Chapter 2
Graphical Learning Strategies

2.1 Introduction

The objectives of this chapter are to review graphical learning strategies research and to discuss some approaches which have been used to teach them. **Section 2.2** presents a classification of mapping systems[1]. **Section 2.3** provides a variety of examples of graphical learning strategies. **Section 2.4** investigates some sets of pre-defined links, called **canonical link systems**, used by mapping systems. **Section 2.5** describes a general procedure prescribed for constructing a graphical representation of a text, whereas **Section 2.6** presents some training approaches for graphical strategies. It is argued that none of the approaches investigated can be implemented in the computer in a straightforward manner. Finally, **Section 2.7** presents and criticises a computational attempt to model the problem of teaching a graphical learning strategy.

2.2 Classification of Mapping Systems

Lambiotte et al. (1989) classify mapping systems into *node-based* and *link-based* systems. In node-based systems, 'the appearance of the nodes is varied in order to distinguish relationships among data items' (p. 346), and the only function of links, when they are used at all, is to connect nodes. Consequently, many relationships among concepts cannot be explicitly represented in a node-based system. By contrast, in a link-based system, the links specify how the concepts are related, and the only function of the nodes is to contain information items. In this situation, the appearance of the node, when they exist, is the same and the relationships among concepts are made explicit. In fact, most mapping systems are **hybrid**, using varied types of nodes and links as signalling devices. There is little evidence to indicate what is the best signalling device, but clearly the use of many such devices leads to a trade-off: the use of too many signalling devices may be good for calling attention to important aspects of information, but it may also cause information overload (Lambiotte et al., 1989).

The set of links employed be graphical strategies can be **idiosyncratic** or **canonical**. A canonical set of links assumes that there is 'a small well-defined number

[1] In this book, *map* refers to the graphical product resulting from the application of a graphical learning strategy on a piece of text, whereas *mapping* refers to this activity itself.

of basic relations with which all associations can be expressed, regardless of how they might be represented in natural language' (Lambiotte et al., 1989, p. 348). On the other hand, idiosyncratic links are represented by a multiplicity of labels without regard for consistency or parsimony.

As far as the learner is concerned, the advantages of using a idiosyncratic link system (e.g., concept mapping — see below) is that it is far easier to learn and employ than a canonical link system (e.g., networking). Support for this assertion can be found in Novak & Gowin (1984), where children as young as seven are reported to have learned how to use concept maps. From a computational point-of-view, however, implementing a canonical link system is much simpler than implementing a idiosyncratic one, since having a computer program which understands unconstrained links is tantamount to having a natural language understanding system. There is no comparative study directly contrasting unconstrained (idiosyncratic) versus constrained (canonical) link systems, but research literature has reported learning gains associated with both types of link systems. This research's focus of investigation is on a canonical link system[2].

2.3 Examples of Graphical Strategies

Holley & Dansereau (1984c) present three graphical strategies: **networking** (Holley & Dansereau, 1984b), **mapping** (Armbruster & Anderson, 1984) and **schematising** (Mirande, 1984). Novak and his colleagues (see, e.g., Novak & Gowin, 1984) have developed **concept mapping**; Jonassen (1984) has carried out research into **pattern notes**; and more recently Lambiotte et al. (1989) have come up with **knowledge mapping** as a follow-up of their research into networking. Essentially, all these techniques require the learner to convert text material into two-dimensional diagrams depicting concepts and relationships. These strategies are briefly reviewed below[3]. Lambiotte et al. (1989) point out that, currently, the only graphical learning strategies in evidence are concept mapping by Novak and his associates (e.g., Novak & Gowin, 1984), and networking/knowledge mapping by Dansereau and his colleagues. Lambiotte et al. argue that other 'haphazard' examples of mapping systems found in the literature 'do

[2] As a matter of fact, at the beginning, this research was proposed to investigate an unconstrained link system, namely, concept map as described by Novak & Gowin (1984). It was soon realised, however, that by doing this the current research would no go very far.

[3] One characteristic which distinguishes those representations from other external, graphical representations (see, e.g., Larkin & Simon, 1987; Winn & Sutherland, 1989) is that most of them have a broader, general-purpose utility (e.g., reading, pre-writing activities, brainstorming, etc.). The review presented here, however, is concerned only with their use as strategies for enhancing learning from text.

not represent a carefully sampled domain but a set of idiosyncratic creations by investigators' (Lambiotte et al., 1989, p. 356). Further, they suggest that much of the research in this area does not follow rigorous methodology, and that some critical parameters are yet unknown.

2.3.1 Networking

Dansereau and his colleagues (e.g., Holley & Dansereau, 1984b) proposed networking inspired by semantic network models of knowledge representation (Quillian, 1968; Rumelhart, Lindsay, & Norman, 1972). The strategy, however, does not mirror any network model of memory. The networking process emphasises the identification and representation of relationships between concepts, and employs a set of six canonical links representing constrained relationships: **part of**, **type of**, **leads to**, **analogy**, **characteristic** and **evidence**. These links are represented graphically by arrows labelled bye the first letter of the relationship they represent. For example, **Figure 2–1** represents the relationship *part of* between concepts *hand* and *finger*.

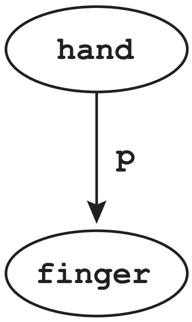

FIGURE 2–1: GRAPHICAL REPRESENTATION OF RELATIONSHIP PART OF BETWEEN HAND AND FINGER IN NETWORKING

The network resulting from a piece of text is usually (but not always) a hierarchical node-link diagram using the set of links provided. The nodes can contain not only isolated concepts, but also paraphrases and images. **Figure 2–2** shows the outcome of the application of networking to a chapter of a nursing book. (**Figure 2–2** is adapted from Holley & Dansereau, 1984b, p. 86.)

The main research findings regarding this strategy can be summarised as follows (adapted from Holley & Dansereau, 1984b).

- networking improves recall of main ideas of the text it is applied to;
- networking does not affect memory recall;

- networking is better for recall tests (e.g., essays) than for recognition tests (e.g., multiple-choice tests);
- students who used networking learned more than those who used paragraph/imagery or no strategy at all (Dansereau, Collins, McDonald, Holley, Garland, Dickhoff, & Evans, 1979).

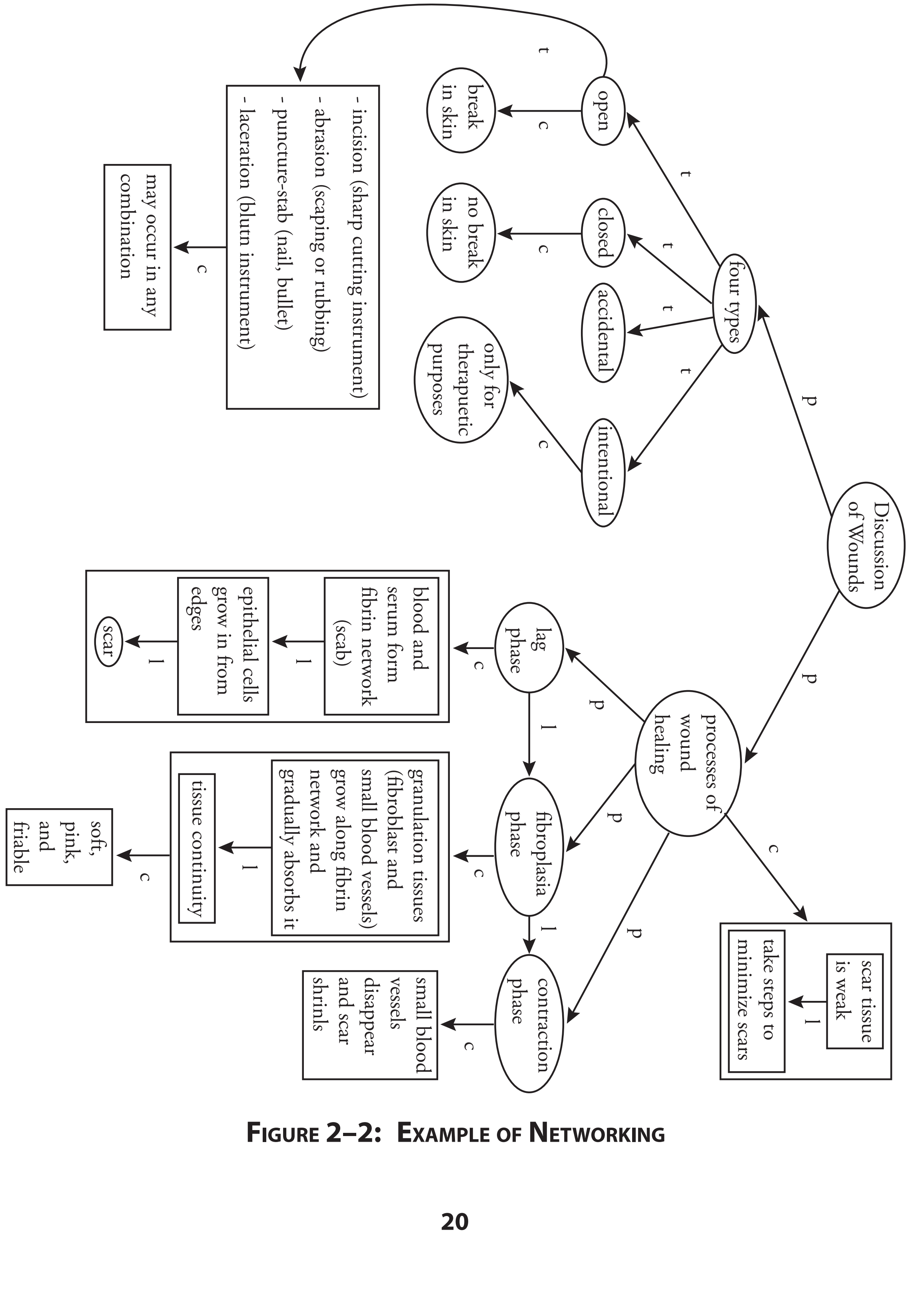

FIGURE 2–2: EXAMPLE OF NETWORKING

Clearly, the set of constrained links employed by networking does not exhaust all the types of relationships that can be found in a text, but the very act of thinking about and classifying relationships probably helps the learner to process the text more carefully. Also, Jonassen (1984) suggests that, by using networking, the learner may be constrained in her analysis of the text, because she is forced to look for concepts which fit that restricted set of links. Thus, the associations which do not fit these relationships may not be included in the final product.

2.3.2 Mapping

Mapping is another example of learning strategy for representing text graphically. According to Armbruster & Anderson (1984), the mapping strategy recognises three levels of text hierarchy: **proposition**, **text unit**, and **frame** (from the lowest to the highest level). A proposition is constituted by a pair of concepts and a relationship connecting them. In mapping, each possible relationship has a unique symbol (or *relational convention*). For example, if A e B are concepts, the proposition *A is an instance of B* will be graphically represented by the diagram in **Figure 2–3**. Armbruster & Anderson (1984) present fourteen types of basic relationships like this. (**Figure 2–3** is adapted from Ambruster & Anderson, 1984, p. 190)

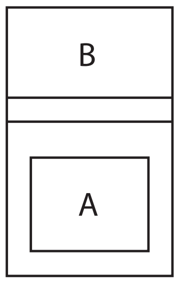

FIGURE 2–3: RELATIONAL CONVENTION REPRESENTING THE PROPOSITION: A IS AN INSTANCE OF B IN MAPPING

Text units, the second level in the text hierarchy of mapping, characterise the structure of response to basic type questions which guide descriptive writing (Armbruster & Anderson, 1984). For example, the text units identified as *descriptions* could represent text which answers (implicit) questions such as: *What is A?*, *Who is A?*, or *Where is A?*. The corresponding unit map is diagrammed in **Figure 2–4** (adapted from Ambruster & Anderson, 1984, p. 167).

The highest level in the text hierarchy of mapping, the text frame, is a generic structure which concerns questions about the generic concepts (e.g., biological systems) of a particular domain (e.g., Biology). The idea is quite similar to that found in schema theory (see, e.g., Rumelhart & Ortony, 1977). As such, a text frame has slots to be filled in by the main ideas associated with the generic concept it represents. The contents of an instantiated slot may be a proposition or, more often, a text unit. **Figure 2–5** shows a complete diagram resulting from the application of mapping on a text about *composting toilets* (Surber, 1984). Notice that the main visual difference between diagrams produced by using mapping and those produced by using networking is that the former employs *spatial relationships* (*sic*), whereas the later employs labelled relationships. Also, according to Holley & Dansereau (1984a), mapping stresses local organisation whereas networking emphasises abstraction of a general framework or schema. (**Figure 2–5** is adapted from Surber & Dansereau, 1984, p. 217.)

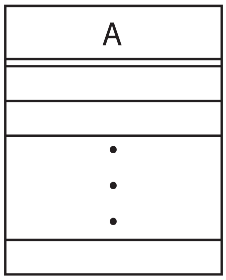

FIGURE 2–4: UNIT MAP REPRESENTING A GENERAL DESCRIPTION IN MAPPING

Armbruster & Anderson (1984) carried out some small-scale experiments which, according to them, presented promising results, but some limitations were also found. These limitations include the long time required to map all ideas in a text, and the low motivation of the students to using the technique. Armbruster & Anderson (1984) concluded that students would profit most from the strategy is they represented *only* the main ideas (i.e., the major concepts and relationships) in the text and if the to-be-mapped material were difficult to learn or remember.

2.3.3 Schematisation

Schematisation is yet another example of graphical representation of text containing concepts and relationships among them. The schematising strategy requires the learner to name and represent concepts as nodes, and to denote the relationships between concepts by means of symbols representing different types of relationships. The basic types of relationships are *static* (e.g., classifications, properties, and comparisons) and *dynamic* (e.g., conditional, cause-and-effect) which are represented by lines and arrows, respectively. A set of symbols representing combined relationships employed by this technique is shown in **Figure 2–6** (adapted from Holley & Dansereau, 1984, p. 13).

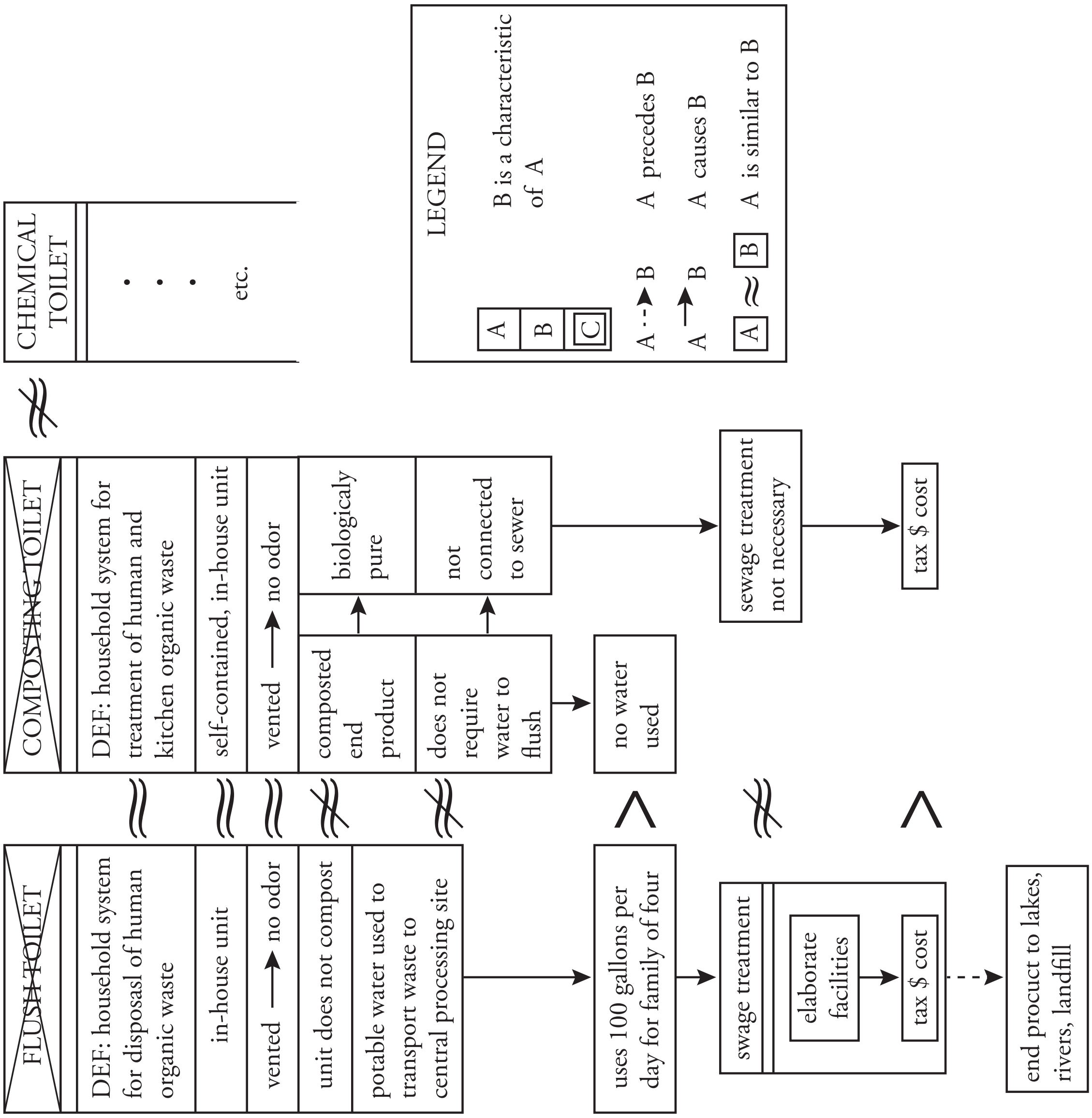

Figure 2–5: Example of Mapping

Relationship	Symbol
Similarity	$=$
Interaction	$\rightleftarrows$
Denial of similarity	$\neq$
Denial of statical relation	$\not-$
Denial of dynamical relation	$\not\rightarrow$
Negative influence	$\rightarrow \ominus$
Positive influence	$\rightarrow \oplus$

Figure 2–6: Relational Symbols Employed by Schematisation

Schematising differs from both networking and mapping in the types of relationships that can be used and also in the resulting diagram. **Figure 2–7** presents an example of a graphical representation obtained through the use of this technique. It appears that this constitutes the weakest way of representing diagrammatically, because the relational notation used says very little (if anything) about the actual nature of the relationships depicted. Although the technique has been used as a study and instructional strategy (Mirande, 1984), there is little empirical evidence to support its effectiveness. (**Figure 2–7** is adapted from Holley & Dansereau, 1984, p. 13.)

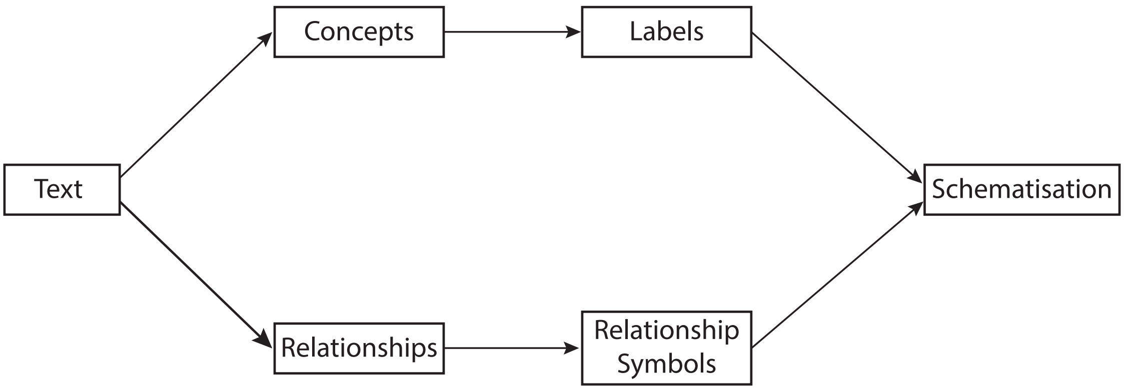

Figure 2–7: Relational Symbols Employed by Schematisation

2.3.4 Knowledge Mapping

Knowledge mapping has evolved from earlier work on networking by Dansereau and colleagues (Lambiotte et al., 1989; McCagg & Dansereau, 1991). As in networking, the number of links is limited, but now they can modified according to the to-be-mapped domains. The graphical visual appearance has also changed and become more complex to include the use of colours, nodes with different types of lines and typefaces, different types of link shapes (e.g., broken lines), and the use of connectives (e.g., AND). Although the maps appear be much more complex than their ancestors, they appear to have a better communication power (for example, the use of colours and bigger typefaces may call more attention for the most important points of the domain). The primary objective of knowledge mapping is the relatively *passive* use of expert-produced maps. That is, in contrast to networks, maps are mostly meant to be studied by students. Indeed, research into knowledge maps has focused on their use as substitute and complements for traditional instructional text and lectures (Lambiotte et al., 1989). This shift in research focus, according to Lambiotte et al., (1989), has been motivated by the fact that even after time-consuming sessions, most students were not able to produce adequate diagrams. Nevertheless, knowledge mapping is actively used by students too (see below).

In a more recent paper on knowledge mapping, McCagg & Dansereau (1991) report that expert-generated maps have at least two potential problems which may hamper their effectiveness. First, they observed that the students pay little attention to relational information; they rather concentrate mostly in the information contained in the nodes. Second, perhaps most important, the students 'may be deprived of understanding that they might have gained from generating their own maps' (McCagg & Dansereau, 1991, p. 318). Despite these problems, McCagg & Dansereau present some evidence that expert-generated maps may facilitate learning under certain ciricunstances.

Patterson, Dansereau, & Newbern (1992) suggest that in its passive use, knowledge map works as a *communication aid* to convey information, rather than a proper learning strategy on its own. These authors suggest that, in such a situation, one advantage of knowledge maps over traditional texts is that the former 'can inform the reader about the main ideas and macrostructure of [the to-be-learned] material' (p. 454). Dansereau, Dees, & Simpson (*in press*) add that such a two-dimensional visual representation may be a more effective communication medium for conveying complex information (e.g., parallel lines of thought) than natural language, since the former tends to cluster related elements, thus facilitating search and inference, whereas the later tends to keep those elements apart (see also Larkin & Simon, 1987).

Student-generated knowledge maps are intended to assist the learner who constructs them in her thinking and learning. McCagg & Dansereau (1991) review some experimental evidence showing that the generation of maps by the students may enhance learning from traditional text, favour group discussion, and improve writing. They warn, however, that research into mapping has not been systematic enough to allow for reliable comparisons among studies. As realised in many other studies (see above), they conclude that 'training students to use the technique can sometimes be difficult and time-consuming' (McCagg & Dansereau, 1991, p. 319). Rewey, Dansereau, Skaggs, Hall, & Pitre (1989) also have a similar view when they state that the major drawback of this approach is that, 'the training process is too lengthy and that the mapping process is too difficult, especially for complex information' (p. 604). Thus, the appeal of the expert-generated maps is that it removes these problems. By using expert-generated map, the students do not have to spend time constructing them, and moreover, these maps are more precise than the counterpart generated by the students themselves.

From a research standpoint, the major findings regarding knowledge mapping can be summed up as follows (Lambiotte et al., 1989; Dansereau, 1994):

- students can acquire more metaknowledge about the to-be-learned domain (e.g., knowledge about the time necessary for learning the material) after a brief exposure to a map than after a brief exposure to a text;
- maps depicting processes or procedures (e.g., the digestive system flow) appear to be generally more effective than their textual counterpart.
- knowledge maps are more effective than text for recalling the macrostructure of a topic, and the macrostructure is acquired earlier when using maps than when text is used; they have no influence in recalling details (microstructure) of a topic.

2.3.5 Concept Mapping

As the outcome a the application of the other graphical strategies depicted above, a concept map is a graphical representation of the structure of a given domain drawn by linking concepts, represented by nodes, with labelled pointers representing relationships among. Thus, the simplest concept map consists of two concepts linked by a word forming a proposition (Novak & Gowin, 1984). In contrast to the other graphical strategies, concept mapping has no constrained set of relationships; that means that any kind of relationship can be used. Nor does the technique use distinct symbols for depicting different relationships, as the preceding graphical strategies do.

The idea of concept mapping was developed with the purpose of evaluation. That is, the original purpose was to provide a means by which a teacher could evaluate her students by examining concept maps drawn by them. To carry out this task, the teacher tries to identify misconceptions, such as misused concepts and relations; missing knowledge, that is, missing concepts and relationships; and other shortcomings, such as poor hierarchies. According to Novak (1990a), the idea of concept maps originated from Ausubel's (1968) assimilation theory of learning, and was developed with the purpose of representing 'what the student already knows' (Novak, 1990b). One of the characteristics of concept maps, according to Novak (1990b), is that they can be successfully used to assess a student's cognitive state of knowledge (i.e., what the student already understand in a given area of instruction) concerning a given subject matter. Moreover, he contends that concept mapping is also a powerful metacognitive tool[4] which facilitates

[4] In fact, broadly speaking, most learning strategies describe above might also be considered. metacognitive. All depends on how they are used by the learner. As Jonassen (1985) puts

meaningful learning, that is learning in which the domain really makes sense, as opposed to learning by rote (see Ausubel, Novak, & Henesian, 1978).

Novak (1990b) claims that any domain can be represented by concept maps. Novak & Gowin (1984) show evidence of this claim by presenting concept maps for a variety of domains (e.g., Mathematics, Physics, basketball). **Figure 2–8** show a concept map drawn by a student after a lesson on *Life Zone in the Ocean* (adapted from Wallace & Mintzes, 1990, p. 1039). As can be seen, in a superficial sense, concept maps are just diagrams indicating relationships between concepts. However, there are certain principles to follow when drawing concept maps. For example, the diagrams should be hierarchical from the most general concept at the top of the map to the most specific at the bottom. This requirement is to conform with Ausubel's theory of learning.

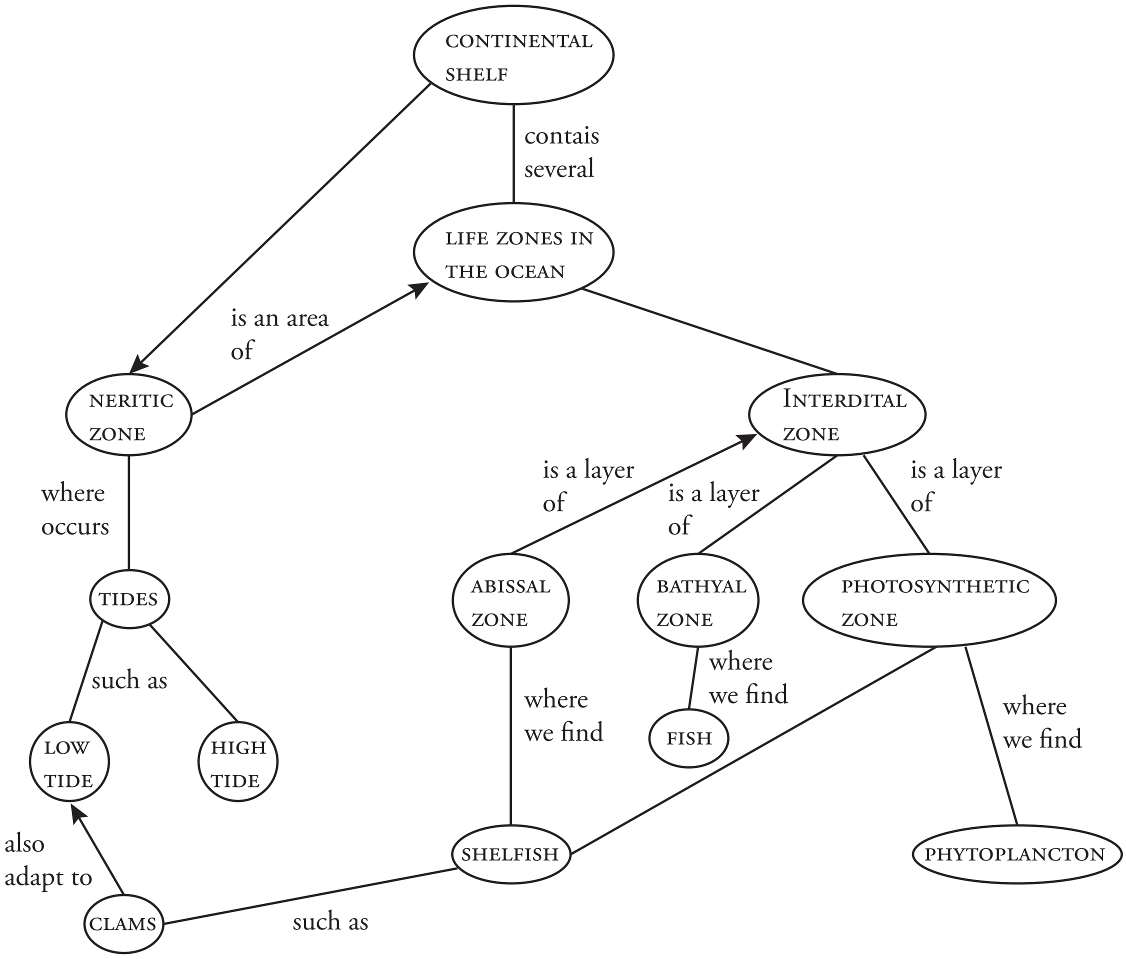

FIGURE 2–8: CONCEPT MAP DRAWN BY A STUDENT ON LIFE ZONES IN THE OCEAN

it, 'Essentially, any activity in which learners question their comprehension of what is presented is potentially metacognitive' (p. 32).

Lambiotte et al. (1989) point out some differences between concept maps and knowledge maps/networks:

- Concept maps are always hierarchical, whereas knowledge maps sometimes are not (e.g., when representing procedures, or comparing and contrasting ideas).
- Concept maps use links with arrows only when a subordinate node is not placed beneath its superordinate node in the hierarchy; that is, it is agreed that the relative vertical position of nodes in the map indicate the direction of the relationships in the absence of arrows. In other words, Novak & Gowin (1984) insist that concept maps must always be hierarchical with top-down orientation.
- Concept maps use idiosyncratic links, whereas knowledge maps use a canonical set of links.

As a learning strategy, according to Howard, 'A [concept] map also can force students to think through their ideas and make gaps in their knowledge and their understanding clear' (Howard, 1987, p. 171). Thus concept mapping could also be seen as a tool for learning through reflection (see, e.g., Collins & Brown, 1988). Moreover, Novak (1990b) points out that the primary benefit of concept maps is for the person who constructs them, that is, concept maps presented by a teacher can be helpful to students, 'but only after they have practice in constructing their own concept maps' (Novak, 1990b, p. 37); otherwise, they may even be confused by concept maps prepared for them.

There are many other possible uses of concept mapping (e.g., evaluation and instructional planning) and most research into concept mapping has focused on demonstrating their large applicability in a variety of contexts (see Novak & Gowin, 1984, for a review).

According to Lambiotte et al. (1989), research has concentrated into upon real educational settings, but they point out a number of issues that have not been adequately addressed by this large body of research: there is no systematic attempt to identify the parameters of concept maps (e.g., the role of labelled links) which are important for facilitating learning; the theoretical links between concept mapping and Ausubel's theory of learning (upon which concept mapping is based) have not been investigated; and worse, there is little *valid* evidence that concept mapping enhances instruction or learning. Lambiotte et al. go on so far as to say that '[research into concept mapping] should be considered primarily as hypothesis generation research, as opposed to hypothesis testing research (Lambiotte et al., 1989, p. 355).

2.3.6 Pattern Notes

Pattern notes (Jonassen, 1984, 1987) or *mind maps* are diagrams invented by Buzan (e.g., 1989) as a means of representing ideas from memory. In a pattern note, the main idea is written down in the centre of the diagram, the secondary ideas are arranged over radial lines coming from the centre, then less important ideas are connected to the secondary ideas, and so forth, until all relevant ideas are depicted (see example in **Figure 2–9**, adapted from Jonassen, 1987, p. 5). At the end, related ideas, which have not been linked together yet, are then connected by lines (this is not the case in **Figure 2–9**). Jonassen (1987) argues that, rather than forcing knowledge structures to fit into the hierarchy (as concept mapping does, for example), the procedure used for construction of pattern notes is unconstrained in this regard.

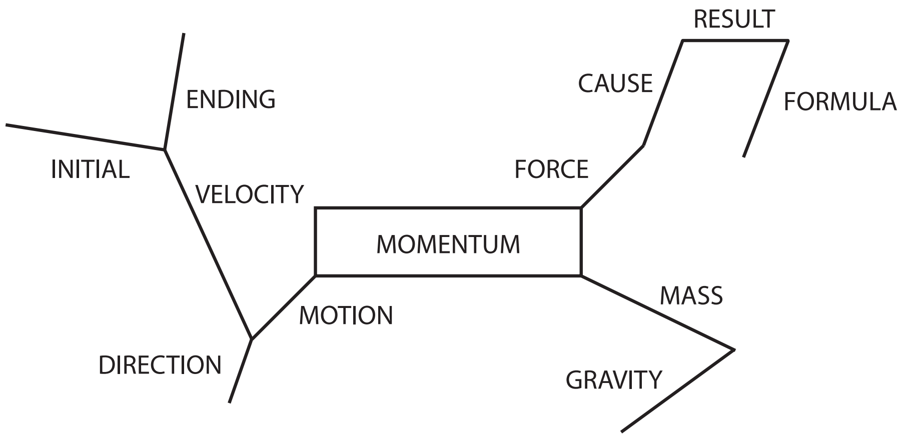

Figure 2–9: Example of Pattern Note of Some Physics Concepts

Jonassen (1984) suggests some advantages of pattern notes: they mirror the unique arrangement of ideas (i.e., the cognitive structure — Jonassen, 1987) in one's memory; the *physical* distance between two ideas, measured by the number of contiguous links between them, is roughly equivalent to the *semantic* distance between the two concepts in memory; and the technique can be learned very quickly (what seemingly constitutes a major advantage over other graphical strategies). According to Jonassen (1984), the great effectiveness of the use of pattern notes as a cognitive strategy occurs when they are used as recall and review aids. The main educational application of pattern notes appear to be brainstorming and note-taking, though they can have many other applications in education (see Jonassen, 1984).

The main drawback of the pattern notes strategy is that the diagrams do not say anything about the nature of the relationships among the ideas depicted. In order to try to overcome this shortcoming, Jonassen (1984, 1987) has extended this technique by including what he calls *post hoc semantic analysis* of pattern notes. As in schematising and mapping, special symbols are used to represent a constrained set of relationships. However, in this case, the symbols appear to be more intuitive and easier to use than in some of the preceding strategies. The post hoc semantic analysis requires the learner to identify and then represent the relationships among the ideas by drawing those symbols at the intersection of ideas in a traditional pattern note. **Figure 2–10** (adapted from Holley & Dansereau, 1984, p. 13) shows some of the relational symbols used in post hoc semantic analysis of pattern notes, and **Figure 2–11** (adapted from Jonassen, 1984, p. 173) presents the pattern note of **Figure 2–9** after a post hoc analysis with the relational symbols attached.

RELATIONSHIP	SYMBOL
Example	Eg
Part of a Whole	p/w
Cause/Lead to	⇨
Confirmation	∵

FIGURE 2–10: RELATIONAL SYMBOLS EMPLOYED BY SCHEMATISATION

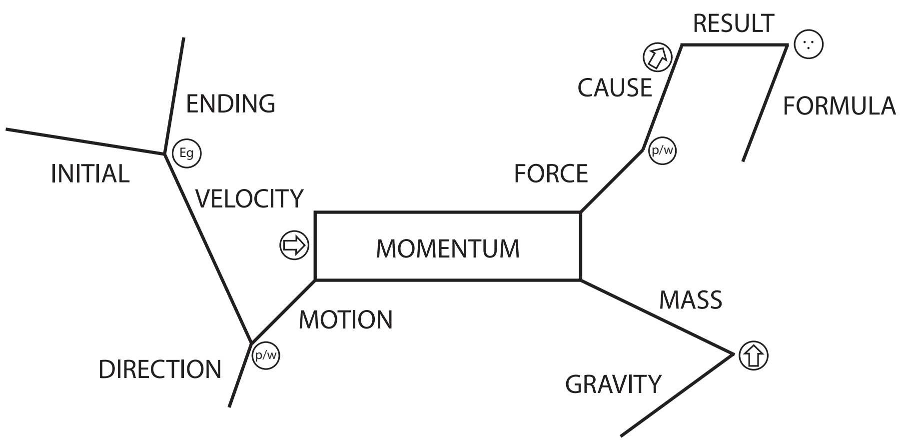

FIGURE 2–11: EXAMPLE OF PATTERN NOTE WITH ATTACHED RELATIONAL SYMBOLS

There is no empirical evidence of the effectiveness of the use of pattern notes (either with or without post hoc analysis) as a learning strategy. Also, Jonassen does not present any evidence that pattern notes with post hoc analysis are easy to use. It appears that only when they are used alone (i.e., as originally conceived by Buzan) are they easy to use.

2.4 Canonical Link Systems

As seen in **Section 2.2**, a **canonical link system** consists of a set of links, specified in advance by a researcher, to be used in a mapping system. There follows an analysis of the canonical link systems used by some bodies of research investigated[5]. This analysis served as the basis for the choice of links used in the system describe in the next chapter. In the descriptions below, links are followed by keywords. These keywords represent those relationships which the links are expected to cover as well as their intended meanings. Keywords are not always provided, however.

In general, no researcher provides any rationale for the links they use. As Lambiotte et al. (1989) point out, there is a trade-off between richness and parsimony: 'the issue rests on whether we can agree upon a small number of link labels that are powerful enough to represent all relationships in a domain without needing such a large set that the labels lose their consistency' (p. 357). This trade-off seems to justify the intuition underlying the chosen sets of canonical links are provide, when they are available.

Holley & Dansereau (1984b)

The canonical links Holley & Dansereau (1984b, pp. 84–5) use are classified in the following three categories (p. 85): **hierarchy** (part, type); **chain** (leads to); **cluster** (analogy, characteristic, evidence). These links have the following intended meanings:

Part (of): The content in the lower node is part of the object, idea, process or concept contained in a higher node. Keywords: part of, segment of, portion of.

Type (of): The contents in a lower node is a member or example of the class or category of processes, ideas, concepts or objects contained in a higher node. Keywords: type of, category, example of, kind of.

[5] This analysis concentrated in Dansereau's research group because they are the only researchers in the field of learning strategies who provide some justifications or experimental evidence for the links they use. In contexts other than learning strategies (e.g., hypertext, collaborative writing), however, there are many link systems (see, e.g., Sharples, Goodlet, & Clutterbuck, 1994).

Leads to: The object, process, concept or idea in one node leads to or results in the object, process, idea, or concept in another node. Keywords: leads to, result in, causes, is a tool of, produces.

Analogy: The object, process, concept or idea in one node is analogous to, similar to, corresponds to, or is like the object, process, concept or idea in another node. Keywords: similar, analogous to, like, corresponds to.

Characteristic: The object, process, concept or idea in one node is a trait, aspect, quality, feature, attribute, detail or characteristic of the object, process, concept or idea in another node. Keywords: has, characterised, feature, property, trait, aspect, attribute.

Evidence: The object, process, concept or idea in one node provides evidence, facts, data, support, proof, documentation, or confirmation for the object, process, concept or idea in another node. Keywords: indicates, illustrates, demonstrates, supports, documents, proof of, confirms, evidence of.

Holley & Dansereau (1984b) do not provide any rationale for those links, but they do present some experimental evidence. Early in their research, a set of 13 links was identified within a 'prototypical textual material that undergraduate students could be expected to encounter' (p. 84). Nonetheless, this set of 13 links proved to be difficult to remember and use. Then, a set of four links was created, but theses links were too general and thus inadequate to represent some relationships. Finally, the researchers arrived at the six-link system proposed, which represented a 'compromise between specificity and utility' (p. 84).

Lambiotte et al. (1989)

The canonical links Lambiotte et al. (1989) use are classified according to the following categories:

Dynamic: influences, next, leads to.
Static: type, part, characteristic.
Instructional: analogy, example, comment.

Lambiotte et al. (1989) neither provide any further explanation about the meaning of the links nor any rationale. What they argue is that they found the set of links to be 'useful in the mapping of most academic and technical domains'. They also contend that the number of links is limited to 'conform to typical short-term memory capacity in order to ease the burden for map users as well as for map producers' (p. 336), and that this constraint is useful for relationship-guided search (see **Section 2.6.3**). Nevertheless, they admit that, 'it may difficult for educators and researchers to agree upon an exact set of link names' (p. 336), and that 'links and link-type usage are of crucial importance, but as yet this belief is base more on logical argument than on empirical evidence' (p. 337).

McCagg & Dansereau (1991)

McCagg & Dansereau (1991) present canonical links rather similar to those used by Lambiotte et al. (1989) (p. 320):

Dynamic: results, influences, next, leads to.
Static: type, part, characteristic, definition, function.
Explanatory: analogy, example, comment.

McCagg & Dansereau (1991) do not provide any rationale for their links. They argue that labels can influence both map construction and processing, and contend that 'The richness of the k[nowledge]-mapping linking system allows for the use of the technique in a variety of content areas such as statistics, human physiology, and psychology.' (p. 319). They provide no evidence, however.

Summary **Table 2–1** may be helpful for comparing the various link systems employed by the diverse map systems investigated[6].

Link	Holley & Dansereau	Lambiotte et al.	McCagg & Dansereau
TYPE	yes	yes	yes
PART	yes	yes	yes
LEADS TO	yes	yes	yes
RESULTS	LEADS TO	LEADS TO	yes
INFLUENCES	no	yes	yes
NEXT	no	yes	yes
CHARACTERISTIC	yes	yes	yes
DEFINITION	no	no	yes
FUNCTION	no	no	yes
ANALOGY	yes	yes	yes
EXAMPLE	TYPE	yes	yes
COMMENT	NO	yes	yes

[6] Link NOT has been included in this table simply to call the attention to the fact that no mapping system investigated at this stage uses this odd link. It is used by Feifer (1989), in a system described below.

Link	Holley & Dansereau	Lambiotte et al.	McCagg & Dansereau
EVIDENCE	yes	no	no
NOT	NO	no	no

Table 2–1: Summary of Link Usage

2.5 How to Construct a Graphical Representation of Text

Goetz (1984) proposes the following procedure for constructing a graphical representation, which could be employed by a learner using any of the graphical learning strategies discussed above:

1. Select the material to be mapped. Goetz (1984) suggests that the material should require intensive study. McKeachie (1984) adds that learning of difficult, unfamiliar expository material profits more from graphical strategies; he warns, however, that this kind of material is the most difficult to map.
2. Decide the level (i.e., in terms of macrostructure or microstructure) at which to represent text. To do this, the learner should skim the text in order to determine its difficulty and density of concepts. Goetz (1984) suggests that a microstructure level is convenient only for small units of text.
3. Identify at least two concepts and the relationships between them.
4. Represent graphically the concepts and relationships.
5. Identify and represent graphically at least (1) a new concept and its relationship to an already represented concept; or (2) two new concepts and the relationship between them.
6. Repeat **Step 5** until all relevant concepts and relationships are represented — which depends on the level of the representation decided in **Step 2**. Goetz (1984) warns that deciding what are all the relevant concepts and relationships is not a trivial matter.
7. Check the map to see if it matches the text. Goetz (1984) proposes that, if there is a lot of text to be graphically represented, 'waiting until completion of the representation to check it may lead to a lot of wasted time and effort, particularly if improper representational decisions are made early on' (p. 65).
8. Store the graphical representation (for future reference).

Although most procedures for constructing graphical strategies appear to be simple, the execution of their steps usually is not. The main trouble with procedures like the one just described is that they are too general and vague to be helpful. That is, simply asking the learner to follow a procedure like the one above is not enough for him to learn how to apply a learning strategy. Therefore, some teaching approaches have been developed to fulfil this purpose.

2.6 Graphical Learning Strategies Training

Just & Carpenter (1987) suggest that a strategy can be taught in several different ways, and it seems that the effectiveness of the strategy does not depend upon the teaching method employed. Despite this, Dansereau (1985) believes that 'different training methods have differential impacts on the students' attitudes and behaviors'. Weinstein & Underwood (1985) present some evidence for this belief. These authors found that providing too many examples before the learner has had the opportunity of practising and receiving feedback about the use of a strategy can inhibit the proper acquisition and use of the strategy. This is particularly true for strategies which involves the use of heuristics (e.g., elaboration strategies, which are guided by the general principle of relating the to-be-learned information to the student's prior knowledge), instead of a precise algorithm. Weinstein & Underwood suggest that, when the instructor provides many examples of the use of such a heuristic strategy, the students tend to interpret the instructor's style of usage of the strategy as the (only) right way of using it.

Some approaches which have been used in training students to use learning strategies will be presented next. Notice that the focus here is on graphical strategies training, despite the fact that some approaches provide a more general teaching framework.

2.6.1 Building-Block Approach

Dansereau (1985) provides two alternative approaches for learning strategies training. One, which he call *building-block* approach, teaches learners first how to apply subcomponents of the strategy to simplified training material, before they are taught how to use the whole strategy with unconstrained material. For example, using this approach for training students to employ networking involves having them apply the strategy to single sentences, then to paragraphs, and finally to larger passages. Although this seems to be the most used approach, it presents some disadvantages. First, mastering the application of the technique with small, out-of-context passages does not ensure mastery of it for larger text units. As a result of this, the learner has to modify her strategy when faced with real texts. Second, the large difference between training and actual material may cause lack of motivation for the learner. Finally, it may be difficult for the learner to acquire the general pattern (*gestalt*) of the strategy.

The problem with this approach is that the use of examples of applications of graphical strategies to paragraphs and sentences out of context may appear artificial to the learner. In conclusion, the experiments conducted by Dansereau and his colleagues lead them to conclude that this is not the a satisfactory approach, and they claim that many students can never learn the strategy appropriately by using it Holley & Dansereau (1984b).

2.6.2 Modelling Approaches

A more profitable approach for training graphical strategies, according to Holley & Dansereau (1984b), is to have the students use actual text at the outset and construct *approximate* diagrams without concern with identifying the correct relationships among nodes. When the student feel comfortable with this initial stage, they are then taught how to refine their diagrams and correctly include those relationships. The training method commonly used by Dansereau and his colleagues for implementing this approach for training networking is by means of **modelling**.

Modelling consists of demonstrations of correct strategy usage by an expert thinking aloud while applying the strategy. After listening the expert's demonstration, the students are asked to apply the strategy by themselves to a given body of material. Then, the teacher reviews the diagrams constructed by the students and provide them with feedback, which in turn consists of an optimal version of the network containing both annotations indicating how the various parts of the diagram were derived and suggestions about how to improve the diagrams. Finally, the students compare the optimal version with their own versions.

In another version of modelling, called *interactive peer modelling* by Dansereau (1985), the students work in pairs. In each pair, one student plays the role of a teacher processing the material orally, while the other student listens and criticises the first. Periodically, the students reverse their roles.

2.6.3 Link-Guided Approach

Dansereau, Dees, Chatham, Boatler, & Sympson (1993) describe a very simple approach for teaching graphical mapping[7]. They ask the learner to start with a few key ideas in the text and 'grow' the map by asking herself about the relationships (e.g., 'What does this idea lead to?', 'What are some characteristics of

[7] Jonassen (1984, p. 171) presents a similar set of guidelines for 'semantic analysis of guidelines for 'semantic analysis of pattern notes.'

this idea?', and so on). These questions are tied to the canonical set of links employed. Then, after the map has grown, the learner is advised to organise it so as to make it easier to understand.

The algorithm suggested by Dansereau et al. (1993, pp. 18–20) is as follows:

1. Create a starting node and part it in a central location on your map.
2. Ask questions (in any order) and draw the answers on the map.
3. Pick another important concept or idea, and repeat the procedure from **Step 2** on.

The authors warn, however, that this technique is a 'rough guideline' and that mapping does not have rigid production rules. Therefore, the learner should be flexible in asking and answering the suggested questions. They do not provide evidence about the effectiveness of this approach.

2.6.4 Novak & Gowing's Differential Approaches for Training Concept Mapping

Novak & Gowin (1984, pp. 29–34) suggest a number of different approaches which could be used for teaching students in various grades how to construct concept maps. With regard to adult students, the target population of this research, they suggest the following procedure[8] (pp. 32–4):

1. Select one (or two) meaningful paragraph(s) from a text, and ask the students to read the selected material and pick out the key concepts in the material. Present the list of key concepts to the students and discuss with them which concepts represents the most important, most inclusive ideas.
2. Construct and present to the students a list containing the key concepts hierarchically ordered, with the most important concept coming first, then the next most important concept, and so on until all concepts have been ordered.
3. Construct a concept map, using the ordered list as a check list. Ask the students to help to choose the linking words to be used to label relationships among concepts in the map.

[8] Actually, Novak & Gowin divide their training procedures into two parts: (1) *preparatory* and (2) *mapping* activities. The preparatory activities consist of introductory instruction about the notions of concepts (i.e., objects and events), concept words and linking words (i.e., relationships). The instructional objective of this introductory instruction is to have the students learn how concept words and relationships are put together in sentences to convey meaning. In summary, the preparatory activities amount to concept teaching, not strategy training itself. Thus, the procedure presented here refers only to the mapping activities presented by those authors.

4. Look for cross links, that is, links between concepts in two separate parts of the map. Ask the students to help to choose the labels for these cross links.
5. Reconstruct the map if it does not have a *good look* (e.g., it presents poor symmetry). Tell the students that reconstructions may be necessary before they are able to draw adequate maps.
6. Discuss the quality of the map and present possible structural improvements in it[9].
7. Ask the students to choose a passage of a text and repeat the foregoing steps by themselves (or in groups of two or three).
8. Discuss the maps constructed by the students and call their attention to the fact that maps should reflect the interpretation of the text by the map maker.
9. Ask each student to draw a concept map for a domain for her own interest (e.g., sport, hobby). Encourage discussions among the students about these maps.
10. Include questions involving concept mapping in the subsequent test so as to illustrate the value of this technique as an evaluation tool.

Novak & Gowin(1984) do not present any experimental evidence of effectiveness of their procedures, be it in instructional or motivational terms.

2.6.5 Comments on Training Approaches: Suitability for a Computer Implementation

The building-block approach described above seems easy to implement in the computer, but, as pointed out, it does not lead to satisfactory results. Thus, it has been discarded as a basis for this research. Interactive peer modelling may serve as a basis for a computer program which implements a non-conventional teaching paradigm, such as knowledge negotiation, but it is not very helpful for implementation of a conventional paradigm such as the one employed by this research. The link-guided approach is not actually a training approach, but instead constitutes a set of heuristic guidelines whose educational effectiveness has not been reported. Novak & Gowin (1984) put too much emphasis on both hierarchy and the final appearance of concept maps. Also, their procedure is intended be used with concept maps, which employ unconstrained link names, and hardly could be effectively implemented in the computer using the

[9] Novak & Gowin also suggest some score criteria for concept maps which should be discussed with the students in order to show them how their scores could be maximised.

current state of knowledge about natural language processing (see, e.g., Allen, 1989). Finally, the expert modelling approach is difficult to implement even in the presence of an expert mapper and was not originally devised to be used as an interactive, individualised tutorial. Even so, it does provide some basis for a computer implementation, and thus it has served to guide the design of the approach presented in **Chapter 3**.

2.7 Sherlock: A Computational Approach

Sherlock[10] is a program that purports to train a learner in graphic mapping while she reads a text (Feifer, Dyer, Baker, Fowers, & Read, 1986; Feifer, Dyer, Baker, & Fowers, 1987; Feifer, Dyer, & Baker, 1988; Feifer, 1989). In addition to an off-line text to be represented graphically, Sherlock provides the learner with: (1) a set of concepts, represented by words inside rectangles (*icons*); and (2) a set of links which the learner is expected to use to connect the concepts. The six canonical links provided are (Feifer, 1989, p. 7):

PART Meaning: one concept is part of the other concept. Keywords: is a part of, is a segment of, is a portion of

IS-A Meaning: one concept is a member, subset or example of the other concept (class). Keywords: is a type of, is an example of, is a king of, is in the category of.

LEADS Meaning: one concept leads to or results in the other concept. Keywords: leads to, results in, causes.

EQUIV Meaning: the concepts are the same. Keywords: is just like, is the same as, is the definition of.

PROP Meaning: one concept is an attribute of defining property of the other concept. Keywords: is an attribute of, is characteristic of, is a property of.

NOT Meaning: the two concepts are different. Keywords: is not like, is distinct from, cannot be.

Feifer (1989) does not provide any rationale or justification for the use of those links at all. He does not say where his links come from, but it seems clear they are adapted from Holley & Dansereau (1984b) (see **Section 2.4**). Note that, roughly, in Feifer's system, 'IS-A' corresponds to 'type', 'LEADS' corresponds to 'analogy', and ' PROP' corresponds to 'characteristic' in Holley & Dansereau's

[10] This program should not be confused with another Sherlock, an ITS developed by Lesgold and his colleagues (e.g., Lesgold, Lajoie, Bunzo, & Eggan, 1992) devoted to teaching electronics troubleshooting.

notation. Note also that 'NOT' is unique to Feifer's system, and he does not use Holley & Dansereau's 'evidence'. It is also interesting to note that 'NOT' neither is an unusual relationship name nor has any intuitive usage (e.g., one is not certainly expected to link all concepts in a text which are different from each other by means of 'NOT'; otherwise, the map would be too cluttered).

Sherlock consists of the following components:

- a *graphical interface* which allows the learner to draw a map and translate her inputs into an internal representation;
- a *knowledge base* containing both the program's understanding of the text and the background knowledge represented in a semantic network;
- a *production system* representing the skills and strategies employed in the construction of maps. These rules are based on strategies used by subjects during pilot studies and represent plans for building graphic maps. They represent both the strategy used by Sherlock would use and the strategy it assumes the learner will use to build a graphic map.
- an *analyser* which constructs the learner model;
- a *learner model* which represents the program's beliefs about the learner's understanding of the text, graphic elements, and mapping skills. It should have been built by modifying the representation of both the text and graphical strategies, but it is not fully implemented. The only part of the learner model which is implemented is concerned with the learner's interpretation of the icons provided (see below).
- a *tutor* which diagnoses the learner's inputs based on the learner model and provides appropriate tutoring.

Sherlock intervenes when the learner gets stuck or when she makes a mistake. According to Feifer et al. (1988), the program constructs hypotheses about the cognitive processes used by the learner, and then uses them as the basis of its interventions. Because there can be more than one *correct* graphical representation of text, the program must recognise unanticipated but correct, or incorrect, inputs. Feifer et al. (1988) observe that the program's capacity to recognise unanticipated, correct inputs is especially important.

Feifer (1989) conducted pilot studies in an attempt at modelling the graphical mapping task. His ultimate goal was to find out a definition of a formal model of graphic mapping, but he found it very difficult, mostly because links and icons may be ambiguous. His main findings were that it is difficult to determine the learner's cognitive struct ure from actions (i.e., the mapping task) alone, because there is too much variability in graphic mapping. In his first pilot study, Feifer (1989) determined three basic reasons by which a learner would not make an anticipated link: (1) differences in the understanding of the text domain; (2) differences in strategies for building graphic maps; and (3) differences in understanding(interpretation) of icons.

Feifer et al. (1988) make the point that, due to the peculiar nature of the task involved, the program must be able to keep track of bot h declarative and procedural knowledge the learner could be using during the map construction. As they put it,

> It is impossible to determine what procedural knowledge led to a particular link if we do not know what declarative knowledge the learner has of the text. Likewise, it is impossible to infer the declarative knowledge the learner has of the text if we do not know the strategy the learner is using. (Feifer et al., 1988, p. 500).

The declarative knowledge (including the necessary background knowledge) concerning the program's understanding of the text is represented by means of a semantic network package based on Fahlman's (1979) NETL, which was originally designed to classify concepts through a combination of spreading activation and marker passing. Sherlock uses the spreading activation mechanism of this semantic network wit h two purposes: (1) to classify a learner's plan as a specialisation of one of its plans; and (2) to determine the relationship between any two concepts. Feifer (1989) provides several details about the role played by this network and its mechanism of spreading activation. Most of those details are beyond the scope of this review, so that what follows are the main conceptual points of his book.

Each icon made available to the learner by Sherlock has a corresponding node containing a unique role[11], called an interpretation-of-icon, in the semantic network. A specialisation (instantiation) of such a role represents a possible interpretation (concept) of the corresponding icon. An icon may have various interpretations associated with it, represented by the several different ways in which its role can be filled in. Each link, in the semantic net, connecting an icon to a corresponding interpretation may have a unique weight representing the probability of this interpretation being correct. The weights are pre-set according to the author's intuition about the probability associated with each interpretation.

[11] A role is a node representing an attribute, characteristic, fact, or argument of another node.

As the learner constructs her map, the program changes the weights to reflect its belief about how she seems to be using (i.e., interpreting) the icon.

With regard to procedural knowledge, Sherlock can be considered a model-tracing tutor (Anderson, Corbett, Fincham, Hoffman, & Pelletier, 1992; Anderson, 1993). That is, the program 'attempts to model the learner's procedural knowledge by deciding which productions in its production system describe [the] knowledge the learner has' (Feifer et al., 1988, p. 502). Each production rule has an associated strength. If the strength associated wit h a given production is greater than zero, the production is considered to be a good strategy; a strength less than zero indicates an erroneous (buggy) production; and a production with strength equals to zero is considered irrelevant (despite being correct). Each antecedent of a production rule has an associated weight, which indicates how important the antecedent is to determining whether the rule is appropriate. The program will believe that the learner has mastered a given rule when, given the antecedents of the rule, the learner takes the action corresponding to it. What follows is an example of a production rule found in the procedural knowledge base of Sherlock (Feifer et al., 1988, p. 502):

IF	An A is probably a B	(weight .7)
AND	It is not as likely that B is an A	(weight .7)
THEN	Make an IS-A link from A to B	(strength .8)

If a production rule is needed only to perform a task (e.g., tutoring), it is represented only in the production system. If a rule is needed both to perform a task and to explain (e.g., rules for building graphic maps), it is represented in both the production system and the semantic network. Feifer (1989) contends that 'This implementation enables Sherlock to model thinking about actions as opposed to just deciding what action to take given a set of circumstances' (p. 62).

When the learner makes a link between two icons, the program activates the corresponding concepts in the network and activation spreads from each of these concepts[12]. Then, the program selects each production whose antecedents match current states of the network. Each matching production is considered a possible production. Possible productions with positive strengths are regarded as correct moves, and the best move corresponds to the production with the greatest positive strength. Possible productions with negative strengths are considered possible explanations for a wrong action. Thus, the goal of the learner modelling carried out by the program is to identify a production which explains the learner's move;

[12] If an icon has more than one possible interpretation, the most likely interpretation is used.

that is, to determine whether any of the possible production leads to the link she has just drawn. This goal is not always met, however. In other words, it is not always possible to anticipate the learner's move. If Sherlock cannot find such a matching production, it will ask the learner to indicate the reasons by which she made the respective link. Then, it uses the learner's answer to separately evaluate the learner's plan and the facts the learner believes.

The program has tutoring rules which are responsible for taking three types of actions:

1. Asking the learner questions (e.g., Why did you do that?) and trying to figure out the reason for her last move. This action is taken when no production rule leads to the link the learner has just drawn. In this situation, the program constructs a question by first finding out all the rules that would lead to that link, and then using instantiated antecedents of these rules as alternative answers for the question. Finally, the question along with its associated possible answers are put together and presented to the learner in form of a menu. If the learner chooses an answer which corresponds to all the antecedents of a given rule, the program assumes that this is the production she has employed. When there is no perfect match between the student's answers and a production, the program uses the weight of each antecedent to find the closest match. If, even after this, there is no good match yet (i.e., they do not agree on at least 80% of the facts), Sherlock considers the possibility that the learner is using an alternative interpretation for the icons, and starts again from scratch. After trying all possible interpretations, Sherlock chooses the closest interpretation that leads to the learner's beliefs. If there is any false fact that the learner believes to be true and that leads to the bad link, Sherlock call the learner's attention to that. If there is any true fact that the learner does not believe and that would lead to a better link, Sherlock again brings it to the learner's attention. Feifer (1989) found some difficulties wit h this questioning approach because some times the learner thinks about one thing and picks a contradictory fact, interprets facts differently from Sherlock, or picks two contradictory facts. Because of these problems, frequently, Sherlock could not decide what plan the learner was using.
2. Determining the cause of an unexpected move and changing the semantic network accordingly to reflect the diagnosis. According to Feifer et al. (1988), though making appropriate changes to all portions of the network and productions to model the learner's state of knowledge is a desideratum,

only changes concerning interpretation of icons have been implemented. Sherlock recognises two cases of alternative icon interpretation when the learner uses an icon to represent (1) an alternative but unexpected concept, and (2) a descendent of the intended concept. In the first case, if the learner's alternative interpretation of the icon is considered correct, the program will raise the weight of the link from the icon to this interpretation (see discussion above), so that this interpretation will thereafter be considered the primary (i.e., the expected) interpretation of the icon in consideration. The inheritance propriety of the semantic network makes it easy for the program to recognise the second case.

3. Providing the learner with feedback to remedy misunderstandings identified by the diagnosis. For example, when the tutor believes that the learner has misunderstood a passage in the text, it tries to find out the source of confusion and then inform her what is wrong with her reasoning (e.g., it suggests that the learner might have overgeneralised). This type of action corresponds to tutoring itself, and although the most important, it is the least explored component of Sherlock. The program simply seems to dedicate most effort to identifying source of errors and does not know what to do with that information.

To sum up, Sherlock's tutoring strategy (algorithm) can be outlined as follows:

- determine the relationship between the two linked icons by spreading activation from the concepts associated to those icons;
- determine whet her the program would have made the same link by verifying if the production system would lead to the same link given the current activation in the semantic network;
- if not, ask the learner why he made the link;
- use the learner's answer to classify the learner's plan as an instance of a known plan;
- use the learner's answer to determine if he is interpreting the icons differently from Sherlock by verifying if there is a mismatch between the learner's beliefs and Sherlock's; if so, evaluate again using the new interpretation;
- provide feedback based on whether Sherlock would have made the same link, the plan Sherlock believes the learner was using, or the mismatch between the learner's beliefs and Sherlock's.

As far as implementation is concerned, Sherlock used a graphical interface developed at UCLA AI laboratory and a semantic net package developed by Gasser, 1988. It runs in Apollo workstations and has 3,000 lines of a dialect of LISP code. Only the consideration text, a two-paragraph-long text (about consideration) from a business law textbook described in his book, has been implanted to test the actual capabilities of Sherlock. Moreover, Feifer (1989) acknowledges that representing a new text and domain requires expertise in knowledge engineering and is a 'formidable task' (p.168).

Criticism of Sherlock's Approach. Sherlock's tutoring strategy reflects an early trend in ITS research, namely emphasis on tutor interventions based upon bug diagnosis (see, e.g., Brown & Burton, 1978; Sleeman, 1982; Stevens, Collins, & Goldin, 1982). There are a number of problems with this approach. Two of these problems are overwhelming: first, from a practical standpoint, the tutor spends a lot of time and effort trying to understand (or guessing) the learner's underlying misconceptions (i.e., reasons for errors); and second, perhaps even worse, from an educational point-of-view, there is little evidence that providing feedback on students' underlying misconceptions enhances learning at all (see Anderson, 1993, Chapter 11, for a criticism of this approach; see also Elsom-Cook, 1993).

Also, Feifer (1989) puts too much emphasis on the problem of icon interpretation. According to Feifer (1989), the difficulty a learner faces in mapping concepts to icons is that 'there is no one-to-one correspondence between icons and concepts any given learner will want to represent' (p. 39). He further argues that,

> In the graphic mapping task, a learner must interpret an icon with a meaning that is consistent with the context in which he is using that icon. Sherlock must maintain all possible interpretations of an icon, and then figure out both the learner's context and his interpretation (Feifer, 1989, p. 55).

It seems that the trouble with icon interpretation has been introduced by Sherlock itself. That is, this is not an inherent problem of graphic mapping. The contention is that there does not appear to be such a problem when one draws a conventional, paper and-pencil map, because the icons (i.e., the boxes representing concepts) are drawn from the text, so that the context is always clear for the learner. A second point is that if a program for teaching graphical mapping had to represent 'all possible interpretations of an icon', it would easily run out of space (unless very short, trivial texts were used). Moreover, there is no guarantee that finding out exactly which interpretation of an icon the learner is using (i.e., the reason for the error) will have any educational effectiveness. That is, it may be sufficient (and much cheaper) to find out that she has misinterpreted the icon (i.e., the nature of the error) and provide the correct interpretation according to the context. Still better is to provide an interface that avoids the problem of icon interpretation altogether. Therefore, it appears that the best solution is to provide the to-be-mapped text on-line so as to keep icons and context close together. This solution has been tried out in the present research (see **Chapter 5**).

In his final evaluation of effectiveness of Sherlock's feedback, Feifer (1989) remarks that, 'With very few exceptions subjects did not believe Sherlock's diagnosis, and thus did not change their beliefs as a result of the feedback' (p. 145). He goes on to point out possible reasons: (1) diagnosis was incorrect half the time, so that if the reasons given for rejecting a link were wrong, the subject did not accept the overall rejection; (2) the feedback merely stated that there was a problem (i.e., it did not explain why there was a problem). Finally, he insightfully concludes that just telling the learning about a mistake (i.e., merely stating that her link was wrong) has little impact, 'It is much more effective to help the learner recognize his own mistakes and discover for himself more appropriate actions'(p. 165).

Another problem with Sherlock's approach seems to be that it takes up the premise that graphical mapping has a strong component of procedural knowledge, as pointed out above. But, a case could be made that procedural knowledge does not play such a significant role in mapping. Instead, it seems that graphical mapping is difficult when the semantics employed in the representation is complicated. Compare, for instance, concept mapping as described by Novak & Gowin (1984), with other graphical strategies presented above. Because concept maps have easier-to-understand semantics (e.g., they do not require either special symbols or links) they can be used by young children. By contrast, a graphical strategy which uses a canonical set of links is much more difficult to employ, because its semantics of links is difficult to learn and apply, and therefore the learner will have to spend some time deciding which link is the most appropriate for each situation. In conclusion, the point is that what must be mostly taught in relation to graphical mapping is the semantics of the graphical representation. This is the general point-of-view followed up by this research.

2.8 Conclusion and Summary of Graphical Learning Strategies

Just & Carpenter (1987) suggest that the decision about which learning strategy is the most appropriate depends upon the material being studied and how well the strategy is executed. Nevertheless, from a theoretical point of view, most common learning strategies (e.g., underlining, note-taking) do not appear to entail cognitive processing sufficient for enhancing learning (see, e.g., Anderson & Armbruster, 1982). On the other hand, graphical learning strategies seem to capitalise on many implications suggested by the various models of learning, recall and memory (Holley & Dansereau, 1984a). In other words, the apparent success of these strategies in fostering learning may be explained by a number of combined cognitive factors. For example, Dansereau (1985) has suggested that graphical strategies are effective because they force the learner to get into deep processing (see, e.g., Cermak & Craik, 1979; Anderson & Reder, 1979), reorganise the to-be-learned material or generate a content schema (see Rumelhart & Ortony, 1977), make use of imagery (see, e.g., Paivio, 1971), or some combination thereof. Thus, he concludes, it is difficult to determine 'which alteration in cognitive activity is responsible [for the success of such a strategy]' (p. 212). It follows that very little is known about why some learning strategies seem to work. Other researchers (e.g., McKeachie, 1984) argue, however, that the activities the learner engages in while using such a strategy are the only factors responsible for the likely success ascribed to graphical strategies. That is, those activities themselves facilitate learning 'regardless of whether or not they result in a spatial representation' (McKeachie, 1984, p. 305). Thus, imagery is not as major an ingredient in the effectiveness of graphical strategies as it might appear[13].

In addition to their seemingly theoretical superiority, most graphical learning strategies present a practical convenience that has not been fully explored by computer scientists: they are much more amenable to computer implementation than non-graphical learning strategies (e.g., summarising). On the negative side, all scientists involved in graphical strategies research seem to agree that they are very difficult to teach students how to use. This happens because, when the use of a learning strategy by the learner is not automatic, it also competes for the limited resources of short-term memory. Thus, if a learner cannot automatically apply the strategies necessary for learning, she will have less space available for the information necessary for meaningful learning to occur (Kozma, 1992). Therefore, instead of reducing the cognitive load associated with text processing, these strategies in fact may increase the cognitive load, because now the learner has to attend simultaneously to two demanding tasks. This problem is much less serious in the case of conventional learning strategies. For example, the

[13] Novak & Gowin (1984), for example, believe that, 'concept maps present a way to visualize concepts and the hierarchical relationships between them', and that '[c]oncept mapping has a potential for enlisting this human capacity for recognizing pattern in images to facilitate learning and recall' (p. 28) (see also Winn, Li, & Schill, 1991; Winn, 1991).

conventional note-taking strategy is normally practised for years at the schools since the very early grades.

The research findings presented in this chapter reveal that the use of learning strategies does not always improve learning, and when they do, improvement appears to be slight. There are many possible explanations for these results: the students might have not spent enough time on the task (the use of learning strategies requires the learner to spend more time on the task than she would do if she were merely reading); the students might have not executed well the processing required by the strategy; the students might have not been trained in the correct use of the strategy; and many other research flaws (see, e.g., Anderson & Armbruster, 1982; Goetz, 1984).

There are other problems associated with research into graphical strategies. Most research into concept maps has focused on demonstrating their large applicability in a variety of contexts, but as Lambiotte et al.'s (1989) review suggests, research into the educational effectiveness of concept maps has resulted in exaggerated claims and lack a systematic approach in hypothesis testing. Other spatial strategies which have been investigated also suffer from the same problem of lack of systematic evaluation, but this is more evident in concept mapping research which has provided a large body of research. To sum up, the facts that graphical strategies are amenable to computer implementation and their training is arduous, along with their potential learning benefits have motivated this research. As can be concluded from the discussion above, conceptually speaking, the cognitive tasks involved in the use of spatial strategies consist simply in breaking the passage down into parts and identifying the relationships among these parts (Weinstein & Mayer, 1986). In practice, however, things may be quite complex.

Some of the graphical strategies (e.g., mapping) depicted above do not have a clear semantics, and thus, are even harder to learn and employ. On the other hand, concept maps and networks, seemingly the only survivors, have semantics which are both clearer and more intuitive: a proposition (i.e., a relationship between two concepts) is simply characterised by two boxes representing the concepts connected by a labelled line representing the relationship itself.

Finally, the approaches and guidelines available for teaching presented in this chapter are not ready to be directly implemented in the computer, so that a more adequate approach must be created with this purpose. The following chapters propose a procedure which is able to cope with training of graphical strategies.