Effective team formation in networked learning settings

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Abstract

Professional development can be achieved by interacting with the abundance of learning materials provided by Internet-based services and by collaborating with other learners. However, knowledge sources are scattered across the Internet, while suitable co-learners are hard to find. Learning professionals require strong self-direction powers to fully benefit from these resources. However, these are not readily available in all learners. Based on social-constructivist/connectivist collaborative learning theory and team formation theory, a model is presented for the effective formation of teams engaging in structured collaborative learning. The model describes the creation knowledge domain representations by centralising learning materials from various sources. It allows learners to define structured learning tasks and provides an answer to the question whether a particular learning task can be addressed sufficiently well in the knowledge domain. Based on team formation theory, it provides the means to form teams of mutual learners and peer-teachers based on bridgeable knowledge differences (an interpretation of Vygotsky's "zone of proximal development") and personality aspects. The model also allows recommending suitable learning materials to the teams. A selection of tools is presented to afford an implementation of the model. These consist of an implementation of the method of Latent Semantic Analysis, a validated learning team formation algorithm and the Big Five personality test. The model is subsequently tested. The results of this test indicate that representations of knowledge domains can be successfully created and that the fit of learning tasks to the learning materials in the domain can be assessed. An experiment with learners (n=64) shows that the implementation can successfully assess prior knowledge and that collaborations based on prior knowledge differences do lead to knowledge gains. Furthermore, learners highly appreciate the learning materials suggested. However, the evidence for a level of knowledge difference between learners at which learning becomes most effective is currently limited. The results are discussed, and conclusions and directions for future research are included.

Keywords

Team formation, self-directed learning, collaborative networked learning, professional development

Introduction

Networked learning (see e.g., McLoughlin, 2002) provides opportunities for self-directed continuous professional development. Goodyear, Banks, Hodgson, and McConnell (2004) defined networked learning as:

> "… learning in which information and communication technology is used to promote connections: between one learner and other learners, between learners and tutors; between a learning community and its learning resources".

Networked learning emerges both inside and across knowledge domains, by learners using intranet or internet-based services such as forums, Facebook, Google +, YouTube, and Linked-in. These services and environments can provide rich sources of knowledge, social communication, and collaboration facilities. In them, professionals can gather information, form interpersonal links, collaboratively create and share knowledge (Koper & Sloep, 2002; Steeples & Jones, 2002; Goodyear, Banks, Hodgson, & McConnell, 2004; Van Rosmalen et al., 2008; Van der Klink, Brouns, Van Bruggen, & Didderen, 2011; Rajagopal, 2013). According to Knowles (1975), self-directed learning occurs when learners themselves take responsibility for identifying learning needs, to develop learning goals, prepare a learning plan, locate learning resources, implement the plan, and afterwards evaluate the results and the process.

However, not all learners score high on self-direction readiness scales (Guglielmino, 2013), while not all services offer readily discoverable learning materials or peer learners. Alvarez and Olivera-Smith (2013) make two important remarks about learning while using these services:

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> "[these services]…on their own are not learning environments per se, but they afford ample and potentially effective opportunities to improve student learning." And:
> "… there is also a danger that, due to the vastness of resources available in the web, students may find themselves drifting in an "information ocean", straining to solve ill-structured problems with little idea of what concepts, rules and principles are required for the solution or of how to organise themselves and what is the best solution"

Furthermore, Milligan & Littlejohn (2014) notice that these learners, due to the gap between the learning offerings and their immediate learning questions, are experiencing difficulties in applying what they learn in their practices.

From these observations a general picture with respect to finding support for collaborative learning in networked settings emerges: In networked learning settings, the wide range of (learning) materials spread over multiple sources makes it difficult for the learner to find appropriate learning materials related to their learning goals and it appears that finding effective teams of peer learners (in contrast to randomly assembled groups) is not well supported.

Networked collaborative learning and knowledge creation processes can take shape as suggested by e.g., Stahl (2006). Stahl's group cognition framework, in a cyclic process, describes phases in which individuals express learning goals, collaborate with peers while using and creating learning materials, which can then again be used to learn from. As such it is based in social constructivist (Palincsar, 2005) or connectivist learning theory (Siemens, 2004; Ravenscroft, 2011). However, the framework leaves open issues with respect to a befitting ecology of learning. It doesn't assure that: i) learner problem statements are related to the environments in which they are made, ii) collaboration takes place between suitable knowledgeable peers, iii) knowledge sources are available that fit the learners needs, iv) suitable peer learners get connected, v) the interactions between learners are structured and connection-building, not fleeting and shallow. For collaborative learning to be effective, one needs to make sure the process actually takes place, and not be left to chance. Stahl (2013) recognises this when he notes:

> "Group cognition… needs appropriate CSCL technologies, group methods, pedagogy and guidance to structure and support groups to effectively build knowledge that can be shown to be a group product not reducible to individual mental representations".

It is therefore that we aim to develop support for small-scale collaborative learning settings inside large-scale networked learning settings. But where to start? Research from the field of computer-supported collaborative learning (CSCL) has long since shown that collaborative designs for online learning should pay attention to the characteristics of the learner, the formation of the team, and the structure of the task (See e.g., Valcke, 2009). Particularly related to forming teams fit for a task, research indicates that team formation needs to take into account the individual learner's prior knowledge, personality traits, the curriculum area, the team size, and the task at hand (Graf & Bekele, 2006; Martin & Paredes, 2004; Wilkinson & Fung, 2002). Based on such findings we defined a model for team formation to support collaborative learning in networked learning settings (see Figure 1).

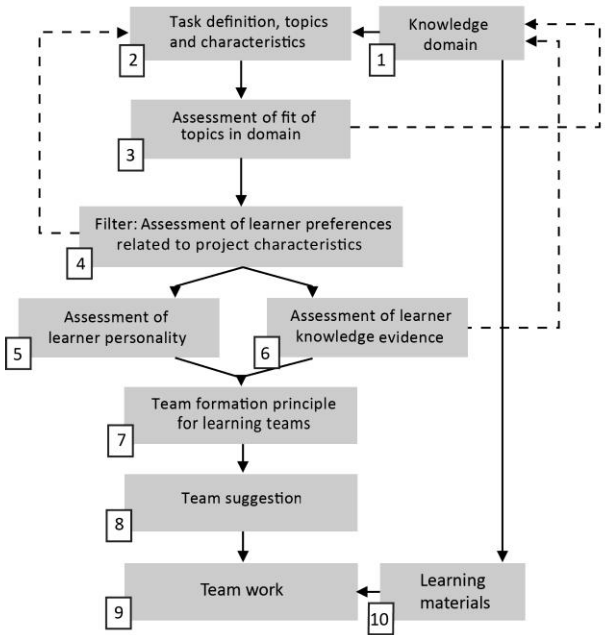

Figure 1: The team formation for collaborative learning model.

The process depicted in Figure 1 starts with the creation of a representation of a particular knowledge domain [1]. This domain can be created by centralising learning materials from various sources. Next, learners can define their learning tasks by describing the topics they want to address in the task, and its characteristics (such as structure, preferred duration, team size, etc.) While this step is basically pedagogy agnostic, it can be based collaborative learning setting such as problem-based or project-based learning [2]. In order to make sure a specific learning task fits to the content in the knowledge domain, a level of fit between the task topics and the knowledge domain is assessed [3]. When this level of fit is deemed sufficient, from this point on other learners can express their desire to be part of the team addressing that particular learning task. To prepare for team formation, they provide their collaboration preferences (such as languages mastered, time schedules, etc.), describe their prior knowledge on the topics, and take a personality test. Learners who, based on their preferences, cannot work together are then filtered out [4]. Following this, the remaining learners' prior knowledge [5] and personality [6] are assessed. A principle for the team formation of learning teams [7] is applied to the outcomes of these assessments. The team formation process ends with a suggestion for a team when one set of prospective team members is found that shows optimum fit to each other with respect to knowledge and personality, and to the task [8]. The team can then start working on the task [9]. As we know to which learning materials in the knowledge domain the task topics refer, these materials can be suggested to the team to learn from [10]. To close the cycle, the results of the team work can be included in the knowledge domain.
Our researched subsequently moved toward how we could implement and test the model.

Implementation of the model

To be able to test various elements of the model we developed an initial implementation, using:

- The method of latent semantic analysis (LSA; Landauer, Foltz & Laham, 1998) to create the knowledge domain representation, for the assessment of the fit of learning tasks to the domain, to determine learner prior knowledge, and to recommend learning materials. LSA was selected because it has shown to be effective in measuring prior knowledge and learning effects, as demonstrated by Wolfe, Schreiner, Rehder, Laham, Foltz, Kintsch, et al. (1998) and Rehder, Schreiner, Wolfe, Laham, Landauer and Kintsch (1998).
- A team formation principle for learning teams (Spoelstra, Van Rosmalen & Sloep, 2014) based on differences in prior knowledge and the Big Five (Barrick & Mount, 1991) personality aspect "Conscientiousness". This particular personality aspect was selected because it is considered to be the most important predictor of a person's future performance in a team (it measures carefulness, thoroughness, sense of responsibility, level of organization, preparedness, inclination to work hard, orientation on

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achievement, and perseverance) (Goldberg, 1990; Jackson, Wood, Bogg, Walton, Harms & Roberts, 2010). The team formation principle was formulated as:

"Learning in a team is facilitated when knowledge on the learning task topics is distributed over the members (allowing each member to learn and teach). However, the differences in knowledge should not be too high, and the team members should show high levels of conscientiousness."

- A formalisation of the principle into the expression depicted in Figure 2, which was put it into algorithmic form and tested with learner data. Both the principle and the outcomes of the algorithm were validated by teaching staff. (Spoelstra, Van Rosmalen, Houtmans & Sloep, 2015).

$$FitL_i = W_K * \frac{\sum_t \sum_l \sum_j \left| DifK_{tjl} \right|}{d_{jt} \cdot zpd \cdot n \cdot k} + W_C * \frac{Avg\_C_i}{Max\_C}$$

Figure 2: Team formation expression for learning teams.

In short, the algorithm calculates the fit of a team to a particular learning task. It does this by taking into account the differences in knowledge between learners on each topic addressed in the task. To evenly distribute learning and teaching burdens on topics, it also takes into account the number of times a member should be considered a teacher (knows more in relation to another learner) or a learner (knows less in relation to another learner) on a topic. With the factor "zpd" it implements a zone of proximal development (Vygotsky, 1978), expressed as a difference in knowledge between learners that leads to optimal knowledge gain. Other aspects taken into account are the number of members in a team, the number of topics in a learning task and the average of the conscientiousness values of the members. It also implements the possibility to put weights on the factors knowledge and conscientiousness.

Theoretically, these instruments afford the implementation of the model. But there are still many questions open: Can we create a knowledge domain representation with LSA which affords qualifying fit between a learning task and the knowledge domain? Does our method for assessing prior knowledge allow for teaming up learners who actually learn from each other? Can learning effects provide an indication for the value of the "zpd" in the team formation algorithm? How do learners appreciate recommended learning materials? We aimed to provide initial answers to these questions by means of an experiment.

Method

Our first aim was to create a knowledge domain representation against which we could assess the fit of learning tasks. This part of the experiment required several preparations related to the use of LSA:

- To create a fine-grained knowledge domain representation, the text of a course on Introductory Psychology was cut up into 2257 numbered documents, which we processed using LSA.
- We defined a learning task in which learners should produce an information leaflet on "Eyesight" (which was addressed in the course) and created four topic descriptions by paraphrasing texts from the learning materials related to eyesight (the workings of the brain, the workings of the eye, how one focusses, and how one sees depth).
- The topic descriptions were used as LSA queries into the knowledge domain to find related documents. This aimed at answering the question whether the learning task fits to the knowledge domain. A result for one topic description (arbitrarily truncated to the 15 highest-relating documents out of the 2257 documents making up the domain), showing the numbers of the related documents is provided in row T. of Table 1.

For the experiment we invited students of a course on Introductory Psychology. As many of our students are job-holding adults working in related fields, we believe they are representative of professionals in search of further development. The participants' prior knowledge of the course content varied from having just started to having absolved the course one year ago. Participation in a survey acted as enrolment into the experiment. This survey noted gender, the number of course chapters studied, and which course chapter was studied last, and contained a full Big Five personality test (Barrick & Mount, 1991), validated for the Dutch language (Denissen, Geenen, Van Aken, Gosling, Samuel & Potter, 2008). A total of 64 participants followed the experiment through to its conclusion.

In assignment 1, as pre-test, we aimed at assessing prior knowledge: all learners were asked to provide written evidence of their knowledge on the four task topics. To activate their prior knowledge we selected between four and six keywords representing the central concepts addressed in the four topics. For example, for the topic “Brain” we presented: “Central nervous system”, “Peripheral nervous system”, “Neurons”, “Neurotransmitters”, and “All-or-none law”. The participants were instructed to limit themselves to 200 words per topic.

To calculate learner prior knowledge on the task topics, we used the learner texts as LSA queries into the knowledge domain in the same way as we did with the topic descriptions. We then compared the document numbers of their LSA results with the document numbers of the LSA results from the topic descriptions. Row L. in Table 1 shows the overlap in documents of which the learner showed knowledge and the documents on which the learner exhibited no knowledge (the empty cells). Row LSA in Table 1 shows the LSA cosine values (which are always between 0 and 1, with 1 indicating a perfect semantic match) of these documents (giving a measure of how well the learner-provided text matched the learning materials).

Table 1: The set of documents related to one topic description (T.), the subset of documents the learner prior knowledge relates to (L.), and the level of learner prior knowledge (LSA), truncated to 2 significant decimals.

T.	103	104	105	106	109	110	115	119	130	131	132	134	373	664	1308
L.	103	104	105		109	110	115	119	130	131				664	1308
LSA	0.30	0.34	0.34		0.33	0.36	0.35	0.39	0.34	0.34				0.31	0.31

From the LSA-values we calculated the learner prior knowledge score on a per-topic basis: we divided the average of the LSA cosine results of the documents occurring in both results by the total number of documents. Using the example above, the learner knowledge score on the topic would be 0.25.
In assignment 2 we aimed at finding a value for the "zpd". To this end we mimicked team work at the level of dyads of learners (which is at the core of the team formation principle for learning teams). We formed dyads of participants in which one member had a lower knowledge score on a topic and one member had higher knowledge score. We did this in such a way that, across all dyads, the knowledge score differences gradually declined. This allowed us to observe the effects on learning of variation in differences in knowledge scores between learners/peer-teachers. We returned to the participants (in their role as learner) their own text on a topic and the text by their dyad partner (in their role as peer-teacher) on the same topic. As intervention, we asked the participants to rewrite their initial text based on what they thought could be improved from reading their peer-teacher’s text and then to send in their new knowledge evidences. We then calculated the knowledge scores for the new knowledge evidences. These acted as post-test. To calculate knowledge gains, the old knowledge scores were subtracted from the new knowledge scores.
Assignment 3 aimed at finding out whether the LSA retrieval results from the topic descriptions could be used to recommend learning materials. We sent the participants four sets of the five highest related documents to the four topics in their learning task (totalling to 20 documents) and asked them whether they thought the documents were relevant to the four topics on which they had provided knowledge evidence in assignment 1. Their answer options used a 5-point Likert scale which ranged from 1 (not relevant) to 5 (highly relevant).

Results

Our results are presented in the order of the research aims as described in the Method section. Figure 2 presents the LSA cosine values of the 15 highest ranking documents in the knowledge domain related to the four topics addressed in the task on Eyesight.

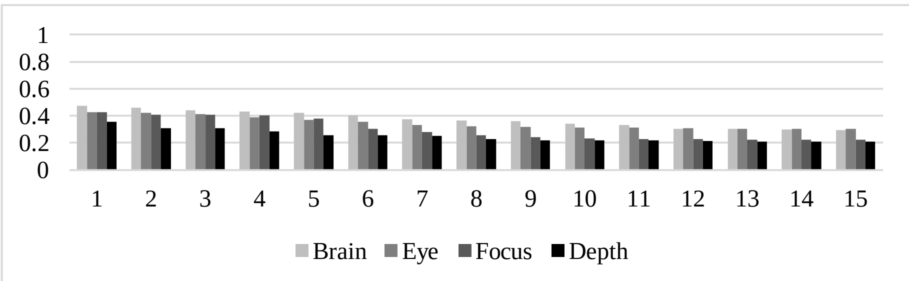

Figure 2: LSA scores of the four topic descriptions for the learning task on “Eyesight”.

For each topic, a profile emerges. The LSA results of the related documents the topic descriptions of Brain and Eye roughly start and end at comparable levels. However, the related documents for the topic descriptions of Focus and Depth show a stronger decline in relevance.

Table 2 shows the overall and the four separate topic related average prior knowledge scores of the participants, their peer-teachers knowledge scores and their knowledge scores after learning from their peer-teacher.

Table 2: Average prior knowledge scores, peer-teacher knowledge scores and learner knowledge scores after learning, truncated to 2 significant decimals.

	Average prior knowledge scores	Average knowledge score of peer-teacher	Average knowledge score after learning
Eyesight overall (n = 64)	0.08	0.20	0.13
Eyesight: Brain (n = 18)	0.13	0.22	0.17
Eyesight: Eye (n = 18)	0.13	0.23	0.17
Eyesight: Focussing (n = 13)	0.02	0.24	0.09
Eyesight: Depth (n = 15)	0.02	0.13	0.08

These scores indicate that on average learners learned from their peer-teacher texts on all topics. When we define possible knowledge gain as the difference in knowledge score in a dyad between a learner's first text and the peer-teacher's text, we observe that for the learning task on "Eyesight", on average, about 40% of the possible knowledge gain was realised.

In order to find an optimum knowledge difference at which most learning occurs, we plotted knowledge gains against knowledge difference between learner and peer-teacher (see Figure 3). It was only when we added a third order polynomial trend line that an indication of an optimum knowledge difference appeared around a knowledge difference of 0.23. However, with an R-square value of 0.1835 the explained variance stayed low.

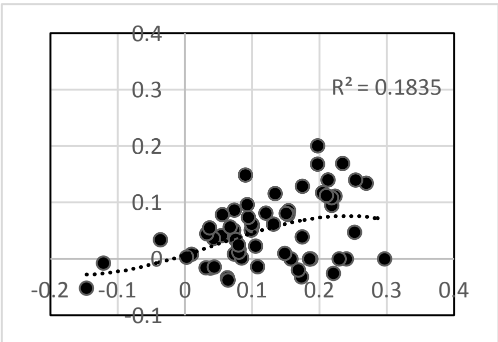

Figure 3: Knowledge gains (vertical axis) and knowledge difference between teacher and learner (horizontal axis), n = 64.

To find out whether our implementation can successfully be used to recommend learning materials, we presented our participants with the four sets of five documents which receive the highest relevance when the topic descriptions were processed for relevance. Figure 4 shows the learners' attributed relevance as learning materials to these documents.

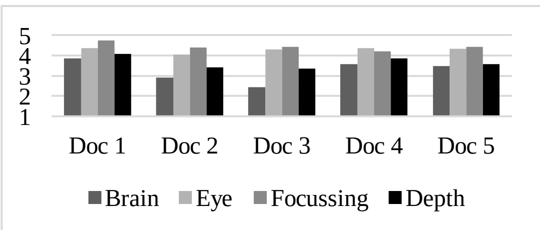

Figure 4: The average learner-attributed relevance of the 5 texts with the highest LSA scores over the 4 topics of the tasks on "Eyesight" on a 5-point Liker scale (n = 64, sd = 0.94)

All sets of learning materials were valued above the average of 3, while all but one set of documents showed a slow decline in appreciation from the first to the last document in the set. This slow decline is in accord with the fact that the materials themselves we presented in order of descending relevance (as determined by LSA).

Discussion

This article puts forward a model intended to support professional learners in defining learning tasks, and finding suitable peers and learning materials. Preparations for an implementation of the model included the creation of the knowledge domain representation. This relied on LSA technology, which showed considerable usability in the complex mix of domain creation, task fit assessment, prior knowledge assessment and the assessment of learning effects. With respect to its use one might argue that it can only process materials in textual form. However, with the advent of technology to automatically transcribe spoken word (from e.g., video learning materials) the inclusion of learning materials form other than textual source is becoming feasible. The way we defined the learning task currently shows dependence on domain knowledge. However, by creating topic descriptions by paraphrasing, and not copying/pasting from the learning materials, we tried to approach the way a learner might write them. Additionally, professionals in search of further development often already have a level of prior knowledge on the topics they aim to study.

With respect to the assessment of fit of a learning task to a knowledge domain, the LSA results (see Figure 2) of the topic descriptions show a profile (slow decline) and a uniform starting point (around 0.4). The profiles for the topics Brain and Eye stay at a relatively higher level compared to the profiles for Focussing and Depth. This might indicate that these two last topics are slightly less well-suited to be addressed in the current knowledge domain. As the topic-related documents also form the basis for the assessments of prior knowledge and for our ability to recommend relevant documents as learning materials, we need to choose these profiles carefully. Therefore, as a general rule, we suggest that topic descriptions should yield related documents with LSA values that are roughly similar and of intermediate height (by being similar, we prevent favouring knowledge on only a few documents; by being not too low, we prevent over-estimating the on-topic-ness; by being not too high the course documents keep their value as learning materials). However, further study is required to consolidate this rule and to determine a threshold below which learning task topics are likely off-domain.

The effects from dyadic collaborations on learning were clearly significant. Several precautions were taken to make plausible that learning had indeed occurred from reading the peer-teacher text: participants were allowed only a short period of time to rewrite their initial texts, they were instructed to write in their own words (no copy-paste of peer-teacher text was found when we inspected the texts), and to stay within the bounds of the predefined maximum text size. At the topic level, we found significant knowledge gains for all topics. Regarding the optimal knowledge score differences leading to the highest knowledge gains, our data proved to be inconclusive. This can be partly due to the (relative) homogeneity in knowledge backgrounds in our population. Furthermore, there was a limited number of cases on which we could build to find an optimal knowledge difference. However, by making the peer-teacher the “knowledge target” for the learner, we believe our approach fits very well in learning settings in which knowledge is co-constructed by means of collaborations between knowledgeable and less knowledgeable team members. The ability to recommend learning materials which learners clearly value can further support the learning process.

Conclusions and future research

This article started off from the observation that collaborative learning in networked learning settings is not always well supported. Modern pedagogical approaches, as embodied in e.g., Stahl's group cognition framework, can inform us on how professionals can engage in small scale networked learning inside large scale networked learning settings. But we put forward that they need to be implemented in a befitting ecology of learning to overcome some of the problems networked learners can encounter. From the definition of a model for team formation for collaborative learning in networks built on strong theoretical backgrounds, we developed an initial implementation. We developed services to create knowledge domains, to support leaners to assess their learning tasks for fit in the knowledge domain and to form effective learning teams around these tasks. These services allow addressing issues related to limited self-direction powers, poor discoverability of learning materials and unstructured learning tasks.

We were able to successfully use LSA in our implementation, notwithstanding the complex mutual dependencies between knowledge domain representation, tasks and knowledge assessments. It does, however, not guarantee easy transferability into other contexts. Therefore future research should not only look into transferability but also into alternatives for the semantics based assessments it affords. We presented a general rule to determine whether a learning task can be supported in a knowledge domain. This would assure learners

that they would be able to find adequate learning materials in the domain. However, further research will be required to refine the criterion, preferably in environments created based on our model.
The current approach to defining general learning tasks (stating aim, duration, and team size) and describing topics on which to work seems to work well. Although this approach offers task structure through the topics that have to be addressed, it might prove expedient when the task structure would be better defined. We suggest additional research into task definition by e.g., using task/planning templates from problem-based or project-based learning to provide additional structure.
We showed that the dyadic collaborations between learners on which the team formation algorithm is based can act as demonstrations for how groups of learners can collaboratively create new learning objects and learn during the process. As we were not able to determine the optimum knowledge difference between learners at which most learning takes place, research into the effects of team formation based on the current algorithm should further refine the value of the parameter "zone of proximal development". It should also include research into whether other personality aspects beside conscientiousness should be considered in the team formation process. All in all, however, we believe we demonstrated the potential of the model and its components very well.

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