Prototype of content-based recommender system in an educational social network

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Abstract. In recent years, the new approaches of using Social Networks in Education (SNE) are arisen. With the goal to suggest the most suitable options depending on users' needs, recommender systems could be included in SNEs. This article presents all stages of development (study of needs, design, implementation and evaluation) a new content-based recommender system included in a social network for video-based learning. It was created and applied in an educational undergraduate activity to learn basic concepts of human computer interaction through the creation of videos by students. 43 students were involved in this activity from two different degrees: Computer Engineering and Media Communication. Apart from using the platform to do the activity, they participated in design and evaluation steps of the recommender system created.

Keywords: Recommendation system, Content-Based, Social Networks in Education.

1 Introduction

Recommendation systems (RS) have become very important. In fact, providing good suggestions can make the difference between the success and failure of a business. One of the main motivations for RS is to help users find what they are looking for. RS seek to maximize the value of usefulness of content for the user [1]. In general, there are three types of RS: content-based, collaborative filtering and a hybrid of the two aforementioned. Depending on the system's characteristics, one or another will be chosen, but the trend of the last few years is to use hybrid systems. The combination provides solutions to the well-known problems encountered by the content-based or collaborative-filtering systems when used separately [2].

RS have also become an important part of social networks. They are used to suggest news, friends and different types of content. Social networks are a special case of an information system that allows one to encounter countless explicit relationships, like users' ratings, and implicit relationships, like the last search done or the duration of time that content was viewed. The extraction of some implicit relationships is relatively simple [3], and the RS can use this data to generate better suggestions.

adfa, p. 1, 2011.

We can find different surveys about recommender systems [4]. Most of the areas where RS are applied are movie suggestions followed by shopping RS [5]. Two examples of RS included in video-based platforms are Youtube [6] and Netflix [7]. Essentially, algorithms use ratings given by the users to predict the rating that the users would give to a film they have not seen yet, in order to provide recommendations. Nowadays, its use is emerging in learning systems [5] [8].

Technologies enhanced learning (TEL) aims to propose, build up and evaluate innovations that will support and improve learning practices [9]. However, there is a need to identify the particularities of TEL recommender systems, in order to elaborate on methods for their systematic design, development and evaluation [10].

Educational recommender systems should be personalized by educational objectives, and not only by users' preferences [11]. However, the assessment of both learner knowledge and learning activities are more difficult than users' interests [12]. Also there is growing interest in social networks focused on learning. For example, Fazeli et al. propose an approach to provide a social recommender for teachers [13]. In fact, RS have different objectives according to the context [14] and consequently, they must take in account different information in order to complete its task successfully.

The article is structured in the following format: this current section has been a short description of recommendation systems, specifying the different contexts in which they can be used and focusing on educational area. The next section describes the educational platform in which we have integrated our recommendation system, and the main characteristics of the activity in which the undergraduate students of two areas participated in. Next, the study of requirements is presented followed by main characteristics of the RS and the evaluation results. Finally, conclusions and future research work are shown.

2 ClipIt

ClipIt is an educational social network developed within the JuxtaLearn European project, which has the goal to promote learning of thresholds concepts through the creation of videos [15]. ClipIt is based on Elgg (http://elgg.org/) and it is composed of several plug-ins. This makes it highly configurable, both in appearance and in functionality. The platform allows students work in group, in order to create and share a video about a threshold concept. ClipIt provides private work spaces to share files. Also it provides discussion forums, which can be public or private. All the documents and videos could be commented and voting. Therefore, students can send and receive suggestions to their peers in order to improve the learning material.

The use of educational social network ClipIt has been tested by students of Computer Engineering and Media Communication, whom created videos related to the basic concepts of human computer interaction. There were 43 students involved in this activity working together for the production of an educational video.

With the goal to facilitate learning, a content-based RS was created, allowing users to find content related to their interests. The requirements collected for the educational social RS, the main characteristics of its implementation and the students' evaluation will be presented in next sections.

3 Study of the needs

RS in an educational context have different objectives than commercial ones [14]. To encapsulate the requirements of the RS, a survey was answered by 43 students, all of them had already interacted with the ClipIt platform.

First, we asked if recommendation systems are useful. 84% of the students responded yes, and 16% said that recommendations are not useful probably because the system was unable to grasp their taste or their current needs. The next question want to find the appropriate number of recommendations to show onscreen. The majority of students, 77%, opted for between one and five recommendations, while 18% preferred between six and ten, and only 5% chose eleven or more. This verifies that users prefer fewer recommendations and, further, that these recommendations must be accurate. In fact, if recommendations are bad, the users will stop using the RS.

We also were interested to know where ClipIt should show recommendations. 41.5% of them indicated that recommendations should been shown near contents that they are currently viewing. 30.2% of them think that the recommendations had their section on the dashboard of ClipIt; and 28.3% suggested that the recommendations have their own section.

Next question is about the different types of content on the platform: Does it have the same relevance for the students? They evaluated the degree of importance of each material on a Likert scale of one "0- irrelevant" to five "5- essential". Analysis of the data revealed that the preference order is the following: videos (average = 3.83), articles (3.37) and blogs (3.09). We will consider these preferences to assign different weights to contents according to its type for recommendation purposes.

Next question was to know the criteria for the personalization of the recommendations (what aspects must be considered and which is its relative importance or weight). Students demand a customization of suggestions according to the material students are currently working on and their personal tastes or interests. Both current materials and personal tastes have the same average (4.16) and they must be taken in mind to personalized recommendations. Information about failed subjects (3.60) or future subjects (3.35) is relegated to second place.

We were interested in what implicit relationships are important to make recommendations in a SNE. Four types of relationships were proposed: friends, classmates, students of the same subject and partners of the same workgroup. 37 out of 43 replied that they prefer recommendations based on the students' opinions in the same subject, 22 based on their work group partners, and 19 based on classmates in the same course. Only 14 out of 43 wanted for friendships to be taken into account. It indicates recommendations provided in an educational social network must consider the relationships between students of the same subject, and placing less importance on friendships, which is the opposite of what occurs in social networks such as Facebook [16]. This result corroborates the common sense. In educational context, the main goal is learning, and in order to achieve that, the opinion of students of the same subject is more important than the opinion of their friends.

4 Recommendation system

The recommendation system created is a content-based system. We chose this type because ClipIt uses tags, providing classification without prior analysis of the content; the users do that. The use of social tagging has its advantages and disadvantages [17]. Quality of the recommendations is directly influenced by the quality of the tags [17].

RS use similarity between content to make the recommendations. Similarity is calculated according to the number of tags in common. One of the problems of including users' tags in RS algorithms is to detect the derived words [18]. As many RS, we use the stemming technique to create a term that reflects the common meaning behind words and reduce derived words to their root form [19]. The user's profile is defined taking in mind his votes and comments. The number of recommendations shown by ClipIt is five, since that was the number of recommendations that the students considered to be adequate as it was presented in previous section.

The first step of the algorithm is to search for the content that the user has rated with more than three over five (content that they had liked or neutral). Meanwhile, it collects information about the content that the user had commented on and rated recently. These high ratings could indicate the user's interests.

The RS has a restriction about similarities between learning contents. Only the 80% of best recommendations will show to users, the remaining 20% will be choosing at random. In our case, the first four are the most-recommended and the last is selected randomly (between most recent content upload to ClipIt). It improves the over-specialization issue of content-based systems. Recommendation system was developed as plugin for ClipIt. Administrator can move its physical location inside the user interface. However, it must be placed near the contents that students are currently viewing as it will be presented in the next section.

5 Evaluation

In order to get an evaluation of our recommender system, we based on user satisfaction [20]. The results of the evaluation of the recommendation system were obtained by using questionnaires. Participation of students during the evaluation stage was voluntary. The recommendation system was tested by 25 students of the URJC.

One question was related to the criteria used by recommendation algorithm. Users suggested that recommended contents were having high relational grade with the materials commented and voted in the platform (average 3.8 over 5). Therefore, users are recognizing the main criteria established by the system to make recommendations. This is a valuable fact because they must know why system recommends a set of contents. This helps users to continue using the recommendations. Also we want know if recommendations fit with their interests. 52% of users believe that the contents are fit mostly with their interests and 8% completely. 24% of users believe that the contents are suited partially with their personal preferences. Finally 16% believe that the recommendations meet their criteria barely.

Finally, some students provided us suggestions to improve our recommender system in the future. They said that information of previous searches in the social network could be used to detect personal interests. Furthermore, they highlighted the importance to take in mind the date when the learning material was uploaded to the platform. This comment agrees with the same need included in RS used in other contexts.

6 Conclusions and future work

The factors that are focused on during the creation of a recommendation system vary according to the application's context. Creating an RS for commercial purposes is different from creating one for educational goals. The RS for educational proposes must suggest content that is closely related to the studied material, and similar users that share the material. Interestingly, friendships have little weight in the SNEs.

This paper shows and explains the content-based recommendation system implemented in ClipIt, an educational social network. According to the research, the number of recommendations shown should be small (between 1 and 5) and should be placed close to the material that is currently being viewed by the student. The recommender process is based on factors and characteristics obtained through the needs study, which was used in a real activity completed by undergraduate students from two different degrees. We have evaluated our recommender system and many users agree with recommendations provided in this educational context. Students are aware of the system criteria which resulting in a good confidence in the recommendations.

For future work, the personalization of the recommender system module and their combination with explicit user's interest could improve the whole process. One question to be solved in the future is: do the needs of the RS in SNEs change if the learning material is different? We can also implement a user-based collaborative filter in order to turn it into a hybrid system for solving well-known problems of RS and improving the suggestions given to the students.

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