Exploring Inquiry-Based Learning Analytics through Interactive Surfaces

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ABSTRACT
Learning Analytics is about collecting traces that learners leave behind and using those traces to improve learning. Dashboard applications can visualize these traces to present learners and teachers with useful information. The work in this paper is based on traces from an inquiry-based learning (IBL) environment, where learners create hypotheses, discuss findings and collect data in the field using mobile devices. We present a work-in-progress that enables teachers and learners to gather around an interactive tabletop to explore the abundance of learning traces an IBL environment generates, and help collaboratively make sense of them, so as to facilitate insights.

Categories and Subject Descriptors
H.5.2 [**Information interfaces and presentation**]: User Interfaces; H.5.n [**Information interfaces and presentation**]: Miscellaneous

General Terms
Design, Human Factors, Experimentation

Keywords
interactive surfaces, learning analytics, learning dashboards, collaboration, reflection, awareness, information visualization, sense-making, inquiry-based learning

1. INTRODUCTION
Similar to the Quantified Self [1] movement, which focuses on collecting user traces and using the data for self-improvement, Learning Analytics can help to understand and optimize (human) learning and the environments in which it occurs [12]. However, capturing learner traces can generate an abundance of data, especially in the context of Massive Open Online Courses (MOOCs) that involve tens to thousands of learners whose activities can be tracked in detail. Reflecting on those traces can help learners to understand what is the optimal setting and context in which they learn best. Teachers can, among other things, use the same traces to find out where learners struggle with what content or activity. Dashboards help present this abundance of data in a way that supports both teachers and learners [14].

[1] `http://quantifiedself.com`

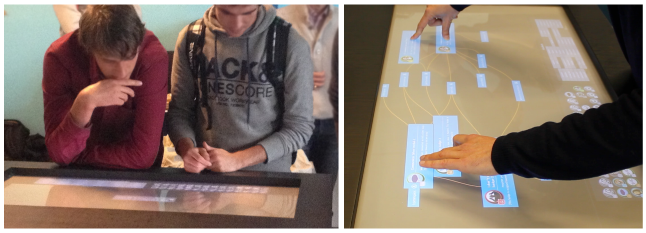

Figure 1: Students gathering around an interactive tabletop, exploring learner traces of a Human-Computer Interaction course.

Teachers show interest in using dashboards collaboratively with learners to discuss their activities, progress and results [3]. Interactive tabletops can facilitate and capture collaboration activities in the classroom [8]. In previous work [2] we explored this platform to visualize learning analytics data (see Figure 1), using the affordances (e.g. large display size, multi-user interaction) of interactive tabletops to create a collaborative sense-making environment [6].

This paper describes our work-in-progress on an interactive tabletop visualization for learner traces that are generated by students in an inquiry-based learning (IBL) environment. Section 2 briefly present the learning environment and the data it generates. Section 3 discusses development details, section 4 explains the design of the tabletop visualization. We discuss our findings and future work in section 5

2. IBL LEARNING TRACES
Contrary to a traditional passive role in a classroom, in Inquiry-Based Learning (IBL), learners assume an active role as explorer and scientist with a focus on learning "how to learn". Teachers try to stimulate learners to pose questions and create hypotheses regarding a specific topic, perform independent investigations, gather data to confirm and

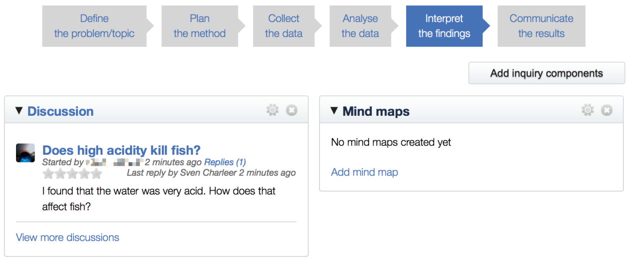

Figure 2: weSPOT Inquiry Environment, presenting 6 phases and 2 active widgets in phase 5 (Interpretation).

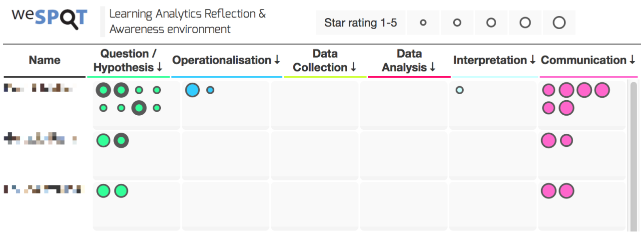

Figure 3: A web-based dashboard for teachers and students providing access to learning analytics data per inquiry.

discuss their findings and generate conclusions. 6 phases of learning activities are often discerned in an IBL process model: problem identification, operationalization, data collection, data analysis, interpretation and communication [9]. As each learner can follow his own route through the IBL process, it is obvious that the sequence and length of these phases differ among students. Individual and collaborative reflection is furthermore vital in every phase. Indeed,*"even at the very beginning when students need to develop a question or a hypothesis, they need to reflect upon the question, and evaluate it before they decide to proceed. They also need to reflect while deciding what kind of data they need to collect, how to proceed to data analysis, and how to communicate their results"* [10].

In the weSPOT Inquiry Environment [2], a teacher can set up an inquiry regarding a specific research topic. For each phase, learners can use a set of widgets (see Figure 2) to e.g. create hypotheses, ask questions, rate and comment on activities, generate mind-maps, etc. By taking pictures, recording videos, entering text and data from measurements through a mobile application, students collect data in the field to support their hypotheses. All activities in the learning environment are logged and stored in a data store and exposed as learning traces through REST services. Teachers and students can access the learning analytics data of a specific inquiry through a web-based dashboard integrated in weSPOT Inquiry Environment 4, and the tabletop application.

3. ITERATIVE DEVELOPMENT

[2]http://inquiry.wespot.net/

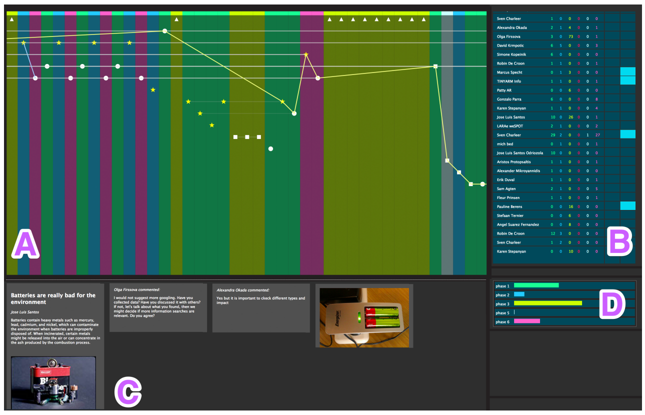

Figure 4: A. The overview of all activities. B. The list of students participating in the inquiry (with student filter options). C. The content behind selected activities. D. Phase filter options.

Following a user-centered rapid prototyping approach, we started from paper prototypes to gather initial feedback on early ideas, gradually developed more functional digital prototypes which have been deployed and evaluated with learners regarding usability.

Web technologies (HTML, CSS3 and JavaScript) facilitate development of quick prototypes and allows us to deploy on most school infrastructures. Interaction is supported through both native browser mouse/touch events and the npTUIClient plug-in [3], allowing the application to run on interactive tabletops, interactive white-boards, tablets, phones and desktop computers. Our interactive tabletop setup currently facilitates up to 5 users.

A centralized filter system using Crossfilter [4] and a modular and event-based architecture facilitates easy creation of new widgets. D3.js [5] and Processing.js [6] help visualize the data. A Node.js [7] back-end generates the web pages while fetching the learning traces from the weSPOT environment.

4. DESIGN

Flexible visual analysis tools must provide appropriate controls for specifying the data and views of interest [5]. Filtering out unrelated information to focus on relevant items is the key control in our learning dashboards due to the abundance of traces learners leave behind. Previous work [3] has shown that there is also a need for context and content to complement the visualized data. We therefore follow the visual information-seeking mantra of "Overview first, zoom and filter, then details-on-demand" [11]: our tabletop visualization presents users with a coordinated set of widgets which contain: (i) a complete overview of all activities (Figure 4.A), (ii) data filters (Figure 4.B/D) and (iii) the content view (Figure 4.C).

[3]https://github.com/fajran/npTuioClient
[4]http://square.github.io/crossfilter/
[5]http://d3js.org
[6]http://processingjs.org
[7]http://nodejs.org

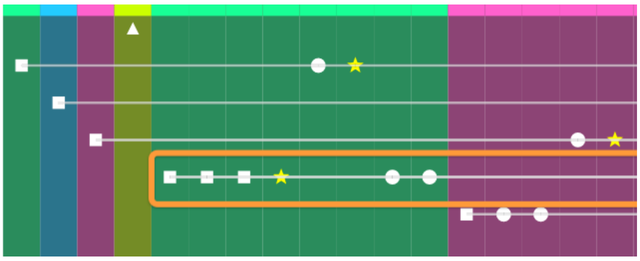

Figure 5: Time-lines per activity thread. The highlighted thread consist of a hypothesis creation followed by 2 edits, a user rating and 2 comments.

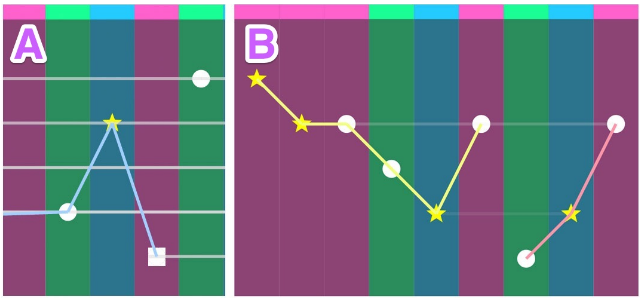

Figure 6: A. The blue path indicates the steps taken by a student. In this case, the student learned something which he then rated. This then lead to the creation of a new hypothesis. B. Visualization limited to a group of 2 students. Individual paths are highlighted. The student indicated by the yellow line has been more active with both commenting and rating activities. The student has also been more active in phase 6 (purple).

4.1 Visualizing IBL Traces

The visualization displays a time-line per *activity thread* (see Figure 5). For instance, the creation of a hypothesis by a learner is followed by every comment on, rating on, and edit of the hypothesis. Squares represent *create* and *edit* events, while circles represent *comment* events. Stars represent a *rating* activity, triangles are *data collection* events. Activities within a single thread are connected by a horizontal line. This enables teachers and learners to see the evolution of an *activity thread*, the comments that may have impacted edits of e.g. the original hypothesis, and the rating trend.

Activities in other *activity threads* can enrich the context of a specific thread. A discussion in one thread might influence the creation of a new hypothesis, or an edit of an existing one. Therefore, every activity is positioned relative in time to all other activities displayed, allowing the users to backtrack through time across multiple threads at once (see Figure 6.A).

IBL phases (see Section 2) in which an activity occurs are indicated by different background colors, matching the colors used of the web dashboard (see Figure 4). The visualization can be panned and zoomed using standard multi-touch interactions.

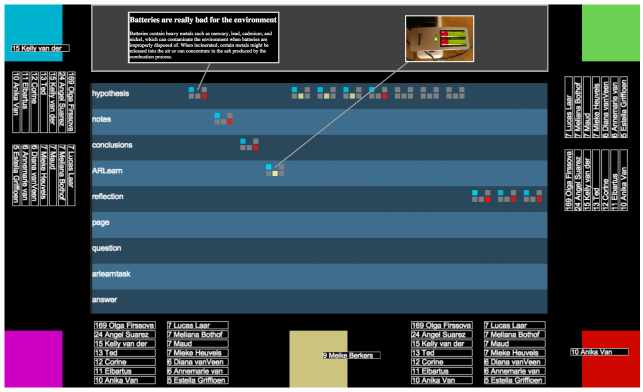

Figure 7: A prototype with 5 filter "drop zones". Dropping a filter value into the blue (top-left) drop zone highlights data points matching the filter result by coloring the top-left part of the glyph.

4.2 Filtering the Data

Using the filter widgets, users can focus on activities by drilling down on one or more phases (see Figure 4.D), or one or more learners (see Figure 4.B). When multiple learners are selected (e.g. a group that works together), the path of each learner can be individually highlighted (see Figure 6.B), in order to provide an overview of work distribution. This can help teachers to find struggling learners in a group. It can also help learners to become aware of uneven work distribution and help to redivide the work. The path can also shed light on the methodology a learner uses to reach a certain result (e.g. Figure 4.A).

The interface of Figure 4 is limited to one person driving the navigation and only supports global filters. To fully use the affordances of the tabletop and create a collaborative sense-making environment, the application must support both individual as well as group work [4]. Figure 7 shows an early prototype that presents 5 participants with individual filtering tools. Global filters result in more tightly coupled collaboration [13], but can disturb individual work. One participant's filter activity could remove data from the visualization another participant is working with. To allow participants to simultaneously filter the data presented on the tabletop, we use the multivariate attributes of a glyph-based visualization [1]. The filter result of each participant is highlighted in the color corresponding to the user interface.

5. CONCLUSION AND FUTURE WORK

Our interactive visualization will be deployed in multiple secondary school pilots [8] across Europe, both on interactive tabletop devices and interactive white-boards. Questionnaires regarding usefulness for both teachers and students will help evaluate our design choices, while interaction logging and video recordings of collaboration sessions can provide insights in whether the application is useful as a sense-making environment.

Our application lets users retrace individual steps taken by (groups of) learner(s), i.e. they can collaboratively (i) re-

[8] `http://portal.ou.nl/web/wespot/pilots`

flect on the rationale of a learner's decisions and actions, (ii) (re-)examine past explanations and conclusions, and (iii) (re-)evaluate past evidence data. Students can learn from peers' activities through exploration, discovery and discussion. The application can be used for evaluation purposes, allowing (groups of) learner(s) and teacher(s) to iterate over every step performed from hypothesis to conclusion together. Pilot data can also help IBL researchers with the discussion and refinement of the IBL model.

Enabling multiple learners and teachers to interact with the visualization simultaneously remains the biggest challenge. We shall further explore the possibilities of glyph-based visualizations to provide unobtrusive global filters, use user position tracking through technology such as Kinect to support the dynamic nature of collaborators around a tabletop and explore data lenses (e.g. GeoLens [15, 7]) to facilitate individual exploration of the data on a shared visualization.

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