Socialize Online Learning: Why We Should Integrate Learning Content Management with Online Social Networks

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***Abstract*—Lifelong learning is a common requirement in today's knowledge society. Traditional teaching approaches fail to deliver learning opportunities if combined with flexibility in time and place, which is another major requirement. Therefore, eLearning systems have evolved in the past decades to Computer-Supported Collaborative Learning and Adaptive Educational Hypermedia Systems. In parallel, the rise of Online Social Networks has changed information flow. In this paper, we revisit the state of modern eLearning systems from the perspective of users affine to Online Social Networks. We argue that the online community-building of social networks bears a significant potential to the attractiveness and success of technology-assisted learning. Therefore, this paper outlines essential building blocks for implementing an eLearning plugin for a commercial Online Social Network sites.**

***Keywords*-online social networks; adaptive educational hypermedia; computer-supported collaborative learning**

I. Introduction

The presence of Online Social Networks (OSN) for personal communication and entertainment leads to an increasing demand for applications that are integrated into the OSN. Whether games are integrated into the OSN or application that track one's sports activities - people tend to share personal information with connected persons in the OSN. Educational Hypermedia has evolved in the past years from static system to dynamic content presentation and delivery platforms. Our work concentrates on sharing learning information and finding people to collaborate in learning.

The demand for collaborative learning in OSNs is triggered by an ongoing change in personal learning. Professionals are on the one hand asked for lifelong learning, and on the other hand work-life-balance is seen as a positive achievement. Furthermore, it is demanded to be flexible to travel. The contradiction of ubiquitous learning and independence of time and place was partially solved by collaborative eLearning systems, which were developed in the past decades to allow users to learn or teach knowledge independent of a user's location. These Systems implement use cases like online training, certification tests or courseware access.

ELearning systems provide computer-supported collaborative learning (CSCL) technologies to allow group interaction for physically distributed users. These systems extend eLearning Content Management Systems (LCMS) [1] by adding inter-group communication on learning topics. Learning material can be manipulated by group collaboration. Internet communication technologies like text chat, audio- and videoconferencing enable implementation of this kind of applications.

CSCL-applications usually demand for an instructor who prepares, holds and analyses course. Course preparation consists of two major activities: User management and course content management. User management requires technical requisites like authentication or authorization mechanisms. Furthermore, the instructor has to be capable to find a group constellation which is suitable from a didactic point of view. Group members have to have a common knowledge in the domain of the course to be able to discuss topics on the same level. The instructor must be able to assess members of a course in order to create a reasonable group constellation. Furthermore, an instructor analyses course results to track changes in a person's knowledge. Thus instructors are a critical resource in CSCL scenarios.

Online Social Networks interaction is initially triggered by the demand of socializing with friends. Recently, further services are integrated into OSNs, which enable the user to lookup and discuss topics of his personal interest with other users. Usually, there is no moderator or facilitator who guides discussions. Discussions can be triggered in an active and passive way. The active way is to start a text-, voice- or video-chat and invite other users to take part in it. Posting messages on one's personal page and wait for a reply of somebody who is looking at the post by coincidence is a passive way of communication. Any user who is authorized to see a post is allowed to post an answer on the user's profile. Discussions and posts on one's personal profile generate different types of content, e.g., text, pictures or videos.

The content generated by users in OSNs can hold a variety of knowledge and learning information. OSN Software platforms are programmable through API or by modifying the software itself. A simple integration of eLearning into OSNs would at first benefit from authorization and authentication mechanisms as well as integrated group communication.

However, our aim is to go beyond the simple exploitation of technical benefits. We will implement an eLearning OSN integration platform which will allow self-paced learning in topics of personal interest. Web pages like online encyclopedias or information portals are widely used to engage people in reading information. Audio- and video-streaming allows multimedial consumption of learning materials. There is a wide variety of Medias for personal education. The difference of self-paced learning to learning in modern eLearning systems like CSCL systems is that these systems allow communication between persons on a learning topic. Communication on a learning topic is recommended, since teaching other people a certain area of one's learning topic further improves one's understanding. Attending in a CSCL based learning community is a possibility to engage in group learning, but these systems usually require an instructor to arrange the discussion. This leads to time restricted learning discussions, which have to be planned in advance.

A learner accustomed to learn on his own pace is hardly fitting into a CSCL group. Nonetheless, he could be interested in discussions while learning. Therefore, we propose an instructor-less learning infrastructure based on an OSN. This will provide natural feedback in dialogs and qualified feedback among users. Furthermore, reputation which can be indicated by "like" (Facebook) or "+1" (Google+) gives an incentive for further communication. The instructor-less infrastructure fits to moderator-less OSN communication.

The removal of an instructor in eLearning scenarios leads to further challenges in designing an eLearning system:

1) How to stimulate a team building process that is effective for learners?
2) How to provide access to the relevant content for a learning group?
3) How to facilitate a consistent learning progress, include feedback and corrective actions?

Team building is often based on learning style recognition. Therefore, we introduce a common learning style model and propose its usage for an OSN integrated eLearning system. We propose to apply mechanisms developed in CSCL and Adaptive Educational Hypermedia (AEH) to answer the given challenges.

CSCL research is focused on finding mechanisms to allow learners to learn in a group of physically distributed people. AEH research focuses on adaption of learning content. Usage data is tracked to dynamically adapt the content to the learners need. Both areas handle with collaboration group forming based on the assumption that learners, who's learning style is similar, could learn together. Additionally, forming a group of learners who have a different learning style could allow a reasonable constellation to help each other.

This paper revisits recent research and proposes its usage for an OSN integrated eLearning system. The proposed system will allow learners to find "learning friends" based on their own knowledge, learning style and availability. This will lead to an on demand group learning experience.

The following sections discuss the structure of the eLearning system. It is discussed in section II which techniques are available to generate and evaluate data in OSNs to build adequate groups. Section III presents the components which will be integrated into an OSN to implement the proposed system. How progress in a learning group can be determined to allow adjustment of the group composition is figured out in section IV. Finally, in section V we conclude and give an outlook for future work.

II. Team Building in Online Social Networks

Popular OSN sites like Facebook [1] or Google+ [2] store personal profiles of each user. Profiles consist of a set of database entries which represent personal information. Personal profiles are linked witch each other through a bidirectional relationship. This relationship is established individually between two users. Therefore, a social network site like Facebook can be seen an undirected graph which edges represent the relationship between users [2].

This section outlines a team building process that is effective for learners. Team building in OSNs is done by finding a subgraph of persons in the OSNs user graph which fulfills the following conditions:

1) Each user-node has the motivation for collaborative learning on a certain topic
2) Learning style of a user-node is appropriate for a balanced group
3) Person's knowledge in the topic is equal among group members

Condition 1 is an intrinsic motivation of a person. The recognition of the motivation can be implemented in different manners but is not demanding. An approach is to set a flag on one's personal profile. This flag initially indicates a person's interest in collaboration. Later on the usage of the eLearning system is monitored to track a user's motivation.

Condition 2 requires information on a users' learning style as well as a mechanism to find a subgraph of the OSN-graph which is balanced in terms of learning. This is achieved by grouping people who learn in a similar learning style. Therefore, in II-A mechanisms that allow us to determine the learning style programmatically are presented.

Condition 3 is about finding groups of learners with a common knowledge base. Since information in OSN is widely spread in different, non-standardized, formats, automatic knowledge estimation through analyzing semantics is

[1] www.facebook.com
[2] plus.google.com

an advanced topic. In II-B approaches to estimate knowledge are discussed.

Finally, in II-C it is described how a group of learners can be formed.

A. Learning Style Assessment

We define learning style in conjunction with Felder and Silverman's theory (FST) [3]. It is broadly accepted as standard way to assess learning styles. Basically, there are four dimensions in FST:

- "Active or Reflective" (Processing)
- "Visual or Verbal" (Input)
- "Sensing or Intuitive" (Perception)
- "Sequential or Global" (Understanding)

The authors of FST propose to use a questionnaire to determine a person's learning style.

Questionnaires have proven to be inappropriate for eLearning environments [4]. Furthermore, questionnaires have to be repeated to detect changes in the user's behavior over time. Similarly, questionnaires are from our point of view not suiting to the OSN usage paradigm. Users are used to get proposals sent from an OSN site. Examples for these proposals are potential friends. If the distance between two nodes in the graph of the OSN is smaller than a certain limit, both users automatically get a request which asks the user if he knows the other person. Then both can choose to request a link between profiles from each other. Our approach is to use similar proposal mechanisms for users who hold the same learning style.

There are many approaches to automatically determine learning styles in research on CSCL and AEH which is based on various input data. Villaverde et al. present in [4] an approach to recognize the learning style automatically based on the input data to an eLearning system. Feed-forward neural networks are used to estimate learning style based on interaction measures. The measures are taken for several actions, e.g., access number of examples, answer changes, chat usage or forum usage. Three of four learning style dimensions are used: perception, processing and understanding. The artificial neurons have to be trained in advance with test probes to configure the neural network. Villaverde et al. were able to configure the neural-network so that the best accuracy was 69.3 %.

There are further approaches to automatically determine the learning style or certain learning style dimensions automatically. Eye gaze movement and mouse moving pattern have shown impact on the Input and Understanding dimension. Tsianos et al. [5] analyzed that eye gaze movement on certain document shows if someone prefers images or text while looking at documents. Similar to eye gaze tracking, Spada et al. [6] are evaluating mouse movement patterns. They found a correlation between vertical mouse movement speed and the Understanding dimension when interacting with an eLearning environment. Both physically interaction measurements give techniques to further improve learning style recognition.

It is challenging to gather the input data without altering the eLearning environment. OSN integrated eLearning applications can benefit from OSN site's technical platform. OSN providers like Google+ or Facebook provide video chat. If someone is in a collaborative eLearning session supported by video chat, the eye gaze movement could be extracted from the video stream. Features like Google+ Hangouts provide collaboration spaces that allow users to work simultaneously in the same application. E.g. documents can be edited by a group. Since applications for this platform are programmable, eLearning plugins can be developed. These plugins can also gather mouse movement data and provide the data for learning style analysis.

B. Knowledge Estimation

The initial design of our platform will perform knowledge estimation by using a user's history in the platform itself. Courses or more granularly eLearning Objects (eLOs), which were consumed by a user, are seen as part of a user's knowledge. Therefore, the Course Runtime Plugin must deliver usage data of certain eLOs. eLOs can be classified in a way proposed by the IEEE LOM Standard [7].

A more advanced method to estimate a user's knowledge and interest is presented by Gotardo et al. [8]. They incorporate usage mining to calculate a user's interest in a certain topic. This is done by measuring the categorie's total access time, most recently used and most frequently used. They inferred a prediction of future interests from user's measured behavior. In the AEH-System LS-Plan [9] a student model is composed of the learning style and cognitive state. The learning style measures are based on FST. The Cognitive State calculated for a given domain is the set of each knowledge item processed by a student. It is furthermore proposed to update the cognitive state through questionnaires and access time of learning objects.

C. Group Formation Engine

Based on learning style recognition and knowledge estimation data, one can calculate closeness in the mean of learning between persons in an eLearning enabled OSN. The group formation engine is proposing a set of users to collaborate with each other based on distance between learners. Dorn, Skopik, Schall and Dustdar present in [10] a team composition discovery metric in their monitoring, mining and analysis research for human interaction and team formation processes. The metric does not just rely on skills. It also takes into account whether people have worked in conjunction with each other formerly. Frequent collaborations are seen as a possible indicator for group efficiency. We use the techniques of Dorn et al. in adaption to our basic data: learning style and knowledge. Dorn et al. model an undirected graph which nodes represent an expert or a user. The edge weight is the number of previous collaboration between experts. Additional, each expert-node has a set of skills. In theory it is possible to find an optimal subset of experts by a multi-objective team composition algorithm. This algorithm takes into account the expertise level in a certain area, whether an expert is available or not and if the resulting team has a collaboration history. The proposed algorithm is related to determining a clique in a weighted graph, which is proven to be NP-complete. Therefore, it is proposed to use heuristics based on genetic algorithms and simulated annealing.

III. Learning Content Management

The second challenge initially discussed (see I-2) is about how content-access is managed. The learning style recognition techniques to form didactically senseful groups discussed above has to be based on an eLearning system to allow the learning itself. However, the access should be available in the OSN site. The content has to be freely available for each user of the OSN. Therefore, we first introduce the LCMS hylOs in III-A, which is able to deliver eLOs in a format compatible to an OSN site. III-B discusses, which extensions have to be integrated into hylOs to gather interaction measures for learning style analysis. How this extended version of hyLos is seamlessly integrated into an OSN is presented in III-C.

A. Hypermedia Learning Object System

We developed the Learning Content Management System (LCMS) Hypermedia Learning Object System (hylOs) [11], [12]. hylOs is an adaptive eLearning content management system and runtime environment, built upon a sophisticated information object model tailored from the IEEE LOM (Learning Object Metadata) standard. hylOs comprises instructional design concepts and tools, a content acquisition and analysis engine for semi-automated generation and annotation of eLearning Objects, as well as an Ontological Evaluation Layer for concluding relations between eLearning Objects, bundled with a sophisticated repository and platform-independent authoring environment. The rigorous use of the XML technology framework ensures a consistent separation of content, structural information, application logic and design elements. hylOs provides adaptive eLearning functions and may attain any look & feel by applying appropriate XSL transforms. Variable content access views like instructional learning paths or individual content explorations based on semantic nets may be compiled for the hylOs repository. Traditional hyperreferences, which provide a separate layer of content traversal, may be customized within hylOs, as well [13]. Links are represented within contextual containers, each one suitable to express a narrative of a specific hyperlinking scheme. hylOs will be extended and integrated into OSNs by the course runtime plugin and an ubiquitous learning extension.

B. Interaction Analysis Engine

The Interaction Analysis Engine is a plugin into a certain OSN site. It is a piece of software that is based on the OSN site's user interface API. Basically, the data to be measured can be divided into two classes. Firstly, communication information which aggregates messaging and chat in the OSN site. Secondly, eLearning plugin information which is provided by the Course Runtime Plugin (see III-C). This information contains usage statistics on content from the LCMS that is displayed in the OSN site for collaborative learning. Usage statistics consist of data like total course display time, time spent per eLo, number of eLo changes in a time frame, an index which indicates sequential or random slide access or usage of external links embedded into a eLo. If possible, physically interaction data, which is described in II-A, are measured. This is dependent upon an OSN site's API capabilities.

C. Course Runtime Plugin

The course runtime plugin delivers eLOs concatenated by a learning path to a user as web content. The user can access this content through the OSN via a plugin that uses the OSN's API. That allows us on the one hand to embed learning content presentation in the OSNs communication mechanisms. On the other hand usage statistics can be linked with a user's personal profile in the OSN. HylOs multiple views and designs, which are based on XML transformations, allows us to present learning content integrated into the OSN. By defining an adequate XSD hylOs content can be transformed in a format compatible to a certain OSN.

Despite of presenting the content, the runtime plugin is responsible for measuring raw input data. Raw input data are the basis for learning style calculation executed by the Learning Style Assessment techniques (see II-A). The input data consists of access logs on learning content and pattern recognition data. The access logs consist of:

- Time spent per eLO
- Total time spent on a learning path
- Count lookup of additional information linked in the eLO

The second type of input data to be measured is pattern recognition data. It will allow the system to implement physically interaction measurements in learning style recognition. The data is collected from input devices like mouse or camera. The interaction data to be extracted by pattern recognition are:

- Overall movement of mouse or eye gaze
- Pausing of movement and position of pause
- Speed of movement

These have to be tracked in the course runtime plugin rather in the OSN directly. The measured data is assigned to eLOs which a user has consumed. E.g., pausing of eye gaze movement on an image can be an important

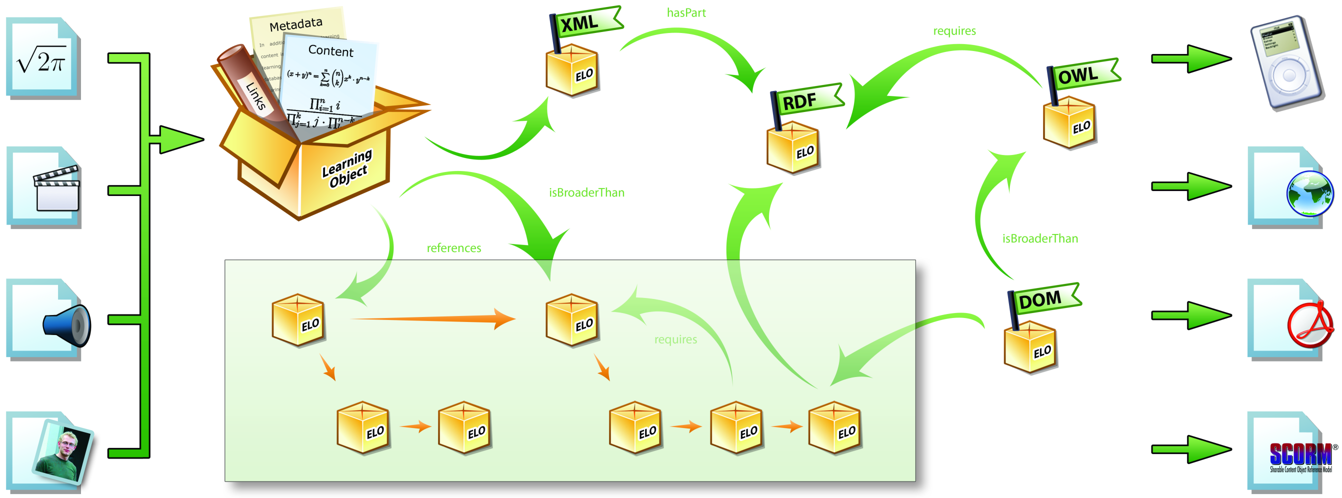

Figure 1. The Hypermedia Learning Object System (hylOs)

information to calculate the learning style. This data can be measured on each eLO available in the system independent of a concrete eLO-composition. This is achieved by hylOs' variable content-access views to learners, following different structural relations indicated by distinguished arrows in figure 1 or specialized publication channels. Additionally, usage statistics provided from the OSN site itself are taken into account. Mobile use of information can be seen as a more casual way of learning. Using a rich client at a desktop PC can indicate more concentrated working. Since OSN sites can be accessed through mobile devices, the access and access times of mobile devices could indicate a certain learning style.

IV. Learning Consistency Monitoring

The last challenge raised in the introduction is about learning consistency (see I-3). It is divided in two areas. The first is about consistency in the sense of learning path flow. IV-A explains how approaches from research in ubiquitous learning help to remain this kind of consistency. The second area we are discussing is about consistency in the sense of group cohesion. IV-B discusses how initially formed groups can be monitored to make sure that the "learning distance" between participants remains reasonable.

A. Ubiquitous Learning

It is common to access OSNs from almost every Internet-connected device available from almost everywhere at random points in time. This extension therefore enables the LCMS hylOs to allow ubiquitous learning (uLearning). uLearning takes place in a ubiquitous computing environment. A ubiquitous computing environment is given by a physical environment in which connected computers interact with each other. These computers can be attached to certain objects to provide digital services for the object. Devices, which are capable to communicate with the computer, can use services offered by the computer.

Ubiquitous learning research focuses on improvement in learning through ubiquitous computing. Sakamura et al. [14] define ubiquitous learning as learning style, which enables learning anything at anytime, anywhere utilizing ubiquitous computing. This leads to learning in several contexts like different places, different levels of noise or different levels of concentration. Our proposed system will adopt the learning content to the user's context. For example it will allow filling small breaks in personal or professional life by learning topics on one's mobile device.

Since the system shall allow learning in the environment available at a time a user wants to learn, the learning content has to be adapted to the learners need in his context. For example, if the user wants to learn a language while driving a car, the system should propose a learning object that just contains audio material. Yu describes in [15] that content provisioning has to take the learner's context into account. They propose ontologies for context, content and domain. The content ontology holds information about the learners learning style as well as further information like location and available learning time. It is used to recommend content to the learner by calculating the semantic relevance, let the user refine the results, generate the learning path that takes into account if the user has already learned required prerequisites and finally augmenting recommendations to propose additional information on the demanded topic. HyLos can be easily extended by these mechanisms. It's Ontological Evaluation Layer for concluding relations between eLOs can be modified to implement the content ontology. Required context input information like locations are integrated by the Course Runtime Plugin. Since linking in hylOs is already implemented in contextual containers, learning paths, which depend on actual context, can be adopted.

B. Group Cohesion

In order to check whether the formed groups learn in an efficient manner, the groups have to be monitored continuously. Reffay et al. [16] determine group cohesion in CSCL systems. They introduce lexical markers to verify the quality of a given group. In their empirical test it was shown that a high occurrence of the first-person plural ('we') in discussion indicates a strong intensity of communication. We propose to control whether an automatically formatted group is viable through the lexical analysis of messages exchanged in an OSN.

V. Conclusion and Outlook

Analyzing the potential of eLearning in community processes of OSNs we revisited mechanisms used in research about CSCL and AHL. We drafted a system based on approaches from both research areas to enable learning in OSN. Through effective and automatic group forming based on learning style and knowledge equableness, it is ensured that one is learning in a group of "compatible" learners. This will be achieved by automatic learning style assessment through neural networks or physically interaction measurements. The challenge of group forming among millions of users is to be solved by a group formation engine, which uses heuristics to find the best matching groups.

In our ongoing work, we will combine our LCMS hylOs with the techniques presented in this paper. The joint system will be based on a commercial online social network site which allows us adjustments of the techniques by gaining experiences with real-world users.

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