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Monitoring of Students' Interaction in Online Learning Settings by Structural Network Analysis and Indicators

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Abstract. Learning as a constructive process works best in interaction with other learners. Support of social interaction processes is a particular challenge within online learning settings due to the spatial and temporal distribution of participants. It should thus be carefully monitored. We present structural network analysis and related indicators to analyse and visualize interaction patterns of participants in online learning settings. We validate this approach in two online courses and show how the visualization helps to monitor interaction and to identify activity profiles of learners. Structural network analysis is a feasible approach for an analysis of the intensity and direction of interaction in online learning settings.

Keywords. Learning; Education, distance; Cooperative behavior

1. Introduction

Learning can be understood as constructive and social process that works best in interaction with other persons [1]. Through interaction and collaboration, students "gradually construct systems of shared meanings" [2]. Studies show advantages of collaboration in learning activities, such as more engaged learning, increased motivation and attention, more active processing of information, improvement of meta-cognitive and social skills and overall better knowledge acquisition and retention [3].

Interaction between students is also considered a key element for successful learning in online settings [4]. However, the teacher needs to address specific challenges of online settings such as reduced transmission of socio-emotional information, more complicated coordination of asynchronous activities and the challenge of lurking, i.e. the more passive participation in online activities [5]. Collaborative online teaching thus needs thoughtful instructional design to facilitate the interactions of the students and a close monitoring of the quantity and quality of interactions.

In this contribution, we present an approach and related indicators to analyse and visualize interaction patterns of participants in online learning settings. We validate this approach in two online courses and show how the visualization helps to monitor interaction and to identify activity profiles of learners. We conclude with recommendations for online teaching.

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2. Methods for Analysis and Visualization of Communication Networks

Interaction patterns in online courses can be analyzed in various ways. Analysis may focus on quantitative numbers such as numbers of contributions, continuity of participation, or number of answers in relation to all contribution [2]. Another line of analysis focusses on the content of messages and tries to characterize these e.g. into questions, answers, agreement or disagreement [4]. Graphical visualization of communication patterns between participants in network diagrams can help to identify interaction patterns [2]. Finally, social network analysis methods can be used to statistically analyse e.g. intensity, cohesion or reciprocity of participants [6].

To monitor effects of collaborative online teaching, we were especially interested in analyzing the interaction network of the participants and its changes over time. We used indicators from structural network analysis and a graphical visualization of network activity.

We took two fully online modules as case study. Both modules were run in 2016 with 16 resp. 15 participants from various professional fields within healthcare. The first module went for four weeks, the second for six weeks. The first module focused on project management, the second on clinical data analytics. The participants in the first course were partly familiar with each other, while participants in the second course mostly did not know each other before. Estimated student workload for both courses was 10 – 15 hours per week. Participants received a certificate upon completion.

As instructional theory, we used the expository 3-2-1-design framework by Michael Kerres as a basis and combined it with the concept of E-tivities by Gilly Salmon [5]. Each course consisted of meta-information (on learning objectives, estimated workload, instructional approach etc.) and a set of learning activities. Each learning activity comprised a structured description of learning objectives, tasks to be done and expected reaction to the solutions of other participants. These learning activities are not meant to test competencies, but to allow the students – alone and in interaction with the others – to accomplish the intended learning process. At the end of each week, participants were asked to write a reflection on their learning progress. For each learning activity, the needed materials (presentation, paper, book chapters, or web sites) were provided by the instructor. Moodle was used as electronic learning platform.

Log data from the learning platform Moodle was exported in anonymized form and analysed using the Talend Open Studio software platform (www.talend.com) and Tableau 10.0 (www.tableau .com). Interaction patterns of participants were analyzed and visualized for each week of the module using the graph visualization and manipulation platform Gephi (www.gephi.org).

Interaction indicators were adapted from the structural analysis by Coll et al [2]. From the three basic types of interaction [7], i.e. learner-content, learner-instructor, and learner-learner interaction, we focus on learner-learner interaction. A written survey and interviews with all participants were conducted at the end of each course to explore satisfaction with the course and learning outcome. In addition, a workload analysis was conducted.

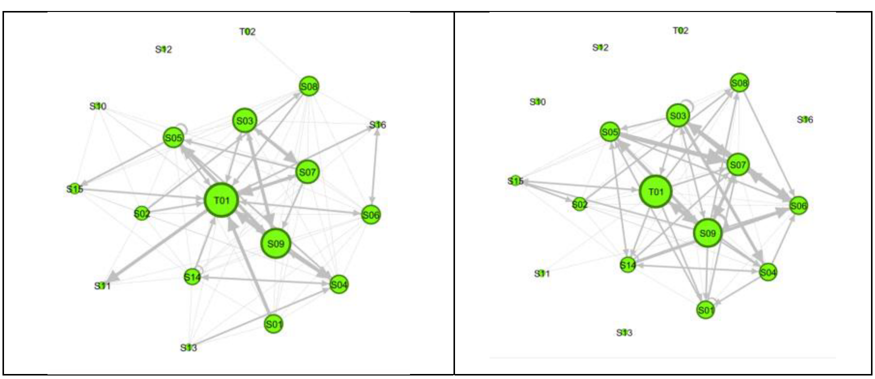
3. Results

Course 1 comprised 29 learning activities and 29 forums with 287 threads and 1,605 posts altogether. 998 forum posts were written by the successful participants, 178 by the course instructor. Course 2 comprised 25 learning activities and 25 forums with 153 threads and 1,232 posts altogether. In this course, 702 forum posts were written by the successful participants, 187 by the course instructor. In course 1, 9 of the 14 participants successfully completed the course. In course 2, 8 of 16 participants successfully completed the course. Table 1 shows indicators of these successful participants. The number show that successful participants reach the threshold for two of the each indicators defined by [2]: Access index > 0.5; contribution index > 0.6; answer-contribution index for the two courses was below, but close to the 0.9 threshold.

Table 1. Interaction network indicators for the successful participants of two online courses. "post" = active contribution to one discussion forum.

	Course 1 (n=9) Min | Max | **Mean** | StandardDev	Course 2 (n=8) Min | Max | **Mean** | StandardDev
Access index (% of days online)	0.56 | 0.94 | **0.80** | 0.13	0.64 | 0.92 | **0.81** | 0.09
Activity index (% of days with at least one post)	0.49 | 0.89 | **0.67** | 0.15	0.44 | 0.86 | **0.63** | 0.15
Reading index (% of read posts in relation to all posts)	n.a. due to chosen settings in the electronic learning platform (automatic email-notification)	
Completion index (activities with at least one post)	0.93 | 1.0 | **0.97** | 0.03	0.76 | 0.95 | **0.86** | 0.07
Contribution index (relation of written posts to number of minimum requested posts)	1.241 | 3.052 | **1.91** | 0.602 (58 requested posts)	n.a. (no requested minimum posts)
Thread-starting index (% of threads that were started by a particular user in relation to all posts of successful students)	0.023 | 0.029 | **0.026** | 0.002	0.011 | 0.161 | **0.036** | 0.047
Answer-contribution index (% of post that are answers to other posts in relation to all post of a student)	0.67 | 0.85| **0.75** | 0.07	0.76 | 0.88 | **0.83** | 0.04

Figure 1 shows the interaction network of course 1. In week 1, the instructor is in the middle of interaction. Starting with week 2, the role of the instructor is less important, and the interaction between participants increases. Figure 2 shows that certain interaction profiles – receiving participant, sending participant, and balanced participant – can be identified based on their individual activities.



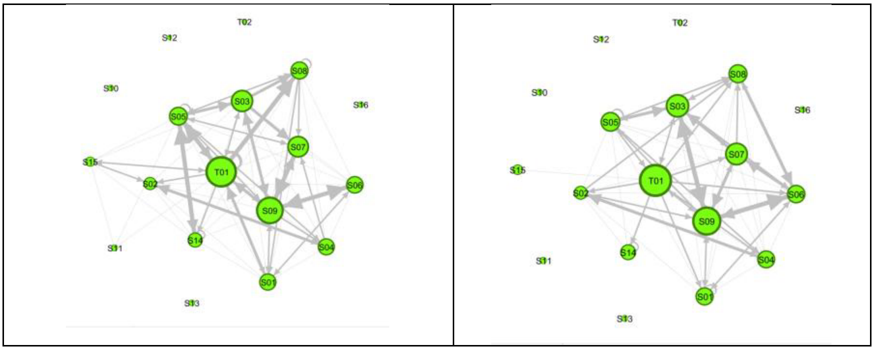


Figure 1. Interaction network in week 1 – 4 in the first course. Circles indicate participants (indicated by Sxx) or the instructor (T01). Size of circles indicates the number of sent messages (larger circle correspond to more posts over the course period). Arrows indicate direction and intensity of communication.

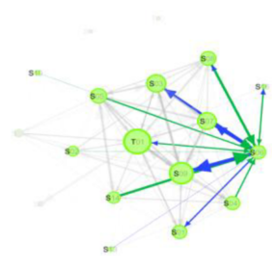
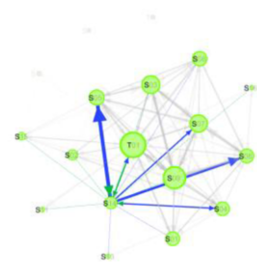
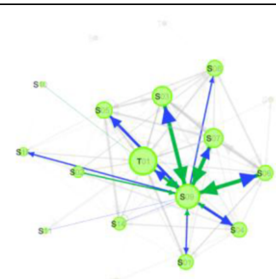
Type of participant	*Example of interaction network*
Receiving participant: Amount of received messages is larger than number of send messages.	
Sending participant Amount of sent messages is larger than number of received messages.	
Balanced participant Amount of received messages and of send messages is nearly equal.	

Figure 2. Various types of participants, with examples of network interaction diagram from course 1.

4. Discussion and Conclusion

Interaction with peers is a prerequisite for learning: "No interaction, no education." [8]. We showed how structural network analysis can help to describe indicators and activity profiles of participants. This information can help to track the activity of participants during the course and to identify those who need teacher support [2]. It also helps to evaluate post-hoc whether the chosen instructional design has led to a collaborative atmosphere within the online course as intended to facilitate learning and to refine the instructional design if needed [9].

Data relating to the learning process of the students in online courses is nowadays easily available through the learning management systems (LMS), but exploitation of this data is still rare [9]. In our case study, the data was extracted manually. For future routine use, automatic procedures need to be developed to allow data extraction and indicator generation.

To assess whether interaction contributes to learning, we will correlate learning outcome with level of interaction. Gunawardena has described how online learners can arrive at a higher level of critical thinking through different stages of interaction with peers: (a) sharing/comparing of information, (b) discovery of dissonance, (c) co-construction of knowledge (d) testing and modification of proposed synthesis, and (e) agreement of newly constructed meaning [10]. The presented indicators and interaction networks do not allow describing in which stage the observed interaction took place. For this, a content analysis of the contributions and posts is needed in addition to the structural analysis. Such an analysis would further contribute to the understanding of online interaction with a focus on a learner-centered instructional design.

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