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Social Network Analysis of Knowledge Construction in Computer-Supported Collaborative Learning

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Abstract

Studying learners' knowledge construction process is the key to understand how learning occurs in computer supported collaborative learning (CSCL) settings. In this study, we selected the discussion interaction on topic of "scaffolding and CSCL" from the online course platform. Then we visually analyzed students' behavior of collaborative knowledge construction by social network analysis, and explored social characteristics of different types of members in the network. The findings indicate that:1) The students who didn't participate in the discussion of knowledge construction, are isolated points in the network, and are introverts in their lives; 2) The students with higher influence in the network are usually active individuals in the class. They actively speak in class and express their personal views. Most of them are class or school student cadres, and they are closely related in real life; 3) Some personal characters, such as environment and social relationships, may have a certain impact on the process of collaborative knowledge construction. These findings will be helpful in designing activities of collaborative knowledge construction, and improving the effect of students' computer-supported collaborative learning.

Key words: knowledge construction; computer-supported collaborative learning; social network analysis

Introduction

Computer supported collaborative learning (CSCL) can be viewed as an e-learning approach that emphasizes meaningful interaction between learners, including through direct communication and mediation of artifacts, as a prerequisite for learning. [1]. Learning will occur at a cognitive, social, or motivational level, usually measured according to various data sources and analytical methods [2]. From the perspective of sociocultural constructivism, learning process is described as the construction of shared meanings [3]. Different forms of interactions exist during this construction activity, and the interactions of members show dynamic changes, which present different social interaction characteristics. Interactive relationships have an influence on the process and quality of knowledge construction [4]. What makes a need to explore the knowledge building behavior and interactive characteristics of CSCL members.

The common assumption of social network analysis (SNA) and CSCL that "relationships matter" is what makes SNA an appropriate way to reveal the structure of relationships resulting from CSCL interactions [2]. SNA provides methods and theories for displaying, discovering and interpreting structural patterns of social relationships among students [5]. It can be combined with quantitative data analysis to achieve a thorough understanding of the learning process [6]. For example, in De Laat's study, SNA is used to focus on the interaction patterns between participants and study their dynamics in CSCL [7]. Zhang Si, etc. [8] used to investigate the interactive network and social knowledge construction behavior patterns of primary school teachers in online collaborative learning activities. Xie Kui, etc. [9] used SNA technology to examine the influence of moderator role assignment on social networks of online classes. Claros et al. [10] put forward a systematic review of SNA indicators used to analyze CSCL scenarios.

Network visualization can be used as a groupthink tool, allowing learners to reflect on their interactions based on the presence or absence of relationships [11] [12]. In this study, we use SNA visually analyzed students' behavior of collaborative knowledge construction in CSCL to explore the structure between members in the network. Then, through further observation, we find out the social characteristics of different types of members in the network and explore the possible impact of these characteristics on their knowledge construction behavior. The following two research questions will be answered.

(1) What are the interaction relationships and structure of members during the process of knowledge construction in CSCL?

(2) What are the social characteristics between students of different types of nodes in the network?

Methodology

A. Participants and settings

The data was collected within a course on "Learning science and technology" addressed to postgraduate students at the Central China Normal University. The course teacher gave a number of learning topics and grouped the classmates to learn the topic. The group will learn the topic firstly and then make discussions on the knowledge forum platform. In the class, all 54 students formed 7 groups to participated in the learning and discussion process.

B. Procedure

The entire collaborative knowledge construction process is as follows: First, the group will learn themselves and discuss the selected topics. This stage is mainly based on group members. But during the whole process of discussion, the other students in the class can also express their opinions or questions and participate in the discussion. After the group discussion, all the students in the class will further discuss the questions or ideas of the topic.

In the initial stage, class students may only stay in the discussion of concepts and the content is easier to understand. In the middle stage, they will reflect through the promising idea tools to deeply think about the discussion, and then carry out the next stage of discussion. Finally, they will make a deeper understanding of knowledge for the learning topic. Throughout the discussion process, class members completed knowledge building through communication, sharing, and collaboration and formed a complex interactive network during the development of the theme seminars.

C. Data collection and analysis

We selected this discussion data of students on topic of "scaffolding and CSCL" from the platform. A group is the main discussion body and the other classmates questioned them. Students' interaction data were analyzed with the UCINET SNA tool to answer the research question 1. Through analysis of basic network attributes to determine the closeness of communication between learners in the interactive network. Centralized analysis to identify core members and edge members in the interactive network, and understand the proportion of core members in the entire network. Through the analysis of the relationship between groups in the network to understand the similarities and differences between members. To answer the research question 2, we further investigated the personality and social background of these different types of students to find out their differences.

Results and discussion

A. Basic network properties

The community map of collaboration knowledge construction process is shown in Figure 1. The basic properties of the network are shown in Table 1, which included the number of nodes, the number of connections, network density, clustering coefficient and average distance.

This network is a sparse network involved 53 members with 106 connection ties showing a network density of 0.062. There is only 6.2% of connections in the network and two connections per member on average. The cohesiveness of the network is acceptable. The clustering coefficient is 0.237, average distance is 2.419. That means two members can establish a connection by at least two people. Besides, it can be seen from the community map that the students numbered S20, S36 and S43 are isolated points in the network. They only responded to the topic initiated by a certain classmate, and did not participate in the whole discussion.

TABLE I
BASIC PROPERTIES OF SOCIAL NETWORK

Number	Properties	Value
1	nodes	53
2	connections	106
3	network density	0.062
4	Clustering coefficient	0.237
5	average distance	2.419

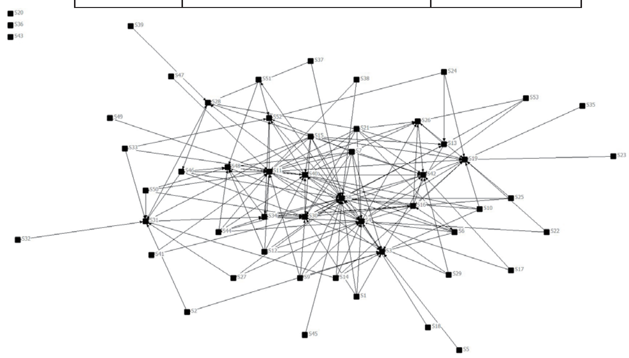

Figure.1 Collaborative knowledge building community

B. Central analysis

1) Degree centrality

Degree Centrality refers to the number of connections held by an actor in the network. It describes the number of interactions and capabilities of members and depends on the number of direct connections with other members. If the degree centrality is high, it means the members have great power in the social network and are the core members of the network.

Table 2 shows some members' value of the degree centrality. From the table we can see that S8 has the highest degree of centrality and is the core member of the whole network. Other students such as S4, S11, S40 et al, their values are relatively higher, so they are the most active member of the network.

TABLE II
DEGREE CENTRALITY OF SOCILA NETWORK

Member	Degree	NrmDegree	Share
S8	27.000	51.923	0.081
S4	23.000	44.231	0.069
S11	21.000	40.385	0.063
S40	17.000	32.692	0.051
S30	15.000	28.846	0.045
S19	14.000	26.923	0.042
S3	13.000	25.000	0.039
S42	13.000	25.000	0.039
S48	11.000	21.154	0.033
S15	11.000	1.154	0.033

2) Betweenness centrality

The betweenness centrality refers to the number of bridges where a node acts as the shortest path between the other two nodes. The more times a node acts as an intermediary, the greater its betweenness centrality, and it has greater control over other members. If the betweenness centrality of a member is zero, it means there is none member can send messages through him, and he can't control any other member at all.

Table 3 shows some members' value of the betweenness centrality. From Table 3, it can be seen that member S4 has the highest degree of betweenness centrality of 191.433. Therefore, he is the most powerful member in the network and he has the ability to guide and control the interaction of other actors. Other members, such as S8, S11and S40 also have a high degree of betweenness centrality and strong interaction ability in the network. They may be the "link" that connect the whole network.

TABLE III
BETWEENNESS CENTRALITY OF SOCILA NETWORK

Member	Betweenness	NBetweenness
S4	191.433	7.218
S8	160.675	6.059
S11	139.667	5.266
S40	137.725	5.193
S30	107.592	4.057
S28	104.250	3.931
S34	82.592	3.114
S19	81.658	3.079
S31	50.567	1.907
S42	43.133	1.626

3) Closeness centrality

It refers to the average length of the shortest path from each node to other nodes. That is to say, the closer a node is to other nodes, the closer it is to the center. The value of closeness centrality can mainly indicate that the control degree from the other members. If the distance between a member and all other members is very short, then the member's closeness centrality is higher, which indicates that the member is not controlled by others and less dependent on other members in information transmitting.

Table 4 shows some members' value of the closeness centrality. From Table 4, it can be found that S3, S8, S4 and S11 have shorter distance of receiving replies from other members and shorter distance of replying to other members. They have a high degree of closeness centrality, indicating that these members are not controlled by other members, and are at the center in the network.

TABLE IV
CLOSENESS CENTRALITY OF SOCILA NETWORK

Member	In Farness	Out Farness
S3	253.000	2756.000
S8	342.000	1894.000
S4	352.000	1884.000
S11	358.000	1890.000
S34	366.000	893.000
S19	367.000	1895.000

C. Core-Periphery structure analysis

The core-periphery structure can divide the group members into two categories: one is the core group with close connection with each other, whose members belong to the core figure; the other is the periphery l group with little or no connection with each other, whose members belong to the periphery figure. The structural model is shown in Table 5.

From Table 5, we can see that there are 20 members of the core figure, among which the members with higher centrality, such as S4 and S8. In addition, the centrality of members such as S1 is not very high, but it is also the core figure. To further verify the core status of these 20 members, we use Katz coefficient to calculate the influence of these six members and get the influence index of the core members. As shown in Table 6, the top 10 members of the Katz impact index are listed.

For example, the total influence index for all other members of S15 is 0.063, and the index he had been influenced by other members is 0, the total influence ranks first among all members. The influence of other members is also high, which is consistent with the core-edge structure analysis results. From this, it can be seen that these members have been actively involved in discussions, frequently exchanged ideas and interaction with other members. They are the core members of social networks.

TABLE V
CORE PERIPHERY STRUCTURE MOODLE

Category	Number	Member
Core member	20	S1, S3, S4, S6, S7, S8, S9, S11, S12, S15, S16, S19, S21, S26, S30, S31, S34, S40, S42, S48
periphery member	33	S2, S5, S10, S13, S14, S17, S18, S20, S22, S23, S24, S25, S27, S28, S29, S32, S33, S35, S36, S37, S38, S39, S41, S43, S44, S45, S46, S47, S49, S50, S51, S52, S53

TABLE VI
CORE MEMBER KATZ IMPACT INDEX

Member	RowS	ColS
S15	0.063	0
S7	0.057	0
S21	0.051	0
S4	0.045	0.096
S11	0.04	0.097
S40	0.04	0.068
S12	0.034	0
S16	0.034	0.017
S6	0.029	0.006
S8	0.029	0.148

Through analyzing the social interaction characteristics of members in the process of collaborative knowledge construction depended on three indicators: basic attribute of the network, centrality and core-edge structure, the core members and inactive members of the discussion are identified. To further understand the characteristics of these students, we interviewed teachers and students around them, and found that the members with higher centrality and influence index, such as S8, S4 and S11, were active individuals in the class. They expressed their opinions and spoke actively in class. Most of them served as class or school student leaders. However, inactive members, such as isolated members S20, S36 and S43, are usually silent in the classroom. They are less motivated to participate in classroom discussions, and always introverted.

Conclusion

In this study, the discussion content of students in the course is chosen to analyze the process of students' cooperative knowledge construction with the method of social network analysis. Try to find out the interactive relationship and structure among members and analyze the similarities and differences of different types of members in the network.

The research results show that, (1) through the analysis of the basic attributes of the network, it is found that the selected cooperative knowledge construction network is sparse network with 53 Students forming 106 connections, and the density of this network is 0.062. There are isolated points, so some members have not participated in the discussion in the process of knowledge construction. (2) Because all the discussions did not involve teachers, the core of all discussions is the class members. The members such as S8, S4, S11 have the higher centrality and influence through the central analysis. They have shown strong interaction ability and control the flow of information in the network. (3) The core characters in the network were found out through Core- Periphery structure analysis. In addition to members with higher centrality, other members such as S1 and S26 are also the important role of the whole discussion process. While members such as S2 and S5 have been on the edge of the network, they rarely responded to the discussion content and did not actively initiate topic discussions. Through further analysis, it is found that core members and marginal members have different personalities, and most of the core members serve as class or school student cadres. Isolated members are usually silent. This indicates that environment and social relationships may have a certain impact on the process of collaborative.

Limitations and future work

The application of SNA in CSCL will be able to analyze the interaction between individual and group processes [13]. We can analyze the interaction and participation characteristics of class members in the process of knowledge construction through SNA. Teachers can take some intervention measures or scaffolding strategies to guide students’ discussion to achieve a deep understanding of the subject based on the results. However, the analysis of SNA results is usually limited to describing network attributes by visually examining the social graph and reporting SNA measurements [14]. CSCL learning outcomes exist at all levels and require multiple approaches to research. Some researchers have used SNA to distinguish virtual courses and used statistical analysis to develop a new method for different indicators [15]. Future studies may link SNA findings with quantitative indicators of cognitive, social, and motivational outcomes collected from other research methods to better understand the impact of knowledge construction on learning outcomes.

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