Work in Progress: Knowledge Networks and Computer-Assisted Learning

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Abstract

Experts and learners organize knowledge into networks of knowledge bits (nodes) which are interconnected by relational links. This paper discusses a network model used by teachers and learners for a knowledge domain (say thermodynamics) consisting of knowledge nodes and links like curriculum and course structures and links. Course structures tend to first focus on knowledge clumps (say ideal gases) and individual nodes (say gas constants) and the links interconnect these nodes in a forward-directed, prerequisite manner. On the other hand, novice learners focus on individual nodes (say definition of entropy) and then look back for links to prerequisite nodes (say definition of heat transfer) as they build their own knowledge networks. Expert forward-directed network search strategies are compared to novice backward-directed strategies in this paper.

The goal of an expert AI search is to find a problem solution given inputs to the network while the goal of the learner is to find the perquisite knowledge required to master a knowledge node. Expert search strategies are then amenable to expert system AI strategies such as Bayesian statistics, cosine similarity and fuzzy logic. Learners seek to master the individual nodes and the relational links between nodes so that they can construct their own expert knowledge network. The strategies for meeting the learner goals are then completely different from those of the expert and not suited to well-known AI searching methods.

This paper also discusses the requirements of an AI system designed to assist the learner in meeting their goals as efficiently as possible. A brute force AI system which assists learners with building links and their knowledge network is discussed in this paper.

Introduction

The objective of this paper is to describe an artificial intelligent tutor system based on the concepts of and research on knowledge organization. A knowledge network based on the annotated graph approach to the organization of knowledge is presented in this paper. A brute force approach to tutoring learners with mastering a knowledge domain is also described. The results of student node tracking are also reported.

Constructivist theory of education is to assist students with the construction of their own understanding of a knowledge domain. Bruner [1] considered knowledge of a domain to be embedded in a structure and "grasping the structure of a subject is understanding it in a way that permits many other things to be related to it meaningfully. To learn structure, in short, is to learn how things are related." As stated by Montfort, et al. [2] these structures are continuously modified and evolving as individuals scaffold simple structures into more complex structures through conceptual understanding while developing expertise. Anderson [3] describes intelligence as “intelligence is the accrual and tuning of many small units of knowledge that in total produce complex cognition. The whole is no more than the sum of its parts, but it has a lot of parts.”

Larkin [4] defines formal domains as “domains involving a considerable amount of rich sematic knowledge but characterized by a set of principles logically sufficient to solve problems in the domain”. Many STEM disciplines are formal knowledge domains organized by certain principles and rules. These principles and rules are well known to experts and challenging to the novice/student. Lee, et al. [5] state that learning to solve problems in these domains “can be characterized as a search through a space of hypothesis about the rules for solving these problems”. Computer-assisted-instructional (CAI) systems are intended to help students navigate through this space of hypothesis as they discover and master the rules connecting this space

Anderson [6] and Ritter, et al. [7] in a comprehensive review of research on cognitive tutors state that there are three principles underlying the knowledge of a domain and mastering this knowledge: “First: there are two types of knowledge: procedural and declarative. Second: the knowledge required to accomplish complex tasks can be described as a set of declarative and procedural knowledge components relevant to the task. Third: both declarative and procedural knowledge become strengthened with use (and weakened with disuse).” The importance of practice and feedback is stated by Ambrose, et al. [8]; “goal-directed practice coupled with targeted feedback are critical to learning.”

Based upon these works we might conclude that formal knowledge consists of “sets of principles” or “knowledge components” organized in “in a structure” made up of “conceptual and procedural knowledge” that individuals “search through” as they scaffold simple structures into more complex structures. Formal STEM knowledge may then be represented as a network of concepts and procedures (knowledge components or nodes) like that of Figure 1 where principles and components are linked by rules and procedures (links or edges).

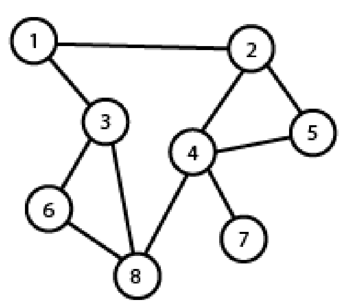

Figure 1: General Knowledge Network

Bedard and Chi [9] point out that the difference between the expert and novice is how they organize their knowledge and how they traverse their network. For example, consider a novice approach to solving a typical dynamic motion problem involving acceleration and Newton's law of motion. Experts tend to focus on previous knowledge like force (node 3 of Figure 2), mass (node 4) and acceleration (node 1) which leads them to Newton's law of motion (node 8). Experts then tend to traverse their knowledge network in a forward direction as suggested in Expert Mode of Figure 2. Novices typically direct their focus on the problem solution node (node 8) to find a procedure, like an equation, to follow to obtain a solution. If they do not understand a concept, like acceleration (node 1), they will jump to another node (node 4) in their search for a solution procedure. Students generally traverse their network in the backward sense as they add new nodes and links to their network.

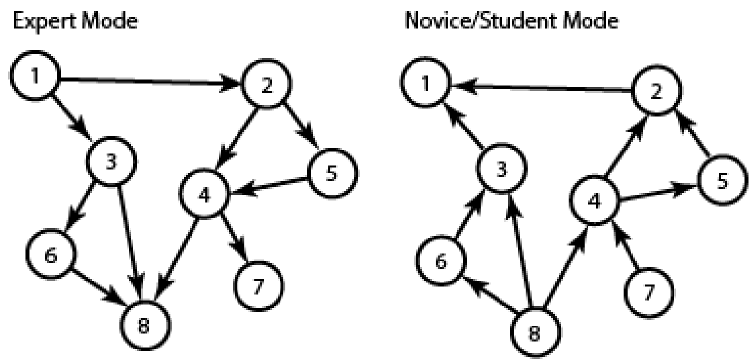

Figure 2: Knowledge Network Modes

Novices and experts build their knowledge networks by scaffolding previous knowledge networks or nodes based upon a prerequisite structure which is shown in the network of Figure 2. Inspection of any curriculum or course syllabus clearly illustrates the concept of scaffolding. For example, students study differential equations before studying control systems. The structure of a learning scaffold forms the knowledge network as illustrated by the node 2 to 4 link of Figure 2. The knowledge to be learned in node 4 is based, in part, upon the knowledge of node 2. Novices frequently must work backward through the network as they learn new knowledge based upon prerequisite knowledge.

When a novice is studying and mastering a node, the network links orient back to the concepts and prerequisites as illustrated in the Novice/Student Mode network of Figure 2. That is, novices may need to look back since they may not be able to recall or did not master the concepts and procedures required to understand the knowledge of a particular node. Students must then reflect upon the previous links and nodes in a search for that knowledge which is interfering with their learning that node.

The challenge for a computer-based-expert (CBE) system is to find the answer or correct procedure given bits of information generated by experts and data input by the user or instrumentation. Thus, given nodes 1, 2 and 5 of figure 2, CBE systems lead to the answer node 4. A lot of expert system research has been done and continues to be done on various expert system scenarios. Many algorithms and software packages are available for CBE systems, Hopgood [10]. A review of the history of neural networks and recent status of deep learning neural networks was reported by Schmidhuber [11]. A recent comprehensive review by Almasari [12] of some 68 intelligent tutoring systems include several systems based upon CBE.

CAI systems differ from CAE systems in that the goal is now to find the missing preexisting knowledge that is interfering with the learning of a node. Woolf [13] describes the considerations for CAI as well as the application of Bayesian networks, Markov chains, decision theory and fuzzy logic to CAI. She also discusses some of the software that is available and has been developed for CAI. One of the challenges of CAI is represented in the knowledge network of Figure 3 where a novice is in the process of learning node 8. The knowledge that was not learned previously or has been forgotten and is interfering with learning node 8 could be any one of the shaded nodes of Figure 3. Hopgood [10] describes this as a backward-faced rule-based network. But, unlike rule-based expert systems (e.g., automotive diagnosis systems) the specific interfering node is unknown and depends upon many factors such as individual student mastery of prior nodes, proximity of time at which previous nodes were learned, amount of practice with preceding nodes as well as other factors. Artificial intelligence which addresses these issues needs to be embedded in CBI systems to accommodate the needs of the user in a dynamic, user sensitive and efficient manner.

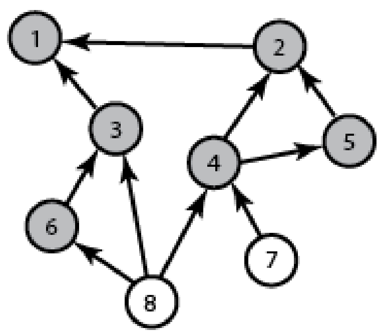

Figure 3: Computer-Based Learning System Challenge

KnowNet

KnowNet is an approach to CAI developed by the author, including software, which addresses some of these concerns. Specifically, KnowNet attempts to identify the node or nodes that interfere with students learning a node. It has been coded for general use and can be populated by experts for any knowledge domain. The author has populated, some 160+ nodes, a knowledge network for the typical introduction to engineering thermodynamics knowledge domain.

Each node in a typical KnowNet network like that illustrated in Figure 3 consists of a knowledge component and procedure/concept assessments which test the links to prior nodes as shown in Figure 4. For example, Carnot's first principle, "no heat engine can be more efficient than a completely reversible engine when both utilize the same energy reservoirs", is a knowledge component comprising a single node, node 8 of Figure 3 or initial node of Figure 4. The learner's understanding and mastery of a node is checked by assessment questions covering the node's concepts and procedures. Assessments for this example node then might be: questions testing the student's understanding of the procedure for calculating thermal efficiency, node 3, the concept of energy reservoirs, node 4, and the concept of heat engines, node 6. The number of assessments associated with a node depends upon the number of procedures and concepts covered by the node. Ideally, there is at least one assessment exercise for each concept or procedure included in the node, but this is not required when the node represents a completely new component of knowledge or the node is on the border of the knowledge domain. For example, node 8 of Figure 3 uses three assessments to measure the mastery of the knowledge in node 8 and node 1 is on the border of the knowledge domain and does not require any assessments.

Each incorrect response to an assessment question includes the immediate linkage or linkages to pre-knowledge nodes interfering with the mastery of the node being studied. In the example of Figure 3 nodes 3, 4 and 6 are directly related to the mastery of node 8. Subsequent links identify all the knowledge nodes, like the shaded nodes of Figure 3, that may also be the source of the knowledge interfering with learning a node. It is also possible that there is more than one interfering node among the shaded nodes of Figure 3. The challenge of an intelligent tutor as stated by Anderson [6], Ritter, et al. [7] and Woolf [13] is to identify those nodes in the inverted tree of shaded nodes in Figure 3 that are interfering with an individual student's learning a node, provide the student with an a review of the missing knowledge of the interfering nodes and give the student practice with the missing knowledge.

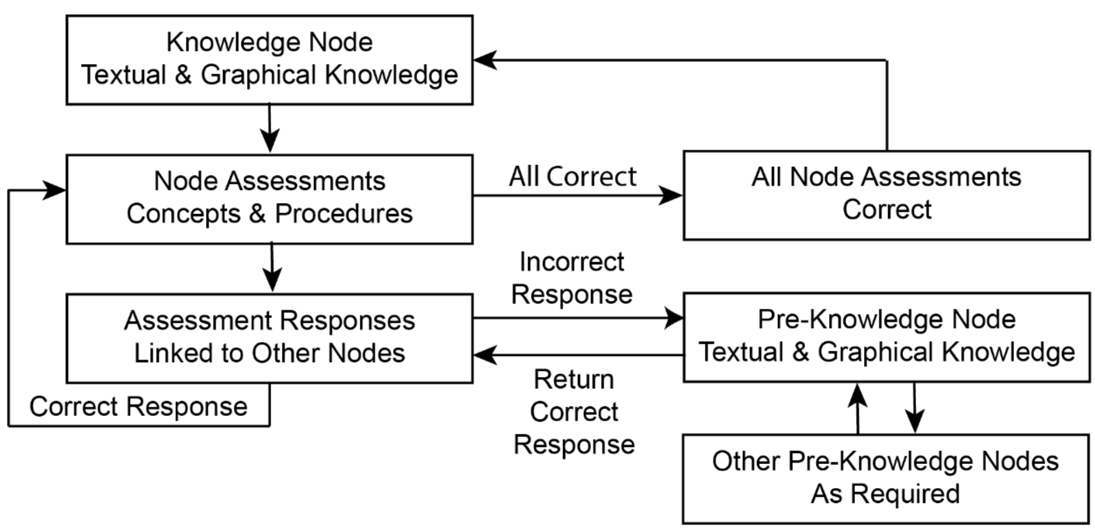

Figure 4: KnowNet Organization Diagram

Each KnowNet node consists of a knowledge component in text and accompanying graphic, if needed, as illustrated in Figure 4. One or more multi-choice assessment questions are included with each node. Each answer choice has one or more links to pre-knowledge nodes.

Novice learners begin by studying the initial knowledge node of Figure 4. After studying the node learners are required to answer one or more assessments covering the node concepts and procedures. If all assessment responses are answered correctly learners return to the initial node where they may elect to proceed to another node. But. if an assessment response is incorrect learners are directed to a pre-knowledge node linked to the assessment. The pre-knowledge node is administered in the same manner as the initial node. That is, after reviewing the pre-knowledge learners complete another set of assessments covering the pre-knowledge. If one of the pre-knowledge assessments is answered incorrectly learners are directed to another pre-knowledge node. Once learners have completed all pre-knowledge assessments correctly, they are returned to the preceding assessments. This process is continued until all node assessments have been answer correctly.

The nodes and linkages of a knowledge network like KnowNet are determined by knowledge domain experts. This expertise is often embodied in textbooks for mature STEM courses. Panels of experts and delphi processes like those used to develop concept inventory assessments can also be used to create a knowledge network. The KnowNet developed by the author for the introductory engineering thermodynamics domain is based upon the well-developed textbooks of Cengal and Boles [14] and Moran, et. al [15]. as well as several others. These textbooks are widely utilized and have been through several editions which have incorporated many suggestions offered by experts in this knowledge domain. Hence, they provide an excellent compendium of knowledge nodes and node links.

Artificial Intelligence

The current KnowNet version employs a brute force intelligent tutor. As it is not known which of the shaded nodes of Figure 3 are interfering with the learning of node 8 KnowNet works up the tree until it reaches all nodes where all assessments are answered correctly or a terminal node. For example, presume that a student is tested on the node 8 to 6 link of Figure 3. The knowledge of node 6 is then reviewed and the node 6 to 3 link assessment conducted. If this assessment indicates that there is further missing knowledge, node 3 needs to be reviewed and the node 3 to 1 link assessment would then be administered. Let's assume that this assessment indicates that the student understands the knowledge of node 1 by correctly answering any assessment questions of node 1. KnowNet will then go no further and proceed to start back down the tree pursuing unassessed links that were bypassed along the way.

A typical KnowNet review scenario of node 8 is illustrated in Figure 5. The dashed (also N) links indicate that no review was conducted while the solid (also R) links indicated that a review was conducted. The shaded nodes indicate nodes that were reviewed and assessed. In this example, there are six nodes shown in Figure 3 that a student must know in order to learn the knowledge of node 8. Inspection of Figure 5 reveals that the student has mastered one of the six nodes and that only five nodes need to be reviewed. Review of Nodes 3 and 1 is marginal in the sense that a review is determined by the context of the current node and its assessment. For example, node 8 is not directly related to node 3, but is indirectly related through node 6 and no direct review is needed. Node 1, like nodes 5 and 7, is on the edge of this knowledge domain and no assessment can be made beyond this node(s). As additional knowledge domains become available, they can be interconnected through appropriate links.

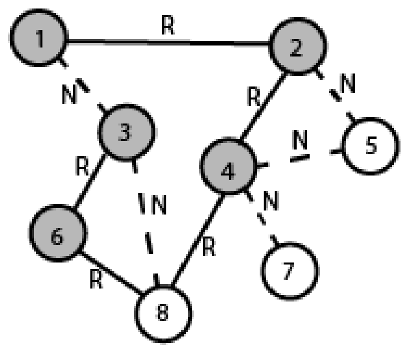

Figure 5: Typical KnowNet Student Review Scenario (R - Reviewed and N = Not Reviewed)

This brute force approach to an intelligence tutor assures that any missing knowledge will be covered through the search. But it is not terribly efficient as demonstrated by the shaded nodes of Figure 5 all of which are visited based upon the learner's assessment responses. Nodes 1 and 3 of that figure are only partially related to Node 8 depending on the context of nodes 2 and 6. But, nodes 1 and 3 are required to be visited and all assessments therein correctly answered. Although review is useful it is not efficient when the real interfering issue is node 2.

This approach to intelligent tutoring is tailored to individual students because the various N and R paths of Figure 5 are determined by individual student response to the various assessments. For example, another student may correctly respond to the node 6 to 3 link assessment and that link would now be a N link instead of a R link and node 3 would not need to be reviewed. Another student may correctly respond to all three node 8 assessments and no reviews would be necessary.

KnowNet's intelligence is through and exhaustive in that all necessary interfering nodes are reviewed by the student. No priorities are assigned to the interfering nodes to moderate navigation through the network. Only the network architecture determines how students navigate the network. Node 1 of the Figure 5 example may be the primary interfering node for a student and the student must work through several other nodes to get to the root knowledge needed to learn node 8. Although this is inefficient it does have pedagogical value in that it gives students practice with and review of other potentially interfering nodes.

Findings

KnowNet usage data were collected during the Spring semester of 2019 from 20 honor students enrolled in an introductory engineering thermodynamics course. A small portion (10%) of the course grade was based upon KnowNet usage. Students received full credit for this portion of their grade if they visited 100 or more nodes during the semester. Partial credit was awarded for fewer than 100 visits and no extra credit was awarded for more than 100 visits. In order to discourage users from “clicking-through” the nodes a timer was used to require users to spend at least two minutes with a node.

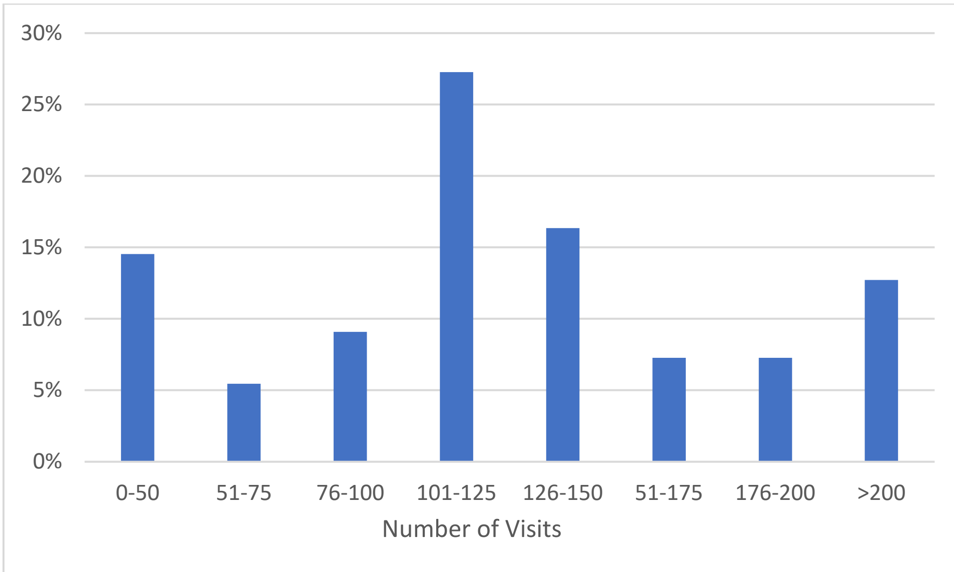

Figure 6: Student KnowNet Node Visits

The percentage of total student visits is presented in Figure 6. Note that students may have viewed more than one node if answering an assessment incorrectly. Each visited initial and pre-knowledge node counts as a single visit in the data of Figure 6. Over 25% of the visits were visited 101-125 times. This was expected because students had to make 100 visits to receive full course credit. Students did find value in that 43% of the visits of individual nodes were greater than the minimum required 100 visits. The lowest number of visits (0-50) is attributable to students who elected to either drop the course during the semester or felt that the extra effort was not proportional to the credit awarded. The remaining 15% of the visits below the required number may be due to students who did well enough with the other 90% of the course credit that they did not need full credit for the KnowNet portion of their grade. These students may have also simply lost interest in KnowNet or found that it was not adding value to their learning.

Node visit sequences were also tracked. Thus, if a student started at node 8 of figure 4 and then visited node 3 based upon the node 8 to 3 assessment link the sequence was recorded. Most of these sequences terminated with the initial node indicating that they understood the knowledge of that node and did not need any review. The second most occurring sequence consisted of two node visits. The assessments of the first node indicated that the knowledge of the second node was lacking and a review was conducted. Typically, the second node occurred very close in the course sequence to the first node. Students then had at that time insufficient experience with the knowledge of the second node to be able to see the relation between the two nodes. A very small number of sequences visited three or more nodes. Some, a very small number, sequences were visited five or six nodes.

Conclusion

The concept of knowledge networks and application of artificial intelligence to intelligent tutors as applied to a specific learning system was discussed. KnowNet which is a specific application of a knowledge network was developed for a specific STEM knowledge domain. Although this paper uses the knowledge domain most familiar to the author to illustrate KmowNet, it is general and may applied to any relational knowledge domain that is typical of STEM knowledge. An authoring user interface is currently under development and will be available to others wishing to develop their own knowledge networks. Each node in KnowNet consists of knowledge components and assessments to test the links to prerequisite nodes that may be interfering with the learning of a node. The entire network is then constructed by knowledge content experts with nodes and assessment links as described in this paper. A brute force tutor has been incorporated into KnowNet to assure that all possible nodes interfering with learning a node are reviewed by the user.

Student usage data in the form of number of visits and visit sequences were recorded and analyzed. This data indicated that students did find value in knowledge networks as a means for learning the knowledge domain since approximately one-half of the visits exceeded the number of visits required to earn their course grade. Analysis of the visit sequences indicated that most students found what they needed in the initial visited node and may not have completed the node assessments as they were perceived as being unnecessary. The next most visited sequence consisted of an initial node and follow-up node which was very close in the course sequence to the initial node.

Observations and user comments indicated that the brute force approach to tutoring was inefficient in that students were required to visit many nodes that they did not find particularly helpful. Consequently, a Baysian-like approach to assigning probabilities of interference to nodes in the interfering tree is under development. Unlike a Baysian approach which reassigns all node and link probabilities when an assessment indicates a review is needed, KnowNet only updates the probability of a single interfering node for all nodes. Once this development is completed users will be directed to the most probable inferring node first and then to the next most probable node second and so on until they demonstrate comprehension of the node being reviewed at which point the visits are terminated.

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