Identifying the Goal, User model and Conditions of Recommender Systems for Formal and Informal Learning

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Abstract. This article addresses open questions of the discussions in the first SIRTEL workshop at the EC-TEL conference 2007. It argues why personal recommender systems have to be adjusted to the specific characteristics of learning in Learning Networks. Personal recommender systems strongly depend on the context or domain they operate in, and it is often not possible to take one recommender system with a specific purpose from one context and transfer it to another context or domain. The article describes a number of distinctive differences for personalised recommendation to learners when compared to recommendations for consumers. Similarities and differences for informal and formal learning are discussed and used to define the recommendation goal that recommender systems in informal learning networks have to address. The article further suggests an evaluation approach for recommender systems in Learning Networks.

Keywords: SIRTEL, information discovery, usability of digital information, technology-enhanced learning, lifelong learning, personal recommender systems, collaborative filtering, learner profiling, evaluation

1. Introduction

This article argues to differentiate e-commerce recommender systems from recommender systems in Technology Enhanced Learning (TEL). It further distinguishes formal and informal learning, describing specific similarities and differences of these types of learning to e-commerce recommender systems.

The increasing use of *Recommender Systems* (RSs) that support users in finding their way through the possibilities on offer on the WWW is obvious. Many online companies like *amazon.com*, *netflix.com*, *drugstore.com*, or *ebay.com* (Linden et al. 2003; Schafer et al. 1999) are using a RS to direct the attention of their costumers to other products in their collection. The general purpose of recommender systems is to pre-select information a user might be interested in (Adomavicius and Tuzhilin 2005). The main recommendation goal of e-commerce RSs is to provide consumers with information to help them to decide which products to purchase. Existing successful examples from e-commerce may inspire and help us when designing and developing specific RSs for TEL.

In TEL, RSs deal with information about learners and Learning Activities (LAs), and would have to combine different levels of complexity for the different learning situations the learner may be involved in. The main recommendation goal for TEL RSs is to provide learners with suitable LAs in order to support their competence development. Therefore, RS in TEL have to consider relevant pedagogical rules describing pedagogy-oriented relations between learners' characteristics and LA-characteristics. For example: from Vygotsky's "zone of proximal development" follows the pedagogical rule 'recommended LAs should have a level a little bit above learners' current competence level' (Vygotsky 1978). Thus, RSs in TEL have to take into account competence levels in order to suggest an appropriate LA.

However, only talking about TEL ignores the broad spectrum of many different types of learning. Learning can for instance roughly be distinguished into formal and informal learning (Colley et al. 2002). Formal learning includes learning offers from universities or schools. Formal learning is highly structured, leads to a specific accreditation and has domain experts that guarantee quality. Informal learning happens to everybody from daily life activities related to work, family or leisure, it is less structured (in terms of learning objectives, learning time or learning support), and it does not lead to a certain accreditation. Informal learning may be intentional but in most cases it is non-intentional (incidental).

In literature the terminology of informal learning especially describes the learning phase of so called *lifelong learners* that are not participating in any formal learning context like universities or schools. Lifelong learners are acting much more self-directed and they are responsible for their own learning pace and path (Longworth 2003; Shuell 1992). In addition, the resources for their learning might come from many different sources: expert communities, work context, training or even friends might offer an opportunity for an informal competence development. The learning process is also not designed by an institution or responsible teachers like in formal learning but it depends to a very large extent on individual preferences learners have or choices that learners take. In general, when taking up 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. The learners are free to decide what, when, where and how they want to learn.

Coffield (2000) criticises that the action plans to achieve the knowledge society with lifelong learning (EU Commission 2000) are always considering the importance of informal learning, but the focus of learning remains on formal provision, qualifications and accountability. This may change, because the lifelong learners can get TEL support by the concept of Learning Networks (Koper and Tattersall 2004). This concept addresses many lifelong learning issues mentioned above and provides an infrastructure for distributed learners and stakeholders in certain domains. The design of a Learning Network (LN) is learner-centred and its development evolves bottom up through the participation of the lifelong learners. The LN approach focuses on the support of the neglected informal learning part that is becoming more important through the Web 2.0 development nowadays. It tries to balance the use of formal and informal learning offers by providing technology that specifically supports informal learning. Therefore, it is in contrast to other learning environments, which are designed only top down, because their structure, learning resources, and learning plans are predefined by an educational institution or domain professionals (e.g., teachers).

In LNs, the lifelong learners are able to publish their own LAs, or share, rate, and adjust learning activities from other learners. The learners are able to act in different roles (teachers, learners, or knowledge providers) in different LNs in parallel.

Therefore, the concept of LNs has several things in common with the Web 2.0 development. Web 2.0 also enables the users to add, share, rate, or adjust information. Popular services like *wikipedia.org*, *flickr.com* or *youtube.com* benefit from that development and are proof of the change in interaction with the World Wide Web (WWW). Before the Web 2.0 age the majority of users were only able to consume information from the WWW. The Web 2.0 technologies lifted the barrier of adding information to the WWW and enable much more users to contribute information to it. As a result, the amount of information available on the WWW increases dramatically. This has also an effect on LNs, because most of the informal LAs are based on contributions of learners and stored in the above mentioned Web 2.0 services. The learners may find it hard to get an overview of available learning activities and to identify the most appropriate LAs (Koper and Tattersall 2004).

Therefore, learners have a navigation problem in finding and selecting suitable information, like appropriate products to customers in e-commerce systems. The need to support users with the selection of information or giving reference to relevant information is becoming more important. We have to consider the differences in the recommendation goal of RSs for e-commerce and for learning. In the learning context we have to consider that a learner has a learning goal and wants to achieve a specific competence in a certain time, whereas a customer using an e-commerce system wants to buy a product on a specific quality level in a specific price range.

In the following sections, we will further explore this navigation problem and elaborate the differences of RSs in e-commerce to RSs in, especially informal, LNs. For this purpose, we will now first give an overview about related work in the field of RSs for TEL (second section). In the third section, we will then discuss specific differences and similarities between e-commerce RSs and RSs for TEL in general, as a first step. In a second step, we will explain additional differences of RSs for formal learning with RSs for informal learning. Based on this section, we will we suggest an evaluation approach that is more suitable for assessing RSs in learning (fourth section). Finally, we present our conclusion and further research plans.

2. Related work

There are already many approaches to support learners with RSs, but only few of them are evaluated. There are also already several overviews with different foci available for RSs in TEL (Drachsler et al. in press; Nadolski et al. submitted; Vuorikari et al. 2008). In the following section we want to refer to recent activities in the field which were partly presented at the Social Information Retrieval in Technology Enhanced Learning (SIRTEL) workshop 2007.

A detailed evaluation of suitable recommendation techniques and a technical model of RS for LNs that follows the argumentation of this article can be found in Drachsler et al. (in press). There we discuss advantages and disadvantages of several Collaborative Filtering techniques and how they can be integrated into LNs. Further, we report first experiences with a RS that applied a Stereotype Filtering algorithm and an ontology in an experimental pilot in the domain of Psychology. The course content and a prototypical version of a RSs were implemented in a Moodle environment (Dougiamas 2007). A screenshot of the learning environment with the implemented

RS is shown in Figure 1. This first study examined the effects of the navigation support on the completion of LAs measured (effectiveness), needed time to complete them (efficiency), satisfaction with the system (satisfaction), and the variety of learning paths (variety). The RS positively influenced all measures (Drachsler et al. 2008).

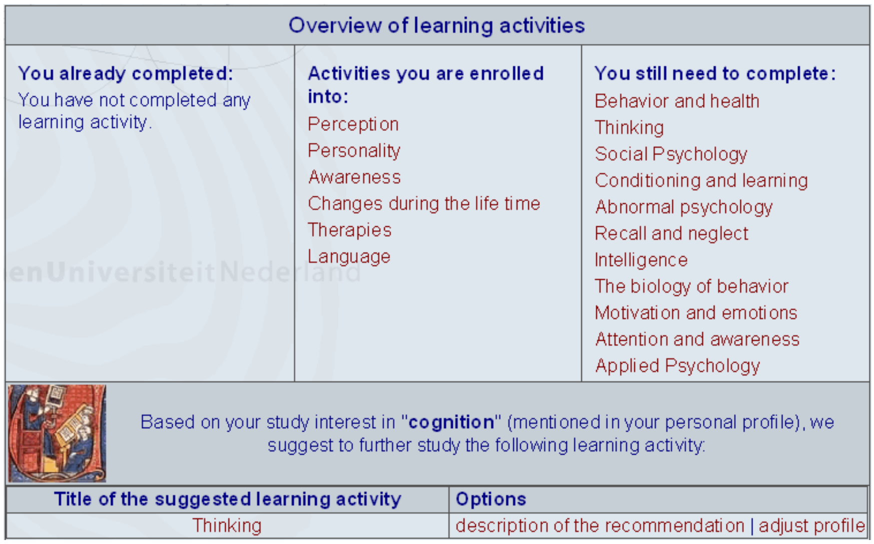

Figure 1: The Moodle learning environment with the implemented PRS. Based on the enrolled courses and the interest of the learner in 'cognition', the RS suggests a LA about 'Thinking' as the next most suitable LA.

Currently, the research in RSs for TEL is developed from two main perspectives. One (top down) perspective enhances filtering techniques via well defined educational metadata and educationally influenced filtering decisions. The other (bottom up) perspective evaluates learner provided information like 'tags', 'ratings' or 'behavior data' in order to support the learners with appropriate recommendations.

Regarding the first perspective interesting research was done by (Karampiperis and Diplaros 2007). They propose a methodology that starts with the generation of a matrix that represents the educational characteristics of the learning resources. On this matrix they apply an additional filtering process based on educational "footprint" (learning paths) by the learners. This is a rather new approach to the analysis and generation of recommendations that takes learning paths in to account. It applies an innovative 'image segmentation technique' to enhances the filtering process of the learning resources. Another very interesting study in this perspective uses a Collaborative Filtering simulator called CollaFiS (Manouselis et al. 2007) to parameterize, execute and evaluate all considered variations of algorithms. This research may serve as a first step towards the understanding and appropriate specialization of a Collaborative Filtering for formal learning.

For the second perspective intensive research is going on in the field of RSs for TEL in combination with user tagging. Using user created 'tags' introduce the problem of human inconsistency within the tags especially when learners tag in different languages (Vuorikari 2007; Vuorikari et al. 2007). But especially for informal LNs it would be an advantage for the learners to identify 'peer –learners' through shared tags. LNs are also a kind of distance education that have to bridge the isolation of the learners in the network. Therefore, the visualisation of the learners behind shared tags (Klerkx and Duval 2007) enables the learners to explore social relationships and can be supportive for community building in informal LNs (Sloep et al. 2007).

In addition to these two perspectives, there are also Social Network Analysis (SNA) approaches that are used in the context of SIRTEL. An advantage of SNA is the possibility to recommend LAs to learners based on their behavior in the network which aggregate implicit ratings to the LAs. Instead of explicit ratings by learners, this approach analyses the participation of learners in LAs like in discussion forums or wikis. The assumption behind this approach is that learners who participate in discussion of a topic are interested in it. The approach assumes that the more learners contribute to a discussion, the more they show an interest in the topic. Similar research is carried out with Latent Semantic Analysis (LSA) for different kinds of learning situations (Iofciu et al. 2006). LSA is also a probabilistic technique that requires no explicit ratings from learners in order to draw recommendations. It requires textual corpora in order to suggest content to learners.

Regarding research in informal LNs we see benefits from following approaches in the SIRTEL field: simulation studies with RSs, learner support through community provided tags and ratings, and analysis of networks with probabilistic technique like SNA or LSA.

3. Moving from e-commerce RSs to RSs for informal learning

The users of software differ in many characteristics, such as their status, expertise, preferences and even the reason for using the software; therefore to enhance the usability and satisfaction of such systems, it is extremely important to address these factors in an appropriate way (Benyon 1993).

This especially applies to RSs because they are strongly domain dependent and it is therefore not always possible to apply one RS from a particular domain with a specific recommendation purpose into another domain with different domain characteristics. Reasons for that are the variety of available recommendation techniques (Adomavicius and Tuzhilin 2005), the adjustment of these techniques to the specific conditions of the domain (like the environment, and data structure), and the specific user models and recommendation goals. If two domains own similar domain conditions and share a similar user model and recommendation goal then it is likely that the recommender algorithms can achieve similar results. From the technical point of view researchers have proven to apply recommendation algorithms to other domains after appropriate experimental testing and parameterization of recommendation algorithms (Herlocker et al. 2002; Manouselis et al. 2007). But an algorithm for book shop will hardly be applied for recommending insurances to a customer, because they require a deeper reasoning (Felfernig 2005). The recommendation purpose, the domain conditions, and the underlying data set of an insurance company are rather different from those of a book shop. Comparable differences apply to recommendations in TEL.

This (third) section will be split into two subsections. Section 3.1 will describe different recommendation goals, user models and environmental conditions for RSs in e-commerce when compared to TEL RSs. Section 3.2 will describe these differences when comparing RSs for formal learning to RSs for more informal learning.

3.1. Differences between RSs for e-commerce and RSs for TEL

In the following section we want to describe e-commerce RSs, their recommendation goal, user characteristics and environmental conditions. From these descriptions we will mention some differences and similarities with TEL.

Recommendation goal

The main recommendation goal of e-commerce RSs is to provide consumers with information to help them to decide which products to purchase (Schafer et al. 1999). Beside this main goal three sub goals can be distinguished:

- Converting Browsers into Buyers
  Visitors on e-commerce web sites often browse the site without the intention to purchase anything. RSs are used to suggest products to the consumers they might wish to purchase.
- Increasing Cross-sell
  RSs should also support cross-sell offers by suggesting additional products for the customers based on those products in the shopping cart.
- Building Loyalty
  Loyalty is becoming an essential business strategy. On a long term perspective e-commerce systems want to get away from the typical one turn interactions and establish a relationship of trust with the customer, especially because the compotators are just one click away. For this long term goal a detailed user profile is needed to offer personalised recommendations of products to the customers.

RSs in TEL have as main recommendation goal to support the learners in their competence development in order to achieve a specific learning goal. This learning goal is connected to a specific competence that has to be mastered on a certain competence level. Different from buying products, learning is always an effort that takes more time and its support needs more than just a good commercial argumentation. Therefore, the recommendation goal is more complex as in e-commerce RS. It is more than “Converting Browsers into Learners”. Learning is a highly individual development. Learners never achieve a final end state after a fixed time. Instead of buying a product and then owning it, learners always achieve a specific level of a competence that has various levels below and above. RSs in TEL have to contribute to a long term learning goal of learners whereas e-commerce RS typically support the one turn interactions with the customer in a shorter timeframe.

Regarding the “Increasing cross-sell” goal, RS in TEL surely needs to suggest additional LAs to learners based on those learning goals they aim for. However, learners and LAs change over time and context. The purpose of a specific LA may vary across various stages of a learning process (McCalla 2004). This means for the "Increasing cross-learning" that it is sometimes necessary to suggest the same or very similar LAs to learners if they are still on the same competence level. In e-commerce nobody would be satisfied with a recommendation for the same book in a different layout.

Building loyalty has much to do with trust and satisfaction in a specific system. In TEL satisfaction is measured during various stages. Learners are satisfied if they get suitable recommendations for their specific learning goals. But satisfaction in learning is based on mastered competences. Therefore, satisfaction for a RS in TEL will depend on the amount of support the RS provides to the learning process as a whole.

User model

For all of the recommendation goals above more or less personal information is required. Besides the standard personal information, like name and age, e-commerce RSs require additional attributes like ZIP code, income, job, credit card number, shipping address, occupation, and shipping preference (Ardissono and Goy 2000).

Learner modeling (Aroyo, 2006) in TEL has to use information about the learning process, which is closely connected to guidelines from educational, psychological, social, and cognitive science. RS in TEL may need to recommend different LAs to learners with the same learning goal, depending on individual proficiency levels, specific interest and their context. For instance, learners with no prior knowledge in a specific domain should be advised to study basic LAs first, where more advanced learners should be advised to continue with more specific LAs. E-commerce recommendations are entirely based on the interests and the tastes of the consumer, whereas preferred LAs of learners might not be the pedagogically most adequate (Tang and McCalla 2004). Learning is an effort for a learner, therefore they tend to select easier LAs rather than more ambitious LAs. But in order to achieve a learning goal on a higher competence level it is required to master more ambitious LAs as well.

Environmental conditions

E-commerce systems can rely on experts who maintain their product catalog and take care for the semantic relationships between their products. Also the products itself are well defined through standardised and detailed information for the product catalog. E-commerce systems are therefore top down driven systems with high maintenance support. Hence, most of the e-commerce data sets are quite densely filled with metadata and behavioral information of consumers. Most of the time, they exceed thousand of products and consumers with information about millions of transactions (ratings or user behaviour). Therefore, they suffer from an information overload but they still have to be able to provide recommendations in reasonable time.

For TEL we will most likely not have thousand of LAs nor exceed millions of transactions. Therefore, the environmental conditions are different to the e-commerce world.

3.2. Differences between RS for informal learning and RS for formal learning

There are also some particular differences between formal and informal learning. As mentioned in the introduction, TEL can roughly be distinguished into formal and informal learning. There is hardly one recommendation algorithm that covers the whole learning domain. In formal learning, a RS can rely on predefined learning plans (curriculum) from educational institutions with locations, known teachers and accreditation procedures. It can suggest courses to learners in a university in a specified order, or can offer alternative time tables. Informal learning depends on emerging information from various providers, with most of them being non institutional. Further, there is an absence of maintenance of metadata and of predefined semantic relationships between LAs.

In the following we describe the recommendation goal, environmental conditions and a required user model for informal learning.

Recommendation goal

Main recommendation goals for informal learning would be:

- Structure LAs in a pedagogical way
  The world of informal learning relies on the contribution of educational offers that emerge from the bottom upwards. These educational offers in LNs are mainly aggregated through RSS or ATOM feeds from Web 2.0 services. A RS in informal learning aims to bring structure to a dynamic and emergent space of LAs. Therefore, the main task for a RS in informal learning is organising the LAs in a pedagogical way to improve the competence development of the informal learner. The RS would benefit through applying learning strategies derived from educational psychology research (Koper and Olivier 2004) into their recommendation strategy. Such strategies could use *pedagogical rules*, like “go from simple to more complex tasks”.
- Suggest emerging learning paths to learners
  A RS in informal LNs is not only focusing on recommendations for a singular product, e.g. a lecture book. It is focusing on supporting the learning process of the learners. A RS that aims on such a learner support should make advantage of emerging data in a LN and support the learner with a ‘*Recommendation of Sequences of Learning Activities’*. Similar to some music recommender where recommendations of sequences of songs (playlist) are thinkable, a RS in informal LNs should use successful learning path which consists of several LAs in order to reach a specific learning goal. These learning paths are a valuable resource for starting learners. They emerge through frequently positively rated LAs and their sequence. Similar to a navigation system for cars the learners can then decide to use the most efficient (time saving) or most effective (focus on quality) learning paths in order to reach the learning goal.

Related to these two recommendation goals, the recommendation task of a RS in informal LNs can be defined according to Herlocker (2004) as ‘*Find Good Items’* and ‘*Recommend Sequence’* (Herlocker et al. 2004). Informal learning is less structured than formal learning or when buying any e-commerce product. Therefore, all ordering information provided by the community, like ratings and tags, should be taken into account to fulfill the recommendation goals. The ordering information has to be very intuitive, because complex structuring will overwhelm the community and will not be used at the end.

User model

Learners in LNs are in need of an overview of available LAs, and must be able to determine which of these would match their learner profile. Such learning profile should contain learning goal, prior knowledge, learner characteristics, learner grouping, rated LA, learning paths, and learning strategies. A detailed description of these attributes can be found in (Drachsler et al. 2007).

In formal learning similar characteristics have been used to design learner models that represent individual preferences and cognitive level of learners. The focus of the modeling in intelligent tutoring systems was on the learner's knowledge, his interest, background, goals, tasks and individual traits or the context (Brusilovsky 2007). For this purpose several techniques like scalar models, overlay models, perturbation models or genetic models have been introduced. As already mentioned, in informal LNs we do not have comparable conditions. In general, it is beneficial for the recommendation goals to have as much information as possible available. But this information has to emerge from the bottom upwards. Therefore, learner models in informal learning are less granulated and fed with dynamic information processes like Latent Semantic Analysis (LSA) (van Bruggen et al. 2004).

Environmental conditions

A good example to show the different conditions between e-commerce, formal and informal learning is *Ad targeting*. It is an attempt in e-commerce to identify which consumers should be made an offer based on their *prior behavior*. *Prior behavior* in this context means that an e-commerce RS reacts sensitively to specific events of a customer life. It takes into account the already '*purchased products*' of a customer and suggests tailored products to the customer. For instance if a consumer has a new-born baby, advertisements for diapers and other child related products are displayed within the consumer's price range. Purchased products are always a fixed list of distinct products that the user bought. It's a clear description of the shopping behavior of a consumer. Additionally, the purchased products include further information about product categories and are therefore able to make deeper reasoning about the consumer.

When we compare the context of *prior behavior* of a consumer (called Ad targeting) with prior behavior of learners, then we have to compare *purchased products* with *prior knowledge*. Prior knowledge is a rather complex characteristic when compared to a list of purchased products. It is based on various levels for each knowledge domain. Accreditation procedures currently are mostly executed in face to face meetings between teachers and learners.

In formal learning *prior knowledge* can be modeled in a similar way like in e-commerce systems. Already completed courses by the learner could be taken into account in order to suggest a new course on a specific competence level to the learner. This especially works at the university level where European standard ECTS points (European Credit Transfer System) have been allocated to any course. In this situation, a well defined 'knowledge domain model', relying on a 'network of concepts models' and a 'user model', is required to suggest courses on a specific competence level to the learners.

Formal learning also shares several other similarities beside the *Ad targeting* example with the e-commerce domain. Many formal learning systems like (Aroyo et al. 2003; De Bra et al. 2002; Kravcik et al. 2004) having equally fine granulated knowledge domains and can therefore offer personlised recommendations to the learner. These systems are mainly used in 'closed-corpus' applications (Brusilovsky and Henze 2007) where the learning content can be described by an educational designer through semantic relationships. Many of these systems take advantage of *Adaptive Hypermedia* technologies like metadata and ontologies to define the relationships, conditions, and dependencies of learning objects and learner models. Universities already hold well structured formal relationships like predefined learning plans (curriculum) with locations, known teachers and accreditation procedures. All this metadata can be used to recommend courses or personalise learning through the adaptation of the learning material or the learning environment to the students (Baldoni et al. 2007). One interesting direction in this research is the work on *Adaptive Sequencing* which takes into account individual characteristics and preferences for sequencing learning objects (Karampiperis and Sampson 2005). Similar to the e-commerce field there are many design activities needed before the runtime and also during the maintenance of the learning environment. In addition, the knowledge domains in the learning environment need to be described in detail. These aspects make Adaptive Sequencing and other Adaptive Hypermedia technologies more or less useless for informal LNs without having any highly structured knowledge domain and fine granulated LAs in a specific e-learning standard.

When we consider our *Ad targeting* example for informal learning we recognise the lack of structure in informal learning. Prior knowledge in informal learning is a rather diffuse parameter because it relies on information given by the learners without any standardisation. To handle the dynamic and diffuse characteristic of prior knowledge and to bridge the absence of a knowledge domain model probabilistic techniques like LSA are promising (van Bruggen et al. 2004). The absence of maintenance and structure in informal learning is also called the 'open corpus problem'. The open corpus problem applies when an unlimited set of documents is given that can't be manually structured and indexed with domain concepts and metadata from a community (Brusilovsky and Henze 2007). The open corpus problem also applies to informal LNs. Therefore, bottom up recommendation techniques like Collaborative Filtering are more appropriate because they require nearly no maintenance and improve through the emergent behavior of the community. Thus, if we want to address the informal part of learning we have to think about different environment conditions, the lack of maintenance, and less formal structured LAs. Despite of that LAs in LNs are mainly structured through tags and ratings given by the lifelong learners.

Beside the already mentioned differences for prior knowledge in informal learning there are also differences in the data sets which derive from environmental conditions. Normally, the *numbers of ratings* obtained in a RS is usually very small compared to the number of ratings that have to be predicted. Effective prediction by ratings based on small amounts is very essential for RSs and has an effect on the selection of a specific recommendation technique. Formal learning can rely on regular evaluations of experts or students upon multiple criteria (e.g., pedagogical quality, technical quality, ease of use) (Manouselis et al. 2007), but in informal learning environments such evaluation procedures are unstructured and few. Formal learning environments like universities have integrated evaluation procedures because they have to report on a regular base a quality evaluation to their funding body. With these integrated evaluation procedures and again employed maintainers more dense data sets can be expected. As a conclusion the data sets of informal learning are characterized by the *Sparsity problem*, caused by sparse ratings in the data set. Multi-criteria ratings might also be beneficial for informal learning to overcome the *Sparsity problem* in data sets. These multi-criteria ratings have to be reasonable for the community of lifelong learners. The community could rate LAs on various levels like *required prior knowledge level* (novice to expert), the *presentation style of LAs* (bad to good), and maybe on a level of *fun* because keeping students satisfied and motivated is a rather vital criteria in informal learning. These explicit rating procedures should be supported with several indirect measures like '*Amount of learners using the LA*', '*Amount of adjustments of a LA*' in order to measures the up-to-dateness of a LA.

Informal learning is therefore different to well structured domains, like in e-commerce or formal learning. RSs for informal learning have no official maintenance by an institution and rely on its community. Further, informal learning offers are most of the time not prepared in well defined metadata structures. E-commerce and formal learning are top down designed and develop learning offers (closed-corpus), whereas informal learning offers are emerging from the bottom upwards through the communities (open-corpus). Therefore, we are hardly able to apply a recommendation strategy from e-commerce or formal learning into informal learning approaches. It appears that the recommendation task and the environmental conditions are too different.

The combination of top down and bottom up recommendation approaches are still an open research question that for instance the European project Mature is focusing on (Braun et al. 2007). Nevertheless, there are promising developments that might bridge the gap between formal top down and informal bottom up environments. Content analysis techniques like LSA might assign documents automatically to specific domain concepts in the future.

4. An evaluation framework for RSs in TEL

In the world of consumer RSs, there are several data sets with specific characteristics (the *MovieLens* dataset, the *Book-Crossing* data sets, or the *EachMovie* dataset) available. These data sets are used as a common standard or benchmark to evaluate new kinds of recommendation algorithms (Goldberg et al. 2001; O'Sullivan et al. 2002; Sarwar et al. 2002). Furthermore, consumer product recommendation algorithms are evaluated based on common technical measures like accuracy, coverage, and performance in terms of execution time (Adomavicius and Tuzhilin 2005; Burke 2002; Herlocker et al. 2004).

Accuracy empirically measures how close a RS predicted ranking of items for a user differs from the user's true ranking of preference. Coverage measures the percentage of items for which a RS is capable of making predictions. Performance observes if a RS is able to provide a recommendation in a reasonable time frame.

In TEL there are neither standardized data sets nor standardized evaluation procedures available to evaluate pedagogy driven RSs for formal or informal learning. But focusing only on technical measures for PRSs in TEL without considering the actual needs and characteristics of the learners is questionable. Thus, further evaluation procedures that are complementary to technical evaluation approaches are needed.

A pedagogy driven RS for TEL that takes into account learner characteristics and specific learning demands also should be evaluated by learning evaluation criteria. Therefore, we suggest to mix technical evaluation criteria with educational research measures. Further, for certain research in RS in learning, especially for LNs, also SNA aspects are an important measure. Educational research measures are needed to evaluate whether learners actually do benefit from using a RS. Therefore we suggest the following frameworks for the analysis of the suitability of RS in TEL.

Measurements	**Parameters**
Technical measures	1. Accuracy 2. Coverage 3. Performance
Educational measures	1. Effectiveness 2. Efficiency 3. Satisfaction 4. Drop-out rate
Social Network measures	1. Variety 2. Centrality 3. Closeness 4. Cohesion

Table 1: An evaluation framework for RS in TEL

From an educational point of view, formal or informal learners only benefit from learning technology when it makes learning more effective, efficient, or more attractive. In educational research common measures are Effectiveness, Efficiency, Satisfaction, and the Drop-out rate. Effectiveness is a sign of the total amount of completed, visited, or studied LAs during a learning phase. Efficiency indicates the time that learners needed to reach their learning goal. It is related to the effectiveness variable through counting the actually study time. Satisfaction reflects the individual satisfaction of the learners with the given recommendations. Satisfaction is close to the motivation of a learner and therefore a rather important measure for learning. Finally, the Drop-out rate mirrors the numbers of learners that drop out during the learning phase. In educational research the Drop-out rate is a very important measure because one aim is to graduate as many learners as possible during a learning phase.

The SNA (Wasserman and Faust 1999) measures are needed to estimate the benefit coming from the contributions of the learners for the network as a whole. These are more specific measures that are mainly related to informal LNs. SNA give us various insights into the different roles learners own in a LN. Typical SNA measures are Variety, Centrality, Closeness, and Cohesion. Variety measures the level of emergence in a LN through the combination of individual learning paths to the most successful learning routes. Centrality is an indicator for the connectivity of a learner in a LN. It counts the number of ties to other learners in the network. Closeness measures the degree a learner is close to all other learners in a network. It represents the ability to access information direct or indirect through the connection to other network members. Cohesion indicates how strong learners are directly connected to each other by cohesive bonds. Peer groups of learners can be identified if every learner is directly tied to every other learner in the LN.

These evaluation criteria can be conflicting. For instance, learners with many rated LAs get a central role in a LN from the SNA perspective. They get many direct ties to other learners through the huge amount of rated LAs. From an SNA perspective these learners are beneficial for the LN because they contribute heavily to it. But from the educational research perspective the same group of learners may be less important because their educational measures are quite poor. It might be that they needed much more study time (Efficiency) or complete less LAs successfully (Effectiveness) compared to others learners in a LN.

To sum up this section, an appropriate evaluation of RSs in TEL requires an evaluation framework that goes beyond existing technical evaluation in RS research. Therefore, we suggest to extend the technical evaluation approach with classic educational research measures and SNA aspects. Besides adding additional evaluation criteria, the relation between the criteria from each approach should be considered for formal and informal learning.

5. Conclusion

We have argued to adjust RS in TEL in accordance to the specific flavors and demands of learning like informal and formal learning (first section). We have given an overview about research in RSs for TEL (second section). We have further compared RSs in the domain of e-commerce to RS in TEL. We described differences between RSs for formal learning and informal learning based regarding the recommendation goal, the user model and environmental conditions (third section). Finally, we suggested an evaluation framework for RSs in TEL that combines classical RS measures with educational science measures and social network analysis aspects. We could conclude that RSs for informal learning should support the efficient use of available resources to improve the educational aspects, taking into account the specific characteristics of learning.

Currently, we are running a series of simulations in Netlogo where we test the impact of item- and user-based Collaborative Filtering techniques and their combination in recommendation strategies for different sizes of informal LNs. We decided to use simulations, because they can support defining requirements before starting the costly process of development, implementation, testing and revision of RS in field experiments. Furthermore, field experiments with real learners need careful preparation as they cannot be easily repeated or adjusted within a small time frame. The simulation software enables us to test recommendation strategies in different situations and conditions in LNs (larger amounts of LAs and learners, more informal learning) to better evaluate the emergent effects of the RS.

On a long term perspective we also intend to evaluate user-based tagging and rating mechanism for navigation support to learners in informal LNs.

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