CONNECTIVIST COMMUNICATION NETWORKS

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ABSTRACT

Facing the challenges of the digital age concerning lifelong learning, this contribution presents an approach to dynamically establish Connectivist communication networks. According the statement "the pipe is more important than the content within the pipe" by Georg Siemens, learning in digital age includes the connection of people to share required information. For this purpose, the Wiki-Learnia learning platform, which collects context information about users, is combined with the InterLect software, which identifies topics and semantic relations of contents. Based on mapping of both data sources, a wide range of matched users can be found for a specific content-related communication channel. By analyzing the course of conversation at runtime, participants can adaptively be added and removed from communication. Consequently, the presented solution serves as a just-in-time learning approach for finding direct help by experts.

KEYWORDS

Context-aware Communication, Connectivism, Topic Modeling

1. INTRODUCTION

Caused by the penetration of digital information and communication technologies in all areas of life, people of the *digital age* (Castells 1999) are faced with ever-changing demands and decreasing *half-life of knowledge* (Siemens 2005) (Gonzales 2004), that lead to the need of a continuous learning process in terms of *lifelong learning*. Castells talks about the *Network Society* "[…] where the key social structures and activities are organized around electronically processed information networks. […] It's about social networks which process and manage information […]" (Castells 2001). This view is shared by Georg Siemens and Stephen Downes, who examined the limits of current learning theories in view of rapidly progressing technology and its implications for learning processes in digital age (Siemens 2005) (Downes 2012). In their approach called *Connectivism*, they depict learning as "[…] the ability to construct and traverse those networks […]" (Downes 2007). It's about connecting with people in a network to share specialized knowledge and experiences ("collecting knowledge through collecting people" (Stephenson 1998)).

In order to support these processes, we have the goal to combine two powerful tools. On the one hand, the learning platform Wiki-Learnia (chapter 2) uses Web 3.0 technologies in order to create and find user-centered learning contents and people (Waßmann et al. 2014). On the other hand, the InterLect tool (chapter 3) semantically analyzes textual contents in order to detect main topics and semantic relations between materials (Nicolay et al. 2015). A combination of both tools (chapter 4) will deliver *Connectivist communication networks* consisting of experts for direct help. The high potential of such an approach was revealed by the evaluation of a similar solution from the Open Universiteit Nederland, which figured out positive effects on the level of relationship characteristics and mutual support (Fetter et al. 2012).

2. WIKI-LEARNIA

Designed as a social network, Wiki-Learnia automatically tracks *primary* context information (Dey and Abowd 1999) like user ID (Who is?), visited pages (Where is?), activities (What is?) and time (When is?). Based on this data, Wiki-Learnia can take into account several *secondary* contexts' information that are manually given by the user or automatically reasoned by the system. These include *background* information

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like age, languages and social connections; *preferences* such as media type, maximum expenditure of time and learning/didactic concept; *knowledge* in terms of completed Wiki-Learnia modules, experiences, skills etc.; and *learning targets* that are divided into general interests as well as coarse- and fine-grained targets according to (Mayer et al. 2009).

Besides the user model, Wiki-Learnia offers a collaborative editor to create semantically processed learning data. At the beginning of the underlying content structure, there's a *learning object (LO)* that includes learning material like an image, a PDF or a video, that will be enriched with metadata such as name, description and keywords. Furthermore, an ordered list of LOs (a *learning path*) with additional meta-information forms a *learning unit (LU)*. Among other things, it's defined by required knowledge (pre-condition) and fine-grained learning targets (post-condition) which is the basis to semantically connect LUs (post-condition of a LU could be pre-condition of another one etc.). The same principle is used on higher levels: several, ordered LUs form a *learning module (LM)* which in turn depicts coarse-grained learning targets as well as pre- and post-conditions. Any longer, completing numerous LMs can satisfy long-term targets defined by general interests.

Taking into account the ideas of Connectivism, authors can add users in terms of profile pages with attached bulletin boards, and communication channels like text and video chat, or forums as so-called *learning connections* to LUs and LMs. In this way, people are connected with other users with same learning targets and background knowledge for cooperative learning. Besides to this static approach, there's also a mechanism to dynamically connect people regarding specific context information as explained in (Waßmann et al. 2016). The presented approach takes into account inter alia the content that users are visiting at runtime. While the current algorithm just adds users with exact matches of LOs, LUs or LMs, the tool described below can find more participants dealing with similar topics.

3. INTERLECT

InterLect analyzes sequences of lecture content (such as sets of lecture slides) and extract semantic topics as well as relations to approximate the underlying expert model of a docent (Nicolay et al. 2016). To examine semantic topics we use “Latent Dirichlet Allocation” introduced by (Blei et al. 2003). To reconstruct semantic structures, we examine relations between topics on lecture material, such as temporal proximity and topics sharing the same resources. The expert model then can be approximated as simplified “Topic-Map” (Marius et al. 2008) (Fig. 1).

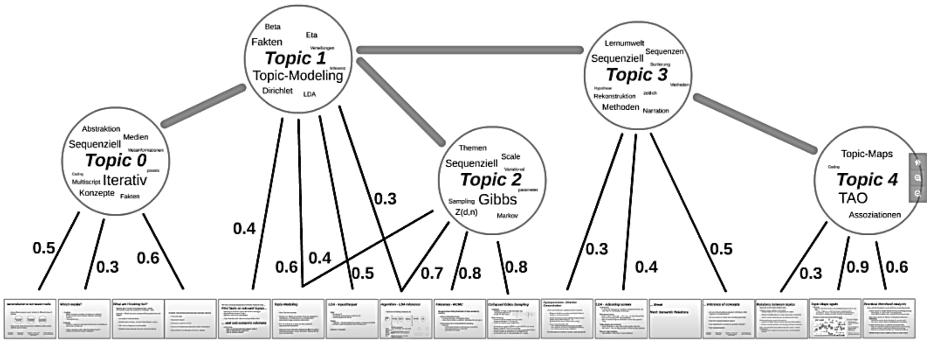

Figure 1. A simplified Topic-Map examined from a set of lecture slides (occurrences) consisting of “Word-Clouds” (Topics) and relations derived from temporal proximity and shared resources (associations)

Latend-Dirichlet-Allocation (LDA) is the most widespread algorithm used for Topic-Modelling of unsorted sets of documents. In our case documents are ordered sequences of lecture slides containing lecture information. LDA is performed by Gibbs Sampling (Darling 2011). LDA infers a set of topics T from a set of Slides S with a overall vocabulary V. Therefore LDA calculates Topics t as a discrete distribution on the probability of appearance for all words v of V. On top, LDA provides a distribution of topics and their probabilistic intensity for all slides s of S. Condensed, every slide has a distribution over the intensity of participating topics while topics are defined by most relevant terms on that topic.

To refine our inferred topics, on the first hand, we increase the proportion of relevant phrases using a set of filters to reduce the vocabulary, such as unification of upper- and lowercase, removal of stop words, stemming of grammatically deformations, and the removal of numbers, to short terms, and high frequent words. On the second hand, we currently looking into an inclusion of meta-information provided by the lecturer using Labeled LDA (Ramage et al. 2009) and meta-information derived from the slide's layout, such as increasing a relevance weights for visually highlighted terms.

In difference to the common use case of “LDA” (analyzing unsorted documents), information in a lecture contain an intended teaching path derived from docent’s expert knowledge. This path allows us to assume relational implications, such as semantic relationships between topics appearing on common slides or close temporal proximity; bottom-up dependencies indicating a pre/post condition between topics that follow each other; and scopes by co-occurring topics commonly on many slides.

4. CONNECTIVIST COMMUNICATION NETWORKS

Consequently, InterLect analyzes lecture material regarding relevant words and relations that are derived from observed teaching paths to deliver an associated meta-network. As a next step, we include the algorithm into Wiki-Leania to identify topics and relations of existing LOs, LUs and LMs. We evaluate, how LOs can be summarized into LUs and include information from observed teaching paths to connect LUs via generated pre- and post-conditions into lecture-supporting LMs. Considering this initiation phase, InterLect then is able to autonomously identify semantic relations between new material and the training set.

These circumstances enable Wiki-Learnia to enhance the described static approach (chapter 2) of connecting people in Connectivist communication networks. Learners get in touch with like-minded users and experts by manually searching for content-associated LUs and LMs. The actual algorithm simply compares the search term with given, author-generated keywords that are statically attached to the material. InterLect can be used to automatically find and update those tags in order to guarantee an optimized finding of fitting contents with associated learning networks.

Furthermore, there's a dynamic approach do automatically establish Connectivist communication channels which is described in (Waßmann et al. 2016). Implemented as a live chat that will be initialized by a person seeking for help, the current prototype automatically adds users founded on given keywords of same content history, knowledge and learning targets. InterLect can also figure out persons dealing with topic-related material that's not included in this set: *not yet semantically processed content* (e. g. new created articles or uploaded files), and *public statements* within the social network of Wiki-Learnia like bulletin board messages, forum replies or comments. As a consequence, a wider range of matching users can be added into the Connectivist learning networks.

In (Van Rosmalen et al. 2008) the authors present a similar solution that automatically adds fitting users to a dedicated wiki page in order to collaboratively work out the solution for an asked question. In contrast, our approach presents synchronous communication channels that enable content-related live discussions regarding underlying LOs, LUs or LMs. By analyzing topics of the chat conversation at runtime (using InterLect), participants will automatically be added and removed from the dynamic channel. Also individual preferences of the initiator like spoken languages, role within the system (e. g. learner, author, tutor) and social connections are considered by the algorithm. Besides problem-based learning groups, our solution includes further use cases like author meetings, tutoring and assessment.

5. CONCLUSION

The idea of combining the two applications Wiki-Learnia and InterLect has revealed the high potential regarding an improved mechanism to establish Connectivist communication networks. While the former one collects different context information of users, the latter one identifies semantic meta-information of contents. By mapping both data, people with similar interests or problems can dynamically get in contact in context-aware communication channels for discussions, learning and other things. In terms of Connectivism, the presented solution supports the automatic creation of expert networks to enhance the exchange of information. This delivers a just-in-time learning approach to overwhelm the challenges of digital age. In future, the solution might gain in importance due to the upcoming *forth industrial revolution* (Schwab 2016), which intensifies the application of IT in work and life processes.

In further work, synonym databases (e.g. OpenThesaurus) can be used to enhance the search algorithms. Combined with technologies like Tin Can API also external sources and platforms can be analyzed in order to overcome network boundaries. Besides to the presented cooperation between both applications, there're some more scenarios that will be pursued in future. Among other things, this includes automatic semantic tagging and automatic pre- and post-condition acquisition of LMs, LUs and LOs that can lead to a automatic creation of learning paths with adaptively exchangeable learning contents.

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