Digital Learning Projection

Learning performance estimation from multimodal learning experiences.

Daniele Di Mitri (✉)

Welten Institute, Research Centre for Learning, Teaching and Technology
Open University of the Netherlands
Daniele.Dimitri@ou.nl

Abstract. Multiple modalities of the learning process can now be captured on real-time through wearable and contextual sensors. By annotating these multimodal data (the input space) by expert assessments or self-reports (the output space), machine learning models can be trained to predict the learning performance. This can lead to continuous formative assessment and feedback generation, which can be used to personalise and contextualise content, improve awareness and support informed decisions about learning.

1 The problem

Digital tools used for learning leave multiple data traces which can be scrutinised to get meaningful insights to improve teaching and learning [7]. This approach is at the basis of the learning analytics research. However, looking exclusively at the data available from one system risks to incur into the so-called "streetlight effect", i.e. searching for the lost key in the darkness only under the street lights, these being the only visible spots. The majority of learning management systems (LMSs) used for gathering educational data were not designed with analytics in mind: the digital traces that they record are poorly explanatory of the actual learning. In addition, modern learning is not limited to one single platform but is distributed across several media and resources [10]: there is a lot more happening "beyond the LMS" which needs to be taken into account [8]; for example the knowledge exchange happening in social media platforms [6]. Furthermore, learning is ubiquitous [2]: it happens everywhere, not only online in the "virtual world" (the digital space) but also offline, in the "real world" (the physical space) [3]. If we exclude from the domain of analysis moments like reading a book, having a face-to-face meeting and all the "offline" activities that do not leave immediate digital footprints as they are not mediated by digital devices, we end up jeopardising the digital representation of the learning process. Hence, new data must be generated by observing multiple modalities of learning; that will eventually lead us towards a more complex data representation which can be the basis for analysis and inference. The *Internet of Things* approach, can support this challenge. Several sensors and microprocessors can be used and applied also in education for capturing learning fragments and translating them into data [9]. Head movements, gaze, vital signals (heart rate, skin conductance, EEG), posture, gestures, handwriting, spoken words. All these "behavioural particles" have very low semantics if considered singularly [5], but if combined and integrated with information about the learning context and activity can become fine grained "digital projections" which can be mined and analysed with the aim to generate feedback and automatise formative assessment. This multimodal data collection has been conceptualised by Blikstein [1] with the name of *multimodal learning analytics*. Each modality requires an unique approach of collection, modelling and analysis. Some of these data streams are continuous and auto correlated (e.g. heart rate) . Some other signals are occasional, voluntary human activities which should be seen as sequences of events happening randomly rather than continuous streams. The chronological order by which the different voluntary actions are performed can play a role in determining the success of learning performances. The actions are observed are executed in random order and have a sparse distribution. There is also an high inter-subject variance i.e. each learner executes a set of actions substantially different from their peers. To conclude time-dependent observations are useful to keep track of different learning moments of the learning journey as well as for discovering recurrent action-patterns.

2 Proposed solution

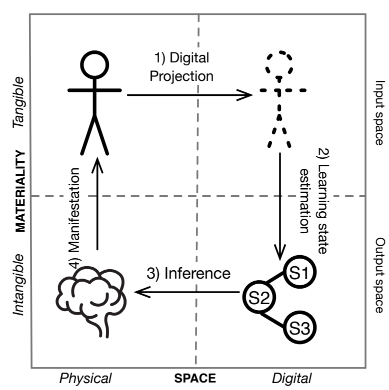

Fig. 1. Blueprint of Cognitive Inference

The exposed background lead us to envision the *blueprint of cognitive inference* through a multimodal digital projection. The core idea consists in inferring the intangible cognition and knowledge of the learners. The catch consists in back-tracking what is intangible, namely the human mind processes which underpin learning, by projecting in the digital space what is tangible, namely all the measurable modalities which surround learning. The approach is represented in figure 1 and consists of four phases. The first step is the *digital projection*, that happens when all the attributes of learning happening across physical and digital spaces are digitalised into data by mean of sensors and trackers. The second step corresponds to the exploitation of the collected data with data-intensive methods. It grounds its logic in the machine learning and autonomous agents theories. The idea is that by observing how people learn and how they perform in learning it is possible, with the help of machines to learn generalisation models, which based on history can estimate the current learning performance. This approach requires to clarify both the selected attributes (the input space) as well as the learning performance that is the output space of the model. The third step corresponds to the cognitive inference, which is the derivation of learner's affect and cognition, characterises in the learning process. This dimension is intangible and implicit as the processes take place in the human brain. Finally the last step refers to the link existing between cognitive states and the behaviour manifested in learning, the process through which being in a certain phase of the learning process influences physiological responses and behaviours.

2.1 Design and methods

The research project lasts four years and consists in four main tasks: 1) a preliminary experiment, 2) a literature literature review, 3) a technology prototype and a 4) main experiment.

1) Preliminary experiment – "*Learning Pulse: a machine learning approach for predicting performance in self-regulated learning using multimodal data*" [4], accepted as full paper at LAK17 combined data like heart rate, step count, weather condition and learning activity and looked whether they can be used to predict self-reported learning performance (stress, productivity and flow) in self-regulated learning settings. The insights got from this study grounded this research proposal.

2) Framework – Planned literature review to search for similar multimodal data experiment and related learning performance used. This information should then be compiled into a framework that aim to establish of a new paradigm of investigation of learning: predictive applications using real-time multimodal data collection and machine learning methods. This framework will report on: techniques used to collect data, learning performance indicators used, data analysis approaches used and results.

3) Technology prototype – Wearable Experience for Knowledge Intensive Training (WEKIT) is a European project (Horizon 2020, 2.7M Euro) whose aim is to develop and test a novel way of industrial training through smart wearable technology and augmented reality. The core of this project consists in developing an *Experience capturing API* by wiring the smart glasses (Microsoft Hololens) with different wearable sensors through a software architecture which will enable to capture, annotate, re-enact practical learning experiences.

4) Main experiment – Planned experiment, doctor training using manikins: trainees are guided through this simulation program and need to fulfil some check-lists (e.g. checking heart rate, injecting medications). The multi-sensor scenario which these training labs provide is an ideal setup for using the WEKIT prototype. The aim is to track both the expert doctors and the trainees, checking movement, speed, precision and trying with machine learning techniques to predict their performance.

3 Main contribution

This research can bring added value to education and learning, especially in work and practice based learning settings. While data-driven applications are proliferating, there is yet no integrated vision for using data to support processes like learning. With this research we show how to connect tangible and multimodal events to intangible cognitive abstractions which we name learning performance. If machine learning models are trained to estimate the learning performance accurately enough, that would allow to create personal cognitive tutors which can automatically assess the learner in a formative way by identifying where the learner stands in the process. This information can be used for personalisation, contextualisation or for just increasing awareness about the learning process.

4 Questions to reviewers

Is the proposal sound and relevant for the AIED research community? In your knowledge were there similar research conducted? How to frame the proposal and the research questions in more clear boundaries? How to prevent the *garbage-in-garbage-out* effect when dealing with noisy sensors?

References

1. Blikstein, P.: Multimodal learning analytics. Proceedings of the Third International Conference on Learning Analytics and Knowledge - LAK '13 p. 102 (2013), http://dl.acm.org.myaccess.library.utoronto.ca/citation.cfm?id=2460296.2460316
2. Bruce, B.C.: Ubiquitous Learning , Ubiquitous Computing , and Lived Experience. Intermational Conference of Networked Learning pp. 583–590 (2007)
3. Delgado-Kloos, C., Hernández-Leo, D., Asensio-Pérez, J.I.: Technology for Learning across Physical and Virtual Spaces J. UCS Special Issue. Journal of Universal Computer Science 18(15), 2093–2096 (2012)
4. Di Mitri, D., Scheffel, M., Drachsler, H., Börner, D., Ternier, S., Specht, M.: Learning Pulse : a machine learning approach for predicting performance in self-regulated learning using multimodal data. In: LAK '17 Proceedings of the 7th International Conference on Learning Analytics and Knowledge (2017)
5. Dillenbourg, P.: The Evolution of Research on Digital Education. International Journal of Artificial Intelligence in Education 26(2), 544–560 (2016), http://dx.doi.org/10.1007/s40593-016-0106-z
6. Ferguson, R., Shum, S.B.: Social learning analytics. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge - LAK '12 pp. 23–33 (2012), http://dl.acm.org/citation.cfm?doid=2330601.2330616
7. Greller, W., Drachsler, H.: Translating Learning into Numbers : A Generic Framework for Learning Analytics Author contact details :. Educational Technology & Society 15(3), 42 – 57 (2012)
8. Pardo, A., Kloos, C.D.: Stepping out of the box: towards analytics outside the learning management system. 1st International Conference on Learning Analytics and Knowledge (LAK11) pp. 163–167 (2011)
9. Schneider, J., Börner, D., van Rosmalen, P., Specht, M.: Augmenting the Senses: A Review on Sensor-Based Learning Support. Sensors 15(2), 4097–4133 (2015)
10. Suthers, D., Rosen, D.: A unified framework for multi-level analysis of distributed learning. In: Proceedings of the 1st International Conference on Learning Analytics and Knowledge - LAK '11. pp. 64–74. ACM (2011)