Recommendation strategies for e-learning: preliminary effects of a personal recommender system for lifelong learners

RECOMMENDATION STRATEGIES FOR E-LEARNING: PRELIMINARY EFFECTS OF A PERSONAL RECOMMENDER SYSTEM FOR LIFELONG LEARNERS

Hendrik Drachsler, Hans G. K. Hummel, Bert van den Berg, Jannes Eshuis, Adriana J. Berlanga, Rob Nadolski, Wim Waterink, Nanda Boers & Rob Koper Open University of the Netherlands

Abstract

This article presents research on personal recommender systems for lifelong learning. The personal recommender systems supports lifelong learners in Learning Networks. A first version was evaluated in an experiment during an Introduction Psychology course of the Psychology Department at the Open University of the Nederlands. The learning activities of the psychology course and the personal recommender system were integrated into a Moodle environment, which operates as an emulated Learning Network. Therefore, no curriculum structure was applied and the students were allowed to study the learning activities in any order they wanted.

The implemented personal recommender system combines a top-down, ontology-based recommendation technique with a bottom-up, stereotype filtering technique. Both techniques were combined in a recommendation strategy that decided which of the techniques were most suitable for the current situation a learner was in.

This article presents preliminary results of the experiment and discusses the advantages and disadvantages of the used recommendation strategy. It further argues for the benefit of recommendation strategies for a personal recommender system in e-learning in general.

Keywords

navigation, recommender systems, collaborative filtering, ontologies, recommendation strategies, learning networks.

Introduction

The concept of lifelong learning makes learners more self-directed and responsible for their own learning path [1]. Nowadays, lifelong learners are supported by advanced learning technology to structure and organise their lifelong learning process. The concept of *Learning Networks* [2] addresses these issues and provides an infrastructure for distributed learners and stakeholders in certain domains within the European TenCompetence project[1]. The design of a Learning Network (LN) is learner-centred and its development evolves bottom-up through the participation of the lifelong learners. Therefore, it is in contrast to other learning environments, which are designed top-down because their structure, learning resources, and learning plans are predefined by an educational institution or domain professionals (e.g., teachers).

In LNs, the lifelong learners are able to publish their own learning activities (learning resources), or share, rate, and adjust learning activities from other learners. The learners are able to act in different roles (teachers, learners or knowledge providers) in different LNs in parallel. Besides the sharing of learning activities, the learners create through their emergent behavior most popular competence development paths (learning paths) in the LN. These learning paths could be used as resources to achieve most required competences in an efficient manner.

The concept of LNs is similar to the *Web 2.0* development in the Internet nowadays. Web 2.0 enables the users to add, share, rate or adjust information. Popular services like *wikipedia.org, flickr.com* or *youtube.com* benefit from that development and are proof of the change in the interaction with the Internet. Before the *Web 2.0* age the majority of users were only able to consume information from

[1] http://www.tencompetence.org

the Internet. The *Web 2.0* technologies lifted the barrier of adding information to the Internet and enable much more users to contribute information to it. As a result, the amount of information available on the Internet increases dramatically. Therefore, it is a common problem for users of the Internet to select or discover information they are interested in. The need to support users with the selection of information or giving reference to relevant information is becoming more important. For that reason, *Personal Recommenders Systems* [3] are becoming increasingly popular for suggesting information to individual users. Learners in LNs are in a similar situation like users on the Internet. The amount of available information increases rapidly and confuses the learners which learning activity is most suitable for them. The learner-centered design of LNs forces the learners to decide which information might be most suitable to their current learning situation. As a consequence, the navigation problem of selecting most suitable learning activities from an increasing amount of information is challenging for the learners. Thus, the integration of a personal recommender system for lifelong learners in LN would be beneficial for them.

The design of a personal recommender system (PRS) for e-learning is different from the design of common recommender systems (RS) in the Internet. Instead of recommending items based on taste a PRS in e-learning has to recommend learning resources to improve personal competence development plans. Although lifelong learners are in a similar situation to the users looking for information on the Internet, there are a number of differences in their needs for personalized recommendation. Self-directed lifelong learners are in need of an overview of available learning activities, and must be able to determine which of these would match their personal needs, preferences, prior knowledge, and current situation. The system has to support the learner in deciding what learning activities are of value to achieve a needed competence [4]. The motivation for any recommender system (RS) is to assure an efficient use of available resources in a network. The motivation for a PRS for lifelong learning is the improvement of a personal learning path according to pedagogical issues and available resource. Hence, a PRS for lifelong learning has to search for potential learning activities and recommend the most suitable learning activities to the individual learner. One way to implement pedagogical decisions into a PRS is to use a variety of recommendation techniques in a recommendation strategy.

Recommendation strategies are a combination of different recommendation techniques to improve the overall accuracy of any recommender system, and to overcome disadvantages of one singular recommendation technique [5]. In addition, they can be used to apply specific recommendation techniques to particular situations a learner is in. The decision to change from one recommendation technique to another can be done according to pedagogical reasons. These pedagogical reasons are derived from specific demands of lifelong learning [6]. Therefore, some recommendation techniques are more suitable for specific demands of lifelong learning than others. For instance, for LNs collaborative filtering is a promising recommendation technique because it requires no maintenance by the learners and works nearly automatically.

In this article we discuss the use of recommendation strategies for different kinds of learning situations. Then, we argue in the second section that a pedagogically inspired recommendation strategy in a PRS improves support in learning environments. We expect that a better alignment of the characteristics of learners and learning activities will increase the efficiency of the learning process and minimize the amount of time learners need for finding suitable learning activities. In the third section we present an experiment with a PRS that combined an ontology-based recommendation technique with a stereotype-filtering technique in one recommendation strategy. In the fourth section we discuss preliminary results of the experiment. Finally, we draw further conclusions for the use of recommendation strategies in PRS for e-learning and give an outlook about future research plans.

Recommendation strategies and their benefit for e-learning

Most RS are strongly domain dependent and it is not possible to apply one RS from a particular domain in another domain. One reason for that is the variety of available recommendation techniques [3] and another reason is the adjustment of these techniques to the specific demands of the domain.

But using a RS from one domain in two different contexts is less of a problem then using it in a different domain. For instance, there are many RS for the domain 'music' available on the Internet (e.g., *last.fm*, *pandora.com*). All of them seem to do a reasonable job, otherwise they would be pejorative and less users would use them. Behind each of these systems, different recommendation strategies with different recommendation techniques are in use. For instance, *pandora.com* [7] is an expert driven RS that provides recommendations given by music analysts. It is based on the *Music Genome Project* where each song is analyzed by using up to 400 distinct musical characteristics. It can be classified as a Knowledge-based RS [8] using an ontology to classify songs. Ontology's use relationships between attributes of user profiles and domain knowledge to infer conclusions about given situations [9]. Attribute-based recommendation techniques benefit form that kind of knowledge driven systems. They recommend items based on the matching of their attributes to a user profile. The attributes could be weighted for their importance to user and are most of the time also part of the knowledge domain.

Whereas *last.fm* [10] is a social recommender system, it applies a user-based collaborative filtering techniques [11]. Based on the assumption, that users who rated the same item similarly probably have the same taste, this technique recommends unseen items already rated by similar users. In contrast to *pandora.com*, it knows little about the quality of a song. It predicts that if a user and a group of other users enjoy many of the same artists, the current user will probably enjoy other artists popular with that group. Several kinds of collaborative filtering (CF) techniques are available they base their recommendations on social, community driven information (e.g., user behavior like ratings or implicit histories). Other examples of CF techniques are stereotype filtering or item-based filtering [5]. Stereotype filtering recommends items that are preferred by similar users based on profile attributes of the users instead of user ratings. Item-based filtering assumes that items rated similarly are probably similar. Therefore, it recommends items with highest correlation (based on ratings to the items).

It is cumbersome to measure if *pandora.com* offers recommendations with a higher quality than *last.fm*. Nevertheless, *last.fm* is able to recommend many more songs, because no human information is required to rate the value of a song. The community of *last.fm* is rating the songs and according to these emergent user data *last.fm* provides its recommendations. However, both techniques are used successfully for recommending music to users.

For e-learning we have a different situation [6]. Learning can be differentiated into the two contexts of '*formal learning*' and '*informal learning*'. Formal learning includes learning offers from universities or schools. They are highly structured, lead to a specific accreditation and have domain experts that guarantee quality. Informal learning is less structured, does not lead to a certain accreditation and includes nearly each learning possibility. Both kinds of learning situations are so different that the use of one general recommendation technique is hardly possible.

For formal learning like in universities, ontology or metadata recommendation techniques might be suitable. Universities have well structured learning plans (curriculum) with locations, known teachers and accreditation procedures. All this metadata could be used to recommend courses to students.

In informal learning we have less structure and there are no official persons available for maintaining any kind of ontology. Therefore, bottom-up recommendation techniques like CF are more appropriate because they require nearly no maintenance and improve through the emergent behavior of the community.

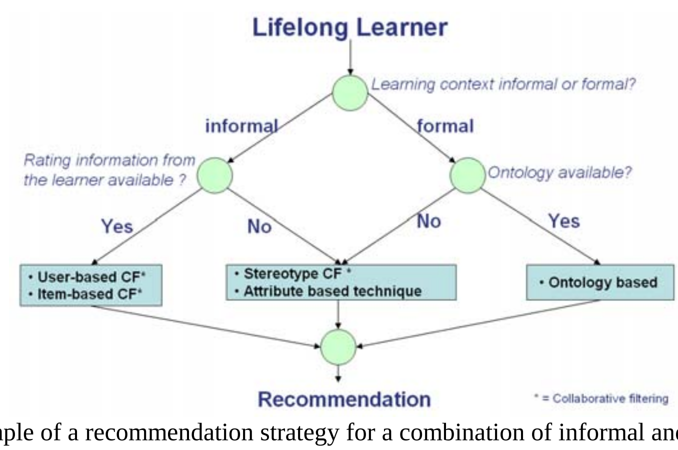

Figure 1. Example of a recommendation strategy for a combination of informal and formal learning

However, a PRS for lifelong learning and especially for LNs has to include both learning situations, because lifelong learners are able to participate in formal and informal learning situations. Consequently, a PRS with a recommendation strategy that enables recommendation based on formal and informal learning has to include bottom-up and top-down recommendation techniques which meet these requirements.
Figure 1 shows an example of a recommendation strategy that distinguishes between recommendations for informal or formal learning according to specific indicators. It illustrates one possible situations, but there are also situations thinkable when rating techniques might be useful in formal learning. The combined recommendation strategy can even be designed more granulated. For instance, the informal part of the recommendation strategy can be further distinguish through the use of two kinds of CF techniques. The technique with the most satisfying results for a learner would be used to provide the recommendation. Figure 1 includes an intermediate step if no rating information and no ontology is available. In that case it recommends based on a stereotype filtering technique or an attribute-based technique. For both techniques profile information about the learner is needed.
In conclusion, recommendation strategies enable us to create optimised PRS for informal learning or formal learning or additionally for a combination of both learning situations. We are able to combine top-down and bottom-up approaches taking into account the specific demands of learning and design an general PRS for both learning situations.
In the following section we will describe a first approach of a PRS that takes into account an ontology recommendation technique (top-down) with a CF technique (bottom-up) to recommend learning activities to learners in an emulated LN.

Method

To test our assumption:

- H1: A better alignment of learner characteristics and learning activities will increase the efficiency of the learning process.
- H2: Through that improved alignment the amount of time learners need for finding suitable learning activities will be reduced.

We carried out an experiment in a regular “Introduction Psychology” course offered by the Department of Psychology at the Open University of the Netherlands. The course content and a prototypical version of a PRS based on a recommendation strategy were implemented in a Moodle environment [12].

Participants

No prior knowledge was required from the participants to attend the introduction course. The participants were informed that they were taking part in an experiment with a new learning environment. But they did not know that one learning environment contained a PRS and the other did not. The participants were randomly assigned to an experimental group, that was offered recommendations or a control group, that proceeded through an identical course without any recommendations. In total 251 participants subscribed and both groups contained equal amounts of learners (around 125 learners per group). Around twenty percent (n=28) in the experimental group and around thirty percent (n=38) in the control group did not log into the Moodle environment. This group of non-starters is not included in our study of the effects of the recommendation strategy. This leaves a group of 185 learners who did enter the Moodle environment; 87 in the control group and 98 in the experimental group. From the 98 participants in the experimental group 60% were women, within an average age of 38,5 years, and 70% of the participants had a higher professional education or university level. In the control group 65% were woman, within an average age of 34,7 years, and 62% of the participants had a higher educational level.

Materials

The emulated LN we designed in a Moodle environment was adjusted to our experimental settings. Figure 2 shows an overview of the system interface for a learner in the experimental group. The overview is divided into three columns. The right column shows the learning activities the learner has to study. The middle column presents the courses the learner is enrolled for. Finally, in the left column all completed courses by the learner are listed. Below the overview of courses an explanation of the recommendation is given. In this case, the PRS at the bottom of the screenshot recommended ‘Sociale Psychologie’. Next to the given recommendation there are additional options to get further information about the recommendation and a link to adjust the preferences in the learner profile.

Figure 2. Overview page of the experimental group with an advice

The learning activities took an average of 12 hours to complete. Formal completion of an learning activity was established through the use of a multiple choice test consisting of seven equally weighted questions. A score of 60% or more indicated a successful completion of a learning activity. In Moodle, each learning activity was modeled as a separate entity.

From literature studies it appears that PRSs with a combined recommendation strategy provide more accurate recommendations compared to single techniques PRSs [13-15]. In the implemented PRS, an ontology-based recommendation technique and a stereotype recommendation technique where combined. The ontology used personal information of the learner (e.g., interest) and compared that with the domain knowledge. Stereotype filtering used profile attributes of the learners (e.g., motivation, study time) to create learner groups and recommend learning activities preferred by similar learners.

The PRS that was developed for that experiment provides advice of the next best learning activity to follow based on the interest of learners (ontology recommendation), and on the behavior of the peers (stereotype filtering). When only information about the learner’s interest was available, the ontology-based recommendation technique was used to generate the recommendations, otherwise the stereotype filtering technique was applied. The underlying recommendation strategy is presented in figure 3.

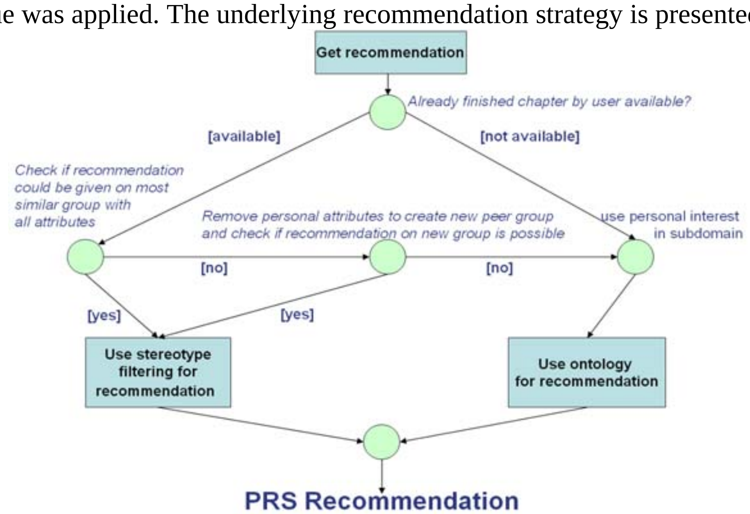

Figure 3. Recommendation strategy for the implemented PRS

The use of the stereotype filtering was prioritized and the ontology approach was used mainly to cover the ‘cold-start problem’ [16] of the stereotype filtering technique. The stereotype filtering technique was personalized through attributes of the personal profile of the learners. These attributes created specific peer-groups the learners were located in. The stereotype filtering technique tried to provide a recommendation mainly based on a peer-group where all attributes were similar. If it was not possible to give any advice it disabled one of the personal attributes and tried to make a recommendation based on larger peer-group with less shared attributes.
In a second step, and only in the case that the stereotype filtering was not able to provide any recommendation, the PRS created an advice on the ontology-based recommendation technique. The ontology consist of two top domains (e.g., ‘Environmental Psychology’) that contained several sub domains (e.g., ‘environment’, ’development’, ’clinical’) which contained n numbers of courses.
The learners had to select a special interest (one of the *sub domains* of the ontology) in their profile. If the learners had chosen a *sub domain* i.e. ‘clinical’, they received recommendations on courses that are located in that particular *sub domain*. If none of these courses were completed so far, the PRS randomly recommended one of them. If one course was already completed by the learner the other courses were recommended. If all courses of the *sub domain* ‘clinical’ were completed the ontology recommended a course that was part of the *top domain* ‘Environmental Psychology’.

Procedure

At the beginning of the experiment login information was provided according to the random assignment of the participants to the experimental group or the control group. Both groups received the same treatment; they were able to ask questions related to the content or the learning environment to one tutor in a forum. The participants were informed that they did not have to follow the learning activities in a certain order. Further, they were allowed to complete learning activities in their own pace. Furthermore, they were able to register for a final exam whenever they wanted without completing any of the multiple choice online tests. The final exam was planned at the 18th of January and a additional date at the 17th of April 2007. The experiment ran almost six months, from the 5th October 2006 until the 17th of April 2007. During this period no further information about the experiment was given.

Analysis

In the experimental period of six months, measures were taken every two weeks. According to our assumptions mentioned at the beginning of this section, we monitored the completion of courses and the time that the participants took for these completions. Following this assumption, the participants in the experimental group with a PRS should be able to complete more courses in the same time than the control group. We further assumed that more persons in the experimental group should reach a goal of ten completed courses in less time. We also monitored which recommendation technique was used to provide the recommendations.

Preliminary Results

In this section we present some preliminary observations that look promising according to our assumptions mentioned in the Method section.
Figure 4 shows how often the recommendations techniques were used during the experiment. During the first month the cold-start problem of PRS occurred, because there was no data available for stereotype filtering. Nearly all recommendations in this period were covered by ontology-based recommendations. But starting from the second month, stereotype filtering has been used more often and became equally used compared to the ontology based recommendations at the end of the experiment.

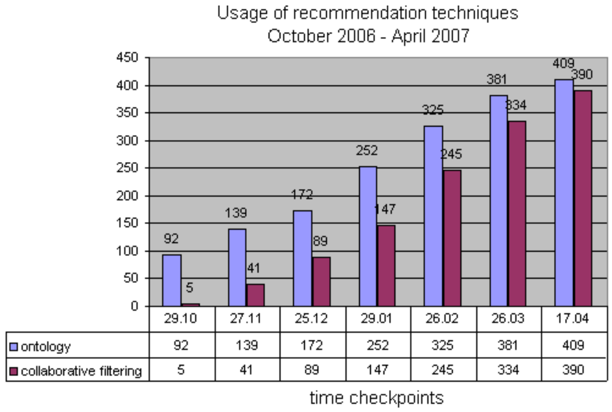

Figure 4. Usage of recommendation techniques during the experiment

Figure 5 and figure 6 show preliminary observations of both groups. Figure 5 shows, according to our assumed effects, that the experimental group (with a PRS) continuously completed more courses successfully than the control group (without a PRS). Furthermore, figure 6 demonstrates that the experimental group even needed less time to complete the courses successfully. Only in January the control group was able to overrule the experimental group on the level of completed courses. This exceptional behavior can be explained with the date of the first exam. We assume, that some of the learners in the control group were additionally extrinsic motivated to complete the learning activities in preparation of the exam.

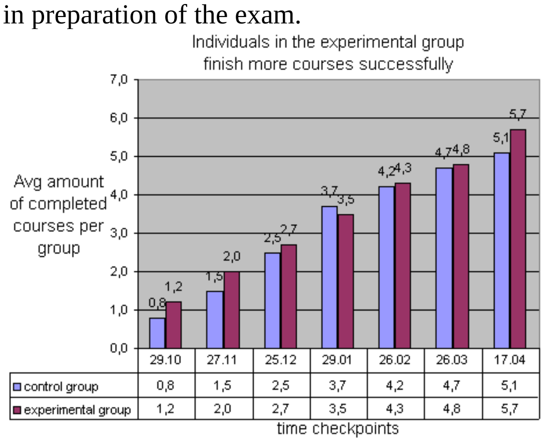

Figure 5. Average completion of courses per group

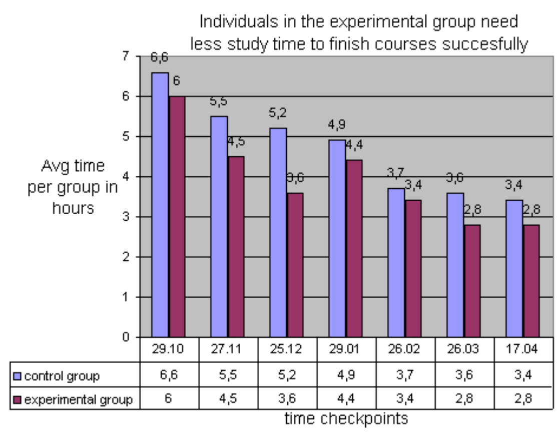

Figure 6. Average time to completed courses per group

Conclusions

A first conclusions that could be drawn from this experiment is that the combination of recommendation techniques worked as we wanted. By using ontology-based recommendations the ‘cold-start’ problem of stereotype filtering was successfully tackled. During the start of the experiment, ontology-based recommendations were given more often because stereotype filtering needed time to collect data for providing recommendations. But starting from the second month of the experiment stereotype filtering became increasingly dominant.

According to our assumptions, it seems that the experimental group was able to progress more efficiently by completing more courses than the control group in the same time. Even with these positive experiences the generalization of the recommendation strategy is limited. The ontology can not easily be adjusted to other contexts. The adjustment of the ontology requires domain experts and technology knowledge to adjust a ontology. Especially in the area of lifelong learning this is hardly done by the learners. Instead of creating new barriers for the use of learning technology we have to make it easy as possible.

In conclusion we want to prevent the use of top-down approaches that requires expert driven information like ontologies in bottom-up communities like LNs. Therefore, we want to increase classification and clustering of information in LNs through the use of additional CF techniques or collaborative rating and tagging mechanisms. Nevertheless, we are aiming additionally for a combination of top-down and bottom-up technologies in a general recommendation strategy. Therefore, we want to develop a web service that addresses different learning situations and could be connected to different kinds of learning environments.

Acknowledgment

The present work was carried out as part of the TENCompetence project, which is (partly) funded by the European Commission (IST-2004-02787) (http://www.tencompetence.org).

References

1. Longworth, N., (2003) *Lifelong learning in action - Transforming education in the 21st century*, London: Kogan Page.
2. Koper, R. and C. Tattersall, (2004) *New directions for lifelong learning using network technologies.* British Journal of Educational Technology, 35(6): p. 689-700.
3. Adomavicius, G. and A. Tuzhilin, (2005) *Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions.* IEEE Transactions on Knowledge and Data Engineering, 17(6): p. 734-749.
4. Hummel, H.G.K., B. Van den Berg, A.J. Berlanga, H. Drachsler, J. Janssen, R.J. Nadolski, and E.J.R. Koper, (2006) *Combining Social- and Information-based Approaches for Personalised Recommendation on Sequencing Learning Activities.* International Journal of Learning Technology.
5. Setten, M., (2005) *Supporting people in finding information. Hybrid recommender systems and goal-based structuring*: Telematica Instituut Fundamental Research Series No. 016 (TI/FRS/016).
6. Drachsler, H., H.G.K. Hummel, and E.J.R. Koper, (2007) *Personal recommender systems for learners in lifelong learning: requirements, techniques and model.* (submitted).
7. Westergren, T.(2007) *Pandora. Music Genome Project.* [cited 08.07.2007] Available from: http://www.pandora.com/corporate/mgp.
8. Felfernig, A., (2005) *Koba4MS: Selling complex products and services using knowledge-based recommender technologies*. in *7th IEEE International Conference on E-Commerce Technology*. München, Germany.
9. Middleton, S.E., D.C. De Roure, and N.R. Shadbolt, (2002) *Capturing Knowledge of User Preferences: ontologies on recommender systems.* Arxiv preprint cs.LG/0203011.
10. last.fm.(2007) *last.fm the social music revolution*. [cited 08.07.2007] Available from: http://www.last.fm/help/.
11. Herlocker, J.L., J.A. Konstan, A. Borchers, and J. Riedl, (2004) *Evaluating Collaborative Filtering Recommender Systems.* ACM Transactions on Information Systems, 22(1): p. 5-53.
12. Dougiamas, T.(2007) *Moodle*. [cited 12 June 2007] Available from: http://moodle.org/.
13. Melville, P., R.J. Mooney, and R. Nagarajan, (2002) *Content-boosted collaborative filtering for improved recommendations*. in *18th National Conference on Artificial Intelligence*. Edmonton, Alberta, Canada.
14. Pazzani, M.J., (1999) *A framework for collaborative, content-based and demographic filtering.* Artificial Intelligence Review, 13(5): p. 393-408.
15. Soboro, I.M. and C.K. Nicholas, (2000) *Combining content and collaboration in text filtering*. in *the IJCAI Workshop on Machine Learning in Information Filtering*. Stockholm.
16. Herlocker, J.L., J.A. Konstan, and J. Riedl, (2000) *Explaining collaborative filtering recommendations.* Proceedings of the 2000 ACM conference on Computer supported cooperative work: p. 241-250.