Recommender Systems for Learning

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4 authors, including:

Hendrik Drachsler
DIPF - Leibniz Institute for Research and Information in Education
297 PUBLICATIONS   **9,123** CITATIONS

erik duval
KU Leuven
285 PUBLICATIONS   **9,322** CITATIONS

Katrien Verbert
KU Leuven
206 PUBLICATIONS   **8,406** CITATIONS

Nikos Manouselis, Hendrik Drachsler, Katrien
Verbert and Erik Duval

Recommender Systems for Learning

– An introduction –

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Preface

Recommender systems are extremely popular as a research and application area, with various interesting application domains such as e-commerce, entertainment, and others. Nevertheless, it was only around early 2000 when the first notable applications appeared in the domain of education, since relevant work was generally considered to be connected to the area of adaptive educational systems.

Today, research around recommender systems in an educational context has significantly increased. Responding to this growing interest, this book expands the relevant chapter on Recommender Systems in Technology Enhanced Learning (by Manouselis, Drachsler, Vuorikari, Hummel and Koper) that was published in the Springer Recommender Systems Handbook (2011) and provides an extensive and in depth analysis of the recommender systems currently found in relevant literature. This book aims to briefly introduce recommender systems and to discuss a wide and representative sample of issues that people working on recommender systems for learning should be expecting to face. It serves as an overview of work in this domain and therefore especially addresses people that start studying or researching relevant topics and want to position their work in the overall landscape.

All the bibliography covered by this book is available in an open group created at the Mendeley research platform[1] and will continue to be enriched with additional references. We would like to encourage the reader to sign up for this group and to connect to the community of people working on these topics, gaining access to the collected blibliography but also contributing pointers to new relevant publications within this very fast emerging domain.

We hope that you will enjoy reading this book as much as we enjoyed working on it.

Athens, Heerlen, & Leuven
March, 2012

Nikos Manouselis
Hendrik Drachsler
Katrien Verbert
Erik Duval

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[1] http://www.mendeley.com/groups/1969281/recommender-systems-for-learning/

Acknowledgements

Contents

Acronyms

AEH	Adaptive Educational Hypermedia
CAM	Contextualised Attention Metadata
CSCL	Computer Supported Collaborative Learning
EDM	Educational Data Mining
IR	Information Retrieval
ITS	Intelligent Tutoring System
KSA	Knowledge, Skills, Abilities
LAK	Learning and Knowledge Analytics
LMS	Learning Management System
LOM	Learning Object Metadata
MCDM	Multi-Criteria Decision Making
MUPPLE	Mash-Up Personal Learning Environment
OAI	Open Archives Initiative
PSLC	Pittsburgh Science of Learning Center
TEL	Technology Enhanced Learning
VLE	Virtual Learning Environments

Chapter 1
Introduction and Background

Abstract In this chapter, we start with a short introduction to the increase that has been witnessed in the past few years in applications of recommender systems at the TEL domain. Then we provide some background on the area of recommender systems, by defining recommender systems and outlining their basic types. A comparison with relevant work in TEL is tried, particularly focusing on adaptive educational hypermedia, learning networks, educational data mining, and learning analytics. A discussion on their similarities and differences is also made, so that relevant work can be better positioned in the TEL research landscape.

1.1 Introduction

Technology enhanced learning (TEL) aims to design, develop and test sociotechnical innovations that will support and enhance learning practices of both individuals and organisations. It is therefore an application domain that generally covers technologies that support all forms of teaching and learning activities. Since information retrieval (in terms of searching for relevant learning resources to support teachers or learners) is a pivotal activity in TEL, the deployment of recommender systems has attracted increased interest.

This should be more or less expected since a traditional problem in TEL has been the better findability of (mainly) digital learning resources. For instance, digital learning content is being regularly produced, organised and published in different types of TEL environments such as (Ochoa 2011):

1. *Learning Object Repositories* like Learning Resource Exchange[1], Connexions[2] or Maricopa Ex-change[3];

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[1] http://lreforschools.eun.org

[2] http://cnx.org

[3] http://www.mcli.dist.maricopa.edu/mlx/

2. *Learning Object Referratories* like MERLOT[4], OER Commons[5] or GLOBE[6];
3. *Open Courseware* sites like MIT OCW[7] or OpenLearn[8];
4. *Learning Management Systems* and Course Management Systems like Blackboard[9] and Moodle[10].

Various opportunities emerge for users to be exposed to this plethora of digital learning resources, in closed communities or in public and in both formal and nonformal settings. Potentially all user groups of TEL systems would find attractive services that help them identify suitable learning resources from this overwhelming variety of choices. As a consequence, the concept of recommender systems became extremely appealing for TEL research. This is also reflected in the increasing networking and publication activities of researchers working on such applications. Recent examples include the Workshop series of Social Information Retrieval for Technology Enhanced Learning (SIRTEL 2007-2009), the RecSysTEL Workshop on Recommender Systems for Technology Enhanced Learning (Manouselis et al. 2010), the 1st dataTEL workshop on data sets for Technology Enhanced Learning (Drachsler et al. 2010; 2011; to appear), and several relevant special volumes of journals and books (Vuorikari et al. 2009; Verbert et al. 2010; Santos and Boticario 2012; Santos and Boticario in press; Tang et al. to appear). These efforts resulted a number of interesting observations, the main ones being that:

a) There is a large number of recommender systems that have been deployed (or that are currently under deployment) in TEL settings;
b) The information retrieval goals that TEL recommenders try to achieve are often different to the ones identified in other systems (e.g. product recommenders);
c) There is a need to identify the particularities of TEL recommender systems, in order to elaborate on methods for their systematic design, development and evaluation.

Attempting to explore such particularities of this application domain, our book extends the analysis of Manouselis et al. (2011) in order to make a somewhat comprehensive introduction of how recommender systems are deployed in TEL settings. Its main contribution is that it discusses a wide and representative set of issues that people working on recommender systems for learning should be expecting to face. It does not serve as an exhaustive review and analysis of available approaches and systems, but gives a rather fair overview of work in this domain.

The remainder of this book is structured as it follows. This chapter introduces recommender systems and discusses their relevance to similar areas in TEL. Chapter 2 focuses more on describing TEL as a recommendation context, defining the

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[4] http://www.merlot.org

[5] http://www.oercommons.org

[6] http://globe-info.org

[7] http://ocw.mit.edu

[8] http://openlearn.open.ac.uk/

[9] http://www.blackboard.com

[10] http://moodle.org

TEL recommendation problem and identifying relevant goals, supported user tasks, and variables of the TEL context that can be considered when making a recommendation. It also reviews data sets that are currently available from TEL applications and discusses how they could be useful for research on TEL recommender systems. Chapter 3 offers a comprehensive analysis of 42 recommender systems that have been found in relevant literature. Chapter 4 describes current challenges in the field and gives an outlook of future research trends in TEL recommender systems.

1.2 Recommender Systems

1.2.1 Definitions

Malone et al. (1987) provided an overview of intelligent information sharing systems, referring to a fundamental categorisation of systems that generally support access to highly dynamic information resources (Belkin and Croft 1992; Baudisch 2001; Hanani et al. 2001). More specifically, they distinguished cognitive filtering systems as the ones that characterise the contents of an information resource (shortly referred to as an item) and the information needs of potential item users, and then use these representations to intelligently match items to users; and sociological filtering systems as the ones that are working based on the personal and organisational interrelationships of individuals in a community. Early information sharing systems belonged to the first category and were based on text-based filtering, which works by selecting relevant items according to aset of textual keywords (Konstan 2004). Collaborative filtering systems were first introduced as representatives of the second category. They addressed two problems of text-based systems:

- The problem of overwhelming numbers of on-topic items (ones which would be all selected by a keyword filter), which has been addressed by the introduction of further evaluating the items based on human judgment about their quality.
- The problem of filtering non-text items, which has been addressed by judging them solely upon human taste.

Therefore, early recommender systems were based on the notion of collaborative filtering, and have been defined as systems that "...help people make choices based on the opinions of other people." (Goldberg et al. 1992). As years came by, the term "recommender systems" has prevailed over the term "collaborative filtering systems". It first described systems in which "...people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients." (Resnick and Varian 1997). Finally, it evolved to a meaning that is more or less valid today, covering "...any system that produces individualised recommendations as output or has the effect of guiding the user in a personalised way to interesting or useful objects in a large space of possible options." (Burke 2002; Burke and Ramezani 2011). Even though this definition covers also the classic text-based filtering systems, Burke (2002) states that two criteria distinguish recommender systems

from text-based ones: the criterion of 'individualised' and the criterion of 'interesting and useful' content. Table 1.1 provides an overview of relevant definitions that we have identified in the literature, extending the initial collection reported in Manouselis and Costopoulou (2007).

1.2.2 Types

In the literature, recommender systems have been usually classified into two basic types, according to the way recommendations are made (Adomavicius and Tuzhilin 2005):

- *Content-based recommendation*, in which the user is recommended items similar to the ones he has preferred in the past. Content-based recommendation systems analyse a set of items and/or descriptions previously preferred by a user, and build a model or profile of user interests based on the features of these items (Lops et al. 2011; Pazzani and Bilsus 1997).
- *Collaborative recommendation*, in which the user is recommended items that people with similar tastes and preferences liked in the past. Collaborative recommendation (or collaborative filtering) systems predict a user's interest in new items based on the recommendations of other people with similar interests (Schafer et al. 2007; Ekstrand et al. 2010).

Moreover, other types of recommender systems have been also proposed in the literature. For instance, Burke (2002; 2007) distinguishes the following ones (in addition to the two described above):

- *Demographic recommendation*, which classifies the users according to the attributes of their personal profile, and makes recommendations based on demographic classes.
- *Utility-based recommendation*, which makes suggestions based on a computation of the utility of each item for a user, for whom a utility function has to be stored.
- *Knowledge-based recommendation*, which suggests items based on logical inferences about user preferences. A knowledge representation (e.g. rules) about how an item meets a particular user need is necessary.

Furthermore, Adomavicius and Tuzhilin (2005) also distinguish recommenders in those that aim to predict absolute values of ratings users would give to yet unseen items, from preference-based filtering, i.e. predicting the relative preferences of users. Finally, hybrid recommendation has also been identified. Recommender systems of this type combine two or more of the aforementioned types in order to gain better performance and address the shortcomings of each type (Burke 2002; 2007).

Table 1.1: Overview of definitions related to recommender systems.

Goldberg et al. 1992	"Collaborative filtering simply means that people collaborate to help one another perform filtering by recording their reactions to documents they read."
Resnick et al. 1994	"Collaborative filters help people make choices based on the opinions of other people."
Shardanand and Maes 1995	"Social information filtering essentially automates the process of 'word-of-mouth' recommendations: items are recommended to a user based upon values assigned by other people with similar taste."
Resnick and Varian 1997	"In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients."
Pennock and Horvitz 1999; Goldberg et al. 2001	"The term 'collaborative filtering' describes techniques that use the known preferences of a group of users to predict the unknown preferences of a new user; recommendations for the new users are based on these predictions. Other terms that have been proposed are 'social information filtering' and 'recommender system'."
Schafer et al. 2001	"Recommender systems use product knowledge -either hand-coded knowledge provided by experts or 'mined' knowledge learned from the behavior of consumers- to guide consumers through the often-overwhelming task of locating products they will like."
Burke 2002; Lops et al. 2011	"...any system that produces individualised recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options."
Konstan 2004	"Recommender systems use the opinions of members of a community to help individuals in that community identify the information or products most likely to be interesting to them or relevant to their needs."
Herlocker et al. 2004	"Recommender systems use the opinions of a community of users to help individuals in that community more effectively identify content of interest from a potentially overwhelmingset of choices."
Deshpande and Karypis 2004	"Recommender systems - a personalized information filtering technology used to either predict whether a particular user will like a particular item (prediction problem) or to identify aset of N items that will be of interest to a certain user (top-N recommendation problem)."
Hung 2005	"A personalized recommendation system can provide one-to-one service to customers based on customers' past behavior and through inference from other users with similar preferences. The aim of personalization is to offer customers what they want without asking explicitly and to capture the social component of interpersonal interaction."
Schein et al. 2005	"Recommender systems suggest items of interest to users based on their explicit and implicit preferences, the preferences of other users, and user and item attributes."
Smyth 2007	"Recommender systems try to help users access complex information spaces."
Burke 2007	"Recommender systems are personalized information agents that provide recommendations: suggestions for items likely to be of use to a user... A recommender can be distinguished from an information retrieval system by the semantics of its user interaction."
Ekstrand et al. 2010	"...other users' opinions can be selected and aggregated in such a way as to provide a reasonable prediction of the active user's preference."

1.3 Relevant Systems in Educational Applications

1.3.1 Adaptive Educational Hypermedia

Web systems generally suffer from the inability to satisfy the heterogeneous needs of many users. To address this challenge, a particular strand of research that has been called adaptive web systems (or adaptive hypermedia) tried to overcome the short-comings of traditional 'one-size-fits-all' approaches by exploring ways in which Web-based could adapt their behaviour to the goals, tasks, interests, and other characteristics of interested users (Brusilovsky and Nejdl 2004). A particular category of adaptive systems has been the one dealing with educational applications, called adaptive educational hypermedia (AEH) systems.

Adaptive web systems belong to the class of user-adaptive software systems (Schneider-Hufschmidt et al. 1993). According to Oppermann (1994) a system is called adaptive "if it is able to change its own characteristics automatically according to the user's needs". Adaptive systems consider the way the user interacts with the system and modify the interface presentation or the system behaviour accordingly (Weibenzahl 2003). Jameson (2001) adds an important characteristic: a user-adaptive system is an interactive system which adapts its behaviour to each individual user on the basis of nontrivial inferences from information about that user.

Adaptive systems help users find relevant items in a usually large information space, by essentially engaging three main adaptation technologies (Brusilovsky and Nejdl 2004): adaptive content selection, adaptive navigation support, and adaptive presentation. The first of these three technologies comes from the field of adaptive information retrieval (IR) (Baudisch 2001) and is associated with a search-based access to information. When the user searches for relevant information, the system can adaptively select and prioritise the most relevant items. The second technology was introduced by adaptive hypermedia systems (Brusilovsky 1996) and is associated with a browsing-based access to information. When the user navigates from one item to another, the system can manipulate the links (e.g., hide, sort, annotate) to guide the user adaptively to most relevant information items. The third technology has its roots in the research on adaptive explanation and adaptive presentation in intelligent systems (Moore and Swartout 1990; Paris 1988). It deals with presentation, not access to information. When the user gets to a particular page, the system can present its content adaptively.

As Brusilovksy (2001) describes, educational hypermedia was one of the first application areas of adaptive systems. A simplified architecture of the layers within an educational AEH system that has been developed simplifying the elaborate one found in Karampiperis and Sampson (2005) is presented in Figure 1.1. This architecture includes: a layer including the representation and organisation of knowledge about educational content (learning resources), the domain (domain ontology), and the user (user model); a layer that includes the adaptation mechanisms and rules; and a layer that provides the run-time adaptation results to the user. A number of pioneer adaptive educational hypermedia systems were developed between 1990 and
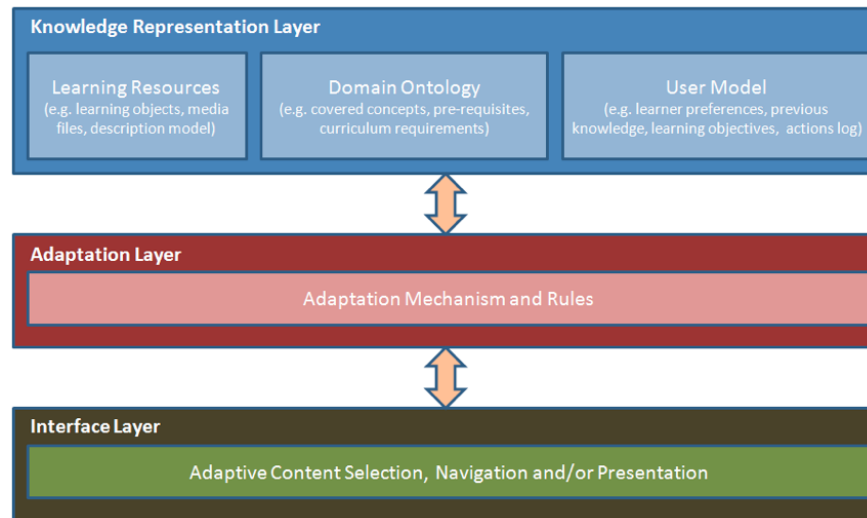
Fig. 1.1: Generic layers within a simplified example architecture of an educational AEH (adapted from: Karampiperis and Sampson 2005; Manouselis et al. 2011)

1996, which Brusilovksy roughly divided into two research streams. The first stream includes systems created by researchers in the area of intelligent tutoring systems (ITS) who were trying to extend traditional student modelling and adaptation approaches developed in this field to ITS with hypermedia components (Brusilovsky et al. 1993; Gonschorek and Herzog 1995; Prez et al. 1995). The systems of the second stream were developed by researchers working on educational hypermedia in an attempt to make their systems adapt to individual students (De Bra 1996; De La Passardiere and Dufresne 1992; Hohl et al. 1996; Kay and Kummerfeld 1994).

AEH research has often followed a top-down approach, greatly depending on expert knowledge and involvement in order to identify and model TEL context variables. For example, Cristea (2005) describes a number of expertise-demanding tasks when AEH content is authored: initially creating the resources, labeling them, combining them into what is known as a domain model; then, constructing and maintaining the user model in a static or dynamic way, since it is crucial for achieving successful adaptation in AEH. Generally speaking, in AEH a large amount of user-related information (characterising needs and desires) has to be encoded in the content creation phase. This can take place in formal educational settings when the context variables are usually known, and there is significant AEH research (e.g. dealing with learner and domain models) that can be considered and reused within TEL recommender research.

1.3.2 Learning Networks

Another strand of work includes research where the context variables are extracted from the contributions of the users. A category of such systems includes learning networks, which connect distributed learners and providers in certain domains (Koper and Tattersall 2004; Koper et al. 2005). The design and development of learning networks is highly flexible, learner-centric and evolving from the bottom upwards, going beyond formal course and programme-centric models that are imposed from the top downwards. A learning network is populated with many learners and learning activities provided by different stakeholders. Each user is allowed to add, edit, delete or evaluate learning resources at any time.

The concept of learning networks (Koper et al. 2005) provides methods and technical infrastructures for distributed lifelong learners to support their personal competence development. It takes advantages of the possibilities of the Web 2.0 developments and describes the new dynamics of learning in the networked knowledge society. A learning network is learner-centered and its development emerges from the bottom-up through the participation of the learners. Emergence is the central idea of the learning network concept. Emergence appears when an interacting system of individual actors and resources self-organises to shape higher-level patterns of behaviour (Gordon 1999; Johnson 2001; Waldrop 1992).

We can imagine users (e.g. learners) interacting with learning activities in a learning network while their progress is being recorded. Indirect measures like time or learning outcomes, and direct measures like ratings and tags given by users allow to identify paths in a learning network which are faster to complete or more attractive than others (e.g. Drachsler et al. 2009a; Vuorikari and Koper 2009). This information can be fed back to other learners in the learning network, providing collective knowledge of the 'swarm of learners' in the learning network. Most learning environments are designed only top-down as often times their structure, learning activities and learning routes are predefined by an educational institution. Learning networks, on the other hand, take advantage of the user-generated content that is created, shared, rated and adjusted by using Web 2.0 technologies. In the field of TEL, several European projects address these bottom-up approaches of creating and sharing knowledge, such as the TENcompetence project (Wilson et al. 2008) or the LTfLL project (Drachsler et al. 2010).

Following a similar approach, in Research Networks researchers are interconnected over Web 2.0 tools and are informed about latest research activities. This combined information of a specific research community easily becomes overwhelming, thus also researchers face an information overflow issue. Customised awareness support tools are needed to visualise and explore the collected data. But also recommender systems are becoming increasingly important to support researchers in the daily work process (Reinhardt et al. 2011a; Reinhardt et al. 2011b).

Another category of systems that formulate and define their context variables following a bottom-up approach, are Mash-Up Personal Learning Environments (MUPPLE) (Wild et al. 2008). First such approaches were created by (Liber 2000; Liber and Johnson 2008; Wild et al. 2008). The iCamp EU-initiative explicitly ad-
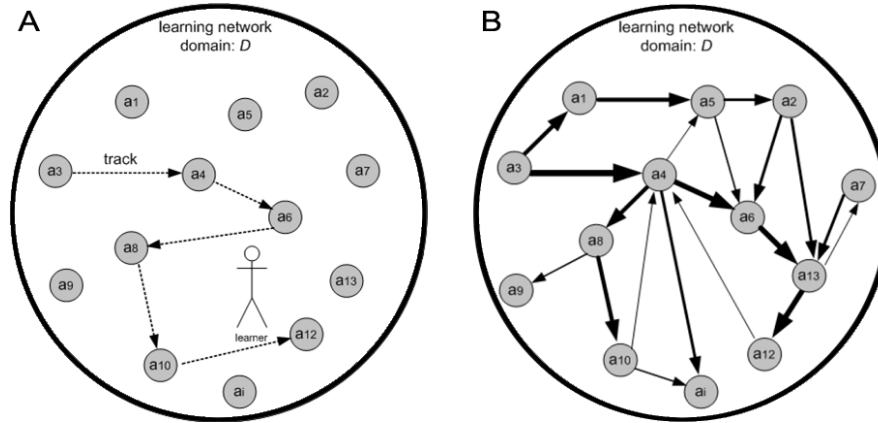
Fig. 1.2: Evolution of a learning network from Drachsler (2009b) (left (A): starting phase with a first learner moving through possible learning activities; right (B): advanced phase showing emerging learning paths from the collective behavior of all learners)

dresses the integration of Web 2.0 sources into MUPPLE, by creating a flexible environment that allows learners to create their own environments for certain learning activities. MUPPLEs are a kind of instance of the learning network concept and therefore share several characteristics with it. They also support informal learning as they require no institutional background and focus on the learner instead of institutional needs like student management or assessments. The learners do not participate in formal courses and neither receive any certification for their competence development. A common problem for MUPPLEs is the amount of data that is gathered already in a short time frame and the unstructured way it is collected. This can make the process of user and domain modelling demanding and unstructured. On the other hand, this is often the case in recommender systems as well, when user and item interactions are explored, e.g. in order to identify user and item similarities.

1.3.3 Educational Data Mining and Learning Analytics

Educational Data Mining (EDM) is an emerging discipline that has attracted significant interest during the past years (Romero et al. 2008; Baker 2010). This interest leads into the creation of a relevant scientific society (International EDM society), a dedicated journal (Journal of EDM) and an annual conference that has already reached its fifth edition (http://www.educationaldatamining.org). By definition (Baker 2010), EDM explores the application of data mining methods in order to explore the types of data collected in educational environments and understand better the user activities and learning context. It covers topics such as processes or

methodologies followed to analyse educational data, ways to integrate data mining with pedagogical theories, as well as applications that are used for improving educational software or teacher support, for improving understanding of learners' domain representations, and for improving assessment of learners' engagement in the learning tasks.

Traditional data mining methods are used to support mining educational data sets, but trying to discover and take advantage of the unique features of educational data. Baker and Yacef (2010) classified the EDM areas into: prediction (e.g. classification, regression, density estimation); clustering; relationship mining (e.g. association rule mining, correlation mining, sequential pattern mining, causal data mining); distillation of data for human judgment; and discovery with models. In EDM, whether educational data is taken from students' use of interactive learning environments, computer-supported collaborative learning, or administrative data from schools and universities, it often has multiple levels of meaningful hierarchy, which often need to be determined by properties in the data itself, rather than in advance. Furthermore, issues of time, sequence, and context also play important roles in the study of educational data. The work in this area can be considered to be relevant to the domain of recommender systems for educational applications, since many recommender systems apply data mining techniques in order to cluster users, find correlations and improve their recommendations (Romero and Ventura 2010).

In addition, an emerging strand of research is around the topic of the so-called Learning and Knowledge Analytics (LAK), as reflected by a number of conferences and special issues in recent years (Siemens 2010; Siemens and Gasevic 2011). Among others, the analysis of learner data and identification of patterns within these data are researched to predict learning outcomes, to suggest relevant resources and to detect error patterns or affects of learners. The definition of Learning Analytics by Siemens (2010) describes them as the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning. This definition reveals that Learning Analytics are very closely related to EDM, with a particular emphasis on knowledge representation and reasoning (Romero and Ventura 2007). This is perfectly justified since, in an increasing number of scientific disciplines, large data collections are emerging as important community resources (Chervenak et al. 2000). These data sets are used as benchmarks to develop new algorithms and compare them to other algorithms in given settings. For instance, when data sets are intended to be used for recommendations algorithms, various data types such as explicit (ratings) or implicit (downloads and tags) can serve as potential relevance indicators.

1.3.4 Similarities and differences

Many of the AEH systems address formal learning (e.g. Aroyo et al. 2003; De Bra et al. 2002; Kravcik et al. 2004), have equally fine granulated knowledge domains and can therefore offer personalised recommendations to the learners. They take

advantage of technologies like metadata and ontologies to define the relationships, conditions, and dependencies of learning resources and learner models. These systems are mainly used in 'closed-corpus' applications (Brusilovsky and Henze 2007) where the learning resources can be described by an educational designer through semantic relationships and is therefore a formal learning offer. As mentioned before, in formal educational settings (such as universities) there are usually well-structured formal relationships like predefined learning plans (curriculum) with locations, student/teacher profiles, and accreditation procedures. All this metadata can be used to recommend courses or personalise learning through the adaptation of the learning resources or the learning environment to the students (Baldoni et al. 2007). One interesting direction in this research is the work on adaptive sequencing which takes into account individual characteristics and preferences for sequencing learning resources (Karampiperis and Sampson 2005). In AEH there are many design activities needed before the runtime and also during the maintenance of the learning environment. In addition, the knowledge domains in the learning environment need to be described in detail. These aspects make adaptive sequencing and other adaptive hypermedia techniques less applicable for TEL recommendation, where informal learning networks emerge without some highly structured domain model representation.

In informal learning networks, mining techniques need to be used in order to create some representation of the user or domain model. For instance, prior knowledge in informal learning is a rather diffuse parameter because it relies on information given by the learners without any standardisation. To handle the dynamic and diffuse characteristic of prior knowledge, and to bridge the absence of a knowledge domain model, probabilistic techniques like latent semantic analysis are promising (van Bruggen et al. 2004). The absence of maintenance and structure in informal learning is also called the 'open corpus problem'. The open corpus problem applies when an unlimited set of documents is given that cannot be manually structured and indexed with domain concepts and metadata from a community (Brusilovsky and Henze 2007). The open corpus problem also applies to informal learning networks. Therefore, bottom-up recommendation techniques like collaborative filtering are more appropriate because they require nearly no maintenance and improve through the emergent behaviour of the community. Drachsler et al. (2008b) analysed how various types of collaborative filtering techniques can be used to support learners in informal learning networks. Following their conclusions we have to consider the different environmental conditions of informal learning, such as the lack of maintenance and less formal structured learning objects, in order to provide an appropriated navigation support to recommender systems. Learning networks are mainly structured by tags and ratings given by their users, being therefore in contrast with the institutionalised Learning Management Systems (LMSs) like Moodle (http://moodle.org) or Blackboard (http://www.blackboard.com) that are used to better manage learning activities and distribute learning resources to learners.

Besides the already mentioned differences for prior knowledge in informal learning, there are also differences in the data sets which are derived from environmental conditions. Normally, the numbers of ratings obtained in recommender systems is

Name	Short description	Advantages	Disadvantages	Usefulness for TEL
Collaborative filtering (CF) techniques				
1.User-based CF	Users that rated the same item similarly probably have the same taste. Based on this assumption, this technique recommends unseen items already rated by similar users.	- No content analysis - Domain-independent - Quality improves over time - Bottom-up approach - Serendipity	- New user problem - New item problem - Popular taste - Scalability - Sparsity - Cold-start problem	- Benefits from experience - Allocates learners to groups (based on similar ratings)
2.Item-based CF	Focus on items, assuming that items rated similarly are probably similar. It recommends items with highest correlation (based on ratings to the items).	- No content analysis - Domain-independent - Quality improves over time - Bottom-up approach - Serendipity	- New item problem - Popular taste - Sparsity - Cold-start problem	- Benefits from experience
3.Stereotypes or demographics CF	Users with similar attributes are matched, then recommends items that are preferred by similar users (based on user data instead of ratings).	- No cold-start problem - Domain-independent - Serendipity	- Obtaining information - Insufficient information - Only popular taste - Obtaining metadata information - Maintenance ontology	- Allocates learners to groups - Benefits from experience - Recommendation from the beginning of the RS
Content-based (CB) techniques				
4. Case-based reasoning	Assumes that if a user likes a certain item, s/he will probably also like similar items. Recommends new but similar items.	- No content analysis - Domain-independent - Quality improves over time	- New user problem - Overspecialisation - Sparsity - Cold-start problem	- Keeps learner informed about learning goal - Useful for hybrid RS
5. Attribute-based techniques	Recommends items based on the matching of their attributes to the user profile. Attributes could be weighted for their importance to the user.	- No cold-start problem - No new user / new item problem - Sensitive to changes of preferences - Can include non-item related features - Can map from user needs to items	- Does not learn - Only works with categories - Ontology modeling and maintenance is required - Overspecialisation	- Useful for hybrid RS - Recommendation from the beginning
Data-Mining (DM) techniques				
6. Decision Trees (C4.5, ID3)	A decision tree represents a set of classifications created from a set of rules. They start form a single classification and branch out based on classification rules mined from the data.	- Easy to understand - High representation power	- Overspecialisation in small datasets - Can become very broad	- Visualize differences of learners from the data - Alternative approach to expert driven ontologies
7. *K*-Nearest Neighbor (Isodata, Forgy)	Does not build an explicit model instead exams the categories of the *K* most similar data points. K-means is often used in TEL recommenders to compute similarity of vector-based approaches.	- Simple approach only two parameters to select - Robust to noise - High representation power	- Difficult to select distance function *d* - Irrelevant data needs to be removed - Slower than model-based recommendations	- Recommend similar peers, or contents to learners - Cluster learners in groups
8. Vector-based models (TF-IDF, Singular value decomposition, Matrix Factorisation)	Vector-based approaches characterise items and users as vectors of factors in a 3D space. A high correlation between an item and a user can be used as recommendation but also predictions can be created.	- Suitable for sparse datasets - Can take temporal differences into account - Can take various implicit information into account does not need explicit ratings	- Content depended (Items with same context but different terms are not matched) - User keywords have to match semantic space	- Useful to monitor and predict learner performance - Can adapt to increased knowledge level of learners - Can mark learning resources that are not popular anymore

Table 1.2: A selected list of recommendation techniques used in TEL and their usefulness for learning. Extend version based on initial table of Drachsler et al. (2008a).

usually very small compared to the number of ratings that have to be predicted. Effective prediction by ratings based on small amounts is very essential for recommender systems and has an effect on the selection of a specific recommenda-

tion technique. Formal learning can rely on regular evaluations of experts or students upon multiple criteria (e.g., pedagogical quality, technical quality, ease of use) (Manouselis et al. 2007), but in informal learning environments such evaluation procedures are unstructured and few. Formal learning environments like universities often have integrated evaluation procedures for a regular quality evaluation to report to their funding body. With these integrated evaluation procedures more dense data sets can be expected. As a conclusion, the data sets in informal learning context are characterised by the 'Sparsity problem' caused by sparse ratings in the data set. Multi-criteria ratings could be beneficial for informal learning to overcome the 'Sparsity problem' of the data sets. These multi-criteria ratings have to be reasonable for the community of lifelong learners. The community could rate learning resources on various levels, such as required prior knowledge level (novice to expert), the presentation style of learning resources, and even the level of attractiveness, because keeping students satisfied and motivated is a vital criteria in informal learning. These explicit rating procedures should be supported with several indirect measures like 'Amount of learners using the learning resource' or 'Amount of adjustments of a learning resources', in order to measure how up-to-date the learning resource is.

Informal learning is therefore different from well-structured domains, like formal learning. Recommender systems for informal learning have no official maintenance by an institution, mostly rely on its community and most of the time do not contain well-defined metadata structures. Moreover, formal learning is characteristically top-down designed and the learning contents are a closed-corpus that can only be edited by domain experts; Informal learning contents emerge from the bottom-upwards through communities contributions (open-corpus) and every community member can adjust and contribute information. Therefore, it will be difficult to transfer and apply recommender systems even from formal to non-formal settings (and vice-versa), since user tasks and recommendation goals are often substantially different.

A critical assessment of recommender techniques regarding their applicability and usefulness in TEL has taken place by Drachsler et al. (2008a). Table 1.2 provides an initial overview of advantages and disadvantages of each technique, and reports the envisaged usefulness of each technique for TEL recommenders. Nevertheless, it aims to serve as an initial basis for such a discussion, since a more detailed and elaborate survey of all existing recommendation methods and techniques can take place in the future.

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