Using Social Network Analysis to Evaluate Individual Contributions in Online Collaborative Learning Communities: A Case Study of Reading Groups

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Abstract: Research on online collaborative learning communities still faces the challenge of evaluating individual contributions. Social Network Analysis (SNA) has been proposed as an innovative method to facilitate teachers observing group members' social interaction and assessing their learning engagement and performance in collaborative learning activities. Accordingly, adopting a case study approach, this study employed SNA to evaluate individual contributions in online collaborative reading groups. New algorithms were put forward to help identify opinion leaders and detect group polarization in small group reading. The results revealed that the proposed method can be used to successfully recognize opinion leaders and group polarization phenomenon which serves as important information source for teachers to orchestrate and regulate collaborative learning groups. This study provides new insight into using SNA to evaluate individual contributions in online collaborative learning communities.

Keywords: Social network analysis, individual contributions, online collaborative learning, opinion leader, group polarization

1. Introduction

With the development of computer technology, online collaborative learning has been extensively used as an influential teaching paradigm (Hernández-Sellés, Muñoz-Carril & González-Sanmamed, 2019). Under the circumstances of COVID-19 pandemic, it has become an increasingly important method for promoting student interaction in distance learning. Although the benefits of collaborative learning have been well documented in literature, it remains as a challenge for teachers to evaluate individual's contributions in learning groups. This is particularly true in the context of massive online collaborative learning which demands substantial cognitive capacity of teachers to assess multiple groups' learning performance and provide just-in-time scaffoldings and interventions (Bao et al., 2021).

Under this background, the current study aims to evaluate individual contribution with Social Network Analysis (SNA) which has been proposed as an effective way to analyse the interactive model of a group and evaluate students' online discussion performance (He, 2012; Lin, Hu, Hu, & Liu, 2016; Karen, Richard & Roger, 2014). With SNA, this study further evaluated each group member's contribution in online collaborative reading communities in which students needed to work as a group to complete specific reading tasks. Additionally, the study also used algorithms related to centrality measures to make the evaluation more accurate, which can better demonstrate the results of SNA. Eventually, with the support of SNA maps and algorithms, this study successfully evaluated individual contribution in groups, and bridged the gap for research on assessing individual contributions in collaborative learning processes.

2. Method

2.1 Participants

The study conducted an experiment in an undergraduate English language course at a key university in northern China. Students were randomly divided into groups of four to six members, and each group was asked to work together to finish a collaborative reading activity and submit a reding report. To satisfy the need of collaborative reading, this study used Wiki as the platform for students to discuss and write their group reading report. As a collaboration tool, Wiki has been verified to be a beneficial tool when used in online collaborative language learning practices (Li, 2012). One week after the task was issued, all groups submitted their reading reports, and the teacher of the course scored them. Eventually, we had Group A with 4 members who received the lowest score, and Group B with 6 members who achieved the highest score. Adopting a case study approach, we used the discussion data of these two groups to evaluate individual contributions with SNA method.

2.2 Research questions

This study proposed three research questions regarding using SNA to observe students' behavioral contribution, personal influence, and social cognition respectively:

- ★ How can SNA be used to assess individual contributions in small group reading?
- ★ How can SNA be used to identify opinion leaders (OLs) in small group reading?
- ★ How can SNA be used to detect group polarization (GP) in small group reading?

Through the answers to these three questions, this study can not only better illustrate the function of SNA in evaluating individual contributions but can also further identify the most influential individuals (i.e., OLs) and the general trend of social relationship development (i.e., GP) during the whole collaboration process.

2.3 Data analysis methods and algorithms

The study collected online discussion data from the two groups mentioned above and filtered out those invalid ones that were responses that were off topic. After the procedure, the study finally constructed the Social Network Analysis maps (SNA maps) for each group. In addition, to validate the information received from the SNA maps, the study measured the importance of the nodes in the network by calculating the Degree Centrality (DC), and the formula for calculating DC is presented as follows.

$$\mathrm{C}_d(v_i) = \sum_{i=1, i\neq j}^{n} w_i^{out}$$

In this formula, *j* denotes all the nodes except node *i*, while *i* denotes the requested node (group member). In addition, *w* stands for weight, which in the SNA map denotes the size of the nodes. Therefore, w_i^{out} represents the weight of the out-degree from *i* to *j*, and the centrality of node *i* (v_i) is the sum of w_i^{out}. Calculation of DC is the direct measurement of node centrality in SNA. The greater the centrality of a node, the more important the individual represented by the node is in the social network relationships.

Considering the different group size, we also normalized the DC to improve the accuracy of the centrality calculation. The normalization formula is as follow, where *n* represents the total number of people in a group:

$$\mathrm{C}'_d(v_i) = \frac{\mathrm{C}_d(v_i)}{n-1}$$

In this scenario, the practical meaning of the formula is the average number of chats per member to each other member of the group. By comparing the magnitude of the normalized DC (NDC), we can detect the most active member in the group discussion (i.e., OLs) and compare the activeness of the members in the two groups.

Apart from OLs, however, it is also significant to note the general trend shown in the two maps. The gap within the group may be the most decisive factor leading to the different final scores of the two groups. In order to quantify the trend of SNA maps and related data, we introduce another formula:

$$G_p = \frac{(C'_d(v_i))_{max} - (C'_d(v_i))_{min}}{avg(C'_d(v))}$$

In this formula, G_p stands for group polarization, which describes how a group polarizes in the process of online collaborative learning. $C'_d(v_i)_{max}$ and $C'_d(v_i)_{min}$ denotes the maximum and the minimum of NDC of a group respectively, and $avg\ (C'_d(v))$ represents the average of NDC of a group. The higher the G_p, the greater the gap of participation among members within the group. If G_p exceeds 1, the gap in the group is even more serious.

3. Results

The study finally constructed the SNA maps for the two groups (Figure1&2). The nodes in the maps represent members of the group (A1-A4, B1-B6). Lines between the nodes represent the number of conversations existing between the two members, and the size of the node represents the collection of statements made by this member.

By observing the SNA maps of Group A and Group B, we can find that in Group A, student A2 obtains the largest size and has the thickest lines, while in Group B student B2 demonstrates similar performance, indicating that A2 and B2 may be the most active and influential students in the two groups respectively. Besides, by comparing the SNA maps of the two groups, we can see that the nodes in Group B are generally larger, and the lines are thicker than those in Group A, which indicates that the discussion of Group B members may be more active than that of Group A.

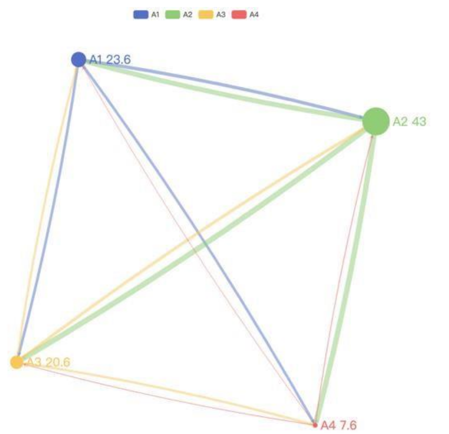

Figure 1. SNA Map of Group A

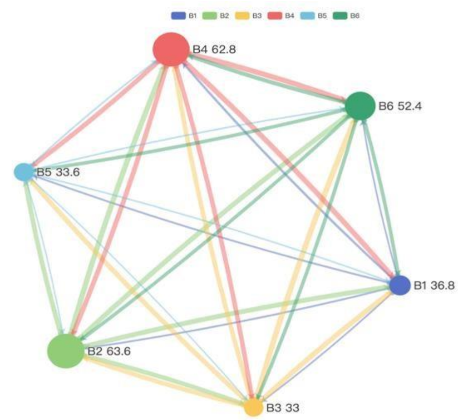

Figure 2. SNA Map of Group B

According to the algorithms, we obtained the quantitative results as shown in table 1 to validate the information received from the SNA maps:

Table 1. *Normalized Degree Centrality (NDC) of Members*

Group A	$C'_d(v_i)$	Group B	$C'_d(v_i)$
A1	23.66	B1	36.8
A2	43	B2	63.6
A3	20.66	B3	33
A4	7.67	B4	62.8
		B5	33.6
		B6	52.4

The results clearly revealed that the most active student or the OL in Group A is A2, while it is B2 in Group B, which is consistent with the information provided by the SNA maps. Besides, with the algorithm of G_p, we can analyze the development trend of group discussion as well. Here, we finally learn that the G_p in Group A is 1.49 and that of Group B is 0.65. Therefore, this study can eventually interpret that the situation in Group A is generally guided by student A2, but the voices or opinions of others may not be well accepted. However, the ideas of students in Group B are better accepted and applied by the whole group.

4. Discussion and conclusion

Now we can answer the three questions the current study has proposed. For research question 1, SNA can generate a social network map connecting the individual data, presenting the general performance of each member as well as the entire group. For question 2 and 3, with the help of the algorithms proposed in this study, we can easily confirm the OLs, and GP revealed by the SNA map.

Existent research about OL points out that OLs can play active and positive roles in guiding group cooperation (Li, Li & Kou, 2022; Li & Wei, 2020). In our study, they did play their roles, but we also need to be aware that GP happened as well. Generally, GP occurs when group members end up being more extreme in their position on a given issue after participating or being exposed to a discussion led by someone (Isenberg, 1986). Thus, during the process of collaborative learning, it is pivotal for teachers as well as students to discover and value ideas from each member, otherwise the positive role of OL may result in a negative outcome as the creativity of others may be stifled.

To conclude, SNA can act as a useful tool when it comes to evaluating individual contributions, identifying opinion leaders, and detecting possible group polarization in collaborative learning. This can serve as important bases for teachers to orchestrate and regulate groups so as to avoid homogenization in online collaborative learning. Future studies can use the results of SAN to further explore how to encourage OLs to prevent rather than intensify GP, which can be an effective method to improve the quality of online collaborative learning.

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