Deliverable D 4.1 –

Educational Data Visualisation Approaches and Open Learner Modelling

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CONTENTS

1 INTRODUCTION

This deliverable is concerned with visualising educational data. Rather than the many examples over many years of the use of graphics and animation to help teach subject content, we are here concerned with visualising data about learners' *learning*.

We begin with an introduction to research in visual analytics more generally, to situate the work on learning visualisations. We then consider learning analytics portals and dashboards, which most commonly visualise activity, performance or interaction data. We end by looking at open learner models, which typically show visualisations of competencies, understanding or skills, based on inferences about learning rather than the raw countable data. In between we consider other kinds of educational data visualisation, that are nether activity counts nor inferences about knowledge, but rather, ways of using students' products to generate some information about their learning. This could be viewed as intermediate between the other types of data that are visualised.

Our main concerns in LEA's Box are with learning analytics visualisations and open learner models. It will be seen that the former, mostly numerically-based data, more often tends to be presented as the familiar graphs, charts, plots, etc., while the latter, usually knowledge or skill-based information has a lower tendency to use these standard methods of conveying data, instead using a variety of simple and complex, sometimes structured, visualisations.

This Deliverable provides an overview of some of the similarities and differences within and across types of learning visualisation, with a need for further evaluation of the relative utility of different visualisations during the remainder of the project.

2 Visual Analytics

The field of visual analytics grew from the fields of scientific and information visualisation, and also encompasses a range of other fields (Wong and Thomas, 2004). The field is said to unite the strengths of people and computers in the processing of data (Keim et al., 2010), combining data visualisation and data analytics with human-computer interaction in order to solve problems (Zhang et al., 2012).

Most of the World's data has been produced very recently (Zhang et al., 2012), and in line with this, it has been argued that acquiring data is no longer a problematic issue: the current question is to how to make sense of the data that is available (Keim et al., 2010). People use both internal (mental) and external (e.g. diagram) representations during problem-solving (Larkin & Simon, 1987), and the provision of additional visualisations may also help support human reasoning processes, if done appropriately. In the context of information visualisation, it has been suggested that the purpose of visualising information is often to generate 'insight' (Pousman et al., 2007), which includes the possibility of noticing information that may otherwise be unnoticed (Saraiya et al., 2005). Smuc et al. (2009, p.31) define insights as "the understanding gained by an individual using a visualization tool (or parts thereof) for the purpose of data analysis, which is a gradual process toward discovering new knowledge".

Fekete et al. (2008) suggest that information visualisation may be most useful in exploratory tasks, where although an analyst may have an end point in mind, they perhaps have no specific goal for exploring the data. Wong and Thomas (2004) explain that abstract visual metaphors allow users to detect both expected and unexpected information in large and changing information spaces. Yi et al. (2008) identify four processes: (i) provide overview, which encompasses the methods used by an analyst in gaining an overview of the data; (ii) adjust, which is the way in which the analyst explores data (filtering, selecting and changing their view of the data); (iii) detect pattern, which relates to the discovery of structure and trends in the data; and (iv) match mental model, which is the link between real world knowledge and expertise (mental model) and the visual representation.

Visualisation tools have been created which, in addition to visualising existing datasets, also allow users to visualise their own data of various types, and often to share it with others. For example, Many Eyes allows quick upload of data, and offers web-based data visualisation in a range of formats, including treemap, network diagram, stack graph, bubble chart, geographical map, scatterplot, tag cloud (Viégas et al., 2007). Such advances have made data visualisation possible even for those who have little or no technical expertise. Figure 1 gives some examples of visualisations created using Many Eyes, which are representative of many visualisation applications. Comparative data can also be visualised using Many Eyes, as shown in Figure 2. These typically use size or position to describe the data. These and similar examples can typically be created from spreadsheets.

Figure 1: Examples of data visualisations

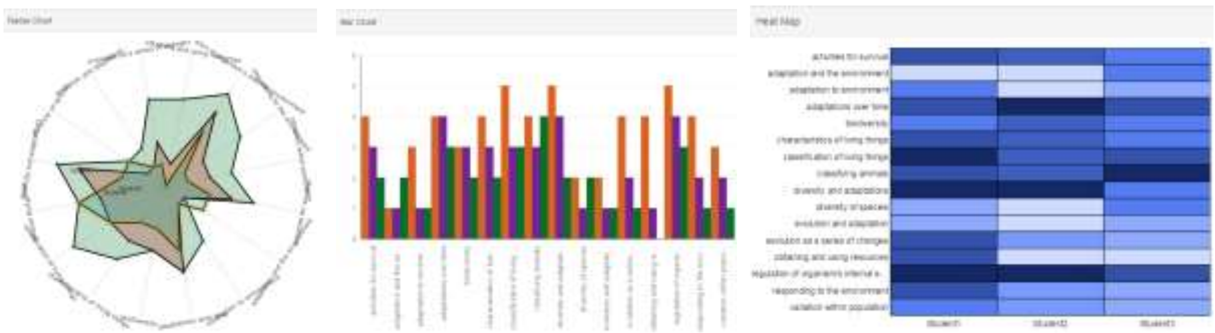

Figure 2: Examples of comparative visualisations

Many other visualisation methods have also been used in a variety of contexts. Common approaches include: lines, dots, glyphs (combining multiple visual variables, e.g. colour, size, shape), icons, clockmaps, plots, charts, maps, trees, networks, enclosure diagrams (e.g. sunburst, treemap), geographical maps (Parsons & Sedig, 2014). However, there remains a need for investigation into the relative cognitive utility of different visualisation methods (Parsons & Sedig, 2014).

VizDeck, a web-based visual analytics tool, automatically recommends appropriate visualisations of relational data according to the statistical properties of the data (Perry et al., 2013). An initial evaluation found this automated approach to be especially effective for aggregating results, comparing trends in data, and visual exploration of a scientific dataset; and the authors suggest the potential to increase the automation of visualisation selection in visual analytics systems.

Zhang et al. (2012) presented a comparative review of state-of-the-art commercial visual analytics systems: their review covers both general purpose visual analytics tools as well as business specific tools. Their findings show that the tasks supported by all reviewed visual analytics systems fell into the categories of *exploration*, *dashboards*, *reporting* and *alerting*. Users can explore data and generate hypotheses through a visual analytics system. Dashboards are the interfaces through which findings are communicated, and the users can select, filter and drill down to relevant information. Reporting refers to the generation of static reports, and alerts are where the system informs users about information of potential interest.

Surveying evaluations in information visualisation, Lam et al. (2012) identified evaluations that were classified as either *process* or *visualisation*. Process: identifies the information processing practices, work or analysis; assesses how a visualisation tool supports data analysis and reasoning about the data; assesses the communicative value of visual information with reference to goals; aims to understand how a visualisation tool supports data analysis performed collaboratively. Visualisation: aims to measure objectively, how features affect people's performance; elicits subjective perceptions and feedback about a tool; and captures and measures the characteristics of a visualisation algorithm. As indicated above, Parsons and Sedig (2014) highlight the need for systematic study of the ways in which visualisations influence cognition, for example, to support: higher-order thinking processes; discovery of the structure of information spaces; and decision-making.

Thus, there is a large body of research on visual analytics, that can be applied in research on visual analytics for education, as well as extended (for example, linking visualisation methods with cognitive utility, as urged by Parsons & Sedig, 2014). This report first considers the area closest to general visual analytics research: the more common types of learning analytics visualisations or dashboards. It then considers educational data visualisation where some aspect of the learner's learning is visualised (as opposed to their activity, performance or interaction behaviour), and finally describes approaches in open learner models – externalisations of models of learners, which are usually applied in personalisation of educational interactions.

3 Learning Analytics Visualisations

Learning analytics and data visualisation have gained much interest in recent years. This Section presents two key areas of learning analytics visualisations: the first, learning portals which are now in common use in schools (and elsewhere); and the second, learning analytics dashboards, with examples often based in research – though, as yet, there is still relatively little evidence for the relative effectiveness of different visualisations. This is in line with the discussion above, of the relative lack of research into the cognitive utility of different visualisations in visual analytics more generally.

3.1 Learning Portals

In the education context, users such as teachers may use a portal that has been chosen for use across their institution as a whole. In the UK, for example, Frog Education http://www.frogeducation.com, which won the 2015 ICT Company of the Year – Between £1m and £10m turnover, at the UK Bett Awards which celebrate and showcase achievements in ICT in or for education). Schools are already routinely using such products, for example in Birmingham alone there are very many schools of various types selecting Frog Education; the following are just a small selection illustrating the different types of school that have opted for this product: Glenmead Primary School (https://glenmead-bham.frogprimary.com/); The Phoenix Collegiate Secondary School (http://www.phoenixcollegiate.org/); Broadway Academy (http://www.broadway-academy.co.uk/); Archbishop Ilsley Catholic School (http://www.ilsley.bham.sch.uk/); Hodge Hill Girls School (http://www.hodgehgs.bham.sch.uk/); Queensbridge School for Visual and Performing Arts (http://www.queensbridge.bham.sch.uk/); James Brindley School - for children in hospital or otherwise unable to attend school because of medical conditions (http://www.jamesbrindley.bham.sch.uk/); The University of Birmingham School, the first UK university school which opens in September 2015 (http://www.universityschool.bham.ac.uk/). VLEs or learning portals with enhanced reporting options are, therefore, not only the subject of research, but are indeed at the centre of learning in schools.

Amongst the benefits of such portals, Frog Education's website advertises the possibility to allow teachers to identify gaps in knowledge and monitor progression – much as other approaches to learning analytics (see Section 1.3) using, for example, simple visualisations that adopt the traffic lights metaphor. Amongst the uses of Frog is to update parents on their children's progress, allowing them to more easily be involved in their children's learning. In addition, the aim is to move from time spent on reporting, to supporting teaching and learning. Other such environments that provide reporting functions for students, parents and teachers include amongst many others: itslearning (www.itslearning.com); GEPI (http://gepi.mutualibre.org); and 3sys (http://www.wcbs.co.uk/products/3sys).

The well-publicised Khan Academy (www.khanacademy.org) acts like a portal to a range of activities, allowing information on topics mastered and those needing further practice to be seen, as well as using badges to indicate progress. This is illustrated in Figure 3 (top, mastery of topics; bottom, badges earned).

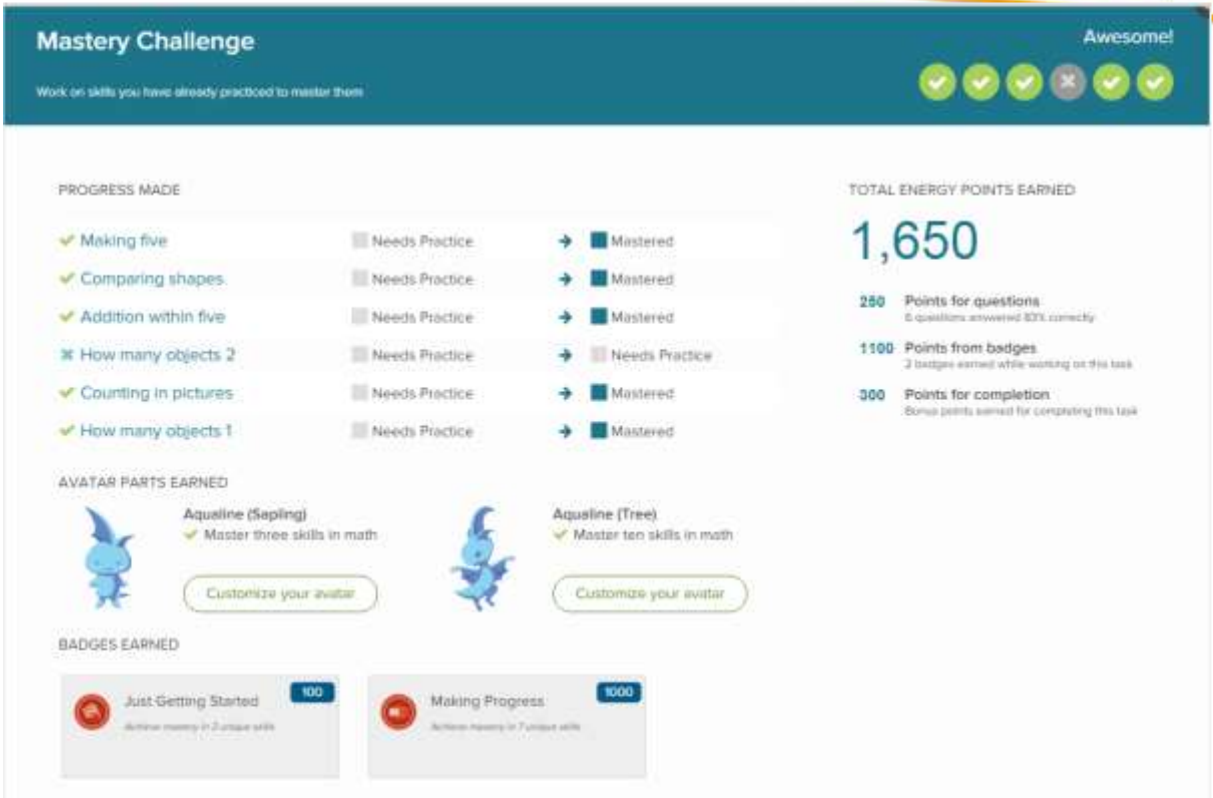

Figure 3. Khan Academy (www.khanacademy.org)

The remainder of this section follows up on these examples of a VLE/portal in routine practical use, from the perspective of research on learning analytics and, in particular, research into learning dashboards which may provide more detail in the information reported than typically occurs in reporting.

3.2 Learning Dashboards

As 'big data' arrived in education, the potential was identified for learning analytics to track learning, reveal patterns, or identify at-risk students, as well as to guide reform and support educators in improving teaching and learning (Siemens & Long, 2011). This interest has resulted in research into the use of learning analytics dashboards as a useful way to display learning data (e.g. Brown, 2012; Charleer et al., 2014; Duval, 2011; Verbert et al., 2013). Dashboards have been used at all levels, including institutional, regional and national level (West, 2012). Based on an investigation of many learning analytics tools, Dyckhoff et al. (2013) identify the role of learning analytics as to: track activities; capture interaction with resources and other students; obtain data from other systems; provide feedback and overviews; highlight important items; offer different perspectives on data; offer comparison options; highlight correlations; identify problems and provide early warnings; and support decision-making. Importantly, learning analytics visualisations enable learning analytics data to be actionable – i.e. usable as a support for support decision-making (Brown, 2012).

In classroom use, while learning visualisations often reflect counts of activity data (e.g. number of pages visited, interaction patterns with materials or other students, time online), there is increasing recognition that learning analytics are about *learning*, and so should reveal *pedagogically useful* information (Gašević et al., 2015). For example, in a learning analytics toolkit for teachers, teachers can be supported in understanding large datasets to help them reflect on their teaching, by comparing activity and/or performance indicators: e.g. a chart showing whether exam performance is higher for those who interacted with an online exercise on a continual basis (Dyckhoff et al., 2012). Teachers can be helped in their action research questions (e.g. relating to quality of materials or interactions between students, and their pedagogical approaches) by including teacher data in indicators (Dyckhoff et al., 2013). Social learning analytics dashboards can help teachers interpret learner-learner interactions, for example, by counting interaction activities (e.g. ratings, followers, etc., in social networking); analysing forum contributions (e.g. discourse analytics for content or help requests); identifying class leaders and disconnected students (Ferguson & Buckingham Shum, 2012). Learners can also receive feedback about their interaction with others in social learning situations: for example, that they have demonstrated reasoning and extended arguments, but have not tended to challenge others (Ferguson & Buckingham Shum, 2012). Visualisations of affective states (e.g. boredom and frustration) may also be available (Ruipérez-Valiente et al., 2015). Furthermore, learners and teachers may benefit from portable dashboards, for ease of use across platforms (Vozniuk et al., 2013).

Figures 1 and 2 in the previous section on Visual Analytics were created using sample performance data (from learning about adaptations in biology). These and the other visualisation methods described for visual analytics more generally are also commonly found in visual learning analytics, or learning analytics dashboards. For example: bar chart (Dyckhoff et al., 2012; Jacovina et al., 2015; Park & Jo, 2015; Santos et al., 2012); bubble chart (Tervakari et al., 2014); circle packing visualisation (Tervakari et al., 2014); histogram (Leony et al., 2012; Tervakari et al., 2014); network (Ferguson & Buckingham Shum, 2012; Tervakari et al., 2014); pie chart (Jacovina et al., 2015; Tervakari et al., 2014); radar plot (Ferguson & Buckingham Shum, 2012); scatterplot (Park & Jo, 2015); table (Santos et al., 2012); tag cloud (Tervakari et al., 2014); timeline (Dyckhoff et al., 2012; Leony et al., 2012; Santos et al., 2012).

As can be seen from this list and the corresponding references, it is often the case that multiple visualisations are available in learning dashboards. As well as the performance examples given in Figures 1 and 2, other data as described above, can also be presented (e.g. activity data such as participation in discussions, learner-learner interaction, interaction with online materials and exercises). Some examples from LEA's Box are shown in Figure 4 (top left, bar chart showing quantitative interaction data on the number of sessions, time taken, score, points earned; top right, competencies or learning goals on a radar plot, with data coming from different sources displayed in different colours; bottom left, levels of competency indicated by the size and colour of associated bars; bottom right, traffic light colours indicating competency levels and the number of contributing sources of data). The two top visualisations are similar to those used in many of the learning analytics solutions listed above; the bottom two are less common.

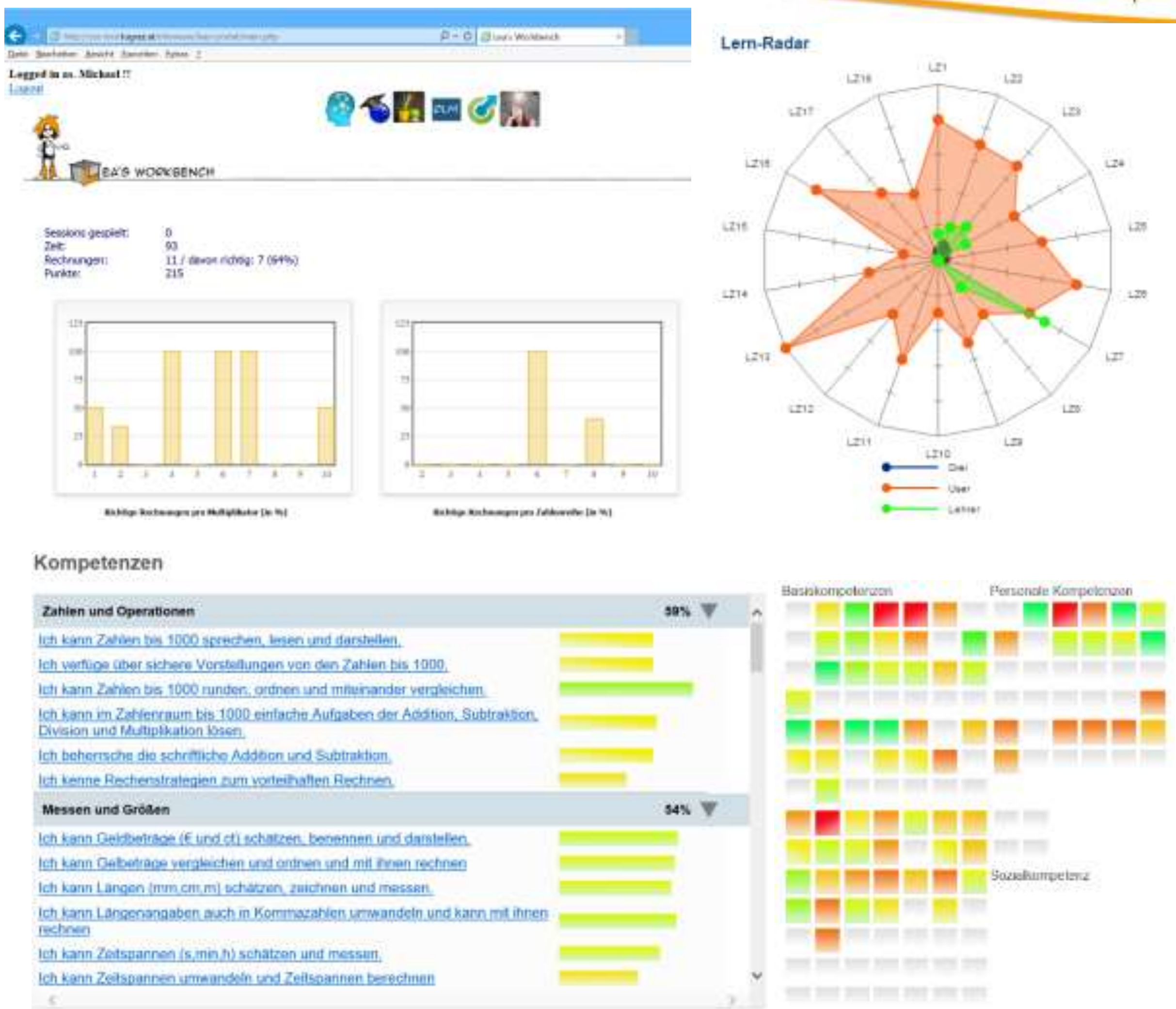

Figure 4. Examples of learning analytics visualisations in LEA's Box

While, as can be seen from this section, there are a many ways to visualise learning analytics data, it has been found that students may not necessarily understand the meaning of available (e.g. Park & Jo, 2015), and that some visualisations may be preferred over others (Vatrapu et al., 2013). While there are now many learning analytics dashboards, and in line with the situation in visual analytics more generally, further study of the relative utility of the range of visualisations would be useful.

As the field of learning analytics matures, there is greater recognition for the need for meaningful learning visualisations – i.e. they should be usable to support pedagogical decisions (see e.g. Gašević et al., 2015). It is likely that learning analytics dashboards will be transformed over the coming years.

4 Visualisation of Learning

While learning analytics visualisations often relate to activity or performance data, some types of educational data visualisation aim to visualise learning. Here we consider a few examples of how both innovative and more traditional visualisations are being used, where the visualisations are closely linked to learning.

4.1 Domain-Specific Learning Visualisations

Visualisation is often used in learning computer science-related subjects, such as programming or algorithms. An example is shown in Figure 5 from Khan Academy's 'Intro to JS: Drawing and Animation' (www.khanacademy.org). Here a learner can see that the placement of the face outline is incorrect in the code they edited. This example is directly linked to code to create drawings, and so the relationship between the two is clear. However, this idea of visualisation can be also used to illustrate the functioning of a student's code that is not intended for drawing or animation, by illustrating the effects of code. Some tools visualise the effects of a student's program or an algorithm using graphics and animation. For example, PathFinder (Sánchez-Torrubia et al., 2009) highlights where errors are found in a student-created graph by changing the colour of the node, and by showing the corresponding code in red. Jhavé (Naps & Rossling, 2007) is an algorithm visualisation tool that allows visualisation of a student's code. Thus, the student can see the effects of their code through the visualisation of it.

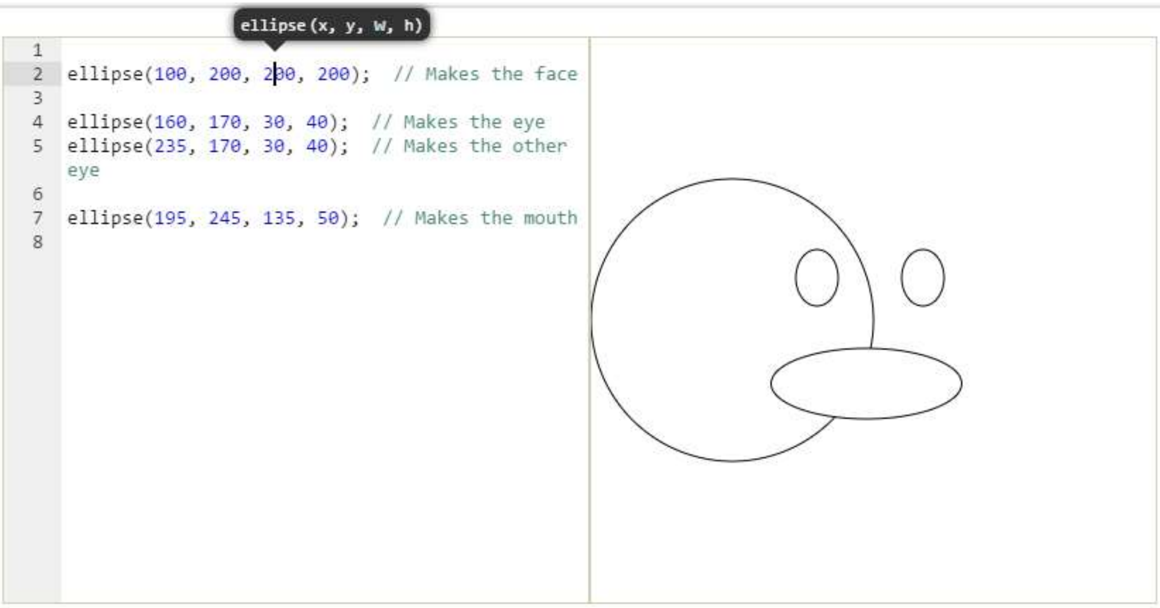

Figure 5: Khan Academy: Intro to JS: Drawing and Animation (www.khanacademy.org)

Another subject where learning data resulting from a student's work or attempts at achieving a goal is language learning. Such tools may permit students to compare their own attempts to those of a native speaker. For example, WinPitch (Martin, 2004) is a speech analyser and visualiser that allows students to listen to words or sentences pronounced by native speakers, and view the resulting spectrograph. They can compare this with their own pronunciation of the same word or sentence. rEcho (Zhou et. Al., 2007) is a computer assisted language learning tool that provides students with a visual comparison (formant, tone, vocal tract shape and motions) for a native speaker and for the student's own pronunciation.

Benefits of environments such as those in this section are that, in addition to the many examples of graphics and animation to help learners understand processes, these visualisations help learners to understand the state of their own learning, and can facilitate reflection on their developing knowledge – especially when they are able to compare their own production to that of an expert. The difference between these examples and those from learning analytics given previously, is that aspects of visualisation are inherent to the specific subjects being studied: here, computing and second language learning.

4.2 Domain-Independent Learning Visualisations

The previous section gave examples from visualisation in subject-specific contexts. These allow in-depth visualisation that is less easily achieved for visualisations available for use more generally. Nevertheless, some approaches take a domain-neutral approach.

Wordle (http://www.wordle.net/) allows users to create free wordclouds online. It has been used 'in-the-wild' in a range of contexts, including mainstream media, personal usage such as in blogs or to illustrate song lyrics, and education (Viejas et al., 2009). Simple visualisations can be creatively used in classrooms. As well as being used to illustrate word frequency in texts, with larger words indicating higher frequency of that word in a submitted text, instructors can also use them to reflect students' writing and progress over time, back to the students. This has been done, for example, for university students learning a foreign language, where the combined texts of all students was used to create a word cloud for each of the drafts of a text (Baralt et al., 2011). Students were able see these word clouds at each stage, to recognise the group's progress and compare this across drafts to see, for example, how their vocabulary was increasing, and identify grammatical inconsistencies (e.g. correct versus incorrect verb declensions). The instructor was able to direct attention to items in the word clouds as appropriate during their writing workshops. Used in this manner, the word clouds can be seen as representations of various stages of group learning. Given that it is text-based, this approach can be applied in a variety of subjects.

Complex approaches are also possible. For example, a Hasse diagram is a directed graph that reads from bottom to top, which is used to represent the structure of a domain, and to visualise a learner's progress through this domain. Therefore, a Hasse diagram shows all the possible competences (or the complete knowledge space), with the learner's path highlighted. An example from LEA's Box is given in Figure 6. As long as users understand the meaning of this complex visualisation, they can look at the learning path(s) indicated. For example, a teacher can observe routes students have taken, while advanced level students may compare their own learning paths with those of others.

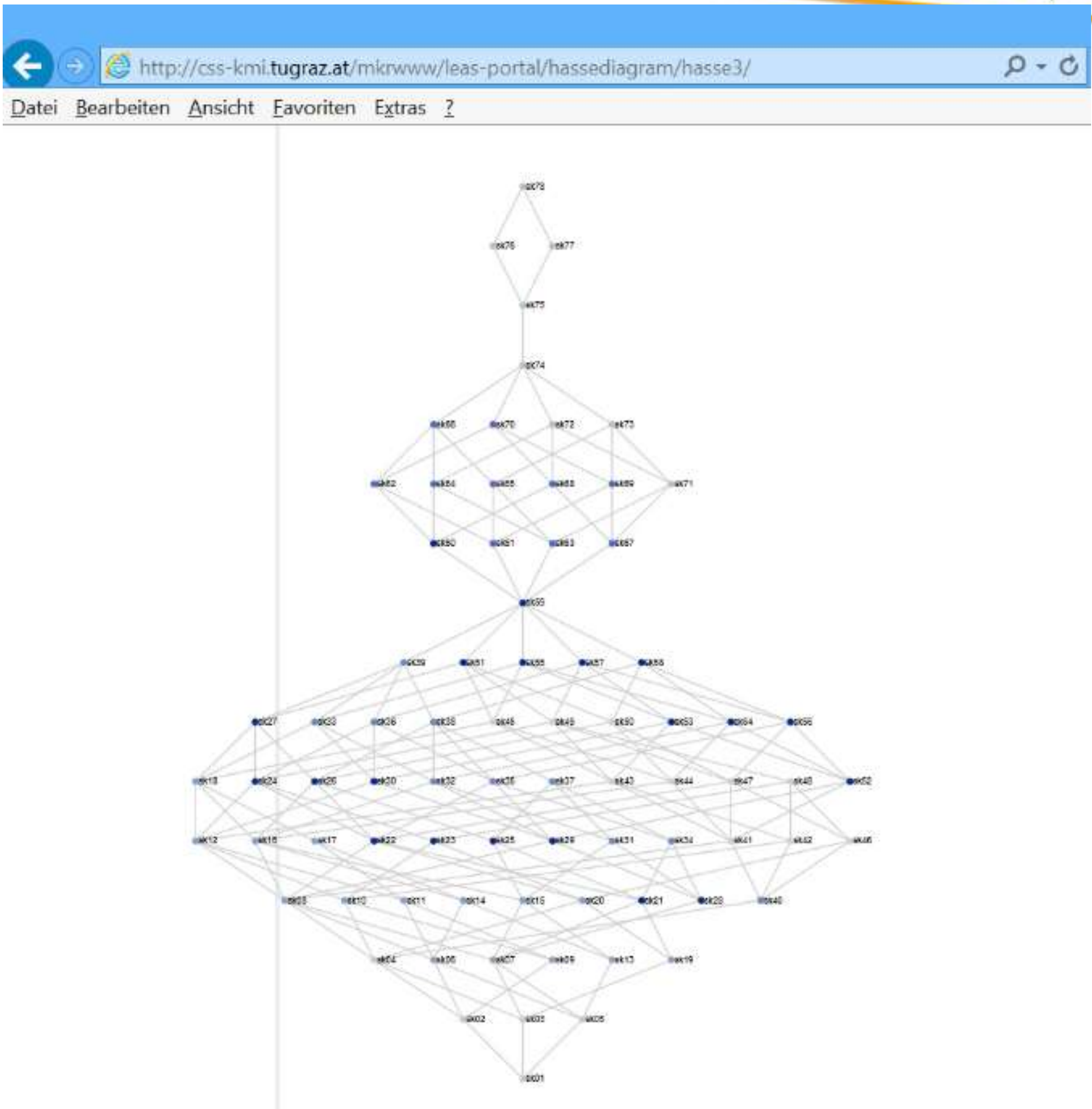

Figure 6: Hasse diagram

Approaches such as in the Wordle example (Baralt et al., 2011) can be quite easily used in a range of contexts. Hasse Diagrams are very much more complex, but can also be used generally if an appropriate structure is built. Thus, the same approach may be used across a range of subjects, which allows information about learning or progress to be presented in a consistent way for students. This is, of course, also true of many learning analytics approaches. The examples here, however, can be used independently of a portal or institutional VLE, especially the simple approach offered by tools such as Wordle. Therefore, if a teacher finds a visualisation that is currently not possible with the tools they have available, they can easily supplement their teaching with other learning-based visualisations. An example of the use of Wordle to visualise the contents of this document is given in Figure 7. This reflects the content based on word frequency, where it can be easily seen that the core issues relate to data, learning and visualisation. In an educational setting, individuals or groups could use such visualisations to reflect on or prompt discussion on the most common terms displayed in each visualisation, and work out which are the most important concepts.

If the visualisation does not convey what they expect, they can revisit the document to check whether it is written according to the requirements.

Figure 7: A word cloud visualisation of the content of this document (created with www.wordle.net)

5 Open Learner Model Visualisations

As is the case for learning analytics and other visualisations of learning, there have been various ways of displaying open learner models (OLM). A very common method of visualising the learner model is to use a set of skill meters relating to topics, competencies, understanding, etc., which may also be structured to show sub-topics, sub-competencies, specific concepts, and so on (e.g. Bull et al., 2010; Corbett & Bhatnagar, 1997; Duan et al., 2010; Long & Aleven, 2013; Mitrovic & Martin, 2007; Weber & Brusilovsky, 2001). Figure 8 gives examples of skill meters from the Next-TELL OLM (Bull et al., in press); and OLMlets (Bull et al., 2010).

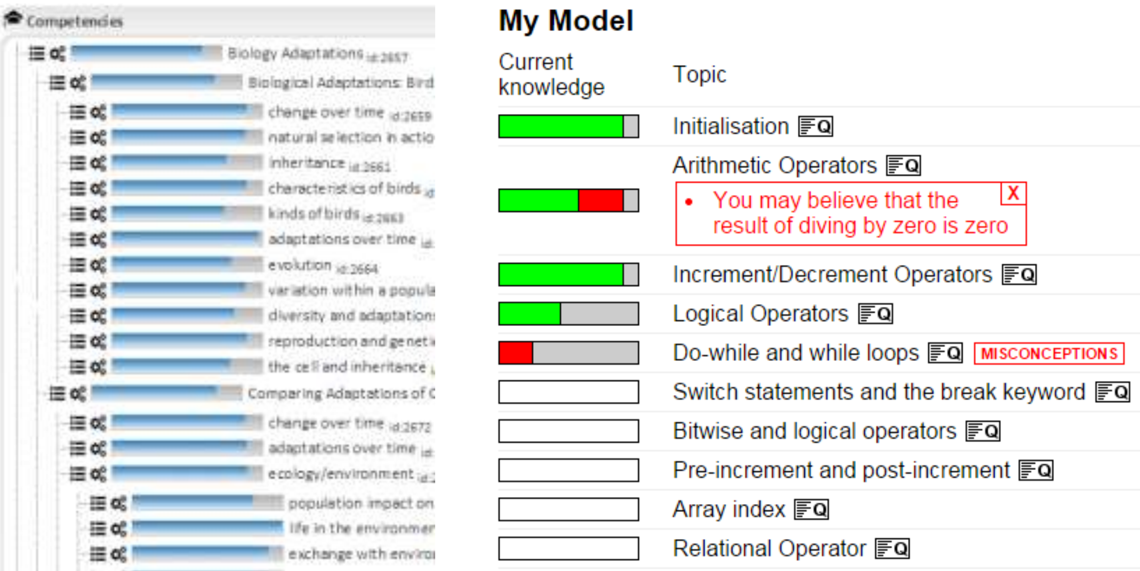

Figure 8: Next-TELL OLM skill meters (left), OLMlets skill meters (right)

Typically, skill meters indicate the extent of understanding, or level of skill or competency as a subset of expert knowledge/skill, by the shaded portion of the corresponding meter. In the Next-TELL OLM example (left of Figure 8), the hierarchical structure of the domain is also shown. In the OLMlets example (right of Figure 8), the extent of misconceptions held is shown (in red), and a link (labelled misconceptions) allows learners to view a brief description of the specific misconceptions that have been identified, during an interaction. (The misconceptions are not automatically displayed, to allow the opportunity for learners to try to discover the problem for themselves, if they so wish.)

Other simple visualisations include ranked lists. For example, the left of Figure 9 shows the ranked skill meters of UMPTEEN (Bull et al., 2007), and the right of Figure 9 shows the ranked list in Flexi-OLM (Mabbott & Bull, 2004). While the previous skill meter examples maintained a consistent sequence in the competency labels, to allow users to find the relevant information when they have a specific competency or area of the curriculum in mind, the ranked layouts allow learners and teachers to most quickly identify strengths and weaknesses.

Figure 9. UMPTEEN skill meters (left), Flexi-OLM ranked list (right)

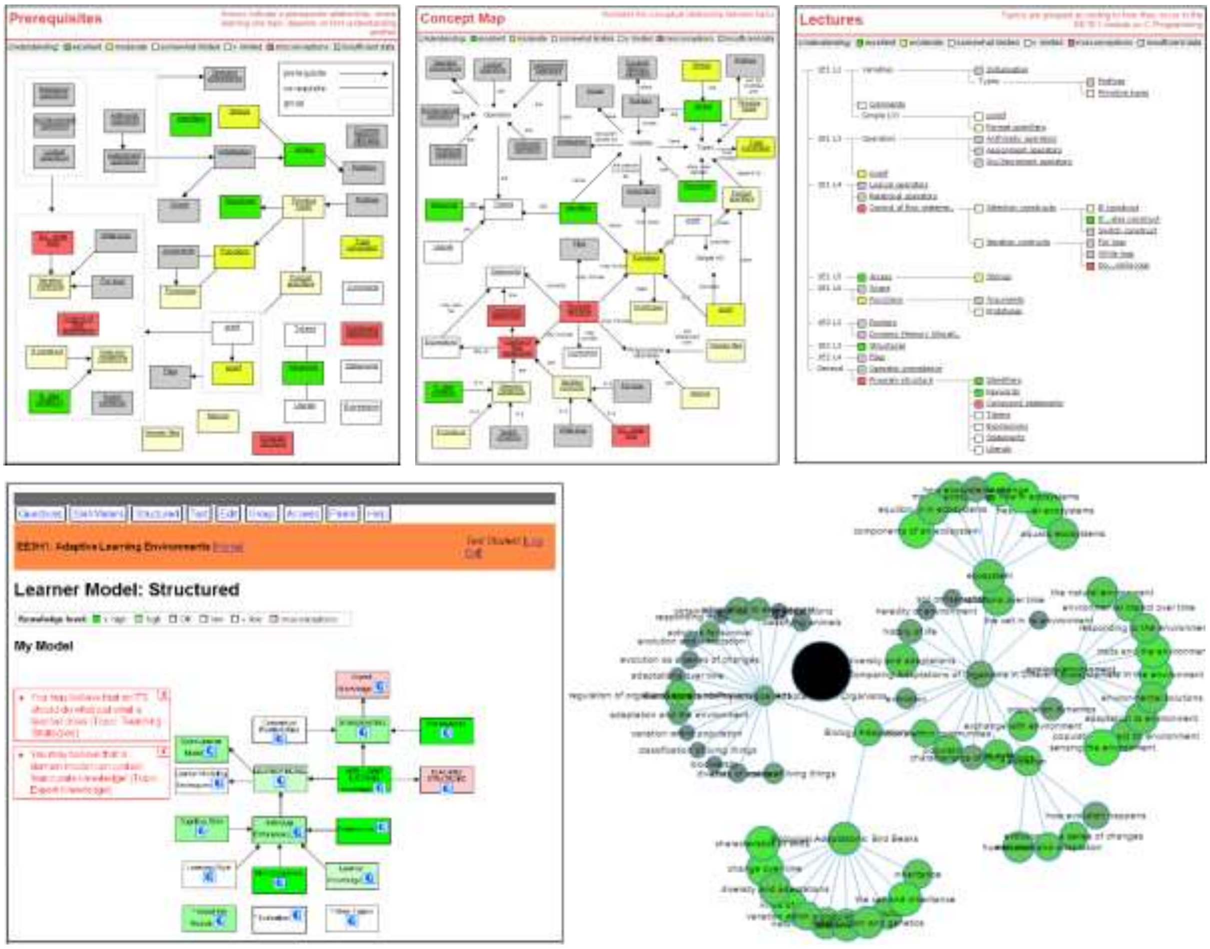

Figure 10: The Flexi-OLM pre-requisite structure (upper left), concept map (upper middle), lecture structure (upper right); tOLMlets concept map (lower left); the Next-TELL and LEA's Box OLM network view (lower right)

Other learner model visualisations that have been used in a variety of systems include map views such as concept maps (e.g. Duan et al., 2010; Mabbott & Bull, 2004; Perez-Marin et al., 2007) or pre-requisite maps (Mabbott & Bull, 2004); and hierarchical tree structures (e.g. Conejo et al., 2011; Duan et al., 2010; Kay, 1997; Mabbott & Bull, 2004). Figure 10 gives examples of visualisations showing such relationship information, from Flexi-OLM (Mabbott & Bull, 2004): upper left, pre-requisite structure; upper middle, concept map; upper right, lecture structure. The lower left of Figure 10 shows a concept map with a smaller number of topics (Ahmad & Bull, 2009). Network visualisations (bottom of Figure 10) can show similar structural information (e.g. the LEA's Box and Next-TELL OLMs (Bull et al., in press)).

Along with the general increase in data visualisation, new methods of information visualisation have developed. These are now also beginning to be adopted in OLMs, for example: overview-zoom-filter treemaps (e.g. Bakalov et al., 2011; Bull et al., in press; Kump et al., 2012) where users can drill-down to the next layer of information, and similar sunburst views (Conejo et al., 2011); and tag or word clouds (Bull et al., in press; Mathews et al., 2012). Figure 11 shows examples from the Next-TELL OLM (Bull et al., in press), also used in the LEA's Box OLM. The treemap (upper) indicates how the extent of understanding of topics, concepts or skills are illustrated by the size of cells, and when clicking on a cell (in this example, ecology/environment), extent of understanding of the topics in the next layer of the hierarchy are shown. In the word cloud (lower), strengths are indicated by large blue text (left), with weaker areas of understanding shown in large black text (right). This visualisation is better for a quick overview of extremes, whereas the treemap allows exploration of larger hierarchies within a smaller space. The network visualisation from Figure 10 also allows exploration to be focussed within specific areas, by expanding and collapsing nodes. While the Flexi-OLM visualisations in Figure 10 do not permit such interactions, given that they fit comfortably on the screen in the context for which they were designed, this is less of a requirement. However, some similar structures do provide this functionality to accommodate potentially large structures (e.g. Kay, 1997); as do some skill meter visualisations (e.g. Weber & Brusilovsky's (2001) adaptive hypermedia ELM-ART system, which includes skill meters alongside the structured, expandable navigation links).

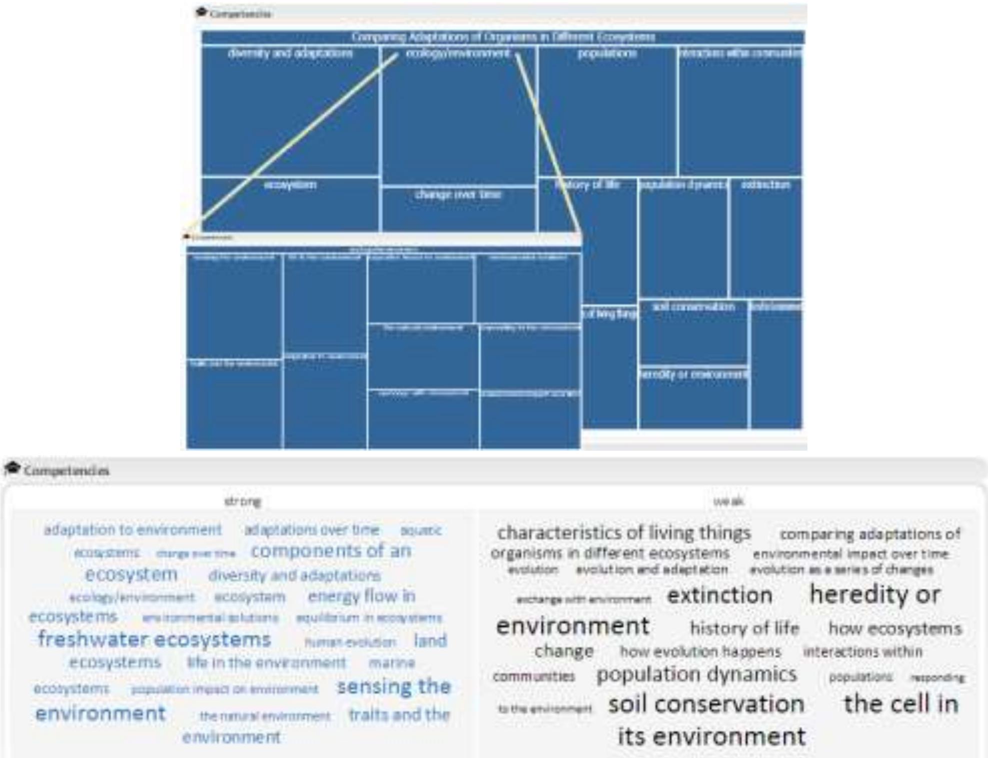

Figure 11: The Next-TELL and LEA's Box OLM treemap (upper) and word clouds (lower)

While many OLMs use a single visualisation, as can be seen from the above descriptions, some systems provide multiple visualisations (e.g. Bull et al., 2010; Conejo et al., 2011; Duan et al, 2010; Johnson et al., 2013; Mabbott & Bull, 2004; Mazzola & Mazza, 2010). This permits users to flexibly access their learner model in different ways, as suits their current goals, as well as catering for different preferences (Mabbott & Bull, 2004; Sek et al., 2014).

The above example visualisations are general, in the sense that they could be used in a range of subject areas. Other general visualisations include the number of arrows in a target to portray skill level (Brusilovsky et al., 2004); and trees at different stages of growth to indicate knowledge level, with dying trees indicating misconceptions (Lee & Bull, 2008). These are similar to the simplicity found in skill meters (e.g. Figure 8). The latter are illustrated in Figure 12.

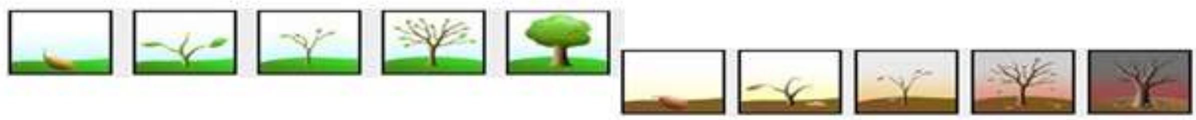

Figure 12: The Fraction Helper OLM trees, with summer green growth indicating increasing skill and bare trees indicating increasing skills but with some misconceptions.

General visualisations that are more similar to those typically found in learning analytics have also been used, such as bar charts and pie charts (Mazzola & Mazza, 2010), tables (Bull et al., in press; Conejo et al., 2011); and radar plots (Bull et al., in press; Mathews et al., 2012). In addition, domain-specific visualisations have been developed, for example, audio chords and music notation matching the learner's music understanding (Johnson & Bull, 2009) and animations of the execution of programming code, and of chemical reactions for comparison to expert knowledge, including animations of the outcome of misconceptions in these subjects (Johan & Bull, 2010).

In contexts where multiple visualisations are available, it has been found that while there may be general tendencies, there are also some individual differences in learner preferences for the visualisation(s) to access (Bull et al., in press; Mabbott & Bull, 2004; Thomson & Mitrovic, 2010).

5.1 Learning Analytics Dashboards and Open Learner Models

While research in learning analytics dashboards and open learner models originated in different sub-fields of Technology-Enhanced Learning, they are beginning to be mentioned in the same publications (e.g. Bull et al., 2013; Durall & Gros, 2014; Ferguson, 2012; Kalz, 2014; Kay & Bull, 2015; Nussbaumer et al., 2015; Shoukry et al., 2014). Although an intelligent tutoring system (i.e. with a learner model), some systems provide data more typical of learning analytics than OLMs: i.e. it is the activity data rather than inferred information about learning, that is shown (e.g. Jacovina et al., 2015). This can also be the case for adaptive educational hypermedia (e.g. Papanikolaou, 2015). It is also possible for activity data and knowledge data to be combined, for example, with activity or performance information supplementing or providing evidence for the knowledge or skill data (Bakalov et al., 2011; Bull et al., 2014; Kay, 1997 Verginis et al., 2011; Weber & Brusilovsky, 2001); or for activity visualisations from different tools to be used separately from the OLM to which the tools contribute data (Johnson et al., 2013). Furthermore, as learning analytics starts to consider issues such as prompting metacognition (e.g. Durall & Gross, 2014) or self-directed learning (e.g. Dawson et al., 2012), which are amongst the original aims of open learner models (see Bull & Kay, 2007), it is likely that designers from both fields will benefit from the ideas, lessons and findings of each other.

6 SUMMARY

This Deliverable introduced the general field of visual analytics, which has been applied in a variety of areas and tools. In that context, Zhang et al. (2012) identified four categories of visual analytics: exploration, dashboards, reporting and alerting. In the context of this Deliverable, we have focussed on dashboards and visualisations in particular, with learning analytics dashboards and portals, representations relevant to learning yielded from learners' products or interactions, and open learner models. However, many of these can sometimes also be used for reporting, exploring data and alerting users to new or important information. Parsons and Sedig (2014) found a need to clearly identify which types of visualisation are most appropriate for visual analytics, and this is also the case in learning analytics dashboards. In open learner model research, there has been some investigation into the different visualisations used by learners, with findings suggesting that there are individual differences, but also some more general preferences (e.g. Bull et al., in press; Mabbott & Bull, 2004; Thomson & Mitrovic, 2010). Here, too, further investigation might help determine whether certain visualisations are more appropriate in certain cases, or whether individuals should be able to access visualisations according to their own choices.

Future research in LEA's Box will follow up on this latter point, with reference to actual use of the visualisation tools by students and teachers, as well as their stated preferences, and the context of their use. This will include investigation into new visualisations developed during the project. Data may be visualised in different ways, for example, the countable data often at the core of learning analytics visualisations commonly uses standard charts, graphs and plots, etc., while open learner models tend to use different types of visualisation, such as skill meters, concept maps, hierarchical structures or, more recently, enclosed structures such as treemaps. We will aim to investigate the extent to which different visualisations suit different purposes for viewing data, and different data types. With this we aim to help researchers and developers in both learning analytics and open learner modelling to decide which visualisations are most effective for their purposes, if any, and how much autonomy (ad when autonomy) over choice of visualisation is helpful for the user.

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