

A COMPUTER-BASED APPROACH FOR TRANSLATING TEXT INTO CONCEPT MAP-LIKE REPRESENTATIONS

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Abstract. Unlike essays, concept maps provide a visual and holistic way to describe declarative knowledge relationships, often providing a clear measure of student understanding and most strikingly, highlighting student misconceptions. This poster session presents a computer-based approach that uses concept-map like Pathfinder network representations (*PFNets*; Shavelson & Ruiz-Primo, 2000) to make visual students' written text summaries of biological content. A software utility called *ALA-Reader* (www.personal.psu.edu/rbc4/) was used to translate students' written text summaries of the heart and circulatory system into raw proximity data, and then Pathfinder *PCKNOT* software (Schvaneveldt, 1990) was used to convert the proximity data into visual *PFNets*. The validity of the resulting *PFNets* as adequate representations of the students' written text was considered by simply asking the students and also by comparing the correlation of human rater scores to the *PFNet* agreement-with-an-expert scores, (*PFNet* text score Pearson $r = 0.69$, ranked 5th out of 12). The concept-map like *PFNet* representations of texts provided students (and their instructor) with another way of thinking about their written text, especially by highlighting correct, incorrect, and missing propositions in their text. This paper provides an overview of the approach and the pilot experimental results. The actual poster session will in addition demonstrate the free *ALA-Reader* software and will also how to procure and use *PCKNOT* software.

1 Introduction

Regarding science *content and process* knowledge, there may be a natural relationship between concept maps and essays. For example, it is becoming common practice in science classrooms to use concept mapping, especially in collaborative groups, as a precursor for writing about a topic. (The concept map activity replaces the much-despised "outlining" approach). For instance, *Inspiration* software converts concept maps into outlines at the click of a button. The reverse is also the case; essays can be converted into concept maps. For example, probably the first large-scale use of concept maps in assessment was conducted by Lomask, Baron, Greig, and Harrison (1992). In a statewide assessment (Connecticut), Lomask and colleagues converted students' essays of science content knowledge into concept maps, and then scored the concept maps using a quantitative rubric. Their assumption is that the two capture some of the same information about students' science content and process knowledge.

2 Method and Tools

Twenty-four graduate students who are experienced practicing teachers enrolled in an educational assessment course used *Inspiration* software to create concept maps on the structure and function of the human heart while researching the topic online. Later outside of class, using their concept map they wrote text summaries as a precursor for the in-class activities of scoring the concept maps and text summaries (essays). In class, students discussed multiple scoring approaches and then working in pairs, scored all of the text summaries using a 5-point rubric that focused on three areas, content, style, mechanics, and overall.

2.1 *ALA-Reader* software

ALA-Reader is a software utility that we developed in our lab to translate written text summaries (i.e., less than 30 sentences) into a proximity file that can then be analyzed by Knowledge Network and Orientation Tool for the Personal Computer (*PCKNOT*) software (Jonassen, Beissner, & Yacci, 1993; Schvaneveldt, 1990; Schvaneveldt, Dearholt, & Durso, 1988). *ALA-Reader* is a text-representation tool, but its underlying approach was derived from three sources, the extensive text-summarization tool literature (e.g., see the collected papers in Mani & Maybury, 1999), the Pathfinder literature, and Walter Kintsch's work on propositional analysis. According to Barzilay and Elhadad (1999), text summarization is "the process of condensing a source text into a shorter version, preserving its information content" (p.111). Actually, text representation is a simpler problem than text summarization, especially if the genre of the text sample is known ahead of time (thus the solution is less brittle), the content domain is not too big, the text sample is not too big, and especially the key terms in the text (and their synonyms and metonyms) can be clearly specified. The text summaries of the structure and function of the human heart and circulatory systems used in this investigation fit these requirements.

ALA-Reader uses a list of important terms selected by the researcher (maximum 30 terms) to look for the co-occurrences of these terms in each sentence of the student's text summary. The 26 terms used here (and their synonyms and metonyms) were identified through text-occurrence frequency analysis followed by biology expert selection. *ALA-Reader* analyzes terminology co-occurrence and then converts term co-occurrence into propositions, which are then aggregated across all sentences into a proximity array. For example, imagine a simple text about taking your pets on a trip. Given five important terms such as "cat", "dog", "pet", "car" and "truck", the co-occurrences of these terms in the text in three sentences are easily captured (see Figure 1). The first sentence contains "pets", "dog", and "cat" and so "1s" are entered into the co-occurrence table for these terms, but not for "car" and "truck", and so on for each sentence.

Sentences		Co-occurrence table				
I have two <u>pets</u> , my <u>dog</u> is named Buddy and my <u>cat</u> is named Missy.	→	cat	dog	pet	car	truck
My <u>dog</u> likes to ride in my dad's <u>truck</u> .	→	1	1	1	0	0
But not Missy (metonym for <u>cat</u>), she will only ride in my mom's <u>car</u> .	→	0	1	0	0	1
...more sentences here		1	0	0	1	0

Figure 1. A simple text and its co-occurrence table.

Next the co-occurrences of terms in each sentence are converted into propositions. For example, the terms that co-occur in the first sentence, "pets", "dog", and "cat", combine to form three propositions, pet-dog, pet-cat, and dog-cat. These three propositions are shown in the first sentence proposition array (see the left panel of Figure 2)

	First sentence					Second sentence					Third sentence				
	cat	dog	pet	car	truck	cat	dog	pet	car	truck	cat	dog	pet	car	truck
cat	-					-					-				
dog	1	-				0	-				0	-			
pet	1	1	-			0	0	-			0	0	-		
car	0	0	0	-		0	0	0	-		1	0	0	-	
truck	0	0	0	0	-	0	1	0	0	-	0	0	0	0	-

Figure 2. Each sentence terms co-occurrences converted to propositions.

Finally, the propositions are aggregated (not summed) across all of the sentences into one proximity array. For example, if you aggregate all of the proposition arrays for all three sentences, you will obtain the text proximity array shown in the left panel of Figure 3. This proximity array is saved by *ALA-Reader* as a *.prx file that can be directly read by the *PCKNOT* software, which can produce the *PFNet* shown in the right panel of Figure 3 and also can compare the students' *PFNets* to each other and to an expert referent *PFNet*.

Proximity array					
	cat	dog	pet	car	truck
cat	-				
dog	1	-			
pet	1	1	-		
car	1	0	0	-	
truck	0	1	0	0	-

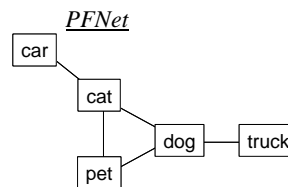


Figure 3. The text proximity array and its *PFNet* representation.

2.2 *PCKNOT* software

PCKNOT (Schvaneveldt, 1990) is software that converts raw proximity data into *PFNet* representations and then compares the similarity of *PFNets* to an expert referent *PFNet*. It uses a mathematical algorithm to determine a least-weighted path that connects all of the important terms. The resulting *PFNet* is a concept-map like representation purported to represent the most salient relationships in the raw proximity data. The links describe the least weighted path (see the right panel of Figure 3). To score a student's text proximity raw data, *PCKNOT* was used to convert all of the students' raw text proximity data from *ALA-Reader* into *PFNets*. Then the

students' *PFNets* were compared to the *PFNet* derived from a text summary written by an expert Biology instructor. The students' proposition-agreement-with-the-expert scores ranged from 0 to 20. These agreement scores were linearly converted to a 5-point scale (i.e., divide by 4 and then round up to the nearest whole number) in order to conform to the 5-point text score scale used by the human raters.

2.3 Comparing text scores (from human raters) to the ALA-Reader/*PFNet* text scores.

To help determine whether the *PFNet* representations actually capture the vital content propositions in the written text, we compared the *PFNet* text scores to the scores of eleven pairs of raters. The raters were the same students who had developed the concept maps and written texts, but had now put on their "teacher" hats. The scores for each written text are shown in Table 1, ordered from best (raters J and K, Pearson $r = 0.86$) to worst (raters H and I, Pearson $r = 0.11$). The *ALA-Reader / PFNet* text scoring approach obtained scores that were moderately related to the combined text score, Pearson $r = 0.69$, and ranked 5th overall.

	J & K Raters	E & F Raters	L & X Raters	P & Q Raters	<i>PFNet</i>	A & B Raters	J & O Raters	C & D Raters	N & M Raters	T & U Raters	G & V Raters	H & I Raters	Combined
Text O	2	1	2	2	1	2	3	1	4	3	4	5	2.5
Text U	2	3	2	1	1	3	4	2	5	4	4	5	3.0
Text B	2	3	3	3	1	4	3	3	4	4	4	4	3.2
Text F	2	3	4	3	2	3	4	3	4	2	5	5	3.3
Text T	3	4	3	3	3	3	4	3	4	4	3	3	3.3
Text E	2	4	3	4	1	5	4	3	4	4	4	5	3.6
Text Q	2	3	4	5	1	4	4	3	5	3	5	4	3.6
Text V	3	4	4	3	2	4	4	3	4	4	4	4	3.6
Text I	3	3	5	3	2	5	3	5	4	4	3	4	3.7
Text D	4	4	3	3	3	4	5	5	4	4	5	4	4.0
Text K	4	5	4	5	2	4	4	4	5	3	4	5	4.1
Text N	5	5	5	5	1	4	4	3	5	4	4	5	4.2
Text L	4	4	5	5	3	4	4	4	5	4	4	5	4.3
Text J	5	4	4	4	4	5	4	3	5	5	5	5	4.4
Text P	5	4	5	5	3	5	5	3	5	4	4	5	4.4
Text C	4	5	5	4	5	4	5	5	5	4	5	4	4.6
Pearson $r =$.86	.82	.79	.74	.69	.69	.66	.66	.59	.42	.30	.11	
rank =	1	2	3	4	5	6	7	8	9	10	11	12	

Table 1. Scores for each text from 12 sources.

3 Summary

In this pilot study, graduate students used *Inspiration* software to create concept maps while researching the structure and function of the human heart online, these concept maps were used to write text summaries, and then the text summaries were translated into concept map-like representations using computer-based software tools. The findings suggest that this approach captures some aspects of science content and/or process knowledge contained in the students' text summaries. The concept-map like *PFNet* representations of texts provides students (and their instructor) with another way of thinking about their written text and their science content knowledge, especially by highlighting correct, incorrect, and missing propositions. Given a little thought, there are multiple ways that this approach can be used instructionally. For example, one of our near

term goals is to embed the text-to-map system into writing software and also to use the approach for answer judging (relative to an expert) of extended constructed response items in online instruction.

In this poster session, the implications for epistemology, cognition, and ethics of automatically translating written text into maps are not considered, though these are of interest, especially if the approach matures. The spotlight of this current investigation is pragmatic and focused on the software tools for translating written text into concept map-like representations. Most significantly, these tools are very open-ended, which will allow researchers to apply the tools across a considerable breadth of interests, theories, hypotheses, and research questions. For example, which text should be used as the “expert referent” for comparison? In the present version of the tool, students’ text can be compared to textbook passages, to different “kinds” of expert texts, and even to each other. Also, what is the role of the important terms? This pilot used only “concrete concept” terms. But different terms can be used to mark the same set of student texts, producing different scores. Scores based on “concept” terms will capture different information from the students’ text than scores based on “relationship” terms, and some mix of the two forms of terms may be optimal. Additional research and refinements are necessary to develop and prove or disprove the approach, though this first step is encouraging. To speed up the process, we hope to influence as many researchers as possible to try it out and make suggestions.

4 Acknowledgements

This Research Project was supported by a competitive SRS grant provided by the CEO of the Great Valley School of Graduate Professional Development, Dr. William Milheim, and travel funds to present at CMC 2004 were provided by Dr. Arlene Mitchell, Head of the Education Department.

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