Personal recommender system for learners in learning networks

Educational Technology Expertise Center
Open University of the Netherlands

Technology Development PhD project proposal

This project falls in the following topic(s):

Learning Networks
- ☐ Software Architectures
- ☐ Knowledge Resource Sharing & Management
- ☐ Learning Activities & Units of Learning
- ■ Competence Development Programs
- ☐ Networks for Lifelong Competence Development

1 Candidate
Hendrik Drachsler

2 Project title
Personal recommender system for learners in learning networks

3 Summary
This project is about the design and development of *navigation services* for distributed learning networks (Koper & Sloep, 2005). Such services should recommend most suitable learning activities to learners regarding their personal needs and preferences. For this purpose we aim to develop a *personal recommender system* (PRS), that will use combinations of various prediction techniques (Van Setten, 2005).
Learning networks can be filled with lots of learning activities stemming from different providers. Such networks are dynamic, because each member could add or delete content at any time. A personal recommender system is needed to support learners in selecting learning activities from a learning network that will enable them to achieve their (formal or informal) learning goal in a specific domain.
It is expected that such support will minimize the amount of time learners need for finding suitable learning activities. The personal recommender system filters suitable learning activities regarding the needs and preferences of individual learners. A better alignment of the characteristics of learners and learning activities is expected to increase both effectiveness and efficiency of learning progress through the network.

4 Research team

	Name and titles	Expertise/function	Department
a. Chair	dr. Hans Hummel	Project lead	OUNL/OTEC
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e. Co-supervisor			

5 Duration
Begin date: 01-04-2006
End date: 31-11-2009

6 Review

01.10.2006	Sent out to reviewers
01.12.2006	Deadline for reviews

On September 29, 2006 a version of this PhD plan was sent out for an external review by three key stakeholders and experts in the field: Prof. Dr. Anton Nijholt (University of Twente, Netherlands); Dr. Alexander Felfernig (University Klagenfurt, Austria); and Dr. rer. nat. Ralf Klamma (RWTH Aachen, Germany).
Reviewers where asked to comment on the relevance, problem definition, quality and feasibility of the plan and to provide suggestions for improvement of the project. They were also asked to score the project plan with eiter ‘A’ (accept without any revisions), ‘B’ (accept with minor revisions), or ‘C’ (accept with major revisions).

Reviewers’ comments were received at the end of December 2006. Reviewers assessed the overall quality of the project plan with a ‘B’. We carefully addressed all comments and suggestions made and drew up a revised version of the plan. This document is the final version of the plan which was approved by the programme on March 16, 2007.

7 Project plan status

30.06.2006	Project plan worked out in the standard template / draft
29.09.2006	Approved by submitters / final draft
01.10.2006	Approved for review by the Programme
19.12.2006	Last review received
16.03.2007	Revisions made and approved by the Programme
	Approved by MT OTEC

1. Introduction

The need for navigation

In the current era of lifelong learning, learners are free to decide what, when, where and how they want to learn. Learners are very flexible regarding their individual competence development, and are also more responsible for their own learning path. On the one hand lifelong learners are free to choose any kind of educational offer, but on the other hand they are also fully responsible for the results of the learning process (Longworth, 2003). In this situation lifelong learners need advice to decide what are the most suitable learning activities to meet their individual learning goals. Learners find it hard to get an overview of all available learning activities and it is not an easy task to identify the most suitable learning activities.
For distributed Learning Networks (LN), a navigation service would be a helpful tool to advise learners on suitable learning activities matching to their needs and preferences. The re-

quired navigation service goes beyond classical navigation approaches like the *breadcrumb trail* (Molando & Resnick, 2002) or other software guidance strategies (e.g., go forward, backward, use favorites). The navigation service has to behave like a consultant. To provide such a navigation service, a *personal recommender system* (PRS), which is well known from web services like *amazon.com* (Linden, Smith, & York, 2003), is needed. Until now there is no such personal recommendation system to support lifelong learners in learning networks.

The main problem

The main problem for learners is their lack of orientation when choosing suitable learning activities. In order to provide personal recommendations for an individual learning path to take, we have to consider the individual learning history and individual learning goals for each learner. This PhD project will treat the navigation problem by addressing following question: How can we recommend suitable learning activities – regarding to the learner profile and learning history – to reach the learning goals in a more efficient and effective manner? For this purpose different kind of common prediction techniques, like *social-based* and *information-based* techniques (Van Setten, 2005), could be adapted to the needs of learners in learning networks.

This approach to PRS introduces a couple of questions that have to and will be addressed: How should personalized recommendations be created? What kind of information will be needed to personalize recommendations? How should we define the relationship between different attributes of a learner to create a suitable personalized recommendation? Are some attributes of learners more important than others? What kind of recommendation strategies and techniques are suitable for various kind of navigation problems and how can we adjust or re-invent recommender systems in various learning networks? How could we measure the efficiency and effectiveness of PRS in a learning network?

Hypotheses

We want to improve the effectiveness and the efficiency of the learning process. Related hypotheses to these objectives are the following:

- H1: People with a PRS finish more learning activities, because they don't have to spent that much time for selecting suitable learning activities to them.

- H2: The drop-out rate for people who are using a PRS should be less, because the PRS recommended the most appropriated learning activities to them.

- H3: People with a PRS need less time to finish learning activities successful, because the PRS recommended the most appropriated learning activities to them.

- H4: People with a PRS need less time to achieve a specific learning goal, because the PRS recommended the most suitable learning activities to them.

Suitable techniques

Like other recommender systems we are using similar techniques like *collaborative filtering, data mining, data clustering* and *information retrieval.* But creating recommendations in learning networks is quite different from other domains. Most studied domains for recommender systems are music, books or movie recommendations (Basu, Hirsh, & Cohen, 1998; Herlocker, Konstan, Borchers, & Riedl, 1999; Herlocker, Konstan, Borchers, & Riedl, 2004). For a recommender system in education it is important to understand the individual situation of learners. For a RS in education it is important to understand the individual situations of the learners. Other RS used in the learning domain (Andronico *et al.*, 2003; Zaiane, 2002) don't address the lifelong learner. They mainly established a RS in the same way like a RS for e-commerce without focusing on specific attributes of the learning domain. They just watch at the footprints of successful learners and recommend based on this data like Amazon looks for products of other customers. There is no reference to any pedagogical theory or learner specific characteristics.

Ideally a RS has to differentiate for learners' cognitive development, learning styles, motivation and other characteristics as well as for the recommended learning content. A technique is suitable when it helps to improve the effectiveness or efficiency of the learning process.

Besides this, the learner and content characteristics change over time. For instance, the purpose of a specific learning object may vary across various stages of learning; the same object may fulfill different roles at different stages (Herlocker et al., 1999; McCalla, 2004a). Where other recommender system are using *user modelling*, we have to adjust this towards *learner modelling* (Aroyo, 2006). Learner modelling is connected to educational, psychological, social and cognitive science. For instance, learning activities preferred by learners might not be pedagogically appropriate for them. By contrast, in the other, more familiar domains, recommendations are made based purely on users' interests. In a learning network, even for learners with the same interest, we may need to recommend different learning activities, regarding to the competence level and goals of the learner.

For instance, learners without any prior background on a specific domain should probably get recommended to study more general learning activities first. More advanced learners with some prior knowledge of a specific domain, should probably get recommended to focus on more specific learning activities relating to their situation (Tiffany Ya Tang & Gordon McCalla, 2003).

Recommender systems for lifelong learning networks are even more complex, because lifelong learning entails both *formal learning* and *informal learning* offerings, which are more loosely connected to a specific domain (Helen Colley, Phil Hodkinson, & Janice Malcolm, 2002). To cater for all formal and informal learning activities, different kind of prediction techniques have to be selected and combined to provide adequate recommendations. For informal lifelong learning, the recommender system has to be developed according to a *bottom-up approach* in order to give learners control to personalize the recommendations. In this situation, recommending based on *folksonomy* driven information (Mathes, 2004) seems to be a suitable approach. For formal lifelong learning, dealing with competence development programs from official providers with fixed curricular for specific domains, the recommender system has to be developed according to a *top-down approach.* In this situation, recommendations based on a *semantic web* (Berners-Lee, Hendler, & Lassila, 2001) seem most suitable. With top-down approaches all relationships between the *metadata* are predefined by domain experts. The lifelong learners will only be able to behave in this predefined *ontology* and could not go beyond the borders of it. The learners are not able to change the metadata or to personalize the use of it, like they can with bottom-up approaches.

Relation to other components in a learning network

The following section will describe how a personal recommender system is related to other components in a learning network. The following is based mainly on the domain model of the TENCompetence project (Koper, 2005b).

Positioning service
Effective navigation requires a well-defined starting point; we call this the *positioning* of a learner (Kalz, van Bruggen, Giesbers, Rusmann, & Koper, 2005). The positioning problem deals with the mapping of prior learning experiences to competences connected to the competence development programs a learner has chosen according to his goals. An automatic or semi-automatic technique to position a learner in a LN is important because it describes which learning activities could be skipped because the learner already has acquired them. If there is no positioning information available, the navigation service has to include all available learning activities without taking into account the history of the learner.

Learning path specification
Besides the relation between *position* and *navigation*, a PRS could benefit from *learning standards* like a *learning path specification*, which would enable exchange of effective learning paths. Such a specification has not been developed yet. If such a specification becomes available, a PRS could use the specification to provide recommendations on suitable learning paths. Such recommendation would add value to learning networks, because the learners are then able to plan their learning paths and compare them with other ones.

ePortfolio specification
For several prediction techniques, the navigation service will need detailed information about the learner that will be stored in a learner profile; this information is modeled according to the *ePortfolio specification* of TENCompetence. Learners should be able to make selections of this information regarding their needs and preference, in order to personalize the recommendations.

The TENCompetence project aims to deliver (before the project ends in 2009) both a *learning path specification*, *ePortfolio specification* and a *positioning service* to enable navigation in learning networks. To get an overview of their relations, see the use case depicted in Figure 1.

Learner
In Figure 1, the actor in the Use Case is displayed in the role of a learner.

Edit profile
The learner has the option to create and edit her profile in the *ePortfolio specification*. In the profile she could define her preferences, needs and information about her educational background. The information of the profile could have consequences for the recommendation if the learner selects a recommendation technique that uses the learner profile data. The profile data are stored according to the *ePortfolio specification*.

Specify goal
The learner has to define a certain learning goal to get recommendations. The learning goal will be defined in the *ePortfolio*. Based on the selected or predefined prediction technique the recommendation engine starts to search for suitable learning activities.

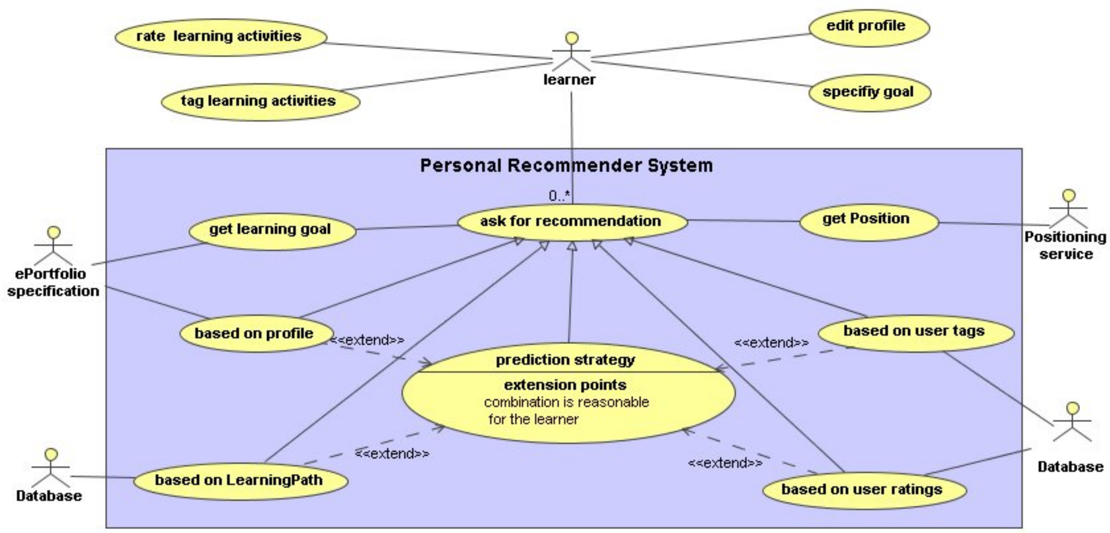

***Figure 1*: Use case for Personal Recommender System in a Learning Network**

Ask for recommendation
The learner could ask for a recommendation. Based on the selected recommendation technique, she will get an advice on the most suitable learning activity.
Before advising any recommendation the navigation service will wait for input of the *positioning service* and the *ePortfolio specification* to get the current position and the learning goal of the learner. With this information the PRS will analyze suitable learning activities. The provided recommendation could be based on different kind of prediction that are suitable to the learner. These singular predictions could also be combined in various ways to a multiple prediction technique called *prediction strategy*.

Tag / rate learning activities
The learner is also able to rate or add tags to specific resources. These resources could be classified as knowledge resources (websites, documents, computer programmes, et cetera) and learning activities (study tasks, units of learning, learning paths). Within the TENCompetence project, we will research mechanisms for rating and tagging knowledge resources and learning activities.

Prediction techniques can be based on following information:

- *based on profile*

Based on the learner profile, suitable learning activities will be recommended to the learner. Therefore the PRS has to get information about the learner from the *ePortfolio specification*.

- *based on learning path*

Based on the learning paths, suitable learning activities will be recommended to the learner. Therefore the PRS has to access a database with stored learning paths.

- *based on learner rating*

Based on already rated learning activities by other learners, suitable learning activities will be recommended to the learner.

- *based on learner tagging*

Based on tags (keywords) given by the learner to learning activities, the learner is able to find other learning activities with the same or similar tags added by other learners.

(If a combination of prediction techniques is reasonable for the current situation of the learner, different prediction techniques could be combined. For example, the learner could get a recommendation based on similar learner profiles and based on their ratings to learning activities.)

2. Objectives

Primary objectives

- Development of a Personalized Recommender System (PRS) to recommend most suitable learning activities for individual users in a learning network.

Secondary objectives

- The PRS supports the selection of both informal and formal learning paths and learning activities.
- The PRS supports both top-down and bottom-up approaches to recommendation, depending on to the current situation of the learner.
- The PRS combines different kinds of prediction techniques for recommendation, depending on the current situation of the learner.

3. Intended results

Technology outcomes

The technology outcomes of the project will be three, consecutive versions of a PRS, that will be published in the public domain and will be peer-reviewed:

1. The first release (last quarter of 2006) will be tested within an experimental set-up, in collaboration with the Psychology Department at the OUNL. This first release will use a combination of collaborative filtering and learner profile metadata. Learners will be students of the introductory psychology course (240 study hours) needing advise on study tasks to follow. Study tasks will be implemented in Moodle (http://moodle.org) as the course management system. The PRS will be developed in PHP and MySQL. We will adapt Moodle to the general requirements of a learning network. Examplary requirements are (Koper, 2005):
   - “The objective of any LN is to offer long lasting, evolving facilities for the members to improve and share their expertise and build the competencies needed in a disciplinary field.”
   - “The LN should offer facilities for members to create, search, get/access and study LNs, ANs, UOLs and learning resources as a means of building expertise and competence.”
2. A second release of the PRS will be tested in 2007 by a simulation of a learning network with virtual learners (Koper, 2005a). It will be based on the experience and results of the first experiment and elaborated with user ratings. This version will be developed in JAVA in order to be able to use the DUINE Toolkit (Van Setten, 2005), that offers an open source framework for recommendation systems.
3. A third and more advanced personal recommendation system in 2008 will be based on the experiences of both studies, and will be tested in an experimental setup, in collaboration with the *health care pilot* within the TENCompetence project. After some final adjustments, this will offer the final PRS for this project.

Publication outcomes

The publication outcomes of this project will be four articles (SSCI/SC listed):

1. Personal Recommender Systems for learning networks: theoretical approach.
2. Personal Recommender System for learning networks: empirical study with psychology students.
3. Personal Recommender System for learning networks: simulation study to evaluate the value of learner ratings of learning activities.
4. Personal Recommender System for learning networks: empirical study with health care students.

4. Relevance

The OUNL provides distance education, while attempting to exploit the advantages of ICT to address various needs of lifelong learners, as its core business. Therefore a new form of education delivery should be developed that goes beyond course and program centric models, and envisions a learner-centered and learner-controlled model of lifelong learning (Koper & Sloep, 2005). At the moment several projects like the internal *ISIS* project (Individualised Support in Sequencing) and *Positioning in learning networks* project are dealing with components that will be integrated in the infrastructure for Learning Networks, as it is aimed in the TENCompetence project.

Navigation is one mechanism that can be responsible for increased efficiency and self-organization in finding the required learning activities. Learners need the possibility to get more control to select suitable learning activities, but at the same time should not be overwhelmed by extra responsibilities that go with it. Without adequate navigational support, learners might easily get lost in information without any sense of orientation. This PhD work will examine the value of navigational support in making personal choices and progress by providing learner-centered information on learning activities in learning networks that might be suitable to reach their aimed competence.

5. Further elaboration

The majority of current web-based learning systems are closed learning environments, where courses and materials are fixed. The only dynamic aspect is the organization of the materials that can be adapted to allow some individualisation of the learning environment.

Learning networks are more open in the sense that learning activities could be added, adapted, or deleted by any member of the learning network. In traditional adaptive e-learning systems, the delivery of learning material is personalised according to the learner model. However, the materials inside the system are a pre-designed by the system designer or tutor. In learning networks, the learning activities and learning materials are added and integrated into the system by and during lifetime of the community.

Our approach is very close to the *ecological approach* proposed by McCalla (McCalla, 2004b). Similar to his research, learning networks will be filled with increasing amounts of learners and learning activities over time, and then something like natural selection will determine what information is useful and what is not. Our approach also is in line with learner-centered and constructivist pedagogical theories on learning (Bannan-Ritland, Dabbagh, & Murphy, 2002), and see learners engaged in authentic learning activities and supported by technology to achieve their learning goals.

Members of such complex, self-organizing learning networks can be expected to need guidance in finding and composing their most suitable learning activities (path guidance), in order to attain their learning goals in the most effective and efficient way. Learning paths lead to certain competence levels. Most efficient learning paths lead to the a competence level in a shorter time period, or to a higher competence level in the same amount of time. There, the '*most suitable*' learning activity in this respect could mean either the *most efficient* path, a path of the *highest quality* (when learners want to get the best results out of their learning efforts), or the path that seems *best adapted to personal preferences or needs* (as will be the case with learners that have specific needs, motivations, handicaps, or face other situational circumstances).
The learner is put centre-stage in this self-organised, distributed e-learning systems, which calls for more learner-centred navigation services. Current navigational services mostly are of a rather general, uniform nature and not cater for specific needs, motivations and preferences of individual learners. Learners will need feedback that includes qualifications about most suitable learning activities to study (e.g., quality rates, characteristics of those learning activities). The ultimate goal of navigation support in such lifelong learning networks is to provide more personalised feedback to *all* learners, on both the quality and suitability of *all* available learning activities.
It is likely that several learning routes may lead to the selected goal in personal competence development programs. A PRS than is required to provide the learner with a personalized recommendation on the best learning activity or path. The recommendations should be updated dynamically when the learner has completed an learning activity or when other learning activities have been added to the learning network.

The current research on recommender system is going in the direction of 'knowing your techniques', but also 'knowing your domain and your user' (McNee, Riedl, & Konstan, 2006). It is for this reason, that the choice of clustering algorithms, data mining algorithms and particular constraints on each algorithm are highly contextualized to the domain. McCalla (2004) argues why future research work on recommending learning objects, with the aim to discover what algorithm works best, where and for what purpose, is important. This research is also important to examine the structure of learner models that can be gathered, the kinds of information that may be useful and for what purpose. Further research goals are to get more standardized rules to recommend learning activities to learners for specific purposes.
To address this domain focus for designing recommender systems, we will use principles of self-organisation to advice learners on most suitable learning activities to proceed with, by analysing the activities already followed by others. Furthermore, we will map characteristics of learners (stored in their ePortfolios) onto characteristics of available learning activities or learning paths to provide individualised advice. The ROMA project (Janssen *et al.*, 2005) already explored some basic principles of self-organization combined with collaborative filtering of successful learning activities by others..

Prediction techniques

Two groups of prediction techniques can be distinguished:

1. *Social-based (or data-based) prediction techniques* analyze behavior and characteristics of users without using the content of the items; they use the known behavior and characteristics of the current user and other users to deduce the predicted interest in the item for the current actor.
2. *Information-based (or knowledge-based) prediction techniques* analyze the content of the item and other items and the knowledge about the current user to deduce the predicted interest of the item for the current actor.

Prediction techniques could also be combined in so called *Hybrid prediction techniques*. The idea behind hybrid prediction techniques is that a combination of algorithms can provide more accurate recommendations, since disadvantages of one algorithm can be compensated by others. (Malone, Grant, Turbak, Brobst, & Cohen, 1987) mentioned that a combined approach is taken by most useful systems. That will also be the case for our PRS in a learning network. The main data mining techniques we are focusing on are *collaborative filtering* and *case-based reasoning*.

Social-based prediction techniques

There are a couple of techniques in the field of social-based prediction techniques, e.g. *item-item filtering, filtering based on stereotypes and demographics*, *popularity* or *average* and *collaborative filtering* (CF). The basic idea behind CF (also called social filtering) is that people who have rated the same items the same way in the past probably have the same taste. Based on this knowledge one can predict how much a person likes an unseen item when similar actors have already rated that item.

CF basically consists of three steps. In the first step, the similarity between the current actor and those other actors who have rated the item for which a prediction is calculated based on how the current actor and each of the other actors have rated the same items in the past. The second step is to select a subset from all other actors that have rated the item by selecting only the most similar actors. The final step is to use the similarities and the ratings for the item of the selected similar actors to calculate the predicted rating. (Herlocker et al., 2004) provide an overview of design choices and alternative algorithms in CF. CF is an accurate domain-independent prediction technique, especially for content that cannot easily and adequately be described by metadata (Setten, 2005).

Information-based prediction technique

In the field of information-based prediction techniques, the main techniques are *information filtering*, *attribute-based prediction* and *case-based reasoning* (CBR). CBR is based on the assumption that if an actor likes a certain item he will probably also like similar items. CBR as a prediction technique looks at all items a actor has rated in the past and determines how similar they are to the current item. For those items that are similar enough, the old ratings are used to calculate a predicted rating for the new item.

CBR is especially good in predicting how interested a user is in the same types of information or in slightly different versions of the same information. The key aspect of CBR is determining the similarity between two items. However, such goals are domain-dependent, which makes the way to calculate similarity between items to meet those goals also domain-dependent (Setten, 2005).

The folksonomy aspect

In addition to the described prediction techniques, and in relation to the need for making learners responsible for their own learning paths, we want to use *folksonomy* tagging systems whenever possible, as opposed to expert driven ontologies (like the Semantic Web). The Semantic Web is working well in well-organized domains with a small corpus, formal categories, stable and restricted entities. A good example is the *periodic table of the elements*. It has only about hundred elements, the categories are simple and derivable (protons don't change because of political circumstances). The more of those characteristics hold true, the better an ontology is likely to fit the domain (Shirky, 2005). For learning networks we aspect a large corpus, both formal and informal categories and unstable entities (tags). Those are reasons why we want to use folksonomy techniques besides the semantic web approach.

Folksonomy, which stands for *folk taxonomy*, is a technique to add metadata to documents by community members. Through the folksonomy, a community is able to build their own personalized taxonomy. Many examples of this approach are present today, such as *Del.icio.us* (http://del.icio.us) that permits collaborative tagging of shared website bookmarks. Collaborative tagging describes the mechanism by which many users add metadata in the form of keywords to community-shared content. Collaborative tagging is a promising method of allowing members of the learning network to link keywords or tags to the learning content. In the Semantic Web approach, all relationships between tags would heave to be predetermined by domain experts. Part of this research will be how generated folksonomies (by different learners or a community), could lead to suitable recommendations.

Project Roadmap

The roadmap for the development of three consecutive PRS (Figure 3) describes what, when and how the different prediction techniques will be evaluated to finally meet the needs for a PRS for learning networks at the end of the project in 2009. During the research period we will incrementally design and test various versions of a PRS in the context of three consecutive studies.

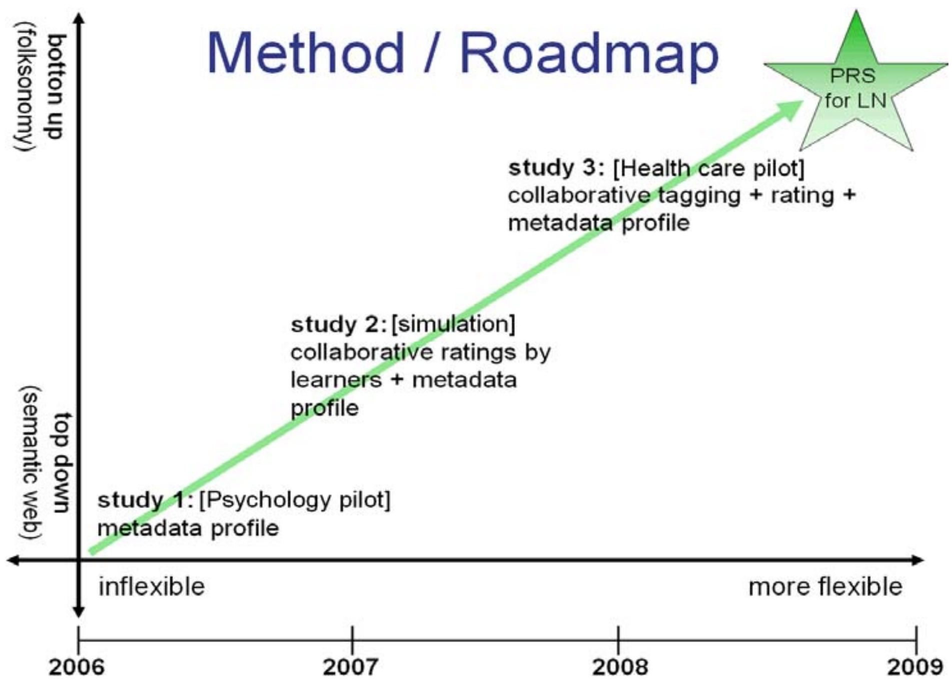

***Figure 2*: Roadmap for the development of a Personal Recommender System for Learning Networks**

Study 1 will be an experimental pilot in the domain of Psychology, study 2 will be a simulation with a demo tool, and study 3 will be an experimental pilot in the domain of Health Care.

Study 1 (inflexible recommendation)

The first study will build on earlier experimentation with navigation at the OUNL that applied indirect social navigation principles to advise learners on the next best activities (Janssen *et al*., 2005). The recommendation technique will build on the collaborative filtering algorithm of the ROMA project, and will be further extended by combining this with personal information about the learner (like *study motive, study interest in a subdomain* and available *study*

time). The recommender system will record successful completed learning activities by other learners and recommend the next best learning activity to the individual learner.
This is close to a top-down approach, because - in the controlled vocabulary of personal information characteristics we use - learners can not create their own profile metadata, like would be the case with using a bottom-up folksonomy approach. In this study, what kind of personal information will be used for the recommendation is decided by the 'experts' of the learning network. The recommendation will be based on quantitative information about successful completions of activities by learners with similar profiles.

Study 2 (more flexible recommendation)
The next study will apply direct ratings by learners of various learning activities on offer. The recommendations will be based on direct ratings (e.g., 0-5 stars) by other learners who are located in the same or similar peer-groups. This approach takes the learner into account and asks for her individual feedback. It is one step closer to folksonomy techniques (Mathes, 2004), because the learner is asked to rate items and bring her opinion into the learning network. The approach still depends on the profile of the learner, which attributes are pre-defined by domain experts.

Study 3 (most flexible recommendation)
The most advanced version of a recommender service will combine suitable prediction techniques. In the context of lifelong learning, we prefer the use of folksonomy techniques whenever possible, but we also may need to use ontologies or predefined metadata for special cases (e.g., when exact matching is needed for formal learning, when the learner specified a profile and a learning goal but not enough is information available for recommendation).

6. Method

To evaluate the effectiveness and efficiency of the navigation service, a series of studies will be launched, that were presented in the previous section. This section further elaborates the methodical setup of the studies.

Study 1
The first study will use a first release of the PRS in an experiment that starts October 2006. The experiment is carried out in the context of the regular "Introduction Psychology" course as offered by the Department of Psychology at the OUNL. The experiment will last about four months and when registration ends we expect around 200 students. The experiment ends after the first examination opportunity (January 24, 2007). Study guidance will be provided through Moodle where the course will be divided into a number of study tasks, each linked to chapters of a textbook and with specific learning goals and characteristics. This restricted collection of formal activities from a single provider will serve as the 'mini-curriculum' on which navigation support is provided.
The students will be divided randomly into two groups. The experimental group will be provided the PRS, which is based on collaborative filtering and their profiles (to create similar peer-groups). The control group will use the same collection of learning activities, but will no be provided any recommendation on the order to study them.
To personalize the recommendation, the advices will be based on the specific peer-group learners are located in. These peer-groups will be defined through additional information in the profile (study time, study motive and study interest in a specific subdomain of Psychology). The learners first have to fill in their profile before being guided to the Moodle courses.

If no recommendations can be based on collaborative filtering, advise will be based on user profile information. When needed, the internal algorithm will deselect specific attributes in the user profile until a recommendation could be provided. (The learners are not allowed to decide which attributes will be used for the recommendation. The experimental group would be divided over many subgroups which would complicate data analysis). This internal algorithm for personalized recommendations provided in Study 1 is schematized by Figure 3.

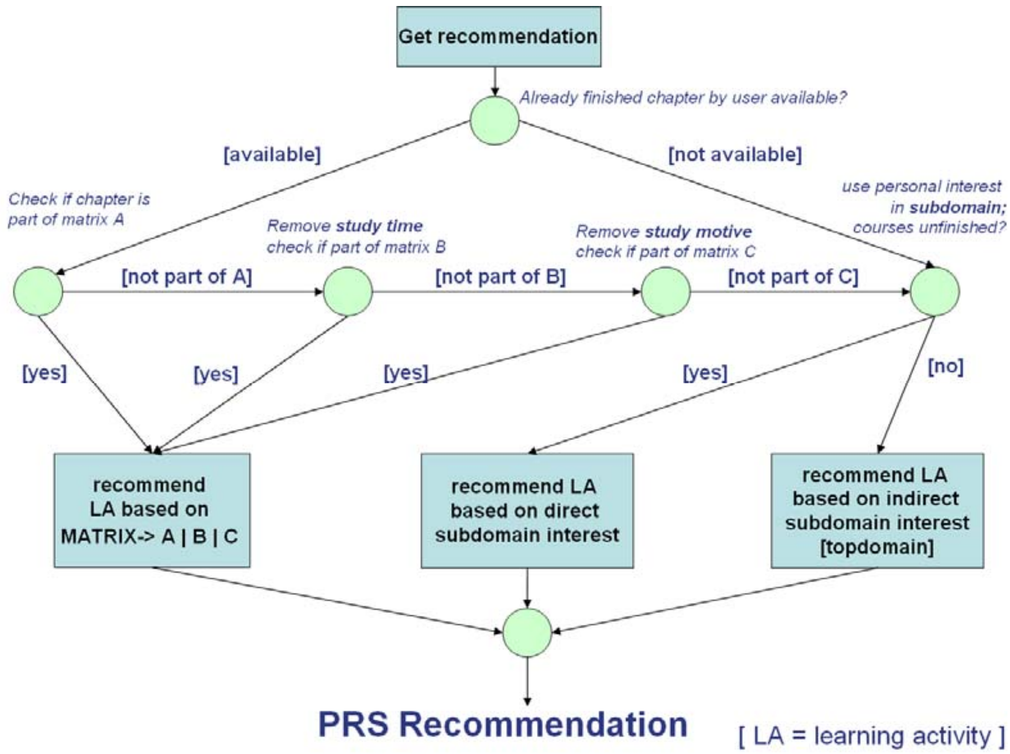

Figure 3. **Prediction strategy for the PRS in study 1**

Study 2

We will use the results and the conceptual proof-of-concept from the first experiment, and extend this approach with other information and prediction strategies to feed and experiment with recommendations. For this purpose we want to simulate a distributed learning network beyond the practical constraints of real user testing. A suitable framework for a prediction engine is offered by the DUINE Toolkit (Van Setten, 2005). The DUINE Toolkit is a software package that allows developers to create prediction engines for their customized applications. Such predictions can be used to personalize recommendation, especially when recommending what learning activities are (not) of interest. It also provides a demo tool that could be used to simulate learners in a learning network and analyze various prediction strategies. The main advantage of the DUINE Toolkit is that it can combine *multiple prediction techniques* into *prediction strategies*, in order to provide more accurate predictions.

Study 3

The third study will take place in 2008, and will be carried out in the context of the European *TENCompetence* integrated project. This pilot study will use an advanced, more flexible personal recommendation system for a learning network in the domain of Health Care. We will implement the system and collect data for the final configuration of the PRS for learning net-

works. The third study will use a more bottom-up approach, that also includes mechanisms of free tagging and folksonomies.
Combining recommendation techniques might cater for specific cases and situations in a learning network. For instance, for formal learning activities the predefined learner profile metadata might be used to support learners' first steps into a learning network. Especially for more informal learning activities, learners may add collaborative tagging or rating on top of that to further personalize the metadata in their profiles. Through the use of collaborative tagging learners are able to add tags (own defined metadata) to learning activities. These tags will be connected to their profile. Through collaborative tagging they get the opportunity to overcome the limits of the predefined profile and create their own "buddy system", that searches for people that are using the same tags for similar activities. The personal recommendations then go beyond the predefined profile, and take interests into account that have been expressed by learners themselves.
Both the advantage and risk of the folksonomy-driven approach is its dependency on learner activity and on the dynamics of the learning network as a whole. Learning networks become more valuable with more additional learning activities inside, and more learners rating or tagging these activities. A motivated community of learners in a learning network will thus create a powerful network enabling highly personalized recommendations, but a less motivated community will not reach a similar level, so the recommendations will have a lower quality.

7. Fit in Technology Development Programme

In a learning network the learners can create their own learning activities, can build their own learning plans and can share their learning activities and their learning paths with peers and institutions. The navigation service will be needed to support learners to select the best opportunities the learning network provides for their needs and preferences. The navigation service will be able to recommend different kind of learning activity or learning paths to the learner. The need for a navigation service is also related to other elements of the TENCompetence infrastructure, like the *positioning service, learning path specification,* and *eportfolio specification.*

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8. Project planning

Literature study

Phase	Activity	Period	Output
Analysis	- study literature and general approaches - searching for suitable models, tools and techniques for PRS	1/4/06-15/12/06	- inventory / framework of suitable strategies and prediction techniques (to input article 1)

Study 1

Phase	Activity	Period	Output
Analysis	- define use case requirements for study 1 - search for suitable techniques (e.g., ROMA project)	1/4/06-15/5/06	- process model
Design	- create class model - user interface design	30/6/06-30/6/06	- Design PRS (v1) - set up development environment
Development	- build prototype of an navigation tool - prepare first pilot exp	02/8/06-25/8/06	- Developed prototype (v1)
Implementation	- integration and system development	25/8/06-	

	- field testing of integrated system in pilot	5/9/06	
Evaluation	- evaluate (of usability (subj), - maintaining the experiment - collecting empirical data - documentation, writing, presentation	01/10/06- 01/03/07	- Submission article 1 - Publication source code

Study 2

Phase	Activity	Period	Output
Development	- improve the navigation service - prepare for simulation	01/02/07 - 01/04/07	- Design PRS (v2)
Development	- prepare for study 2 - learn tools (e.g., DUINE Toolkit)	01/04/07- 01/06/07	- Design simulation - Submission article 2
Implementation	- integration and system development - field testing of integrated system in simulation	01/06/07 – 01/09/07	- Developed prototype (v2)
Evaluation	- evaluate (of usability (subj), appreciation (subj), and actual increases (obj)) - documentation, writing, presentation	01/09/07- 31/12/07-	- Submission article 3 - Publication source code

Study 3

Phase	Activity	Period	Output
Development	- improve the navigation service - prepare for third study	08/01/08- 01/04/08	- Design PRS (v3)
Implementation	- integration and system development - field testing of integrated system in pilot	01/04/08- 01/09/08	- Developed prototype (v3)
Evaluation	- evaluate (of usability (subj), appreciation (subj), and actual increases (obj))	01/09/08- 31/03/09	- Submission article 4 - Final version, Publication source code

Finishing PhD work

Phase	Activity	Period	Output
	Revisions, Thesis writing	01/04/09 – 01/10/09	Thesis

9. External financial support for the project

This PhD project is funded by and carried out in the context of the European TENCompetence Integrated Project.

10. Costs (material)

Materials and apparatus	Cost in k€
Software	3
Books	1
Total	4

11. Explanation/justification of material costs

Software to research possible tools, literature for desk research on existing approaches.

12. Costs (travel)

Purpose + Justification	**Cost in k€**
3 * International conferences	6
1 * National conferences	1
1 * Doctorial Workshop	2
2 * Summer Schools	4
Total	15

13. Appendices attached

Does not apply.