Integrated Analytic Dashboard for Virtual Evaluation Laboratories and Collaborative Forums

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***Abstract*—This paper presents a new Learning Analytics dashboard which integrates all the information gathered by a virtual evaluation laboratory deployed at our institution and, also, the collaborative evaluation forums used by students in our courses. As an example, a subject focused on the configuration of network services has been chosen to implement our approach. Our proposal will be able to graphically show the students' progress both in an experimental and collaborative way at the same time. Therefore, lecturers can guide each student through the learning process based on his/her particular knowledge-level and grade her/him at the end of the term. Some specific techniques are needed by the system, in our case Learning Analytics techniques are used, in order to observe the students' behavior and their level of proficiency. In particular, a set of evaluation events for each activity, the students' social network, the students' timeline for their activities and some relevant metrics associated to them are given.**

***Index Terms*—Learning Analytics (LA), Assessment and Evaluation Strategies, Virtual/Remote Laboratories, Collaborative Forums, Distance Education.**

I. Introduction

The evaluation procedure is a key element within the process of learning. Basically, it allows faculty to check whether educative objectives are accomplished, not only by students, but also by all the participants involved in an educative program [1], such as pedagogical resources. As a consequence, lecturers are required to adapt the learning process to students' needs or preferences, enforcing or extending it if necessary, according to the European Higher Education Area (EHEA) [2]. The importance of evaluation procedures is greater at distance Universities since their students' learning process is different from that of face-to-face universities. In distant Universities, students must be more independent and self-demanding since there are no tight schedules. So, this heavily affects the evaluation process. By means of evaluation, faculty can select the suitable learning results and adapts dynamically the subject contents to students [3].

As a consequence, some specific techniques are needed for defining the students' level of proficiency and analyzing their interactions with the educational platforms and systems to be used during the process of customization. One of the most recent research areas for these types of learning experiences is *Learning Analytics (LA)* [4], [5]. Its main goal is to discover and organize the existing information in order to extract useful knowledge during the teaching/learning process. An interesting general approach that uses LA for monitoring the learning activities occurring in a student personal workspace can be found in [6]. Within the area of LA, our work focuses on the field of evaluation. In this case, the process of LA will be focused on the information gathered from both an automatic evaluation laboratory and students' evaluation forums. In particular, we have integrated all data into a common framework in order to perform the evaluation process more efficiently in terms of student's progress and collaborative learning located in evaluation forums. Students' interactions using the tools provided by lecturers with other students, instructors, or learning objects can generate a large amount of relevant data. This information or parts of it may be indicative of the learning progress of students.

Thus, this work presents a Learning Analytics dashboard for analyzing the students' progress and their collaborative learning by using an automatic evaluation system deployed in our institution, named AutoES (AutoEvaluation System) [7]. As an example, a subject focused on the configuration of network services has been chosen to implement our proposal. The system will contain quantitative and qualitative information for lecturers about the students' experimental and collaborative progress during the evaluation procedure. In addition to this, we include survey results, which illustrate the ease of use and usefulness of AutoES. These data will be validated by means of a set of learning parameters and their graphical visualization. In particular, our dashboard shows a set of evaluation events for each activity, the students' social network, the students' timeline for their activities, and some relevant metrics associated to them.

The rest of this paper is organized as follows. In Section II, the background and motivation of this work are given. Section III presents the virtual evaluation laboratory employed for this work and defines the learning context. After that, our proposal of a new Learning Analytics dashboard is detailed in Section IV, in terms of data aggregation, computation of the chosen learning parameters, and their graphical visualization. Finally, Section V highlights our final remarks and suggests guidelines for future work.

II. Background

In recent years, adaptive hypermedia has been widely used for the development of customized Web-based courses in

the field of Education [8]. Therefore, the students' learning process was guided, adapting both pedagogical resources and learning ways to specific user's features. Since lecturers adapt course materials to students' skills and usage data dynamically [9], they were able to acquire more knowledge in less time. ELM-ART [10] and TANGOW [11] are some examples of traditional educational adaptive systems. The students' interaction in these types of architectures is different from face-to-face students, as stated in [12]. In particular, students have to be able to adapt their communication way to the user interfaces of the adaptive systems. Additionally, it is essential to ensure that the proposed activities within the system are correctly adapted to the students' needs [13], so that they feel comfortable interacting with the educational environment.

It is also important to adapt collaborative issues taking into account the students' behaviors. The most relevant research works related to adaptation in Computer Support for Collaborative Learning (CSCL) systems are COALE [14], WebDL [15], and COL-TANGOW [11]. COALE is a collaborative environment where different exercises are recommended to students. However, students are free to choose the next exercise to be performed. The main goal in WebDL is to facilitate user access to services. It focuses on adaptive support for navigation. COL-TANGOW is also a system that supports the dynamic generation of adaptive Web-based courses. These courses are generated at run time by selecting, at every step and for each student, the most suitable activities to be proposed.

Nowadays, the evolution of the Web 2.0 allow us to develop sophisticated techniques to analyze more efficiently the students' learning process, in order to improve the learning contents and structure of a course. One of the most recent research areas is *Learning Analytics (LA)* [4] in order to discover and organize the information contained in the educational platform.

Within the area of LA, our general work focuses on using data mining techniques in the field of evaluation [16]. Data mining techniques have led to a gradual replacement from data verification to knowledge discovery. In this work, we are particularly interested in analyzing, by employing a LA dashboard deployed in our institution, both the gathered information from an automatic evaluation system, AutoES [7], and the forums' evaluation messages into a common and unique point of view. From these data, lecturers will be able to discover behavior patterns within the students' progress, experimental and collaborative at the same time, in the context of the evaluation procedure. Therefore, lecturers can guide each student through the learning process based on his/her particular level of proficiency and grade her/him.

III. The Virtual Evaluation Laboratory: AutoES

In this section, we describe the virtual evaluation laboratory employed in this work, AutoES, and its learning context. Additionally, the students' opinions about the system are shown in order to be validated by the integrated LA dashboard proposed in this work.

A. Description

The main objective of our virtual evaluation laboratory, AutoES [7], is to manage the self-evaluation of practical activities and the continuous assessment of the students' progress. It is a service-oriented application, which is considered as the latest generation of Internet-based platforms [17]. Using our system, students will be able to perform a self-evaluation of their activities and, additionally, the system will be able to solve all the errors made in the activity or configure it completely, with a penalty in the mark for the activity.

Our system has several main benefits for the members of the learning community, specially, within the field of a distance higher education. First, it minimizes the response time in correcting students' practical activities, allowing the continuous evaluation process to be performed smoothly. Furthermore, it provides a more detailed monitoring of the students' progress, thereby reducing the time spent on the assessments themselves. The importance of these benefits is really significant, since the number of students enrolled in a course with a distance methodology can become very high. Thus, lecturers can focus on other tasks, such as dynamic adaptation of new activities to students' necessities or expanding the existing ones, which in turn improves the learning process more than devoting their time to correcting the students' activities.

The proposed system is made up of two different parts: the lecturers' view and the students' view. From the lecturers' view, lecturers can perform subject management tasks such as selecting the activities for the subject, creating different groups with activities adapted to the students' level, checking students' progress by means of reports, etc. The Web application, named *Lab Manager*, is accessible by lecturers through any Internet browser.

From the students' view, the system can automatically configure and/or evaluate a particular activity. For this purpose, the system will download a handler via the Internet, named "lab-client", and run it inside the students' virtual infrastructure, in order to analyze and/or configure the most important configuration elements and generate an evaluation/configuration report. So, students find out which parts of a particular activity are wrong and, additionally, the system can help students when they are not able to do a part of the activity. All this information will be automatically updated on the server side so that it can be used by lecturers to improve the learning process and to decide on the students' marks.

B. Learning Context

In order to focus this work, our service-oriented system will only use activities related to the configuration of network services. Its scope is much broader, since this system has been designed and implemented as a modular system, which is independent of the design and implementation of specific activities. In this regard, we focus on the "Network Services Management in Operating Systems" (NetServicesOS) course belonging to the "Communications, Networks, and Content Management" post-graduate program at Spanish University for Distance Education (in Spanish, Universidad Nacional de Educación a Distancia – UNED). The duration of the subject

are 15 weeks in the first semester of the academic year. The mains goals of the NetServicesOS are the deployment and configuration of several network services for Windows and Linux operating systems, such as DNS, DHCP, FTP, Web, ..., using virtual machines (VMs).

Thanks to the use of our service-based system, lecturers can track the progress of a large number of students and adapt dynamically the learning/teaching process. Students can also receive lively feedback on their activities – which was totally impossible with our traditional evaluation system based on explanation reports for each activity.

Since the UNED university follows a distance methodology, the principal element of interaction among participants in the learning/teaching process (students and lecturers) are forums [18], which motivate the learning/teaching process of the subject and allow the formation of virtual social communities. Lecturers play a vital role in promoting a suitable learning space that motivates the interaction among students. In our particular case, lecturer participants provide students with a set of practical activities which require a great interaction among students to solve them. Lecturers have created a dedicated forum related to the activities for these purposes. The interactions in forums are also taken into account by lecturers when calculating students' final grades.

IV. Proposal of a new Learning Analytics (LA) Dashboard

We propose a new Integrated LA dashboard based on all the information gathered by both AutoES and collaborative evaluation forums employed by students during the course. The LA process is focused on all the information gathered from the LMS that are crucial for the lecturer's daily-work, specially when applying a distance methodology. For this reason, a clear necessity of processing all this information appears in order to allow lecturers to extract interesting conclusions for the dynamic adaptation of the learning process to students. The monitoring tools included in current LMSs are not enough for the LA purposes.

In this sense, our proposed LA dashboard is able to graphically show the students' progress both in an experimental and collaborative way at the same time. Therefore, lecturers can guide each student through the learning process based on his/her particular level of proficiency and grade her/him at the end of the term. In particular, the data aggregation, the computation of learning parameters, and their visualization are detailed below.

A. Data Aggregation

Within the context of the evaluation activities, we have found out two learning process. First, the practical experimentation with the virtual machines picked up by AutoES, and second, the students' knowledge creation through the discussion in the evaluation forums. These learning process are highlighted by lecturers when they are questioned about how they evaluate. Therefore, if we want to represent the whole learning process into our dashboard, we must merge these two sources of information: AutoES' events and forums' evaluation messages.

Each student's interaction is represented by an event within this "merging" process. An event is a structured data generated by a student which happens at a particular time, and it could produce an output result. Thus, a student can produce a set of events inside our learning context, namely:

- Creation of a user at AutoES (*created event*).
- When a user starts AutoES tool (*unchanged event*).
- A successful evaluation, that produces a report as an output result (*success event*).
- A failed evaluation, that produces a report as an output result (*fail event*).
- Publication of a new thread message inside the evaluation forum, where the message is the output result (*init message event*).
- Response to a previous message inside the evaluation forum, where the message is the result (*response to event*).
- Initiates a new activity, and the previous activity is finished (*added to event*).
- When a user gives up the AutoES tool (*removed event*)

For our analysis, we are not interested in all messages located at the forums. In this sense, previously, we have classified the messages in several topics categories by using the cluster k-means algorithm and a bag-of-words approach. So, we can correlate messages with the evaluation activities due to their content and, additionally, filter which messages are relevant for the learning/evaluation process. Messages not related to the evaluation activities or whose contents are not relevant, are dropped form our study.

As a result of this merge process, there are 2179 events inside our database, where 1583 are forum related events, as we can see the resulting detected events depicted at Figure 1.

A initial approach of the statistical analysis of these events shows some relevant results. Each practice takes eleven days to be solved by a student in average. There are 36 students from the whole classroom that decided to work with AutoES.

Also it is relevant that students execute more than once the evaluation of each practice if he/she has obtained a successful evaluation. As an example, the first activity, when a user is successfully evaluated, is evaluated nine times in average. This situation occurs more often at the beginning of the use of AutoES rather than in the last part. So, students need a period of time for learn how to use the tool. And AutoES output must be improved in order to help students.

Another relevant result is that failed evaluations are more common at the firsts activities rather than the last ones. While the average of failed evaluations of first practice is three by student; the average of failed evaluations of the last activity is 0.47.

If we pay attention to the correlation of messages and evaluation activities we have found out that most of the failed evaluations are followed by a message event, almost 73%. Also, at least the 80% of students have posted a correlated message when they are moving from one activity to other. And a 68% students who did not use AutoES have replied to the doubts of the AutoES students. This means that the doubts

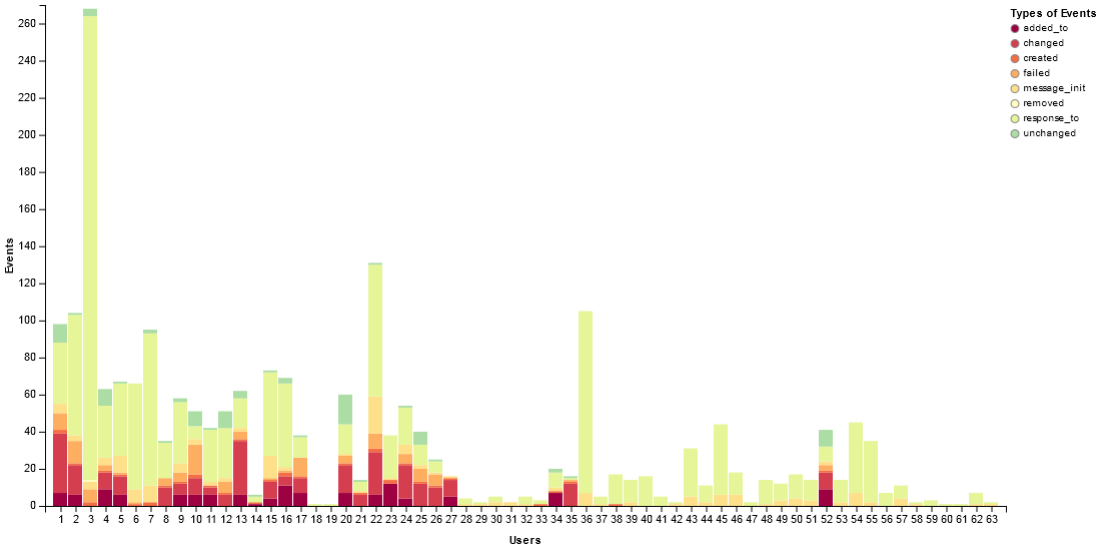


Fig. 1. Events per User by Including Students' Forums Interactions.

are more related to the development of the experiment itself instead of the use of AutoES.

But there is high percentage of quitting the platform. At least 12 students left the use of the platform at the end of the course. Half of them have quitted the platform during the first activity. Their activity is in some cases average, although most of them have posted less message than the average number of messages. From those 12 students, only three of them are in the average number of messages. Lecturers must detect easily these students and should offer them additional help to prevent their desertion from the platform.

B. Computing of the Learning Parameters

Lecturers should evaluate, not only the results, but also the experimental process conducted in the student's virtual environment. For that purpose, we have computed three parameters that represent their learning outcomes. The *"On time"* parameter is focused on the time spent for the realization of the evaluation activity. For the whole population, the average time to solve each activity is computed. Each student's time is compared to this average result by computing the student's corresponding *z-score*. A higher z-score means that the student is delayed with regard to its group and he/she is at risk of quitting. In contrast to this, a lower value means that he/she is solving the activities quickly.

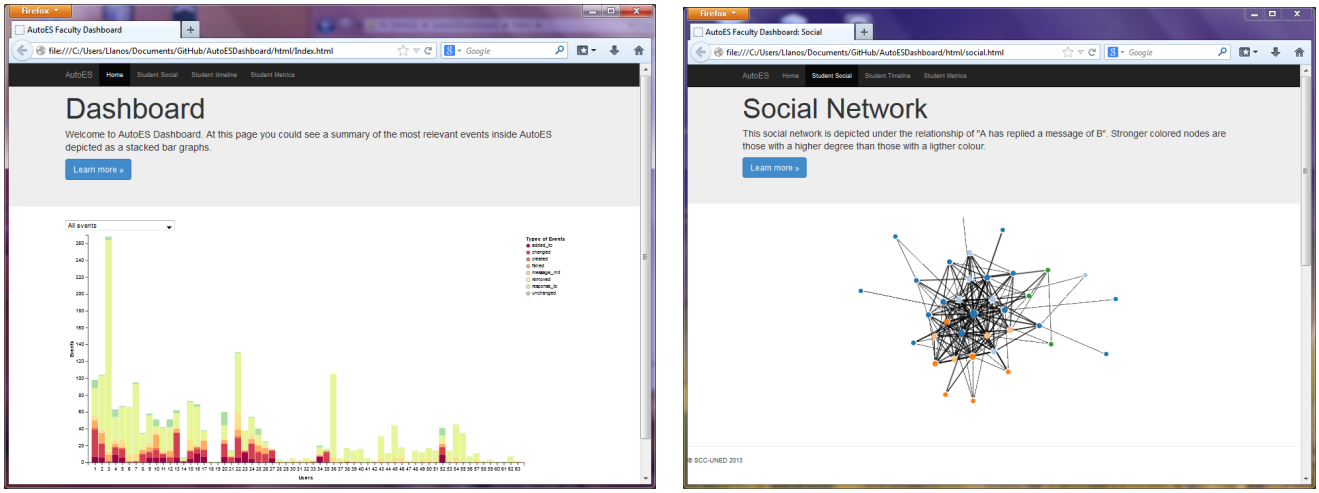
In a similar way, the second parameter is devoted to analyze the number of failed evaluations for each student. The number of failed evaluations per activity, the time between failed evaluations, and the student's z-score, calculated by comparing each students' statistics with the average of all the students', are also calculated. A high z-score value means that the student has problems to solve the activity, so the lecturer should offer some additional help. It is also a source of frustration for the student and he/she may decide to quit. Finally, the third parameter is correlated to successful evaluations. It is computed similarly to the failed evaluation parameter.

On the other hand, Social Network Analysis (SNA) provides a powerful mechanism for understanding how human relationships are created and developed, as well as detecting communication patterns and structures that should appear from these interactions [19], [20]. According to this, a *Social Network* (SN) can be represented as a directed graph in which *nodes* are individual or grouped users and *links* are the relationships among people. Nodes are also used to represent concepts, events, ideas, and other learning elements. These networks are usually built upon gathering and processing the information obtained from the LMS, where interactions among nodes are established to deducting new knowledge within a social community.

In our particular case, the creation of a SN graph for the analysis of educational communities is based on the messages published in discussion forums. More in detail, links between two nodes, where each node represents a particular student, are weighted with the amount of messages exchanged [21]. Thus, the analysis performed of the resulting social network allows lecturers to analyze the interest propagation of their group of students, as observed in Figure 2(b)

We have computed four basic parameters inside the social network that helps lecturers to analyze the student's progress and its level of proficiency. There are a variety of different measures to measure the importance, popularity, or social capital of a node within a social network:

- *Degree centrality* focuses on individual nodes, it counts the number of edges that a node has. This value represents the *interactivity* level of the student; that is, how often the student posts in forums.
- *Betweenness centrality* of a node is the sum of the fraction of all-pairs shortest paths that pass through that node. Nodes that occur on many shortest paths between other nodes in the graph have a high *betweenness centrality* score and are more likely to behave as a *hub* or *broker* in the network.
- *Eigenvector centrality* of a node, which is proportional



(a) Main Interface of the Dashboard

(b) Representation of the Social Network into the Dashboard

Fig. 2. Lectuters' Visualizations in our Proposed LA dashboard (Home View and Social Network).

to the sum of the centrality scores of its neighbors. A node is important if it is connected to other important nodes. A node with a small number of influential contacts may outrank one with a larger number of non popular contacts. Thus, this parameter measures the relevance of the neighbors of a student.

In addition to popularity measures, we pay attention to the *clustering coefficient* for each student. The neighborhood of a node that represents a student is a set of nodes connected to it by an edge, not including itself inside the social network. The clustering coefficient of a node is the fraction of pairs of its neighbors that have edges between one another. Locally, this indicates how concentrated the neighborhood of a node is. A higher clustering coefficient means that the student has been exchanging messages with a high portion of the classroom.

C. Visualization of Learning Parameters

Next, some of the user interfaces of our proposed system for faculties will be shown. Graphical interfaces have been developed in order to interact with the system easily. Figures 2 and 3 show the most relevant lecturers' interfaces of our proposed LA dashboard.

When a faculty starts browsing in the home view of our LA dashboard, he/she can visualize several graphs that summarize all the events, as can be seen in Figure 2(a). In addition to offer a global view of what happens in AutoES and evaluation forums at the same time, the lecturer can also observe (as a colored calendar) the set of events generated by each student, as presented in Figure 3(b). This way, a lecturer can easily verify the generated events, and why they are produced.

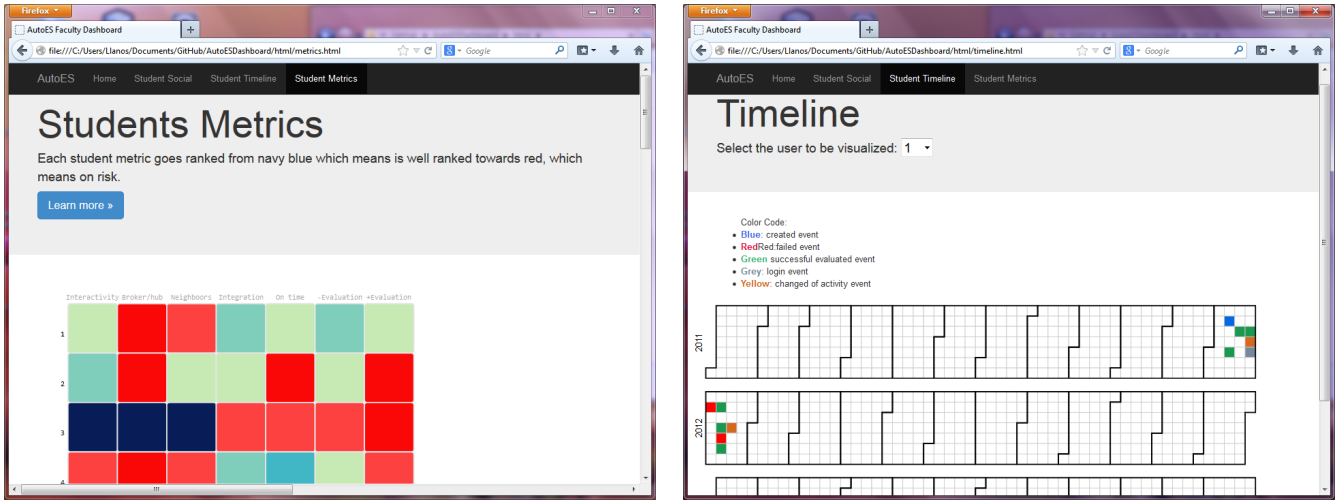
As we mentioned above, we offer lecturers the possibility of examining the social network generated in the course. The size of students' node is directly proportional to his/her network degree. Additionally, the virtual students' communities represented by the social network are computed by following the Louvain method [22]. Students in the same community are colored with the same color. This visualization is represented at Figure 2(b).

Finally, we include a graphical visualization for the previously explained parameters, see Figure 3(a). Each parameter is represented by a different color.

V. Conclusions and Future Work

Distance education is supported by using e-learning platforms and virtual/remote laboratories, which allow lecturers to carry out the process of teaching/learning. Some specific techniques are needed to analyze the students' needs and progress in order to make relevant improvements to a virtual course. For this reason, we propose a new Learning Analytics dashboard which integrates all the information gathered by an virtual evaluation laboratory, AutoES, and, the collaborative forums' messages related to the evaluation process. This system has been used for the evaluation of activities belonging to the NetServicesOS subject, but it would be easily transferable to other environments. Our proposal will be able to show the students' progress from an experimental and collaborative point of view at the same time. In particular, a set of evaluation events for each activity, the students' social network, the students' timeline for their activities and some relevant metrics associated to them are given. Therefore, lecturers can guide each student through the learning process based on his/her particular knowledge-level and, of course, grade her/him in the end of the term.

As a future work, we plan to improve the functionality of the system by using alternative parameters for the analysis of the aggregated data from AutoES and forums' messages, this way improving the adaptation of the evaluation resources to achieve a more intelligent curricula [16]. Also, a simplified version of the dashboard in conjunction with final results will be designed for students, including a recommendation system. Finally, different frameworks or contexts from EHEA, as the proposed ones by the ASEE Educational Research Methods (ERM) Division [23], could be explored in order to analyze if the results obtained are similar and/or it is need of making some changes.



(a) Table Summary of the Student's Metrics in the Dashboard

(b) Calendar Interface by Representing Each Student's Event

Fig. 3. Lecturers' Visualizations in our Proposed LA dashboard (Metrics and Calendar).

REFERENCES

[1] L. Schrum, M. D. Burbank, and R. Capps, "Preparing future teachers for diverse schools in an online learning community: Perceptions and practice," *The Internet and Higher Education*, vol. 10, no. 3, pp. 204 – 211, 2007. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1096751607000395

[2] Spanish Government. Ministry of Education, Culture and Sports, "What is bolonia? (in spanish)," On-Line, 2009, date of last access: April 28, 2014. [Online]. Available: http://www.queesbolonia.gob.es/queesbolonia/inicio.html

[3] C. Saul and H.-D. Wuttke, "Towards a high-level integration of interactive tools with e-assessments," *Advanced Learning Technologies, IEEE International Conference on*, vol. 0, pp. 597–598, 2012.

[4] T. N. M. Consortium, "The horizon report (2011 edition)," On-Line, 2011, date of last access: April 28, 2014. [Online]. Available: http://net.educause.edu/ir/library/pdf/HR2011.pdf

[5] T. Elias, "Learning analytics: Definitions, processes and potential," On-Line, 2011, date of last access: April 28, 2014.

[6] V.-A. Romero-Zaldivar, A. Pardo, D. Burgos, and C. D. Kloos, "Monitoring student progress using virtual appliances: A case study," *Computers and Education*, vol. 58, no. 4, pp. 1058 – 1067, 2012.

[7] S. Ros, A. Robles-Gómez, R. Hernández, A. Caminero, and R. Pastor, "Using virtualization and automatic evaluation: Adapting network services management courses to the ehea," *Education, IEEE Transactions on*, vol. 55, no. 2, pp. 196–202, may 2012.

[8] P. Brusilovsky and E. Millán, "User models for adaptive hypermedia and adaptive educational systems," in *The Adaptive Web: Methods and Strategies of Web Personalization*, ser. Lecture Notes in Computer Science, P. Brusilovsky, A. Kobsa, and W. Nejdl, Eds. Springer Berlin Heidelberg, 2007, pp. 3–53.

[9] A. Kobsa, J. Koenemann, and W. Pohl, "Personalized hypermedia presentation techniques for improving online customer relationships," *The Knowledge Engineering Review*, vol. 16, pp. 111–155, 2001.

[10] G. Weber and P. Brusilovsky, "Elm-art: An adaptive versatile system for web-based instruction," *International Journal of Artificial Intelligence in Education*, vol. 12, pp. 351–384, 2001.

[11] R. M. Carro, A. Ortigosa, E. Martín, and J. H. Schlichter, "Dynamic generation of adaptive web-based collaborative courses," in *CRIWG*, 2003, pp. 191–198.

[12] L. Tobarra, A. Robles-Gómez, S. Ros, R. Hernández, and A. C. Caminero, "Discovery of interest topics in web-based educational communities," in *Computers in Education (SIIE), 2012 International Symposium on*, oct. 2012, pp. 1–6.

[13] I.-H. Hsiao and P. Brusilovsky, "The role of community feedback in the student example authoring process: An evaluation of annotex," *British Journal of Educational Technology*, vol. 42, no. 3, pp. 482–499, 2011. [Online]. Available: http://dx.doi.org/10.1111/j.1467-8535.2009.01030.x

[14] N. Furugori, H. Sato, H. Ogata, Y. Ochi, and Y. Yano, "Coale: Collaborative and adaptive learning environment," in *Proceedings of CSCL 2002*, 2002, pp. 493–494.

[15] E. Gaudioso and J. Boticario, *Supporting personalization in virtual communities in distance education*. World Scientific Publishing Company, 2002.

[16] A. Robles-Gómez, S. Ros, R. Hernández, L. Tobarra, A. C. Caminero, R. Pastor, M. Rodríguez-Artacho, M. Castro, E. SanCristóbal, and M. Tawfik, "Towards an adaptive system for the evaluation of network services," in *2013 Frontiers In Education Conference - Energizing the Future, 2013. FIE'13. 43rd Annual*. IEEE, oct. 2013, pp. 1–7.

[17] S. Ros, R. Hernández, A. Robles-Gomez, A. C. Caminero, L. Tobarra, and E. S. Ruiz, "Open service-oriented platforms for personal learning environments," *IEEE Internet Computing*, vol. 17, no. 4, pp. 26–31, 2013.

[18] K. Kreijns, P. A. Kirschner, and W. Jochems, "Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research," *Computers in Human Behavior*, vol. 19, no. 3, pp. 335 – 353, 2003.

[19] R. Hanneman and M. Riddle, "Introduction to social network methods (online textbook)," On-Line, 2005, date of last access: April 28, 2014. [Online]. Available: http://http://faculty.ucr.edu/~hanneman/nettext/

[20] J. P. Scott, *Social Network Analysis: A Handbook*. SAGE Publications, Jan. 2000.

[21] S. Dawson, L. Lockyer, A. Bakharia, E. Heathcote, L. Macfadyen, P. Long, R. Phillips, and P. Poronnik, "SNAPP," On-Line, 2011, date of last access: April 28, 2014. [Online]. Available: http://research.uow.edu.au/learningnetworks/seeing/snapp/index.html

[22] V. Blondel, J. Guillaume, R. Lambiotte, and E. Mech, "Fast unfolding of communities in large networks," *J. Stat. Mech*, p. P10008, 2008.

[23] "American Society for Engineering Education Educational Research and Methods Division," Web page at http://erm.asee.org/, date of last access: April 28, 2014.