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Towards a Recommender Strategy for Personal Learning Environments

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Abstract

Personal learning environments (PLEs) aim at putting the learner central stage and comprise a technological approach towards learning tools, services, and artifacts gathered from various usage contexts and to be used by learners. Due to the varying technical skills and competences of PLE users, recommendations appear to be useful for empowering learners to set up their environments so that they can connect to learner networks and collaborate on shared artifacts by using the tools available. In this paper we examine different recommender strategies on their applicability in PLE settings. After reviewing different techniques given by literature and experimenting with our prototypic PLE solution we come to the conclusion to start with an item-based strategy and extend it with model-based and iterative techniques for generating recommendations for PLEs.

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Keywords: Personal Learning Environments; Recommender Strategies; Collaborative Filtering; Activity Model

1. Introduction

According to Henri et al. [1], personal learning environments (PLEs) refer to a set of learning tools, services, and artifacts gathered from various contexts to be used by the learners. Furthermore Van Harmelen [2] states that PLEs aim at empowering learners to design (ICT-based) environments for their activities so that they can connect to learner networks in order to collaborate on shared outcomes and acquire necessary (professional and rich professional) competences through using the PLE. However user studies in the fields of higher education [3] and workplace learning [4] evidence that learners – and even teachers! [5] – have varying attitudes towards and hand-on skills in using ICT for learning.

Against this background, educators and learners have to rethink the way they teach and learn with these novel technologies. Moreover, they have to be prepared for using PLE technology, e.g. through specific features supporting them (cf. Knapper and Cropley [6]). As a possible solution approach, Resnick and Varian [7] argue that the application of recommender technology could be a useful instrument, as recommendations are necessary if users have to make choices without sufficient personal experiences of alternatives. This aspect is considerably the case for

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informal learning activities of (lifelong) learners who try to utilize PLE technology in their different contexts in order to achieve their goals. Thus recommendations could be valuable for various aspects of PLE-based learning activities, e.g. for retrieving relevant artifacts, finding relevant peers or tools, getting suggestions for learner interactions in a specific situation, etc.

In this paper we try to approach recommender strategies for supporting collaborative activities in PLE settings. Therefore we characterize PLE-based learning and highlight the usefulness of recommendations in this scope. Then we review state-of-the-art technology and literature according to the requirements of PLE-based collaboration. Furthermore we summarize findings from a preliminary case study with our prototypic PLE solution. The paper concludes with a proposal on how to approach a PLE recommender strategy and a discussion of problematic issues.

2. The use of recommendations for PLE-based learning ecologies

A typical situation for PLE-based collaboration is depicted in Fig. 1. A learner is involved into 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 and by using four different tools (RSS Feed, Google Mail, YouTube, and Twitter). This example shows that PLEs are strongly focusing on the learner who interacts with different entities, i.e. tools, content artifacts (like emails or Tweets), peer actors, etc.

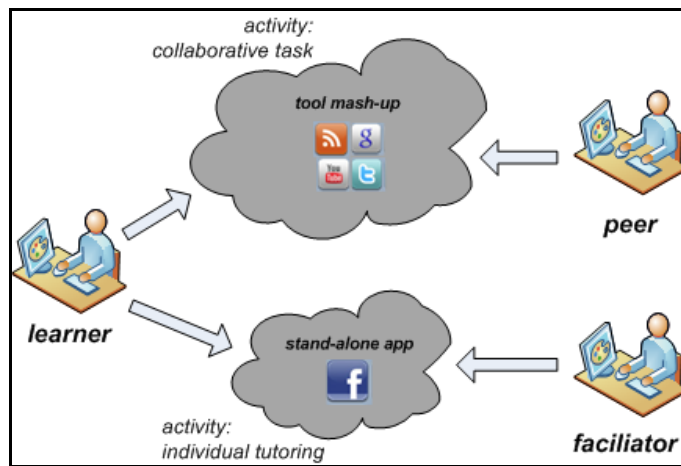


Fig. 1. Example scenario for PLE-based collaboration (see also Wild et al. [8])

Following the Actor-Network Theory (ANT) based model of learning ecologies by Klamma and Petrushyna [9], the environment of a learner includes the following possible ‘neighbors’:

- **Processes:** *Lifelong learning activities* carried out at the workplace, for educational reasons, or due to personal goals (e.g. a job task in a business process, attending a course for further education, or a spare time activity requiring the acquisition of new competences)
- **Media:** *Collection of learning resources* required for or created in these activities (e.g. the Wikipedia platform, learning objects repository, or simply the Internet)
- **Artifacts:** *Documents* and other (digital or real-world) artifacts collaboratively created and accessed by learners (e.g. Wiki articles or a joint paper)
- **Agents:** *Actors*, no matter if humans or software (e.g. peer learners or functionality provided via Internet)
- **Communities:** *People sharing the same environment*, e.g. in terms of having common interests, working on the same artifacts, being connected to the same actors (e.g. a group of learners trying to achieve a course goal or a special interest group for a specific topic)

From the perspective of a learner, a recommender strategy could comprise these five entities: (1) interaction

recordings for whole activities being appropriate for a high-level goal, (2) media collections (i.e. repositories containing valuable information), (3) single documents for a specific situation, (4) peer learners or learning tools relevant for an activity, or (5) entry points to communities which are helpful for one's topics and tasks.

In practice, recommender systems are well explored in the field of technology-enhanced learning. Amongst others, Ghidini et al. [10] report about the APOSDLE prototype which aims at supporting knowledge workers at their workplace by providing recommendations for artifacts, learning events, and expert users for a user's current situation (working task). Thereby, recommendations are generated on the basis of a network structure connecting working tasks, users, competences, learning events (instructions), and artifacts [11]. In sum, the APOSDLE approach works well but is restricted to one type of recommender strategies and normally to a narrow domain. The following section gives an overview of possible recommender strategies and reviews their applicability for PLEs.

3. Review of recommender strategies for PLEs

With respect to Resnick and Varian [7], recommendations are a well-known concept to support users in making choices without sufficient experiences of the alternatives. Coming to fame particularly by their application in eCommerce platforms (like Amazon.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*” [12]. By processing information on collaboration among different actors, systems and data sources, recommendations can be generated through information filtering, so-called collaborative filtering techniques which aim at predicting appropriate items on the basis of interaction data of many users within a community [13]. Overall, recommendations can be characterized according to certain dimensions.

First of all, one can distinguish between different types of recommendations, reaching from item-based over model-based up to hybrid ones. Item-based recommender systems, as elaborated by Wang et al. [14], focus on a set of items which should be ranked (cf. top-n recommendation problem) according to the relevance for a user or an application domain (e.g. peer learners, tools, and artifacts in different PLE activities). Deshpande and Karypis [13] state that model-based recommenders use a probabilistic model, for instance a user model or any other model describing relations between different entities, to predict appropriate items. Hybrid approaches include item-based and model-based components of generating recommendations.

Secondly, recommendations can be distinguished by the method the data is captured (cf. Claypool et al. [15]). The scale ranges from explicit user input (e.g. the ‘Like’ button at Facebook.com) to implicit user input, i.e. systems that collect user interaction data and automatically generate recommendations (e.g. Google search field suggesting query terms).

Thirdly, recommendations can be generated according to different techniques as well as by a one-pass algorithm or iteratively. Techniques comprise the usage frequency (top-n recommendations [13]), single and multi-attribute [16] decision making, the application of clustering techniques [17], network structures and metrics [11], or a PageRank like approach [18]. Similarly, algorithms can be time-triggered and generating recommendations in one pass or iteratively (e.g. PageRank). Romero and Ventura [19] summarize the most relevant data mining approaches in (formal) educational settings over the last 15 years: (a) statistics and visualization, (b) clustering and classification techniques, (c) association rule mining and sequential pattern mining, and (d) text mining. Concerning the informal character of learning with PLE technologies, the techniques (a) to (c) are also relevant for collaborative filtering, while (d) is highly important if user-generated content has to be processed – an example is given in section 5.

Finally, it has to be mentioned that recommender systems are always accompanied by problematic issues. Papagelis and Plexousakis [20] report about these three challenges: (1) Sparsity occurs if too few of the items available are sufficiently described to generate recommendations, e.g. on the basis of item attributes. (2) Scalability refers to the need of providing high quality recommendations promptly if the number of users and items scales up very quickly. (3) Cold-start describes the case in which a number of items cannot be recommended due to missing information about these items. Typically, the cold-start problem occurs in combination with clustering [21].

In the scope of PLE settings, as characterized in the last section, particular item-based techniques are of relevance for a first move towards recommendations for PLE users. Based on a trivial top-n algorithm, the data tracking from PLE usage can be easily analyzed according to the before-mentioned entities (activity patterns, tools, artifacts, peer learners, and communities). In a further step, single attributes of these entities (e.g. profile information of users or metadata about documents) can be applied to refine the ranked recommendations and avoid sparsity and cold-start

issues. As these items can partially be given by users, it is necessary to address problematic issues of user-generated content. Amongst others, Körner et al. [22] mention problems like hypo/hypernym detection and the application of tag semantics to increase the quality of Folksonomies. In addition Körner and his colleagues state that the performance of tag recommender algorithms can be improved by knowledge about tag usage and motivation (cf. categorizers vs. describers).

Moreover, a semantic model (e.g. the Activity Theory based model of lifelong learning activities introduced by Wild et al. [8]) can be utilized for a clustering approach (i.e. to link learner interactions, tools, and artifacts to existing activities) and for a model-based recommender strategy similar to the network structure used in the APOSDLE project [11]. As a final step, an iterative approach towards generating recommendation, such as the 3A contextual ranking described by El Helou et al. [18], might be valuable for overcoming cold-start problems.

4. PLE prototype and approach towards generating recommendations

With respect to the ANT-based model of PLE ecologies (section 2) we have implemented a client-sided PLE prototype in the form of a Firefox add-on. ‘PACMan’ – which stands for Personal Activity Manager – allows users to manage their online resources and tools according to a very simple model of learning activities.

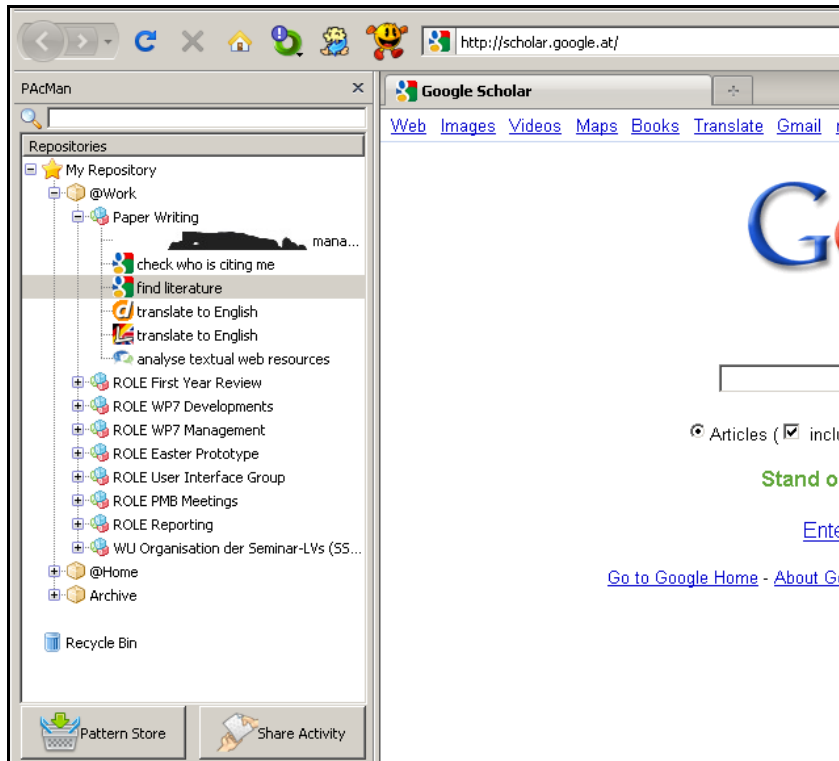


Fig. 2. Personal Activity Manager (PACMan) realized as Firefox extension

Fig. 2 shows the PACMan add-on as part of the browser. Pressing the PACMan icon in the navigation bar opens up the side-bar displayed on the left-hand side of the figure and containing a tree-view of one’s learning activity space. Here users can organize their web resources and online tools in terms of contexts (e.g. ‘@Work’, ‘@Home’, and ‘Archive’ in the figure) and activities (e.g. ‘Paper Writing’), whereby an activity contains the relevant learner interactions (i.e. the action tags and the corresponding URLs). Users can create and modify this activity structure on each possible level (contexts, activities, and resources). They can also enter the names for the contexts, activities and resources arbitrarily. Due to this possibility to tag the different entities, it is obvious that recommendation mining

will underlie typical problematic issues of user-generated content if the PACMan recordings of many users should be brought together (see also remarks on this aspect given in the last section).

Beside the facilities to design and manage one's learning environment in terms of contexts, activities and (web) resources, PACMan also offers search functionality for querying the user data which is stored locally (see search field on top of the tree-view). Furthermore the add-on realizes a recycle bin mechanism (icon below the activity space) in order to prevent accidental deletion of data, as known from operating systems.

Finally and displayed at the bottom of the side-bar, PACMan provides facilities to connect to a pattern repository which allows sharing PLE experiences with others. The need for and the concept of a pattern repository is well documented by Mödritscher et al. [23]. In short, it enables practice sharing in PLE settings, as users can publish patterns of their activities, retrieve and instantiate other patterns available on the repository, and get recommendations for different aspects within a PLE. Our prototypic pattern repository is realized as a component for the OpenACS server (<http://openacs.org>), is based on the object-oriented scripting language XoTCL and extends the Wiki generator component XoWiki (<http://openacs.org/xowiki>). PACMan as well as the pattern repository component (called PLEShare) are open source and accessible via SourceForge (<http://sourceforge.net/projects/rolewp7>). Besides, we provide PACMan also via the Mozilla Add-on Developer Hub under the URL <https://addons.mozilla.org/en-US/firefox/addon/176479>.

With this prototypic infrastructure, a client-sided PLE solution and a pattern repository in the back-end, it is possible to collect user data for an evaluation study which is described in the upcoming section. Of course, the PLE can be also based on other architectural styles, like a server-sided platform, which would allow data gathering at a central point but might be disadvantageous from other aspects like privacy, trust, responsiveness, user control, etc. These different attitudes towards PLE technology are not relevant for this paper, as we have used the prototypic infrastructure only to collect and analyze recordings of PLE usage to argue for a possible recommender strategy.

5. Preliminary evaluation and discussions

By applying our client-sided PLE prototype and the pattern repository, a preliminary study was conducted to capture and characterize real-world data created and shared by PLE users. Therefore, 8 researchers from the field of technology-enhanced learning and information systems were asked to design two typical activities: (1) one on searching literature relevant for a contribution to be submitted to their favorite conference, and (2) one describing all steps necessary to plan the participation at this conference. After the test users submitted their experiences on these two research activities, we analyzed the data through quantitative and qualitative methods.

On the one hand, we ran a trivial top-n algorithm to determine the usage frequency of activity names, action/resource tags, and URLs. Table 1 summarizes these numbers in short, whereby first column stands for the number of the items per PLE-related entity (users, contexts, patterns, patterns resources/actions, and URLs). The second column comprises how many items occurred, while the third column counts the number of identical and the forth column the number of similar items. Similarity was determined through a qualitative analysis according to different categories (high-level topics, top-level domains) and manually.

Table 1. Number of items of each PLE-related entity

| PLE Entity | No. items | No. identical items | No. similar items |
|------------|-----------|---------------------|-------------------|
| Users | 8 | 0 | 0 |
| Contexts | 8 | 8 | 8 |
| Patterns | 17 | 0 | 10 |
| Resources | 99 | 13 | 53 (topics) |
| URLs | 99 | 0 | 33 (domains) |

The first row, the entity 'Users', is given due to our test users, having no identical or similar 'items'. The second row, 'Contexts', is also a result of the study setup, as users were asked to create one context with the name of this study. Addressing the patterns (third row) it can be observed that each user published two patterns – as instructed in the study –, whereby one user split up the travel planning activity into flights and hotels, which was not explicitly

forbidden. The fourth row, ‘Resources’, indicates that 13 of the 99 items occurred more than once (5 twice and 1 even three times). Analyzing the resource names (action tags) closer, we identified five high-level topics (location, flights, hotels, conference websites, and a specific research topic) to which 53 resource items can be assigned. This kind of PLE entity evidences that natural language processing (NLP) techniques are necessary to cluster action tags (user-given natural language) into adequate categories (e.g. high-level topics). Finally, the fifth row shows that 99 URLs were used in the activities of the test users, whereby none of them occurred more than once. Analyzing the URLs according to the top-level domains, we could assign 33 of them to 9 different tools, e.g. Google Scholar (9), ACM (5), Google Maps (4), Holidaycheck.com (4), etc. At this level, clustering could lead to recommendations on tool level, i.e. suggesting Google Scholar for finding literature.

Overall, this first evaluation study showed that the number of interactions (resources) and URLs grows faster than the number of activities due to the semantic structure behind PACMan (a context contains activities which in return contain resources and URLs). This first set of user data also indicates that it makes sense to analyze certain attributes of the entities, for instance the top-level domain names or high-level topics. Thus, clustering or other similarity techniques for user-given input (i.e. tags of resources, activities, contexts, etc.) are useful to increase the quality of recommendations and their ranking. Fig. 3 shows that the distribution of URLs is flat while the action tags already follow a very weak power law distribution. Clustering items according to topics or top-level domains (similar actions and URLs) lead to more significant power law distributions, even for this small set of user data. We then can use the semantics hidden in the data e.g. to recommend the most frequent items identified within the same or similar activities.

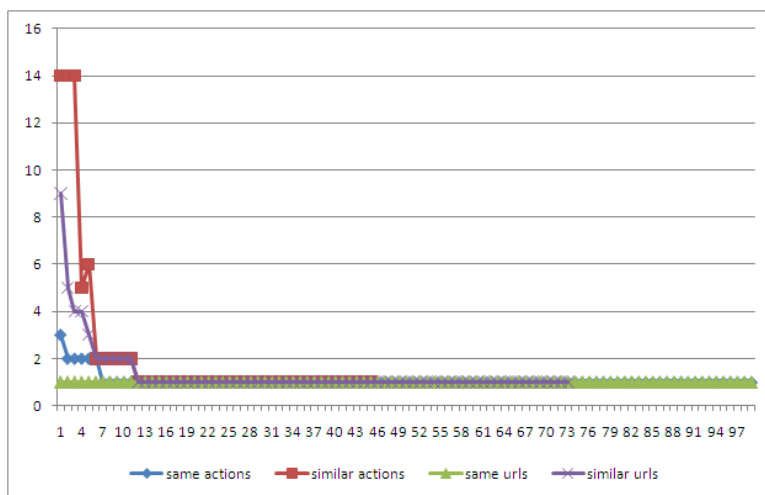


Fig. 3. Distribution of action tag and URL occurrences (identical and similar ones)

So far we showed what can be recommended in a certain situation, i.e. within the same or a similar activity. Nevertheless the model of the learning activities can be also utilized to generate recommendations before one starts an (informal learning) activity. For instance, if a learner is looking for a specific activity in the context of her job the activities related to the ‘@Work’ context (see Figure 2) or to the colleagues at her organization should be ranked more prominently. Therefore, the next step of our research will address an approach to measure the similarity between different activities on the basis of the learner interaction recordings captured with our browser-based PLE tool and shared over a pattern repository. Consequently, activity patterns can be suggested to users with respect to their profile and their current learning context. Besides, user-designed PLEs also require strategies to overcome typical shortcomings of user-given content, like considering synonyms or grammatical variations on mining action tag frequency of similar activities. Hereby, NLP techniques – ranging from stemming, stop words removal or part-of-speech tagging to high-level concepts such as latent semantic analysis – can be applied to cope with these problematic issues.

At this stage, evaluation of the quality of the recommender strategies is still an open issue although first

considerations have been made already. Amongst others, it is possible to conduct user studies in order to calculate the perceived accuracy (no. of well-rated items compared to no. of overall items) and the novelty of the recommendations (no. unknown items compared to no. overall items). Moreover, the recommender strategy can be compared to other approaches, like the 3A contextual ranking approach [18] which builds upon a very similar semantic model of learning activities. On a more pedagogical level, Al-Hamad et al. argue for more accurate recommendations if the system mimics the knowledge of an experienced educator [24]. To transfer this finding to the scope of personal learning environments, we would have to consider motivational elements for educators (and tech-savvy PLE users) so that they actively share their learning experiences with the community through a pattern repository. Then, we could analyze this data either on the basis of usage statistics or according to explicit user feedback given by adequate features (such as an ‘I like’ button).

6. Conclusions and future work

In this paper we sketched a possible strategy for generating recommendations within PLE settings. Therefore we characterized collaborative activities in such scenarios and built upon a model of learning activities in order to capture learner interactions with the environment and to generate recommendations. From a more pragmatic perspective we have started with a simple item-based strategy which we realized prototypically with a client-sided PLE solution and server-sided backend service of a pattern repository.

The pattern repository which allows learners to publish patterns of their activities generates the recommendations from this user data, in a first step through a trivial top-n algorithm. We collected a first set of user data in a preliminary study. The analysis of this data indicates that it contains valuable information, the data itself as well as structural information, which can be used to generate recommendations for PLE users who are in need of support in the domain or with specific tasks (activities). However in this paper we just described the very first steps in the direction of PLE recommendations. Future work comprises the extension of the recommender strategy through multi-attribute and clustering techniques, a hybrid approach including model-based generation of recommendations, as well as an evaluation strategy.

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