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Investigating Cognitive Network Models of Learners' Knowledge Representations

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Abstract

This commentary discusses how research approaches from Cognitive Network Science can be of relevance to research in the field of Learning Analytics, with a focus on modelling the knowledge representations of learners and students as a network of interrelated concepts. After providing a brief overview of research in Cognitive Network Science, I suggest that a focus on the cognitive processes that occur in the knowledge network, as well as the mechanisms that give rise to changes in the structure of knowledge networks, can lead to potentially informative insights into how learners navigate their knowledge representations to retrieve information and how the knowledge representations of learners develop and grow over the course of their educational careers. Learning Analytics can leverage these insights to design adaptive learning or online learning platforms that optimize learning, and inform pedagogical practice and assessment design that support the development of effective and robust knowledge structures.

Keywords

Cognitive network science, knowledge representations, concept networks, learning, network growth

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1. Introduction

Network Science is an interdisciplinary field that uses mathematical graph theory to study complex systems from diverse areas, ranging from social systems, the World Wide Web, to language and cognitive systems (for overviews see Newman, 2008; Watts, 2004). A key characteristic that unites these diverse systems is that complex relational information across independent entities within those systems can be readily represented as a network of nodes and edges. Nodes represent the basic units or entities that make up the system (e.g., individuals in a social network or concepts in a semantic network), whereas the edges that connect pairs of nodes represent an important relationship being modelled in the network (e.g., friendship ties in a social network or associative relations between concepts).

Given the flexibility and usefulness of network science for a variety of disciplines, it is hardly surprising to see network science approaches used in the field of Learning Analytics (LA) as well. The goal of LA is to collect, measure, and analyze data related to educational practice to derive important knowledge about learners in various educational contexts (Buckingham Shum, 2012; Poquet et al., 2021). Insights gained from LA are especially important for informing education policy, decisions about pedagogical and assessment design, expenditure on learning technologies, or identification of "at-risk" students for potential intervention, just to list a few examples (Avella et al., 2016).

The availability of Big Data in LA demands more sophisticated methods of data analysis and visualization. When the data depicts a web of complex relationships and interactions, network science approaches can be especially useful. A straightforward example can be found in social network analysis research frequently conducted in LA, where nodes in this network represent individuals (e.g., learners or teachers), and edges depict some form of interaction or collaborative activity between individuals. The social network then provides a snapshot of collaborative patterns in educational settings that can be used to predict academic success or model student engagement. The networks discussed in the special section in this issue depict such social networks (Saqr & López-Pernas, 2022; Mallavarapu et al., 2022; Stasewitsch et al., 2022).

In addition, LA researchers study networks that do not necessarily involve individuals as nodes in the representation, providing a neat demonstration of the flexibility of network science methods. The networks discussed in this special section depict networks of clickstream data generated by learners in a large online course, and networks of phases in self-regulated learning, respectively (Zhang et al., 2022; Malmberg et al., 2022). It is also common to find research making use of word co-occurrence networks to conduct a semantic analysis of content generated by learners (Nkhoma et al., 2020). All these studies provide new insight into different aspects of the learning process; for instance, learners' distribution of attention (Zhang et al., 2022, this issue) and their metacognitive strategies (Malmberg et al., 2022, this issue), that would not have been possible without the network science approach.

1.1. What is Cognitive Network Science?

An important aspect of LA that could also benefit from the application of network analysis is a representation of the *knowledge structures* acquired by learners. The present commentary will illustrate how ideas from Cognitive Network Science could be applied to model such knowledge representations as conceptual networks. Cognitive Network Science (CNS) is an emerging area of research in cognitive psychology where network science techniques are used to study various aspects of cognition, including language processing, memory, learning, language acquisition, and creativity (for an overview see Siew et al., 2019). The predominant type of network analyzed and investigated in CNS is a language network of words and concepts. In this network, nodes represent individual words or concepts, and edges can represent a variety of relationships that exist between words. For instance, in a phonological language network the edges represent phonological or sound-based similarity between words (i.e., */cat/–/bat/*; Vitevitch, 2008), whereas in a semantic network the edges represent semantic relations (i.e., cat–dog; Steyvers & Tenenbaum, 2005).

The core idea underlying CNS is that these language networks provide a fruitful way of representing the complexity of the mental lexicon, the part of long-term memory that resides in the minds of people. This enables researchers in the cognitive and language sciences to tackle questions related to 1) how the structure of the lexicon affects language-related processes, and 2) how the lexicon develops over the lifespan.

1.2. Knowledge Representations of Learners

The methodology and approaches developed in CNS could be especially relevant for the measurement and quantification of knowledge representations of learners, which should be of interest to LA researchers. In this specific context, knowledge representations broadly refer to domain-specific bodies of knowledge that learners acquire over the course of their educational career. An important point is that this knowledge is more than a simple collection of memorized, known facts. Knowledge representations reflect meaningful and sophisticated sets of associations between concepts and ideas that can itself be further interrogated and developed to gain new knowledge (diSessa & Sherin, 1998; Linn, 2006). This relational perspective of knowledge lends itself nicely to the application of network science methods to further analyze and model its structural properties (Siew, 2020). Below, I provide a couple of reasons that will hopefully convince LA researchers of the utility of modelling learners' knowledge representations as a network.

First, it appears that one of the key outcome variables that stakeholders in higher education typically want to maximize or be able to predict more accurately is the learner's academic performance and achievements, operationalized as their course grades (Avella et al., 2016). To some extent, this is an understandable choice as course grades are easily available and provide a convenient measure of the success of educational policies or pedagogical decisions. However, quantifying knowledge representations of learners could potentially provide new, more nuanced ways of measuring student learning outcomes, to complement commonly used benchmarks such as course grades that may reflect biases in the specific assessment or teaching instruments chosen by instructors (Buckingham Shum, 2012). Cognitive modelling of what learners know can potentially inform the design of adaptive learning and online learning platforms for optimal learning and student engagement.

Second, quantifying the knowledge representations of learners provides an important first step toward gaining deep insight into the learning process itself. Using network science approaches to model knowledge networks respects the inherent complexity and vagueness of knowledge representations, while also making this endeavour tractable. More importantly, this places more focus on the learning process and not just learning outcomes. Specifically, LA researchers stand to gain new insights into how learners retrieve and search for information in their knowledge networks, and how these knowledge networks develop and change over time.

1.3. Goals of the Present Commentary

This commentary focuses on how network science methods can be applied to model the knowledge representations of learners as a network of interrelated concepts. It is hoped that this commentary will 1) convince LA researchers to include formal investigations of knowledge representations in their research programs and perhaps encourage collaborations with cognitive and learning scientists in psychology, and 2) showcase how research themes and approaches in CNS could be relevant more generally to LA research through a brief discussion of specific topics tackled by the papers in this special section.

The rest of the commentary is split into two parts. Section 2 (Part 1: Retrieval and Search in Knowledge Networks) focuses on the processes that occur in the knowledge network. Specifically, how does the structure of knowledge networks affect cognitive processes, such as information retrieval and search, that occur within the network? LA researchers may gain new information related to the cognitive processes that learners use when they engage with their knowledge representations over the course of learning activities or during classroom assessments. Section 3 (Part 2: Development and Growth of Knowledge Networks) focuses on the development of the knowledge network. Specifically, how does the structure of knowledge networks change over the longer term, and how can network growth mechanisms be used to track their developmental trajectories? LA researchers may gain new insight into longer-term learning processes that shape the developing structure of learners' knowledge networks.

2. Part 1: Retrieval and Search in Knowledge Networks

In contrast to the early days of modern network science, which emphasized the development of metrics that quantify the structural properties of networks, recent research in network science emphasizes the need for a deeper understanding of how processes from different dynamic regimes implemented in the same network could lead to drastically different network behaviours (Cheng et al., 2018; Hens et al., 2019). Clearly, depicting network structures only provides part of the explanation needed to fully account for complex network behaviours. Although delineating the structure of the network certainly is crucial for understanding the processes that occur within the network (Strogatz, 2001), it is just as important to consider the nature of these processes. This section first describes prior work in CNS demonstrating how the structure of the mental lexicon affects various language-related processes such as retrieval and search and how these processes can be implemented and simulated in a network, before discussing potential applications of this approach to knowledge modelling and other topics in LA.

2.1. Prior Work in Cognitive Network Science

In the area of psycholinguistics, network science measures of centrality provide different ways of quantifying the micro- and macro-level structure of thousands of words in a language network (see Vitevitch et al., 2014, for an overview of these measures). To date, this body of research on language networks demonstrates that the structural properties of words in the language network (as indexed by various network centrality measures) have behavioural effects on the speed and efficiency of word recognition (Chan & Vitevitch, 2009; Goldstein & Vitevitch, 2017; Luce & Pisoni, 1998). Recent computational work further illustrates how these behavioural effects can be accounted for by implementing a simple process of spreading activation in the phonological network (Siew, 2019; Vitevitch et al., 2021). This is a significant idea because it emphasizes the importance of considering the structure of the cognitive network in tandem with the processes that operate within the network (Strogatz, 2001).

To illustrate this idea in more detail, consider the finding that words with lower local clustering coefficients were more likely to be inaccurately retrieved in a study of false memories (Vitevitch et al., 2012). In the false memory paradigm, participants are given lists of words (i.e., the blue words in Figure 1) during the study phase. When asked to later recall this list, the authors found that participants inadvertently retrieved words with lower local clustering coefficients that were not presented at the study phase (i.e., the red words in Figure 1), and suggested that the less densely connected local neighbourhoods of low clustering coefficient words in fact led to more activation being transmitted to the target word, which was then "falsely recalled." Siew (2019) later found support for Vitevitch et al.'s (2012) explanations when she conducted computational simulations of spreading activation in a language network to specifically test this verbal explanation — providing an important demonstration of how structure and process should be considered in tandem to provide meaningful explanations for empirical findings.

A commonly used task in cognitive psychology to investigate how people search their semantic memory is the semantic fluency task (also sometimes known as the category fluency task; Troyer et al., 1998), where the goal is to list as many members or examples of a given semantic category, for instance, "animals" or "food items," within a fixed time limit. The key underlying assumption is that the responses generated by participants reflect the outputs of a search mechanism implemented in their cognitive representations of that domain of knowledge (i.e., people's general knowledge of animals and food items; Abbott et al., 2015; Hills et al., 2012). This search mechanism is modelled as a random walk through a network representation, such that the path taken by the random walker necessarily affected by the underlying structural characteristics of the network (Abbott et al., 2015). With readily accessible computational methods for analyzing fluency responses as semantic networks (Christensen & Kenett, 2019; Zemla & Austerweil, 2018), researchers have successfully used this methodology to understand human creative abilities (Kenett et al., 2014, 2016), semantic organization of bilinguals' mental lexicons (Borodkin et al., 2016), and, more recently, students' conceptual representations of academic domains (Siew & Guru, under review).

Finally, in an exploratory study that may be most directly relevant to the field of LA, Siew (2018) showed that concept maps constructed by psychology undergraduates could be re-analyzed as concept networks. This enables the quantification of the structure of concept networks using macro-level network science metrics such as average shortest path length (ASPL) and global transitivity. Furthermore, ASPL proved to be significantly associated with quiz scores, even after accounting for the total number of concepts generated (i.e., network size). Given that higher ASPL was associated with better quiz performance, Siew (2018) speculated that larger ASPLs reflected more well-developed knowledge structures that may enable more widespread activation of concepts, thus facilitating quiz performance.

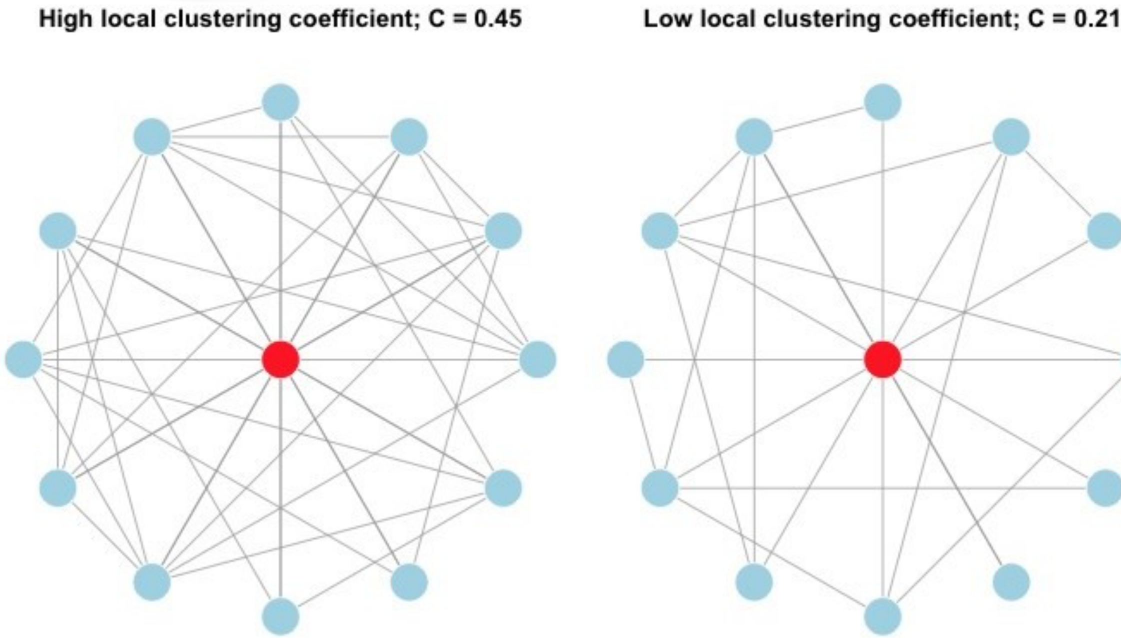

Figure 1. Networks depicting the neighbourhood connectivity structure of the red words (nodes) in the centre (left: a word with high local clustering coefficient; right: a word with low local clustering coefficient). Even though both words have the same number of neighbours (i.e., degree), their internal connectivity structure is quite different. In the false memory task, only the blue words (nodes) are presented to the participant in the study phase, and red words (nodes) may be inadvertently recalled during the retrieval phase.

2.2. Potential Applications in Learning Analytics

The knowledge representations of learners could be directly estimated using the concept mapping approach. Learners could be asked to generate a visualization whereby they generate a set of concepts related to a given domain (alternatively, a fixed set of predefined concepts could also be provided) and arrange those concepts in a way that reflects their interrelations (Kinchin et al., 2000). Learners can specify links that connect concepts based on different kinds of relationships (e.g., similarity, analogy, or causal relationships). These concept maps can then be readily re-coded as a network of concepts and their relationships. Finally, network analysis can be applied to derive new insights into the nature of students' understanding of those domains of knowledge. Such an approach has been used successfully to study conceptual representations of novice teachers and students (Koponen & Nousiainen, 2014, 2019).

Another possibility is to use the semantic fluency task as a more implicit method of measuring the overall knowledge structures of learners. For instance, Siew and Guru (under review) provided such a proof-of-concept by showing that the semantic fluency task could be used to obtain an estimate of students' conceptual representations of academic subjects such as Biology and Psychology. A comparison of network structures derived from university students and network structures derived from high school students showed that the concept networks of university students were larger, contained fewer local clusters (potentially reflecting better differentiation of similar concepts), and had a longer ASPL (potentially reflecting broadening of overall knowledge), as compared to the concept networks of high school students.

The next step is to connect the structural information gleaned from knowledge networks to predict or explain learners' academic performance. Furthermore, when combined with computational simulations of spreading activation or random walks in knowledge networks, the researcher could potentially obtain and test various explanations for *why* and *how* particular structural characteristics of knowledge representations have positive or negative effects on academic performance. Here are some questions that could be addressed when considering the interaction of cognitive processes and the structure of the knowledge network. Which centrality metrics are most predictive of students' ability to accurately retrieve specific concepts from a knowledge network? Are centrally located concepts in a knowledge network more easily accessible by the learner, or do they face additional competition for activation as compared to concepts located in the periphery? Another question could be related to how macro-level network metrics that characterize global representations of domain knowledge can influence search processes or random walks that occur in the knowledge network. Can these measures provide new information about how learners navigate their own knowledge representations as they search for connections and ideas or reflect on their learning? Are knowledge networks with more efficient network structures for navigation (e.g., as indexed by greater "small-worldness"; Humphries & Gurney, 2008; Kleinberg, 2000) indicative of academic success as well as future success after graduation?

The papers in this special section have made excellent use of network science techniques to describe the structure of various types of networks. For instance, Saqr and López-Pernas (2022) conducted a meta-analysis of several centrality measures in a social network of interactions in online forums to discover those with the most consistent associations with student grades. Mallavarapu et al. (2022) analyzed collocation networks of participants' physical proximity in a virtual learning exhibit. Finally, Stasewitsch et al. (2022) created a bipartite network representation of instructors and teaching projects to understand innovation diffusion in higher education.

In line with the core idea of the previous section, that is, any explanation of a behavioural phenomenon should include a consideration of both network structure and network process, I suggest that the empirical work conducted by LA researchers could be complemented with computational simulations of spreading activation or random walks in networks. The LA researcher could then potentially obtain and test various explanations of *why* and *how* a particular network structure is important or meaningful for a given behavioural observation or phenomenon. As pointed out by Mallavarapu et al. (2022, this issue), the collocation network merely provides a representation of the "potential" for communication and collaboration among participants in Connected Worlds, but not actual evidence of that collaboration. Similarly, the bipartite network in Stasewitsch et al. (2022, this issue) depicts potential pathways or affordances for teaching innovations to be spread, but not actual diffusion processes. The results reported in Saqr and López-Pernas (2022, this issue) could be augmented with additional considerations of the mechanisms behind *how* the degree or eigenvector centrality of students in online communicative settings specifically contribute to their academic success. Such "processes" could be empirically tested by collecting additional data from learners, or computationally explored through implementations of spreading activation (e.g., using the *spreadr* R package; Siew, 2019), random walks, or diffusion processes (e.g., the *netdiffuseR* R package; Yon & Valente, 2017) on network representations. For instance, computational experiments could be conducted on the bipartite network in Stasewitsch et al. (2022, this issue) to see which nodes in the network, when "activated," might lead to widespread activation to as many nodes as possible in the network. This may inform stakeholders which group of instructors to target in order to maximize the "spread" of teaching innovations.

3. Part 2: Development and Growth of Knowledge Networks

Another core research theme in CNS involves leveraging network science techniques to understand how the structure of the mental lexicon changes over the lifespan (Wulff et al., 2019). In other words, what underlying mechanisms could explain the process of vocabulary acquisition in early life, as well as changes in the semantic memory structures of older adults?

Network science provides us with models of network growth that can be used to begin addressing these questions. The most prominent network growth model is preferential attachment, first proposed by Barabási and Albert (1999) to account for the observation that many real-world complex networks have a power-law (or scale-free) degree distribution. The power-law degree distribution refers to the probability distribution of the degrees of nodes in the network — there are only a few hubs with several connections, whereas most nodes have only a few connections. The main idea behind the preferential attachment model is that nodes with many connections are more likely to gain new connections as the network grows, leading to the long-tailed, power-law-like degree distributions frequently observed in networks. An alternative way of thinking about the preferential attachment model is that it exemplifies the "rich-gets-richer" effect, since "rich" nodes tend to become "richer" in their connections.

Network scientists have explored and developed alternative versions of preferential attachment; for example, temporal or "trendy" preferential attachment (Mokryn et al., 2016) and preferential attachment that penalizes older nodes (Dorogovtsev & Mendes, 2000). As we will see later, CNS has also developed alternative network growth mechanisms such as preferential acquisition and lure of the associates, to specifically account for the development and growth of cognitive and language systems.

3.1. Prior Work in Cognitive Network Science

The seminal paper of Hills et al. (2009) compared the ability of three different network growth models (preferential attachment, preferential acquisition, and the lure of the associates) to explain the growth of early semantic networks (i.e., the semantic representations of young children). Whereas the preferential attachment growth mechanism emphasizes the importance of structure that already exists in the child's lexicon, the other two growth mechanisms emphasize the structure of the language environment that learners are embedded in and are exposed to. *Preferential acquisition* predicts that new words that act as hubs in the language environment are likely to be learned next, whereas *lure of the associates* predicts that new words that have more connections or "lures" to the existing lexicon are more likely to be acquired (see Figure 2 for a visualization of network growth models). Across various studies, it has been shown that in the context of early semantic network growth, preferential acquisition was the network growth model that best accounted for the empirical data on language acquisition (see also Fourtassi et al., 2020; Sizemore et al., 2018; Stella et al., 2017).

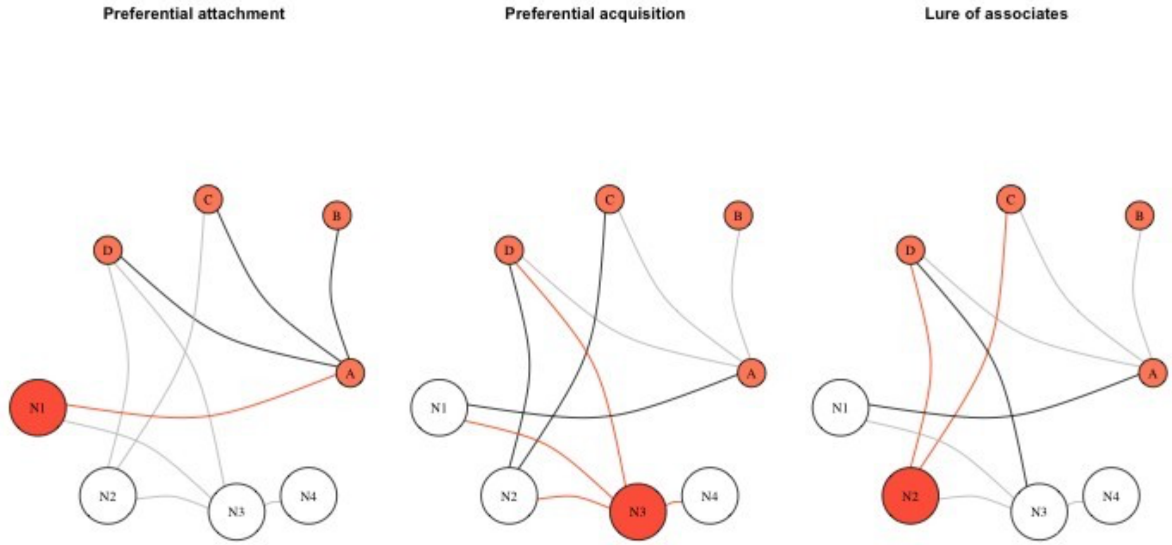

Figure 2. Network visualizations of network growth models described in the text. Smaller nodes are known concepts to the learner, larger nodes are unknown concepts. The larger red nodes represent the predictions of the growth models (i.e., which unknown concept is acquired next). Even though the network structures are identical in all three cases, each of the models makes a different prediction based on the connectivity structure that the growth model emphasizes (edges highlighted in red/black).

However, when the language network under consideration is constructed from different edges or represents a more mature network, different network growth mechanisms appear to be important (see Hills & Siew, 2018, for a discussion). In a phonological network where the connections represented phonological similarity, early language development was better characterized by preferential attachment, but growth of a mature phonological lexicon was better characterized by an inverse form of preferential attachment where words with few edges were more likely to gain new edges (Siew & Vitevitch, 2020a). In a study of paired associates learning in adults, where participants had to learn to associate pairs of random words, Mak and Twitchell (2020) found that words with many connections in a semantic network of free associations were more likely to be successfully paired with other words. The authors interpreted their results as providing strong evidence of a preferential attachment mechanism driving the formation of new links in a mature lexicon (see also Mak et al., 2021).

3.2. Potential Applications in Learning Analytics

As previously discussed in Part 1, it is possible to estimate knowledge networks of learners in various ways. An analysis of how knowledge networks develop over time would require longitudinal measures of these network structures over the course of a semester or the learner's educational career, depending on the time scale one is interested in. This sequence of static network representations can then be analyzed and their structural change modelled using network growth models. For instance, to test the hypothesis that preferential attachment is a significant driver of how knowledge networks develop over time, one could generate predictions for how nodes (i.e., concepts) in knowledge networks would gain new connections based on the network structure at time t, and see how well those predictions align with the updated network structure at time $t+1$. If existing concepts in the knowledge network have many pre-existing links to other concepts, is it also easier to connect new concepts to these already "rich" concepts?

An important point to note is that the preferential attachment model and other variants, such as temporal preferential attachment (Mokryn et al., 2016) and inverse preferential attachment (Siew & Vitevitch, 2020b), focus on the structure of the existing network (i.e., what the learner already knows) for explaining the network's future growth. In other words, it is the structure of the learner's known knowledge that guides the future development of the network. Within an educational context, however, it is likely that a consideration of the structure of the learning environment that is external to the learner is necessary for achieving a complete understanding of knowledge development. Network growth mechanisms that come from the field of CNS can be particularly relevant in this respect.

Recall that the preferential acquisition growth model states that concepts that stand out as hubs in a child's language environment are likely to be acquired by the child. Similarly, in online learning environments or academic texts, one might ask which concepts or ideas are made more "central" (Christianson et al., 2020), and do learners show better uptake of those concepts? To take it one step further, could it be possible to specifically craft or modify the presentation of content based on the learner's own knowledge network to optimize that learner's unique knowledge development trajectory? Another intriguing idea is to consider the interrelations between existing knowledge and new knowledge, as captured by the lure of the associates model. The lure of associates model predicts that a new phonological word form that is connected to many known words in the phonological lexicon facilitates its entry into the lexicon (Storkel, 2001; Storkel et al., 2006). In an educational context, are learners better able to acquire new knowledge if their instructors or the design of adaptive learning platforms increase the number of connections between what learners already know and the new content that they are trying to learn about?

A few papers in this special section dealt with dynamic network structures. Mallavarapu et al. (2022) tracked dynamic change in collocation networks to provide a measure of "collaborative temperature" of the group over time. Malmberg et al. (2022) analyzed time series psychometric networks to describe temporal patterns of self-regulation learning states among learners. Both papers showcase how dynamic networks can be summarized and visualized in powerful ways; although they say less about the underlying mechanisms that drive dynamic changes in the network structures.

As illustrated in this section, applying network growth mechanisms to formally model change in network structure could provide a powerful framework for testing competing explanations for why certain structural changes were observed in the network. The insights gained could inform decisions on education policy and pedagogical design. For instance, implementing network growth modelling in the collocation networks of Mallavarapu et al. (2022, this issue) could provide new information about whether specific characteristics of nodes in the network (e.g., its degree in the previous time step) could inform its future likelihood of being a part of certain network structures identified in the paper (i.e., crowd, coterie, clique, or singleton). As a final example, tracking the development of bipartite networks of teachers and teaching projects through the lens of network growth models could help ascertain the "sweet spot" of the value of degree that would optimize innovation diffusion in Stasewitsch et al. (2022, this issue). If instructors with a high degree are not gaining as many connections in the next time step as compared to instructors with a lower degree (i.e., a case of inverse preferential attachment), that could provide support for the authors' suggestion that the complexity of the teaching project (as indexed by contributions from many people with various expertise) is an important factor that influences which projects are more easily "shareable" in the network.

Despite the highly speculative nature of this section, it is hoped that LA researchers will see the potential of leveraging network growth models to track the knowledge network development of learners. Modelling knowledge growth as network growth could lead to new ways of designing textbooks and learning materials or the architecture of online learning environments in ways that facilitate the learning processes (as formalized by the network growth models) to nudge learners toward the development of efficient, effective knowledge network structures. At this point, it is useful to briefly consider other areas of LA that could also benefit from these ideas. LA researchers interested in students' interpersonal relations may find it valuable to use network growth models to understand how social networks in classroom settings develop over the course of an academic year. For instance, do "initially popular" students continue to become even more popular over time (i.e., reflecting a preferential attachment growth model of friendship links)? In an online environment where students communicate and interact with each other, network growth modelling could be relevant in providing explanations for the emergence of particular trajectories of online communications among students, and how various elements (e.g., teacher-specific qualities or lesson/course design) may affect these trajectories. Finally, modelling students' university course enrollment as networks of course co-enrollments could provide new insights into students' decisions about which courses to pursue in university. Which modules or courses lead to further exploration into a particular discipline (i.e., forming effective gateways or "lures" in the parlance of lure of the associated growth model)? At a macro-level, how do network growth profiles of course co-enrollments reflect broader trends and changing interests and demands of the student population? Leveraging network growth modelling to understand structural change in networks will move the field of LA beyond a descriptive analysis of temporal sequences of static network representations toward explanations and mechanisms of what factors actually drive change in a variety of networks that LA researchers are interested in.

4. Concluding Remarks

Given that the core goal of LA is to collect, measure, and analyze data related to educational practice to derive important knowledge about learners that can inform decision making and policy change (Buckingham Shum, 2012), measuring the knowledge representations that learners are actually acquiring and developing should form an important component of LA's research endeavors. This commentary illustrates how such knowledge representations can be measured using the tools of network science, and how research approaches developed in Cognitive Network Science — an emerging research area that uses network science methods to study cognitive and language systems — can augment the insights gained from knowledge networks. As discussed in Part 1, modelling the processes (e.g., spreading activation, random walks) that occur in the knowledge network can tell us how the structure of the knowledge network affects the way learners navigate their knowledge representations or retrieve information from it. As discussed in Part 2, modelling the growth or development of knowledge networks could provide new ways of considering how the structure of existing knowledge and the structure of the external learning environment could interact in ways to promote learning and knowledge growth. I also briefly discussed how these ideas could be more generally applied to other areas of LA research showcased in the series of papers in this special section. While network science provides a host of metrics that can be readily used to quantify the structure of complex, relational data in LA, an in-depth consideration of the cognitive processes and developmental trajectories of knowledge networks provides a rare level of detail into the knowledge representations that learners are acquiring.

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