

them. In this study, we explore the feasibility of the analysis of concept maps using data mining methods, and investigate the possibility of using concept maps as a research tool to understand college student’s learning.

2. DATA COLLECTION

We first describe participants in this study, concepts provided to them, and data collection procedure.

2.1 Participants

Data were collected from 10 college Critical Inquiry (CI) courses designed to help underprepared students to either acquire study skills or efficacy/motivation. The CI courses was chosen due to the large enrollment members, of approximately 300 students per semester, and they provide specific learning contexts through pairing the CI courses with other subject courses such as psychology, chemistry, biology, education, and archeology. The primary purpose of pairing the CI courses with other subjects courses is to facilitate student to learn better in a specific subject area. A total of 111 students participated in the study by drawing their concept maps. Based on the information students provided, 58 students were females, most students were Caucasian (n=83), and most students were freshmen (n=94).

2.2 Concepts

A total of 112 concepts were designed for this study. We reviewed the concepts with the two instructors who taught the study skill course. The 112 concepts consist of seven categories including classroom learning (e.g., listening, reading, or discussion, total 41 concepts), action for study (e.g., self-explanation, annotations, or memorization, total 18 concepts), learning tools (e.g., notes, charts, or textbooks, total 22 concepts), internal trigger (e.g., inquiry, curiosity, or creativity, total 4 concepts), motivation (e.g., will, confidence, or inspire, total 12 concepts), school facilities (e.g., library, web, or writing center, total 7 concepts), or people (e.g., teacher, classmate, or parent, total 8 concepts).

2.3 Procedures

Two weeks after mid-term exam week, we visited each class and administered the concept maps to students. In each class, we provided a 10-minute orientation about concept maps and drew one map for students on a whiteboard as a demonstration. Students were asked to respond to the question “*how do you learn in a college class?*”. They drew their concept maps with pen and pencil since the class room was a regular class room that didn’t have computers for individual students.

3. CONCEPT MAP MINING

Through discussions with education researchers, we listed their interesting queries to the students’ concept maps. In this work, we focused on two problems: “Which concepts are frequently used in students’ concept maps?” and “Which sub concept structures are commonly observed in students’ concept maps?”. For answering the first question, we conducted frequent item set mining task [1] to the concept map data, and for the second question, we used sub-graph mining task [9].

3.1 Data preprocess

TID	Items
1	{Repetition, Listening, Attendance, Me, Confidence, Teacher}
2	{Prepare, Lecture, Me, Quiz, Teacher, Flash cards, Charts}
3	{Assignments, Study, Friend, Teacher, Notes, Activities}
4	{Quiz, Prepare, Lecture, Creativity, Me, Teacher, Time, Note}
...	...

(a) Transaction data



(b) Graph data

Figure 2: Input data formats for data mining

After collecting students’ hand-drawn concept maps, we digitalized them. Concept maps can be represented by graphs, consisting of nodes(or vertices), which represent concepts, and arcs(or edges), which represent relationships between the concepts. In the graphs of concept maps, vertices should have labels associated with them. Edges may have associated labels and directions represented by arrows. Vertices and edges may have their own weighted value to designate their significance.

Although a list of predefined concept names and relationship names were provided, students misspelled some names or gave wrong concept and relationship names different from the predefined names. We also noticed, that in several instances synonyms or plurals of the same word were used as labels, and that some students did not follow a standard in the labeling of nodes and edges or in the use of arrows to denote direction on the edges. Our digitalization process checked all inconsistent concept names and relationship names in the concept maps.

3.2 Frequent association concept mining

In order to find common concepts students have used for their concept maps, we applied a methodology known as association analysis to the concept data. Association analysis task in data mining is useful for discovering interesting relationships hidden in large data sets. The uncovered relationships are represented in the form of association rules or a sets of frequent items [17; 1]. For example, a frequent item set, {Lectures, Notes} suggests that a strong relationship exists between lecture and note in learning strategy. The frequency of the associated items is often measured with support. The *support* of an item-set x is defined as the fraction of all transactions that contain x , i.e., $s(x) = \frac{sc(x)}{N}$, where N is the total number of transactions, and $sc(x)$ is the *support count* of x , $sc(x) = |\{t_i | x \subseteq t_i, t_i \in T\}|$. If the support of item-set x is greater than a given support threshold, x is called a frequent item-set.

For the association analysis, data should be prepared with transaction data format. We transformed our digitalized concept map data to concept transaction data as shown in Figure 2 (a). Each row in this table corresponds to a transaction that contains a unique identifier labeled TID, and a set of concepts used by a student in drawing his/her concept map. Here, a relationship between two concepts is not included in the transaction. There are many algorithms for association analysis [1; 3; 17]. We used Apriori algorithm [1]

for our analysis. Four different minimum frequency thresholds 30%, 40%, 50% and 60% were used.

3.3 Frequent sub-concept map mining

The second analysis is performed in order to derive a set of common sub structures among the collection of concept graph data. We applied frequent sub-graph mining task [17; 6] to our concept map data. Each concept map can be represented as a graph data as shown in Figure 2 (a). A concept graph $G = (V, E)$ is composed of a concept vertex set V and a set of edges E connecting between pairs of vertices. A graph $G' = (V', E')$ is a sub-graph of another graph $G = (V, E)$ if its concept vertex set V' is a subset of V and its edge set E' is a subset of E . The frequency of a sub-graph is also measured by support. The support for a sub-graph g is defined as the fraction of all graphs that contain g as its sub-graph, i.e., $s(g) = \frac{sc(g)}{|GD|}$, where GD is a collection of graphs, and $sc(g)$ is the support count of g , i.e., $sc(g) = |\{G_i | g \subseteq G_i, G_i \in GD\}|$. Sub-graphs (sub-concept map structures) g such that $s(g) \geq minsup$ are frequent sub-graphs. There are several algorithms for frequent sub-graph mining such as FSG [9], gSpan [22] and SPIN [8]. We fed the concept graph data to the FSG algorithm [9]. Figure 2 (b) shows an example of input data format for the FSG algorithm. The required order for a valid graph data begins with ‘ t ’ followed by all vertexes in the graph and finally by all the edges. Three different frequency thresholds, 10%, 20% and 30% were used for our analysis.

4. RESULTS

107 concept maps among 111 maps were analyzed. Four concepts maps were deleted because the concepts were not recognizable or students did not follow the instructions. Given the 112 concepts, a total number of 110 concepts were used. The maximum number of concepts and lines a student used were 39 and 31 respectively in each concept map, and the average concepts and lines students used were 13 and 14 respectively.

Given 112 concepts, only 15 concepts: ‘teachers’, ‘me’, ‘notes’, ‘lectures’, ‘time’, ‘repetition’, ‘textbooks’, ‘listening’, ‘flashcard’, ‘parents’, ‘reading’, ‘annotation’, ‘study’, ‘tutor’ and ‘activity’ concepts are used by students with 30% frequency. Among association patterns having two concepts, {teachers, me}, {teachers, notes} and {me, notes} showed very high frequency of over 60%. Among patterns having three concepts, {teachers, me, time}, {teachers, lectures, repetition} and {teachers, textbooks, repetition} showed over 50% frequency. Two concept sets having four items, {teachers, lectures, repetition, time} and {teachers, textbooks, repetition, time} showed around 30% frequency.

In the sub-graph mining, the size of the patterns is measured by the number of edges. Table 1 shows sub-concept map structures with at least 10% frequency. When the threshold was set to 30%, three types of frequent sub-concept map patterns were found such as “me-listening” ($sc = 34$ out of 107), “teacher-lectures” ($sc = 44$), and “me-notes” ($sc = 49$). When the threshold comes to 20%, a total of 15 frequent sub-concept map structures were observed. Among them, 12 sub-graph structures were about ‘me’ strategies or actions, 2 sub-graphs were about ‘teacher’ related patterns, and 1 sub-graph was between me and teacher. Last, when the threshold was 10%, a total of 47 simple sub-graphs were

discovered where 36 sub-graphs were ‘me’ initiated concepts, 6 sub-graphs were ‘teacher’ related concepts, 5 sub-graphs explain between teacher and me, with one or more of the other elements.

5. DISCUSSION

In this study, it was found that most students learn through ‘me’ initiated behaviors (e.g., “me-listening” or “me-ask”) or using learning tools (e.g., “me-notes” or “me-textbooks”). Learning through active interaction with teachers or peers was not observed. This indicates that early level college students focus on individual learning rather than learning through interaction with others. It may also reflect lecture oriented college courses. However, readers should consider that too many concepts given to students may have resulted in difficulty identifying patterns between students and others.

From this initial research, we found both possibilities and challenges when using concept maps in this capacity in an educational context. First, when used with data mining techniques, concept maps can be useful to interpret large sets of concept maps. As can be seen in our data analysis,

Relevant concept	Frequency (Support count)	Frequent sub-concept map patterns
Me(Students)	49	Notes - Me
	34	Listening - Me
Teachers	44	Lectures - Teachers
Me(Students)	31	Teachers - Me
	30	Textbooks - Me
	29	Flashcards - Me
	29	Lectures - Me
	29	Reading - Me
	28	Study - Me
	27	Attendance - Me
	24	Annotation - Me
	21	Pay attention - Me
	22	Flashcard - Me - Notes
Teachers	22	Notes - Teachers
Etc.	21	Teacher - Lecture - Me
Me(Students)	16	Questions - Me
	16	Review - Me
	16	Discussions - Me
	15	Assignments - Me
	14	Study - Me
	14	Memorization - Me
	13	Classmates - Me
	12	Asking - Me
	12	Class - Me
	18	Lecture - Me - Notes
	16	Listening - Me - Reading
	15	Reading - Me - Notes
	15	Attendance - Me - Notes
	14	Notes - Me - Teacher
	14	Annotation - Me - Notes
	13	Study - Me - Notes
	12	Listening - Me - Notes
	11	Textbooks - Me - Flashcard
	11	Annotation - Me - Textbook
	11	Reading - Me - Teacher
	11	Lecture - Me - Textbooks
	11	Attendance - Me - Textbooks
Teachers	11	Listening - Me - Pay attention
	15	Discussion - Teacher
	14	Questions - Teacher
	13	Teach - Teachers
	12	Listening - Teacher
Etc.	18	Teacher - Notes - Me
	13	Lectures - Teacher - Me
	11	Teacher - Questions - Me
	12	Teacher - Lecture - Me - Note

Table 1: Frequent sub concept map patterns

when using different thresholds, we were able to find certain patterns of students' learning in a college classroom. Although most of the patterns were simple such as "me-listening" or "me-annotations", this does not mean the concept mapping was an ineffective method to capture sophisticated pictures of students' learning. The simple patterns can be attributable to the large list of 112 pre-designed concepts. Because students had too many choices, students' concept maps became very diverse. However, through this initial phase of study, we were able to find the most frequently referenced concepts for future study. With limiting the number of concepts, e.g., 30 concepts, we may be able to find more detailed pictures of college students' learning. In our future study, we will compare and contrast patterns of concept maps to students' self-report motivation or metacognition. For example, we can divide students into several groups based on their self-report questionnaires, and then compare how the patterns of concept maps are similar or different between groups. We are also planning to use students' final grades as a way to validate the patterns of learning. The study will be appealing to those who are interested in concept maps as an alternative tool for research as well as data mining in education.

6. REFERENCES

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