Driving Data Storytelling from Learning Design

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ABSTRACT

Data science is now impacting the education sector, with a growing number of commercial products and research prototypes providing *learning dashboards*. From a human-centred computing perspective, the end-user's interpretation of these visualisations is a critical challenge to design for, with empirical evidence already showing that 'usable' visualisations are not necessarily effective from a learning perspective. Since an educator's interpretation of visualised data is essentially the construction of a *narrative* about student progress, we draw on the growing body of work on Data Storytelling (DS) as the inspiration for a set of enhancements that could be applied to data visualisations to improve their communicative power. We present a pilot study that explores the effectiveness of these DS elements based on educators' responses to paper prototypes. The dual purpose is understanding the contribution of each visual element for data storytelling, and the effectiveness of the enhancements when combined.

CCS CONCEPTS

• **Information systems** → Data analytics; • **Human-centred computing** → Visualisation design and evaluation methods

KEYWORDS

dashboards; data storytelling; visualisations; visual design

1 INTRODUCTION

In recent years, educational dashboards and visualisations (which we will also refer to as "visual learning analytics" [5]) have gained considerable attention in the field of learning analytics (see recent reviews in [3, 24]). Borrowing from big data and web analytics in other domains, learning analytics dashboard aggregates indicators, from one or more sources, about students' activity and/or learning, using one or more visualisations [24, 28]. Teacher-facing dashboards are intended to help educators gain a better understanding of their whole course, reflect on their teaching strategies and identify students who require specific attention [19, 28]. Similarly, student-facing dashboards are intended to help students reflect on aspects of their learning behaviour and potentially assist them in, for example, managing time effectively, accessing key learning resources, or gaining a richer picture of their progress [3, 20].

Although the dashboard concept is intuitively attractive, its effectiveness is still unclear when it comes to the very complex set of skills that are part of learning [4, 12, 26]. Studies report, for instance, that the value of teacher dashboards may depend on the degree to which they have been involved in co-designing them [10], and their data literacy [8]. By contrast, the value of student dashboards could be a function of a complex mix of learner characteristics [4, 26] or their alignment with students' particular needs [20]. Additional barriers to adoption may include the potential misalignment between the visual analytics and the intended learning/instruction goals set for the learners' tasks; and the orchestration challenges and time constraints teachers and learners may have to interact with the interfaces [22].

This paper proposes a *Learning Design* driven data storytelling approach, with a conceptual model driven by theoretical foundations in InfoVis and DS. The model builds not only on sound InfoVis and DS principles, but connects them to

the learning context defined by the teacher's intentions, which are commonly explicitly or implicitly stated in their learning designs. We take a first step toward investigating the feasibility of the approach with an exploratory study analysing teachers' reactions to hand-crafted prototypes based on the principles. While we hope that these principles will be valuable for designers handcrafting visualisations (the usual context for applying DS), we foresee that they could be *automatically* implemented in dashboards to dynamically enrich visualisations of data that are unknowable in advance. In brief, the contribution of this paper is a Learning Design driven data storytelling approach, providing the rationale for combining data storytelling foundations and the teacher's learning design, for developing visual learning analytics interfaces.

The remainder of the paper is structured as follows. Section 2 discusses current visual learning analytics challenges reported in the literature, and presents the foundations of data storytelling. Section 3 describes the proposed Learning Design driven data storytelling approach and compares it with a typical data-driven dashboard design approach. Section 4 describes an exploratory study with teachers, to illustrate the application of the model. The paper concludes in Section 5, with reflections on the feasibility of this work and further directions of data storytelling for learning analytics.

2 BACKGROUND

2.1 Related Work

Although "learning dashboards" and other visual learning analytics have been getting significant traction in recent years [3, 24], there have also been numerous reports pointing to the limitations and possible pitfalls of rolling out these products (e.g. [4, 12, 20, 26]). The design of effective dashboards in educational contexts is complex. First, a recent review [3] pointed to the absence of design choice justifications reported in several research outputs presenting educational dashboards usage. A current review finds poor evidence of grounding in the learning sciences [11]. Another survey [20] reports that both commercial and scientific dashboards commonly feature poor interface design and lack of usability testing, and the choice of what data is to be visualised does not commonly correspond with what students and educators really want or need, in part, because they are not regularly consulted as part of the design process [10].

In parallel to the visual and design factors noted above, researchers and designers can easily overlook the learning context and the audience for whom these visualisations have been created [24]. This may cause a disparity between users' and designers' perspectives. Sometimes, designers and researchers want to communicate multiple insights or dimensions of data about students' experience. This can lead to the design of complex visualisations that are often hard to interpret [5] especially "at a glance". Moreover, teachers and students are encouraged to interpret these visualisations in a limited time and, even if the data can be interpreted correctly, they may fail to understand the "call to action" for reflection, or adapting their behaviour [9]. Aligning

learning design with the learning analytics tools has been identified as a key issue within the learning analytics community, that requires collective effort [2, 17].

Our approach is aimed at providing a way to address some of the problems highlighted above by providing a Learning Design driven approach to bring Data Storytelling and general visual design principles into the design of visual learning analytics. To the best of our knowledge, no prior dashboards proposed in the Learning Analytics literature use such an approach. The closest work to ours has been conducted by Klerkx et. al [13] who suggested general considerations regarding the design of visual and interaction properties of learning dashboards.

2.2 Foundations of Data Storytelling

Data Storytelling (DS) can be described as an *"information compression"* technique, to help an audience focus on what is most important to communicate via data visualisation [23]. DS builds on both classic Information Visualisation (InfoVis) guidelines [27] and narrative storytelling foundations (e.g. plots, twists and calls to action [16]). In the following sub-sections, we describe a set of data storytelling principles we have distilled from literature on data visualisation and narrative; and a set of data storytelling visual elements that can be added to the design of visualisations and dashboards.

2.2.1 Data Storytelling Principles. Tufte [27] suggested that a visualisation should incorporate *"graphical excellence"*, meaning that it has *"to reveal data with clarity precision and efficiency"*. In the same way, Ryan [23] stated that the goal of using visuals is *"to communicate a key message clearly and effectively"*, emphasising the context and meaning through visual enhancements (e.g. changes in size, colours, saturation). While visualisations are intended either to *explore* or *explain* insights, DS is focused on the latter. The goal of DS is to communicate insights through the combination of *data, visuals* and *narrative* [6]. Thus, DS is not applicable to exploratory visualisation interfaces. Instead, DS is aimed at explaining what is happening in the data and why a feature is important. In this context, DS has been widely used by journalists as a means to engage and inform through *"interactive graphics and narratives"* [25]. Current reported uses of DS techniques have focused on helping presenters tell more compelling stories through a clear (written or spoken) narrative supported by data visualisations [14]; communicating scientific data [18]; and teaching dynamic networks in an educational context [1].

Ryan [23] and Knaflic [14] have identified a set of *"golden principles"* that can be applied when crafting a story with data. Although both authors use different languages, they coincide in the following DS principles that we can use to further define what DS is:

DS is goal oriented. As discussed above, the data visualisation or dashboard needs to be aligned with a purpose or intention. This can help designers and researchers to have clear boundaries about what needs to be communicated and what does not. Although it may sound simple, many learning data visualisations can be designed to invite students or teachers to
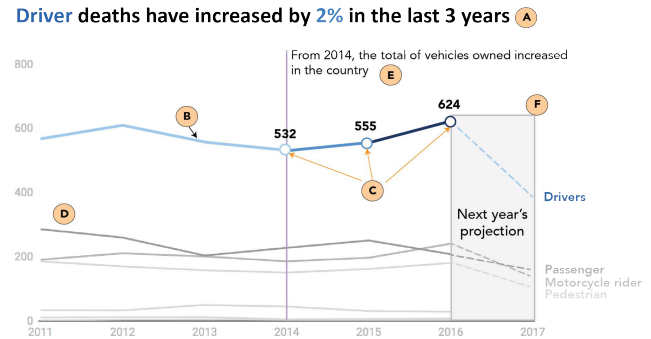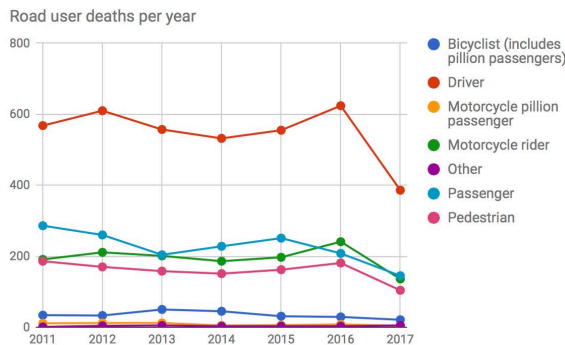
Figure 1: Data Storytelling example using a dataset on road deaths in Australia. Left: A typical chart without DS elements. Right: Improvement with DS elements: A) Descriptive *Title*; B) Highlight critical data with a *Thicker line* (i.e. driver deaths); C) Show only key *Data points*; D) De-emphasise less important data by *Decluttering* ; E) Add key contextual data with *Labelled line*; F) Highlight key sections of the graph with *Shading*.

explore the data without a clear goal in mind. This motivated our Learning Design driven approach.

DS drives the audience's focus of attention. Visual and narrative elements should be used to create meaning in the visualisation. This can be done by using specific elements (e.g. lines, shapes, size, colours, contrast) to highlight or emphasise key aspects to direct attention. Narrative text can also be added to explicitly explain how to interpret visuals elements.

DS relies on choosing an appropriate visual. Certain visualisation techniques work better for certain purposes. For example, line charts can effectively show changes over time [23]. By contrast, Knaflic [14] dedicates a whole chapter to justifying why pie charts should not be used.

DS relies on core InfoVis design principles. Clutter in data visualisations adds visual complexity to the graph and makes it harder to find insights [14, 23]. Tufte [27] refers to this as maximising data-ink ratio. *Decluttering* is achieved by removing elements (e.g. unnecessary headers, chart features, borders, grids) that do not add informative value to the graph. Other design aspects are important, for example, Knaflic [14] proposes the addition of *titles* to drive the intent of the visual, and *captions* to explain important features of the data. General principles related to *alignment, use of colour, shape* and *texture* are information design decisions that can have a strong impact on sensemaking.

The next sub-section describes some visual elements that can be added or removed from the data visualisations in order to translate these DS high level principles into concrete actions.

2.2.2 Data Storytelling Visual Elements. In [14], Knaflic describes how to improve graphs by adding or removing visual elements with the aim of supporting DS principles. We explain each of these DS elements with an example. Figure 1 (left) presents the output of a visualisation tool (Google spreadsheets) that we used to plot a real dataset: road user deaths per year in Australia, with a 12-month projection (bitre.gov.au). Figure 1 (right) presents the same data visualisation with DS enhancements inspired by Knaflic's work [14]. A critical insight we wish to emphasise is the increase in driver deaths in the last 3 years. If we compare both graphs, we can see how this message

is better understood Figure 1 (right), without getting lost in exploring the visualisation. For instance, it can be seen how the **title** (A) gives a succinct message that is intended to explicitly communicate the main insight of the visualisation. Also, we can see how **highlighting a line** draws visual attention to the drivers' trend (B). Highlighting specific relevant **data points** and removing irrelevant data points makes explicit which data support the claim in the title (C). Removing grids, legends and data point markers eliminates distractions (D), while adding **text labels** with a narrative message about the context, helps to gain a better understanding of the data (E). Finally, the **shaded area** provides meaning to sections of the graph by dividing it into actual data and data projections (F). The critical question is as follows: given these DS principles and elements, how can these be contextualised specifically to educational contexts?

3 APPROACH

In this section, we introduce our Learning Design driven conceptual model. When learners or teachers face a dashboard or visualisation, Verbert et al. [28] propose that the first stage in the "awareness-sensemaking" process is simply i) **visualising and presenting the data** to the user. Next, since "*data in themselves are not very useful*", the second stage expects that users will ii) **formulate questions** and assess how data is useful or relevant for addressing those questions. The final two stages are concerned with the sensemaking process by which users iii) **respond to those questions** (e.g. creation of new insights) in order to iv) **perform actions** accordingly (e.g. for educators to modify the learning context, or students their behaviours). This process then continues iteratively in what Verbert and colleagues call the "learning analytics process model".

Figure 2 (left) summarises this regular data-driven approach to visualise learning datasets. For clarity, in our diagram we draw a distinction between (raw) learner data (presented as Data) and the analytics that are needed to present distilled views of these data for human consumption. These analytics include the *Processing* performed on the raw data (e.g. aggregating functions, machine learning, prediction models), and the *Visual*
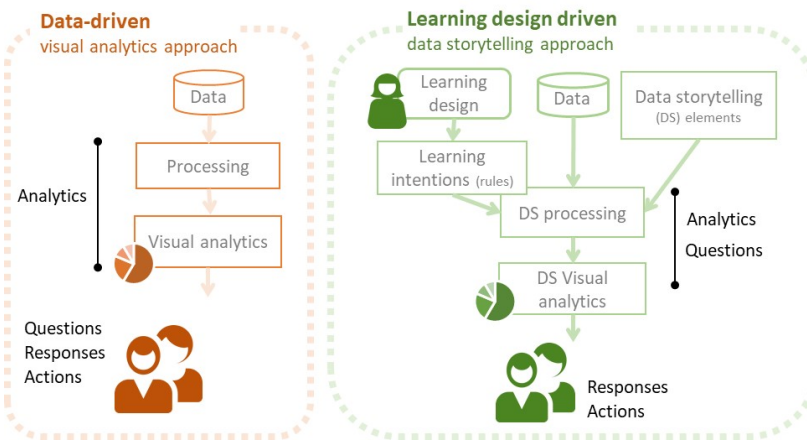
Figure 2: Conceptual model: Left: Conventional data-driven visual analytic approach. Right: Learning Design driven, data storytelling approach to support sensemaking.

analytics that render the data. In short, the process of formulating questions, generating insights from the analytics (or 'data' according to [28]) to respond to those questions, and acting, is driven by the user. In this scenario, the designer of the learning analytics has the challenge of generating interfaces for a number of possible questions that learners or educators could have.

This is the conventional data visualisation approach used in most learning analytics dashboards (e.g. see recent reviews in [3, 13]). Teasley [26] has referred to this approach as "one-size-fits-all" dashboard design. Notable exceptions are visualisations that incorporate mechanisms that allow user input such as customisable dashboards (e.g. see initial explorations in [21]), and personalised visualisations that automatically adapt according to individual's personal traits [15]). These initial attempts are still in the research lab and have not yet been adopted by the learning analytics community. Teasley [26] has suggested that personalised visualisations may help address some of the already identified negative effects of dashboards and visual analytics that have been reported.

Our approach sits in between "one-size-fits-all" dashboards (simple to produce) and adaptive personalisation (complex to produce and train). Figure 2 (right) depicts our proposed conceptual model. We propose to scaffold the formulation of user questions by enabling the dynamic modification of critical features of the visualisations. The goal is to translate the learning intentions of the educator into data storytelling elements that highlight particular aspects of the data. Figure 2 (right) shows three boxes aligned at the top as the foundations of our Learning Design driven data storytelling approach. These are the teacher's learning design, the learner's data, and the data storytelling elements. Our model considers that a teacher's pedagogical intentions, explicitly or implicitly specified in the learning design, can be translated into **rules** which can be read by a data processing system. Once student data has been collected, these rules can be used to reveal interesting behaviours or indicators in student activity to which we wish to draw the

educator's or learner's attention (e.g. when a student has low performance in an activity because she could not complete a correct step, or when a certain performance threshold is reached).

Variations in data can, to some extent, be detected automatically with no domain knowledge. Certain properties of lines/curves (e.g. peaks and troughs, intersections, gradients), and time-series data (e.g. three consecutive low performance episodes in a particular session), can be used by the system to highlight a multitude of changes in a graph, but also quite possibly irrelevant. The addition of *learning design* information provides the basis for more powerful filters, since the educator can define what the *meaningful* features are likely to be. For example, perhaps the first two of the students' three "low performance episodes" are entirely expected by the educator and accounted for in the learning design, so the dashboard should only highlight the third event as a salient indicator. In terms of Verbert et al. "learning analytics process model" [28], directing the user's attention to identify interesting features at a glance should help them focus on questions that are relevant for learning/teaching, since they have been identified and curated in the learning design. The goal is a more productive sensemaking process for users to respond to those questions and perform actions.

In summary, while the data storytelling elements play a critical role for emphasising or de-emphasising visual elements of a dashboard, the learning design (materialised as rules) provides the contextual information to decide *which* patterns or events should be foregrounded. This way, the proposed Learning Design driven data storytelling approach aims to keep humans 'in-the-loop', not just as consumers of the learning analytics, but also able to shape what is being shown in the interface.

4 ILLUSTRATIVE STUDY

This section presents an exploratory study that illustrates the feasibility of our approach. The section is divided into three sub-sections that present the following: 1) a description of a collaborative learning situation from where a dataset was captured and student-facing dashboards were used; 2) the design rationale of hand-crafted DS-enhanced versions of the dashboards; and 3) an evaluation study with teachers, to understand the role played by the data storytelling elements to support sensemaking.

4.1 The Learning Situation

Fifteen undergraduate students, ranging from 21 to 26 years old, enrolled in an introductory Database Systems subject from a University, were asked to use a multi-display interactive tool [7] as part of their regular classes, to practice database design related concepts. This tool includes a collaborative Entity-Relationship (ER) diagram editor distributed across tablets and an interactive tabletop and a multi-display dashboard setup for post-hoc. The system captures interactions (e.g. insert, delete,
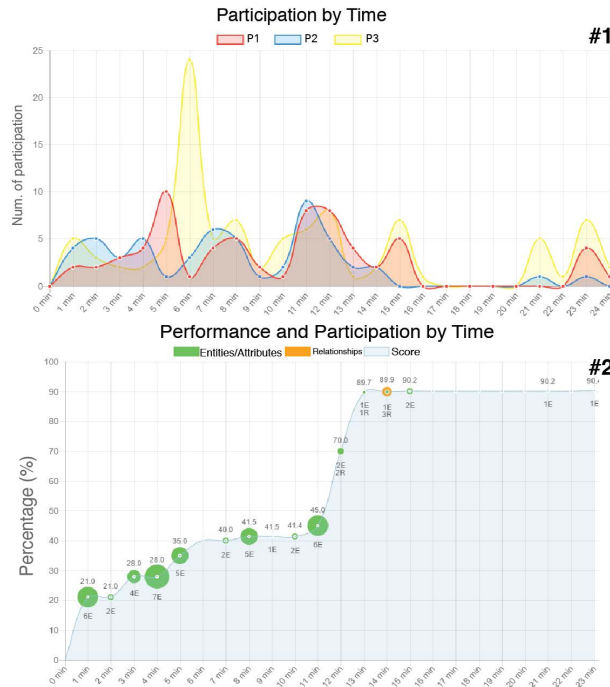
Figure 3: Original visualisations rolled to students. Top: Participation of each group member. Bottom: Evolution of the group's Performance.

move, edit) with objects (entities, attributes, relationships) that students perform when designing ER diagrams. With the data logs and the input solution from the teacher, the tool automatically generates a dashboard containing information about social and epistemic aspects of the activity, aiming at supporting the teacher debrief and student's reflection.

Five teams were allocated 30-minute sessions to design a ER diagram for a given case study. Figure 3 shows two visualisations about their **Participation** (top) and **Performance** (bottom) automatically generated from a session. **Participation** shows the number of interactions by each student plotted on a timeline. Each student is identified as P1, P2 and P3 and differentiated with colours (yellow, blue and red). **Performance** shows how the solution evolved through time. Each data point

indicates the number of entities/attributes (green) and/or relationships (orange) added to the solution. The data point label (above each point) depicts the current (automatically calculated) grade of the whole diagram according to the objects added up to that time. The text label below each point shows the number of entities/attributes (e.g. 6E) or relationships (e.g. 1R) added to the design in 1-minute window.

These and other visualisations were shown to the students and their reactions were reported in [7]. A critical outcome of this study was that students used the dashboard visualisations as an analytical tool. It allowed them to explore the data, but not necessarily to focus on specific insights critical from a pedagogical purpose. This authentic scenario also motivated the need for enhancing these visualisations with DS elements to prompt specific reflections based on the intended learning design.

4.2 Designing enhanced visualisations

In this section, we describe the design process to add DS elements to the original visualisations shown to students (depicted in Figure 3). Note that although in this study the visualisations were hand-crafted, the purpose is to provide a detailed explanation of how this process can be automated.

Step 1: Understanding the context. Our context is shaped by the teacher's learning design. The teacher wanted to provide particular information to students/groups in order to improve their awareness about collaboration skills. Also, she wanted to know the how students' ER diagrams evolved, determining missing concepts and relationships throughout the design process.

Step 2: Mapping teacher's intentions with rules. Our second step consisted in extracting the teacher's intentions to be represented through DS elements. For instance, the teacher explicitly stated that she had two critical learning intentions, which were also the drivers of the design of the two visualisations generated for the students:

Learning intention 1 (LI1 – Participation): All students within a group should ideally participate equally.

Learning intention 2 (LI2 – Performance): Some specific database elements are critical and should be included early in the database design. This can directly impact the quality of the final design.

Table 1: Cases illustrating how to map intentions, rules and DS elements.

Visualisation	Intentions	Rules	DS elements	Example
LI1: Participation	Highlight whether the group is contributing equally or not	Rule 1: if dominating(P1,P2,P3) == 'P1' in slot_time(x): 　message = "P1 dominated the activity during x minutes"	text label; colours	Fig. 2 -1 (B)
	Summarise the overall group contribution	Rule 2: if balanced(P1,P2,P3) == 1: 　message = "All participants had a balanced Participation through the time activity"	Title; Size	Fig. 2 -1 (A)
LI2: Performance	Highlight database elements that increase the design's quality	Rule 3: if entity == 'Beca': 　add_point(entity) 　add_score(line) 　message = "Entity Beca"	text label; data point; colour; shape	Fig. 2 -2 (D)
	Summarise the overall group Performance	Rule 4: if overall_Performance(team) >= 75: 　message = "High-performing team"	Title; Size	Fig. 2 -1 (A)

From these intentions, we built rules that can be implemented in order to automate the generation of new visualisations by translating the teacher's learning intentions into DS elements. For instance, for LI1 we can create an informally expressed rule **(R1)**: *"if a student is dominating the activity in a pre-defined time slot (e.g. for 5 minutes), show [personalised message]"*. For the case of *LI2*, we can create a rule **(R2)**: *"if [name of a key entity or relationship] is added into the solution, add a marker indicating the name of the entity (or relationship)"*.

Step 3: Translating rules into DS elements. From the of DS elements defined in the previous section, we designed a set of rules to encode the learning design intentions with visual elements into a new set of visualisations that incorporate the foundations of data storytelling. Table 1 lists how some rules were used to encode each learning intention, focused on Participation (rules 1 and 2) and Performance (3 and 4) respectively.

Rule 1: if the teacher's intention is to know if the group is participating equally or not, the rule will search for patterns in the graph where this behaviour is explicit: if a student was dominating (i.e. Participation of one student is higher than the other two students) by x minutes (x being defined by the teacher), a visual indicator could be generated on the visualisation itself highlighting this behaviour (see *if-then rule* in Table 1, row 1). For example, visual elements can be added to the graph such as a text label with a narrative or triggering a visual alarm.

Rule 2: If the teacher's intention is to know the overall team Participation, the rule will determine if all students featured a balanced Participation (e.g. using an entropy function). A message could be set to explain this behaviour (see *if-then rule* in Table 1, row 2). Then, adding the resulting message as a big title in the graph could be a way to depict this behaviour.

Rule 3: If the teacher's intention is to identify when a database element that makes the task Performance increase is added (this element also being defined by the teacher), then the rule can insert a key data point when a student performed this action (see *if-then rule* in Table 1, row 3). Visual elements that supports this rule include: shapes and colours to differentiate different type of elements, data labels to emphasise current score and text labels to describe the name of the entity.

Rule 4: If the teacher's intention is to visualise the overall team Performance and assess if this score corresponds to low or high Performance, a rule can be formulated to determine this depending on the team's final score and an *x threshold* (x being defined by teacher's expertise, see *if-then rule* in Table 1, row 4). We can place the resulting message in the title of the graph or as a caption on the graph.

Step 4: Crafting the visualisations. The final step corresponds to generating the visualisations with DS elements, by applying the rules that were defined previously. A set of visualisations was prototyped using a graphic design software (Figure 5). In addition to the mapping of intention-rule-elements, we completed three additional steps regarding the design of the visualisations. 1) Removing elements that do not add value to the
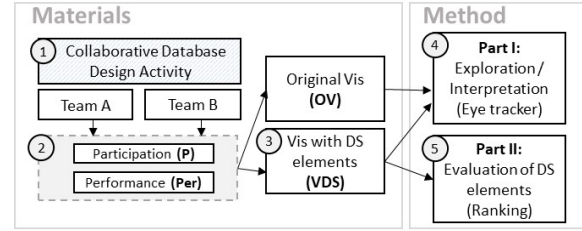

Figure 4: Methodology followed to illustrate how DS plays a role when interpreting visualisations.

graph. This step is known as decluttering. Therefore, we proceeded to make everything into grey scale to then highlight and/or emphasise only important aspects according to the rules. This step can be observed in Figure 5-C, where we remove grids, legends, data points. Also, axis labels were rotated, as suggested by Knaflic [14] so text could be easily read horizontally. 2) Emphasise lines to show trending in the Performance (Figure 5-bottom, element E). 3) Add context through a shaded area (shapes and colour) with respect to the learning design (Figure 5, F corresponding to the reflection stage).

4.3 Teacher Evaluation Study

This section describes an exploratory study conducted with the aim of generating understanding about the role of the data storytelling elements to support sensemaking. Through this study, we illustrate how teachers explored and interpreted visualisations with and without DS elements.

4.3.1 Study Setup. A study was carefully designed to expose teachers to a number of visualisations with DS elements (VDSs) and original visualisations (OVs) shown previously to the students [7]. Figure 4 presents an overview of the study setup. The intention of this study is not to experimentally test two conditions (e.g. visualisations with or without DS elements) but rather to focus on generating understanding of the potential role that data storytelling elements can play to support interpretations of visual learning analytics and dashboards. With this study, we tried to obtain evidence to address the following motivations (M1-4):

M1 - Ease of interpretation and orchestration. Examining the usability of visualisations with DS and their power in supporting teachers' monitoring for orchestration of the collaborative activity [22].

M2 - DS elements helpfulness. Understanding which DS elements are most helpful to support storytelling through learning visualisations.

M3 - Focus of attention. Exploring whether VDSs drive teachers' focus of attention to specific elements (such as text labels, the title and key data points) as intended. By contrast, we expect the focus of attention of teachers more equally distributed (less focused) whilst inspecting the OVs shown to the students.

M4 – Visual scanning trajectories. Providing insights into what look teachers when exploring the VDSs at a first glance.

Participants. Six associate teachers (T1-6 - 1 female, 5 males; age range: 26-39 years) from ESPOL University were asked to participate in this study. All teachers had experience in teaching (avg.: 2.33 years), five of them had experience teaching

the database systems course and all of them had experience teaching software design.

Materials. We prepared a total of eight visualisations using data from the study described in section 4.1 (see Figure 4-1). These visualisations were generated from 2 randomly selected student teams (A and B). We picked the original visualisations (OVs) as shown to the students during the reflection task (see Figure 4-2). Then, we applied DS principles and elements to each of the OVs, resulting in a second set of 8 prototypes (see Figure 4-3). Figure 5 depicts one of the resulting set of VDSs generated from team A's Participation and Performance data respectively. In short, each teacher would inspect data from two teams, in terms of Participation and Performance, through visualisation with (VDS) and without (OV) data storytelling elements.

Method – The pilot study consisted of two parts. A think-aloud protocol was used during the whole pilot study.

Part 1 (Figure 4-4) consisted of three tasks. For the *first task*, each teacher explored both the original (OVs) and the prototyped visualisations (VDSs). The researcher asked teachers to explore the visualisations and tell a story about what happened with the team based on what they could interpret from the data **(M1, M3 and M4)**. We randomised the presentation of team's data (A or B); thus, teachers explored 4 visualisations: 2 OVs (Participation and Performance) and 2 VDS (Participation and Performance) of either team A or team B. During the whole part 1, data from an eye tracker (Tobii X-60 Pro) was recorded, with the aim of understanding how teachers visually explored the visualisations. The *second task* involved the exploration of visualisations regarding their perceived usefulness. Here, teachers explored the following sequence of visualisations: OVs about Participation for team A and B, OVs about Performance for team A and B, VDSs about Participation for team A and B, and VDSs about Performance for team A and B. Teachers were asked to provide commentary on the ease of interpretation and support for orchestration and evaluation **(M2)**. In a *third task*, teachers compared both versions: OV and VDS about Participation for a random team (A or B) and OV and VDS about Performance for a random team (A or B) (e.g. Figure 3-top and Figure 5-top in the same screen). Teachers were asked to verbalise their thoughts about which of the two versions helped them interpret better the story and insights behind the data. Also, teachers were asked to suggest any change or addition to the VDSs **(M1** and **M2)**.

Part 2 (Fig. 5-5) involved the evaluation of specific DS elements **(M2).** For this task, teachers were asked to rank each of the DS elements (A-F) in regards of the perceived helpfulness for storytelling. A 5-point scale was created to allow teachers to rank the role that each DS played in the VDS about Participation and Performance.

Video-recordings, eye tracking data, screenshots and responses to the questionnaires were gathered and organised for its subsequent analysis. A post-hoc semi-structured interview was conducted with each teacher after each session for them to explain any additional aspect of the experience.

4.3.2 Analysis and Results. A mixed methods analysis approach was followed, aimed at triangulating quantitative

evidence collected via the ranking instrument, and eye tracking data with teacher's qualitative reactions. In this subsection, we present our analysis in order to answer each of our motivations.

M1 – Ease of interpretation and orchestration. In the comments, five teachers converged in relation to the ***ease of interpretation*** that VDSs provided. They also provided a more compelling story about what happened during students' activity due to the context added through the DS elements. For example, T1 expressed this as follows: "*these visualisations (with DS) show me exactly what I need. I don't have to guess what happened in the activity*". T3 added that *"...this (VDS) [provides] a summary of the whole graph. With the original visualisation, I would have to explore the whole visualisation in order to understand team's Performance"*; and T4 expressed the following: *"the [DS] visualisation shows me what elements students have created very clearly, compared to the other [OV] visualisation"*

In terms of ***orchestration***, teachers also mentioned that, adding contextual information to the VDSs helped them understand the behaviour of the group. In the VDSs about **Performance**, for example, associating text labels to key data points (i.e. the names of entities and relationships added by students) helped teachers understand the causes of potential unintended mistakes, so they could provide students with feedback if this visualisation would be generated in real-time or to guide a data-informed post-hoc reflection. For the VDS about **Participation**, T4 expressed that "*the shaded area in the graph made me aware that groups took very different amounts of time to*
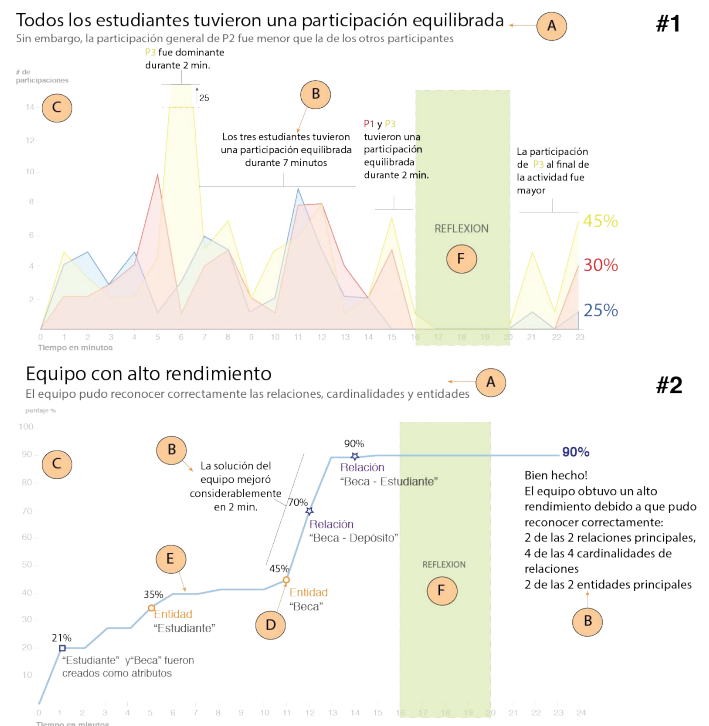

Figure 5: Visualisations after applying DS principles and DS elements (A-F). Top: Participation of three students. Bottom: Evolution of the group's Performance.

reflect and so, with this information, I would encourage students to reflect for a longer time before submitting a final version of the task". Another teacher [T3] mentioned that "*the title showed the right message of the graph regarding the team's Participation, which made me think that this group needed to collaborate more equally*". However, the selection of the narrative that appears in the title needs to be carefully crafted. For instance, T2 and T3 did not agree with the title VDS about participation. While exploring the visualisation, when they read the title, they asked why the title showed *"balanced Participation"* for team A, even if the graph showed how one student (P3, yellow see Fig. 4 top) dominated the activity. After comparing both teams' Participation, they could understand that both of them behaved differently, and they agreed that *"unbalanced"* Participation did not mean *"bad collaboration"*. This is an important implication for the potential automation of the data storytelling elements. In this case, none of the teachers inspecting the visualisations were involved in the learning design and in the definition of the translation rules. Thus, more work is needed to evaluate how teachers as designers of the rules would react to the visualisations with DS elements automatically crafted based on their own rules and the risks of over-prescriptive messages.

Regarding the comparison of both visualisations positive comments were expressed for VDSs in terms of supporting interpretation. For instance, most of the teachers mentioned that they preferred to explore visualisations with DS elements rather than the original version, giving the same comments as mentioned above. Moreover, regarding the comments made about what they would change to VDSs, all the teachers agreed that, for the VDS about Participation, instead of having straight lines, they would prefer smoother lines (e.g. curves) because they visually look better. Another criticism about the design was related with the balance of additional text labels, as the visualisation could become complex. In fact, one teacher [T6] mentioned that text labels *"add noise and graph complexity"* and that the text label information may be in occasions *"redundant with no extra information"*.

M2 – DS elements helpfulness. Figure 6 shows the final rankings by the six teachers after inspecting the two types of VDS. According to teachers' perception, they ranked the prescriptive **title** as a critical element to facilitate the sensemaking of both types of visualisations. Five of them agreed that the title served to indicate what was the main message from the visualisations before going deeply into inspecting the details from the visualisations. This was stated by two teachers, as following: [T4] *"[the title] shows an overall description of the graph, which helps to interpret faster the visualisation"* and that

Figure 6: Ranking of DS elements to support storytelling in visualisations.

[T1] *"[title] was important to summarise and understand the story"*.

Next in the ranking of DS elements regarding the VDS Participation, is the **shaded area** (Fig. 6, left). Teachers made an explicit comment about how the shaded area helped them to better interpret the sudden drop of activity in the visualisation: [T2] *"[the shaded area] explains what students were doing. Without this, I would think that students were doing nothing related to the activity"*; [T3] *"it adds context to the visualisation, to know what happened during the activity"*; and [T4] *"if I had to review this information after the class, this would help me to remember what happened in that point."* However, this element was ranked as the least helpful in the VDS about Performance. Differences in both visualisations can be explained by the fact that to understand Participation, the teacher needs to be more aware of the behaviour of the team (e.g. *why* there was a drop in the activity), whereas for task Performance, teachers did not perceive that it would help to understand the context.

Ranked in second and third place, for VDS about Performance (Figure 6, right) and participation (Figure 6, left), respectively, were **text labels** adding narrative. Teachers pointed out that text labels facilitated the narrative explanation of what occurred in different moments and ease of reading by describing what happened during the activity: [T2] *"[the text labels] helped me to see what happened when the three students were really collaborating (for visualisation about Participation). The first thing I read in the graph were the labels, which pointed me to explore in detail the data presented"*

Decluttering was ranked in third place for VDS about Performance (Figure 6, right). Teachers expressed that the information in the VDS graph was presented more clearly than in the OV: *"removing the green background, grids and big circles, made easier to explore the information."*

Notably, other elements which in principle are important for data storytelling [14] were lower ranked. These included for example the highlighted data points and using a thicker line to highlight activity. For instance, teachers mentioned that **data points** are useful for showing only relevant information and that the thicker **line** makes easier to focus the attention one the information. With this, we are not arguing that these elements should not be consider for further explorations in learning dashboards. We agree that teachers could perceive other elements as more helpful for them. Indeed, exploring heatmaps and trajectories **(M3 – M4)** could help us to understand how data points and labels plays an important role when focusing attention to interpret the graph.

M3 – Focus of attention. To better discern differences in where attention is drawn in a teacher's first encounter with a dashboard, we generated heatmaps based on the first 60 seconds from the eye tracking data. The heatmaps were scaled so that 1 second's fixation corresponds to deep red (Figure 7- hotspots). It can be seen that for the OV (Figure 7, top) many hotspots are spread through the main line and legends suggesting that the teacher dedicated a considerable time to inspect each data point in the time series. This exemplar is representative of what it was similarly observed in the other teachers' heatmaps. Due to space
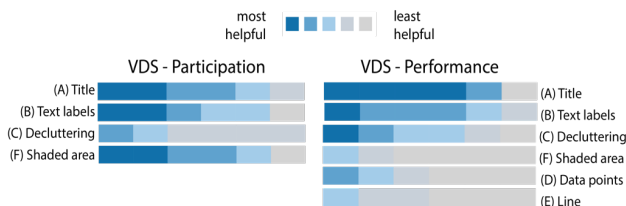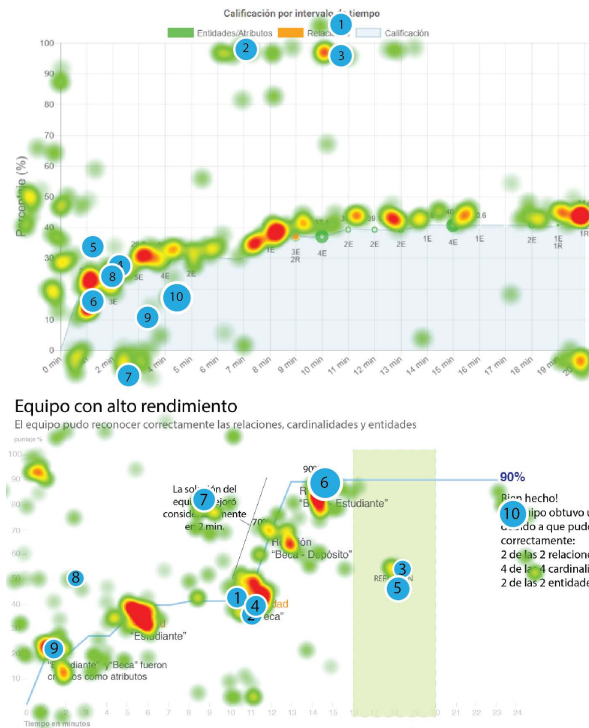
Figure 7: Heatmap and gaze plots (blue dots) showing how a teacher [T6] explored the visualization about Performance for the first 60 secs: an OV (top) and a VDS (bottom).

limitations, exemplars from other teachers can be electronically accessed in the following link (https://goo.gl/QQumyz). In the interviews, most teachers said they struggled with interpreting the small numbers and letters in each data point and had to consult the legend to remember the meaning of each colour. Although this is a simple design issue quite easy solved during the decluttering of the graph, it is a subtle DS consideration that can have a critical impact whilst teachers inspect a graph.

The VDS example heatmap (Figure 7, bottom) depicts how the text label and key data points drew the visual attention. Here, the teacher only focused on the highlighted data points rather than the axis or grid. Having a clear design, with key data points and text labels (entities names and percentage of the score) to support what the data wants to show, seemed to be effective in reducing visual clutter, with more focused attention.

This can be confirmed with the comments left by the teachers: *"this [referring to the VDS] did not make me think too much .... In the previous one (OV) I did not know what the 6E means"*; *"I like it, here (referring to VDS about Performance) I did not spent time on exploring the visualisation, rather it shows me directly what I need to know."* This suggests that removing unnecessary details from the graph and adding DS elements that emphasise only critical data points may give teachers more time to focus on making sense of the learning task to respond to the critical visual learning analytics questions, instead of spending time just in making sense of the graph.

M4 - Trajectories when exploring VDS. Eye tracking data allowed us to create the visual trajectories of teachers whilst exploring the visualisations. We generated gaze plots depicting the scanning pattern for the first ten sequences for each visualisation to extract the trajectory followed by teachers at a first glance. Figure 7 (blue dots) illustrates an example of the trajectories followed by T6 when exploring OV and VDS about Performance. In the OV (Figure 7, top), we can observe how the teacher started to look at the legend (1-3); then he stared at the green dots (data points) from the left part of the graph (4-6). Next, he briefly inspected the x-axis labels (7) to continue exploring data points (8-10). In brief, we notice that the teacher's gaze was concentrated in one spot of the graph to understand what the green dot and the numbers meant. In commenting during the exploration of the visualisation, this teacher expressed that he could not understand the numbers and colours immediately: *"... ok.... 5E, this means that students add 5 elements.... Oh, I see, 5 entities"*.

By contrast, when inspecting the VDS (Figure 7, bottom), the teacher started to look at the middle of the visualisation (1), where a text label was present. Next, he moved to the closest text label (2), which belongs to a data point description, to then shift his attention to the text label of the next data point (3). Next, he looked to another text label, this time located above, corresponding to the explanation of the shaded area marked as "reflection" (4) to then go back to inspect the rest of the line backwards (5-8). Subsequently, he fixed his attention again on the first text label he initially inspected (9). Finally, he shifted his attention to read the title. One explanation that we can get from this behaviour is that, the teacher fixed his attention in almost (4 out of 5) data points at a first glance, which is the intention of providing the DS elements. During the exploration of the graph, the teacher gave a good interpretation of this, by stating that everything was clear. A final thought is that, although it is clear once the teachers get familiarised with the data visualisations the trajectories for the OV would be more focused, there is no need to rely on teacher's learning curve of the visualisations for them to focus on what is important in the data.

To investigate how all teachers collectively explored the visualisations, we generated directed graphs that aggregated the first 10 sequential visual steps each teacher performed on the DS elements in the VDS about Participation and Performance. The most followed trajectories were: **data points → text label** and **text label → data points** in both cases. This suggests that textual summaries may support the reading of the data points of the visualisation. This is aligned to the comments expressed by teachers described above in terms of helpfulness (**M4**) and ease of interpretation added by the DS elements (**M3**). However, while adding text labels can be promising to support understanding of the visualisation, other factors could also have caused this behaviour. For instance, it is well known that our visual system looks at closest objects in order to find a relation (Gestalt principle of proximity [14]).

4.3.3 Study summary and limitations. Our results suggest that DS elements have the potential to help teachers explore visualisations with less effort. All teachers could interpret both

the VDSs and OVs, but they explicitly expressed most affinity with the VDSs. A limitation of this study is that, due to the low number of teachers, these results cannot be generalised in the way permitted by an experimental lab study with a statistically meaningful number of subjects. However, this was a methodology to elicit rapid formative feedback from teachers about a prototype extension to a dashboard deployed with students, showing real student data. By making use of eye-tracking technology we could understand teachers' behaviours when exploring these visualisations, with fine-grained detail on fixations and trajectories.

5 CONCLUSION AND FURTHER DIRECTIONS

We have proposed a conceptual model for bringing DS principles to support the interpretation of questions in teachers and students-facing dashboards. We aligned the learning design with DS by extracting rules from the teacher's intentions, providing the basis for prioritising which features to foreground. Moreover, we suggested how these rules can be applied in manually generated prototypes. Our intention is to add these DS elements automatically, and to this end, a pilot study with teachers helped explore teachers' interpretations of learning visualisations. Results indicated that teachers perceived the prescriptive title, text labels and shaded areas as elements that add contextual information. Evidence from eye tracking data allowed us to gain a better understanding about the elements that drove teachers' attention during the first minute of seeing the dashboard. Teachers' behaviours point to the critical role that both narratives and visuals play in explaining the data.

These results are encouraging and provide the basis to further investigate the means for crafting personalised and context-dependent dashboards. We see the potential of learning design driven DS elements to support sensemaking by guiding the user to *"one learning story per visualisation"*, given that learning is a complex task. We hope that both, designers and researchers, can gain value from this conceptual model as a step towards *dashboards contextualised specifically to learning*. Future work will seek to deploy VDSs in authentic settings in order to perform a longitudinal, authentic study with students and teachers. For next steps, we will involve teachers and students in the design process of Learning Analytics dashboards. In addition, we intend to evaluate how teachers might adjust their learning activities based on the insights they might gain from dashboards whose design they have helped to shape.

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