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Understanding our Analytics: A Visualization Survey

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ABSTRACT: Visualization is already a part of Learning Analytics, used to convey or clarify observations of and patterns from the data. We examine what types of visualizations and supporting features are included in commercial and academic analytics solutions. From this comparison, we find that there is another academic field, Information Visualization, that can be brought to bear on Learning Analytics. By introducing these new techniques and theory, we must make a determination on visualization approach in analytics; exploratory or targeted, informed solutions based on sound pedagogical input. Our analysis suggests that investigating applying Information Visualization would be a worthy area of endeavour.

KEYWORDS: Learning analytics, data visualization, Information visualization, survey, exploration

1. MOTIVATION

The entire purpose of Learning Analytics is to enable practitioners to take appropriate action in response to any exceptions in their teaching. An underlying assumption of this is that: a) the practitioner understands the information provided in the first place, and b) could and do take appropriate actions. The response, while not unimportant, is somewhat individual – based on the practitioners training, experience, and teaching philosophy as well as institutional policy. This observation indicates that communicating the information or message from analytical and predictive models becomes paramount (Siemens & Baker, 2012). The field of Information Visualization explores how information is communicated and shared graphically (Yi J. , Kang, Stasko, & Jacko, 2008). Analytics (not just within the education sector) is about discovering, sometimes complex, patterns within data sets and communicating them (Bose, 2009); Information Visualization provides an obvious possible solution. We are therefore investigating how many and which visualization theories and tools are employed in Learning Analytics products, tools, and dashboards. SOLAR has published investigations linking Learning Analytics and Information Visualization previously (Charleer, Klerkx, & Duval, 2014). This paper goes further in linking visualization theory and Learning Analytics applications and suggests possible avenues for our field to explore in the future.

2. VISUALIZATION TAXONOMIES

There have been many taxonomies of visualization using particular models based on: a Data State Model (Chi, 2000); models of the dataset (Tory & Möller, A Model-based Visualization Taxonomy, 2002); specific

tasks/usages (Schneiderman, 1996); the algorithms used (Tory & Möller, Rethinking Visualization: A High-Level Taxonomy, 2004); and differences between user groups (Chengzhi, Chenghu, & Tao, 2003). Some argue (Friendly, A Brief History of Data Visualization, 2006) that Bertin created the first systematic taxonomy in his work 'Semiologie Graphique' (Bertin, 2011). This system builds an organization around relating particular graphical elements to features in the underlying data. Bertin named these relations Retinal Variables (also termed Visual Variables in referring work). Keim et al. use these observations to define Visual Analytics (Keim, et al., 2008); a distinct field focused on improving understanding by leveraging the human visual system to make judgments about patterns, values, and importance.

Most people, if not all, are inherently aware of the most common visualization techniques – irrespective of knowledge about the wider field. These include the humble line, bar, area, and Scatterplots; pie and donut charts; and tables. As part of the computing revolution, technology has been applied to visualization as well. The extra power spawned 'better looking' forms of these charts as well as three-dimensional variants and methods (Robertson, Card, & Mackinlay, 1993). The research in the Information Visualization community has defined new chart types, such as the Bubble Chart and Tag Clouds (Viegas, Wattenberg, van Ham, Kriss, & McKeon, 2007), and Stream Graphs (Byron & Wattenberg, 2008) among many others.

3. (MORE) ADVANCED VISUALIZATION TECHNIQUES

The definition of 'advanced' in this case would depend on the audience. To the Information Visualization community, items such as Heat Maps or techniques like Brushing are simply another tool in the bag. However, these same techniques in the educational/learning technology community are considered advanced and not frequently used. We will adopt the educational view for this comparison, as many practitioners will not be visualization experts. This section provides an introduction to various techniques used in analytics products. We have assumed the common types are already understood/recognised.

Badges/Glyphs

Badges, alternatively Glyphs (Borgo, et al., 2013), are symbolic icons used to define a situation summarily. When designing glyphs and badges care must be taken to ensure that for any set of inputs the same glyph must be used, i.e. the algorithms must be deterministic. Shape, size, color, and opacity are available to convey different factors, as well as combinations of shapes. Typically, we would strive to include an iconic quality; the ability for the glyph to be easily recognized at a glance and from a distance.

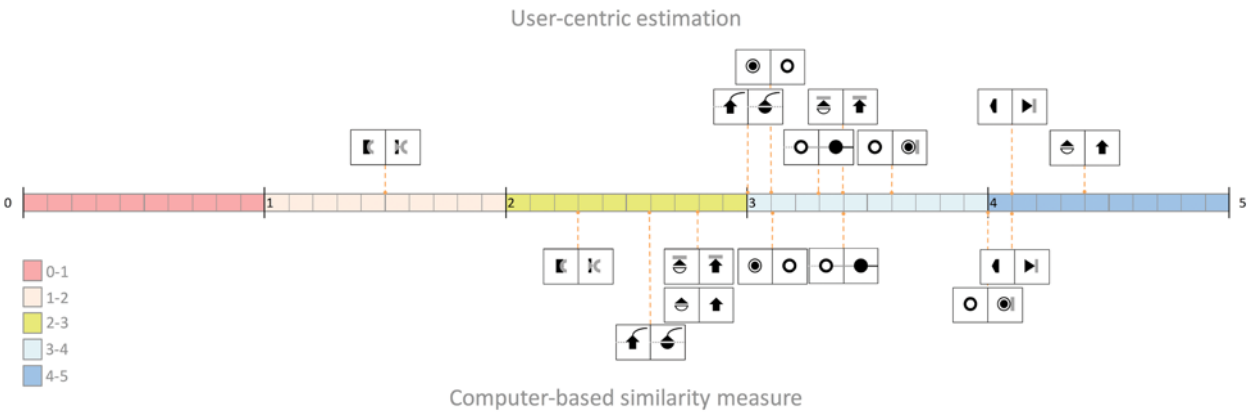

Figure 1: Glyph-based Visualization Example (Legg, Maguire, Walton, & Chen, 2017). The Glyphs are shown in the boxes attached to the timeline. Each one represents a different state of the object and so can reoccur along the length of the observation.

Headline Figures

While not strictly a visualization technique, the use of a summary statistic can convey a powerful comparative message – assuming viewers understand the range and a sense of good/bad for that metric. Typically, these are percentages or integers but may be scaled depending on range and resolution required. Often the statistic is combined with a badge or traffic light to lend further assistance as the shape and color give the comparative context.

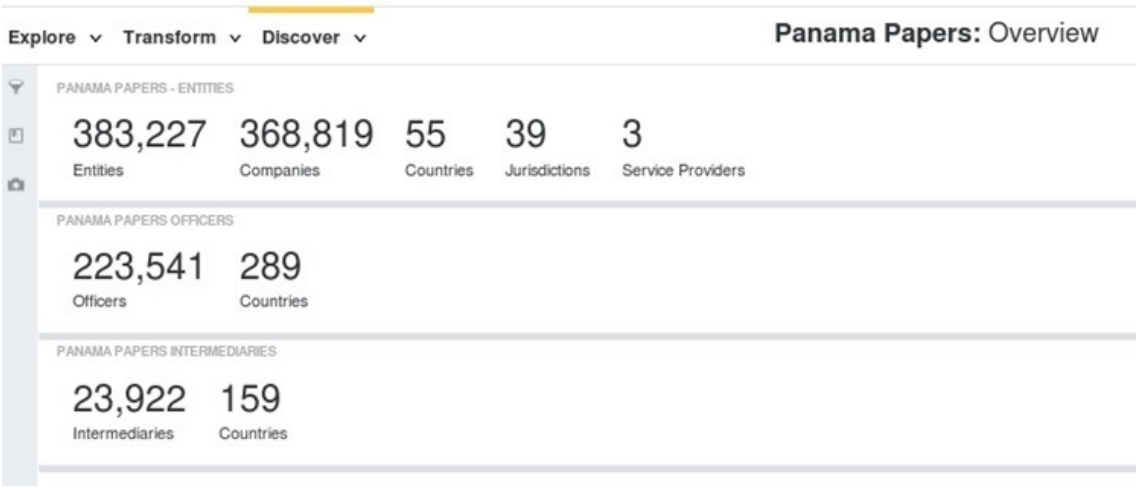

Figure 2: Examples of Headline Figures. In this example, the figures do not have any badges or other classification as they just state facts about the dataset. Often Headline Figures show summary or totals rather than individual data points.

Scatterplots

Most viewers would recognise a Scatterplot when shown one. However, the name is not as widely recognized (Friendly & Denis, 2005). Often just referred to as a 'graph', the Scatterplot compares two variables from a given object. When adding color, size, and glyphs to the plot additional dimensions can be conveyed. However, it is important not to combine too many of these features to avoid information overload.

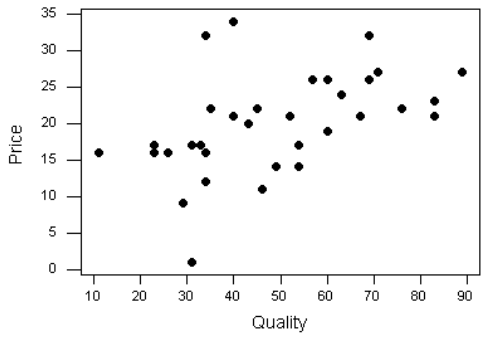

Figure 3: An example Scatterplot linking price with quality in a random dataset. This figure shows the relationship, between those two variables for each object, but makes no conclusions on wider trends.

Heat Maps

Heat Maps are typically a 2-dimensional (but can be 3D) grid comparing two categorical variables in the data set. Its origins date back to the 19th century but underwent a revival in the mid-2000s (Wilkinson & Friendly, 2009). Each cell then represents a count at that intersection, becoming more colorful, more opaque, darker, or similar for a greater or lesser value.

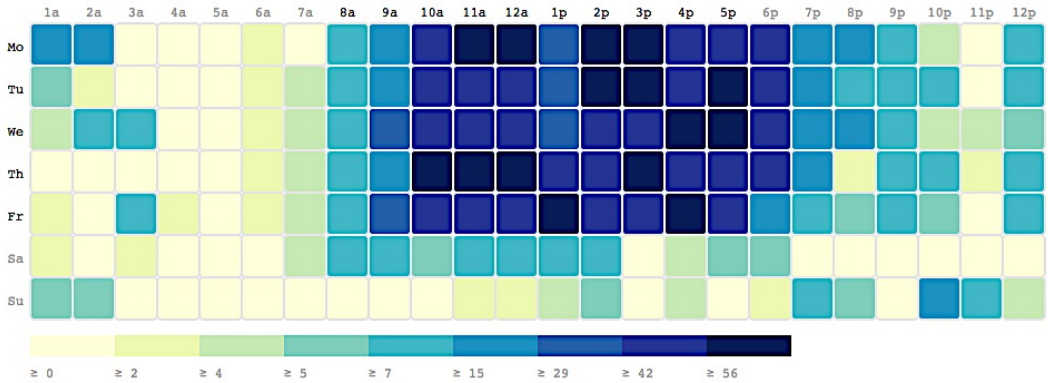

Figure 4: An example Heat Map with a Light-Dark Palette[1]. This example also provides the scale for ease of translation to numerical values.

[1] Reproduced from http://bl.ocks.org/tjdecke/5558084, image credit: Tom May.

Sunburst Charts

Originally descended from the TreeMap (Johnson & Schneiderman, 1991), the Sunburst Chart combines a radial design (similar to a Donut or Pie Chart) with layers to show relative contributions to the whole. In this chart, the segment size is used to show proportion and layers to show the hierarchical relationship to the root population. An early example is visualizing the amount of data stored in a file system, where each ring is a subdirectory (Stasko & Zhang, 2000).

Figure 5: An example Sunburst Visualization showing numbers of source files in different directories within the Flare library.[2]

Florence Nightingale Rose / Aster Plot

The Florence Nightingale Rose is named after its creator, the selfless British Nurse. She first used this visualization to support her arguments regarding sanitary conditions and their link to disease in the Crimea (Nightingale, Farr, & Smith, 1859). Originally used in 1859 (see Figure 6), this style of visualization has enjoyed a resurgence in contemporary Information Visualization (Li, Zhang, & Sun, 2016), (Kwon, et al., 2017).

[2] Reproduced from https://bl.ocks.org/mbostock/4063423, image credit: Mike Bostok, design credit: John Stasko.

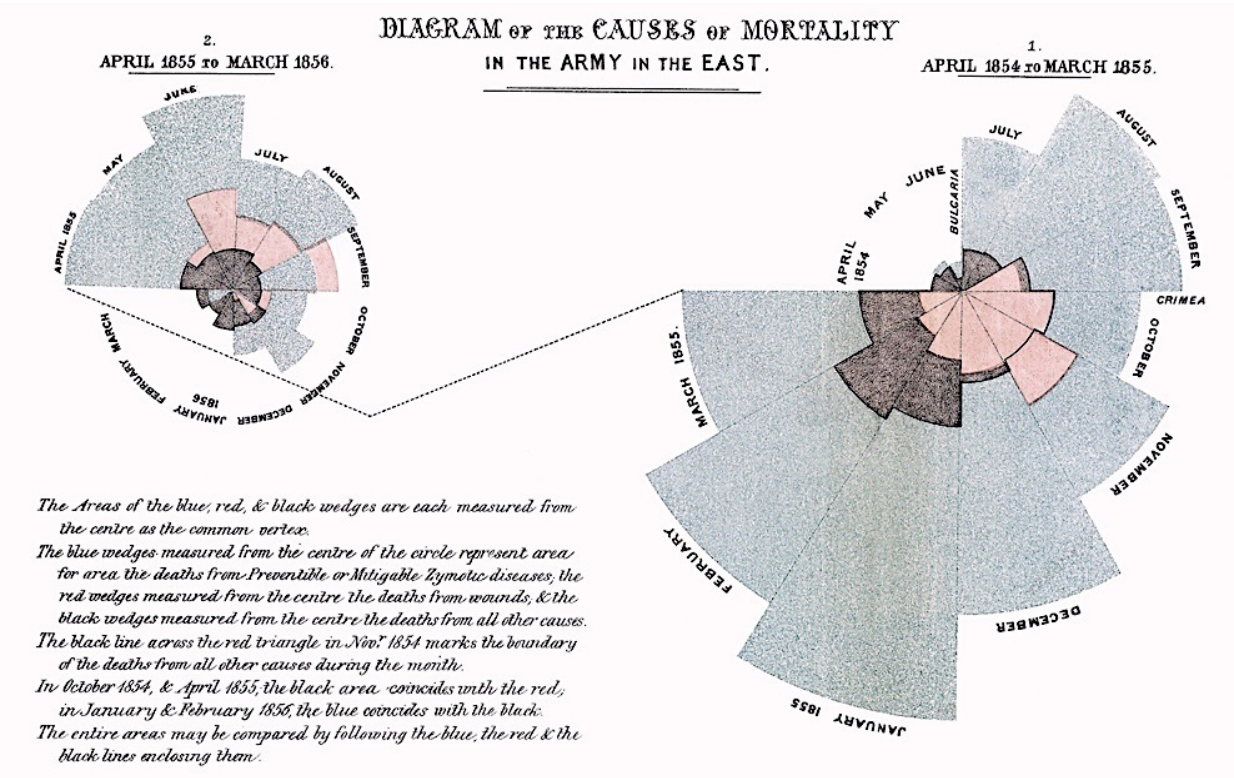

Figure 6: Reproduction of the original Nightingale Rose.[3]

Bubble Charts

Similar to scatter plots, Bubble Charts show a relationship between two variables. However, as the size, color, and other properties of each bubble can be varied, they can be used to encode other information as well. The origins of this chart appear to be lost. However, visualization websites[4] point to French civil engineer Charles Joseph Minard (1859) as one possible answer. When using Bubble Charts care must be taken to ensure that information is not double encoded; for example, in both position and size.

[3] Image taken from http://www.historyofinformation.com/expanded.php?id=3815.

[4] https://cartographia.wordpress.com/2008/06/16/minards-map-of-port-and-river-tonnage/ and https://visage.co/data-visualization-101-bubble-charts/

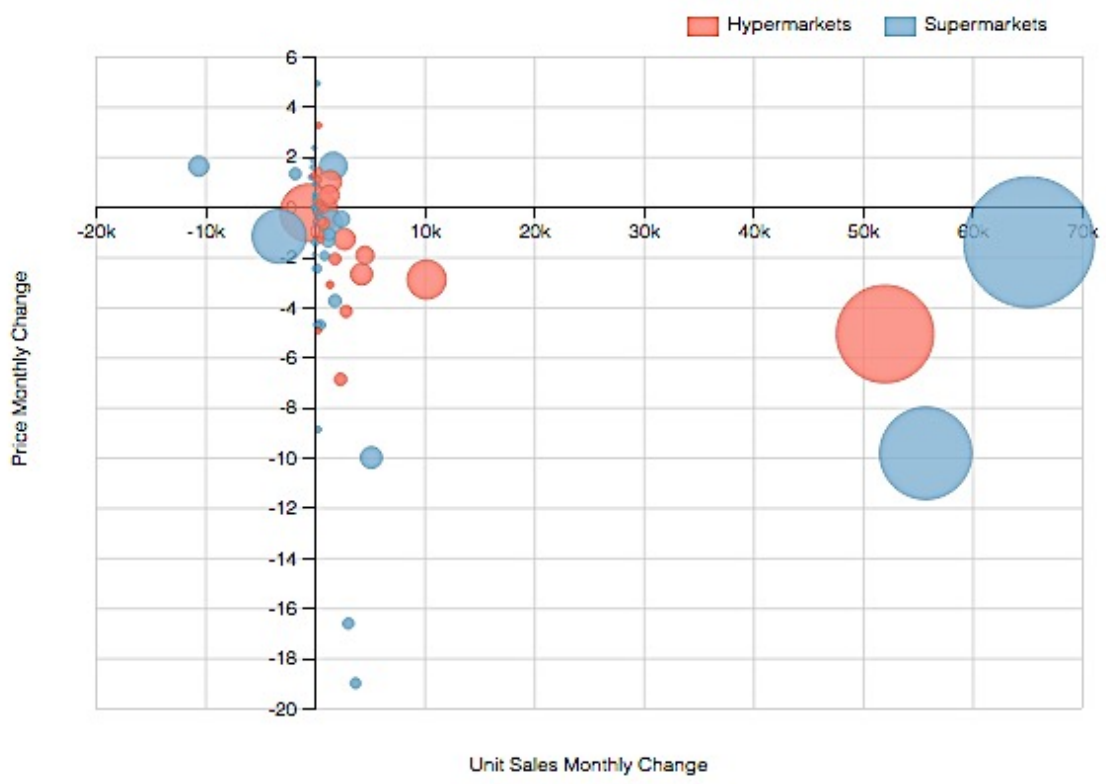

Figure 7: Bubble Chart showing the difference in Price Variation and Sales Volume Variation for two Store Types.[5] Sizes of the bubbles show the extent of the variation of the value. The center of the bubble is plotted at the average for that store on both axes. The roundness illustrates the relationship between the differences of the two factors.

Radar/Spider Plots

Originally termed 'star plots,' in use from 1877 (Friendly & Denis, Milestones in the history of thematic cartography, statistical graphics, and data visualization: an illustrated chronology of innovations, 2004); this visualization type has seen a modern revival. This plot provides a multivariate comparison for multiple series of data. It offers a similar view as Parallel Coordinate Plots but around a common center using polar co-ordinates. Differentiation between objects comes by either trying to maximize or minimize the area of the polygon created for each set of observations. Quite often a radar plot will be used to show how 'well rounded' a solution is; creating a large near circular polygon rather than one with a distorted spike toward one factor.

[5] Reproduced from http://dimplejs.org/examples_viewer.html?id=bubbles_standard.

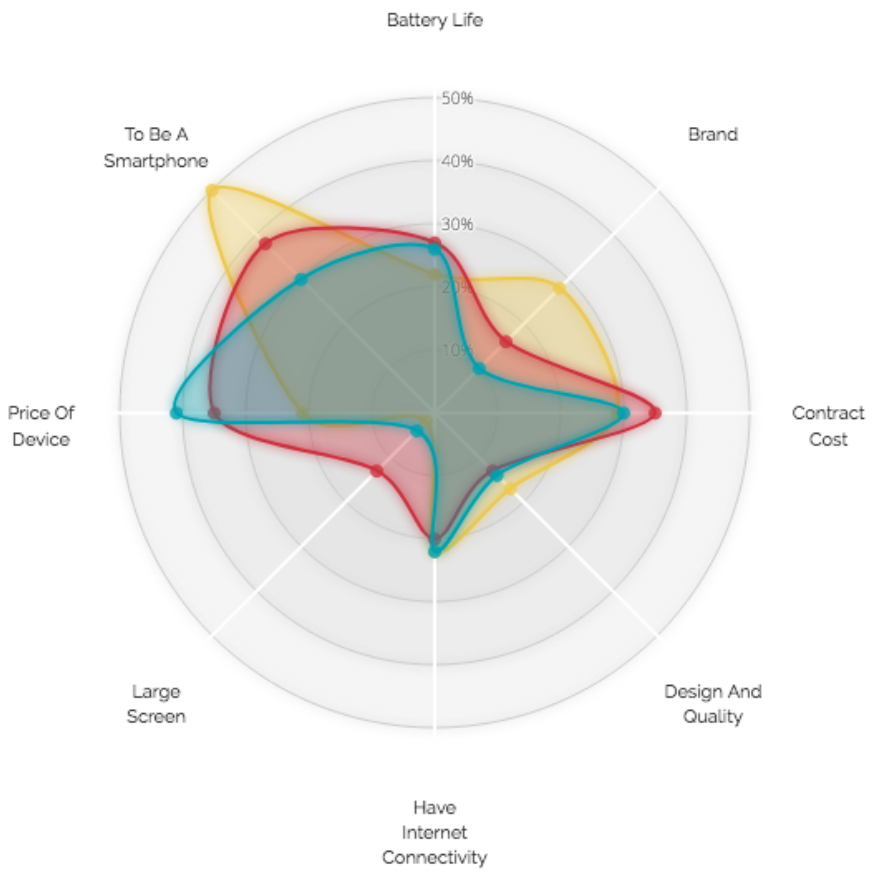

Figure 8: A Radar Plot Comparing Three Alternative Cellular Telephone Models. In this particular plot, the goal is to neither maximize nor minimize the overall area but to compare relative positions on each of the axes independently.

4. LEARNING ANALYTICS TOOLS WITH VISUALIZATIONS

We have assembled the following list of popular or most cited products and tools in the Learning Analytics arena. The information about them is taken from either published academic work or data sheets/demonstrations. We acknowledge that these sources of data are never going to be feature complete. However, this review is only concerned with the types of visualization used. Almost all tools support visualization of results, regardless of if any particular institution or organization chooses to implement them.

Using the sources cited later in this section (products are numbered for cross-referencing purposes), as well as any other media provided from those locations, we have created the following mapping of products to the types of visualizations in use – shown in

. The results are grouped in the same way as in Section 3. Wherever possible we have used demonstrations of these tools or videos thereof to gain an appreciation of the features available. However; in situations

where these are not available, we have relied on pictures and data sheets for the product.

Throughout this exercise, we have made a careful distinction between using/offering a visualization type and using that visualization effectively. The latter calls for a much deeper understanding of the goals and needs of each/every implementing institution.

Table 1: Comparative Listing of the Learning Analytics Products/Tools Examined.
Tools are numbers for cross-referencing purposes with the notes later in this section.

	Product Features			Standard Visualizations							Advanced Visualizations							
Tool	Standalone Tool	VLE Integrations	Predictive Model	Tables	Line Chart	Bar/Column Chart	Area Chart	Pie Chart	Donut Chart	Traffic Light	Badges	Headline Figures	Scatterplot	Heat Maps	Sunburst Chart	Florence Nightingale Chart	Bubble Chart	Radar/Spider Plot
Commercial																		
1 BB Predict	X	X	X	X	X	X		X	X	X	X	X						
2 D2L	X	X	X	X		X									X	X		
3 MGH Insight	X	X	X	X	X	X												
4 Pearson	X		X	X							X							
5 SAP	X		X	X		X												
6 Acrobatiq	X	X	X	X		X		X					X	X				
7 Captivate	X		X	X		X			X		X							
8 Cornerstone	X			X	X	X	X		X								X	
9 Tribal		X	X	X		X	X		X			X						
10 Xyleme	X	X	X	X	X	X		X										
11 Eurekos	X		X	X		X						X						X
12 KlassData		X	X	X	X	X												
13 SEAtS	X	X	X	X		X			X		X	X						
14 Renaissance	X			X	X	X		X					X					
Academic																		
15 Signals		X	X	X						X								
16 OU Analyse		X	X	X	X		X			X	X	X						
17 NTU	X		X	X	X	X				X	X	X						
18 LOOP		X	X	X	X	X	X	X					X	X				
19 UMBC		X		X	X													

	Product Features			Standard Visualizations							Advanced Visualizations							
Tool	Standalone Tool	VLE Integrations	Predictive Model	Tables	Line Chart	Bar/Column Chart	Area Chart	Pie Chart	Donut Chart	Traffic Light	Badges	Headline Figures	Scatterplot	Heat Maps	Sunburst Chart	Florence Nightingale Chart	Bubble Chart	Radar/Spider Plot
Total Uses	13	12	16	19	10	15	4	5	5	4	6	6	3	2	1	1	1	1

The first major division in this product space is between products created by commercial educational technology companies, external to any specific institution, and those crafted by academic institutions themselves. Almost all industry-created products would be available commercially, where academic tools tend not to be.

Commercial Products

1. Blackboard Analytics, Predict & X-Ray Analytics (Blackboard Inc., 2016)

Designed to integrate seamlessly with their Blackboard Learn Virtual Learning Environment (VLE), Analytics and Predict add both analytic and predictive functions using the underlying student data set. X-Ray Analytics allows integration of third-party VLE and campus records systems. Using X-Ray Analytics adds in much-needed extra dimensions of the student experience to the analytical model. It does, however, require time-consuming adaptation to standardize the underlying data source with X-Ray Analytics expectations.

2. D2L Brightspace Insights (D2L Corporation, 2017)

Insights is again built with D2L's VLE in mind; however, Insights can be configured to use any data set that can be exposed via the Caliper Analytics Standards (IMS Global, 2017). This standards-based approach aims to cut the integration time and effort.

3. McGraw-Hill Education Connect Insight (McGraw-Hill Education, 2017)

A more standalone product than most, in that it includes assessment methods and grading facilities. This tool will link with traditional VLEs, limited to the supported set through their 'plugin' interfaces. As a result, the analytics presented are specifically regarding assessments. The patterns exposed can be more in depth regarding achievement rather than retention, academic completion risk, or other metrics.

4. Pearson MyLab | Mastering (Pearson Education Inc., 2017)

MyLab and Mastering, both from Pearson Education, are the replacements to their OpenClass product.

With more focus on engaging students using their own devices and real-time feedback; these products appear to lack a predictive element. However, visualizations are used in the Reporting Dashboard for instructors. The product literature refers to a component 'Classroom Catalytics' which provides some deeper insight into the patterns of responses/learning within the same cohort.

5. SAP SuccessFactors (SAP SE, 2016)

As SuccessFactors is intended for a commercial (rather than educational) audience, the distinction between VLE, analytics, assessment, and outcomes are somewhat blurred. A commercial audience looking at Learning Analytics is more interested in improving business outcomes or similar. Most of SAP's marketing literature is trying to convince corporations to implement VLEs and analytics in the same way an educational institution would.

6. acrobatiq Learning Analytics (Acrobatiq, LLC., 2017)

This product focuses on assessment analytics, providing instructors with detailed metrics about how and where their students are having difficulties. As such, it requires assessment tasks to be set up within the acrobatiq platform. There are general mentions of integrating their product within an existing VLE, but most deployments use the acrobatiq Courseware product.

7. Captivate Prime (Adobe Systems Inc., 2017)

Another offering designed with corporate users rather than educational ones. The large selling point of Captivate Prime is its 'Fluidic Player.' This software is intended to allow playback of a wide range of media in one tool, instead of users needing to switch to another application – installing it where necessary. Adobe has heavily invested in Gamification techniques with Captivate, this type of user tracking leads to rich metrics and reports.

8. Cornerstone Analytics/Reporting (Cornerstone OnDemand Ltd., 2017)

Cornerstone has developed a full HR stack, tracking recruitment and training, as Software as a Service (SaaS). This suite is entirely corporate-orientated, we have included it here as it does contain an element of Learning Analytics just not set in education. The metrics developed by Cornerstone relate to a corporate body concerning skill deployment and development. These are still analogous to Mastery as discussed in the education arena.

9. Tribal Student Insight (Tribal Group plc., 2015)

Student Insight is designed to be compatible with all VLEs. To this end, Tribal have created a method of conveniently labeling data in other systems (such as the VLE, campus management system, and library systems), without a specialist integration task. Their initial focus is on identifying students at risk of dropping out, but take into account all other data available.

10. Xyleme Analyze (Xyleme, Inc., 2017)

Xyleme has designed their Analyze product to work alongside a companion VLE. However, with the use of

the eXperience - also known as TinCan - API (Rustici Software, LLC, 2017), can act as a data warehouse for other VLE and campus management systems. As the eXperience API is designed to accommodate changing and emerging assessment types and activities, this process could be a time-consuming one.

11. Mentorix Eurekos (Mentorix ApS, 2017)

Eurekos is a full featured VLE, with a stated aim of being designed for Blended Learning. This VLE has visualizations and analytics built-in, but will also expose activities via the eXperience API formats. The Eurekos platform aims to meet both educational and enterprise needs, using Packages that encompass the full curriculum, assessment, and reporting for a subject.

12. KlassData Analytics (KlassData, 2017)

KlassData have produced a plugin to provide analytics on events occurring inside a Moodle VLE installation at no cost to users. This plugin ultimately maps activities, assessment, and actions in Moodle to one or more items in the eXperience API. Much of the functionality is more appropriately labeled reporting, but there are elements of forecasting present.

13. SEAtS Software Learning Analytics (SEAtS Software Ltd., 2017)

The SEAtS platform is an implementation of the Student Success Plan[6], a philosophy and supporting systems to intervene and advise students on their individual paths. SEAtS use the concept of 'touch points', both physical and digital, to record engagement with studies. These digital touch points may be a simple as viewing a web page or submitting an assignment to as complex as a series of related actions to complete an activity.

14. Renaissance Learnalytics (Renaissance Learning, Inc., 2017)

Learnalytics is the analytics component of Renaissance's Star product line. This suite is aimed at primary and secondary education markets (K-12 in U.S. terms). At this level, the metrics are very heavily focused on core abilities and skills, such as reading and math. Therefore, the analytics are designed to show what elements of those skills need improvement to inform how they can be improved.

Academic Solutions

15. Purdue University Course Signals (Arnold & Pistilli, 2012)

Purdue University's Course Signals system is held as the first/best example of an effective learning analytics system. Course Signals is an in-house implementation using the Blackboard Learn VLE as the backing data store. Purdue has augmented events and activities usually logged by the VLE, to include intervention and contact information. The fundamental goal of the project is to improve student retention and highlight cases where a student may be in difficulty. To support this effort, Purdue have also added

[6] https://www.apereo.org/projects/student-success-plan

an on-demand predictive algorithm to assess student risk.

16. Open University (Kuzilek, Hlosta, Herrmannova, Zdrahal, & Wolff, 2016)
The Open University (OU) is a specialist distance learning institution in the UK. Almost all their interactions with students are via their customized Moodle VLE. 'OU Analyse' is their in-house developed analysis and reporting environment based on those digital interactions with students. The OU implementation is considered one of the most stable Learning Analytics platforms in the UK.

17. Nottingham Trent University (JISC, 2016)
Nottingham Trent University (NTU) had developed a staff facing Business Intelligence (BI) system using the commercial Cognos system. While this operated efficiently for staff, students did not have any visibility of the data that was used to evaluate them. NTU, as part of the JISC investigation into analytics, developed an in-house solution in partnership with an external contractor. This implementation is held up as an example of excellence within the UK HE sector.

18. LOOP (Corrin, et al., 2015)
Developed by the University of Melbourne, in conjunction with other Australian universities, this tool is a plug-in for the Moodle VLE. In a similar vein to other plugin solutions, administrators must map activities and logs from Moodle into so-called 'Learning Events' to use for prediction and visualization. LOOP is one of the few solutions developed with a focus on visualization, so it features some of the more advanced/exotic methods and theories.

19. University of Maryland, Baltimore County (John, 2013)
Rather unusually, UMBC has taken a student-first approach to developing their analytics platform. The major feature of this platform is Compare My Activity (CMA). It is an add-on to the Blackboard Learn VLE, placing extra detail into students' Grade Book view. Only minimal visualization is used, displaying a metric value in a table alongside an average for the same cohort/module class.

5. DISCUSSION

Almost all tools surveyed include some kind of prediction system. This feature was included in the comparison as the results are shown in some graphic element. We are not looking to evaluate or compare the make-up or efficacy of these models. We believe that it wouldn't be possible to complete such an objective comparison without fully implementing all systems on the same data set. We therefore focus on the visual aspects. To make the most of any form of analytics system, practitioners must understand what they are aiming to retrieve from their data. The patterns and connections that a predictive model will uncover need to have some form of context to be useful. Often, we describe this context in terms of a question (or analytic question).

Most Learning Analytics tools are produced commercially. Our comparison highlights a fundamental

difference between commercially and academically produced tools. In order to target the widest possible market, commercial producers most often offer a standalone and VLE integrations. When developing internal solutions, the institution would have access to documentation, support, and even development resources for their chosen VLE. Targeting that VLE (or other systems) would make both business and technical sense instead of generalizing the work. Commercial systems must remain generic in order to appeal to a mass market. These questions are most likely going to be answered with a standard set of visualizations. Internal tools, on the other hand, could be far more tailored to the pedagogic needs of the institution. With this kind of tailoring, the insight may be intrinsic to the questions and not require any visualization support. Figure 9 illustrates this dichotomy graphically, showing the split between commercial and academic usage. The overall smaller counts are due to less public information being available about internal/academic tools.

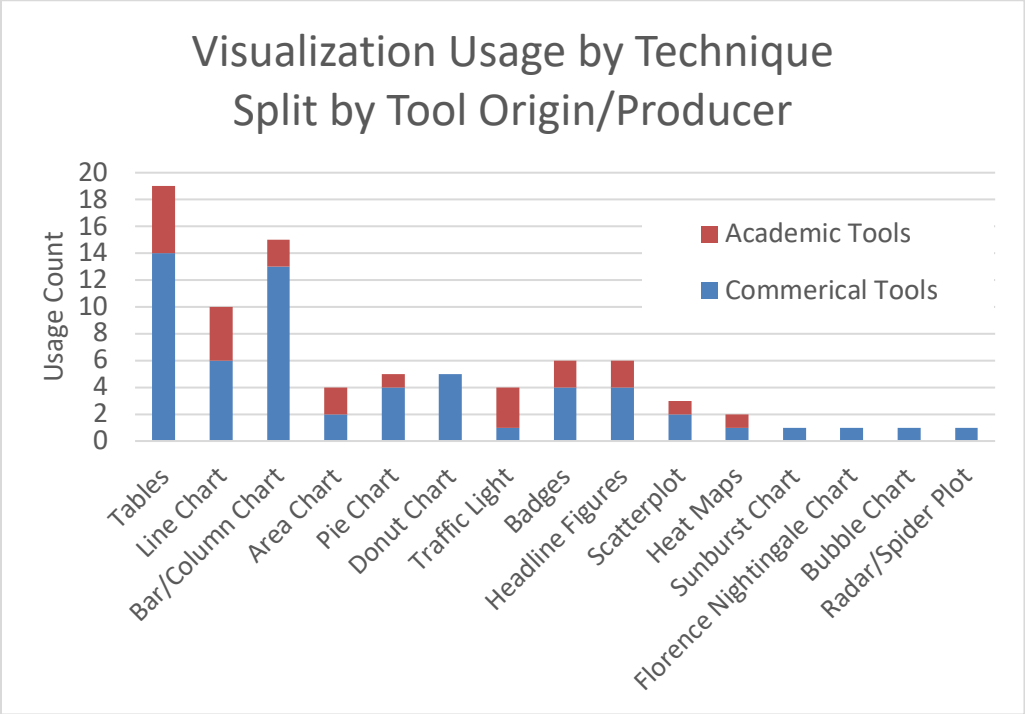

Figure 9: Visualization Technique usage, split by tool producer type (academic/commercial).

From the comparison, the use of advanced (or less traditional) visualizations is clearly lower, something that Sclatter confirms in his research (Sclatter, 2017). Figure 10 illustrates the stark difference graphically. Unfortunately, from this type of survey, we cannot attribute a cause for this trend. The most often included advanced visualization is badges, this is due to the current trend of gamification (Deterding, Dixon, Khaled, & Nacke, 2011). While there are many possible reasons for a lack of more advanced visualization there is an often-overlooked external factor – the users. From an Human-Computer Interaction standpoint, developers should offer tools appropriate to the users of the system.

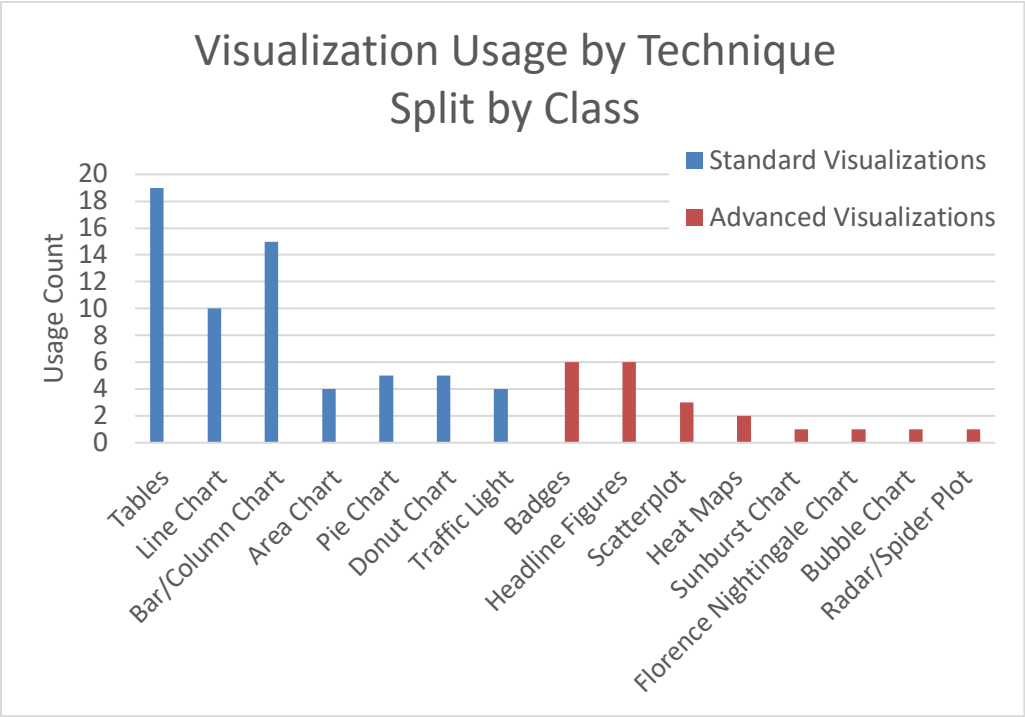

Figure 10: Visualization Usage by Technique. This chart compares usage of standard to advanced techniques by how many tools utilise/offer them.

One feature that is widely used among analytics platforms is tables. While this may seem obvious, using tables to show lists of data can sometimes obscure patterns. When using tables care needs to be taken to avoid information overload. Often presenting too much (or all) of the numerical data is just as confusing as a poorly designed graph. Cooper suggests that this may be an artifact of the types of questions being asked of the data (Cooper, 2012). Collectively we appear to be guilty of only asking 'what happened?' rather than the more enlightened 'why did it happen?'. When asking why, the analytics task becomes about unearthing patterns or factors beyond the immediately obvious.

Contemporary Information Visualization theory doesn't only cover charts and other graphical representations, it by definition includes elements of interaction. This means that charts should no longer remain a static picture, but allow the viewer an element of control (Yi, Kang, & Stasko, Toward a deeper understanding of the role of interaction in information visualization, 2007). The most basic element of interaction is selection (or deselection), being able to pick an item in some form (Keim D. A., 2002), enabling almost all other interactions. Once items can be selected, the user gains the ability to decide what items should be shown, known as filtering. Filtering can be used to reduce information overload, but only once a user has identified a focal point for themselves. It is important to stress Interaction does not necessarily need to reduce the items or information shown but the view may be refocused. Brushing is analogous to highlighting but would also show related items if they weren't shown before. When

introducing interaction patterns, the tool moves from reporting data graphically to allowing users to explore their data set. Exploration may therefore lead to deeper insights separate from the original analytic question. Ritsos and Roberts agree with this view. They argue that there should be more reliance on visual reasoning (Ritsos & Roberts, 2014), a task at which humans excel. If we assume this premise is correct, standard visualizations have limited ability to reveal any extra patterns or insight.

Fundamentally, practitioners and learning analytic designers need to focus on what outcome we wish to achieve. Dyckhoff et al. suggest that the ultimate response to analytics should be self-reflection on the part of the teacher (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). If this is the case; there is no reason to trawl for deeper patterns, making the visualizations a mere reporting exercise. Dyckhoff's view makes a fundamental assumption that the teacher is responsible for differing performances within the cohort. While 'learning styles' have been discredited (Reiner & Willingham, 2010), there are other solutions teachers can try. Rather than trial and error, better analytics could directly inform these choices. If the overall goal is to place the learner in control of their learning, then the communication will need to be on their terms. Often with commercial solutions the intended audience is the institution, and as such make assumptions of the users' pedagogical knowledge.

So far, we have only considered the system-teacher, and system-institution view. Learning Analytics will always include the student/learner as well. In non-compulsory (including adult) education, transparency concerns would demand that teachers, students, and institutions are provided the same view. We cannot make the same pedagogical expectations of students as we can teachers. We must, therefore, either present a different view to various stakeholders, possibly breaking transparency; or find alternative solutions. Each group will have differing motives, interests, and use cases. If the variety is small enough, fixed solutions may be able to work. If, however, there are large differences a more freeform and exploratory environment could be more appropriate. Only after detailed requirements analysis, taking the multiple user groups into account, would we be able to answer the question.

6. CONCLUSION

In conclusion, the field of learning analytics finds itself at a crossroads. It could either embrace the full range of data science and its linked fields – chiefly Information Visualization or, focus on the search for the correct pedagogical questions to ask of the analytics we have. When all of the motivations and stakeholders are considered, the picture becomes murkier. Student access, transparency, consumer protection, changing curricula, and other factors may force the decision.

At this juncture, investigating more advanced forms of visualization – including interaction – would be a worthy course of study. We believe that by introducing an exploratory dimension to learning analytics, practitioners could begin to develop new insightful analytic questions creating a positive impact on their teaching. Information Visualization provides more than just the exploratory interaction patterns, adding

multivariate (rather than the usual two) graphic elements. These could be used to enhance or highlight patterns, separations, and distinctions that previous depictions would not show.

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8. WORKS CITED

Acrobatiq, LLC. (2017). *Learning Analytics.* Retrieved June 12, 2017, from acrobatiq Corporate Website: http://acrobatiq.com/products/learning-analytics-3/

Adobe Systems Inc. (2017). *Captivate Prime Features.* Retrieved June 12, 2017, from Adobe UK Corporate Website: http://www.adobe.com/uk/products/captivateprime/features.html

Arnold, K. E., & Pistilli, M. D. (2012). Course Signals at Purdue: Using Learning Analytics to Increase Student Success. *Proceedings of the 2Nd International Conference on Learning Analytics and Knowledge (LAK '12)* (pp. 267-270). Vancouver: ACM.

Bertin, J. (2011). *Semiology of Graphics: Diagrams, Networks, Maps* (illustrated ed.). (W. J. Berg, Ed.) Redlands, CA: ESRI Press.

Blackboard Inc. (2016, December 13). *Blackboard Predict Data Sheet.* Retrieved June 12, 2017, from Blackboard Inc. Corporate Website: http://www.blackboard.com/resources/pdf/datasheet%20-%20predict%20-%20rev20161213.pdf

Borgo, R., Kehrer, J., Chung, D. H., Maguire, E., Laramee, R. S., Hauser, H., . . . Chen, M. (2013). Glyph-based Visualization: Foundations, Design Guidelines, Techniques and Applications. *Eurographics (STARs)*, (pp. 39-63).

Bose, R. (2009). Advanced analytics: opportunities and challenges. *Industrial Management & Data Systems, 109*(2), 155-172.

Byron, L., & Wattenberg, M. (2008). Stacked Graphs - Geometry & Aesthetics. *IEEE Transactions on Visualization and Computer Graphics, 14*(6), 1245-1252.

Charleer, S., Klerkx, J., & Duval, E. (2014). Learning Dashboards. *Journal of Learning Analytics, 1*(3), 199-202.

Chengzhi, Q., Chenghu, Z., & Tao, P. (2003). Taxonomy of Visualization Techniques and Systems--Concerns Between Users and Developers are Different. *Asia GIS Conference.* Wuhan.

Chi, E. H.-h. (2000). A Taxonomy of Visualization Techniques using the Data Dtate Reference Model. *Information Visualization, 2000. InfoVis 2000. IEEE Symposium on* (pp. 69-75). Salt Lake City: IEEE.

Cooper, A. (2012). A Brief History of Analytics. *JISC CETIS Analytics Series, 1*(9).

Cornerstone OnDemand Ltd. (2017). *Analytics Features.* Retrieved June 12, 2017, from Cornerstone OnDemand Corporate Website: https://www.cornerstoneondemand.co.uk/analytics

Corrin, L., Kennedy, G., de Barba, P., Bakharia, A., Lockyer, L., Gašević, D., . . . Copeland, S. (2015). Loop: A learning analytics tool to provide teachers with useful data visualisations. *32nd Australasian Society for Computers in Learning in Tertiary Education Conference (ASCILITE '15)* (pp. 409-413). Perth: ASCILITE. Retrieved from http://research.moodle.net/78/1/Corrin%20(2015)%20Loop-%20A%20learning%20analytics%20tool%20to%20provide%20teachers%20with%20useful%20data%20visualisations.pdf

D2L Corporation. (2017). *Brightspace Insights.* Retrieved June 12, 2017, from D2L Corporate Website: https://www.d2l.com/en-eu/products/insights/

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: defining gamification. *Proceedings of the 15th international academic MindTrek conference: Envisioning future media environments*, (pp. 9-15).

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. *Educational Technology & Society, 15*(3), 58-76.

Friendly, M. (2006). A Brief History of Data Visualization. In C.-h. Chen, W. K. Härdle, & A. Unwin (Eds.), *Handbook of Computational Statistics: Data Visualization.* Heidelberg: Springer-Verlag.

Friendly, M., & Denis, D. (2005). The early origins and development of the scatterplot. *Journal of the History of the Behavioral Sciences, 41*(2), 103-130.

Friendly, M., & Denis, D. J. (2004). *Milestones in the history of thematic cartography, statistical graphics, and data visualization: an illustrated chronology of innovations.* Statistical Consulting Service, York University.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64-71.

IMS Global. (2017). *Caliper Analytics*. Retrieved June 12, 2017, from IMS Global: https://www.imsglobal.org/activity/caliper

JISC. (2016). *Case Study I: Analytics at Nottingham Trent University.* JISC. Retrieved June 13, 2017, from https://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-I-Nottingham-Trent-University.pdf

John, F. (2013). Using analytics at UMBC: encouraging student responsibility and identifying effective course designs. *EDUCAUSE Center for Applied Research. Retrieved from https://net.educause.edu/ir/library/pdf/ERB1304.pdf.*

Johnson, B., & Schneiderman, B. (1991). Tree-maps: a space-filling approach to the visualization of hierarchical information structures. *Visualization, 1991. Visualization '91, Proceedings., IEEE Conference on*, (pp. 284-291).

Keim, D. A. (2002). Information visualization and visual data mining. *IEEE transactions on Visualization and Computer Graphics, 8*(1), 1-8.

Keim, D., Andrienko, G., Fekete, J.-D., Görg, C., Kohlhammer, J., & Melançon, G. (2008). Visual Analytics: Definition, Process, and Challenges. In A. Kerren, J. T. Stasko, J.-D. Fekete, & C. North (Eds.), *Information Visualization* (pp. 154-175). Heidelberg: Springer-Verlag.

KlassData. (2017). *SmartKlass (tm) | Learning Analytics Plugin.* Retrieved June 12, 2017, from KlassData Corporate Website: http://klassdata.com/smartklass-learning-analytics-plugin/

Kuzilek, J., Hlosta, M., Herrmannova, D., Zdrahal, Z., & Wolff, A. (2016). OU Analyse: Analysing at-risk students at The Open University. *Learning Analytics Review*, 1-16.

Kwon, B., Kim, H., Wall, E., Choo, J., Park, H., & Endert, A. (2017). AxiSketcher: Interactive Nonlinear Axis Mapping of Visualizations through User Drawings. *IEEE Transactions on Visualization and Computer Graphics, 23*(1), 221-230.

Legg, P. A., Maguire, E., Walton, S., & Chen, M. (2017). Glyph Visualization: A Fail-Safe Design Scheme Based on Quasi-Hamming Distances. *IEEE Computer Graphics and Applications, 37*(2), 31-41.

Li, H., Zhang, J., & Sun, J. (2016). A visual analytics approach for deterioration risk analysis of ancient frescoes. *Journal of Visualization, 19*(3), 529-542.

McGraw-Hill Education. (2017). *Connect Features for Educators.* Retrieved June 12, 2017, from McGraw-Hill Education: http://www.mheducation.com/highered/platforms/connect/features-educators.html

Mentorix ApS. (2017). *Eurekos for Education.* Retrieved June 12, 2017, from Eurekos Product Website: https://www.eurekos.com/education

Nightingale, F., Farr, W., & Smith, A. (1859). *A contribution to the sanitary history of the British army during the late war with Russia.* John W. Parker and Son.

Pearson Education Inc. (2017). *Pearson Higher Education | MyLab Mastering.* Retrieved June 12, 2017, from Reporting Dashboard: https://www.pearsonmylabandmastering.com/global/educators/features/reporting-dashboard/index.html

Rao, R., & Card, S. K. (1994). The table lens: merging graphical and symbolic representations in an interactive focus+ context visualization for tabular information. *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 318-322.

Reiner, C., & Willingham, D. (2010). The myth of learning styles. *Change: The magazine of higher learning, 42*(5), 32-35.

Renaissance Learning, Inc. (2017). *Learnalytics.* Retrieved June 12, 2017, from Renaissance Corporate Website: http://www.renaissance.com/learnalytics/

Ritsos, P. D., & Roberts, J. C. (2014). Towards more visual analytics in learning analytics. *Proceedings of the 5th EuroVis Workshop on Visual Analytics*, (pp. 61-65). Barcelona.

Robertson, G. G., Card, S., & Mackinlay, J. D. (1993). Information Visualization Using 3D Interactive Animation. *Communications of the ACM, 36*(4), 57-71.

Rustici Software, LLC. (2017). *XAPI Overview.* Retrieved June 2017, 2017, from XAPI: http://experienceapi.com/overview/

SAP SE. (2016). *SuccessFactors Product Brochure.* Retrieved June 12, 2017, from SAP SuccessFactors: https://www.successfactors.com/content/dam/successfactors/en_us/resources/brochures-product/learning-analytics.pdf

Schneiderman, B. (1996). The Eyes Have It: A Task by Data Type Taxonomy for Information Visualization. *Visual Languages, 1996. Proceedings., IEEE Symposium on* (pp. 336-343). Boulder: IEEE.

Sclatter, N. (2017). *Learning Analytics Explained.* New York: Routledge.

SEAtS Software Ltd. (2017). *Learning Analytics.* Retrieved June 12, 2017, from SEAtS Software Corporate Website: https://www.seatssoftware.com/learning-analytics/

Siemens, G., & Baker, R. S. (2012). Learning Analytics and Educational Data Mining: Towards Communication and Collaboration. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12)* (pp. 252-254). Vancouver: ACM.

Stasko, J., & Zhang, E. (2000). Focus+ context display and navigation techniques for enhancing radial, space-filling hierarchy visualizations. *Information Visualization, 2000. InfoVis 2000. IEEE Symposium on* (pp. 57-65). IEEE.

Tory, M., & Möller, T. (2002). *A Model-based Visualization Taxonomy.* Technical Report 6, Simon Fraser University, Computing Science Department.

Tory, M., & Möller, T. (2004). Rethinking Visualization: A High-Level Taxonomy. *Information Visualization, 2004. INFOVIS 2004. IEEE Symposium on* (pp. 151-158). Austin: IEEE.

Tribal Group plc. (2015, March 5). *Student Insight Brouchure.* Retrieved June 12, 2017, from Tribal Group Corporate Website: http://www.tribalgroup.com/media/72452/po-tribal-student-insight-v2-mar15.pdf

Viegas, F. B., Wattenberg, M., van Ham, F., Kriss, J., & McKeon, M. (2007). ManyEyes: a Site for Visualization at Internet Scale. *IEEE Transactions on Visualization and Computer Graphics, 13*(6), 1121-1128.

Wilkinson, L., & Friendly, M. (2009). The history of the cluster heat map. *The American Statistician, 63*(2), 179-184.

Xyleme, Inc. (2017). *Product | Analyze.* Retrieved June 12, 2017, from Xyleme Corporate Website: http://www.xyleme.com/product/analyze

Yi, J., Kang, Y.-a., & Stasko, J. (2007). Toward a deeper understanding of the role of interaction in information visualization. *IEEE transactions on visualization and computer graphics, 13*(6), 1224-1231.

Yi, J., Kang, Y.-a., Stasko, J. T., & Jacko, J. A. (2008). Understanding and Characterizing Insights: How do People Gain Insights Using Information Visualization? *Proceedings of the 2008 Workshop on BEyond time and errors: novel evaLuation methods for Information Visualization (BELIV '08)* (p. 4). Florence: ACM.