TOWARDS A MODEL FOR NAVIGATION SUPPORT IN LEARNING NETWORKS

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Abstract: This article presents ongoing work that, by means of simulations, attempts to find out the characteristics that should be taken into account for more efficient and effective individualized support in completing learning activities in a Learning Network. A preliminary model based upon learners' profile, peer behaviour, characteristics of both the learning activities and learning context is introduced; it is accompanied by a program flow of its implementation in a simulation environment and by initial results that suggest that a combination of navigation support mechanisms does have a positive effect on the number of graduate students.

Keywords: navigation; recommender systems; collaborative filtering; content-based; simulation; Learning Networks.

1. Introduction

Lifelong learning requires a major shift in the design of current learning and training systems. As information and communication technologies may play a central role in this change, analysis and investigation of the requirements for supporting lifelong learning are needed. For this change the theoretical notion of Learning Networks has been proposed (Koper and Sloep, 2002). These networks are conceptualized as self-organizing learner-centred on-line communities designed to facilitate lifelong learning. In such networks learners participate actively, creating and sharing activities, learning plans, resources, and experiences with peers and institutions. Learning networks are formed by participants and learning activities. Participants can be learners, teachers, providers or managers, while learning activities can be any type of resource or events that help learners to acquire a competence. Examples of learning activities are courses, lessons, assignments, blogs, websites, or sets of them (called units of learning) offered in the Learning Network.

Within this framework, one of the issues we are investigating is how to support learners' navigation to find his/her way in the Learning Network (Hummel et al., 2007). This is to say, given the vast amount of available learning activities, learners need advice or suggestions that assist them to choose those learning activities that best fit their needs.

The use of recommender systems might facilitate coping with this issue; using different models and techniques, these systems attempt to help users to diminish the information overload by delivering personalized items, content and services (Adomavicius and Tuzhilin, 2005) . Basically, memory-based techniques, which collect information about users and items to calculate recommendations, are divided into content-based techniques, collaborative filtering techniques, and hybrid techniques. In the first case items are suggested based on those that the user liked before. In the second, items are suggested based on those that users who have the same profile liked and, in the third, a combination of the previous two techniques is used (for a detailed overview see Drachsler et al., in press).

Practical applications of these techniques include, for instance, recommending products to buy (www.amazon.com, www.half.ebay.com) or movies to watch (movielens.umn.edu, www.everyonesacritic.net). In eLearning environments these techniques have been used, for example, to recommend learning activities (Zaïane, 2002, Andronico et al., 2003), courses (Farzan and Brusilovsky, 2006), papers on the Web (Tang and McCalla, 2003) or reading lessons (Hsu, 2008).

However, providing recommendations in Learning Networks is a different matter. In other areas the recommendation is based on interest, rating or user's history, while for learning purposes other factors have to be considered. For instance, even if an item might be interesting for a learner, it might not pedagogically relevant if it does not align with his/her prior knowledge and skills.

We hold that recommendation mechanism should not only consider learners' interest, but also learners' competences, learning goals, prior knowledge, as well as learners' preferred learning strategies.When advising the next learning activity to follow, effective navigation support needs to consider the profile of the learners, characteristics and usage data of learning activities, as well as learning context characteristics.

In the long term, we aim at increasing learners' goal attainment and minimizing their study time through recommendations that advice the learner the best next learning activity to follow. We plan to conduct experiments and run simulations to identify relevant variables for navigation support and their impact for the recommendations provided. Moreover, through simulations we can explore different learning context characteristics, such as the number of learners, the number of learning activities or the number of learning activities to be completed, that might have an influence in navigation support mechanisms. Finally, simulated environments bypass some practical constraints of field experiments.

In this article, we will focus on a preliminary model to simulate Learning Networks that include navigation support mechanisms. Simulations will help us to explore different research topics as, for instance, the difference between social-based mechanisms (based on collaborative filtering) and information-based approaches (based on metadata), and the recommendation mechanisms needed for formal and informal learning environments (Hummel et al., 2007).

The preliminary model and simulation described in this article follows a well established approach towards social science simulations (Gilbert and Troitzsch, 1999), and it is nurtured by collected data from an experimental pilot (Drachsler et al., in press). This experiment investigated to what extent different recommendation strategies influence learners' goal achievement and reduce the time they need to find and complete learning activities. For this purpose a prototypical personal recommender system (PRS) was developed. It provides advice to the learner of the next best learning activity to follow based on is her/his topic of interest (classified in domains), and on the behaviour of the peers. When only information about the learner's interest was available, a content-based technique was used to generate the recommendations, otherwise a collaborative filtering technique was applied. For more information, see (Drachsler et al., in press).

The experiment provided some promising results, but at the same time faced some practical constraints. For instance, as in most of the formal curricula, learners needed to complete all learning activities to pass the course. Therefore, even though learners were provided with recommendations, in the end, the PRS recommended all learning activities and, when few remaining activities were to be completed, the quality and personalisation of the advice decreased. This made it difficult to compare and evaluate the effectiveness and efficiency among the recommendations provided. Other issues were the limited number of learners and learning activities, and the lack of rating mechanisms to improve the recommendations.

As already mentioned, simulated environments facilitate dealing with these and other practical constraints, as well as with time and money limitations. The remainder of this article explains a preliminary model for navigation support in Learning Networks and its implementation in a simulation environment.

2. Method

Figure 1 shows a preliminary model for navigation support. It is based on the experiment with the prototypical PRS and on previous work on simulating Learning Networks (Koper, 2005), which used the NetLogo (Wilensky, 1999) multi-agent simulation environment.

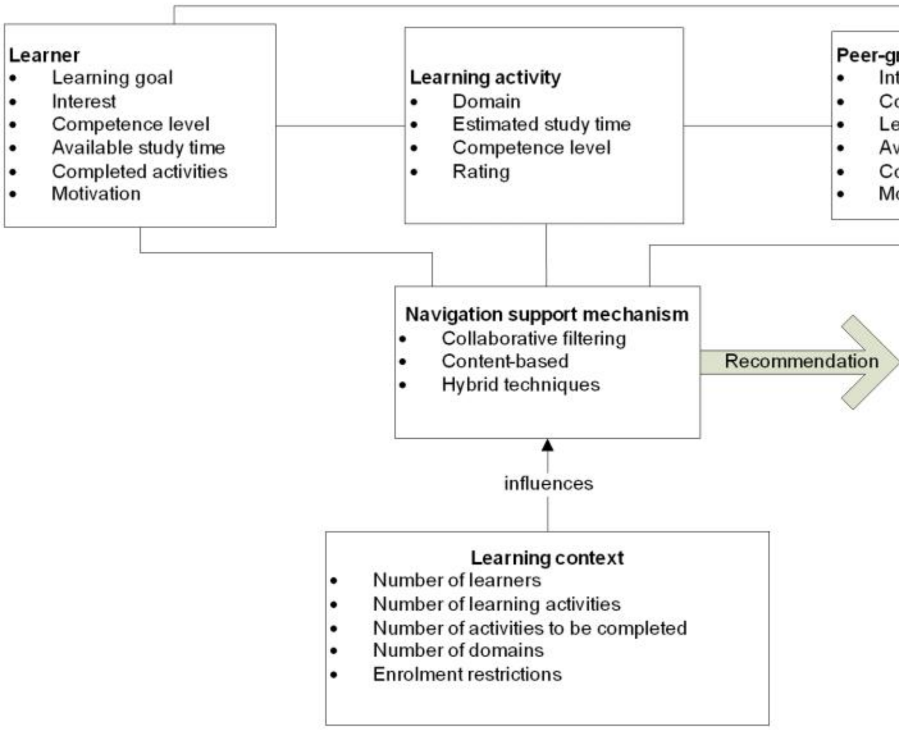

Figure 1. Initial model for navigation support

The model considers the profile of the learner and of the peer-group, as well as the characteristics of the learning activities. The learner profile comprises learning goals (learning activities to be completed), interest (e.g., specific topics), competence level, available study time, completed activities, and motivation; whereas the peer-group profile is an aggregation of the learners' behaviour (Drachsler et al., in press). Each learning activity is characterized by the domain it belongs to, the estimated study time needed to complete it, the competence level it targets, and its ratings. Learners are linked to the learning activities they have completed and related to a peer-group when they share the same profile.

Additionally, different learning context characteristics are expected to influence the scope of the navigation support mechanisms. These characteristics are the number of learners, the number of learning activities, the number of learning activities that have to be completed to acquire a competence, the number of domains and the enrolment restrictions (i.e., learners can/cannot join the course once it started).

Figure 2 shows the initial program flow designed to simulate navigation support. During the setup procedure the following characteristics can be considered/defined: the navigation support mechanism, the learning context characteristics, and the settings of the simulation.

The navigation support mechanisms can be set as content-based and/or collaborative filtering. The former can be based on interest, and the latter can be based just on one or a combination of interest, available study time, or competence level. The learning context characteristics include the definition of the number of: domains, learning activities, learning activities to be completed, and learners. Finally, the settings of the simulation include chance to follow the recommendations (obedience) and a criterion for the accuracy of the recommendation (match factor).

Considering these values, the setup procedure initializes the environment as follows:

- The defined number of domains is randomly assigned to each learning activity,
- A random competence level (from 1 to 3) and study load (from 1 to 4) are assigned to each learning activity,

- A random interest (one of the domains), competence level (from 1 to 3) and available study time (from 1 to 4) are assigned to each learner,
- For each learner the motivation value is initialized with a starting value,
- All other values defined on the interface are set: number of learning activities to be completed (learning goal), life cycle of the simulation (number of weeks), match factor and obedience.

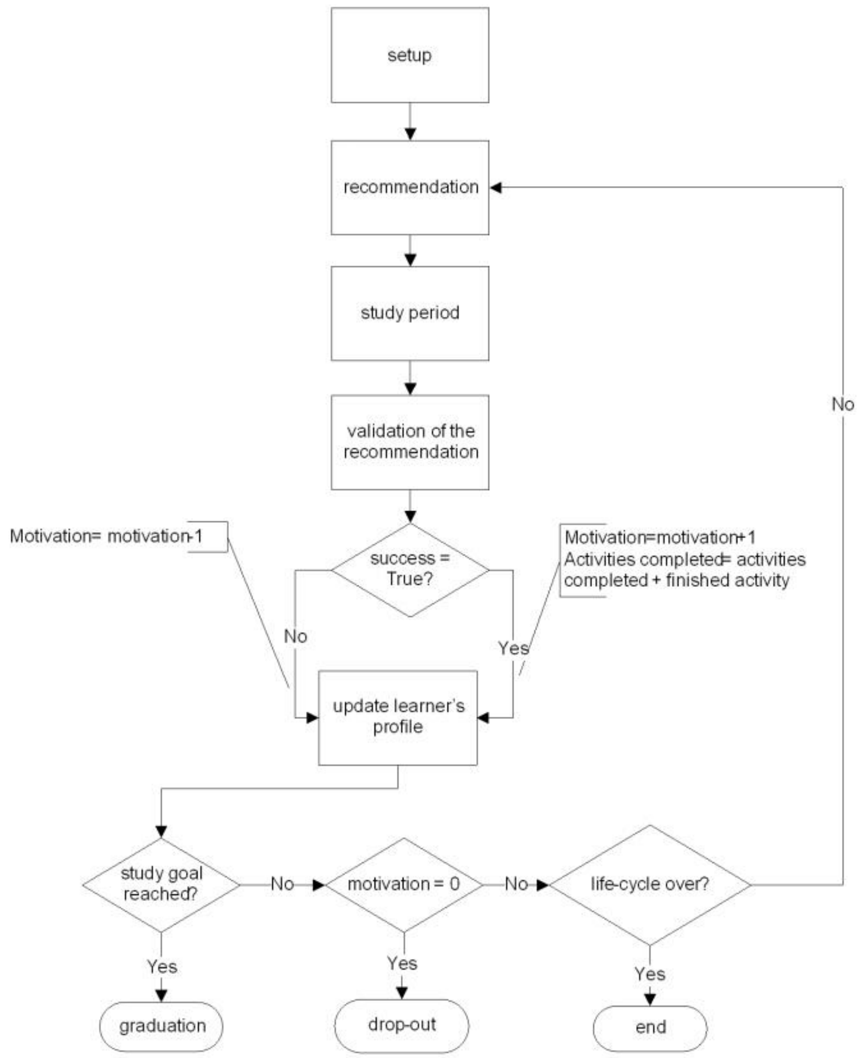

Figure 2. Simulation program flow

The recommendation process aims at finding the best next learning activity to generate the advice. To generate the recommendation it takes into account the navigation mechanisms values indicated in the setup process. The content-based technique is entirely based on the learner's interest, whereas the collaborative filtering technique uses an algorithm that looks for peers whose interest is in the same domain, and their competence level and study time is less or equal than the current learner's competence level and study time. When a peer is found, the activities that the learner has done are randomly recommended to the current learner. If more than one peer was found, then a random selection is applied. A content-based technique is used to prevent the cold start problem (i.e., information about the peers is not yet available).

Once a recommendation has been given, the study period begins; it lasts until the learner's available study time is equal to the estimated study time of the recommended learning activity. After this, the validation process of the provided recommendation starts.

This process assumes that a perfect or sufficient match leads to a successful completion of the learning activity. The match considers if the competence level and study load of the advised learning activity were, correspondingly, smaller or equal to the learner's competence level and to the learner's study time, and if the domain of the learning activity was the same as the learner's interest. Additionally, weight factors are used to influence one criterion or the other (e.g., learner's interest is more important than study time). If the match value is equal or higher than the match factor provided in the setup procedure, then the advice is classified as successful.

This process is the input for updating the learner's profile. If the given advice was successful, then the learner's motivation increases and the advised learning activity is included in the set of "completed activities", otherwise, the learner's motivation decreases.

In the next step, if the learner's study goal is reached (i.e., the learning activities to be completed are finished), then the learner is considered as "graduated student" and, therefore, is not active in the run anymore. If the learner's study goal is not reached yet, then the learner's motivation is verified, if it is equal to zero, it is assumed that the learner dropped-out and, again, the simulation run ends for this learner. Finally, if the time cycle of the simulation (indicated in the setup process) is over, the simulation ends, otherwise, it provides the next recommendation.

Currently we are implementing and testing this program algorithm.

Figure 3 presents the interface. It includes, on the left side of the screen, the characteristics to be considered in the setup procedure for running the simulation:

- Navigation support mechanisms (filtering strategy): content-based based on interest (on/off) and/or collaborative filtering. The latter can be based on one or a combination of: interest, available study time and competence level (each of them: on/off),
- Learning context characteristics: number of domains (1-50), learning activities (nb-LAs) (1-3000), learning activities to be completed (nb-LAs-to) (1-3000), and learners (nb-LNUs) (1-2000),
- Settings of the simulation: match factor (match-f) (0-1) and chance to follow the recommendation (obedience) (0-1).

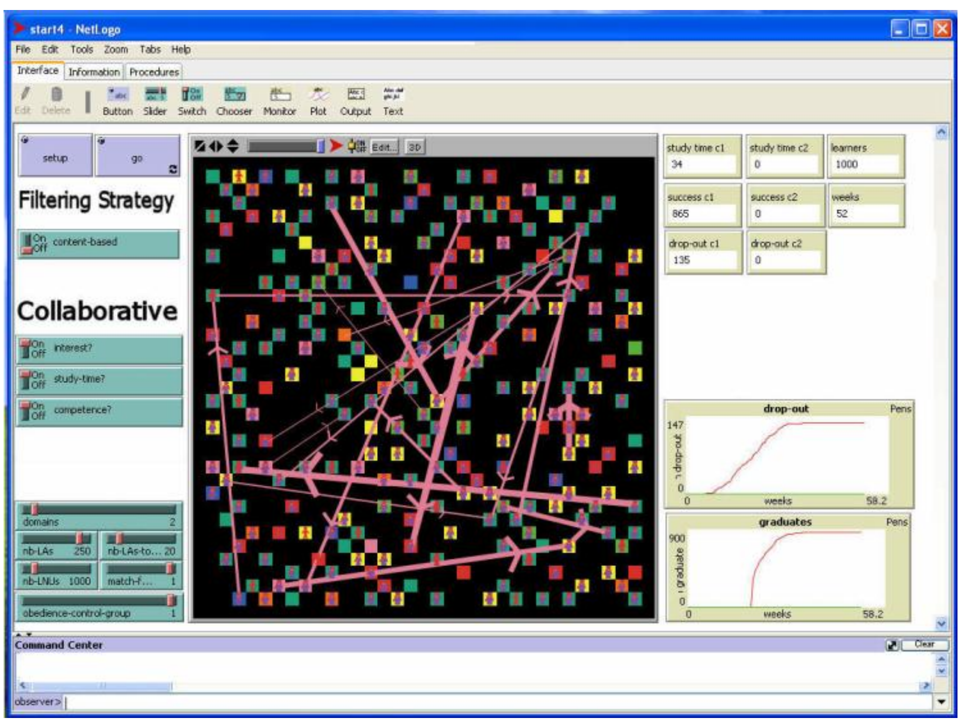

Figure 3. Screen-shot of the simulation in NetLogo

When the simulation starts, the defined number of domains is randomly assigned to each learning activity. Then, when it is running, the centre of the screen presents the learners as "turtles" who are exploring an environment (Learning Network) that consist of learning activities ("patches"). In the right part of the screen, the number of active, drop-out, successful (graduated) learners are displayed, as well as the number of weeks of the simulation cycle. Moreover, in the right bottom part of the screen two graphs show the tendency of drop-outs and graduates over the number of weeks.

3. Preliminary results and future work

Up to now, we have conducted two series of 64 simulation runs to explore if navigation support mechanisms have a positive influence on the number of graduates. In each series the number of learners was changed. The first one used only collaborative filtering, while the second used a combination of content-based technique and collaborative filtering techniques (i.e., combined filtering). The values of the simulation were as follows:

- Content-based technique: on (only for series 2),
- Collaborative filter technique: interest, study time, competence level (series 1 and 2),
- Domains: 7,
- Learning activities: 250,
- Number of learning activities to be completed: 20,
- Number of students: 100, 500, 1000,
- Match factor: 1 (i.e., the recommendation should match 100%),
- Obedience: 1 (i.e., the student follows all the recommendations).

After running the series, we found that, no matter the number of learners, the percentage of graduates is higher if a combined filtering mechanism is used. Moreover, no matter the navigation support mechanism used, the number of learners does have an impact on the percentage of graduates. The percentage of graduates increases if the number of learners increases. Even more, if a combined filtering technique is used in a Learning Network where 1000 learners participate, then more than the 90% of the learners will graduate. Figure 4 shows the two series and their tendency. Axis X contains the number of learners and axis Y the percentage of graduates. Series one is labelled as "collaborative filtering" and series 2 as "combined filtering".

As future work, we will analyze how a realistic distribution for values of motivation and obedience can be included in the simulation program, we will reshape the model by adding new characteristics, such as prior-knowledge and multi-rating, enhance the advice procedure by considering weights of the learners' characteristics while looking for suitable learning activities, and incorporate new recommendation mechanisms such as tagging. Finally, we would like to incorporate personalized competence development programmes that define for each learner different learning goals and number of learning activities to be completed for acquiring a competence.

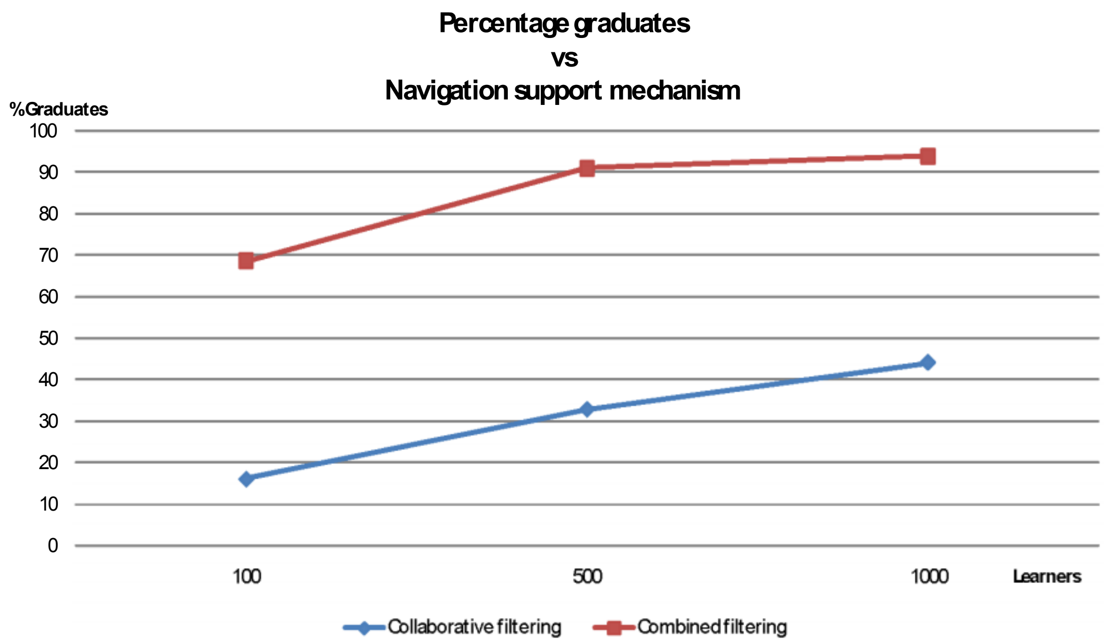

Figure 4. Initial results

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