

New Opportunities with Open Learner Models and Visual Learning Analytics

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Abstract. This paper compares approaches to visualising data for users in educational settings, contrasting visual learning analytics and open learner models. We consider the roots of each, and identify how each field can learn from experiences and approaches of the other, thereby benefiting both.

Keywords: Open learner model, OLM, visual learning analytics, VLA.

1 Introduction

Open learner models (OLM) can be understood as learner models that allow a user, usually the learner, to view the internal system's learner model data in a human-understandable form. This allows learners to either act on the information, possibly with system guidance, to further their learning; and/or to reflect on it, then follow up with appropriate learning activities to achieve desired learning outcomes. OLMs typically aim to give learners greater control over their learning, as the learner model data can support their decisions about their learning [12]. Instead of seeing the system's underlying rules, numerical values, logical or conceptual structures, etc., about their knowledge and skills, the human-understandable nature of the OLM may be graphical, and so more readily understood. Learner models constructed in a variety of ways have been opened to users, for example: Bayesian networks [22]; concept maps [18]; constraint-based models [17]. Illustrating the variety of ways that learner models may be opened to users, Figure 1 shows three visualisations (of eight) from the Next-TELL OLM [1, 10], also used in the LEA's Box (learning analytics toolbox) OLM (<http://www.leas-box.eu>). The reason for this particular choice for Figure 1 is to highlight that each visualisation is generated from the same underlying learner model, thus indicating that visualisations are not necessarily tied to particular learner modelling techniques. OLMs have been identified as an important sub-topic in learner modelling [7], and have also demonstrated significant learning benefits [14, 16, 17].

With the rapid emergence of big data in numerous fields, substantial interest has also grown in this area in education. Learning analytics, a relatively new field, includes the visualisation of learning-related data to help users interpret the vast amounts of data now available [15, 19]. The approach has some similarities to OLMs,

and learning analytics dashboards are being developed to support user interpretation of the data [21].

However, while visual learning analytics (VLA) approaches have received substantial attention, their focus is very often on issues such as performance level, activity completion, navigation to information, or other behaviour-focussed statistics. We highlight three of the key differences between VLA and OLM in the next section.



Figure 1. skill meter, concept map and overview-zoom-filter treemap visualisations from the Next-TELL and LEA's Box OLMs

2 Open Learner Models and Visual Learning Analytics

There are three important differences between the state-of-the-art in VLA and OLM:

1. VLA tends to take a more statistical approach, presenting the corresponding outcomes (such as number of pages viewed, or performance), for the user to then interpret; but OLM already presents processed data to the user, *from the learner model* (showing their competencies; or extent of coverage of material, perhaps in the form of a strategy used to try to gain understanding).
2. VLA is usually *targeted at teachers or other stakeholders* such as school or educational leaders, although the importance of learning visualisations to support learning is now growing (e.g. [8]). In contrast, OLMs have typically been developed *primarily for learners*, to help them reflect on, and take decisions about their learning, though there is also a history of OLMs shown to other stakeholders such as teachers [10], individual peers [4] or groups [20].
3. VLA's origin, based on recognition of the potential value of existing learning data, aimed to make this easier to interpret, and for people to use it. In contrast, OLMs came from intelligent tutoring systems, with the learner model designed so that the system could adapt the interaction to suit the individual learner's needs. Opening the learner model made it a *first class learning* resource in its own right [2, 13]. Although OLMs began long before big data was so prevalent, they are now also looking towards big data, and approaches suitable for today's online learning contexts, for example: domain-independent reusable services for other systems [6, 13], or aggregated from multiple external systems, with visualisation of the combined evidence to the user [5, 13], are being developed.

Thus, OLMs could be viewed as a specific kind of learning analytics, in that the visualisation is of the learner model rather than activities undertaken, performance, behaviour, etc. However, with a few exceptions [3, 8, 9, 11], there has been relatively little reference to learning analytics visualisations together with OLM.

3 Conclusions

Both visual learning analytics and OLMs aim to make data available to help users to interpret aspects of students' learning. A core difference, however, is that in OLMs, inferences relating to learning have already been made during the learner modelling process. An approach similar to this, even if not part of an adaptive system, may be useful to those working on learning analytics visualisations. A teacher may benefit from seeing (graphical) data that they do not need to further interpret to make it immediately useful to support their decision-making. Achieving the above, VLA could also become more commonplace in environments for students. The potential for learning analytics to facilitate metacognition has already been recognised. This was a foundation aim of OLMs [2], and so VLA for metacognition may be further enhanced by approaches already explored in OLM systems. While there are some exceptions, we have also identified the different target users in VLA and OLM research. Both fields may benefit from considering the utility of the approaches to other user types - all stakeholders have some kind of interest in learning data. Finally, OLM research could benefit substantially by the attention given to making big data understandable, found in VLA research, as classrooms are increasing bringing large amounts of data about learners as well as data that may reasonably contribute to learner models that is sourced away from the formal learning setting. This latter situation is perhaps where experiences from VLA have much to offer OLM research in Artificial Intelligence in Education: we can look forward to using techniques from learning analytics to contribute to learner modelling processes with increased data, combined with the more learning-focused visualisations of OLMs, and providing OLM visualisations for a greater range of stakeholders.

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