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Integrating Concept Mapping into Information Systems Education for Meaningful Learning and Assessment

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Abstract

Concept map (CM) is a theoretically sound yet easy to learn tool and can be effectively used to represent knowledge. Even though many disciplines have adopted CM as a teaching and learning tool to improve learning effectiveness, its application in IS curriculum is sparse. Meaningful learning happens when one iteratively integrates new concepts and propositions into her existing cognitive structure. It is the process of how one acquires deep and applicative knowledge in certain domains such as Information Systems (IS). As important as meaningful learning is in IS education, there is a scarcity of method to assess it effectively. This study reports a series of experiments of adopting CM as a tool to enhance and evaluate students' learning, especially meaningful learning in IS education. Based on theoretical foundation of CMs and prior related empirical work, we designed a series of assignments that require students to complete CMs in three participating courses. We also designed and implemented a tool to help analyzing the CMs with certain level of automation. The completed CMs are collected and analyzed to answer our research questions. We believe the results demonstrate the utility of CMs in IS education as an effective tool to understand and assess students' meaningful learning. Our work also experimented with various methods to use CMs and the findings provide valuable insights as to how CM-based teaching and learning tools can be integrated into IS curricula seamlessly.

Keywords: Concept map, meaningful learning, assessment, information systems education, pedagogical tool.

1. INTRODUCTION

In the ACM & AIS Curriculum Guidelines (Topi et al., 2010) for Undergraduate Degree Programs in Information Systems (IS), critical thinking (CT) is listed as one of the five foundational knowledge and skills. CT skills must be acquired through meaningful learning (Mayer, 2002), during which students acquire and build knowledge and cognitive processes, which are needed for them to become effective problem solvers in IS fields. Therefore, it is essential for IS educators to understand the nature and assess the quality of meaningful learning in order to design teaching artifacts that foster effective problem solving skills.

Meaningful learning was identified by Ausubel (Ausubel, 1963) as the most important learning principle. It is signified by integrating new concepts and propositions with existing relevant ideas in some substantive ways, within one's cognitive structure. This is an iterative process in which learners must continue to refine, rectify, rearrange, and reorganize the content and structure of their knowledge so that their cognitive structure can be improved. Opposite to rote learning (Novak, 1993; Novak & Gowin, 1984), meaningful learning can be signified by: (1) Includes clarification of relations between concepts; (2) Involves self-assisted learning; and (3) Can be conducted in the form of scientific research and/or artistic production. It was also pointed out that though idiosyncrasy exists in individual concept structures, sufficient commonality and isomorphism in individual meanings make it possible to have dialogue and sharing. Therefore, being able to communicate and share concept structures within one's cognitive structure is the key to understand and evaluate meaningful learning.

To better understand and assess meaningful learning, we need an effective tool to visualize it and Concept Map (CM) is such a tool. CM was introduced by Novak (Novak & Gowin, 1984) as a graphical tool for representing knowledge structure in the form of a graph. The nodes of the graph represent concepts. The edges that run between concepts represent relationships. Concepts and relationships between them formulate propositions. The simplicity of constructing a CM makes it an easy tool for anyone to represent her knowledge structure for others to see and understand (Cañas et al., 2005). Compared to other mapping techniques, CMs have solid underlying theories (Novak & Cañas, 2008).

To construct high quality CMs, one needs to constantly integrate newly acquired concepts and relationships into existing CMs, and the structures of the CMs need to be modified to accommodate the changes. The continuous iterative process of such integration signifies meaningful learning rather than rote learning. This makes CMs an excellent tool to visualize meaningful learning. In turn, the quality of CMs may be used to assess the magnitude and nature of meaningful learning.

Figure 1 summarizes the relationship between CM, active learning, and assessment. The cognitive structure is a voluminous collection of concepts and their relationships. Meaningful learning is the iterative refinement and enrichment of this structure. The cognitive structure exists in one's mental world and is not directly accessible by others. Like a cognitive structure, CM is a graph collection of concepts and their relationships and can be iteratively refined and enriched. Unlike a cognitive structure, CMs exist in the physical world and can easily be accessed by others. In active learning using CM, a student captures new information in a CM and iteratively refines it (L1 in Figure 1). This process in turn helps refine the cognitive structure, i.e. active learning (L2). In assessment, relevant portion of the cognitive structure is captured by a CM (A1), which can then be assessed (A2).

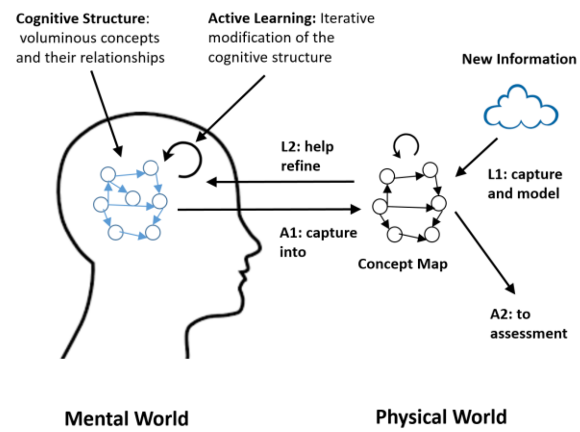

Figure 1. Relationship between CM, Active Learning, and Assessment

In this study, we focus on building various CM-based tasks into teaching in the IS curriculum at the University of Houston-Clear Lake (UHCL). Furthermore, the quality of completed CMs are analyzed both qualitatively and quantitatively. The analysis results provide us valuable insights on how students learn meaningfully. The rest of the paper is organized as follows. Section 2 provides a survey on related theoretical and empirical work. Section 3 describes in detail the designed CM-based tasks, and their analysis and assessment. We then discuss the results in Section 4 and conclude with future research directions in Section 5.

2. RELATED WORK

The constructs used in CMs are simple and impose little cognitive burden on users-Concepts, Relationships, and Propositions. A concept is usually a word or a short phrase representing perceived regularity or pattern in events or objects, or records of events or objects. Generally speaking, there are two equally important categories of concepts in IS (Zendler, Spannagel,

& Klaudt, 2011). The first are content concepts such as algorithm, architecture, and data. The other are process concepts such as problem solving, problem posing, analyzing, and generalizing. The practical components focus on content concepts and corresponds to the technical-oriented classes in IS curricula such as DBMS. The theoretical components focus on the process concepts and corresponds to the theoretical-oriented classes in IS curricula such as IS Theory. Related concepts can be linked through relationships to formulate meaningful statements that represent the content and structure of one's knowledge body. A set of inter-connected CM constructs often suggest certain knowledge domain/field. Cross-domain links may occur if one's knowledge is comprehensive and the learning is meaningful since rote learning often remains at the "know-what" level. A simple concept map to explain what is concept map and how it is related to CT and meaningful learning is in Figure 2.

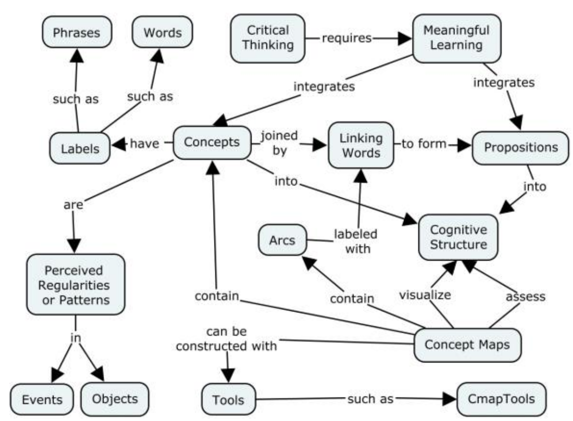

Figure 2. Concept Map of Concept Map and Meaningful Learning. Partially adopted from (Cañas et al., 2004)

The underlying theory of CMs is cognitive learning (Ausubel, 1963, 2012) which builds on several principles. The key principle is meaningful learning. To facilitate meaningful learning, the learner must assimilate new knowledge (clear and relevant concepts and propositions) into existing cognitive structure. CMs is the perfect candidate for this task because the construction of a CM instantiates the process of conducting meaningful learning. Once the CMs are completed, we can gauge students' meaningful learning through the quality of the CMs. Therefore, we need to have effective methodology to evaluate the "goodness" of CMs.

The criteria used in the evaluation of CMs usually measure the content and/or the structure of the CMs. The content evaluation of the CMs may measure various characteristics of CM components such as concepts, propositions, and their formed structures. The structure evaluation of the CMs usually looks at the interconnectedness of the CMs (Strautmane, 2012; Yin, Vanides, Ruiz-Primo, Ayala, & Shavelson, 2005). Content evaluation often is based on a "master map"—a CM compiled to be used as the "gold standard". Structure evaluation often measures various topological characteristics of the CM. However, there is no fixed formula of "goodness of CM" (Cañas, Novak, & Reiska, 2015) since the "goodness" can be very subjectively based on various factors. For example, the purpose of CMs has an impact on what are to be considered as good CMs. The purposes may include knowledge elicitation, cognitive structure formation, assessment, etc.

In addition, there are many different ways CM-based tasks can be designed and executed to represent knowledge and/or to assess learning, as summarized in (Strautmane, 2012). The variables of the tasks may include the following: (1) Whether a focus question is used (Derbentseva, Safayeni, & Cañas, 2007)? A focus question provides a focal point for the learner to acquire, structure and assimilate a topic of knowledge. The CMs constructed accordingly should contain relevant concepts and their connections meaningfully organized to answer the focus question; (2) Whether certain types of assistance are provided by the instructors? For example, will part of the concepts, or structure, or both be provided to the constructor? How CM-based tasks are administered affects how CMs are constructed, and the quality of them in turn.

As much as CMs are widely adopted in other disciplines, their application in IS education is rather limited. For example, in (Weideman & Kritzinger, 2003), thirteen applications of CMs in education are summarized, none of which is in a domain related to computing. In the limited cases where CMs are used in IS curriculum, assessment of the learning and knowledge structure is not the focus. For instance, CMs were adopted to gauge undergraduate students' understanding of content from MIS modules delivered in classroom setting (Gregoriades, Pampaka, & Michail, 2009) in order to test whether significant differences exist between Asian and European students learning styles and outcomes. Though CMs have been used to assess students' understanding, the scope is narrowed on a limited number of IS concepts (Freeman & Urbaczewski, 2001). In other studies, CMs have also be used as a tool to teach and evaluate critical thinking in IS curriculum (Wei & Yue, 2016).

The IS education community has a wide range of assessment tools, many of which have been proven effective in certain aspects, to some degree. Standard test questions such as multiple choice and T/F may be good at assessing "know-what"—usually results of rote learning. On the contrary, meaningful learning addresses "know-why" and "know-how". Writing assignments, hands-on projects, and case studies are often utilized for those. However, the deliverables of these assignments cannot effectively represent the cognitive processes and structures, which are important to understand the meaningful learning involved. The graphical structure that CMs provide can fit in this void.

In this study, we take a holistic approach to integrate CM-based tasks as pedagogical tools into IS curriculum at UHCL. Different types of CM-based tasks are designed and executed. Mechanisms to evaluate the quality of the CMs are implemented. Tools are built to increase the automation level of the evaluation process. The evaluation results are interpreted based on theoretical and empirical work. This project is considered as the early phase of an effort to design and build a CM-Centered learning environment tailored to IS education (Cañas & Novak, 2014).

3. EXPERIMENT DESIGN

In this study, we used five classes in three Computer Information Systems (CIS) courses at both graduate (G) and undergraduate (U) levels for testbed. Two major categories of IS courses are used: one type is technical oriented database classes where the focus is "content concepts" including definition, algorithm, data structure and more. The other is more theoretical oriented IS classes where the focus is "process concepts" including theories, frameworks, and problem solving procedures. The details of participating classes are summarized in Table 1.

Our research focus is to explore "How CMs can be effectively used to assess meaningful learning in IS education?" More specifically, we would like to seek answers to the following questions:

- What impact does CM-assignment design have on the outcomes?
- How do students perform on CM-assignments and what are the insights?
- Are there significant differences between CM-assignments performance of students at different academic levels?
- Are there significant differences between CM-assignments performance of students from classes of different natures?
- What features of CMs can be used to assess meaningful learning? More specifically, we would focus on the content and the structure of the CMs.
- What modifications need to be made for future CM-assignments?

Class #	Course	Level	Concept Type
1	Design of Databases (DOD)	U	Content
2			
3	Infor. Systems Theory & Practice (ISTP)	U	Process
4			
5	Strategic Information Systems (SIS)	G	Process

Table 1. Summary of Participating Classes

CM-based Tasks

For all participating classes, instructors prepared the students for the CM-assignments as follows: (1) Conduct brief in-class introduction of CMs with examples (around 20 minutes); (2) Distribute more learning material on constructing CMs for further reading; (3) Distribute CmapTools tutorials to help students grasp the diagramming tool they are going to use to complete the assignments; (4) Assign small in-class CM exercises and provide instructor feedback. Pre-CM short surveys were also conducted and the results show that the majority of the students had not been exposed to CM before. Afterward, the CM-assignments are distributed as regular homework assignments and students were given one week to complete them.

For the purpose of constructing CMs, we adopted CmapTools (Cañas et al., 2004). This tool was chosen over other diagramming tools because: (1) It is developed by the Florida Institute for Human and Machine Cognition (IHMC) based on their years' research on knowledge representation; (2) It is free for download and use for educational purposes; (3) It has an excellent user interface; (4) It provides network-based sharing and collaboration environment, which makes larger scale and longitudinal study on CMs possible; (5) It provides support to incorporating multimedia elements into the CMs; (6) It allows the CMs to be exported in various formats such as XML files, which makes it possible to automate some analysis of the CMs.

CM-construction assignments can come in different forms. For example, a focus question may be given to the students. Alternatively, an initial set of concepts may be provided to help the students to start on the construction. The given concepts can either be provided in a list or in a pre-defined structure. In this study, the details of the CM-assignments design for each participating class is summarized in Table 2. The focus question given to the ISTP class is "How could businesses develop competitive strategies using information systems?" For other classes, the CM-assignments are given based on specific teaching segments including "relational database model" (for one of the DOD classes), "Information Technology Architecture and Infrastructure (for SIS)", and "Social and Ethical Issues of information systems (for ISTP)". For the last one, the initial set of concepts provided to students include: Ethics, Accountability, Information Systems, Information, Moral dimension, Quality of life, Data, Piracy, Ethical issues, Intellectual property, Privacy, Control, Social issues, Political issues, Data analytics, Ethical analysis, Law, Security, Fair information practices, Ethical principles, Customer data, Computer crime. With this initial set, students are asked to construct a CM with at least 40 concepts.

Class #	Focus Question?	Initial Concepts?	Sample Size
1	N	N	28
2	N	Y	24
3	Y	N	26
4	N	Y	27
5	N	Y	19

Table 2 CM-Assignments Details

Analysis and Evaluation of CMs

The completed CMs are turned in electronically in both .cmap and .cxl files. The .cmap file is the native file format for CMapTools and the .cxl file is basically exported XML file that can be parsed to extract details of the CMs. The .cxl files contain three major types of information: (1) General information of the CMs such as title, publisher, and date; (2) Content of the CMs including concepts (nodes), relationships (edges), and the labels of the nodes and edges; (3) Display information of the CMs such as the location of the nodes and edges, basically the graph layout information of the CMs. The first two types of information are useful in capturing and understanding the knowledge represented by the CMs and will be the foci of our analysis.

Completed CMs have a lot of information embedded in them and it is impractical to go through them manually. Various studies have tried to use different techniques to analyze CMs, most of which have the focus of gauging the quality of the CMs (Cañas, Bunch, Novak, & Reiska, 2013; Jain, Gurupur, & Faulkenberry, 2013). Some other tools have the capabilities of comparing CMs to master CMs by seeking similarities (Lamas, Boeres, Cury, Menezes, & Carlesso, 2008; Marshall, Chen, & Madhusudan, 2006). For our study, we designed and implemented Concept Map Analysis Framework (CMAF), a tool to analyze students' CMs. The design goals include: (1) Provide automated analysis and feedback to students who turn in CMs as assignment deliverables; (2) Provide summary reports of submitted CMs of a class to the instructor; (3) For each CM, provide a quality analysis report; (4) Provide results of comparison between student CM and the master CM. The framework is also designed in an extensible way so future research and teaching needs can be fulfilled. The architecture of CMAF is shown in Figure 3.

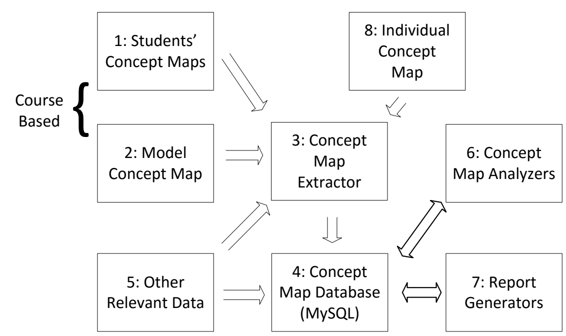

Figure 3. The Architecture of CMAF

The tool is database-centric and implemented in Python. Students turn in their CMs labeled with their IDs. The CM Extractor extracts required elements from the CMs and stores them in the database (MySQL). Other relevant data such as course, assignment, and student information can also be used by the CM Extractor and the CM Database. CM Analyzer can retrieve CMs from the CM Database and the analysis results can be stored back to the CM Database. Report generators can generate appropriate reports upon request for different purposes.

At this stage, the tool is capable of reading .cxl files, parse and analyze the CMs, store the parsing and analysis results into a database, and generate various reports on CMs upon requests. The analysis of the CMs focuses both on the content and the structure of the CMs. Python NetworkX Package ("NetworkX-High Productivity Software for Complex Networks," 2014) is used to deliver topological measures of the CMs. In the next phase, we plan to extend the tool's functionality by including similarity analysis, i.e., comparison between students' CMs and master CMs provided by the instructor.

With the help of the tool, we were able to batch process the CMs. In addition to extraction and storing all components of the CMs, we also process the information to obtain a set of significant measures of the CMs. A summary of those measures is provided in Table 3 and Table 4. Note that many of the structure measures are borrowed from standard Social Network Analysis (SNA) (Wasserman & Faust, 1994).

Measure	Definition
n_nodes	Number of concepts in CM
n_edges	Number of linkages between pair of concepts in CM
n_chars	Number of characters in the labels
n_words	Number of words in the label

Table 3 Captured Content Measures of CMs

Measure	Definition
n_center	Number of nodes that are centers
n_periphery	Number of nodes that are periphery nodes
density	Graph density
is_connected	Boolean value to denote if the CM is connected or not
radius	Minimum eccentricity
diameter	Maximum eccentricity
degree	Number of edges for a node
in_degree	Number of incoming edges
out_degree	Number of outgoing edges
deg_cent	Degree centrality
close_cent	Closeness centrality
between_cent	Betweenness centrality

Table 4 Captured Structure Measures of CMs

As an example, Appendix 1 shows a CM created by an above-average student in the undergraduate DoD class in a CM assignment to capture concepts in the relational databases and the relation model by using CMAP. Table 5 shows the values of captured content and structured measures of the CM.

This information is useful in assessment and providing feedback to the student. Appendix 2 shows a feedback report generated by CMAF to the student producing the CM in Appendix 1.

CMAF is currently under active development and we will present it in more details in a future paper. Meanwhile, readers interested in learning more about CMAF may contact the authors.

Measure	Sample CM Value
n_nodes	*28*
n_edges	*37*
n_chars	*12.43*
average(n_words)	*1.82*
average(n_center)	*3*
n_periphery	*6*
density	*0.098*
is_connected	*true*
radius	*4*
diameter	*7*
average(degree)	*0.98*
average(in_degree)	*0.049*
average(out_degree)	*0.049*
average(deg_cent)	*0.3*
average(close_cent)	*0.095*
average(between_cent)	*0.095*

Table 5 Graph Measures of Sample CM in Appendix 1

4. ASSESSMENT RESULTS AND DISCUSSION

Due to the limited space, we select only part of our analysis results for description and discussion in this paper as follows.

Grading CMs against Master CM

One way to evaluate the quality of a student's CM is to compare it against the master CM provided by the instructor. This process can be very time consuming since automation of this process is hard to achieve. Because of the free form of concepts, relationships, and propositions, detailed grading of CM elements requires manual work and domain expertise.

Scoring of CM based on quality of the elements have been studied (McClure & Bell, 1990; McClure, Sonak, & Suen, 1999). We adopted and modified the previous scoring methods to evaluate students' work. Basically, the instructor created a "master CM", against which student work were compared to obtain Holistic Score, Existential Score, and Relational Score. Holistic score was used to assess the overall understanding of the content (i.e., the subject matter). The Holistic Score measures the "general goodness" of the CMs and is often assigned by the graders who are familiar with the purpose of the assessment. Existential score captures the presence or lacking of required concepts, weighted by their relative significance in the CM. CMs that contain more "significant" concepts in the master CM scores higher in this aspect. Relational score measures the existence and correctness of relationships between concepts, and relationships are also weighted. CMs that include more heavy-weighted relationships score higher in this aspect. These three different scores were combined in a weighted-manner to compute the overall score. The overall score is calculated on a 1-10 scale as $Overall = (10 \times \frac{E}{E_{max}} + 10 \times \frac{R}{R_{max}} + H)/3$, where E and R are the Existential and Relational scores respectively. E_{max} and R_{max} are the highest achievable existential and relational scores and they can be calculated using the master CM. The graders, based on their understanding of the content, also assign the weights of the concepts and relationships. H is the holistic score on a 1-10 scale and the assignment of a value for H relies on the grader's criteria and domain knowledge. Using this method, completed CMs by students were graded and the general findings are as follows: (1) Students tend to achieve higher existential score than relational score; (2) Overall high score is rare compared to the master CM; (3) High holistic score doesn't necessarily correlate with high existential and/or relational scores; (4) Grading score, especially the relational score, correlates positively with course grade. A possible implication of this is that students who are better in meaningful learning (required to achieve high relational scores) generally perform better than others in the class, where knowing and memorizing facts is not sufficient. In addition, by observing the CMs by students, instructors can gain insights as to how to improve teaching to facilitate meaningful learning such as: (1) What concepts do many students fail to include in the CMs, especially those concepts that are essential to learning objectives? The instructor may consider modify teaching to emphasize those important concepts. (2) What are the commonly missed/incorrectly labeled relationships that need more clarification? (3) Is the teaching structured in the way to help students see connection between topics? This can be done by observing the existence and/or absence cross-topic relationships. Currently, instructors do most of the grading against master map manually. We plan to include at least part of this process into our CMAF.

General Features of CMs

Some general features of CMs include: (1) The number of concepts (nodes) in a CM (#N); (2) The number of relationships (edges) in a CM (#E); (3) Whether the CM is connected (C); and (4) Number of words (NW) in the edge labels of a CM. In Table 6, the mean and standard deviation of node count and edge count compared to those of master CMs are summarized.

C	#N			#E		
#	**Avg**	**Std**	**Mast.**	**Avg**	**Std**	**Mast.**
1	28.8	19.6	20	29.1	19.7	24
2	25.1	5.0	30	29.9	6.5	43
3	27.1	11.8	40	36.8	18.9	47
4	46.9	9.6	55	53.5	12.1	58
5	49.8	19.1	60	54.4	23.3	65

Table 6 CMs Nodes and Edges Count

For technical classes (Class 1), average numbers of concepts and relationships from students' work are 43% and 22% more than those of the master CM. This assignment doesn't have a focus question or any initial concepts to start with, which leaves the solution space wide open. In-depth analysis of CMs from Class 1 suggests that the CMs (1) Are less connected; (2) Have higher number of distinct concepts and relationships; (3) Have more verbose concepts; and (4) Have less verbose relationship labels.

For IS theory classes (Classes 4 and 5) with initial concepts provided, the average number of concepts and edges provided by the students are closer to those of the master CMs (85.5% of nodes and 93.1% of edges for Class 4, 83.3% of nodes and 83.1% of edges for Class 5). Therefore, the initial given concepts help improve the coverage of necessary concepts and set the proper scope of the concepts. In addition, it can be seen that standard deviation of edge count is usually significantly higher than that of node count, which suggests that students' capabilities in creating meaningful relationships between concepts vary more compared to their capabilities in coming up with concepts. Teaching tools should be designed to help students see connections between what they have learned.

We view the complete CMs as graphs, a disconnected CM means there are segments not connected to others and each segment usually is a topic/subdomain. Disconnected CM suggests that the author has trouble establishing connections between topics in the same knowledge area. Obviously, the cross-topic connections should carry more value when measuring the quality of CM since "putting the whole picture together" requires true learning in depth. Our analysis results give some insights on this matter as follows: (1) The two classes with focus on "content concepts" (database technologies) have much higher percentage of connected CMs, i.e., no broken pieces in the CMs (89.3% and 95.8% respectively). The three classes with focus on "process concepts" (IS theories) perform worse and the connected percentages are 56.0%, 44.4%, and 78.9%. For the knowledge area of DBMS, the content and structure are more maturely established and stable, which makes it easier for the students to see the holistic view. For IS theory classes, the topics are more diverse and students tend to lose track of the connectedness. However, with advancement in the program, this aspect gets improved as we can see graduate students (78.9%) perform much better than undergraduate students. Furthermore, we also found that in IS theory classes, CMs have higher number of words in the concept labels than DBMS classes. This often happens because concepts in IS theory classes are more abstract and students have more trouble in coming up with precise and succinct concepts. In some extreme cases, a whole sentence is used as a concept. What the students fail to realize is that very long concept label is a good indication that more complicated structure such as propositions should be used instead, as seen in the example shown in Figure 4.

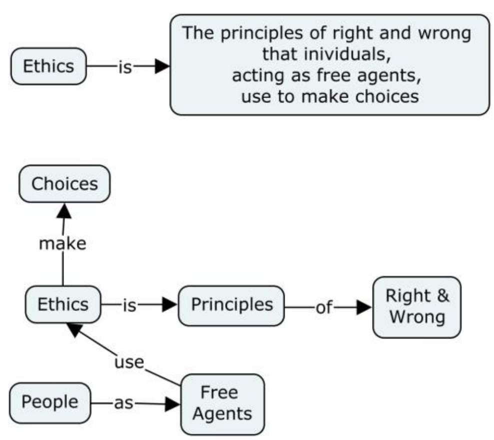

Figure 4. Example of a Very Long Concept

Structure Features of CMs

In this section, we illustrate our findings by analyzing CMs as graphs using network analysis techniques provided in NetworkX, with focus on selected features. For a node in a graph, its eccentricity measures the longest distance between it and any other nodes. The minimum eccentricity of a graph is its radius and the maximum eccentricity is the diameter. The nodes whose eccentricity equals to the radius are called center. The nodes with eccentricity equals to the diameter are called periphery. For a node, the number of edges connected to it is called the degree. For directed graph, there are in-degree and out-degree. Centrality is used to measure the relative importance of a node in a graph, based on how connected is this node to others. Four different centrality measures are studied including degree, betweenness, closeness, and load centrality (Wasserman & Faust, 1994).

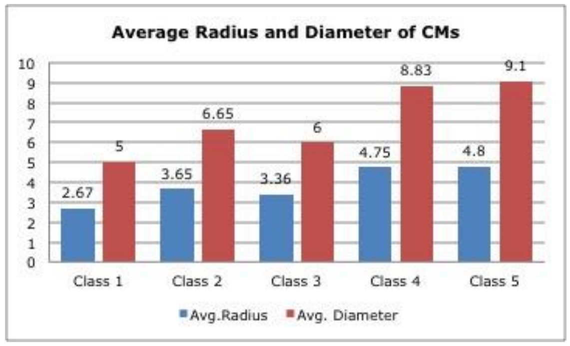

Figure 5. Comparison of Radius and Diameter

As seen in Figure 5, CMs from DOD classes (Classes 1 & 2) are more "round" and CMs from the IS theory classes have more "spikes" because the diameters are longer. In other words, we tend to see longer chains of concepts in IS theory CMs. It indicates those CMs are more of depth and suggests hierarchies. Going through the details of the CMs, it is discovered that some most popular relationships between concepts are "is a", "is type of", and "is part of" and their variations. In the completed CMs, the largest value of diameter is 15 (in the undergraduate IS theory class), which means the author was able to expand from one concept to another as far as 15 steps.

Degree of a node measures how many other nodes it connects to. In the case of CM, for each concept, its degree indicates how many other concepts are connected to it. For all collected CMs, we calculate their average degrees, i.e., generally each concept in the CM is linked to how many other concepts. This measure and its range vary significantly cross the classes, as seen in Figure 6. The graduate IS theory class has the widest range of average degree count compared to others.

In addition, we conducted t-tests to find out if significant differences exist between the means of average degree counts. The results are summarized as follows.

- Between the two databases classes, the class that was given an initial set of concepts to start with has significantly higher average degree count (t=-5.1392, df=42.536, p<0.0001).
- Between the two undergraduate IS theory classes, the class that was given a focus question to start with has significantly higher average degree count (t=-2.3047, df = 35.971, p=0.01). The highest average degree count is 15 and it happens in one of the CMs where the concept "Information Systems" is the center of the CM and has links to many other lower level topics.

These observations inform us that by providing an initial set of concepts and/or a focus question, we can encourage students to seek more relationships between concepts. Probably the starting concepts and focus question can act as anchors of the CMs.

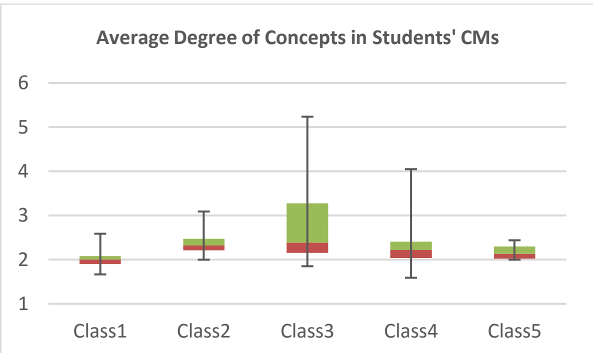

Figure 6. Boxplots of Average Degree of Concepts in CMs for All Five Classes

In SNA, centrality is a measure to represent the significance of a node. There are different types of centrality measures. Degree centrality is defined based on the degree of a node, i.e., the number of edges between the node and its neighbors. In CMs, a node with high degree centrality signifies important concepts, i.e., central ideas in the knowledge area. Between centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. In CMs, a node with high betweenness centrality is a concept that act as gateway between topics within the domain. A CM contains high betweenness centrality concepts suggests that the author has a holistic view of the learning content. The central concepts from the database classes are more well-defined and the CMs should have higher degree centrality. As to the IS theory classes, contents covered are more dispersed and we expect to see many related topics organized in the CMs. Therefore, IS theory CMs should have higher betweenness centrality. Using our collected CMs data, we performed t tests to test our hypothesis and the conclusions are drawn as follows: (1) The database classes CMs have significantly higher degree centrality than IS theory classes (t = 3.4796, df = 120.242, p<0.001); (2) The IS theory classes CMs have significantly higher betweenness centrality than database classes (t = -6.5823, df = 192.602, p < 0.0001). These findings provide us insights how to design CM assignments to encourage higher quality work based on different nature of the knowledge areas in IS.

5. CONCLUSIONS AND FUTURE RESEARCH

CM is an effective tool to represent one's knowledge. The content and quality of CMs can provide valuable insights into what and how the authors have learned. In this study, we designed a series of CM-based assignments to understand students' meaningful learning in two IS courses- a technical and a theory class. We also designed and implemented a tool to extract elements from the students' CMs and conducted various analysis of the results. From our study, we gained the following insights:

- CMs are an excellent tool from which instructors can gauge students' learning and improve teaching.
- Learning curve to CMs and CmapTools is short, which makes incorporation of it into the teaching feasible.
- CM-based assignments come in different formats and this has an impact on the outcomes including whether a focus question or initial concepts are provided. For example, proper focus questions and initial set of concepts can improve the quality of the students' CMs, especially for IS theory classes.
- CMs constructed for different classes in IS curriculum vary in many features and those should be taken into consideration when designing the assignments.
- Quantitatively grading the CMs using master CMs requires time and expertise. Though the grading can provide interesting findings, one should be cautious against using the scores without proper interpretation.

We believe there is a lot more to be explored about the usefulness and utility of CMs in IS education, especially to understand students' learning. Our current works can be considered as pilot studies on a graphical tool with high potential in IS education. Our experimental designs are limited by the small sample sizes, the small number and variety of participating IS classes, the absences of control groups, and the lack of a strong theoretical model. Furthermore, we have tested only a few variety of CM assignments. As a flexible graphical tool, the kind of CM assignments can be very rich and a taxonomy of these CM assignments in the context of IS education has not been studied systematically. Both the assessment methods and the CMAF tool are in their early stages and much can be improved. Based on the lessons learnt in this series of preliminary studies, we will address these limitations and expand the scope and depth of our study and continue to improve our CMAF.

6. ACKNOWLEDGEMENT

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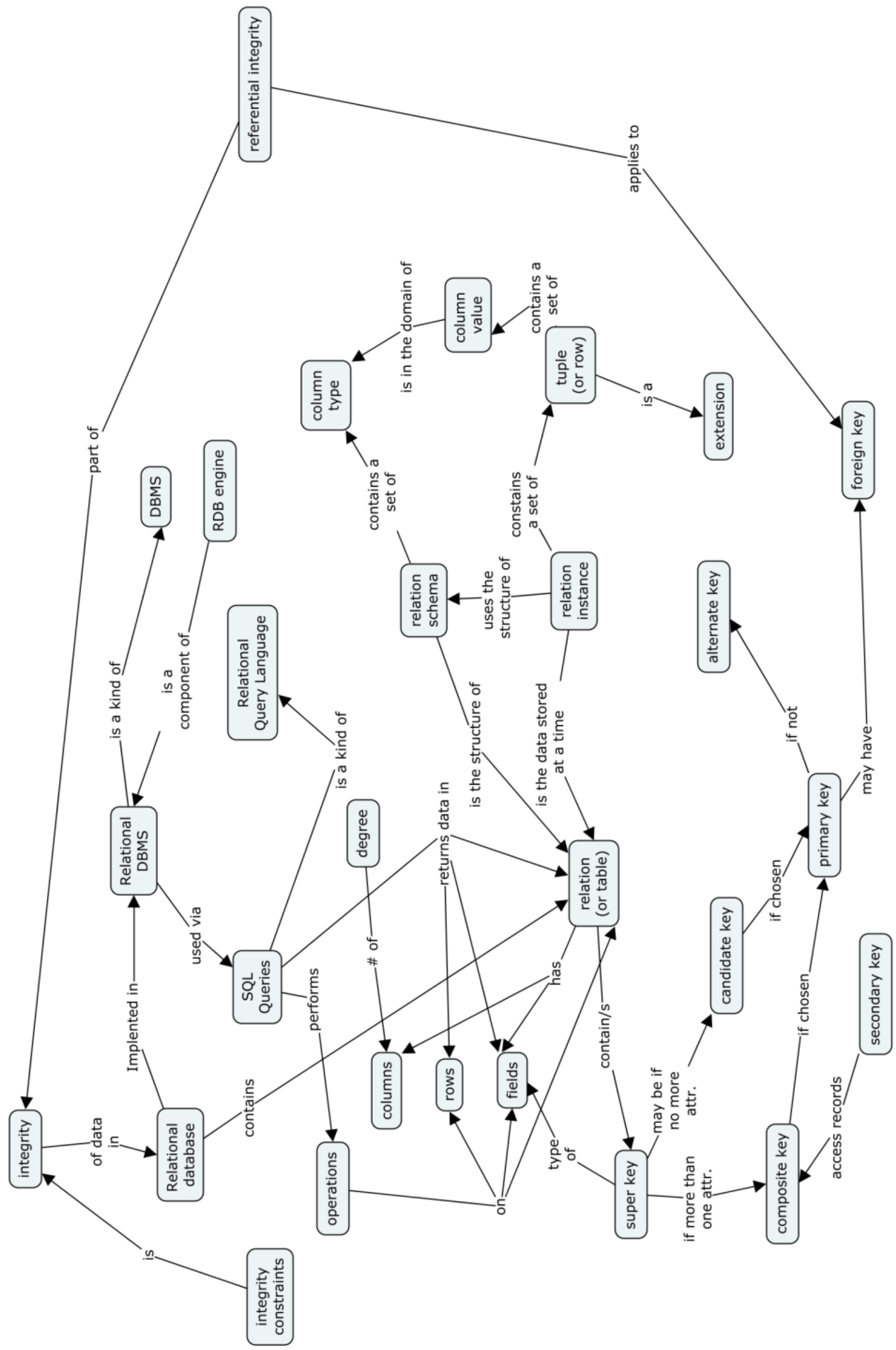
Appendix 1 An example CM of a student taking the undergraduate database class



Appendix 2. CMAP report to the student creating the CM in Appendix 1

```
CMap Report
===========
HW #3 Concept Map
CSCI 4333 spring 2016

Number of students: 24
Average number of concepts: 25.12.
Average number of links: 30.33.
Average connectivity: 1.21.

Suggested model solution:
   Number of concepts: 30.
   Number of links: 43.
   Connectivity: 1.43.

Student id: xxxxxxx
===================
Number of concepts: 28.
Number of links: 37.
Connectivity: 1.32.

Concepts and number of edges coming in and out from them.

  n Concept                          # from # to #total
-------------------------------------------------------
  1 relation (or table)                   3    5      8
  2 SQL Queries                           5    1      6
  3 Relational DBMS                       2    2      4
  4 fields                                0    4      4
  5 primary key                           2    2      4
  6 operations                            3    1      4
  7 super key                             3    1      4
  8 integrity                             1    2      3
  9 tuple (or row)                        2    1      3
 10 Relational database                   2    1      3
 11 relation instance                     3    0      3
 12 composite key                         1    2      3
 13 relation schema                       2    1      3
 14 column value                          1    1      2
 15 foreign key                           0    2      2
 16 columns                               0    2      2
 17 rows                                  0    2      2
 18 referential integrity                 2    0      2
 19 candidate key                         1    1      2
 20 column type                           0    2      2
 21 integrity constraints                 1    0      1
 22 secondary key                         1    0      1
 23 degree                                1    0      1
 24 RDB engine                            1    0      1
 25 extension                             0    1      1
 26 alternate key                         0    1      1
 27 Relational Query Language             0    1      1
 28 DBMS                                  0    1      1
```

