# Initial Knowledge and the Intensity of Online Discussion

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**Abstract:** The effect of pre-service physics teachers' prior knowledge of the subject on their roles and intensity in the online discussions is studied. Network analysis of initial knowledge and social network analysis of discussion reveal that both have characteristic structural features which are typical for each student. These features, however, are not correlated. Results show conclusively that structure and extension of student's initial knowledge cannot explain activity and role in online discussions.

# Introduction

This explorative study asks if students' background knowledge affects the structure of online discussions they conduct. Consequently, we introduce here methods to monitor and analyze the structure of content knowledge and structure of online dialogue, to correlate the structural features of both. Motivation of our research is to find the best practices for blended university course. Structure of online dialogue has been extensively discussed in many research reports addressing computer supported collaborative learning (CSCL) but dialogical structure has not been related to students' background knowledge. While several studies show that more active groups also achieve better learning outcomes (e.g. Schellens & Valcke, 2005; Järvelä, Malmberg & Koivuniemi, 2016), it is still an open question if background knowledge affects the dialogical activity. On the other hand, it has been shown that argumentation in CSCL environment might not increase domain-specific knowledge (Wecker & Fischer, 2014). Therefore, it could be possible that motivated students are more active and have higher knowledge before and after online discussions.

#### Method

Data for this study was collected from a history of physics course for pre-service physics teachers. Students (n=10) made associative semantic chains with 12 individual concepts and four associations for each six time periods that constituted a time span of about 350 years of history of science from 1572 to 1928. In addition, short explanations of associations were requested. These exercises were done to help them contextualize and temporalize historical knowledge for face-to-face discussion before studying article which was connected to themes relevant for the period under exploration. After reading the article, students conducted asynchronous online discussions. The discussion was pre-structured by guiding questions about the topic of the article.

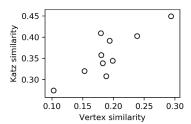
The structure of students' initial knowledge was analyzed in form of networks, which were generated from students' pairwise term and word association chains for each student individually and for each period. In addition, one aggregated networks containing all pairwise associations were constructed for each period, and one network also covering all periods. On average aggregated networks consisted of 260 nodes and 330 links. Each students' contribution for the aggregated networks were evaluated using Jaccard similarity coefficient calculated on basis of the Degree and Katz centrality; the higher the similarity of a given student's network to the aggregated network, the higher the student's contribution to the overall body of knowledge.

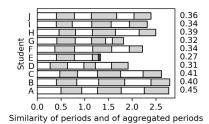
All in all, there were 24 online discussions with total of 984 messages with average of 41 per discussion. The discussions were reduced to networks consisting messages as nodes and edges representing responses i.e. who answered to whom. Social network analysis (SNA) was then used to detect patterns in discussions, in form of triadic census. More specifically the number of nine functional roles based on triadic patterns as presented by McDonnel et.al (2014) were computed for each student in each discussion. The average for each role in the episodes were also calculated. Intensity as a number of each of the nine roles for each student was represented as a diverging heatmap around the average to detect which students and on which roles were represented more than the averages.

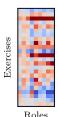
Now we have the measures which allow us to correlate the structural measure (Katz similarity) characterizing the content of students' initial knowledge with the structural measure (role intensity) characterizing the participation in discussions. The Correlations analysis is based on Kendall-tau ranking correlation as well as on Pearson correlation.

### Results

The similarity of students' network to aggregated network are shown in Figures 1a and 1b. Figure 1a shows that both the Degree and Katz centrality indicates equal similarities, ranging from 27% similarity to 45% similarity. Figure 1b shows the Katz similarities for each student per timeperiod and how the similarity to aggregated network accumulates when periods are accumulated. One of the ten heatmaps representing roles in discussions are shown as an example in figure 1c.







<u>Figure 1</u>. Correlation of similarities (a), similarity for each student (b) and one heatmap (c) as example, where blues and red represent roles which are below or over the average, respectively.

Heatmaps were used to deduce each student's participation on discussions and to resolve the roles the student took in discussions. Discussion patterns stay somewhat constant across all the discussions. Of the ten students who completed the course, only half participated for each of the discussions. One (A) of the five had all the roles clearly under the average and the rest four had mainly over. The other five students who participated to only some discussion had roles mainly under the average, but with some also over. Additionally, student A had highest similarity for aggregated network and high similarities overall, but the student had lowest roles in the discussions. Student E has rather small similarities after third period, but the student also didn't participate in the later discussions. Other students did not have any type of correlation between discussion activity or patterns and similarities. The correlation analysis reveals total absence of any statistically significant correlations between the role intensities and initial knowledge. The plausible hypothesis that intensity or role in discussion could be determined by the initial knowledge is thus untenable. Reasons for distinct roles the different students have in discussions must be sought then elsewhere than from structure and extend of initial knowledge.

# **Discussion**

Results show that variation in similarities seems rather insignificant between students across all periods. This seems to indicate that the roles, and the quality, of the discussions are not affected by the prior understanding of the context. This constancy implies some student related factor which determines the role, although on basis of results presented here it is not likely to be the initial knowledge of the student. Small similarities with missing discussion for student E is probably explainable with lack of participation with the exercises that might arise from motivation or scheduling problems. Student A's high similarity and low role intensity could be explained by assuming that who knows don't really need collaboration and therefore the participation is superficial and shallow; student who knows, don't really benefit from discussions and does not invest effort in it. Interestingly, though, in feedback all students expressed satisfaction on online discussions and evaluated them mainly positively and valuable. On basis of this explorative study we conclude that student's initial knowledge is not a likely factor deciding the participation in discussions. A next question we need to answer is that if the final knowledge is affected by participation on discussions and whether changes between initial and final knowledge states can be correlated with discussion intensity and roles within it. The present study demonstrates that for such a correlative and more extensive study we now have suitable tools and methods.

#### References

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