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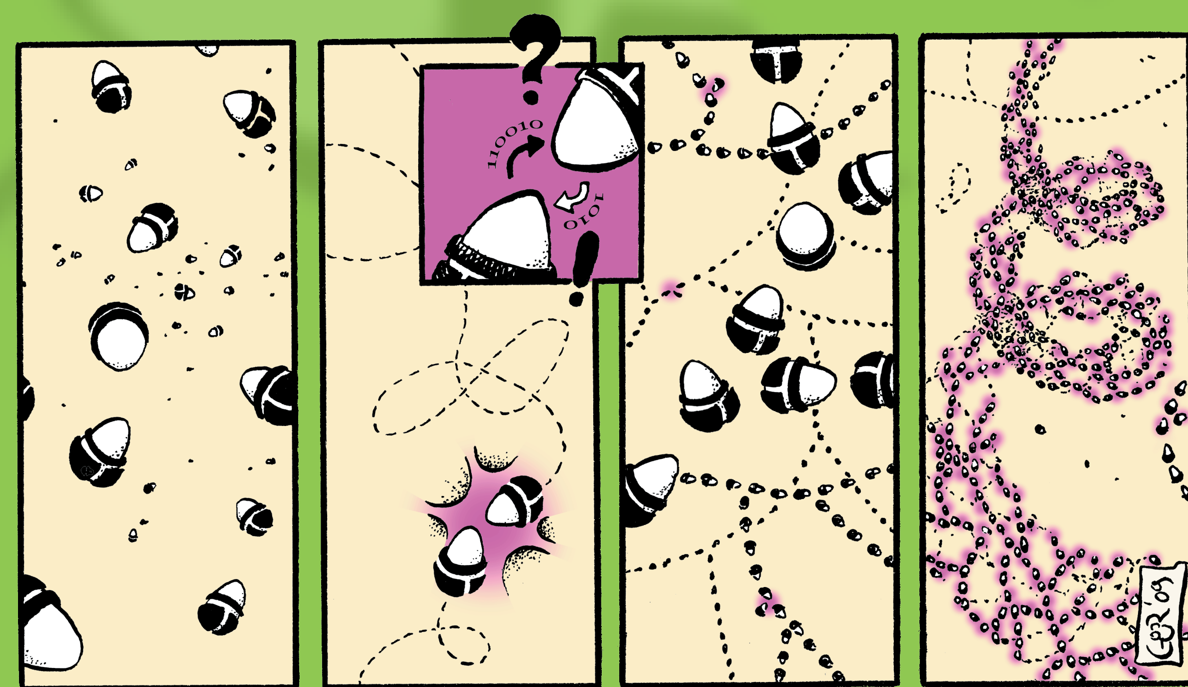

Open**Universiteit**Nederland

Navigation Support for Learners in Informal Learning Networks

(Navigatie ondersteuning voor lerenden in informele leernetwerken)

Navigation Support for Learners in Informal Learning Networks

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Navigation Support for Learners in Informal Learning Networks

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Synopsis

Learners increasingly use the Internet as source to find suitable information for their learning needs. This especially applies to informal learning that takes place during daily activities that are related to work and private life. Unfortunately, the Internet is overwhelming which makes it difficult to get an overview and to select the most suitable information.

Navigation support may help to reduce time and costs involved selecting suitable information on the Internet. Promising technologies are recommender systems known from e-commerce systems like *Amazon.com*. They match customers with a similar taste of products and create a kind 'neighborhood' of like-minded customers. They look for related products purchased by the neighbors and recommend these to the current customer.
In this thesis we explore the application of recommender systems to offer personalized navigation support to learners in informal Learning Networks. A model of a recommender system for informal Learning Networks is proposed that takes into account pedagogical characteristics and combines them with collaborative filtering algorithms. Which learning activities are most suitable depends on needs, preferences and goals of individual learners.

Following this approach we have conducted two empirical studies. The results of these studies showed that the application of recommender systems for navigation support in informal Learning Networks is promising when supporting learners to select most suitable learning activities according to their individual needs, preferences and goals. Based on these results we introduce a technical prototype which allows us to offer navigation support to lifelong learners in informal Learning Networks.

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Chapter 1

Introduction

Introduction

The Internet has evolved as the most frequently used medium in the 21st century and is continuously growing. The increasing amount of information on the Internet enables people to access almost anything they need. On the other hand, the Internet opens the door for a plethora of information that makes it difficult to get an overview and to select the most suitable information.
This selection problem also applies to learners who get lost on the Internet. Learners use the Internet to find suitable information for their learning needs. Nowadays, they even can create, share, and use learning activities in Learning Networks. In Learning Networks learners are connected with each other and can benefit from the contributions of their members. This especially applies to informal learning that takes place during daily activities that are related to work and private life and does not lead to a certain accreditation. Furthermore, learning is no longer only a part of youth and adolescent but also it may happen during the whole life of a person – *Lifelong Learning*.
Promising technologies to support people, in order to navigate to the most suitable information, are recommender systems. They are successfully applied at e-commerce web sites like *Amazon.com,* where people receive recommendations based on the products they are interested in. The recommender system matches customers with a similar taste of products and creates a kind 'neighborhood' of like-minded customers. It looks for related products purchased by the neighbors and recommends these to the current customer. This navigational support by recommender systems may help us to reduce time and costs involved in selecting suitable information on the Internet. They inspired us to improve the selection of suitable learning activities. This will help learners in selecting learning activities according to their individual needs, preferences and learning goals.

In this thesis we explore the potential of recommender system technology to recommend learning activities to lifelong learners in informal learning settings. The general research question of this thesis is:

> *How can we best recommend suitable learning activities to lifelong learners in informal Learning Networks, taking into account their personal needs, preferences, and learning goals?*

This general introduction now first describes the Knowledge Society and the concept of Lifelong Learning. It will introduce the needs of individual learners to select more personalized learning activities. The second section explains the changes that have appeared within the Web 2.0 development efforts and their impact on the Knowledge Society and Lifelong Learning. The third section describes recommender systems which enabled a paradigm shift in economy by fostering an individual taste-driven digital market. The fourth section introduces the concept of Learning Networks, which describes the future of personalized learning in the Knowledge Society, with the use of Web 2.0 tools. The fifth section presents some more specific problems within the general research question. The sixth and last section gives an outline of the content of this thesis.

The Knowledge Society and the concept of Lifelong Learning

In 1998 a first dawn of a change in the educational system was initially formulated by the UNESCO committee headed by Jacques Delors. The committee explained that the distinction between initial and continuous education will become outdated, and with the advent of the Knowledge Society, a new concept of learning is needed to support learning throughout the whole life. In the year 2000, the European Commission (European Commission, 2000) took over this new educational concept and presented a kind of 'Marshal Plan' for Europe to become a Knowledge Society for the highly competitive global market of the future. The so called *Memorandum of Lifelong Learning* describes the high demands for the Knowledge Society like highly educated people, higher qualification and accreditation possibilities, better interoperability between work and education, and enhanced support for personalized ways of learning. The *Lifelong Learning concept* became the central idea to shape the future of the educational system. In the future, the traditional formal school system will remain important to educate young people, but as the education is an ongoing process, they will need to learn throughout their whole life. Learning no longer remains limited to the context of a regular school or university, but is becoming increasingly integrated into workplace learning and personal development, where formal and informal learning activities have become intertwined. Especially informal learning has a major impact on the Knowledge Society as it is frequently used by adults to improve their competences. Lifelong Learning demands the educational system to adapt its organizations to the prior knowledge, habits, and preferred media of the learners to offer better opportunities for personalized learning activities throughout the life. This thesis aims to in-

crease the amount of suitable learning opportunities to lifelong learners by offering navigation support for selecting more tailored learning activities.
In the future, learning will become lifelong and the Knowledge Society will be increasingly based on information technology and the Internet (Cornu & Wibe, 2005). The Internet is already being used as 'the additional alternative learning resource' at educational institutes. The main characteristic of the Knowledge Society is that the learners, teachers and available learning activities are combined in networks which means that many activities like learning activities, course planning, and selecting learning activities are no longer organized in top-down hierarchical ways. Instead, activities emerge, and are created from the bottom upwards, which means that they originate from the interaction of learners, teachers and learning activities.

The Web 2.0 developments

The networked Knowledge Society is more than ever empowered by the Web 2.0 development efforts. The so called Web 2.0 lifted the barrier of adding information to the Internet and enables people to contribute information to the Internet. It forces a tremendous change in society by democratizing the creation and dissemination of, and access to information for all people. The passive audience of the Internet is becoming more active and strongly interconnected. The Web 2.0 technology enables loose collaboration between people, which changes the usage of the Internet from a passive, consumption-driven user model to an active, production-driven model. For instance, people can interact with each other in fast and cheap ways by using publicly available blogging services like *blogger.com* or exchange information in social networks like *facebook.com*. They can publish and follow each other by receiving short status messages on *twitter.com* and are therefore increasingly informed about detailed activities of others in their network.
The Web 2.0 tools will have influence on our educational system and the way we learn. In our view the networked Knowledge Society will soften institutional boundaries and strengthen informal learning. For instance, learners do no longer have to limit themselves to the lecture on the 'Introduction to the Semantic Web' at their local university. They can also surf to web sites like *videolectures.net* or *youtube.com/edu* and look for the best rated lectures about the semantic web. They can participate in the local forums and comment on the online lecture. As a consequence, they become free to study whatever and whenever they want. In addition, they receive recommendations for related and addition-

al lectures on the web site, thus they have wider learning offers and options on the Internet than at their local university. Furthermore, the learners can use the Internet to find the experts on semantic web and follow their blog or twitter messages to get the most recent information about the semantic web. Also, they can publish their own learning experiences and conclusions and share them with others on the Internet. Institutional boundaries consisting of fixed time schedules, locations, local peer students, and limited lecture possibilities will become outdated.

On the other hand, all the advantages of Web 2.0 tools will not replace traditional learning arrangements. Also in the future, learners have to pass an assessment to receive a certain certification. Therefore, the Web 2.0 tools will not replace the way we learn something from the very beginning. Especially, beginners need guidance and personal support to master a new competence. But the Web 2.0 tools offer new possibilities to further develop expertise and to stay up-to-date with the increasing amount of information in the Knowledge Society. Current business models of universities have to be reconsidered to meet the demands of these possibilities. Learning activities will be increasingly accessible for free on the Internet. Thus, universities have to offer more additional educational services like guidance and assessments instead of investing in lectures and learning activities.

The next generation learners will naturally use the Web 2.0 tools, they will group themselves around topics in learning communities and learn from and with their peer learners. The learners will act as experts and beginners at the same time on different topics. They take advantage of the user-generated content that will be created, shared, rated and adjusted by the use of Web 2.0 technologies. Consequently, the learners can benefit of content provided by others (user-generated content), they can choose from a huge amount of suitable content on various competence levels and languages. As a result, the problem of getting access to the resources is becoming less important because there are multiple providers (other users) that offer similar information for free. For that reason, supporting the selection of the most suitable information for personal needs becomes ever more important. The work described in this thesis strongly builds on the application of Web 2.0 tools when recommending user-generated content to lifelong learners. Recommender systems on top of Web 2.0 technology are therefore central to support learners in informal Learning Networks.

Recommender systems

The main purpose of recommender systems on the Internet is to pre-select information a user might be interested in (Herlocker, Konstan, & Riedl, 2000). They have already been very successfully applied in e-commerce systems to support customers to buy most suitable products (Adomavicius et al., 2005). They are becoming even more popular today for suggesting suitable information to individual users since many products can be ordered as a digital version or printed on demand. Recommender systems successfully brought personalization to the e-commerce market. They broke with traditional concepts of the physical mass market of products towards an emerging digital economy. (Anderson, 2007) describes these changes as a paradigm shift in his book 'The Long Tail'. According to 'The Long Tail', recommender systems enable us to recommend books or other media to people which would be already out of print or no longer stored physically. Instead of offering media that is available physically in a store at the moment, they enable us to recommend products to customers without the barrier of physical storage. The top-seller hit-driven marketing approach is no longer dominating the economy but an individual taste-driven marketing approach is becoming most important (Anderson, 2004). Companies like iTunes, Amazon, and Netflix take advantage of these new economic changes by selling products digitally and having non-top-seller products besides top-seller products available. Providing non-top seller products is the core business of 'The long tail' because there are so many more of them than top-seller products that selling small amounts of many non-top-seller products quickly emerges into a huge market.

The attentive reader might have already noticed that recommender systems are closely related to the issues we discussed with the Knowledge Society and Lifelong Learning. Keywords like 'digitally available', 'emerging information', and 'personalization' are indicators that recommender systems have potential when addressing the needs of lifelong learners in the Knowledge Society. In this thesis, we will take up some of these problems. We specifically will address the selection of information created with Web 2.0 tools by inhabitants of the networked Knowledge Society. In the following section we introduce the concept of Learning Networks that deals with the learning processes within this networked Knowledge society. Learning Networks are a promising concept to point out the idea of flexible, personalized learning in the Knowledge Society.

Learning Networks

The concept of Learning Networks (Koper & Sloep, 2002) provides methods and technical infrastructures for distributed lifelong learners to support their personal competence development. It takes over the possibilities of the Web 2.0 developments and describes the new dynamics of learning in the networked Knowledge Society. A Learning Network is learner-centered and its development emerges from the bottom-up through the participation of the learners.

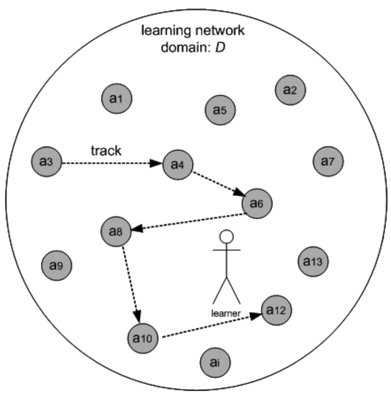


Figure 1.1: Starting phase of a Learning Network with a first learner moving through possible learning activities.

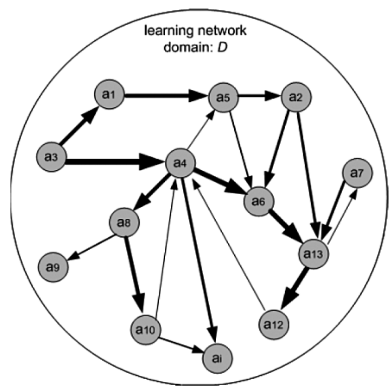


Figure 1.2: Advanced phase of a Learning Network, showing emerged learning paths caused by the collective behavior of all learners in the network.

Emergence is the central idea of the Learning Network concept. Emergence appears when an interacting system of individual actors and resources self-organises to shape higher-level patterns of behavior (Gordon, 1999; Johnson, 2001; Waldrop, 1992).

We can imagine learners interacting with learning activities in a Learning Network while their progress is being recorded. Indirect measures like time or learning outcomes and direct measures like ratings and tags given by the learners allow to identify paths in a Learning Network which are faster to complete or more attractive than others. This information can be fed back to other learners in the Learning Network, providing collective knowledge of the 'swarm of learners' in the Learning Network. Most learning environments are designed only top-down since their structure, learning activities, and learning routes are predefined by an educational institution. Learning Networks take advantage of

the user-generated content that is created, shared, rated and adjusted by using Web 2.0 technologies.
This thesis aims to contribute to more personalized ways of learning in the Knowledge Society. To improve the personalization we apply recommender system technologies in the concept of informal Learning Networks and adjust these technologies to needs of learners.

Main problems addressed by this research

Our main research question can be further defined into four main problems that we need to address to give an answer to the question.

1. Distilling criteria to apply recommender systems to informal learning.
   We have to evaluate if we just can apply recommender systems from e-commerce for learning and how we can combine pedagogy knowledge with recommender system technology? Therefore, we have to further analyze the context of informal Learning Networks. We have to compare the recommendation goal and conditions of existing e-commerce recommender systems to informal Learning Networks. In addition, we have to analyze if recommender systems in formal learning contexts work similar to informal learning context. Do they share the same recommendation goals, tasks, and conditions or are there particular differences between formal and informal learning that have to be considered in the recommender system. Besides this initial analysis, we have to think about evaluation methods to measure the impact of recommendation systems for learners and Learning Networks. Which measures can be used to indicate that a learner is satisfied with a recommended learning activity and how can that be recorded? Therefore, we need to analyze:

   1.1. What are the differences in requirements between e-commerce recommender systems and recommender systems for learning?
   1.2. What are the differences in requirements between recommender systems for formal and informal learning?
   1.3. How can we measure the impact of recommender systems for learning?

2. Selecting recommendation technologies that are suitable for informal learning.
   Recommender systems were developed in the past with various technologies. They consisted of pre-described ontologies, machine-learning algorithms, and data-mining technologies. It is a common practice to combine technologies that are most suitable for the target domain in single recommender system. Therefore, we have to explore:

   2.1. What are advantages and disadvantages of recommendation technologies for learners in informal Learning Networks?
   2.2. What is the most appropriate recommendation technology to combine learning science with recommender systems?

3. Designing experiments to test the effects of recommender systems on learning outcomes.
   In order to evaluate recommender systems for Learning Networks we have to set up experiments to test their impact on learners and Learning Networks. Learning Networks can contain different amounts of learning activities and learners. Furthermore, considering the emerging amount of learners and learning activities their size changes over time. Therefore, it is important to know how recommendation technologies are affected by different sizes of Learning Networks. On the one hand, we have to focus on the individual experiences of learners with a recommender system in a Learning Network; on the other hand, we have to test recommender systems under different sizes of Learning Networks. Therefore, we need to define a control group that we can compare based on certain evaluation criteria with treatment groups using recommender systems. Therefore, we have to explore:

   3.1. Do learners supported by recommender systems perform 'better' than learner without recommender systems?
   3.2. How does a recommender system behave under different sizes of Learning Networks?

4. Implementing effective navigation support for informal learning.
   In order to make the recommender system usable for lifelong learners and to other researchers we need to develop a prototype. Therefore, we have to

specify the requirements that are important for the learners. We need to apply solutions for previous problems and to explore how we can finally design the recommender system. We have to analyze:

4.1. How does an user interface of a recommender system for informal learning look like?
4.2. Which data are needed from learners and the Learning Networks to provide recommendations?

Outline of the thesis

The theoretical foundation of the thesis is given in Chapter 2 and 3. Chapter 2 addresses problem one and offers answers to problem two. The empirical work of the thesis is presented in two consecutive studies presented in Chapter 4 and 5. Both chapters offer answers to the questions in problem three. Finally, in Chapter 6 we combined the conducted research in a prototypical recommender system for informal Learning Networks called 'ReMashed' and offer a solution for problem four.

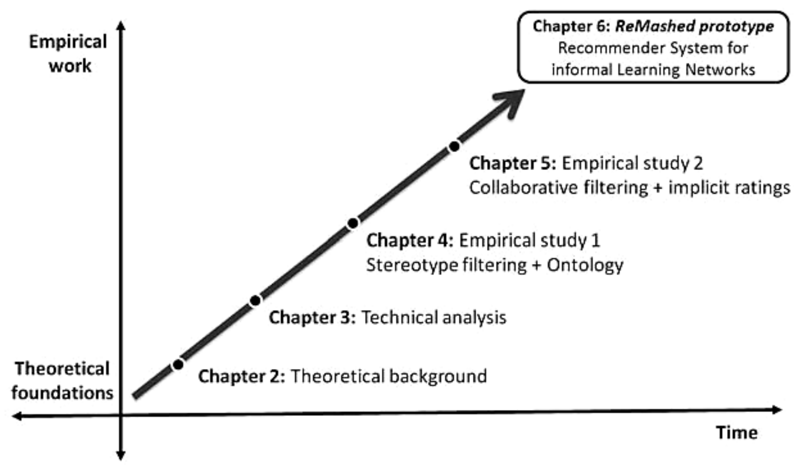


Figure 1.3: Milestones of the conducted research for the development of a recommender system for informal Learning Networks.

Theoretical foundations

The first step in the theoretical foundations was a comprehensive literature research in order to discover related work and to define the recommendation goals, suitable user models, and pedagogical conditions for a recommender system in informal Learning Networks. Chapter 2 presents the details of this literature analysis. It describes a number of distinctive differences for recommendations to learners compared to recommendations to consumers. Similarities of and differences between informal and formal learning are discussed and used to define the recommendation goals and tasks that recommender systems in informal Learning Networks have to address. Finally, Chapter 2 suggests an evaluation framework for recommender systems in Learning Networks to measure the impact of recommender systems on the learners and on the Learning Network.

In Chapter 3 we take up the requirements defined in the Chapter 2 to design a first recommender system. Existing recommender systems and recommendation technologies used for consumer products were assessed on their suitability for providing recommendations in Learning Networks. Chapter 3 proposes a combination of recommendation technologies that appear suitable to offer recommendations to learners in Learning Networks. Further, we present an initial model for the design of recommender systems in informal Learning Networks. With this technical evaluation we concluded the theoretical foundations and started to test or recommendation approach under empirical settings.

Empirical work

After having defined suitable recommendation technologies and a first recommender system model in Chapter 3, we selected a recommendation technique called stereotype filtering for the first empirical study. In this study our main focus was on the evaluation of the impact of a recommender system on the actual learners. Therefore, we selected mainly learning related measures from the suggested evaluation framework in Chapter 2. In this first pilot study we implemented a recommender system in an experimental Moodle environment in the domain of Psychology. In this study 250 learners participated and were monitored over an experimental period of four months. All participants were provided the same course materials, but only half of them were supported with a recommender system. Chapter 4 describes the effects of the recommender system on the completion of learning activities, needed time to complete them, satisfaction of the learners with the system, and the variety of personalized learning paths within the Learning Network.

In Chapter 5 we present the second empirical study that investigated the impact of recommender systems on Learning Networks in different sizes. In this study, we evaluated the effects of recommender systems in Learning Networks of different sizes and vice versa. Therefore, we selected besides the learning related measures also recommender system related measures from the evaluation framework in Chapter 2. We designed a Learning Network using the Netlogo multi-agent programmable modeling environment. The simulation tool models a Learning Network in which learners search for, enroll in, study and rate learning activities. Within this simulation we evaluated two additional recommender technologies from Chapter 3 on their effects for navigation support of learners in informal Learning Networks of different sizes. The learning activities were either recommended based on peer learner experiences (user-based filtering) or on competence development needs of individual learners taking into account the prior knowledge of learners (item-based filtering). Each of the algorithms was implemented in a treatment group and compared to a control group without navigation support. Chapter 5 presents the underlying simulation model, the experimental set up, the recommendation technologies, and discusses its empirical results.

Technical prototype

A final step of our research was the development of the 'ReMashed' prototype that builds on top of the basic research carried out in Chapters 2 to 5. Chapter 6 describes this prototype which is intended to evaluate recommender systems for personalized learning in informal Learning Networks. In ReMashed learners can specify certain Web 2.0 sources and combine them in a Mash-Up Personal Learning Environment, an interface for an informal Learning Network. The learners can rate user-generated content of other members and train a recommender system for their personal learning needs. ReMashed therefore has three main goals: 1. to provide a recommender system for informal Learning Networks, 2. to offer an environment for testing new recommendation approaches and methods for researchers, and 3. to create informal user-generated content data sets that are needed to evaluate new recommendation algorithms for learners in informal Learning Networks.

General discussion

Finally, in Chapter 7 'General Discussion', we look back at the conducted research and its findings. This thesis mainly attempts to make a contribution to the Technology Enhanced Learning (TEL) field by using recommender system for learners. We will review to what extend our work did indeed address the further development and deployment of TEL for the Knowledge Society. Further, we discuss what kind of insights we gained from the conducted research on navigation support for learners in informal Learning Networks. Finally, we put forward suggestions for future research.

Chapter 2

Identifying the goals, user model and conditions of recommender systems for informal learning

This chapter is based on: Drachsler, H., Hummel, H. G. K., & Koper, R. (2009). Identifying the Goal, User model and Conditions of Recommender Systems for Formal and Informal Learning. *Journal of Digital Information,10* (2) Retrieved July 7, 2009 from http://journals.tdl.org/jodi/article/view/442/279.

Abstract

This chapter addresses open questions of the discussions in the first Social Information Retrieval in Technology Enhanced Learning (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 chapter describes a number of distinctive differences for personalized 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 chapter further suggests an evaluation approach for recommender systems in Learning Networks.

Introduction

This chapter argues to differentiate e-commerce recommender systems from recommender systems in Technology Enhanced Learning. 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 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, Smith, & York, 2003; Schafer, Konstan, & Riedl, 1999) are using a recommender system 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 & Tuzhilin, 2005). The main recommendation goal of e-commerce recommender systems 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 recommender systems for TEL.

In TEL, recommender systems deal with information about learners and learning activities, 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 recommender systems is to provide learners with suitable learning activities in order to support their competence development. Therefore, recommender systems in TEL have to consider relevant pedagogical rules describing pedagogy-oriented relations between learners' characteristics and learning activity-characteristics. For example: from Vygotsky's "zone of proximal development" follows the pedagogical rule 'recommended learning activities should have a level a little bit above learners' current competence level' (Vygotsky, 1978). Thus, recommender systems in TEL have to take into account competence levels in order to suggest an appropriate learning activity. 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, Hodkinson, & Malcolm, 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 & 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 (European 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 & 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 is learner-centred and its development evolves bottom-up through the participation of the lifelong learners. The Learning Network 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 activities, and learning plans are predefined by an educational institution or domain professionals (e.g., teachers).
In Learning Networks, the lifelong learners are able to publish their own learning activities, 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 Learning Networks in parallel. Therefore, the concept of Learning Networks 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 techno-logies 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 Learning Networks, because most of the informal learning activities 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 learning activities (Koper, Rusman, & Sloep, 2005).
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 recommender systems 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 recommender systems in e-commerce to recommender systems in, especially informal, Learning Networks. For this purpose, we will now first give an overview about related work in the field of recommender systems for TEL (second section). In the third section, we will then discuss specific differences and similarities between e-commerce recommender systems and recommender systems for TEL in general, as a first step. In a second step, we will explain additional differences of recommender systems for formal learning with recommender systems for informal learning. Based on this section, we will we suggest an evaluation approach that is more suitable for assessing recommender systems in learning (fourth section). Finally, we present our conclusion and further research plans.

Related work

There are already many approaches to support learners with recommender systems, but only few of them are evaluated. There are also already several overviews with different foci available for recommender systems in TEL (Drachsler, Hummel, & Koper, 2008; Nadolski et al., 2009). 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.

Currently, the research in recommender systems 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 & Diplaros, 2007). They propose a methodology that starts with the generation of a matrix that represents the educational characteristics of the learning activities. 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 activities. Another very interesting study in this perspective uses a Collaborative Filtering simulator called CollaFiS (Manouselis, Vuorikari, & Van Assche, 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 recommender systems 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, Ochoa, & Duval, 2007). But especially for informal Learning Networks it would be an advantage for the learners to identify 'peer –learners' through shared tags. Learning Networks 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 & Duval, 2007) enables the learners to explore social relationships and can be supportive for community building in informal Learning Networks (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 learning activities to learners based on their behavior in the network which aggregate implicit ratings to the learning activities. Instead of explicit ratings by learners, this approach analyses the participation of learners in learning activities 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 Learning Networks we see benefits from following approaches in the SIRTEL field: simulation studies with recommender systems, learner support through community provided tags and ratings, and analysis of networks with probabilistic technique like SNA or LSA.

Moving from e-commerce recommender systems to recommender systems 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 recommender systems because they are strongly domain dependent and it is therefore not always possible to apply one recommender system 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 technologies (Adomavicius & Tuzhilin, 2005), the adjustment of these technologies 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, Konstan, & Riedl, 2002; Manouselis, Vuorikari, & Van Assche, 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 recommender systems in e-commerce when compared to TEL recommender systems. Section 3.2 will describe these differences when comparing recommender systems for formal learning to recommender systems for more informal learning.

Differences between recommender systems for e-commerce and recommender systems for TEL

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

Recommendation goals

The main recommendation goal of e-commerce recommender systems is to provide consumers with information to help them to decide which products to purchase (Schafer, Konstan, & Riedl, 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. Recommender systems are used to suggest products to the consumers they might wish to purchase.
- Increasing Cross-sell
  Recommender systems 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 personalized recommendations of products to the customers.

Recommender systems 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 recommender system. 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. Recommender systems in TEL have to contribute to a long term learning goal of learners whereas e-commerce recommender systems typically support the one turn interactions with the customer in a shorter timeframe.
Regarding the "Increasing cross-sell" goal, recommender system in TEL surely needs to suggest additional learning activities to learners based on those learning goals they aim for. However, learners and learning activities change over time and context. The purpose of a specific learning activity may vary across various stages of a learning process (McCalla, 2004). This means for the "In-

creasing cross-learning" that it is sometimes necessary to suggest the same or very similar learning activities 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 recommender system in TEL will depend on the amount of support the recommender system provides to the learning process as a whole.

User models

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 recommender systems require additional attributes like ZIP code, income, job, credit card number, shipping address, occupation, and shipping preference (Ardissono & Goy, 2000).
Learner modelling (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. Recommender system in TEL may need to recommend different learning activities 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 learning activities first, where more advanced learners should be advised to continue with more specific learning activities. E-commerce recommendations are entirely based on the interests and the tastes of the consumer, whereas preferred learning activities of learners might not be the pedagogically most adequate (Tang & McCalla, 2004a). Learning is an effort for a learner, therefore they tend to select easier learning activities rather than more ambitious learning activities. But in order to achieve a learning goal on a higher competence level it is required to master more ambitious learning activities 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 standardized 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 learning activities nor exceed millions of transactions. Therefore, the environmental conditions are different to the e-commerce world.

Differences between recommender system for informal learning and recommender system 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 recommender system 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 learning activities.

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

Recommendation goals

Main recommendation goals for informal learning would be:

- Structure learning activities 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 Learning Networks are mainly aggregated through RSS or ATOM feeds from Web 2.0 services. A recommender system in informal learning aims to bring structure to a dynamic and emergent space of learning activities. Therefore, the main task for a recommender system in informal learning is organising the learning activities in a pedagogical

way to improve the competence development of the informal learner. The recommender system would benefit through applying learning strategies derived from educational psychology research (Koper & 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 recommender system in informal Learning Networks 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 recommender system that aims on such a learner support should make advantage of emerging data in a Learning Network 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 recommender system in informal Learning Networks should use successful learning path which consists of several learning activities in order to reach a specific learning goal. These learning paths are a valuable resource for starting learners. They emerge through frequently positively rated learning activities 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 recommender system in informal Learning Networks can be defined according to Herlocker et al. (2004) as ‘Find Good Items’ and ‘Recommend Sequence’. 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 fulfil 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 models

Learners in Learning Networks are in need of an overview of available learning activities, 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 learning activity, learning

paths, and learning strategies. A detailed description of these attributes can be found in (Drachsler, Hummel, & Koper, 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 Learning Networks 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 recommender system 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, Mizoguchi, & Tzolov, 2003; De Bra et al., 2002; Kravcik, Specht, & Oppermann, 2004) having equally fine granulated knowledge domains and can therefore offer personalized recommendations to the learner. These systems are mainly used in 'closed-corpus' applications (Brusilovsky & 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 & 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 Learning Networks without having any highly structured knowledge domain and fine granulated learning activities in a specific TEL 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 in-

dexed with domain concepts and metadata from a community (Brusilovsky & Henze, 2007). The open corpus problem also applies to informal Learning Networks. Therefore, bottom-up recommendation technologies 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 take into account different environmental conditions, the lack of maintenance, and less formal structured learning activities. Despite of that learning activities in Learning Networks 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 recommender system 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 recommender systems 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 & Costopoulou, 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 learning activities on various levels like required prior knowledge level (novice to expert), the presentation style of learning activities (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 learning activity', 'Amount of adjustments of a learning activity' in order to measures the up-to-dateness of a learning activity.
Informal learning is therefore different to well structured domains, like in e-commerce or formal learning. Recommender systems for informal learning have no official maintenance by an institution and rely on its community. Fur-

ther, 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 to 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.

An evaluation framework for recommender systems in TEL

In the world of consumer recommender systems, 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, Wilson, & Smyth, 2002; Sarwar et al., 2000). Furthermore, consumer product recommendation algorithms are evaluated based on common technical measures like accuracy, coverage, and performance in terms of execution time (Adomavicius et al., 2005; Burke, 2002; Herlocker et al., 2004).

Accuracy empirically measures how close a recommender system 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 recommender system is capable of making predictions. Performance observes if a recommender system 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 recommender systems for formal or informal learning. But focusing only on technical measures for recommender systems in TEL without considering the actual needs and charac-

teristics of the learners is questionable. Thus, further evaluation procedures that are complementary to technical evaluation approaches are needed.
A pedagogy driven recommender system 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 recommender system in learning, especially for Learning Networks, also SNA aspects are an important measure. Educational research measures are needed to evaluate whether learners actually do benefit from using a recommender system. Therefore we suggest the following frameworks for the analysis of the suitability of recommender system in TEL.

Table 2.1: An evaluation framework for recommender system 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

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 learning activities 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 & 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 Learning Networks. SNA give us various insights into the different roles learners own in a Learning Network. Typical SNA measures are Variety, Centrality, Closeness, and Cohesion. Variety measures the level of emergence in a Learning Network 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 Learning Network. 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 Learning Network.

These evaluation criteria can be conflicting. For instance, learners with many rated learning activities get a central role in a Learning Network from the SNA perspective. They get many direct ties to other learners through the huge amount of rated learning activities. From an SNA perspective these learners are beneficial for the Learning Network 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 learning activities successfully (Effectiveness) compared to others learners in a Learning Network.

To sum up this section, an appropriate evaluation of recommender systems in TEL requires an evaluation framework that goes beyond existing technical evaluation in recommender system 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.

Conclusions

We have argued to adjust recommender system 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 recommender systems for TEL (second section). We have further compared recommender systems in

the domain of e-commerce to recommender system in TEL. We described differences between recommender systems 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 recommender systems in TEL that combines classical recommender system measures with educational science measures and social network analysis aspects. We could conclude that recommender systems 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 Learning Networks. We decided to use simulations, because they can support defining requirements before starting the costly process of development, implementation, testing and revision of recommender system 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 Learning Networks (larger amounts of learning activities and learners, more informal learning) to better evaluate the emergent effects of the recommender system.
On a long term perspective we also intend to evaluate user-based tagging and rating mechanism for navigation support to learners in informal Learning Networks.

Chapter 3

Recommender systems for learners in Learning Networks: requirements, techniques and model

This chapter is based on: Drachsler, H., Hummel, H.G.K., & Koper, R. (2008). Personal recommender systems for learners in lifelong learning: requirements, techniques and model. *International Journal of Learning Technology 3*(4), 404 - 423.

Abstract

In this chapter existing recommender systems and recommendation techniques used for consumer products and other contexts are assessed on their suitability for providing navigation support in a Learning Network. Similarities and differences are translated into specific demands for learning and specific requirements for recommendation techniques. The chapter focuses on the use of memory-based recommendation techniques, that calculate recommendations based on the current data set. We propose a combination of memory-based recommendation techniques that appear suitable to realize personalized recommendation on learning activities in the context of TEL. An initial model for the design of such systems in Learning Networks and a roadmap for their further development are presented.

Introduction

The main purpose of recommender systems on the Internet 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. For instance, the well-known company *Amazon.com* (Linden, Smith, & York, 2003) is using a recommender system to direct the attention of their users to other products in their collection.

Although lifelong learners are in a similar situation like consumers looking for products on the Internet, there are a number of distinct differences in their search behavior and needs for personalized recommendation. Self-directed lifelong learners are in need of an overview of available learning activities, and must be able to determine which of these would match their personal needs, preferences, prior knowledge and current situation. The motivation for any recommender system is to assure an efficient use of available resources in a network. The motivation for a recommender system in TEL needs to improve the 'educational provision' (the ratio of output and input, to be expressed as goal attainment or time spent to find suitable resources). A recommender system 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 aim of this chapter is to provide specific requirements and suitable techniques for their realization, as well as an initial model and roadmap for their design and development. For this purpose we will now first describe existing recommender systems in order to draw up more specific requirements for recommender system in Learning Network (second section). Based on these specific requirements, we will examine the advantages and disadvantages of current recommendation techniques and their usefulness in Learning Networks (third section). We then continue by presenting our initial model for recommender system in Learning Networks (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 recommender system in Learning Networks.

Recommender systems for lifelong learners

Every recommender system serves a specific purpose and functions in a specific context. Related to their purpose and context, they operate according to their own pre-defined recommendation techniques or strategies. In a recommendation technique, one single technique is used to create the recommendation. Because every single recommendation technique has its own advantages and disadvantages, we need to combine techniques to increase the accuracy of recommendations (Hummel et al., 2007). Using a combination of recommendation techniques is called a recommendation strategy (Van Setten, 2005). Recommendation strategies use domain specific or history information about users or items to decide which specific recommendation technique provides the highest accuracy for the current user. In this section we first describe how recommender system depends on their product and context. We will then list specific demands for learning and specific requirements for recommender system in lifelong Learning Networks.

Recommender systems

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

One of the first recommender system for TEL was the Altered Vista system (Recker, Walker, & Lawless, 2003). In this system a Collaborative Filtering technique was used to explore how feedback provided by learners on learning activities can be stored and given back to a community. Similar research projects in the area of recommending learning activities to learners based on different kind of Collaborative Filtering techniques are the RACOFI system (Anderson et al., 2003), the I-Help system (Tang & McCalla, 2003; Tang & McCalla, 2004a, 2004b), and the CELEBRATE system (Manouselis, Vuorikari, & Van Assche, 2007). Most of these systems mentioned are using Collaborative Filtering techniques that are personalized by individual strategies (e.g., by direct or indirect ratings). They are often designed for a specific community and cannot easily be used for another.

Recommender systems with designs different from the above-mentioned systems are the QSIA, the CYCLADES, and the CoFIND system. The QSIA system (Rafaeli et al., 2004; Rafaeli, Dan-Gur, & Barak, 2005) is used to promote collaboration and further formation of learner groups. The specialized ability of this system is the use of an automated Collaborative Filtering algorithm or buddy system. In the QSIA system, learners are free to decide whether they want advice given by buddies (added friends) or to use an anonymous Collaborative Filtering technique. The CYCLADES system is an interesting step towards a general recommendation service (Avancini, Candela, & Straccia, 2007). This system also used a Collaborative Filtering technique with user-based ratings, but did not just apply the technique to one community. The CoFind system (Dron et al., 2000a; Dron et al., 2000b) followed a very interesting approach by applying for the first time folksonomies for recommendations. CoFind developers stated that predictions according to preferences were inadequate in a learning context and therefore more user driven bottom-up categories like folksonomies are important. All these systems used digital resources that are freely available in repositories of the Open Archives Initiative. The advantage of the system is the possibility to offer recommendations over learning activities that are developed by different institutions. This approach is exemplary for the Open Education Resources movement nowadays (Hylén, 2006). Generally speaking, recommender system in TEL deal with information about learners (users) and learning activities (items), and would have to combine different levels of complexity for the different learning situations the learner may be involved in.

Furthermore, recommender systems 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 for designing a recommender system is to define the users and purpose of a specific context or domain in a proper way (McNee, Riedl, & Konstan, 2006). 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?*'

Specific demands for learning

For recommender system in Learning Networks it will not be possible to simply take or adjust an existing recommender system for recommending consumer products. There are a number of specific demands for learning to deal with: 1. the importance of the context of learning, 2. the inherent novelty of most learning activities, 3. the need for a learning strategy, and 4. the need to take changes and learning processes into account.

First of all, for a recommender system 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 a Learning Network can be positioned within distance education. Therefore, we start the discussion about the support for decision making in Learning Networks from this perspective. Learners in distance education are influenced mainly by forum information, information provided by the tutor, or through face-to-face meetings and curricula. Curricula influence learners because most of the time they force rather than suggest a certain order of learning activities. Students in distance education have to rely even more on curriculum structure because they have a higher barrier to communicate with teachers or students. Recommender systems provide additional support for decisions; 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 recommender system that have been used in TEL were established in the same way like in e-commerce without taking into account specific attributes or conditions of the learners or the context of learning. They monitor the history of successful learners and recommend learning activities accordingly (Andronico et al., 2003; Zaiane, 2002), like amazon.com looks for successful (i.e., frequently bought) books to advice potential buyers and does not consider specific learner characteristics.

When designing a recommender system for lifelong learners we have to be aware of our target group of learners. For instance, movielens.org (famous movie recommender system) demands new users to rate a specific amount of movies until the system is able to provide personalized recommendations, based on movies 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 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 would already know them they would no longer be potential learning activities. Moreover, learners should at least 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. 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. In the domain of learning, it is unlikely that a learner already knows certain learning activities. Requiring learners to rate an initial set of learning activities, like in movielens.org, therefore seems not feasible. Other mechanisms to specify a learner profile have to be invented.

A third important demand is that, for a recommender system to support a learning process, we have to take into account learning theories to decide upon a learning strategy to support this process. Recommender systems 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 learning activities in a program).

A fourth difference, when comparing learning content to books and movies, is that 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 modeling (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 the tastes of the user, preferred learning activities might not be pedagogically most adequate (Tang & McCalla, 2003). Even for learners with the same interest, we may need to recommend different learning activities, depending on individual proficiency levels, learning goals and context. For instance, learners with no prior know-ledge in a specific domain should be advised to study basic learning activities first, where more advanced learners should be advised to continue with more specific learning activities.

Specific requirements for recommender system in Learning Networks

Recommender systems that advice learners must take into account the specific character of the learning context. This subsection explains following specific learning characteristics and related requirements for a recommender system in a Learning Network: learning goal, prior knowledge, learner characteristics, learner grouping, rated learning activities, learning paths, and learning strategies.

First of all, we need to know what the learners want to learn (learning goal). Related to this, 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). Learners may want to reach learning goals on specific competence levels like beginner, advanced or expert levels.

In the third place, other relevant information about learner characteristics would help the provision of more personalized recommendations, like information about their individual needs (e.g., 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).

Like consumer product recommender system use demographic information about their users, a recommender system for lifelong learners could use learner information to aggregate learner groups (learner grouping, or user profiling). Such learner grouping could 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 items (i.e., suitable learning activities).

In the fifth place, aggregated ratings of learning activities as awarded by other learners may provide valuable information (rated learning activities). Learners with the same learning goal or similar study time per week could benefit from ratings received from more advanced learners.

In the sixth place, beginning learners could benefit from history information about the successful study behavior of more advanced learners in the same learning network (learning paths). From frequent positively rated learning activities and their sequence, most popular learning paths will emerge. Most successful learning paths regarding to efficiency and effectiveness could be recommended.

Finally, recommender system in Learning Networks would benefit when we apply learning strategies derived from educational psychology research (Koper & Olivier, 2004) into recommender system. Such strategies could use pedagogical 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 learning activities, but not the actual design of specific learning activities themselves.

In summary, the aim for recommender system for lifelong Learning Networks is the development of a recommendation strategy that is based on most relevant information about the individual learner and the available learning activities, history information about similar learners and activities, guided by educational rules and learning strategies, aimed at the acquisition of learning goals.

Suitable techniques

In this section we assess existing techniques for recommender system on their usefulness for recommender system in Learning Networks. There are many recommendation techniques, but all could be classified as either model-based or memory-based techniques (Adomavicius & Tuzhilin, 2005).

Model-based techniques periodically analyze data to cluster them in estimated models. For instance, 'genre' would be a class in a movie world 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 recommender system use techniques like Bayesian models (Chien & George, 1999; Condli et al., 1999), neural networks (Jennings & Higuchi, 1993), or Latent Semantic Analysis (Hofmann, 2004; Schein et al., 2002; Soboro & Nicholas, 2000). These require a large corpus (more than 10,000 items) to estimate their models and provide accurate recommendations (Balabanovic, 1998; Denhière & Lemaire, 2004). Once a model is estimated, it is able to create recommendation for a large corpus in an efficient way. However, we do not expect such large corpora of learning activities in one Learning Network, especially during the experimental stage we will find ourselves in the upcoming years. Therefore, we will focus on memory-based recommendation techniques.

Table 3.1: Memory-based recommendation techniques (CF = Collaborative Filtering).

Name	*Short description*	*Advantages*	*Disadvantages*	*Usefulness for TEL*
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 - 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)
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 - Domain-independent - Quality improves - Bottom-up approach - Serendipity	- New item problem - Popular taste - Sparsity - 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 - 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				
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 - Domain-independent - Quality improves	- New user problem - Overspecialization - Sparsity - Cold-start problem	- Keeps learner informed about learning goal. - 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 - 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 modeling and maintenance is required - Overspecialization	- Useful for hybrid RS - Recommendation from the beginning

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 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 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 recommender system (Balabanovic & Shoham, 1997; Claypool et al., 1999; Good et al., 1999; Melville, Mooney, & Nagarajan, 2002; Pazzani, 1999; Soboro & Nicholas, 2000). Examples are cascading, weighting, mixing or switching (Burke, 2002; Van Setten, 2005). A Hybrid recommender system could combine collaborative (or social-based) with content- (or information-) based techniques. If no efficient information is available to carry out Collaborative Filtering it would switch to a Content-based technique. Table 3.1 provides an overview of memory-based recommendation techniques, listing their (dis)advantages and potential usefulness for Learning Networks, which will be described in the remainder of this section.

Collaborative-filtering techniques

Collaborative Filtering techniques (or social-based approaches) use the collective behavior of all learners in the Learning Network. This subsection now first describes user-based and item-based Collaborative Filtering, and then stereotypes filtering.

User- and item-based Collaborative Filtering: 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 3.1). Item-based techniques correlate items by mining (similar) ratings, and then recommend new, similar items (see Figure 3.2). 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 (Herlocker et al., 2004).

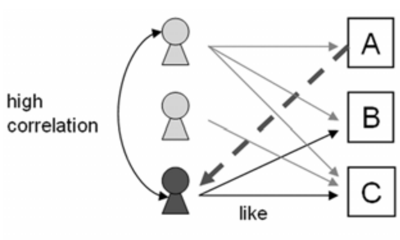


Figure 3.1: User-based Collaborative Filtering (Kim, 2006)

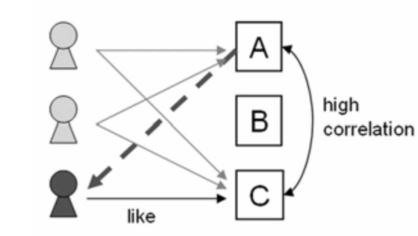


Figure 3.2: Item-based Collaborative Filtering (Kim, 2006)

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 Collaborative Filtering 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 this problem. New users first will have to give a sufficient amount of ratings to items in order to get accurate recommendations based on user-based Collaborative Filtering (new user problem). New items have to be rated from a sufficient amount of users to be recommended (new item problem). Another disadvantage for Collaborative Filtering 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 Collaborative Filtering is the scalability. Recommender systems 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. This problem does not apply to Learning Network, because not that many users and items will populate specific Learning Network.

User- and item-based Collaborative Filtering: usefulness for Learning Networks.

User- and item-based techniques are useful for Learning Networks which are dealing with different topics (domains). They do not have to be adjusted for specific topics, which is important because we expect many Learning Networks for different topics. Collaborative Filtering techniques can identify learning activities with high quality, allow learners to benefit from experiences of other, successful learners. The bottom-up rating mechanism holds promise for self-directed Learning Networks because no top-down maintenance for identifying high quality learning activities is required. Collaborative Filtering 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 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 Collaborative Filtering have to be combined with other Collaborative Filtering techniques, like stereotypes and demographics, in recommendation strategies to enable recommendation during the start phase of the recommender system.

Figure 3.3: Demographics filtering (Kim, 2006)

Stereotypes / demographics: advantages and disadvantages.

Preferred items can be recommended to similar users based on their mutual attributes (see Figure 3.3). Advantages are that they are domain independent, and (when compared to user- and item-based Collaborative Filtering) 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 Learning Networks.

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.

Content-based recommendation 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.

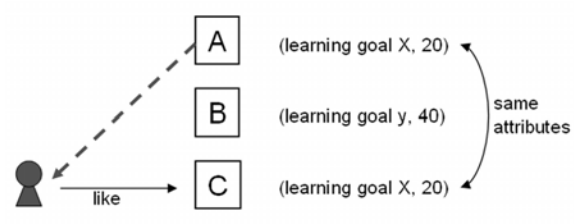


Figure 3.4: Case-based reasoning (Kim, 2006)

Case-based reasoning: advantages and disadvantages.

It recommends items with the highest correlation to items the user liked before (see Figure 3.4). The similarity of the items is based on the attributes they own. These techniques share some advantages of most Collaborative Filtering 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. 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 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. 'For example, a person with no experience in Greek cuisine would never receive a recommendation for even the best Greek in town' (Adomavicius & Tuzhilin, 2005, p. 737).

Case-based reasoning: usefulness for Learning Networks.

Case-based reasoning is useful to keep the learner informed about aimed learning goals. Learning activities 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 recommender system 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 available learning activities and learners. For example, if not enough data are available for Collaborative Filtering, the recommendation strategy could switch to case-based reasoning.

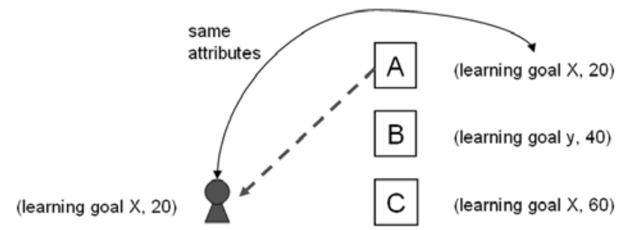


Figure 3.5: Attribute-based techniques

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 (see Figure 3.5). Attribute-based techniques can therefore be used from the very beginning of the recommender system. Likewise, adding new learning activities 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 recommender system by changing profiles or the relative weight of attributes. A description of needs in their profile is mapped directly to available learning activities in the Learning Networks.

A serious disadvantage is that an attribute-based recommendation is static and not able to learn from the network behavior. That is the reason why highly personalized recommendation cannot 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 Networks. In addition, the overspecialization can be a problem, especially if learners do not change their profile.

Attribute-based techniques: usefulness for Learning Networks.

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, and available study time) to characteristics of learning activities. There are learning technology specifications, like (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 the IMS-LD standard are its reputation and the availability of tools. The described recommender system will use suitable metadata from IMS-LD to provide information for recommendation techniques, like attribute-based recommendations and stereotype-filtering. Attribute-based filtering seems to be 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 recommender system and for new learners in a Learning Network. If sufficient history data become available, the recommendations can be incrementally based on Collaborative Filtering techniques that are more flexible and learnable.

Initial model

In this section we present our initial model for a recommender system in Learning Networks. We focus on the description of the recommender system, but start by briefly mentioning most related components in the Learning Network infrastructure, which are based on the TENCompetence domain model (Koper, 2006).

Related components of the Learning Network infrastructure.

A Learning Network is a collection of actors (learners and institutions) and learning activities (unit of learning) which are supported by information and communication technologies (see Figure 3.6).

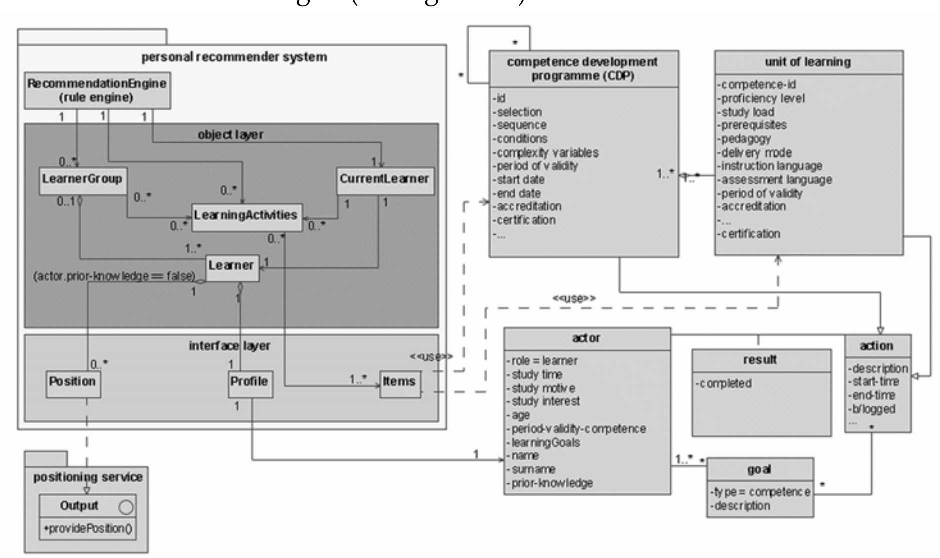


Figure 3.6: Class model of a recommender system and related components in Learning Networks.

Layers of the recommender system

The recommender system can be described by two layers and a core recommendation engine (see UML class diagram in Figure 3.6). 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 required data from the Learning Network (like learner profile, behavior data, index of learning activities). The Profile class exchanges data between the *RecommendationEngine* class and the Learning Network. It is responsible for obtaining required data for the profile and behavior data of the Learner. The Position class is responsible for obtaining the current position of the learner in the Learning Network. It works as an interface between the positioning service, which assesses the prior knowledge of a learner, and the personal recommender system, which provides the recommendations. The Items class analyses available learning activities, and returns an array of items to the *LearningActivities* class.

The object layer creates suitable learner groups. Based on the profile and behavior data of the current learner the object layer will detect similar learners and group them. The Learner class collects required data about learners, creating a profile for the requesting learner and inputting the *LearnerGroup* class. It requires the Profile and Position classes (from the interface layer) to obtain required data for the requesting learner. The *CurrentLearner* class is an instance of the Learner class, representing the requesting learner and providing all information of this learner to the *RecommendationEngine*. The *LearnerGroup* class generates an array of relevant (similar, successful) learners. It collects available data about relevant learners to provide a recommendation based on Collaborative Filtering, using the Learner class to select matching learners and provide a list to the *RecommendationEngine*. The *LearnerGroup* class obtains information through the Learner class. Finally, the *LearningActivities* class is responsible for selecting suitable learning activities and for allocating them to the *LearnerGroup* or the *CurrentLearner* classes. It also provides a list of available learning activities directly to the *RecommendationEngine* if necessary.

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

Conclusions

We have argued for the need of navigation support in lifelong Learning Networks (first section). We have analyzed common consumer product recommender system in relation to more specific requirements for recommender system in such lifelong Learning Networks. We concluded that such recommender system should take into account learning goals, prior knowledge, learner characteristics, learner groups, rating, learning paths, and learning strategies (second section). We have presented various 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 (third section). We have presented and explained an initial class model of such recommender system in Learning Networks (fourth section).

Recommender systems for Lifelong Learning should support the efficient use of available resources in a Learning Network to improve the educational provision, taking into account the specific characteristics of learning. Recommender systems in Learning Networks have to be driven by pedagogical rules, which could be part of a recommendation strategy. The recommendation strategy looks for available data to decide on which technique(s) to select for which situation.

Some challenges will arise when developing and testing such recommender systems and recommendation strategies. At the start phase of the recommender system, the 'cold-start' problem limits the provision of suitable recommendations. 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.

Future research has to further analyze which attributes of learners and learning activities and which recommendation techniques perform best. We will incrementally design and test various versions of recommender systems in the context of consecutive studies. We will design the most important Lifelong Learning conditions as realistic as possible. Therefore, we will take major aspects of Lifelong Learning, like 'self-direction' and 'taken responsibility for your own learning' into account for our experiment. An advanced recommender system will be based on results from all prior studies, and will combine most successful techniques in a recommendation strategy.

Chapter 4

Effects of a recommender system for learners in a Learning Network

This chapter is based on: Drachsler, H., Hummel, H.G.K., Van den Berg, B., Eshuis, J., Waterink, W., Nadolski, R.J., Berlanga, A.J., Boers, N., Koper, R. (2009). Effects of the ISIS Recommender System for Navigation Support in self-organised Learning Networks. *Journal of Educational Technology and Society. 12*(3), 122-135

Abstract

Learners in complex, self-organizing Learning Networks have problems finding suitable learning activities and need guidance to find and select most suitable learning activities, in order to attain their learning goals in the most efficient way. Several research questions regarding efficiency and effectiveness deal with adequate navigation support through recommender systems. To answer some of these questions an experiment was set up within an Introduction Psychology course of the Open University of the Netherlands. Around 250 students participated in this study and were monitored over an experimental period of four months. All were provided the same course materials, but only half of them were supported with a recommender system. This study examined the effects of the navigation support on the completion of learning activities (effectiveness), needed time to comply them (efficiency), actual use of and satisfaction with the system, and the variety of learning paths. The recommender system positively influenced all measures, by having significant effects on efficiency, satisfaction and variety.

Introduction

It is a common problem for users of the Internet to select or discover information they are interested in. The need to support users with the selection of information or giving reference to relevant information in order to improve their self-organization is becoming more important. This is where navigation plays a major role. Navigation has been defined as "the process of determining a path to be travelled by any object through any environment" (Darken & Sibert, 1993) to attain a certain goal. Therefore, the object requires a position, feedback about the environment, and an idea about its goal. The learners in dynamic and informal Learning Networks are in need of supportive information in order to self-determine their position, to self-regulate their learning path, and to adjust their competence development to their learning goal. Considering this definition, navigation support in informal Learning Networks has major influences for the self-organization of the learners. Information about other learners' behavior is beneficial for the individual learner in the self-determination and self-regulation of the learning process.

We have carried out an experimental study with personalized navigation support within the ISIS project, and this chapter presents the setup and results from that study. Members in complex, self-organizing, informal Learning Networks need guidance in finding and composing their most suitable learning activity

(route guidance), in order to attain their learning goals in the most efficient way (Prins et al., 2008). The innovation of the research is the implementation of existing recommender system technologies into self-organized, informal Learning Networks to support lifelong learners. Therefore, our focus is more on the evaluation of the learning outcomes through personal navigation support systems like recommender systems and less on measures like algorithm performance of the machine-learning field (Huang, Zeng, & Chen, 2007; Sarwar et al., 2000) which heavily influence the recommender system research.
The main purpose of recommender systems on the Internet is to filter information a user might be interested in. For instance, the company Amazon.com (Linden, Smith, & York, 2003) is using a recommender system to direct the attention of their users to other products in their collection. Existing 'navigation services' help to design and develop specific solutions for lifelong learners. Recommenders systems (Adomavicius et al., 2005) are becoming increasingly popular for suggesting tailored information to individual users. In this chapter we discuss the effects of the ISIS experiment with a recommender system for Learning Networks. Section two will describe our approach to navigation support in TEL, and presents our hypotheses for the experiment. In the method section (third section) we describe the experimental setup and the used recommendation strategy. In the results section (fourth section) we will describe measured observations and effects in response to the hypotheses. Finally, the fifth section discusses the effects and limitations of the study, and gives an outlook on future research.

Our approach to navigation support in technology-enhanced learning

In TEL navigation support is needed when learners fall short of answers to questions like: How do I find learning activities that best match my situational circumstances, prior knowledge, or preferences? Recommender systems are promising tools for a better alignment of learner needs and available learning activities. The motivation for recommender system in self-organized Learning Networks is enabling more personalized learning paths, while at the same time taking into account pedagogical issues and available resources. One way to implement pedagogical decisions into a recommender system is to use a variety of recommendation techniques in a recommendation strategy (Van Setten, 2005).

Recommendation strategies are a combination of different recommendation techniques to improve the overall accuracy of any recommender system, and to overcome disadvantages of one singular recommendation technique. Such recommendation strategies are implemented into hybrid recommendation systems, because they combine different recommendation techniques in one recommender system (Hummel et al., 2007). Recommendation strategies can be used in TEL to apply specific recommendation techniques in particular learning situations. The decision to change from one recommendation technique to another can be done according to pedagogical reasons, derived from specific demands of Lifelong Learning (Drachsler, Hummel, & Koper, 2008).
The recommender system that we used in ISIS combined a top-down, ontology-based recommendation technique (Middleton, Shadbolt, & De Roure, 2004) with a bottom-up, stereotype filtering technique (Sollenborn & Funk, 2002). Both techniques were combined in a recommendation strategy that decided which of the techniques were most suitable for the current situation a learner was in. If stereotype filtering was used to create a recommendation the next best learning activity was based on the most popular learning activity of a specific learner group using Collaborative Filtering. In case the ontology was used to create the recommendation, learner preferences (taken from their user profiles) were matched to the domain ontology to recommend the most suitable next best learning activity.
The following 4 hypotheses were tested in the ISIS experiment, where the control group was provided with the Moodle learning environment and a text book; whereas the experimental group was additionally provided with a recommender system that recommended best next learning activity based on successful choices of other learners with similar profiles.

H1. The experimental group will be able to complete more learning activities than the control group (Effectiveness).

H2. The experimental group will complete learning activities in less time, because alignment of learner and learning activity characteristics will increase the efficiency of the learning process (Efficiency).

H3. The experimental group has a broader variety of learning paths than the control group because the recommender system supports more personalized navigation (Variety)

H4. The experimental group will be satisfied with the navigation support of the recommender system (Satisfaction).

In the next section (method section) we will describe the experimental setup and the used recommendation strategy in more detail. In section four results and statistical effects will be presented.

Method

To test our hypotheses in an authentic learning situation, we carried out an experimental study within the regular 'Introduction Psychology' course as offered by the Psychology faculty of the Open University of the Netherlands (OUNL). This new course was offered as alternative next to the existing, old version of the course. The learning activities and the recommender system were implemented in the Moodle LMS (Dougiamas, 2007).

Participants

No prior knowledge was required from the participants to attend the Introduction Psychology course. A total of 244 participants subscribed to this pilot. Both the experimental and control group contained an equal amount of learners (122 learners per group) because the learners were randomly allocated. 24 participants (19.7%) in the experimental group and 30 participants (24.5%) in the control group never logged into the Moodle environment. This group of non-starters was not included in our analyses. This leaves a group of 190 learners who did enter the Moodle environment; 98 in the experimental and 92 in the control group.

From the 98 participants in the experimental group 60% of them were women, within an average age of 38,5 years, and 70% of the participants had a higher professional education or university level. In the control group 65% of them were woman, within an average age of 34,7 years, and 62% of the participants had a higher educational level.

The group of actual starters had to be further differentiated into active and passive learners, because not all of the learners actually used or made progress in the Moodle environment. From the 98 participants in the experimental group 72 learners completed learning activities; from the control group 60 learners completed learning activities. Thus, in total a group of 132 were active learners during the experiment. We used this total amount of active learners to analyze hypotheses 1 (Effectiveness), hypotheses 2 (Efficiency), and hypotheses 3 (Variety). The group of participants was further characterized by an average age of 36.5 years, 62.5% being female students, and 66% having a higher education level.

Materials

The Learning Network

Moodle was adjusted to the experimental setup. Figure 4.1 shows the overview screen of learning activities for a learner in the experimental group. The overview is divided into three columns. The right column shows the learning activities the learner still has to study. The middle column presents the courses the learner is already enrolled for. Finally, in the left column all completed courses are listed. Below an explanation of the recommendation is given. In this screen, the recommender system has recommended 'Thinking' as next best course. Next to the recommendation there are additional options to get further information about the recommendation and to adjust the preferences set in the learner profile.

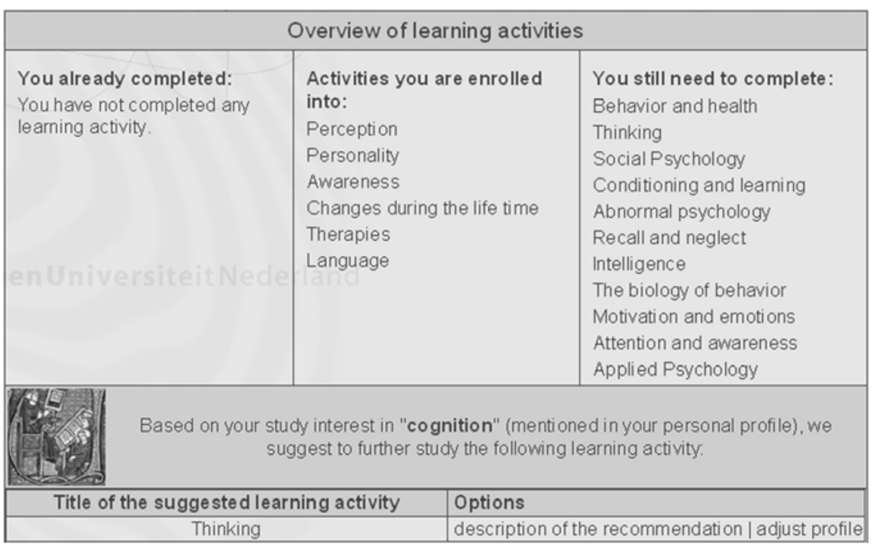


Figure 4.1: Overview page of the experimental group with a recommendation

The Learning Network contained 17 learning activities with an average study load of 12 hours. Formal completion of each learning activity was assessed by multiple-choice tests consisting of seven equally weighted questions. A score of

60% or more was considered as a successful completion of the learning activity. With the Moodle environment the learners received an Introduction to Psychology handbook that contained additional information to the 17 learning activities. All learning activities were separate entities in Moodle, setup according to the same didactical structure. The Moodle environment contained all further learning materials, including support and guidance, task assignments, progress tests, additional pictures and links, summarizations, and other attractive learning tasks.

The recommender system

The recommender system with a combined recommendation strategy provide more accurate recommendations when compared to single techniques recommender systems (Melville, Mooney, & Nagarajan, 2002; Pazzani, 1999; Soboro & Nicholas, 2000). The implemented recommender system combined an ontology-based recommendation technique with a stereotype filtering technique. The ontology used personal information of the learner (e.g., interest) and compared that with the domain knowledge to recommend the most suitable learning activity. Stereotype filtering used profile attributes of the learners (e.g., interest, motivation, study time) to create learner groups and recommend learning activities preferred by similar learners.

The recommender system advices the next best learning activity to follow based on the interest of learners (ontology-based recommendation), and on the behaviour of the peers (stereotype filtering). If only information about the interest of a learner was available, then ontology-based recommendation technique was used, else the stereotype filtering technique was applied. The underlying recommendation strategy is presented in Figure 4.2.

The use of the stereotype filtering was prioritized and the ontology approach was used mainly to cover the 'cold-start problem' (Herlocker, Konstan, & Riedl, 2000) of the stereotype filtering technique. The stereotype filtering technique was personalized through attributes of the personal profile of the learners. If it was not possible to give any advice it disabled one of the personal attributes and tried to make a recommendation based on larger peer group with less common attributes (Figure 4.2).

Only in the case that the stereotype filtering was not able to provide any recommendation, the recommender system created ontology-based recommendations. The ontology visualized in Figure 4.3 consists of two top domains (e.g., 'Environmental Psychology') that contain several sub domains (e.g., 'learning'), each containing two or three courses (or learning activities) (e.g., 'recall and neglect'). The learners had to select a special interest (one of the sub domains of the ontology) in their profile. If the learners had chosen a sub domain (e.g., 'clinical'), they received recommendations on courses located in that particular sub domain. If none of these courses had been completed by others so far, the recommender system randomly recommended one of them. If one course had already been completed by the learner the other course(s) was/were recommended. If all courses of the sub domain (e.g., 'clinical') were completed the ontology recommended a course that was part of the top domain 'Environmental Psychology'.

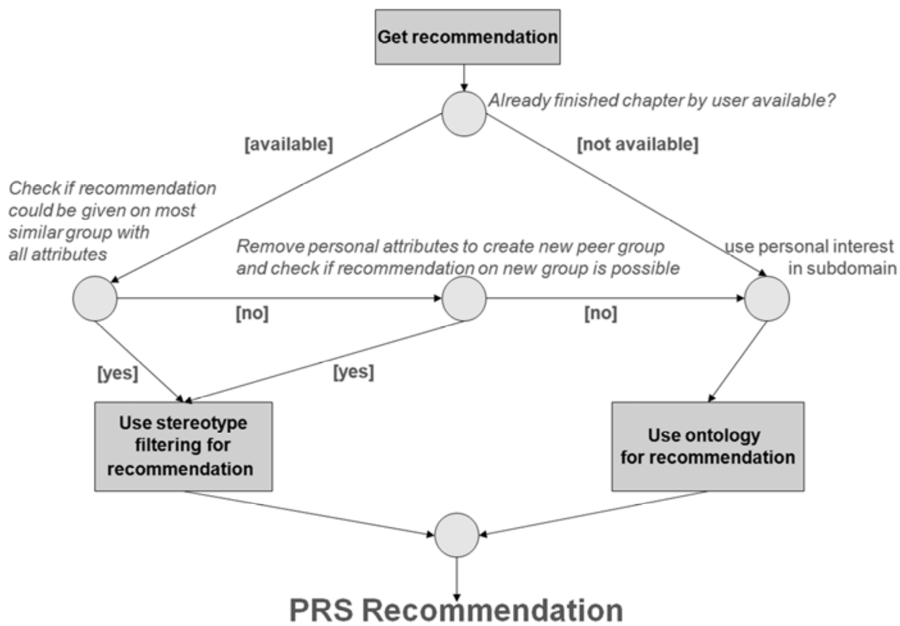


Figure 4.2: Recommendation strategy of the implemented recommender system

Only in the case that the stereotype filtering was not able to provide any recommendation, the recommender system created ontology-based recommendations. The ontology visualized in Figure 4.3 consists of two top domains (e.g., 'Environmental Psychology') that contain several sub domains (e.g., 'learning'), each containing two or three courses (or learning activities) (e.g., 'recall and neglect'). The learners had to select a special interest (one of the sub domains of the ontology) in their profile. If the learners had chosen a sub domain (e.g., 'clinical'), they received recommendations on courses located in that particular sub domain. If none of these courses had been completed by others so far, the recommender system randomly recommended one of them. If one course had already been completed by the learner the other course(s) was/were recommended. If all courses of the sub domain (e.g., 'clinical') were completed the ontology recommended a course that was part of the top domain 'Environmental Psychology'.

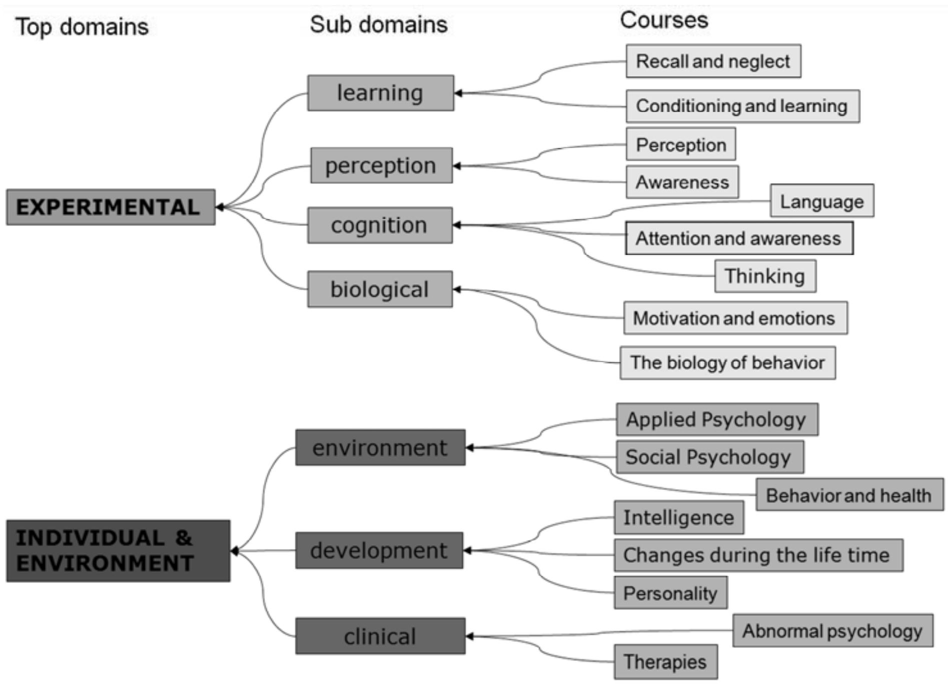


Figure 4.3: Structure for ontology based recommendations

Procedure

The participants could voluntarily register for the new version of the course, and were informed that they were taking part in an experiment with a new learning environment. They were not informed that only half of the students would receive additional navigation support. The participants were randomly assigned either to the experimental group or the control group. Both groups received the same treatment (course materials); all were able to ask questions to a tutor in a forum. In order to draw conclusions to self-organised informal Learning Networks both groups got a maximum of freedom for their studies. Both groups were informed that they did not have to follow the learning activities in a certain order or pace. In principle they were able to study the course over years.

As a consequence not all students started their study in October; some of them started later, (dynamic starting point). Furthermore, they were allowed to complete learning activities at their own pace. Students could register for a final exam whenever they wanted, even without completing any of the multiple choice online progress tests available. The experiment ran for four months, from early October 2006 until late January 2007. During this period no further information about the experiment was given to the participants. In the experimental period of four months, measures were taken every two weeks.

Analysis of Effectiveness and Efficiency

In order to deal with a selection problem in our experiment we defined a goal attainment of 5 completed learning activities out of 17 in total. Our aim was to support as much learners as possible to complete these 5 learning activities as fast as possible. To measure the effectiveness and efficiency of the recommender system learners were taken into account that applied to the following rule; completed more than 5 learning activities, or successfully completed the final exam, or were still studying at the measure point. This rule leaves a number of 101 students at the end of the experiment (n=52 in the experimental group and n=49 in the control group). Regarding the individual dynamic starting points of the students the recorded measure in Table 4.1 contained 0 values in case students started later (see Table 4.1).

Table 4.1: This table represents the 'raw' recorded measures of the biweekly measure points. The 0 values are related to the individual starting point of the participants.

Table 4.1
Example table of biweekly recorded measures.

Learner	**Biweekly measure points**						
	Oct	**Oct 2**	**Nov**	**Nov 2**	**Dec**	**Dec 2**	**Jan**
1	1	2	4	7	7	7	8
2	0	0	0	1	3	5	9
3	0	0	0	0	0	1	1
4	1	2	3	4	4	4	4

In order to ran a MANOVA analysis all individual starting points of the students were moved in one 'starting' column through deleting the 0 values. Therefore, Table 4.1 was transformed into a study progress table (see Table 4.2). Table 4.2 differentiate from Table 4.1 through moving the individual starting points into one 'starting' column (first column), and the duplication of the study results towards the end of the Table 4.2 if the students applied to the above mentioned rule.

To test hypothesis 1 and 2, we analyzed the measures taken using SPSS 12. To avoid inflated Type I error due to multiple tests, a priori tests of specific contrast scores were used. The effectiveness and efficiency was analyzed by means of linear and quadratic trend analysis. Averaged completion scores and averaged completion time during the two experimental periods were transformed into linear and quadratic trend contrast scores by means of computation of orthogonal polynomials. We applied multivariate analysis of variance (MANOVA) for repeated measures on these a priori chosen contrast scores with Group as between subjects factor and Time (or Progress) as within subjects factor. A significant interaction of contrast scores with Group was followed by testing of simple contrast effects. Due to the a priori character of these tests, they were performed with the conventional Type I error of .05 (Tabachnick & Fidell, 2001).

Table 4.2: This table shows the actual study progress of all active learners. Therefore, all 0 values from Table 4.1 are deleted and the individual starting points were moved into one 'starting' column (first column).

Table 4.2
Example table of prepared biweekly measures for MANOVA analysis.

Learner	**Study progress per learner per measure point**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
1	1	2	4	7	7	7	8
2	1	3	5	9	9	9	9
3	1	1					
4	1	2	3	4	4	4	4

Analysis of variety of learning paths

To test hypotheses 3, the variety of learning paths, we analyzed the behavior of the learners with a Graph Theory approach (Gross & Yellen, 2006). Therefore, we modeled the Learning Network in Netlogo 4 (Tisue & Wilensky, 2004), and observed the completion of learning activities by the learners. If a learner completed for instance first learning activity 1 and second learning activity 7 it was counted as traffic between learning activity 1 and learning activity 7. A line was drawn between both learning activities in the graph when the traffic became larger than 3. If the learning path was used even more frequently, the traffic line got thicker and changed its color. Consequently, the thickest path was used most often and the thinnest path was used only three times.

Analysis of satisfaction with the recommender system

To test hypothesis 4, the general satisfaction of the recommender system, we conducted an online recall questionnaire. This questionnaire was sent to all 190 participants in both groups at the end of the experiment. We received answers from 52 people in total, thus we had a response rate of 27%. From the control group 24 out of 92 learners responded and from the experimental group 28 out of 98 learners. The response rate of the control group was 22% and the response rate of the experimental group was 27%.

Results

Effectiveness

The amount of progress made by learners in both groups as indicated by the number of learning activities completed after four months (half-way) of the experiment is represented in Figure 4.4. The overall completed learning activities (the overall progress of both groups) over time was denoted by a significant positive linear trend ($F(1,99) = 203.22$ $p < .001$) and a significant positive quadratic trend ($F(1,99) = 40,31$, $p < .001$). There was no significant effect of Group for effectiveness on the linear and quadratic trend.

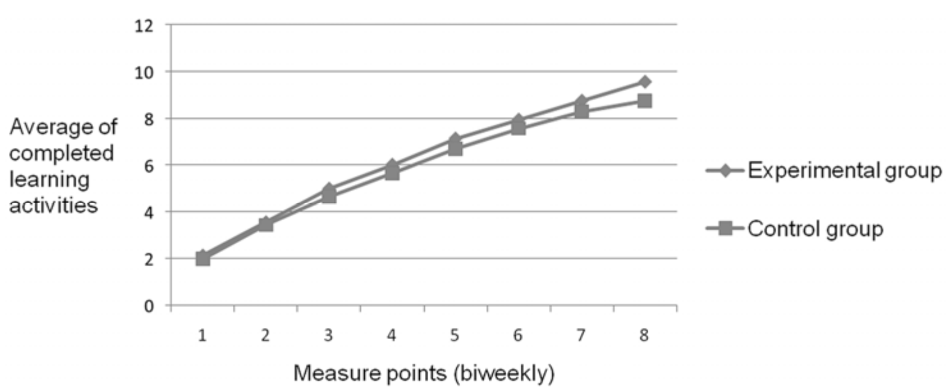


Figure 4.4: Progress of learners on completion of courses during the experimental period

Efficiency

The time learners spend after four months is represented in Figure 4.5. The overall effect of time was denoted by a significant positive linear trend (F(1,99)

= 101.32, $p < .001$) and a significant positive quadratic trend ($F(1,99) = 4.3$, $p < .05$). The experimental group, needed constantly less time to complete equal amounts of learning activities. This result was also confirmed by SPSS with a significant effect of Group on the quadratic trend ($F(1,99) = 5.14$, $p = .026$). No significant effect of Group was found on the linear trend. Simple effects analysis showed that for the control group the curve got a declining trend at the end, whereas the experimental group behaved increasingly linear.

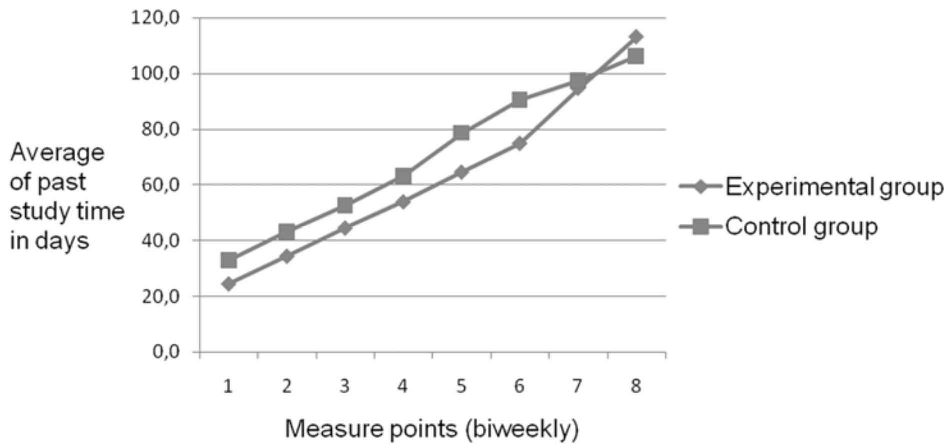
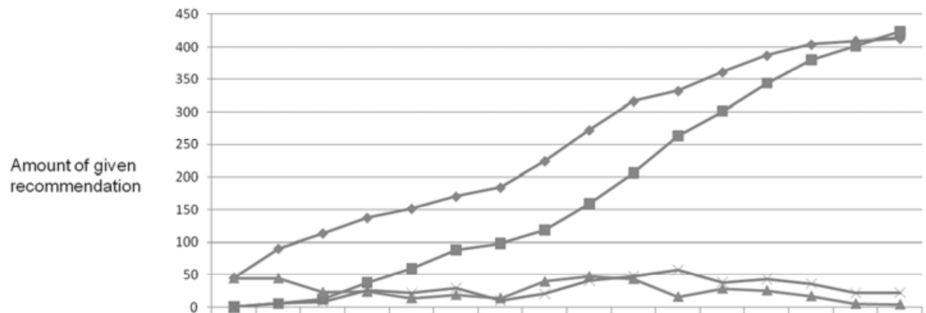


Figure 4.5: Average study time during the experimental period

Figure 4.6 shows how often the recommendations techniques were used during the experiment in the distributed and cumulated values. During the first month the cold-start problem of the recommender system occurred, because there was no data available for stereotype filtering. Nearly all recommendations in this period were covered by ontology-based recommendations. But starting from the second month, stereotype filtering has been used more often and became equally used, when we consider distributed numbers at the end of the experiment.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
cumulated ontology	45	90	113	137	151	170	184	224	272	316	332	361	387	404	409	413
cumulated stereotype filtering	0	5	12	38	59	88	98	118	159	206	263	301	344	380	401	423
distributed ontology	45	45	23	24	14	19	14	40	48	44	16	29	26	17	5	4
distributed stereotype filtering	0	5	7	26	21	29	10	20	41	47	57	38	43	36	21	22

Measure points (biweekly)

Figure 4.6: Usage of recommendation techniques during the experiment

Variety of learning paths

To compare the emerged learning paths of both groups we placed all learning activities in Netlogo 4 in a circle. Learning activity 1 is the starting chapter of the additional given book labeled as the ‘biology of psychology’. The numbers attached to the nodes in the graph mark the chapter number from the additional given psychology book. Figure 4.7 presents the emerged learning paths of the control group, and Figure 4.8 presents the emerged learning paths of the experimental group. Both Figures were drawn with the recorded user behavior at the end of the experiment.

For the control group we see (Figure 4.7) that most of the participants followed the order of the textbook that was given to the Moodle environment. For the experimental group (Figure 4.8) many more thin and medium size lines reflect the influence of the recommender system. The participants in the experimental group have taken more personalized learning paths than the control group. They hardly followed the chapter order of the textbook.

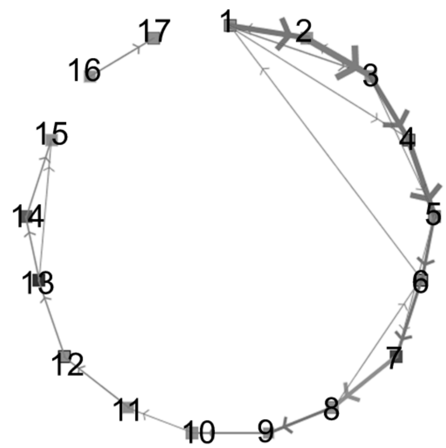


Figure 4.7: Emerged learning path of the control group at the end of the experiment.

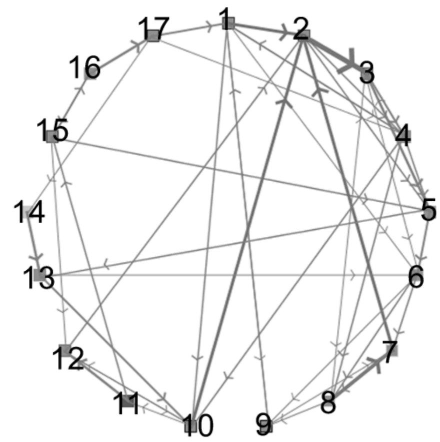


Figure 4.8: Emerged learning path of the experimental group at the end of the experiment.

Satisfaction of the recommender system

In this section we present the most relevant answers from the online recall questionnaire of the experimental group regarding the satisfaction of the recommender system. We also asked for the general usage of the recommender system as an indicator for satisfaction. The results of the questions about the general use can be found in Table 4.3. The more detailed questions about the satisfaction are shown in Table 4.4.

In Table 4.3, Question 1 it is shown that 64% (n=18) of the participants used the recommender system during the whole period, 4% (n=1) did not use it the whole time because the explanation of the recommendation was not clear enough for them, and 32% (n=9) answered that they did not use the recommender system the whole period because they also wanted to follow the book. For question 2 46% (n=13) answered that the recommender system helped them to organize the study in a more personalized way, whereas 54% (n=15) of the learners answered that the recommender system did not help them to organize their study in a more personalized way.

Finally, the learners were asked about their 'obedience' to the system, i.e., how often they follow up on the advice that was given to them (Table 4.3, question 3). 32% (n=9) answered they had followed the advice very often, and 29% (n=8) answered they had followed the advice often. 11% (n=3) were neutral to this question and around 29% (n=8) answered that they seldom / or very seldom had followed the advice.

Table 4.3
General question about the usage of the recommender system from the experimental group (n = 28).

Questions	Values				
	Yes	**No, because of technical problems**	**No, because the description of the recommendations were not transparent to me**		**No, because I also wanted to follow the book**
Did you use the recommender system during the whole period of the course?	64% (n=18)	0% (n=0)	4% (n=1)		32% (n=9)
	Yes	**No**			
Do you think the recommender system helped you to structure the learning activities in a more personalized way?	46% (n=13)	54% (n=15)			
	Very often	**Often**	**Neutral**	**Seldom**	**Very seldom**
How often did you follow the recommendation that was given to you?	32% (n=9)	29% (n=8)	11% (n=3)	11% (n=3)	17% (n=5)

We were also interested if the recommender system followed the expectation of the learners (Table 4.4, Question 1). 14% (n=4) / 21% (n=6) of the learners answered that the recommendations followed their expectations (i.e., what they themselves wanted to do next) very good / good. 61% (n=17) were neutral about the recommender system and only 4% (n=1) answered that the recommender system was less in line with their expectations.

To further analyze the impact of our recommendation strategy, we asked the learners if they were more satisfied with the recommendation given in the beginning or at the end of the experiment (Table 4.4, questions 2 and 3). We wanted to know if the learners noticed any differences in the given recommendation over time, since the ontology recommendation was mainly used in the beginning of the learning progress and the stereotype filtering technique was used mainly at the end of the learning progress. Surprisingly, the learners rated their satisfaction for both periods quite different. 7% (n=2) and 18% (n=5) were positive about the recommendations during the first two month (ontology). But

7% (n=2) and 39% (n=11) rated the last two month more satisfying. It seems that they are more satisfied with recommendations based on the stereotype filtering. A minor percentage 4% (n=1) and 7% (n=2) were less satisfied with the recommendations. Nevertheless, nobody was unsatisfied with the recommendations.

Table 4.4
Detailed responses about the benefit of the recommender system from the experimental group (n = 28).

Questions	Values				
	Very good	Good	Neutral	Less	Very less
Did the recommendation of the recommendation system follow your expectations for studying the next learning activity?	14% (n=4)	21% (n=6)	61% (n=17)	4% (n=1)	0% (n=0)
How satisfied have you been with the recommendation given by the recommendation system during the first two month of your studies?	7% (n=2)	18% (n=5)	71% (n=20)	4% (n=1)	0% (n=0)
How satisfied have you been with the recommendations given by the recommender system during the last two month of your studies?	7% (n=2)	39% (n=11)	46% (n=13)	7% (n=2)	0% (n=0)

Conclusions and Discussion

Based on the results of the experiment we can draw several conclusions for our research on navigation support in self-organized, informal Learning Networks for lifelong learners. According to our 4 hypothesis, we can now conclude the following.

Effectiveness

The experimental group was consistently found to be more effective in completing learning activities than the control group during the experimental period. Even with these promising observations, we have not found a significant difference; therefore, hypothesis H1 cannot be confirmed. It might be that this is due to the fact that the experimental period was too short and further observations might be more successful.

Efficiency

The experimental group consistently needed less time to complete equal amounts of learning activities, which effect was found to reach significance after 4 months. Therefore, hypothesis H2 could be confirmed. This result shows that our approach to navigation support and our recommendation strategy enhance the efficiency of learners in self-organized, informal Learning Networks.

Variety of learning paths

The variety of personalized learning paths increased by the recommender system. The experimental group from the beginning onward created more personalized learning paths. Some of these personalized learning paths also caused (by emergence) successful learning paths taken by other learners. Considering this results in combination with the positive effect on efficiency and satisfaction it appears that the personalization and the support of self-organization in informal Learning Networks were beneficial for the learners. The experimental group outperformed the control group and used the recommender system. Based on this result we also confirm hypothesis H3.

Satisfaction

The qualitative data about satisfaction from the recall questionnaire underlined the quantitative results about the actual use of the recommender system. The learners accepted the recommender system for supporting them in their self-organized navigation through the learning activities. 64% of the participants used the recommender system over the whole experimental period very often or often. 46% have the impression that the recommender system helped them to organize their learning progress in a more personalized way. The experimental group was more satisfied with the recommendations based on stereotype filtering. This is an interesting finding and will have influence on our future research. Regarding the informal characteristic of Learning Networks, we want to use more bottom-up techniques like Collaborative Filtering instead of top-down ontologies. In future research we are planning to combine these bottom-up techniques with learner ratings and tags, which have been proven to be appropriate for self-organization in informal environments like Learning Networks. However, because of the positive responses from the learners and actual usage data we can confirm hypothesis H4.

Limitations and future research

We have reported positive outcomes to our study. However, we have to point the reader to some serious limitations as well. Besides the limitations already mentioned in the previous result section, there are some more general limitations to this study, regarding the experimental setup we applied.
First, although our research addresses lifelong learners in self-organized and informal Learning Networks, the practical character of the experiment, embedded in a formal course with real students that wanted to be accredited, excluded some of the navigational and motivational problems faced by lifelong learners. For the future research of Learning Networks we envision more informal learning activities without a formal assessment, therefore we are planning to have an additional experimental pilot where open educational resources (OER) and their communities are used. An experimental pilot with OER is more similar to Learning Networks, thus a Learning Network could exists out of different mixed OER, formal learning offers, or separated learner contributions in once.
Second, the experimental setup did not force learners to actually take the recommended next step, and we do not know to what extent learners actually followed up the advice. The problem is the definition of what constitutes a 'followed recommendation'. Did learners follow a recommendation when they navigated to a recommended learning activity? Or did learners follow a recommendation when they stayed longer than 5 minutes in the recommended learning activity? As a result, the improved efficiency cannot be unambiguously ascribed to the recommender system itself. The mere presence of a navigation support tool may have stimulated the experimental group. An additional experiment involving a control group receiving random recommendations would help clarify this point. We were not able to provide faked recommendation to the control group because of ethical reasons. It would have been not fair to confuse the control group with random recommendations, because they also were real students that paid the same amount of money for the course.
Third, we have to mention one limitation for effect on efficiency. There is a difference between the measured 'elapsed time' that students took to complete a learning activity and the actual 'study time' they needed to successfully complete a learning activity. Elapsed time as measured through the Moodle environment is an assistant indicator for real study time.
Finally, we decide to show only the 'best next learning activity', based on our recommendation strategy to the learners. We did that for experimental reasons,

otherwise the analysis would have been even more complex. Alternatively, we could have given both groups the same user interface with all the learning activities listed, the only difference being that in the experimental group the learning activities are reordered according to the recommender system's priorities while the control group gets a standardized ordering. This would have provided a more similar environment for both groups, but also might force the learners to select always the first learning activity on the list. Nevertheless, in real life a list or a sequence with suitable recommendations on different characteristics might be more valuable for the learners than a single recommendation. Further research is needed to address these limitations and to reveal whether alternative recommendations would have a greater impact on effectiveness, efficiency, variety, and satisfaction for lifelong learners in self-organized Learning Networks. Additional information given to the recommendation of a learning activity could be success rates, required competence levels, average amount of study time, subjective ratings, or tagging information given by other learners. Despite the limitations of the presented study, we believe it (at least partially) proofs that the use of navigation support based on a personalized recommendation strategy offers a promising way to advise learners on their self-organization in Learning Networks.

Chapter 5

Effects of recommender systems in Learning Networks of different sizes

This chapter is based on: Drachsler, H., Van den Berg, B., Nadolski, R., Hummel, H.G.K., & Koper, R. (submitted). Simulating an Informal Learning Network with Contextualized Recommendations: Effects on the Competence Development of Learners. *Journal of Artificial Societies and Social Simulation (JASSS).*

Abstract

This simulation study explores the use of two different Collaborative Filtering algorithms; a user-based and an item-based approach which are contextualized in pedagogical manner to support learners in selecting learning activities. The learning activities are either recommended based on peer learner experiences or on competence development needs of individual learners taking into account their prior knowledge. Each of the Collaborative Filtering algorithms is implemented in a treatment group and compared to a control group in Learning Networks of different sizes. The simulation tool models a Learning Network in which learners search for, enroll in, study and rate learning activities. This chapter presents the underlying simulation model, the experimental setup, and the applied recommendation techniques. The study confirmed that learners with navigation support by recommender systems yield to more graduation, less study time and more satisfaction compared to learners without navigation support. Further, comparing the two treatments against each other showed a better performance of the item-based approach regarding study time and satisfaction of the learners.

Introduction

This chapter addresses navigation support of learners in informal Learning Networks of different sizes by recommender system technologies. Therefore, we have to take into account the specific conditions of Learning Networks for the recommender system. Informal learning activities are emerging from the bottom upwards through their communities. Thus, there is an absence of maintenance and structure in informal learning that is also called the 'open corpus problem' (Brusilovsky & Henze, 2007). The open corpus problem applies when an unlimited set of documents is given that can not be manually structured and indexed with domain concepts and metadata from a community. The learning activities in Learning Networks are mainly structured by tags and ratings given by the learners. Therefore, bottom-up recommendation techniques like Collaborative Filtering are more appropriate than semantic recommendation techniques like ontologies because they require nearly no maintenance and improve through the emerging behavior of the community. A recommender system for informal learning has to behave as independent as possible without any maintenance by an institution and rely on the data that is already given.
In this study we explored two additional pedagogical contextualized Collaborative Filtering algorithms in an informal Learning Network simulation regarding their usefulness for recommendation strategies for hybrid recommender systems. Hybrid recommender systems combine single re-commendation techniques in order to provide more accurate recommendations. Several studies

have already demonstrated the superiority of hybrid techniques when compared to single techniques for recommender systems (Balabanovic & Shoham, 1997; Claypool et al., 1999; Good et al., 1999; Melville, Mooney, & Nagarajan, 2002; Pazzani, 1999; Soboro & Nicholas, 2000). Since Learning Networks can exist in various conditions it is expected that a hybrid recommender system is most suitable for Learning Networks (Hummel et al., 2007). Such hybrid recommender systems can address certain sizes of Learning Networks by firing the most suitable recommendation technique for certain situations a learner might be placed. Such situations could be that a learner have not rated any learning activities or owns already a broad history of completed learning activities. Our approach wants to extend a study by (Nadolski et al., 2009) by evaluating new promising recommendation approaches and analyze the impact of recommender systems on learners in Learning Networks of different sizes. We especially, want to observe how differently the recommendation algorithms perform in Learning Networks of different size. This is important information for the combination of recommendation techniques in hybrid recommender systems. Therefore our main goals are: 1. evaluate new recommendation techniques, 2. test their performance in Learning Networks of different size and 3. explore their usefulness for recommendation strategies for hybrid recommender systems in informal Learning Networks. We applied the same learner- and learning activity models like Nadolski et al. and further design two different Learning Networks with different dense data sets regarding the amount of learners, available learning activities, and ratings in the system. In contrast to Nadolski et al. we test a pedagogical contextualized version of user- and item-based Collaborative Filtering algorithms without combining them in a recommendation strategy directly. Further, we extend the evaluation approach from Nadolski by combining the educational measures with measures from recommender system research as suggested by Drachsler, Hummel and Koper (2009). In the following sections we first discuss related work (section two). We explain our methodology approach in multiple subsections regarding the simulation model, the applied software and the implemented recommender system technology (section three). We present the results of the simulation study (section four) and finally discuss the findings and its impact for future research (section five).

Related work

We designed the simulation tool following the approach for simulations for social scientists by Gilbert & Troitsch (2005). They explained that simulation studies can be designed through abstracting a model from a research target and further develop a simulation for that model. An advanced step in simulation design is the comparison of the simulation results with data collected in field studies of the research target. According to this method we based the parameters and conditions of our simulation on findings of previous studies (see Figure 5.1). We run several iterative studies which combine findings from field studies with conclusions of simulation studies in order to guarantee the validity of assertions for informal Learning Networks.

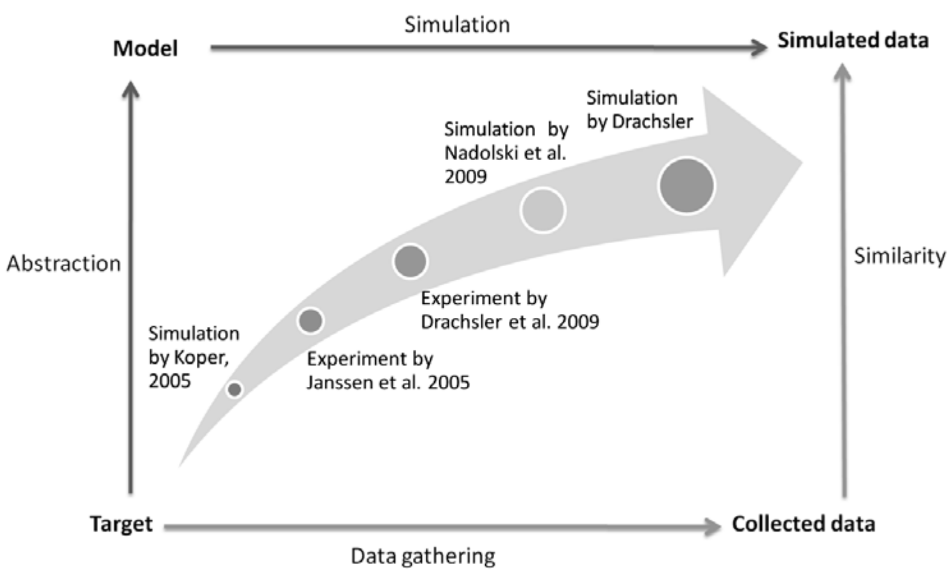


Figure 5.1: Methodology approach for simulation in social science (Gilbert & Troitzsch, 2005). In the middle of the figure related research studies carried out regarding navigation support of learners in Learning Network from 2005 until 2009 are shown.

The iterative studies started with a simulation study by (Koper, 2005) to test the theory behind the informal Learning Network approach. In a second step, a first field test experiment was conducted by (Janssen et al., 2005) to gather experience based on real data. They applied a rather simple Collaborative Filtering algorithm without taking into account any preferences or profile information of the learners. Janssen et al. found positive effects on effectiveness (completion rates of learning activities) though not on efficiency (time taken to complete learning activities) for the experimental group as compared to the control group. In a third step, an additional field experiment was carried by (Drachsler et al., 2009) to gather additional real data with a more personalized Collaborative Filtering approach. They applied a hybrid recommendation strategy consist of a stereotype filtering algorithm that was triggered by preferences of the learners with an ontology for the cold-start of the recommender system. Drachsler et al. found a positive significant effect on efficiency in their study after a runtime of four months. The latest simulation study that builds on the earlier field studies was designed by Nadolski et al. They compared various cost intensive ontology based recommendation strategies with light-weight Collaborative Filtering strategies. Therefore, they created treatment groups for the simulation through combining the recommendation techniques in various ways. Nadolski et al. tested which combination of recommendation techniques in recommendation strategies had a higher effect on the learning outcomes of the learners in a Learning Network. Nadolski et al. concluded that the light-weight Collaborative Filtering recommendation strategies are not as accurate as the ontology-based strategies but worth-while for informal Learning Networks when considering the lack of maintenance in Learning Networks. Nadolski et al. study confirmed that providing recommendations leads towards more effective, more satisfied, and faster goal achievement than no recommendation. Furthermore, their study reveals that a light-weight Collaborative Filtering recommendation technique including a rating mechanism is a good alternative to maintain intensive top-down ontology recommendation techniques.

We continue the research with the sophisticated simulation model by Nadolski et al. to explore additional recommendation techniques for hybrid recommendation strategies for informal Learning Networks. With the simulation tool we want to identify promising recommendation techniques for different conditions of Learning Networks to finally combine them in a hybrid recommender system that fits to different Learning Networks characteristics.

As already mentioned in the introduction our approach wants to extend the study by Nadolski et al. by evaluating additional recommendation techniques for different sizes of Learning Networks. Therefore, we focus on three different aims: 1. Evaluation of additional recommendation techniques, 2. Test their performance in Learning Networks of different size also by adding classic recommender system measures like Recall, Precision and F1 and 3. Explore their usefulness for recommendation strategies for hybrid recommender systems in informal Learning Networks in order to know in which conditions they work most effective and are useful for a particular Learning Networks.

We applied the same *Learner* and *learning activity* models and further designed 4 different Learning Networks with different dense data sets regarding the amount of learners, available learning activities, and ratings in the system. We tested user- and item-based Collaborative Filtering techniques without combining them in a recommendation strategy with other recommendation techniques. Different to Nadolski et al. we do not deal with sub domains as they are needed for ontology based recommendations. Further, we see a Learning Network related to one domain with various learning goals and competence levels of the learning activities inside.

As a contribution to the SIRTEL discussion (Social Information Retrieval for Technology-Enhanced Learning) (Duval, Vuorikari, & Manouselis, 2009; Duval et al., 2007, 2008) we want to evaluate the effects of user- and item-based Collaborative Filtering especially on the emerging effects of personalized recommendations in Learning Networks to support the learning outcomes of lifelong learners. An important addition in this study is contextualization of the Collaborative Filtering algorithms by pedagogical reasoning. Based on our earlier experience (Drachsler, Hummel, & Koper, 2008), we believe that a recommender system for learning has to take pedagogical reasoning and learning characteristics into account to support learners on their learning process. Therefore, a recommender system for learners requires deeper reasoning than in other domains (Drachsler, Hummel, & Koper, 2009; Tang & McCalla, 2009). Simple semantics like "People who liked X also liked Y" might be misleading for learning recommender systems. For recommender systems in Learning Networks we might need semantics like "People who studied X, Y, and Z on competence level 3 and prior knowledge level 2 seem to have the same learning goal, thus we recommend studying W". Thus, in our simulation study we introduce pedagogy research results like Vygotsky's "zone of proximal development" that follow the pedagogical rule 'recommended learning activities should have a knowledge level that is a bit above learners current competence level' (Vygotsky, 1978).

We extended the previous research on simulations by defining two new foci for the evaluation of recommender systems in Learning Networks. First, we want to apply a pedagogical contextualized version of user- and item-based Collaborative Filtering techniques for Learning Networks. Secondly, we want to test these algorithms in 4 Learning Networks with different dense data sets regarding the amount of learners, available learning activities, and ratings in the system. Therefore, we added also recommender system measures like *Precision, Recall and F1* to the simulation tool. We do so by contextualizing the Collaborative Filtering algorithm with a prior knowledge level, learning goal, study time, and already studied learning activities. Further details about this pedagogical contextualization can be found in section *Pedagogical contextualization of the Collaborative Filtering techniques*.

Method

We tested the treatment groups in 4 Learning Networks of different sizes with learners that followed a low-level learning goal at level 1 and learners that followed a high-level learning goal at level 3 (includes three level of competences). One small Learning Network consists of 150 learners and 60 learning activities, and the other one of 60 Learners and 150 learning activities. The large Learning Network consists of a Learning Network with 400 Learners and 250 learning activities and the other large Learning Network of 250 Learners and 400 learning activities. With these 2 * 4 sizes of Learning Networks setup we got 8 different experimental settings. Thus, we followed a 2 * 4 experimental settings design (see Figure 5.2).

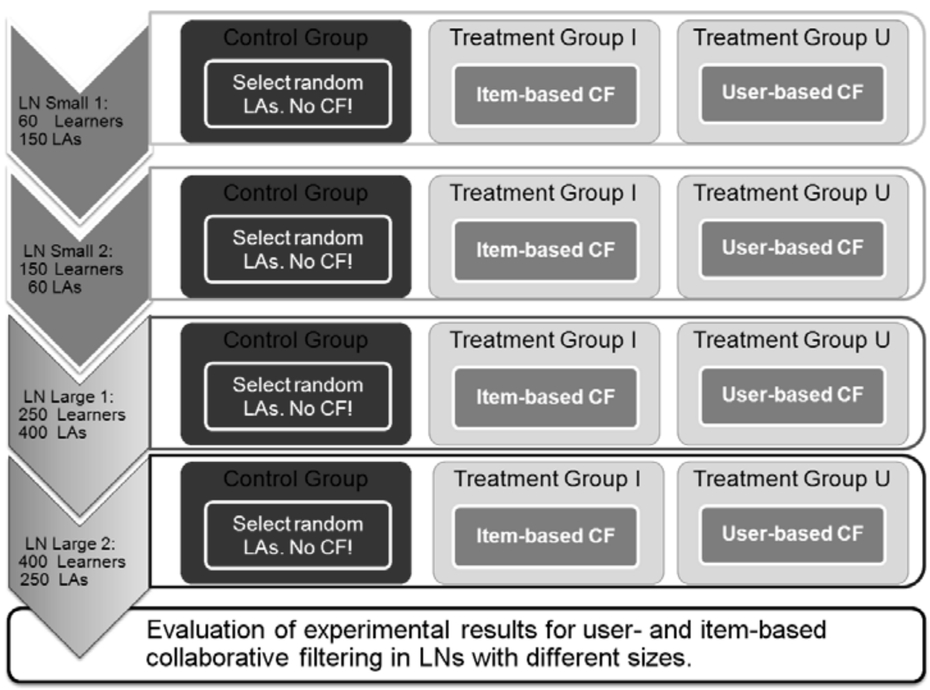


Figure 5.2: Experimental setup for the simulation study. The following setting was applied for learners that followed learning goal at level 1 and learners that followed learning goal at level 3.

We tested the following 9 hypotheses in the 8 different experimental settings where the control group gets no recommendations; whereas treatment group I gets navigation support provided with a pedagogical contextualized item-based Collaborative Filtering algorithm, and treatment group U gets recommendation support based on a pedagogical contextualized user-based Collaborative Filtering algorithm.

The treatment groups will be better than the control group according to:

- H1. They will complete more learning activities (Effectiveness).
- H2. They will complete learning activities in less time (Efficiency).
- H3. They will be more satisfied by faster competence development (Satisfaction).

Treatment I will be better in small Learning Networks than treatment U because there will be less expertise of peer learners in the network. Therefore, adaptation of individual needs to the learning process will be better in case of:

- H4. Treatment group I will complete more learning activities (Effectiveness).
- H5. Treatment group I will complete learning activities in less time (Efficiency).
- H6. Treatment group I will be more satisfied by faster competence development (Satisfaction).

Treatment U will be better in large Learning Networks than treatment I because there will be more expertise of peer learners available. Therefore, treatment U will be better in case of:

- H7. Treatment group U will complete more learning activities (Effectiveness).
- H8. Treatment group U will complete learning activities in less time (Efficiency).
- H9. Treatment group U will be more satisfied by faster competence development (Satisfaction).

In the following section we present the adapted simulation model for our simulation tool. It is based on previous work by Koper (2005) and largely in line with the latest model described by Nadolski et al. (2009). This conceptual simulation model represents the minimized set of learning activity- and Learner characteristics. The model will be elaborated in three subsections: The *Learning Network Interaction Model*, the *Recommender System Interaction Model*, and a *Flow chart of a one exemplary simulation run*. Afterwards we explain the recommender system technology. This section is further divided into a description of the *Netlogo simulation environment* and the *Recommender system technology*. Finally, we describe the *Configuration of the simulation* and explain the *Analysis of the used measures*.

The simulation model

Regarding the evaluation of item- and user-based Collaborative Filtering for the navigation support of learners in Learning Networks, we excluded *preferences* that were used for ontology-based recommendations from the initial *Learner Model* designed by Nadolski et al.. The remaining *Learner Model* and *Learning Activity Model* are in line with the previous research. Therefore, the detailed formulas to calculate the relationship of the models can be found in the article by Nadolski et al. in Table 2 on page 10. Both models present our approach to simulate learners acting with learning activities (Nadolski called them learning activities therefore we have to adjust learning activities to learning activities) in a Learning Network. In order to clarify the relations between the different simulation objects we divided the simulation model into a *Learning Network Interaction Model* and a *Recommender System Interaction Model*. Both models consist of the same sub models of learning activity and Learners but they make advantage of different attributes in these models. Therefore, we colored attributes that were not needed for the description of one of the Interaction models darker than the used attributes. As the darker attributes still are part of the model we did not remove them to prevent confusion. Thus, the active attributes of a model are lighter than the inactive attributes.

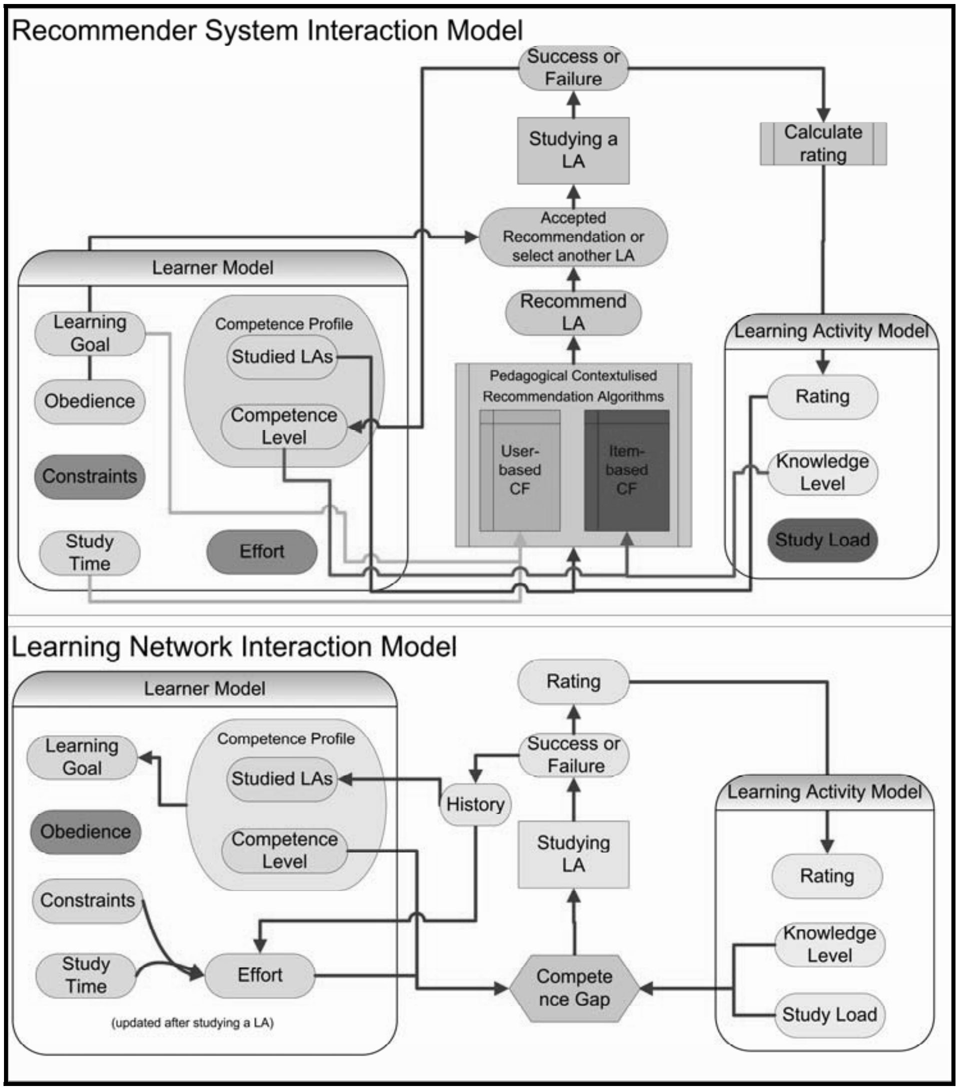


Figure 5.3: The underlying simulation model of the simulation consisting of *Learning Network Interaction Model* and a *Recommender System Interaction Model*. The models show the pendency between the *Learning Activity Model* and the *Learner Model* regarding the Learning Network as such and the recommender systems.

The Learning Network Interaction Model

The Learner Model

The *Learner Model* consists of variables we explain now in detail:

- The *Learning Goal* is a randomly distributed variable that defines the goal or interest of a learner.
- The *Competence Profile* is restricted to one competence which can include up to three *Competence Levels*. It is assumed that a learner will only start studying learning activities that can contribute to reach the *Learning Goal*. Successfully completed learning activities contribute to their associated *Competence Level*.
- Each *Competence Level* included in the *Learning Goal* has its own amount of learning activities that has to be successfully completed for its mastery.
- The *Competence Level* of the learner indicates the learner's achievement with respect to the *Learning Goal* and the influences by the results of *Success / Failure* value after the study period, thus it is a dynamic variable.
- The learner *Effort* is at the start of the simulation normally distributed amongst learners, but it changes dynamically during the learners study. The *Effort* value determines if a learner will drop out or not (Ryan & Deci, 2000). If the *Effort* gets below zero, a learner will drop out and will not graduate. *Effort* depends on *previous Effort*, *Competence Gap* between learners and learning activities, *Constraints,* and the *History* of *Success / Failures* values. Several successes in a row are expected to increase *Effort* (more motivated), whereas failure will have negative influences on the motivation of a learner, ultimately a learner could drop out of the Learning Network.
- *Constraints* are related to the research by (Koper, 2005). Koper mainly modeled negative constraints so called disturbance factors. Nadolski et al. added also positive factors and called these *Constraints*. *Constraints* are related to a learning flow, a noisy or quiet environment, stress, etc. They influence the amount of *Effort* learners want to invest for studying. Constraints are a randomized factor for each studied learning activity. For calculation purposes, we define constraints as '1' in case of positive effects, '-1' in case of negative effects, and '0' in case of a neutral effect.
- *Obedience* differs between learners but remains constant for each learner in the simulation. *Obedience* represents whether or not learners follow a

recommendation (Walker et al., 2004). In one of the previous studies we identified an obedience level of 60% (Drachsler et al., 2009) which is similar to other studies (Bolman et al., 2007). Thus, we aligned the *Obedience parameter* in the simulation with the result from the real world.

- The *Study Time* has the same scale as the simulation frequency (1 run = 1 week). It is also randomly distributed among the learners. It has an influence in case of a competence gap between a learner and a learning activity. A high *Study Time* can bridge the *Competence Gap* by investing more *Effort*.

The Learning Activity Model

The *Learning Activity Model* consists of variables we explain now in detail:

- *Rating* of a learning activity is based on the behavior of the learners and computed as an indirect measure. Ratings are influenced by whether or not the learner successfully completes a learning activity, and the *Effort* the learner spends. Except for *Rating*, all characteristics in the *Learning Activity Model* remain unchanged.
- The *Knowledge Level* is randomly distributed variable among the learning activities. It is a constant that represents the complexity of the learning activity.
- *The Study Load* is the time a learner has to invest before doing a learning activity examination.

The Actions between the Learner and Learning Activity Model

- The *Competence Gap* measures alignment between the *Competence Level* of the Learner and the *Knowledge Level* of the learning activity. A pedagogical reasonable match occurs if the *Knowledge Level* is one level above the *Competence Level of a Learner* (Vygotsky, 1978). Mismatches for competences will have a negative influence on learner's *Effort*, whereas good matches will increase *Effort*. Consequently, for learning activities that are a bit beyond learners' *Competence Level* more *Effort* can lead to their successful completion.
- If *Success* is true, the learner passes the learning activity examination and achieves the *Knowledge Level* corresponding to the learning activity and the learning goal and *Competence Level* will improve. A *Failure* will be registered in the *History* of the model and can have an influence on the

learner's *Effort* if the *Failures* occur more recently. A *Failure* will not decrease the *Competence Level* of a learner.

The Recommender System Interaction Model

- The same models apply for the *Recommender System Interaction Model* but different attributes of the previous explained models are used for the computation of the Learning Network. For instance the *Obedience* parameter is now needed to calculate if a learner obeys a recommendation or not. Also the recommendation algorithms and the rating mechanism are shown as a process to indicate that they are computed in this model.

- The most important object is the *Pedagogical Contextualized Recommendation Algorithm* shown as process in the model. It contains the item- and user based recommendation algorithms. For both algorithms the past studied learning activities and the Learning Goal of the learner is important. But both algorithms are differently pedagogical contextualized.

- The item-based algorithm (green) takes into account the current *Competence Level* of a learner and the required *Knowledge Level* of the learning activity. It orders the most best rated learning activities according to Vygotsky's rule and recommends learning activity that are one level above the *Competence Level* of the current learner.

- The user-based algorithm (yellow) makes advantage of the Learning Goal and the Study Time to cluster groups of Learners. From this sub selection of 'peer learners' it recommend best rated learning activities that are studied by the peers but so far not completed by the current learner. More details about the algorithms can be found in section *Pedagogical contextualization of the Collaborative Filtering techniques*.

Flow chart of the simulation

Having explained the underlying models we now want to present a flow chart diagram that explains how the simulation tool works for the computation of one study week (see Figure 5.3).

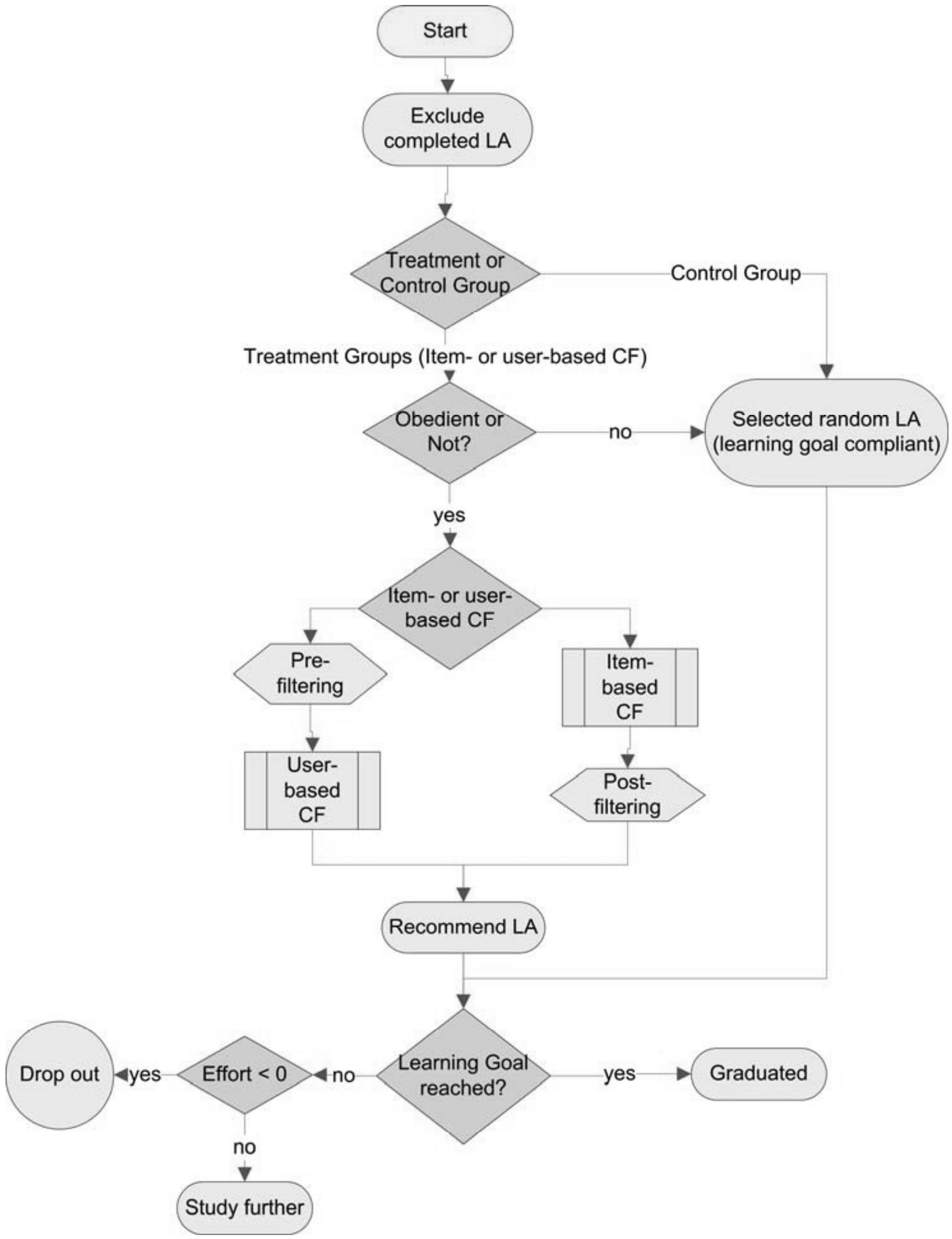


Figure 5.4: Flow chart of one simulation run.

In the beginning all completed *learning activities* are excluded from the *learning activities* that can be selected. Based on the *Treatment Groups* the learner belongs to, the simulation either decides for a random *learning activity* or they got a recommendation for specific *learning activities* based pedagogical contextualized by item- and user-based Collaborative Filtering. Only learners belonging to the *control group* will not get random recommendations. They always choose 'common sense' means that they act according to their *Learning Goal* but get a random learning activity that fits to their learning goal. Learners in *treatment groups* will always get recommendations and their obedience level determines the chance whether they obey or not. If they do not obey, they will always choose a learning activity 'common sense' similar to the control group complying with their learning goal. So, learners not following recommendations act like learners in the control group. Depending if the learner belongs to the user-based or item-based Collaborative Filtering the simulation does either *Pre-filter* suitable peer learners based on the *Learning Goal* and the *Study Time* and completed learning activities and looks for the best rated learning activity afterwards (user-based), or it first predicts the rating for all learning activities for a current learner and then *Post-filters* the most suitable learning activities based on the *Competence Level* of the learner and the *Knowledge Level* of the learning activity for the current learner (item-based filtering). The outcome of the algorithms is than recommended to the learners. Based on the success the learners have with the selected learning activity they either *Graduated* (if the *Learning Goal* is reached), or they *Drop out* (if the *Effort* becomes smaller than 0), or they just *Study further* (in this case they restart at the beginning of the flow chart).

Materials

The Netlogo simulation environment

The simulation model is implemented into a simulation environment called NetLogo 4.02 (Tisue & Wilensky, 2004; Wilensky, 1999). Figure 5.4 shows an integrated picture of the program flow in the simulation environment. NetLogo is a programmable modeling environment for simulating natural and social phenomena. It was authored by Uri Wilensky in 1999 and is in continuous development at the Center for Connected Learning and Computer-Based Modeling. NetLogo is following the swarm-based theory (Bonabeau, Dorigo, & Theraulaz, 1999) for modeling complex systems developing over time. It is therefore appropriate to model emerging effects like learners in an informal Learning Network. With the NetLogo scripting language researcher can easily give instructions to hundreds of independently working 'agents' or in our case learners. This makes it possible to explore the connection between the micro-level behavior of the learners supported by pedagogical contextualized filtering in a Learning Network and the macro-level impacts that emerge from the interaction of the learners in the Learning Network. The existing tool allows us to test new algorithms in this set up before running cost intensive real time experiments.

Configuration of the simulation tool

During the set up the following characteristics can be considered/defined (see Figure 5.5):

- which treatment groups should be enabled
- the learning goal: ranging from low-level goal (include 1 competence level) towards high-level goal (includes 3 competence levels)
- the Learning Network conditions (number of learners, number of learning activities, and the number of learning activities for each competence level in the Learning Goal to be achieved)
- the runtime of the simulation in years

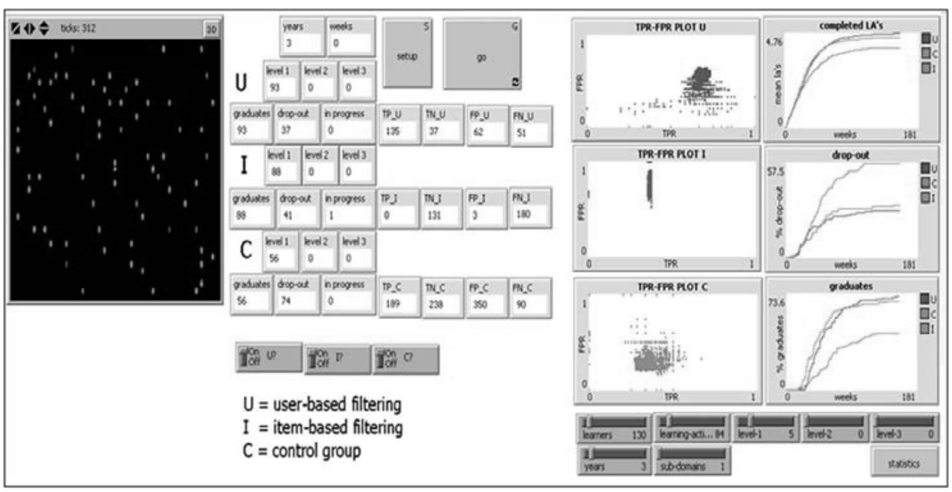


Figure 5.5: Screenshot of the simulation tool. On the left side a visual impression of the Learning Network is given. In the middle further details of the experimental groups U=User-based filtering, I = Item-based filtering, and C =Control group is presented. The amount of graduates, drop-outs and learners in progress are shown. On the right side, the completion of learning activities, graduations of learners and the drop-out rate is shown in the graphs. Additionally, the recordings of the Precision, Recall and F1 of the recommendation algorithms are shown. On the bottom, configurations panels of the simulation tool are placed.

Considering these values, the set up procedure initializes the environment as follows:

- each learning activity is initialized with a random competence level (1 to 3) and an estimated study time

- each learner is initialized with an uniformly distributed random: learning goal and available study time
- each learner starts with learner competence level 0 and will have the same learning goal
- each learner starts with a normally distributed random effort (M = 10, SD = 3).

Conditions of the simulation tool

Every condition in the simulation was replicated 12 times (i.e., N = 12 runs) to justify the use of classical statistic techniques on resulting data (Law & Kelton, 2000), analyzed with SPSS version 15 and Excel 2007. The source of the simulation program and simulation outcomes can be found at: http://hdl.handle.net/1820/1986. Each condition included *three treatment groups* User-based (U), Item-based (I) and one Control group (C).
For all runs, only 'graduates' or 'drop outs' were allowed after run length. In other words, no participants were 'still studying' after run length. The 8 settings and 3 treatment groups were used to test our 9 main hypotheses and to explore further differences between treatment group I and treatment group U.

The recommender system

Collaborative Filtering is one of the widely used recommendation technologies. It characterizes the relation between users and items implicitly by their previous interactions. The simplest example is to recommend the most used item to all users. Researchers in the machine-learning field are advancing Collaborative Filtering algorithm to provide personalized recommendation to users. Thus, specific item- and user-based Collaborative Filtering approaches are available. The main advantages of the techniques are the usage of 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, Konstan, & Riedl, 2000).
As mentioned earlier, for the simulation we want to focus on user-based and item-based Collaborative Filtering approaches and apply these for the support of learners in Learning Networks. We decided to apply the Slope-one algorithm (Lemire & Maclachlan, 2005) for user-based Collaborative Filtering and the Pearson correlation (Anderson et al., 2003) for the item-based approach to predict the rating of a learner for learning activities. Both approaches are further contextualized by pre-filtering the user-based approach and post-filtering the

item-based approach (see section *Pedagogical contextualization of the Collaborative Filtering techniques*).

We use the following notation to describe the Collaborative Filtering problem in Learning Networks. We notated the learning activities in the following 'LA'. The problem input is an $M \times N$ transition matrix $A=(a_{ij})$ associated with M learners $L = (L_1, L_2, \ldots, L_M)$ and N learning activities *learning activity* = $(LA_1, LA_2, \ldots, LA_N)$. We focus on recommendations based on transactional data between learners and learning activities. That is a_{ij} can take the value of 0 or 1, with 0 representing the absence of any transaction and 1 representing a successfully completed learning activity between L_i and LA_j. We considered a Collaborative Filtering algorithm output to be *likely values* for interesting learning activities for individual learners. The recommendation consists of a ranked list of K learning activities with the highest likely values for an individual learner.

User-based Collaborative Filtering

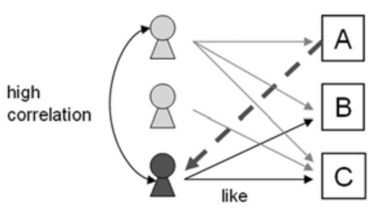


Figure 5.6: Technical drawing of user-based Collaborative Filtering algorithm (Kim, 2006)

User-based Collaborative Filtering correlates users by mining their (similar) ratings and then recommends new learning activities that were preferred by similar users (see Figure 5.6). The algorithm first computes a learner similarity matrix $WL = (wl_{st}),\ s, t = 1, 2, \ldots, M$. The similarity value wl_{st} is calculated based on the row vectors of A using for instance the *slope one* algorithm. A high similarity value wc_{st} indicates that learner s and t may have similar preferences since they have previously purchased a set of common learning activities. $WL \cdot A$ gives potential values of the learning activities for each learner. The element at the lth row and lath column of the resulting matrix aggregates the value of the similarities between learner l and other learners who have purchased learning activity la previously. In words, the more similar other learners to the target learner are, the more likely the target learner will also be interested in their learning activities because they seem to have the same background. Ratings are determined using the Slope-one algorithm ($f(x) = x + b$) by (Lemire & Maclachlan, 2005). It aims to predict the ratings of one individual based on his past ratings and on a database of ratings contributed by other users.

Item-based Collaborative Filtering

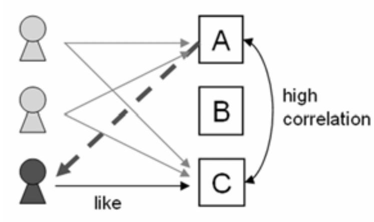


Figure 5.7: Technical drawing of item-based Collaborative Filtering algorithm (Kim, 2006)

Item-based techniques correlate the items by mining (similar) ratings and then recommend new, similar items (see Figure 5.7). The item-based algorithm is therefore different from the user-based algorithm only in that item similarities are computed instead of user similarities. In our case, this algorithm first computes a learning activity similarity matrix $WLA = (wla_{st})$, s, $t = 1, 2, \ldots, N$. Here, the similarity value wp_{st} is calculated based on column vectors of A. A high similarity value wp_{st} indicates that learning activity s and t are similar in the sense that they have been studied by similar learners. $A \cdot WLA$ offers the *likely value* of the learning activities for each learner. Here, the element at the lth row and lath column of the resulting matrix aggregates the values of the similarities between learning activity la and other learning activities previously purchased by learner l. In words, the more similar to the target learning activity the learning activities studied by the target learner are, the more likely the target learner will also be interested in that learning activity. Ratings are determined using the Pearson r correlation (Anderson et al., 2003). Pearson r is a common measure of the correlation (linear dependence) between two items.

Pedagogical contextualisation of the Collaborative Filtering techniques

Contextualized recommender systems also called context-aware recommender systems (Lemire et al., 2005) take into account for instance the location of a user (or additional information like date, season or the temperature) and relevant identifies objects near to the user (Dey, Abowd, & Salber, 2001). In our case we want to take into account already mentioned aspects like prior knowledge, study time and learning goals to embed pedagogical reasoning into the recommendation. Context-aware recommender systems can be distinguished between

1. contextualized pre-filtering, 2. contextualized post-filtering, and 3. contextualized modeling.

These approaches distinguish from each other. For contextualized pre-filtering the contextual information selects data according to the context, the ratings are predicted using a traditional recommender on the pre-selected data. Thus, it uses the contextual information to select the most relevant data for generating recommendations.

Post-filtering is slightly different, the ratings are predicted on the whole data using traditional recommender approaches and further contextualize the top-N rated items to a user. Thus, it ignores context during the recommendation phase instead it adjusts the ranking of top-N recommendation using the contextual information.

For our simulation tool we decided to focus on pre-filtering for the user-based approach and post-filtering for the item-based approach as we did not offer any multidimensional rating system behind.

The pre-filter procedure for user-based Collaborative Filtering was triggered by matching suitable learners together. A suitable learner was identified by comparing the learning activity-history of learners with each other, and the peer should follow the same learning goal and should have the same competence level and study time. As an example if the current learner has successfully completed learning activity 'Y', peers should also have completed learning activity 'Y' successfully. But peers should also have studied other learning activities as well, which is not yet completed by the current learner. From this combined list of candidate learning activities a random one was chosen from the top-5 list of learning activities.

The post-filtering procedure for item-based filtering was triggered by creating a similarity matrix based on the Pearson correlation r. On top of this matrix we added a filtering mechanism that results a top-n list of predictions. We filtered learning activities on the base that they had to be in line with the learning goal of the current learner, further the candidate learning activities had to follow Vygotsky zone of proximal development (Vygotsky, 1978). Thus, the candidate learning activities had to be one level above the competence level of the learner to be recommended to the learning activity. Therefore, the item-based approach is more driven by the needs of a learner instead of interaction with other peer-learners.

Data set

Regarding the gap of available data sets for the evaluation of recommender systems for learning and especially for Learning Networks, we decided to use synthesized data sets (Konstan et al., 1997) in the simulation rather than applying a data set that imperfectly matches the properties of a Learning Network. Therefore, we modeled the learning activities in the simulation with a fixed number of characteristics and learners which own preferences like learning goal, study time and competence level. For the design of a simulation tool that acts as a first evaluation phase for recommender algorithms in Learning Networks we decided to use synthesized data sets rather than imperfectly adapted data sets. Furthermore, with the ongoing research in this field we expect that in the future data sets will be available to improve our simulation tool.

Procedure

Encoding of the Hypotheses

According to Drachsler, Hummel. and Koper (2009), we applied six measurements to evaluate the impact of the recommender system algorithms on the learners. Three measures from the educational research field (Effectiveness, Satisfaction, and Efficiency) and three measures from recommender system research (Precision, Recall, and F1). Precision and Recall are the most popular metrics for evaluating information retrieval systems. They are also common for the evaluation of recommender systems (Basu, Hirsh, & Cohen, 1998; Sarwar et al., 2000; Sarwar et al., 2002). In the following section we further describe the measures:

- Effectiveness

Learners will drop out if their effort falls below zero and when they consequently fail to reach their learning goal. Reaching their learning goal equals graduating. Identifying effectiveness of the recommender system will be based upon the percentage of learners reaching their learning goal (Graduates). A higher percentage of graduates indicate more Effectiveness.

- Satisfaction

Satisfaction is measured when learners achieve their learning goal. We suppose that a higher proportion with broad satisfaction (effort > 14) at learning goal completion indicates that they are more satisfied at graduation than a lower proportion with broad satisfaction at graduation. The amount of effort is related to satisfaction with the learning progress as a whole.

- Efficiency

Efficiency is measured as the total time to graduate. Learners graduated if they reached their learning goal within the Learning Network. The impact of recommender systems on time efficiency is determined by identifying learners' total study time for achieving their learning goal: time to graduate. The less time they need to graduate, the more efficient they are.

- Precision

Precision is defined as the ratio of relevant learning activities selected by the recommendation algorithm compared to a number of learning activities selected by the learners. It shows the percentage of the recommended learning activities the learner truly likes.

- Recall

Recall is defined as the ratio of relevant learning activities selected by the recommendation algorithm to a total number of relevant learning activities available. It represents the probability that a relevant learning activity will be selected by the learners.

- F1-Measure

The F1 Measure balances Precision and Recall into a single measurement. Related research applies F1 to measure accuracy of recommender system classification (Schafer, Konstan, & Riedl, 1999), while F1 provides the primary measurement for comparing different techniques, comparing Precision and Recall provides important additional insights into the utility of a recommender algorithm.

Analysis of Effectiveness, Efficiency and Satisfaction

The measure for the hypotheses was tested by using regular statistical methods in SPSS 15. We applied the analyses of variance on a global level, continuing with Bonferroni's correction when using multiple comparisons at a more detailed level. Here, multiple comparisons were always conducted between the control group and one of the treatment groups. We also compared both treatment groups against each other. A significant interaction of contrast scores within the groups was followed by testing of simple contrast effects. Due to the a priori character of these tests, they were performed with the conventional Type I error of .05 (Tabachnick & Fidell, 2001).

Analysis of Precision, Recall and F1

Precision and Recall are computed from a 2 * 2 confusion matrix, like the one shown in Table 5.1. The confusion matrix combines the observed classifications for a phenomenon (columns) with the predicted classifications of a model (rows). Therefore, the items to recommend must be separated into two classes — relevant or irrelevant. Thus, we transform the rating scale of 1–5 stars into a binary scale by converting every rating of 2.5 – 5 to 'relevant' and all ratings of 1 – 2.5 to 'irrelevant.' This allows four possible classifications for each instance: true positives (TP - correct recommendations), true negatives (TN - correct rejections), false positives (FP - false recommendations), or false negatives (FN - missed recommendations). In Table 5.1, the white fields are the correct classifications (the true positives and the true negatives). The other fields present errors of the recommendation algorithm. For a perfect model we would only see the true positive and true negative fields filled out, the other fields would be set to zero.

Table 5.1: Format of a confusion matrix

		Observed	
		True	**False**
Predicted	**True**	True Positive (TP)	False Positive (FP)
	False	False Negative (FN)	True Negative (TN)

The Precision, Recall and F1 measures are calculated by formulas on base of this confusion matrix (see Table 5.2). The simulation tool recorded all observed and predicted values over a simulation run and stored them in a separated file. In Excel we computed the measures of the recommender system algorithms for each run and took the average and standard deviation of 12 conducted runs as a final result.

Table 5.2: Precision, Recall and F1 measures and the formulas for their calculation.

Measures	Formula
Precision (p)	TP / (TP + FP)
Recall (tpr)	TP / (TP + FN)
F1-Measure	(2 * tpr * p) / (tpr + p)

Results

The result section presents findings regarding our 9 hypothesis for the 8 conditions relating to the differences found between the 3 treatments. Subsection 'Treatment groups vs. Control groups' addresses test results of our hypothesis regarding the treatment groups compared to the control group. Subsection 'Treatment groups vs. Control groups' compares the results of treatment groups against each other. An overview of the data means and standard deviations can be found in Table 5.3.

Table 5.3: Overview of the performance of groups in 8 Learning Networks of different sizes.

Type of LN	Variables	Treatment					
Learning Goal - Level 1							
		User-based CF (U)		Item-based CF (I)		Control (C)	
Small LN[1] - 150 learners 60 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	67,6%	3,8%	64,7%	5,6%	22,8%	5,1%
	Satisfaction	41,8%	4,0%	33,7%	5,8%	6,8%	2,6%
	Efficiency (hours)	2160,6	469,8	1855,7	355,91	2455,3	379,1
	Precision	70,3%	3,8%	59,2%	3,5%	34,1%	3,4%
	Recall	66,0%	3,7%	90,0%	1,9%	59,8%	2,9%
	F1	68,1%	3,7%	71,4%	2,9%	43,3%	2,9%
Small LN[1] - 60 learners 150 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	58,2%	58,3%	63,2%	63,3%	19,7%	7,1%
	Satisfaction	33,2%	8,8%	30,3%	5,8%	5,0%	4,6%
	Efficiency (hours)	2017,7	417,5	1855,4	377,3	2421,1	445,1
	Precision	70,2%	2,4%	76,5%	2,4%	34,6%	2,9%
	Recall	69,7%	2,6%	74,1%	4,9%	60,8%	2,7%
	F1	70,7%	2,5%	75,2%	3,3%	44,0%	2,1%
Learning Goal - Level 3							
Small LN[1] - 150 learners 60 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	46,4%	14,0%	53,7%	5,5%	24,0%	0,0%
	Satisfaction	43,3%	0,0%	46,9%	5,4%	18,7%	0,0%
	Efficiency (hours)	2986,3	385,1	2973,6	424,9	3120,6	344,5
	Precision	95,4%	0,7%	63,6%	0,0%	40,0%	0,0%
	Recall	95,0%	0,9%	61,3%	0,0%	60,3%	0,0%
	F1	95,2%	0,7%	62,4%	0,0%	48,1%	0,0%
Small LN[1] - 60 learners 150 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	57,1%	6,6%	71,5%	16,6%	29,0%	7,3%
	Satisfaction	55,7%	7,4%	53,3%	8,2%	26,9%	7,3%
	Efficiency (hours)	3031	413,1	3021,4	421,3	3182,4	473,1
	Precision	66,2%	2,9%	55,5%	2,0%	44,3%	2,1%
	Recall	63,4%	3,3%	86,9%	2,0%	59,6%	2,4%
	F1	64,7%	3,0%	67,7%	1,7%	50,8%	1,9%

Type of LN	Variables	Treatment					
Learning Goal - Level 1							
Large LN[1] - 400 learners 250 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	68,8%	3,9%	68,3%	3,9%	20,8%	5,9%
	Satisfaction	42,9%	5,3%	35,9%	5,1%	6,5%	2,8%
	Efficiency (hours)	1916,82	385,818	1836,26	357,574	2413,83	445,3
	Precision	71,5%	1,0%	58,6%	1,3%	37,3%	1,7%
	Recall	71,9%	0,9%	88,1%	1,1%	59,7%	0,9%
	F1	71,7%	0,9%	70,4%	1,0%	45,9%	1,3%
Large LN[1] - 250 learners 400 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	67,6%	3,8%	64,7%	5,6%	22,8%	5,1%
	Satisfaction	41,8%	4,0%	33,7%	5,8%	6,8%	2,6%
	Efficiency (hours)	1935,37	389,9	1847,1	361,5	2377,8	443,1
	Precision	72,5%	1,2%	58,0%	2,0%	38,1%	2,4%
	Recall	72,3%	1,6%	78,5%	1,9%	59,8%	1,2%
	F1	72,4%	1,2%	66,7%	1,5%	46,5%	1,9%
Learning Goal - Level 3							
Large LN[1] - 400 learners 250 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	65,5%	4,0%	71,5%	4,7%	32,7%	6,3%
	Satisfaction	64,3%	4,0%	65,6%	4,0%	30,1%	6,5%
	Efficiency (hours)	2924,6	382,6	2898,4	395,1	3172,2	449,2
	Precision	66,7%	0,9%	56,7%	0,8%	44,0%	2,1%
	Recall	67,6%	0,8%	92,6%	0,7%	59,6%	1,0%
	F1	67,1%	0,7%	70,3%	0,6%	50,6%	1,5%
Large LN[1] - 250 learners 400 learning activities							
		M	*SD*	*M*	*SD*	*M*	*SD*
	Effectiveness	61,9%	5,1%	65,2%	2,2%	31,9%	4,0%
	Satisfaction	60,7%	5,4%	61,6%	2,4%	29,6%	3,9%
	Efficiency (hours)	2967,9	401,4	2965,9	385,9	3159,4	448,5
	Precision	68,8%	1,1%	55,7%	1,1%	44,0%	1,9%
	Recall	68,6%	1,5%	88,7%	0,9%	59,7%	1,1%
	F1	68,7%	1,2%	68,4%	1,0%	50,7%	1,5%

[1] LN = Learning Network

Treatment groups vs. Control group

Effectiveness

Analyses of variance showed for all 8 conditions a significant difference in the percentage of Graduates between the control group and the treatment groups (Table 5.4). This confirms hypothesis H1, both recommendation algorithms yield to more graduation than no recommendations. Each condition showed that the control group always had significant fewer graduates than all other groups.

Table 5.4: Overview about significant results regarding Effectiveness between treatment groups and control group.

Goal	Type of LN	Analyze of variance		p	Multiple Comparisons
		F	*MSE*		(mean difference between two groups, p < .05*)
Level-1	Small LN - 150 L 60 LA	F (2, 5399) = 694,017	517,762	<.05	C less graduate than any *T*
	Small LN - 60 L 150 LA	F (2, 2159) = 191,777	1,62E+02	<.05	C less graduate than any *T*
Level-3	Small LN - 150 L 60 LA	F (2, 5399) = 65,553	487,334	<.05	C less graduate than any *T*
	Small LN - 60 L 150 LA	F (2, 2159) = 33,630	51,675	<.05	C less graduate than any *T*
Level-1	Large LN - 400 L 250 LA	F (2, 14399) = 1826,104	1,45E+03	<.05	C less graduate than any *T*
	Large LN - 250 L 400 LA	F (2, 8999) = 907,442	754,33	<.05	C less graduate than any *T*
Level-3	Large LN - 400 L 250 LA	F (2, 14399) = 315,851	7,65E+02	<.05	C less graduate than any *T*
	Large LN - 250 L 400 LA	F (2, 8999) = 147,329	4,30E+02	<.05	C less graduate than any *T*

*Notes: C = control group. T = both treatment groups. Different 'n'-s in the F-statistics as conditions differ in number of graduates, LN = Learning Network, L = Learner, LA = Learning Activities

Efficiency

Analyses of variance showed for all 8 conditions a significant difference in time to graduate between the treatment groups and the control group (see Table 5.5). This confirms hypothesis H2 that both recommendation algorithms yield to faster graduation than no recommendations.

Table 5.5: Overview about significant results regarding Efficiency between treatment groups and control group.

Goal	Type of LN	Analyze of variance		p	Multiple Comparisons
		F	*MSE*		(mean difference between two groups, p < .05*)
Level-1	Small LN - 150 L 60 LA	F (2, 2030) = 245.161	3,95E+10	<.05	C more time to graduate than any T
	small LN - 60 L 150 LA	F (2, 1015) = 95,106	1,55E+07	<.05	C more time to graduate than any T
Level-3	small LN - 150 L 60 LA	F (2, 2309) = 22,527	3519493	<.05	C more time to graduate than any T
	small LN - 60 L 150 LA	F (2, 1026) = 11,075	2039589	<.05	C more time to graduate than any T
Level-1	large LN - 400 L 250 LA	F (2, 7573) = 890.309	1,30E+08	<.05	C more time to graduate than any T
	large LN - 250 L 400 LA	F (2, 4651) =484,981	7,26E+07	<.05	C more time to graduate than any T
Level-3	large LN - 400 L 250 LA	F (2, 8045) = 270,731	4,37E+07	<.05	C more time to graduate than any T
	large LN - 250 L 400 LA	F (2, 4768) = 86,294	1,42E+07	<.05	C more time to graduate than any T

*Notes: C = control group. T = both treatment groups. Different 'n'-s in the F-statistics as conditions differ in number of graduates, LN = Learning Network, L = Learner, LA = Learning Activities

Satisfaction

Analyses of variance showed again for all 8 conditions a significant difference in the percentage of broad satisfaction at graduation between the treatment groups and the control group. The control group always had significant smaller percentages of graduation with broad satisfaction than any treatment group. This confirms hypothesis H3 regarding the positive effects of both algorithms (Table 5.5).

Precision, Recall and F1

As presented in Table 5.3 in all 8 conditions a high difference in the percentage of Precision, Recall and the combination of both in F1 appeared between the control group and the treatment groups (Table 5.3). The algorithms of the treatment groups performed overall more accurate than the random selection. This finding supports the results that the treatment groups received more accurate recommendations and where therefore able to performed more efficient and effective compared to the control group. The measures of the control group stayed rather stable in all 8 experiment settings with a Precision rate around 34%, a Recall rate around 59%, and the F1 measure around 50% which also indicates the randomness in the selection of learning activities.

Table 5.6: Overview about significant results regarding Satisfaction between treatment groups and control group.

Goal	Type of LN	Analyze of variance		p	Multiple Comparisons
		F	*MSE*		(mean difference between two groups, p < .05*)
Level-1	Small LN - 150 L 60 LA	F (2, 2030) = 54,279	1,78E+03	<.05	C more effort to graduate than any *T*
	Small LN - 60 L 150 LA	F (2, 1015) = 28,455	8,75E+02	<.05	C more effort to graduate than any *T*
Level-3	Small LN - 150 L 60 LA	F (2, 2309) = 25,219	317,373	<.05	C more effort to graduate than any *T*
	Small LN - 60 L 150 LA	F (2, 1026) = 7,517	55,536	<.05	C more effort to graduate than any *T*
Level-1	Large LN - 400 L 250 LA	F (2, 7573) = 252,578	6913,158	<.05	C more effort to graduate than any *T*
	Large LN - 250 L 400 LA	F (2, 4651) = 143,307	4,11E+03	<.05	C more effort to graduate than any *T*
Level-3	Large LN - 400 L 250 LA	F (2, 8045) = 108,880	6,91E+02	<.05	C more effort to graduate than any *T*
	Large LN - 250 L 400 LA	F (2, 4768) = 49,051	2,90E+02	<.05	C more effort to graduate than any *T*

*Notes: C = control group. T = both treatment groups. Different 'n'-s in the F-statistics as conditions differ in number of graduates, LN = Learning Network, L = Learner, LA = Learning Activities

Treatment Group I vs. Treatment Group U

Effectiveness

Regarding the Effectiveness of both treatments we did not find any significant difference between both groups. However, treatment I performed often better according to descriptive measures. But the difference was not found to be significant. Therefore, we have to reject hypothesis H4 and H7 because none of the algorithm performed significant better in a certain Learning Network than the other one.

Efficiency

We found difference between treatment group I and treatment group U regarding Efficiency on learners that followed 1 learning goal. Treatment group I, needed constantly less time to complete equal amounts of learning activities. This result was also confirmed by SPSS with a significant effect for the 4 Learning Networks with learners following one learning goal (see Table 5.7). Treatment group I performed here significant faster than treatment group U. We did not find this difference for the Learning Networks where learners followed 3 learning goals.

Table 5.7: Overview about significant results regarding Efficiency between treatment group I and treatment group U.

Goal	Type of LN	Analyze of variance		p	Multiple Comparisons
		F	*MSE*		(mean difference between two groups, p < .05*)
Level-1	Small LN - 150 L 60 LA	F (2, 2030) = 245.161	3,95E+10	<.05	T(I) needed less time to graduate than T(U)
	Small LN - 60 L 150 LA	F (2, 1015) = 95,106	1,55E+07	<.05	T(I) needed less time to graduate than T(U)
	Large LN - 400 L 250 LA	F (2, 7573) = 890.309	1,30E+08	<.05	T(I) needed less time to graduate than T(U)
	Large LN - 250 L 400 LA	F (2, 4651) =484,981	7,26E+07	<.05	T(I) needed less time to graduate than T(U)

*Notes: T (I) = item-based Collaborative Filtering. T (U) user-based filtering. Different 'n'-s in the F-statistics as conditions differ in number of graduates, LN = Learning Network, L = Learner, LA = Learning Activities

Further, it seems to make no difference whether the algorithms where applied in small or large Learning Networks, neither if the Learning Network consist of more user or more items. Therefore, we partly accepted H5 for small Learning Networks with learners following 1 learning goal but we have to reject H8.

Satisfaction

Analyses of variance showed for all 4 conditions on learning goal 1 a significant difference in the percentage of satisfaction at graduation between the treatment groups I and U (see Table 5.8). Treatment group I was found to be significantly more satisfied than Treatment group U. This confirms hypothesis H2 that both recommendation algorithms yield to more satisfaction than no recommendations. This result partly confirms H6 as all Learning Networks with students following 3 learning goals showed no significant difference between treatment I and U. We have to reject H9 as no large Learning Network showed positive effects for treatment group U.

Table 5.8: Overview about significant results regarding Satisfaction between treatment group I and treatment group U.

Goal	Type of LN	Analyze of variance		p	Multiple Comparisons
		F	*MSE*		(mean difference between two groups, p < .05*)
Level-1	Small LN - 150 L 60 LA	F (2, 2030) = 54,279	1,78E+03	<.05	T(I) had less effort to graduate than T(U)
	Large LN - 250 L 400 LA	F (2, 7573) = 252,578	6913,158	<.05	T(I) had less effort to graduate than T(U)
	Large LN - 400 L 250 LA	F (2, 4651) = 143,307	4,11E+03	<.05	T(I) had less effort to graduate than T(U)

*Notes: T (I) = item-based Collaborative Filtering. T (U) user-based filtering. Different 'n'-s in the F-statistics as conditions differ in number of graduates, LN = Learning Network, L = Learner, LA = Learning Activities

Precision, Recall and F1

As presented in Table 5.3 in all 8 conditions the F1 measures overall showed similar values for treatment group U and treatment group I. Most of the time, there are no high difference between both groups. Nevertheless, the F1 measures of the treatment I are in 3 out of 4 small Learning Networks better than the treatment U. Therefore, treatment U shows better F1 values in 2 out of 4 large Learning Networks, whereas one large Learning Network shows equal values and one shows better results for treatment I.

Overall, it appears that the treatment U had rather consistent Precision, Recall and F1 measures in its dissemination over all Learning Networks, whereas treatment I most of the time showed a high Recall value and a rather low Precision value. According to Herlocker et al. (2000) such an effect indicates the length of the list of items to be recommended. When more items are recommendable, then the Recall value increases and the Precision value decreases. This result is reasonable when we reconsider the algorithm design. The recommendable learning activities from treatment U were pre-filtered by peer-learners therefore the result set of similar learning activities was smaller. Treatment I first computed the similarity measures of all learning activities and filtered on top of all similar learning activities the most suitable for the current competence level and learning goal of a current learner. Thus, treatment I had most of the time a larger result set than treatment group U. In combination with the prior knowledge contextualization this approach was more effective for the navigation support on the learners than treatment U with peer learner contextualization.

Finally, we have to state that the results of small Learning Networks with 150 learners and 60 learning activities show an exceptional run of all conducted simulations. Treatment U had very high Precision, Recall and F1 values and also treatment I was rather consistent in this setting. This seems to be related to a selection problem, because disseminating 60 learning activities over a learning goal consisting of 3 competence levels resolves into small amounts of different learning activities in the Learning Network. Thus, there was no real selection problem anymore.

Conclusion and future research

This last section starts with a summary and discussion of results. Thereafter, we address the limitations of this simulation study and finally, we give an outlook for future research.

Important findings and discussion

Like Nadolski et al. (2009) our simulation study demonstrate the advantage of navigation support by recommender systems in informal Learning Networks. We can confirm findings by Nadolski et al. that navigation support by a treatment is still better than the control group without any navigation support. This can be further extended by knowing that the item-based treatment I outperformed the user-based treatment U regarding Efficiency and Satisfaction measures in Learning Networks with learners focusing on learning goal at level 1. Nadolski et al. further found that ontology-based recommendations mostly result in better graduations and in less time to graduate than Collaborative Filtering approaches in Learning Networks with learners following learning goals at level 3. This may explain why we did not found significant differences between user- and item-based Collaborative Filtering as both algorithms are part of the Collaborative Filtering family.

However, we are surprised that both treatments did not differentiate in Learning Networks of different sizes, even if there are more learning activities or more learners in the Learning Network. By introducing complex learning goals both treatments got more equal to each other based on their measures. Even the control group got than closer to them based on its educational measures. This might be related to the total amount of learning activities in the simulation. The amount of alternative learning activities per learning goal decreases because they are distributed on multiple complexity levels. Therefore, the amount of alternative learning activities gets smaller and less personalization is possible. Consequently, also the influence and the differences between both treatments decreases and their measures conform to each other. For follow-up studies we should enlarge the amount of learning activities if complex learning goals are part of the research. This conclusion also has an impact on real world experiments. The support of learners with complex learning goals requires large Learning Networks with multiple alternative learning activities, otherwise contextualized recommendation techniques are rather limited in their navigation support on learners.

Table 5.9: Total numbers of values found to be significant different between treatment I and U.

Level-1	User-based Collaborative Filtering (U)		Item-based Collaborative Filtering (I)	
Small LN - 150 L - 60 LA	M	SD	M	SD
Effectiveness (%)	67,63%	3,80%	64,67%	5,63%
Satisfaction (%)	41,83%	4,05%	33,67%	5,80%
Efficiency (hours)	2160,6	469,8	1855,7	355,91
Small LN - 60 L 150 LA				
	M	SD	M	SD
Effectiveness (%)	58,19%	9,10%	63,19%	9,40%
Satisfaction (%)	33,19%	8,83%	30,28%	5,85%
Efficiency (hours)	2017,7	417,5	1855,4	377,3
Large LN - 400 L - 250 LA				
	M	SD	M	SD
Effectiveness (%)	68,77%	3,92%	68,25%	3,87%
Satisfaction (%)	42,88%	5,25%	35,94%	5,10%
Efficiency (hours)	1916,82	385,818	1836,26	357,574
Large LN - 250 L - 400 LA				
	M	SD	M	SD
Effectiveness (%)	67,63%	3,80%	64,67%	5,63%
Satisfaction (%)	41,83%	4,05%	33,67%	5,80%
Efficiency (hours)	1935,37	389,9	1847,1	361,5

**Notes: T (I) = item-based Collaborative Filtering. T (U) user-based filtering. LN = Learning Network, L = Learner, LA = Learning Activities*

Further, treatment I with the item-based pedagogical contextualization (Competence level information about the learner and knowledge level information of the learning activity) had a stronger impact than treatment U with the peer-grouping contextualization by the user-based approach. Treatment I often performed significant better than the treatment U according to Efficiency and Satisfaction. Looking only at the total of numbers (see Table 5.9) of the significant differences we can see that treatment I with post-filtering enabled learners to study faster and contributed stronger to their competence development. A prove of this is also the higher amount of satisfied learners which invested less effort and completed learning activities more often. We do not believe that these results are related to the similarity algorithms (Slope-one or Pearson r), rather than to the pre- and post-filtering methods. Treatment U had fewer learning activities to select from because the pre-filtering personalized the amount of similar learning activities to the costs of smaller result sets of learning activities compared to treatment group I. A prove of this smaller amount of suitable learning activities of treatment U are also the higher Recall and the lower Precision rates of treatment I. These values indicate larger results sets of learning activities that can be recommended to the learners. As a conclusion, the combination of the prior knowledge post-filter from treatment I was more effective for the navigation support on learners than the pre-filtering by peer learners from treatment U.

Limitations

Compared to other researchers that take advantage of simulations we face similar limitations; 1. The Simulation only models part of the world, 2. The simulation simplifies real world conditions, 3. Some decisions in the simulation are made on arbitrary choices and 4. Limited access to real data sets.
Regarding 1, the incompleteness of a simulation is always present as it represents only a part of the real world and always misses some features. Nevertheless, we have to stress how and where improvements for the current simulation can be done. One major constraint is a lack of direct learner interaction within the Learning Network, only indirect social interactions by the recommendation algorithm are modeled. In reality there is always a combination of indirect and direct social interaction and direct social interaction has an impact on choices to be made. Further, we did not design learning activities that emerge by contributions of the learners. In the current simulation we made a scalable amount of learning activities that existed from the very beginning until the end of the simulation.
Regarding 2, the simplification of the real world is related to the first point. One example is how competences are modeled within the simulation. In the real world competences are not isolated; they always build on other competences and they are closely related to each other. Our conceptual simulation model does not deal with competence relations or hierarchies therefore it is rather simple. Another example is the definition of a learning activity, when we consider user-generated content as a source for informal Learning Networks, it is hard to determine if particular content is equal to a learning activity. However, in our simulation we purely modeled learning activities, in the real world there might be much more noise in informal Learning Networks as not any content is suitable for a learning activity.

Regarding 3, we were sometimes forced to make arbitrary choices as a lack of knowledge about real behavior was missing. For example obedience is randomly distributed on the learners but its factor remains static. In real life, obedience is influenced by the satisfaction of the learner with the recommendations. However, there is a lack of psychological knowledge regarding negative and positive behavior towards recommendations. When do learners reject a recommendation and when they are satisfied with particular recommendations.
A disadvantage is the limited availability of rated data sets from informal Learning Networks. There is still to less data available even when we build the simulation already on iterative research results. Further, there is no standardized way to use a rated data set for simulation studies. The creation of usable rated data sets should be addressed in follow-up experiments to offer input for future simulations.

Future research

Results from our simulation studies will have to be further validated in real-life experiments. Future experiments on Learning Networks with real learners should verify the value of navigation support by pedagogical contextualized Collaborative Filtering recommendations. After proving similarity between real world experiments and the presented simulation studies we can continue iterations between simulations and field experiments to provide valuable insights into the technical infrastructure to provide recommendations to learners in Learning Networks.
Actually, we planned to run a follow-up experiment in the domain of Open Educational Resources (OER) regarding informal Learning Networks. But OER are most of the time created by domain experts instead of the learners themselves thus they do not really fit our concept of informal Learning Networks. Therefore, we want to take up the user-generated content idea and focus on information sources from Web 2.0 service like delicious and blog systems. Such a pilot study would solve two problems at once. First of all, it would enable us to test the algorithms we created and pre tested in the simulation study in real life settings and extend it with tagging information. Secondly, it would help us to create a data set of a particular domain that can be used afterwards as input for a follow-up simulation study.
Inspiring examples of such a pilot study are Personal Environments like *iGoogle* or *Netvibes*. They enable users to combine information sources from different providers or networks into one place. After doing so the users can observe the

latest information of their sources and networks at a personal page. In order to make advantage of this technology we have to design a Personal Learning Environment (PLE) that enable learners to include sources from Web 2.0 services into the PLE. PLEs are in contrast to other approaches of virtual learning environments (VLE) like Moodle or Blackboard, which are designed along common educational structures like universities. VLEs are top-down designed and focus on the needs of institutions to mange learners, learning activities, and learning plans. PLEs explicitly address informal learning processes of learners. To test the impact of recommender systems we have to add a recommender system to the PLE to personalize the information of the emerging Learning Network of the learners to offer individual recommendations based on their tags and ratings to the learners. In order to apply the tested algorithms of this study the learners have to specify their learning goals and the competence level besides their favorite Web 2.0 sources.

Chapter 6

ReMashed – Recommendations for Mash-Up Personal Learning Environments

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Abstract

The following chapter presents a Mash-Up Personal Learning Environment called ReMashed that recommends learning activities from emerging information of a Learning Network. In ReMashed learners can specify certain Web2.0 services and combine them in a Mash-Up Personal Learning Environment. Learners can rate information from an emerging amount of Web2.0 information of a Learning Network and train a recommender system for their particular needs. ReMashed therefore has three main objectives: 1. to provide a recommender system for Mash-up Personal Learning Environments to learners, 2. to offer an environment for testing new recommendation approaches and methods for researchers, and 3. to create informal user-generated content data sets that are needed to evaluate new recommendation algorithms for learners in informal Learning Networks.

Introduction

Nowadays, Internet users take advantage of services like *iGoogle* or *Netvibes* to create a personal view on information they are interested in. *iGoogle* and *Netvibes* offer a Personal Environment (PE) that allows their users to add and combine different information sources of the Internet at one place. The advantages for the users are obvious; they can observe and read the latest information from an information provider without browsing to the source. Further, by integrating Web 2.0 services like *Flickr*, *Delicious* or *Slideshare* the user can follow other users and integrate networks of users into such a PE. The fuel for this interoperability is the XML standard RSS (Really Simple Syndication). Every common service or blogging software takes advantage of it to spread its information in the Internet. RSS enables users of PEs to be notified about latest update on their favorite information sources.

The existing of PEs inspired researchers in TEL to explore this technology for learning purposes. As a consequence Personal Learning Environments (PLEs) were invented for learners (Liber, 2000; Liber & Johnson, 2008; Wild, Kalz, & Palmer, 2008; Wilson, 2005). PLEs are a kind of instance of the Learning Network concept (Koper & Sloep, 2002; Koper & Specht, 2006; Koper & Tattersall, 2004) and therefore share several characteristics with it. Learning Networks consist of user-generated content by learners who are able to create, comment, tag, rate, share, and study learning activities. Learning Networks make advantage of the wisdom of the crowd theory and Web 2.0 developments (Surowiecki, 2005). By the emerging behavior of such a Learning Network it may consist of a large amount of learning materials. Learning Networks are bottom-up driven because their content is not created by specially trained and paid domain experts but rather by their members. These networks explicitly address informal learning because no assessment or accreditation process is connected to them. PLEs also support informal learning as they require no institutional background and focus on the learner instead of institutional needs like student management or assessments. The learners do not participate in formal courses and neither receive any certification for their competence development. Similar to the PE concept, PLEs are used to combine different sources of information on the web that is supportive for the individual learner regarding their personal competence development. Most of the time, the sources are free to use and selected by the learner. PLEs are therefore in contrast to existing Virtual Learning Environments (VLEs) like Moodle or Blackboard that are offered by institutions to distribute learning material to learners. VLEs focus more on the institutional needs and offer support for business processes of educational institutes like Universities.

A common problem for Mash-Ups and PLEs is the amount of data that is gathered in a short time frame. The learners can be overwhelmed by the information they get or they might have problems selecting the most suitable learning material for their personal competence development. On the one hand, PLEs provide learners much more freedom to choose learning material from a number of providers, on the other hand the learners have an increasing responsibility for the results of their own learning process (Longworth, 2003). In such a situation it is hard to get an overview of available learning material and to identify the most suitable for them. Therefore, we developed a recommender system that offers advice to learners based on their Web 2.0 resources regarding suitable learning materials to meet their individual competence development. The combination of different Web 2.0 services to recommend information based on mashed tag and rating data was not done so far and especially not for learners in Mash-Up Personal Learning Environments. Thus, ReMashed offers a new approach by mashing data of users from various Web 2.0 service to provide tailored recommendation to them.

The main purpose of recommender systems on the Internet is to pre-select information a user might be interested in. Existing 'way finding services' inspire us when designing and developing specific recommender systems for learners. For instance, the well-known company *amazon.com* (Linden, Smith, & York, 2003) is using a recommender system to direct the attention of their users to other products in their collection. The motivation for a recommender system for

Mash-Up Personal Learning Environments is to improve the 'educational provision'; to offer a better goal attainment and to spend less time searching for suitable learning activities. The system takes advantage of bottom-up emerging information like tags and ratings from user-generated content. Traditional recommendation techniques are adjusted with learning related characteristics to provide recommendations to the learners (Drachsler, Hummel, & Koper, 2009).
In the following sections we first discuss related work (section two). After that we introduce the ReMashed system (section three). We present the results of the satisfaction analysis of a first ReMashed pilot (section four) and finally discuss the findings and its impact for future research (section five).

Related work

Nowadays, 'mashing' information becomes a widely used activity on the Internet. Various tools provide the opportunity to combine information from other sources in a new way (*Yahoo Pipes*, *Dapper*, *Openkapow*, *Chickenfoot*, *Greezemonkey* etc.). Users do not need special programming skills to use the mashing tools in order to combine different Internet sources. The users can take advantage of public APIs of Web 2.0 services and standardized XML formats like Jason to mash data in a new way.
In the TEL field several European projects address these bottom-up approaches of creating and sharing knowledge. The *TENcompetence* project addresses learners in informal Learning Networks (Wilson, Sharples, & Griffith, 2008). The *iCamp* project explicitly addresses the Mash-Up Personal Learning Environments and calls them MUPPLE (Wild, Moedritscher, & Sigurdarson, 2008). They created an easy to program and flexible environment that allows learners to create their own MUPPLE for certain learning activities.
However, these systems face the problem that the emerging behavior of these bottom-up approaches combines large amounts of data. With the ReMashed system we want to offer navigation support for such emerging bottom-up PLEs to help learners to find the most suitable data for their learning goals.
From the recommender system research extensive investigations are going on to take advantage of tags in recommender systems (Garg & Weber, 2008; Shepitsen et al., 2008; Symeonidis, Nanopoulos, & Manolopoulos, 2008; Wu, Zubair, & Maly, 2006). Single services like *Delicious* or *Flickr* offer recommendations to their users based on their data and also researcher take advantage of

single Web 2.0 services to create recommender systems (Garg & Weber, 2008; Sigurbjörnsson & Van Zwol, 2008).
The combination of different Web 2.0 services to recommend information based on mashed tag- and rating-data is still lacking especially for the support of learners in Mash-Up Personal Learning Environments.

The ReMashed system

A prominent working example of ReMashed from a different domain is the *MovieLens* project created by the *GroupLens* research group (Konstan et al., 1997; Miller, Riedl, & Konstan, 1997; Resnick, 1994). They offer a movie service where people can rate movies and get recommendations for movies. Besides this attractive service, *GroupLens* created a frequently used data set for the development of recommender systems and related research (Good et al., 1999; O'Sullivan, Wilson, & Smyth, 2002; Sarwar et al., 2000).
In line with the MovieLens system, ReMashed is intended for three things: 1. to provide a recommendation system for Mash-up Learning Environments to learners, 2. to offer researchers an experimental system for the evaluation of new recommendation algorithms and strategies for learners in Mash-up Learning Environments, and 3. to create user-generated content data sets of multiple learning domains for further research purposes.
Differently to MovieLens and famous e-commerce recommender systems which follow simple semantics like 'People who liked X also liked Y', ReMashed needs to apply more knowledge driven recommendation algorithms to take pedagogical reasoning into account. Therefore, the recommendation algorithms have to take into account pedagogical reasoning to address the need of learners (Drachsler, Hummel, & Koper, 2008). One approach could be to filter the most suitable information according to the learning goals and knowledge level of the current learner. Most promising therefore are context-aware recommender systems (Adomavicius et al., 2005).

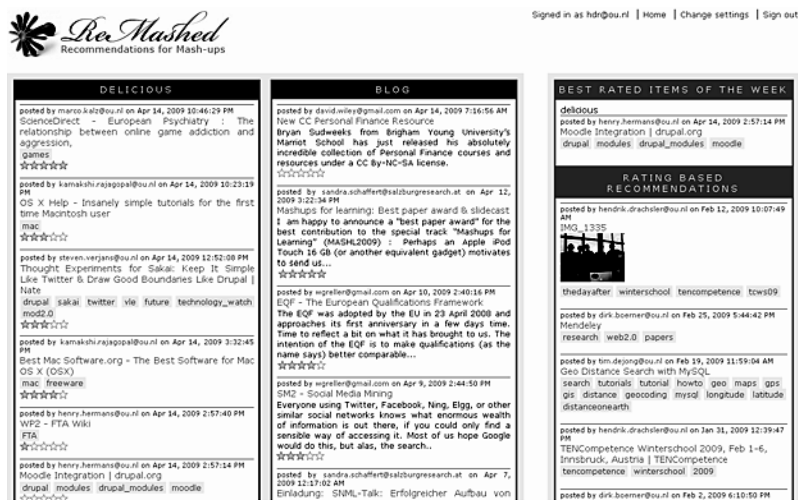

Figure 6.1**:** Overview page of the ReMashed system. On the left side, the mashed information from delicious and blogs are shown. On the right side, the rating-based recommendations for the current learner are shown.

In order to test our recommendation approaches for Mash-Up Learning Environments we designed a Mash-up (see Figure 6.1) that enables learners to integrate their sources from Web 2.0 services (*Flickr*, *Delicious*, *Blogs*, *Twitter*, *Youtube* and *Slideshare)*. The system allows the learners to personalize emerging information of a community to their preferences. Therefore, the learners rate information of the Web 2.0 services in order to define which contributions of other members they like and do not like. ReMashed takes the preferences into account to offer tailored recommendation to the learner.
The system explicitly addresses informal learning as it makes advantage of the emerging behavior of Learning Networks by the contributions of the learners. An example of this is the learning goal specification in the learner profile. The learners can specify three main learning goals which we called ‘Interests’ and specify in a self assessment what their current knowledge level is for their interests (see Figure 6.2).
In order to encourage the emergence and grouping of learners, we supported the learning goal input box by a simple auto-suggest / auto-completion algorithm (Wusteman & O'hiceadha, 2006) which is fed with existing tags in the system and already entered learning goals of other learners. Thus, the learner can already use emergent information from other users in the Learning Network or if needed specify a new learning goal that can be a pattern for other learners in the future.

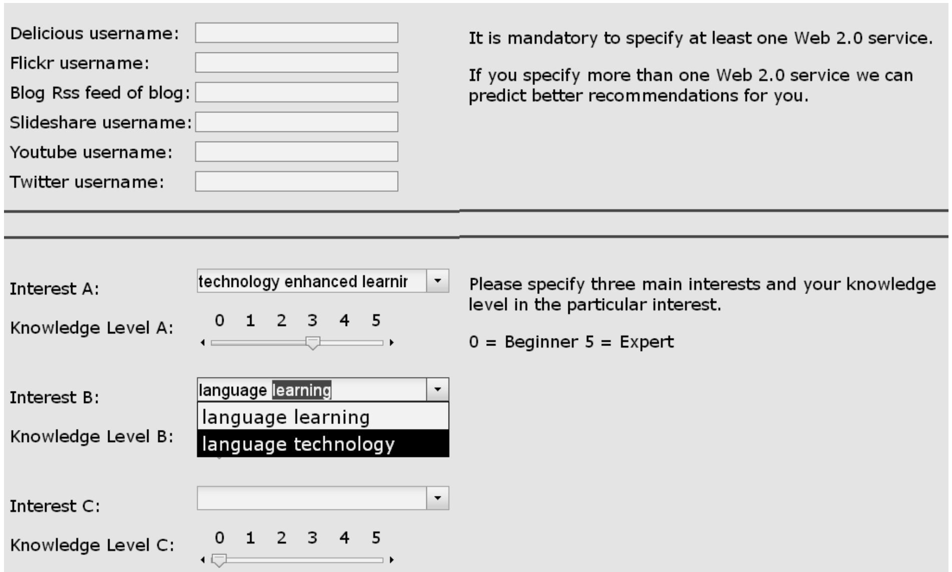

Figure 6.2: The learner profile of the ReMashed system. Besides specifying accounts for different Web 2.0 services the learners can specify three main Interests (learning goals). Further, they can indicate their knowledge level in the particular field of interests in a self-assessed way.

ReMashed uses Collaborative Filtering (Herlocker, Konstan, & Riedl, 2000) to generate recommendations. It works by matching together users with similar tastes by their tags and ratings about learning activities. Each member of the system has a 'neighborhood' of other like-minded users. Ratings and tags from these neighbors are used to create personalized recommendations for the current learner. The recommender system combines tag and rating based Collaborative Filtering algorithms in a recommendation strategy. Such a recommendation strategy defines certain situations at what moment which recommendation algorithm should be used. After a learner sign in for the first time the system has no rating information from the new user (cold-start situation). Thus, the recommender system uses the tagging information of the specified Web 2.0 services from the user to offer first recommendations. It computes the similarity between the tag cloud of the current learner with other learners and items. After the learner started to rate information of the Web 2.0 sources of other users the recommender system also uses the ratings for recommending learning activities besides the tag based recommendations.

Technical architecture

The ReMashed system is an Open Source project based on PHP5, Zend Framework 1.7 with the Dojo Ajax framework, MySQL database, Apache Server and the Duine recommendation engine. ReMashed is following the Model-View-Controller programming concept (Leff et al., 2001) and is therefore fully object oriented. It consists of five sub-systems (see Figure 6.3), a user interface, a data collector, a user logger, a recommender system and the Duine prediction engine (Van Setten, 2005).

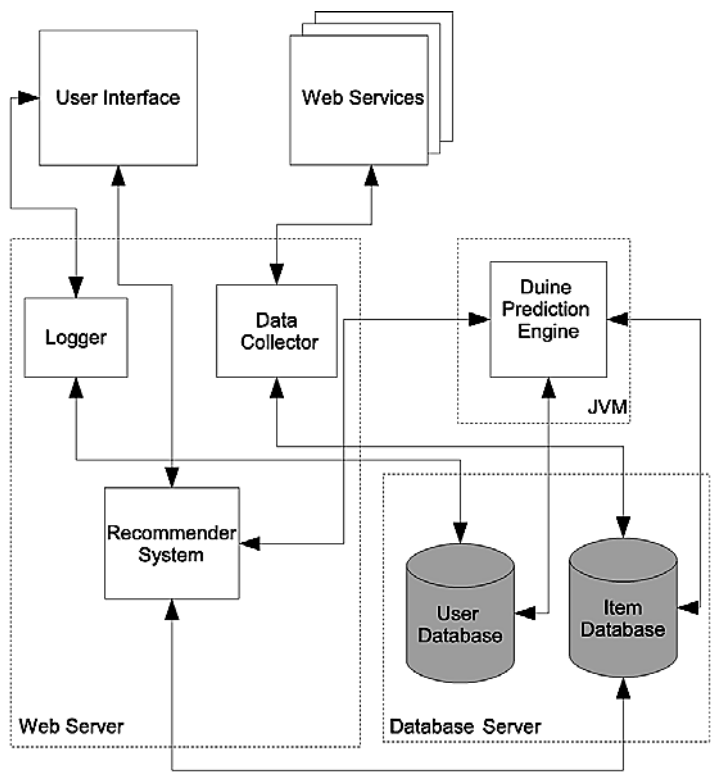

Figure 6.3: Technical architecture of the ReMashed system.

- The *User Interface* is responsible for user interaction, authentication of users, registration of new users, and updating of user data.
- The *Data Collecto*r establishes the connection between the Web 2.0 services and gathers new data into the ReMashed database via a CRON job that runs every hour.
- The *Logger* offers logging methods to the other subsystems. It stores log messages and monitors user actions in the system.

- The *Recommender System* composes the recommendations for every user and puts them into the database. It allows to implement new recommendation algorithms but it also provides a connection to the Duine 4.0 prediction engine that can be used to compute recommendations for the learning material.
- The *Duine Prediction Engine* offers extensive options for configuring various recommender algorithms. It provides a sample of most common recommendation algorithms that can be combined in algorithm strategies, thus forming of new recommendation strategies is also possible with the system.

The recommender system

One of the main intentions of the ReMashed system is to create an evaluation system for recommendation algorithms and strategies for informal Mash-Up Personal Learning Environments. Therefore, the way the recommendations can be created is as flexible as possible. The system offers several possibilities for creating new recommendation approaches (see Figure 6.4). Single algorithms can either be programmed in PHP using the *Algorithm* interface, or the Duine prediction engine can be used to create new algorithms based on JAVA and the provided library of algorithms. Figure 6.4 shows the UML diagram of the implemented recommender system.

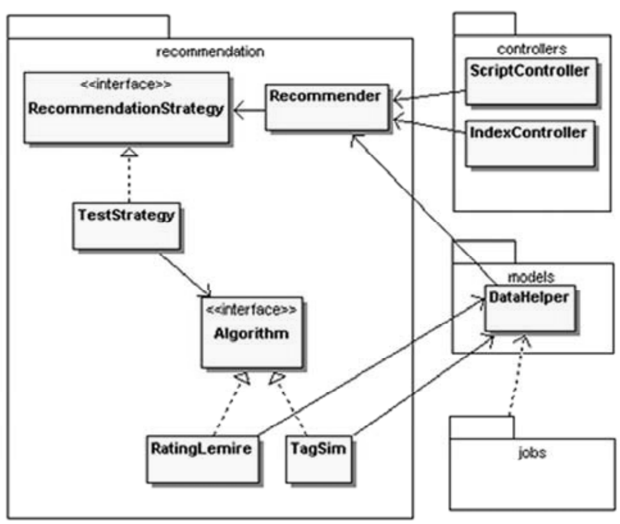

Figure 6.4: UML Diagram of the underlying recommender system for ReMashed

The recommender system mainly consists of the following classes:

- *The Recommender* class creates and stores recommendations for every user according to the information contained in the currently associated *TestStrategy* interface. The *Recommender class* is also responsible for the communication with the Duine prediction engine. The *Recommender* class collects the recommendations and passes them on to User Interface of the ReMashed system.
- *The TestStrategy class* is an instance of the *RecommendationStrategy* interface. Objects of this class control the way the recommender system works. It tells the recommender system what instances of algorithm to use, what recommendations to prepare and whether the Duine prediction engine must be used or not. Also, the selection of recommendations to be returned can be manipulated. This allows us to filter the recommendations according to pedagogical issues like prior-knowledge, learning goal etc.
- *The SlopeOne* class is an instance of the *Algorithm* interface. For the first software evaluation we used the Slope-one algorithm by Lemire (Lemire & Maclachlan, 2005) for the rating based recommendations. Instead of this instance of algorithm also other algorithms like the Pearson correlation (Anderson et al., 2003) could be applied.
- *The TagBased class* is also an instance of the *Algorithm* interface. For the first software evaluation we used an own tag based algorithm to provide recommendation already during the cold-start of the system. Similar to the SlopeOne instance this algorithm can also be replaced by another tag based algorithm like the approach by Shepitsen et al. (2008) (Shepitsen et al., 2008). Our algorithm gives recommendations for a current learner based on the similarity of tags between the target item and the items of the user. The algorithm computes similarity values by comparing the tags of the target item with the collection of all tags the user has given to his/her items. The number of times a tag of the target item matches one of the tags given by the user is divided by the total number of tags given by the user. This calculation returns a number between 0 and 1, where 0 shows no match and 1 indicates a perfect match between the user and the item.

In the first evaluation phase of the ReMashed system we applied a rather simple recommendation strategy but it already makes advantage of the emerging behavior of the informal Learning Network behind. For the tagging information we used an own recommendation algorithm. For the ratings of the user we applied the Slope-One algorithm by Lemire (Lemire & Maclachlan, 2005). The algorithms were combined in the recommendation strategy. The recommendation strategy used the tag-based algorithm when no rating information was available in the system. It identifies the cold-start situation (Schein et al., 2002) for the current learner and recommends items based on tags of the Web 2.0 services of the learner. After the learner started to rate information above a certain threshold the rating based Slope-One algorithm was enabled and additional recommendations were provided to the learner. In the beginning only 10 recommendations by the tag based recommender algorithm were provided. After the rating information was available the learner received additional 10 recommendations by the Slope-One algorithm.

Satisfaction analysis of the ReMashed system

To evaluate the satisfaction of the users with the ReMashed system we started a first evaluation phase at the TENCompetence Winterschool 2009. Besides the participants of the Winterschool also external users where allowed to sign up for the evaluation phase. In total 49 people from 8 different countries subscribed to the evaluation and contributed content and ratings to the ReMashed prototype. The evaluation phase ran for one month and was concluded with an online recall questionnaire.

We received answers from 19 participants in total, thus we had a response rate of 38%. In this section we present the most relevant answers from the online recall questionnaire regarding the satisfaction with the ReMashed system. The results of the questions regarding the use of Web 2.0 services can be found in Table 6.1. The questions about the satisfaction with the ReMashed system are shown in Table 6.2 and Table 6.3. Because the satisfaction questions were not always answered by all 19 participants we added the total amount of answers per questions in Table 6.2 and Table 6.3.

The questions regarding the usage of Web 2.0 in Table 6.1 are informative for us as they give an idea which tools are used how frequently. This information is rather important to us for the further development of the ReMashed system. The most frequently used services are social bookmarking services. Nearly all participants 84% (n=16) answered that they use social bookmarking quite often. On the second place services like *Flickr*, *Slideshare* and *YouTube* (for bookmarking favorite movies) were elected. 37% (n=7) of the participants regularly use a kind of *Flickr*, 36% (n=7) of them a presentation service like *Slideshare* and also 37% (n=7) use their *YouTube* accounts to bookmark videos. Rather interesting is that only 15% (n=3) mentioned that they upload videos to *YouTube*. Micro blogging was voted on the third place even before normal blogging activities. 32% (n=6) of the participants regularly use a micro blogging tool like *Twitter* and only 21% (n=4) of them recently wrote in a normal blog. When we consider this subjective information we have to stress that blogging is used more often than it is indicated in the questionnaire. Blogging and social bookmarking data were one of the most often saved data in the database.

Table 6.1
General statements about the usage of Web 2.0 services and their integration in the ReMashed system (Total amount n = 19 = 100%).

Questions	Values				
	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
I keep track of my work results on a blog or research diary.	16% (n=3)	5% (n=1)	32% (n=6)	11% (n=2)	37% (n=7)
I bookmark interesting resources in a social book-marking tool like Delicious.	42% (n=8)	42% (n=8)	5% (n=1)	5% (n=1)	5% (n=1)
I upload pictures to a picture service like Flickr.	5% (n=1)	32% (n=6)	21% (n=4)	26% (n=5)	16% (n=3)
I upload my presentations to a presentation service like Slideshare.	11% (n=2)	26% (n=5)	21% (n=4)	21% (n=4)	17% (n=5)
I use a micro blogging tool like Twitter.	11% (n=2)	21% (n=4)	11% (n=2)	21% (n=4)	37% (n=7)
I upload video streams (movies) to a movie sharing system like YouTube.	0% (n=0)	15% (n=3)	37% (n=7)	26% (n=5)	21% (n=4)
I use YouTube to add / bookmark movies I like to my account.	5% (n=1)	32% (n=6)	16% (n=3)	16% (n=3)	32% (n=6)

However, the observation regarding *Flickr*, *YouYube* and *Slideshare* are quite important because if they are used less often, than their presentation size can be limited in the User Interface.

In an open question we asked the participants if they miss any Web 2.0 services. We received 9 answers; the participants wanted to see social networks like *Linkedin*, *Facebook*, and *MySpace* to be integrated into the system. Further, an online mind mapping tool like *Mindmeister* was mentioned. A valuable remark was the suggestion to create clusters of the various Web 2.0 services that are competitors. Instead of focusing on one service like *Flickr* we should offer the category pictures and integrate for instance *Picassa* besides *Flickr*.

In Table 6.2 we asked questions regarding the general satisfaction with the ReMashed system and the offered recommendations. 63% (n=12) of the participants were overall satisfied with the ReMashed system. To further analyze the impact of our recommendation strategy, we asked the learners if they were more satisfied with the recommendation given in the beginning or at the end of the experiment (Table 6.2, questions 2 to 5). We wanted to know if the learners noticed any differences in the given recommendation over time, since the cold-start situation of the rating based algorithm was present in the beginning. Further, the rating base recommendation should have become more accurate over time. 20% (n=3) of the participants were very satisfied and 40% (n=6) were satisfied with the tag-based recommendation in the beginning of the test phase. Thus, our own tag-based algorithm did a reasonable job regarding the cold-start of the system. The participants were at the end evaluation phase no longer very satisfied with the tag-based algorithm, but still 69% (n=11) were satisfied with its recommendations. Regarding the rating-based algorithm surprisingly no differences were identified between the start and the end of the evaluation phase by the participants. They rated both time frames similar.

In Table 6.3 we asked the participants for the ultimate choice between the tag-based algorithm and the rating-based algorithm. Which recommendation technology did satisfy them more at the end of the ReMashed pilot? We see a tendency that people were more satisfied with the tag-based recommendations. Reasons for that could be plenty; the participants could have rated to less so that the rating-based algorithm did not improve enough over time or appeared to late in the evaluation phase because the participants did not provide enough ratings.

At the end of the questionnaire we offered an open question for general remarks. This opportunity was used by 13 participants. The most frequent remarks where regarding 1. privacy issues, 2. static behavior of the system, 3. interoperability, and 4. influencing the provided recommendations.

Regarding 1, some of the participants were afraid that their personal data from the Web 2.0 service would be fetched and used in the system, therefore they did not offer all their service accounts to the system. We stressed in the start phase of the evaluation that only public data will be used but some people missed this information. To prevent this for future evaluations we will add a hint to the user profile.

Table 6.2
Questions regarding the satisfaction of the participants regarding the ReMashed system.

Questions	**Values**				
	Very satisfied	**Satisfied**	**Unsatisfied**	**Very unsatisfied**	**Total amount**
How satisfied are you overall with the ReMashed system?	5% (n=1)	58% (n=11)	26% (n=5)	11% (n=2)	100% (n=15)
How satisfied have you been with the tag-based algorithm in the beginning of the ReMashed pilot?	20% (n=3)	40% (n=6)	27% (n=4)	13% (n=2)	100% (n=16)
How satisfied are you now with the tag-based algorithm at the end of the pilot phase?	0% (n=0)	69% (n=11)	19% (n=3)	13% (n=2)	100% (n=16)
How satisfied have you been with the rating-based algorithm after it appeared in the system?	8% (n=1)	53% (n=7)	31% (n=4)	8% (n=1)	100% (n=14)
How satisfied are you now with the rating-based algorithm at the end of the pilot phase?	8% (n=1)	54% (n=7)	31% (n=4)	8% (n=1)	100% (n=13)

The remarks regarding 2, the static behavior of the system addressed missing features for collaboration like a live chat or *Google* tools. In order to attract participants for future evaluation we either have to extend the functionality of the current ReMashed system towards a fully scaled PLE or develop a web service that can be connected to existing Mash-Up Personal Learning Environments.

Table 6.3
Question regarding the satisfaction of the participants regarding the ReMashed system.

Questions	Values		
	Tag-based recommendations	**Rating-based recommendations**	**Total amount**
Which recommendation technology did satisfy you more at the end of the ReMashed pilot?	58% (n=7)	42% (n=5)	100% (n=12)

Conclusions and future research

This chapter presented the ReMashed system, an evaluation tool for recommender systems for learners in informal Learning Networks. The chapter showed the design and implementation of a recommender system in a Mash-Up Personal Learning Environment and a first usage evaluation by a group of 48 users. It described the technical architecture with classes of the recommender we designed for this flexible, specific use within Learning Networks.

The most obvious future research will be the evaluation of new recommendation algorithms regarding their impact on learners in informal Learning Networks. Therefore, we first want to review suitable algorithms and adjust them to our goals.

Based on the satisfaction analysis we want to develop ReMashed further in two different ways. One way is the integration of additional PLE features to have an attractive environment for participants for future experiments. The other way is the development of a web service to offer recommendation for other Mash-Up Personal Learning Environments. The user should be able to specify sources and receive recommendation via RSS for their PLEs.

The challenging part thereby is to get ratings into the system. This can be done with a small widget that can be integrated into the PLE of the users. Thus, we have to cut the data set into smaller pieces and provide users with them. The users can rate the items on a frequently base in order to train the recommender system for their needs. This widget approach is rather important as the gathered data over the Web 2.0 service grows faster than the ratings in the system.

Chapter 7

General Discussion

Introduction

In this thesis we have addressed the problem of selecting the most suitable learning activity from an emerging amount of possibilities for individual learners in informal Learning Networks. In the first part, we created the theoretical foundations to develop a recommender system for informal Learning Networks. We have contributed to a definition of recommendation goals for recommender systems in informal learning. We were interested how pedagogical rules can be integrated into recommender systems and have identified the required domain knowledge for this purpose. Further, we have reviewed the most suitable recommendation technologies and have suggested an evaluation framework to measure the impact of recommender systems for informal Learning Networks. In the second empirical part, we have tested different recommender systems in experimental settings for providing navigation support to lifelong learners. Finally, we have developed a prototype that integrates our findings for recommender systems in informal Learning Networks.
In this concluding chapter, we will now discuss and reflect on the outcomes of this thesis. We will start with a review and discussion of the results and point out the practical implications and limitations of our work. Finally, we will give an outlook on future research.

Review of the results

Theoretical foundations

In this thesis we first have determined the theoretical foundations for designing a model for a recommender system for informal Learning Networks. This topic was worked out in Chapter 2 and 3 with different foci in both chapters. Chapter 2 distinguished recommender systems for learning from traditional e-commerce recommender systems. As a next step, formal and informal learning were distinguished by describing their similarities and differences. Chapter 3 built on top of this meta-analysis and identified potential Collaborative Filtering approaches and discussed their effects on the recommendation goals and tasks for recommender systems in informal Learning Networks.

Identifying the goals, user model and conditions of recommender systems for informal learning

In Chapter 2, we analyzed the differences and similarities of e-commerce recommender systems and recommender systems in formal and informal learning environments that were based on varying (1) recommendation goals; (2) user models; and (3) environmental conditions.

First of all, the recommendation goals of e-commerce recommender systems are in contrast to our research objectives. Their main goals are to convert browsers into buyers, to increase cross sell of products, and to build a loyalty relationship to the customer. Recommender systems in TEL should provide learners with suitable learning activities according to their competence developments. We concluded that recommender systems in TEL have to structure learning activities in a pedagogical way; and have to suggest emerging learning paths to learners.

Secondly, e-commerce recommender systems require different user models than recommender system in TEL. They demand information like zip code, income, credit card type, home address, shipping preferences and a list of already purchased products. TEL user models are rather different to e-commerce user models. They require information about learning goals, prior knowledge, learner preferences (current preference for a type of media), learning paths taken and information about completed, rated or tagged learning activities.

Thirdly, the environmental conditions of e-commerce recommender systems differ from TEL recommender systems. E-commerce systems are maintained on a daily basis by a product catalog and semantic relations. The products as such are well defined by metadata descriptions. Most of the time, their product catalog implies a rather huge data set with thousands of products and customers with millions of transactions. Recommender systems in formal learning environments share some similarities with e-commerce recommender systems in this sense. Surely, they have to use different user models but some of the recommendation goals and especially the environmental conditions of both are comparable. Many formal learning systems have well maintained product catalogs, with equally fine-grained courses, and learning content that is designed by an educational designer holding well-defined semantic relations. Also prior knowledge information can be modeled in a similar way like in e-commerce systems when the competence development is stored in the system. In contrast to that are recommender systems for informal learning environments. The learning content is not maintained on a daily basis, but gets tagged, rated and adjusted by individual learners on an irregular basis. Furthermore, prior knowledge in informal learning is a rather diffuse parameter because it relies on information given by the learners which is not standardized in any way. This leads to different data sets and conditions for recommender system in informal learning environments.

We concluded in Chapter 2, that designer of informal Learning Networks first need to address the different environmental conditions, user models, and the lack of maintenance and structured learning activities, in order to offer appropriate navigation support with recommender systems. Such recommender systems have to take advantage of emerging information like tags and ratings to select the learning activities for the individual learner. Additionally, we proposed an evaluation framework for recommender systems in informal Learning Networks that provides a mix of technical evaluation criteria with educational measures for evaluating the impact of such recommender systems on the learners.

Recommender systems for learners in Learning Networks: requirements, techniques and model

After differentiating e-commerce recommender systems from recommender systems for informal learning, we reviewed in Chapter 3 already conducted research on recommender system in TEL. We found that most of the recommender systems applied traditional recommendation approaches from e-commerce to the TEL domain. Their recommendation goal is mainly focused on suggesting suitable information rather than taking into account certain pedagogical requirements. Therefore, we further specified the pedagogical requirements of recommender systems in informal Learning Networks. We proposed the following characteristics: learning goal, prior knowledge, learner characteristics, learner grouping, rated learning activities, learning paths, and learning strategies. We analyzed traditional recommendation technologies that appear promising to meet these characteristics. Chapter 3 discusses and presents an overview of the advantages and disadvantages of suitable recommendation approaches. Because every single recommendation technology has its own advantages and disadvantages, we concluded that hybrid recommender systems are most suitable. They are build on a combination of single recommendation technologies and compensate disadvantages of single technologies in a recommendation strategy.
Finally, Chapter 3 suggests a model of a recommender system that can be connected to a domain model of a Learning Network. Such an integrated recom-

mender system needs information from other components of a Learning Network to meet the mentioned requirements.

Empirical part

In the second part of this thesis we conducted two experimental studies to evaluate the impact of recommendation technologies for Learning Networks. In Chapter 4 we described and discussed the results of a field test with a first prototype of a recommender system that was integrated into a Moodle learning environment. In Chapter 5 we created a simulation environment to test algorithms for their effects on Learning Networks of different sizes. Finally, in Chapter 6 we describe the 'ReMashed' prototype that takes into account the experiences of the conducted research. The prototype is intended to evaluate the navigation support by recommender systems for informal Learning Networks in real life conditions.

Effects of a recommender system for learners in a Learning Network

Chapter 4 describes the results of an empirical study with a first recommender system prototype integrated into a regular 'Introduction Psychology' course as offered by the Psychology faculty of the Open University of the Netherlands (OUNL) into a Moodle environment. In the experiment we tested if the experimental group, supported with a recommender system, was more effective, efficient, satisfied, and whether they took more personalized learning paths when compared to the control group, that was not offered this navigation support.
To verify our hypotheses we looked at a combination of logging data like study time, amount of complete courses, the order of completed courses and an online questionnaire.
We found that the recommender system positively influenced all measures, by having significant effects on efficiency between both groups ($F(1,99) = 5.14$, $p = .026$). Thus, the experimental group, needed constantly less time to complete equal amounts of learning activities. Further, the participants in the experimental group have taken more personalized learning paths through the 17 courses. Finally, it is important to note that the general satisfaction with the recommender systems was positive.

Effects of recommender systems in Learning Networks of different sizes

As a next step of the practical part, we investigated the impact of recommendation technologies on learners in informal Learning Networks of different sizes and different dense data sets. Therefore, we designed a simulation tool that models a Learning Network using the Netlogo multi-agent programmable modeling environment. We applied two new recommendation technologies for the navigation support of learners; a user-based approach (treatment group U) and an item-based recommendation approach (treatment group I), which were contextualized in a pedagogical manner.

Chapter 5 describes the results of various simulation runs. We hypothesized that the treatment groups would be better than the control group according to Effectiveness, Efficiency, Satisfaction, Precision, Recall and F1. The comparison of the control group to the treatment group U and I showed a significant difference on all measures for all eight conditions. Therefore, we could confirm that navigation support by recommender systems indeed leads to more graduation, less study time and more satisfied learners.

The most interesting part of the study was the comparison of the treatment groups with each other. We found the following results:

- None of the treatments performed significantly better regarding the graduation of learners (Effectiveness).
- Treatment group I significantly needed less time (Efficiency) to complete equal amounts of learning activities in all small and large Learning Networks where learners followed less complex learning goals at level 1.
- Treatment group I was found to be significantly more satisfied (Satisfaction) than Treatment group U in all small and large Learning Networks where learners followed less complex learning goals at level 1.
- It appeared that the treatment U had rather consistent Precision, Recall and F1 measures, whereas treatment I most of the time showed a high Recall values and a rather low Precision values. Treatment I had most of the time a larger result set than treatment group U. In combination with the prior knowledge contextualization this approach was more effective for the navigation support on the learners than treatment U with peer-learner contextualization.
- Surprisingly, we did not find any difference for Learning Networks where learners followed more complex learning goals at level 3. Further, it seems to make no difference whether the algorithms where applied in small or large Learning Networks, neither if the Learning Network consists of more users or more items.

We note that the simulation study demonstrated the advantage of navigation support by recommender systems in informal Learning Networks compared to the control group. This can be further extended with the findings that especially the item-based approach of treatment group I outperformed user-based approach of treatment group U regarding measures of efficiency and satisfaction for learners that followed a less complex learning goal at level 1.

ReMashed – Recommendations for Mash-Up Personal Learning Environments

A technical prototype that integrates all findings of the research described in Chapter 2 to Chapter 5 was presented in Chapter 6. The proposed system called 'ReMashed' is an evaluation tool for recommendation algorithms and strategies for learners in informal Learning Networks. ReMashed serves three different goals: to provide a recommendation system for Web 2.0 sources of learners, to offer researchers a system for the evaluation of recommendation algorithms and strategies for learners in informal Learning Networks, and to create user-generated content data sets for different domains that are needed for future research on recommender systems in informal Learning Networks. With the ReMashed system we want to offer an instance of an emerging Learning Network that offers navigation support to learners to find the most suitable learning activities for their learning goals. It enables learners to integrate their sources from Web 2.0 services (flickr, delicious, blogs, twitter, Youtube and Slideshare). The system allows the learners to personalize the emerging information of a community to their preferences. The learners rate information of the Web 2.0 services in order to define which contributions of other members are supportive for them or not. ReMashed takes the preferences into account and offers tailored recommendation to the learner.

Practical implications

In the introduction we have argued that informal learning plays a major role in the Knowledge Society, where learners are connected to various experts, learners, and communities on the Internet. Learners no longer just consume provided information, but will be actively producing content with Web 2.0 tools. This increases the need of pedagogical driven navigation support that can recommend most suitable information to the informal learner. From the studies carried out, we can now derive the following nine practical implications clustered according to the four main problems that are related to our general research question.

1. Distilling criteria to apply recommender systems to informal learning.

    1.1. Recommender systems from e-commerce systems cannot easily be applied for learning. They have different recommendation goals, user models and environmental conditions. E-commerce recommender systems apply rather simple semantics like 'People who liked X also liked Y' which are misleading for recommender systems in learning. For recommender systems in learning more complex semantics are needed that take into account pedagogical characteristics like prior knowledge or learning goals of learners.

    1.2. Recommender systems for formal and informal learning also have to be designed rather differently. Even when they have common pedagogical characteristics, they do not share similar learner models and environmental conditions. Recommender systems in formal learning environments can to a larger extend rely on top-down expert driven information, whereas recommender systems for informal learning environments have to take advantage of bottom-up emerging information.

    1.3. In order to evaluate the impact of recommender system algorithms in Learning Networks a combination of technical measures (like accuracy, precision and recall) have to be used with traditional educational measures (like effectiveness, efficiency, satisfaction and drop-out rates). Especially, in case of Learning Networks, also measures from social network analysis can be applied (like variety and centrality).

2. Selecting recommendation technologies that are suitable for informal learning.

    2.1. There is no recommendation technology that perfectly addresses Learning Networks. But the use of hybrid recommender systems, a combination of single recommendation technologies in a recommendation strategy, can partially solve disadvantages of Collaborative Filtering algorithms and also address certain pedagogical situations by switching from one algorithm to another.

2.2. Context-aware recommendation approaches are most suitable to integrate pedagogical characteristics like prior knowledge as they offer technologies to pre- or post filter the Collaborative Filtering results.

3. Designing experiments to test the effects of recommender systems on learning outcomes.

3.1. The conducted research showed that it is possible to improve the performance of learners by offering personalized recommendations to them. It was possible to pre-select learning activities from the Learning Networks according to the indirect (like study time and completion rates) and direct measures (like tags and ratings) of informal learning. The experimental groups thereby overall showed a better performance towards their learning goals than control groups without navigation system support. When learners follow complex learning goals that consist of various competence levels, different Collaborative Filtering approaches do not significantly differentiate from each other regarding their impact on the performance of learners. Significant differences only appear when learners attain less complex learning goals.

3.2. Simulations studies are useful to evaluate recommender systems in Learning Networks of different sizes. They enable us to observe the emerging behavior of learners in Learning Networks under different conditions. Simulations offer fast solutions to explore different experimental settings where real-life experiments need very careful preparation and cannot easily be repeated or adjusted within a specific timeframe.

4. Implementing effective navigation support for informal learning.

4.1. The development of an interface for a recommender system for informal learning is possible by presenting the emerging information of the Learning Networks in a very structured way to the learners. By adding a rating layer on top of the emerging information the learners can specify which information they are interested in and which they are not. Recommendations for suitable learning activities can then be created based on the ratings and tags given by the learner.

4.2. It is possible to personalize the emerging information of Learning Networks by taking into account user-generated content of the individual learner. Various Web 2.0 content, tags and ratings of an individual learner can be combined to pre-filter information. In addition, learning goals and related prior knowledge levels specified in a self assessed way are supportive for recommender system in informal Learning Networks.

These practical implications are beneficial for many other challenges in Learning Networks and the Knowledge Society as well. For instance, Collaborative Filtering and other recommender system technologies can be applied also to recommend peer-students, experts, or educational web services.

Limitations of this research

The navigation approach we propose has a relatively restricted focus on supporting learners in finding most suitable learning activities in informal Learning Networks according to their individual needs. Nevertheless, this relatively restricted focus is based on multiple decisions regarding used technology and methods. Consequently, conducting the same research plan with different recommendation technologies and methods most probably will offer additional insights.
For this reason, we will report in the following section three general research issues when conducting experiments on navigation support in informal Learning Networks, and afterwards we will present three more particular limitations of the studies we have carried out.

General limitations

- When did a learner follow a recommendation?
  This is a methodology problem we stumbled over that also applies for future research in this domain. Our experimental setups did not force learners to actually take the recommended next step, and we do not know to what extent learners actually followed up advices. The problem is the definition of what constitutes a 'followed recommendation'. Did learners follow a recommendation when they navigated to a recommended learning activity? Or did learners follow a recommendation when they stayed longer than 5 minutes in the recommended learning ac-

tivity? As a result, the improved efficiency cannot be unambiguously ascribed to the recommender systems itself. One solution for this issue would be a classic research approach having a real treatment group and a control group just receiving a faked treatment like random recommendations. But that approach is also cumbersome as it distracts and disturbs the control group with random recommendations. First of all, this is an ethical issue as it confuses learners that are real students that paid the same amount of money for their studies. Secondly, the evaluation of the results would be affected as well, because the positive effect of navigation support by Collaborative Filtering would be compared to an abnormal setting that has an additionally affect on the behavior of the control group.

- The measurement of efficiency
  There is a difference between the measured 'elapsed time' that learners took to complete a learning activity and the actual 'study time' they needed to successfully complete a learning activity. Elapsed time is only an indirect measure for real study time because it is counted from the beginning when a learner entered a learning activity. It is not clear if he already studied related learning material, what would also count to study time.

- Complexity of simulations
  Adding too much complexity to simulations does not make them more realistic than rather less comprehensible. Modeling too many parameters in a simulation is leading to very complex simulation models. Such a complex model can hardly be judged on its outcomes because the parameters affect each other in an incomprehensible ways. Thus, a sufficient balance of complexity and simplicity has to be found to make simulation effective.

Particular limitations

- Our experiment within Psychology excluded some of the navigation and motivational problems faced by learners in informal Learning Networks. The experiment had to deal with administrational issues that occur when a commercial course is used to carry out a scientific experiment. Institutional rules, like the demand that every learner had to receive a book that already offers a pre-structure of the provided learning content, affected the experimental conditions. Therefore, we were not able to design the experiment as restricted to informal learning as we wanted.

- Our second study with the simulation tool also has some limitations. First of all, using a simulation always simplifies real world conditions. The incompleteness of a simulation is always given as it represents only a part of the real world and always misses some features. One major constraint in our research is a lack of direct learner interaction within the Learning Network, only indirect social interactions by the recommendation algorithm are modeled. In reality there is always a combination of indirect and direct social interaction and direct social interaction has an impact on choices to be made. Further, we did not design learning activities that emerge by contributions of the learners. In the current simulation we made a scalable amount of learning activities that existed from the very beginning until the end of the simulation.

- The limited access to rated real life data sets (like the MovieLens or Jester datasets, REFs) that model content and rating behavior of learners in informal Learning Network was a disadvantage. Such a dataset would make TEL recommender system research much more comparable and standardized.

Future research

This thesis opens various possibilities for future research on navigation support of learners in informal Learning Networks. In general the evaluation of most suitable recommendation algorithms offers an endless sea of possible combinations of similarity measures and recommendation approaches. A high percentage of research in machine-learning, data-mining and recommender systems is conducted in this sea of combinations. Besides considering different recommendation technologies for this research it is also possible to focus on one specific recommendation algorithm that will be adjusted in iterative steps. Most promising therefore are context-aware recommender systems (Lemire, Boley, McGrath, & Ball, 2005). These recommender systems use for example geographical location of a user to recommend relevant resources. Such contextualization can be applied for instance, when multilingual educational resources are recommended. Additionally, context awareness is promising to embed pedagogi-

cal reasoning like prior knowledge, learning goals or study time into Collaborative Filtering driven recommender systems.
Additionally, the use of multi-criteria ratings for informal Learning Networks is rational. Learners could rate learning activities not only on base of their taste, they could also rate the complexity level of learning activities or the amount of study time that is required to complete the learning activities. Such multidimensional ratings could improve the suitability of pedagogical driven recommendations.
Finally, for future research the recommendation goal can be changed from recommending most suitable learning activities to recommending suitable experts, peer-learners, most suitable learning paths or even educational web services or widgets that might be beneficial for certain tasks.

The provided insights and tools in the practical part of this thesis are beneficial for future research in this domain. The simulation tool and the ReMashed system enable researcher to follow an iterative approach by testing algorithms in the flexible simulation environment for certain Learning Networks, and afterwards the most promising algorithms can be evaluated under real-life conditions in the ReMashed system. Besides this general research perspective additional developments on our tools might open new streams of possible research. The following section gives an overview of intended developments for the simulation tool and the ReMashed environment to foster the research on navigation support for learners in informal Learning Networks.

Future developments of the simulation

In order to strengthen our iterative approach between simulations and real-life experiments, the simulation tool needs to become more interoperable on two levels.

1. Integrating real life data sets
   The simulation tool has to enable to use real life data sets; therefore it needs a database interface to access data sets from the external systems like ReMashed. This will improve the forecasting of the simulation tool and increase the accurateness of the simulation outcomes.

2. Coherent algorithm design
   To increase the interoperability of the used recommendation algorithms, the simulation tool should use the same recommender system framework (currently the DUINE prediction engine). This would enable a coherent and standardized way for the design of new recommendation algorithms and minimize efforts to transfer an algorithm from the simulation environment to the ReMashed system.

At last, the pre-processing of the analysis of the simulation tool can be improved. For instance, in order to compare the algorithms according to accuracy and precision in a ROC analysis the data of the confusion matrix have to be recorded over time (instead of in a final confusion matrix that only contains the total sums).

Future developments of the ReMashed system

The future developments of the ReMashed system rely on two different perspectives with various subcategories; one perspective is the end-user perspective and another one is the researcher perspective.

Regarding the end-user perspective ReMashed has to improve on two points:

1. Serving multiple communities of Learning Networks
   Therefore, an administration layer has to be implemented that allows to easily setting up new Learning Networks for various domains. Besides this administrative extension the integration of additional features (i.e. integrating peers from social networks like facebook) may improve the loneliness of informal learners towards the organization of learning communities. Retrieved information from social networks can be used to improve the recommendations and strengthen the communities; for instance, users that have certain social relationships will likely want to share their media with their community. The type of relationship between users can effect which kind of recommendations are given.

2. Improve interoperability to other Personal Learning Environments
   ReMashed has to provide RSS feeds of the emerging information sources and the recommendations provided in the system. This will increase its interoperability to other Personal Environments like iGoogle or Netvibes

and must for the Web 2.0 age. Thinking this idea further, a widget interface to the ReMashed system is required to enable learners to integrate recommendations from ReMashed into their Personal Learning Environment. Such a widget has to provide recommendations and the possibility to rate content from the emerging information in the ReMashed system to further personalize the needs of the learners.

On a researcher perspective, ReMashed opens the following possibilities for future research:

1. Providing user-generated content data sets of various domains
   From the harvested data of different communities within ReMashed a data set can be created that bridge the gap of missing data sets for recommender systems in TEL. Comparable to the famous MovieLens data set, a standard for the evaluation of recommender system algorithm in TEL can be created and offered to other researchers in this domain. Further, when considering different ReMashed communities in health, education or public affairs, these data sets can also be used to develop solutions for the cold-start problem of recommender system by providing an already rated data set for a particular domain.

2. Evaluation of new recommendation algorithms
   The general purpose of ReMashed is the evaluation of new recommendation algorithms in real life conditions. The mentioned data sets can be used for the evaluation of new recommendation algorithms regarding their impact on learners in informal Learning Networks.
   According to the iterative research approach new recommendation approaches could be tested first with a test data set in the simulation environment and afterwards integrated into a certain Learning Network of the ReMashed system to be tested under real life conditions.

New lines of research

We presented how recommender systems can be used to support individual learners in the Knowledge Society to get access to most suitable information to advance the innovative use of knowledge within this society. We also showed how learners can make advantage of informal learning – the unused body of knowledge – to follow their informal learning goals and competence development plans.

A high potential for future research and developments offers a switch of perspective from the individual learner to the organizational level. Becoming a knowledge organization that suits the demands of the upcoming Knowledge Society also requires making innovative use of emerging information within an organization. The findings and results of this thesis can be applied for commercial services for knowledge organizations. For instance the prototypical version of ReMashed can be further developed for information dissemination and managing tasks within organizations. Because the organizations often have classified information more restricted tools for information sharing are needed. Free accessible Web 2.0 services that are open to the Internet can hardly be applied for this purpose. Thus, a kind of closed IntraWeb 2.0 solutions (own blogging or twitter system) could be used within the organizations to strengthen the knowledge dissemination. The produced content could emerge in similar interfaces like the suggested ReMashed system, without fearing to lose classified information to third parties. The members of the organization could share relevant content in secure environments to support their informal learning at their workplace within their own organization. Similar recommendation approaches like we evaluated in this thesis could then be applied to support the informal learning and the competence development within a knowledge organization of the future.

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Summary

Summary

In this thesis we explored the potential of recommender systems to recommend learning activities to lifelong learners in informal learning settings. The general research question of this thesis is:

> *How can we best recommend suitable learning activities to lifelong learners in informal Learning Networks, taking into account their personal needs, preferences, and learning goals?*

The increasing amount of information on the Internet enables people to access almost anything they need. On the other hand, the Internet opens the door for a plethora of information that makes it difficult to get an overview and to select the most suitable information. This selection problem also applies to lifelong learners in informal Learning Networks.

Promising technologies to support people, in order to navigate to the most suitable information, are recommender systems. In this thesis we explored the navigation support of recommender systems to improve the selection of most suitable learning activities according to individual needs, preferences and learning goals of lifelong learners.

We analyzed this challenge first on a theoretical level in Chapter 2 and 3 and afterwards on an empirical level in Chapter 4, 5 and 6. Finally, we presented practical implications of the research in Chapter 7. In the following sections we summarize the findings of the thesis.

Theoretical Foundations

Identifying the goals, user model and conditions of recommender systems for informal learning

In Chapter 2 we found differences in requirements between e-commerce recommender systems and recommender systems for learning. We distinguished their requirements based on (1) recommendation goals, (2) user model, (3) and environmental conditions.

Firstly, we found that the recommendation goal of recommender systems for informal learning is to structure learning activities in a pedagogical way to enable a consistent competence development of learners. Further, recommender systems have to take advantage of emerging learning paths and suggest most efficient or effective learning paths to learners.

Secondly, e-commerce recommender systems require a different user model than recommender systems for learning. E-commerce recommender systems require information like zip code, income, credit card type, shipping address, shipping preferences and the already purchased products. User models for learning are rather different, they require information about learning goals, prior knowledge, learner preferences (current preference for a type of media), taken learning paths and information about completed, rated or tagged learning activities.

Thirdly, also the environmental conditions of e-commerce recommender systems are different to the conditions of recommender systems for learning. E-commerce systems are maintained on a daily basis by a product catalog and semantic relationships. Also the products as such are well defined by metadata descriptions. Most of the time, their product catalog implies a huge data set with thousands of products and customers with millions of transactions. Recommender systems in informal learning environments face different situations. The learning activities are not maintained on a daily basis. They get tagged, rated and adjusted by individual learners on irregular basis. This leads to different data sets in informal Learning Networks a recommender system has to deal with. In addition, we found that recommender systems for formal learning in educational organizations share some similarities with e-commerce recommender systems. Especially the environmental conditions of both are comparable. Many formal learning systems have well maintained product catalogs, with equally fine-grained courses, and learning content that is designed by an educational designer holding well-defined semantic relations.

As a conclusion, in order to address informal learning with recommender systems we have to take into account different environmental conditions, user models, a lack of maintenance and less structured learning activities. Instead, we have to take advantage of emerging information like tags and ratings to select and structure the learning activities for the individual learner. To meet these requirements for informal learning bottom-up recommendation technologies like Collaborative Filtering are most appropriate because they require hardly any maintenance and improve by the emerging behavior of the community.

As a last step in Chapter 2 we created an evaluation framework to measure the impact of recommender systems on the learning outcomes (see Table 2.1). Therefore, we combined technical evaluation criteria from recommender system research with educational research measures, and Social Network Analysis' measures.

Recommender systems for learners in Learning Networks: requirements, techniques and model

Based on this first analysis of recommendation goals, user models, and environmental conditions, we investigated in Chapter 3 different recommendation technologies that appear promising for informal learning. We found that every single recommendation technique has its own advantages and disadvantages and listed the most suitable for our aims in Table 3.1. We concluded that hybrid recommender systems are most appropriate, because they build up on a combination of single recommendation techniques by compensating disadvantages of single techniques in a recommendation strategy.

Empirical findings

After we defined recommendation goals, user models, an evaluation framework, and most suitable recommendation techniques we tested our theoretical results in two experiments and created a first technical prototype for lifelong learners in informal Learning Networks.

Effects of a recommender system for learners in a Learning Network

In Chapter 4 we presented our first experiment where we tested if an experimental group, supported with a recommender system, showed differences compared to a control group without a recommender system. The recommender system consisted of a stereotype filtering technique (see Table 3.1) and an ontology combined in a recommendation strategy. We found that the recommender system positively influenced the study time on a significant level. The experimental group, needed constantly less time to complete equal amounts of learning activities. Further, the participants in the experimental group have taken more personalized learning paths than the control group because they explored many more personalized learning path through the Learning Network.
After these promising results we needed to test how recommender systems behave in Learning Networks of different sizes. Therefore, we created a simulation tool to test recommendation techniques from Table 3.1 in different Learning Networks.

Effects of recommender systems in Learning Networks of different sizes
In Chapter 5 we presented our second experiment where we evaluated the effects of recommender systems in Learning Networks of different sizes. We designed a simulation tool that models a Learning Network using the Netlogo multi-agent programmable modeling environment. In this experiment we applied a user-based Collaborative Filtering and item-based Collaborative Filtering technique from Table 3.1. Each of these techniques were implemented into a treatment group (item-based filtering - treatment group I, and user-based filtering - treatment group U) and compared to a control group without navigational support. Chapter 5 describes the results of eight simulation runs, each presenting a different amount of learning activities and learners in a Learning Network.
The comparison of the control group to both treatment groups showed for all eight Learning Networks a significant difference in the percentage of graduation, study time and the satisfaction of learners. The treatments groups performed significantly better on the educational measures of Table 2.1. The most interesting part of the study was the comparison of the treatment groups against each other. We found that none of the treatment groups performed significant better in a certain Learning Network regarding the graduation of learners. But treatment group I showed significant differences on the satisfaction of learners and their study time when they followed less complex learning goals. They were more satisfied and needed less time to achieve their learning goals. Surprisingly, we have not found these differences for Learning Networks when learners followed complex learning goals, consisting of multiple competences. Furthermore, we have not found any difference between small and large Learning Networks, neither when the Learning Network consists of more learners or more learning activities.
In order to test the findings from our experiments in more real world research we developed a technical prototype called 'ReMashed' that was used by 50 lifelong learners in a Learning Network.

ReMashed – Recommendations for Mash-Up Personal Learning Environments

In Chapter 6 we presented a technical prototype ReMashed that integrated findings of the conducted research from Chapter 2 to 5. ReMashed enabled lifelong learners to sign up with their Web 2.0 tools and rate information created by other learners. ReMashed explicitly address the recommendation goals, user model, and environmental conditions of informal learning. It showed how recommender systems can take advantage of emerging Web 2.0 information from lifelong learners in a Learning Network. It recommended most suitable resources based on tags and ratings of individual learners. Furthermore, the learners were able to specify learning goals and prior knowledge levels in a self assessed way.

Practical implications

In the Introduction of this thesis we stated four main problems with nine questions that are part of our general research question. Based on the theoretical analysis, the empirical findings in two experiments, and practical experiences with the ReMashed prototype, following nine practical implications for navigational support of lifelong learners in informal Learning Networks were found: (1) Recommender systems from e-commerce systems cannot easily be applied to learning. They have different recommendation goals, user models and environmental conditions. (2) Recommender systems for formal and informal learning also have to be designed rather differently. Even when they have common pedagogical characteristics, they do not share similar learner models and environmental conditions. (3) In order to evaluate the impact of recommender system in Learning Networks a combination of technical measures with educational measures have to be used. Especially, in case of Learning Networks, also measures from social network analysis can be applied. (4) There is no single recommendation technique that perfectly addresses Learning Networks. But the use of hybrid recommender systems can partially solve disadvantages of single Collaborative Filtering algorithms and also address certain pedagogical situations by switching from one algorithm to another. (5) Context-aware recommendation technologies are most suitable to integrate pedagogical characteristics like prior knowledge as they offer options to pre- or post-filter the Collaborative Filtering results. (6) The conducted research showed at least partly that it is possible to improve the performance of learners by offering personalized recommendations to them. It was possible to pre-select learning activities from the Learning Networks according to the indirect (like study time and completion rates) and direct measures (like tags and ratings) of informal learning. (7) Simulations studies are useful to evaluate recommender systems in Learning Networks of different sizes. They enable us to observe the emerging behavior of learners in Learning Networks of different sizes. (8) The development of an interface for a recommender system for informal learning is possible by presenting the emerging information of the Learning Networks in a very structured way. Learners can specify which information they are interested in and which they are not by adding a rating layer on top of the emerging information of a Learning Network. (9) It is possible to personalize the emerging information of Learning Networks by taking into account user-generated content of the individual learner. Various Web 2.0 content, tags and ratings of an individual learner can be combined to pre-filter information.

These theoretical guidelines and practical implications need to be further examined and validated for other forms of navigational support for lifelong learners. The general discussion contains some suggestions for future research and follow-up studies for the Learning Network simulation and the ReMashed prototype. This thesis offers sufficient proof to conclude that research on navigational support by recommender systems for informal learning is needed, timely and promising. It appears feasible to conduct experimentally controlled studies within authentic learning situations like ReMashed offers. The societal trends and the need for more personalized learning possibilities justify an increase of this type of research.

Samenvatting

Samenvatting

In dit proefschrift hebben we de mogelijkheden van adviessystemen onderzocht die leeractiviteiten aanbevelen aan levenslang lerenden binnen informele leeromgevingen. De algemene onderzoeksvraag van dit proefschrift is:

Hoe kunnen we op de beste wijze geschikte leeractiviteiten aanbevelen aan levenslang lerenden binnen informele leernetwerken, rekening houdende met hun persoonlijke behoeften, voorkeuren en leerdoelen?

De toenemende hoeveelheid informatie op het internet verschaft mensen toegang tot bijna alles wat zij nodig hebben. Aan de andere kant biedt het internet een overdaad aan informatie, waardoor het moeilijk wordt om een overzicht te krijgen en om de meest geschikte informatie te selecteren. Dit selectieprobleem betreft ook levenslang lerenden in informele leernetwerken.
Adviessystemen zijn veelbelovende technologieën om het vinden van de meest geschikte informatie te ondersteunen.
In dit proefschrift onderzochten we de navigatieondersteuning van adviessystemen om de selectie van de meest geschikte leeractiviteiten, aangepast aan individuele behoeften, voorkeuren en leerdoelen, te verbeteren.
We hebben deze uitdaging allereerst in hoofdstuk 2 en 3 geanalyseerd op een theoretisch niveau en daarna in hoofdstuk 4, 5 en 6 op een empirisch niveau. Tenslotte hebben we praktische implicaties van het onderzoek beschreven in hoofdstuk 7. Onderstaand volgt een opsomming van de resultaten van dit proefschrift.

Theoretische grondslagen

Identificatie van de doelen, het gebruikersmodel en de voorwaarden voor adviessystemen voor informeel leren.

In hoofdstuk 2 vonden we verschillen in voorwaarden waaraan commerciële adviessystemen en adviessystemen voor onderwijsdoeleinden moeten voldoen. We onderscheidden hun voorwaarden, gebaseerd op (1) aanbevelingsdoelen, (2) gebruikersmodel en (3) omgevingscondities.
Allereerst hebben we ontdekt dat het belangrijkste doel van aanbevelingen door adviessystemen is het structureren van leeractiviteiten op een pedagogische wijze, om een consistente competentie-ontwikkeling van lerenden mogelijk te

maken. Verder maken adviessystemen gebruik van ontstane leerpaden om de meest efficiënte of effectieve paden aan lerenden aan te bieden.
Ten tweede vereisen commerciële adviessystemen een ander gebruikersmodel dan adviessystemen voor onderwijsdoeleinden. E-commerce adviessystemen vereisen informatie, zoals zip code, inkomen, creditcardgegevens, verzendadres, voorkeuren voor verzending en de reeds aangekochte goederen. Gebruikersmodellen binnen het onderwijs zijn nogal afwijkend, ze vereisen informatie over leerdoelen, verworven kennis, leervoorkeuren (huidige voorkeur voor een soort media), reeds bewandelde leerpaden en informatie over voltooide, gespecificeerde of vastgestelde leeractiviteiten.
Ten derde wijken ook de omgevingscondities van commerciële adviessystemen af van de adviessystemen voor onderwijsdoeleinden. E-commerce systemen worden dagelijks onderhouden door een productcatalogus en door semantische verhoudingen. Ook de producten zelf zijn goed gedefinieerd door beschrijvingen van de metadata. Meestal impliceert de productcatalogus een enorme dataset met duizenden producten en klanten met miljoenen transacties.
Adviessystemen in een informele leeromgeving moeten met verschillende situaties rekening houden. De leeractiviteiten worden niet dagelijks onderhouden. Ze worden op een ongestandaardiseerde wijze vastgesteld, gespecificeerd en aangepast door individuele lerenden. Dit leidt ertoe, dat een adviessysteem rekening moet houden met afwijkende data sets in informele netwerken. Bovendien stelden we vast, dat adviessystemen voor formeel leren in onderwijsorganisaties enigszins overeenkomen met commerciële adviessystemen. Vooral de omgevingscondities van beiden zijn vergelijkbaar. Veel formele leersystemen hebben goed onderhouden productcatalogussen met duidelijker omschreven cursussen en leerinhoud. Deze zijn ontworpen en beschreven door een onderwijsontwerper, die zich heeft gehouden aan een gestandaardiseerde semantische beschrijving.
Concluderend, om informeel leren met adviessystemen te benaderen, moeten we rekening houden met afwijkende omgevingscondities, gebruikersmodellen, een gebrek aan onderhoud en minder gestructureerde leeractiviteiten. In plaats daarvan moeten we gebruik maken van de groeiende informatie zoals 'tags' en 'ratings' om de leeractiviteiten voor individuele lerende te selecteren en te structureren. Om tegemoet te komen aan de voorwaarden voor informeel leren zijn de niet-hiërarchische aanbevelingstechnologieën, zoals Collaborative Filtering, het meest geschikt, want zij hebben nauwelijks onderhoud nodig en verbeteren het gedrag dat binnen de gemeenschap ontstaat. Als laatste stap in hoofdstuk 2 hebben we een evaluatieraamwerk gecreëerd om de invloed van adviessyste-

men op de leeruitkomsten te meten. (zie tabel 2.1). Daartoe combineerden we technische evaluatiecriteria voor onderzoek naar adviessystemen met onderwijskundige en Social Network Analysis criteria.

Adviessystemen voor lerenden in leernetwerken: voorwaarden, techniek en model

Gebaseerd op de eerste analyse van aanbevelingsdoelen, gebruikersmodellen en omgevingsvoorwaarden onderzochten we in hoofdstuk 3 verschillende aanbevelingstechnologieën die veelbelovend lijken voor informeel leren. De bevindingen waren, dat iedere aanbevelingstechniek zijn eigen voor- en nadelen heeft en we hebben de meest geschikte technieken opgenomen in tabel 3.1. We concludeerden, dat hybride adviessystemen het meest geschikt waren, omdat deze gebaseerd zijn op een combinatie van verschillende aanbevelingstechnieken, waarbij nadelen van individuele technieken worden gecompenseerd in een aanbevelingsstrategie.

Empirische uitkomsten

Na het definiëren van de aanbevelingsdoelen, gebruikersmodellen, een evaluatieraamwerk en de meest geschikte aanbevelingstechnieken hebben we de theoretische resultaten getest binnen twee experimenten en hebben we een eerste technisch prototype ontwikkeld voor levenslang lerenden in informele leernetwerken.

Effecten van een adviessysteem voor lerenden in een leernetwerk

In hoofdstuk 4 hebben we ons eerste experiment beschreven, waarbij we getest hebben of de resultaten van een experimentele groep, ondersteund door een adviessysteem, verschillen vertoonden met die van een controlegroep, die niet door een adviessysteem ondersteund werd. Het adviessysteem bestond uit een stereotype filtertechniek (zie tabel 3.1) en een op een ontologie gebaseerde aanbevelingsstrategie. Het resultaat was, dat het adviessysteem de studietijd op een aanzienlijke wijze positief beïnvloedde.

De experimentele groep had voortdurend minder tijd nodig om een gelijk aantal leeractiviteiten te voltooien. Verder kozen de deelnemers van de experimentele groep meer gepersonaliseerde leerpaden dan de deelnemers van de controlegroep, omdat zij veel meer gepersonaliseerde leerpaden binnen de leernetwerken verkenden.

Na deze veelbelovende resultaten hebben we onderzocht hoe adviessystemen zich gedragen in leernetwerken met een verschillende omvang. Daartoe hebben we een simulatie ontworpen om de aanbevelingstechnieken uit tabel 3.1 te testen binnen verschillende leernetwerken.

Effecten van adviessystemen in leernetwerken van verschillende omvang

In hoofdstuk 5 hebben we ons tweede experiment beschreven, waarbij we de effecten van adviessystemen in leernetwerken van verschillende omvang evalueerden. We ontwierpen een simulatie dat een leernetwerk modelleert met gebruik van de Netlogo multi-agent programmeerbare modelleeromgeving. In dit experiment pasten we een gebruikersgebaseerde 'Collaborative Filtering' en een onderwerpgebaseerde 'Collaborative Filtering' uit tabel 2 toe. Ieder van deze technieken werd geïmplementeerd binnen een experimentele groep (onderwerpgebaseerde filtering - onderzoeksgroep I, en gebruikersgebaseerde filtering - onderzoeksgroep U), en werden elk vergeleken met een controlegroep zonder navigatieondersteuning. Hoofdstuk 5 beschrijft de resultaten van acht simulatie runs, die ieder een verschillend aantal leeractiviteiten en een verschillend aantal lerenden in een leernetwerk vertegenwoordigden.
De vergelijking van de controlegroep met de beide experimentele groepen toonde bij alle acht de leernetwerken een significant percentageverschil in afronding, studietijd en tevredenheid van de lerenden. De experimentele groepen presteerden aanzienlijk beter op basis van de onderwijskundige criteria uit tabel 2.1. Het meest interessante onderdeel van de studie was de vergelijking van de beide experimentele groepen. Hieruit bleek, dat met betrekking tot de afronding van activiteiten door lerenden geen van de experimentele groepen beter presteerde in een bepaald leernetwerk. Maar bij groep I bleken er aanzienlijke verschillen met betrekking tot tevredenheid van lerenden en studietijd te bestaan wanneer ze minder complexe leerdoelen volgden. Ze waren meer tevreden en hadden minder tijd nodig om hun leerdoelen te bereiken. Verassend genoeg vonden we deze verschillen niet bij leernetwerken waarbij lerenden complexe, uit meerdere competenties bestaande leerdoelen volgden. Verder hebben we geen verschil gevonden tussen kleine en grote leernetwerken, ook niet als leernetwerken bestonden uit meerdere lerenden of meer leeractiviteiten.
Om de uitkomsten van onze experimenten te testen in een meer realistisch onderzoek ontwierpen we een technisch prototype genaamd ReMashed. Dit prototype werd gebruikt door 50 levenslang lerenden in een leernetwerk.

ReMashed - aanbevelingen voor 'Mash-up' gepersonaliseerde leeromgevingen

In hoofdstuk 6 beschreven we een technisch prototype, genaamd ReMashed, waarin een aantal uitkomsten van onderhavig onderzoek zijn geïntegreerd. ReMashed maakt het voor levenslang lerenden mogelijk om zich via hun Web 2.0 tools te registreren en informatie te waarderen die door andere lerenden is aangemaakt. ReMashed richt zich expliciet op aanbevelingsdoelen, het gebruikersmodel en de omgevingscondities voor informeel leren. Het toont aan hoe adviessystemen voordeel kunnen hebben van uit Web 2.0 ontstane informatie van levenslang lerenden in een leernetwerk. Het beveelt de meest geschikte bronnen aan, gebaseerd op tags en waarderingen van individueel lerenden. Verder konden de lerenden, door zelf te toetsen, leerdoelen en eerder verworven kennisniveaus specificeren.

Praktische toepassingen

Bij de introductie van dit proefschrift noemden we vier problemen met negen vragen, die deel uitmaken van de algemene onderzoeksvraag. Gebaseerd op de theoretische analyse, de empirische uitkomsten van twee experimenten en de praktische ervaring met het ReMashed prototype, alsmede praktische aanbevelingen voor navigatieondersteuning van levenslang lerenden in informele netwerken, kunnen we nu wat betreft deze vragen de volgende conclusies trekken: (1) Commerciële adviessystemen kunnen niet gemakkelijk toegepast worden binnen het onderwijs. Ze hebben verschillende aanbevelingsdoelen, gebruiksmodellen en omgevingscondities. (2) Adviessystemen voor formeel en informeel leren moeten nogal verschillend ontworpen worden. Zelfs als ze gemeenschappelijke pedagogische eigenschappen hebben, komen de leermodellen en omgevingscondities niet overeen. (3) Om de invloed van adviessystemen in leernetwerken te evalueren moet een combinatie van technische criteria en onderwijskundige criteria worden gehanteerd. Bij leernetwerken kunnen vooral criteria van Sociale Netwerk Analyse worden toegepast. (4) Er is geen enkele aanbevelingstechniek die perfect voldoet voor leernetwerken, maar het gebruik van hybride adviessystemen kan gedeeltelijk de nadelen van individuele Collaborative Filtering algoritmen oplossen, en ook inspelen op bepaalde pedagogische situaties door het wisselen tussen algoritmen. (5) Contextgebonden aanbevelingstechnologieën zijn bijzonder geschikt om pedagogische karakteristieken, zoals verworven kennis, te integreren, omdat ze mogelijkheden bieden tot het vooraf of achteraf filteren van de Collaborative Filtering resultaten. (6) Het on-

derhavige onderzoek toonde, op zijn minst gedeeltelijk, aan, dat het mogelijk is om de prestaties van lerenden te verbeteren door hen gepersonaliseerde aanbevelingen aan te bieden. Het was mogelijk om vooraf geselecteerde leeractiviteiten uit de leernetwerken te selecteren die overeenkwamen met indirecte- (bijvoorbeeld studietijd en gerealiseerde cijfers) en directe criteria (zoals tags en waarderingen) voor informeel leren. (7) Simulatiestudies zijn nuttig om adviessystemen in leernetwerken van verschillende omvang te evalueren. Ze maken het ons mogelijk om het emergente gedrag van lerenden in leernetwerken van verschillende omvang te observeren. (8) De ontwikkeling van een interface voor een adviessysteem voor informeel leren is mogelijk door de emergente informatie uit leernetwerken op een heel gestructureerde manier aan te bieden. Lerenden kunnen specificeren in welke informatie ze wel of niet geïnteresseerd zijn door een waardering aan de emergente informatie van een leernetwerk toe te voegen. (9) Het is mogelijk om de emergente informatie van gebruikers binnen een leernetwerk te personaliseren door rekening te houden met de individuele lerende. Diverse Web 2.0 inhoud, tags, en waarderingen van een individuele lerende kunnen worden gecombineerd tot vooraf gefilterde informatie.
Deze theoretische richtlijnen en praktische toepassingen moeten verder onderzocht en gevalideerd worden voor andere manieren van navigatieondersteuning voor levenslang lerenden. De algemene discussie omvat enkele voorstellen voor toekomstig onderzoek en follow-up studies, met name voor de simulatie van leernetwerken en het Remashed prototype. Dit proefschrift levert voldoende resultaten om te mogen concluderen dat onderzoek naar navigatieondersteuning bij adviessystemen voor informeel leren zowel noodzakelijk, relevant als veelbelovend is. Het blijkt uitvoerbaar om experimentele studies uit te voeren binnen authentieke leersituaties.De maatschappelijke trends en de behoefte aan meer gepersonaliseerde leermogelijkheden rechtvaardigen een toename van dit soort onderzoek

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Curriculum Vitae

Curriculum Vitae

Hendrik Drachsler, was born on the 16th of November 1977 in Wiesbaden, Germany. He studied educational sciences and computer sciences at the University of Duisburg. In 2002 he worked for the spin-off LOCALITE from the Fraunhofer Gesellschaft, where he developed a knowledge management tool in the domain of medical navigation systems. The software was used for an online user support system, to create the software manual, and to create quality tests for the medical navigation systems based on ISO 9001 standard.

In 2004 Hendrik started his academic career as research assistant at the Fraunhofer Institute for Applied Information Technology (FIT). He was granted by the Friedrich-Ebert-Stiftung to extend his research on technology-enhanced learning. At FIT he participated in the development of a Hard- and Software simulator for transesophageal echocardiography. His Master thesis on sensorimotor and mental model training of medical professionals in transesophageal echocardiography was completed in May 2006 and was qualified as outstanding.

In April 2006 Hendrik joined the Open University of the Netherlands where he worked until now in the European funded Integrated Project TENCompetence (6th Framework Programme). Hendrik has more than 20 publications in the field of technology-enhanced learning and he serves as reviewer and programme committee member for international conferences and journals. In his current work Hendrik is focusing on new methods to improve informal learning for lifelong competence development by the use of Web 2.0, social software and recommender systems. More information and a full list of publications and activities are available at http://elgg.ou.nl/hdr/weblog.

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