Chapter 4
Multi-decision Approaches for Eliciting Knowledge Structure

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4.1 Knowledge and Knowledge Structure

What is the nature of knowledge and of expertise and how can it be measured? Investigators' beliefs about the nature of knowledge determine the set of tools that they use to consider this issue and the tools they use inevitably alter their understanding of what knowledge is and is not (Sternberg & Preiss, 2005). Our connectionist bias follows Anderson (1984) that structure is the essence of knowledge (p. 5), and knowledge structure refers to how information elements are organized. Knowledge structure may be a facet of declarative knowledge (Mitchell & Chi, 1984), but Jonassen, Beissner, and Yacci (1993) go further to suggest 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 their ideas, we propose that knowledge structure is the precursor of meaningful expression and is the underpinning of thought; said differently, knowledge structure is the mental lexicon that consists of weighted associations between knowledge elements (Rumlehart, Smolensky, McClelland, & Hinton, 1986).

Further, knowledge structure can be externally maintained and propagated through actions and artifacts such as this volume, and these are a residue of the actor's/author's knowledge structure. The implication is that knowledge structure can be intentionally elicited from an individual in various ways, but it can also be derived from existing artifacts, for example, from essays and concept maps (see Chapter 7, this volume). We hold a reductionist view that although an artifact must be interpreted or reconstructed by the reader, unless the information in the artifact is unintelligible, incoherent, or ambiguous, the reader will likely recapture to a greater or lesser extent the original author's knowledge structure.

Representations of knowledge structures derived from existing artifacts are probably highly constrained by the task and purpose of the artifact. Along these lines,

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most text signals such as headings, underlining, and highlighting emphasize and thus convey the structure of the text and this almost certainly must augment the artifact's knowledge structure in the reader. Thus text signals and other devices are features of an artifact that deserve attention because of their likely direct effect on readers' knowledge structure.

Conceptually, "structure of knowledge" implies patterns of relationships that are complex to express or investigate. Learning simply involves modifying the connection weight between units in the network, but these few changes may have unexpected or hard to predict effects on the entire set of relationships involved. If so, from a measurement viewpoint, this means that if knowledge structure can be measured, it should be a fairly stable set of associations that primarily change incrementally through experiences, reflection, and consolidation, although occasionally it can dramatically shift conformation (e.g., a flash of insight). Currently, these patterns of relationship can be most easily represented visually and mathematically as networks. 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, combining, analyzing, representing, and comparing knowledge structures. Any tools liberate but also constrain our musings. After careful consideration, we have focused on *Pathfinder* analysis as the optimal tool at this time (Schvaneveldt, 1990).

However, the *Pathfinder* approach for eliciting relatedness data depends on a pairwise rating approach that uses many single decisions and so is tedious, tiring, and time consuming, especially when more than 20 terms are compared. This chapter describes two computer-based multi-decision approaches for eliciting relatedness raw data that were specifically designed to complement *Pathfinder* analysis in revealing the salient associations as a path of nodes. 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 relative to the pairwise approach. Serendipitously, we determined while preparing this chapter that combing these two multi-decision approaches for eliciting relatedness data may provide an even better measure of knowledge structure that appears to capture both local and global associations better than the pairwise approach.

4.2 Relatedness Data and Its Analysis and Representation

There are several traditional approaches used 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 a few ways to analyze and represent that data, for example, hierarchical cluster analysis, 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 approaches for eliciting concept relatedness and is considered by some as the most valid approach (Jonassen et al., 1993, p. 32). Because it is nearly context free, free word association most likely tends to elicit a general knowledge structure (versus an actuated knowledge structure discussed later), 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, p. 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,” 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 Fig. 4.1).

Besides clustering the terms in a different visual way, and that there are links between terms in the *PFNET* but not in the MDS representation, the two representations associate many of the terms similarly, for example, bug–insect–fly–bird–wing, moth–butterfly, and blue–sky–color–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 “Is MDS better than *Pathfinder* analysis?” “Are both representations correct?” or “Is one representation better for some purposes than the other?”

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 three dimensions). Both MDS techniques and *PFNET* scaling are data reduction and representations approaches, but as pointed out in Fig. 4.1, 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 two-dimensional for our benefit, which 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 representing the higher dimensional raw data in fewer dimensions. By convention, high stress (>0.15) means a poor representation and low stress (<0.1) 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 are more accurately represented than are shorter distances because the MDS algorithm uses all raw data values but magnifies the effect of large values thus giving more consideration to low relatedness raw data (Roske-Hofstrand & Paap, 1990, p. 63) 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, and the MDS distances between terms within a tight cluster of terms are more likely to misrepresent the relatedness raw data.

The *Pathfinder* analysis approach is nearly the opposite; closeness counts in horse shoes, hand grenades, and *PFNETs*. *PFNETs* are graphs where terms or other entities (called nodes) are joined by links (called edges) to indicate strong relationship between those terms. The “path” part of *Pathfinder* refers to the objective of the

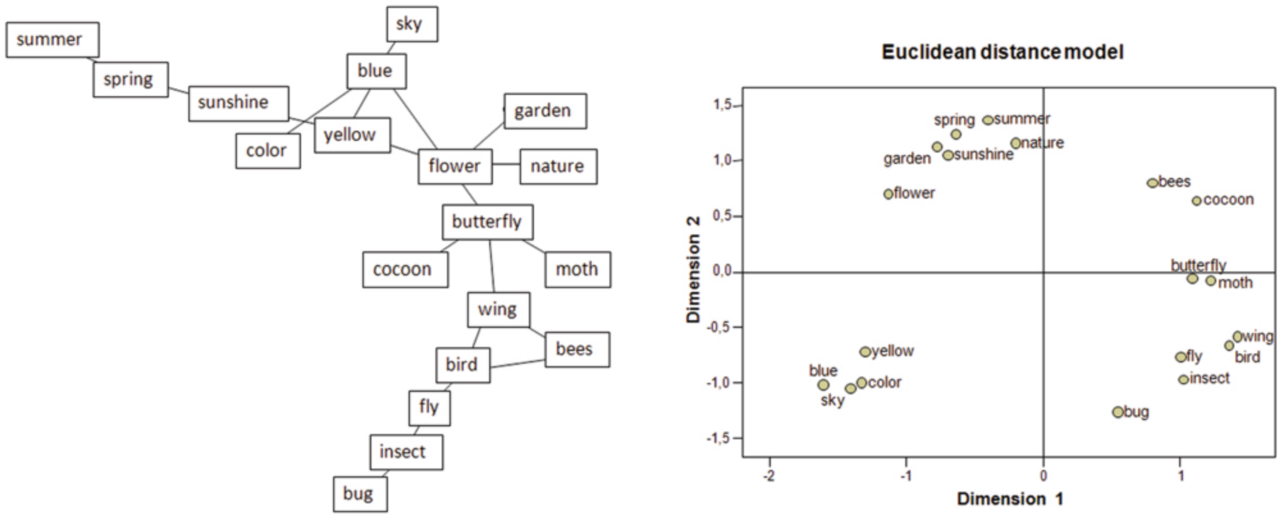

Fig. 4.1 *Pathfinder* Network representation (*left*) and multidimensional scaling (*MDS*, *right*) of the intersection coefficient association data from Deese (1965, p. 56)

approach to determine a least weighted path connecting all of the terms, thus forming a connected graph where there is a path of links to connect any node to any other node in the network. Establishing the path among all terms primarily depends on the high relatedness raw data elements (i.e., nearness), and as a result, most of the low relatedness raw data elements are disregarded in the analysis (Roske-Hofstrand & Paap, 1990). Jonassen et al. (1993, p. 74) says that *PFNETs* represent local 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." Note that the relatedness raw data by itself has concurrent validity for some cognitive outcomes, for example, predicting the order of recall of a list of terms. But *Pathfinder* analysis extracts additional psychologically valid information about the structure of memory beyond that in the original relatedness raw data while MDS does not (Cooke, Durso, & Schvaneveldt, 1986, p. 548). *Pathfinder* capability to reduce a large relatedness data set while highlighting and representing just the most critical information makes it an attractive analysis and visual representation alternative.

4.3 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 very 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 require 105 comparisons while 30 terms require 435 comparisons; the number of decisions 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, Johnson, & Acton, 1991); more terms mean better validity.

Because there is often a need for utilizing many terms in an investigation, an elicitation approach was needed that is at least as valid as the pairwise approach but that is more efficient. Two multi-decision approaches 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). However, multi-decision approaches must provide more information on the screen, and this extra information will tend to establish a specific context that may influence the relatedness raw data. So the next section begins with a discussion of the likely role of context when eliciting relatedness raw data, then describes the listwise and sorting approaches, then reports two experimental investigations that utilized these multi-decision approaches, and finally proposes combining the raw data sets from the two approaches as an optimal elicitation approach (with experimental data provided to support this idea).

4.3.1 The Role of Context

When relatedness data is elicited, we argue that the perceived context likely influences participants' relatedness responses by increasing the activation state of some ensembles (e.g., concepts, terms) and inhibiting the activation of others. This "actuated" knowledge structure arises on the fly as a subset of the participant's full internal knowledge structure in response to the purpose, task, and setting. With increased context information, some terms that may otherwise be peripheral or absent may take on a central role in the actuated knowledge structure conformation due to the influence of context. From a measurement point of view then, 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 (i.e., a subset of the general structure). Since context likely influences what is actually captured during an elicitation task, the context that is set by the elicitation task probably matters a great deal in the structure of knowledge that is obtained.

As far as we can tell, the role of context when eliciting relatedness data has not been previously considered nor has the likely effect of context on the structure of knowledge that is obtained been specifically examined. If context does influence the resulting knowledge structure, 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 summary of the lesson or course content associated with the task, a purpose for the task, a case, a problem-based scenario, the list of terms to be rated, or perhaps even a story narrative. 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 judgment for each pair of terms from the list.

Sometimes a story provides 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 actuated knowledge structure for this situation, the following 14 terms (i.e., requiring 91 pairwise relatedness judgments) were presented: 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: "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 h (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 h (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 but incorrect *PFNETs*; spending 2 h asking or just listening to someone else asking yes–no questions resulted in knowledge structures that were more alike. 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). Specifically, for all three of the nonsolver groups, the terms "man" and "shotgun" were central high-degree nodes (with four links) while for the solver group, the term "remedy" was the central high-degree node (with four links). The solver group had correctly concluded that the man had hiccups that were then cured by fear of the bartender's shotgun. We believe that the solver group knowledge structure was initially like that of the active nonsolver and passive nonsolver groups up to the moment of solution; at that moment the solvers' knowledge structure radically shifted with this insight. Insight is a "flash of illumination" (Metcalfe, 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 the question, once solved, is the new knowledge structure conformation 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 each individual's own representation of the puzzle. But spending more time with yes–no questions was sufficient to drive a more similar conformation probably incrementally. Then solving the puzzle suddenly altered that specific conformation into a new and different specific conformation (or alternately, maybe the conformation shift allowed the solution to pop out).

So both too much and too little information in the prompt can influence the knowledge structure obtained. Because of the likely effects and influence of the prompt on the relatedness ratings, 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, we suggest that the list of terms to be compared should be displayed initially but should also be constantly available during the task to maintain the linguistic context. The likely influence of context was an important consideration in the design of the listwise and sorting approaches described in the next section.

4.3.2 Computer-Based Listwise and Sorting Multi-decision Approaches

The listwise approach was developed as an alternative to the pairwise approach to more efficiently 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 far more efficient than the pairwise approach; 15 terms require 15 decisions and 30 terms require 30 decisions and so on. Thus if the listwise approach is valid, it should be very useful with long lists of terms (see the left panel of Fig. 4.2).

The sorting task approach was also developed to quickly elicit local and global relatedness data. Here, participants are shown all of the terms from a 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 to represent the local and global relatedness of the terms as distances. The raw data output for follow-up analysis is an array of the distances between all of the terms (see the right panel of Fig. 4.2).

4.3.3 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 approach is better?

Because the lesson structure was finite and known, the lesson structure could be compared with the participants' data. To do this, two referent arrays were created, 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 each topic area. Based on these two referents, the listwise task was a bit better

Fig. 4.2 The listwise approach (*left*) and the sorting approach (*right*)

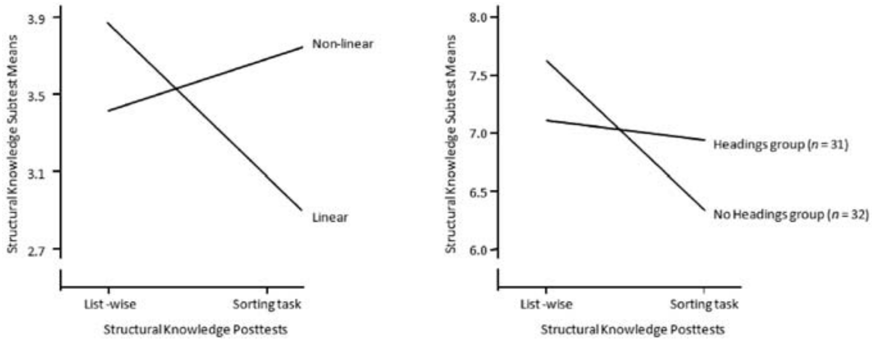

Fig. 4.3 The significant interaction of relatedness task and knowledge structure (*left*) and of the Headings treatment with knowledge structure posttests (*right*), from Clariana and Marker (2007, pp. 186–187)

at eliciting the linear subtopic structure and the sorting task was better at eliciting the nonlinear topic structure (see the left panel of Fig. 4.3).

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 the right panel of Fig. 4.3). To account for this finding, we speculate that the text without headers treatment tends to establish a very linear knowledge structure that is more accurately measured by the listwise task, while the text with headers treatment establishes a less linear, clustered knowledge structure that is more accurately measured by the sorting task.

Besides these findings, previously unreported correlation data from Clariana and Marker (2007) presented here now (see Table 4.1) show that 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 ($r = 0.62$ compared to $r < 0.24$), while for the Headings group both the sorting task and listwise measures correlated with the constructed response verbatim declarative knowledge posttest.

4.3.4 *Listwise and Sorting Approaches Compared to the Pairwise Approach*

Clariana and Wallace (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 terms that were covered during the course. Results indicate that the three approaches obtain knowledge structural representations by

Table 4.1 The No Headers and Headers treatment group correlations (from Clariana & Marker, 2007)

	A	B	C	D	E
No Header treatment group (N = 32)					
A. CR Posttest (15 max.)	1				
B. Sorting task (linear)	0.24	1			
C. Sorting task (nonlinear)	–0.02	–0.37*	1		
D. Listwise task (linear)	0.62**	0.30	–0.21	1	
E. Listwise task (nonlinear)	0.08	0.04	0.20	0.00	1
Header Treatment group (N = 31)					
A. CR Posttest (15 max.)	1				
B. Sorting task (linear)	0.22	1			
C. Sorting task (nonlinear)	0.49**	0.09	1		
D. Listwise task (linear)	0.44*	0.36*	0.39*	1	
E. Listwise task (nonlinear)	0.37*	0.30	0.30	0.04	1

$^{*}p < 0.05$; $^{**}p < 0.01$.

Pathfinder analysis that substantially overlap but are differently sensitive to linear and nonlinear knowledge structure.

First, it was reported that the two multi-decision approaches were faster than the pairwise approach, but not as fast 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). Next, 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 4.2). For total group averaged relatedness data, the listwise and pairwise approaches were most alike (71% 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. The listwise approach

Table 4.2 Links in common (above the diagonal) and percentage 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

	P	L	S	Lin	Non
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)

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 were equally reflective of the actual course structure (36 and 7%).

The *PFNET* visual representations of the group averaged data from Clariana and Wallace (2009) are shown in Fig. 4.4; the numbers beside the terms in the figure 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). Note that the term "Internet" (e.g., 2a) was a central high-degree node (i.e., an important concept) for the pairwise and listwise *PFNET* representations (see the top panels of Fig. 4.4) but the sorting task *PFNET* has no high-degree nodes at all (see the bottom panel of Fig. 4.4). Although the listwise and sorting average group *PFNETs* were structurally quite like the pairwise average group *PFNET* (e.g., 71 and 57% overlap), inspection of *individual* participants' listwise and sorting *PFNETs* indicates that these were quite different structurally than those students' pairwise *PFNETs*. *Individual* participants' pairwise *PFNETs* were all 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), with most having branching (e.g., similar in appearance to the pairwise group *PFNET* in the top left panel of Fig. 4.4). In slight contrast, nearly every *individual* 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 (e.g., similar in appearance to the sorting group *PFNET* in the bottom panel of Fig. 4.4). But in stark contrast, *individual* participant's listwise *PFNETs* were typically *not* connected graphs; all have exactly 15 links, and most have branching (contrast the listwise group representation in the top right of Fig. 4.4 to the *individual* representation on the left side of Fig. 4.5).

With the listwise approach, a worst case scenario for establishing a path between all nodes would be that all of the rating 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. This would obtain a highly disconnected representation consisting of five separate cycle graphs and yet it *perfectly* represents the nonlinear structure of the course content and strongly represents its linear structure (see the right side of Fig. 4.5). This pattern of "clustering" was present in some participants' listwise *PFNETs* but was not common (see, for example, 10a–10b–10c configuration on the left side of Fig. 4.5), possibly because participants tend to associate terms linearly (Meyer & McConkie, 1973, p. 113) and so the listwise approach may especially elicit and capture linear associations. One problem with disconnected graphs is that it is not clear which clusters of terms are more related to what other clusters. For example, in the right panel of Fig. 4.5, it is not clear whether cluster 1–2a–2b is closer to 3–4a–4b or 10a–10b–10c; all clusters are equally disconnected from each other.

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 the sorting nor listwise approach fully obtains *PFNETs* that precisely resemble the individual's pairwise *PFNET*. Thus, although the sorting and especially the listwise approaches seem to be quite satisfactory

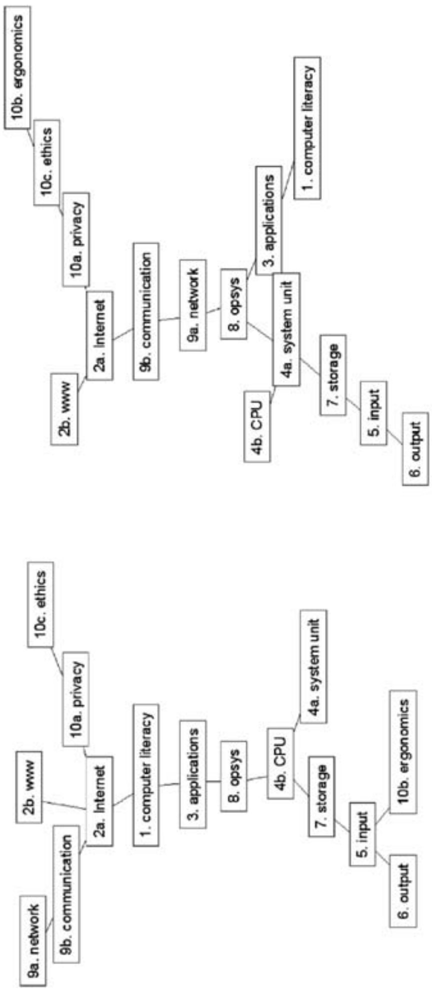

Fig. 4.4 The *PFNETs* derived from the pairwise (*top left*), listwise (*top right*), and sorting (*bottom*) averaged group raw proximity data

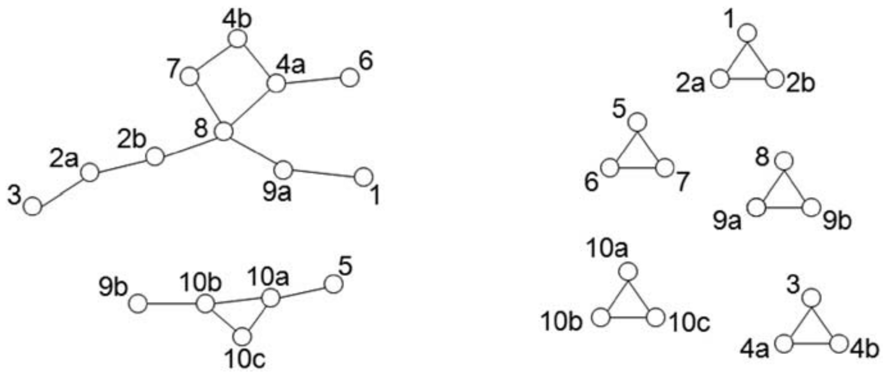

Fig. 4.5 The listwise *PFNET* disconnected graph representation of a randomly selected participant (*left*) and a hypothetical listwise *PFNET* (*right*)

for group average representations, these two approaches may be less adequate for purposes that require representations of individual's knowledge structure.

While writing this chapter, 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 which clusters go together (global), and yet maintains the most critical linear associations due to the contribution of the listwise task (local). If this approach obtains valid *PFNETs* comparable to those obtained from the pairwise approach, then for long lists of terms, this combined approach would be considerably faster to complete and thus more efficient. Thus, the relatedness data from the study by Clariana and Wallace (2009) are *reanalyzed* in order to compare the new combined sorting-plus-listwise measure to the pairwise measure; the findings of this new analysis are reported here for the first time.

4.3.5 Sorting and Listwise Combined Approach

To combine the sorting and listwise raw data, first the sorting task distance raw data for each individual were converted to a 0–1 scale by dividing each distance value in the array by the maximum distance observed in that array (e.g., a distance of 32 pixels divided by the maximum for that array of 929 is 32/929 = 0.042) and then this scaled value is inverted by subtracting it from one (1–0.042 = 0.958), thus changing it from a distance/dissimilarity value where smaller values mean greater relatedness to a similarity value where larger values mean greater relatedness. Scaling and then inverting of the sorting data were necessary so that the listwise and sorting raw data would both be similarity data, and then the listwise and sorting values in each complementary cell of the two arrays can be simply added to form the new sorting-plus-listwise measure.

The participants' data from the previous investigation were reanalyzed here by randomly assigning all participants into two equivalent groups, A or B, and then Groups A and B were partitioned by median split of final course grade into high- and low-achievement 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* which were compared to each other (see Table 4.3).

Table 4.3 Percent *PFNET* overlap between high- and low-achievement Groups A and B

	Group A				Group B			
Group and approach	A	B	C	D	E	F	G	H
Group A								
A. High Group A, combined	1							
B. High Group A, pairwise	60%	1						
C. Low Group A, combined	86%	53%	1					
D. Low Group A, pairwise	83%	52%	76%	1				
Group B								
E. High Group B, combined	*93%*	60%	86%	76%	1			
F. High Group B, pairwise	79%	*53%*	64%	69%	71%	1		
G. Low Group B, combined	79%	47%	*79%*	76%	79%	57%	1	
H. Low Group B, pairwise	48%	58%	48%	*53%*	48%	48%	48%	1
Referents								
Linear referent	36%	27%	36%	35%	36%	43%	29%	35%
Nonlinear referent	24%	15%	32%	23%	24%	0%	24%	15%

The combined approach was very consistent, obtaining a 93% overlap between the group average *PFNETs* for the high achievers in Groups A and B (see Table 4.3) compared to 53% overlap for the pairwise approach and 79% overlap between the group average *PFNETs* for the low achievers in Groups A and B (see Table 4.3) 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 indicates that the combined approach reflected the course topic coverage, both linear and nonlinear, in most cases considerably better than did the pairwise approach (about 60% compared to about 48%). To better comprehend these different data representations, the pairwise, listwise, sorting, and combined listwise-plus-sorting *PFNETs* of the student with the best course grade are presented (see Fig. 4.6).

This student's listwise *PFNET* dominated the combined *PFNET* structure, except that the links between terms 7 and 9a and between 2a and 3 in the listwise *PFNET* did not occur in the combined *PFNET*; also the two separate portions of the listwise *PFNET* were joined between terms 1 and 10b (see Fig. 4.6). This top student's

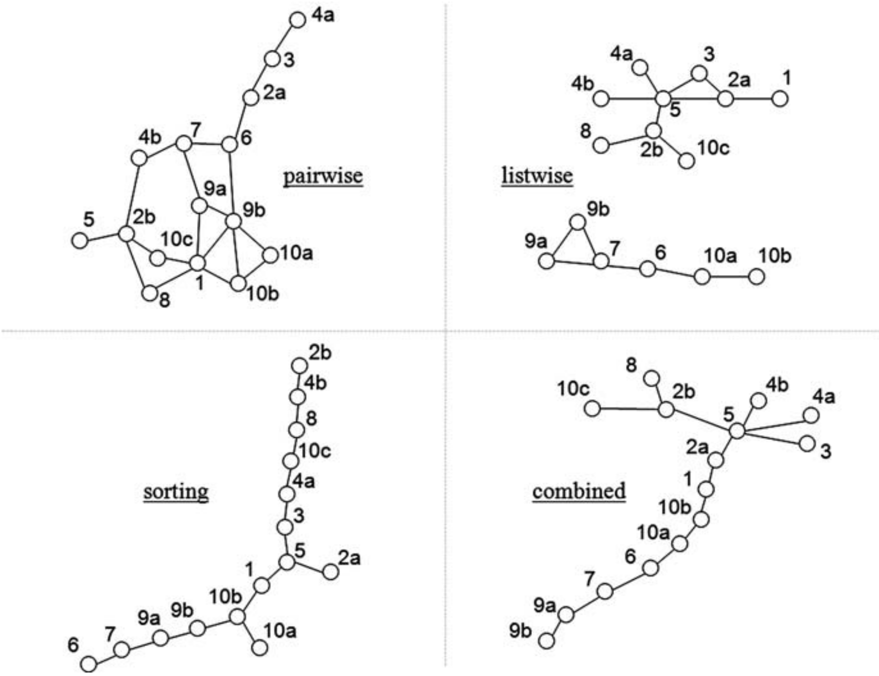

Fig. 4.6 Pairwise, listwise, sorting, and combined listwise-plus-sorting *PFNETs* of the top-performing student

pairwise *PFNET* has six links that match the linear and one that matches the nonlinear course referents and 13 links that do not match the course structure (i.e., *pairwise PFNET* course organization, 7/20 = 35% overlap), while her combined *PFNET* has five links that match the linear and one that matches the nonlinear course organization and eight links that do not match the course structure (i.e., *combined PFNET* 6/14 = 43% overlap). The pairwise *PFNET* has two central (high-degree) nodes, terms 9b and 1, while the combined *PFNET* has one central node, term 5.

Thus the combined sorting-plus-listwise approach appears to provide a better measure than the pairwise approach that is more consistent across the two groups (e.g., a measure of reliability) and has better concurrent validity. However, an alternate explanation is that two measures are better than one! Possibly using the pairwise rating approach twice and combining the two runs would result in better (more reliable and valid) pairwise comparisons too; we can't be certain. However, recall that the pairwise rating approach is notoriously time consuming for the participants to complete and the original design intent of the sorting and listwise approaches was to improve efficiency, i.e., to obtain data that are comparable to the pairwise approach but require less time to complete. This data and analysis indicates that the combined sorting-plus-listwise approach achieves this efficiency objective; but considerable further research is needed to confirm this.

4.4 Summary 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 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 most 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 toward those context variables rather than capturing the participants' knowledge structure (the Goldilocks' principle). To obtain an optimum, 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 (clustered) knowledge structure. A moderately strong correlation ($r = 0.62$) 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 kinds of posttest measures. Instructors and researchers should be made aware that eliciting knowledge structure probably alters knowledge structure (an intervening test effect).

An investigation by Clariana and Wallace (2009) 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 the relatedness data from both. Previous raw data from Clariana and Wallace (2009) were used to generate the combined listwise-plus-sorting data set and these new data were compared to the pairwise data using a group average approach. The combined *PFNETs* were considerably more consistent across equivalent 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 (20 or more terms). These results support further research to confirm or refute this combined approach. Our hope is that these approaches will be validated and extended and that other investigators will incorporate these ideas and methods into future software tools to advance the systematic analysis of knowledge through new multi-decision approaches.

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