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Towards Textual Reporting in Learning Analytics Dashboards

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***Abstract*—In this paper we present the SoftLearn Activity Reporter (SLAR) service which automatically generates textual short-term reports about learners' behavior in virtual learning environments. Through this approach, we show how textual reporting is a coherent way of providing information that can complement (and even enhance) visual statistics and help teachers to understand in a comprehensible manner the behavior of their students during the course. This solution extracts relevant information from the students' activity and encodes it into intermediate descriptions using linguistic variables and temporal references, which are subsequently translated into texts in natural language. The examples of application on real data from an undergraduate course supported by the SoftLearn platform show that automatic textual reporting is a valuable complementary tool for explaining teachers and learners the information comprised in a Learning Analytics Dashboard.**

I. Introduction

One of the most active areas in learning analytics [1] is the development of user interfaces that enable both teachers and learners to understand and optimize what is happening in a course. In this context, learning analytics dashboards (LADs) [2] have emerged as applications that support a variety of forms to visualize and interact with the data collected in a learning environment. Typically, LADs are oriented to a specific learning context and therefore they include graphical tools specifically designed for achieving a purpose such as detecting isolated learners [3], understanding collaboration process among learners in social environments [4] or visualizing the effort indicators of learners to evaluate their progress during a course [5]. A good review and evaluation of LADs is found in [6].

However, most of the LADs are entirely based on graphical visualizations that are not easy to interpret by many teachers and learners, especially when the amount of data to visualize along the time dimension is very high (e.g., interactions among learners in collaborative and/or social environments). To overcome this issue and facilitate LADs understanding, we propose the development of tools and techniques which automatically generate linguistic descriptions of the data shown in the graphical visualization tools. We do not consider these linguistic descriptions, also known as *textual reports*, as an alternative to the graphical visualization tools, but as a complementary tool that explains in plain natural language what teachers and learners are visualizing. This is the focus of the paper.

The research field of linguistic descriptions of data (LDD) [7] intends to automatically produce natural language texts that convey the most relevant information contained (and usually hidden) in the data. It uses a number of modeling techniques taken from the soft computing domain (fuzzy sets and relations, linguistic variables, etc.) that are able to adequately manage the inherent imprecision of the natural language in the generated texts. Either alone or in combination with other natural language generation data-to-text (D2T) techniques [8], [9], LDD models and techniques have been used in a number of fields of application for textual reporting in domains such as meteorology forecasts, domestic power supply or economy, among many others (for more details see the review in [10]). To the best of our knowledge, none of the LDD or D2T techniques we are aware of have been used until now in the field of learning technologies as a tool to provide learners and/or teachers with linguistic reports automatically generated from the data produced in the learning process, with the only exceptions of [11], which generates feedback reports for students based on several performance factors, and [12], which focuses on describing the learner's rating in a specific learning activity.

In this paper, we present the SoftLearn Activity Reporter (SLAR) service, which automatically generates textual reports of the learners' activity that takes place in a virtual learning environment. This tool has been integrated as a service in SoftLearn [13], [14], a process mining-based platform that facilitates teachers the learners' assessment. SLAR extracts the relevant information from the data collected by SoftLearn, creating intermediate descriptions through linguistic variables and temporal references, which are later translated into natural language texts. We have tested this LDD tool using real data provided by 72 learners enrolled in the Educational Technology undergraduate course of the Degree in Pedagogy at the Faculty of Education of the University of Santiago de Compostela.

The paper is structured as follows: Section II describes the LDD approach which automatically generates textual reports; Section II-B presents a number of examples that help to understand how the textual reports are generated; and Section III summarizes the main contributions of the paper.

II. Automatic Textual Reporting in SoftLearn

SoftLearn [13] [14] is an assessment platform that operates as one of the learning analytics services of a big data-based

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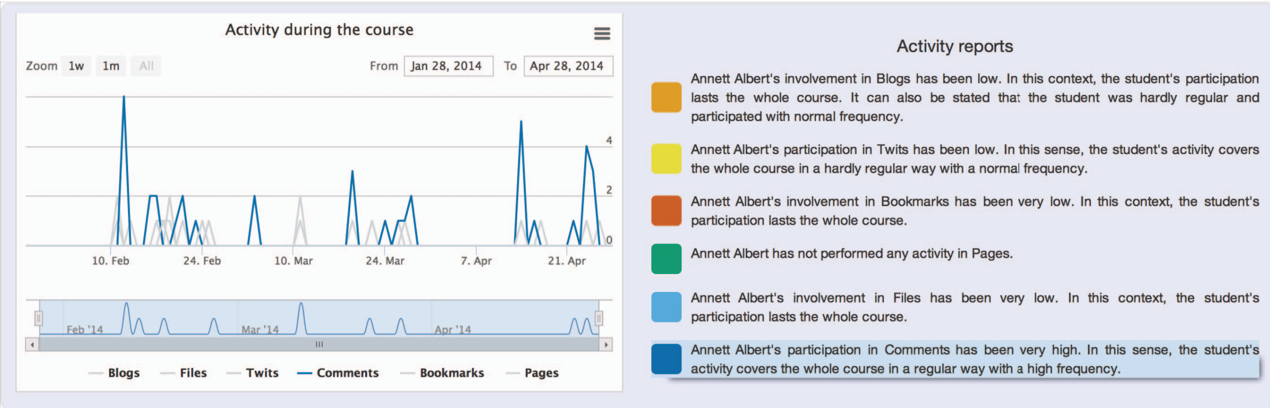


Fig. 1. General overview of SoftLearn dashboard for teachers including automatically generated natural language activity reports.

architecture specifically designed to capture, store and make available in real time the large amounts of data generated by the students of a course. In this architecture, a learning activity sensor captures the students' events that produce the learning relevant data. Data is stored in a graph-based database through Experience API interfaces and is sent in real time to the learning analytics services of the architecture. These services, like SoftLearn, are in charge of processing the data to extract valuable information about the learning processes. In this architecture, SoftLearn allows teachers to assess the performance of the students, providing information about their learning process and behavior throughout the course. The graphical user interface of the SoftLearn e-learning platform [13] allows teachers to (i) understand the learners' behavior through the visualization of the learning paths followed by the learners and (ii) also facilitates the evaluation of the learning activities carried out by learners during the course. Regarding the latter, the dashboard in SoftLearn provides in a graphical way different statistics about the students and their activity levels in the different portfolio elements of the course, such as blogs, comments, bookmarks, etc (Fig. 1).

In this context, the functionality of the dashboard has been now extended and enhanced with the inclusion of the SLAR service which provides automatically generated natural language reports built from every student activity data in each portfolio element. These reports allow teachers to better understand the students activity, which can also be visualized through time charts, facilitating the students assessment by means of a rubric based on the students learning process, its social interaction, motivation, collaboration with other students, and content structure. SLAR is based on linguistic description techniques adapted from the soft-computing field and natural language generation data-to-text (D2T) systems. In particular, it follows a similar approach as GALiWeather [7], a natural language weather forecast generation service.

A. Service architecture

The approach we have developed automatically converts student activity data into textual reports through a two-staged pipeline process (Fig. 2). In the first stage the service extracts the relevant information from the student's activity data as a set of language-independent linguistic terms (also known as intermediate linguistic descriptions [7]). This information serves as input to the second stage, in which the final textual reports are generated through the use of natural language templates.

1) Service input data: As mentioned above, SoftLearn distinguishes several portfolio elements. These include blogs, files, twits, comments, bookmarks and pages. For each of them, the activity level of every student in a given course is tracked on a daily basis. As a consequence, a teacher can visualize the involvement of a student during the course period through SoftLearn dashboard. For example, Fig. 1 shows the activity of a certain student in the portfolio element "Comments" for the whole course period.

In this context, the report generation system provides textual information for each individual portfolio element from its associated activity data.

2) First stage: Linguistic description generation method: The first stage of our solution obtains an intermediate linguistic description for a student's activity in every portfolio element within a temporal window: semester, course, etc. Each description is a set of linguistic labels and relevant data extracted from the student's activity data series (Fig. 1) about several relevant features:

- *Participation level.* Provides information about the absolute participation of the student.

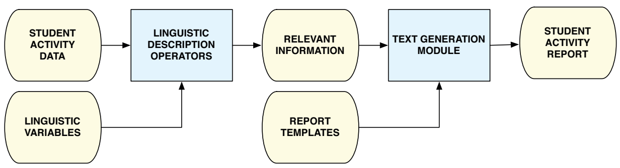


Fig. 2. General schema of the SLAR (SoftLearn Activity Reporter) service for the automatic generation of natural language reports.

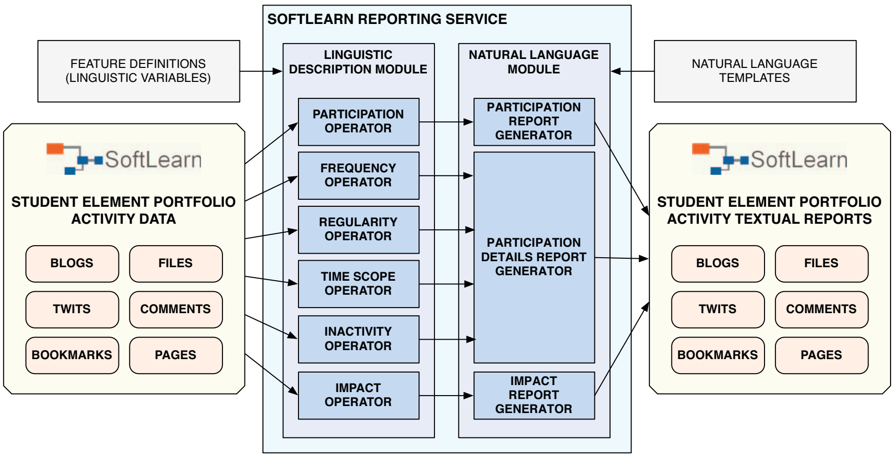


Fig. 3. Module correspondence between the linguistic description and report generation stages.

- *Regularity*. Provides information about how regular a learner is in his/her activity, i.e., how much the student's inactivity period lengths deviate from the average inactivity length.
- *Frequency*. Provides information about how frequent a student is in his/her activity, i.e., the less time between tracked activity the more frequent the student is.
- *Activity time scope*. Provides information about the learner's activity temporal window within the course period, i.e., when the student starts participating and when this activity ends.
- *Inactivity periods*. Provides information about the period length of most inactivity.
- *Impact*. Provides information about the impact of the student's activity from data about the number of "likes" and comments received from other learners as a result of his/her activity.

For each of these features we have defined a set of terms or labels that categorize the different possibilities that may be of interest to consider and implemented associated operators which select the fittest label for each feature. Table I displays the defined labels for each feature. These can be independently defined and configured for each portfolio element (for instance, the definition of *HIGH* participation in "Comments" might be different from its definition in "Blogs", since to participate in the latter usually requires more effort from the learner).

TABLE I. LABELS DEFINED FOR EACH OF THE SOFTLEARN INDICATORS

Feature	Labels
Participation level	*VERY LOW, LOW, NORMAL, HIGH, VERY HIGH*
Regularity	*STRICTLY REGULAR, REGULAR, HARDLY REGULAR, IRREGULAR, VERY IRREGULAR*
Frequency	*VERY LOW, LOW, NORMAL, HIGH, VERY HIGH*
Activity time scope	*BEGINNING, HALF, END* (of the course period)
Inactivity	Numeric value
Impact	*VERY LOW, LOW, NORMAL, HIGH, VERY HIGH*

Regarding the feature operators, these receive as input the activity data and their corresponding label set (except the "Inactivity" operator, which does not use labels) and perform several calculations to determine the label better describing the original input data. As an example output result of these operators, Table II shows a linguistic description including relevant information about the activity data shown in Fig. 1.

This extracted information in form of intermediate linguistic descriptions serves as input to the second module, whose task is to translate the language-independent descriptions into easily comprehensible natural language texts.

3) Second stage: Natural language generation: The natural language generation stage of this application consists of a domain-specific module which has also been divided into different logical components. From a global perspective, each of these components receives the intermediate linguistic description (Table II) generated by their associated operators and generates the textual reports.

More specifically, we divided the task of producing the final reports into three components. The first one deals with the existence of student activity and the activity level (this information is provided by the operator for the "Participation level" feature). The second one provides additional information about this activity, through the aggregation of the information provided by the "Regularity", "Frequency", "Activity time scope" and "Inactivity" feature operators. Finally, the third component produces reports about the learner's activity impact on other students.

The reports produced by these three components are fused

TABLE II. EXAMPLE OF A LINGUISTIC DESCRIPTION FOR THE ACTIVITY DATA IN FIG. 1.

Participation level	VERY HIGH
Regularity	REGULAR
Frequency	HIGH
Activity time scope	BEGINNING - END
Inactivity	16
Impact	LOW

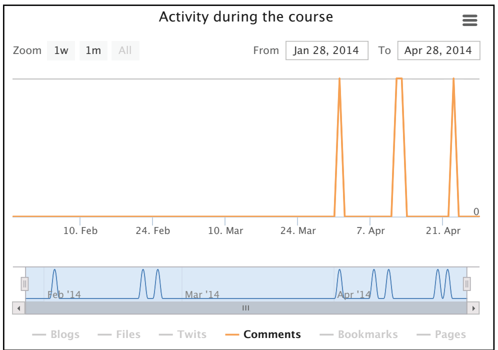
and finally returned as single natural language text which is then displayed in SoftLearn's dashboard. Figure 3 provides a detailed graphic description of how each feature in the linguistic description stage relates to each component in the NLG stage, thus extending the schema in Fig. 2.

We have defined language-specific templates in structured text files containing generic natural language sentences for each report generator component. These are loaded by the service and provided to their corresponding NLG component. Using the information contained in the intermediate linguistic description, each NLG component identifies the scenario cases defined in the templates and maps the linguistic terms from the description into natural language expressions.

This technology allows us not only to provide reports in different languages just by changing the output templates, but also to support alternative templates for the same output language in order to provide different ways of expressing the same information. This helps when dealing with repetitiveness issues when reading several reports at a time.

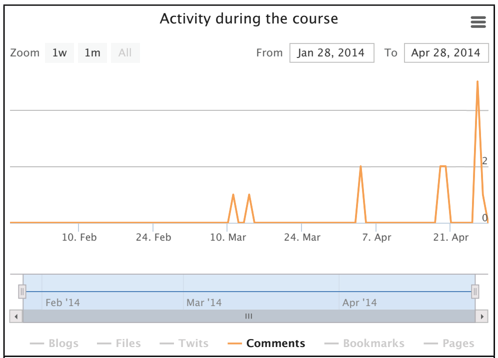
B. Reporting examples

We have applied the SLAR service on real anonymized data extracted from 72 students enrolled during the first semester 2015 in the Educational Technology undergraduate course of the Degree in Pedagogy at the Faculty of Education of the University of Santiago de Compostela. This course was developed in a blended learning mode with virtual activities, where students undertake learning activities through a social e-portfolio with blogs, micro-blogging tools, favorites, pages, etc. Specifically, our test data tracks the number of times a student performs an activity on a daily basis in the portfolio element "Comments", as well as how many comments and "likes" they get from other learners. Since the diversity of data allows for many different situations, we present in this section several examples of reports for students with diverse activity patterns.



Leonarda Wingler's involvement in Comments has been very low. In this context, the student's participation only started towards the course end.
Finally, regarding Leonarda Wingler's activity impact on other learners, it can be deemed as normal, since the student received 9 likes and 15 comments.

Fig. 4. Automatic report example obtained from real data for a rather inactive student.



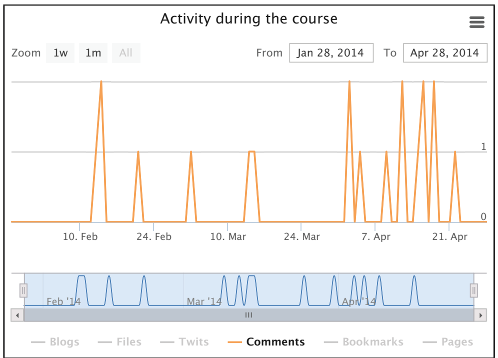
Marianna Matteo's involvement in Comments has been low. In this context, the student's participation started halfway course. It can also be stated that the student was irregular and participated with low frequency, besides being inactive for periods of up to 42 days.
Finally, regarding Marianna Matteo's activity impact on other learners, it can be deemed as very low, since the student received 2 likes and 0 comments.

Fig. 5. Automatic report example obtained from real data for a less inactive learner.

For instance, Figure 4 shows a report for a student with almost no activity during the whole course until the ending period. As a consequence, the report reflects this situation and does not offer information about regularity or frequency due to the learner's scarce participation.

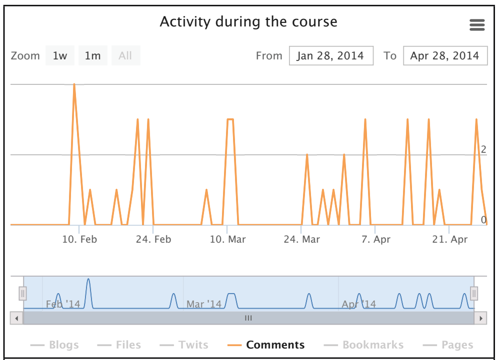
In other cases, as displayed in Fig. 5, learners do participate a bit more and consequently more information can be conveyed about their behavior. In this second example there is a low activity starting towards the middle of the course period. It is also worth mentioning that this report includes inactivity information.

Figures 6 and 7 display reports about students with an



Nora Contos's participation in Comments has been normal. In this sense, the student's activity covers the whole course period in a regular way with a high frequency.
Finally, regarding Nora Contos's activity impact on other learners, it can be deemed as normal, since the student received 9 likes and 17 comments.

Fig. 6. Automatic report example obtained from real data for an active student.



Rosanna Cookson's involvement in Comments has been very high. In this context, the student's participation lasts the whole course. It can also be stated that the student was very regular and participated with high frequency.
Finally, regarding Rosanna Cookson's activity impact on other learners, it can be deemed as very high, since the student received 36 likes and 19 comments.

Fig. 7. Automatic report example obtained from real data for a very active learner.

opposite behavior to the previous first two examples. In fact, a quick look at both activity plots shows that the learners in the last two examples might follow similar activity patterns. However, the reports prove that, despite their apparent visual similarity, some significant differences exist between them.

Actually, according to the textual reports, the student's participation in Fig. 6 is normal, whereas the learner's activity in Fig. 7 is very high. Such apparent incoherence is explained if we carefully observe that the plot scales are different, showing that the student with normal participation only participates twice a day at most and the learner with very high involvement often reaches three and up to four activities per participation day.

In this sense, and especially for Fig. 6 and Fig. 7, the textual reports are a coherent way of providing objective information that can complement visual dashboards and help teachers to understand in a comprehensible manner (natural language) the behavior of their students.

III. Conclusions

We have presented the SoftLearn Activity Reporter (SLAR) service that automatically generates textual short-term reports for the students' behavior in virtual learning environments. This solution combines linguistic descriptions of data techniques together with a template-based Natural Language Generation (NLG) approach. SLAR has been integrated in the SoftLearn platform to complement and enhance the information provided by its graphical visualization tools with the textual reports of the data shown in those tools, helping teachers to understand in a comprehensible manner the students' behavior during the course. Furthermore, we have tested our solution with real data generated by 72 learners of the Educational Technology undergraduate course of the Degree in Pedagogy at the Faculty of Education of the University of Santiago de Compostela.

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