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Commentary

Applications of Network Science to Education Research: Quantifying Knowledge and the Development of Expertise through Network Analysis

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Abstract: A fundamental goal of education is to inspire and instill deep, meaningful, and long-lasting conceptual change within the knowledge landscapes of students. This commentary posits that the tools of network science could be useful in helping educators achieve this goal in two ways. First, methods from cognitive psychology and network science could be helpful in quantifying and analyzing the structure of students' knowledge of a given discipline as a knowledge network of interconnected concepts. Second, network science methods could be relevant for investigating the developmental trajectories of knowledge structures by quantifying structural change in knowledge networks, and potentially inform instructional design in order to optimize the acquisition of meaningful knowledge as the student progresses from being a novice to an expert in the subject. This commentary provides a brief introduction to common network science measures and suggests how they might be relevant for shedding light on the cognitive processes that underlie learning and retrieval, and discusses ways in which generative network growth models could inform pedagogical strategies to enable meaningful long-term conceptual change and knowledge development among students.

Keywords: education; network science; knowledge; learning; expertise; development; conceptual representations

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1. Introduction

Cognitive scientists have had a long-standing interest in quantifying cognitive structures and representations [1,2]. The empirical evidence from cognitive psychology and psycholinguistics demonstrates that the structure of cognitive systems influences the psychological processes that operate within them. Classic studies in cognitive psychology demonstrated that experts are able to uncover the deep structure of physics problems whereas novices tend to overemphasize surface features of the same problems [3], and that expert chess players have better memory for meaningful chess formations than novices [4]. Together, such studies show that the cognitive representations that experts and novices construct are different, and experts' hierarchical organization of cognitive structures enable them to make new inferences or solve problems in their domain of expertise more effectively [5]. More recent literature in psycholinguistics shows that structural properties of words in the mental lexicon and semantic memory affects many cognitive and language related processes, such as word recognition [6,7] and production [8,9], cognitive search [10], word learning [11], and children's vocabulary development [12,13]. Taken together, this indicates that a complete understanding of cognitive processes is not possible without considering the structure of the cognitive representations that these processes necessarily interact with [14].

The notion that the structure of the cognitive system affects the psychological processes that operate in that system is especially important within the context of education and learning. All educators aspire to teach students important, meaningful, and useful information about the world. This implies teaching with the goal of students acquiring meaningful knowledge and becoming experts in a given domain, rather than with the goal of students assembling a random assortment of facts and information lacking in cohesiveness. However, it is striking that within the field of cognitive science of learning, the literature seems to mostly emphasize the processes and mechanisms underlying learning, with less consideration of the cognitive or knowledge structures that students possess.

A recent tutorial paper by [15] provided a comprehensive overview of cognitive learning strategies that have been well supported by the empirical research. Such strategies included spaced practice, interleaving, retrieval-based practice, elaboration, concrete examples, and dual coding; although little was mentioned about how these strategies contributed to the development of students' knowledge representations. This is curious considering that other research in the cognitive sciences has previously demonstrated that expertise is associated with the development of complex, hierarchical cognitive structures that enhance performance on highly skilled tasks [5]. This commentary provides a broad review of the research conducted in the fields of cognitive psychology and psycholinguistics that demonstrate the relevance and usefulness of network analysis as a way to quantify and measure cognitive structure. In the later part of the commentary, the author's own views on some of the ways in which the network science approach could be applied to examine the knowledge structure of students are presented. There are two main aims of this commentary: the first is to demonstrate how network science methods could be harnessed to quantify these conceptual representations and track the development of expertise, and the second is to urge and inspire cognitive psychologists, educators and learning scientists to deeply consider the internal structure of the conceptual representations that learners are acquiring.

As an example, consider a prominent empirical finding in the cognitive science of learning literature—retrieval-based practice, which is the finding that being tested on the material that you are trying to learn helps you learn the material better than simply restudying the material [16,17]. The typical experimental protocol in these studies is to provide students with a text passage to study, with one group of students having more opportunities to restudy the material and another group of students being repeatedly tested on their knowledge of the material. It is the latter group (i.e., retrieval group) that out-performs the former (i.e., restudy group) on the test administered at the end of the experimental session. However, it is important to point out that such an experimental design is limited in its ability to examine how learners represent, acquire, and ultimately retrieve a hierarchical, complex organization of concepts because the implicit assumption in these studies is that the number of "informational units" that students retrieve on the test serves as a reasonable proxy for what students have learned. Hence, it is difficult to know if retrieval-based learning can be readily translated to the learning of knowledge that has a more complex, hierarchal structure, particularly in a realistic setting where the informational space that learners are embedded in is complex, ambiguous, and noisy. Such studies are unfortunately unable to directly inform educators about the cognitive processes involved in the construction of deep, meaningful knowledge structures.

It is suggested that the main reason for why investigations of students' knowledge representations are not prominently featured in the cognitive science of learning literature is that it is notoriously difficult to quantify "knowledge". There are many valid ways of defining and representing knowledge, which is a keenly debated topic in philosophy of science and epistemology [18,19]. The approach suggested in this paper makes the necessarily simplifying assumption that knowledge can be reasonably represented as a network structure of nodes and edges, where nodes represent isolated units of information (i.e., concepts) related to a general topic area and edges or connections represent some sort of relationship that could exist between these concepts (e.g., associative, sequential, co-occurrence, if-then, etc.). While it is important to acknowledge that this is certainly not the only way to define and quantify knowledge, representing knowledge as a network of interconnected concepts brings with it quite a few methodological advantages.

First, it permits the application of tools and techniques from network science that can be brought to bear on questions related to (i) quantifying the internal structural properties of the knowledge that students are acquiring and (ii) tracking the development of expertise and knowledge acquisition. Second, conceptualizing knowledge as a network of interconnected concepts is analogous to the way in which cognitive scientists have historically modeled the structure of semantic memory—as a network of concepts that are connected based on associative relationships or shared features [20,21]. Hence, the application of behavioral paradigms commonly used to estimate the structure of semantic memory in cognitive psychology and psycholinguistics could potentially be adapted to estimate the knowledge landscapes of students. Finally, it is worth noting that representing knowledge as a network of interconnected concepts aligns a bit more closely with our intuition of what meaningful knowledge looks like—that knowledge is more than simply learning new information, but is also about making new connections and building associations between ideas.

Before proceeding, it is worthwhile to point out that there are some areas in the education sciences that are already using network analysis in interesting ways. One example is the application of network analysis to study the social networks of students collaborating and interacting asynchronously on an online learning platform [22]. As another example, researchers analyzed the epistemic frames of students using network analysis to track how students' "ways of knowing" evolved over the course of an online game [23]. As a final example, Wise and Cui [24] analyzed the reflection essays of dental students as word co-occurrence networks. However, it is important to point out that these papers do not focus on analyzing the students' knowledge structures of a given domain; i.e., these investigations focused on epistemic frames or ways of knowing [23], looked at the social interactions among learners [22], or ref [24] analyzed reflection essays rather than objective measurements of domain-specific knowledge and skill [24]. This commentary specifically focusses on the internal knowledge structure of students, i.e., what they know (rather than how they know, as in [23]), because a key aim of education is to nurture novice students to become, or at least approximate, experts in a given subject or domain area. Although it is by no means easy to measure expertise in fine-grained ways [25], it is suggested that network analysis could be a useful methodological framework for education research as it could offer education researchers new, and more fine-grained, insights into the developmental trajectories of conceptual structures and perhaps some ideas as to how to optimize its developmental trajectory.

In the rest of this commentary, two areas in which the application of network analysis could be especially relevant to the research conducted in the learning and education sciences are further discussed. The first section provides a gentle introduction of the ways in which knowledge or conceptual structure can be measured and represented as a network of interconnected concepts, and how network analysis can be used to quantify the structural characteristics at various levels of the knowledge network. The second section is more speculative in nature, focusing on how long-term conceptual change and knowledge development might be quantified via a network science framework. The section concludes with brief discussion of two specific examples in which the tools of network analysis could be beneficial for educators in informing the design and planning of course syllabi and lessons in order to maximize the development of subject expertise among students.

2. Representing Knowledge Structures as Networks

Knowledge is more than simply a collection of disparate facts about a given topic; it includes the complex nature of the interrelationships among a body of factual information. This section demonstrates how techniques from network science lend themselves well to capturing the relational nature of knowledge. The conceptual structure of a learner's knowledge can be explicitly quantified and represented as a network of interconnected concepts, where nodes represent distinct conceptual units, and edges or connections are placed between concepts that share a meaningful relation.

Although networks are conceptually straightforward, it is not always clear how these networks might be constructed. This section first describes methods commonly used by cognitive scientists to measure and quantify semantic networks and shows how these methods could be extended to measure students' knowledge structures. This is followed by a brief overview of network measures that permit an analysis of the structure of knowledge networks at multiple scales as well as a brief discussion of how these network measures might be relevant for educational research and practice.

2.1. Measuring Knowledge Structures

The most straightforward way of measuring students' knowledge is to simply ask them to construct a concept map, that is, a diagrammatic representation consisting of concepts connected to other concepts [26]. Although concept maps are frequently used in education research and as a teaching and learning tool [27], they are frequently analyzed qualitatively—for instance, relying on visual inspection to determine if the concept map has a "chain", "spoke-like", or "net-like" structure [27]. Expertise is said to be reflected in the visual complexity of the concept maps generated; hence, students with greater expertise tend to generate "net-like" concept maps, whereas students with lower levels of expertise tend to generate "chain" or "spoke-like" concept maps [27,28]. However, more detailed information about the underlying structure of students' concept maps can be derived using the tools of network science as the concept maps produced by students can be readily converted into a network of concepts and then analyzed quantitatively. Such an approach has been used to quantify the knowledge structures of pre-service teachers [29] and undergraduate students [30], revealing differences in the structural properties of the knowledge representation of experts and novices.

Within the field of cognitive psychology, there has been much research devoted to the measurement and quantification of the structure of semantic memory, the part of the long-term memory that is dedicated to the storage of general facts about the world. Semantic memory is commonly represented as a semantic network of interrelated concepts or words [20,31].

One way of quantifying the structure of semantic memory is by using a free association task, where participants provide associative responses to a given cue word [32–34]. For instance, when given a cue word "dog", a participant might respond with associative responses such as "cat", "bone", and "bark". It is particularly useful to note the existence of large, freely available behavioral databases consisting of thousands of association norms for various languages (e.g., the Small World of Words project; website: https://smallworldofwords.org/en). Free association norms are commonly used to study the internal structure of semantic memory [31] as well as the semantic processes that operate within semantic memory [35]. In these semantic networks, connections are placed between cues and the associative responses to the cue (e.g., dog—cat, dog—bone, dog—bark). Within the context of the education sciences, it is possible to curate a list of cues that target relevant concepts in a subject (e.g., for a biology class, potential cues could be "cell", "evolution", "DNA") and present these cues in a free association task [36]. While free association data are typically aggregated and represented as a single network, in principle it is possible to construct separate association networks for different populations (e.g., for better or less well performing students) or across longitudinal designs (e.g., students who complete the free association task at the beginning or at the end of the course).

Another way of measuring semantic similarity among concepts is through the use of a feature listing or feature production task [37]. In this paradigm, when given a cue word, participants generate as many features that are associated with that word as they can. For instance, the cue "dog" might elicit features such as "has legs", "barks", "is furry". Again, large databases of feature production norms are readily available for researchers to analyze the internal conceptual structure of words [38]. Feature networks can be constructed by connecting concepts that share the same features, and network analysis of feature networks have provided new insights into language development [39,40] and semantic processing [41]. Within the context of the education sciences, students could be asked to list features or properties of key concepts. Staying within the biology example, students could be asked to list features associated with the concepts of "cell" or "evolution", and these concept-feature pairs could be used to construct feature-based networks.

The category fluency task (or semantic fluency task) is also commonly used to study the structure of semantic memory. In this task, participants list as many items from a category (such as animals) as possible within a pre-specified time limit (usually one to three minutes). One striking characteristic of fluency data generated in this task is that individuals tend to list semantically related items sequentially [42]. For instance, a participant asked to list animals might list a sequence of pets ("dog", "cat", "hamster") before switching to another cluster of animals (zoo animals like "lion", "giraffe", "zebra"). Hence, it is possible to estimate a semantic network of a given category from a corpus of fluency data, at both the population or group-level and at the level of individuals [43]. The behavioral data obtained from this task has been used to study how people forage or search their semantic memory for information [10] and examine the mechanisms underlying semantic memory impairment among patients with Alzheimer's disease [44]. Within the context of the education sciences, this task could be adapted to measure students' knowledge structures—instead of listing category members from a general category such as animals, students could be asked to list as many concepts or ideas as possible related to a given subtopic in a general field (e.g., electromagnetism in physics) or within a general topic (e.g., physics). Similar to the free association task, it is possible to construct separate fluency networks for different populations (e.g., for better or less well performing students) or across longitudinal designs (e.g., students who complete the free association task at the beginning or at the end of the course).

Finally, computational methods from natural language processing could be adopted to measure the knowledge structure of textbooks and other reading materials that students are exposed to. The development of computational tools to extract meaning from billions of words has informed research on word recognition [45,46], semantic memory structure [10], and diachronic changes in word meanings [47]. These tools rely on distributional semantics, where words are embedded in vector spaces that reflect their co-occurrence relationships [48,49]—words with similar patterns of co-occurrence relationships with other words are said to be most semantically similar [50]. Co-occurrence relationships among words in a corpus can be represented as a language network where edges are placed between words that co-occur with each other in a corpus [51,52]. Note that this approach differs from the methods discussed previously that derive network representations from behavioral data provided by students. In this case, the focus is on quantifying the information spaces, or the learning environment, that students are exposed to, which over time shape the internal knowledge representations of students to some extent. Research in language development indicates that children's cognitive and vocabulary development are influenced by the quantity and quality of language input provided by the parent or caregiver [53,54], and children tend to learn words that are central or stand out in the semantic landscape of words that they are exposed to [39,55]. These results suggest that it is important to consider the role that the structure of the "input" provided to the students plays in their learning and the development of their knowledge networks.

2.2. Measuring the Network at Multiple Scales

Once the learner's knowledge is represented as a network, we can analyze that network in various ways to gain insights into the structural properties of that knowledge representation. This section describes the network measures commonly used to analyze networks at three different scales (see Figure 1)—at the level of individual nodes (micro-level), at the level of the entire network (macro-level), and at the level of intermediary sub-groupings of the network (meso-level)—and briefly considers how these measures might be interpreted within the context of a knowledge network. Table 1 provides a summary of common network measures and their potential application to the educational sciences.

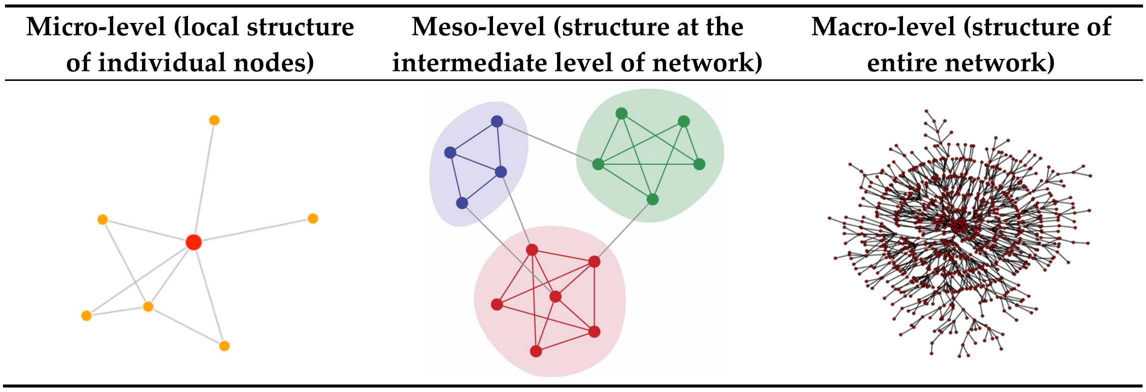


Figure 1. Visual depictions of various levels of analysis of a network.

Table 1. Commonly used network measures and their potential application to the educational sciences. Measures in italics were discussed in the paper.

Network Measure	Level of Analysis	Potential Educational Application
Degree Local clustering coefficient *Closeness centrality* *Betweenness centrality*	Micro-level	• Identification of central or bridging concepts • Measure of efficiency of retrieval • Measure of effectiveness of integration into memory
Community structure (modularity)	Meso-level	• Communities reflect themes or major topics in a discipline
Average degree *Global clustering coefficient* *Average shortest path length* *Small world index* Network diameter	Macro-level	• Compare network characteristics of expert and novice networks • Compare network characteristics before and after educational intervention

2.2.1. Micro-Scale of the Network

At the level of individual nodes, centrality measures are frequently computed to provide some indication of "importance" of a given node in the network. There are many different centrality measures that have been developed in the network science literature [56] and while it is beyond the scope of this review to discuss all of them, this section will focus on the following measures of degree, closeness centrality, and betweenness centrality to provide a flavor of how these network measures could be relevant for the education and learning sciences.

Degree refers to the number of immediate connections that a node has. Within the context of knowledge networks, a high degree node has many neighboring, closely related concepts, whereas a low degree node has few neighboring, closely related concepts. The degree of a concept in a knowledge network could have implications for (i) the efficiency of retrieval of the concept and (ii) the effectiveness of integrating a new concept into memory. In a situation where a student is required to retrieve a specific concept (e.g., on a test), the activation of a high degree concept might lead to the activation of other closely related concepts and elicit greater competition among activated concepts, analogous to psycholinguistic work showing that words with many similar-sounding neighbors experience more competitive effects and tend to be recognized less quickly [57]. Whereas in the context of learning a new concept, having many neighboring concepts might facilitate the learning of that concept, analogous to research in word-learning that indicate that newly acquired words with many neighbors tend to be better integrated into long-term memory structure as these words have more connections to existing lexical representations [58].

Closeness centrality measures the extent to which a node is "close" to other nodes in the network. A node with high closeness centrality is close to many nodes in the network as there is a short path between the target node and all other nodes, whereas a node with low closeness centrality is far from many nodes in the network as there is a long path between the target node and all other nodes. Psycholinguistic studies have shown that the closeness centrality of words in a lexical network affects the speed of retrieval of words in a word recognition task, such that words with greater closeness centralities tend to be recognized more quickly than words with lower closeness centralities [59,60]. Similarly, we may expect that concepts with high and low closeness centralities to also have some influence on learning and retrieval processes. For instance, concepts with high closeness centralities may represent especially important concepts that occupy central locations in the knowledge space and that need to be grasped in order to facilitate connections to other concepts.

Betweenness centrality measures the extent to which a node lies on the shortest path between any two nodes in the network. A node with high betweenness centrality frequently lies in "between" the shortest path between all possible pairs of nodes in the network, whereas a node with low betweenness centrality does not tend to lie on the shortest path between all possible pairs of nodes in the network. Betweenness centrality is a potentially important network measure for education and learning scientists to consider because concepts with high betweenness centralities might represent landmark concepts that are crucial linking concepts that bridge distant concepts in a knowledge space, and it could be informative for how students navigate the knowledge network.

2.2.2. Macro-Scale of the Network

Macro-level network measures provide an indication of the overall structure and connectivity of the network as a whole, and reflects the global organization of the knowledge network. Some of these macro-level networks measures are simply averages of the corresponding micro-level metric. For instance, the *average degree* of the network is computed by averaging the degrees of individual nodes.

Other examples of macro-level network measures include *average shortest path length* and *global clustering coefficient*. Average shortest path length (ASPL) refers to the average of the length of the shortest path between all possible pairs of nodes in the network. Global clustering coefficient refers to the number of closed triangles relative to the total number of triangles that is possible for a given number of nodes in the network [61]. A ubiquitous characteristic of many real-world networks is that they tend to have low ASPLs and high amounts of local clustering relative to a random network with the same number of nodes and edges [61]. Networks with such properties are said to have a "small-world" structure, and have important implications for understanding cognitive search and human memory because the emergence of a small-world structure may be associated with the trade-off of reducing distance between nodes and the cost of creating long-range links between nodes that are far away (as in brain networks; [62]).

Within the context of knowledge networks, measuring the small worldness of these networks could provide an indication of efficiency and navigability within the internal knowledge structures of students [63]. Macro-level measures such as ASPL and global C could be used to compare the network structure of knowledge networks obtained from different populations (e.g., between experts and novices) or before or after an educational intervention. For instance, one might expect experts to have a knowledge network with a greater *small world index* (i.e., more "small-worldness"; [64]) as compared to novices who may have a knowledge network that resembles more of a random network. The more random network structure of novices may reflect pre-existing misconceptions or misunderstandings of a topic that are manifested as inaccurate edges and/or missing edges between concepts. To provide another example, evidence of a successful educational intervention might be reflected in global changes in the knowledge network that improves its overall efficiency and navigability.

2.2.3. Meso-Scale of the Network

Many real-world networks also possess *community structure*, which refers to a meso-level property of networks in which there are subgroupings of nodes whereby nodes are better connected to nodes within the same subgroup as compared to nodes outside of the subgroup [65]. There are many community detection algorithms in the literature, each providing a slightly different way of partitioning the network into communities [66]. Within the context of education sciences, communities of nodes in knowledge networks may reflect natural sub-topics within a broader field, potentially revealing non-intuitive sub-topics that are difficult to detect or reflecting themes and topics in a domain that could be useful for guiding the design and planning of courses and modules. For instance, [67] conducted a community detection analysis on knowledge landscapes of the history of science and found that thematic groupings emerged around person-centered landmarks. Community detection methods could also be used to identify bridge concepts that link two or more communities (i.e., concepts that lie on the "edge" of communities), which might represent especially important concepts that require extra attention so that students may build connections across "disparate" sets of information and build a more cohesive knowledge network.

2.3. Summary

This section provided a gentle introduction to how methods from cognitive psychology could be used to infer knowledge and conceptual networks, and how these networks could be analyzed at different levels, or scales, of the network structure. An introduction to some network science measures and their potential applications to education research is also provided. The main takeaway from this section is that representing what students know as a "knowledge network" affords the application of network analysis to quantify various aspects of its structure, which have the potential to inform research in the educational and learning sciences. Indeed, it is striking that researchers interested in understanding learning, encoding, and retrieval processes among students are not capitalizing on the tools of network analysis to investigate the underlying knowledge networks that students are necessarily constructing over the course of their learning [15,16]. In addition, representing concepts and their interrelationships as a complex network aligns more closely to our intuition that knowledge is inherently relational in nature, and that expertise is reflected in an interconnected, well-integrated organization of concepts in a given domain.

3. Quantifying the Development of Expertise through Network Analysis

One important goal of education is to build domain expertise among students so that they not know only a lot about a given domain, but are able to connect ideas and concepts in meaningful ways. This section focusses on how long-term conceptual change and knowledge development might be quantified via the network science framework. The first part of this section reviews the burgeoning literature in language development research that uses generative network growth models to investigate the growth of language networks among children, and suggests how these generative network growth models could be applied to examine the development of knowledge networks. The second part is admittedly quite speculative, but briefly considers two specific examples in which the tools of network analysis could be beneficial for educators in the design and planning of course syllabi and lessons in order to maximize the development of subject expertise among students.

3.1. Using Generative Network Growth Models to Track Conceptual Development

Not only do children experience a growth spurt in vocabulary size over the course of early language acquisition, the underlying structure of their language networks also undergoes rapid changes. There is a growing number of papers that have used the tools of network science to investigate the development of language networks in early life [12,13,40,55,68,69]. Particularly relevant to this work are generative network growth models developed by network scientists to examine the mechanisms to explain the various structural features of networks.

One prominent example of a generative network growth model is preferential attachment, where new nodes are more likely to attach to existing nodes in network that already have many connections [70]. Networks grown via the mechanism of preferential attachment have a power law degree distribution, where there are few "hub" nodes with many connections and many nodes with fewer connections [70]. When adapted for the context of language acquisition, generative network growth models could be considered as learning biases or algorithms that can ultimately shape the overall structure of the learner's mental lexicon. As compared to a random acquisition model where new words are randomly added to the language network, language networks that prioritize the acquisition of words that have many semantic connections (i.e., high degree) in the learning environment are more probable given the empirical data [39,55]. This network growth model is known as preferential acquisition in the literature [39]. In other words, children appear to learn new words that occupy "central" locations and would otherwise "stand out" in the language environment that they are exposed to. In contrast, the preferential attachment model did not provide good fits to the empirical data. Overall, the literature suggests that language acquisition processes in young children appear to be more sensitive to the structure of the language environment that they are exposed to (i.e., preferential acquisition) rather than to the internal structure of the children's existing vocabulary (i.e., preferential attachment).

These generative network growth models could similarly be translated to learning within the educational context. Figure 2 provides an overview of three network growth models commonly investigated in language development and suggests how they might be relevant in an educational context. Recall that the preferential attachment model states that the learner would be more likely to learn new nodes that, when added to the network, tend to be connected to existing nodes with many connections. In the context of a knowledge network of concepts, this model corresponds to learning that is driven by the internal connectivity of a learner's existing knowledge network. Here, prior knowledge plays a strong role in guiding the concepts that are most likely to be acquired, such that richly connected concepts tend to become more richly connected over time. This jives with education research showing that prior knowledge of learners strongly affects how they search, process, and interpret new pieces of information [71–73]. The preferential acquisition model states that the learner would be more likely to learn new nodes that have many connections in the learning environment. Hence, it is the structure in the external, learning environment that learners are exposed to that drives growth in the knowledge network, whereby salient, "landmark" concepts are most likely to be learned. Finally, the lure of the associates model states that the learner would be more likely to learn new nodes that would form many connections with existing nodes in the network [58]. Within the context of a developing knowledge network, this is analogous to learning that is driven by making connections between a learner's existing knowledge and the material to be learned. New concepts that have many "hooks" and connect readily to many aspects of what the learner already knows are more readily integrated into the knowledge network.

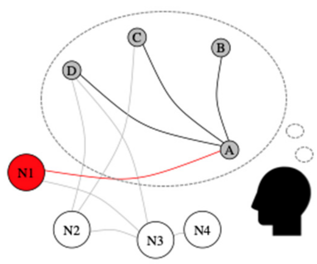
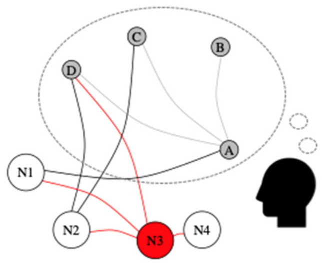
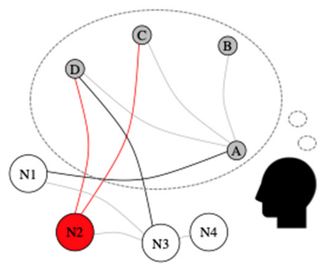
Preferential Attachment.	**Preferential Acquisition**	**Lure of the Associates**
		
Internal structure drives growth	*External structure drives growth*	*Connections between internal and external structure drive growth*
○ Learner's prior knowledge drives growth ○ "Rich" concepts become more richly connected	○ Structure in the learning environment drives growth ○ Salient, "landmark" concepts are learned first	○ Connections made between classroom material and current knowledge drive growth ○ Concepts with more "hooks" are learned first

Figure 2. Modeling the growth of knowledge networks with generative network growth models. Smaller, grey nodes represent concepts already known by the learner (i.e., prior knowledge). Larger white and red nodes represent the concepts to be learned (i.e., the external, learning environment). Connections between concepts indicate the existence of a meaningful relationship between the concepts. Connections in bold are relevant for computing the network growth model prediction. Red nodes represent the concept that is most likely to be acquired based on the network growth model prediction.

When applied to the context of education and learning, these network growth models could potentially provide new ways of quantitatively tracking the learning trajectories of students. It could also be important for helping educators decide what sort of learning or teaching strategy would be most appropriate given the interactions between the student's current knowledge and the nature of the content to be acquired. For instance, when the learner is very new to a topic, preferential acquisition might be a more useful approach as the focus is on capitalizing on structure in the new content to facilitate learning. In the classroom, the educator could emphasize central, landmark ideas in the discipline and make them more salient to students. On the other hand, when the learner has accumulated more knowledge about the topic, we might expect that the structure of the existing knowledge network would begin to drive learning in different ways (i.e., preferential attachment). An educator might also exploit the lure of the associates mechanism by making explicit as many connections as possible between a student's existing knowledge and the new material, scaffolding the development of the learner's knowledge network.

3.2. Network Science in Educational Design

Educators are essentially designers. Wiggins et al. argue that much of what teachers do is to craft course syllabi, curriculum, lesson plans, learning activities, and assessments in order achieve certain educational goals [74]. If one of these educational goals involves the development of students' knowledge in a given domain, network science approaches could be useful for helping educators achieve this goal. The subsequent sections briefly consider two ways in which network science approaches could be relevant in guiding educational design through optimizing the development of knowledge networks.

3.2.1. Backward Design and Network Growth Optimization

Backward design is the idea that educators should "begin with the end in mind". Engaging in deliberate and focused instructional design requires teachers to first think about what are the sorts of learning and understandings that students should achieve at the end [74]. The first stage of backward curriculum design involves deeply considering what students should know and understand by the end of the course, before designing appropriate assessments to assess student learning and before planning learning experiences and instruction that would enable students to achieve the learning goals identified in the first stage.

From a network science perspective, the end-goal of education could be concretely envisioned as students attaining an end-state knowledge network that is large in size (i.e., students should know a lot about a given domain), but also has a small world structure (i.e., students are making meaningful, non-random connections between ideas), rather than simply acquiring a random assortment of facts. As discussed above, small world structure in real-world networks has important implications for understanding the efficient transmission of information flow in the network. For instance, various language networks that represent the structure of the mental lexicon have small world structure that allows for activation to spread rapidly throughout the network, permitting rapid navigation within the network [75] and efficient lexical processes related to word retrieval and lexical selection [76,77]. Acquiring a knowledge network that has small world structure should allow students to navigate their knowledge networks efficiently and could form an important foundation for students to extend upon their current knowledge or generate new knowledge. In addition, a small world knowledge network should be more robust to the random forgetting of facts over time.

To this end, network science approaches could be relevant in two ways. First, in addition to traditional assessment methods, the behavioral paradigms used in the cognitive science to estimate the structure of semantic networks (as reviewed in Section 2.1) could be adopted to quantify the structure of students' knowledge networks of a given topic. This could serve as an additional indicator that informs the educator (and students) about whether educational goals are being met. For instance, the knowledge network of a class of students could be estimated using the free association task at the beginning and at the end of the course, providing a visually compelling indicator of the complexity of the knowledge that the students have gained over the course of the semester, or conversely revealing sparse, underspecified areas of the knowledge network. Second, if obtaining a "small world knowledge network" were an explicit educational goal, educators could "reverse-engineer" the processes that need to occur in order for that goal to be achieved. At the very least, this informs educators' design decisions with respect to the type of learning and teaching activities that would be most effective for students to build strong associations among closely related concepts (i.e., achieving high levels of local clustering) as well as draw non-intuitive or long-distance connections between less immediately obvious sets of concepts (i.e., reducing the overall distance between concepts in the network).

3.2.2. Enduring Understandings and Gap Filling in Networks

An integral part of effective instructional design is to identify "big ideas", or enduring understandings at the heart of a discipline, that are important for students to know [74]. An enduring understanding is an important idea that is central to the discipline and that is essential in order to attain an in-depth understanding of the area. Unfortunately, Wiggins et al. [74] do not say much about what these enduring understandings or big ideas should be and it is ultimately left to the domain expert to figure out. However, this is easier said than done as important ideas that may be intuitive to domain experts are not necessarily obvious to the layperson. Network science methods could be valuable in providing a quantitative analysis of expert knowledge structures in order to identify central or bridging concepts by computing various network measures of centrality. This approach has been used by Koponen and colleagues to analyze the knowledge structures of experts and to identify concepts that represent global landmarks in the knowledge landscape [29,67,78,79].

Finally, the evidence suggests that students tend to mis-regulate their learning [80,81]. In other words, students are not accurate judges of how well they have learned a topic, particularly if the topic was challenging [81]. It may be possible to improve metacognitive or self-regulatory skills of students by being strategic about the introduction of core principles and specific ideas in the discipline that purposely creates "gaps" in the knowledge space. Computational simulations conducted by [55] showed that young children acquire new words in a fashion that purposely creates gaps, or sparsely connected areas, in their language networks, which persist for some time before being filled in. The authors suggested that this process of gap formation and gap filling may be especially important for building language networks with a robust global structure despite the variability of the language input that children are exposed to [82,83]. Perhaps a similar process could be induced among students trying to acquire a complex network of discipline knowledge. The presence of "unknowns" in the knowledge landscape might naturally motivate learning based on information seeking strategies that attempt to reduce uncertainty [84], for example, via an information seeking strategy of searching for specific pieces of information to fill in knowledge gaps. By being explicit and upfront about the enduring understandings that students should take away from the course, educators could mimic a universal property of learning in complex environments by intentionally "setting up" an underspecified knowledge network that contains knowledge gaps. Educators could then design constructive learning activities and assessments that enable students to proceed from learning about coarse-grained concepts to fine-grained concepts, leading to the development of a robust and in-depth knowledge landscape.

3.3. Summary

This section provided an overview of generative network growth models, as well as a brief review of how these models have been used within the context of language development and how they could potentially be adapted to investigate long-term conceptual change in knowledge networks. The main takeaway from this section is that long-term conceptual change and knowledge development could be meaningfully quantified via the network science perspective. Generative network growth models could be used to examine the development of knowledge networks, and it is further suggested that the network science perspective could offer a useful conceptual framework for assisting educators in the design and planning of course syllabi and lessons in order to enhance the development of subject expertise among students.

4. Conclusions

Ultimately, the goal of education is to inspire and instill deep, meaningful, and long-lasting conceptual change in the knowledge landscapes of students. This commentary puts forward the idea that the network science approach could be useful in helping educators to achieve this goal. Although it is not easy to quantify or measure expertise [25], network science approaches could be useful for measuring the knowledge networks of students, and provide new ways of quantifying and tracking the development of domain expertise. By representing student knowledge as a network of interconnected concepts, the tools of network science and behavioral paradigms from cognitive psychology could be combined to measure and quantify the structure of such knowledge networks at various levels of analysis, as discussed in Section 2. In addition, the tools of network science could be relevant for investigating the developmental trajectories of knowledge structures, and further inform instructional design to maximize the acquisition of meaningful knowledge, as discussed in Section 3.

A deep consideration of the knowledge representation that students are acquiring provides an important complement to the current dogma in the field of cognitive science of learning, which predominantly focusses on the "process" of learning [15], as well as other areas of the learning sciences, which has focused on a variety of aspects ranging from the social network structure of learners [22] to how students develop their epistemic frames [23]. Although network science methods permit the quantification of knowledge representations and their developmental trajectories, long-term conceptual change will likely emerge from real-time feedback loops where the processes of retrieval and learning interact with, and are grounded within, the structure of knowledge landscapes that students are building.

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