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Towards more Visual Analytics in Learning Analytics

Panagiotis D. Ritsos [1] and Jonathan C. Roberts[1]

[1]School of Computer Science, Bangor University, UK

Abstract

Learning Analytics is the collection, management and analysis of students' learning. It is used to enable teachers to understand how their students are progressing and for learners to ascertain how well they are performing. Often the data is displayed through dashboards. However, there is a huge opportunity to include more comprehensive and interactive visualizations that provide visual depictions and analysis throughout the lifetime of the learner, monitoring their progress from novices to experts. We therefore encourage researchers to take a comprehensive approach and re-think how visual analytics can be applied to the learning environment, and develop more interactive and exploratory interfaces for the learner and teacher.

Categories and Subject Descriptors (according to ACM CCS): H.5.2 [Information Interfaces and Presentation]: User Interfaces—Theory and Methods

1. Introduction

Over the past two decades e-learning, online-learning, remote-learning and especially Technology-Enhanced Learning (TEL) environments have flourished. Not only have the technologies matured, but also the breadth of subjects that use these e-learning environments has increased. There are now many different e-learning tools that are available to the educator and learner: electronic classrooms, video tuition, podcasts of lessons, blogs, online questionnaires and quiz environments, etc. These e-learning environments provide learning experiences for individuals or groups, synchronously or asynchronously, remote or co-located with the teacher. In fact, it is often useful to use the e-learning environments in a traditional lecture/laboratory class setting, in a blended learning style, where the students and teacher are co-located.

The widespread use of Learning Management Systems (LMSs), often also referred to as Virtual Learning Environments (VLEs), such as Moodle and Blackboard, results in an ever-increasing amount of data, collected by educational institutions. Analyzing and visualizing that data, beyond the fairly basic reporting and visualization capabilities of current tools, have the potential to depict underlying factors that affect the learning and teaching processes and allow us to improve them. The dynamic analysis and visualization of the data can also help users as they learn.

Current LMSs focus on visualizing results of the student's performance, displaying it as a dashboard that can be viewed at the end of a period or after an event, such as an exam, and do not analyze the learning process itself, or consider the situation or physical environment of learning. There is a huge opportunity to built upon these concepts and expand the area of Visual Analytics (VA) for Learning Analytics (LA).

In this paper we investigate LA, describing how practices of VA can be used to further the experience of the learner. LA is a relatively new field and therefore the subject is gradually being defined. A recent and widely accepted definition of LA appeared in the call for papers of the first International Conference on Learning Analytics and Knowledge (LAK 2011) and was adopted by the Society of Learning Analytics Research (SOLAR) [Fer12]:

> *Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs*. [SL11].

Our intention is to engender the Visual Analytics community into developing a wider approach to LA and to consider the issues and opportunities such and endeavour entails. Our long-term hypotheses are as follows:

- there is a need to develop tools that assist the learner throughout the whole process of learning, i.e., tools that aid and supports the learners from the very beginning when the users are novices, and help them advance into expert level, as well progress from shallow thinkers to deep thinkers.

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- a wider range of data should be captured; from assessment and exam results, to usage statistics, attitudes and emotions.
- more analytics will aid the users themselves, as they learn. They will become more *active* and *reflective* learners, i.e., more experiential learners [K*84]. Ultimately, as they become more aware of the processes of their own learning they will be more effective learners.

We have been working with educators and researchers in computer-assisted, interpreter-mediated communications training [RGB*13, BSG*13], and we have been developing online tools – especially immersive, 3D environments – that enable these language learners to practice and explore different scenarios. While this is a particular use-case in terms of computer-assisted learning and teaching, it is a useful scenario to hook our thoughts onto. Insights gained [BSG*13] through this scenario can be applied to other constructionist approaches to learning and, consequently, offer an important starting point in developing new visual analytic interfaces for any type of learning.

2. Background and interpreter-learning use-case

Our experience with LA stems from several sources and has been developing over many years. Not only do we have experience of teaching computing science and educating the next generation of visualization engineers, but since 2011 we have been collaborating with the aforementioned interpreting researchers and practitioners.

The research goals of our interpreter colleagues are to investigate different aspects of learning, teaching and study of Inter-cultural Communication Practice (ICP). Specialised training in inter-cultural communication, particularly in demanding business, legal and medical scenarios has become very important, due to the increased multilingualism that results from the extend of migration that is occurring over the world and in particular in Europe.

Specifically, interpreting researchers are interested in training and preparing students in *inter-cultural communication* skills. In other words, they are teaching *dialog* and *negotiation* skills across different spoken languages. There is somewhat an assumption that students of ICP know several languages and therefore the focus is to develop techniques of verbally interpreting from one language to another. There is also an assumption that the students need to improve their own multi-language skills as well as understand different cultural aspects.

The students follow a broad curriculum, with an emphasis on experiential learning [BT07]. For instance, students need to *observe* others through visits to court-rooms or conferences where professional interpreters are working, *practice* with sets of exercises of increasing difficulty (to improve their skills), acknowledge *feedback* from tutors on their progress, *reflect* upon their own work, and maybe *critique* other people's work. These are skills that are cross-cutting to other disciplines.

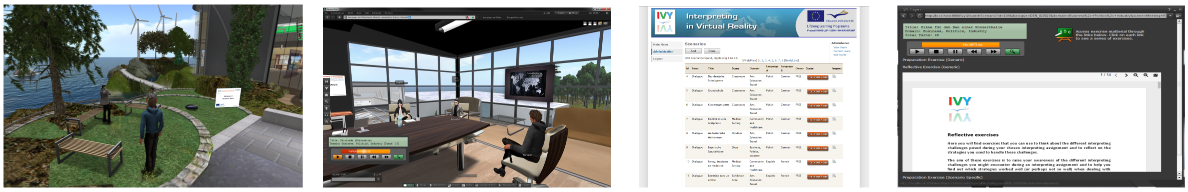
In our current tools, learners use a selection of pre-recorded audio scenarios. These are delivered to the students through an online learning-environment [RGB*13, BSG*13], called IVY-VE (Interpreting in Virtual Reality - Virtual Environment). In particular, IVY-VE supports several modes. In *practice* mode, students can learn by being immersed in pre-recorded scenarios where, say, two people are having a conversation and the interpreter verbalizes the communication, which can be recorded for analysis, reflection or marking purposes. In *live* mode the students can interact in real-time with other students, who can take on the roles of the interpreter, interlocutors or observers. All this takes place in a three-dimensional virtual world. The learners select a scenario, they are tele-ported to a virtual world location that is suitable for the scenario, and they can then play through and act out the scene. We have developed hundreds of scenarios in IVY-VE (Fig. 1c), and have modelled different locations such as offices, landscapes (see, Fig. 1b and Fig 1a), classrooms, medical settings, court rooms and shops. IVY-VE also includes a series of exercises (Fig. 1d).

Let's consider an imaginary student named Georgina. She speaks English, German and Polish and wishes to practice interpreting between English and German. Her chosen scenarios are in a police interrogation room; therefore she researches police vocabulary and practices, and interrogation procedures and environments. She starts by looking at the online exercises, which direct her to perform research and take notes about the subject. Georgina then uses the online video material to practice. She plays ten different bilingual interrogation examples. Some of the interlocutors are aggressive, others are shy and passive. For each of the ten scenarios that Georgina performs, she records her own voice as she interprets the scenario and annotates over her delivery. She repeats the scenario many times, to improve her performance, recording each version. For some scenarios she pauses to perform additional research.

Consequently, all of Georgina's actions yield various types of data. For instance, the time spent in each exercise could be indicative of a scenario's difficulty. The audio of her interpreter performance can be used to pinpoint errors in her interpreting. Her annotations act as an aide-memoir to herself and also to provide additional data on her activity to the learning tool. The tool provides formative feedback in the form of a visualization dashboard and displays her progress as well as the types of material that she excels and struggles over. Filtering and zooming in specific interpreting tries can, potentially, show her advancing proficiency in police interrogation scenarios.

2.1. Some relevant learning models

The learning process that interpreters have to go through is similar in many respects to the learning process followed



(a) View of the IVY virtual world (b) Scenario in and office scene (c) Administration Panel (d) Exercises within the VE

Figure 1: Different views from the IVY-VE used for training and simulation in interpreter-mediated communication. The system is based on the synergy of a virtual world and an online, learning content management system. A series of extensions to the current infrastructure include student activity and progress statistics, grading monitors etc.

for other fields [BK12] and therefore, many of the lessons learned through the interpreters use-case are applicable to other educational domains. We believe established learning models can act as an overarching strategy for LA systems. In most subjects and corresponding to Bloom's taxonomy students need to: acquire knowledge, comprehend and *understand* facts, *apply* knowledge to specific and real-world situations, *analyze* and breakdown different ideas into smaller and simpler parts to support generalizations, *synthesize* and compile alternative solutions, and *evaluate* to make and defend different judgements [BEF*56]. While different fields may have different emphasis on different parts of Bloom's taxonomy, such as focusing on analysis or evaluation, the goal in each subject is clear: to move the students from being novices to experts.

In fact, Bloom himself wanted students to focus on mastering the subject, rather than merely remembering facts [BT07]. This process of developing expertise is clearly expressed by Dreyfus et al. [DDA86] who describes a five part model of moving *novices*, to *beginners*, developing *competence*, becoming *proficient* and finally *expert*. This learning model likewise fits with the structure of observed learning outcomes model (SOLO) by Biggs and Tang [BT07], where the complexity of the students' grasp on the subject develops from being pre-structural, unistructural, multi-structural, relational to extended abstract. In addition, Bloom's model not only includes a cognitive dimension, but also emotions and physical skills. In fact his model is expressed in three domains, all potentially observable by a LA system:

- Cognitive domain, that includes intellectual capability, such as knowledge, or thoughts.
- Affective domain, that includes feelings, attitudes, emotions and behavior.
- Psychomotor domain, that includes manual and physical skills.

3. Learning Management Systems, MOOCs and Learning Analytics

In addition to the aforementioned use of LMSs many educational institutions offer their educational material online. Recent Massive Open Online Courses (MOOCs) like Harvard's and MIT's eDX, and Standford's Coursera, offer an unprecedented access and opportunity for people to access top-class educational programs. Consequently, all that online activity can yield a large amount of data. All those digital breadcrumbs [WI12], coupled with profile information and inter-curriculum correlations and comparisons can be analyzed and give the opportunity for better performance prediction, increase the opportunities of intervention and offer new levels of personalization of the teaching process.

Moreover, MOOCs adoption is likely to increase. Indicatively, Yuan and Powell [YP13] report that Udacity teamed up with Google, NVIDIA, Microsoft, Autodesk, Cadence and Wolfram to develop new courses. Along with the maturation of these e-learning tools, the field of LA has been emerging, over last decade, but has gained significant attention and momentum in the last two years [Fer12]. Similarly, there has been recent substantial growth (in the education sector) in the application of business intelligence, web analytics and data mining concepts at educational institutions.

In current LA systems data is traditionally displayed through dashboards. In 2010 Dawson reported that the dashboards included in popular learning tools were basic or nonexistent [Daw10]. In fact, the designs (appearance) of dashboards are still fairly traditional and utilize only basic visualization concepts, often resembling the tabular style layout found on Google analytics' dashboard or Microsoft's analytic interface of Twitter data. Therefore these dashboards do not include the rich possibilities of visualization designs.

There are many tools that provide dashboard visualizations. For example, GLASS (Gradient's learning analytics system) [LPdlFV*12] provides bar charts and line-graph visualizations, while tools such as StepUp! [VDK*13] provide an holistic view for the teachers to see every student, and use sparkline visualizations to display trends over time for each student; wakoopa [Duv11] includes dashboard displays.

Currently there are few tools that move beyond traditional dashboard approaches. For instance, SNAPP [BD11] provides a network visualization that demonstrates the social connection and interaction of a student. Loco-analyst [JGB*08] provides context aware analysis, SAM [GVDP12] (the student activity monitor) includes bar charts along with Parallel Coordinate Plots.

As Slade and Prinsloo argue, LA primarily intends to be a moral and educational practice, resulting in more successfull learning [SP13]. However, a series of important implications arise in terms of usage ethics, privacy and access. These are implications also often encountered in VA systems, where real data are concerned. For instance, questions such as what type of data a learning system collects and how the data leads to genuine insights about a learner's performance, who controls and owns the data, who can access it and where it is stored, require careful consideration and further research [SP13].

4. The potential of Visual Analytics in Learning Analytics

Ferguson [Fer12] writes that there are three major factors contributing to the current state of play in LA: *big data*, *online learning* and *policies*. Handling and understanding Big Data are two of the great challenges and biggest opportunities of modern information technology [ZE11]. For a review of Educational Data Mining, we refer the reader to the work by Romero and Ventura [RV10].

Learning data is 'big-data' not only because of its size, but because of the complexity, unstructured nature, heterogeneity, dependency on time and diversity. Just considering our use-case of the interpreters, we have *variety* in different types of data (from user clicks, audio, video, material selection, annotation, comments, user/mentor commentary etc.) which are stored in different formats. We also have data that is temporal (not only video captures, but also the users' sessions and timings over their selections, for instance).

Consequently, there are many opportunities to bring visualization into LA as a first-class-citizen. What is needed is consideration of VA from the start, not as an after-thought. In fact, as aforementioned, the current tools that do provide VA capability only focus on visual dashboards. This results in a learning environment that is predominantly static by nature, and affords little interaction. While the current learning tools do utilize several visualization types, these focus on traditional representation styles, including bar charts, line graphs, scatterplots or sparklines. These visualizations typically represent simple statistical information such as grades from tests, dials to illustrate user-load, line-graphs of user logins etc.

Visualization and VA can transform LA; it has potential to go beyond mere analysis. It offers users the capability to gain insights on how the learning process can be improved through actions and enables interventions, user self-awareness and therefore adaptation to their behaviour, determination of their performance and better curriculum mapping. There are therefore challenges and opportunities for VA researchers to provide more informative visualizations, new interaction methodologies, better ways to manipulate data, and, ultimately, provide value for both teachers and learners.

From our experience through the IVY project and by considering related work, we propose the following recommendations to develop more Visual Analytics in Learning Analytics:

1. Make VA a first-class citizen and move beyond post-produced dashboards. Developers need to think how they can design learning systems, integrating monitoring, analysis and interactive visualizations throughout various stages of the learning process.
2. Apply knowledge and practices from the VA domain in order to design better LA interfaces; for example, learn from ideas in uncertainty visualization to create better interfaces for the leaner, as they learn.
3. Utilize big data from multiple users for more accurate outcomes. The multi-user nature of many LMSs and MOOCs allows the collection of vast amounts of data that can aid in more accurate analysis and identification of trends, both from the teacher's and learner's points of view. Moreover, such an approach can help identify and promote social aspects of the learning process.
4. Integrate visualization techniques of data provenance to create more accountable learning environments.
5. Consider how learners can be more active in their learnings. For example, practices and strategies from established learning models, especially experiential approaches like Bloom's and Kolb's, can promote the leaners's involvement and can enable LA systems to have a profound influence through the learning process.
6. Integrate new interaction modalities, like haptics [PR10, PRRR13], affective computing techniques [Pic00] and tangible interfaces [SH10], to enable a more interactive and enthralling learning experience.

5. Conclusion

We are strong advocates of the fact that Learning Analytics will continue to develop and their use in teaching and learning will be widely adopted. The complex datasets that this field generates will provide a huge opportunity for researchers in Visual Analytics to create new and novel interactive visual depictions and interfaces.

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