

## MULTI-LEVEL ANALYSIS STRATEGY TO MAKE SENSE OF CONCEPTS MAPS

*Beat A. Schwendimann, École Polytechnique Fédérale de Lausanne, Switzerland*  
*Email: beat.schwendimann@gmail.com, www.schwendimann.org*

**Abstract.** Making sense of concept maps is an ongoing challenge for the concept mapping community. This paper introduces a multi-level analysis strategy by combining quantitative and qualitative methods to triangulate changes in students' concept maps. Quantitative analysis includes overall, selected, and weighted propositional analysis using a knowledge integration rubric (Linn, 2000) as well as network analysis to describe changes in network density and prominence of selected concepts. Research suggests that scoring only selected propositions can be more sensitive to indicate conceptual change because it focuses on key concepts of the map. Qualitative analysis includes topographical analysis methods to describe the overall geometric structure of the map and an analysis of link types. This paper suggests that a combination of quantitative and qualitative analysis methods can capture different aspects of concept maps and provide a rich description of changes in students' understanding of complex topics.

**Keywords:** Multi-level analysis, network analysis, qualitative analysis, quantitative analysis, Knowledge Integration Map

### 1 Introduction

Concept maps can serve as rich sources of several different forms of information, for example presence or absence of connections and concepts, quality of connections, different types of link labels, different types of networks, and spatial placement of concepts. Many existing analysis methods do not capture the manifold alternative concepts students represent in a concept map and tend to lose information by representing concept maps scores as a single number, for example by scoring components of the concept map either qualitatively by counting the number of concepts, links, hierarchy levels, and examples (Novak & Gowin, 1984), by qualitatively evaluating propositions (McClure, Sonak, & Suen, 1999), or by comparing students' concept maps with a benchmark map (for an overview of concept mapping analysis methods see (Cathcart, Stieff, Marbach-Ad, Smith & Frauwirth, 2010)). However, no single scoring method can accurately describe the many different forms of information in concept maps. This paper uses a form of concept map, called Knowledge Integration Map (KIM) (Schwendimann, 2011c), to illustrate the need for a more comprehensive multi-level analysis method for concept maps. KIM analysis combines both propositional, network, and topological analysis methods. Using quantitative and qualitative analysis methods in combination can provide complimentary insights of connections between concepts and allows tracking changes in the quality of concept maps.

#### 1.1 Knowledge Integration Maps (KIM)

Markham (Markham, Mintzes, & Jones, 1993) found that the major differences in content knowledge of novices and experts are a lack of integration, lack of cross-links between concepts, and a limited number of hierarchical levels. Integrating complex concepts requires connecting concepts from different fields. This paper uses concepts from biology education as examples; in particular evolution with connects to the fields of genetics and cell biology. Knowledge Integration Maps differ from classical concept maps in several characteristics (see table 1). KIMs aim to elicit and scaffold cross-field connections through the spatial arrangement of concepts in specified drawing areas.

**Table 1:** Comparison between classical concept maps and KIMs

	<b>Classical concept map</b>	<b>Knowledge Integration Map</b>
Design	Hierarchical arrangement of concepts	Non-hierarchical placement of concepts in specified drawing areas
Analysis of concepts	No weighted concepts	Weighted concepts (Indicator concepts)
Analysis of links	No weighted relations	Weighted relations (Essential connections)

Concept mapping tasks are found in many different forms and provide different amounts of constraints. Tasks range from open tasks where students can freely choose their concepts and labels to highly directed tasks where students fill in concepts out of a given list into blanks in a given skeletal network structure (Novak & Cañas, 2006). KIMs aim for a balanced design by providing students with a small set of concepts but allowing them to generate their own connections and labels. This design allows comparing maps of different students with each other. KIM worksheets consists of five elements: 1) Focus question, 2) Specified drawing area (in the evolution example, genotype and phenotype), 3) Instructions, 4) Given list of concepts, and 5) Starter map (see figure 1).

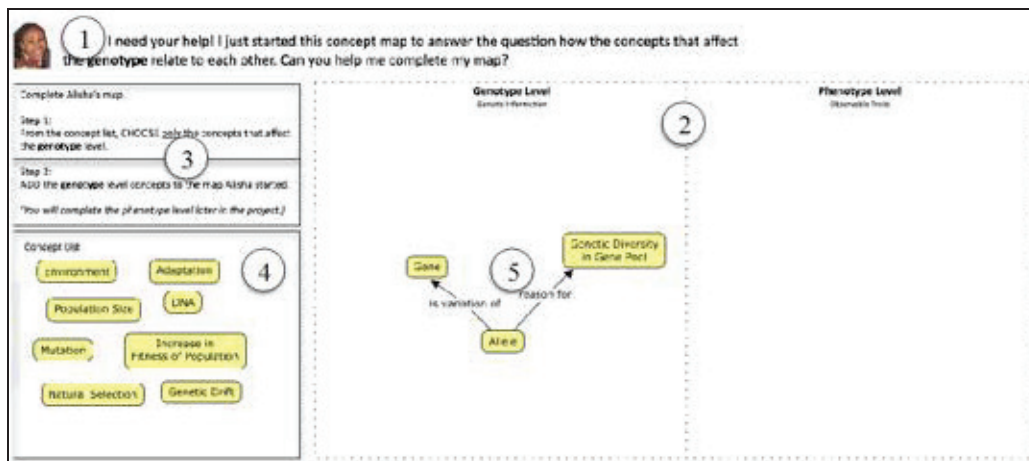


Figure 1: Knowledge Integration Map worksheet

Based on an evaluation of major biology textbooks, eleven concepts have been selected for the forced-choice design of the Knowledge Integration Map. The number of concepts was kept low in order to keep to size and complexity of the KIM reasonable for the given time constraints for its creation. A total of 55 connections are possible between the given 11 concepts, but not all propositions are of equal importance. (Considering each direction individually and allowing for circular links to same concept,  $11 \times 11 = 121$  connections would be possible). Students need to decide which connections are essential to represent their understanding. Additionally, each connection can go in either direction and be described by many different labels. Students need to match the directionality of the connection with the label and construct a label that accurately describes the nature of the relationship. As the map constrains students to only one connection between two concepts, students need to develop decision-making criteria. To model expert understanding, the given list of concepts includes only normative evolution concepts, but no non-normative concepts such as “need”, “intentionality”, or “want”. Alternative concepts can be expressed through concept placement and link labels.

## 2 Forms of KIM analysis

The research literature indicates that concept map analysis is no trivial task and it can use a wide variety of scoring methods. Concept maps can be analyzed either qualitatively or quantitatively.

### 2.1 Quantitative concept map analysis

Concept maps contain several elements that can be quantitatively evaluated: Concepts, hierarchy levels, propositions, and overall network structure. Links and concepts can be easily counted but their amount provides little insight into a student’s understanding. A higher number of links does not necessarily mean that the student understands the topic better as many links might be invalid or trivial (Austin & Shore, 1995). Evaluating the number of hierarchy levels has been suggested by Novak and Gowin (1984). The existence of hierarchies is linked to higher levels of expertise, but hierarchy levels can be difficult to differentiate and some concept maps can be non-hierarchical but still valid maps. Propositions, the composite of two concepts, a link label, and an arrow, can be evaluated in order to learn about students’ understanding. It can be decided to evaluate all propositions equally, to weight certain propositions more than others (Rye & Rubba, 2002), or to analyze only certain indicator propositions (Ruiz-Primo et al., 2009). Scoring all propositions (‘total accuracy score’) is time consuming and does not differentiate links that show deeper understanding and trivial links. There are two alternatives to a ‘total accuracy score’: The ‘convergence score’ (Yin 2005) is the proportion of accurate propositions out of all possible propositions in the benchmark map. An alternative to scoring all links is to focus only on a small number of selected links (‘essential links’) (Yin 2005). Ruiz-Primo et al. (2009) suggest that scoring only essential links is more sensitive to measuring change because it focuses only on the key concepts of the concept map. However, analyzing only isolated propositions does not account for the network characteristics of a concept map. Quantitative propositional analysis alone could lead to the same score for a list of isolated propositions and a network of the same propositions. Network analysis can be used to describe the connectedness of a KIM through density and prominence indicators of selected indicator concepts.

### 2.1.1 Benchmark KIM

An expert-generated KIM can be used to identify the overall structure, central concepts, and essential connections (see figure 2). However, a benchmark map should not be interpreted and used as the single correct solution but as an expert-generated suggestion that allows identifying central concepts and connections for a detailed analysis. The benchmark KIM indicates how many and which connections and concepts experts generate.

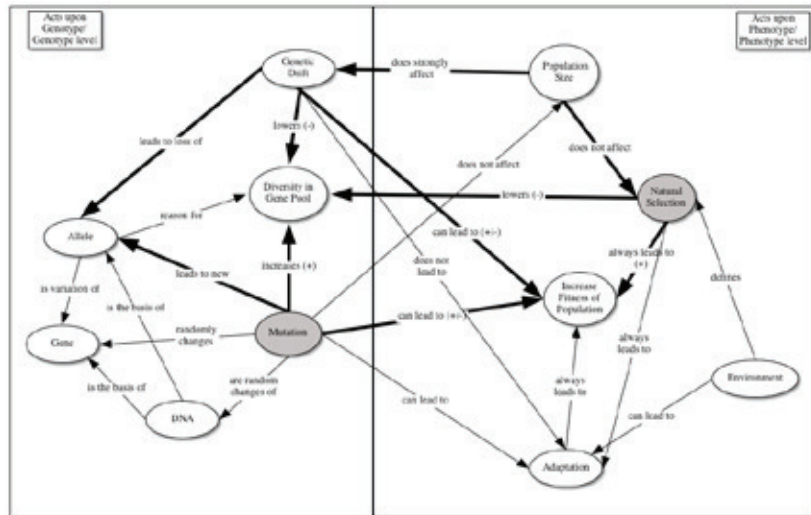


Figure 2. KIM benchmark map. Indicator concepts (grey), essential connections (bold)

#### 2.1.2 Indicator concepts

Ruiz-Primo suggested that knowledge is organized around central concepts, and to be knowledgeable in a field implies a highly integrated conceptual structure (Ruiz-Primo et al., 1997). Analyzing how connected selected concepts are in a KIM can identify learners’ understanding of the importance of concepts. For the KIM network analysis, one concept from each level (“mutation” for genotype/ “natural selection” for phenotype) has been selected as the ‘indicator concept’. Indicator concept analysis describes the number and kind of connections to other concepts. The criteria for selecting indicator concepts were: 1) Centrality in the expert benchmark KIM (see figure 2), and 2) Importance according to evolutionary theory literature.

#### 2.1.3 KI rubric for concept maps

Propositional scoring included 1) scoring of all propositions (‘total accuracy score’), and 2) scoring of only essential propositions. Individual propositions were analyzed using a five-level knowledge integration rubric (see table 2).

Table 2: KIM knowledge integration rubric

KI Score	Link label quality	Link Arrow	Sample Propositions
0	None (No connection)	None (No connection)	None
1	Wrong label	Wrong arrow direction	Genetic variability includes mutation
2	a) No label b) Correct label c) Incorrect label	a) Only line b) Wrong arrow direction c) Correct arrow direction	a) Mutation -- genetic variability b) Genetic variability –contributes to > mutation c) Mutation – includes > genetic variability
3	No label	Correct arrow direction	Mutation --> Genetic Variability
4	Partially correct label	Correct arrow direction	Mutation – increases -> Genetic Variability
5	Fully correct label	Correct arrow direction	Mutation – causes random changes in the genetic material which in turn increases -> Genetic Variability

#### 2.1.4 Concept Placement Analysis

KIMs ask students to sort out concepts into domain-specific areas (‘levels’) (for example genotype and phenotype). Concept placement is an additional level of information that indicates how students categorize concepts. Connecting concepts within a level indicates students’ understanding of the relations between closely

related concepts. Cross-links are of particular interest as they can indicate “creative leaps on the part of the knowledge producer” (Novak & Cañas, 2006) and reasoning across ontologically different levels (Duncan & Reiser, 2007). As concepts might be wrongly placed by students, an observed cross-connection might actually be a connection between two concepts of the same level (“uncorrected cross-link”). To account for such cases, a “corrected cross-link” variable indicates intra-domain connections even if the concepts were wrongly placed.

## 2.2 KIM network analysis

Commonly used quantitative propositional methods of analysis do not capture changes in the overall network structure. Network analysis uses the frequency of usage of essential concepts as indicators for a more integrated understanding. The network analysis method is based on social network analysis (Wasserman & Faust, 1994). As students develop a more complex understanding, they might also identify certain concepts as more important and connect them more often. Network analysis method can identify changes in ‘centrality’ (outgoing connections) and ‘prestige’ (incoming connections) of expert-selected indicator concepts (‘mutation’ for the genotype level; and ‘natural selection’ for the phenotype level) (using an adjacency matrix). The two network variables ‘centrality’ and ‘prestige’ can be combined to a total ‘prominence score’ (Importance Indicator) for each indicator concept. Multiplied with the KI score for each connection, a ‘weighted prominence score’ for each of the two indicator concepts can be calculated.

## 2.3 Qualitative KIM analysis

Qualitative analysis methods complement quantitative descriptions of concept maps by tracking changes in the geometrical structure (topology) and types of propositions.

### 2.3.1 KIM topological analysis

Quantitative analysis methods focus only on isolated propositions and can therefore not give an account of the network character of a whole map. Kinchin (2000, 2001) suggested a framework of four qualitative classes (simple, chain/linear, spoke/hub, net) to describe the major geometrical structure of a concept map. Yin (2005) extended Kinchin’s framework by two additional classes (tree and circle). The analysis methods developed for KIMs further extends Yin’s framework. As Knowledge Integration Maps are divided into domain-specific levels (for example genotype and phenotype), the geometrical structure of each level needs to be described (empty, fragmented, linear, tree, hub, circular, or network). Coding includes each possible combination of geometrical structures in the two levels. Changes in the topology of KIMs can indicate changes in students’ knowledge integration.

### 2.3.2 Qualitative proposition type analysis

To describe semantic changes in the relations between concepts, qualitative variables are needed. The concept mapping literature suggests a number of different link types. For example, Fisher (2000) distinguished three main types of propositional relations in biology that are used in 50% of all instances: whole/part, set/member, and characteristic (p204). O’Donnell distinguished between three types of relations in knowledge maps: Dynamic, static, and elaboration (O’Donnell, Dansereau, & Hall, 2002). Lambiotte suggested dynamic, static, and instructional relation types for concept maps (Lambiotte, Dansereau, Cross, & Reynolds, 1989). Derbentseva distinguished between static and dynamic relations in concept maps (Safayeni, Derbentseva, & Cañas, 2005).

To create a taxonomy of link types, higher order variables are needed. KIM analysis used the structure-behavior-function (SBF) framework to create the super-categories of the taxonomy. The SBF framework was originally developed by Goel (Goel & Chandrasekaran, 1989) to describe complex systems in computer science, and then applied to complex biological systems by Hmelo-Silver (2004).

- Structure: What is the structure (in relation to other parts)? These variables describe static relations between concepts. Static relations between concepts indicate hierarchies, belongingness, composition, and categorization.
- Behavior: What action does it do? How does it work/influences others? These variables describe the dynamic relations between concepts. Dynamic relations between concepts indicate how one concept changes the quantity, quality, or state of the other concept.

- Function: Why is it needed? These variables describe functional relations between concepts, for example “want” (intentionality) or “need” (teleological).

The sub-categories for the taxonomy emerged from KIM analysis (see table 7). Categorizing link labels allows tracking and describing how connections changed ontologically. To trace changes in relation types, a link label taxonomy has been developed for KIMs (see table 3). The relation categories also include negations, e.g. “does not lead to”, or “is not part of”.

**Table 3:** Categories of different types of KIM relations

Super-Category	Sub-Category	Code	Examples
UNRELATED	No Connection	0	
	No label (just line)	1	
	Unrelated label	2	
STRUCTURE What is the structure (in relation to other parts)?	Part-Whole (Hierarchical)	3	Is a/are a; is a member of; consist of; contains; is part of; made of; composed of; includes; is example of
	Similarity/ Comparison/ Contrast	4	Contrasts to; is like; is different than
	Spatial Proximity	5	Is adjacent to; is next to; takes place in
	Attribute/Property/ Characteristic (Quality (permanent) or State (temporary))	6	Can be in state; is form of
BEHAVIOR What action does it do? How does it work/ influence others?	Causal-Deterministic (A always influences B)	7	Contributes to; produces; creates; causes; influences; leads to; effects; depends on; adapts to; changes; makes; results in; forces; codes for; determines
	Causal-Probability (Modality)	8	Leads to with high/low probability; often/rarely leads to; might/could lead to; sometimes leads to
	Causal-Quantified	9	Increases/ decreases
	Mechanistic	10	Explains domain-specific mechanism/ adds specific details or intermediary steps
	Procedural-Temporal (A happens before B)	11	Next/ follows; goes to; undergoes; develops into; based on; transfers to; happens before/during/after; occurs when; forms from
FUNCTION Why is it needed?	Functional	12	Is needed; is required; in order to; is made for
	Teleological	13	Intends to; wants to

### 3 Discussion and Implications

This paper proposes that a combination of qualitative and quantitative analysis methods can provide complementary information to triangulate changes in learners’ concept maps of complex topics. Concept maps as assessment tools have been used to track conceptual changes in a wide variety of contexts. However, the mixture of different kinds of concepts (for example physical object, process, abstract construct, property, etc.) and different types of links (for example causal, correlational, temporal, part-whole, functional, teleological, mechanical, probabilistic, spatial, etc.) can make analysis challenging and time-consuming (McClure, Sonak, & Suen, 1999). This paper identified several methods and variables, such as KIM cross-links, indicator concepts’ prominence scores, weighted essential link scores, network analysis, topological analysis, and qualitative propositional analysis, that can be more efficient and sensitive than scoring each proposition in isolation.

Cross-links can indicate the integration of knowledge across levels. Experts and advanced novices develop well differentiated and highly integrated frameworks of related concepts (Chi, Feltovich, & Glaser, 1981; Mintzes, Wandersee, & Novak, 1997). Cross-links are of special interest as they can indicate creative leaps on the part of the knowledge producer (Novak & Cañas, 2006).

Network analysis of indicator concepts describes changes of the centrality and prestige of indicator concepts. Improved understanding of a complex topic can be tracked through an increase in the prominence of indicator concepts. Distinguishing certain concepts as being important can be interpreted as a shift from a surface-level understanding to a higher-order understanding.

Concept maps aim to represent only selected important connections as not all possible propositions are equally meaningful. More connections do not necessarily mean a better map and deeper understanding. It is not necessary to generate every possible connection and include every possible concept but be purposefully selective. Similarly, concept map analysis can focus on essential links. Essential links can be identified through expert-generated KIMs. Research (Ruiz-Primo et al., 2009; Schwendimann, 2011a, 2011b) suggests that focusing on weighted essential links can reveal a greater variety of understanding while being more time-efficient.

The analysis of isolated propositions does not account for the network character of KIMs. Network density and prominence scores of selected indicator concepts can describe changes in the network structure of KIMs. The topological structure of a KIM can indicate shifts in learners' knowledge structure. A "network" structure indicates a more integrated understanding than a 'fragmented' concept map structure.

Qualitative proposition type analysis can indicate shifts in learners' understanding. For example in evolution education, a shift in the prominence of normative evolution concepts 'mutation' and 'natural selection' and a decrease of teleological concepts 'need' or 'want' can indicate an improved understanding of the mechanism of evolution. More quantified relations can be seen as an indicator for deeper understanding (Derbentseva et al., 2007).

No single analysis method can capture and track the rich information present in concept maps. This paper concludes that only using complementary methods in concert allows describing alternative ideas and triangulating changes in concept maps. A comprehensive analysis of concept maps might combine human and automated evaluation using both quantitative and qualitative methods. Further research is needed to more fully and more efficiently make sense of concept maps.

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