Towards Qualitative Insights for Visualizing Student Engagement in Web-based Learning Environments

Rubiela Carrillo
Université de Lyon, CNRS
Université Lyon 1, LIRIS, UMR5205, F-69622
Villeurbanne, France
rubiela.carrillo-rozo@liris.cnrs.fr

Élise Lavoué
Université de Lyon, CNRS
IAE Lyon, Université Lyon 3, LIRIS, UMR5205, F-69622
Lyon, France
elise.lavoue@liris.cnrs.fr

Yannick Prié
Université de Nantes
LINA - UMR6241 CNRS
Nantes, France
yannick.prie@univ-nantes.fr

ABSTRACT

Learning Sciences argue that student engagement is composed of behavioral, motivational and cognitive dimensions. Many proposals in Learning Analytics have provided teachers with quantitative indicators focusing only on students' behaviors, such as the number and the duration of their actions with the learning environment. In this paper, we propose visual representations of cognitive indicators to add explanatory elements to behavioral indicators. We describe our general architecture for collecting and aggregating data used to build the proposed visualizations. We illustrate the use of these indicators in various pedagogical scenarios oriented towards supporting teachers in students' actions and performances understanding.

Keywords

Web-based learning environment; learning analytics; student engagement; visual analytics; indicators; qualitative clues

1. INTRODUCTION

1.1 Context: The MétaÉducation Project

Our research take place within the MétaÉducation Project that brings together three companies and two research entities: ITOP[1] Education, a publisher of educational software, Erdenet[2], a publisher of interactive learning path applications, Vodkaster[3], a social network of films and TV Shows, the Institut de Recherche et d'Innovation of Centre Pompidou (IRI[4]) aimed at studying the use of new technologies, and our research unit in Computer Sciences and Information Technologies (LIRIS[5]).

The aim of this project is to develop a Web-based environment where students and teachers can access, create, and gather educational contents. They also can use social services like resource annotation and sharing with peers.

The MétaÉducation environment integrates four software components:

1. An application for linking heterogeneous Web resources to create learning paths;
2. An application for creating mind maps from heterogeneous Web documents;
3. An application for video annotation;
4. A virtual learning environment that centralizes the access to MétaÉducation resources and Web applications.

All these components share a common database of resources created by publishers or teachers working on MétaÉducation software applications. That is why different types of resources can be stored in the database: images, videos, parts of annotated videos, mind maps, or learning paths.

1.2 Research Questions

We are interested in studying student engagement in various pedagogical scenarios to propose visual representations of engagement indicators so as to support teachers' comprehension of students' actions. We focus our research on two Web applications that allow learners to construct rich learning documents, that can be modelled with a rather similar structure composed of elements and links.

The mindmapping tool called "Renkan"[6] associates heterogeneous resources to *nodes* and allows to *link* them spatially. A node can be associated to a resource or only represent a concept. A link can refer to a resource and/or describe a relation type between two nodes.

The Learning Path tool called "BeLearner"[7] associates pedagogical elements such as interactive units and resources. An *interactive unit* represents a communication means between teachers and students, and takes the form of questions or video annotations. *Resources* are related to interactive units in the sequential structure of a learning path. Interactive

[1]http://www.itopeducation.fr
[2]http://erdenet.fr/site/
[3]http://www.vodkaster.com/
[4]http://www.iri.centrepompidou.fr/

[5]http://liris.cnrs.fr/
[6]http://renkan.iri-research.org/renkan/
[7]http://www.belearner.com/

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units can also be inserted into resources (e.g. questions or annotations can be inserted into video resources).The learning path structure can be linear, hierarchical or even take a closed form.

Both "Renkan" and "BeLearner" support knowledge construction and learning. Students' actions on these tools can be collected, analyzed and visualized to facilitate the understanding of student engagement. To this end, we aim to answer this general research question:*How can we identify students' engagement from their interaction traces with such knowledge construction tools?*

The following questions have to be addressed in order to answer our general question:

1. Which indicators can represent student engagement?
2. What data should be collected from students' interactions to produce these engagement indicators?
3. How to visually represent these engagement indicators to support teacher comprehension?

2. RELATED WORKS

2.1 The Dimensions of Student Engagement

Concepts such as motivation, persistence, learning strategies, and efficacy are related to engagement. However, these concepts are not clearly delimited and their definitions overlap [3]. For example, engagement can be considered as a motivational component [8], or as the result of a convenient motivational arrangement [10]. We rely on the works of Pintrich [12] and Fredricks [5] to consider engagement as a meta-construct with three dynamically linked dimensions: behavioral, motivational, and cognitive. We review their works to define a theoretical framework for our approach.

Behavioral engagement refers to observable behaviors. A teacher observing the following three students' behaviors could think they are engaged: positive conduct, such as following the rules and adhering to classroom norms; involvement in learning and academic tasks, including effort, persistence, attention, and contribution to the class; and participation in school related activities [5]. Social aspects like the participation in collective academic or extra-school (e.g.recreational) activities are also included in this dimension.

Motivational engagement covers interest, affect, and value perceived by students when carrying out learning tasks. Positive emotions during learning tasks benefit the learning process, while negative emotional reactions like anxiety reduces the cognitive performance and causes psychological distress [16]. Pintrich and Schunk [13] argue that there are three perspectives of learners' interest: personal, contextual, and psychological. Personal interest is a relatively stable and enduring disposition, and is usually directed towards some specific activity or topic. Contextual interest refers to those contextual features that make some task or activity interesting. Psychological interest represents a psychological state of interest resulting from personal and contextual interests.

Cognitive engagement refers to learning strategies. There are three types of learning strategies: cognitive, self-regulatory, and resource management [12]. Elaboration and organizational learning strategies are cognitive strategies that stimulate content comprehension and deep treatment of learning material. These strategies include actions related to the manipulation of the content structure like synthesizing, arranging notes, organizing or structuring content trough mind maps, and selecting principal ideas from a text [10].

Motivationally and cognitively engaged students are likely to be behaviorally engaged. However, behaviorally engaged students are not always cognitively engaged [10]. A classical example from Linnenbrink and Pintrich is when students pay attention to the teacher (keeping eye on her/him), but think about something else. Therefore, behavioral engagement indicators are not enough to monitor and assess student engagement.

2.2 Engagement in Learning Analytics

Several approaches from Learning Analytics provide visualizations of the behavioral engagement dimension of students through indicators. LMS (Learning Management Systems) such as Moodle, Blackboard or Canvas track student actions and propose dashboards that represent their participation in courses with indicators such as the number of logins, post or visits per day, or assignment states by color codes in statistical graphics (e.g. timelines, barcharts and tables). These visualizations support teachers in monitoring students' activities by providing information about what they have done or not. But they do not provide explanations on the observed students' behaviors, for instance why some students have a low or a high level of participation (e.g. why a student did not visit frequently a learning resource?).

Course Signals in the Purdue dashboard [2] provides other examples of visualizations to support teachers in their monitoring of students' activities. An overview of students' participation actions is available with stoplight colored symbols to identify students at risk. Students' actions on the learning environment and academic results are used to compute these risk indicators. Teachers can neither understand why students performed the learning actions on the platform nor how they obtained their results.

The dashboard proposed by Santos et al. [14] presents richer indicators such as the student time per day spent by activity, the global time spent per activity compared with the average time, the time spent per application, and the time per application compared with the time of other members of the group per day. All these indicators describe student behavior using participation indicators, but do not to explain it. Similar lack of explanations on students' actions can be retrieved in the majority of Web-based learning dashboards in the literature. For instance, GLASS [9] displays the frequency of student actions (i.e. events) and work team, and the frequency of student actions and work team per activity type (i.e. compile, visit an URL, star text edit). ViSEN [15] represents the student completion rates for several learning tasks from course interactions (i.e. page clicks), study time, submissions and questionnaire scores.

Other proposals like SAM (Student Activity Meter) [7] and Mastery Grids [11] provide interactive dashboards for the exploration of students' indicators with different levels of visualization. SAM uses various visualization techniques and allows to dive into details from a line plot graphic. However, these visualizations only offer statistical results that are too limited to explain how or why students performed their actions. Mastery Grids represents students' actions indicators using levels of learning contents (i.e. the topics of a course and the associated resources), but their representations lack links between student actions and the moment in time when

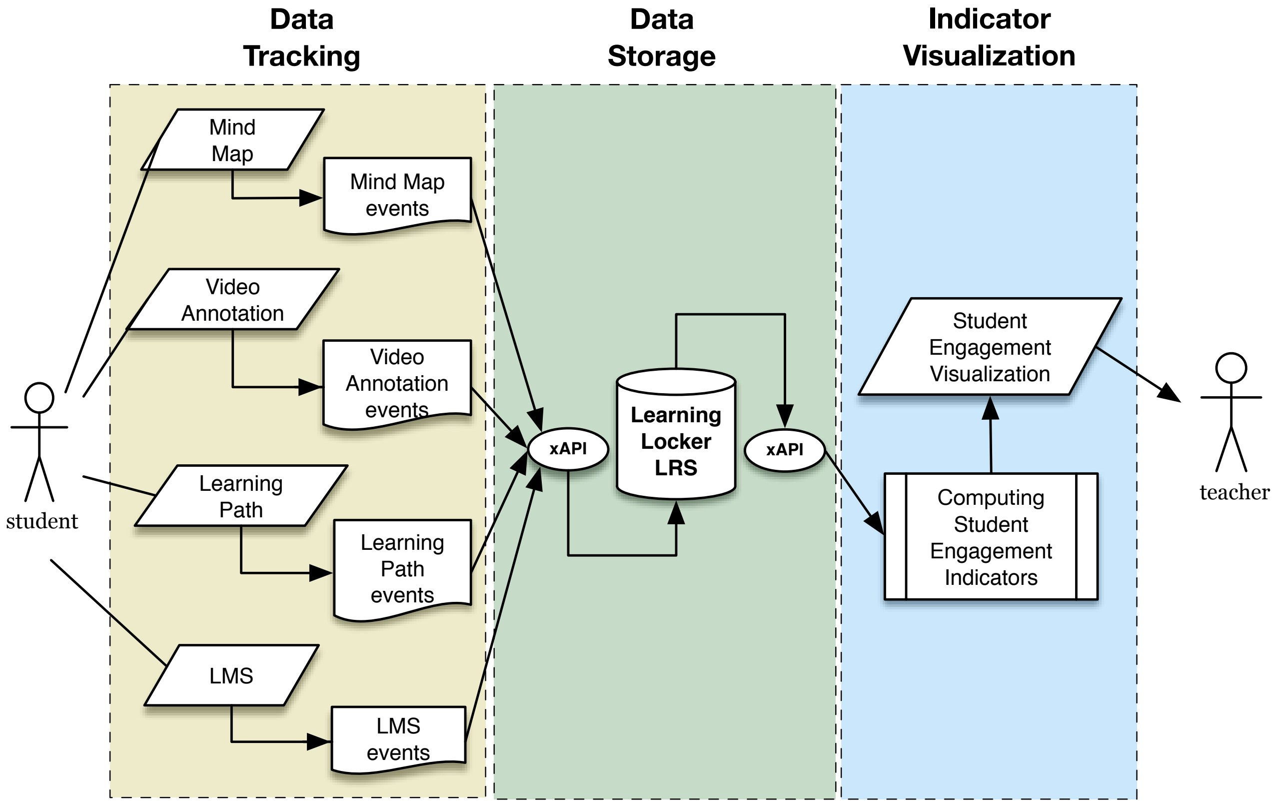

Figure 1: Data Flow Architecture for the MétaÉducation environment

the occur. A simplified timeline shows the current week in the course but not the time point when a student action was performed.

Anderson et al. [1] and Coffrin et al. [4] present two approaches which go beyond computing numbers of actions or durations. They use statistical analysis to process students' actions in MOOCs and visualize students' behavior patterns. Nonetheless, users must be skilled in data processing to obtain visualizations because these are not generated automatically.

The approaches we presented provide indicators that represent students' behaviors. Engagement is often represented by statistical summaries of student participation that hardly describe mental investment or cognitive learning strategies. Cognitive indicators are on the contrary frequently computed from self-reported instruments like surveys [6], and rarely related to behavioral indicators in visualizations to explain student actions and results.

3. OVERVIEW OF OUR APPROACH

We want to identify students' engagement from their actions when they are constructing learning resources. We raised in 1.2 several questions related to: engagement indicators; collected data; and indicator visualizations. In this section we present our data flow architecture and propose some visualizations of cognitive and behavioral engagements. We illustrate our proposal with examples from mindmapping document construction. We assume that this approach can be applied for learning path construction, as both types of documents are basically composed of elements and links.

3.1 Data Flow Architecture

Web Technologies combined with Learning Analytics methods use automatic tracking of user data. However, frequent questions are often raised about what should be tracked to obtain useful information and avoid noisy data, and how to integrate student data from heterogeneous learning contexts with different software components. Obtaining engagement indicators means identifying adequate student actions from all the possible interactions with the resources on the learning applications.Selected students' actions alone are usually not sufficient for computing interesting indicators, that is why contextual information is often associated to events.

Figure 1 illustrates our simplified data flow architecture from student data tracking to visualization. We use TinCan API[8] (also called xAPI) which provides a common framework for collecting and exchanging users' actions as events. According to TinCan API, events must have three mandatory properties: actor, verb, and object. We added the "timestamp" property to ensure that all collected data are linked to student actions timecodes. We also defined contextual properties for events from selected student actions on the Mind Map and Learning Path applications. Collected data is stored in the Learning Record Store (LRS) Learning Locker[9].

[8]http://tincanapi.com/
[9]http://learninglocker.net/

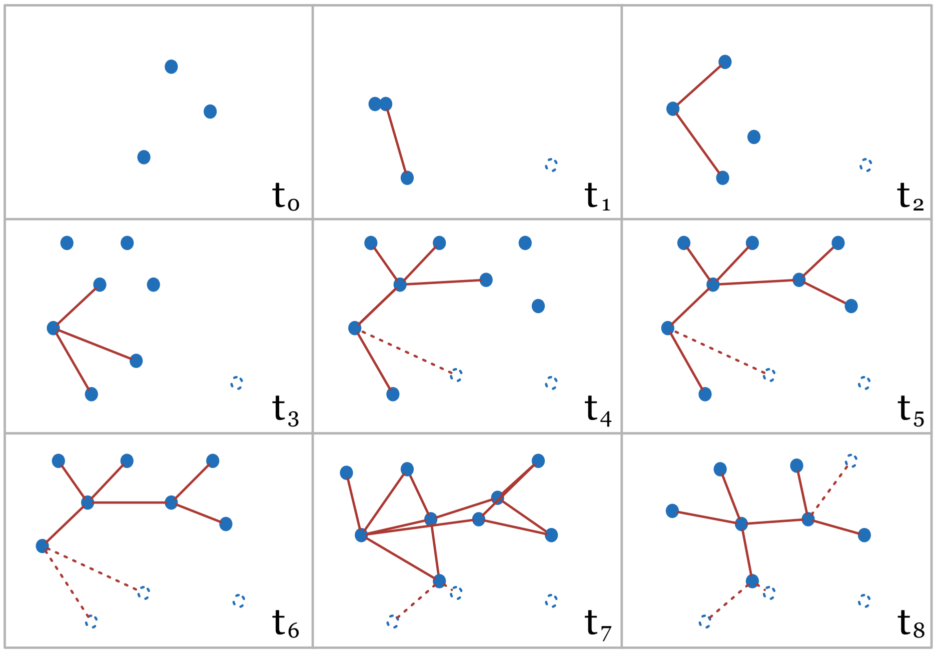

Figure 2: Simplified representation of a mind map document during its construction. The Mind Map structure changes with modification actions on their elements (i.e nodes and links).

3.2 Engagement Indicators

Teachers should be provided with indicators that reveal clues related to all dimensions of student engagement. As detailed in 2.1, student engagement theories define engagement by three dimensions: behavioral; motivational; and cognitive. We have seen that in order to better support understanding of student engagement and academic results, behavioral indicators should be enriched with cognitive and motivational indicators. Hence, we propose to build *behavioral indicators from student participation actions*, and *cognitive indicators from their modification actions on the learning documents structures*. These behavioral and cognitive indicators will be computed from students' interaction traces.

Student participation indicators are defined by the *number of actions* and their *duration* on a time period, namely a session of the learning task. The number of logins on a learning application by time period, the number of times a learning resource was accessed, and the time spent on a learning document are examples of student participation indicators. Statistical methods are used to build them. The following actions are related to learning documents structural modifications (occurring on elements and/or links) that can help define cognitive engagement indicators: "*create*", "*add*", "*update*", "*delete*", "*move*", and "*insert*". For example, a student may delete node or link elements from a mind map document in a learning session. Here, our interest is not in the number of nodes or links deleted but in the "action of deletion" in itself: Which node(s) or link(s) did s/he delete? When did s/he do it? How did s/he modify the structure of the mind map document? The behavioral indicators we can build from such action events and the associated contextual information can give meaning to mere students' actions, and describe with more details the engagement process.

3.3 Indicator Visualizations

We argued in the preceding section that cognitive engagement indicators may add explanatory elements to behavioral indicators to understand students' actions and performances. Here we propose two visualizations of these indicators computed from students' interaction with learning resources. We go on illustrating our approach with the construction of a mind map document as a general learning resource composed of elements and links. Our purpose is to visualize cognitive (Figure 2) and behavioral (Figure 3) engagement information so that they complement each other. The passage from one visualization to another one is possible through interaction.

The first visualization (Figure 2) shows one student actions during a learning session (e.g. from t_0 to t_8), using a Small Multiple visualization technique. Each frame is a simplified representation of one mind map nodes and links at instant t_i. The aggregation of frames offers an overview of the mind map construction process. Nodes and links in a particular frame can be compared to those in other frames to identify structural changes during mind map construction process. Deleted nodes and links are drawn by dotted edges. Visualizing deleted elements may help to realize changes in document structure size and complexity, as well as highlight possible organizational and elaboration strategies with learning contents.

The second visualization (Figure 3) is displayed by clicking on any node from the first visualization. It allows going deeper in understanding the actions that have been performed on the selected node during the whole learning session. Actions are represented using Event Viewer visualization technique. In our example, "move" actions on the selected node can be revealed by changes of its spatial position from one frame to another. Hence, frames between t_3 and t_4, and t_6 and t_7 provide evidence that the selected

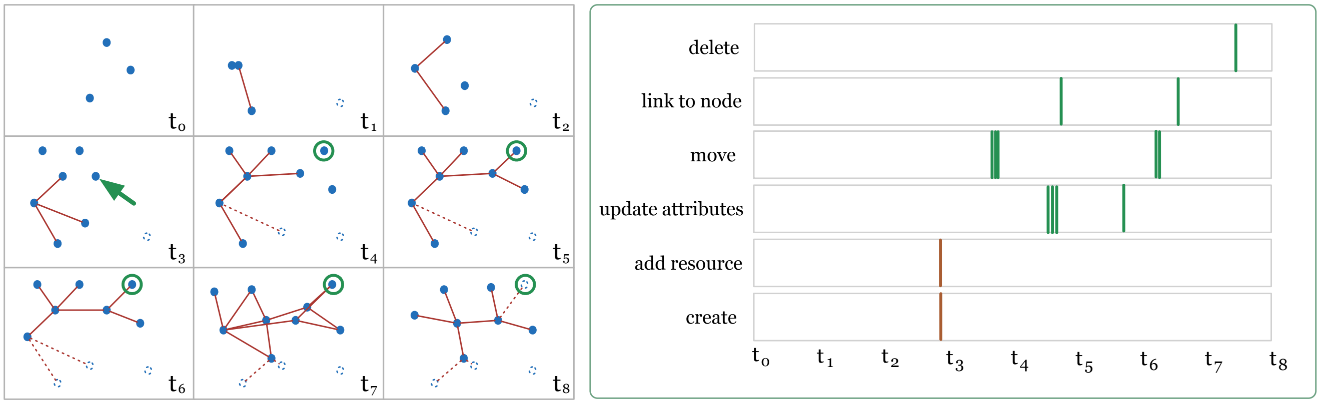

Figure 3: The actions that have been performed on a node element from a mind map document during its construction. The selected node is shown with a green arrow for the frame it was selected on, and with a green circle on each frame it appears.

node has been "moved". Student actions are represented by vertical lines. Orange vertical lines represent events corresponding to the frame containing the selected node. Here, a node was selected when the teacher clicked on one node in frame t_3.

The representation of the students' actions are coherent in the two visualizations. For instance, the teacher can see that the "move" action has been performed several times: between t_3 and t_4, and t_6 and t_7 in the Figure 3, and that confirms the information on the "move" actions from the small multiple visualization.

The visualization proposed in Figure 3 may help the teacher get information on when a particular action has been carried on a specific element (e.g. addition of a resource, creation of a link to another element, deletion). The teacher can also see if an action was repeated, the most frequent actions, the order of the actions on the selected node for the time period, and if there are patterns of actions following each others.

4. CONCLUSION AND FUTURE WORKS

In this paper, we proposed two visualizations of learners' cognitive and behavioral engagement. These indicators are based on students' actions as individuals. A higher level visualization could present actions of all students in a class, to give an overview of their engagement. Teachers could so identify students with extreme values of actions number and duration, and go to details to understand them. The visualizations presented in Figures 2 and 3 could provide details for identified students by providing visual representation of cognitive and behavioral indicators for a time period of the learning session.

We are currently setting up data collection in ecological conditions, with real learners. The proposed visualizations will also be applied to the learning paths construction tool. We aim to develop these visualizations using an iterative and participatory approach. For this, we work closely with teachers who can make remarks and express their needs for the monitoring of learners' engagement on knowledge construction web applications.

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