May I suggest? Three PLE recommender strategies in comparison

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Abstract

Personal learning environment (PLE) solutions aim at empowering learners to design (ICT and web-based) environments for their activities in different learning contexts and even for transitions between these contexts. Hereby, recommender systems which are highly successful in other application areas comprise one relevant technology for supporting learners in PLE-based activities. In this paper we examine the utilization of recommender technology for PLEs. However, being confronted by a variety of educational contexts and due to different research approaches dealing with recommenders, we present three strategies for providing PLE recommendations to learners. Consequently, we compare these recommender strategies by discussing their strengths and weaknesses in general.

1. Introduction

Over the last decades, recommender systems have been successfully applied in various areas, like online retailing (cf. Amazon) or social networking (cf. Facebook). Due to the success of this kind of technology, research on technology-enhanced learning (TEL) has started to deal with recommender strategies for learning, as documented by workshop proceedings (Manouselis et al., 2010) and special issues in journals (Santos and Boticario, 2011). Addressing more learner-centric TEL streams, recommendations seem to be a powerful tool for personal learning environment (PLE) solutions (Mödritscher, 2010). In PLEs, personalized recommendations help filtering information based on “soft” but significant context boundaries (Wilson et al. 2007), giving learners the opportunity to take the best of an environment where shared content differed in quality, target audience, subject matter, and is constantly expanded, annotated, and repurposed (Downes, 2010).

This paper addresses the generation and provision of PLE recommendations within the EU project ‘ROLE’ (abbreviation for ‘Responsive Open Learning Environments’, cf. http://www.role-project.eu). As ROLE deals with a wide range of educational scenarios and even with transitions between learning contexts, we present three different strategies, each one aiming at supporting certain needs of learners.

The paper is structured as follows. The upcoming section summarizes our understanding of personal learning environments and gives a brief overview of recommenders for TEL and PLEs. Then, we describe the three recommender approaches being developed in the ROLE project. Furthermore we discuss benefits and disadvantages for their application in PLEs before the paper is concluded, and future work is indicated.

2. PLEs, PLE recommendations, and related work

According to Henri et al. (2008), personal learning environments (PLEs) refer to a set of learning tools, services, and artifacts gathered from various contexts to be used by the learners. A typical situation for PLE-based collaboration is depicted in Figure 1. A learner is involved in two activities, an individual tutoring session in which she consults the facilitator via Facebook and a task in which she collaboratively works on an outcome together with a peer actor using four different tools (RSS Feed, Google Mail, YouTube, and Twitter). This example illustrates how learners interact with their PLEs consisting of different entities, i.e. tools, content artifacts (like emails or Tweets), peer actors, etc.

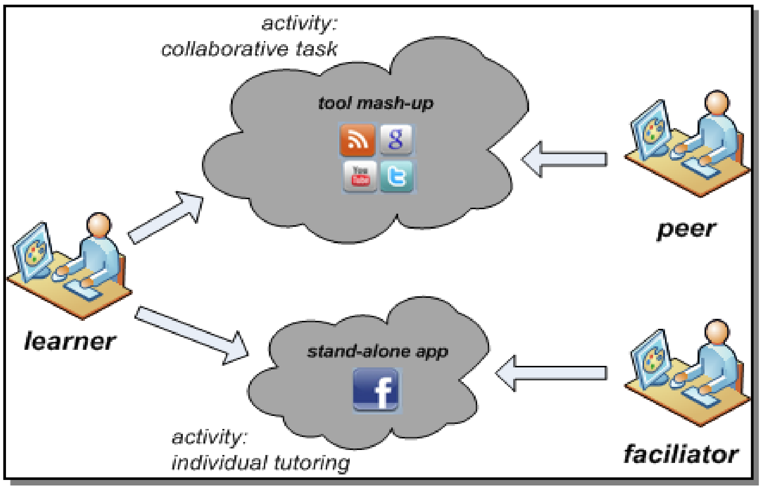

Fig. 1: Example scenario for PLE-based collaboration (see also Wild et al., 2008).

According to Van Harmelen (2008), web-based PLEs aim at empowering learners to design (ICT-based) environments for their activities by allowing them to build, connect, and expand learner networks in order to collaborate on shared outcomes and acquire necessary (professional and rich professional) competences. However user studies in the fields of higher education (Ullrich et al., 2010) and workplace learning (Kooken et al., 2007) evidence that learners – and even teachers! (Windschitl and Sahl, 2002) – have varying attitudes towards hand-on skills in using ICT for learning.

Against this background, PLE solutions should provide facilities for empowering learners in using this kind of technology. One possible solution is the application of recommender technology, because recommendations are necessary if users have to make choices without sufficient personal experiences of alternatives (Resnick and Varian, 1997). This aspect is considerably the case for informal learning activities of (lifelong) learners who try to utilize PLE technology in highly different contexts in order to achieve their goals. Thus recommendations could be valuable for various aspects of PLE-based learning activities, e.g. for formulating concrete learning goals or needs, retrieving relevant artifacts, finding relevant peers or tools, getting suggestions for learner interactions in a specific situation, etc.

Coming to fame particularly by their application in eCommerce (like Amazon.com) or social networking platforms (like Facebook.com), recommender systems describe "*systems that produce individualized recommendations as output or have the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options*" (Burke, 2002). Recommenders can follow various different strategies, such as item-based ones (e.g. content artifacts or links to users), model-based ones (e.g. by applying probabilistic models or networked structures), collaborative filtering (based on user-given data-sets), or hybrid strategies (cf. Mödritscher, 2010). Moreover, Verbert and Duval (2011) outline the importance of building upon real-world data-sets, e.g. in the form of user interaction data or (implicit and explicit) user feedback, to develop and improve TEL recommender systems.

A lot of research on recommendation services has been done in the last few years. Amongst others, theoretical work on this issue proposes models and ontologies for recommendations in the educational domain (Santos and Boticario, 2010) or recommendation frameworks based on content and context (Broisin et al., 2010). On a more practical level, other approaches deal with concrete facilities like social navigation elements for educational libraries (Brusilovsky et al., 2010), ranking algorithms for lecture slides (Wang and Sumiya, 2010), people finder for workplace learning (Beham et al., 2010) or even algorithms for predicting student performance (Thai-Nghe et al., 2010).

However, in the ROLE project we are facing new challenges which have led to the development of different recommender strategies for PLE settings.

3. Three different PLE recommender approaches

A grand challenge of the EU project ROLE concerns the wide range of learning contexts to be supported through responsive open learning environments. As being targeted by the vision of the project (cf. http://www.role-project.eu/?page_id=406), ROLE claims to support learners in different educational contexts, starting with formal and informal learning scenarios at universities and at workplaces and reaching to the many contexts of lifelong learning. Moreover, it is even a goal to support transitions between these contexts, as indicated by the five test-beds ('university to company' transition, 'individual to shared competences' transition, 'formal to informal learning' transition etc). Consequently, the project focuses on integrating flexible infrastructures, i.e. widget technology, into existing learning platforms and on different approaches to personalize learning, amongst others by providing context-sensitive PLE recommendations to the learners.

In the upcoming subsections we briefly describe three of these recommender strategies being developed in the project and following different paradigms.

3.1 Federated Search and Collaborative Recommendation Widget

The first approach developed within the ROLE project is implemented as a federated search and recommendation widget exploiting the usage of resources by people sharing the same learning and/or social context. The 'Binocs' widget (see Figure 2) employs a federated search engine that aggregates heterogeneous resources and forwards them to a recommender system. Recommended resources ranging from wiki pages, videos, to presentations can be saved, shared, assessed, and re-purposed according to each user's interest.

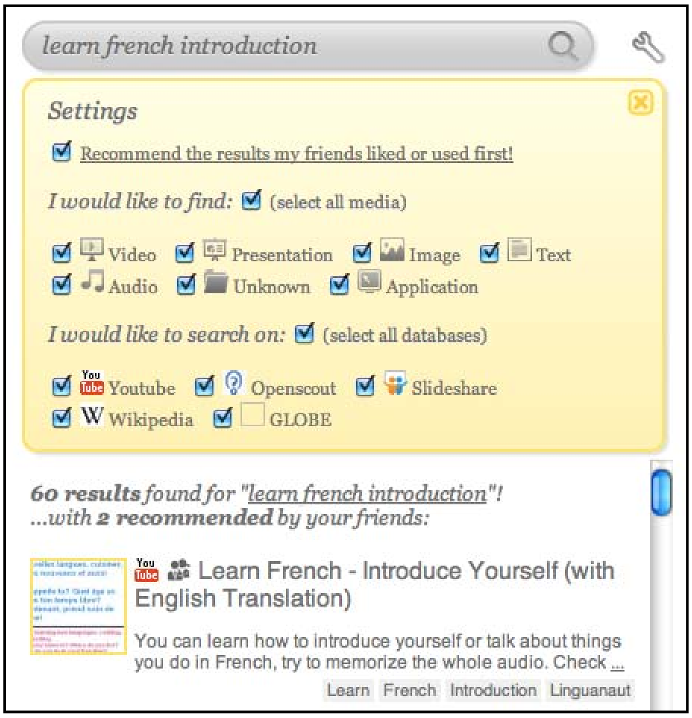

Fig. 2: Federated search and collaborative recommendation widget ‘Binocs’ displaying the results for the query ‘learn french introduction’ and the opened settings menu.

To rank resources, the recommender system takes the following user actions into account: (1) selecting a resource from a search result, (2) liking or disliking a search result (using a thumbs up and down feature) and (3) previewing a search result. The learning and social context can be derived from the course (e.g. all students from a course share similar interests), the business setting (e.g. all employees of the sales department) or from the user’s friends and contacts in the widget container (via the OpenSocial API (Mitchell-Wong et al., 2007)). The recommender system relies on an algorithm influenced by Google's original PageRank algorithm (Page et al., 1999) and based on the 3A interaction model (El Helou et al, 2009). In the absence of previous user interaction with a resource, ranking is still possible based on the resource relevance to the search query.

A preliminary evaluation of the widget’s usability and recommendation usefulness is summarized in Govaerts et al. (2011a). The evaluation helped to improve the user interface, and revealed that users prefer Google results due to their diversity. The widget’s results were biased to media, while Google provides a wider range of Web pages. This can be remedied by adding more repositories to the federated search engine to drive the recommendations. On the other hand, pilot users agreed on the usefulness of the collaborative recommendations on top of the search results. We plan to evaluate the use of the recommender system further through the analysis of user online feedback (by clicking on top N recommended items) and through user surveys in real-life scenarios.

Two more usability and usefulness evaluation studies of the Binocs widget being used in a PLE were conducted (Govaerts et al., 2011b). One was done in the context of Business English courses at the Shanghai Jiao-Tong University (SJTU, http://www.sjtu.edu.cn) where the widget is used to provide access to social media resources (e.g. YouTube and SlideShare). The second evaluation was conducted in a business setting, more specifically within an international corporation, FESTO (http://www.festo.de) where the widget is used to assist sales people by offering more efficient search over multiple product databases. The results for the widget in the business setting are more positive than in the university. Potential explanations are the higher stability of the learning environment at FESTO and the slow internet connection perceived at the SJTU, which could have biased the evaluation of our federated search and recommendation services. Moreover it was noted that extending the available repositories would be helpful to get richer search results.

3.2 Community-based PLE recommender

A second recommender going beyond collaborative recommendations within a single widget is implemented as part of a practice sharing approach for learning communities (see Mödritscher et al., 2010). Basically, the idea is to integrate a pattern repository into existing PLE solutions so that users can voluntarily share their PLE usage experiences as 'good practices' with peers. Thereby, a pattern repository is a web-based service (with a RESTful API) which allows storing and retrieving patterns of PLE-based activities, i.e. recordings of learner interactions with a tool mash-up used for a specific situation (see also right-hand side of Figure 3). Overall, this practice sharing approach is intended to be for informal learning settings, thus supporting life-long learners in achieving their personal needs but also in succeeding at the workplace or in further education.

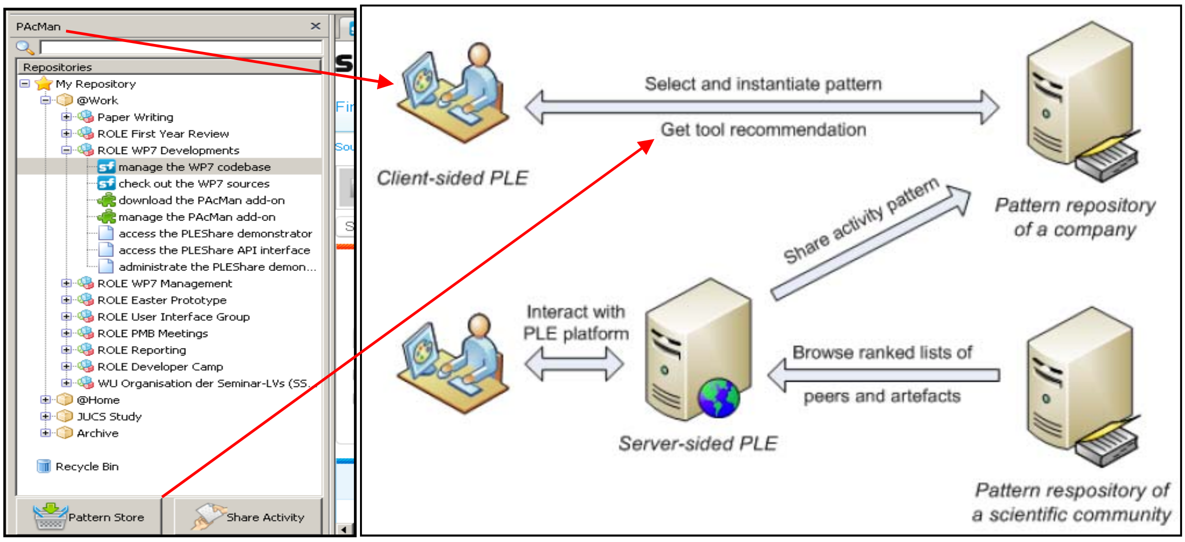

Fig. 3: Client-sided PLE solution PAcMan (left) and proposed architecture of a PLE practice sharing infrastructure (right, taken from Mödritscher et al., 2010).

The data for this recommender approach is captured through facilities of the PLE which enables users to share such an activity pattern in a simply way. A prototypic version of the pattern repository has been integrated in two different PLE like solutions, a client-sided one (PAcMan add-on, cf. https://addons.mozilla.org/en-US/firefox/addon/176479) and in OpenSocial-based widget containers (like iGoogle or Liferay). The format of the activity patterns to be shared has to be specified by the PLE developers who aim at integrating the pattern repository. For the PAcMan add-on, the shared data is given as JSON which consists of web resources being structured according to a simple activity model (an activity is a list of user-tagged URLs; see also left-hand side of Figure 3). Data capturing in OpenSocial containers is realized through a widget which records all events triggered by the widget on a mash-up page if it has been added to this page. After pressing the 'Share' button, the recording of learner-triggered events (user interactions) is stored to the repository on the basis of the Contextualized Attention Metadata (CAM) schema.

As the format of the shared activity patterns depends on the PLE solution submitting the data, a recommender strategy has to be implemented for each data format. Currently, the standard algorithm available can be characterized as a collaborative filtering (CF) technique, as it measures the occurrences of each item (pattern titles, users having shared patterns, user-generated tags, and URLs). The recommendations can be retrieved by the PLE solutions through the RESTful API and according to different entities (patterns, peers, user tags, tools, and artifacts) and different strategies. Next to the default strategy ('global top-n') it is planned to provide local top-n recommendations. Hereby, locality could refer to the patterns used for generating the recommendations, e.g. by using the patterns of a clique or for a specific search term only. For the first case, Mödritscher (2010) describes a study in which a few patterns of a research group was captured for a (work-related) scenario. Results showed that the distribution of item occurrences follows a power law, and the network of activities, resources (URLs) and user-generated tags tend to have characteristics of a scale-free network, which is an indicator that this collaboratively created data-set is suitable for generating useful recommendations for users (cf. experiences on music recommendations by Cano et al., 2006).

Overall, this strategy for generating and providing PLE recommendations seems to be reasonable, as it already works with smaller sets of data and allows personalizing recommendations e.g. according to learner's clique, a search term, or other contextual information. So far, recommendations are only provided on the level of activity patterns – if a user opens the 'Pattern Store' of the PAcMan add-on (see Figure 3) she can either query the patterns or receives recommendations in terms of the most frequent downloaded patterns. A more sophisticated strategy would be to suggest items (peers, artifacts, tools, or resource tags) according to specific situations, e.g. for a certain clique or a given goal of a learner. As retrieved sub-sets of activity patterns lead to scale-free networks, it is planned to provide two kinds of recommendations: (a) the must-sees which comprise the hubs in the PLE network structure and are always displayed to the user; (b) the might-be-of-interest suggestions, i.e. items of the long tail which are recommended from time to time or also triggered by a certain context or user interaction.

3.3 Psycho-pedagogical recommender

In contrast to collaborative filtering strategies, the psycho-pedagogical recommender is not based on large, community-generated data-sets. However, it is developed according to a theoretical model and relevant taxonomies (Fruhmann et al., 2010) on the one hand and user data on the other hand. In order to empower learners to build their learning environments and to use those for learning, this recommender strategy deals with providing guidance in self-regulated learning situations. While experienced learners are capable in using PLE technology without getting external support, many learners need some kind of guidance and support to go through the learning process (cf. Dabbagh and Kitsantas, 2004; Efklides, 2009). The main aim of the psycho-pedagogical recommender is to provide guidance especially with respect to self-regulated learning and to find appropriate resources (artifacts, tools, peers) fitting to the competence of the learner.

There are two kinds of data which is used for generating psycho-pedagogical recommendations. First user model data is taken into account, comprising learning goals and competences required at the moment. Also preferences, such as the degree of guidance needed, are considered. A second kind of data is given in the form of learning models which serve as basis for the recommender algorithm. The SRL process model describes how learning should ideally happen in a self-regulated way. It is a formalization of self-regulated learning in the context of ROLE. The SRL process model is related to general and concrete learning activities on the cognitive and meta-cognitive level. Learning tools are also related to learning activities, which describes the way of learning possible with certain tools. These relations are specified in advance and form an important basis of the recommendation strategy.

The recommendation strategy is closely related to these learning models and to each of its elements. The recommender tries to guide the learner though the learning process according the SRL process model. Therefore (cognitive and meta-cognitive) learning activities are recommended depending on what the learner has already done. The learner has to give feedback what has been done (which recommended learning activity has been performed). In order to recommend learning resources (at the moment only tools), the learning goals and competences are taken into account. Tools are recommended if they fit to the goals of the learner and if learners can actually use them for successful learning. Preferences such as the degree of guidance are also taken into account, which has effect how detailed recommendations are.

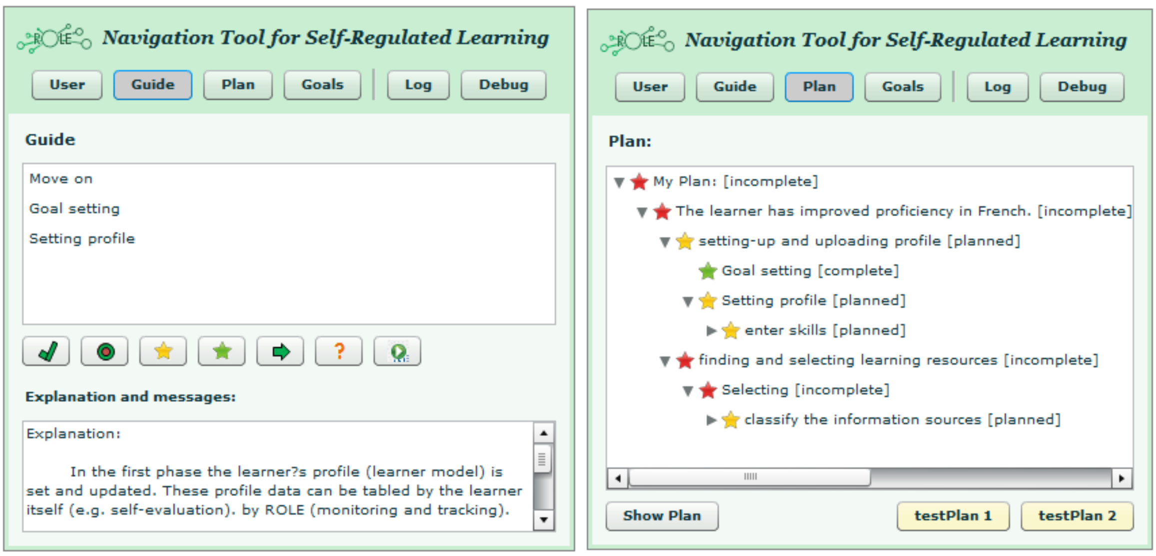

Fig. 4. Psycho-pedagogical recommender realized and provided in the form of widgets (left: guidance widget, right: learning planning widget).

According to the recommendation strategy the learner is provided with two kinds of recommendations, learning activities and learning resources. Both are presented on a list of possible choices, where the user can also report back which one she has chosen. In addition to these recommendations the learner also gets explanations, which is important because self-regulated learning is difficult to adopt. Furthermore, the learner gets an automatically generated learning plan which is updated each time an interaction takes place. So the learner gets visual feedback and orientation what has been planned or completed and a general overview on this state in the SRL process. The user interface has been implemented as a widget (see Figure 4). It uses a service in the background where the models and user data are stored and where the recommendation strategy is implemented.

Further work will concentrate on the integration of artifacts and peers to be recommended, usage of log data as input data, and on an improved user interface.

4. Discussion of the PLE recommender strategies and future work

Considering the different goals and techniques of the PLE recommenders being developed in the ROLE project, it is obvious that each one has specific benefits and shortcomings. Basically a user scenario for our recommenders could look like this. In the beginning a learner has a specific need and decides to start a new activity to address this need and achieve some goal, e.g. creating an outcome like a document together with some colleagues. In a first step, a PLE recommender has to support the learner by formulating her learning need and suggesting PLE designs so that she gets an idea what an environment for fulfilling the need could look like. Then, after reusing and adjusting such a PLE design or creating a new one from scratch, a PLE recommender should provide links to artifacts, peer users, or tools which are appropriate for the current activity.

Collaborative recommendations are realizable with a certain degree of accuracy without threatening the users' privacy (see also Machanavajjhala et al., 2011). However, this recommender is highly tailored to a specific context, namely information retrieval, as the Binocs widget enables federated search in different media and content repositories. In the scope of PLEs, this recommender supports learners in finding appropriate artifacts for their different activities. Additionally it is also possible that the widget points to peers that are relevant to query terms, if the privacy policy allows this. However, the widget does not recommend learning activities and does not take learner network structures in to account. So, the usefulness of the federated search and collaborative recommendation widget supports learners in the second phase of PLE-based collaboration rather than in designing their environment.

The community-based PLE recommender, on the other hand, has been developed on top of a simple semantic model, namely the notion of activities which are used to structure one's learning context and to capture information on user interactions and the context. Following a collaborative filtering (CF) approach, the pattern repository provides both recommendations of pre-given (shared) PLE designs in the form of tagged bookmarking collections as well as recommendations on artifacts, tools, and peers generated according to contextual information. Both kinds of recommendations can be requested by a PLE solution through the Web-API, whereby items can be differentiated between 'must-haves' (most frequent items) and 'might-be-of-interest' (items from the long tail; see also Mödritscher , 2010). Although perfectly supporting the two phases of the before-mentioned PLE scenario, this recommender suffers from typical weaknesses of CF techniques, namely the cold-start problem (no data on new user and items) and sparsity (no or less user ratings;

cf. Adomavicius and Tuzhilin, 2005). The application of clustering techniques and usage data is currently evaluated in order to refine the recommender algorithm.

Finally, the psycho-pedagogical recommender also supports the two phases of PLE-based learning. On the one hand, a learner can use the planning widget to start an activity and determine her goal. On the other hand, she can use the guidance widget to design and adjust the environment for her current activity. As this recommender is based on a more complex and pre-defined semantic model and structured, pre-processed usage data, it has clear advantages if less or no data is given. In this case, the psycho-pedagogical recommender claims to use expert-given rules to suggest goals and/or widgets. On the negative side, it can identify and recommend new items much slower, as the generation of recommendations is at least a semi-controlled process which involves pedagogical experts.

With these recommender approaches we believe that we cover the most critical issues for supporting learners in designing and using their PLEs. The most positive aspect of developing these three strategies next to each other concerns the weaknesses of single recommenders we have highlighted before. In case of lacking good recommendations for a specific case - e.g. if the community-based recommender does not have enough data on items or users – the learner can try to make use of suggestions of another recommender. This multi-approach also gives us flexibility to support different scenarios in the very heterogeneous test-beds of the ROLE project. While some test-beds are based on instructions and organizational driven learning (SJTU, FESTO) others have a strong focus on informal settings and collaboration. Here we can vary the strategies for learner support.

To conclude, at this point the three recommenders are on rather different maturity levels. While Binocs is ready to be used by end-users the pattern repository approach relies on the integration within existing PLE systems, i.e. also facilities to provide recommendations to the end-users, and the psycho-pedagogical recommender lacks the full implementation of all features. So, next to finishing development work on the latter two recommenders future work also comprises a user study for evaluating the recommenders ‘in action’.

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