Knowledge-Building Analytics Based on Network Science

Ayano Ohsaki [1,2], Jun Oshima [2] and Ritsuko Oshima [2]

[1] *Advanced Institute of Industrial Technology, Japan*
[2] *RECLS, Shizuoka University, Japan*

Abstract
The analysis perspectives in learning analytics have become an increasingly important issue, as learning analytics has gained more attention. To further develop learning analytics, this study demonstrates how network science affects knowledge-building analytics and presents future research directions. The analysis methods used in knowledge building, which is a prominent theory of the knowledge creation metaphor, have been developing based on network science. This is because there is a theoretical link between network science and analysis methods used in knowledge-building discourse. In knowledge building, how learners engage with emergent knowledge in a community is a critical analysis perspective. Hence, analytical tools in knowledge-building discourse have been developed based on network science used to analyze complex systems. Moreover, recent studies have advanced analysis methods by adding the perspectives "unit of analysis" and "temporal network" from the discourse analysis and network science theories. In addition, multiple analysis methods created by adding further network analysis methods as other layers have shown extensive potential. In conclusion, this study argues for the potential of the application of network science to data analysis in relation to learning theory.
Keywords
Knowledge building, Network science, Discourse analysis, Socio-semantic network analysis, Knowledge creation

1. Background

This study describes how network science affects knowledge-building analytics and future research directions. When applying network science to analyze learning data, learning theories must be understood. In particular, data analysis perspectives have become more important in the age of big data due to the increasing affordability of sensor devices, the expansion of online education, and the development of analysis technology [1,2]. Therefore, the challenge facing the application of network science to learning data analytics is the adaptation of the knowledge of network science to learning theory. Based on knowledge-building theory, we have developed analytical methods for knowledge-building discourse (KB discourse) to be derived from network science. This study aims to aid in the development of analytical methods to be used in network science in future learning analytics. To achieve this, we present knowledge-building theory and the development of analytical methods based on this theory. Furthermore, we discuss future directions for research.

1.1. Theoretical framework of knowledge building

Over the past 30 years, knowledge building has gained attention as a new learning approach in the knowledge-creation metaphor [3,4]. Knowledge building aims to advance collective knowledge rather than existing knowledge acquisition or participation in communities [3,5]. Moreover, learners create knowledge objects through knowledge building [6]. Knowledge-building research involves practices in classrooms, learning environment design, computer-supported collaborative learning (CSCL), and

Proceedings of the NetSciLA21 workshop, April 12, 2021
EMAIL: ohsaki-ayano@aiit.ac.jp (A. 1); joshima@inf.shizuoka.ac.jp (A. 2); roshima@inf.shizuoka.ac.jp (A. 3)
ORCID: 0000-0001-5072-0135 (A.1); 0000-0002-9885-448X (A. 2)

development analysis methods [5,7,8]. In particular, discourse analysis is the most critical approach to capturing the nature of knowledge building and it has been developed based on knowledge in the field of network science.

1.2. Knowledge-building discourse

Discourse has an essential role in the knowledge-building community because knowledge objects are shared and typically improved through group discourse [5,9]. Discourse data can be collected from online media and conversations. For instance, the CSCL system "knowledge forum (KF)" possesses an interface for asynchronous online discourse consisting of adding notes to existing notes and many studies have analyzed data on the KF [7,9]. In other words, regardless of media, deciphering changes in the interactive discourse of learners in a group that aims to create new knowledge can help researchers and teachers understand the knowledge-building process and support learning.

We consider network science to be the theoretical method for analyzing KB discourse. This is because knowledge building sees ideas representing the advancing knowledge of a community as an emergent and distributed phenomenon [5]. Furthermore, Jacobson and Kapur [10] discussed the importance of considering learning as the manifestation of complex systems instead of simple casual explanations and the possibility of applying the methodology for complex physical and social systems to the learning sciences. Additionally, network science is a discipline that seeks to understand the network behind complex systems as a foundation for understanding the complex systems themselves [11]. Consequently, Oshima et al. [12] developed a computational analysis tool, "knowledge building discourse explorer (KBDeX)," by combining knowledge building and network science theories.

1.3. Socio-semantic network analysis

KBDeX analyzes KB discourse via socio-semantic network analysis (SSNA), which is a type of network analysis method for KB discourse. SSNA can capture the transitions of both the network structure of learners and the words in discourse [5,12]. Knowledge-building theory is based on scholarly knowledge advancement and emphasizes knowledge creation in groups [5]. Hence, when capturing collective knowledge advancement, it is essential to consider ways of tracing changes in ideas. Ideas are represented as clusters of words in network science because communities share and improve ideas using words in their discourse for collective knowledge advancement. In other words, as discourse progresses, the entire network becomes more robust; for example, a new cluster is created and connected to other networks. We assume that the total degree centrality calculated by SSNA can determine how a network changes.

Total degree centrality is the sum of the degree centralities of the words that appear and represents the cluster structure of words [12]. The transitions in the total degree centralities illustrate how ideas change during discourse because the total degree centrality indicates how words create ideas. "Degree centrality" is a general metric in network science and shows how many nodes are connected to a target node [12]. In a previous study, the transitions in total degree centralities showed the differences in the changing ideas between high- and low-learning outcome groups [13].

Moreover, knowledge of network science also affects solutions to practical problems in the classroom when network science theory matches learning theory. Previously in discourse analysis, analysts needed to qualitatively analyze and interpret all discourse data. However, having teachers read all the discourse data of all groups in classrooms to redesign learning environments is not very feasible. To address this, a mixed-method approach combining SSNA and in-depth dialogical analysis was proposed [14]. This mixed-method approach calculates pivotal points, which are potential significant change points, using the total degree centralities for an in-depth dialogical analysis. Through this method, analysts can focus on the pivotal points to read the data thoroughly and grasp how learners engage in collective knowledge advancement.

2. Analytical perspectives for knowledge-building discourse

After the analysis approach using SSNA was developed [12,14], analysis methods for KB discourse were improved. This section introduces two essential improvements to analysis algorithms in recent studies [15,16] as examples of applying network science to learning data.

2.1. Unit of analysis

The first analytical perspective is the “unit of analysis” in which utterances are considered interrelated. In knowledge-building theory, collective knowledge advancement occurs through discourse [5,9]. In discourse analysis theory, utterances interact within a topic [17]. Accordingly, the appropriate scope for interactions between utterances must be set. In other words, analyzing whole discourses may yield erroneous results [18]. For proper analysis, the scope of influence of utterances must be properly determined. One computational solution to this important analytical problem is the “moving stanza window method” [19]. In this method, a scope named a “window size” is set as the unit of analysis based on a hypothesis of how many previous utterances are related to the current utterance. By focusing on the unit of discourse, the discourse context close to real situations can be analyzed.

Based on these studies, Ohsaki and Oshima [15] applied the moving stanza window method [19] to KB discourse analysis to create a unit of analysis by considering the interactions of utterances. They used the proposed method to analyze data on collaborative problem-solving in a high-school biology class and confirmed that the new method enhanced the visualization of changes in ideas.

2.2. Temporality

Temporality is the second critical perspective in KB discourse analysis. Human activities do not occur at regular intervals and consist of both concentrated activities called “bursts” and long waiting times [20]. Hence, aggregative data analysis is inadequate for analyzing when and how activities change. In the network science field, studies of epidemics and information technology show the importance of temporal networks [11,20,21]. An aggregative network sums all interactions, whereas a temporal network considers interaction times to have a lifetime [11]. Therefore, the concept of a time limitation for interactions, namely “network lifetime,” can be used to understand interactions in greater detail.

Collaborative knowledge advancement is also a human activity. To capture the more realistic processes of knowledge advancement, the burst-like nature of changing ideas should be captured. A recent study successfully used the network lifetime to visualize when ideas change intensively and when ideas are not changing [15]. Moreover, Ohsaki and Oshima [16] visualized the phenomena of changing ideas in a classroom using timestamp information with an SSNA algorithm combined with the moving stanza window method and network lifetime.

3. Conclusions and future directions

In this study, we explained how network science affects KB discourse analysis. When applying knowledge of other disciplines, including network science, to learning data, researchers need to consider learning theories. This means that analytical methods or tools that fit the perspectives of analysis based on learning theory are necessary. In knowledge building, it is critical to determine who develops ideas and how. Network science has an important role in the analysis of emergent ideas in KB because network science is a discipline used to analyze complex systems. From this coherency, network science has affected the advancement of analysis methods for KB discourse with an emphasis on theoretical backgrounds. Consequently, SSNA has been proposed as an analysis method for both human and word networks, the mixed-method approach using SSNA has been applied to implement methodologies in classrooms, and the application of the moving stanza window method and network lifetime have visualized the phenomena of changing ideas and further illustrated realistic scenarios in classrooms by adding timestamp information [12,14–16,19].

In future work, network science should be applied to multiple analysis approaches and to algorithm improvement. Analysis methods for KB discourse have developed continuously. For example, beyond the focus of this study, a multilayered analysis approach was developed by adding analysis in a metacognitive layer to the mixed-method approach using SSNA [22]. In that study, the authors conducted a double network analysis composed of SSNA and epistemic network analysis (ENA) [2]. ENA has the theoretical background of an epistemic frame to understand complex cultural practices [2]. The epistemic frame conducts analysis from the perspective of the link between culturally relevant meanings within a discourse [2]. This example shows that multiple analyses using network analysis based on theories could more appropriately capture learning. However, the results could be misleading if each analysis perspective is incoherent. A connection like a skewer is required among analysis and network sciences theories when applying network science to learning data.

4. References

[1] Wise, A. F. & Shaffer, D. W. "Why theory matters more than ever in the age of big data". Journal of Learning Analytics (2015): 2(2), 5-13.

[2] Shaffer, D. W. Quantitative Ethnography. Cathcart, 2017.

[3] Paavola, S., Lipponen, L., & Hakkarainen, K. "Models of innovative knowledge communities and three metaphors of learning". Review of Educational Research (2004): 74(4), 557–576.

[4] Chen, B. & Hong, H.-Y. "Schools as knowledge-building organizations: Thirty years of design research". Educational Psychologist (2016): 51(2), 266-288.

[5] Scardamalia, M. & Bereiter, C. Knowledge building and knowledge creation: Theory, pedagogy, and technology. in: K. Sawyer (Ed.) The Cambridge Handbook of the Learning Sciences, 2nd ed., 2014, pp. 397–417. Cambridge University Press.

[6] Bereiter, C. Education and mind in the knowledge age. Routledge, 2002.

[7] Scardamalia, M. Collective cognitive responsibility for the advancement of knowledge. in: B. Smith (Ed.) Liberal Education in a Knowledge Society, Open Court, 2002, pp. 67–98.

[8] Scardamalia, M., & Bereiter, C. Creating, crisscrossing, and rising above idea landscapes. in: R. Huang, Kishuk, J.K. Price (Eds.) ICT in Education in Global Context, Springer, Berlin, Heidelberg (2016): pp. 3-16.

[9] Scardamalia, M. & Bereiter, C. "Smart technology for self-organizing processes". Smart Learning Environment (2014):1(1), 1-13.

[10] Jacobson, M. J., & Kapur, M. Learning environments as emergent phenomena: Theoretical and methodological implications of complexity. in: D. Jonassen & S. Land (Eds.), Theoretical foundations of learning environments, Routledge, 2nd ed., 2012, pp. 303–334.

[11] Barabási, A. Network science. Cambridge University Press, 2016.

[12] Oshima, J., Oshima, R., & Matsuzawa, Y. "Knowledge building discourse explorer: A social network analysis application for knowledge building discourse". Educational Technology Research and Development (2012): 60(5), 903–921. https://doi.org/10.1007/s11423-012- 9265-2

[13] Oshima, J., Ohsaki, A., Yamada, Y., & Oshima, R. Collective knowledge advancement and conceptual understanding of complex scientific concepts in the jigsaw instruction. in: Making a Difference: Prioritizing Equity and Access, Proceedings of the 12th International Conference on

Computer Supported Collaborative Learning (CSCL), International Society of the Learning Sciences, (2017): 1, pp. 57–64.

[14] Oshima, J., Oshima, R., & Fujita, W. "A mixed-methods approach to analyze shared epistemic agency in jigsaw instruction at multiple scales of temporality". Journal of Learning Analytics (2018): 5(1), 10–24.

[15] Ohsaki, A. & Oshima, J. A Socio-Semantic Network Analysis of Discourse Using the Network Lifetime and the Moving Stanza Window Method. in: B. Eagan, M. Misfeldt, & A. Siebert-Evenstone (Eds.) Advances in Quantitative Ethnography. ICQE 2019. Communications in Computer and Information Science, Springer, 2019, vol 1112, pp. 326–333.

[16] Ohsaki A. & Oshima J. Socio-semantic Network Analysis of Knowledge-Creation Discourse on a Real-Time Scale. in: A.R. Ruis & S.B. Lee (Eds.) Advances in Quantitative Ethnography. ICQE 2021. Communications in Computer and Information Science, Springer, 2021, vol 1312, pp. 170-184. https://doi.org/10.1007/978-3-030-67788-6_12

[17] Gee, J. P. Social Linguistics and Literacies: Ideology in discourses, 3rd ed., Routledge, 2018

[18] Csanadi, A., Eagan, B., Kollar, I., Shaffer, D., W., & Fischer, F. "When coding-and-counting is not enough: using epistemic network analysis (ENA) to analyze verbal data in CSCL research". International Journal of Computer-Supported Collaborative Learning (2018): 13(4), 419–438.

[19] Siebert-Evenstone, A. L., Irgens, G. A., Collier, W., Swiecki, Z., Ruis, A. R., & Shaffer, D. W. "In search of conversational grain size: Modeling semantic structure using moving stanza windows". Journal of Learning Analytics (2017): 4(3), 123–139.

[20] Barabási, A. "The origin of bursts and heavy tails in human dynamics". Nature (2005): 435, 207–211.

[21] Holme, P. & Saramäki, J. "Temporal networks". Physics Reports (2012): 519(3), 97 –125.

[22] Oshima, J., Oshima, R., & Saruwatari, S. "Analysis of students' ideas and conceptual artifacts in knowledge-building discourse". British Journal of Educational Technology (2020): 51(4), 1308-1321. https://doi.org/10.1111/bjet.12961