Concept Maps: A Theoretical Note on Concepts and the Need for Cyclic Concept Maps

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Abstract

This paper, theoretically, examines concepts, propositions, and establishes the need for and develops an extension to Concept Maps (CMaps) called Cyclic Concept Maps (Cyclic CMaps). The Cyclic CMap is considered to be an appropriate tool for representing knowledge of functional or dynamic relationships between concepts. The Concept Map (CMap), on the other hand, is viewed as an appropriate tool for representing hierarchical or static knowledge. The two maps complement each other and collectively they capture a larger domain of knowledge, thus forming a more effective knowledge representation tool.

Introduction

Concept Maps (CMaps) are used around the world by educators and researchers alike. The *Journal of Research in Science Teaching* alone has published numerous articles on CMaps during the last 15 years, including a special issue dedicated to the topic. Researchers have been interested in CMaps as a knowledge representation tool for instruction (Edmondson, 1995, Ferry et al., 1998, Horton et al., 1993), learning (Chmeilewski and Dansereau, 1998; McCagg, 1991), and evaluation (Aidman and Egan, 1998; Rice et al., 1998).

The present work was motivated, in part, by noting the paradox of CMaps. That is, a Concept Map is supposed to represent knowledge, but it is not able to represent one of our highest forms of knowledge, as in the laws of physics, which are expressed in mathematical equations. The purpose of this paper is twofold: First, to point out that the CMap is a useful knowledge representation tool, primarily for representing "static" relationships between concepts. Second, "dynamic" relationships between concepts can be represented in Cyclic Concept Maps (Cyclic CMaps), which represent the functional relationships among a constellation of concepts. The ability to represent both static and dynamic relationships in a single map may increases the power of the representational system.

Between the two practical ends of "problem identification" and a "potential solution" is a theoretical bridge, which was developed by re-thinking the basic constructs of CMaps. The practitioner may find this paper more theoretical than the typical article in this area. Assuming a reasonable treatment of theoretical issues by the authors, it is worth recalling Lewin's (1951) famous quote about the relationship between "theory" and "practice." His insightful observation was that "there is nothing so practical as a good theory."

This paper is organized in the following manner. First, the theory and research on CMaps will be reviewed and questions about *concepts*, *labels*, and *propositions* will be raised. Second, a theoretical analysis of these basic elements of CMaps will be provided. Third, CMaps will be considered as an appropriate knowledge representation tool only for the static relationships between concepts. And finally, Cyclic CMaps will be discussed both as a "stand alone" knowledge representation system and as an extension to CMaps. Several Cyclic Concept Maps are constructed and used for the demonstration and the discussion of the properties of Cyclic CMaps.

The Theory and Research on Concept Maps

Joseph Novak and his colleagues developed Concept Maps in the early 70's, while they were studying science concept learning in children (Novak and Gowin, 1984). The CMap is a knowledge representation tool in the form of a graph comprised of boxes connected with labeled arcs. Words or phrases that denote concepts are put inside the boxes, and relationships between different concepts are specified on each arc. Propositions (*node – link – node* triads) are a unique feature of concept maps, compared to other similar graphs.

Propositions consist of two or more concept labels connected by a linking relationship that forms a semantic unit (Novak and Gowin, 1984). Concepts are defined as "perceived regularities in events or objects, or records of events or objects, designated by a label" (Novak, 1998, p.21). A significant variation of a proposition is a crosslink, which shows the relationships between ideas in different segments of the map. To see a relationship between two different concepts is associated with insight. Links specify the relationship between concepts by words or signs/symbols. Arrows are used to designate the directionality of the relationship; if an arrow is not used, it is assumed that the direction of the relationship is downward.

Novak (1998) emphasized the importance of hierarchical structures in concept mapping. Thus, CMaps should have more inclusive, general concepts at the top of the hierarchy with progressively reducing generality at the lower levels, which consist of less inclusive, more specific concepts. Based on this principle, CMaps are generally read from the top to the bottom.

Concept mapping is based on Ausubel's theory of learning (Ausubel, 1968), which emphasized the difference between meaningful and rote learning. Meaningful learning, the theory argued, builds one's cognitive structure by assimilating new concepts into learner's existing conceptual structure. Novak (1998) described concept mapping as a "major methodological tool of Ausubel's Assimilation Theory of meaningful learning."

The literature in this area has been primarily concerned with application of CMaps to a variety of situations. One area of investigation is the comparison of CMaps to other forms of knowledge representation. A study comparing different forms of lecture aids was conducted by Lambiotte and Dansereau (1992). In this study, students' recall of the material presented in a lecture was assessed depending on support material used during the lecture: CMaps, outlines, and lists. All lecture aids used in this study were constructed by an expert in the area. General results did not show significant difference of CMaps over the other two types of aids. However, authors point out that for students with low prior knowledge, CMaps was the most beneficial form of aid, while students with high prior knowledge benefited more from lists.

Hall, Dansereau, and Skaggs (1992) also assessed recall of information either in the form of normal text or CMap. The authors found a significant difference favouring CMaps as a tool for representation in one subject domain (autonomic nervous system), and did not find significant difference for another subject domain (research design). One of the explanations for these differences provided by the authors was the type of subject matter presented. Particularly, the degree of abstractness of the domain was emphasised, presuming that the way in which CMaps represent information is more suitable and beneficial for a more specific domain (autonomic nervous system), and does not have any advantages over plain text representation for a more abstract domain (research design). This suggests that a decision to use CMaps as a form of representation must depend on the characteristics of the knowledge domain to be represented.

Some researchers have applied CMaps as a knowledge engineering or managing tool. Cañas, Leake, and Wilson (1999) have described Design Retrieval and Adaptation Mechanisms for Aerospace (DRAMA) framework developed in collaboration with NASA. This framework was built by combining the organization of CMaps with Case-based Reasoning methodology of knowledge retention. The main purpose of DRAMA, state the authors, is to enhance the capture, accessibility, and reuse of experts' knowledge in aerospace industry. Several advantages of such combination are discussed.

Ford et al. (1991) describe the knowledge acquisition tool ICONKAT. There, CMaps are used as a tool to elicit knowledge from experts along with Kelly's repertory grid (Kelly, 1955). CMaps were used to provide a high-level overview of the domain. ICONKAT represents a "theory-based" tool, authors argue, that combines two related theories of cognition: Ausubel's assimilation theory and Kelly's personal construct theory, incorporating the main methodological tools of these theories and combining them in one system. Ford et al. (1996) also described a nuclear cardiology expert system NUCES where a system of CMaps were used for navigation in the system. In these studies Concept Mapping was applied as a major methodological tool for knowledge engineering without questioning or examining its validity.

Many of the studies of Concept Mapping are done in the context of education literature. Usually the CMaps are reported as having positive value or effect (e.g. Kinchin, 2000a, 2000b; Edmondson, 1995; Markow and Lonning, 1998). For example, Edmondson (1995) discussed the positive effect of CMaps in the development of a problem-based veterinary curriculum (Edmondson, 1995). Similarly, Willerman and MacHarg (1991) examined the use of CMaps as an "advance organizer" for grade eight students in a science unit dealing with physical and chemical properties of the elements. The authors reported that the use of a CMap at the beginning of the unit resulted in a significant difference in performance at the end of the unit on an administered test, compared to a control group that did not use CMaps.

The positive impact of the use of CMaps for instruction and learning in secondary biology education was discussed by Kinchin (2000a, 2000b). Building on the research of others, Kinchin (2000b) discussed the advantages of Concept Mapping in secondary biology education for planning and preparation of the lesson by a teacher, as an opportunity for meaningful learning on behalf of a student, and suggested the positive effect of using CMaps for the revision and summarising of the material by students. Kinchin (2000b) emphasised "pupil-produced maps" as the ones that are most beneficial in the learning process, arguing that CMaps are able to reveal students' misconceptions in learning that are not captured by traditional assessment tools. Some of the issues regarding the use of CMaps for assessment are discussed and the classification of CMaps is proposed based on the structure of the map ("spoke – chain – net") as an indication of restructuring in the learner's understanding (Kinchin, 2000a). However, classification itself is not sufficient for adequate evaluation.

Soyibo (1995) described the use of concept mapping to identify differences in the presentation of the topic of respiration by six different biology textbooks. Soyibo (1995) suggested that applied analysis of CMaps is "a good way to compare the organization and elaborative structure of specific topics in textbooks" (Soyibo, 1995).

Markow and Lonning (1998) tested the effect of CMap construction in college chemistry laboratories. Despite the fact that multiple choice assessment tests did not reveal any difference in students' conceptual understanding between the experimental and control group, the authors reported that the students had a strong positive attitude towards the use of CMaps for a better understanding of chemistry laboratory concepts (Markow and Lonning, 1998).

Many researchers have investigated the application of CMaps as an evaluation tool for classroom learning. For example, McClure, Sonak, and Suen (1999) compared six different scoring methods of CMaps and found them all to be correlated with each other. Roberts (1999) compared different scoring methods for CMaps and developed a scoring method for CMaps of statistical content (university level). Even though an improvement in the score of CMaps was not obtained, the author felt positive about using CMap as an evaluation tool, since CMaps are powerful in revealing students' misconceptions (Roberts, 1999).

Williams (1998) and Markham and Mintzes (1994) compared CMaps constructed by novices to those made by experts. Both studies reported significant differences in the CMaps of experts and novices; Williams (1998) based on the subjective comparison of CMaps and Markham and Mintzes (1994) based on numerical scores. The authors argue that these subtle differences revealed by the analysis demonstrate the ability of CMaps to capture differences in the knowledge and understanding of the subject matter, and is evidence toward possibilities of using CMaps as a research and evaluation tool. Markham and Mintzes (1994) highlighted the difference in traditional scores and CMap scores as signifying that CMaps are able to capture differences between meaningful and rote learning, whereas traditional techniques can not.

Theoretical Questions

Although the research concerns are often practical, the theoretical issues inevitably arise. For example, the basic assumption of CMaps concerning the hierarchical structure of knowledge is questioned by Ruiz-Primo and Shavelson (1996) in the following quote:

Methodologically and conceptually, there is no need to impose a hierarchical structure. If the content structure is hierarchical, a hierarchical map should be observed. Harnish, Sato, Zheng, Yamaji, and Cornnell (in press) proposed different map structures (e.g., spider maps, hierarchical maps, and chain maps) to represent different types of content structures. (p. 578)

Hibberd et. al. (2002) considered the question of structure of CMaps and pointed out that there is evidence in support of both hierarchical and network structures, and thus, an open debate.

In addition to asking questions about the hierarchical structure, one may question the fundamental constructs of CMaps. For example, the following questions may be raised. Can propositions in CMaps adequately represent all forms of conceptual knowledge? To answer this question, it is necessary to ask what is a *concept*? Is it the same as a *category*? What is the relationship between a concept and a *label*? What is a *proposition* and how does it create meaning? As it will be shown in this paper, these questions are neither trivial, nor have they been adequately answered in the literature.

Categories & Concepts

Consider a category with identical members, for example, squares with 2 cm sides which have the same colour and thickness, each drawn on a set of identical index cards. The perceived variability in this category is almost zero; that is, the category is maximally homogenous. The only difference among the squares is in their spatial location.

Let each member of a category have **n** perceived properties (Tversky, 1977). The members are similar with respect to some properties and different with respect to other properties. The perceived variability in a category is a direct function of the number of properties which are different, and an inverse function of the degree of similarity of the members with respect to the similar properties. Thus, in the above example, the perceived variability in the category of squares increases as more squares of different colours are included in the category, and decreases when the category has squares with sides varying from 2 cm to 3 cm, as opposed to sides varying from 2 cm to 5 cm.

Psychologically, what makes a category a category? That is, how much variability is acceptable within a category before the category is split into two or more sub-categories? There are at least two ways to answer this question. One approach is to examine the inner-structure of a category by noting the similarity among the members. The emphasis may be on the fact that some members are more informative (prototype) about the content of the category than others (Rosch, 1978; Taylor, 1995), or on the development of a measure of perceived similarity for the members based on their situation-specific availability (Medin et al., 1993; Medin and Shoben, 1988).

A second and less studied approach is to consider categorization as a part of larger system of classification. How the variability is distributed may be considered as a function of the overall amount of perceived variability in the set and the purpose of the task in hand (Cañas, 1985; Cañas et al., 1985; Raymond et al., 1989). According to the Gestalt theory, the two forces, which determine the final equilibrium in the distribution of variability, are the result of the interplay between the forces for unification of similar members into the same category and forces of segregation of different members into separate categories (Koffka, 1935). These forces have been quantified as the ratio of perceived variability within categories to the perceived variability between categories. The experimental task was to develop a system of classification for retrieval of proverbs in response to different queries (Cañas, 1985; Cañas et al., 1985; Raymond et al., 1989).

The overall distribution of perceived variability is also related to the cognitive bottleneck in the number of categories which can be readily discriminated (Miller, 1956). For example, Higgins and Safayeni (1984) have shown that the number of categories in taxonomies for administrative tasks remain within Miller's 7 ± 2 across different taxonomies of different researchers. Hierarchical structure keeps the number of categories in a manageable range at any given level of hierarchy (Rosch, 1978). However, the variability within each category increases in the higher levels of the hierarchy. The question is what happens to the psychological experience of a category as variability increases.

Consider the above example of identical squares, where it was noted that perceived variability in the category increases by transforming the identical squares into squares with different sizes and colours. Note that variability may further increase by including any four sided geometric shapes, and increase even further by removing the constraint on the number of sides.

Let a continuum from perceived low variability (e.g. identical squares) to perceived high variability (e.g. geometric shapes) represent possible categories within the domain of geometric shapes. Note that there is a tight coupling between the members of the category and the category name when the variability is low or a basic level category (Rosch et al., 1976), and a loose coupling between the members and the category name when the variability is high. That is, the category squares can be identified with relatively few exemplars, whereas the category geometric shapes will require many more exemplars reflecting the range in membership, and it is more likely to be misidentified.

In contrast, when variability is high, the category, psychologically, will tend to break up into more homogenous sub-categories. For example, the category geometric shapes may decompose into sub-categories such as triangles, rectangles, and shapes with more than four sides. What keeps a high variability category together is a concept, which abstracts or imposes at least one property to define the category and set the entry criteria. The abstracted property may be visible or invisible (Wittgenstein, 1958). For example, in the category *squares*, the abstracted property is visible, whereas in the concept *things bought on sale*, the abstracted property is not visible.

Knowledge, in part, is expressed in concepts. People use concepts in their daily lives. For example, stereotypes are used to express personal knowledge of people and the social world (Kunda, 1999). Here concepts are used based on similarity of properties like age, gender, size, colour, religion and so forth. From a scientific point of view, concepts in stereotyping can easily be criticized because the concepts are based on superficial properties, and not able to capture the more fundamental, essential properties of being human. For example, the psychological experience of frustration is the result of a barrier between a person and a goal (Lewin, 1935), regardless of how the person may have been stereotyped.

Scientific concepts, which have contributed to the advancement of knowledge, are based on abstraction of what Lewin (1926) called the *genotype* properties. For example, as an abstraction, the concept of mass in physics is a property common to all things. To note this property means ignoring all phenotype properties like shape, size, colour, function, etc.

Bronowski (1976) has noted that a significant historical abstraction in development of human knowledge was the separation of number from what was being counted, for example, instead of *5 apples*, the concept *5* as a number. Mathematics is concerned with relationships and form as opposed to content. Feynman (1999) pointed out "mathematics is only patterns" (p. 175). This is precisely why Whitehead (1967) considered mathematics as the highest form of abstraction in human thinking.

Murphy (2002) has suggested that concepts are a non-linguistic representation of a class of entities, and words are labels that map onto our conceptual structure. That is, the root of all concepts is found in psychological categories of something without a label, a view shared by many researchers (Medin, 1983; Smith and Medin, 1981; Novak, 1998). Note that this view is reasonable when the degree of abstraction is from low to medium (e.g. squares to geometric shapes), but does it apply to high-level abstraction in mathematical concepts? What does it mean, for example, to say that the concept of rate of change has a cognitive representation, as a category of things or events, outside of its formulation and description in calculus? What class of entities are grouped together? The point is entities are irrelevant, since everything changes the class of those entities with a rate of change includes everything (e.g. rollercoaster in motion, stones, rare birds in Africa, computer chip, etc.). Here, the concept is a precise description of the changing relationships between two states of any entity and corresponding states in time. Thus, at the high level of abstraction, the concept may **not** necessarily be a category. Concepts may exist at the level of description; that is, knowledge by description as opposed to knowledge by observation (Russell, 1961).

It is worth pointing out that the recent progress in cognitive psychology for understanding the inner structure of categories has been with the implicit assumption that all categories or concepts represent exemplars. The classical view of concepts as ideals (Plato, 1858), and concepts based on definition (Hull, 1920), have been rejected, primarily because they do not account for the variability in membership of everyday concepts (Smith and Medin, 1981). Nonetheless, there is the recognition that there are different concepts, and it is possible to make useful distinctions among them based on structure, process, and content (Medin et.al., 2000). For example, the concept "justice" is more abstract and different than object-based concepts such as "dogs and boats" (Medin et.al., 2000).

To summarize, we have discussed variability in a category, grouping on the basis of overall physical similarities, abstraction of relatively few visible or invisible properties, whether these properties are essential or superficial, the notion that there are degrees of abstraction and mathematical concepts represent maximum abstraction, and that such concepts need not be represented by exemplars.

Labels

Words are one system used to describe and to name concepts. It is the job of the dictionaries to document and keep track of at least the major usage of words in different times and in different contexts. The Oxford English Dictionary (electronic reference), for example, gives many different meanings associated with the word *square*. In addition to a geometric shape, the word could mean a person with conventional values. In the past, the word has been used to refer to dispute, in the context of music it refers to a simple beat, and it may mean to make things even, just to give a few examples from many citations.

The simple observation is that when a concept is named, the word brings with it a past and a future of possible meanings. Thus, naming a concept increases the variability of the concept for the decoder who may be unfamiliar with the context in which the concept was encoded and used. The frequently cited Wittgenstein (1958) discussion of the concept of *game* illustrates the high variability in the concept and the difficulty of finding the common property for all those instances that can be called a *game*.

A concept can be disambiguated either directly or indirectly. The direct approach depends on descriptions, definitions, and exemplars; whereas an indirect approach utilizes analogies between concepts (e.g. computers are like the human mind). Some researchers have suggested that more abstract concepts may be understood through metaphors as opposed to exemplars (Gibbs, 1997).

In connection to the relationship between the label and the concept, to equate a concept to a category or a class of entities (Murphy, 2002) suggests the psychological availability (Tversky and Kahneman, 1973) of entities for each concept at the time of message encoding and decoding. If the entities were mentally connected to the concept, then one would expect a relative ease in generating examples for all concepts. But this is not what happens. In fact, most people may have difficulty giving an example for abstract concepts like intelligence, motivation, personality, and social dilemma, just to name a few. One possible explanation is that many concepts exist in our minds at the level of label with minimal description without reference to any entity. Duimering and Safayeni (1999), for example, discuss formal hierarchical communication in organizations as primarily concerned with the valence of concepts for positive image construction, as opposed to their true mapping to a class of entities.

Mathematics, instead of ordinary language, is the formal language of physical sciences (Dantzig, 1954). In an interview, Feynman (1999) discussed the role of mathematics in physics in the following manner:

For one thing, you need the math just to understand what's been done so far. Beyond that, the behaviour of sub-nuclear systems is so strange compared to the ones the brain evolved to deal with that the analysis has to be very abstract: To understand ice, you have to understand things that are themselves very unlike ice. ...what we have found in this century is different enough, obscure enough, that further progress will require a lot of math. (pp. 193 - 194)

The point is mathematics, as the language of science, is not just symbols as names for concepts, but it is a system of relations with logic and reason built into its inner structure (Feynman, 1975, 1999).

The above discussion raises many theoretical issues, such as how are highly abstract concepts represented cognitively, which are beyond the scope of this paper. At this point, the relevant arguments are as follows. First, concepts are not necessarily equivalent to categories, particularly for a high level of abstraction. Second, concepts may exist at the level of description. Third, a label is a code for a concept, which increases the variability of its possible meanings for the decoder who may not be familiar with the context in which the message was encoded. Fourth, mathematics is the formal language of physical sciences, which not only represents knowledge, but also possesses structural properties affecting conceptual possibilities in science.

Relationship between Concepts

Let affordances (Gibson, 1979; Norman, 1993) of a concept refer to its possible meanings. For example, in the previous section it was noted that the concept *square* has many different meanings; each meaning is an affordance of the concept. Some information about the specific meaning can be provided in the context of the communication. That is, a reduction of possible affordances to a particular meaning occurs as the result of concepts interacting with each other. The statement *life is about learning*, for example, is experienced as meaningful by activating *human experience* in the affordances of concept *life* and *human learning* in the affordances of concept *learning*. Alternatively, the concept *life* can be associated with *plants* in a proposition and the concept will, most likely, be decoded in a biological sense, which is another affordance of the concept.

Murphy (2002) discusses the importance of context in the selection of meaning. The context may be based on the social interactions in a community (Clark, 1996), or on the relationship between concepts in a statement (Curse, 1986). The relationship between concepts may be static or dynamic. The static relationship reduces the uncertainty in the labels by connecting the concepts in a proposition. The dynamic relationship is concerned with co-variation among the concepts.

Static Relationships

How many different types of static relationship can two concepts (C1 and C2) have? One possibility is **inclusion**, where **C2** is part of **C1**. For example, *squares* (C2) are part of *geometric shapes* (C1). A second possibility is **common membership.** Here, **C2, C3, Cn** are part of **C1**. *Squares* (C2) and *triangles* (C3), for instance, are related to each other since they both belong to *geometric shapes* (C1). These two types of relationship have also been recognized by Jonassen (2000) and are, of course, fundamental to the construction of conceptual hierarchical structures.

A third type of relationship is **intersection**, where **C1** is the meaning generated by crossing **C2** and **C3**. Most communications are intersections, and there are several ways of constructing an intersection. The following are some examples as opposed to a complete listing. C2 and C3 may have common membership in a super-ordinate category as in *squares have one more side than triangles*, or they may be unrelated concepts as in *life is about learning*. The probabilistic propositions are the result of a connection between C2 and a sub-part of C3. For example, the statement *geometric shapes may be symmetrical* is an intersection between the concept of *symmetry* and a subset of the concept of *geometric shapes*.

Finally, the similarity between C2 and C3 may be the basis of the intersection (e.g. rectangles are like squares). Note that similes, such as *the soldier fought like a lion*, and analogies, such as *learning how to live is similar to learning how to bike*, are also based on drawing attention to the similarity between two very different concepts in order to create a new meaning, C1.

The static relationships between concepts help to describe, define and organize knowledge for a given domain. CMaps, in their present form, are primarily designed to represent static relationships. The basic unit of representation is a proposition defined as two concepts plus a relationship, which is stated on the link between concepts.

It is possible to object to this assessment of CMaps, since the link may indicate a dynamic relationship such as concept C1 causes (changes, influences, or leads to, etc.) concept C2. This issue will be discussed in the next section, after discussing the nature of dynamic relationships in science. However, at this point, we will examine the frequency of dynamic links in CMaps.

The list of Concept Map linking terms from Jonassen (2000, p. 71) contains a total of 76 words/phrases that are considered to be appropriate for use in CMaps. This list was carefully analysed in search of linking phrases that would be suitable to represent dynamic relationships. That is, relationships that reflect the effect of a change in one concept on another one. With the "liberal" way of counting, any phrase that could potentially even vaguely represent a dynamic relationship was counted as dynamic (e.g. *regulates*, *determines*, or *provides*). The liberal counting resulted in less than 24% of the list. However, if one conservatively considers only phrases that are clearly dynamic (e.g. *is a function of* or *causes*), then the count is less than 7% of the total number of phrases. It is also worth noting that such dynamic linking phrases as *leads to*, *changes*, or *correlates with* were not even on the Jonassen's (2000) list. It appears that dynamic relationships do not constitute a major portion of potential links in CMaps.

In addition, the linking phrases from the set of CMaps in the IHMC Public Cmaps server (Cañas et al, 2003) were analyzed. The complete list contains more than 34,000 English linking phrases.

The most liberal counting of the dynamic relationships constitutes less than 4% of the total numbers of phrases in that list. With a more conservative counting, the number drops to less than 1%. It is worth pointing out that the number of linking phrases in conservative counting may be an overestimation of the actual number of dynamic relationship. Because it is impossible to analyse every proposition to determine whether it is dynamic or not, the counting assumed that if a link could potentially represent a dynamic relationship, it would be used accordingly in the CMap. In any case, even with the most liberal counting, the number is less than 4% of the total relationships represented. This suggests that in practice CMaps are rarely used to represent dynamic relationships between concepts.

Dynamic Relationships

The dynamic relationship is concerned with the description of a system of influences among concepts from different domains. More specifically, for any two concepts, the question is how the change in one concept affects the other concept. Two types of dynamic relationships are possible (Thagard, 1992). Those based on **causality** (e.g. travel time is an inverse function of the speed for a given distance), or those based on **correlation/probability** (e.g. academic performance in high school is a good predictor of academic performance in university).

Scientific knowledge is based on both static and dynamic relationships among concepts. However, the progress in modern science is attributed to mathematical formulations of dynamic as opposed to static relationships among concepts. Whitehead (1967) noted: “Classification is necessary. But unless you can progress from classification to mathematics, your reasoning will not take you very far” (p.28). He considered classification as a “halfway house between concreteness of individual things and the complete abstraction of mathematics” (p.28).

Rapoport (1968) discussed the dynamics of causality expressed in mathematical equations in comparison to ordinary language in the following quote:

The formal language of mathematical physics is literally infinitely richer than the ‘vulgate’ language of causality, because the equation which embodies a physical law (such as that of propagation of heat or electromagnetic waves, or the law of gravity) contains within it literally an infinity of ‘if so … then so’ statements, one for each choice of values substituted for the variables of the equation. (p. XIV)

Simon (2000) pointed out that change in one variable within an equation causes a change in a whole system of structural equations in which the variable is a component. In other words, the laws of physics (e.g. Newton’s Law of Gravitation, Ohm’s Law) as a tightly coupled system of interrelated variables simultaneously explain and define the concepts.

Based on the above discussion, dynamic relationships in science have the following three properties. First, the significance of the connection lies in how change in one variable affects another variable. Second, there are usually more than two variables at work (e.g. $F = m \times a$; $V = I \times R$). Third, the equation represents a system of relationships in which explanation of any component behaviour is only possible within the context of interaction among all components.

Note that CMaps falls short on every one of the above properties of dynamic relationships. More specifically, propositions in CMaps do not state how change in one concept will affect another one, the relationship between concepts are unidirectional, and propositions are typically about only two concepts as opposed to several constructs within a single system of simultaneous interactions.

A natural question is whether mathematical equations are the only means of representing dynamic relationships. Historically, the systems approach has addressed the question of dynamic representation and has applied it successfully to many different domains which will be briefly reviewed in the next section.

Cyclic Concept Maps (Cyclic CMap)

Educators and researchers in the field of biology experience the need for cyclic representation as cycles are fundamental to all biological systems (Bertalanffy, 1972). For example, Buddingh (1992) discussed strategies and observations for teaching the concept of homeostasis for which "neither tradition nor theory seem to exist to support biology education about this concept" (p.127). Similarly, Brinkman (1992) reported on his investigation into teaching biological cycles and found that students had difficulty with the functioning of concepts like plants and manure in the food cycle.

Cañas (2003) has observed that when people are constructing CMaps, they sometimes show a tendency to connect concepts in a cycle, and he would have to stop them in order to encourage construction of hierarchical relationships. In other words, a certain form of knowledge may already be encoded in the basic cyclic structure. Similarly, Lambiotte and Dansereau (1992), comparing CMaps to two other forms of lecture aids, found that "students with more well-established schemas for the circulatory system performed less well when the structure was imposed by an outline or a knowledge map" (Lambiotte and Dansereau, 1992, p. 198). They suggested that students with higher prior knowledge already possess models of the domain that are more sophisticated than those presented in the outlines or maps. Given that knowledge is about the circulatory system, it may well be that the sophisticated models were, in fact, in cyclic form which were incompatible with CMaps.

Cyclic CMaps represent an extension to classical CMaps, enabling the representation of dynamic functional relationships among the concepts. A cycle is built from a constellation of concepts, which represents a group of closely interconnected constructs. Cyclic CMaps capture interdependencies or how a system of concepts *works together*. A constellation of concepts is defined as two or more concepts that are in a closed loop relationship with each other. That is, the n^{th} concept is related back to the first concept (C1 to C2 to C3 ….to Cn to C1), as shown in Figure 1.

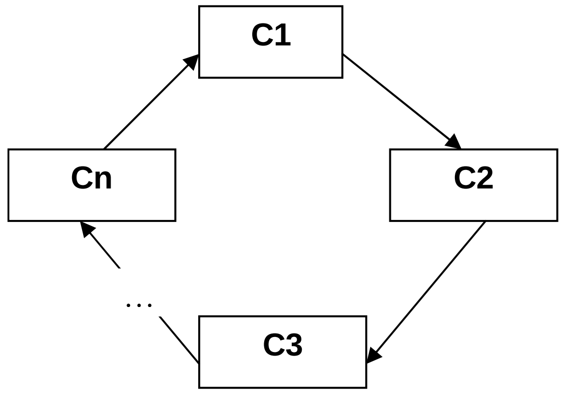

Figure 1: Cyclic loop of concepts forming a constellation.

Fundamentally, the relationships between concepts in Cyclic CMaps are dynamic in that each concept is influenced by the changes in the preceding concept, and it contributes to changes in the subsequent concept. Thus, Cyclic CMaps may be considered as cyclic dynamic relationship among a set of concepts as they vary. The basic unit of analysis is a cycle of concepts. Each concept may vary in the same (+) or opposite direction (-) of the preceding concept.

Conceptually, almost always, the links are either (+) or (-), meaning that any two connected concepts either change in the same direction or in the opposite direction. Thus, the link may be described by C1 (+ or -) C2, or C1 *changes in the same (or opposite) direction as* C2. Note that the increase or decrease in the state of the concept is not explicitly represented. Furthermore, the increase or decrease cannot be represented in the description of the concept, since it may lead to logical inconsistencies, and therefore difficulties in decoding. For example, in the cycle C1 (+) C2 (+) C3 (-) C1, if the propositions read as: ***increase in C1*** leads to *increase in C2, increase in C2* leads to *increase in C3,* and *increase in C3* leads to ***decrease in C1***. This would result in both increase and decrease in concept C1. Similar difficulties develop if *increase* or *decrease* is used in the link.

The reason for this representational difficulty is that all negative feedback loops (odd number of negative links in the Cyclic CMap) tend to oscillate up and down within a range of their steady state (Beer, 1972; Sterman, 2000). That is, the Cyclic CMap will naturally switch between states of *increase* and *decrease*, reflected as a local switch in the state of each concept. In the above example, after one cycle of traversing the Cyclic CMap, the state of C1 changes to *decrease* which causes a switch to *decrease* in the state of C2, which switches C3 to a *decrease*, which brings C1 back to its initial state of *increase* and so on.

The above considerations point to a basic principle for both knowledge encoders and knowledge decoders. Namely, **Cyclic CMaps must be traversed at least twice**. This is the only way that one can get an understanding of the rhythm of the dynamic system. Note that in addition to the oscillating pattern, there can be continual increase and continual decrease patterns, which happen when all links change in the same direction (+). Here, it is possible to use the language of increase or decrease, since there are no switches in the direction of change.

Systems Thinking

Cyclic relationship among concepts is the basis of cybernetics (Wiener, 1961), and systems thinking and modeling (Ashby, 1957; Forrester, 1961; Beer, 1974; Sterman, 2000). The approach has played a significant role in the modeling and understanding of organized complexities (Rapoport, 1968) in biological, electro-mechanical, and social systems (Beer, 1993). For example, the cyclic relationship between input, transfer function, output, and the difference between desired output and the actual output, which is fed back into the system for corrective purposes (negative feedback), can be applied to how a thermostat regulates the room temperature, or how the specialized cells detect blood sugar level changes and release insulin to keep the output within a desirable range (steady state).

This line of thinking has also been applied in different areas of psychology. Human action has been modelled, in cognitive psychology, as a cycle of Test - Operate - Test - Exit (Miller et al., 1960), or GOMS model (Card, Moran, Newell, 1983). Similarly, Katz and Khan (1978) developed their role model in social psychology as a system of communication between expectations, behaviour, and a feedback loop for modification of expectations. As another example, Safayeni et al. (1992) have modelled computerized performance monitoring systems based on cyclic and dynamic relationships between concepts of behaving systems, information collecting systems, and information evaluating systems.

System dynamics has been used to model complex situations in industry, representing management’s concepts and their dynamic interrelationships (Sterman, 2000). There is also the argument that system dynamics can be an effective representational tool in education (Forrester, 1992). The System Dynamics in Education Project (SDEP) was founded in 1990 at the Massachusetts Institute of Technology under the direction of Professor Jay W. Forrester, founder of system dynamics with the primary focus of using and promoting system dynamics in education.

Tension in the Cycle of Concepts

The change in the state of each concept may be discrete or continuous, measurable or vague. Nevertheless, each proposition can provide information about how change in one concept can affect the subsequent one.

When decoding a concept within a cycle of concepts, it is possible that a concept may mean one thing in the context of the connection to one concept, and may take on a different meaning as it connects to another concept. For example, in the cycle *experience → learning → confusion → experience* shown in Figure 2, the concept *learning* in the context of *experience* leading to *learning*, means becoming competent with respect to some activity. Whereas, *learning* contributing to *confusion* activates the meaning of *learning* as the messy process that it is, and how it may often be associated with conceptual uncertainties. Let “tension” refer to a notable change in the meaning of the concept as the context changes. As the two meanings for the concept become more incompatible, the amount of tension experienced by the decoder will increase.

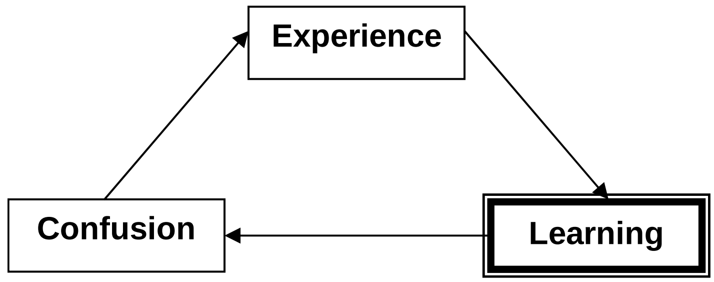

Figure 2: Cyclic Cmap of interrelationship among Experience, Learning, and Confusion

Tension between two meanings or two different ways of seeing a situation can be insightful. In problem solving, Gestalt psychologists (Kohler, 1927; Wertheimer, 1982) theorized that insight is the result of restructuring the elements of the situation such that the path to the solution can be "seen." Similarly, the wit or the intelligence in humour is often the result of change in the meaning of the concept and a different view of the situation (Koestler, 1969). The observation that cross-links between different segments in the CMap contributes to creativity (Novak, 1998) may well be for the same reason. Not all tensions, of course, are mentally productive, indicating that the change in the meaning may simply be a different view of the situation without any useful insight.

The above discussions suggest that cyclic relations among concepts were developed within a context of cybernetics and have been applied to a variety of domains for representation of dynamic relationships. Further, cyclic relationships can be used as Cyclic CMaps either by themselves or in conjunction with CMaps. The next section will provide a number of different illustrations for the application of Cyclic CMap.

Four Illustrations and Discussion of Cyclic Concept Maps

In this section, Cyclic CMaps will be constructed and discussed for the four situations. First, Cyclic CMaps will be used for knowledge that is usually expressed in mathematical equations, as in the laws of physics. Second, it will be shown how a Cyclic CMap can be constructed based on selected concepts from an existing CMap. Third, hybrid map, which combine both CMaps and Cyclic CMaps, will be constructed. Fourth, Cyclic CMaps as a stand alone system will be considered, since knowledge may have been encoded only in the cyclic form.

Illustration 1: Mathematical Equations

Consider the situation in which $C1= C2 \times C3$. This basic representation can be found in formulas of physics such as: Force = Mass X Acceleration, Speed = Distance / Time, and so on. It should be noted that Cyclic CMaps will not be as precise as the mathematical equations. In other words, there is an information loss when a mathematical relationship is represented as a Cyclic CMap since precise functional relationships are substituted by statements like "change in the same direction" or "change in the opposite direction." On the other hand, when knowledge is not formulated in a conceptually rigorous manner, then Cyclic CMaps will increase the informational content, which will be further discussed in the context of a hybrid maps.

When representing a functional relationship among concepts in the classical CMaps, it is difficult to express a mathematical formula simply as a hierarchical relationship. A formula is usually stated in words and shown as a single concept (or as one box) in CMaps. Cyclic CMaps provide an opportunity to express mathematical relationships subject to constraints which will be discussed below.

Let C1, C2, and C3 represent the three vertices of a triangle. Since changes in the state of C1 can be accommodated by changes in the state of C2, C3, or an infinite number of possible adjustments to C2 and C3 simultaneously, it is necessary to introduce a constraint. More specifically, assume the value of one concept is constant while changes are considered in the context of the relationship between the other two concepts. Thus, changes in C1 may be accommodated by either change in C2 with C3 being constant or vice versa. Similarly, changes in C2 are viewed with either C1 or C3 being constant. Thus, for example, the representation for Force = Mass × Acceleration as a Cyclic CMap is shown in Figure 3.

Another way in which the representation of a mathematical equation becomes crude in Cyclic CMaps is by simplifying exact functional relationships into changing in the same direction (designated by a +) or changing in the opposite direction (designated by a -) functional relationships. Note that since the precise functional relationship is only represented as a direction of change, the specificity of a functional change for a given variable is not represented.

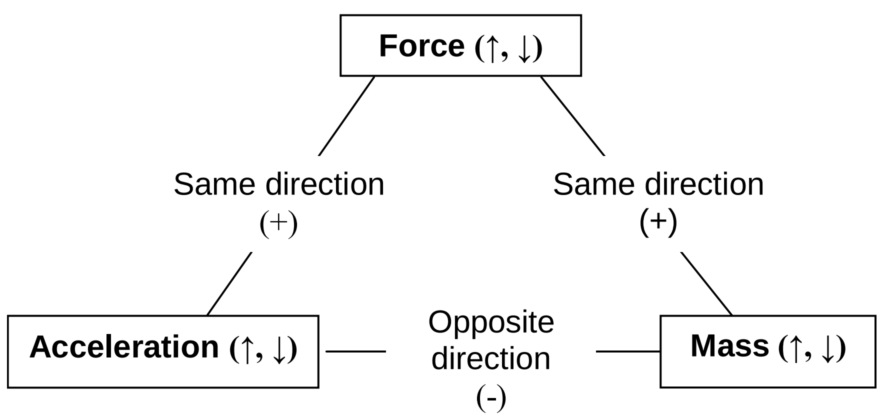

Figure 3: Cyclic CMap of F = m × a. "+" means "change in the same direction;" "-" means "change in the opposite direction."

Illustration 2: Cyclic CMap from an Existing CMap

Cyclic CMaps can often be constructed based on existing CMaps, which reveal different information about the interrelationships among the selected concepts. To create a dynamic cycle from an existing CMap, one needs to select the header concept from the map and to "quantify" it by identifying one relevant aspect of this concept that can change in quantity or quality, Then, identifying other related concepts that affect and are affected by the changes in the header concept. Finally, "quantifying" all concepts and arranging them into a meaningful Cyclic CMap.

Consider the CMap about concept maps in Figure 4 by Novak.[1] A Cyclic CMap based on 5 concepts from the CMap in Figure 4 is shown in Figure 5. The Cyclic CMap loop, concentrating on the *quality* of the concept "*Concept Map*" suggests that as the *quality of concept maps* improve, it is more likely that it will contribute to *the quality of effective teaching*, which leads to increase in *the quality of effective learning*, which positively influences *the quality and/or quantity of* discovered *interrelationships*, which leads to more *creativity (the quality and/or quantity of)*, which increases the probability of constructing a better *concept maps*.

The following observations are worth noting. First, the five concepts are from different parts of the CMap. Using CMap terminology, it can be viewed as five interconnected cross-links. Second, the constellation provides a different kind of information than the CMap. Although all five concepts were already in the CMap, they were part of other connections and not interrelated

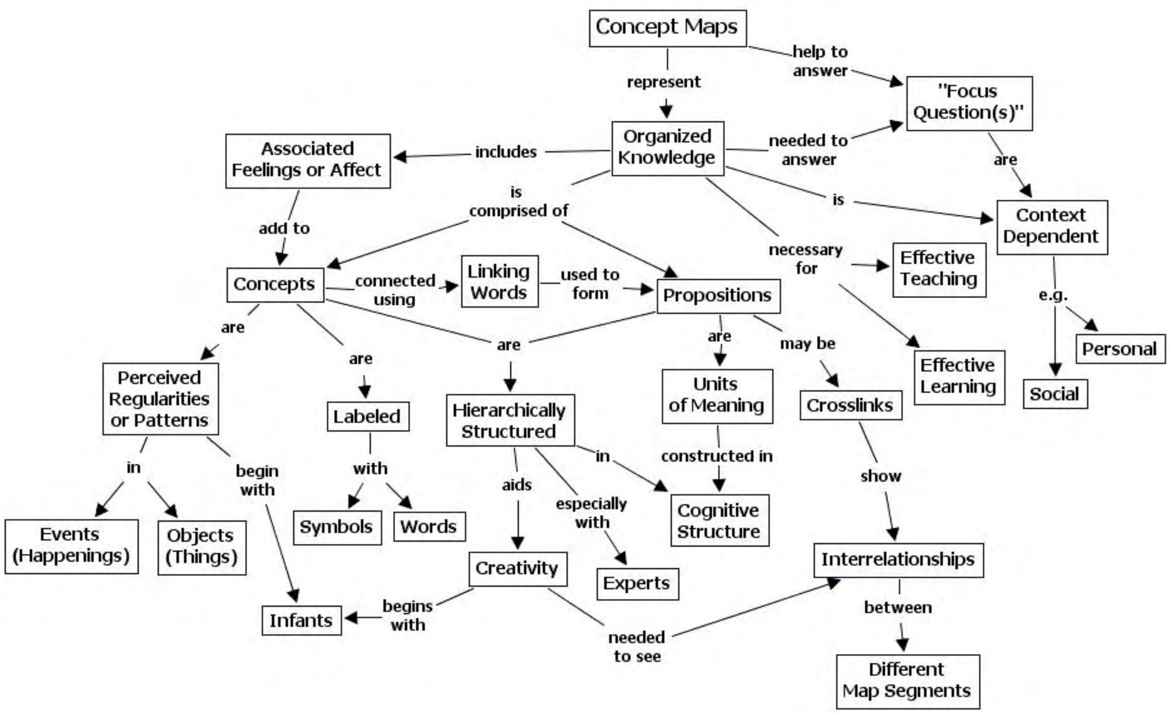

Figure 4: Concept Map about Concept Maps by Joseph Novak.

[1]Downloaded from the IHMC Internal Cmap server, part of the CmapTools network (Cañas et al 2003).

within a single loop. For example, the concept *Concept Maps* was only connected to *Organized Knowledge* in the CMap, whereas in the Cyclic CMap it is directly connected to both *Creativity* and *Effective Teaching*, and indirectly to *Interrelationships* and *Effective Learning*. This suggests that one kind of additional information provided by Cyclic CMaps, in comparison to CMaps, is **contextual information**. That is, a concept in a cycle of interrelated concepts is part of a more complex theoretical framework and its meaning is a function of the loop as a single meaningful system or "gestalt."

A second kind of additional information, in comparison to CMaps, is **transformational information**, which is information about the changes in the states of interrelated concepts. The Cyclic CMap, in the above example, points to the quality of the *Concept Maps*, as opposed to a categorical or absolute *Concept Maps*, being related to *Effective teaching*. Actually, the label *Concept Map* is more appropriate in the Cyclic CMap if it is changed to *Quality of Concept Maps*. Adding a quantifier (in this case *quality*) to a concept makes it more dynamic. Similarly, quantifiers (quality or quantity) need to be added to the other concepts in the Cyclic CMap. The Cyclic CMap then expresses, for example that as (the quantity or quality of) *Creativity* increases, so does the likelihood of constructing better (quality) *Concept Maps,* and so forth. Implicit in the transformational information is the notion that a poorly constructed CMap may not be a useful teaching tool, and without some degree of creativity a useful CMap can not be constructed.

A third observation about Cyclic CMaps concerns the direction in the loop. It was noted that

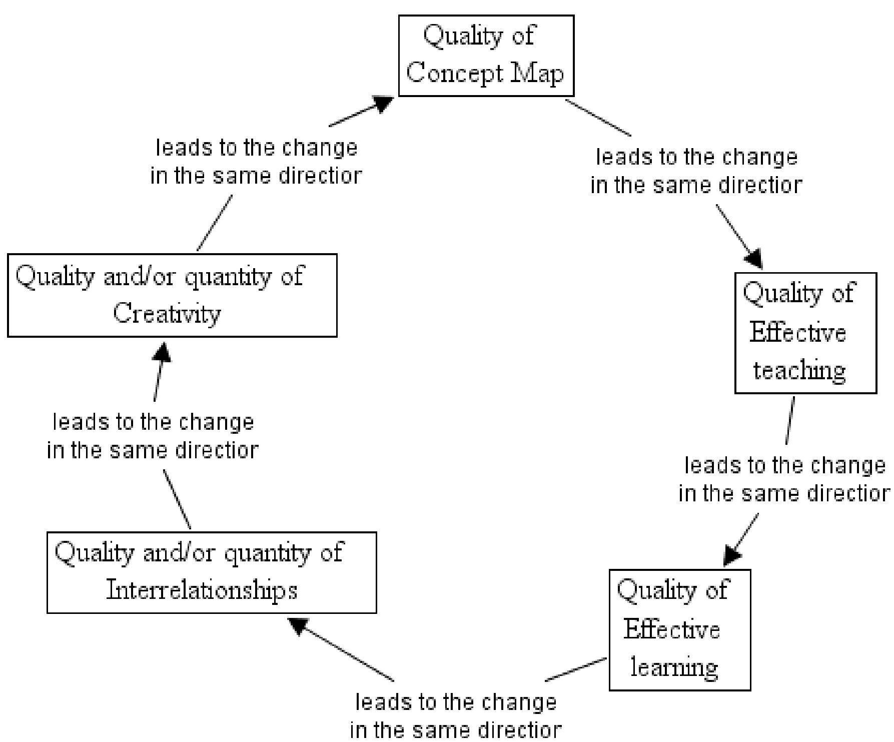

Figure 5: A Cyclic CMap based on five concepts from the CMap from Figure 4.

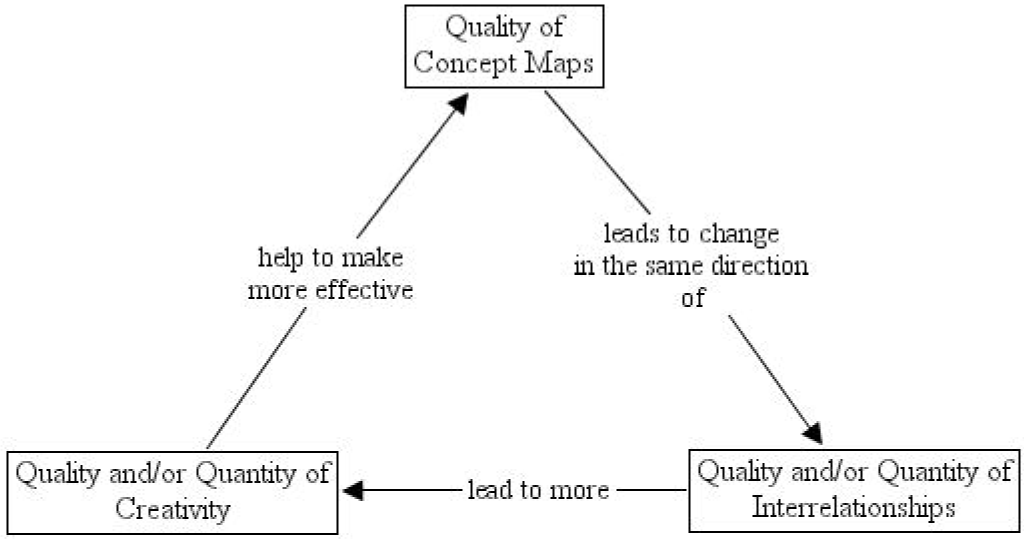

Figure 6: Cyclic CMap of 3 concepts.

when representing a mathematical equation (illustration number 1) direction was unnecessary. However, direction was used in the cyclic map in Figure 5, and it seems that some propositions may be asymmetrical. That is, more meaningful in one direction than the opposite direction. For example, the proposition that "increased Quality of *Concept Maps* may contribute to increased Quality of *Effective Teaching,"* may be judged to be more meaningful than the proposition that "increased Quality of *Effective Teaching* may contribute to better Quality *Concept Maps."* Similarly, "increased Quality of *Effective Teaching* leading to increased Quality of *Effective Learning"* seems more meaningful than "increased Quality of *Effective Learning* leading to increased quality of *Effective Teaching."* It may well be that one assigns a higher probability to the "truth" of one proposition in comparison to the other.

Fourth, Cyclic CMaps may contract or grow by exclusion or inclusion of concepts. For example, Figure 6 shows a different Cyclic CMap by excluding the concepts of *Effective Teaching* and *Effective Learning*. Of course, starting with the concepts *Concept Maps*, *Interrelationships*, and *Creativity*, and then including *Effective Teaching* and *Effective Learning*, will be an example of growth of a Cyclic CMap. Thus, it is possible to have several Cyclic CMaps reflecting the relationship among different sub-sets of a set of concepts (see Figure 7).

Fifth, in a cyclic map, different cyclic constellations can be represented in a different colour simultaneously (Figure 7), to show how concepts interact in different cycles. An alternative will be to present each cyclic map separately. Cyclic CMap can be a standalone or linked to the original CMap for a more complete representation of the topic.

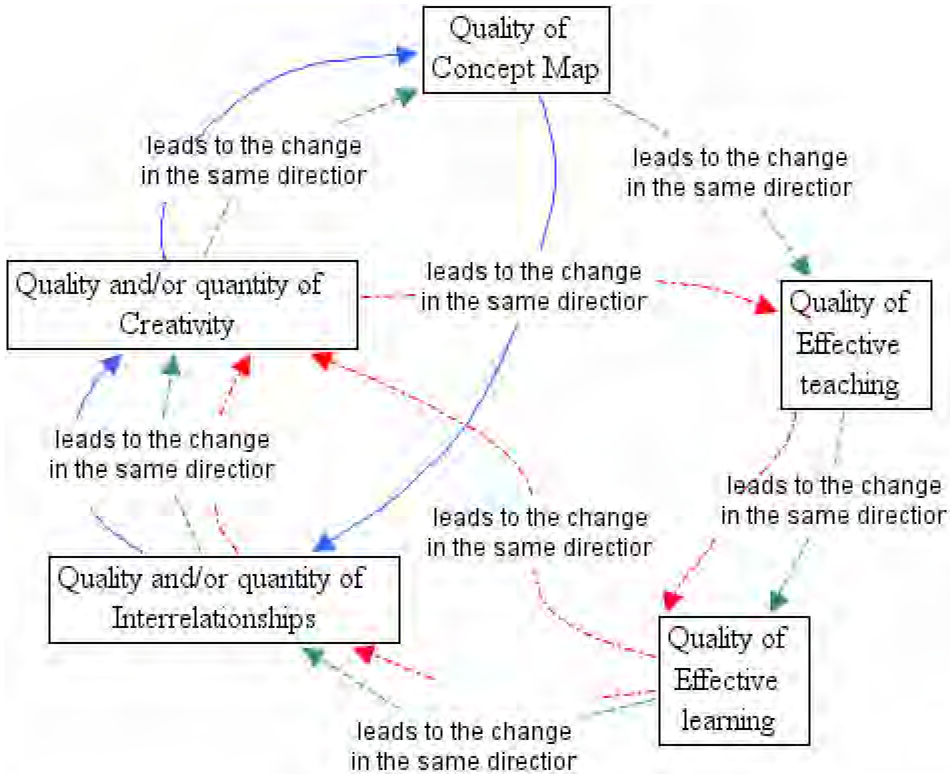

Figure 7: Cyclic CMap reflecting the relationship among different sub-sets of a set of concepts.

Illustration 3: Hybrid Maps (Thermostat)

The map of a thermostat presented in Figure 8 is a hybrid map where Cyclic CMap (cycle describing the operation of the system) is presented in a different colour along with a CMap describing parts of the system. In this case, a hybrid of a CMap and a Cyclic CMap give more information about the system's operation, and describe the process more accurately, showing that it is a continuous, cyclic, dynamic system. The CMap portion provides basic information about the components of the system while the Cyclic CMap portion represents how the system works, and how the components interact in the cyclic process of regulating the temperature. In this case, the two types of maps are "concatenated." Figure 8 also shows how the Cyclic CMap portion breaks the hierarchical nature of the traditional CMap.

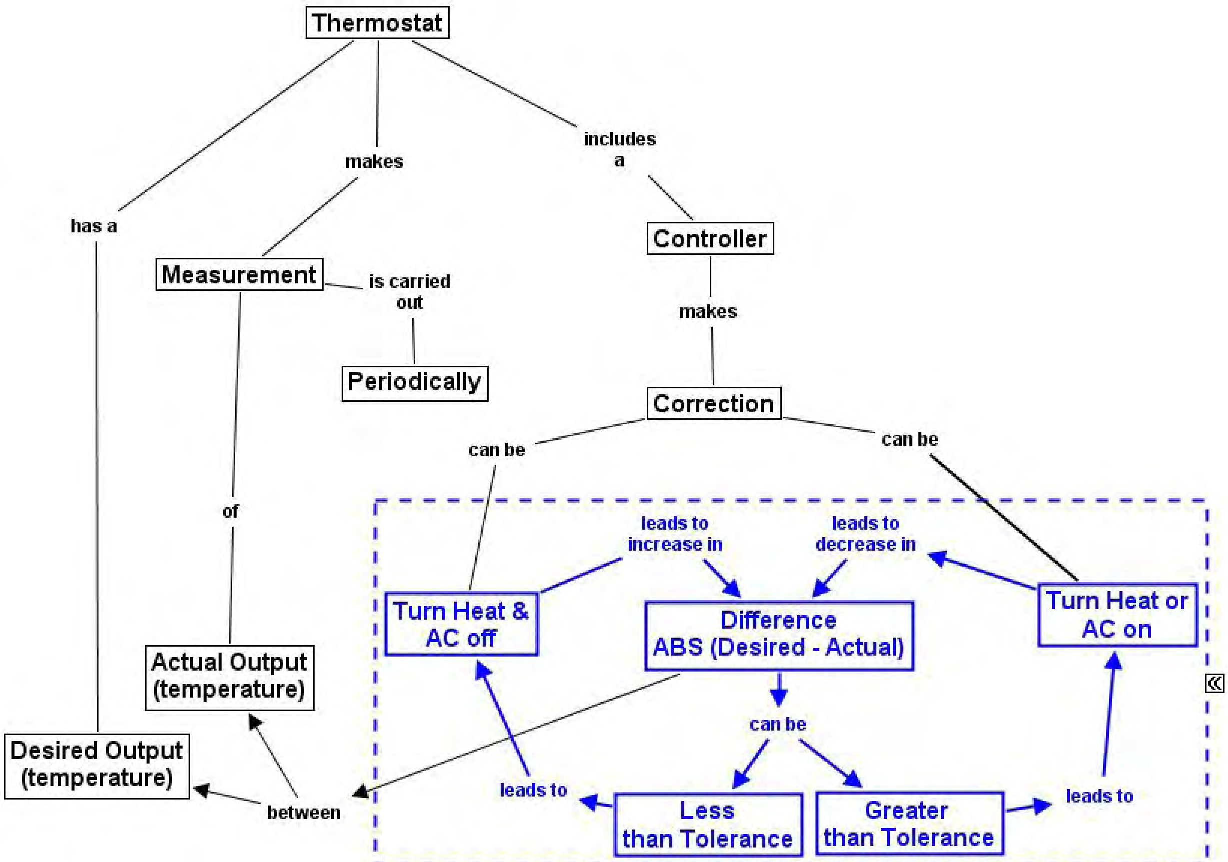

Figure 8: Hybrid map of a thermostat.

Taking advantage of the features provided by electronic versions of CMaps provided by software programs such as CmapTools, the split between the CMap and Cyclic CMap portions can be further emphasized by making the Cyclic CMap a "submap" (called a Big Node in CmapTools) and representing it as in Figure 9. Clicking on the "icon" to the right of the Cyclic CMap's box in Figure 8 and to the right of the *Positive or Negative* concept in Figure 9 reduces/enlarges the Cyclic CMap portion.

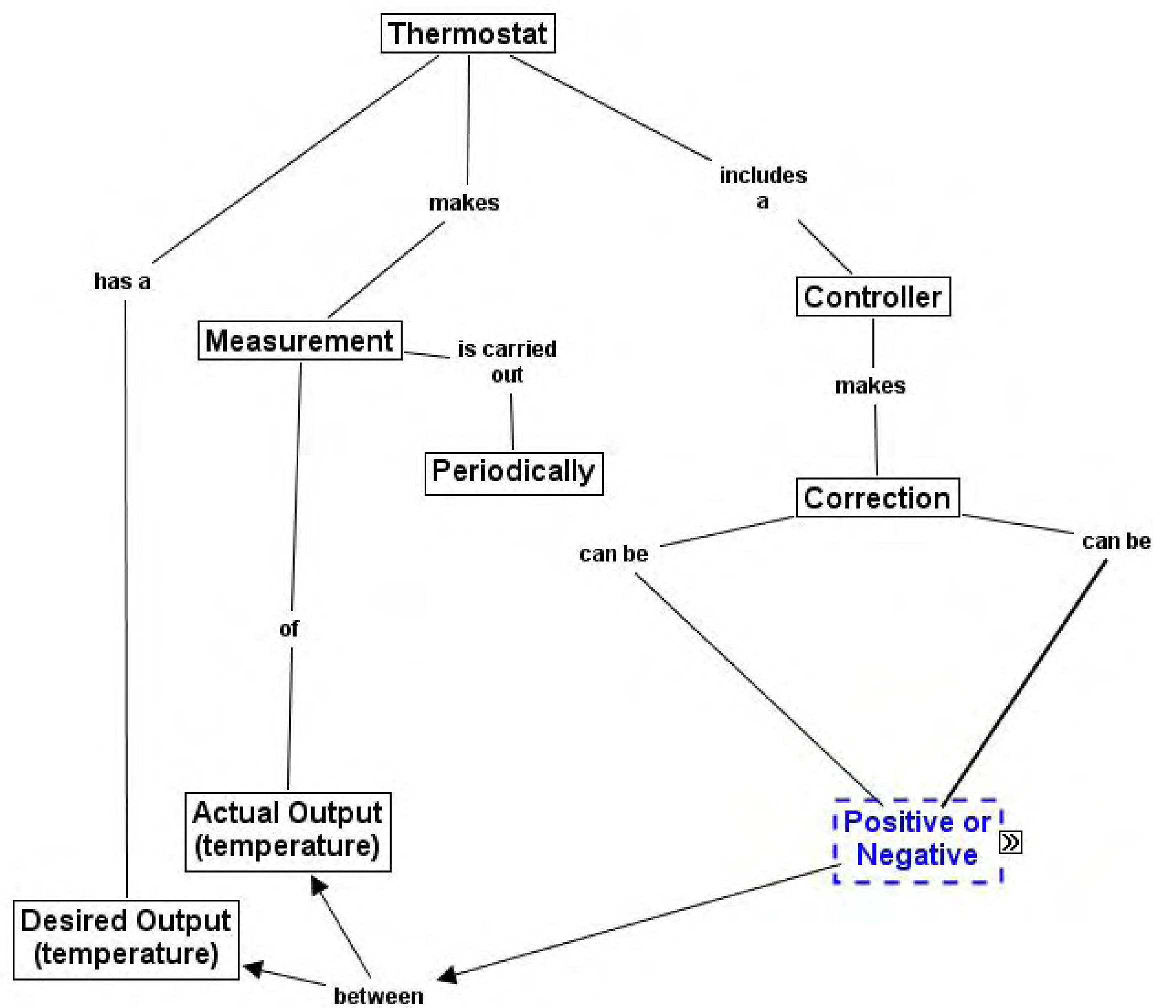

Figure 9: Hybrid map of a thermostat showing the Cyclic Cmap portion reduced to the concept "Positive or Negative", which can be expanded by clicking on the icon at its right

Illustration 4: Standalone Cyclic Concept Maps

Knowledge about dynamic systems, it was argued, may best be represented by standalone Cyclic CMap. For example, the Katz and Khan's role model (1978) is based on the following cycle of concepts. Expectations and their communication from the role senders leads to interpretation of messages, experience of conflict, and subsequent behaviour on the part of the role receiver, which in turn modifies the expectations of the role senders. The representation of the role model (Figure 10) is different than the original model, in order to reflect the properties of Cyclic CMaps.

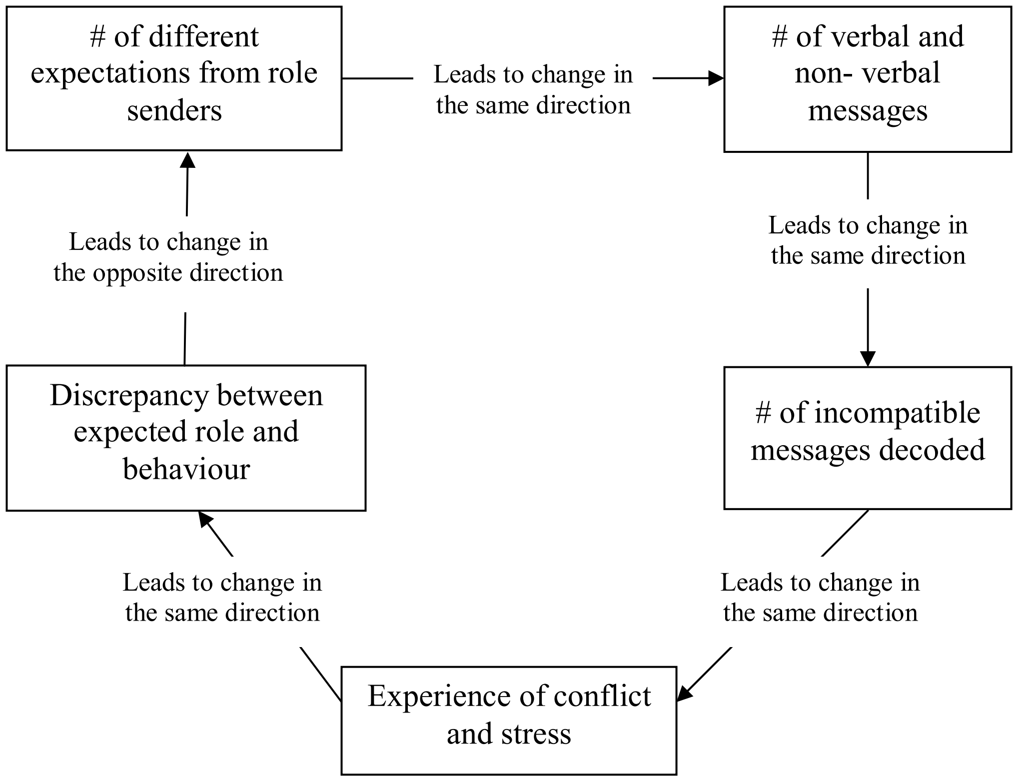

Figure 10: Cyclic CMap of Role Model.

There are a number of observations worth noting. First, stand alone Cyclic CMaps may be necessary for some applications. That is, the encoder may not see classical CMaps as an appropriate representational system in order to answer the question. For example, an expert may have problems representing the response to the question of *what is a role model* as a CMap since his knowledge is already encoded as a dynamic Cyclic CMap.

Second, there is no logical constraint on the number of concepts in a single loop of a Cyclic CMap; however, psychologically, Miller's (1956) number 7 (+ or - 2) may well be a constraint for both knowledge encoders and knowledge decoders. That is, the comfort zone in conceptualization of a system of concepts is about half a dozen concepts. This hypothesis can be tested by counting the number of variables that are used in a variety of conceptually cyclic models in both social and physical sciences.

Third, as it has been pointed out, many dynamic systems tend toward equilibrium. For example, in the Cyclic CMap for role model the *Discrepancy between the expected role and behaviour* may decrease the *# of different expectations from the role senders*, and thus may serve as a corrective mechanism that may lead the system to reach stability at some level. The notion of equilibrium should not be interpreted with any kind of positive connotations, since the steady state of a system may be dysfunctional. For example, there are jobs where the steady state of the role is full of conflicts and stress, and everyone agrees that “it comes with the territory.”

Research Questions

From a practical point of view, the efficiency and the effectiveness of Cyclic CMaps for knowledge encoding and decoding require further investigation. Comparative studies between CMaps and Cyclic CMaps may be one strategy. For example, based on this paper, it may be hypothesized that Cyclic CMaps should be more effective than CMaps when representing dynamic relations between concepts, whereas CMaps should be more effective when the relations are static. A second strategy is to directly investigate the properties of the Cyclic CMap. For example, with respect to “meaningful learning”, one may ask if learning becomes more meaningful since the concepts are all interconnected as a part of a single loop.

There are fundamental questions that may be investigated within the context of a more theoretically ambitious research program. For example, what happens in the mind as it considers dynamic relations between a set of concepts? What is the difference between static and cyclic thinking? What cognitive processes are involved in the activation of a concept? How many concepts can be dynamically conceptualized at once? What if they are changing in different directions? Similarly, there are basic research questions when the process of decoding and map traversing are examined. For instance, suppose the decoder is stopped and asked to recall as many steps and concepts as they can. What information is being picked up and in what order? These are all questions that require additional examination.

Summary

Categories and concepts were considered with respect to the amount of variability in their membership, their degree of abstraction, and the extent to which the abstraction reflected the essential as opposed to superficial properties of the elements. Scientific concepts, it was argued, represented a high level of abstraction, often expressed in mathematics, of essential properties of the concrete.

Labels were considered to increase the variability of a concept or a category due to the multiplicity of meanings associated with a word. The labels for concepts at the highest level of abstraction (e.g. mathematics), were discussed as mental representations based on description as opposed to membership which makes up a category or a concept.

The relationships between concepts were considered as the context for reducing the uncertainty between the possible meanings of a concept. The notion of affordances was used to suggest how a concept’s intended meaning is selected in a proposition. Several types of relationship between concepts were discussed.

Static relationships between concepts were considered as means of organizing scientific knowledge in a hierarchical form, and dynamic relationships were viewed as means of representing scientific knowledge about how change in one concept affects another one. Thus, both static and dynamic representational systems were considered as necessary for representing knowledge.

The basic idea of Cyclic CMaps was discussed within the context of a brief review of cybernetics, and examples of the application of cyclic thinking in psychology. To think of organized complexities as a system has a proven track record for knowledge modelling in both physical and social sciences. Thus, one view of this paper is that it simply recognizes the possibility of using system thinking in conjunction with hierarchical thinking as a more powerful tool for both encoding and decoding of knowledge.

The Cyclic CMap was further discussed within the context of four illustrations. It was pointed out that when a Cyclic CMap is used with mathematical formulas, certain constraints had to be added and there was an information loss. On the other hand, when concepts from a CMap were used to construct a Cyclic CMap, there was an information gain.

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