Using Language Technologies to Diagnose Learner's Conceptual Development

Adriana J. Berlanga[1], Marco Kalz[1], Slavi Stoyanov[1], Peter van Rosmalen[1],
Alisdair Smithies[2], Isobel Braidman[2]
[1] *Centre for Learning Sciences and Technologies (CELSTEC), Open University the Netherlands*
adriana.berlanga@ou.nl; marco.kalz.ou.nl; slavi.stoyanov@ou.nl; peter.vanrosmalen@ou.nl
[2] *Medical School, University of Manchester, UK*
alisdair.smithies@manchester.ac.uk; isobel.braidman@manchester.ac.uk

Abstract

Formative feedback can provide information about how learners develop their competences in a knowledge domain. This information can determine learners' progress and is essential in suggesting remedial actions which overcome gaps in knowledge. Finding this information, however, is a time consuming task. This paper elaborates the theoretical background of conceptual development, and argues that it can be (semi-)automatically diagnosed using Language Technologies. It also presents, as future work, a description of a pilot that will be conducted to explore how existing tools that automatically generate concept maps, can be used to diagnose learner's conceptual development.

1. Introduction

During their studies, learners need formative feedback about their level of understanding of the domain of study. From the tutor's perspective, providing this feedback requires performing several tasks, for example considering the learner's position regarding the curriculum, assessing his/her level of understanding, identifying possible knowledge gaps, and suggesting remedial actions. In the context of lifelong learning, these are time consuming tasks, especially as learners may have different learning goals and backgrounds, and may follow different learning paths.

We believe that providing this feedback should be part of the next-generation support and advice services needed to enhance individual and collaborative building of competences and knowledge creation. Our aim is to offer services that support learners by providing formative feedback about their conceptual development, and suggest possible ways of filling knowledge gaps. The premise is that Language Technologies, particularly Latent Semantic Analysis [1], could be used for this. LSA creates a mathematical model in which both the domain knowledge and the knowledge of the learner can be projected thereby enabling the progress of the learner to be analysed.

The proposed analysis is based on the observation that learner's conceptual development is closely reflected in the textual utterances learners express as part of their evolving domain knowledge [2]. More precisely, the concepts used and their relations expressed by novices and experts change through time in a systematic, experience based fashion.

Diagnosing learner's conceptual development, therefore, can be performed by comparing the knowledge of a learner with the knowledge an expert-learner would have, or it is required to have, in a particular context. To perform such comparisons different methods and tools could be used as, for example, tools which create concept maps –e.g., [3] [4]–, semantic networks that represent knowledge and distinguish between levels of expertise –as described in [5, 6] –, or LSA technologies [7].

Based on this premise, we will determine whether, in certain learning scenarios, LSA performs equally well or sufficiently better in diagnosing and monitoring learner's conceptual development than other methods and tools. If the result of this comparison is negative, we will ascertain whether the solution might be a combination of LSA with existing methods and tools. Our purpose is to reduce the constraints imposed by existing methods and tools that aim at conceptual development (e.g., the expertise and time required to use them, pre and post-tasks required), and thereby extend the number of situations in which learners can obtain formative feedback regarding their conceptual development.

This paper describes work that has been carried out, from a theoretical and exploratory point of view, in order to investigate how conceptual development can be identified if Language Technologies will be used. The next section describes the theoretical background of conceptual development, which focuses on medical learners, as they will be our experimental target population. Concept maps will be discussed as they are one of the most common methods used to represent cognitive structures and are therefore valuable for diagnosing conceptual development. Existing tools for creating concept maps will then be compared. Finally, the last section describes the pilot scenario that will be conducted. Its main aim is exploring the current viability of the available tools to analyse a learner's conceptual development.

2. Theoretical background

In diagnosing conceptual development one has to cope with interrelated qualitative changes that occur and turn learning into a stage-like process, in which each stage is characterized by different learning processes and different effects on their knowledge structures. These differences are due to structural changes in the knowledge base development from novice to expert [2]. Therefore, diagnosing learner's conceptual development could be performed by comparing the knowledge of a learner with the knowledge an expert-learner would have, or it is required to have, in a particular context.

2.1 Learners as experts and novices

Aristotle said the expert "straightway" does 'the appropriate thing, at the appropriate time, in the appropriate way' [9]. An expert can be also defined as a top performer who excels in a particular field such as arts or athletes. In research on expertise, and particularly in the context of conceptual development, an expert is defined as a professional who achieves a certain level of success in his/her occupation [10].

According to Arts et al. [11], research on expertise, in areas such as Management and Medicine, has shown that experts and novice differ in their problem-solving skills, knowledge use, information processing, time required for diagnosing, and on the organization of their knowledge structures. Experts make more appropriate diagnoses than novices, provide more accurate problem solutions and use less theoretical knowledge during problem solving than novices. Furthermore, experts use less time to provide diagnosis and distinguish better between relevant and non-relevant information than students, who tend to reason on both relevant and irrelevant information [12].

In addition, experts have elaborated, well structured and organized mental frameworks that activate to interpret information and problems, and to create a suitable solution [2, 13]. In contrast, novices do not easily activate their mental frameworks which are, furthermore, less accurate, completed, organized and structured [14]. In fact, Nievelstein et al. [14] found that, in the private law domain, knowledge becomes structured more hierarchically with increasing expertise. Novices' knowledge appears to be highly fragmented and concepts loosely connected. These findings correspond to those of expertise research in other domains as Physics [15], Management [11], and Medicine [5].

Specifically in Medicine, the learning process has been split by Boshuizen and colleagues [2, 10] into three levels: knowledge accreditation, knowledge encapsulation and illness script formation. Each one of them corresponds to an expertise level: novice, intermediate and expert (see Table 1; for a detail description see [10]). Novices structure knowledge in networks, which represent small steps of reasoning with self-explanations. They rely only on knowledge networks which are less rich and less easily activated than illness scripts. They require more information and, as a result, semantic networks must be reasoned step-by-step. Their reasoning is less ordered, less goal-oriented, more time consuming and it is based on less plausible hypotheses resulting in less accurate diagnoses than those from experts. Intermediate students increase the step size by gathering together a multitude of detailed concepts 'encapsulated' under one higher order concept. Finally, experts use illness scripts to structure knowledge. When they deal with a case they activate ready-made illness scripts as a whole, which means no small steps between them are taken. This activation depends on information about conditions, fault, and consequences [12].

Table 1. Expertise level, knowledge structure, learning and reasoning process [10, 16]

Expertise Level	**Knowledge structure**	**Learning**	**Reasoning process**
Novice	Networks (incomplete, and loosely linked)	Knowledge accretion, integration and validation	Step by step process
Intermediate	Networks (tightly linked and integrated)	Encapsulation	Big steps (but still one at the time)
Expert	Illness scripts	Illness script for formation	Groups of steps activated as a whole
	Memory traces of previous cases	Instantiated scripts	

In this context the question is how medical students can be supported so they get formative feedback based on their current level of expertise in a particular context, i.e. the difference between their level and the level required in such a context (the "expert level"), an identification of their knowledge gaps, and recommendations of remedial actions. To this end, the first step is to measure the learner's conceptual development. The next section elaborates further on this topic.

2.2 Measuring conceptual development

In order to assess the individual's knowledge of a particular domain, Goldsmith et al.[8] propose a structural approach that consist of analyzing how she/he organizes the concepts of such a domain. This approach involves three steps: knowledge elicitation, knowledge representation, and evaluation of an individual's knowledge representation.

Knowledge elicitation

Knowledge elicitation is defined as the process of describing domain specific knowledge underlying human performance [17]. In short, knowledge elicitation techniques measure the learner's understanding of the relationships among a set of concepts [18]. Methods that support this activity include categorization (e.g., card sorting, word association), graphical reporting methods (e.g., concept maps, semantic networking) and verbal reporting methods (e.g., think aloud, essay questions).

Knowledge representation

The second step of the process is to define some representations of the elicited knowledge that reflect underlying organization of the data [8]. Advanced statistical methods (e.g., cluster analysis, tree constructions, dimensional representations, pathfinder nets) are used to identify the structural framework underlying the set of domain concepts.

In some cases, eliciting and representing knowledge are performed together. While in others, knowledge representation is achieved by pre-processing the elicitation knowledge, structuring and adding useful information, in such a way that it can be evaluated in the next step of the process.

Evaluation of the representation

The third step is to evaluate the individual's knowledge representation relative to some standard (e.g., expert's organisation of the concepts in the domain, reference model, etc.). Normally, researchers follow one of the three following approaches [8]: qualitative assessment of derived representations; quantifying the similarities between a student representation and a derived structure of the content of the domain; or comparing the cognitive structures of experts and novices. Interestingly, semantic networks have been used to represent knowledge and compare cognitive structures of experts and novices [5, 6].

3. Existing tools for automatic construction of concept maps

As discussed before, our aim is to offer services that support learners by providing formative feedback about their conceptual development, and suggest possible ways of filling knowledge gaps. The premise is that Language Technologies could be used for this.

For this purpose, language technology tools will be used to identify/approximate the conceptual development of learners. We will follow the three steps described earlier: knowledge elicitation, knowledge representation and evaluation of the individual's knowledge.

As a means of eliciting and representing a learner's knowledge, it has been decided to start with the exploration of the cognitive map method, which is one of the most common ways of representing cognitive structures. This decision was taken on the basis of the appropriateness of concept maps for representing the learners' representations of subject matter structure. Furthermore, research evidence demonstrates that concept maps are well suited for eliciting knowledge [19], and are better for evaluating learners of different ages than classical assessment methods such as tests and essays [20, 21]. The creation of concept maps, however, is a complex and time consuming task. It requires training and practice to understand how the relevant concepts should be identified and how to make relationships between them.

There are already a number of tools for the automatic construction and support of concept maps: Knowledge Network and Orientation (KNOT, PFNET) [3]; Surface, Matching and Deep Structure (SMD) [22]; Model Inspection Trace of Concepts and Relations (MITOCAR) [23]; Dynamic Evaluation of Enhanced Problem Solving (DEEP) [24]; jMap [25], Leximancer [26], and ProDaX [27]. Table 2 depicts these tools in terms of the data collection they require and the analysis and comparison they perform.

These tools have some common characteristics: (a) they can (semi-)automatically construct concept maps from a text; (b) they use a sort of distance matrices; (c) they propose a quantitative analysis of the maps; and (d) most of them are concerned with conceptual development of learners.

Amongst their differences, we have found that, even though, they all use some sort of Language Technology analysis, not all of them refer to it explicitly. The SMD and jMap can use as input not only text but also concept maps. These tools also differ on the scoring schemas they use to perform the quantitative analysis: DEEP uses the number of nodes and links; SMD uses propositions or the number of the links of the shortest path between the most distant nodes.

Table 2. Existing tools for construction of concept maps (adapted from [4])

	Data Collection	Analysis	Comparison
KNOT	Concept pairs/Propositions	Quantitative Analysis	Direct comparison of networks with some statistical results
SMD	Concept map or natural language	Quantitative analysis is calculated using tools	Unlimited comparison
MITOCAR	Natural language	Quantitative analysis included multiple calculations using tools	Paired comparisons for semantic and structural model distance measure
DEEP	Annotated causal maps	Quantitative/qualitative analysis is done mostly by hand	Unlimited comparisons, showing details relative to concepts
jMap	Concept maps, causal maps, or belief networks	Quantitative analysis (calculated using tools)	Superimposes maps of individual (n=1) and group of learners (n = 2+) over a specified target map
ProDax	Association Data, Cross-Tables, Two-Way Two-Mode Data, Coordinates	Non-Metric Multidimensional Scaling/Cluster-Analysis	Comparison of maps based on Procrustean Transformation
Leximancer	Concept maps	Content analysis and relational analysis (proximity, cognitive mapping)	Imposes tags in a single map over user-defined tags (names, concepts, files, etc.)

Most of the referred concept mapping tools provide opportunities to identify the conceptual gap between a learner's concept map and a criterion map (which is, in fact, an expert map), or to compare a learner's concept maps in different periods of time. However, only SMD, jMap and, in some extent DEEP, purposely provide a visualisation of this progression towards the criterion. Most of these mapping approaches construct and analyse individual maps. jMap visualises and assesses changes observed in either individual or collective maps. Nevertheless, jMap is the only tool restricted to produce a particular type of maps, namely causal maps.

KNOT, SMD, MITOCAR and Leximancer report on reliability and the correlation of validity criteria. Typically, they consist of the automatic scores generated by these tools, human concept mapping scores and human essay scores.

4. Future work

In this paper we have argued that Language Technologies can be used to measure conceptual development. As a first step, we aim at identify existing tools that can be used to this purpose. In this paper we present the theoretical background regarding conceptual development and an analysis of existing tools for construction of concept maps.

Currently, we concentrate on implementing a pilot scenario for medical learners. The objectives of the pilot are:

- To show if existing tools that generate concept maps can be used to monitor learner's conceptual development.
- To compare and set aside metrics derived from concept maps based tools with direct diagnosis of conceptual development of textual output.
- To evaluate what can already be used with the current stage of available tools and what should be developed.

Our approach is to use the tools that create concept maps based on an input text, which were described earlier, particularly Leximancer and KNOT. At the same time, INFOMAP/LSA [28] tools will be used to see the differences between both results. As input, "think aloud" protocols, converted into written text, will be used. The narrative of the pilot has been defined as:

1. Using as an elicitation method a think aloud protocol, medical students will be asked to describe their understanding of a topic of study, explaining the concepts related to the topic, and the relationships between the concepts. This input will be converted into written text (i.e., the learner's text).
2. A tutor will provide a set of typical case descriptions for the selected case, which represent the level of knowledge a learner should have at this stage (i.e., the expert level).
3. The learner's text and the expert text will be evaluated in two ways:
    a. (manually) converted to fit into an existing concept map tool and subsequently analysed with this tool.
    b. analysed and compared with the help of INFOMAP/LSA with an initial set of

indicators, e.g. co-occurrence of concepts, relations between them, missing concepts, etc.

4. The results of step 3.a and 3.b will be compared and a report for the tutor will be complied.
5. The tutor will give feedback on the usefulness and the quality of the report.

It is expected that this pilot will put forward a better understanding to what extent the existing tools for automatic construction of concept maps can be used to diagnose conceptual development, and/or if combining existing tools with Language Technologies is a better solution to enrich the formative feedback provided. It is also expected that the pilot will point out new pedagogical and technical areas to be explored further, while, at the same time, helping to define a set of requirements for developing a first version of a service for diagnosing conceptual development.

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