural, read/write and kinesthetic (VARK) (Fleming, 1995) description of learning styles as an important element in the user profile.

Marian et al. (2015) propose the use of ERS to help students find colleagues who can help them overcome a certain problem in learning particular course content. Using ERS to connect students with potential tutors appears in a number of different systems. In some cases, this ability is not the system's only purpose but an addition to its recommendations about learning objects or materials, as was done by Amer-Yahia et al. (2009) and Geyer-Schulz et al. (2001). Also, one of the goals of ELARS is the capability to recommend suitable colleagues while forming a group to work on a particular problem or on a particular project. When this capability is built into ERS, students usually have the freedom to independently decide whether to accept the recommendations and connect with suitable colleagues or to ignore them.

Determining a personalized learning path is one of the goals of a number of ERS. These systems use various input parameters in order to define the unique path through learning materials for each user. Thus, Chin Ming et al. (2005) conducted curriculum sequencing in a way that the system uses incorrect student answers to devise further learning paths so that the user can acquire an adequate level of knowledge of the course content. On the other hand, Latha and Kirubakaran (2013) have built ERS, whose algorithm uses graph theory and knowledge about different learning styles to recommend different PLP for each user.

Chin Ming et al. (2007) compare the level of initial knowledge of each user with the complexity of individual learning objects. Based on the results obtained by this comparison, ERS gives a recommendation regarding further learning paths. In addition, Onah and Sinclair (2015) have designed the construction of the PLP based on a comparison of the user profile, and the desired learning goal determined by the user. ERS monitors the progress of the user and redirects the learning path to ensure the acquisition of all the knowledge needed for successful further learning.

In order to achieve the most optimal operation of the algorithms used in the ERS, various methods of artificial intelligence (fuzzy sets, artificial neural networks, evolutionary strategies) or their mutual combinations are used. Therefore, Tejeda-Lorente et al. (2015) and Jamsandekar and Mudholkar (2013) use fuzzy inference techniques for processing data on the success of students with the aim of better monitoring student progress through the course content.

Artificial neural networks are used in order to develop algorithms that have the ability of self-learning based on the data of a given domain (Negnevitsky, 2005). In ERS artificial neural networks are used to model complex relationships between the users' profile and their expressed interests (De Gemmis et al., 1999) and to model connections between the recommended objects and other parameters that ERS use to determine specific recommendations for individual user (Gediminas & Tuzhilin, 2005; Jamsandekar & Mudholkar, 2013; Van Meteren, & Van Someren, 2000). Besides, fuzzy sets and artificial neural networks are frequently combined in hybrid systems of artificial intelligence. This approach can achieve better overall results in the same environment, compared to cases in which only one of these methods is used.

Methods of artificial intelligence based on evolutionary computation include the use of genetic algorithms, evolutionary strategies and genetic programming (Negnevitsky, 2005). Of these different techniques, genetic algorithms and different evolutionary strategies are usually used in ERS.

Consequently, Sengupta et al. (2011) use the Ant Colony Optimization (evolution strategy) approach to identify effective and optimal learning paths for system users. This system is oriented toward obtaining information on unknown terms encountered by the user during their learning process. Chin Ming et al. (2005) use genetic algorithm to generate a personal learning path for the user, while Cayzer and Aickelin (2002) use the model of the biological immune system in order to obtain a set of possible recommendations. From this set of possible recommendations, the system's algorithm can choose the most optimal recommendation with respect to the user's needs.

Guidelines for Future Research and Development

Although future research and development in the field of ERS will certainly include improvement of accuracy and precision as well as upgrade of existing algorithms designed for determining appropriate recommendations, there are other areas in which we can expect further development.

ERS can be divided into systems designed for operating in the open, and systems designed for operating in a structured formal learning environment. Although part of the functionality and operating principles of these systems does not depend on the particulars of the learning environments, some parts must be adapted to the specifics that are distinct between the two environments (Drachsler et al., 2009). Because of these diversities, the systems developed for one environment may not be easily (without major changes in the way they work) used in a different learning environment.

Currently used systems are specialized for one of these two learning environments. One area of future research and development will certainly be directed towards building ERS that will be able to function adequately with minimal changes in both environments.

With the introduction of the Bologna process in higher education, the teacher's workload has increased significantly, particularly in the area of continuous monitoring and evaluation of students' work. According to Poza-Lujan et al. (2016) the increased workload of teachers is due to the impact of applied continuous evaluation strategies. The results of this research indicate that there is a great discrepancy between the increase in teachers' workload and the increase in students' achievements. The ERS used today usually do not include mechanisms that are designed to help teachers reduce their workload. The systems are mostly oriented towards the needs of students, and in a few cases, have built-in algorithms aimed to assist teachers as it was done by Bhojak et al. (2012). The data that are usually collected by ERS can be used to significantly assist teachers.

Based on the perceived lack in functionality, one of the areas of further research and development of ERS, especially in formal learning environments, will certainly be focused on giving adequate support to teachers. The systems should be able to completely take over part of the teacher's workload, especially when it comes to continuous monitoring and evaluation of students' work throughout the semester.

Although in the field of education, algorithms developed for ERS and evaluated within one course can be used unchangeably in another course (algorithms do not depend on the content that is taught), systems usually do not link learners' achievements in different courses. In fact, considering that today educational programs are based on learning outcomes and the acquisition of pre-defined general and specific competencies, the results achieved in one course could be used to make recommendations in another course.

If, while working on the content of one course, a learner is able to reach a higher level of knowledge (in accordance with Bloom's taxonomy), the learner should be able to use that higher level of knowledge in another course. By using these adopted mechanisms, the learner should achieve the required results faster in a new area of learning. The acquired general competencies in one course are applicable to all future courses. In this way, the data collected in the context of one course could be used as an element in determining the recommendations in a different course. From this it follows that one of the areas for further research and development in the field of ERS can certainly focus on connecting learning outcomes across several different courses, and using them for designing recommendations in completely different courses.

There are differences in the needs of learners who attend a certain course in purely electronic format such as an e-course (inside virtual learning environment) compared to learners who attend hybrid courses which include an e-component combined with traditional learning techniques (inside hybrid learning environment). If these groups of learners use ERS, the system should be able to take this difference into account when making recommendations.

Learners attending the course that takes place only inside virtual learning environment (e-course) are connected with other learners and teachers almost exclusively through ICT. In this case, the whole process of learning takes place in a virtual environment, thus ERS must be able to help learners in all stages of their study (choosing courses, modules within the courses, appropriate literature, adequate colleagues for teamwork, learning tools, etc.). On the other hand, learners who attend a course conducted inside a hybrid learning environment usually use ICT to supplement traditional forms of learning.

This difference can be most noticeable for group assignments and teamwork. Learners in a hybrid-learning environment can work on part of their assignment without using ICT, in direct contact with other learners or teachers. In addition, in cases when they use Web 2.0 tools in the context of the assignment, they will use them differently from the learners who learn only inside a virtual learning environment. These learners do not have the opportunity to transfer a segment of their work from the virtual to the real environment.

In line with the above, one of the areas in which further development and research in the field of ERS can be expected is to enable these systems to take into account the difference in the physical proximity of learners (defined by the learning environment they share) and the different needs of learners that arise from that circumstance.

Regardless of the learning environment in which learners learn, one of the more prominent characteristics is that they do not study continuously. Learners usually organize their learning in such a way that they devote only a short period of time to an assignment right before the due date/time. In this way, learners use most of the time intended for working on an assignment for other activities. When confronted with this problem, ERS that use tracking of learners' on-line activities for creating recommendations are incapable of appropriately dealing with this problem. Still, ERS could be used to motivate learners to work continuously in order to better organize the time devoted to learning and to achieve better overall learning results.

The currently used ERS are usually based on the premise that this problem does not exist. For this reason, they do not incorporate methods designed to encourage learners to work continuously, nevertheless, they expect the learners to do so. ERS could be used to address this problem, so one of the areas for further research and development of these systems could be to examine the possibilities of incorporating non-invasive ways of motivating learners to work continuously.

With further development of the constructed algorithms for determining recommendations, the presented guidelines for further research and development suggest that there are areas that are insufficiently explored and developed which, however, have the potential to increase the efficiency of ERS.

Conclusion

Recommending can be defined as a process in which the system helps users to discover new objects (in the field of education courses, learning objects, learning materials, colleagues, etc.) by producing recommendations based on usually very complicated and not necessarily consistent data on their previous achievements, and their prior on-line behavior. On the other hand, to make ERS effective, it is necessary to gain the learner's trust in these systems as early as possible. The critical period for building this trust is at the very beginning when the learner encounter ERS for the first time (otherwise there is a real possibility that the learner could withdraw from using the system, because it is seen as additional workload).

When devising ways of communicating between learners and the ERS, it is extremely important to take into account the pedagogical standards together with the particularities of the learning environments within which the learning and teaching process will take place. The differences that exist between various educational methods, suitable for use in different areas of study, impose the need for system flexibility in order to satisfy the needs of all users.

Taking these differences into account, it is possible to design and build ERS that will provide satisfactory service to the learners and teachers who will use them. The discussed areas for future development of ERS confirm that there are still numerous possibilities for further scientific advancement in the field of ERS.

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Obrazovni sustavi preporučivanja: pregled stanja sa smjernicama za daljnja istraživanja i razvoj

Sažetak

Obrazovni sustavi preporučivanja (ERS) sve se više koriste kao alati za pomoć studentima i nastavnicima tijekom implementacije procesa učenja. Najvažnija razlika između ERS-ova i komercijalnih inačica sustava preporučivanja u pedagoškim je principima koji odgovaraju procesima učenja i poučavanja. Razlike u obrazovnim metodama koje se koriste u različitim obrazovnim situacijama, kao i njihova povezanost s područjem koje se uči, postavljaju polazne parametre za dizajniranje ERS-a. U ovom je članku dan pregled evolucije ERS-ova do trenutno postignutog nivoa razvoja, prikazane su osnovne metode na kojima su ERS-ovi dizajnirani, kao i uobičajeni problemi s kojima se ERS-ovi susreću u svojem radu. Na primjerima danas korištenih ERS-ova raspravljano je o klasifikaciji ERS-ova po njihovim posebnostima i osnovnim pristupima na kojima počiva njihov rad. Na temelju provedene analize, uz usavršavanje i nadograđivanje postojećih algoritama, određeno je pet područja u kojima se može očekivati buduće istraživanje i razvoj: izgradnja univerzalnog ERS-a, ERS-ovi namijenjeni primarno nastavnicima, ERS-ovi koji povezuju studentske uspjehe u različitim kolegijima, ERS-ovi koji uvažavaju fizičku udaljenost studenata i primjena ERS-ova za motiviranje studenata na kontinuirani rad.

Ključne riječi: *e-učenje; ishodi učenja; obrazovno okruženje; alati Weba 2.0.*

Uvod

Korištenje preporuka tijekom procesa analize raspoloživih činjenica u procesu odlučivanja jedna je od osnovnih metoda kojima se ljudi koriste prilikom donošenja odluka (Jamil i Megias, 2008; Prem i Vikas, 2010). S razvojem računala i interneta tijekom proteklih desetljeća, kao i uslijed povećanja količine dostupnih integriranih informacija, pojavila se potreba za izgradnjom sustava kojima bi osnovna namjena bila određivanje najtočnijih i najsmislenijih preporuka koje će olakšati snalaženje i pronalaženje relevantnih informacija. S ciljem zadovoljavanja te potrebe tijekom protekla dva desetljeća razvijeni su sustavi preporučivanja (Cremones i sur., 2011; Gediminas i Tuzhilin, 2005).

Danas je u uporabi velik broj različitih sustava preporučivanja. Njihov je rad utemeljen na različitim pristupima i tehnikama, a razvoj novih i unapređivanje postojećih sustava vrlo je aktivno područje znanstvenog istraživanja (Manouselis i sur., 2012). Taj je razvoj utemeljen na kontinuiranom razvoju statističkih metoda, strojnog učenja, umjetne inteligencije, dubinskog pretraživanje podataka i sl. (Prem i Vikas, 2010).

Osnovni je cilj ovog članka prikazati evoluciju sustava preporučivanja s naglaskom na sustave koji se koriste u obrazovnim procesima, opisati trenutnu razinu njihove razvijenosti korištenjem primjera ERS-ova koji su danas u aktivnoj upotrebi, kao i dati smjernice za buduće istraživanje i razvoj.

U članku je najprije prikazana evolucija ERS-ova do trenutno postignute razine razvoja. Nakon toga detaljno su opisane osnovne tehnike preporučivanja na kojima se temelji rad ERS-ova. Uobičajeni problemi s kojima se u radu susreću ERS-ovi (automatsko prikupljanje podataka, problem novih korisnika i novih sadržaja, prevelika sličnost preporučenih sadržaja, problem premalenog uzorka i problem prijevare) prikazani su nakon toga, a zatim dani primjeri danas korištenih ERS-ova grupiranih prema osnovnim karakteristika svoga dizajna i namjene. Na temelju prikazanoga određeno je i raspravljano o pet potencijalnih područja u kojima se mogu očekivati buduća znanstvena istraživanja i razvoj ERS-ova (izgradnja univerzalnog ERS-a, ERS-ovi namijenjeni primarno nastavnicima, ERS-ovi koji povezuju studentske uspjehe u različitim kolegijima, ERS-ovi koji uvažavaju fizičku udaljenost studenata te korištenje ERS-ova za motiviranje studenata na kontinuirani rad). Na kraju rada dan je zaključak.

Evolucija obrazovnih sustava preporučivanja

S razvojem interneta velika je količina informacija postala dostupna velikom broju korisnika. Ta je situacija dovela do problema snalaženja i pronalaženja relevantnih informacija unutar velikog broja dostupnih informacija. S ciljem rješavanja tog problema razvijeni su sustavi za filtriranje informacija koji su i danas u svojim različitim oblicima osnovni element u pristupu rješavanju problema prevelike količine dostupnih podataka (De Gemmis i sur., 1999).

Prvi sustavi preporučivanja razvijeni su za komercijalne svrhe. Osnovni cilj tih sustava bio je preporučivanje proizvoda potencijalnim kupcima u internetskim trgovinama. S druge strane, razvoj interneta otvorio je i mogućnost korištenja tih novih tehnologija u obrazovanju.

U početku je korištenje tih novih tehnologija u obrazovanju bilo usmjereno prema dostavljanju materijala pripremljenih na tradicionalan način osobama koje se obrazuju. U toj su fazi materijali bili najčešće digitalne inačice klasičnih udžbeničkih materijala te su korisnici bili samo pasivni primatelji digitaliziranih sadržaja. Materijali se nisu mogli koristiti na drugačiji način ili drugačijim redoslijedom od onoga koji je zamišljen prilikom njihove pripreme.

S ciljem rješavanja tog problema, a kako bi se postigla individualizirana distribucija pripremljenih materijala za učenje, razvijeni su različiti pristupi. Utemeljeni na inteligentnim i prilagodljivim algoritmima razvijeni su *inteligentni tutorski sustavi* (ITS), *prilagodljivi hipermedijski sustavi* (AHS) i *sustavi preporučivanja* (RS) (Brusilovsky, 2008). Ti su sustavi uveli interaktivnost kao i komunikacijske mogućnosti, evaluaciju i praćenje napretka polaznika tijekom učenja (Kamal i sur., 2014). Također, ti su sustavi omogućili uvođenje individualizacije putem prilagodljive navigacije unutar sadržaja za učenje i/ili prilagodljive prezentacije materijala za učenje.

U toj je fazi razvoja jedna od osnovnih prepreka daljnjem uvođenju novih tehnologija u obrazovni proces bio nedostatak tehničkih vještina postojećeg obrazovnog kadra, posebno kod osoba kojima osnovno područje rada nije bilo povezano s informatikom. Praktično korištenje *informacijskih i komunikacijskih tehnologija* (ICT), zatim napredak u korištenju e-učenja, zahtijevali su od nastavnika posjedovanje naprednih znanja iz područja računarstva i informatike koje oni nisu posjedovali.

S ciljem rješavanja uočenog problema, dizajnirani su uniformirani sustavi koji se mogu jednostavno implementirani bez potrebe za dodatnim obučavanjem nastavnika. Ti su sustavi osmišljeni kao sustavi zatvorenog tipa namijenjeni e-učenju s *top-down* pristupom organizaciji sadržaja za učenje i cijelih kolegija. Izgrađeni *sustavi za e-učenje* (LMS) danas se uobičajeno primjenjuju na svim razinama obrazovanja (Martinez i sur., 2009).

Većina LMS-ova dizajnirana je za korištenje isključivo u zatvorenim obrazovnim okruženjima (Sikka i sur., 2012). Priprema i organizacija sadržaja i materijala za učenje kao i njihovo korištenje u potpunosti je utemeljeno na centraliziranom pristupu osmišljenom od nastavnika. Ti se sustavi koriste s ciljem nadogradnje klasičnih nastavnih metoda frontalne nastave u predavaonicama te omogućavanja učenja na daljinu (Kroop i sur., 2015). Kombiniranje tradicionalnih metoda poučavanja s korištenjem LMS-a kao nadopune procesu poučavanja omogućilo je nastanak hibridnih modela učenja i poučavanja.

U proteklih deset godina na internetu se dogodila promjena u metodama korištenim za organizaciju, izradu i prezentaciju sadržaja nazvana Web 2.0. Osnovna razlika u odnosu na prijašnje razdoblje jest u tome što je fokus pomaknut s autora sadržaja prema korisnicima tih sadržaja na način da su korisnici dobili mogućnost aktivnog sudjelovanja u pripremi i organizaciji dostupnih sadržaja. Taj se napredak neminovno prenio i na daljnji razvoj ERS-a i pristup u izgradnji e-učenja (Aini Abd Majid, 2014; Colvin i Mayer, 2008).

Posljedica implementacije pristupa Weba 2.0 u obrazovanju bila je pomicanje fokusa sa sustava za učenje kao pomoćnog alata za e-učenje prema korisnicima tih sustava kao polazne točke prilikom organiziranja procesa e-učenja. Različiti stilovi učenja i poučavanja (El-Bishouty i sur., 2014; Felder i Silverman, 1988), kao i novi alati za učenje koji su nastali razvojem tehnologija Weba 2.0 (poput alata YouTube, Diigo, SlideShare i sl.), stvorili su potrebu za individualizacijom procesa učenja u skladu s potrebama svakog pojedinog polaznika. Tijekom procesa učenja današnji polaznici kombiniraju materijale za učenje organizirane unutar zatvorenih LMS-ova sa slobodno dostupnim materijalima, kao i alatima Weba 2.0. Na taj način polaznici grade svoje *vlastito okruženje za učenje* (PLE) unutar kojega, uz korištenje već postojećih materijala za učenje, mogu stvarati nove sadržaje koji će postati dostupni drugim polaznicima (Anido-Rifon i sur., 2015; Drachsler i sur., 2009).

Kontinuirano povećanje količine dostupnih materijala za učenje unutar zatvorenih LMS-ova, ali posebno među slobodno dostupnim materijalima na internetu, dodatno je pojačalo problem pronalaska pravih materijala koji će u potpunosti odgovarati potrebama svakog polaznika. Zbog navedenoga se ističe i razlika između tradicionalnog *top-down* pristupa (unutar formalnih obrazovnih struktura) i otvorenih *bottom-up* pristupa prisutnih izvan formalnih obrazovnih struktura, kao i međusobno kombiniranje tih dvaju pristupa.

Opisana evolucija različitih pristupa i tehnika na internetu neminovno je utjecala na dizajniranje i metode rada ERS-ova. Ipak, važno je naglasiti da su temelji ERS-ova utemeljeni na nekoliko osnovnih metoda prikazanih u sljedećem poglavlju.

Osnovne tehnike za stvaranje preporuka

Algoritmi koji se koriste u ERS-ovima utemeljeni su na sljedećim osnovnim metodama (Anandakumar i sur., 2014; Drachsler i sur., 2015; Gediminas i Tuzhilin, 2005): kolaborativnom filtriranju (CF), preporučivanju utemeljenom na sadržaju (CB), preporučivanju utemeljenom na znanju (KB) i hibridnim pristupima (HA).

Kolaborativno filtriranje utemeljeno je na podatcima prikupljenim u obliku povratnih informacija od korisnika (ocjena o sadržajima kojima se korisnik koristio i koje je ocijenio) i pronalaženju sličnosti u prikupljenim ocjenama između različitih korisnika sustava. Na temelju uočenih sličnosti između različitih korisnika, algoritam će preporučiti sadržaj koji je slično ocijenjen od nekog drugog korisnika (Chatti i sur., 2013; Lee Vee, 2001). Kolaborativno se filtriranje može podijeliti u dva osnovna pristupa (Cremones i sur., 2011; Drachsler i sur., 2007; Prem i Vikas, 2010): pristup utemeljen na sličnosti korisnika i pristup utemeljen na modelu.

U pristupu utemeljenom na sličnosti korisnika korisnici sustava grupiraju se po sličnosti u grupe te se na osnovi težinski kombiniranih vrijednosti ocjena svih članova grupe određuju preporuke za određenog korisnika (taj pristup obuhvaća i pristupe kolaborativnog filtriranja utemeljene na sadržaju, na korisniku ili stereotipu korisnika).

U pristupu utemeljenom na modelu korisnici i sadržaji se prikazuju vektorima u niskodimenzionalnom vektorskom prostoru u kojem su direktno usporedivi te se na taj način mogu estimirati nepoznati podatci o ocjenama pojedinih sadržaja na temelju sličnosti dvaju vektora.

Preporučivanje utemeljeno na sadržaju počiva na usporedbi sadržaja koji se preporučuje s iskazanim interesom korisnika (Lops i sur., 2011). Iako interes korisnika iskazan za određeni sadržaj može biti prikupljen eksplicitno (kroz korisnikovo ocjenjivanje sadržaja) odnosno implicitno (praćenjem korisnikovih aktivnosti), sam opis sadržaja koji se preporučuju ovisi o dostupnim podatcima koji se mogu koristiti za izradu opisa sadržaja (Cremonesi i sur., 2011; De Gemmis i sur., 1999).

Preporučivanje utemeljeno na znanju se koristi u slučajevima kada ocjene korisnika o sadržaju preporučivanja ne predstavljaju dovoljno dobar ulazni skup informacija potreban za rad algoritma preporučivanja koji sustav koristi. Da bi se po ovoj metodi određeni sadržaj preporučio sustav preporučivanja se gradi oko unaprijed izgrađenog ekspertnog sustava u kojemu je kroz korištenje AKO-ONDA pravila predstavljeno znanje o povezanosti sadržaja koji se preporučuju i njihove potencijalne korisnosti u skladu s iskazanim interesom korisnika.

Korištenje ove metode za određivanje preporuka ograničeno je na specifična područja u kojima se sadržaji koji se preporučuju značajno ne mijenjaju s vremenom. Unošenje promjena u ekspertne sustave može biti iznimno težak i vremenski zahtjevan proces zbog potrebe za formalnim prikazom znanja ljudskog stručnjaka određenog za kreiranje i održavanje baze podataka na kojoj počiva cijeli sustav (Negnevitsky, 2005).

Hibridni pristupi su napravljeni kao kombinacije različitih pojedinačnih metoda koje se obično koriste u algoritmima sustava preporučivanja (Anandakumar i sur., 2014). Osnovna ideja je da se kombiniranjem komplementarnih metoda može proizvesti sustav koji će iskoristiti prednosti uz istovremeno minimiziranje nedostataka svake od pojedinih metoda.

Uspjeh hibridnog pristupa značajno ovisi o mogućnosti kombiniranja pojedinih metoda te je potrebno voditi računa da u određenim slučajevima još uvijek mogu postojati nedostaci koja mogu značajno utjecati na kvalitetu generiranih preporuka.

Uobičajeni problemi u Obrazovnim sustavima preporučivanja

U radu ERS-a postoji nekoliko uobičajenih problema. Algoritmi koje sustavi koriste moraju biti u stanju nositi se s ovim problemima te danas korišteni algoritmi pokazuju više ili manje uspješne rezultate u njihovom rješavanju. Najizraženiji problemi s kojima se ERS-ovi moraju nositi su: automatsko prikupljanje podataka, problem novih korisnika i novih sadržaja, prevelika sličnost preporučenih sadržaja, problem premalenog uzorka i problem prijevare.

Kod *problema automatskog prikupljanja podataka* glavni je problem je u tome što korišteni algoritmi imaju ograničenu sposobnost automatske analize sadržaja koji preporučuju. Sadržaji koji su u svojoj naravi tekstualni (poput knjiga, internetskih stranica i sl.) mogu se relativno jednostavno automatski opisati (korištenjem različitih pristupa prikupljanju podataka direktno iz teksta). Najrazvijeniji algoritmi su napravljeni za analizu tekstualnih sadržaja (Santos i Boticario, 2011). U svojem radu oni koriste ključne riječi i fraze koje se nalaze u tekstu te ih uspoređuju s parametrima pretraživanja. Što je korelacija između ovih podataka veća raste i vjerojatnost da određeni tekstualni sadržaj odgovara korisniku sustava te mu može biti preporučen (Gediminas i Tuzhilin, 2005).

Međutim, sadržaji koji nisu tekstualnog karaktera (poput video i audio sadržaja, multimedijskih obrazovnih materijala i sl.) predstavljaju složeniji problem za automatsko opisivanje. Za preporučivanje audio i video sadržaja, postojeći se algoritmi oslanjaju na tekstualnu verziju audio podataka i osnovne oznake postavljene od strane kreatora sadržaja ili njegovih korisnika. Nažalost, samo na temelju ovih informacija ne može se postići zadovoljavajuća razina razumijevanja audio i video sadržaja, svakako ne na nivou koji je neophodan za stvaranje uspješne preporuke. Iako su razvijeni algoritmi kojima je cilj automatsko opisivanje navedenih sadržaja (Jie i sur., 2009), u velikom je broju slučajeva još uvijek moguće točan opis sadržaja osigurati isključivo kroz direktni unos podataka od strane osobe koja je sadržaj izradila.

Neovisno o tipu sadržaja za opis kojega je potrebno automatski prikupiti informacije, postoji i problem kategorizacije različitih sadržaja unutar istog područja. U slučajevima kada su dva različita dokumenta predstavljena istim skupom parametara koji su prikupljeni automatski od strane sustava, sustav te dokumente ne može međusobno razlikovati uzimajući u obzir njihovu kvalitetu. Ovaj je problem najizraženiji u ERS-ovima zasnovanim na preporučivanju utemeljenom na sadržaju (Cremonesi i sur., 2011; Van Meteren i Van Someren 2000).

Problem novih korisnika i novih sadržaja pojavljuje se u situacijama kada ERS po prvi put dođe u kontakt s korisnikom ili sadržajem koji se može preporučiti. U tim slučajevima sustav nema dovoljno informacija o korisniku ili sadržaju da bi mogao generirati smislenu preporuku (Al Mamunur i sur., 2008). U takvim situacijama sustav ovisi o manualno unesenim inicijalnim podatcima o korisniku, odnosno sadržaju koji se preporučuje od korisnika ili administratora sustava.

Od novog korisnika sustav može zatražiti da unese određene informacije u svoj korisnički profil kako bi se mogle odrediti inicijalne preporuke (najčešće u obliku ocjenjivanja određenih sadržaja koji se preporučuju ili davanjem osnovnih podataka o sebi poput imena, starosti, osobnih preferencija i sl.). Takav pristup predstavlja eksplicitni način prikupljanja podataka koji ovisi o kooperativnosti korisnika. U slučaju da korisnik odluči ne surađivati sa sustavom na odgovarajući način (ne želi dati točne podatke ili unese netočne ili nepotpune podatke), sustav neće moći dati odgovarajuće preporuke.

S druge strane, u slučaju kada se podatci prikupljaju implicitno bez potrebe za suradnjom korisnika, prikupljeni podatci o interesu korisnika, načinu na koji se koristi sustavom, odnosno sadržajima koji su preporučeni i sl. bit će točniji (Reddy, 2016). Ipak, da bi se podatci prikupili implicitnim putem, korisnik se sustavom mora koristiti određeno vrijeme. Tijekom tog vremena sustav bi trebao generirati preporuke kojima će korisnik biti zadovoljan. U slučaju kada zbog nedostatka podataka o korisniku sustav generira pogrešne preporuke, postoji opasnost da korisnik odustane od daljnjeg korištenja sustava uvjeren da je sustav neuspješan.

U formalnom obrazovnom okruženju problem novog korisnika može biti djelomično riješen korištenjem informacija o korisniku koje su prikupljene tijekom ranijih obrazovnih situacija (najbolje ako postoji poveznica sa sadržajem konkretnog kolegija). Ipak kod takvog prikupljanja podataka postoji problem privatnosti, kao i problem označavanja korisnika na temelju prijašnjih radova (dobrim ili lošim), što ne mora odgovarati sposobnostima i uspjesima korisnika u okviru kolegija unutar kojega se ERS planira koristiti.

Osim problema određivanja korisničkog profila novog korisnika, postoji i problem određivanja parametara novih sadržaja koji se mogu preporučivati. Novi sadržaji koji se dodaju sustavu trebali bi biti jednako tretirani kao i sadržaji o kojima je sustav već prikupio dodatne informacije. U formalnom obrazovnom okruženju nastavnik može unijeti odgovarajuće informacije i time riješiti problem. Međutim, u otvorenom obrazovnom okruženju postoji opasnost da se novi sadržaji za učenje ne tretiraju od sustava identično kao i stariji sadržaji zbog nedostatka informacija o njima. U tim slučajevima sustav preporučivanja ovisi o dostupnim informacijama o sadržajima za učenje koje mogu ovisiti o drugim korisnicima sustava (putem ocjenjivanja i sl.). Taj je problem najizraženiji u ERS-ovima utemeljenim na preporučivanju utemeljenom na sadržaju odnosno preporučivanju utemeljenom na kolaborativnom filtriranju (Al Mamunur i sur., 2008; Gediminas i Tuzhilin, 2005).

Problem prevelike sličnost preporučenih sadržaja najviše je izražen u slučajevima kada ERS preporučuje isključivo sadržaje koji imaju visoku podudarnost u odnosu na profil korisnika. U takvim slučajevima postoji opasnost da se korisniku preporučuju isključivo vrlo slični sadržaji. Posljedica je toga da korisnik ostaje unutar vrlo uskog područja u sadržaju koji se preporučuje, pa sustav ne nudi korisniku sadržaje koji bi za njega bili zanimljivi, ali se slabije podudaraju s profilom korisnika.

Kod ERS-a taj je problem izraženiji u otvorenim obrazovnim okruženjima u kojima se preporuke najčešće određuju na temelju usporedbe profila korisnika i sadržaja koji se preporučuju (Sunil i Saini, 2013). U formalnim obrazovnim okruženjima nastavnik može ispraviti uočeni propust sustava i osigurati raznolikost u preporučenim sadržajima (u skladu s ciljevima kolegija).

S druge strane, u otvorenim se obrazovnim okruženjima navedeni problem najčešće pokušava riješiti preporučivanjem slučajno odabranog sadržaja uz uvažavanje da postoji odgovarajuća povezanost sadržaja i iskazanog interesa korisnika (Cremonesi i sur., 2011; Gediminas i Tuzhilin, 2005). Taj je problem najizraženiji u ERS-ovima utemeljenima na preporučivanju utemeljenom na sadržaju odnosno preporučivanju utemeljenom na kolaborativnom filtriranju (Al Mamunur i sur., 2008; Gediminas i Tuzhilin, 2005).

Problem premalenog uzorka pojavljuje se u sustavima preporučivanja kada generiranje preporuka ovisi o ocjenama sadržaja od korisnika sustava ili na osnovi grupiranja korisnika sa sličnostima u korisničkim profilima. Ako su određeni sadržaji koje sustav može preporučiti ocijenjeni od malog broja korisnika ti se sadržaji, neovisno o njihovoj kvaliteti, neće često preporučivati drugim korisnicima. Također, problem premalenog uzorka može se pojaviti i između korisnika sustava. Korisnik sustava koji se dobro ne uklapa ni u jednu grupu korisnika neće dobivati dobre preporuke.

U formalnim obrazovnim okruženjima ti se problemi mogu riješiti intervencijom nastavnika. Međutim, u otvorenim obrazovnim okruženjima postoji opasnost da problem ostane neriješen, što za posljedicu ima onemogućavanje zadovoljavajućeg iskustva u korištenju sustava za sve njegove korisnike (Gediminas i Tuzhilin, 2005). Taj je problem najizraženiji u ERS-ovima utemeljenim na preporučivanju utemeljenom na kolaborativnom filtriranju.

Problem prijevare u ERS-ovima povezan je s podatcima koje u sustav unosi korisnik. Ti se podatci mogu odnositi na temeljne podatke u profilu korisnika, ali i na podatke prikupljene testiranjem koji se koriste za praćenje napretka korisnika u okviru kolegija. Iako u otvorenim obrazovnim okruženjima problem prijevare nema smisla, u formalnom obrazovnom okruženju gdje ostvareni uspjeh na nekom zadatku može imati posljedice na cjelokupni uspjeh korisnika, mogućnost prijevare postaje moguća. Prijevare se mogu dogoditi za vrijeme kada polaznik nije nadgledan tijekom korištenja ERS-a (odgovori na pitanja u testovima dani su uz korištenje nedopuštene pomoći kolega, nedopuštenih materijala i sl.).

Taj je problem relativno neistraženo područje pogotovo u okviru ERS-a korištenih u formalnim obrazovnim okruženjima i najizraženiji je u ERS-ovima utemeljenim na kolaborativnom filtriranju odnosno preporučivanju utemeljenom na sadržaju.

Primjeri obrazovnih sustava preporučivanja

Danas je u uporabi velik broj različitih ERS-ova. Njihova je namjena modernizacija obrazovnog procesa u okviru formalnog odnosno otvorenog obrazovnog okruženja. Ti su sustavi najčešće dizajnirani na temelju hibridnog pristupa, zbog čega njihov rad obilježava kombiniranje različitih metoda i pristupa u procesu generiranja preporuka. Obrazovni sustavi preporučivanja mogu se podijeliti na sustave koji preporučuju materijale i/ili objekte za učenje, povezuju studente s kolegama za zajednički rad ili s tutorima, omogućavaju personalizaciju putova učenja kroz sadržaje za učenje u skladu s potrebama pojedinog studenta ili pomažu u stvaranju vlastitih putova učenja (PLP).

Također, materijali za učenje koje ERS-ovi preporučuju mogu biti podijeljeni na materijale unutar formalnih obrazovnih okruženja i one koji su slobodno dostupni na internetu. S obzirom na široku primjenu alata Weba 2.0 u e-učenju, većina ERS-ova preporučuje kombinacije tih materijala. Osim navedenoga, neki ERS-ovi pomažu nastavnicima preuzimajući dio praćenja rada studenata (Tejeda-Lorente i sur., 2015) ili pronalazeći dostupne materijale namijenjene razvoju objekata učenja (Gallego i sur., 2013).

Jamil i Megias (2008) istražili su korištenje sustava preporučivanja unutar LMS-a s ciljem preporučivanja objekata učenja unutar formalnog obrazovnog okruženja uz dodatak kojim se preporučuju i objekti učenja slobodno dostupni izvan LMS-a. Sunita i Lobo (2012) razvili su sustav preporučivanja koji studentima preporučuje kolegije dostupne unutar LMS-a uz uzimanje u obzir najbolje povezanosti između dostupnih kolegija i interesa pojedinog studenta.

PLORS (Imran i sur., 2016) je ERS implementiran unutar LMS-a koji preporučuje različite objekte učenja s ciljem personalizacije unutar formalnog obrazovnog okruženja utemeljenog na praćenju prijašnjih aktivnosti studenata koje se uspoređuju s drugim studentima i njihovim aktivnostima. Imran i Aniza (2011) razvili su ERS koji povezuje objekte učenja s ocjenama koje su dali uspješni studenti u prethodnim generacijama te preporučuje objekte učenja generacijama novih studenata na temelju sličnosti s prethodnim generacijama i prikupljenih ocjena.

Prilikom izgradnje korisničkog profila koji se koristi za generiranje preporuka jedan su od osnovnih elemenata stilovi učenja. Prilagođavanjem objekata učenja pojedinim stilovima učenja može se znatno poboljšati rezultate obrazovnog procesa (Balaraman et al., 1996; Bernhard, 1997; Felder i sur., 2000; Felder i Silverman, 1988; Swart, 2016) kako u formalnom tako i u otvorenom obrazovnom okruženju. Tako El-Bishouty i sur. (2014) istražuju ERS koji pomaže nastavnicima da prošire materijale za e-učenje tako da ih prilagode stilovima učenja njihovih studenata. Također, sustav ELARS (Hoic-Bozic i sur., 2016), kao jedan od važnih elemenata u profilu korisnika, koristi se VARK (Fleming, 1995) modelom stilova učenja.

Marian i sur. (2015) istražuju korištenje ERS-a koji bi pomagao studentima u povezivanju s kolegama koji im mogu pomoći u rješavanju problematičnih dijelova gradiva na koje nailaze u sadržajima koje uče. Korištenje ERS-a s ciljem povezivanja studenata s potencijalnim tutorima pojavljuje se kao mogućnost u većem broju različitih sustava. U nekim slučajevima ta sposobnost sustava nije i njegova jedina svrha već se radi o dodatku uz preporučivanje objekata učenja ili materijala za učenje kao što su to napravili Amer-Yahia i sur. (2009) i Geyer-Schulz i sur. (2001). Također sustav ELARS kao jedan od svojih ciljeva ima i mogućnost preporučivanja odgovarajućih kolega tijekom procesa stvaranja grupa za rad na određenom problemu ili projektu. Kada je ta mogućnost ugrađena u ERS, studenti obično imaju slobodu u odlučivanju žele li prihvatiti preporuku te se povezati s predloženim kolegama ili je žele zanemariti.

Određivanje personaliziranih putova učenja jedan je od ciljeva većeg broja ERS-ova. Ti se sustavi koriste nizom različitih parametara kako bi odredili jedinstveni put kroz materijale za učenje za svakog studenta. Chin Ming i sur. (2005) proveli su raščlanjivanje kurikula tako da se sustav može koristiti netočnim odgovorima studenata za određivanje budućeg puta učenja s ciljem da studenti usvoje odgovarajuću razinu znanja iz sadržaja kolegija. S druge strane, Latha i Kirubakaran (2013) izgradili su ERS čiji se algoritam koristi teorijom grafova kombiniranom sa znanjem o različitim stilovima učenja da bi odredio različite putove učenja za svakog studenta.

Chin Ming i sur. (2007) uspoređuju inicijalnu razinu znanja svakog studenta sa složenošću pojedinog objekta učenja. Na temelju provedene usporedbe ERS određuje preporuku za daljnji put učenja. Također, Onah i Sinclair (2015) su osmislili određivanje PLP-a na temelju usporedbe profila korisnika i željenog cilja učenja koji određuje korisnik. ERS prati napredovanje korisnika i preusmjerava put učenja s ciljem osiguravanja usvajanja neophodne razine znanja koja osigurava uspješno daljnje učenje.

S ciljem postizanja optimalnog rada algoritama koji se u ERS-ovima koriste, upotrebljavaju se različite metode umjetne inteligencije (neizraziti skupovi, umjetne neuronske mreže, evolucijske strategije) ili njihove međusobne kombinacije. Tako se Tejeda-Lorente i sur. (2015), kao i Jamsandekar i Mudholkar (2013) koriste tehnikom neizrazitog zaključivanja za procesuiranje podataka o uspjehu studenata s ciljem boljeg praćenja napredovanja studenta kroz sadržaj kolegija.

Umjetne neuronske mreže se najčešće koriste s ciljem razvoja algoritama koji imaju sposobnost samoučenja utemeljenog na podatcima unutar određenog područja (Negnevitsky, 2005). U ERS-ovima umjetne se neuronske mreže upotrebljavaju za modeliranje složenih odnosa između profila korisnika i njihovih interesa (De Gemmis i sur., 1999), kao i za modeliranje povezanosti preporučenog objekta i drugih parametara kojima se sustav koristi prilikom generiranja specifičnih preporuka za pojedinačnog korisnika (Gediminas i Tuzhilin, 2005; Jamsandekar i Mudholkar, 2013; Van Meteren, i Van Someren, 2000). Također, vrlo se često neizraziti skupovi i umjetne neuronske mreže kombiniraju u hibridni sustav umjetne inteligencije. Takav pristup ima mogućnost postići bolje ukupne rezultate u radu u odnosu na korištenje samo jedne od navedenih metoda u istom okruženju.

Metode umjetne inteligencije utemeljene na evolucijskom računanju obuhvaćaju upotrebu genetičkih algoritama, evolucijskih strategija i genetičkog programiranja (Negnevitsky, 2005). Od svih navedenih tehnika u ERS-ovima najčešće se koriste genetički algoritmi i različite evolucijske strategije.

Tako se Sengupta i sur. (2011) koriste evolucijskom strategijom utemeljenom na funkcioniranju kolonije mrava s ciljem određivanja optimalnog puta učenja za korisnike sustava. Sustav je orijentiran na identificiranje nepoznatih pojmova s kojima se korisnici sustava susreću tijekom učenja. Chin Ming i sur. (2005) koriste se genetičkim algoritmom za generiranje personaliziranog puta učenja za korisnika, a Cayzer i Aickelin (2002) koriste se modelom biološkog imunološkog sustava s ciljem generiranja skupova mogućih preporuka. Iz tako izgrađenog skupa mogućih preporuka algoritam sustava odabire optimalnu preporuku s obzirom na traženja korisnika.

Smjernice za buduće istraživanje i razvoj

Iako će buduća istraživanja i razvoj u području ERS-ova sigurno uključiti unapređivanje točnosti i preciznosti, kao i nadograđivanje postojećih algoritama koji se koriste za određivanje preporuka, postoje i druga područja u kojima se može očekivati daljnji razvoj.

ERS-ovi se temeljno mogu podijeliti na sustave koji su dizajnirani za rad u otvorenim odnosno sustave koji su dizajnirani za rad u strukturiranim formalnim obrazovnim okruženjima. Iako dio funkcionalnosti i načina rada tih sustava ne ovisi o posebnosti obrazovnih okruženja, neki se njihovi dijelovi moraju prilagoditi posebnostima koje razlikuju ta dva obrazovna okruženja (Drachsler i sur., 2009). Zbog navedenih različitosti sustavi razvijeni za jednu vrstu okruženja ne mogu se jednostavno (bez znatnih promjena u načinu rada) koristiti u drugoj vrsti obrazovnog okruženja.

Sustavi koji se danas aktivno koriste specijalizirani su za rad u jednom od ta dva obrazovna okruženja. Jedno od područja budućih znanstvenih istraživanja i razvoja svakako će biti usmjereno na izgradnju ERS-a koji će, uz minimalne izmjene, moći zadovoljavajuće funkcionirati u oba okruženja.

S uvođenjem Bolonjskog procesa u visokom obrazovanju opterećenje nastavnika je znatno povećano, osobito u području kontinuiranog praćenja i evaluacije rada studenata. Istraživanja poput (Poza-Lujan i sur., 2016) povezuju povećanje opterećenja u radu nastavnika u vidu kontinuiranog praćenja studenata s uspjehom koji studenti postižu. Rezultati ovog istraživanja pokazuju da postoji značajno odstupanje između povećanog opterećenja nastavnika i povećanja uspjeha studenata. Danas korišteni ERS-ovi najčešće nemaju ugrađene mehanizme dizajnirane za pomoć nastavnicima s ciljem smanjenja njihova opterećenja. Ti su sustavi uglavnom orijentirani ponajprije prema zadovoljavanju potreba studenata, a samo u manjem broju slučajeva i u manjem obimu posjeduju algoritme namijenjene potpori nastavnicima, npr. u sustavu koji su napravili Bhojak i sur. (2012). Podatci koji se prikupljaju od ERS-a mogu se koristiti i za važnu pomoć nastavnicima.

Na temelju ovog uočenog nedostatka u funkcioniranju ERS-ova jedno od područja budućeg istraživanja i razvoja, posebno u okviru formalnih obrazovnih okruženja, moći će biti usredotočeno na davanje odgovarajuće potpore nastavnicima. Sustavi bi svakako trebali moći u potpunosti preuzeti na sebe dio nastavnikova opterećenja, posebno u području praćenja i evaluacije rada studenata tijekom semestra.

Iako su u području obrazovanja algoritmi razvijeni za ERS provjereni unutar jednog predmeta, mogu se neizmijenjeni koristiti u okviru nekog drugog predmeta (algoritmi ne ovise o sadržaju koji se poučava), sustavi najčešće ne povezuju uspjehe koje polaznici ostvare u različitim predmetima. U stvari, uvažavajući činjenicu da su današnji obrazovni programi utemeljeni na ishodima učenja te stjecanju unaprijed definiranih općih i posebnih kompetencija, postignuća polaznika u okviru jednog predmeta mogu biti upotrijebljena za generiranje preporuka u nekom drugom predmetu.

Ako je polaznik sposoban za vrijeme rada u okviru jednog predmeta dosegnuti odgovarajuću višu razinu znanja (u skladu s Bloomovom taksonomijom), polaznik bi trebao moći upotrijebiti usvojeno u okviru nekog drugog predmeta. Korištenjem usvojenoga polaznik bi trebao biti u stanju brže postići tražene rezultate u novom području učenja. Usvojene opće kompetencije u okviru jednog predmeta mogu se upotrijebiti kao element u generiranju preporuka u okviru drugog predmeta. Iz navedenoga slijedi da jedno od područja budućeg istraživanja i razvoja ERS-a može biti povezivanje ishoda učenja u nizu različitih predmeta i njihovo iskorištavanje prilikom generiranja preporuka u sadržajno potpuno različitim predmetima.

Između polaznika koji pohađaju određeni predmet u isključivo elektroničkom obliku kao e-predmet (unutar *online* obrazovnog okruženja) i polaznika koji pohađaju hibridno organiziran predmet koji uključuje e-komponentu kombiniranu s tradicionalnim tehnikama poučavanja (unutar hibridnog obrazovnog okruženja) postoje razlike u njihovim potrebama. Ako se ti polaznici koriste ERS-om, sustav bi morao imati sposobnost uvažavanja razlika prilikom generiranja preporuka.

Polaznici koji pohađaju predmet koji se odvija isključivo unutar *online* obrazovnog okruženja (e-predmet) povezani su s drugim polaznicima i nastavnicima isključivo putem ICT-a. U tom slučaju cjelokupan se proces učenja odvija unutar *online* obrazovnog okruženja tako da korišteni ERS mora biti u mogućnosti pomoći studentima u svim fazama njihova obrazovanja (odabir predmeta, modula unutar predmeta, odgovarajuće literature, odgovarajućih suradnika za zajednički rad, alata za učenje i sl.). S druge strane polaznici koji pohađaju predmet koji se izvodi unutar hibridnog obrazovnog okruženja obično se koriste ICT-om kao nadogradnjom tradicionalnim oblicima učenja.

Navedena razlika najviše dolazi do izražaja u grupnim zadacima i timskom radu. Polaznici unutar hibridnog obrazovnog okruženja mogu odraditi dio zadatka bez korištenja ICT-a u direktnom kontaktu s drugim polaznicima i nastavnicima. Također, u slučajevima kada se tijekom izrade zadataka koriste alatima Weba 2.0, njima će se koristiti na drugačiji način u odnosu na polaznike koji uče isključivo unutar *online* obrazovnog okruženja. Ti polaznici nemaju mogućnost prenijeti dio svojega rada iz *online* obrazovnog okruženja u realno.

U skladu s navedenim jedna od tema budućeg istraživanja i razvoja u području ERS-a odnosit će se na izgradnju sustava koji će moći uzeti u obzir razlike u fizičkoj udaljenosti polaznika (određenoj u obrazovnom okruženju koje dijele) i razlika u potrebama polaznika koje proizlaze iz tih okolnosti.

Neovisno o obrazovnom okruženju u kojem polaznici uče, jedna od istaknutijih karakteristika u njihovu učenju je nekontinuirano učenje. Polaznici najčešće organiziraju svoje vrijeme koje posvećuju izradi određenog zadatka tako da iskorištavaju samo kratko vremensko razdoblje prije roka za predaju rezultata. Na taj način polaznici koriste većinu vremena koje je određeno za izradu zadatka na neke druge aktivnosti. Kada se ERS-ovi koji se u svojem radu koriste praćenje polaznikovih *online* aktivnosti prilikom generiranja preporuka susretnu s tim problemom, oni ne mogu na odgovarajući način iznaći rješenje. Ipak, ERS-ovi mogu biti upotrijebljeni s ciljem motiviranja polaznika na kontinuirani rad kako bi polaznici na bolji način organizirali svoje vrijeme koje posvećuju učenju te na taj način ostvarili bolje ukupne rezultate.

Danas korišteni ERS-ovi najčešće su utemeljeni na premisi da navedeni problem ne postoji. Zbog toga u njih nisu ugrađene metode dizajnirane za poticanje polaznika na kontinuirani rad iako sustavi očekuju da polaznici na taj način rade. ERS-ovi se mogu iskoristiti na taj način tako da jedno od budućih područja istraživanja i razvoja tvih sustava ide prema uključivanju neinvazivnih načina dizajniranih s ciljem motiviranja polaznika na kontinuirani rad.

Zajedno s daljnjim razvojem već izgrađenih algoritama za generiranje preporuka, prikazani potencijalni smjerovi budućeg istraživanja i razvoja ukazuju na to da i dalje postoje područja koja nisu dovoljno istražena i razvijena te imaju potencijal povećavanja uspješnosti ERS-ova.

Zaključak

Preporučivanje se može definirati kao proces u kojemu sustav pomaže korisniku u otkrivanju novih objekata (u području obrazovanja predmete, objekte učenja, materijale za učenje, suradnike i sl.) dajući preporuke koje su utemeljene na vrlo složenim i ne nužno konzistentnim podatcima o njihovim prijašnjim postignućima i njihovu *online* ponašanju. S druge strane, da bi ERS bio uspješan, izrazito je važno pridobiti povjerenje polaznika što je prije moguće. Kritično doba za izgradnju povjerenja je u početku kada polaznici prvi put susreću ERS (u protivnom postoji realna mogućnost da polaznik odustane od daljnjeg korištenja sustava smatrajući ga dodatnim opterećenjem u odnosu na ostale preuzete obaveze).

Prilikom osmišljavanja načina komunikacije između polaznika i ERS-a iznimno je važno uključiti pedagoške standarde zajedno s posebnostima predviđenih obrazovnih okruženja u kojima će se odvijati proces učenja i poučavanja. Razlike koje postoje između raznovrsnih obrazovnih metoda pogodnih za uporabu u različitim područjima učenja, stvaraju potrebu za fleksibilnosti sustava s ciljem zadovoljavanja očekivanih potreba svih korisnika.

Uzimajući navedene razlike u obzir, moguće je dizajnirati i izgraditi ERS koji će pružiti zadovoljavajuću uslugu polaznicima i nastavnicima koji će ih upotrebljavati. Opisana različita područja pogodna za budući razvoj ERS-ova potvrđuju da postoji mnogo mogućnosti za daljnji znanstveni napredak u području ERS-ova.