Educational Recommender Systems

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Abstract – Today, Educational Recommender Systems are commonly accepted tools used to assist students in their learning process. The algorithms in these systems are based on few different approaches such as content-based recommendations, collaborative filtering and knowledge-based recommending. Systems usually combine these approaches forming so called hybrid approach which takes advantage of the strengths and minimize the weaknesses of individual approaches. While most systems provide assistance only to individual users there are a few systems (such as ELARS) that also creates recommendations for groups of users. In this way, these systems encourage group work as one of the important forms of the student education. During the designing phase pedagogical principles of work with students must be taken into account. The principles on which recommending algorithm and communication with students are based must match the specifics of the planned educational process. Differences in educational methods used in a variety of educational situations, and their dependence on the field of study, create the need for flexibility of the system. Only by designing them on these initial assumptions Educational Recommender Systems will be able to respond in an appropriate manner to the needs of teachers and students who use them.

Keywords – Collaborative Filtering, Recommender system, Content-based recommending, ELARS

I. INTRODUCTION

Using recommendations in the decision-making process is one of the fundamental elements that people apply when making decisions [1, 2]. The development of computers and the World Wide Web in the past decades as well as the consequential increase of available integrated information logically imposed the need for designing and construction of systems whose main purpose would be to determine the most accurate and meaningful recommendations that would facilitate orientation and enabled finding relevant information. In order to satisfy these needs over the last two decades Recommender systems have evolved [3, 4].

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 improvement of existing systems is very active area of scientific research. This development is based on the continuing evolution of statistical methods, machine learning, artificial intelligence, data mining, information retrieval etc [2].

The aim of this paper is to present the evolution of the Recommender systems, present level of development with examples of Educational Recommender Systems that are in active use today (including *ELARS – E-Learning Activities Recommender System* developed at the Department of Informatics at the University of Rijeka) and to give guidelines for future research and development.

II. EVOLUTION OF 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 presented the problem of orientation and finding the relevant information (called Information Overload Problem). In order to address this problem information filtering systems were developed and today, in their various forms, they are the main solution for the information overload problem [5].

First systems that were developed were intended for commercial use. Main objective of these systems were to recommend products to potential customers in on-line shops. On the other hand, the beginning of the World Wide Web opened up the possibility of using new technologies in the education.

At the beginning, using these new technologies in education was oriented only toward delivering traditionally prepared learning materials to designated learners. These materials were mostly digitized versions of the 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 prepared.

To solve this problem and to achieve the personalized distribution of prepared learning materials different approaches have been developed. Based on intelligent and adaptive algorithms *Intelligent Tutoring Systems* (ITS), *Adaptive Hypermedia Systems* (AMH) and *Recommender Systems* were developed [6]. These systems introduced interactivity and were enhanced by incorporating communication capabilities, evaluation and monitoring of learners progress. Also, these systems enabled the introduction of personalization with adaptive navigation through learning materials and/or adaptive presentation of prepared learning materials.

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

In order to solve this problem, a uniform system that can be easily implemented without much need for further training of teaching staff were developed. These systems were designed as closed systems for e-learning with 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 (for example MudRi in University of Rijeka that is based on Moodle platform).

The majority of LMS are designed and used as closed learning environments [7]. Preparation and organization of learning materials as well as their use is entirely based on a centralized organization of the learning content done by teachers. These systems are used with the aim of supplementing usual face-to-face teaching experiences in the classroom and facilitate distance learning [8]. This combination of traditional teaching methods and the use of LMS as a complement to the process of teaching enabled rise of the hybrid model of teaching and learning.

In 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 was shifted from the authors of the presented materials towards the user of the materials in a way that users are given the opportunity to actively participate in the preparation and organization of the available materials. This progress is inevitably passed on to the future development of educational systems and e-learning approaches.

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 users of these systems as a starting point for organizing e-learning. Different styles of teaching and learning [9, 10] 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 existing materials, they can create new learning materials that will become available to other learners [11].

Continuous increase in the number of available learning materials, both within the closed LMS but especially of the 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 differentiation between traditional top-down approach (within the formal educational structures) and open bottom-up approach (present outside the formal educational structures) as well as combination of these two approaches.

III. BASIC TECHNIQUES

The algorithms used in the Recommender systems are based on following basic techniques [3, 6]:

- Collaborative Filtering (CF) - recommendations are based on previous ratings of items of recommendation collected from all users,
- Content-based recommending (CB) - recommendations are based on the similarity between the content of items of recommendation while taking into account the items that the user has used and positively rated and that coincide with the specifications in the user profile,
- Knowledge-based recommending (KB) – recommendations are based on previously defined expert knowledge on how much can certain item of recommendation be useful to user,
- Hybrid approaches (HA) - recommendations are based on combining various individual techniques shown above.

More detailed descriptions of these basic techniques are shown below.

A. Collaborative Filtering (CF)

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, algorithm would recommend items that are similarly rated by other users.

Collaborative filtering can be further divided into two main approaches [2, 4, 6]:

- 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 for targeted user are predicted (this approach also encompasses *Item-based CF*, *User-based CF* and *Stereotype-based CF*),
- model-based approach (latent factor models) - 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.

B. Content-based recommending (CB)

Content-based recommending is based on comparing the content of the items of recommendation with contents that are of interest to the user. While the interest of users for certain content can be collected explicitly (by user ratings) or implicitly (by tracking user activities), description of items of recommendation depend on the available data used for describing items content.

Describing the content of the items should be carried out automatically. Items with associated textual content (such as books, web pages, et.) are usually easily described (using various different approaches for Information retrieval). However the problem occurs in items that are not textual (such as video or audio content, multimedia educational materials, etc.). Although various algorithms which aim to identify the content of these types of materials were developed [12], it is still often a case that appropriate item's description can be obtained only through direct entry of data by the creator of the content.

Also, with text contents which are most appropriate for this kind of recommending, there may be situations in which different content are represented using the same set of parameters. This can make them mutually indistinguishable, so the recommender algorithm is unable to distinguish between high quality and less quality work.

C. Knowledge-based recommending (KB)

Knowledge-based recommending is used in cases where the items ratings provided by users are not good enough input for the system's prediction algorithm. To recommend an item in these cases system is built around pre-defined 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.

Use of this type of algorithms 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 database on which the whole system is built [13].

D. Hybrid approaches (HA)

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

IV. Current Problems in Recommender Systems

In Recommender systems there are a few common problems. 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 Recommender systems (with basic techniques correlations) are:

- Automatic information retrieval (CB),
- Cold-start (New User/Item) problem (CB, CF),
- Content overspecialization and non diversity (CB, CF),
- Sparsity and Gray Sheep problem (CF),
- Fraud problem (CB, CF),

A. Automatic information retrieval problem

Today's algorithms have limited ability to automatically analyze the content of items that are recommended. Most developed algorithms are tailored for the analysis of textual content. They use keywords and phrases that are found in the text and compare them with search parameters. The higher the correlation between these data the greater the likelihood that a particular text can be recommended to designated user [3].

On the other hand, multimedia content present more complicated problem. In recommending audio or video content, existing algorithms rely on textual version of audio data and the basic tags set by the creator of the content or subsequent users. On the basis of these information satisfactory understanding of the content cannot be achieved, certainly not at the necessary level for successful recommending.

Regardless of the kind of content that needs to be described through automatically collected information, there is a problem of the categorization of different content related to the same topic. In fact, if there are two different documents presented by the same parameters collected automatically by the system, they cannot be mutually distinguishable. The consequence of this problem is that the system in these cases is not able to differentiate the quality of the content of documents that are recommended.

This problem is dominant in content-based (CB) Recommender systems [4, 14].

B. Cold-start (New User/Item) problem

When user or item that could be recommended encounter Recommender system for the first time, system does not have enough data about this user or this item to be able to prepare a meaningful recommendations [15]. In this case, the system depends on the manually entered initial parameters about the user or the items of recommendation by the user or system administrator.

New user may be asked by the system to enter some information to their profile that can be used to determine the initial recommendations (usually in the form of reviewing certain items or through the fulfillment of basic data when logging into the system like first and last name, age, 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 properly (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 (interest, how user use the system or contents that are recommended, etc.). However, for the implicit data collection user must use the system for a certain period of time. During this period a system should make recommendations with which the user will be satisfied. If due to lack of data on the user system gives the wrong recommendations, there is a risk that the user withdraws 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's about user that are collected during earlier educational tasks (preferably related to the content of the observed 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 users on the course during which Recommender system will be used.

In addition to the problem of determining profile of the new users, the problem is the determination of the parameters of the new items that are recommended. If new items that would be recommended are added to the system they should be treated equally by the systems as existing items on which system has already collected additional information. In formal education teacher can provide the necessary information to address this problem. However, in open education surroundings there is a danger that the new learning objects would not be treated like that by the system due to the lack of information about them. In these cases Recommender systems rely on available information about learning objects that are in some cases dependant on the other users of the system (through ratings etc.).

This problem is dominant in content-based (CB) and collaborative filtering (CF) Recommender systems [3, 15].

C. *Content overspecialization and non diversity*

In cases where the Recommender system is only recommending items that score highly with user's profile, there is a risk that the user will be recommended only very similar items. In such cases, the user stays within a limited area in the content which is recommended, and a system does not offer content that would be of interest to user but are not highly evaluated in relation to the user's profile.

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

On the other hand, in open education systems, the most common approach for solving this problem is introduction of random selection of content that will be recommended, taking into account that there is a proper correlation between this new content and content the user is interested in [3, 4].

This problem is dominant in content-based (CB) and collaborative filtering (CF) Recommender systems.

D. *Sparsity and Gray Sheep problem*

If the recommendation in the Recommender system depends on the ratings of items by the users of the system, then there can appear the sparsity problem. In fact, some items that the system can recommend will be evaluated by a small number of users with the result that these items, regardless of their quality, will not be widely recommended to other users.

In addition to the items content, the problem of sparsity could appear among system users. If the recommendation is done on the basis of the grouping and comparing the users, the user who does not fit well in any of the groups will not get good recommendations.

In the formal educational systems, these problems can be solved through interventions done by teachers. However, in open educational systems, there is a risk that they remain unresolved, thus preventing satisfactory use of the system for all users [3].

This problem is dominant in collaborative filtering (CF) Recommender systems.

E. *Fraud problem*

With the development of the Recommender systems, primarily in the commercial application, their recommendations have become an important factor in the user decision making process regarding commercial products. Because of their ability to influence the user decisions, the problem of fraud has emerged as one of the problems that the Recommender systems must be able to cope with.

The most common forms of fraud that are taking place in the commercial Recommender systems are related to the impact of the ratings of certain products on users decisions. Fraud is usually committed through artificially raising the ratings of certain products (push attacks) or descending ratings of the competing products (nuke attacks). During the execution of those frauds ratings of products are artificially raised or lowered in a meaningful range around the mean score between the highest and lowest value in order not to arouse suspicion [2].

Fraud problem in the Educational Recommender Systems is related to the data entered by the user. These data could be basic data of users profile or the data collected through tests used for monitoring user advancement through the course. Although fraud problems do not make sense in open Educational Recommender Systems, in formal education settings where the success rate may have consequences for the overall success of the user, there is the possibility of fraud. This can happen when user is not monitored during the use of the Recommender system (test questions are answered with unauthorized assistance by a colleague, unauthorized reading, etc.).

These problems are relatively unexplored area in particular in the context of Educational Recommender system especially in formal education settings. This problem is dominant in collaborative filtering (CF) and content-based (CB) Recommender systems.

V. EXAMPLES OF RECOMMENDER SYSTEMS

Today, a large number of different Recommender systems are in practical use. For systems that are used for commercial purposes, the main goal is to increase customer satisfaction by ensuring good recommendations while achieving economic growth.

On the other hand, the Educational Recommender Systems aims to facilitate the modernization of the educational process, whether in a formal or free open environment in which education is conducted. Usually, these systems are hybrid in their design and behavior and they combine various techniques and approaches to generate recommendations. Educational Recommender Systems can be divided into systems that are recommending learning materials or learning objects, colleagues for joint implementation of activities or for tutoring work, different educational paths through the learning materials that correspond to individualized users preferences or help in building ones personalized learning path (PLP).

Also, learning materials that recommender systems recommend to users can basically be divided into materials within the formal educational environments (LMS) and freely available materials on the World Wide Web. Given the widespread use of Web 2.0 tools for e-learning, most recommender system recommends a combination of those materials. Also some educational Recommender systems are helping teachers by taking over part of the monitoring of students [16] or finding materials for the development of learning objects [17].

In [1] the authors explore the use of Recommender systems within the LMS with the aim to recommend learning objects within formal courses as well as expansion to the recommendations with learning objects freely available outside the LMS. In [18] authors develop Recommender system which recommends courses available in LMS to students, taking into account the best combination of available courses and the interests of the individual user.

PLORS [19] is Recommender system within the LMS that recommends different learning objects, with the aim of personalizing the formal educational process, based on monitoring of previous students activities and comparing it with other students and their activities. In [20], the authors develop a Recommender system that associate learning objects with previous good learners' ratings and are recommending learning objects to future generations of students in terms of their similarities with previous generations and collected ratings.

When building a user profile used 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 [10, 21, 22], both in the formal and open educational environments. Thus, in [9] the authors propose Recommender system that will help teachers in expanding the material for e-learning in a way to adapt them to different learning styles of their students. Also, the system ELARS [6] as an important element in the user profile use VARK [23] description of learning styles.

In [24], the authors propose the use of Recommender system for helping students to find colleagues who can help them overcome a certain problem while learning part of the course material. Using a Recommender system to connect students with potential tutors appears in a number of different systems. In some cases, this ability is not system's only purpose but addition to recommending learning objects or materials as was done in [25]. Also, the system ELARS for one of its goals has capability to recommend suitable colleagues while forming a group to work on a particular problem or work on a particular project. When this capability is built into the Recommender System, students usually have the freedom to independently decide whether to accept the recommendations or to ignore them.

Determining a personalized learning path is one of the goals of number of Recommender systems. These systems use various input parameters in order to define the unique path through learning objects for each user. Thus, the authors in [26] conducted curriculum sequencing in a way that system uses incorrect students answers to devise further learning path in order for user to acquire an adequate level of knowledge of the course content. On the other hand, the authors in [27] have built s system whose algorithm use graph theory and knowledge about different learning styles to recommend different PLP for each user.

In [28] the authors compare the level of initial knowledge of each user with the complexity of individual learning objects. Based on the results obtained by this comparison, the system gives a recommendation on the further learning path. Also, the authors in [29] design the construction of the PLP based on a comparison of the user profile and the desired goal of learning determined by the user. The system monitors the progress of the user and redirects learning path to ensure the acquisition of all the necessary knowledge needed for the successful further learning.

In order to achieve the most optimal operation of the algorithms used in the Recommender systems various methods of artificial intelligence (fuzzy sets, neural networks, genetic algorithms) or their mutual combinations are used. Thus, the authors in [16] and [30] use fuzzy inference techniques for processing data on the success of students with the aim of better monitoring of students progress through the contents of the course.

Neural networks are used in order to develop algorithms that have the ability of self-learning based on the data of a given domain [13]. In Recommender systems, neural networks are used to model complex relationships between the users profile and their expressed interests [5] and modeling connection between the recommended objects and other parameters that the system use to determine the specific recommendations for individual user [3, 14, 31]. Also, very often fuzzy and neural networks are combined in hybrid systems of artificial intelligence. This approach has the possibility to achieve better overall results in the same environment compared to the cases in which only one of these methods are used.

Methods of artificial intelligence based on evolutionary computation include the use of genetic algorithms, evolutionary strategies and genetic programming [13]. Of these different techniques, genetic algorithms and different evolutionary strategies are mostly used in Recommender systems.

Thus, the authors in [31] are using Ant Colony Optimization (evolution strategy) approach in order to identify effective and optimal learning path for system users. This system is oriented toward obtaining information on unknown terms encountered by the user during their learning process. In [26] the authors use genetic algorithm to generate a personal learning path for the user, while in [32] authors use a model of the biological immune system in order to obtain the set of possible recommendations. From this set of possible recommendations, system's algorithm can choose the most optimal with respect to the user needs.

ELARS [6, 33] personalize collaborative learning activities that are performed using Web 2.0 tools. The system is used together with the chosen LMS and a set of Web 2.0 tools. By its design, ELARS can make recommendations on the level of individual activities during the learning process with the possibility of making individual and group recommendations. System consist of three main components: the activity model, the subsystem for user modeling and the subsystem for determining recommendations, each designed for a different purpose.

Activity model is used for describing learning design, subsystem for user modeling are responsible for collecting and analyzing data in order to build a model of each student and model of groups of students while subsystem for determining recommendations determines and gives students different types of recommendations (optional e-tivities, suitable collaborators, Web 2.0 tools and advices for increasing their level of activity).

Today, most of the research in the field of Recommender systems is focused on the development and optimization of different versions of already used algorithms. These systems usually aim to make recommendations on the level of whole courses, learning objects as parts of the courses or different learning materials. In smaller number of cases, developed algorithms are used to recommend suitable colleagues or provide feedback information about student's progress (the system prepares the data collected in a form suitable for use by teachers or students).

VI. Guidelines for Future Research

Although future development and research in the field of Educational Recommender Systems can relate to training and upgrading of existing algorithms designed for determining appropriate recommendations, there are other areas in which we can expect further scientific research.

Educational Recommender Systems can basically be divided into systems for operating in the open (bottom-up) and systems for operating in a structured formal (top-down) learning environments. Although part of the functionality and operating principles of these systems does not depend on the specifics of the learning environments, other parts must be adapted to the specifics that are distinct between these environments. Because of this diversities, systems developed for one environment may not be easily (without major changes in the way they work) used in the different 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 a system that will be able to adequately function unchanged in both environments.

With the introduction of the Bologna process teacher's workload has increased significantly, particularly in the area of continuous monitoring and evaluation of students work. Research as [34] links increasing workload of teachers due to continuous monitoring of students with the success of students. Results of this research indicate that there is a great discrepancy between the increasing workload of teachers and increase in students' achievements. Today used Educational Recommender Systems usually do not include mechanisms that are designed to help teachers in reducing workload. The systems are mostly oriented towards the needs of students, and in a few cases, to a lesser extent, have built-in algorithms aimed to assist teachers. The data that is collected by Recommender Systems can be used to assist teachers (preparing data for teachers use, automatic processing of data, continuous monitoring of students achievements etc.).

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

Although in the field of education, algorithms developed for Educational Recommender Systems evaluated within one course can be used unchanged in another course (algorithms do not depend on the content that is taught), systems usually do not link the achievements of students in different courses. In fact, considering that today study programs are based on learning outcomes and the acquisition of pre-defined general and specific competencies, achieved results of students in one course could be used in the process of making recommendations in the different course.

If, while working on content of one course, a student is able to reach an appropriate higher level of knowledge (in accordance with Bloom's taxonomy) student should be able to apply adopted mechanisms in another course. By using this adopted mechanisms student should faster achieve the required results in a new area of learning. Acquired general competence in one course is 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. It follows that one of the areas for further research and development of Educational Recommender Systems can certainly be in connecting learning outcomes through several different courses and using them for designing recommendations in completely dissimilar courses.

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

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

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

Due to the above, one of the areas in which further development and research in the field of Educational Recommender Systems can be expected is in enabling these systems to take into account the difference in the physical proximity of students (defined through learning environment they are sharing) and the differences that arouse from that circumstance.

Regardless of the learning environment in which students learn, one of the more prominent feature of learning among our students is non-continuous learning. Students usually organize their time devoted for the given assignment in a way that they use only a short period of time before the deadline set for submission of the results. In this way, students use most of the time intended for working on the given assignment for some other activities. When confronted with this problem, Educational Recommender Systems that use tracking of students' on-line activities for creating recommendations are incapable to appropriately deal with this problem. Still, Educational Recommender Systems could be used to motivate students to work continuously in order to better organize their time devoted to learning and to achieve better overall learning results.

Currently used Recommender Systems are usually based on the premise that this problem does not exist. For this reason, they don't have incorporated methods designed to encourage students to work continuously, but they expect students to do so. Educational Recommender Systems could be used in this manner so one of the areas for further research and development of these systems could be to incorporate non-invasive ways designed for the purpose to motivate students to work continuously.

With the further development of the already constructed algorithms for determination of recommendations, presented potential areas for further research and development suggests that there are still insufficiently explored and developed areas that have the potential to increase the efficiency of Educational Recommender Systems.

VII. CONCLUSION

Recommending can be defined as a process in which 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 earlier on-line behavior. On the other hand, to make Educational Recommender Systems effective, it is necessary to gain students trust in these systems as early as possible. Critical period for building this trust is at the beginning when students encounter systems for the first time (otherwise there is a real possibility that a student could withdraws from the use of the system, considering it an additional burden in relation to their existing workload).

When devising ways of communication between students and the Educational Recommender system, it is important to take into account pedagogical standards together with the expected learning environments within which the learning process will be carried out (and the system will be used). The differences that exist between various educational methods, suitable for use in different areas of study, impose the need for systems' flexibility in order to satisfy anticipated needs of students.

Taking these differences into account, it is possible to design and build Educational Recommender Systems that will provide satisfactory service to students and teachers who will use them.

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