# Recommendations for learners are different: Applying memory-based recommender system techniques to lifelong learning

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**Abstract.** This article argues why personal recommender systems in technology-enhanced learning have to be adjusted to the specific character of learning. Personal recommender systems are strongly depend on the context or domain they operate in, and it is often not possible to take one recommender system from one context and transfer it to another context or domain. The article describes a number of distinct differences for personalized recommendation to consumers in contrast to recommendations to learners. Similarities and differences are translated into specific demands for learning and specific requirements for personal recommendation systems. Therefore it analyses memory-based recommendation techniques for their usefulness to provide pedagogically reasonable recommendations to learners.

**Keywords:** technology-enhanced learning, lifelong learning, personal recommender systems, collaborative filtering, content-based recommendation, user profiling

## 1. Introduction

The increasing use of R*ecommender Systems* (RS) that support users in finding their way through the possibilities on offer in the Internet is obvious. For instance, the well-known company amazon.com [1] is using a recommender system to direct the attention of their costumers to other products in their collection. The main purpose of recommender systems is to pre-select information a user might be interested in. Existing 'way finding services' may inspire and help us when designing and developing specific recommender systems for lifelong learning [2].

RS can be classified in multiple ways; they are classified by their recommendation approach [3], by the techniques that are used [4], or the effects that the used algorithms distinguish from each other [5]. Furthermore, Manouselis & Costopulou suggested a framework that is based on existing taxonomies and categorizations of recommender systems to analyze and classify them in a standardized way [6]. Following the specific focus of this article, we want to differentiate them by considering the type of products they recommend, and the context they operate in. We can differentiate RS that recommend 'simple' consumer products like music, movies, clothes or other items of daily use, and RS that recommend ‘complex’ consumer products like insurances or bank accounts (also known as Knowledge-based RS [7]).

In Technology-Enhanced Learning (TEL), RS deal with information about learners and Learning Activities (LA), and would have to combine different levels of complexity for the different learning situations the learner may be involved in.

Furthermore, RS strongly depend on the *context* or *domain* they operate in, and it is often not possible to take a recommendation strategy [8] from one context and transfer it to another context or domain. The first challenge for designing a RS is to define the users and purpose of a specific context or domain in a proper way [9]. For TEL a crucial question is: “How do the context and domain of learners in lifelong learning look like and who are the relevant stakeholders here?”

The aim of this article is to provide specific requirements and suitable techniques to create a *Personal Recommender System* (PRS) for lifelong learners. For this purpose we will now first describe specific demands for learning in general (second section). Based on these specific demands, we will define requirements for PRS in TEL (third section). Further we examine the (dis)advantages of current memory-based recommendation techniques and their usefulness for PRS in TEL (fourth section). In the concluding section we discuss our approach and further research issues when developing and testing consecutive and more advanced versions of PRS for TEL.

## 2. Specific demands for lifelong learning

Lifelong learners are in a similar situation like consumers looking for information on the Internet, but there some particular differences in their need for personalized recommendations. Self-directed lifelong learners are in need of an overview of available LA, and must be able to determine which of these would match their personal needs, preferences, prior knowledge and current situation. The motivation for any RS is to assure an efficient use of available resources in a network. The motivation for a PRS in TEL needs to improve the ‘educational aspects’ for the learners. For instance, the learners have to be able to find suitable LA in less time. Therefore, it will not be possible to simply take or adjust an existing RS for recommending consumer products.

The individual context of the learner and the conditions of the domain are important influencing factors for a RS in education. A PRS has to take into account the specifics and requirements steming from the target group. In the case of the prominent website movielens.org new users have to rate some movies right after they enter the system otherwise no personalized recommendations can be presented. Such an initial data set is needed to solve the ‘cold-start’ problem [5].

In the lifelong learning context all potentially valuable LA are unknown to the learners so they are not able to rate them in advance. Because of this the above presented way to solve the cold-start problems is not feasible.

Another specific requirement for our context is the support of the learning process. A learning strategy [10] which takes into account several learning theories or pedagogically motivated rules is the most promising way to address this issue. RS for lifelong learning should consider phases in cognitive development, preferred media and characteristics of the learning content when designing instruction (i.e., when selecting and sequencing LA in a program). Dron has argued for the consideration of educational theories (pedagogical flexibility concept) in top-down systems like in Knowledge-based RS [11]. From his point of view pedagogical approaches should already be considered during the design of a system. With the use of recommendation strategies we could apply the concept of pedagogical flexibility as well for bottom-up techniques like collaborative filtering. Therefore, the recommendation strategy decides internally which recommendation technique will provide the most suitable results for the current situation of a learner.

Another complicating matter is that – when comparing learning content to movies or books – the cognitive state of the learner and the learning content may change over time and context. The purpose, role and context of specific LA may vary across various stages of learning [12]. Traditionally learner modeling tries to model the learning process by taking into account knowledge from educational, psychological, social and cognitive science [13]. Whereas MovieLens recommendations are entirely based on the interests and the tastes of the user, preferred LA by the learners might not be pedagogically most adequate [14]. Even for learners with the same interest, we may need to recommend different LA, depending on individual proficiency levels, learning goals and context. For instance, learners with no prior knowledge in a specific domain should be advised to study basic LA first, where more advanced learners should be advised to continue with more specific LA.

## 3. Specific requirements for PRS in TEL

As argued in the last part of the paper a PRS that should advice learners must consider the specific character of the learning context. This subsection explains the following specific learning characteristics and related requirements for a PRS in TEL: 1. learning goal, 2. prior knowledge, 3. learner characteristics, 4. learner grouping, 5. rated LA, 6. learning paths, and 7. learning strategies.

The target and goal of the learner is the basic information a PRS needs to have. In addition a PRS should have information about the prior knowledge of a learner regarding the target LA. The proficiency level of the learner should fit to the proficiency level required to complete LA. Some learners might want to reach learning goals on a specific competence levels like beginner, advanced or expert level.

Learner characteristics and preferences would contribute to the provision of more personalized recommendations, like information about their individual needs, like time constraints, or preferences for distance education or problem-based learning.

Demographic information about the users can also considerably help to improve recommendations. A PRS for lifelong learners could use learner information to aggregate learner groups (*learner grouping,* or *user profiling*). Such learner grouping has to focus on relevant learning characteristics, like similarities in learning behavior (e.g., study time, study interests and motivation to learn). Instead of using demographic information about users, we can also apply stereotypes of the learning context to filter appropriate LA.

Aggregated ratings are an alternative method for the recommendation of LA. Learners with the same learning goal or similar study time per week could benefit from ratings received from more advanced learners.

For beginning learners history information about the successful study behavior of more advanced learners (*learning paths*) are promising ways to guide them. From frequent positively rated LA and their sequence, most popular learning paths will emerge. The most successful and efficient learning paths could be recommended.

Finally, PRS in TEL benefit when we apply learning strategies derived from educational psychology research [10] into PRS. Such strategies could use rules, like "go from simple to more complex tasks" or "gradually decrease the amount of contact and direct guidance", as guiding principles for recommendation. This entails taking into account metadata about specific LA, but not the actual design of specific LA themselves.

In summary, the aim for PRS for TEL is the development of a recommendation strategy that is based on most relevant information about the individual learner and the available LA, history information about similar learners and activities (learning paths), guided by educational rules and learning strategies, aimed at the acquisition of learning goals. The suggested approach is able to recommend on different levels of granularity of learning resources comparable to the *Abstraction Layer* in [15]. It could recommend learning paths, LA or just learning objects to a learner. Most important issues therefore is an adequate description of the mentioned items. A model for different levels of granularity of learning resources in the domain of lifelong learning can be found in [16].

## 4. Suitable techniques

In this section we assess existing memory-based recommendation techniques for RS on their usefulness for PRS in TEL. We focus on memory-based techniques because memory-based techniques are most adequate to our experimental setups [17].

*Memory-based techniques* continuously analyze all user or item data to calculate recommendations, and can be classified in following main groups: Collaborative Filtering, Content-based techniques, and Hybrid techniques. *Collaborative filtering techniques* (CF) recommend items that were used by similar users in the past; they base their recommendations on social, community driven information (e.g., user behavior like ratings or implicit histories). *Content-based techniques* (CB) recommend items similar to the ones the learners preferred in the past; they base their recommendations on individual information and ignore contributions from other users. *Hybrid techniques* combine both techniques to provide more accurate recommendations. Several studies already demonstrated the superiority of hybrid techniques when compared to single techniques for RS [18-20]. Examples are cascading, weighting, mixing or switching [8, 18]. A Hybrid RS could combine collaborative (or social-based) with content- (or information-) based techniques. If no efficient information is available to carry out CF it would switch to a CB technique. Table 1 provides an overview of memory-based recommendation techniques, listing their (dis)advantages and potential usefulness for TEL, which will be described in the remainder of this section.

| Memory-based recommendation techniques | | | | |
|---|---|---|---|---|
| Name | Short description | Advantages | Disadvantages | Usefulness for e-learning |
| **Collaborative filtering (CF) techniques** | | | | |
| 1.User-based CF | Users that rated the same item similarly probably have the same taste. Based on this assumption, this technique recommends unseen items already rated by similar users. | - No content analysis<br>- Domain-independent<br>- Quality improves<br>- Bottom-up approach<br>- Serendipity | - New user problem<br>- New item problem<br>- Popular taste<br>- Scalability<br>- Sparsity<br>- Cold-start problem | - Benefit from experience<br>- Allocate learners to groups (based on similar ratings) |
| 2.Item-based CF | Focus on items, assuming that items rated similarly are probably similar. It recommends items with highest correlation (based on ratings to the items). | - No content analysis<br>- Domain-independent<br>- Quality improves<br>- Bottom-up approach<br>- Serendipity | - New item problem<br>- Popular taste<br>- Sparsity<br>- Cold-start problem | - Benefit from experience |
| 3.Stereotypes or demographics CF | Users with similar attributes are matched, then recommends items that are preferred by similar users (based on user data instead of ratings). | - No cold-start problem<br>- Domain-independent<br>- Serendipity | - Obtaining information<br>- Insufficient information<br>- Only popular taste<br>- Cold-start problem<br>- Obtaining metadata information<br>- Maintenance ontology | - Allocate learners to groups<br>- Benefit from experience<br>- Recommendation from the beginning of the PRS |
| **Content-based (CB) techniques** | | | | |
| 4. Case-based reasoning | Assumes that if a user likes a certain item, s/he will probably also like similar items. Recommends new but similar items. | - No content analysis<br>- Domain-independent<br>- Quality improves | - New user problem<br>- Overspecialization<br>- Sparsity<br>- Cold-start problem | - Keeps learner informed about learning goal.<br>- Useful for hybrid RS |
| 5. Attribute-based techniques | Recommend items based on the matching of their attributes to the user profile. Attributes could be weighted for their importance to user. | - No cold-start problem<br>- No new user / new item problem<br>- Sensitive to changes of preferences<br>- Can include non-item related features<br>- Can map from user needs to items | - Does not learn<br>- Only works with categories<br>- Ontology modeling and maintenance is required<br>- Overspecialization | - Useful for hybrid RS<br>- Recommendation from the beginning |

**Table 1.** Memory-based recommendation techniques and their (dis)advantage for TEL

### 4.1. Collaborative filtering techniques

Collaborative filtering techniques (or social-based approaches) use the collective behavior of all learners in a learning environment. Parts of the collaborative filtering techniques are user-based and item-based collaborative filtering, and stereotype filtering.

*User- and item-based collaborative filtering: advantages and disadvantages.* Main advantages of both techniques are that they use information provided *bottom-up* by user rating, that they are *domain independent* and require *no content analysis*, and that the *quality of the recommendation increases over time* [21].

However, collaborative filtering techniques are limited by a number of *disadvantages*. First of all, the so called '*cold-start' problem* is due to the fact that CF techniques depend on sufficient user behavior from the past. Even when such systems have been running for a while, adding new users or new items will suffer the 'cold-start'. Another disadvantage for CF techniques is the *sparsity* of past user actions in a network. Since these techniques are dealing with community driven information, they support *popular taste* stronger than unpopular. Learners with unusual taste may get less qualitative recommendations, and others are unlikely to be recommended unpopular items (of high quality). Another common problem of CF is the *scalability*.

RS which are dealing with large amounts, like amazon.com, have to be able to provide recommendations in real-time with number of both users and items exceeding millions.

*User- and item-based collaborative filtering: usefulness for TEL.* User- and item-based techniques are useful for learning environments which are dealing with different topics (domains). They do not have to be adjusted for specific topics and no top-down maintenance for identifying high quality LA is required. CF techniques can identify LA with high quality, allow learners to *benefit from experiences* of other, successful learners. CF techniques can be based on pedagogic rules that are part of the recommendation strategy. Characteristics of the current learner could be taken into account to *allocate learners to groups* (e.g., based on similar ratings) and to identify most suitable LA. For instance, suitable LA can be filtered by the entrance level that is required to study the LA. The prior knowledge level of the current learner would than be taken into account to identify the most suitable LA. To solve the cold-start problem, user- and item-based CF have to be combined with other CF techniques, like stereotypes and demographics, in recommendation strategies to enable recommendation during the start phase of the RS.

*Stereotypes / demographics: advantages and disadvantages.* Through stereotype filtering items can be recommended to similar users based on their mutual attributes. *Advantages* are that they are *domain independent*, and (when compared to user- and item-based CF) they do not require that much history data to provide recommendations. Therefore stereotypes / demographics are useful to solve the '*cold-start*' problem. They are also able to recommend similar but yet *unknown* items, and have learners discover preferable items by '*serendipity*'.

Main *disadvantages* are that obtaining stereotype information can be annoying for users, especially when many attributes need to be filled in. Such information has to be collected in dialogue with users and stored in user profiles. When *insufficient information* is collected from users, the recommendations will be hampered.

*Stereotypes / demographics: usefulness for TEL.* The stereotype recommendation technique is an accurate way to allocate learners to groups if no behavior data is available. In combination with techniques that suffer from the 'cold-start' problem, stereotypes complement a recommendation strategy, enabling valuable recommendations from the very beginning.

### 4.2. Content-based recommandation techniques

Content-based techniques (or information-based approaches) use information about individual users or items. This subsection now first describes case-based reasoning, and then attribute-based techniques.

*Case-based reasoning: advantages and disadvantages.* It recommends items with the highest correlation to items the user liked before. The similarity of the items is based on the attributes they own. These techniques share some *advantages* of most CF techniques: they also are *domain-independent, do not require content analysis* and the quality of the recommendation *improves over time* when the users have rated more items.

The *disadvantage* of the *new user problem* also applies to case-based reasoning techniques. More specific disadvantages of case-based reasoning are *overspecialization* and *sparsity*, because only items that are highly correlated with the user profile or interest can be recommended. Through case-based reasoning the user is limited to a pool of items that are similar to the items he already knows [3].

*Case-based reasoning: usefulness for TEL.* Case-based reasoning is adequate to keep the learner informed about aimed learning goals. LA are recommended to a learner which are similar to the ones preferred in the past. When a learner wants to reach a higher competence level for the learning goal, the PRS can also structure the available LA by applying pedagogic rules as defined in the recommendation strategy. This technique complements the recommendation strategy by adding an additional data source for available LA and learners. For example, if not enough data is available for CF techniques the recommendation strategy could switch to case-based reasoning.

*Attribute-based techniques: advantages and disadvantages.* A major *advantage* is that *no 'cold-start' problem* applies to attribute-based recommendation. These techniques only take user- and item attributes into account for their recommendation. Attribute-based techniques can therefore be used from the very beginning of the RS. Likewise, adding new LA or learners to the network will not cause any problem. Attribute-based techniques are *sensitive to changes* in the profiles of the learners. They can always control the PRS by changing their profile or the *relative weight of the attributes*. A description of needs in their profile is mapped directly to available LA.

A serious *disadvantage* is that an attribute-based recommendation is static and *not able to learn* form the network behavior. That is the reason why highly personalized recommendation can not be achieved. Attribute-based techniques work only with *information that can be described in categories*. Media types, like audio and video, first need to be classified to the topics in the profile of the learner. This requires *category modeling* and *maintenance* which could raise serious limitations for learning environments. Also the *overspecialization* can be a problem, especially if learners do not change their profile.

*Attribute-based techniques: usefulness for TEL.* Attribute-based recommendations are useful to handle the '*cold-start*' problem because no behavior data about the learners is needed. Attribute-based techniques can directly map characteristics of lifelong learners (like learning goal, prior knowledge, available study time) to characteristics of LA. There are learning technology specifications, like IMS-LD [22], that can support this technique through predefined attributes. It is an appropriate technique to complement the other techniques we presented before. Both attribute- and case-based recommendations allow us to provide recommendation at the start of the PRS and for new learners in a learning environment. If sufficient history data become available, the recommendations can be incrementally based on CF techniques that are more flexible and learnable.

## 5. Conclusions

We have argued for the need to adjust PRS in TEL to the specific character of learning rather than using RS from other contexts (first section). We defined specific demands of learning (section 2) and concluded that such PRS should take into account learning goals, prior knowledge, learner characteristics, learner groups, rating, learning paths, and learning strategies (third section). We have presented various memory-based recommendation techniques that appear promising to meet these

requirements. We concluded that *hybrid memory-based recommendation techniques* could provide most accurate recommendations, by compensating disadvantages of single techniques in a recommendation strategy (fourth section).
PRS for lifelong learning should support the efficient use of available resources to improve the educational aspects, taking into account the specific characteristics of learning. PRSs in TEL have to be driven by pedagogical rules, which could be part of a recommendation strategy. Recommendation strategies look for available data to decide on which technique(s) to select for which situation. When not enough data are available for any kind of recommendation technique, the recommendation strategy should select technique(s) that provide(s) the most suitable recommendation in the current situation the learner is in.

In future research we will incrementally design and test various versions of PRS in the context of three consecutive studies. The *first study* is an experimental field study in the domain of Psychology (study already completed). This study used a recommendation strategy build with stereotype filtering (obtaining information from learner profiles) and attribute-based recommendations, and was carried out with small numbers of LA (about 20) and learners (about 150). The *second study* will contain a series of simulation studies using NetLogo (in preparation). This study will include larger amounts of LA (around 500) and learners (around 1000), to better evaluate the emergent effects of a PRS. We will use user- and item-based recommendation techniques (using ratings) and combine them with case-base reasoning (using personal information) in one recommendation strategy. The *third study* will be another experimental field study in the domain of Health Care. An advanced PRS will be based on results from both prior studies, and will combine most successful techniques in a recommendation strategy. In this last study we intend to include user-based tagging and rating and combine this information with attribute-based recommendation techniques.

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