Recommendation of Educational Content to Improve Student Performance: An Approach based on Learning Styles

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Abstract: Virtual learning environments are a powerful tool in the teaching-learning process and can provide a variety of utilization data that can be explored by data mining techniques to improve the understanding of student behavior and performance. By using Learning Analytics, it is possible to identify potential problems, such as student dropout or failures before they become irreversible, and indicate corrective actions to be taken by teachers. In this context, content recommendation plays a prominent role since choosing the proper content for a certain audience may motivate them to become more involved in the learning process. However, in distance education settings nowadays, teachers do not know their students, thus it becomes difficult to select the content most suitable to their needs. In this paper, we propose a content recommendation architecture that takes into account the learning profile of students enrolled in an LMS to customize content recommendations to each learner's style. A profile assessment tool, based on the Honey-Mumford learning style taxonomy was implemented and some preliminary data obtained. We devised a recommendation scheme that considers the euclidean distance between students' learning styles when suggesting content to be studied. Our preliminary results indicate this approach may be beneficial to improve the teaching-learning process and student performance as a whole.

1 INTRODUCTION

Learning Management Systems (LMSs) have been considered a valuable tool in the teaching-learning process, being used mainly in distance learning but also in formal teaching. Such tools are intended to provide content to students to assist them in studying a particular subject. Coupled with this, these environments have the potential to generate a wealth of data about their utilization by students and teachers, which can be explored to help understand students' behavior and performance aspects.

Educational Data Mining is a field of research that has as its object of study such aspects, using statistical and machine learning methods, and techniques, to explore and analyze data originating in an educational context in order to better understand the different variables involved in this complex process of teaching-learning mediated by virtual tools (Romero and Ventura, 2010).

An emerging area in this context is Learning Analytics, which deals with the study of technology-mediated learning and has its roots in diverse areas such as educational data mining, business intelligence, web data analysis, and recommendation systems. More specifically, Learning Analytics refers to the measurement, collection, analysis and presentation of data about learners and their contexts in order to understand and optimize the learning process and the environments in which it takes place (Baker and Inventado, 2014) (Ferguson, 2012).

In face-to-face teaching, adjustments in the teaching-learning process occur based on teachers' experience in analyzing student feedback and taking corrective actions that they deem appropriate. However, teachers' performance has been increasingly hampered by the increasing size of the classes, given the recent massification of education.

In the current context of education mediated by learning management systems, this difficulty is even more noticeable, since the amount of students enrolled in classes becomes overwhelming and eventu-

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ally overloads the instructor. Thus, he cannot provide personalized attention to each student and may lose track of each individual's context. Thus, new approaches are welcome to identify problematic situations in the teaching-learning process at their inception, such as student potential to dropout or fail a course.

One key aspect of this process is content recommendation (Mendes et al., 2017). It aims to provide educational material to students to increment their knowledge about a subject and their chances of succeeding. However, simply suggesting content to students as if they were a homogeneous body may not yield the intended results since each student has their own learning style. In this paper, we develop a web-based tool to collect student data via a questionnaire based on the Honey-Mumford taxonomy, aiming to identify students' learning profiles. This information serves as input to a recommendation system that assists teachers and students in choosing the better-suited activities or materials for distinct learning styles in a class. We have performed some preliminary validation that indicates promising results yet to be measured.

The remainder of this paper is organized as follows: Section 2 deals with the main theoretical aspects related to this research. Section 3 proposes a methodology, mediated by an LMS, to help teachers follow their students' progress within a course, identify potential problematic situations and take appropriate actions to remedy them. To this end, a recommender architecture, based on student learning styles is described in Section 4 and some preliminary results presented in Section 5. Section 6 summarizes the paper and indicates some directions for future work.

2 THEORETICAL BACKGROUND

2.1 Learning Styles

Each person is a unique being, differing from others in the way they think, act and relate to others. Similarly, each human being has their own way of learning, those who learn by doing and those who observe, those who are multitasking, and those who need to focus on one task at a time.

Several studies intend to classify students according to the way most favorable to their learning, that is, according to their learning style, seeking to identify the best way for a student to assimilate the knowledge that is transmitted.

For (Kolb, 2014), learning is the process by which knowledge is created through the transformation of experience. And knowledge is not something that can simply be transmitted or acquired, it is the result of a process and can be created and recreated continuously. Kolb also believes that people can be classified according to their way of learning into learning styles (or preferences) as diverging, converging, assimilating, and accommodating. This classification can be used to provide teachers with information so that they consider the best way their students can learn and thus be able to achieve better success in their teaching.

Honey and Mumford have identified, based on Kolb's work, four learning styles or preferences: Activist, Theorist, Pragmatist, and Reflector. The authors recommend that, to maximize personal learning, each student should know their own learning style and then look for opportunities to learn using that style.

In order to assist the student in obtaining their learning style, Honey and Mumford have developed a Learning Style Questionnaire (Honey, 2001). This questionnaire consists of 80 yes/no answer questions, where the respondent points out as true the statements to which he agrees. At the end, a score is obtained for each style (Activist, Theorist, Pragmatist and Reflector). This score refers to the student's intensity in that profile, and may range from Very low preference to Very strong preference for each of them.

Activists are people who learn by doing. They learn best when engaging in new experiences and working with others to solve problems, games and simulations of real situations. Reflectors learn by watching and thinking about what is happening. They like to consider all the implications before giving an opinion. Theorists like to understand the theory behind actions. They like to analyze and synthesize, and they are uncomfortable with subjectivity. And finally, Pragmatists like to try things out. They like new ideas that can be put into practice.

The VARK model is another approach to learning style classification proposed by (Fleming and Baume, 2006). This model is based on classifying learners into four modalities, or learning preferences, namely: visual, aural, read/write and kinesthetic.

Such classification is accomplished by applying a form containing 64 questions, where answers will be marked according to a student's individual preferences. In the end, the form presents the summary of the answers within each of the modalities, and the individual can be part of more than one modality.

Each modality has its own characteristics. For example, aural learning is the learning style in which one learns through the aural sense. An aural learner has listening and speaking as the primary means of learning. Behaviors such as repeating content aloud for memorization, or even the preference for videos, podcasts, and participation in study groups are more common in people of this style.

(Fleming and Baume, 2006) believe that the use of questionnaires to define learning styles can be useful, but its real value lies in the self-knowledge it can generate to each person when analyzing the score obtained. This classification can serve as input for teachers so that they can choose the most appropriate activities for each modality.

In (Bartle, 1996), another classification of student profiles aimed at games and gamified environments, the so-called Bartle Archetypes, is proposed, which may be helpful in composing student profiles and in understanding the reasons behind high dropout rates, for example. Bartle believes players are motivated by the autonomy, challenges, relationships, and sense of power provided by games, and knowing how to leverage these elements to maintain student motivation and interest is extremely valuable.

Bartle proposes categorizing players into four profiles according to how they relate to and act in games. Achievers are driven by the goal of the game and strive to achieve it, accumulating wealth, scoring points and collecting as many items as possible. Explorers are interested in finding out as much as possible about the game, finding secret passages and unraveling the entire game world; students with this profile prefer to know all the paths or stages they should go through before beginning the journey. Socializers prefer to relate to other players, even outside the game environment; and finally, Killers are concerned with asserting their existence in competition with other players or the environment.

If teachers can better identify and understand their students learning styles, they will be able to provide better educational experiences to them and lead each individual on a more efficient path according to their profile.

In this paper, we use the aforementioned Honey-Mumford questionnaire to assess students' profiles in order to assist them in selecting educational content better suited to their learning preferences, as described in Section 4.

2.2 Educational Data Mining

Educational Data Mining (EDM) uses traditional and statistical machine learning methods and techniques to explore and analyze data obtained from educational contexts. The main objective of this approach is to analyze the different variables involved in the teaching-learning process and use them to develop predictive models in order to classify students according to their performance (Fernandes et al., 2019).

EDM makes use of educational systems databases to understand students and their learning styles more thoroughly in an effort to devise educational strategies that will increase their academic achievement and success rate at the end of each term.

According to (Chalaris et al., 2014) based on (North, 2012), EDM consists of a process divided into six steps or phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The business understanding step consists in understanding the objectives and requirements of the project. Understanding the data allows us to identify any data quality issues as well as interesting subsets for formulating non-obvious hypotheses. Data preparation comprises necessary tasks such as data cleaning, transformation, and selection, in order to build the final data set to be used in the modeling phase, where different techniques can be applied. Modeling is followed by the Evaluation step, which determines the feasibility of applying the model and whether business objectives have been met. The final step is Deployment, which specifies how to employ the developed models and the actions to be taken.

There are many data mining techniques that can be applied to educational data and each can provide useful results that help solve many educational problems. Data mining tasks, such as grouping, can reveal overall student characteristics, while prediction (classification and regression) and relationship mining (association, correlation, sequential mining) can help teachers mitigate student dropout rate, retention, increase individual performance and improve learning outcomes. This can help provide a more customized learning process, maximize the efficiency of the education system, and reduce the cost of educational processes (Zhang et al., 2010).

2.3 Recommender Systems

Recommender systems have been one of the major direct applications of artificial intelligence in people's lives. Due to a large amount of data that is generated daily on the internet, it is common for systems integrated into websites to filter products and services with a higher chance of pleasing the user. They work as a friend, who, by knowing your taste, recommends websites, videos, movies, music, and products.

In such systems, recommendations are solely data-driven, without human intervention, and users' historical patterns are identified and analyzed to recommend products and services that the users themselves did not know they needed.

However, recommendations can be made not only for selling products, but also for content such as news, articles, multimedia content, and even tourist attractions (Smirnov et al., 2016). Recommendations can be made based on what people with similar profiles might like, the so-called collaborative filtering (Sarwar et al., 2001), or based on user history, namely, content-based filtering (Van Meteren and Van Someren, 2000). Content-based filtering is based on finding content similar to what the user has been consuming and then recommending new content to them, while collaborative filtering recommends content that has been consumed by other users with a similar profile. In an educational context, recommendation systems can be applied to e-learning tasks for recommending resources such as articles, books, podcasts, or videos to students with the aim to tutor them and make them achieve better performance.

3 METHODOLOGY

In this research, we propose a methodology that allows teachers to monitor the progress of students in a course, identifying potential problem situations early on, so that it is possible to offer differentiated treatment to students who need it. Thus, we expect to minimize problems such as demotivation, failure, and student dropout, increasing the success rate of the teaching-learning process as a whole.

We assume the course will be mediated by a Learning Management System (LMS), in face-to-face or distance education settings. LMSs often generate a wealth of data about their use by students and teachers that, if well explored, can become a valuable tool for tracking student achievement.

In Figure 1, we present a general scheme of how we believe the proposed methodology can interconnect the different actors and entities of the teaching-learning process. The LMS is the intermediary element and teachers are responsible for providing content, tasks, quizzes, questionnaires and various activities, which will be read, watched and solved by students during a course. In this process of interaction of students and teachers with the LMS, usage statistics are generated, such as number of content views, comments made by students, percentage of successes/failures for a task, number of attempts, compliance with deadlines, among many other aspects. Those statistics are computed globally, by class and individualized by student.

This **Data Collection** phase will generate educational datasets obtained from LMS use, which will serve as input to an **Educational Data Mining** phase where machine learning models will be used to prematurely identify students who are likely to fail a course, are candidates to drop out, disoriented as to what content to study or which tasks to solve, among other problems. Data mining will also enable students to be classified into learning profiles so that they can receive customized service. Finally, based on the previous classification, we come to an **Intervention** phase, in which semi-automatic preventive and corrective actions will be triggered by the system, and validated by the teacher, in order to rescue a student with problems and increase their likelihood of completing the course successfully.

One point to consider is that students are individuals with different characteristics, interests, and goals, so a given content or assignment that seems attractive or simple to one person can be boring or complicated to someone else. Therefore, it is important to identify the Learning Profile of the students enrolled in a course, for example, by means of a questionnaire applied to each student when registering in the LMS.

Thus, content that is likely to be more attractive to the profile into which a given student fits will be recommended. Besides, if that student has any issues during the course, he may receive corrective actions that are more appropriate to his profile. We believe that adjusting the content and tailoring corrective actions to each student's learning profile or style are essential, as it allows, in a context of such diverse and numerous classes, to provide more personal, customized treatment, as if the students had the teacher by their side all the time. We even intend to adapt the system interface to a student's profile, thus seeking to provide a differentiated and potentially more motivating user experience.

This approach does not intend to dismiss the figure of the teacher as a mediator and facilitator of the teaching-learning process, quite the opposite. The master will have even more tools at hand, stemming from the methodology and products to be developed, which will allow him to conduct the course more effectively, acting globally and also individually.

Another important point is that students' profile, initially collected from the application of questionnaires, can and should be adjusted throughout their history in a given course or LMS, thus inferring new behaviors and preferences that the students themselves not even perceived as their own characteristics until then. We consider this adequacy of the content and corrective actions to the student profile as an important contribution to be achieved in this research. Although current technology allows the massification of educational content, reaching an increasing number of students, it fails when considering that everyone learns and feels content the same way, what can often contribute to failure.

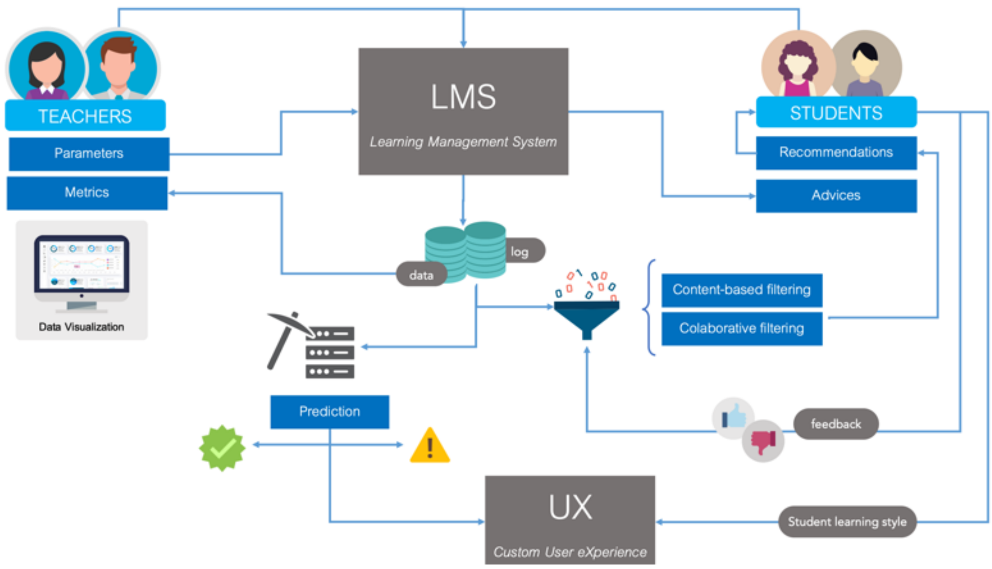

Figure 1: Overview of actors and entities in a teaching-learning process interacting by means of an LMS.

4 RECOMMENDER ARCHITECTURE BASED ON LEARNING STYLES

This paper is focused on recommending educational content to students in order to help them achieve greater success in their courses. This applies to students who have had a good performance and may be interested in augmenting their knowledge, and also to individuals who have been experiencing difficulties and may need some extra material for self-study and improvement.

Our Recommender module (Figure 1) uses as input the datasets collected by the LMS in order to provide content recommendation using collaborative filtering. A well-known problem in recommender systems is the cold-start problem, which is related to low precision when recommending content to a new user, since the system has hardly any information about their preferences. In order to circumvent this problem, the proposed recommender architecture leverages previously obtained students' learning style information in order to provide customized content recommendations, tailored to a student's profile. Thus, it is possible to suggest more accurate and useful content to learners.

Let us assume a given student is having problems with a UML modeling topic in a Software Engineering course. Since this student is new to the LMS, the system has limited background information on their preferences, considering they have not yet contributed much by rating available content. In this case, the system would end up recommending a generic, seemingly adequate content to the student, that might or might not be useful. In the latter case, the student might feel demotivated and even discredit future recommendations made by the LMS.

But now suppose the LMS has additional information about the student, concerning how much they belong to a certain learning style according to the Honey-Mumford taxonomy, for example. In the questionnaire we applied to the students there are four groups of 20 questions each, aimed at assessing a person's conformity to one of the four styles, as specified by the aforementioned researchers (Figure 2).

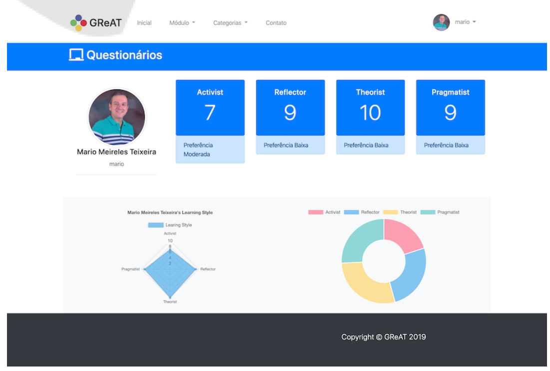

Figure 2: Result of an individual's learning style according to the Honey-Mumford approach.

In the case of a student who recently signed up to the LMS, there is limited information about what content might be useful to them. Consequently, the system will try to predict their ratings to content they have not yet used by calculating the similarity between the new student and other students who have been in the LMS for a longer period. The similarity in this case will be computed as follows:

$$sim_{u_1,u_2} = \sqrt{\begin{array}{l}(u_1 activist - u_2 activist)^2 + \\ (u_1 reflector - u_2 reflector)^2 + \\ (u_1 theorist - u_2 theorist)^2 + \\ (u_1 pragmatist - u_2 pragmatist)^2\end{array}} \qquad (1)$$

Note that the similarity between users u_1 and u_2 is given by the euclidean distance between their preferences in each of the four learning styles: Activist, Reflector, Theorist, and Pragmatist. In this way, we can predict the evaluation $P_{u,i}$ a given user u would give to content i using the formula:

$$P_{u,i} = \frac{\sum_v \ (r_{v,i} \cdot sim_{u,v})}{\sum_v \ sim_{u,v}} \qquad (2)$$

Here, $r_{v,i}$ is the rating provided by user v to content i. This implies that content ratings provided by users with similar learning styles will have stronger impact on ratings predicted for new users of the same kind. In Figure 3, we depict a general scheme of how our approach should work.

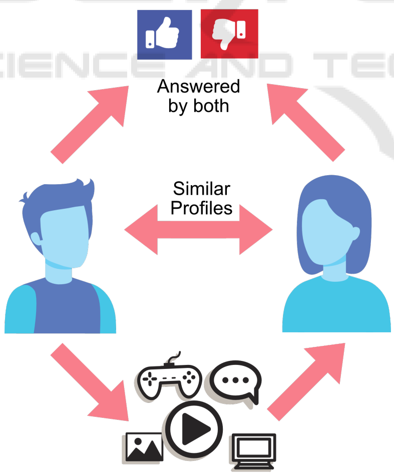

Figure 3: Educational content recommendation weighted by learning style similarity.

As the student progresses through the LMS, by interacting and rating content, content recommendations become more precise and tailored to their preferences and learning style.

5 PRELIMINARY RESULTS

The proposed recommender architecture based on learning styles still deserves further validation. It has not been widely used in courses with a larger group of students. Up to this point, our results have been very promising and style-based recommendations seem rather adequate.

Figure 4 shows the dashboard for a user highlighting his related peers and also some content recommendations he might enjoy. Figure 5 shows the system's content catalog tagged by subject and learning style.

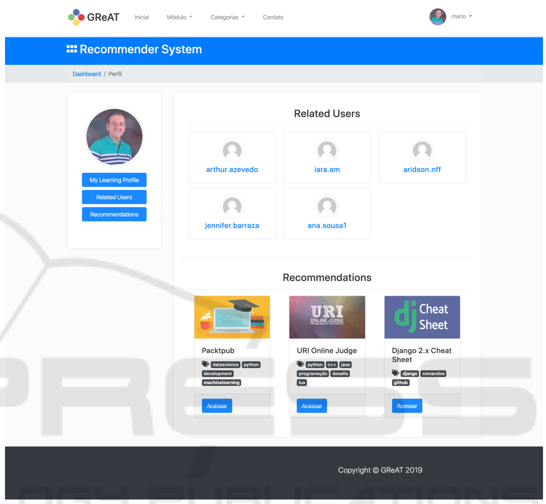

Figure 4: User dashboard.

6 CONCLUSION

Educational Data Mining has been used as a tool for decades in order to analyze data originated in educational environments and improve educators' understanding of the different variables involved in such a complex scenario. Learning Analytics, an emerging discipline, collects and analyzes data about students seeking to enhance the learning process and the environments where it occurs.

This paper describes a high-level methodology for students' performance follow-up and fine-tuning in Learning Management Systems (LMSs) where data about LMS usage is measured, collected, analyzed, and used to make predictions about learners' performance and point out potential failures in the learning process before they occur, suggesting corrective actions to be taken by the teacher and students.

An essential role is such a scenario is content recommendation. We advocate that the use of learning

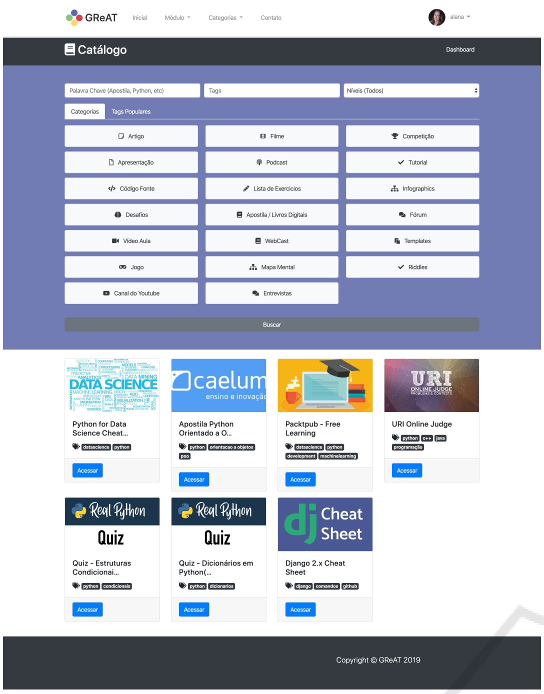

Figure 5: Content catalog.

profiles as additional information for picking out content can provide better content selections that will fulfill students' needs and expectations. In this paper, we detailed a Recommender Architecture based on Learning Profiles to be used in an educational setting mediated by a Learning Management System. Our recommender uses collaborative filtering to select content similar to what a user has already studied and leverages student profile information to filter the content most suitable to a user's needs. Thus, peer rating as well as profile indications will guide content selection and improve the learning process. In future work, we even intend to adapt content by taking into account the learner's profile.

Further validation should be performed in classroom in the near future but our preliminary results firmly indicate we are in the right track.

REFERENCES

Baker, R. S. and Inventado, P. S. (2014). Educational data mining and learning analytics. In *Learning analytics*, pages 61–75. Springer.

Bartle, R. (1996). Hearts, clubs, diamonds, spades: Players who suit muds. *Journal of MUD research*, 1(1):19.

Chalaris, M., Gritzalis, S., Maragoudakis, M., Sgouropoulou, C., and Tsolakidis, A. (2014). Improving quality of educational processes providing new knowledge using data mining techniques. *Procedia-Social and Behavioral Sciences*, 147:390–397.

Ferguson, R. (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5/6):304–317.

Fleming, N. and Baume, D. (2006). Learning styles again: Varking up the right tree! *Educational developments*, 7(4):4.

Honey, P. (2001). Honey and mumford learning styles questionnaire. *Peter Honey Learning. Retrieved April*, 25:2007.

Kolb, D. A. (2014). *Experiential learning: Experience as the source of learning and development*. FT press.

Mendes, M. M., Carvalho, V. C., Araújo, R. D., Dorça, F. A., and Cattelan, R. G. (2017). Clustering learning objects in the ieee-lom standard considering learning styles to support customized recommendation systems in educational environments. In *2017 Twelfth Latin American Conference on Learning Technologies (LACLO)*, pages 1–8. IEEE.

North, M. (2012). *Data mining for the masses*. Global Text Project Athens.

Romero, C. and Ventura, S. (2010). Educational data mining: a review of the state of the art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 40(6):601–618.

Sarwar, B. M., Karypis, G., Konstan, J. A., Riedl, J., et al. (2001). Item-based collaborative filtering recommendation algorithms. *Www*, 1:285–295.

Smirnov, A. V., Ponomarev, A., and Kashevnik, A. M. (2016). Tourist attraction recommendation service: An approach, architecture and case study. In *ICEIS (2)*, pages 251–261.

Van Meteren, R. and Van Someren, M. (2000). Using content-based filtering for recommendation. In *Proceedings of the Machine Learning in the New Information Age: MLnet/ECML2000 Workshop*, pages 47–56.

Zhang, Y., Oussena, S., Clark, T., and Kim, H. (2010). Using data mining to improve student retention in higher education: a case study. In *In International Conerence on Enterprise Information Systems*. Citeseer.