Chapter 6
Individualised Navigation Services in Learning Networks

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6.1 Introduction

In this chapter we propose hybrid recommendation techniques for Personalised Recommendation Services (PRS) as a novel approach to set up individualised navigation in Learning Networks. Such an approach combines the collaborative filtering of information about others' behaviour with matching information connected to individual learners and activities. Such an hybrid approach or recommendation strategy has hardly been used in education but appears powerful to address some of the practical problems that practitioners will face when using either technique alone. Some common problems, like the cold-start problem for collaborative filtering and the problem of maintaining metadata information for learners and learning activities, will be described. This chapter will also serve as an introduction to the remaining three chapters of this navigation section and introduce the main concepts involved in

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providing (individualised) navigation services. In order to provide the reader with the necessary overview, we will present a model of navigation in Learning Networks. The model will make clear how PRS should be related to learning technology specifications required, like the learning path specification, the learner profile description, and the competence description, as well as to possible recommendation techniques, like information-based and social-based techniques. Every reader will immediately recognise problems with way-finding on the Internet in general. The accelerated growth of the World Wide Web has turned the Internet into an immense information space with much, very diverse and often poorly organised content. Successfully searching and finding information on the Web turns out to be hard, especially for novice users. Results with secondary school children for instance indicated that experienced WWW-users are more proficient in locating relevant information than novice WWW-users (Lazonder et al. 2000). The observed differences were ascribed to the experts' superior skills in operating web search engines. Hölscher and Strube (2000) found that online users need additional Internet skills training for query-based searching and intersite navigation. Other researchers have developed a variety of tools (like a task-specific portal to structure information, worksheets for reflective web use, process-worksheets, prompts, and discussion sessions) that help regulate the search process (Brand-Gruwel and Gerjets 2008).

In distributed Learning Networks (Koper and Sloep 2003) online users are confronted with similar problems in finding information, i.e., in navigating towards the most relevant learning activities. They are populated by groups of professionals that usually are more heterogeneous than in regular education: various ages, needs, motivations and preferences characterise the professionals. Individual professionals therefore will need individualised navigation support. The problem of finding information can haunt professionals during their stay in dynamic Learning Networks, especially when learning activities may be added or withdrawn and where learners may change their learning plans. This problem is aggravated if the learner also has to choose from the offerings of various content providers, that might vary strongly on several aspects. Navigation services will then be needed to help the learner find and select most adequate activities. Personalised Recommender Systems are meant to enable individualised learning paths that lead the learner through an effective study progress.

Because of the fact that information in Learning Networks is always aimed at learning towards a certain goal, such navigation services have to take into account additional pedagogical issues (e.g., activities have to build on the existing competence level of the learner, dependencies on prerequisite activities and practical constraints have to be taken into account). Compared to looking at interesting news or movies, or to listening to preferential music tracks on the Web, learning activities cannot be studied in any order, they have to be carefully sequenced.

Most curricula have been designed carefully by professionals in the field. It has been learners' main task to follow the sequence that was designed in the curriculum. It is highly questionable whether available curricula contain the most suitable order for each learner. Besides, from a professional development perspective, learners will not just follow available curricula like is the case in more regular education.

At various stages of their lives they will face the task to select and mix both formal and informal learning activities, taken from different providers and sources (like the Internet, peer discussions, or training courses). In the absence of any 'designed order' of a curriculum, it will be hard for learners to select and sequence the right learning activities. Learners' problems in 'way-finding' (the process of selecting and sequencing learning activities, which we consider synonymous to 'navigation') will decrease the efficiency of education provision (the ratio of output to input) and increase the costs. Moreover, traditional institutional facilities like course catalogues or face-to-face study advice do not offer adequate guidance within the context of distributed networks for professional development, in which learners have to make well-informed choices from the vast amount of learning activities offered by different providers such as institutions, tutors or peers.

Although research reveals a relation between advice and drop-out rates, advice appears to be just one of many factors (Rovai 2003). There may be other alternatives for costly face-to-face advice (e.g., domain specific diagnostic self-tests), but this section will focus on Personalised Recommender Systems (PRS) Personalised Recommender Systems (PRS)that advise learners on suitable learning activities and paths towards certain learning goals. We focus on a specific type of PRS based on a combination of collaborative filtering information about the behaviour of other learners (social-based approach) with information about learning activities and needs and preferences of learners (information-based approach). These hybrid systems provide learners with individualised navigation services that advise suitable learning activities and paths towards certain learning goals, like the attainment of competences. The combination of the social-based approach with the information-based approach has hardly been applied in learning (Herlocker et al. 2004).

This first chapter of the navigation section will provide you an overview of the main navigation concepts involved and the main questions that need to be resolved when applying this combined approach to Learning Networks. Important practical issues that will be addressed are: what are the most adequate recommendation techniques and how can they best be combined into recommendation strategies, what are the most relevant elements and attributes (from learners and learning activities) to be taken into account in the PRS, and how can we assure interoperability between learning activities and learning paths.

The second section of this chapter provides a short introduction to relevant work, relevant learning technology specifications (uniform descriptions of competence, learner profiles, and learning paths), and existing recommendation techniques. The third section presents a preliminary model of the elements and attributes involved in navigation services. An important guideline here is that PRS should not rely on rather specific and intensive data provisioning and maintenance. Finally, the fourth section arrives at some conclusions and suggestions for future research into navigation services.

The character of this first chapter has to be of a more conceptual nature in order to better understand the remainder of the section. The character of the next three chapters will be more practical. The next chapter, Chap. 7, of this navigation section provides some concrete guidelines on practical issues and choices when actually setting up a concrete PRS in a Learning Network, with examples from an experiment in the domain of Psychology. Chapter 8 of this section describes practical guidelines on how simulation studies can help you in designing more light-weighted PRS that will enable more effective, more satisfied, and faster goal attainment. Chapter 9 of this section will then propose a concrete learning path specification that could facilitate the navigation process.

6.2 Learning Technologies for Personalised Recommendations

We start this section by introducing related work on personalised recommendation (Sect. 6.2.1) from other domains. Then some guidelines on using relevant learning technologies (Sect. 6.2.2) and recommendation techniques (Sect. 6.2.3) to enable such personalised recommendation in Learning Networks are provided.

6.2.1 Relevant Work

Most readers will be familiar with recommender systems that offer advice when looking for books, movies or music (e.g., amazon.com). Such applications are based on collaborative filtering of information obtained from the behaviour of other buyers on the web (others that bought this book, also bought these books). Some even take ratings or tagged interests by individual users into account (others that like Tarantino as director, also like these directors). Review studies do not mention such personalised recommender systems in learning (e.g., Brusilovsky 2001; Burke 2007; Herlocker et al. 2004). This probably is the case because the educational field imposes additional and specific demands on the advice required. Main differences between selecting books for reading and selecting learning activities for study are the degree of voluntariness and required order (as most learning activities are required to obtain some learning goal or prerequisite to another), and the possibility to establish an explicit completion (as most learning activities are to be assessed for successful completion). Such differences impact learner's motivation, and the way personalised recommendations for learning activities should be provided. Preliminary explorations in the e-learning domain are yielding promising results, and by setting up simulation studies you can gain more insight into the additional dynamics of Learning Networks.

A simulation study of a recommender system to support learners in a Learning Network has been reported by Koper (2005). He simulated rules for increasing motivation and some other disturbance factors in Learning Networks, using the Netlogo tool. Learners had to complete a certain set of learning activities, and after each completion were 'set' to complete the best next learning activity, based on the successful completion of next learning activities by others. Amongst other factors, the provision of this indirect social navigation accounted for about 5–12% of the increase in goal attainment (completion of the set), depending on the 'matching error'. An interaction effect showed that recommendations can compensate for bad matching.

Related to this simulation study are some real-life experiments we carried out, as have been reported by Janssen et al. (2007) and Drachsler et al. (2008). The aim of the Janssen study was to recommend most efficient learning paths (like with the 'shortest route' provided by the GPS in your car) in general, leaving the learner and learning activity characteristics out of scope. The Drachsler study (for further information, see Chap. 7) also explored which paths are most *attractive* or *suitable* for individual users (like with the routes suited for bicycling). Authors offered learners a similar recommendation (Most successful learners continued with Y after having completed X). The recommendations in the first study did not take personal characteristics of learners (nor possible 'matching error') into account. In the second experiment collaborative filtering information was combined with personal information taken from a user profile, an hybrid approach that appeared to solve some common problems when using collaborative filtering only (e.g., the cold start problem). In both studies, the indirect social navigation appeared to enhance effectiveness in a Learning Network (completion of the set of learning activities), but only in the second study did it increase efficiency (the time it took to complete them).

Although these first results of applying recommender systems for sequencing learning activities in real-life Learning Networks appear promising, significant effects appeared to be still relatively small and to depend on the availability of sufficient amount of learners and elapsed time. A promising way to further explore possible improvements is by means of simulation studies. Where 'matching error' was limited to competence levels of learners and learning activities in the Koper study, mismatching can also occur on other learner characteristics such as personal needs, preferences and circumstances. In another simulation study by Nadolski et al. (2008), we did not only take the competence gap but also the preference gap and some other learner and activity characteristics into account (for further information, see Chap. 8). In this respect, Bocchi et al. (2004) found that learner characteristics accounted for about 30% of retention rates in an online MBA program. Personalised recommender systems filter specific data from learning activities and learners that fit individual needs, interest, preferences, constraints or circumstances. Results show such an hybrid approach to be most effective. Relevant recommendation techniques to be combined in such an approach will be described in Sect. 6.2.3 of this chapter. We will now first turn to relevant learning technology to be used for navigation services.

6.2.2 Learning Technology Specifications

Learning technology specifications are needed to enable interoperability, reuse and exchange of learning objects and actions. We discuss three of such specifications that are closely related to navigation services and personalised recommendation in a Learning Network for a certain domain: learner's start position in that domain (based on learner's prior learning history or *e-portfolio*), the aimed *competence* profile for that domain (also called the competence description), and the *learning path* from already acquired competence towards the acquisition of new competence. Way-finding or navigation services support selecting and sequencing available learning activities into an individualised learning path. A learning path description is currently non-existent but needed to uniformly describe different possible combinations of learning actions that lead to certain learning outcomes. E-portfolio and competence specifications do exist but need elaboration to sufficiently cater for personalised recommendations.

Therefore, personalised recommendation in a Learning Network needs to combine and use following pieces of the learning technology puzzle (some to be further addressed in the remainder of this and consecutive chapters): Uniform and meaningful description of (both formal and informal) *learning paths*; *Learning activities* that are addressable and meaningfully described; Uniform *e-portfolios* that define needs and preferences; Uniform *competence descriptions* that define proficiency levels; A learning path processing engine able to compute what remains to be done by the learner to acquire the competence profile; An engine recording completion of activities and propagates this to associated systems; and Information *matching techniques* to enable personalised recommendations. To exchange competences and learning activities and -paths in an interoperable way, we will first need learning technology specifications describing these concepts in a both uniform and meaningful way. Some descriptions and future directions are provided below.

Learning path description. If all providers would use a common language to describe their learning programs and activities, personalised recommender systems could better support learners deciding between various paths to reach aimed competences. When the learning paths taken by predecessors could be stored in a commonly used format, novice learners could benefit from the choices made and experiences gained by more expert learners that have already acquired the competence, by finding and following the paths of (similar) peers. But unfortunately, no such commonly used format exists. A number of existing approaches to (formal) curriculum modelling (e.g., CDM 2004; XCRI 2006) do work in this direction. Tattersall et al. (2007) propose IMS-LD (2003), a specification for modelling learning designs, as a strong candidate to model learning paths as well, and demonstrate that its selection and sequencing constructs appear suitable on both the level of learning activities (units-of-learning) as well as on higher levels of granularity (like professional competence development programmes). They note that, in addition to the curriculum structuring concepts covered by IMS-LD, other information will be required to provide learners with more personalised advice on learning content.

Janssen et al. (2008) have built on this approach and propose a number of key elements to describe learning paths relevant to navigation on a basic level. Besides learning activity, learning objective and prerequisite, these elements include structure (for grouping dependent learning activities), method (for ordering learning activities into a scenario), conditions (to model the order to accommodate personalisation), and metadata (including additional criteria). Additional criteria could include, for instance, information about study costs, required study time, mode of delivery, teaching place, guidance, way of assessment, etc. This information will be helpful in achieving more personalised overviews of available learning paths. Chapter 9 of this section will provide some concrete guidelines when using this learning path specification for navigation purposes.

E-portfolio description. Describing and recording learner's history and profile becomes of crucial importance for professional development. Competences are not only attained through formal education, but also through work, at home or in any other context where problem solving takes place. Currently, educational providers have little possibilities to adapt their formal programmes, and to take into account individual needs and preferences or prior knowledge attained through other (formal) education. It becomes even harder for them if they are asked to take into consideration competences acquired through less formal or informal learning. Uniformity in assessment (to measure and accredit) and e-Portfolios (to store) to enable this in the future constitute a research field on its own. The IMS Learner Information Package (IMS-LIP 2001) and ePortfolio (IMS-ePortfolio 2004) specifications ensure exchange of learner records, by linking to produced artefacts and formal achievement records like references. However, fields describing learner information are open and optional, so these specifications do not provide classifications of specific learner information that is easy to interpret uniformly.

Berlanga et al. (2008) have drawn up some additional requirements for an e-portfolio description to be useful for more personalised navigation in Learning Networks. They have argued that e-Portfolios should allow learners to present themselves, to reflect on how they acquire competences, and to show and manage their social presence in the Learning Network. To this end, e-Portfolios should integrate, respectively, rhetorical, pedagogical, social, and technical perspectives. The rhetorical perspective is needed to show the learner's competences mastered, including a history of the professional competence development programs, and learning activities the learner has followed, an overview of communities the learner has been involved in, and the showcases she has created. The pedagogical perspective aims at supporting learner's self-reflection, so the learner can define the competences she masters, review and create (new) professional competence development programs, and assess her competences. The social perspective aims at fostering interaction (by creating and maintaining a personal profile as well as contacts within the Learning Network) and social help support (by defining mechanisms for peer-support). The technical perspective is needed to support the other three perspectives.

Competence description. Cheetham and Chivers (2005) define competences as the integrated application of knowledge, skills (or competencies), experience, contacts, external resources and tools to solve problems at a certain level of performance in a certain occupation or any other context. According to this definition, competence is related to three dimensions: the *type* of competence (i.e., cognitive, functional, personal, professional or ethical); an occupation or performance *context*; and the proficiency*level* of a person with respect to an occupation or context. The IMS Reusable Definition of Competency or Educational Objectives (IMS-RDCEO 2002) and the IEEE Reusable Competency Definitions (IEEE-RCD 2006) specifications do not have much semantic value, since they simply attach IDs for a registry and URIs, and only reference to more controlled models. The HR-XML consortium (2006) goes one step further in the description of a competence and includes classes (as free text fields) where 'evidence' (with reference to learner portfolio) and 'proficiency level' (complexity, intensity, quantity) *can* be described.

We suggest that a competence description should at least include an interoperable classification of *type* of competence and proficiency *level*, and preferably also have a classification of *context*. Sicilia (2005) proposes the formalism of ontologies to express more details in competence schemas, in order to be connected to learner profiles and learning activities. Matching learning activities to the right learners requires ontological structures and more meaningful descriptions of competences in a registry (Ng et al. 2005). Prins et al. (2008) have stressed the importance of identifying the complexity of learning and performance situations for personalised recommendation, and propose to extend current competence definitions with a context-concept, named a 'learning and performance situation' (LP-situation). This context-concept will further be determined by values on three factors: a complexity factor, a proficiency level and a performance indicator. Inclusion of such a context-concept will also help defining the proficiency level and to design learning tasks and CDPs. Authors propose to use various (local) schemas for defining these determining factors, but to have one mapping function towards uniform proficiency levels. This way we could find a compromise between maximal flexibility to individual providers to define their own factors and values, and a uniform mapping mechanism to enable a more meaningful exchange of competence definitions.

Closely related to competence definitions is the concept of a *competence map* that defines the relations between various competences. It could be questioned whether there should be such maps for more informal Learning Networks since the professional should decide on the most suitable order and preferred structure. Assuming that such a predefined structure is desirable and possible, several research questions need to be answered that pertain to the hierarchical organisation in the map, to aligning particular customs for structuring certain domains, and to connecting such maps to navigation (and other learner support) services.

6.2.3 Recommendation Techniques

Let's for now assume that all required information about learners, targeted competences, and required learning activities is available in an exchangeable format. We will then need to decide upon techniques to match information about learners with most suitable activities. There are a number of drawbacks and advantages to current techniques that will be addressed in this section (Chaps. 6, 7 and 8). Our approach is to look for an hybrid approach, combining the advantages of both information- and social-based information techniques. After explaining the concept of information matching, we will describe those two types of techniques. A practical, stepwise tutorial on how to implement an hybrid recommender into a concrete, self-organised Learning Network can be found in Chap. 7 of this book section.

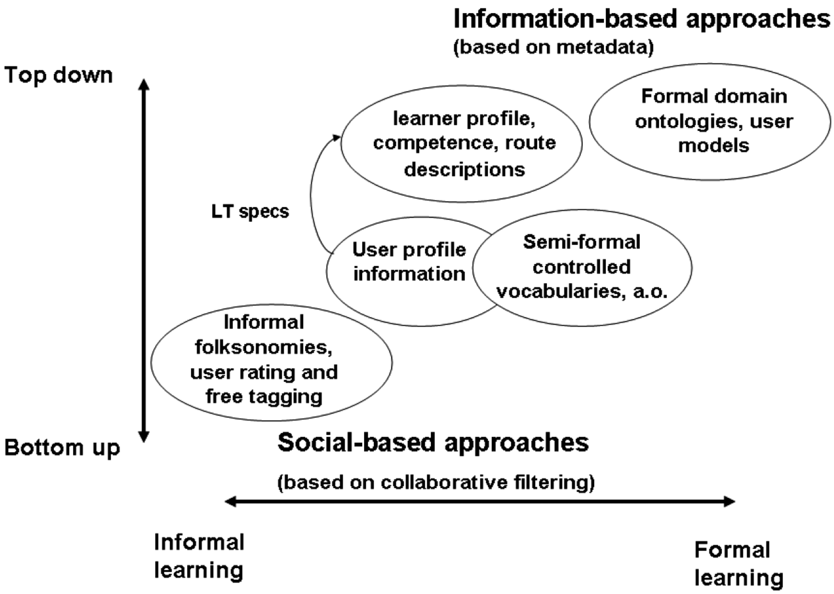

Fig. 6.1 Social-based versus information-based approaches

Information matching orrecommendation techniqueswork with two entities: users and items. Elements of both entities are being associated with a profile carrying certain characteristics. The utility of an item (i.e., learning activity) to a user (i.e., learner) is usually represented by a rating function *R: Users x Items→Ratings*. Recommendations are estimated ratings for items which have not been 'seen' (i.e., enrolled, rated, successfully completed) by the user. Within information matching techniques a distinction is made between *information-based approaches* (based on learning technology standardisation, metadata and semantic web efforts) and *social-based approaches* (based on data mining, social software, and collaborative filtering) (Balabanovic and Shoham 1997; Van Setten 2005).

Figure 6.1 depicts the relation between the two approaches, the type of learning (formal versus informal) and the formalisation of information in terms of learning technology (imposed from the top downwards versus emerging from the bottom upwards).

Information-based approaches. Information-based approaches may use certain keywords or metadata which represent certain characteristics of the learners and learning activities. The system then keeps track of items the user was previously interested in, and recommends items with similar or related keywords or metadata. Similarity of items is calculated with techniques based on item-to-item correlation that may use keywords in documents (Schafer et al. 1999).

Ontological modelling has the immense (potential) advantage of exact matching competence descriptions in the learner profile (user model) with available professional competence development programmes (domain model), sharing common understanding in a machine readable way. Exact matching is often required in more formal learning with, for instance, more discrete criteria to allow students to enter or progress than in more informal learning where more fuzzy matching might suffice.

A serious *drawback of modelling* is the enormous amount of work in enriching resources with metadata and the arbitrary character of such models. For example, main problems in instructional planning are caused by limitations to *learner* modelling, for instance because prior knowledge can not be uniformly compared for all learners. A second limitation is the inability to analyze and capture all important characteristics of the *content* (e.g., How to distinguish an excellent from a poor article that is using the same keywords?). Most categories we employ in life are based on fuzzy concepts rather than on objective rules, e.g., Where's the line between good and excellent? Do we really care about the subtle distinctions in wine-tasting? (Morville 2005). A third drawback is caused by the fact that words in the form of metadata are ambiguous. Our language is filled with synonyms, homonyms, acronyms, and even contranyms (words with contradictory meanings in various contexts). In retrieval the forces of discrimination and description are battling, with full-text search being biased towards description (finding general words with many meanings) (like with Google; see Brin and Page 1998), and unique identifiers (like an ID number of each competence in a registry; see IMS-RDCEO 2002) offering perfect discrimination but no descriptive value whatsoever.

It will neither be possible nor needed to fully model Learning Networks, but certain levels in formalising information can be distinguished. *Ontologies* describe how concepts of the world are related and represented using formal relations. An ontology is a rather strict formalisation into a machine-readable format consisting of entities, attributes, relationships and axioms (Guarino and Giaretta 1995). There are also semi-formalisations holding the middle ground: *Structured metadata* fields (with headers like title, domain, provider of the activity), *facetted classifications*, which permit to assign multiple classifications to an object and to accommodate way-finding that varies by user and task, and *controlled vocabularies* (e.g., fixed categories, keyword lists, audiences) that try to control the language ambiguity.

Social-based approaches. The big advantage of social-based approaches is that they are completely independent of the representation of knowledge in domain or user models. Instead of recommending to a specific user the items similar to previously liked items, this approach recommends the items liked by other users in similar situations or with similar preferences (peer groups). It uses peer opinions to predict the interest of others, and matches users against the database to discover historically similar tastes. It avoids the enormous amount of work in enriching resources. For instance, Li et al. (2005) combine item-based and user-based collaborative filtering, based on the content information and ratings at the same time, which make it possible to alleviate both sparsity and cold start problems. For instance, when a database of learning activities would contain both the ratings of peers (user-based) and tags describing the pedagogical taste (item-based, e.g. programmed instruction or problem-based learning), it would become possible to personally recommend items targeting the taste of users which will be apparent from their history of rating.

A serious *drawbackof recommendations based on social-based approaches* is their limited value for new or few users, that is when it is hard to find similar users or when just a few users have rated the same items, or when no content is available about already attained competences. Clustering then may be an alternative to solve this sparsity problem (Agarwal et al. 2006). Social-based recommendation techniques also suffer from serious limitations when exact matching is required, and when competences in domains go beyond the verbal realm (e.g., hard to express communication or motor skills). Although, for instance, collaborative filtering has been considered as a mainstream social-based technique for recommender systems, applications with actual learning behaviour data for recommending learners have remained scarce.

There also are more technical limitations to collaborative filtering. Collaborative filtering relies on large numbers of users explicitly rating or completing learning activities. When recommendations would solely depend on collaborative filtering, new or few learners would be seriously handicapped by 'cold-start' problems. Furthermore, the events registered in common log files format (as defined by W3C) are extremely low level, which complicates further analysis and more clear cut decisions that might be required in more formal learning curricula (e.g., only learning activities of certain types are allowed, or only grades above a certain threshold are considered sufficient for their completion). This makes it difficult to know which (type of) users are interacting (since only IP addresses are logged) and what (type of) interactions they are engaged in (since only URLs are logged).

One possible solution to (partially) address these limitations is to enhance the logs with additional information drawn from semi-formal descriptions about which learner did what and whether this was successful (Oberle et al. 2003). Especially with small amounts of learners, more information is required for exact matching of learners and activities in formal learning programs, and more information-based (or even ontology-based) approaches will come into play. Using more structured, but less formalised methods to describe learner profiles, competences and learning activities (like structured metadata or controlled vocabularies), might offer a more feasible and intermediate position. Such structured descriptions can be the basis for standardisation through learning technology specification (see learner profile, competence and route descriptions, Fig. 6.1). Another improvement could be to not only analyze the collective, *average* behaviour of peers, but also take individual, *personal experiences* as a starting point. This way not only suitable learning activities, but also suitable peers to study with could be advised. In summary, using Learning Technology specifications, and combining social-based with information-based approaches to match learners and learning activities, might be an approach to way-finding that addresses the cradle-to-the-grave challenge posed by both formal and informal professional development.

6.3 Modelling and Experimenting with Navigation Services

As described before, personalised recommendations should support the learner to *compose most suitable sequences of learning activities* to attain competences. A model for navigation services has been proposed (Sect. 6.3.1) and a study using a personalised recommender that was implemented according to this model will be described (globally in Sect. 6.3.2, and in more detail in the next Chap. 7).

6.3.1 Model for Navigation Services

Our model for navigation servicesin Learning Networks is depicted in Fig. 6.2. The model shows the elements (classes) and values (attributes) that play a role for navigation services. The model is still under development since concrete attributes of the classes are to be decided and validated (denoted by the '. . .'), as well as the interfaces with other services and learning technology specifications. The model intends to describe relevant classes for providing personalised recommendations. The model builds on and partially extends the domain model developed in the TENCompetence project (for direct reference, see http://hdl.handle.net/1820/649) which is also described in Chap. 18 of this book. This section does not explain the (rather complex) model in detail but just describes its main classes relevant here, with illustrations from a use case example which will be elaborated in the next chapter. Our use case deals with a professional interested in finding a personalised learning path in a Learning Network of psychology courses on an introductory university level. According to our model for navigation services (classes between square brackets), an [Actor] (which role can be learner) has a learning [Goal] (of the type 'competence') that make her perform [Actions]. Characteristics of an actor (like study time, study motive, study interest) can be modelled according to the *IMS-ePortfolio* (2004) specification. [Actions] can be aimed at the acquisition of certain [Competences].

In our use case, novice psychology students were provided a Learning Network with a collection of 17, largely independent courses on various topics on an introductory level. Learners were allowed to find and select the most efficient learning path through this collection, depending on their individual needs and preferences. When action are completed with an [Assessment Result] available, one can infer whether the [Competence] is mastered at a certain [Proficiency Level].

Actions can include learning paths (named [CDP]), [Units of Learning] (modelled in IMS-LD), [Activities] (not modelled in IMS-LD) and [Knowledge Resources]. A unit of learning depicts the flow of activities that a learner needs to follow in order to reach certain learning goals, giving certain prerequisites (Please note that in the remainder of this chapter, we simply use the term 'learning activities' to denote both units that are and are not modelled in *IMS-LD*). In our use case,

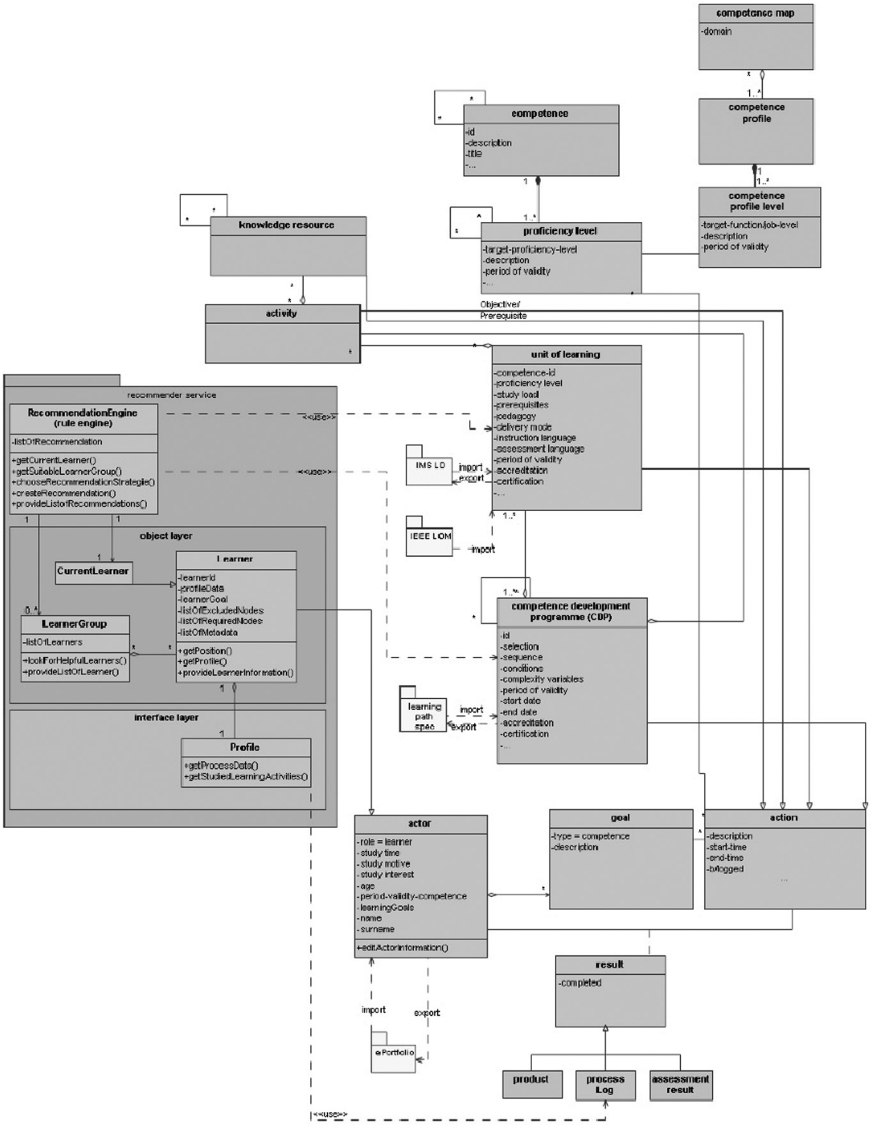

Fig. 6.2 Model for navigation services in Learning Networks

the learning goal is the completion of all 17 courses (equalling a total of 240 study hours), which all are on the same competence level, leading to the acquisition of the next (first) psychology competence level. Mastery of all courses, or goal attainment, will be assessed by a formal exam on location. Completion of each course is assessed by informal (facultative) progress tests provided with each course in the distributed Learning Network.

A learning pathis an ordered set of actions, activities and/or units of learning that can be followed in order to acquire a competence with a certain proficiency level. Learning paths can include selections or sequences of ‘learning activities’, as well as conditions for their composition; attributes of a learning path can be modelled according to a *learning path specification*.

The core of the navigation services model is constituted by the [Recommender Service], where relevant information (from the classes just described) will be updated, integrated and matched to create personalised recommendations. In our use case learners store information about their needs and preferences (i.e., about available time to study, motivation to study, and psychological subdomain of interest) in a user profile (in Moodle), that can be adjusted during study. The recommender system we implemented took into account this user profile information and the completion of courses when advising the individual which course to study next, considering both individual data and collective data from the learner group of students with similar user profiles (other similar students that successfully completed X went on successfully completing Y). Depending on the learning situation (e.g., formal versus informal learning), a ‘recommendation strategy’ can be selected (e.g., more or less formalised information) by a [Recommendation Engine]. This engine takes into account learner positioning and profile information for each [Current Learner] (*information-based*) and/or for each [Learner Group] (*social-based*). In our use case this engine determined for each case whether sufficient data were available about the collective behaviour of the learner group. If this was not the case (cold start problem), the recommender fell back on information stored in the individual user profile.

The Learner Group class calculates and generates data about similar learners, in order to provide the engine with necessary matching information about the ‘peer group’. The [Learner] class gathers all required data about learners (actors with this role) from an interface layer to a *positioning service* (left out of scope in this model, leaving the feedback from the [Position] class null) and the [Profile] information. Our use case was relatively simple in the sense that no prerequisite knowledge or competence was required to enter the Learning Network, nor were exemptions granted based on such prior knowledge or competence. All profile information will be continuously updated when learning activities are completed (using the [Process Log] information) or when the ePortfolio is changed. The learner data are either (subjectively) provided or adapted by the learner, or (objectively) collected.

6.3.2 Experimentation with the Model

First versions of personalised recommender systems (PRS) have been developed at our centre over the last two years, according to the hybrid approach and navigation model that was sketched above. We have both set up a number of simulation studies and implemented a personalised recommender system in a real-life Learning

Network. The simulation results show that the presence of PRS leads to more satisfied and faster graduation. Furthermore, hybrid PRS using rating provide a good alternative for ontology-based recommendations. When setting up a simulation, all elements had to be defined, instantiated and stored, like: learner profile, competence map, recommendation strategy, goal, characteristics of the Learning Network (number of learners, activities, subdomains), preference gap, and competence gap. Carrying out simulation studies (using Netlogo as a tool) has proven to be a cost-effective way of determining the requirements and most optimal parameter settings for effective PRS, since they reveal the consequences of the assumptions that went into the design of the system without having to deal with ethical issues and practical constraints of providing a suboptimal system to actual learners (Berlanga et al. 2007; Nadolski et al. 2008), see also Chap. 8.

A more extensive and empirical study was carried out with a concrete navigation service deployed in an actual Learning Network, actually implementing the exemplary use case sketched in previous section (Sect. 6.3.2). A top-down, ontology-based recommendation technique and a bottom-up, stereotype filtering technique were combined in a recommendation strategy that decided which technique was most suitable for the current learner at the current moment. For practical reasons this system was limited to fixed learner profile metadata in a simple ontology. The current implementation of the system is limited to a fixed set of 17 formal learning activities that constitutes an Introductory Psychology course from one provider. About 250 learners entered this Learning Network, of which half were provided with the personalised recommender system. If only information about the learner was available, stereotype filtering was personalised through attributes of the learner profile. If it was not possible to base the advice on all attributes, the recommendation strategy would disable attributes (in a certain order) and the advice would be based on less attributes. Results showed that students receiving PRS advice completed more learning activities during study, needed less time to complete activities, created more personalised learning paths, and suffered lower drop-out rates (Drachsler et al. 2008), see also Chap. 7.

6.4 Conclusion

This chapter started by arguing that professionals will need personalised navigation support in distributed Learning Networks, when choosing from the offerings of various content providers. Navigation services will then be needed to help the learner find and select most adequate activities and peers to study with. Personalised Recommender Systems are proposed to enable optimised learning paths and effective study. We have provided the reader with an overview of the main navigation concepts, learning technologies and recommendation techniques involved, also as an introduction to the chapters that will follow in this navigation section. It was found that an hybrid approach, combining information-based and social-based recommendation techniques into recommendation strategies is indeed a promising solution to both combine the benefits and limit the drawbacks of both approaches separately.

We proposed a model of the elements and attributes involved in such navigation services. It appears possible to design PRS that do not rely on rather specific and intensive data provisioning and maintenance, but could work mainly on low maintenance data derived from the behaviour of the Learning Network. For Learning Networks, it could therefore be concluded that a hybrid and layered 'metadata ecology' may be ideal, where the slow layers (ontologies) provide stability and the fast layers (folksonomies) drive change. Semantic web tools and learning technology standards provide a solid semantic framework (infrastructure) where there is a need for more formal and explicit characteristics of learners and learning activities to be decided upon from the top down. Where there is a need for less formal and implicit characteristics, free tagging and folksonomies offer more flexible, adaptive user feedback mechanisms to follow informal learning trends, emerging by serendipity and from the bottom up. Applied in practice, both simulation studies and an experimental field study have showed that PRS designed according to this hybrid approach yield to more, faster and more satisfied graduation, and indeed increase the variety of learning paths by self-organisation.

We do acknowledge current limitations when focusing on formal learning contexts with a fixed set of learning activities offered by one single institution. In such a situation, learners' freedom in composing individualised selections and sequences of learning activities could be restricted by (institutional) constraints and prerequisites. Besides, personalisation assumes there will be one most suitable learning path for each individual learner, whereas the personalisation process actually might be more of an optimisation process of self-guided behaviour. In informal Learning Networks, the initial process of actively exploring and finding learning goals and learning opportunities might be more valuable than actually walking the learning path. Self-organisation assumes effective learning to simply emerge as active explorers learn from each others' behaviour, which includes walking dead end streets as well. Therefore, consecutive systems are planned to broaden en generalise our findings to Learning Networks with contributions from various providers that entail both formal and informal learning activities.

Consecutive studies also have to examine ways to retrieve learner information as effortlessly and unobtrusively as possible. We do not have to burden professional, centralised indexers when ontologies could emerge entirely locally (some parts will be shared, some not, which is not an issue). For instance, McCalla (2004), opposed to the semantic-based paradigm, proposes a pragmatics-based approach of tagging learning activities with learner information. Each time a learner interacts with a learning activity, the (current) learner model of that learner is attached to the learning activity. It depends on the learning situation which learner data will be mined for patterns of particular use. More refined reasoning and recommendations will be possible when more and more instances accumulate. In addition to these instances, more standardised metadata could be assigned by professional indexers whenever needed. This ecological approach allows pre-assigned metadata (from ontologies like IEEE-LOM) to be refined or changed based on inferences from end use (from folksonomies tagged by learners).

Our roadmap for future research aims to combine collaborative filtering with both (a) information that can emerge bottom up by using rating or free tagging (folksonomies) of learning activities; and with (b) information that can be distilled from more formalised descriptions (specifications) of competences, learner profiles and learning paths. Future research is being planned to further establish the added value of personalising recommendations in terms of increased progress (effectiveness), decreased study time (efficiency) and experiences of users (satisfaction). Where possible, such information could be automatically added when learners interact with learning activities. When more specific information about learners and learning activities is required, metadata should be pre-tagged according to some ontology of attributes. In order to collect required information, learners will have to be encouraged to (automatically) update their ePortfolio or give ratings to (attributes of) the content. We will also need to establish the extent to which learners are willing to provide the necessary information about their personal needs and preferences. When they would not volunteer to do so but when considered necessary, the potential of incentive mechanisms (Hummel et al. 2005) could be considered to stimulate updating, tagging and rating.

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