Specifying information dashboards' interactive features through meta-model instantiation

Andrea Vázquez-Ingelmo[1][0000-0002-7284-5593], Francisco J. García-Peñalvo[1][0000-0001-9987-5584], Roberto Therón[1,2][0000-0001-6739-8875] and Alicia García-Holgado[1][0000-0001-5881-7775]

[1] GRIAL Research Group, Computer Sciences Department, Research Institute for Educational Sciences, University of Salamanca, Salamanca, Spain
[2]VisUSAL Research Group. University of Salamanca. Salamanca, Spain

{andreavazquez,fgarcia,theron,aliciagh}@usal.es

Abstract. Information dashboards[1] can be leveraged to make informed decisions with the goal of improving policies, processes, and results in different contexts. However, the design process of these tools can be convoluted, given the variety of profiles that can be involved in decision-making processes. The educative context is one of the contexts that can benefit from the use of information dashboards, but given the diversity of actors within this area (teachers, managers, students, researchers, etc.), it is necessary to take into account different factors to deliver useful and effective tools. This work describes an approach to generate information dashboards with interactivity capabilities in different contexts through meta-modeling. Having the possibility of specifying interaction patterns within the generative workflow makes the personalization process more fine-grained, allowing to match very specific requirements from the user. An example of application within the context of Learning Analytics is presented to demonstrate the viability of this approach.

Keywords: Information Dashboards, Meta-model, Information Visualization, Interactions, MDA, SPL.

1 Introduction

Information dashboards have increased in popularity and relevance in several fields. They foster knowledge generation by presenting complex datasets through visual arrangements and encodings. These tools support informed decision-making processes, and data-driven approaches to carry out complex decision flow [1, 2].

However, carrying out data-driven decision making is not a trivial task. First, because a significant amount of data is needed to generate knowledge. And second, because the processes of analyzing such data require that the person leading the decision making or analysis be able to understand and interpret data sets that are often complex and extensive.

But thanks to the evolution of technologies, these analysis tasks are now available to less technical profiles. There are tools that facilitate analysis and knowledge generation from data sets. One of the most popular tools are dashboards [3].

Having a dashboard does not guarantee knowledge generation, though. It is necessary to take into account the audience and the profile of the users who will use these tools. There may be users who can understand complex visualizations, while others will need other visual metaphors to correctly understand their data sets [4].

Especially, there are some contexts in which putting the focus on the audience is crucial. The educative context is one of them. In this context, there are several actors that play crucial roles: teachers, managers, students, etc.

Learning Analytics (LA) dashboards provide a display in which different indicators regarding learners, learning processes, and/or learning contexts are arranged into a set of visualizations [5]. However, the design process of LA dashboards is crucial to leverage their capabilities [6]. It is necessary to take into account the data, the user, and the goals of the dashboard to get the most out of these tools.

In previous works, a dashboard meta-model has been developed [7-9] to specify and instantiate dashboards within any context. The dashboard meta-model defines high-level classes that depict abstract concepts from the domain, such as the elements that compose information visualizations (channels, visual marks, axes, users' goals, variables, datasets, etc.).

The dashboard meta-model can be derived into concrete models to build specific dashboards through a generator by using a high-level syntax. However, there is a dimension that must also be taken into account: the potential user interactions with the dashboard. Interaction patterns help users to interact directly with the data displayed on their screens. Users could highlight data points, select them, filter them, etc., through different events (clicking, hovering, brushing, etc.). These patterns need to be represented within the meta-model at a high-level to allow their instantiation and, subsequently, to obtain fully interactive dashboards.

This work describes the introduction of interaction patterns within a dashboard meta-model and presents an example of application in the context of LA through a generative pipeline and a DSL (Domain Specific Language).

The rest of this paper is organized as follows. Section 2 provides a background on educational and learning analytics dashboards. Section 3 depicts the methodology employed to carry out the research. Section 4 describes the meta-model structure regarding interaction patterns. Section 5 presents a dashboard instantiation framed in the Learning Analytics context. Finally, sections 6 and 7 discuss the results and conclude the work, respectively.

2 Background

As mentioned in the introduction, dashboards are increasingly popular tools because of their usefulness in supporting the visual analysis of complex datasets. The educational context is one of the contexts in which these tools can bring significant benefits since the use of data to make decisions regarding educational processes can improve learning outcomes [10-12].

Educational dashboards [13] are instruments that allow their users to identify patterns, relationships, relevant data, etc., among a set of learning variables. However, the diversity of roles in this context makes the design of educational dashboards a challenge.

In [5], it was found that the majority of users are usually teachers, but students, administrators, and researchers are also among the main users of these tools. Educational dashboards are also diverse in terms of their objectives; self-monitoring, monitoring of other students, and administrative monitoring [5]. This type of research allows us to observe that dashboards are very diverse in the educational context, both in their functionalities and in their design.

Due to these factors, some methods have been sought to design educational and learning analytics dashboards, so that they can be adapted according to their purposes and audience because there is no one-size-fits-all approach [14].

Dashboards should be customized to provide the necessary information in the most effective way. In fact, a study by Roberts et al. confirmed the widespread desire of students for control panels that can be customized, giving them the option of configuring them to display the information that interests them most or that they find most useful [15].

Thus, it is not only the variety of user roles in the educational context but the variety of objectives and profiles among users with the same role, which makes the development of learning analytics dashboards an elaborate activity. In addition, the amount of data generated and its complex structure can make the process of knowledge discovery even more difficult for less technical profiles.

For these reasons, models have been proposed to try to adapt these tools using conceptual models that take into account the indicators, the description, and needs of the users, their preferences, their knowledge of the domain, etc. In [16], a generator of learning analytics dashboards is presented. This generator takes into account the above-mentioned information by structuring it in models that feed a dashboard generator.

As can be seen, control panels in the educational context have increased in popularity due to the benefits that the use of data can bring to decision making. However, to take advantage of them, it is necessary to take into account the users and the context in which they will be employed.

3 Methodology

The methodology employed relies on two paradigms: model-driven development [17, 18] and the software product line paradigm [19, 20].

Model-driven development leverages high-level models (meta-models) to obtain an abstract representation of systems. Meta-models do not only help in the conceptualization of information systems but are also powerful artifacts that support a whole pipeline for developing such systems. These abstract models can be mapped to concrete products, according to the OMG four-layer meta-model architecture [21]: meta-meta model layer (M3), meta-model layer (M2), user model layer (M1) and user object layer (M0).

Concepts of the domain are captured through meta-models and arranged as a set of classes and relationships, yielding a simplified representation of the problem's domain. This representation is structured, thus supporting the processing of meta-models through computational methods.

In previous works, a dashboard meta-model has been presented [7-9, 22]. The dashboard meta-model includes three main parts involved in the development of information dashboards: the user, the layout, and the components of the dashboard.

This work is focused on addressing the specification and instantiation of interaction patterns among dashboard components to obtain interactive and functional information dashboards. A set of core assets have been developed following the SPL paradigm to support a connection between meta-model instantiations and final products. The SPL provides a framework to create components that can be configured and customized with almost no effort (the main effort is made during the development of these core assets) to meet specific requirements.

4 Modeling interaction patterns

Interaction patterns are highly diverse. They can involve the user clicking some parts of the dashboard. They can also involve hovering, brushing, etc. And, on the other hand, they can provoke different effects, such as highlighting some point, showing a tooltip, filter the data, etc.

All these possibilities must be captured through the meta-model in an abstract and coherent manner. Following a domain engineering approach [23, 24], a set of conceptual classes have been identified across dashboards from different domains to model interaction patterns. These classes are depicted in Fig. 1.

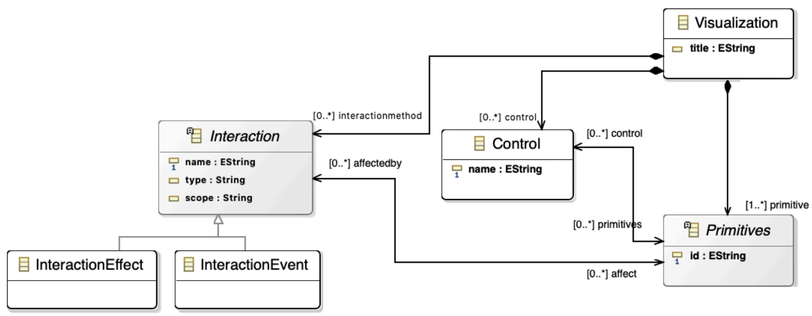

Fig. 1. Meta-model section regarding interaction patterns.

Information visualizations are composed of different elements. Mainly, these visualizations are composed of basic primitives, like visual marks, axes, scales, visual channels, etc. When interacting with a visualization, these primitives will be affected, for example, by changing their colors to highlight them or by showing a tooltip.

Three classes have been identified to reflect interactions in the meta-model. The *Interaction* class, which represents the interaction pattern to be applied to a specific primitive of the visualization. This class is abstract and can be of two types: an event or an effect. This distinction is necessary to represent which events to capture and which effects to apply to the visualization's primitives. For example, clicking in one of the bars from a bar chart is an event, and highlighting that bar (by varying its style) when selected is an effect. With these conceptual classes, it is possible to combine different specifications to obtain fully functional and interactive dashboards.

5 Learning Analytics Dashboard Example

A simple Learning Analytics information dashboard has been instantiated to demonstrate the viability of the generative workflow in this context. To do so, an instance of the Ecore meta-model was developed through EMF (Eclipse Modeling Framework, https://www.eclipse.org/modeling/emf/). This framework provides several features to support model-driven approaches: from meta-model editors to code-generation facilities. In this case, two visualizations are specified: a scatter plot and a parallel coordinates plot (Fig. 2).

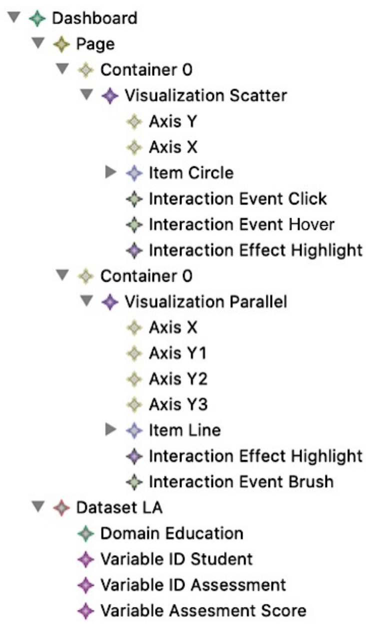

Fig. 2. An excerpt from the meta-model instance.

The elements of these plots encode the values of the input dataset through different channels. These channels are based on scales that map the dataset variables to values that are encoded through the position, color, size, etc. of the visual marks.

The employed dataset to test this application is the Open University Learning Analytics Dataset [25], which contains data from courses presented at the Open University (OU): assessments, scores, students' clickstreams, etc. In this case, the dashboard instance will employ the student ID, assessment ID, and assessment score variables from the dataset.

The instance is then handed to a Python generator [26], which "translates" the structure of the XMI (XML Metadata Interchange) into React code through a set of custom and low-level components.

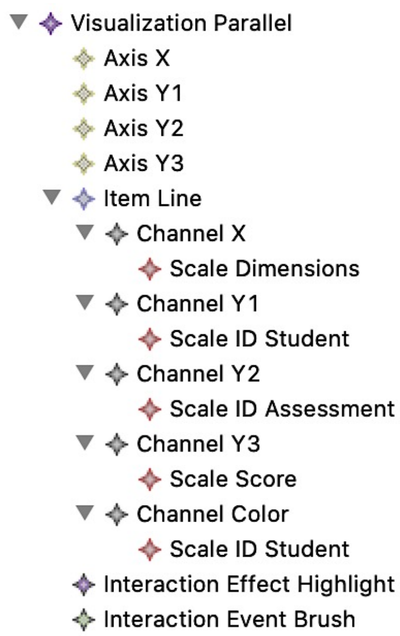

Fig. 3. An excerpt from a visualization's channels and scales.

For example, Fig. 4 presents a generated code excerpt from the dashboard. This code fragment is part of the props that are passed down to a specific React component. In this case, these props specify that the component will attend hovering and clicking events, and, if a data point is selected, it will be affected by highlighting that data point through a custom style.

```
interactions: {
    events: {
        hover: {
            type: 'individual',
            scope: 'global'
        },

        click: {
            type: 'individual',
            scope: 'global'
        }
    },
    effects: {
        highlight: {
            type: 'individual',
            selected_style: {
                ...this.props.dashboardStyle.interactions.hover_highlight
            },
            unselected_style: {
                ...this.props.dashboardStyle.interactions.unhover_highlight
            }
        },
    }
},
```

Fig. 4. React code fragment from the generated dashboard.

The outcome of this process is a React application that hosts the dashboard. The instantiated dashboard shown in Fig. 2 is presented in Fig 5. This dashboard holds two information visualizations. A scatter plot that represents each student on the y-axis and their scores in different assessments on the x-axis. On the other hand, a parallel coordinates plot shows the relationship between students, assessments, and scores, allowing them to detect patterns regarding these variables.

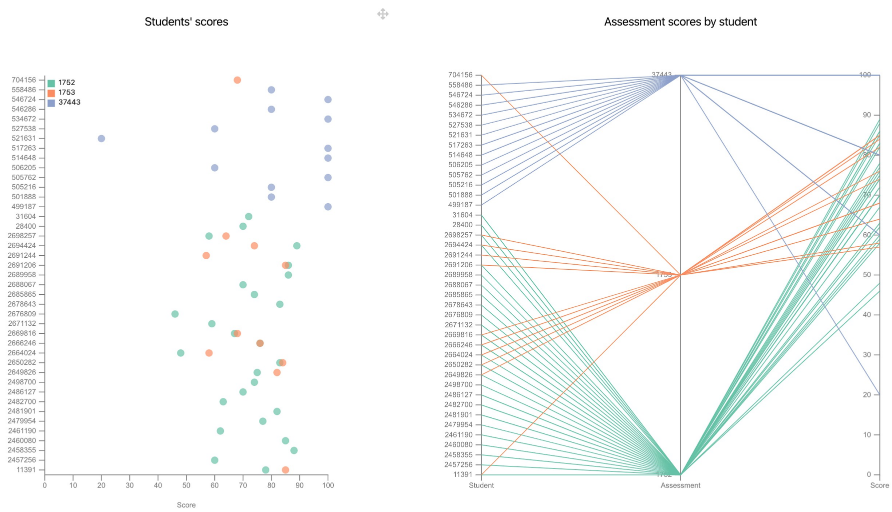

Fig. 5. Screenshot of the generated dashboard.

As shown in Fig. 4, some interaction patterns have been included in the generated dashboard. For example, the scatter plot component lets users hover on data points, provoking a highlight effect (as previously defined in the dashboard instance). Due to this configuration, when a user hovers on a data point in the first visualization, that data point is highlighted throughout the dashboard (Fig. 6).

This approach also allows the combination of different interaction patterns. For example, users can use a brush to select points on the parallel coordinates plot, affecting the scatter plot (Fig. 7).

Fig. 6. Example of the addition of interaction patterns: hovering.

Fig. 7. Example of the addition of interaction patterns: brushing.

6 Discussion

Creating an information dashboard is not a trivial task; it involves the study of the domain, of the users, of the data, as well as the subsequent development process of the designed display. Given the current necessity to rely on data to make better decisions, it is important to have tools that ease knowledge discovery and insight delivery.

A dashboard meta-model has been developed to tackle the personalization of these tools. The meta-model could be seen as a conceptual artifact that supports the design and development processes of dashboards. However, in this case, the meta-model is used as an input for an automatic generative process of information dashboards.

The meta-model can be instantiated through the Eclipse Modeling Framework (EMF), thus obtaining a concrete model of a concrete Learning Analytics dashboard (an M1 model, Fig. 8).

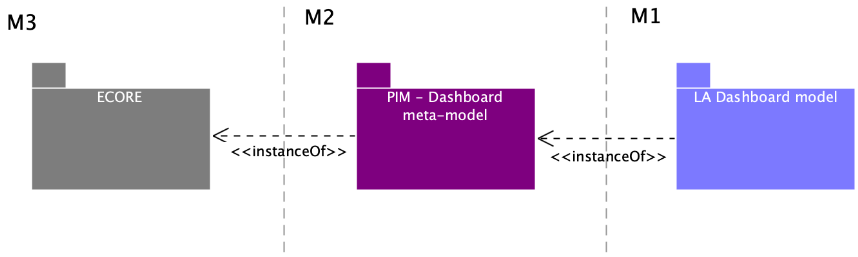

Fig. 8. Meta-model organization following the OMG architecture.

The obtained instance is the input for a dashboard generator, which arranges a set of software assets to compose a dashboard that matches the instance characteristics and features.

This work is focused on the definition of interaction patterns through the meta-model to obtain fully interactive dashboards. Interaction patterns are necessary to deliver good levels of user experience, as well as to improve the visual analysis process [27].

Interactions have been included in the meta-model through two conceptual classes, Event, and Effect, which define the events that the component will be listening to and the effects that the data point selections will have on their visual representation.

Adding interaction patterns to the instantiation process allows a more fine-grained definition of the dashboard features, which can be modified depending on different factors, such as the user expertise [28-30], the data domain [31], the analytical tasks and goals [32, 33], etc.

In this case, a Learning Analytics dashboard has been instantiated. This dashboard takes information regarding students' assessments and their scores. However, as stated in previous sections, it is straightforward to adapt the dashboard instance to other datasets with different variables. This is possible because the meta-model includes entities related to the datasets, their variables and potential operations that could transform data, meaning that they can be configured to support and generate indicators that allow dashboard users to reach meaningful insights related to their information goals.

Learning Analytics dashboards are very diverse, and the context and actors involved in each particular situation are crucial to building useful tools. Having the possibility of configuring information dashboards in a straightforward way allows for shifting the focus from the development process and giving more relevance to the design phases of the dashboard; Which analytic tasks will allow the user to reach his or her information goals? Which data variables should the dashboard display? How many views should the dashboard present? Which visual encodings allow better understanding given the target user expertise? Which interaction patterns would be more useful to support the user's analytical tasks?

Information dashboards are everywhere, but that does not mean that they are useful for everyone. It is crucial to find the best visual encodings, view arrangements, and interaction patterns based on each user's goals, characteristics, and datasets.

Designing a meta-model is a preliminary step to identify which features make a dashboard useful, effective or efficient. The abstract classes and structures of the meta-model can be used as inputs or outputs of external algorithms (for example, machine learning algorithms [31, 34]). Subsequent research will use the identified structures to build algorithms that maximize the usability, reliability, efficiency, etc., of these tools.

The model-driven development paradigm has been combined with a software product line approach to obtain a complete generative pipeline: starting from a conceptual phase (meta-model), software assets (core assets of the product line) were created to support the automatic generation of dashboards.

7 Limitations

Information dashboards usually have several intertwined features, elements and interaction patterns involved. This meta-model tries to capture the majority of them. However, dashboards are indeed very diverse, hampering the abstraction process. The current version of the meta-model supports dashboards based on different views and focused on structured data, but the visualization realm can also involve infographics, reports and other analysis assets that are not, at this time, supported by the presented meta-model.

8 Conclusions

A meta-model for information dashboards has been presented. This meta-model not only includes the visual elements of dashboards (visual marks, channels, axes, etc.) but also intangible components such as interaction patterns.

Including interaction patterns in the meta-model allows a more fine-grained specification and configuration of tailored information dashboards, meaning that not only the visual display can be customized, but also the methods in which users interact with datasets.

An example of application in the context of Learning Analytics has been carried out. This context involves very different actors and stakeholders, which might need different features from dashboards. Relying on the dashboard meta-model can make the development of these tools a more straightforward task.

Future research lines will involve the refinement of the meta-model to include rules and constraints, as well as in-depth user testing to test the usability of different interaction patterns and designs.

Acknowledgments

This research work has been supported by the Spanish *Ministry of Education and Vocational Training* under a FPU fellowship (FPU17/03276). This work has been partially funded by the Spanish Government Ministry of Economy and Competitiveness throughout the DEFINES project (Ref. TIN2016-80172-R).

References

1. Patil, D., Mason, H.: Data Driven. " O'Reilly Media, Inc." (2015)
2. Albright, S.C., Winston, W., Zappe, C.: Data analysis and decision making. Cengage Learning, Mason, OH, USA (2010)
3. Sarikaya, A., Correll, M., Bartram, L., Tory, M., Fisher, D.: What Do We Talk About When We Talk About Dashboards? IEEE Transactions on Visualization Computer Graphics 25, 682 - 692 (2018)
4. Aldrich, F., Sheppard, L.: Graphicacy-the fourth'R'? Primary Science Review 64, 8-11 (2000)
5. Schwendimann, B.A., Rodriguez-Triana, M.J., Vozniuk, A., Prieto, L.P., Boroujeni, M.S., Holzer, A., Gillet, D., Dillenbourg, P.: Perceiving learning at a glance: A systematic literature review of learning dashboard research. IEEE Transactions on Learning Technologies 10, 30-41 (2017)
6. Jivet, I., Scheffel, M., Drachsler, H., Specht, M.: Awareness is not enough: pitfalls of learning analytics dashboards in the educational practice. In: European Conference on Technology Enhanced Learning, pp. 82-96. Springer, (2017)
7. Vázquez-Ingelmo, A., García-Holgado, A., García-Peñalvo, F.J., Therón, R.: Dashboard Meta-Model for Knowledge Management in Technological Ecosystem: A Case Study in Healthcare. In: UCAmI 2019. MDPI, (2019)
8. Vázquez-Ingelmo, A., García-Peñalvo, F.J., Therón, R.: Capturing high-level requirements of information dashboards' components through meta-modeling. 7th International Conference on Technological Ecosystems for Enhancing Multiculturality (TEEM 2019), León, Spain (2019)
9. Vázquez-Ingelmo, A., García-Peñalvo, F.J., Therón, R., Conde González, M.Á.: Extending a dashboard meta-model to account for users' characteristics and goals for enhancing personalization. Learning Analytics Summer Institute (LASI) Spain 2019, Vigo, Spain (2019)
10. Cooper, M.M.: Data-driven education research. Science 317, 1171-1171 (2007)

11. Mandinach, E.B., Honey, M.: Data-driven school improvement: Linking data and learning. Teachers College Press (2008)
12. Custer, S., King, E.M., Atinc, T.M., Read, L., Sethi, T.: Toward Data-Driven Education Systems: Insights into Using Information to Measure Results and Manage Change. Center for Universal Education at The Brookings Institution (2018)
13. Yoo, Y., Lee, H., Jo, I.-H., Park, Y.: Educational dashboards for smart learning: Review of case studies. Emerging issues in smart learning, pp. 145-155. Springer (2015)
14. Teasley, S.D.: Student facing dashboards: One size fits all? Technology, Knowledge and Learning 22, 377-384 (2017)
15. Roberts, L.D., Howell, J.A., Seaman, K.: Give me a customizable dashboard: Personalized learning analytics dashboards in higher education. Technology, Knowledge and Learning 22, 317-333 (2017)
16. Dabbebi, I., Iksal, S., Gilliot, J.-M., May, M., Garlatti, S.: Towards Adaptive Dashboards for Learning Analytic: An Approach for Conceptual Design and implementation. In: 9th International Conference on Computer Supported Education (CSEDU 2017), pp. 120-131. SCITEPRESS, (2017)
17. Pleuss, A., Wollny, S., Botterweck, G.: Model-driven development and evolution of customized user interfaces. In: Proceedings of the 5th ACM SIGCHI symposium on Engineering interactive computing systems, pp. 13-22. ACM, (2013)
18. Kleppe, A.G., Warmer, J., Bast, W.: MDA Explained. The Model Driven Architecture: Practice and Promise. Addison-Wesley Longman Publishing Co., Inc., Boston, MA (2003)
19. Clements, P., Northrop, L.: Software product lines. Addison-Wesley, Boston, MA, USA (2002)
20. Gomaa, H.: Designing Software Product Lines with UML: From Use Cases to Pattern-Based Software Architectures. Addison Wesley Longman Publishing Co., Inc., Boston, MA, USA (2004)
21. Álvarez, J.M., Evans, A., Sammut, P.: Mapping between levels in the metamodel architecture. In: International Conference on the Unified Modeling Language, pp. 34-46. Springer, (2001)
22. Vázquez-Ingelmo, A., García-Peñalvo, F.J., Therón, R., Conde, M.Á.: Representing Data Visualization Goals and Tasks Through Meta-Modeling to Tailor Information Dashboards. Applied Sciences 10, 2306 (2020)
23. Harsu, M.: A survey on domain engineering. Citeseer (2002)
24. Kang, K.C., Cohen, S.G., Hess, J.A., Novak, W.E., Peterson, A.S.: Feature-oriented domain analysis (FODA) feasibility study. Carnegie-Mellon University, Software Engineering Institute (1990)
25. Kuzilek, J., Hlosta, M., Zdrahal, Z.: Open university learning analytics dataset. Scientific data 4, 170171 (2017)
26. Vázquez-Ingelmo, A., García-Peñalvo, F.J., Therón, R.: Taking advantage of the software product line paradigm to generate customized user interfaces for decision-making processes: a case study on university employability. PeerJ Computer Science 5, e203 (2019)

27. Shneiderman, B.: The eyes have it: A task by data type taxonomy for information visualizations. The Craft of Information Visualization, pp. 364-371. Elsevier (2003)
28. Lee, S., Kim, S.-H., Kwon, B.C.: Vlat: Development of a visualization literacy assessment test. IEEE transactions on visualization and computer graphics 23, 551-560 (2017)
29. Maltese, A.V., Harsh, J.A., Svetina, D.: Data visualization literacy: Investigating data interpretation along the novice—expert continuum. Journal of College Science Teaching 45, 84-90 (2015)
30. Toker, D., Conati, C., Carenini, G., Haraty, M.: Towards adaptive information visualization: on the influence of user characteristics. In: International conference on user modeling, adaptation, and personalization, pp. 274-285. Springer, (2012)
31. Dibia, V., Demiralp, Ç.: Data2Vis: Automatic generation of data visualizations using sequence to sequence recurrent neural networks. IEEE computer graphics and applications (2019)
32. Amar, R., Eagan, J., Stasko, J.: Low-level components of analytic activity in information visualization. In: IEEE Symposium on Information Visualization, 2005. INFOVIS 2005., pp. 111-117. IEEE, (2005)
33. Lam, H., Tory, M., Munzner, T.: Bridging from goals to tasks with design study analysis reports. IEEE transactions on visualization and computer graphics 24, 435-445 (2017)
34. Hu, K., Bakker, M.A., Li, S., Kraska, T., Hidalgo, C.: VizML: A Machine Learning Approach to Visualization Recommendation. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 128. ACM, (2019)