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56. Predicting Problem-Solving Performance Using Concept Map

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Abstract

A growing community of researchers applies the concept map for elicitation and representation individual's knowledge structure especially within knowledge-intensive processes in organizations. As an extension of prior works on concept map, this study aims to explore a new indicator of structural properties of concept map from an information entropy perspective to predict an individual's problem-solving performance. From the information processing view of problem-solving, Information Theory provides the framework to formulate a new indicator called EntropyAvg. A controlled experiment was carried out to validate the predictive ability of the new indicator. The results demonstrate that EntropyAvg is able to estimate an individual's problem-solving performance beyond two other widely adopted indicators, i.e., complexity and integration. The theoretical and practical contributions of this study are also discussed.

Keywords: Information theory, Problem solving, Information entropy

Introduction

According to the Assimilation theory (Ausubel et al. 1978), a concept map provides a good elicitation and representation of knowledge structure in an individual's memory (Canas et al. 2003). Knowledge structure, which is often referred to cognitive structure in the literature, is comprised of concepts and their relationships (Jonassen et al. 1993; Preece 1976). Nodes and links are the basic components of concept map (1984) as illustrated in Figure 1. The nodes represent the concepts, indicating the perceived regularities of events or objects with designated labels in a certain domain while the links connecting pairs of nodes denote the relations of concepts. Each node-link-node triplet forms a proposition with a meaningful statement about the object or event. These nodes and links are arranged in a hierarchical fashion with the most general concept at the top followed by more and more specific ones. The segments of a concept hierarchy represent different knowledge domains within the concept map. Links that cross segments, called cross-links, show how a concept in one knowledge domain is related to another and represent creative leaps on the part of the knowledge producer.

Similar techniques could be found in the literature of cognitive mapping (Axelrod 1976; Huff 1990), causal mapping (Bryson et al. 2004; Narayanan and Armstrong 2005), mind mapping (Buzan and Buzan 1996), and knowledge mapping (O'Donnell 1994). They are originated from different areas and have different focus. Compared with other mapping techniques, concept mapping emphasizes on the hierarchical structure among concepts. Research has hypothesized that an individual's performance within knowledge-intensive processes in

general, problem-solving processes in particular, could be predicted by analyzing the structural and/or content properties of concept map developed by the individual (Novak 1998). The close relationship between the individual's knowledge structure and performance in knowledge-intensive processes has been well documented (Anderson 1983). Several studies on problem-solving and reasoning ability have also concluded that successful learners can develop complex and integrated structures of related concepts (Gentner and Stevens 1983; Hong and O'Neil 1992; Wilson and Rutherford 1989). As aforementioned, an individual's knowledge structure can be well represented by his/her concept map. Therefore, researchers have put increasing efforts in generating the reliable and valid predictors of performance through analyzing the properties of concept map (McClure et al. 1999; Ruiz-Primo and Shavelson 1996; Yin et al. 2005). In this study, we particularly focus on analyzing the structural properties of concept map to predict individual's performance in problem-solving processes.

Prior research has proposed and validated several important indicators of the structural properties of concept map for prediction of individual's performance. Among them, knowledge *complexity* and knowledge *integration* are two widely adopted indicators (Kwok et al. 2002-3). Although other indicators, such as *density* and *centrality*, have been proposed by causal mapping techniques (Armstrong 2005), we argue that *complexity* and *integration* are fundamental indicators which represent two distinct dimensions of knowledge structure (for example, *density* has a strong correlation with *integration*) and could work as benchmark to evaluate new indicator for representing new dimensions of knowledge structure. According to prior research, the predictability of those indicators are still limited, which implies that additional indicator(s) may exist and a new exploration should be deserved (McClure et al. 1999; Ruiz-Primo et al. 1996; Yin et al. 2005). Furthermore, the current indicators are mainly based on the Assimilation Theory which emphasizes on the process of "meaningful learning" controlled by the learner, in which new knowledge resides in an existing and relevant aspect of the learner's knowledge structure. However, the process of problem-solving is much broader than the process of meaningful learning (Sternberg and Ben-Zeev 2001). Therefore, alternative perspectives on the structural properties of concept map should be further considered. Recognizing that problem solving process can also be regarded as the process of information processing (Newell and Simon 1972), and acknowledging that information entropy during information processing potentially affects the individual's performance (Cover and Thomas 1991), we propose a new indicator of structural properties of concept map from the information entropy perspective to predict the individual's problem-solving performance.

This study entails both theoretical and practical contributions. Theoretically, this study provides a better understanding of the structural properties of concept map from information entropy perspective, and reveals the impact of the new indicator using information entropy on individual's performance in problem-solving processes. Practically, the verified indicator through an experimental study helps improve the predictability of the existing indicators of concept map, providing the operational guidance for evaluating the performance in problem-solving processes. The new indicator can also be applied to the large-scale automated knowledge assessment, which expands the application scope of concept maps.

Following this introduction, the next section of this paper presents the theoretical foundation and indicator development using information entropy. The third and fourth sections report the controlled experiment and its results of the predictive ability of the proposed indicator

respectively. Finally, we draw the conclusions and discuss about how it can be applied to future works.

Theoretical foundation and indicator development

In this section, we provide the formalism on the structural properties of a concept map. It will be used as the basis for the development of the new indicator. Then we explain the theoretical foundation and the details of the indicator.

Formalism of the structural properties of concept map

According to Novak and Gowin's (1984) definition on concept map, the abstraction of a concept map's structure is a "hierarchical graph", a graph expressed hierarchical structure. The formalism of the structural properties of a concept map is derived from the Graph Theory as follows:

- (1) A concept map is deemed as a hierarchical directed graph, C ;
- (2) Every concept is abstracted into *node* or *vertex*, v ; the set of nodes is represented as $V = \{v_1, v_2, \dots, v_n\}$ with only one root node $v_1 \in V$.
- (3) The link between the concepts is abstracted into *edge*, e ; *edge* is formalized as an ordered pair of two nodes, e.g., (v_1, v_2) , and the set of edges is represented as $E = \{e_1, e_2, \dots, e_m\}$.
- (4) The number of edges that have node v as their terminal node is called the *indegree* $in(v)$ of v , and the number of edges that have v as their initial node is called the *outdegree* $out(v)$ of node v .

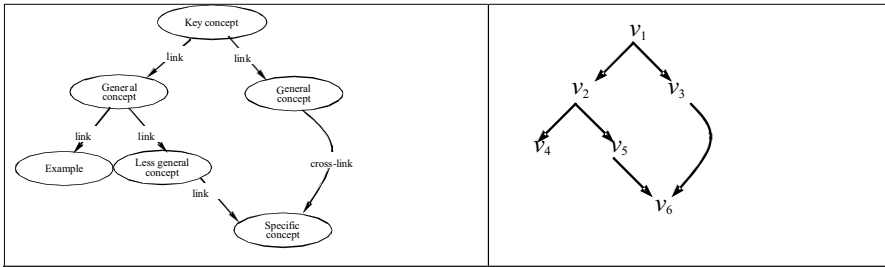


Figure 1: Illustration of a concept map

Figure 2: The formalism of a concept map

By this way, the concept map in Figure 1 is described by the hierarchical graph as illustrated in Figure 2 with the following formalism.

$$C = (V, E),$$

$$V = \{v_1, v_2, \dots, v_6\}, E = \{e_1, e_2, \dots, e_6\},$$

$$e_1 = (v_1, v_2), e_2 = (v_1, v_3), e_3 = (v_2, v_4), e_4 = (v_2, v_5), e_5 = (v_5, v_6), e_6 = (v_3, v_6).$$

In the following parts of the paper, we also adopt the terminologies in Graph Theory to describe the concept map, such as *sub-tree*, *cycle*, *degree*, *parent*, *child*, *leaf*, *branch*, *path*, and *length of path* (Johnsonbaugh 1997).

- (5) A segment of a concept map is deemed as *sub-tree* (neglecting the cross-links). For example, *node set* $\{v_2, v_4, v_5, v_6\}$ with *edge set* $\{e_3, e_4, e_5\}$ composes a segment, and *node set* $\{v_3\}$ with *edge set* \emptyset forms another segment.

- (6) A cross-link joins two segments. In the case of *cycle*, we make the direction of the cross-links from the *parent* to *child*. In Figure 2, the *edge* e_6 from v_3 to v_6 is a cross-link.

(7) The links from one concept to another concept forms a *path* between the two concepts, and the number of links represents the *length of path*. For example, in Figure 2, there are two *paths* between v_1 and v_6 : $P_1 := ((v_1, v_2), (v_2, v_5), (v_5, v_6))$ and $P_2 := ((v_1, v_3), (v_3, v_6))$ and the *lengths of paths* for P_1 and P_2 are $\text{Len}(P_1) = 3$ and $\text{Len}(P_2) = 2$ respectively.

We used adjacency matrix to represent a concept map's structure (Adamson 1996). For any Graph C , its adjacency matrix is expressed as:

$$A(C) = (a_{ij})_{n \times n}, \text{ where } a_{ij} = \begin{cases} 1 & \text{if } (v_i, v_j) \in E \\ 0 & \text{if } (v_i, v_j) \notin E \end{cases} \quad (1)$$

On the basis of adjacency matrix, we utilize the reachability matrix to calculate the number of paths and the length of each path between two nodes by the formula

$$R = A + A^2 + A^3 + \dots + A^{n-1} \quad (2)$$

Indicator development

This study focuses on the structural properties of concept map to generate a new predictor of problem-solving performance. Several indicators based on the Assimilation Theory have been proposed and validated to quantify the structural properties of concept map, which capture two key processes in "meaningful learning", i.e., progressive differentiation and integrative reconciliation (Novak 1998). However, these indicators have the limited explanation power for the knowledge-intensive process in general, and the problem-solving process in particular. This is because the problem-solving process not only includes the process of knowledge assimilation (i.e., meaningful learning), but also other knowledge-intensive processes, such as the process of knowledge application (Sternberg et al. 2001). Noted the information processing process during problem solving (Newell et al. 1972), we further examine the process of constructing the concept map from the information-processing perspective, and apply Information Theory (Cover et al. 1991) to innovatively propose new indicator for analyzing the structural properties of the concept map.

Information Theory deals with the limits and the efficiency of information processing using information entropy (Cover et al. 1991). Several studies have already applied the idea of information entropy to indicate the uncertainty of problem solving processes (Daft and Macintosh 1981; Postrel 2002). In the context of concept mapping, for example two maps in Figure 3 and 4 respectively, we would like to propose a suitable measure to reveal their information uncertainty. Intuitively, with the no change of *complexity* (i.e., number of nodes) and *integration* (i.e., number of cross-links), information uncertainty and disorder increases with the process of broad thinking which results in the width extension and depth condensation during concept mapping. Similarly, information uncertainty decreases with the process of deep thinking which results in the width condensation and depth extension during concept mapping. Comparing the maps in Figure 3 and Figure 4, they have the same *complexity* and *integration*. However, map in Figure 3 has a deeper and less broad structure than then the latter, which reflects the first map creator have a more deep thinking than the latter. According to the literature, although broad thinking to reach a comprehensive understanding to the problem facilitates the problem-solving process, deep thinking helps more to find and justify the solutions in the problem-solving process (West et al. 1985). Thus, it is reasonable for us to predict that the performance of individual who draw the first map would be better than the latter.

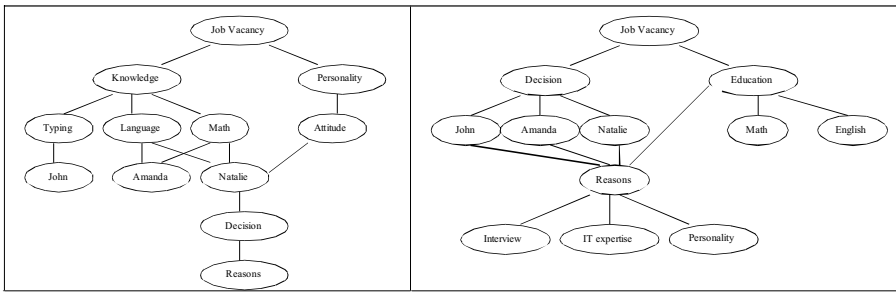


Figure 3. Sample concept map 1

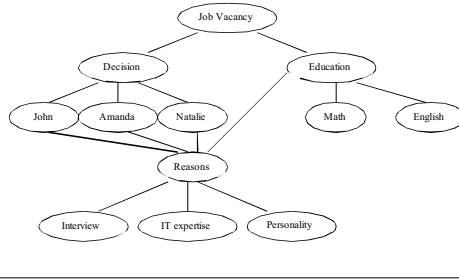


Figure 4. Sample concept map 2

Information Theory provides a good foundation to quantify the information uncertainty of an information item. In the context of concept mapping, each node, and/or edge represents the semantic of a particular domain as perceived by the creator of the concept map. All of them could be deemed as an information item and it is possible to apply the notion of “information entropy” to assess the information uncertainty of them. When individual nodes’ “information entropy” is properly aggregated together, we could get the information uncertainty of the whole map.

According to Shannon’s information model (Shannon 1948), information uncertainty (i.e., information value) of an information item is inversely proportional to the probability of the event described by the information item. It is believed that the number of outgoing links of a concept can provide additional information regarding a concept’s role in the map (Leake et al. 2004). So an event can be interpreted as following the semantic links from one concept to another one in concept mapping. Therefore, the probability of transiting to one of the linked concepts (i.e., node v_j) from a particular concept (i.e., node v_i) can be estimated by the proportion of the number of child nodes of v_j (includes v_j) to the number of all child nodes of v_i (without cross-links). Formally, for node v_i ,

$$\Pr(v_i \rightarrow v_j) = \frac{p}{q}, \quad (3)$$

where p is the number of child nodes of v_j (includes v_j), and q is the number of all child nodes of v_i .

The above estimation is also in accordance with the process of building a decision tree in decision science from the information processing perspective of problem-solving. The principle of decision tree building is to reduce the entropy (uncertainty and disorder) of the dataset until the builder reaches the leaf node that is pure or has zero entropy and represents all instances of one class. The process of making the nodes to the minimum entropy contributes to effective problem-solving (Han and Kamber 2000; Quillian 1968).

Followed the equation (3), we generate the following equation to calculate the information entropy of an arbitrary node v .

$$E_v = \begin{cases} \sum_{i=1}^r -\frac{p_i}{q} \log_2 \left(\frac{p_i}{q} \right) & \text{if } v \text{ is internal node} \\ 0 & \text{if } v \text{ is leaf node} \end{cases}, \quad (4)$$

where

r is the number of branches of node v ,
 p_i is the number of nodes in the i th branch of node v , and
 q is the total number of child nodes of node v , $q = \sum_{i=1}^r p_i$.

Then, we get the map-level indicator *EntropyAvg*, the average entropy of all non-leaf nodes by

$$EA = \frac{\sum_{i=1}^n E_{v_i}}{n-l}, \quad (5)$$

where

n is the total number of nodes in the graph, and
 l is the total number of leaf nodes in the graph.

For example, in Figure 2, the information entropy of node v_1 can be computed as below:

$$E_{v_1} = -\frac{4}{5} \log_2\left(\frac{4}{5}\right) - \frac{1}{5} \log_2\left(\frac{1}{5}\right) = 0.258 + 0.464 = 0.722 \quad \text{and} \quad EA = 0.547.$$

To use equation (5) to analyze the *EntropyAvg* of Figure 3 and Figure 4, we get (only show the non-zero E_{v_i}),

$$EA_{\text{Figure 3}} = \frac{E_{v_1} + E_{v_2}}{12-4} = \frac{0.684 + 1.500}{8} = 0.273, \quad \text{and}$$

$$EA_{\text{Figure 4}} = \frac{E_{v_1} + E_{v_2} + E_{v_3} + E_{v_7}}{12-7} = \frac{0.845 + 1.149 + 1 + 1.585}{5} = 0.916.$$

Therefore, although the two maps have the same *Complexity* and *Integration*, the *EntropyAvg* have a great difference. And it is obvious that map in Figure 3 have a smaller *EntropyAvg* because it expresses depth-focused structure instead of width-focused structure of the map in Figure 4.

Based on equation (5), remaining study will focus on testing the main hypothesis as following:

EntropyAvg of the concept maps is significantly correlated to subjects' problem-solving performance, and *EntropyAvg* provides an incremental predictive ability beyond measures of *Complexity* and *Integration*.

3. Experimental validation

3.1 Overview of the experiment design

This section depicts the controlled experiment which was conducted to examine the predictive ability of the new indicator. In the experiment, participants were asked to solve the same problem, construct their concept maps and submit their choice of the right candidate for the job. We invited two groups of external experts, who were blind to the aim and design of the experiment, to process the concept maps and assess the reports separately. The prototype information system was used to automatically calculate the indicators (i.e., *Complexity*, *Integration* and *EntropyAvg*) of the structural properties of concept map constructed by the participants. The results were exported into SPSS for further data analysis that aims to test the predictive ability of these indicators on the participants' problem-solving performance.

Participants

A total of 40 undergraduates from a business school voluntarily participated in this experiment. No significant differences were found from their age and gender. Before our experiment, all participants were trained in the use of content-free concept map technique to minimize problems arising from misuse. This technique, which is derived from the general concept map technique, emphasizes the structural properties, instead of content properties, of concept maps (Ruiz-Primo et al. 2001). Incentives were also provided to encourage the participation and involvement in the assigned problem-solving task in the form of cash prizes for participation and for the top performing participants. Both the students' participation and the problem-solving performance would not affect their course grades.

Task and procedure

This study employed the choice dilemma task that was a relatively structural problem with no obvious solution(s). The task was about an expanding firm of insurance brokers that planned to recruit a customer services assistant for its front counter. The participants were required to make a choice of which applicant should be given the job, or decide whether the post should be re-advertised.

The actual experiment involved: (1) A facilitator briefly introduced the case, including the requirements of the job, details of the interviewed candidates, and the notes of the interviewer's comments (5 minutes); (2) The participants were asked to define and describe all related aspects of the job vacancy case with the help of facilitator (15 minutes); (3) Each participant was required to draw the concept map of the job vacancy case as the reflection of his/her own knowledge structure (10 minutes); and (4) Each participant was asked to write a report illustrating his/her justifications of the choice and draw a conclusion (10 minutes).

Experimental control

According to previous studies, the sources of error in a concept map testing included the variations of participants' concept mapping proficiency, variations of assessors' domain knowledge and the concept map construction methods (McClure et al. 1999; Ruiz-Primo et al. 1996). Therefore we should discuss these aspects of the experiment control for this experiment.

(1) The control on participants' concept mapping proficiency

We provided training on concept map drawing techniques, especially on the content-free concept map technique. Before the experiment, we employed concept map usage test to make sure every participant had mastered the technique with acceptable proficiency.

(2) The control on assessors' domain knowledge

We employed two groups of assessors in this experiment. Both groups consisted of two external experts from business major who were blind to the experiment settings. The first group kept to the concept map construction steps to put more new concept labels into the standard concept map and input it's data into the computer. The second group complied with the marking scheme to assess the report. The inter-rater reliability of the two groups of assessors was evaluated to eliminate the variation of assessors' domain knowledge that may influence the experiment result.

(3) The control on concept map construction methods

In this study, we utilized the content-free concept map construction methods, which adapted from prior studies (Nelson et al. 2000; Ruiz-Primo et al. 2001), and brought forward the following construction steps.

The assessors provided a set of standard concept labels.

The participants tried their best to use the set of labels and were asked to focus on the position, link and arrangement of concepts instead of generating new concepts. However, participants were allowed to generate a few new concept labels with the agreement of facilitator.

The assessors recast each participant's new concept labels into a new set of standard concept labels, and then inputted the concept map data into computer.

During the processing of all concept maps, the assessors were told not to identify the validity of the results of the participants. It is because the scoring of valid propositions may impose over invalid propositions, which is valuable to support other valid propositions and contribute to the overall knowledge structure for problem solving based on constructivist philosophy (Kinchin et al. 2000). Thus, we can increase the level of automation throughout the whole procedure.

Measures

In this experiment, we intended to test the predictive ability of the proposed indicator (*EntropyAvg*), and its incremental predictive ability by comparing with the other two indicators, i.e., knowledge *complexity* and knowledge *integration* (Kwok et al. 2002-3). The measure of *EntropyAvg* has been described before (Section 2.2). *Complexity* is measured by the number of direct links which reflects the comprehensiveness and differentiation in the articulation and elaboration of knowledge structure. *Integration* is measured by the number of cross links which reflects the interconnectedness and integration of knowledge structure (Kwok et al. 2002-3). All of the three indicators were computed by our prototype information system and worked as the predictors of the problem-solving performance.

The problem-solving performance was measured by assessing participants' reports. Two external experts were invited to identify the justifications reported by the participants and provide a score for each justification ranging from 1 to 3 (1=marginal justification, 2=good justification, and 3=excellent justification). For each report, we calculated the total score of the identified justifications as the final measure of each participant's problem-solving performance. Within-Group inter-rater reliability r_{wg} with the result of 0.89 showed the report scoring is reliable (James et al. 1984).

Results and discussions

Before we measured the validity of the proposed indicator, we first tested and found that the gender and age of participants were both not co-related with their performance. Then, we utilized the descriptive statistics and correlation matrix to establish the basic predictive ability of the proposed indicator. Afterwards, we employed the Hierarchical Regression to identify the incremental predictive ability of the proposed indicator as compared with predictive ability of the indicators used in prior studies, i.e. *Complexity* and *Integration* (Kwok et al. 2002-3).

Table 1 shows the descriptive statistics and correlation matrix of the involved variables. From Table 1, we can see that all three indicators, i.e. *Complexity*, *Integration* and *EntropyAvg*, are significantly related to Performance at 0.05 levels which establish the preliminary predictive ability of the proposed indicator, *EntropyAvg*. Further regression analysis of *EntropyAvg* on Performance shows the result with the R^2 of 0.10 significantly at 0.05 levels. It demonstrates that *EntropyAvg* itself can predict 10% of the variation in Performance, which supports a good predictability of the new indicator.

Table 1: Descriptive statistics and correlation matrix of the involved variables

	N	Mean	S.D.	1	2	3	4
Performance	40	15.40	8.06	–			
Complexity	40	13.07	1.60	<i>-0.265</i>	–		
Integration	40	1.50	0.24	<i>0.348</i>	<i>0.253</i>	–	
EntropyAvg	40	0.71	0.15	<i>-0.249</i>	<i>0.067</i>	<i>0.174</i>	–

Notes: Italicized correlations are significant at $p < 0.10$ (2 – tailed).

To further test the predictability of the proposed indicator, *EntropyAvg*, we conducted Hierarchical Regression analysis on Performance with the control variables of *Complexity* and *Integration*. Table 2 shows the results.

Table 2. Hierarchical regression on performance

Variable Entered	Performance (N=40)		
	B	S.E.	β
Step 1			
Complexity	-1.90	0.74	-0.38**
Integration	14.98	4.96	0.44***
ΔR^2			0.25***
Step 2			
EntropyAvg	-17.00	7.50	-0.31**
ΔR^2			0.10**
R^2			0.35***
Adjusted R^2			0.30**

Notes: Demographic variables were not included in the regression analysis because there was no relation between these variables and Performance in the sample.

** $p < 0.05$, *** $p < 0.01$

As shown in Table 2, although *Performance* was significantly related to *Complexity* ($\beta = -0.38$, $p < 0.05$) and *Integration* ($\beta = 0.44$, $p < 0.01$), which are consistent with prior researches (Khalifa and Kwok 1999; Novak et al. 1984), *EntropyAvg* ($\beta = -0.37$, $p < 0.05$) expressed a significant increase in the predictability on Performance ($\Delta R^2 = 0.10$, $p < 0.05$). Recognizing that the predictability of a single indicator on performance is generally below 10% in prior study (Nadkarni and Narayanan 2005; Ruiz-Primo et al. 2001), such improvement can be deemed as a good support of the predictability of *EntropyAvg*, and we can draw the conclusion that *EntropyAvg* demonstrated the incremental predictive ability beyond measures of *Complexity* and *Integration*. We also can conclude that *EntropyAvg* captures different dimension of knowledge structure due to the fact that the low correlation to *Complexity* and *Integration*. These support our main hypothesis of the study.

From Table 1 and Table 2, we also find that both *Complexity* and *EntropyAvg* are negatively related to the *Performance* under the setting of this experiment. It demonstrated that too many nodes included in the map and too much uncertainty (the big value of *EntropyAvg*) would lower down the performance. *Integration* is positively related to the *Performance* which shows that the more interconnection between nodes may enhance the performance. The negative coefficient of *Complexity* and *EntropyAvg* show that the more comprehensive and complex of the cognitive structure, it is less likely to miss out important information in

problem diagnosis and affects the choice of problem solutions. However, it could increase the cognitive load and leads to confusion and bias in arriving at problem solutions (Newstead and Griggs 1992). The positive coefficient of *Integration* shows support of the importance of interconnectedness and could be well explained by the “integrative reconciliation” of the Assimilation Theory (Ausubel et al. 1978).

Conclusions and future works

This paper proposes a new indicator using information entropy, called *EntropyAvg*, from the structural properties of a concept map, and empirically validates it by conducting a controlled experiment. The results illustrated that the new indicator is a good predictor of problem-solving performance. Also, the *EntropyAvg* captures the incremental variation of the performance beyond that of *Complexity* and *Integration*.

There are still many aspects to measure the structural properties of concept map beyond the typical *Complexity* and *Integration*. For example, 1) the exploitation-to-exploration ratio of a concept map, 2) the new discovered concepts and links ration, and 3) the authoritative concepts ration. But unfortunately, most of them are highly correlated with *Complexity* and *Integration*. Our proposed indicator in this study, derived from information entropy perspective, is one of the typical indicators which could be deemed as one distinct structural property of concept map for predicting the individual’s problem-solving performance, independent to other structural properties of concept map such as *Complexity* and *Integration*. Thus, it provides an alternative for academics and practitioners to manipulate concept map measurements. Also we can expand the application scope of the proposed indicator of the structural properties of different types of concept maps to business enterprise practices, especially in large-scale automated knowledge-based evaluation. In addition, our developed formalism of concept map and indicator has the potential to guide the practitioners in analyzing the structural properties of concept map. It also opens a new direction to refine and derive information-entropy based indicators for structural analysis of concept map and performance prediction.

In this paper, there are three factors related to the setting of the experiment that limit its generalizability. First, the subjects of the experiment consisted of students with similar academic backgrounds. Second, this study imposed a ‘strict’ procedure in terms of duration. Third, the direct performance measure was limited to the specific problem-solving task and process. How would differences in participants’ expertise and background, experimental task and problem-solving task affects the results? Although the results of this study shows some support for the research objectives, it is clear that more research is needed to advance our understanding on the use of concept map to measure individual’s knowledge structure, and predict individual’s performance in knowledge-intensive processes.

Furthermore, as a versatile tool, concept map may be used in other knowledge-intensity areas: It could be a knowledge elicitation tool that effectively acquires knowledge from individuals and exchanges knowledge among individuals; It may be a knowledge representation tool that graphically represents the knowledge structure and enhances the conceptualization of knowledge; It may be a knowledge organization and storage tool that organizes and stores individual thinking related to particular domain, and fosters creativity; and it also may be a decision making tool to support qualitative decision making which was demonstrated in this experimental tasks.

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