Quantitative Evaluation of Concept Maps: An Evidence-Based Approach

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ABSTRACT: Evidence-based approach in educational contexts advocates sustained interaction between practitioners and researchers. In this paper, we present a case of how a practitioner-researcher partnership can help in implementing a robust evaluation method from the analysis of evidence. In the present study, concept maps have been used as a tool for assessment of students' learning. Typically, teachers are required to evaluate concept maps manually. Efforts have been made to automatically evaluate concept maps which are still an active research area. We have come up with a semi-automatic evaluation of concept maps, using log data generated from a concept mapping tool. The log data contains various learner actions such as add/modify concepts and links. Manual evaluation is done on a subset of concept maps. We then apply learning analytic algorithms to the log data to generate a goodness model of the concept map. The generated model can be further used to evaluate the remaining concept maps. The model also shows that several learner actions, such as adding links and connections, seem to be predictors of good concept maps. We discuss how these predictors can serve as an evidence-based practice for teachers and students to incorporate these actions in their teaching and learning. In this paper, we discuss the research study and analysis method in the context of evidence-based practice.

Keywords: Evidence-Based Approach, Learning Analytics, Concept Map

1 INTRODUCTION

In the 21st century, teaching-learning continuum focuses on an evidence-based approach. Prerequisites of this approach are the alignment between curriculum, pedagogy and assessment (Luke, 1999). There has been growing emphasis on collection, analysis and interpretation of information about learners to inform teaching and learning. The process of evidence collection, analysis and interpretation must be an explicit and accountable one to achieve quality educational outcomes by students. The value of the evidence is in its understanding followed by applying appropriate strategies to improve student learning. Practitioners who effectively use assessment data have been pioneers in bringing change in the local classroom (Protheroe, 2001).

Hsieh & O'Neil (2002) reported that the concept map strategy is simple to use and effective on problem-solving along with meaningful learning. Besides these, it also affects learners' achievements and interests (Aghakhani, et al. 2015). Research studies show that the concept mapping can significantly improve learning when compared with lecturing. Concept maps have been widely used as a formative assessment and conceptual knowledge representation tool. In this study, we explored the application of evidence-based practice for evaluation of concept maps. A semi-automatic evaluation was performed in which sixty-three concept maps were manually categorised into three categories. The analysis of the log data was done using rules based and decision tree

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algorithms for further evaluation. The concept maps generated during the intervention were used as evidence of students' learning. The analysis of concept mapping steps served as evidence of productive and unproductive learner actions. We then mapped the steps performed during the evaluation to the LEAF framework (Ogata, et al. 2018).

2 BACKGROUND RESEARCH

2.1 Evidence-Based Practice

In a teaching-learning scenario, evidence includes teacher observations, tests, peer assessments and, formative and summative assessments. It can be used for assessment at different levels which include individuals, groups, courses etc. Learning performance of students can be improved by using evidence in the following ways (Bruniges, 2005; Kvernbekk, 2017):

- As a diagnostic method to improve teaching
- As a motivational method to focus on learners' strengths and weaknesses
- As a means of communication of learners' achievements or course effectiveness

2.2 Concept Map and Its Assessment

Novak & Cañas (2008) described concept maps as graphical tools used to represent and organise knowledge. It consists of concepts, connected by linking phrases. Two concepts connected by a linking phrase represent a unit of meaning (propositions).

Traditionally concept maps have been evaluated based on criteria or via a human-based rubric. The criteria map represents an expert's map which is then used to compare with the concept map of learners. It ensures control of quality and quantity of propositions. Based on the difference identified, instructors give appropriate feedback to the learners (Trumpower & Sarwar, 2010). Concept map assessment varies regarding the emphasis on its features. For some, the emphasis is more on hierarchy and cross-links while others focus on the number of concepts. Typically, they are evaluated manually, which is time-consuming and tiring. Active research has been done to address this issue, and many automatic assessment methods have been proposed based on a computerized assessment (Hirashima, et al. 2011; Pailai, et al. 2017). Most software provides functionalities of construction of concept maps along with automatic assessment. The automatic assessment compares the generated maps with the criteria map for effective assessment. Traditionally these automatic assessments have been criticized for no flexibility during assessment which can be implemented while doing the manual assessment. The computerized assessment requires the strict rules for calculating the concept map score. Attempts have been made to increase flexibility by including features like assessment using graph theory, synonym words etc. There hasn't been much emphasis on the application of learning analytics on concept map data. Wu et al. (2016) examined learners' behavioral patterns of a concept map tool in a collaborative concept map-based online discussion environment. The analysis aimed to understand how the collaborative concept map activity enhanced discussion and social knowledge construction. Wang et al. (2017) developed a concept mapping tool that offers navigational support in the form of hyperlinks, where nodes in the concept map are linked to segments of text. Concept map features (such as total nodes, total links, link/node ratio) and learner actions (such as total actions, navigation actions) were used to model

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the generative strategies of learners. However, their focus was not the assessment of the concept maps but to examine how the navigational support and visual aids in concept mapping support generative learning.

3 EVALUATION

3.1 Procedure and Instrument

In this paper, we report an evaluation study in which video lecture was used to teach two topics on Tree data structure and Linked list data structure in a computer science (CS) undergraduate course. After watching the first video on trees, participants draw the concept map on the same topic by using a concept mapping software known as CmapTools (Cañas et al., 2004). The same activity was repeated for the second topic which was on the linked list. We conducted the study with first-year engineering undergraduate CS students of introductory programming course. The research question for this study was "What are the significant predictors in determining the quality of the concept map?"

3.2 Data Analysis

Following steps were performed to analyze the concept map log generated during the study. The steps are data compiling, data pre-processing and applying the algorithm (Figure 1). These steps will be discussed in the subsequent sections.

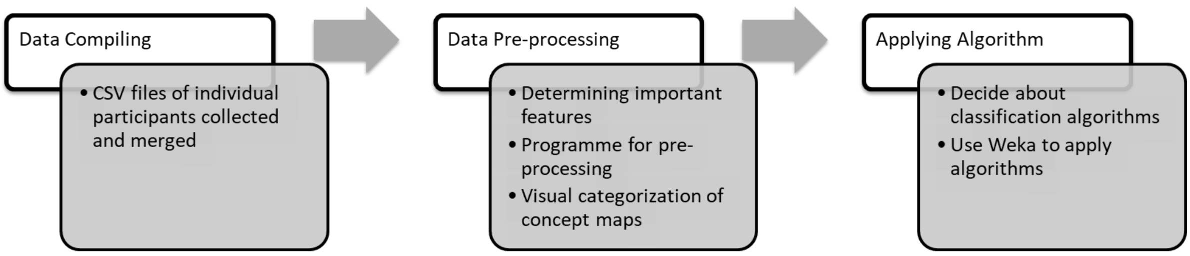

Figure 1: Data analysis process and corresponding steps

3.2.1 Data compiling

In total 63 concept maps were generated. Each of these maps had a raw file (*.cmap) and a CSV file. The CSV file included fields like DateTime [dow mon dd hh:mm:ss:mils zzz yyyy], user id, step number, event id, action type, entity type, entity id and entity description. An example of the values in for *<data, user id, step number, event_id, action_type, entity_type, entity_id, entity_desc>* is *<"Thu Oct 29 15:35:32:81 IST 201X", abc@gmail.com, 1, 1PKDX7MK4-1M6YRQK-159, Add, Concept, ge:1PKDX7MK5-1R553B4-15B, 'Linked list' x:43 y:40 w:44 h:26>*. In this step, all the CSV files were merged into a single file which was used for further analysis in the next step.

3.2.2 Data pre-processing

The following steps were performed in the data preprocessing phase.

- We combined action type and entity type to get concept mapping actions: *Add Concept, Add Connection, Add Linking Phrase, Delete Concept, Delete Connection, Delete Linking Phrase, Modify Text Concept, Modify Text Linking Phrase.*

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- Calculated frequency of each action (example: frequency of Add Concept)
- Calculated ratio of frequency and the total number of steps (example: [frequency of Add Concept)] / [total number of steps])
- Based on the previous step, we chose the following features and added the following columns in the CSV file: Add Concept, Add Connection, Add Linking Phrase, Delete Concept, Delete Connection, Delete Linking Phrase, Modify Text Concept, and Modify Text Linking Phrase
- We further added four more features
  - [Number of remaining concepts] / [Total number of concepts], where number of remaining concepts = [number_concepts_added] – [deleted]
  - [Number of remaining connections] / [Total number of connections], where number of remaining connections = [number_ connections_added] – [deleted]
  - [Number of remaining linking_phrases] / [Total number of linking_phrases], where number of remaining linking_phrases = [number_ linking_phrases _added] – [deleted]
  - Number_of_steps = Total number of steps
- Thirty-two concept maps were evaluated manually by three domain experts. Each concept maps were scored as good, average and bad (Figure 2, 3, 4). This scoring was based on the number of concepts, connections and linking phrases which represent the quality of the concept map. It was then added as the final column of the CSV file.

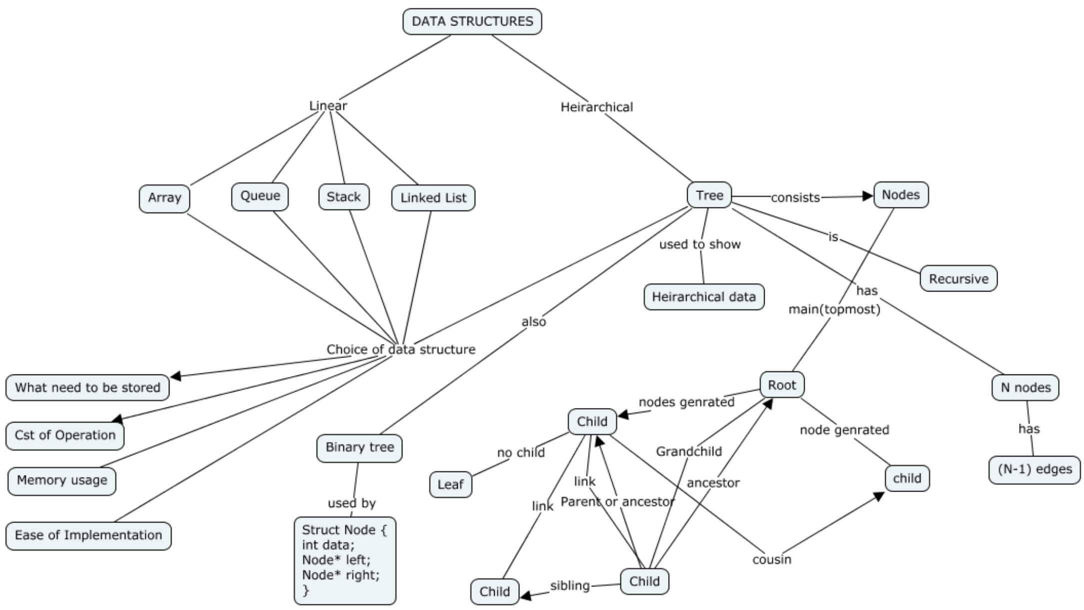

Figure 2: Representative of a good concept map

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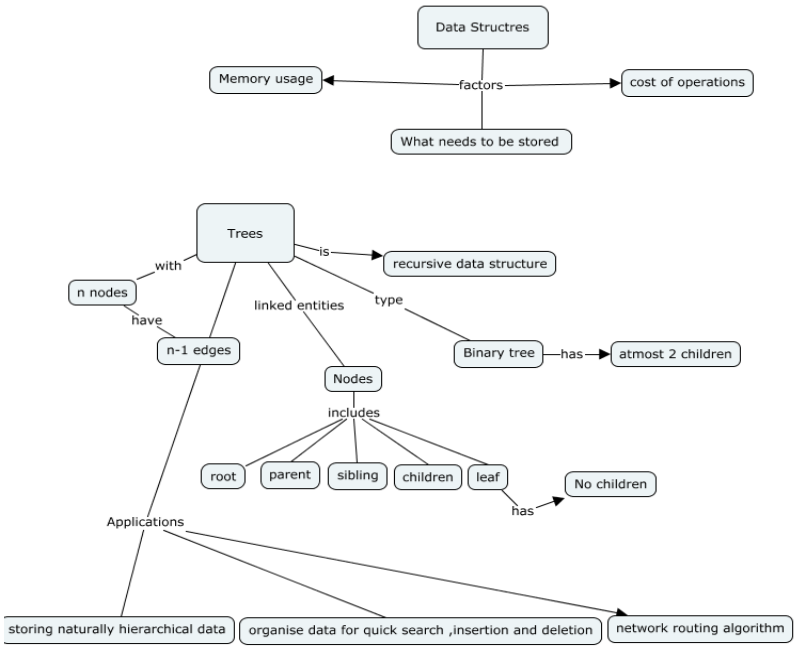

Figure 3: Representative of an average concept map

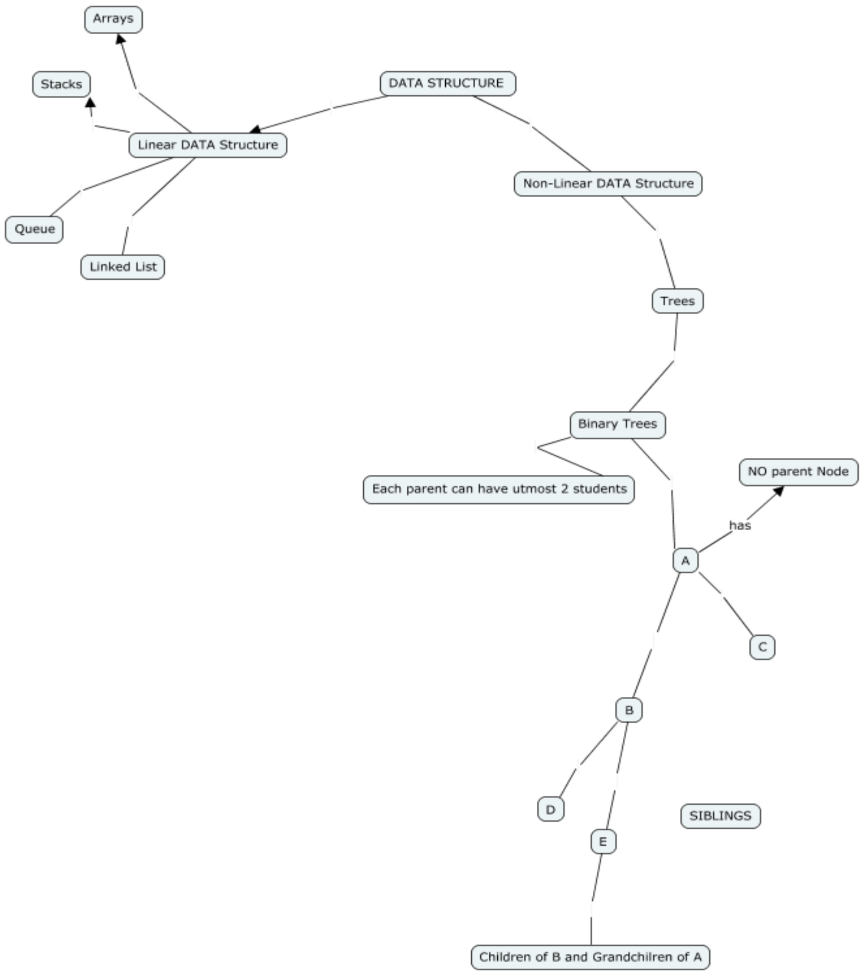

Figure 4: Representative of a bad concept map

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3.2.3 Data Analysis

We used Weka software (V3.6.13) for further analysis and applied various Decision Tree and Rule-Based Classifier algorithms.

3.3 Results

We used these algorithms for analysis of concept map for trees (T) and for linked list (L). Besides this we used two combinations of features:

- **Feature Set 1:** Containing 12 features - *Add Concept, Add Connection, Add Linking Phrase, Delete Concept, Delete Connection, Delete Linking Phrase, Modify Text Concept, Modify Text Linking Phrase, number_concepts_added_deleted, number_connections_added_deleted, number_linking_phrases_added_deleted, CMAP_quality,* and

- **Feature Set 2:** Containing 5 features - *number_concepts_added_deleted, number_connections_added_deleted, number_linking_phrases_added_deleted, CMAP_quality*, and *number_of_steps*

Since we have combined the concept maps T and L, we realised that the average number of steps in both T and L are different. Hence we cannot include the number of steps as a feature. We also included Add and Delete features along with the delete ratio features. In all the cases the cross-validation folds were kept 5. The results of our analysis are summarised in Table 1. For example, in the row, Analysis of concept map T by using 12 features through rule-based algorithms (JRIP) yielded an accuracy of 60.46% along with one rule.

Table 1: Summary of analysis results

Concept map	Feature Set	Algorithm	Type	Accuracy (%)	Result
T	1	Rule based	JRIP	60.46	1 rule
T	1	Rule based	PART	62.79	5 rules
L	1	Rule based	JRIP	-	0 rules
L	1	Rule based	PART	55	2 rules
T + L	2	Rule based	JRIP	68.25	2 rules
T + L	2	Rule based	PART	68.25	4 rules
T + L	2	Decision tree	J48	69.84	Size 9 Leaves 5
T + L	1	Decision tree	J48	69.3	Size 19 Leaves 10

Representative examples of rules and decision trees which emerged (Figure 5) are shown below.

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Example of rules:

- number_of_steps > 325 AND number_connections_added_deleted <= 0.638554: Average (4.0)
- number_of_steps <= 325 AND number_of_steps > 139: Average (32.0/9.0)
- number_of_steps <= 237: Bad (8.0/2.0)
- number_linking_phrases_added_deleted <= 0.44: Bad (15.0/1.0)

Example of a decision tree:

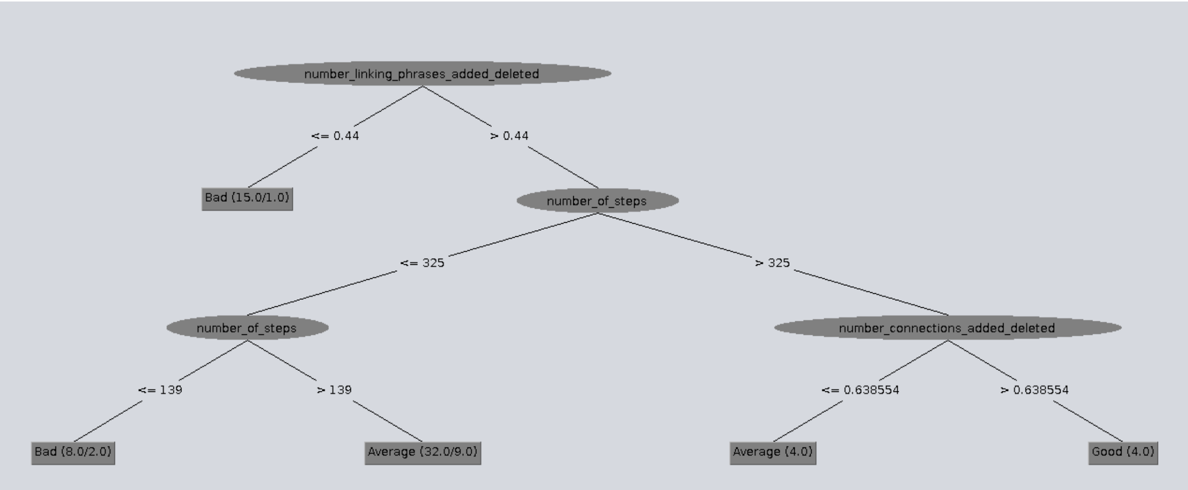

Figure 5: Decision tree generated after analysis of concept maps (T+L)

4 DISCUSSION AND CONCLUSION

We conducted this research with an aim to understand how the semi-automatic evaluation of concept maps and learner action logs can be analysed from the perspective of evidence-based practice. We implemented a study with participants who generated concept maps after experiencing video-based learning intervention. The analysis of concept map was done both manually and through the implementation of the classification algorithms. Two categories of classification algorithms used were - Decision Tree and Rule-Based Classifiers. Deletions of Linking Phrases seem to be a significant predictor of concept map quality. If the percentage of the ratio of linking phrases remaining to the ratio of total linking phrases is less than 44% (deletions were more than 56% of the total linking phrases), then the concept map was considered a bad concept map. Quality of the concept map also depends on the number of steps. Analysis showed that if the number of steps falls below a threshold (in this case 139), the concept map can be classified as a bad concept map. However, since the two concept maps on an average require different steps, we cannot generalize this to both the concept maps. Operations on Linking Phrases and Connections seem to be a significant predictor of concept map quality rather than addition/deletion of concepts.

The evidence-based practice advocates for the sustained interactions between the stakeholders. In a teaching-learning scenario, both the stakeholders - teachers and researchers should be brought together with an aim to improve the learning experience of the students. In the case discussed in this paper, practitioner interacted with researchers and informed them about their difficulties in manually evaluating concept maps. Researchers, thereafter applied learning analytics to create models of ‘good’, ‘average’ and ‘bad’ concept maps. These models helped in providing

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evidence about students' learning, as the practitioner used them to identify students who poorly performed in the concept map based assessment. More specific results from researchers' analysis, for example operations on Linking Phrases and Connections were significantly better predictor of concept map quality as compared to addition and deletion operations, can act as evidence that practitioner can use in making informed decisions when they observe their students struggling with concept map creation activities.

This case can be seen as an instance of the implementation of Learning Evidence Analytics Framework (LEAF) which is based on evidence-based practice (Figure 6). In this case, generation of the concept maps and their log data corresponds to the data plane. Learning analytics plane includes evaluation of concept maps by the use of algorithms. This plane also includes the emerged rules and decision trees which can be used to evaluate the remaining set of concept maps. Finally, the evidence analytics plane corresponds to the informed decisions which can be taken by the practitioners based on results of learning analytics plane.

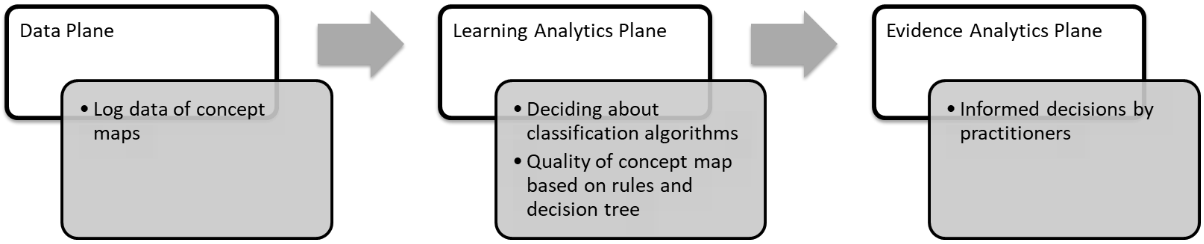

Figure 6: Alignment between LEAF framework and our steps

Our work has a few limitations. Actions for a 'good' concept map could not be analysed effectively. Most of the rules were for 'average' and 'bad' concept maps. This was due to the relatively smaller percentage of 'good' concept maps in the data set. Another limitation is that we applied this evaluation method only to two topics. As part of our future work, we would like to address these limitations along with the issue of the small sample size of participants and sustained interaction with practitioners.

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