

Multi-decision Approaches for Eliciting Knowledge Structure

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Abstract This chapter describes two computer-delivered multi-decision approaches for eliciting knowledge structure. First, some relationships between eliciting relatedness data and its subsequent analysis and representation are discussed. Then several methods of eliciting relatedness data are considered including the implications of establishing the elicitation task context. Next two computer-based multi-decision approaches for eliciting relatedness data, listwise and sorting, are described that were designed specifically to complement the Pathfinder analysis and representation approach and then two experimental investigations using these approaches are reviewed. After considering some limitations of these two approaches, it is argued that combining the two can overcome some weaknesses in individual approaches, and existing data is reanalyzed to examine the adequacy of a combined approach relative to the traditional pairwise approach. Finally the next stage of development of a free software tool is described with possible future applications of this combined approach.

Keywords: eliciting relatedness data, knowledge structure, mental models, multi-dimensional scaling, Pathfinder Networks

Knowledge Structure

What is the nature of knowledge and of expertise and how can it be measured? Investigator's beliefs about the nature of knowledge determine the set of tools they use to consider this issue and colour their understanding of what knowledge is and is not. Following Anderson (1984), structure is the essence of knowledge (p. 5) and knowledge structure refers to how information elements are organized. Knowledge structure may be one facet of declarative knowledge (Mitchell & Chi, 1984) but Jonassen, Beissner, and Yacci (1993) go even further to hold that structural knowledge is a distinct type of knowledge, and that apposite structural knowledge is a critical go-between for declarative and procedural knowledge that facilitates the application of procedural knowledge (p. 4). Amalgamating these ideas, knowledge structure is the pre-meaningful foundation of knowledge; it is the mental lexicon that consists of weighted associations between knowledge elements (Rumelhart, Smolensky, McClelland, & Hinton, 1986) that are used to express meaning. From a measurement viewpoint, this means that knowledge structure is a domain bounded and fairly stable set of associations that develops incrementally but

occasionally can shift dramatically (e.g., insight). Thus it can be measured reliably, at least over short periods of time.

But context factors influence what is actually captured during an elicitation task. An ‘actuated’ knowledge structure arises on the fly as a subset of the full knowledge structure in response to the setting and so tends to be more fleeting or variable over time. The way relatedness or similarity data (Gentner & Rattermann, 1991) is elicited could be goal free and context free or not, the former obtaining a fuller knowledge structure and the latter an actuated conformation (a subset of the general structure). Thus the context that is set by the elicitation task probably matters a great deal in the structure of knowledge that is obtained. We will totally sidestep the question of the influence of personal goals on actuated knowledge structure, but will address the implications of context when eliciting relatedness raw data especially as it relates to multi-decision approaches.

Further, knowledge structure can be externally maintained and propagated through actions and artefacts such as this volume, and these are a residue of the actor’s/author’s knowledge structure. As you read a chapter, you are acquiring its knowledge structure as well as the actual information on the pages. The implication is that knowledge structure can be intentionally elicited from an individual in various ways, but it can also be derived from existing artefacts. The most common artefacts for this purpose are essays and concept maps (see the chapter by Draper and Clariana in this volume). Knowledge structures derived from these kinds of artefacts are actuated rather than general because the linguistic context is highly constrained by the writing task and purpose. Along these lines, most text signals such as headings, underlining, and highlighting *emphasize and thus convey the structure of the text* and this must enhance knowledge structure in the reader sometimes at the expense of subtopic information [REFERENCE]. Thus text signals and other devices are features of an artefact that deserve attention because of their likely direct effect on readers’ knowledge structure.

Conceptually, ‘structure of knowledge’ implies complex patterns and relationships that are difficult to express or study. Several classes of weighted association networks align very well with this conception of knowledge structure and so provide a ready and well established toolset for capturing, representing, analyzing, and comparing knowledge structures. These approaches increase but also constrain ideas for eliciting relatedness data and for representing, analyzing, and comparing it. After consideration, we have focused on Pathfinder analysis (Schvaneveldt, 1990).

This chapter describes two computer-based multi-decision approaches for eliciting relatedness raw data that were specifically designed to complement the intention of the Pathfinder analysis algorithm to reveal salient associations as a path of nodes. These two approaches were developed as an alternative to the traditional pairwise ratings approach commonly used to collect relatedness data for Pathfinder analysis because, for one reason, that approach can be tedious and time consuming if many terms are used and fatigue may negatively affect the data quality. Keeping this in mind, these two ‘new’ elicitation approaches (there is really nothing new under the sun, see Shavelson’s, 1972, 1974 approaches) were developed to increase the efficiency and possibly the accuracy of relatedness data and its representation and analysis. Serendipitously, combing these two approaches for eliciting relatedness data may provide a superior measure of knowledge structure that appears to capture both local and global associations better than the pairwise approach.

The Relationship between Relatedness Data and its Analysis and Representation

There are many approaches to elicit concept relatedness, for example free word association, similarity ratings of pairs of terms, and card sorting (Jonassen et al., 1993). And there are many ways to represent (or re-present) that

data, for example multidimensional scaling (*MDS*) and Pathfinder network (*PFNET*) analysis. But different elicitation and also different representation approaches obtain different measures of knowledge structure. For example, free word association is one of the earliest and may be the valid approach (Jonassen et al., 1993, p. 32). Free word association probably elicits general knowledge structure unless intentionally or unintentionally biased by the task directions, context, situation, or other factors. For example, as one of many free association investigations that he conducted, Deese (1965, pp. 49) asked 50 undergraduates to free associate to a list of related terms such as ‘moth’, ‘insect’, and ‘wing’. During free association, each word from a list is presented one at a time and the participant responds with the first term that comes to mind. When given the list word ‘moth’, his participants responded with terms such as ‘fly’ (10 respondents), ‘light’ (4 respondents), ‘wings’ (2 respondents), and ‘summer’ (2 respondents). This data set (Deese, 1965, p.56) obtains related but different representations when analyzed and displayed by *MDS* or as a *PFNET* (see Figure 1). Besides clustering the terms in a different visual way and that there are links between terms in the *PFNET* but not the *MDS*, the two representations associate many of the terms similarly for example bug-insect-fly-bird-wing, moth-butterfly, and blue-sky-colour-yellow. But not all clusters are the same in both, for example bees-cocoon and butterfly-flower. The same data set produces different representations. Does it make sense to ask “are both representations correct?” or “which representation is better?” or “is one representation better for some purposes than the other?”

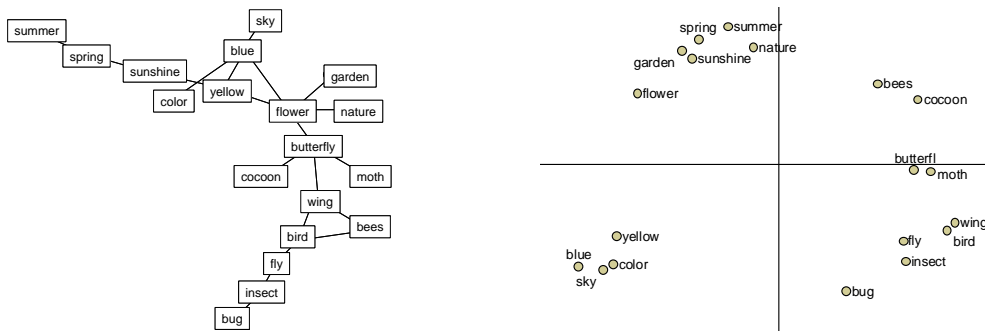


Figure 1. Pathfinder Network representation (left) and multi-dimensional scaling (*MDS*, right) of the intersection coefficient association data from Deese (1965, p. 56).

Relatedness raw data may have a large or small intrinsic dimensionality; but it is hard to visualize and think about high dimensional relations (i.e., above 3-dimension). Both *MDS* techniques and *PFNET* scaling are data reduction and representations approaches, but as pointed out in Figure 1, the algorithms used in *MDS* and *PFNET* reduce the raw data dimensionality in different ways with different results. The central issue in *MDS* representation of relatedness data is to obtain a reduced dimensional display (usually 2-dimensional for our benefit) that intends to preserve the nearness or orderings of all terms in the raw data. The reported stress value (a common measure of fit) indicates how well *MDS* was at re-presenting the higher dimensional raw data in fewer dimensions. By convention, high stress ($> .15$) means a poor representation and low stress ($< .1$) indicates an adequate fit. So unless an *MDS* representation has zero stress, some distances among terms are distorted, and the greater the stress value observed, the greater the distortion. In general, longer distances between terms (i.e., low relatedness) are more accurately represented in the lower dimension than are shorter distances (i.e., high re-

latedness) because the *MDS* algorithm uses all values but magnifies the effect of large values thus giving more consideration to low relatedness raw data (Roske-Hofstrand & Paap, 1990, p.63). Thus low relatedness raw data is accentuated and maintained in the lower dimensional structure at the expense of improved accuracy of the high relatedness raw data. If the stress is not too large, global clustering is likely to be good but local clustering less so, the distances between terms within a cluster of terms are likely to misrepresent the relatedness raw data.

The Pathfinder analysis approach is just the opposite, closeness counts in horse shoes, hand grenades, and *PFNETs*. *PFNETs* are graphs where terms or other entities are called nodes and links are shown to connect pairs of nodes to indicate strong relationship between those terms. The 'path' part of Pathfinder refers to the objective of the approach to determine a least weighted path connecting all of the terms, thus forming a connected graph (a connected graph is one where there is a path of links to connect any node to any other node in the network). Establishing the shortest path among all terms primarily depends on the high relatedness raw data elements and as a result, most of the low relatedness raw data elements are disregarded in the analysis (Roske-Hofstrand & Paap, 1990). Jonassen (1993, p.74) says that *PFNETS* represent local or pairwise comparisons between terms in a domain but not global information. Chen (1999, p. 408) says that Pathfinder analysis provides "a fuller representation of the salient semantic structures than minimal spanning trees, but also a more accurate representation of local structures than multidimensional scaling techniques." If structural knowledge influences our thoughts and actions more through local rather than global structures, we suggest that Pathfinder analysis provides a better match with our neural network in action and so at this point commit time and resources to investigating, improving, and supporting this approach.

Alternative Approaches to Elicit Relatedness Data

Probably the most common approach used to elicit psychological relatedness data for Pathfinder Network analysis is pairwise comparison. To do this, participants are shown pairs of terms and are asked to indicate how related the two terms are, usually on a 1-9 scale with 1 being lowest and 9 highest. This approach obviously directs the participants' moment-to-moment decision making to the local level which is appropriate for follow-up Pathfinder analysis that focuses on these local relationships. However, the pairwise approach is tedious especially if many terms are used. For example, 15 terms requires 105 comparisons while 30 terms requires 435 comparisons; the number of decision required is $n(n-1)/2$ where 'n' is the number of terms considered. Note that a direct relationship between the number of terms compared and the concurrent validity of Pathfinder Network analysis has been reported (Goldsmith et al., 1991), more terms means better validity.

Two multi-decision approach computer programs were designed specifically to support and complement Pathfinder analysis data reduction and analysis, one is a listwise comparison approach and the other is a term sorting task (Clariana, 2002; Taricani & Clariana, 2003; 2006). The next sections discuss the likely role of context when eliciting relatedness raw data, describe the listwise and sorting approaches, and then report two experimental investigations that utilized these multi-decision approaches.

The Role of Context

When relatedness data is elicited, context can influence participants' relatedness responses mainly by increasing the activation state of some ensembles (e.g., terms) and inhibiting the activation of others. The idea is that some terms that may otherwise be peripheral or absent take on a central role in the actuated knowledge structure conformation due to this influence of context. As far as we can tell, the role of context when eliciting relatedness

data has not been previously considered nor has its likely effect on the structure of knowledge that is obtained. If context does influence the resulting knowledge structure artefact, then context must be controlled when eliciting relatedness data.

One way to control context when eliciting relatedness data would be to include more information in the prompt, for example by including a reminder of the lesson or course content associated with the task, a purpose for the task, the list of terms to be rated, or perhaps even a story narrative to frame the task. Probably in most past investigations, the elicitation tasks have used a prompt that does not intentionally set the context. For example, the *Rate* program provided with Pathfinder *KNOT* (2008) software says something such as, “Your task is to judge the relatedness of pairs of concepts. ... Our concern is to obtain your initial impression of overall relatedness. Therefore, please base your rating on your first impression of relatedness.” The *Rate* program does then show the complete set of terms once at the beginning of the task thus setting the linguistic context (Charles, 2000, p. 507), but then the list of terms is hidden as the participant completes each separate pairwise relatedness judgement for each pair of terms from the list.

Sometimes a story is the context. In an investigation of the influence of knowledge structure on insight as measured using Pathfinder analysis with pairwise relatedness raw data (Dayton, Durso, & Shepard, 1990), the eliciting prompt stated, “A man walks into a bar and asks for a glass of water. The bartender pulls a shotgun on the man. The man says ‘thank you’ and walks out. What missing piece of information would cause the puzzle to make sense?” (p. 269) To elicit the acuated knowledge structure for this situation, the following 14 terms (i.e., requiring 91 relatedness judgements) were presented using the pairwise approach: *bar, bartender, friendly, glass of water, loaded, man, paper bag, pretzels, relieved, remedy, shotgun, surprise, thank you, and TV*. There were four treatment groups that interacted passively or actively with different levels of context that included ‘story only’ who read the story (but also could not solve the puzzle) and immediately rated the 14 terms, ‘active nonsolvers’ who read the story and then asked yes-no type questions for up to 2 hours (but also could not solve the puzzle in that time) and then rated the 14 terms, ‘passive nonsolvers’ who read the story and then listened to tape recordings of an active nonsolver asking yes-no type questions for up to 2 hours (but also could not solve the puzzle), and ‘solvers’ who read the story and then asked yes-no type questions until they solved the puzzle and then rated the 14 terms.

The results showed that only the active nonsolvers and the passive nonsolvers had strongly related *PFNETs* (i.e., knowledge structure), thus spending 2 hours asking or just listening to someone else asking yes-no questions resulted in more similar knowledge structures. However, the solvers who also had asked yes-no questions were fairly unlike any of the other groups, solving the puzzle resulted in a very different knowledge structure (or vice versa, the other knowledge structure resulted in solving the puzzle). Specifically, for all three of the nonsolver groups, the terms *man* and *shotgun* were central high degree nodes (with 4 links) while for the solver group, the term *remedy* was the central high degree node (with 4 links). The solver group had correctly concluded that the man had hiccups that were then cured by fear of the bartender’s shotgun. An inference of these findings is that the solver group was similar to the active nonsolver and passive nonsolver groups up to the moment of solution, and then the solvers’ knowledge structure radically shifted with this insight. Insight is a ‘flash of illumination’ (Metcalf, 1986, p. 239) or an ‘aha’ experience, the dramatic and rapid reorganization of knowledge structure to fit the problem context (Dayton et al., 1990). This begs another question, once solved (or even just told the solution) is the new knowledge structure fixed and fairly strongly locked in from that point on?

So in that investigation, the puzzle narrative and the list of terms were insufficient to drive a particular common knowledge conformation, thus the knowledge structure observed is probably each individual’s own personal unbiased representation of the puzzle. But spending more time with yes-no questions was sufficient to drive a more similar conformation probably incrementally, but then solving the puzzle suddenly altered that spe-

cific conformation into a new and different specific conformation (or vice versa, maybe the conformation shift allowed the solution to pop out).

So both too much as well as too little information in the prompt will influence the knowledge structure obtained. Because of the likely effects and influence of the prompt on the relatedness ratings and the resulting knowledge structure artefact, it seems critical to optimize the prompt with enough information to properly frame the task but not too much information that would bias the results. This could be accomplished by saying something such as “recall that the following terms were part of the lesson on ___ in order to ___” or some other such statement or story. Also, in order to establish and maintain the linguistic context, the list of terms to be judged should be displayed initially but should also be constantly available during the task to maintain the linguistic context.

Computer-based Listwise and Sorting Multi-decision Approaches

A listwise approach was developed as an alternative to the pairwise approach to more quickly elicit local relatedness data (*KU-Mapper*, 2005). Here, participants are shown a target term on the left of the computer screen and a list of all other terms on the right and are asked to pick one term from the list that is most related to the target term. Then a second term from the list becomes the target term, and so on until every term has been compared to the list of terms. The raw data output for follow-up analysis is an array of ‘1s’ (links) and ‘0s’ (no links). As with the pairwise approach, the listwise approach obviously focuses only on local relatedness, but the listwise approach is more efficient than the pairwise approach, 15 terms requires 15 decisions and 30 terms requires 30 decisions and so on. Thus if the listwise approach actually works, it should be superior for long lists of terms (see the left panel of Figure 2).

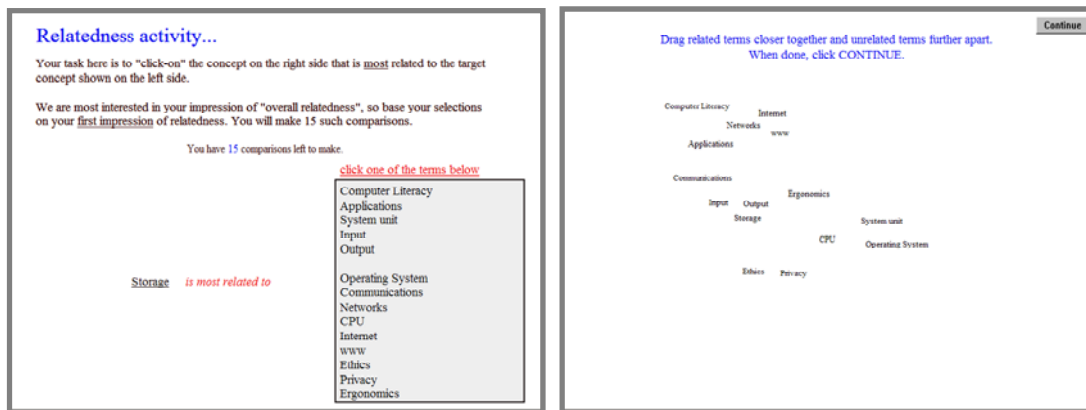


Figure 2. The listwise approach (left) and the sorting approach (right).

A sorting task approach was also developed to quickly elicit local and global relatedness data. Here, participants are shown all of the terms from the list randomly arranged on a computer screen and are asked to drag related terms closer together and unrelated terms farther apart, with no time limit. Essentially, the participant is asked specifically to represent the local and global relatedness of the terms. The raw data output for follow-up analysis are the distances between all terms, which are essentially 2-dimensional *MDS* maps with zero stress (see the right panel of Figure 2).

The Effects of Headings on Knowledge Structure

Clariana and Marker (2007) used these listwise and sorting task approaches to measure the effects of learner-generated lesson headings on knowledge structure. They proposed that memory of related lesson topics would be more like the lesson topic structure for participants who generate lesson headings relative to those who do not. Generating headings during instruction influenced structural knowledge as measured by the listwise and sorting tasks in a predictable way. However, the sorting task and the listwise task obtained different *PFNET* representations, so which is correct?

Because the lesson structure was finite and fully known, lesson structure could be described as two referents for comparison with the participants' data, a 'linear' referent that specified the linear order of 15 subtopics in the lesson and a 'nonlinear' referent that specified all the possible nonlinear links between subtopics within their appropriate topic area. Using these referents, the listwise task was a bit better at eliciting the linear subtopic structure and the sorting task was better at eliciting the nonlinear topic structure (see the left panel, Figure 3).

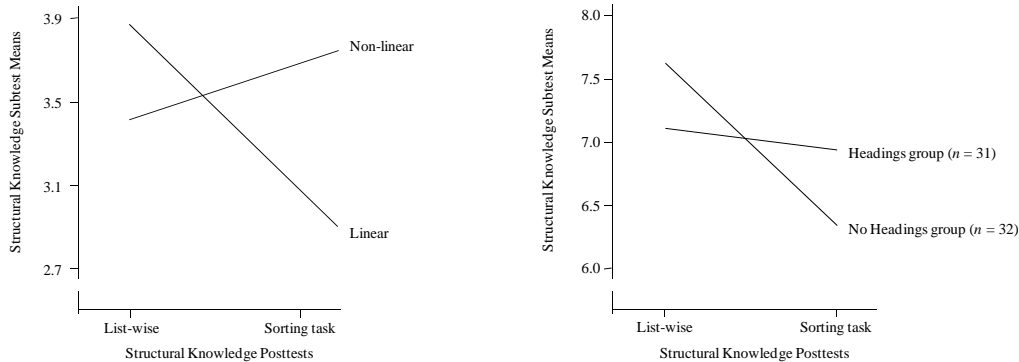


Figure 3. The significant interaction of relatedness task and knowledge structure (left) and of the headings treatment with knowledge structure posttests (right) from Clariana & Marker (2007, pp.186-187).

The authors also reported a significant interaction of the Headings and No Headings treatments with the listwise and sorting tasks posttests. The No Headings group listwise task mean was significantly greater than its sorting task mean while the Headings group obtained nearly identical sorting and rating task means (see right panel, Figure 3). This odd finding suggests that when an individual reads without headings, her knowledge structure is more like the lesson structure (linear plus nonlinear) when measured by the listwise task but at the same time it is *less* like the lesson structure when measured by the sorting task. To account for this confusing finding, we speculate that the lesson without headers tends to establish a very linear knowledge structure that is more accurately measured by the listwise task, while the lesson with headers establishes a clustered (less linear) knowledge structure that is more accurately measured by the sorting task.

Besides these findings, unreported correlation data from Clariana and Marker (2007) indicates that the linear and nonlinear measures for the sorting task or the listwise task were unrelated or negatively related (see Table 1). Also the listwise linear knowledge structure measure of the No Headings Group correlated more with the constructed response verbatim declarative knowledge posttest (i.e., CR Posttest) than did the sorting task measure, while for the Headings Group both the sorting task and listwise measures correlated with the CR posttest. We

suppose that a very linear knowledge structure matching the lesson topics provides some advantage when answering the constructed response verbatim declarative knowledge posttest questions.

Table 1. The No Headers and Headers treatment group correlations (Clariana & Marker, 2007).

	<u>A</u>	<u>B</u>	<u>C</u>	<u>D</u>	<u>E</u>
<i>No Header Treatment Group (n =32)</i>					
A. CR Posttest (15 max.)	1				
B. Sorting task (linear)	0.24	1			
C. Sorting task (non linear)	-0.02	-0.37*	1		
D. List-wise task (linear)	0.62**	0.30	-0.21	1	
E. List-wise task (non linear)	0.08	0.04	0.20	0.00	1
<i>Header Treatment Group (n =31)</i>					
A. CR Posttest (15 max.)	1				
B. Sorting task (linear)	0.22	1			
C. Sorting task (non linear)	0.49**	0.09	1		
D. List-wise task (linear)	0.44*	0.36*	0.39*	1	
E. List-wise task (non linear)	0.37*	0.30	0.30	0.04	1

p<.05; ** p<.01

An Investigation of the Listwise and Sorting Approaches Compared to the Pairwise Approach

Clariana and Wallace (est. 2009) directly compared the multi-decision listwise and sorting task approaches to the more traditional pairwise approach. Undergraduate students ($N = 84$) in an introductory business course completed the three approaches in random order after taking the final examination for the course. All three of the tasks used the same 15 important concept that were covered during the course. Results indicate that the three approaches substantially overlap but are differently sensitive to linear and nonlinear knowledge structure.

First, the two multi-decision approaches were faster than the pairwise approach, but not as much as might be expected. The pairwise approach on average required 447.4 s ($sd = 140.6$), the listwise approach required 193.3 s ($sd = 79.6$), and the sorting task approach required 115.5 s ($sd = 62.7$). The raw relatedness data from each task were averaged together to obtain a total group representation for each of the three approaches, pairwise, listwise, and sorting task (see Table 2). For total group averaged relatedness data, the listwise and pairwise approaches were most alike (71%; 10 of 14 links in common) and then listwise and sorting were next most alike (64% links in common); while the pairwise and sorting task approaches were relatively least alike (57% links in common). A linear and a nonlinear referent were created to reflect the actual structure of the 15 lesson topics as taught during the course, and the group average representations were compared to these referents. As in the earlier study, analysis of the similarity data showed that the listwise task was most sensitive to linear knowledge structure, but interestingly, the pairwise task and not the sorting task was most sensitive to non-linear structure. The listwise approach provided the best reflection of the actual course structure (43% of the linear referent and 7% of the nonlinear referent), and the pairwise and sorting tasks relation to the course structure obtained equal values (36% and 7%). The *PFNET* visual representations of the group averaged data show that the term *Internet* (2a) was a central high degree node (i.e., an important concept) for the pairwise and listwise *PFNET* representations (see the top panels of Figure 4).

Table 2. Links in common (above the diagonal) and percent of total links (below the diagonal) for each group average *PFNET* and the linear and nonlinear referents with the maximum number of links shown on the diagonal.

	<u>P</u>	<u>L</u>	<u>S</u>	<u>Lin</u>	<u>Non</u>
Pairwise (P)	(14)	10	8	5	1
Listwise (L)	71%	(14)	9	6	1
Sorting (C)	57%	64%	(14)	5	1
Linear referent (Lin)	36%	43%	36%	(14)	1
Nonlinear referent (Non)	7%	7%	7%	7%	(11)

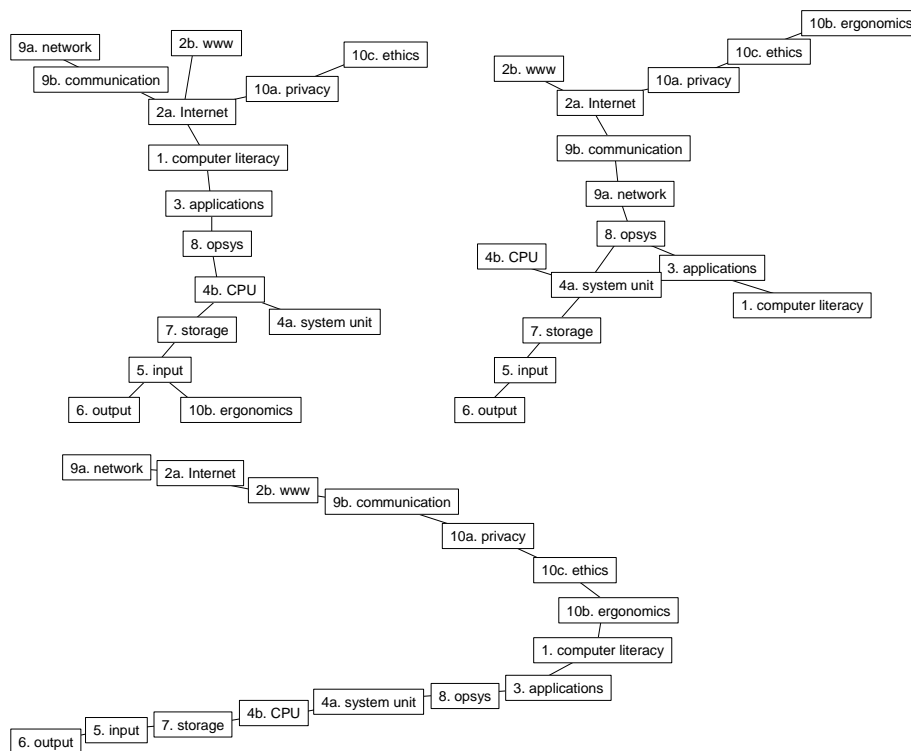


Figure 4. The *PFNETs* derived from the pairwise (top left), listwise (top right), and cluster (bottom) averaged group raw proximity data (from Figure 5 in Clariana & Wallace, nd). The numbers beside the terms indicate the chronological order of presentation of these concepts during the course (e.g., 2a and 2b indicate that these terms were taught in the same lesson with 2a taught just before 2b).

Although the listwise and sorting average group *PFNETs* were mathematically quite like the pairwise average group *PFNET* (e.g., 71% and 57% overlap), examination of individual's listwise and sorting *PFNETs* indicate that these were quite different structurally than that students' pairwise *PFNETs*. Inspection of pairwise *PFNETs* revealed that all are connected graphs (i.e., there is a path from any node to any other node in the graph) with from 14 to 17 links (mode 14) and most have branching (e.g., similar in appearance to the pairwise group *PFNET* in the top left panel of Figure 4). In slight contrast, nearly every participant's sorting *PFNET* is a connected graph with 14 links and no branches, all nodes have two links except for the beginning and ending node (similar in appearance to the sorting group *PFNET* in the bottom panel of Figure 4). But in even greater contrast, participant's listwise *PFNETs* were typically not connected graphs, all have *exactly* 15 links, and most have branching (see the left side of Figure 5). With the listwise approach, a worst case scenario for establishing a path between all nodes would be that all of the decisions resulted in a highly disconnected graph as the participant selects terms only within clusters of concepts, for example, selecting A-B, then B-C, then C-A (see the right side of Figure 5). This sort of 'clustering' was present but not common (see for example 10a-10b-10c configuration on the left side of Figure 5) possibly because participant's tend to associate terms linearly (Meyer & McConkie, 1973, p. 113) and so the listwise approach may especially elicit and capture linear associations. The problem with disconnected graphs with the listwise approach is that it is not clear which clusters of terms are more related to what other clusters. For example, in the right panel of Figure 5, it is not clear that cluster 1-2a-2b is closer to 3-4a-4b or 10a-10b-10c, all are equally disconnected from each other.

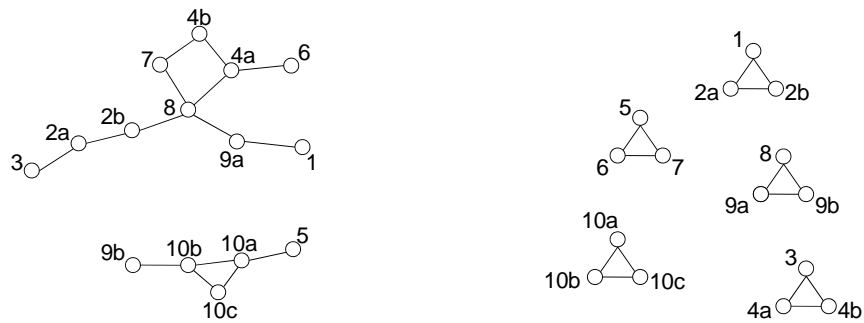


Figure 5. The listwise *PFNET* disconnected graph representation of a randomly selected participant (left) and a hypothetical listwise *PFNET* (right) that is highly disconnected consisting of 5 separate cycle graphs and yet it perfectly represents the nonlinear structure of the course content and strongly represents its linear structure.

So to summarize, it seems that for individual participant's, the sorting and the listwise approaches capture separate aspects of the pairwise approach (i.e., a connected path and branching) but neither approach fully obtains *PFNETs* that resemble the individual's pairwise *PFNET*. Thus, although the sorting and the listwise approaches seem to be satisfactory for group average representations, these two may be less adequate for purposes that require representations of individual's knowledge structure. It occurred to us that combining an individual's sorting and listwise raw data should result in a *PFNET* that is a connected graph (due to the contribution of the sorting task) thus indicating what cluster go together (global), and yet maintains the most critical linear associations due to the contribution of the listwise task (local). If this approach obtains viable *PFNETs* comparable to those obtained from the pairwise approach, then for long lists of terms, this combined

approach would be considerably faster to complete. Next, the relatedness data from the study by Clariana and Wallace (nd) are reanalyzed in order to compare the combined sorting and listwise measure to the pairwise measure.

Analysis of the Sorting and Listwise Combined Approach

The listwise and the sorting task raw relatedness data collected in the previous study by Clariana and Wallace (nd) were added together firsts by scaling the sorting task distances to a zero to one scale and then inverting it by subtracting from one thus changing it from dissimilarity to similarity values (where larger values means stronger relatedness) so that both data sets would be similarity data, and then adding the listwise and sorting values in each complementary cell of the arrays. Then the *PFNETs* were generated for this combined raw data so that each participant had a pairwise *PFNET* and a combined *PFNET*. To better visualize these different representations, the pairwise, listwise, sorting, and combined listwise plus sorting *PFNETs* of the student with the best course grade were established (see Figure 6).

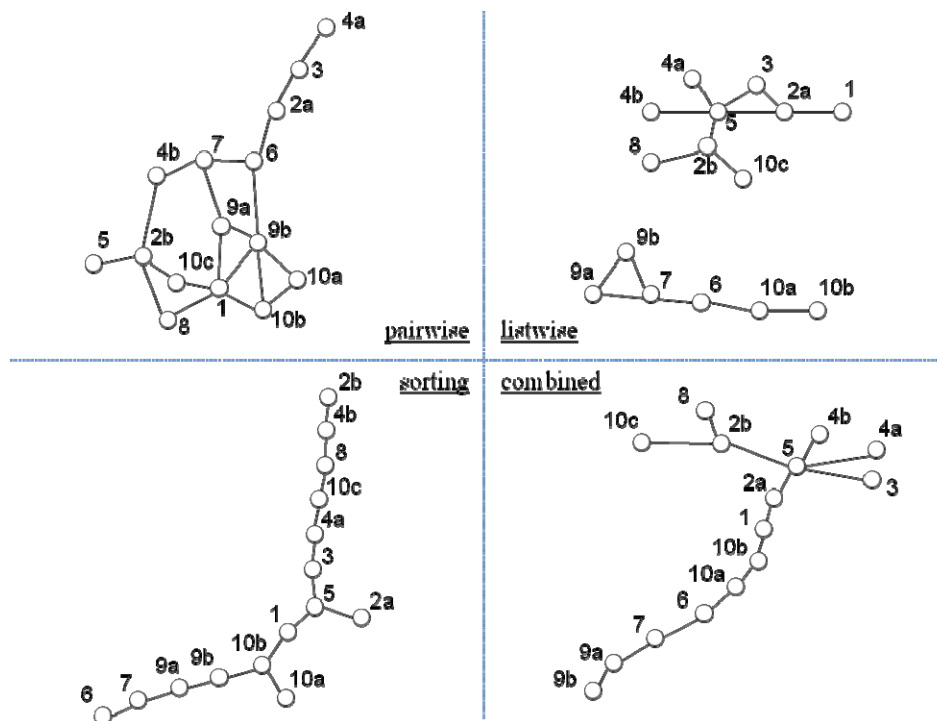


Figure 6. Pairwise, listwise, sorting, and combined listwise plus sorting *PFNETs* of the top-performing student.

The listwise *PFNET* dominated the combined *PFNET* structure, except for the link between terms 7-9a and between 2a-3 in the listwise *PFNET* did not occur in the combination *PFNET*, also the two portions of the listwise *PFNET* were joined between terms 1 and 10b (see Figure 6). This student's pairwise *PFNET* has 6 links that match the linear and 1 that matches the nonlinear course referents (i.e., the course organization, $7/20=35\%$ overlap) and 13 links that do not match the course structure, while his combined *PFNET* has 5 links that match the linear and 1 that matches the nonlinear course organization ($6/14=43\%$ overlap) and 8 links that do not match the course structure. The pairwise *PFNET* has two central (high degree) nodes, terms 9b and 1, while the combined *PFNET* has one central node, term 5.

For further comparisons, the participants' data were randomly assigned to two groups, A or B, by sorting the participants from high to low based on total course grade and then selecting data two at a time and randomly assigning to group A or group B. Then Groups A and B were partitioned by median split into high and low groups. The pairwise and the combined relatedness raw data were averaged for each of these four groups, High Group A ($n=20$), Low Group A ($n=19$), High Group B ($n=22$), and Low Group B ($n=18$), to obtain group average *PFNETs* for comparison. The combined approach was very consistent, obtaining a 93% overlap between the group average *PFNETs* for the high performers in Groups A and B (see Table 3) compared to 53% overlap for the pairwise approach; and 79% overlap between the group average *PFNETs* for the low performers in Groups A and B (see Table 3) compared to 53% overlap for the pairwise approach. Within group comparisons also show higher consistency for the combined compared to the pairwise approach. Analysis of percent overlap between average group performance and the linear and nonlinear referents also indicate that the combined approach reflected the course topic coverage, both linear and nonlinear, in most cases more than did the pairwise approach.

Table 3. Percent *PFNET* overlap between Group A and B high and low groups.

<u>Group and approach</u>	<u>Group A</u>				<u>Group B</u>			
	<u>A</u>	<u>B</u>	<u>C</u>	<u>D</u>	<u>E</u>	<u>F</u>	<u>G</u>	<u>H</u>
<i>Group A</i>								
A. High Group A, combined ($n=20$)	1							
B. High Group A, pairwise ($n=20$)	60%	1						
C. Low Group A, combined ($n=19$)	86%	53%	1					
D. Low Group A, pairwise ($n=19$)	83%	52%	76%	1				
<i>Group B</i>								
E. High Group B, combined ($n=22$)	<u>93%</u>	60%	86%	76%	1			
F. High Group B, pairwise ($n=22$)	79%	<u>53%</u>	64%	69%	71%	1		
G. Low Group B, combined ($n=18$)	79%	47%	<u>79%</u>	76%	79%	57%	1	
H. Low Group B, pairwise ($n=18$)	48%	58%	48%	<u>53%</u>	48%	48%	48%	1
<i>Referents</i>								
Linear referent	36%	27%	36%	35%	36%	43%	29%	35%
Nonlinear referent	24%	15%	32%	23%	24%	0%	24%	15%

Discussion and Conclusion

After considering several methods of eliciting and representing knowledge, our present view of knowledge structure best aligns with the Pathfinder analysis approach. We developed a computer program called *KU-Mapper* to implement two multi-decision approaches based on our view of knowledge structure and that complements Pathfinder analysis, a sorting task and a listwise task. During this development, we realized the likely influence of internal and external context on knowledge structure. Because of the sparseness of elicitation tasks, too little internal instructions/directions tend to misdirect participants and the knowledge structures obtained would not accurately represent their knowledge structure for the domain area, while too much internal or external context information biases the knowledge structure obtained towards those context variables rather than capturing the participants' knowledge structure (the Goldilocks' principle). We determined that the listwise and sorting tasks should include a brief descriptive review of the task domain and that it should include all of the list terms on every screen in order to maintain the lexical context during the elicitation task.

An investigation by Clariana and Marker (2007) suggests that the listwise task is better at eliciting and representing linear knowledge structure while the sorting task better elicits and represents nonlinear (cluster) knowledge structure. A moderately strong correlation ($r = .62$) was noted between the listwise *PFNET* measure and the constructed response verbatim declarative posttest for the group who did not generate headings. Possibly, generating headings while reading tends to shift participants' knowledge structure from linear to nonlinear, and this shift may account for these and for some previous findings of the effects of headings on various posttest measures. Instructors and researchers should be made aware that eliciting knowledge structure probably alters that structure (an intervening test effect).

An investigation by Clariana and Wallace (nd) directly compared the multi-decision listwise and sorting tasks to the traditional pairwise approach. Though individual listwise, sorting, and pairwise *PFNETs* were not strongly related, group average listwise, sorting, and pairwise *PFNETs* were strongly related, with the pairwise and listwise group average *PFNETs* sharing a 71% overlap.

Because of the likely limitations of individual participant's *PFNETs* obtained using the listwise and sorting approaches, a new approach was suggested that combined these two. Previous raw data from Clariana and Wallace (nd) were used to generate the combined (listwise plus sorting) data set and these were compared to the pairwise data using a more robust group average approach. The combined *PFNETs* were considerably more consistent across groups than the pairwise *PFNETs*. These preliminary results suggest that the combined multi-decision approach may be an adequate substitute for the pairwise comparison approach especially when the list of terms is long (30 or more terms). These results support further research to confirm or refute this combined approach. Our next step will be to update *KU-Mapper* to be able to generate the combined proximity data file to make this approach easily available to interested researchers.

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