How Recommender Systems in Technology-Enhanced Learning depend on Context

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1. Extended Abstract

1.1 Background/Rationale

Technology-Enhanced Learning (TEL) can roughly be differentiated into formal and non-formal learning settings. Both settings offer a rather different context that has to be taken into account by recommender systems in order to offer most suitable information to individual learners.

Formal learning, being usually organized according to some curriculum, traditionally occurs in teacher-directed environments with person-to-person interactions. Non-formal learning is described as a learning phase of lifelong learners who are not participating in any formal learning context. They are acting more self-directed and they are responsible for their own learning pace and path. In addition, the learning content for their learning nowadays come from many different Web 2.0 sources like blogs, social bookmarking tools, or sildeshare. The learning process is also not designed by an institution or responsible teachers like in formal learning, but it depends to a large extent on individual preferences learners have or choices that learners take.

Depending on the learning settings, the aims of TEL systems, their environmental conditions, and the tasks that they support also change. Thus, considering the way TEL context variables vary according to the adopted setting, the information needs of the targeted users change. This can greatly affect the design of recommender systems for the different learning settings. In this article we discuss recommendation approaches for formal and non-formal learning settings. In order to make the theoretical discussion more exemplary we describe how both approaches can influence context variables like learning goals and knowledge levels in the ReMashed system [5]. Both approaches can feed the learning goal interface to contextualize the recommendation to offer more suitable content for each learning setting and the individual learners involved.

1.2 The different recommendation approaches

1.2.1 Recommendation approach for formal learning settings

Many recommender systems for formal learning like [1] using fine granulated knowledge domains and can therefore offer personalized recommendations to the learners. They can use metadata and ontologies to define the relationships, conditions, and dependencies of learning resources and learner models. They can take advantage of well structured formal relationships like predefined learning plans (curriculum) with locations, student/teacher profiles, and accreditation procedures to recommend courses or personalize learning.

A promising solution to adjust the learning goal functionality of ReMashed for formal learning settings is the work on *adaptive sequencing* [2]. It takes into account individual characteristics and preferences for sequencing learning content. Adaptive sequencing needs three abstraction layers to add semantics between content and possible learning goals. On the top layer, the learning goal layer, a hierarchy of learning goals needs to be modeled. In the second layer, the conceptual layer, an ontology of domain concepts needs to be created. The lowest layer, the content layer, contains the actual content of the learners. With the adaptive sequencing approach organizations can pre-structure and control the available learning goals within the system. Further, they can easily adjust and cluster the learning goals and their related knowledge level to their needs.

This approach requires a maintenance effort as there are many design activities needed before the runtime and also during the maintenance of the system. In addition, the knowledge domains in the learning environment need to be described in detail. These aspects make the adaptive sequencing approach not applicable for non-formal learning settings.

1.2.2 Recommendation approach for non-formal learning settings

In order to apply ReMashed for non-formal learning settings, we need different recommendation approaches. The absence of maintenance and structure in non-formal learning settings 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 [3]. For instance, learning goals in non-formal learning settings are a rather diffuse parameter because they rely on information given by the learners without any standardization.

Most suitable therefore is the *hierarchical clustering* method. It builds up a hierarchy of items by continuously merging the two most similar items / groups into a new group. In the ReMashed case, an item is a single blog posting or a picture with related tags. We can create a measure for most frequently used keywords for each blog or picture by simply using words counts. The similarity between items / groups can then be measured by similarity measures like Euclidean distance or the Pearson correlation. In each iteration the method calculates the distance between every pair of items / groups and the closet ones are merged together to form a new group. This process is repeated until there is one group with various sub groups. In that way hierarchical clustering creates a kind of automated ontology on top of the available contents.

Similar like the adaptive sequencing approach this automated ontology can be fed into the learning goal interface in ReMashed and present the available learning goals in the system.

1.3 Principal contributions

The main contributions of the paper will be:

- To discuss how different learning settings have influence on the contextualization of recommendations for learners.
- To outline two recommendation approaches for both learning settings taking into account the state-of-the-art research.
- To design an experiment where both approaches are compared to each other based on various technical, educational and organizational measures [4].
- To identify further research directions and challenges for the contextualization of recommender systems in TEL.

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