Personal recommender systems for learners in lifelong learning networks: the requirements, techniques and model

Hendrik Drachsler*, Hans G.K. Hummel and Rob Koper

Educational Technology Expertise Centre
Open University of the Netherlands
Valkenburgerweg 177, 6419 AT Heerlen, The Netherlands
E-mail: hendrik.drachsler@ou.nl
E-mail: hans.hummel@ou.nl
E-mail: rob.koper@ou.nl
*Corresponding author

Abstract: This article argues that there is a need for Personal Recommender Systems (PRSs) in Learning Networks (LNs) in order to provide learners advice on the suitable learning activities to follow. LNs target lifelong learners in any learning situation, at all educational levels and in all national contexts. They are community-driven because every member is able to contribute to the learning material. Existing Recommender Systems (RS) and recommendation techniques used for consumer products and other contexts are assessed on their suitability for providing navigational support in an LN. The similarities and differences are translated into specific requirements for learning and specific requirements for recommendation techniques. The article focuses on the use of memory-based recommendation techniques, which calculate recommendations based on the current data set. We propose a combination of memory-based recommendation techniques that appear suitable to realise personalised recommendation on learning activities in the context of e-learning. An initial model for the design of such systems in LNs and a roadmap for their further development are presented.

Keywords: lifelong learning networks; learning technology; Personal Recommender Systems; PRSs; Collaborative Filtering; CF; content-based recommendation; user profiling.

Reference to this paper should be made as follows: Drachsler, H., Hummel, H.G.K. and Koper, R. (xxxx) 'Personal recommender systems for learners in lifelong learning networks: the requirements, techniques and model', *Int. J. Learning Technology*, Vol. X, No. Y, pp.000–000.

Biographical notes: All of the authors work at the Educational Technology Expertise Centre of the Open University of the Netherlands and are currently involved in projects researching critical facilities for way-finding in learning networks. Hendrik Drachsler is a PhD student carrying out research into personalised recommendation systems. Hans G.K. Hummel works as an Associate Professor and his main interests are focused on way-finding facilities, learning technology specifications and competence-based education. Rob Koper works as a Full Professor and Director of the Technology Development Programme, focusing on self-organised distributed learning networks for lifelong learning.

1 Introduction

The current knowledge-based society requires us to completely reconsider educational practices. For instance, the Commission of the European Union (2000), in its memorandum for lifelong learning, assigned top priority to the realisation of lifelong learning for all citizens in the year 2010. The European Commission aims that lifelong learning should become the guiding concept for personal competence development in the near future in order to deal with recent changes and emerging trends.

First of all, learning can no longer be considered to be a part of childhood and youth alone, but is becoming a lifelong process. Second, learning is no longer limited to the context of a regular school or university campus, but is becoming more and more integrated into workplace learning and personal development, where formal and informal learning activities are intertwined. Third, lifelong learners find themselves placed at centre stage, which means that they are themselves now responsible for their own learning processes, rather than a teacher or teaching institute (Longworth, 2003; Shuell, 1992). Fourth, when taking on this responsibility, lifelong learners need to become self-directed (Brockett and Hiemstra, 1991) and might be performing different learning activities in different contexts at the same time. Learners are becoming free to decide what, when, where and how they want to learn.

Such changes and trends have provided lifelong learners much more freedom to choose learning activities from a number of educational providers while, at the same time, their responsibility for the results of the learning process has increased (Longworth, 2003). In such a situation, learners may find it hard to get an overview of the available learning activities and to identify the most suitable ones (Koper and Tattersall, 2004). To achieve this, lifelong learners need advice to decide on the most suitable learning activities to meet their individual learning goals. This could be achieved by using learning technologies in e-learning environments. Within the internet as a whole, which is a rapidly growing collection of information, we see the development of Recommender Systems (RSs) that support users in finding their way through the possibilities offered. The main purpose of RSs on the internet is to preselect the information a user might be interested in. The existing 'way-finding services' may inspire and help us when designing and developing specific RSs for lifelong learning. For instance, the well-known company amazon.com (Linden *et al*., 2003) uses an RS to direct the attention of their users to other products in their collection.

Although lifelong learners are in a situation which is similar to consumers looking for products on the internet, there are a number of distinct differences in their search behaviour and needs for personalised recommendation. Self-directed lifelong learners are in need of an overview of the available learning activities 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 the efficient use of the available resources in a network. Within the context of e-learning, more specifically, a Personal Recommender System (PRS) has to improve the 'educational provision' (the ratio of output and input, to be expressed as goal attainment or the time spent to find suitable resources). A PRS for lifelong learning, therefore, would have to search for potential learning activities and recommend the most suitable learning activities to the individual learner (or learner group).

The PRS we are aiming for would have to function within an e-learning infrastructure in order to be able to receive and provide the required information. The concept of a Learning Network (LN) (Koper and Sloep, 2003) appears promising and is guided by the concept of lifelong learning. Such networks connect distributed learners and providers in certain domains. Their design and development are highly flexible, learner-centric and evolve from the bottom upwards, going beyond course and programme-centric models that are imposed from the top downwards. An LN is populated with many users and learning activities provided by different stakeholders. Each user is allowed to add, edit, delete or rate learning activities at any time. The concept of an LN (Koper and Tattersall, 2004) shares several characteristics with recent developments known as 'Web 2.0', which have lifted barriers to the contribution of information in the internet and enabled many more users to add data. Many activities, such as searching for information, commercial activities and social interaction, can now be done more effectively on the web (Zajicek, 2007). In the same way, LNs differ from traditional virtual learning environments because they are driven by the contributions of their members, rather than being designed by educational institutions or domain professionals (*e.g.*, teachers). An architecture for such LNs, including services for way-finding support, will be established by the European TenCompetence project.[1] We anticipate that the navigation or way-finding support provided by a PRS within an LN will minimise the amount of time learners need to locate suitable learning activities. Furthermore, we expect that a better alignment of the characteristics of learners and learning activities will increase the efficiency of the learning process.

Having argued for PRSs in LNs, the aim of this article is to provide specific requirements and suitable techniques for their realisation, as well as an initial model and roadmap for their design and development. To this end, we will first describe the existing RSs in order to draw up more specific requirements for PRSs in LNs (the second section). Based on these specific requirements, we will examine the (dis)advantages of the current recommendation techniques and their usefulness for PRSs in LNs (the third section). We then continue by presenting our initial model for PRSs in LNs (the fourth section). In the concluding section, we discuss our combined approach and further research issues when developing and testing consecutive and more advanced versions of PRSs in LNs.

2 Personal recommender systems for lifelong learners

Every RS serves a specific purpose and function in a specific context. Related to their purpose and context, they operate according to their own predefined recommendation techniques or strategies. Each individual recommendation technique uses a single method to create a recommendation. Because every single recommendation technique has its own advantages and disadvantages, we need to combine techniques to increase the accuracy of the recommendations (Hummel *et al.*, 2007). The use of a combination of recommendation techniques constitutes a recommendation strategy (Van Setten, 2005). Recommendation strategies use domain-specific or historical information about users or items to decide which specific recommendation technique provides the highest accuracy for the current user. In this section, we will first describe how an RS depends on its product and context. We will then list the specific requirements for learning and the specific requirements for PRSs in lifelong LNs.

2.1 Recommender systems

RSs can be classified by considering the type of products they recommend and the context they operate in. We can differentiate between RSs that recommend 'simple' consumer products like music, movies, clothes or other items of daily use and RSs that recommend 'complex' consumer products like insurance or bank accounts (also known as Knowledge RSs). RSs for more or less simple consumer products mostly deal with item metadata (such as author, genre, title) and use these in combination with the ratings awarded by the users (*e.g.*, mystrands.com, amazon.com, pandora.com, movielens.org). Many of them also include demographic information about users such as age, sex or civil status (Schafer *et al.*, 1999). Knowledge RSs recommend more or less complex consumer products and use more demographic information about users, but rarely in combination with the ratings for items awarded by the users (Felfernig, 2005). They are largely based on complex semantic ontologies and are more expert-driven when compared to RSs for less complex products. Ontologies relate the demographic information of the users with product information, for instance, to offer the most suitable insurance to a customer.

One of the first PRSs for e-learning was the Altered Vista system (Recker *et al.*, 2003). They used a Collaborative Filtering (CF) technique to explore how the feedback provided by the learners on learning resources can be stored and given back to a community. Similar research projects in the area of recommending learning resources to learners based on different kind of collaborative filtering techniques are the Rule-Applying Collaborative Filtering (RACOFI) system (Anderson *et al.*, 2003), the I-Help system (Tang and McCalla, 2003; 2004a–b), and the Context eLearning with Broadband Technologies (CELEBRATE) system (Manouselis *et al.*, 2007). Most of these systems use CF techniques which are personalised by individual strategies (*e.g.*, by direct or indirect ratings). They are often designed for a certain community and cannot easily be used for another.

RS with different designs than the mentioned ones are the Questions, Study, Interaction, and Assessment (QSIA) system and the Open Collaborative Virtual Archive Service Environment (CYCLADES) systems. The QSIA system (Rafaeli *et al.*, 2004; 2005) is used to promote the collaboration and further formation of learner groups. The specialised ability of this system is the use of an automated CF algorithm or buddy system. In the QSIA system, learners are free to decide on whether they want advice given by buddies (added friends) or to use an anonymous CF technique. The CYCLADES system is an interesting step towards a general recommendation service (Avancini *et al.*, 2007). It also uses a CF technique with user-based ratings, but does not just apply the technique to one community. It uses digital resources, which are freely available in the repositories of the Open Archives Initiative. The advantage of the system is the possibility of offering recommendations for learning activities that are developed by different institutions. This approach is currently exemplary for the Open Education Resources movement (Hylén, 2006).

Generally speaking, RSs in e-learning deal with information about the learners (users) and learning activities (items) and would have to combine different levels of complexity for the different learning situations the learners may be involved in.

Furthermore, RSs strongly depend on the context or domain they operate in and it is often not possible to take a recommendation strategy from one context and transfer it to another context or domain. The first challenge in designing an RS is to define the users and purpose of a specific context or domain in a proper way (McNee *et al*., 2006). For e-learning, a crucial question is: what do the context and domain of the learners in lifelong learning look like and who are the relevant stakeholders here?'

2.2 The specific demands for learning

For PRSs in LNs, it will not be possible to simply take or adjust an existing RS for recommending consumer products. There are a number of specific demands created by the learning context which need to be dealt with:

- the importance of the context of learning
- the inherent novelty of most learning activities
- the need for a learning strategy
- the need to take changes and learning processes into account.

We will address these below.

First of all, for an RS in education, it is important to understand the individual context of the learner (or learner group) and the conditions and rules of the domain. The concept of an LN can be positioned within distance education. We therefore start the discussion about the support for decision-making in LNs from this perspective. Learners in distance education are influenced mainly by forum information, the information provided by the tutor, or through face-to-face meetings and curricula. Curricula influence the learners because most of the time, they force rather than suggest a certain order of the learning activities. Students in distance education have to rely even more on the curriculum structure because they have a higher barrier to communication with teachers or students. PRSs provide additional support for decisions and they can bridge the gap between distance and more regular education. They have already been successfully used on the internet in many commercial community portals (*e.g.*, last.fm, Pandora.com, CDNow.com, Netflix.com).

Most current RSs that have been used in e-learning were established in the same way as in e-commerce without taking into account the specific attributes or conditions of the learners or the context of learning. They monitor the history of the successful learners and recommend learning activities accordingly (Andronico *et al*., 2003; Zaiane, 2002), like amazon.com looking for successful (*i.e.*, frequently bought) books to advise to its potential buyers and does not consider specific learner characteristics.

When designing a personalised RS for lifelong learners, we have to be aware of our target group of learners. For instance, movielens.org (a well-known RS for movies) demands new users to rate a specific number of movies before the system is able to provide personalised recommendations based on the movies that the user (dis)liked in the past. Such an initial data set is needed to solve the so-called 'cold start' problem (Al Mamunur Rashid *et al*., 2002).

This is in contrast to the novelty of most learning activities, because nearly all potential learning activities are (inherently) unknown to the learners. Learners are (by definition) not able to rate learning activities in advance, because if they already knew them, they would no longer be potential learning activities. Moreover, the learners will at least have to read through a learning activity before they are able to rate it. Many people are able to rate movies because they have heard or read about it, or have already seen the movie. In the domain of learning, however, it is unlikely that a learner will already be familiar with certain learning activities. Consequently, it is less of a problem for 'movie lovers' to rate movies in advance to specify a profile than it is for learners to rate learning activities in advance. Requiring learners to rate an initial set of learning activities, as in movielens.org, does not, therefore, seem feasible. Other mechanisms to specify a learner profile have to be devised.

A third important demand is that for a PRS to support a learning process, we have to take into account the learning theories to decide upon a learning strategy to support this process. RSs for lifelong learning should consider phases in cognitive development, the preferred media and the characteristics of the learning content when designing instruction (*i.e.*, when selecting and sequencing learning activities in a programme).

A fourth difference when comparing the learning content to books and movies is that the learners and learning content change over time and context. The purpose, role and context of specific learning activities may vary across various stages of learning (McCalla, 2004). Learner modelling (Aroyo, 2006) has to use information about the learning process and is closely connected to educational, psychological, social and cognitive science. Whereas MovieLens recommendations are entirely based on the interests and tastes of the user, the preferred learning activities might not be the most pedagogically appropriate (Tang and McCalla, 2003). Even for the learners with the same interests, we may need to recommend different learning activities, depending on the individual proficiency levels, learning goals and context. For instance, the learners with no prior knowledge in a specific domain should be advised to study basic learning activities first, while more advanced learners should be advised to continue with more specific learning activities.

2.3 The specific requirements for personal recommender systems in learning networks

PRSs that advise learners must take into account the specific character of the learning context. This subsection explains the following specific learning characteristics and the related requirements for a PRS in an LN: the learning goal, prior knowledge, learner characteristics, learner grouping, the rated learning activities, the learning paths and the learning strategies.

- First, we need to know what the learners want to learn (learning goal).
- Related to the first point, we also need to know if the learners already have any prior knowledge about what they want to learn. The proficiency level of the learning activity should fit the proficiency level of the learner (prior knowledge). The learners may want to reach the learning goals on specific competence levels, like beginner, advanced or expert levels.
- Other relevant information about the learners' characteristics would help the provision of more personalised recommendations, such as information about their individual needs (*e.g.*, the educational institution needs to be reachable by public transport) and preferences (*e.g.*, preference for distance education or problem-based learning) for learning (learner characteristics).

- In the same way that consumer product RSs use demographic information about their users, a PRS for lifelong learners could use learner information to aggregate learner groups (learner grouping or user profiling). Such learner grouping could focus on the relevant learning characteristics, like similarities in the learning behaviour (*e.g.*, study time, study interests and motivation to learn). Instead of using demographic information about the users, we can also apply stereotypes of the learning context in filtering the appropriate items (*i.e.*, suitable learning activities).
- The aggregated ratings of the learning activities as awarded by other learners can provide valuable information (the rated learning activities). Learners with the same learning goal or similar study time per week could benefit from the ratings received from more advanced learners.
- Beginning learners could benefit from historical information about the successful study behaviour of the more advanced learners in the same learning network (the learning paths). From the learning activities which are frequently positively rated and their sequence, the most popular learning paths will emerge. The most successful learning paths with regard to efficiency and effectiveness could be recommended.
- Finally, PRSs in LNs would benefit if we apply the learning strategies derived from educational psychology research (Koper and Olivier, 2004). Such strategies could use pedagogical rules as guiding principles for recommendation, like 'go from simple to more complex tasks' or 'gradually decrease the amount of contact and direct guidance'. This entails taking into account the metadata about specific learning activities, but not the actual design of the specific learning activities themselves.

In summary, the aim for PRSs in lifelong LNs is the development of a recommendation strategy based on the most relevant information about the individual learner and the available learning activities, historical information about similar learners and activities, guided by educational rules and learning strategies and aimed at the acquisition of learning goals.

3 The suitable techniques

In this section, we assess the existing techniques for RSs on the basis of their usefulness for PRSs in LNs. There are many recommendation techniques, but all may be classified as either model-based or memory-based techniques (Adomavicius and Tuzhilin, 2005).

Model-based techniques periodically analyse data to cluster them in estimated models. For instance, 'genre' would be a class in a movieworld system and movies of the same 'genre' could be part of one cluster. The average choice of movies from a specific cluster can then be used to calculate the interest of a user in a specific movie. Model-based RSs use techniques such as Bayesian models (Chien and George, 1999; Condli *et al.*, 1999), neural networks (Jennings and Higuchi, 1993) or latent semantic analysis (Hofmann, 2004; Schein *et al.*, 2002; Soboro and Nicholas, 2000). These require a large corpus (more than 10 000 items) to estimate their models and provide accurate recommendations (Balabanovic, 1998; Denhière and Lemaire, 2004). Once a model has been estimated, a recommendation for a large corpus can be created in an efficient way.

However, we do not expect such a large corpora of learning activities in one LN, especially during the experimental stage we will find ourselves in the coming years. Therefore, we will focus on memory-based recommendation techniques.

Table 1 The memory-based recommendation techniques

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

Memory-based techniques continuously analyse all user or item data to calculate recommendations and can be classified in the following main groups: CF techniques, Content-Based (CB) techniques and hybrid techniques. CF techniques recommend items that were used by similar users in the past; they base their recommendations on social, community-driven information (*e.g.*, user behaviour like ratings or implicit histories). CB techniques recommend items similar to the ones the learners preferred in the past; they base their recommendations on individual information and ignore the contributions from other users. Hybrid techniques combine both techniques in order to provide more accurate recommendations.

Several studies have already demonstrated the superiority of hybrid techniques when compared to single techniques for RSs (Balabanovic and Shoham, 1997; Claypool *et al.*, 1999; Good *et al.*, 1999; Melville *et al.*, 2002; Pazzani, 1999; Soboro and Nicholas, 2002). Some examples are cascading, weighting, mixing or switching (Burke, 2002; Van Setten, 2005). A hybrid RS could combine CF (or social-based) techniques with CB (or information-based) techniques. If no efficient information is available to carry out CF techniques, it would switch to a CB technique. Table 1 provides an overview of the memory-based recommendation techniques, listing their (dis)advantages and potential usefulness for LNs, which will be described in the remainder of this section.

3.1 Collaborative filtering techniques

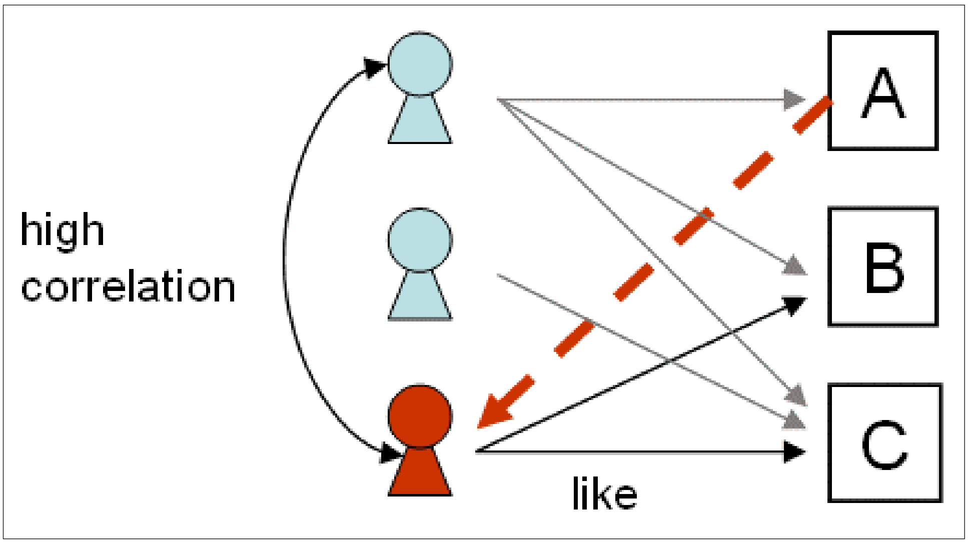
CF techniques (or social-based approaches) use the collective behaviour of all the learners in the LN. This subsection first describes user-based and item-based CF and then stereotypes filtering.

3.1.1 User- and item-based collaborative filtering: the advantages and disadvantages

Both user- and item-based techniques use the same mechanism of correlation for different objects. To underline the differences between these two techniques, we now describe them together. User-based techniques correlate users by mining their (similar) ratings and then recommend new items that were preferred by similar users (see Figure 1). Item-based techniques correlate the items by mining (similar) ratings and then recommend new, similar items (see Figure 2). The main advantages of both techniques are that they use information that is provided bottom-up by user ratings, that they are domain-independent and require no content analysis and that the quality of the recommendation increases over time (Herlocker *et al.*, 2004).

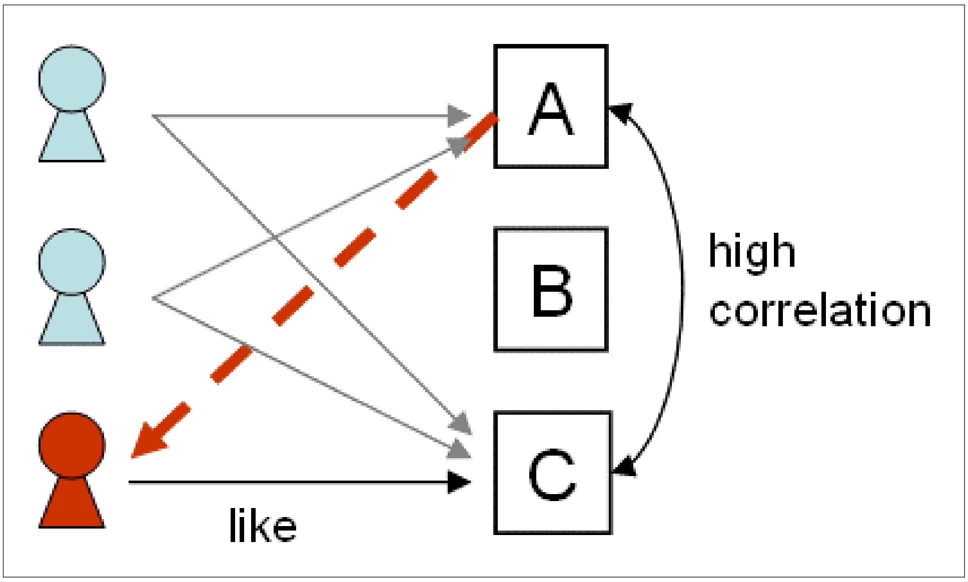
However, CF techniques are limited by a number of disadvantages. First of all, the so-called 'cold start' problem is due to the fact that CF techniques depend on sufficient user behaviour from the past. Even when such systems have been running for a while, this problem emerges when new users or items are added. New users first have to give a sufficient number of ratings for items in order to get accurate recommendations based on user-based CF (new user problem). New items have to be rated by a sufficient number of users if they are to be recommended (new item problem). Another disadvantage for CF techniques is the sparsity of the past user actions in a network. Since these techniques deal with community-driven information, they support popular tastes more strongly than unpopular tastes. The learners with an unusual taste may get less qualitative recommendations, and learners with usual taste are unlikely to get unpopular items of high quality recommended. Another common problem of CF is scalability. RSs which deal with large amounts of data, like amazon.com, have to be able to provide recommendations in real time, with the number of both the users and items exceeding millions. This problem does not apply to LNs because not that many users and items will populate a specific LN.

Figure 1 User-based CF (see online version for colours)



Source: Kim (2006)

Figure 2 Item-based CF (see online version for colours)



Source: Kim (2006)

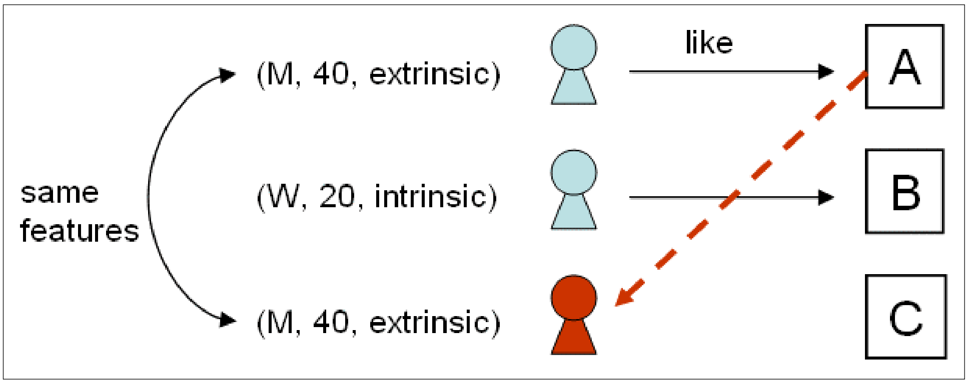
3.1.2 User- and item-based collaborative filtering: the usefulness for learning networks

User- and item-based techniques are useful for LNs which are dealing with different topics (domains). They do not have to be adjusted for specific topics, which is important because we expect many LNs for different topics. CF techniques can identify high-quality learning activities and enable learners to benefit from the experiences of other successful learners. The bottom-up rating mechanism holds promise for self-directed LNs because no top-down maintenance for identifying high-quality learning activities is required. CF techniques can be based on pedagogic rules that are part of the recommendation strategy. The characteristics of the current learner could be taken into account to allocate the learners into groups (*e.g.*, based on similar ratings) and to identify the most suitable learning activities. For instance, suitable learning activities can be filtered by the entrance level that is required to study the learning activity. The prior knowledge level of the current learner would then be taken into account to identify the most suitable learning activity. To solve the cold start problem, user- and item-based CF have to be combined with other CF techniques, such as stereotypes and demographics, in recommendation strategies to enable recommendation during the starting phase of the RS.

3.1.3 Stereotypes/Demographics: the advantages and disadvantages

Preferred items can be recommended to similar users based on their mutual attributes (see Figure 3). The advantages are that they are domain-independent and (when compared to user- and item-based CF) do not require a large amount of historical data in order to provide recommendations. Therefore, stereotypes/demographics are useful in solving the 'cold start' problem. They are also able to recommend similar but yet unknown items and have learners discover preferable items by 'serendipity'.

Figure 3 Demographics filtering (see online version for colours)



Source: Kim (2006)

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

3.1.4 Stereotypes/Demographics: the usefulness for learning networks

The stereotype recommendation technique is an accurate way to allocate the learners into groups if no behaviour 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.

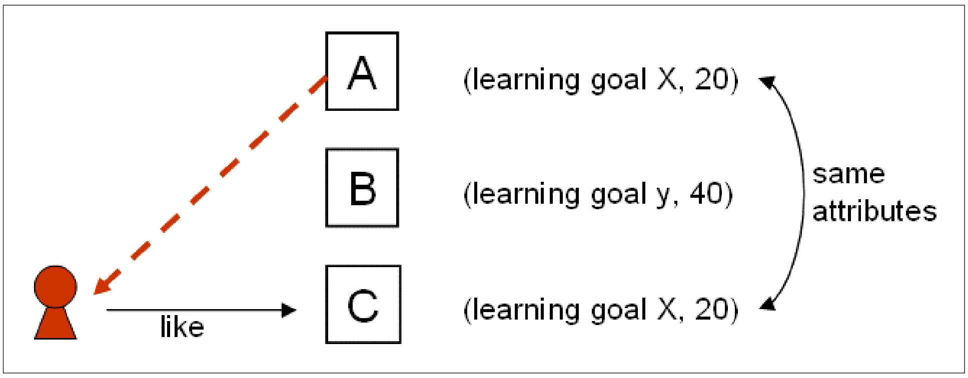
3.2 Content-based recommendation techniques

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

3.2.1 Case-based reasoning: the advantages and disadvantages

It recommends items with the highest correlation to the items that the user liked before (see Figure 4). The similarity of the items is based on the attributes they own. These techniques share some advantages of most CF techniques: they are also domain-independent, do not require content analysis and the quality of the recommendation improves over time when the users have rated more items.

Figure 4 Case-based reasoning (see online version for colours)



Source: Kim (2006)

The disadvantage of the new user problem also applies to case-based reasoning techniques. They are not able to recommend items to a new user when the taste of the new user is still unknown. More specific disadvantages of case-based reasoning are overspecialisation and sparsity, because only the 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. "For example, a person with no experience in Greek cuisine would never receive a recommendation for even the best Greek in town" (Adomavicius and Tuzhilin, 2005, p.737).

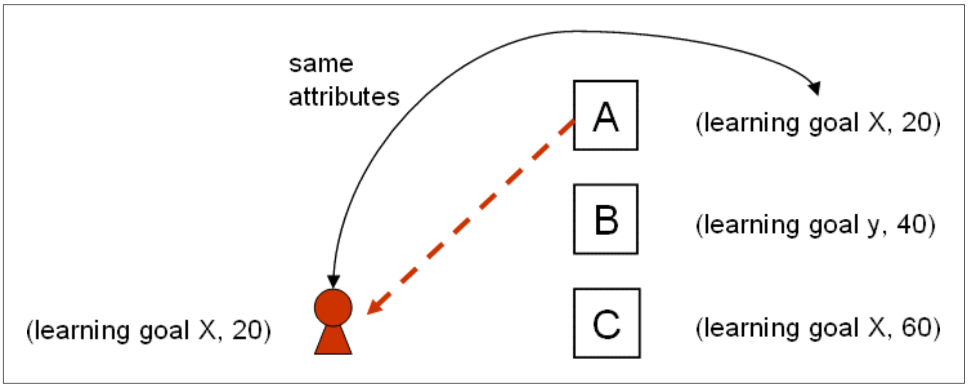
Case-based reasoning is useful to keep the learner informed about the aimed learning goals. Learning activities which are similar to the ones preferred in the past are recommended to a learner. When a learner wants to reach a higher competence level for the learning goal, the PRS can also structure the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

3.2.2 Attribute-based techniques: the 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 learning activities or learners to the network will not cause any problems. Attribute-based techniques are sensitive to changes in the profiles of the learners. They can always control PRSs by changing the profiles or the relative weight of attributes. A description of needs in their profile is mapped directly to the available learning activities in the LN.

A serious disadvantage is that an attribute-based recommendation is static and not able to learn from the network behaviour and this is the reason why highly personalised recommendation cannot be achieved. Attribute-based techniques work only with information that can be described in categories. Media types, such as audio and video, first need to be classified to the topics which are in the profile of the learner. This requires category modelling and maintenance, which could raise serious limitations for LNs. In addition, overspecialisation can be a problem, especially if the learners do not change their profile.

Figure 5 Attribute-based techniques (see online version for colours)



3.2.3 Attribute-based techniques: the usefulness for learning networks

Attribute-based recommendations are useful in handling the 'cold start' problem because no behaviour data about the learners is needed. The attribute-based techniques can directly map the characteristics of lifelong learners (like the learning goal, prior knowledge, the available study time) to the characteristics of the learning activities. There are learning technology specifications, such as IMS Learning Design (IMS-LD, 2003) that can support this technique through predefined attributes. In the TenCompetence project, the use of IMS-LD as a specification to model learning activities is a priority.

The advantages of IMS-LD are its reputation and the availability of tools that support the IMS-LD standard. The described PRS will use the suitable metadata from IMS-LD to provide information for recommendation techniques such as attribute-based recommendations and stereotype filtering. Attribute-based filtering seems to be an appropriate technique to complement the other techniques we previously presented. Both attribute- and case-based recommendations allow us to provide recommendation when a PRS has been newly implemented and for new learners in an LN. If sufficient historical data becomes available, the recommendations can be incrementally based on CF techniques that are more flexible and learnable.

4 The initial model

In this section, we present our initial model for a PRS in an LN. We focus on the description of the PRS, but start by briefly mentioning the most related components in the LN infrastructure, which are based on the TenCompetence domain model (Koper, 2006).

4.1 The related components of the learning network infrastructure

An LN is a collection of actors (learners and institutions) and learning activities (unit of learning) that are supported by Information and Communication Technologies (ICTs) (see Figure 6).

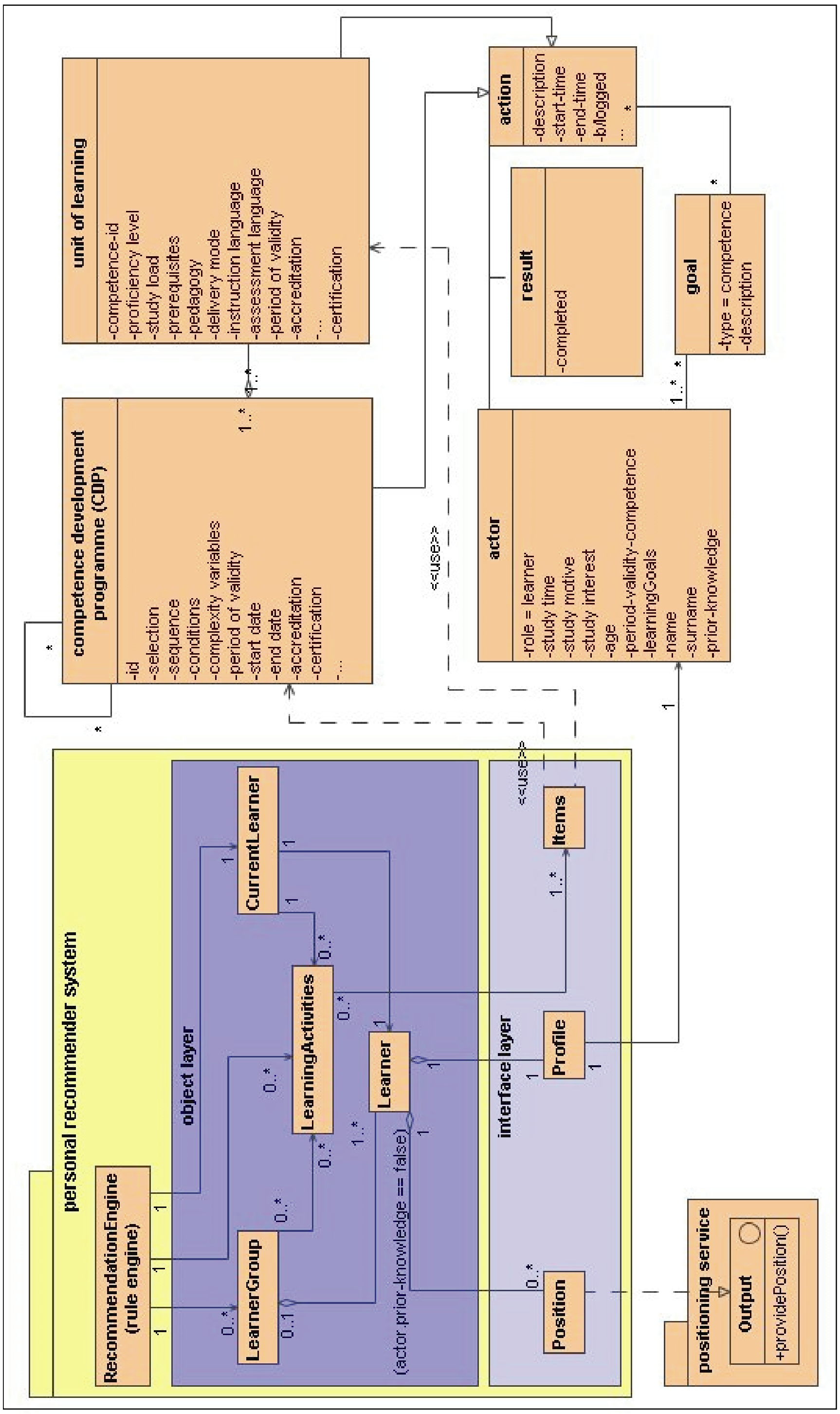
In order to provide recommendations, the PRS needs information from the other components of the LN, such as the positioning service, the actor (learner profile) and the available learning activities (either the units of learning or competence development programmes). If a learner asks for a recommendation, the PRS will load her/his profile and check the available metadata. For instance, if not enough metadata about the prior knowledge of the learner is available, the PRS will request further information from the positioning service. Based on the available learner data, the recommendation strategy of the recommendation engine will choose the most suitable recommendation technique(s). Most recommendations will be specific learning activities (the units of learning); more advanced PRSs are expected to be able to recommend complete competence development programmes as well. Competence development programmes contain collections of units of learning with specific sequences. The sequences constitute successful learning paths towards specific learning goals.

4.2 The layers of the personal recommender system

The PRS can be described by two layers and a core recommendation engine (see Unified Modeling Language (UML) class diagram in Figure 6). The two different layers are the interface layer and the object layer.

The low-level data collection functions are located in the interface layer. The interface layer is responsible for obtaining the required data from the LN (like the learner profile, the behaviour data, the index of learning activities). The Profile class exchanges data between the RecommendationEngine class and the LN. It is responsible for obtaining the required data for the profile and behaviour of the learner. The Position class is responsible for obtaining the current position of the learner in the LN. It works as an interface between the positioning service (which assesses the prior knowledge of a learner) and the PRS, which provides the recommendations. The Items class analyses the available learning activities and returns an array of items to the LearningActivities class.

Figure 6 The class model of a personal recommender system and the related components in a learning network (see online version for colours)



The object layer creates the suitable learner groups. Using data based on the profile and behaviour of the current learner, the object layer detects similar learners and groups them. The Learner class collects the required data about learners creates profile for the requesting learner and inputs the LearnerGroup class. It requires the Profile and Position classes (from the interface layer) to obtain the required data for the requesting learner. The CurrentLearner class is an instance of the Learner class, representing the requesting learner and providing all the information relating to this learner to the RecommendationEngine. The LearnerGroup class generates an array of relevant (similar, successful) learners. It collects the available data about the relevant learners so that it can provide a recommendation based on CF, using the Learner class to select the matching learners and provide a list for the RecommendationEngine. The LearnerGroup class obtains information through the Learner class. Finally, the LearningActivities class is responsible for selecting the suitable learning activities and for allocating them to the LearnerGroup or CurrentLearner classes. It also provides a list of the available learning activities directly to the RecommednationEngine, if necessary.

The RecommendationEngine is the heart of the PRS. It calculates recommendations based on the input from the object layer, the available learning activities and (if available) the pedagogy rules that are implemented as part of the recommendation strategy. This recommendation strategy decides which recommendation technique(s) is/are the most suitable to cater to the needs, preferences and situation of the current learner.

5 Conclusions

We have argued that there is a need for navigation support in lifelong LNs (the first section). We have analysed common consumer product RSs in relation to more specific requirements for PRSs in such lifelong LNs. We concluded that such PRSs should take into account the learning goals, prior knowledge, the learner characteristics, the learner groups, the ratings, the learning paths and the learning strategies (the second section). We have presented various recommendation techniques that appear promising in meeting these requirements. We concluded that hybrid memory-based recommendation techniques could provide the most accurate recommendations by compensating for the disadvantages of single techniques in a recommendation strategy (the third section). We have presented and explained an initial class model of such PRSs in LNs (the fourth section).

The use of RSs within e-learning has remained sparse so far. Most consumer product RSs base their recommendations on a limited understanding of the users and items and do not combine the user profiles and item attributes to provide recommendations. RSs for lifelong learning should support the efficient use of the available resources in an LN in order to improve the educational provision, taking into account the specific characteristics of learning. PRSs in LNs should be driven by pedagogical rules, which could be part of a recommendation strategy. The recommendation strategy looks for the available data to decide on which technique(s) to select for which situation.

Some challenges will arise when developing and testing such PRSs and recommendation strategies. At the starting phase of the PRS, the ‘cold start’ problem limits the provision of suitable recommendations. When insufficient data is available for a certain kind of recommendation technique, the recommendation strategy should select one or more techniques that provide the most suitable recommendation in the current situation.

The future research has to further analyse which attributes of the learners and learning activities and which recommendation techniques perform best. We will incrementally design and test various versions of PRSs in the context of three consecutive studies. We will design the most important lifelong learning conditions as realistically as possible. Therefore, we will take into account major aspects of lifelong learning, like 'self-direction' and 'taken responsibility for your own learning', in our experimental design. The first study is an experimental field study in the domain of psychology (study already completed). This study used a recommendation strategy built with stereotype filtering (obtaining information from the learner profiles) and attribute-based recommendations and was carried out with small numbers of learning activities (about 20) and learners (about 150). To address the lifelong learning characteristics, the participants were informed that they did not have to follow the learning activities in a certain order. Also, they were allowed to complete the learning activities at 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 in the learning environment. The second study will contain a series of simulation studies using NetLogo (in preparation). This study will include the ratings by the learners and experiment with larger amounts of learning activities (around 500) and learners (around 1000) to better evaluate the emergent effects of ratings in LNs. We will use user- and item-based recommendation techniques (using ratings) and combine them with case-based reasoning (using personal information) in one recommendation strategy. The third study will be another experimental field study in the domain of healthcare. In this study, we particularly aim to model the informal aspects of lifelong learning. The healthcare workers will be able to add their own learning activities into the learning environment. These learning activities are community-driven and not connected to any formal assessment. Furthermore, the participants will be able to cluster the learning activities through a user-based tagging mechanism (folksonomies) in a personalised way. The lifelong learners no longer have to decide on their own whether a learning activity is suitable for certain purposes; they can benefit from the tags and ratings provided by the other learners and take that information into account for their self-directed decision process.

An advanced PRS will be based on the results from all the prior studies and will combine the most successful techniques in a recommendation strategy.

Acknowledgement

The Authors' efforts were (partly) funded by the European Commission in TENCompetence (IST-2004-02787) (http://www.tencompetence.org).

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Note

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