Recommender Systems: A Technology to Foster Individual and Collaborative Learning

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Abstract: Recommender systems are used to provide people with personalized information on items that might be of interest to them. There is a growing attention in the learning sciences to employ recommender systems for fostering learning processes. While recommender systems have some features that resonate well with principles in the learning sciences, it is evident that specific adaptation of recommender systems is needed in order to foster individual and collaborative learning. It is argued that in order to make recommender systems valuable tools in educational contexts, the design of these systems should address tensions between system characteristics, individual characteristics, educational characteristics and group characteristics.

Introduction

When we ponder over the movie that we'd like to see next weekend, or want to find out whether the new restaurant in town is worth checking out, we often rely on the experience and recommendations of friends and other people who we trust to be knowledgeable about our tastes and preferences. Recommendations are based on social judgments, i.e. cognitive activities where an individual evaluates whether an item such as a movie or a restaurant is liked or not (Sherif & Hovland, 1961). While social interaction with others often involves sharing one's social judgments, it needs an additional element to turn a judgment into a recommendation: This element is adaptation. In order to be able to adapt a social judgment, a communicator must know about the tastes and interests of a recipient (Wegner, 1987). If this knowledge is available, one can recommend an item even in cases where one's individual social judgment is different. For instance, one could recommend a movie to a friend irrespective of one's own judgment because the friend's favorite actor stars in it.

Recommendations provide a person with valuable cues, thereby giving guidance to one's activities. The larger the space of options, the more it becomes important to have valuable recommendations at hand. Navigating through information spaces like the WWW represents an activity where the number of available options can become exceedingly large. In order to deal with the huge amounts of information, people would benefit from having access to other persons' social judgments, or even better, to receive social judgments that are adaptively tailored to their personal interests. Consequently, many Web environments leave ample room for people to share social judgments: by encouraging customers to write reviews on products, rate items, or discuss them with others. Often, individual social judgments are accumulated over people to arrive at averaged social judgments of an entire collective, as in the case of bestseller lists. However, none of these methods takes the particular interests of a user into account; they lack the adaptive elements of personalization. This is where recommender systems come into play. Out of individual social judgments from users, mostly in the form of item ratings, they compute personalized recommendations that are adapted to a given user (Herlocker, Konstan, Terveen, & Riedl, 2004).

A common method employed to generate personalized recommendations is through collaborative filtering (Herlocker et al., 2004). Collaborative filtering relies on the input of a collective of users, and for each user the system stores behavioral data. This can be accomplished through implicit feedback like user clicks and reading times, or through explicit feedback in the form of user ratings. Similarity metrics between users or between items are then used to generate recommendations for a user.

Users of recommender systems do not directly interact with each other. Thus, their behavior cannot be regarded as collaborative, but rather as collective, i.e. they autonomously contribute to the emergent properties of the overall system. However, the interaction between each individual and the system is collaborative in nature. The system can only generate good recommendations if a user is willing to share social judgments via ratings of items. Without this form of interaction, a recommender system cannot adapt to the interests of a user. In contrast, users of recommender systems often do not take the system output at face value, but try to take the perceived "personality" of recommender systems into account when assessing the quality of recommendations (McNee, Riedl, & Konstan, 2006). Thus, users and recommender systems collaboratively negotiate on the topic at hand, and the ensuing mutual adaptation bears a strong similarity to CSCL processes.

Recommender systems have become quite fashionable in commercial environments, particularly with regard to items where individual preferences can differ widely, e.g. movies or music. However, in recent years the potential of personalized recommender systems for educational purposes has begun to be explored. Several systems have been designed that recommend a broad range of items, among them learning resources on the Web

(Drachsler et al., 2010; Recker, Walker, & Lawless, 2003) or entire courses (Farzan & Brusilovsky, 2006). The applications cover very different areas of learning and education like informal learning (Drachsler, Hummel, & Koper, 2009), mobile learning (Andronico, Carbonaro, Casadei, Colazzo, Molinari, & Ronchetti, 2003), or learning at the workplace (Aehnelt, Ebert, Beham, Lindstaedt, & Paschen, 2008). However, until now empirical evidence from evaluation studies using real learners is very scarce, as most educational recommender system applications have focused on prototype development or testing algorithms. In one of the few exceptions, Drachsler et al. (2010) found faster learning object completion times, a greater variety of learning paths, and higher satisfaction for learners who used an educational recommender system.

Recommender Systems: How They Can Specifically Address Learning

One of the recurring topics among designers of educational recommender systems is that one cannot simply transfer standard recommender systems to learning scenarios on a one-to-one basis; designers have to carefully address specific amendments that should be made in order to fully exploit the power of these systems in educational contexts, both for individual learning and for collaborative learning.

Support for Individual Learning

Our analysis of the design requirements for educational recommender systems is conceptualized around a network of three different factors. A first factor pertains to system characteristics: A recommender system needs data in a particular format, and it uses specific means to aggregate these data and to generate recommendations. A second factor relates to characteristics of a learner such as needs, preferences, and abilities. As a third factor educational characteristics as context come into play: Principles that are regarded as beneficial for learning. Each of the three factors as well as their combination is associated with particular tensions that impact the design of recommender systems (see Figure 1).

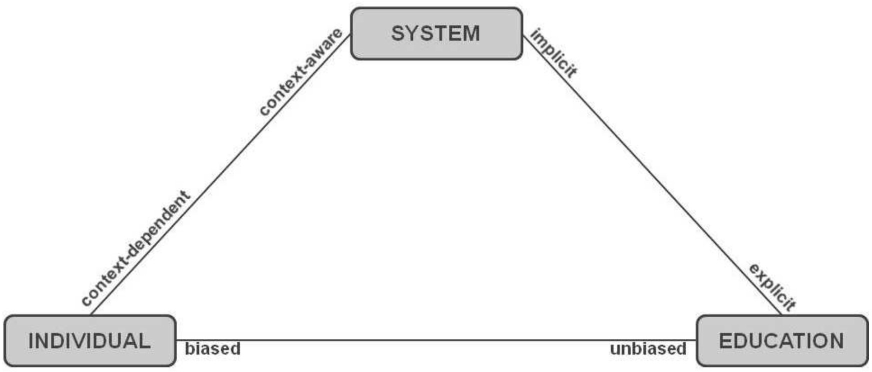

Figure 1. Tensions for the Design of Recommender Systems for Individual Learning.

Context-dependent learners vs. context-aware systems. In order to adapt to a person, a recommender system must be able to properly diagnose the person's situation. However, diagnosing learning is different from diagnosing customer behavior. For instance, when a recommender registers that a customer has viewed a recommended product and bought it afterwards, the system has been successful. In contrast, when a recommender registers that a learner has viewed a recommended item, the success of the recommendation in terms of the amount of learning cannot be measured as easily. Whether an individual has learnt something from a recommended item is highly context-dependent (Drachsler et al., 2009). A novice with a particular learning goal will benefit from a different recommendation than an expert with the same learning goal. As proficiency levels play a major role, Drachsler et al. (2009) have suggested that recommender systems for learning should not be conceptualized around isolated items like learning resources, but rather on sequences and learning paths among connected items. In order to address the context-dependency of learning, recommender system algorithms are often combined with elements from adaptive hypermedia environments like learner modeling techniques, use of metadata, and ontologies (Brusilovsky & Henze, 2007).

Implicit vs. explicit feedback. Recommender systems can rely on explicit feedback (ratings) or implicit feedback (browsing behavior, reading times). From a system perspective, several researchers have stressed the importance of implicit feedback mechanisms (e.g. Wang, 2007) because using implicit feedback is elegant, unobtrusive, and does not burden learners with the additional task of rating items. Moreover, it appears that some scholars do not trust in the accuracy of explicit ratings. For instance, one learner might assign high ratings for learning items that were regarded as very easy, whereas another learner might give high ratings for challenging items. Therefore it might be tempting to completely abandon explicit user ratings for the prediction of useful items. However, from a learning science perspective, explicit ratings have a number of advantages over implicit methods: First, humans are often much better than machines to make judgments about fuzzy categories (Norman, 1993). Second, for learning contexts it should be noted that rating an item is a form of active participation which is regarded - at least for collaborative scenarios - as the main determinant of learning outcomes (Cohen, 1994). Third, explicit ratings require learners to reflect on an item, and reflection is an important meta-cognitive activity (Palincsar & Brown, 1984). Seen in this way, requiring learners to explicitly rate items can contribute to learning rather than diverting from a learning task. Therefore, we believe that educational recommender systems should rely on explicit ratings as much as possible. Of course, in order to get ratings that properly inform a recommender system it is clear that simple overall rating schemes do not suffice. Rather, learners should get an opportunity to rate items on different dimensions. For instance, Drachsler et al. (2009) suggested including ratings on required proficiency levels (e.g. good for novices, boring for experts), ratings on the manner of presentation (e.g. clear and straightforward), or ratings of fun. More sophisticated rating schemes can provide the system with valuable data, and at the same time stimulate learners' reflection on the items they peruse.

Biased vs. unbiased processing. This tension might arise between learner and educational characteristics. Classical recommender systems suggest items based on inferred user taste. However, when it comes to learning, personal taste might not be the best driving force to improve performance (Tang & McCalla, 2004). For instance, it is well known that people have difficulties in processing information in an unbiased way. Information search often underlies a confirmation bias where preference-consistent items are favored over preference-inconsistent items (Jonas, Schulz-Hardt, Frey, & Thelen, 2001). From a learning science perspective, biased information processing is detrimental, as preference-inconsistent information is more likely to evoke beneficial socio-cognitive conflict (Doise & Mugny, 1984). Moreover, unbiased reasoning is an important element of critical and open-minded thinking (Stanovich & West, 1997). Therefore it appears useful for recommender systems to counteract confirmation bias by making salient preference-inconsistent items. Our own empirical research has investigated this issue by analyzing how learners react to preference-inconsistent recommendations (Schwind, Buder, & Hesse, this issue). It was shown that preference-inconsistent recommendations reduced confirmation bias, led to attenuation of initial preferences, and increased elaboration.

In sum, it has become evident that educational recommender systems should take particularities of individual learning into account in order to be successful. First, they need more information about learners in order to generate suitable recommendations. Second, they should make use of sophisticated external rating schemes. And finally, they should be designed in ways that counteract learners' tendencies for preference-consistent, less challenging items. If these issues are addressed, recommender systems should make for a welcome addition to our repertoire of learning technologies.

Support for Collaborative Learning

In order to explore how recommender systems must be designed to support collaborative learning, group characteristics have to be taken into account. To the best of our knowledge no recommender system for the support of collaborative learning groups has been developed yet. Nonetheless, some tentative conclusions can be drawn on how recommender systems should be accommodated in order to foster collaborative learning processes.

In the section on individual learning we outlined that recommender systems must bring three factors into line (system, individual, and educational characteristics), and that tensions among these three factors must be addressed by a recommender system. Turning to collaborative learning, group characteristics come into play as a fourth factor. As a consequence, three new tensions will arise (see Figure 2). In the following, these three tensions are discussed.

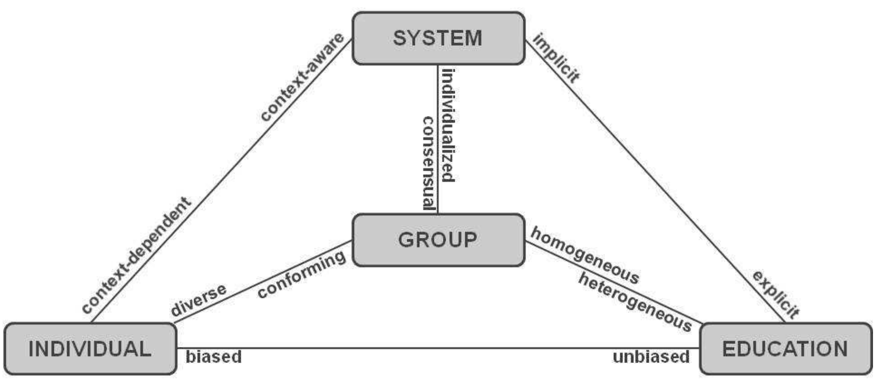

Figure 2. Tensions for the Design of Recommender Systems for Collaborative Learning.

Consensual vs. individualized ratings. In the same way that an individual expresses a social judgment through a rating, groups could be asked to discuss an item, thereby coming to a consensual rating. The system would then treat the group as some kind of "pseudo-user" (O'Connor, Cosley, Konstan, & Riedl, 2001). However, recommendations for this pseudo-user would likely to be of more benefit to some group members than to others. Alternatively, a recommender system could treat a group as a collection of individuals, capturing individual ratings, and providing individualized recommendations, and then leaving it to a collaborative group to negotiate on the output. The consensual approach is more in line with the notion of groups as backdrops for shared meaning making; the individualized approach lends more weight to potential differences among learners.

Diverse individuals vs. conforming groups. This tension relates to the differences between individuals and groups. In a social-psychological review, Hinsz, Tindale, and Vollrath (1997) concluded that for most tasks, interaction reduces initial group diversity. Of course, tasks like group decision making ultimately require some reduction of diversity, but groups have a strong tendency to rush towards conformity to an extent that is detrimental to performance. For instance, groups favor shared over unshared information even when a consideration of unshared information leads to better performance (Stasser, 1992); likewise, majority subgroup factions often prevail over minority factions even when majorities advocate an incorrect judgment (Asch, 1951).

Homogeneous groups vs. learning through heterogeneity. It was already mentioned that interacting groups have a tendency to disproportionately reduce diversity among members. They exert strong pressure to conform, leading to group homogeneity. From a learning sciences perspective, such a tendency is detrimental, as diversity and group heterogeneity are often held to be important antecedents of collaborative learning. For instance, it was shown that collaborative performance is improved if the range of achievement levels among learners is moderate rather than small or large (Webb, 1991). Another productive type of group variability is exemplified by the finding that learning and teamwork are improved if collaborators have different perspectives on an issue, as this is likely to induce socio-cognitive conflict (De Wit & Greer, 2008; Doise & Mugny, 1984).

How could a recommender system for collaborative learning accommodate for these three tensions? A potential solution is to focus on group diversity as a key variable. In order to accomplish this, ratings on items should be yielded in an individualized fashion, but then be aggregated in order to express the range of ratings rather than the average. For instance, the system should not calculate that a group found an item to be difficult on average. Instead, it could be captured that the group expressed a medium range of perceived difficulty. Items with larger variability in terms of achievement levels would then have a higher probability of being recommended. This approach would preserve diversity among group members, but still focus on those aspects that fuel successful collaborative learning.

Conclusions

This paper has investigated the question of whether and how recommender systems could be useful technologies for learning. It was argued that key features of recommender systems fit very well with current principles in the learning sciences: they are peer technologies, they augment self-regulated learning activities with scaffolds, and they offer personalized content. However, classical recommender systems are focusing on user taste, but in learning contexts, relying on user taste is neither a sufficient nor entirely appropriate way to provide good recommendations.

We conceptualized the design space for educational recommender systems around four different factors (system, individual, group, and educational characteristics) and focused on the different tensions that arise between these factors. From this discussion, some recommendations for the design of educational recommender systems can be derived: (1) recommender systems should know more than user taste when providing educationally relevant information, (2) they should focus on explicit ratings rather than implicit capturing of behavioral data, (3) they should provide information that is challenging for learners, and (4) in collaborative learning, they should be designed to preserve group variability. We believe that if recommender systems embody these principles, they can be very powerful tools to foster both individual and collaborative learning.

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