Towards Adaptive Dashboards for Learning Analytic
An Approach for Conceptual Design and Implementation

Dabbebi Ines[1,2], Iksal Sebastien[1], Gilliot Jean-Marie[2], May Madeth[1] and Garlatti Serge[2]
[1]*UBL, University of Maine, LIUM Laboratory, Laval-LeMans, France*
[2]*UBL, Telecom Bretagne, LABSTICC Laboratory, Brest, France*

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Abstract: Designing Learning Analytic (LA) dashboards can be a challenging and complex task when dealing with abundant data generated from heterogeneous sources with various uses. On top of that, each dashboard is designed in accordance with the user's needs and their observational objectives. Therefore, understanding the context of LA and its users is compulsory as it is part of the dashboard design approach.
Our research effort starts with an exploratory study of different contextual elements that could help us define what an adaptive dashboard is and how it fulfills the user's needs. To do so, we have conducted a needs assessment to characterize the user profiles, their activities, their visualization preferences and objectives when using a dedicated dashboard. In this paper, we introduce a conceptual model, which will be used to generate a variety of LA dashboards. Our main goal is to provide users with adaptive dashboards, generated accordingly to their context of use while satisfying the users' requirements. We also discussed the implementation process of our first prototype as well as further improvements.

1 INTRODUCTION

Human has been producing an overwhelming amount of data and information on the Web (John et al., 2016). In a learning situation, every time a learner or a teacher interacts with the learning environment such as taking an online class in a MOOC (Massive Open Online Course) or signing into their virtual learning environment; he leaves behind him a significant amount of digital footprint or traces of his actions (Greller and Drachsler, 2012). Through better use of this data, teachers can be able to adapt their courses and learners can use it to change their learning behaviors. As for the researchers, they are more interested in extracting new knowledge and in exploring the phenomena of learning data exploitation (Verbert et al., 2013). However, in the meantime, information expand faster than our capacity to understand them (Speier et al., 1999). Consequently, it becomes much harder for users to observe, to control and to adjust their learning process. For example, while MOOCs helps teachers to reach thousands of students simultaneously (de Waard, 2015), it also creates a major challenge for them to follow the interactions occurred throughout a learning session effectively. To address the problem of information overload, the adoption of a learning analytic (LA) process is required. LA helps the measurement, collection, analysis and reporting of data about learners and their contexts, along with a purpose of understanding and optimizing learning and the environments in which it takes place (Siemens et al., 2011). The development of this LA process represents a core objective of HUBBLE project (HUman Observatory Based on analysis of e-Learning traces)[1]. This project aims at creating a national observatory with the scope of building and sharing extensive data analysis processes based on traces generated from e-learning environments. This process offers ways to collect a critical mass of digital traces and to calculate a significant set of data called indicators (Iksal and Choquet, 2007). Therefore, the visualization of these indicators in the right way can help different users such as decision makers (teachers, designers, administrators or policy) to extract various facts about a particular learning situation. They can then draw meaningful conclusions about their different decision contexts. Moreover, the visualization task can support other users such as researchers and analysts to share, capitalize and reuse various tools and models, and also dashboard models.

[1]http://hubblelearn.imag.fr/

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Being part of HUBBLE project, the scope of our research work covers the design of reusable dashboard templates based on a user's requirements, and the generation of dynamic, contextual and adaptive dashboards. In fact, the design of a dashboard model should take into account various constraints related to the user's profile and their characteristics, distinct decision and learning contexts, etc. Our research also has a strong connection with existing works where a considerable number of heterogeneous indicators produced by different analysis tools (KTBS (Zarka et al., 2012), UnderTracks (Bouhineau et al., 2013), SMOOPLE (Gilliot et al., 2013), UTL (Iksal and Choquet, 2007)) will be dynamically and contextually visualized.

In order to design an effective contextual dashboard that provides a useful and dynamic way to access to relevant indicators, a central assumption in our work is that it is necessary to work on the identification of both visualization and decision context's elements. Hence, we conducted a needs assessment study to better understand user's requirements in terms of data visualization, which leads us to propose a conceptual design process for a dynamic generation of contextual LA dashboards. The study we have conducted helps us to shape our research question that focuses on: (i) what is the user's visualization and decision contexts? What are the most relevant indicators users need to make decisions? How to present these indicators for maximizing the assistance of the decision-making? How starting from context's description, an efficient dashboard can be provided to meet user's needs? Our work aims to introduce a conceptual model for a dashboard generator process which will be used to generate a variety of LA dashboards according to the different context of use. This paper is structured as follows: in the first section, we provide a brief background on the field of LA dashboards. We present in the second section, the study about user's needs and their different contexts. The process of building an LA dashboard based on the identification of our user's contexts is discussed in section 3. A case study and our first prototype are presented respectively in sections 4 and 5. We draw a conclusion and highlight future works in the last section.

2 RELATED WORKS

Making use of a large amount of data such as produced artifacts (Arnold and Pistilli, 2012), social interactions (May et al., 2011), resource usage (Verbert et al., 2013), time spent (Arnold and Pistilli, 2012) and exercise results (Mazza and Milani, 2004) in LA process aims at providing a better understanding and optimizing the learning experiences (Siemens et al., 2011). To facilitate the process, especially in the decision-making, data analysis tools such as data mining and data visualization techniques are widely used and integrated into learning analytic dashboards.

Data mining techniques can help users to detect new patterns and new knowledge that are likely to be relevant. While it can provide visualization along with tools that support data interpretation, it do not support decision-making (Wolff et al., 2013). It should be noted that it is not how a data mining process is meant to be used in LA as the data visualization is another domain of applications. Plus, data mining techniques are often too complicated for non-experts such as some teachers and students to make use of them and to interpret their meaning.

The other well-known visualization solution is learning analytic dashboard (LAD). LADs have been developed by a number of researchers. They aim at consolidating and arranging a set of the most relevant data related to user's objectives on a single computer screen in order to visualize and monitor them at a glance (Few, 2013). In this section, we present a group of LAD applications that have been deployed over the past few years. Similar to our objectives, these dashboard applications are designed to select and visualize digital footprints in order to support viewers to deal with the huge amount of data streams generated from different sources. While various existing dashboards are targeted to provide users with general information related to only one particular learning environments such as Travis (May et al., 2011) and GISMO (Mazza and Milani, 2004), others go further and work on giving the opportunities to users to control data generated from multiple sources such as REFLET CourseVis (Mazza and Dimitrova, 2007) and Tatiana (Dyke et al., 2009). Concerning evaluation, various research works highlighted the importance of the positive effect on different users given by the use of the dashboard (Santos et al., 2013). A line of existing works has been conducted with learning analytics to help teachers in their activities, for example, to track progress or to make their reports (Kelly et al., 2013), (Xhakaj et al., 2016). Other works have studied the effect of learning analytics on student retention (Nunes et al., 2013), on their performance (Arnold and Pistilli, 2012) or on improving students' engagement (Bouvier et al., 2014). Another example of learning analytic tool is the Open Learning Analytic platform (Siemens et al., 2011). This tool aim at considering the need of four users' categories at the same time: learners, educators, administrators, and researchers.

The problem is, in most cases, dashboards are imposed on users, and provide them general information without considering their abilities, preferences and personal observation objectives (Martinez-Maldonado et al., 2016). In fact, the use of LADs should satisfy users' needs in several contexts. However, having multiple users with different characteristics may imply different requirements for visualization, where the same data can be presented at a different time and in a several ways for various reasons (Olmos and Corrin, 2012). In other words, to increase the dashboard efficiency, it is crucial to consider the variety of users' context during the design process. Even though data visualization can be applied to a wide range of contexts, the creation of a context-aware dashboard tends to be a complicated task (Li et al., 2015). As, the context definition itself is considered to be a challenge mainly because of its differences from one case to another (Baldauf et al., 2007). Several works such as the CAVE platform (Xiaoyan et al., 2012) tried to define their visualization contexts in order to help their users to monitor visualizations regarding different situations. Three context categories are defined: user's problem, knowledge and purpose contexts where the difficulty is to ensure that visualization can not only match the problem, purpose and knowledge of user but also have to be deployed in a way that makes sense.

With the diversity of existing visualization techniques, it remains difficult to represent an accurate data with an adequate visualization technique. For instance, performance results can deliver through several techniques such as histograms, bubble, pies, table, and so forth (Scheuer and Zinn, 2007). Additionally, the diversity of data representations can also be related to the visualization vision that changes from one person to another and regarding their contexts (Silius et al., 2013). To better understand user goals and needs, many research studies tried to explain and to define users needs through the use of several techniques such as inquiry (Xhakaj et al., 2016), interviews (Bakharia et al., 2016), questionnaires (Ali et al., 2012), the evaluation of the dashboard design (Park and Jo, 2015) or survey (Mazza and Dimitrova, 2007). Our proposal has a strong connection with these works. However, our aims are not only based on the study of the users visualization objectives, and user's characteristics, including their visualization preferences, but also the study of their decision-making context in order to pursue users to visualize their desired data in a meaningful way that supports them take action or a decision. We attempt to present an expressive dashboard to be easily interpreted by each user. As a matter of fact, a visual representation can be meaningful to one user, but it may be incomprehensible to another. In the study, we defined different learning context elements that led to the design of a dashboard generator. Our goal with the latter is to provide users with a dynamic dashboard along with the data indicators and their visualization tools at the right moment based on their context of use.

3 DASHBOARD GENERATOR ARCHITECTURE

Answering users' needs regarding LAD represents a central part of our work. For this reason, we place a special focus on identifying the users profiles and their requests. In HUBBLE project, the study of the massive amount of data produced by the interaction of students and teachers with the existing learning technologies, interests not only students and educators themselves as decision-makers, but also researchers, analysts, designers, administrators, and policy makers and so forth. As we are dealing with a wide range of contexts and we are aware of how important to fully explore the user's requirements (Stodder, 2013) throughout the process of designing LAD, the study of the variety of users, their different learning problems, and their intended purposes take a prominent place among our research challenges.

Our work aims at designing a dashboard generator process which enables a dynamic production of different effective dashboards in order to answer various visualization needs expressed by each user in a wide variety of contexts. Hence, each generated dashboard should provide, on the one hand, a set of indicators gathering that facilitates the links between the data and the visualization objective. On the other hand, it should provide adequate visualization components to maximize the value of this relevant set of data to be visualized at the right time.

The core of this generator process is to integrate visualization components, user descriptions and different data/indicators where every set of indicators related to one visualization objective will be gathered together in order to add an additional semantic information (as illustrated in Figure 1). These set of components will act as a semantic framework for storing contextual information required for generating an adaptive dashboard.

However, the problem within this information related to the user's contexts is that they can change rapidly (Dey, 2001), since users themselves may not be able to easily maintain the same preferences or objectives when, for example, observing a dynamic

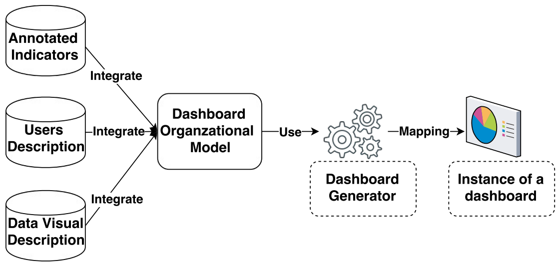

Figure 1: Dashboard generator illustration.

data evolving network. Hence, it can affect the choice of indicators or visualization component selection. Apparently, to bridge the gap between these different dashboard components within a dynamic context, a full description of the user's contexts and desired dashboards are needed. This description aims at facilitating the understanding of the links between existing components and dynamic user's needs.

Our work relies on user-centered (Abras et al., 2004) and context identification design. In the following section, we introduce a contextual study with the aim of better understanding user's requirements. This need's identification will bring us to create the main components for dashboard modeling, including user, visualization, and data models.

3.1 Identifying Users Needs

We conducted a needs assessment study including survey and interviews to investigate different users' contexts. This needs assessment is used to gather a different set of data about our probable end-users. More specifically, it may help us to define what is a user's visualization and decision context? What are the most relevant indicators users need to make decisions? How to present these indicators to maximize the assistance of the decision-making processes? How starting from context's description efficient dashboards can be provided to meet user needs?

To answer these questions, we organized our study into five sections presented in the table 1 where each one describes a contextual factor: who, what, how, when and then? The first section "WHO" aims at gathering data to help the description of users characteristics: their roles, their visualization knowledge level, their activities, their preferences and what kinds of decisions they want to make. This information helps the dashboard generator to identify who is the user, in which category they can be assigned. The second section is dedicated to the identification of "what" information each user needs to visualize to make decisions. The third section is used to identify "when" does it make sense to visualize a particular data and when it can be more useful in a given observational scenario. The section thereafter focuses on what is the best way to visualize data in a given situation for a particular viewer. In other words, each user needs to choose "how" to view each data in order to facilitate its understanding and interpretation. Lastly, in the case of context evolution or change in the situation, a user may detect, for example, some interesting patterns which require to obtain more details or even to get additional data visualization to ensure deep data interpretation. For this reason, it seems necessary for the user to identify also his needs and preferences in such situation in order to improve the dashboards generator adaptation to their new requirements and this new context. For example, how they want to be informed? How can they interact with this evolution? The following table 1 presents highlighted questions raised in our needs assessment.

Table 1: Needs assessment sections and elements description.

WHO?	
User profile and role: tutor, students, etc.	This is about identifying the user category in order to prepare different dashboard versions, if it is possible.
Personal information: name, age, physical condition, etc.	This refers to specific information that can be used for user classification.
Preferences and abilities	This question defines the level of knowledge of the user, and it helps to determine his prior preferences.
Goals and interests	This is the main question to understand what the user wants to do with the dashboard and to explain his needs to have a personal or specific dashboard.
WHAT?	
Analysis scenario	It is helpful to provide the user with a set of data gathered during his assigned analysis scenario.
Desired indicators	Among the list of indicators provided by a given analysis scenario, the user can precisely determine what is most relevant indicators to be visualized in his dashboard and they can explain their choices.

Table 1: Needs assessment sections and elements description (cont.).

HOW?	
Visual representation : Textual, graphical representation or using audio effect, etc.	Each user may prefer or used to a given data visualization technique and thus, it is possible to maintain the same data visualization preference with the dashboard.
WHEN?	
Temporal modality: synchronous, asynchronous or a hybrid visualization,	It defines the possible time of visualization.
Users interaction and collaboration	We study the needs of the integration of collaboration tools to facilitate decision-making via dashboards. This information helps to identify "when" the dashboard should be generated to ensure the communication between a group of users and how interact with dashboard during visualization?
THEN?	
How react during context evolution? Modify graphical representation, notify users, so on and so forth.	This information helps the dashboard generator to propose the relevant adaptive strategy in order to guarantee user satisfaction even with change of context.

3.2 The Needs Assessment Analysis

We targeted several members working on 13 different use cases involved in HUBBLE project through either by contacting them through a survey or an interview about their visualization needs. A use case, as defined in HUBBLE project, can be the study of data gathered during a learning environment or a pedagogical scenario that involve produced by a set of users (teachers, students, researchers, and so on.). Each use case includes a detailed documentation that would allow describing a sequence of events, activities, and users involved in such platform.

Among 13 use cases, we received 10 feedbacks which represent 10 different application of contexts. As a result, we noticed a diversity of users' profiles that could be interested in data visualization, represented in Figure 2. While 4 use cases have targeted the works and the requirements of researchers, 4 others use cases interested in teachers-designers, and the last two use cases are dedicated to teachers and to project managers. Based on the initial results of our needs assessment study, we identified a diversity of user's profile and their different visions about the efficient dashboard related to their situations and contexts. These primary results are detailed as follows:

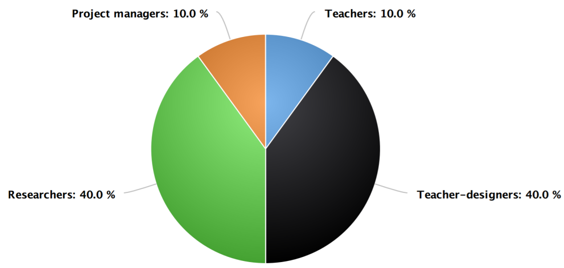

Figure 2: Breakdown of user's profile.

Researcher Vision:

Three out of four use cases involving researchers consider data visualization as a multi-user activity which requires sharing the same dashboard to better collaborate with other researchers. This collaboration requires the integration of different tools of communication to facilitate users' interaction such as chats or forums, and so forth. These researchers expressed the need to visualize data in order to:

1. Study the evolution and the progress of learners in order to identify students behaviors with the aim to allow extracting student series/ patterns of actions.
2. Determine learner typology.

We also understand that user like researcher is able to interpret data with different and complex representations. Regarding their high knowledge level with visualization techniques, they can express easily what they expect to have in terms of graphical representations. For this reason, they expressed their need to have the ability not only to be a dashboard's viewer but also to manage their dashboards by having the right and the possibility to personalize their dashboards directly: the set of data, the choice of data representation, dashboard template, time of visualization, etc.

Teacher-designer Vision:

Regarding the study of the different answers collected from the use cases designed for teachers-designers, we observed that unlike the researchers' demands, three use cases consider the use of dashboards as a single-user activity where sharing information with other users from the same categories is unnecessary to satisfy their visualization needs, especially when they have the need to:

1. Evaluate proposed exercises and courses.
2. Determine the typology of their students.

Some pedagogical designers/teachers proposed to integrate not only visual representations but also sound effects like being informed with alert notifications in order to detect unusual situation. Therefore, it requires the development of a hybrid dashboard that provides real-time visualization and alert notifications during session and proposes a visual overview after session.

Teacher and Pedagogical Team Visions:

Both users have described similar goals and interests. Their main purpose is to:

1. Identify parameters representing the popularity and the healthiness of courses.
2. Determine parameters indicating the reason for both failure and learner success.
3. Understand the situation and interact with students.

For example, in the case of MOOCs, with the remarkable number of registered students, analysts paid attention to the use of simple visualization representation in order to facilitate the interpretation of this massive amount of data, such as using significant colors to indicate success as green color and red one representing fail.

Hence, we can consider that their most important challenge here is to reduce the number of failure students. For this reason, it seems necessary to offer teachers and the pedagogical team a hybrid dashboard. Thus, it may allow them to be reactive and aware of the situation of their students, to be informed about the student's problems and to detect the student risk to be a failure as soon as possible with the aim to help them very quickly. One of their requests is to provide sound effects and alerts and to have also the ability to share some results, if it is necessary, with other users (other teachers or project managers).

Based on the first results of our needs assessment study, namely what and how users need to visualize and to organize the data visualization to get "the best" dashboard for a particular scenario, we represent a proposed model of the different learning context elements related to the dashboard generator's process. This proposed model is described in detail in the following section.

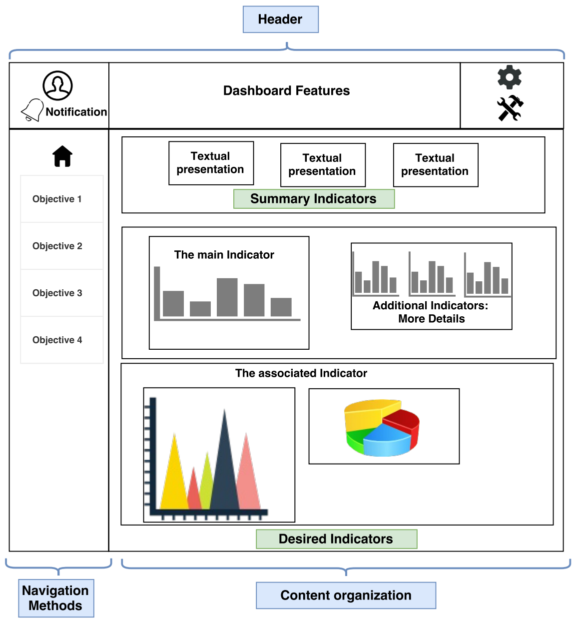

Figure 3: The structure of a generated dashboard.

4 TOWARDS THE GENERATION OF CONTEXTUAL LEARNING DASHBOARDS

Based on our needs assessment analysis of how each end-user perceives his dashboards, we identified a set of dashboard descriptions. The dashboard could be defined as a visual display that enables visualizing the most important indicators produced during the analysis process. In our case, a structure of the dashboard, presented in Figure3, not only have included a set of indicators consolidated on a single computer screen (Few, 2013), but also to regroup and link a set of indicator together based on their relationship. In addition, it has to incorporate different visualization functionalities which may help to manipulate and to highlight the most relevant information. These functionalities can be the use of alert notifications, positioning on the page, and careful use of colors and fonts, etc.

4.1 Dashboard Organizational Model

As introduced earlier in the paper (refer to Figure1), the proposed dashboard generator process, takes into account, every time, the different contextual description provided by each particular user.

Based on this description, we depict in Figure3 a sample of dashboard structure as it will be proposed to our users.

This dashboard template (Figure4) incorporates three basic components. The first component is dashboard headers. Headers provide dashboard identity or logos and incorporate the set of functionalities that it can make the dashboard more useful. It can facilitate the collaboration between a group of users by adding, for instance, sharing tools or chat. Other requested visualization functionalities may be used to re-organize the dashboard structure. The dashboard can also incorporate other functionalities such as alert warning notifications with the aim of providing a hint about unusual events and to highlight the most interesting changes in the dashboard.

The second component represents the choice of the navigation methods and the levels of the content organization. It may allow the representation of the set of presented indicators either on one page or using a menu or tabs with the aim to facilitate the navigation on the dashboard and also it will serve to pool indicators with the same objective together in order to maximize efficiency.

The third component represents the core of the dashboard or the content area which focuses on indicators. It consists of two main elements. The first element -defined as summary indicators in Figure3- consists of the representation of textual indicators that ensure the display of a textual description about the most relevant indicators. The second element concerns the visualization of a set of organized and regrouped indicators. This part takes into account the importance of choice of visualization forms and the choice of which indicators will be grouped together in a way that facilitates understanding and shows the relationship between them.

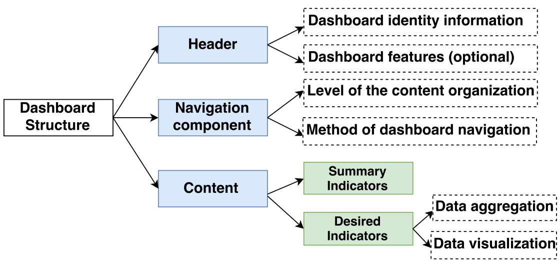

Figure 4: Main components of the dashboard structure.

Organizing dashboard's contents in a meaningful way is considered as a challenging issue where indicators are not designed to be placed anywhere on the dashboard and every item related to another one should be positioned close to each other (Few, 2013). For this reason, we defined relationships between dashboard content in order to set the appropriate way to look at user's objectives. This component is represented by the model in Figure5, and consists of two main relationships:

1. To group main/desired indicators -defined by the user- associated with other selected and proposed indicators that may serve to satisfy the same objectives (refer to the first and the second indicator in Figure3). The simple way to relate associated indicators can add more accessibility to them.
2. Moreover, this component represents a set of different structures for the same information with a different level of detail such as the additional Indicators in Figure3.

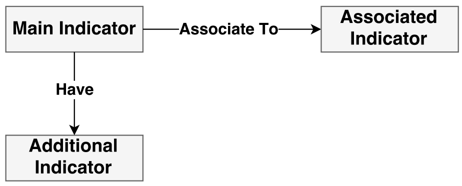

Figure 5: The relationship between indicators.

So, the dashboard generator has to identify the relationship between these indicators and to represent them appropriately for every end-user. In order to achieve that, three main information are required. The first one is related to the user's characteristics. It includes models that define their visualization preferences. The second information corresponds to data representation layer or visualization model, including the dashboard's functionalities. The last component is related to modeling data including the learning scenario and the activities' models.

These different components are represented in Figure 4, in order to provide the user with a set of appropriate data and kind of visualization. In the following paragraphs, we describe these different components.

4.2 Dashboard User Model

The user model is a fundamental component of an adaptive system. Our generator has to adapt the dashboard in different contexts automatically, so, the design of the user model is crucial. It must take into account the analysis of the results we gather in our needs assessment grid. This model has to represent a broad range of assumptions about different users. A user model should consider these two major needs: First, it has to represent the user's multiple visualization objectives. Next, it has to be sufficiently adaptable to integrate the evolution of a user's needs. Our model is initialized with a stereotype, and in a future stage, it will be modified according to the user activity on the dashboard.

In this section, we describe the user model's elements necessary to establish our objectives. This model considers the user's level of visualization knowledge, preferences, interests, behaviors and other facts. The different sections of our user model are the following:

Personal Information: It helps to classify users according to their personal characteristics such as their roles, their visualization objectives. This section has a twofold purpose. On the one hand, it is necessary to the dashboard identification (use case, user id) that will lead dashboard generator to identify the user status. Knowing the use case assigned to our end-user, it may help us to limit the data selection and then help us to provide only interesting data related to user needs. When users log on, they will be driven to their dashboard according to their preferences. In fact, the dashboard generator will present an overview dashboard containing all the latest visualized indicators in order to keep them informed about the last events.

On the other hand, personal information section aims at classifying viewers by their roles, their visualization objectives or even by their skills and abilities. The purpose of user classification is to help in facilitating the display of the right information for each user. Moreover, we will be able to infer other user preferences based on similar profiles in order to enhance the accuracy of the provided data.

- *User id:* It is used to identify the user and to connect him to their session.
- *User role:* It aims at categorizing users by their roles, such as tutor and student.
- *User type:* It indicates whether the user is connected as an individual or is associated with another group of users. In case, the user is related to a particular group of users; dashboard generator will enable the use of collaboration tools to ensure the communication within the group.
- *User status:* It identifies whether the user is active/connected or not. It appears to be a relevant information which helps to ensure the best way of presenting data: the dynamism of data representation. For example, while a newly active user is interested in visualizing real-time indicators, the other user may prefer to have a summative representation and an overview of the interesting information due in a given period.
- *Use case:* Every use case is attached to an analysis scenario and their list of data. This information is important for data selection where each user will be provided with a set of indicator related to his specific use case to ensure data accuracy.
- *Visualization objective:* It describes the user's goals and interests: what he needs to explore, explain or decide. It describes the visualization activity that users care about. It helps also to recognize what users are trying to achieve with the dashboard. Knowing users objectives are considered more than just comprehension; it also involves defining his context. For example, users' goals and interests can be the identification of a particular phenomenon or the evaluation of a group of activities, signaling problems, transfer knowledge.

User's Knowledge: This part describes the visualization experience of the user and their abilities. It is initialized with his previous experience. Users can be a beginner, a competent, a proficient, an expert level: For example, a beginner level user often needs step-by-step support for how to manipulate visualizations while an expert-level user may require more support for personalizing visualization to complete complex tasks.

User's Visual Preferences: A user preference includes the dashboard template, the desired data, users preferred graphics and another in which it describes users adequate dashboard. Users' preferences can be assigned to not only to a particular user but also to an entire group of users sharing similar users' profiles. This section is necessary for the definition of an adaptive strategy in which the automatic creation of information graphics tailored to users' preferences and tasks.

4.3 Dashboard Visualization Model

The main objective of data visualization is to let the viewer get a relevant analysis and understand what is happening. Visual representation does not only represent a significant amount of data coherently but also help to extract new knowledge and/or to let the viewer be a decision maker within this particular context.

However, with the variety of existing visual graphics and a large amount of data, the choice of the adequate data representation may be critical. The choice of a visual form should be easily understood by users and should represent information in a meaningful way to ensure the user's needs by providing familiar visual components to the user and respect their level of visualization knowledge. Presenting a wrong visual graphics or providing a sophisticated type of visualization to a beginner viewer, for example, may lead to wrong data interpretation.

In an attempt to easily provide the best-suited data representation, we devoted the following part to describe and to index the characteristics of our visualization model or a right visual graphic selection:

- *Form of visualization:* It helps to determine the presentation types: It can be a table, chart, text or image.

- *Number of dimensions:* It specifies the amount of information that one single visual form can represent.
- *The quantity of data:* It describes some items that could be displayed for each dimension. Only a few or many?
- *Data structures:* It indicates the appropriates structure of data and format of the information to be represented. This information is necessary to link the desired data with the best visual form.
- *Purpose of visualization:* Another way to offer the suited display from the angle of what user tasks a visualization aims to support. Visualization can help viewers to compare data sets easily or may present composition, data distribution or to highlight the relationship between data. For example, tables are useful to show the differences or similarities between values while a hierarchical data representation shows relationships between groups.
- *Visual granularity:* It allows changing the aggregation of the data to display the desired level of detail.
- *Meta data:* It is optional information that contains details. It serves to index visual representations like if the associated chart is a multidimensional, temporal, hierarchical graph.
- *Similar visualization:* It serves to recommend and to associate other visual graphics that share similar characteristics (number of dimensions, the format of the information) and can be used in the same context or some contexts which fulfill similar objectives. This can help the user to have a different interpretation of the same data.

4.4 Analysis Scenario Model

The key objective of scenario description is to express an additional contextual information like data relationships that allows the dashboard generator to understand, find the right indicators easily and to be able to combine it with other information as needed in a meaningful way. In each specific scenario, all data and indicators are related to satisfying a particular analysis objective. Each specific scenario involves different activities including a set of data. For instance, to identify student engagement, we need to access to each student activities like the number of possible connections established by each student or the amount of exchanging messages between forum's members.

In this section, we define different scenario properties:

Analysis Scenario Description:

- *Learning Scenario Objectives:* Each scenario is associated with visualization goals and interests. Every objective of visualization can be achieved by including one or multiple tasks. For example, to classify of students over time, dashboard generator need to access to every student's activities like student response rates, connection ratio, etc.
- *Use case:* It defines the user's pedagogical context, their field of education or training, used information technology platforms and their users. It helps to associate a list of data for each user.

Activity Description: Each activity is described by a set of data like its users, the activity status to indicate whether the activity is finished, started or ongoing.

- *Task-related purpose:* It defines the specific goal of activity within a particular scenario.
- *Activity status:* The activity status indicates the level of processing activity (planned, started or finished), where a planned activity is yet to begin, a started activity is continuing or ongoing activity and a finished activity is complete. This field is bound with the date and time stamp that provides information about the right moment to visualize the set of indicators/data related to the activity.
- *User of an activity:* e.g. group of students

Dashboard Indicator Description: Every scenario includes a list of indicators related to different activities. The data/indicators should be organized and described in such a way that it can be selected easily by the dashboard generator for a specific context. The part illustrates the data structure and characteristics:

- *Type of data:* Data can be quantitative if it is in numerical form, whether it is continuous and discrete or whether it is qualitative. For instance, line Graphs can be used to display the development of quantitative values over a period of time rather than pie charts and bar charts that can both be effective methods of portraying qualitative data.
- *Number of dimensions:* It indicates the amount of information that one indicator can provide. For example, an indicator can represent user development over time. This indicator provides two information: Time and users work's evolution. Both types of data and number of dimensions aim at bridging the gap between data and visualization model by finding best match data (the type of data) and visual elements and properties (data structure) to pick the right data visual presentation easily.

- *The quantity of data:* When the user has a significant amount of data to visualize, the dashboard generator can propose data visualization at a different level of abstraction in order to be able to facilitate the data interpretation.
- *Meta data:* It associates other similar indicators that are dedicated to the same context, scenario, use cases, users and may have related purpose.

In order to fulfill the requirements identified due to our needs assessment survey and interviews, we proposed and designed a dashboard generator process, which is further presented through the presentation and the implementation of a prototype (section 5).

5 ILLUSTRATIVE CASE STUDY

In HUBBLE project, we had to work on various datasets; each dataset is associated with a use case. A use case is composed of a data and individuals description such as the teacher, researchers, analysts, who were involved in a real learning session. In order to build our first prototype, we did focus and used data from the MOOCAZ case study; it is a MOOC which concerns the creation of a MOOC from A to Z. We received data and observational needs from researchers of the French ENS Cachan. We had two-course sessions with approximately 5000 students in each one. Each course session has a start date, set by the pedagogical teams, and an end date. The learners of the same session follow the MOOC with proposed deadlines. These learners had to work on several proposed chapters that may include videos, quiz, and assessments. During these MOOC sessions, researchers have identified a set of users stereotypes. After conducting its analysis, a visualization of learners categories and their work's evolution during the entire MOOC sessions are needed.

6 PROOF OF CONCEPT OF CONTEXTUAL DASHBOARD

Our dashboard generator is defined as a context-sensitive framework that adapts continuously to many viewers' contexts with the aim at satisfying their described needs where these different components represent together the dashboard context. This framework as illustrated in Figure 1 depends on three fundamental components that are, user, data, and visualization models according to the dashboard structure model discussed in the previous sections.

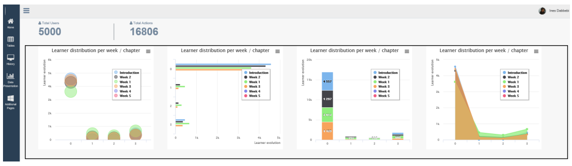

Figure 6: A sample of generated dashboard page: MOOCAZ use case.

To validate our work in a real world setting, we implemented a prototypical tool, an example of a generated dashboard is presented on Figure 6. The prototype helps the viewer to answer their contextual requirements through providing an adaptable visualization solution that satisfies their desired visualization representations of a specific set of indicators. For a first time, the adaptation of the generated dashboard will be done at any time but only on the demand of the users where they can manually configure the entire dashboard. This will be our first step toward the design of adaptive dashboards. As illustrated in Figure 7, the dashboard generator starts by identifying the concerned viewer: his role, his objectives, and his use. These information aim at distinguishing the appropriate analysis scenario including a set of indicators. In the HUBBLE project, indicators are collected, transformed and calculated separately by various analysis platforms: UTL, KTBS, SMOOPLE, UnderTracks.

When some indicator's descriptions meet users' described objectives, they will be selected by the dashboard generator that will prepare a set of associated indicators that serves for the same analysis scenario or user activities (as it is explained in Figure 5) as means of enriching the dashboard's content.

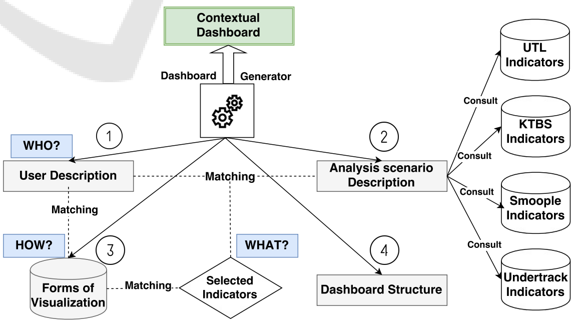

Figure 7: Dashboard generation process.

In the third step or form of visualization selection step, the dashboard generator will take into account the description of the selected indicators such as a number of dimensions, the type of data. This step helps to sort a group of visual representations -already pre-selected based on user preference- then, to select the adequate visual form that matches with the indicator description.

Finally, by having the set of appropriate content depending on users' visualization preferences, the dashboard generator will propose the integration of this content with a set of desired functionalities to the viewer regarding his dashboard description.

As a result of this process implementation, we generate a dashboard's instance, presented in Figure 6 to answer the visualization objective requested by an analyst in our case study MOOCAZ. The user main objective was to study the learners' behavior throughout the MOOC. Three types of pedagogical resources are available to the learners and four possible actions they can do: to watch a video, to download a video, to answer a quiz, to work on an exercise. These different actions are used to determine the learner states. The dashboard generator has provided to the end-user the possibility to visualize the evolution of the learners through a time display in order to enable the study of user behavior week after week. Hence, it may allow learners classification through a comparative visualization form.

To facilitate the indicator interpretation, we regrouped the set of proposed visualization forms answering the same objective together according to dashboard structure defined in Figure 3.

7 CONCLUSIONS AND FUTURE WORKS

The main objective of our work is to provide an adequate learning analytic dashboard by meeting each user's requirements. The design of such LA dashboards requires a deep understanding of users' contexts such as his preferences, his main objectives, and activities and his dashboard's vision. In this paper, we conducted a needs assessment study with 8 use cases out of 13 involved in the HUBBLE project with the aim of generating a solution to meet his identified needs. This study led us to construct a dashboard generator which it based on a set of models that enable the process of learning contextual dashboard design. By describing each of user, data, and visualization component models, the dashboard generator will set the link between these different components to allow data visualization according to different contexts.

We applied the proposed dashboard generator process for designing and deploying dashboard for HUBBLE project's use cases where the results and the experiment demonstrate the feasibility of this process. However, users often have just a slight idea about their preferences, and they are not able to express them precisely. In this case, our aim in the future is that users will not be asked directly for their preferences, but this information will be derived from their behavior while interacting with the dashboard. It requires from the dashboard generator to take into account and to adapt dynamically to this user's context evolution. Therefore, user's visualization preference and the change of context will be captured through the study of their user's interaction history. For example, through the combination of visual activities or the repetitive choice of data representation. Where our tool should tracks and memorizes a sequence of actions and interaction with the dashboard that may describe the choice of data, visual representation, the combination of data, the time of visualization. Having a history provides the dashboard generator with new user visual preferences that help eventually to modify the dashboard's behavior dynamically.

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