How to Capitalise on Mobility, Proximity and Motion Analytics to Support Formal and Informal Education?

Roberto Martinez-Maldonado[1], Vanessa Echeverria[1], Kalina Yacef[2], Augusto Dias Pereira Dos Santos[2], and Mykola Pechenizkiy[3]

[1]University of Technology Sydney, Australia
[2]The University of Sydney, Australia
[3]Eindhoven University of Technology, The Netherlands
Roberto.Martinez-Maldonado@uts.ed.au

Abstract: Learning Analytics and similar data-intensive approaches aimed at understanding and/or supporting learning have mostly focused on the analysis of students' data automatically captured by personal computers or, more recently, mobile devices. Thus, most student behavioural data are limited to the interactions between students and particular learning applications. However, learning can also occur beyond these interface interactions, for instance while students interact face-to-face with other students or their teachers. Alternatively, some learning tasks may require students to interact with non-digital physical tools, to use the physical space, or to learn in different ways that cannot be mediated by traditional user interfaces (e.g. motor and/or audio learning). The key questions here are: why are we neglecting these kinds of learning activities? How can we provide automated support or feedback to students during these activities? Can we find useful patterns of activity in these physical settings as we have been doing with computer-mediated settings? This position paper is aimed at motivating discussion through a series of questions that can justify the importance of designing technological innovations for physical learning settings where mobility, proximity and motion are tracked, just as digital interactions have been so far.

Keywords: physical spaces, wearables, indoor localisation, sensors, mobility, motor learning

In silence and movement you can show the reflection of people.
Marcel Marceau

1 Introduction

Data-intensive approaches aimed at understanding and supporting learning, such as Learning Analytics, Educational Data Mining, Intelligent Tutoring Systems and Artificial Intelligence in Education, have mostly been focused on the analysis of students' interactions with particular learning systems and applications (Khalil & Ebner, 2016; Roll & Wylie, 2016). The student behavioural data that are commonly logged and analysed mostly correspond to the interactions captured by personal computers or, more recently, mobile devices. Although mobile and emerging pervasive technologies have extended capabilities to sense some aspects of the usage context, most student data used to model students' behaviours/strategies or to provide automated feedback are still limited to the interactions between students and learning applications. However, learning goes beyond students' interactions with user digital interfaces. Learning may for example occur while students interact face-to-face with other students or with their teachers. Alternatively, some learning tasks may require students to interact with an ecology of non-digital physical tools, to use the physical space indoors and/or outdoors; or to learn in different ways that cannot be mediated by traditional user interfaces (e.g. motor and/or audio-visual learning) (Santos, 2016). Multimodal learning analytics (MMLA) initiatives have been the most robust approach for considering the complexity of learning tasks (Blikstein, 2013). Multimodal approaches have focused on methods to integrate data corresponding to alternative dimensions of student activity besides clickstreams and keystrokes. For example, multimodal learning analytics have included approaches for automatically analyse speech, handwriting, sketch, gesture, affective states and neurophysiological signals. However, although there have been numerous advances in this area, most of the MMLA studies have been conducted under controlled laboratory conditions (Blikstein & Worsley, 2016). There is still much work needed to find ways in which these multimodal approaches can solve challenges in more realistic, mainstream learning scenarios.

This paper raises the question of how learning analytics can be created for physical learning spaces and learning tasks that include physical activities. This includes the characteristics of the infrastructure needed, the new features and dimensions of student data that need to be created. The key overarching questions motivate this position paper are: How can we envisage the provision of automated support or feedback to students for tasks where physicality has an important place? How can we sense student usage of the physical spaces and objects? How can we sense students' mobility in the learning space? Can we find patterns of learners' interactions in these physical settings as we have been doing in computer-mediated settings? If so, what particular techniques are appropriate for analysing and making sense of the data? Are there any particular ethical implications or risks in exploring data from physical settings that were not present with computer-mediated learning systems? The paper is aimed at motivating our discussion through a series of questions that justify the importance of designing physical learning analytics innovations. These questions emerged from recent literature in learning analytics, technology, enhanced learning and human-computer interaction, more broadly. We focus our position particularly on understanding the possible preliminary avenues of research where mobility, proximity and motion analytics can help us respond questions about or support both learning in formal and informal educational contexts where the physicality of the space, the task or the learning may be paramount.

2 Why are Mobility, Proximity and Motion Analytics Important?

In this section we discuss a number of learning tasks, modalities and/or educational activities where physicality of interactions or learning processes can be supported by learning analytics approaches.

2.1 F-formations in Face-to-face Collaboration.

Learning from others and with others involves physicality to a great extent. When collaborating face-to-face, people do not only communicate verbally but also through gestures, postures, presence and other non-verbal cues (Walther et al., 2005). In addition to these non-verbal communication modes, people also may use the space or multiple artefacts and objects in the collaborative setting. Kendon (1990) defined that a key spatial aspect in face-to-face collaboration refers to the physical arrangement that group members assume around devices or among themselves. These socially and physically situated arrangements are known as f-formations. F-formations are concerned with the proximity and body orientation that collaborators feature during collaborative sessions, which can be indicative of how people position themselves as and within a group. A recent example of this aspect studied from a learning analytics perspective was presented by Thompson et al. (2016) who used a computer vision technique based on video recordings to track collaborators working in a Design Studio. This study suggests that the mobility trajectories of people in the learning space can reflect higher order patterns of collaboration. For example, the most engaged collaborators may show more complex mobility patterns for tasks that require the interaction of collaborators with multiple devices. By contrast, for tasks that require initial planning and discussion, mobility patterns can highlight groups that skip this phase and go straight to hands-on work. Similarly, the first author and colleagues are investigating mobility data of training nurses around medical beds during simulation labs (Martinez-Maldonado et al., 2017). In this case, the students are tracked using a depth sensor. The mobility data was wrangled to generate heatmaps of activity around the patient's bed. By analysing the heatmaps using time series, some initial visually assessed patterns emerged and suggested the presence of patterns that can be associated with distinct types of epistemic approaches to the task. Raca et al. (2014) also explored how motion data obtained with computer vision algorithms can provide insights about student's actions (and those of student's neighbours) during a lecture. Some questions that may be followed up in this area include:

- What are the kinds of tasks and learning scenarios where various f-formations naturally emerge among collaborators?
- How can we measure or evaluate the impact (if it exists) of f-formations on group performance, learning and collaboration?
- How can we capture and integrate other behavioural data while group members collaborate face-to-face?
- How can we link and synchronise mobility data about collaborators with other activity data that is already being captured (e.g. from the online learning system, social networks, etc.)?

- How can we incorporate contextual information (e.g. aspects of the learning/cognitive process, epistemic approaches, behavioural cues) to location data to enhance the sense making process?

2.2 Micromobility in co-present device ecologies.

A second aspect that can be tracked in co-present collaboration corresponds to the concept of Micromobility. This describes how people orient and tilt objects or devices towards one another to share information or jointly reflect based on specific data. Being able to track, analyse and visualise behavioural data linked to this concept can critical for face-to-face learning or reflection scenarios (the latter, where a group of students/educators need to make sense of their own data for example). An example of this approach was presented by Marquardt et al. (2012) who used kinects and accelerometers to capture information about both f-formations and micromobility. Although these authors provided collaborators with non-learning related, quite controlled tasks, they found very distinctive patterns among groups, particularly in the different ways collaborators interact with objects and share information. This demonstrates that even small data points captured by the digital devices in use, such as tilting a screen to allow others to look at the same information, may be indicative of key moments in collaboration. This is an area that does not seem to have been explored in learning contexts yet. Some questions that may be followed up in this area include:

- Is it possible to distinguish explicit student’s actions and intentions from implicit micro-actions and micro-interaction data captured from the devices (e.g. accelerometer data and angle of the device)?
- What data processing techniques would be needed to merge and pre-process these data?
- What algorithms and approaches would be needed to classify micro-mobility actions effectively?
- What are the ethical and technical implications of pervasively tracking these micro data?

2.3 Social interaction, peer communication and networking.

Pentland and colleagues (Eagle & Pentland, 2006; Kim et al., 2008) pioneered in the exploration of using data mining techniques to look for patterns within social networks in physical environments. For tracking face-to-face interactions at a wider scale (e.g. within an organisation, at a conference or in public events), they developed the *sociometric badges*. These sensors can track basic aspects of social interaction such as whether two people were talking to each other, levels of voice, and movement. We are exploring the feasibility of understanding the social networks formed by students when learning to dance. They are aiming to use mobile technologies and indoor localisation technologies to understand how students interact with other students, with different levels of dancing expertise, and how these interactions shape their own learning paths according to their intrinsic motivations. We envisage that these kinds of social interaction data can be exploited through social network analysis for generating understanding in learning environment where collaboration happens not only in small groups, but also through small and heterogeneous interactions within the community. Additionally, it may be possible to learn from the more mature area within learning analytics that have explored patterns within digital social networks. Some questions that may be followed up in this area include:

- Which learning scenarios would benefit from mapping the physical world social networks that students interact in?
- What alternative technological solutions could be used to capture social, physical interaction data in a sustainable manner?
- Can social network analysis techniques be applied to physical social net analysis? What are the ethical issues of tracking activity from students' physical social networks?

2.4 Teacher analytics in the classroom.

To a large extent, classrooms still play a critical role for building lifelong skills for 21st Century learners (O'Flaherty & Phillips, 2015). Besides the diversity in architectural formats, the classroom still basically allows educators to interact with students and provide feedback in situ. The physicality of the classroom is an aspect in education that has been quite overlooked by most learning analytics initiatives in all educational levels. The analysis of mobility of the teacher or the students in the classroom may provide new insights about things that occur in the classroom such as the provision of feedback, the communication among students and with the teacher, or the identification of inactive students. One example of the potential of this type of analytics was suggested by Martinez-Maldonado et al. (2015) who demonstrated the usefulness of manually tracking the teacher's mobility in the classroom in order to understand the impact of the feedback that the teacher provided to the students working in small teams. Other approaches have focused on analysing teacher's actions using video analysis and other computer vision approaches (Echeverría et al., 2014). More recently, Prieto et al. (2016) presented a more elaborated approach to collect teaching analytics automatically using accelerometer data, EEG, audio, video and eye trackers' data to create, what authors call, 'orchestration graphs'. These can potentially be effective indicators of the kinds of learning and teaching processes that occur in face-to-face classrooms. Some questions that may be followed up in this area include:

- In which learning scenarios it would be important to know the actions performed by the teacher (besides small group collaboration classrooms)?
- What are the implications of teaching analytics for learning design or for measuring instructional performance?
- What are the ethical implications of using these data for evaluation (of the teacher)?
- What technological innovations would be needed to implement in regular classrooms to perform teaching analytics at scale?

2.5 Motor learning.

The acquisition of psychomotor or kinaesthetic skills is crucial for many kinds of tasks associated with both formal and informal learning (Harrow, 1972). Examples include learning to play a musical instrument, learning a sign language, dancing, improving handwriting, drawing, training surgical or clinical interventions, improving the technique in sports, practicing martial arts, etc. Santos (2016) has recently highlighted both the importance of supporting these types of widely diverse and important educational tasks and also the potential that data and analytics can offer to leverage motor learning. This is becoming feasible because of the widespread emergence of pervasive sensors (e.g. wearable devices); more advanced and less expensive computer vision devices (e.g. depth/infrared cameras); and more reliable computer vision algorithms. From a multimodal learning analytics perspective, motor learning has started to be addressed through action and gesture analysis (Blikstein & Worsley, 2016). Representative examples of this approach include the recognition of human activity using computer vision (e.g. [Yilmaz and Shah, 2005]) or identifying gestures that differentiate experts from novices (e.g. [Worsley and Blikstein, 2013]). Key questions in this area that remain unanswered include:

- What motor learning or hybrid learning tasks could be supported using mobility, proximity or motion analytics?
- What particular pedagogical/epistemic stance would be required?
- Is motor learning a whole different domain of learning that should be supported differently by emerging learning analytics, or is it just another dimension of human activity that can be tackled through multimodal approaches?
- What kinds of analytics may be useful for informal education scenarios that involve the development of motor skills?

2.6 Learning in and from physical spaces.

The areas discussed above are not necessarily comprehensively covering all the possible learning tasks that can be supported by using mobility, proximity and motion analytics. Other examples include learning tasks that require field work and that are more commonly being supported by mobile (e.g. [Carvalho and Freeman, 2016]) or augmented reality (e.g. [Muñoz-Cristóbal et al., 2014]) technologies. In these scenarios, students can be encouraged to explore the physical space, which can be in the school, in natural areas or in the city, to complete tasks. These may not only require the student to access information or content online but also make sense of it and associate it with the physical context where s/he is. Even it would be possible that students need to access information through embodied interaction modes (e.g. perform tasks or gain access to information depending on their physical location or proximity). Data obtained from localisation and usage logs, and the application of learning analytics techniques, could unveil patterns of the processes that students follow or generate while learning in the physical space. Some questions that may be followed up in this area include:

- What formal and informal educational tasks invite or require students to explore and interact with the physical space where the learning activity unfolds?
- What kind of data, besides indoor/outdoor localisation, can be captured in physical spaces?
- What kind of sensemaking can be performed on location data?
- What kind of analytics innovations could improve learning in physical spaces?

- What are the ethical implications and risks of exploiting these location data for learning analytics?

3 Conclusions

This position paper aims at starting a discussion about the current approaches and the future potential of learning analytics for supporting learning across physical spaces. The learning analytics field and related fields have paid much attention to cognitive or intellectual domains. There has also been a strong interest in supporting the affective domain (Rogaten et al., 2016). It is now time to start supporting psychomotor skills and/or the physicality aspects of a traditional intellectual domian, which are crucial for the full development of a life-long learner. The lack of interest in this domain may be affected by the regular pedagogies and the curricula which may not explicitly include this into the learning tasks. This is the reason why we need to also look at (the so-called) informal learning activities, which have an important role in complementing the more 'thinking-oriented' formal education. Nonetheless, the paper highlights some examples of learning analytics innovations that are tackling this domain. The questions posed for each area aim to trigger discussion and motivate formal studies to support psychomotor learning through Mobility, Proximity and Motion Analytics. Current and future work by authors is aiming to illustrate the feasibility and potential of performing this kind of analytics through three case studies in three different contexts, including: i) health simulation labs; ii) a dance education studio; and iii) regular small-group collaboration classrooms.

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