Using Graph-based Modelling to explore changes in students' affective states during exploratory learning tasks

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ABSTRACT
We describe a graph-based modelling approach to exploring interactions associated with a change in students' affective state when they are working with an exploratory learning environment (ELE). Student-system interactions data collected during a user study was modelled, visualized and queried as a graph. Our findings provide new insights into how students are interacting with the ELE and the effects of the system's interventions on students' affective states.

1. INTRODUCTION
Much recent research has focussed on *Exploratory Learning Environments* (ELEs) which encourage students' open-ended interaction with a knowledge domain, combined with intelligent components that aim to provide pedagogical support to ensure students' productive interaction. The aim of this feedback is to balance students' freedom to explore alternative task solution approaches while at the same time providing sufficient support to ensure that the intended learning goals are being achieved [6]. Here we report on recent work into identifying interaction events that are associated with a change in students' affective state as they interact with an affect-aware ELE called *Fractions Lab*. We adopt a graph-based approach to modelling, querying and visualizing the student-system interactions data, extending preliminary work in this area reported in [8]. In our graphs, nodes represent occurrences of key indicators that are detected, inferred or generated by the ELE, and edges between such nodes represent the "next event" relationship. In contrast, recent work on interaction networks and hint generation (e.g. [4]) uses graphs whose nodes represent states within a problem-solving space and edges represent students' actions in transitioning between states. That work uses the graph-modelled data to automatically generate feedback for the student, whereas we use a graph-based modelling approach to investigate the effects of the system's interventions in order to better understand how students interact with the ELE with the aim of improving its support for students.

2. THE ELE AND USER STUDY
Fractions Lab is an ELE that is part of the iTalk2Learn learning platform targeted at children aged 8-12 years who are learning about fractions. As students interact with Fractions Lab they are asked to talk aloud about their reasoning process. This speech, together with their interactions, are used to detect students' affective states using a combination of Bayesian and rule-based reasoning [5]. Adaptive support is provided based on the student's performance and detected affective state. The affective states detected by Fractions Lab can be ranked according to their effect on learning, based on previous studies (e.g. [7, 3, 1]). For example, being in *flow* is a positive affective state as it indicates that the student is engaging with the learning task well. *Confusion* is mostly associated with realising misconceptions, which also contributes towards learning, while *frustration* and *boredom* are likely to have a negative effect on learning.

We conducted a user study in which iTalk2learn was used by students in a classroom setting. 41 students aged 8-10 took part, with parental consent, recruited from two schools in the UK. Students were given a short introduction to the system. They then engaged with the Fractions Lab ELE for 40 minutes. They then completed an online questionnaire that assessed their knowledge of fractions (the post-test).

The iTalk2Learn platform logged every student-system interaction, such as fractions being created or changed by students, buttons being clicked, feedback being provided by the system, feedback being viewed by students, and the system's detection of students' affective states. This data was then remodelled into a graph form, according to the graph data model shown in Figure 1. We see that the data model comprises two node types: Event nodes, that capture occurrences of key interactions, and EventType nodes, that hold additional metadata about each event. Edges labelled NEXT link together successive Event nodes, allowing us to build up a sequence of events that describe the history of student-system interactions as a student works on a task during a session. An edge labelled OCCURRENCE_OF links each Event node to an EventType node.

The data logged by iTalk2Learn was exported as text, parsed and pre-processed using Python and the Pandas and py2neo

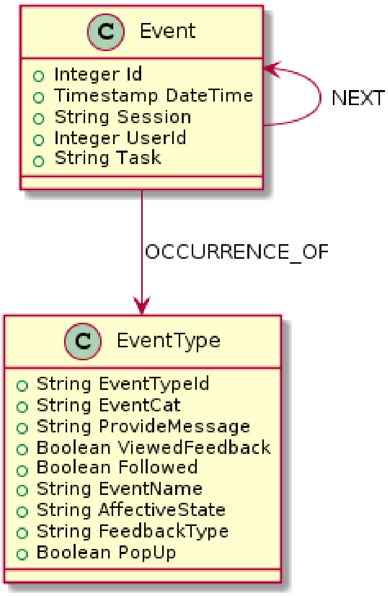

Figure 1: Graph data model for student-system interaction data.

libraries, and then loaded into the Neo4j graph database. To view the resulting data graph we developed a custom visualization tool in JavaScript using the Node.js library. Our tool allows viewing of large-scale changes in affective state as well as details of event sequences. Having interacted with these visualizations, we were interested to explore further the kinds of events that contribute towards changes in students' affective state as they work with Fractions Lab. To do this, we used Neo4j's graph query language, Cypher, to extract the metadata relating to pairs of consecutive events that exhibit a change in a student's affective state. The query below was used to find adjacent Event nodes connected by NEXT, and the EventType nodes they are connected to by OCCURRENCE_OF, such that the affective states associated with the EventType nodes are not equal:

```
MATCH (start_event: Event)-[:OCCURRENCE_OF]->(start_type: EventType),
      (end_event: Event)-[:OCCURRENCE_OF]->(end_type: EventType),
      p = (start_event)-[:NEXT]->(end_event)
WHERE start_type.affective_state in
    ["flow", "boredom", "confusion", "frustration"]
    AND end_type.affective_state in
    ["flow", "boredom", "confusion", "frustration"]
    AND NOT start_type.affective_state = end_type.affective_state
RETURN *
```

3. RESULTS AND CONCLUSIONS

We were interested to explore differences in students' affective states and interactions compared with their performance. Students' performance, based on the post-test score, was on average 3.83 (SD=1.46; min=0; max=6). A median split of students' scores resulted in a higher- and a lower-performing group (high: 27 students; low: 14 students). In order to investigate which interactions moved students into a different affective state we used association rule learning (c.f. [2]) over the data returned by the above Cypher query. We found that students are likely to move from *flow* to *frustration* when provided with reflective prompts in the low-performing group and with open-ended problem solving support in the high-performing group. This might imply that these types of support are imposing too high a cognitive demand on students. Additionally, certain interactions with their fractions may move both categories of student from *flow* to *frustration*. Viewing high-interruption or low-interruption feedback may move low or high performing students, respectively, from *flow* to *confusion*. Finally, we observed a positive effect of Affect Boost messages for both categories of student.

These findings extend earlier ones reported in [5] with a finer-grained analysis of students' affective state changes, identifying several situations where the system's support may need to be modified: (i) reviewing the content of both the high- and the low-interruption messages, to see if the incidences of confusion can be reduced; (ii) considering extending the provision of reflective prompts and open-ended support with additional affect boost messages and hints that students might also select to view, to mitigate against frustration; (iii) considering providing more scaffolds when students are manipulating their fractions, for example additional low-interruption feedback. Exploratory learning environments such as Fractions Lab can generate large volumes of student-system interactions data, making their interpretation a challenging task. We have seen here how modelling such data as a graph can open up new data visualization, querying and analysis opportunities, leading to new insights into how students are interacting with the ELE and the effects of the system's interventions, with the ultimate goal of designing improved support for students.

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