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Towards the Implementation of the Learning Analytics in the Social Learning Environments for the Technology-Enhanced Assessment in Computer Engineering Education*

HERNAN SAGASTEGUI CHIGNE[1], JOSE EMILIO LABRA GAYO[2], MARÍA ELENA ALVA OBESO[2], PATRICIA ORDÓÑEZ DE PABLOS[2] and JUAN MANUEL CUEVA LOVELLE
[1] Antenor Orrego University, Trujillo, Peru.
[2] University of Oviedo, Asturias, Spain.
E-mail: tsagasteguic@upao.edu.pe, labra@uniovi.es, alvamaria@uniovi.es, patriop@uniovi.es, cueva@uniovi.es

In this work we present a formal description of a learning environment framework that gives support to learning analytics. The framework is based on techniques that educational data mining and social network analysis provide. The purpose is to study or discover collaborative relationships that students generate during their learning process and make predictions or assessments about student learning. We also present a new model in the way the learning process is evaluated. This model is more personal and contributes to new possibilities that the digital technologies offer in technology-enhanced assessment.

Keywords: learning analytics; educational data mining; social learning environments; technology-enhanced assessment; informal learning; social network analysis.

1. Introduction

The use of technology in teaching and learning brings new opportunities for education, freeing both the teacher and the student from traditional boundaries and constraints and facilitating academic knowledge, through the open and ubiquitous access provided [1]. Information Technology (IT) represents a set of tools and applications that allow the incorporation and strengthening of new educational strategies. The interest of educators to use these technologies in the teaching process presupposes greater engagement and student motivation increase in understanding the content [2]. The educational innovation and the incorporation of best practices in the educational process increase the need to test their effects on learning and assessment processes.

Learning environments have had an amazing evolution [3], from classic Learning Management Systems (LMS) to Educational Social Networks, Social Learning Environments (SLE) and MOOCs platforms with cooperation, collaboration and new types of learning features like informal learning.

Software tools provided for educational environments are also in evolution, there are a lot of development projects which should be integrated into the learning environments [4, 5]. New features have appeared like learning analytics, educational data mining and social network analysis applied to all forms of educational activities [6], with particular emphasis on educative data analytics to assess the learning performance and students educational relationships in their academic training and to extend traditional methods of assessment to the ones based on the context of technology-enhanced assessment. In this paper we propose:

(a) Formal and technical aspects of Learning Analytics practices and techniques in learning environments. These practices and techniques are based on social network analysis and educational data mining. The learning environments that are considered are educational social networking and social learning environments, but it could also be extended to more traditional LMS.
(b) An alternative or complementary assessment based on data mining about the informal learning that students establish in their activities on a platform or social learning environment.

2. Literature review

2.1 Learning analytics and educational data mining

Long and Siemens [7] defined *learning analytics* as the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs. Powell and MacNeill [8] propose a more general meaning; analytics is the process of developing actionable insights through problem definition and the appli-

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cation of statistical models and analysis against existing and/or simulated future data.

In the NMC Horizon Report 2013 [9] the learning analytics is considered an emergent field of research in the education that aspires to use data analysis as support-decisions on every area of the education, from understanding student data to build better pedagogies, target at-risk students, and to assess whether programs designed have been effective and should be sustained.

Learning Analytics can be seen as a process of connect-making of learning between students. According to connectivism [10], learning is the creation and removal of connections between entities or the adjustment of the strengths of those connections. Siemens [11] describes the importance of learning analytics from the point of view of learning, which is seen as a process of connect-making.

From a technical perspective, Chatti et al. [12] support for Learning Analytics includes methods, such as: statistical and visualization tools or Social Network Analysis (SNA) techniques, and puts them into practice to study their actual effectiveness on teaching and learning improvement. It also borrows from different related fields and synthesizes several existing techniques such as: academic analytics, action research, educational data mining, recommender systems, and personalized adaptive learning.

Educational data mining (EDM) has emerged as an independent research area in recent years [12, 13], [14]. According to [13], EDM is concerned with developing methods to explore the unique types of data that come from an educational context and to use these methods to better understand the students and the settings in which they learn.

Thus, we find that around data and analytics in education, teaching, and learning raises the priority for increased, high-quality research into the models, methods, technologies, and impact of analytics. Two research communities have emerged: *Educational Data Mining and Learning Analytics*. While they share many attributes and have similar goals and interests they also have distinct technological, ideological, and methodological orientations [14].

2.2 Technology-enhanced assessment

The term *Technology-Enhanced Learning* (TEL) is used in the educational world to describe the application of Information and Communication Technologies to learning and teaching. According to [15], the term TEL aims to design, develop and test socio-technical innovations that will support and enhance learning practices of both individuals and organisations. It is therefore an application domain that generally covers technologies that support all forms of teaching and learning activities.

Technology-Enhanced Assessment (TEA) refers to the wide range of ways in which technology can be used to support student assessment and feedback. TEA is the use of technology to improve assessment, understanding this as the heart of the learning experience, how learners are assessed, shapes their understanding of the curriculum and determine their ability to progress [16]. TEA is a response to the emergence of educational principles and practices associated to types of assessment and their respective feedback, to new technology-based tools like tools of social media, social web and its application to education in their proposals for evaluation [17, 18].

3. Method

This section presents a framework based on Social Network Analysis and Educational Data mining and a software prototype that implements this framework. Internet $\mathfrak{F}$ is a computer network and a set of services $(\mathfrak{N}, \mathfrak{L})$ with *nodes* $\mathfrak{N}$ (stations, hosts, servers) sending messages through the *links* $\mathfrak{L}$ (channels), $\mathfrak{L} \subset \mathfrak{N} \times \mathfrak{N}$. A connection is a transmission link from a sender node to a group of receiving nodes. For any collaborative system in a computer network (N, E) of $\mathfrak{F}$ the processes of concurrency, awareness, access control and resource management are duly substantiated by the Groupware and Computer-Supported Collaborative Work [19–21].

Definition 1.— A collaborative environment in a computer network (N, E) is a tuple $\Gamma = \langle S, U, R, F \rangle$. Where; S is a set of sessions in (N, E), U is a set of users (hosts, processes, agents, participants), R a set of shared resources, and F a set of protocols who control the resources.

Definition 2.— A collaborative session is a set of participant Web sites $\langle W_{\propto_1}, \ldots, W_{\propto_n} \rangle$ connected by the network on the collaboration environment Γ, with the condition that there must be a user for each Web site.

According to [19], each site hosts an application which collaborates with other applications of remote sites. Each application implements a set O of operations: $O_{p_1}, O_{p_2}, \ldots, O_{p_n}$. A Website sends events to other sites by an operation independently, when a site receives an event, identifies and executes the operation (or operations) specified by the event [22, 23].

Typical examples of collaborative application are the social network and learning environments. If S_i y S_j symbolize students at the sites $W_{\propto_i}$ and $W_{\propto_j}$, where they are interacting solving their task, then these students form a Social Network. A Social network in real life is a complex system [24] that can be represented traditionally by a formal model of a graph data structure.

For the focus of our work we extend the model of simple graph to multi-node and multi-mode graphs, taking advantage of the contributions of Tang [25] and San Martin [26] in their definitions of social networks extrapolated to social learning environments. Jane Hart [27] establishes that "the heart of a social learning environment is the social network". Thus, our formal proposal of framework for social learning environments is based on well-founded work related to learning environments and social networks [25, 26, 28–31].

Definition 3.—A Social Learning Environment, is a multi-modal multi-relational social network [25], [26] with attributes on actors and relations, i.e. a system $\xi = (N, E, L_N, L_E, \tau, \nu, \epsilon)$ where the network is tripartite with regards to the partition of the node set N in actors, relations, and attributes:

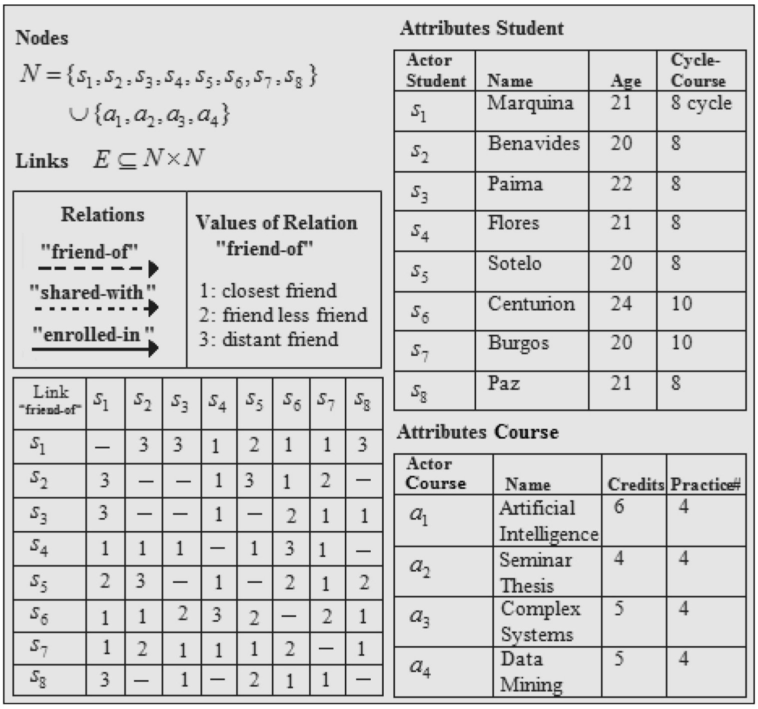
1. The set of nodes $N = A \cup T \cup C$ such that $A \cap T \cap C \neq \Phi$, and a union of the actor set A, with the relation set T, and the attribute set C.
   - For the set of actors A, there exists a finite collection of families (subsets) of actors $\mathscr{A} = \{A_1, A_2, \ldots, A_k\}$ such that every $A_i \subseteq A$ and $\bigcup_{i=1}^{k} A_i = A$.
   - For the set of relations T, there exists a finite collection of families (subsets) of relations $\mathscr{T} = \{T_1, T_2, \ldots, T_j\}$ such that every $T_i \subseteq T$ and $\bigcup_{i=1}^{j} T_i = T$.
   - Both sets of actors A and relations T may be described using attributes.
2. The set E is a set of arcs (corresponding to social ties or links) that admits a partition in families of relations $E = E_{AT} \cup E_{AC} \cup E_{TC}$ with $E_{AT} \cap E_{AC} \cap E_{TC} = \Phi$, where: E_{AT} is the set of arcs between actors and relations, E_{TC} is the set of arcs between relations and attributes and E_{AC} the set of arcs between actors and attributes.
3. L_N is a set of node labels, where $L_N = L_A \cup L_T \cup L_C$ is a disjoint union of the set of actor labels L_A, with the relations labels set L_T, and attribute labels set L_C.
4. L_E is a set of arc labels, where $L_E = L_{AT} \cup L_{AC} \cup L_{TC}$ is a disjoint union of the set of labels of arcs between actors and relations L_{AT}, with the set of labels of arcs between actors and attributes L_{AC}, and the set of labels of arcs between relations and attributes L_{TC}.
5. $\tau = \{\tau_{AT}, \tau_{AC}, \tau_{TC}\}$ is a set of incidence functions, $\nu = \{\nu_A, \nu_T, \nu_C\}$ is a set of node labeling functions y $\epsilon = \{\epsilon_{AT}, \epsilon_{AC}, \epsilon_{TC}\}$ is a set of edge labeling functions. All arcs between the same pair (u, v) with $u \in A$ and $v \in T$ must have different labels.
6. The following condition holds for all edges between the same pair of actors and relations, for all e_1 y e_2 such that $\tau(e_1) = \tau(e_2) = (u, v)$ with $u \in A$ and $\nu \in T$, $e_1, e_2 \in E \Leftrightarrow \epsilon(e_1) \neq \epsilon(e_2)$.
7. For a relation $r \in T$ between two actors $a_1, a_2 \in A$, such that there exist $e_1, e_2 \in E$, and $\tau(e_1) = (a_1, r)$, $\tau(e_2) = (a_2, r)$ with labels $\epsilon(e_1) = p_1$, $\epsilon(e_2) = p_2$. The direction of r can be specified by the ordered pair of participation labels, that is a direction (p_1, p_2) indicates that r starts in a_1 and ends in a_2, the opposite direction is represented by (p_2, p_1).

Figure 1 shows an example data configuration of a learning environment $\xi = (N, E, L_N, L_E, \tau, \nu, \epsilon)$. It discloses the multi-modal multi-relational social network, with multi-relations {friend-of, shared-with, enrolled-in} and multi-attributes. The actors: {Marquina, Benavides, Paima, Flores, Sotelo, Centurion, Burgos, Paz}, are "enrolled-in" courses: {Artificial-Intelligence, Seminar-Thesis, Complex-Systems, Data-Mining}. The relationships "friend-of" describes the degree of friendship that these students have, with the goal to share and collaborate "shared-with" their study notes, class notes, and working papers of practices of courses within those who share tuition.

Relation "friend-of": In a real social network where the labels on its links can be numbers. For example, in the social network of students of adjacency matrix in Fig. 1, if the label of the link **"friend-of"** between the nodes students "Centurion" and "Paz" is 1, it could represent the attribute "closest friend"; if the label between the students "Centurion" and "Sotelo" is 2, it could represent the attribute "friend less friend" or if **"friend-of" equals 3** it could represent the attribute "distant friend". A social learning environment thus represented, is *a multi-mode social network* [25, 26].

Relation "enrolled-in": Similarly the same social learning environment may be *a multi-node social network* [25, 26], i.e. the links (of the relation) may be established between nodes of different types, for example in the Fig. 2, the corresponding nodes to students "Centurion", "Paz" and "Sotelo" are related through the link "enrolled-in" to node course="Artificial Intelligence", as well as the node "Sotelo" also has the link "enrolled-in" with the "Seminar" node. Fig. 2 is an example of multi-node social network on the relationship "enrolled-in" between student nodes and subject nodes.

Graph database. Neo4j is used as a graphical database [32] to store information of the relations and graphs of students on their courses enrolment



Link "friend-of"	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
s_1	–	3	3	1	2	1	1	3
s_2	3	–	–	1	3	1	2	–
s_3	3	–	–	1	–	2	1	1
s_4	1	1	1	–	1	3	1	–
s_5	2	3	–	1	–	2	1	2
s_6	1	1	2	3	2	–	2	1
s_7	1	2	1	1	1	2	–	1
s_8	3	–	1	–	2	1	1	–

Actor Student	Name	Age	Cycle-Course
s_1	Marquina	21	8 cycle
s_2	Benavides	20	8
s_3	Paima	22	8
s_4	Flores	21	8
s_5	Sotelo	20	8
s_6	Centurion	24	10
s_7	Burgos	20	10
s_8	Paz	21	8

Actor Course	Name	Credits	Practice#
a_1	Artificial Intelligence	6	4
a_2	Seminar Thesis	4	4
a_3	Complex Systems	5	4
a_4	Data Mining	5	4

Fig. 1. $N = \{students\} \cup \{courses\}$ multi-nodes of social learning environment.

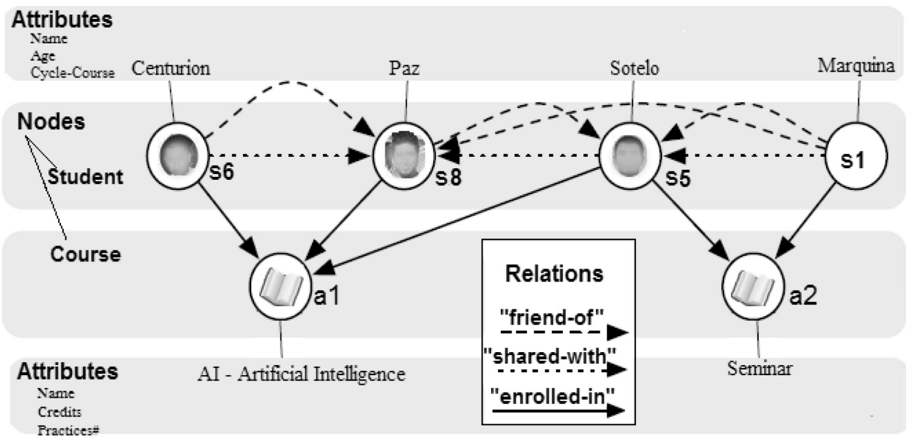


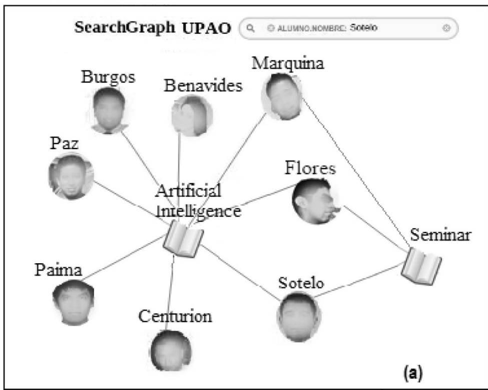
Fig. 2. Social learning environment is a multi-node, multi-node social network with relations "friend-of", and "enrolled-in". Adapted from [26].

or their learning materials sharing. The data model is the graph: using Cypher as graph query language, which is a declarative query language [33].

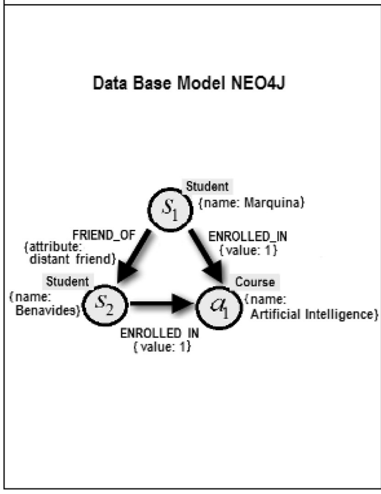
The graph of Fig. 3 part (a), shows the students $\{s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8\}$ enrolled in the subjects (link **"enrolled-in"**) a_1=Artificial-Intelligence a_2, a_3, a_4. Part (b) shows the creation of the graphical database *"DataBase_description.txt"*. Node "AI" is created and labeled as "Course" with its corresponding attributes $AI : Course$ $\{name :' Artificial\ Intelligence', credit : 3\}$ as well as their related nodes.

Graph Visualization. Fig. 4 shows a visualization of the graphical database [34] of the interaction conducted in the social learning environment of the relationships "enrolled-in", "friend-of", "shared-in" between actors {Marquina, Benavides, Paima, Flores, Sotelo, Centurión, Burgos, Paz, ...} with regards to be enrolled in subjects {Artificial-Intelligence, Seminar-Thesis, Complex-Systems, Data-Mining}, be friends, or share the educational materials {"working papers of practices", "study notes", "class notes"}.

Step1. The GRAPHENEDB host [35] (add-on of HEROKU [36]) has stored the graphical database NEO4J *"DataBase_description.txt"* of the students {Marquina, Benavides, Paima, Flores, Sotelo, Centurión, Burgos, Paz, . . .} enrolled in subjects {



Link "enrolled-in"	a_1	a_2	a_3	a_4
s_1	1	1	1	1
s_2	1	0	1	1
s_3	1	0	0	1
s_4	1	1	0	1
s_5	1	1	1	1
s_6	1	0	1	1
s_7	1	0	1	1
s_8	1	0	1	1




```
***** Data Base Students and Course in NEO4J ******
***** SEARCHGRAPH-UPAO ******************

CREATE (AI: Course{name: 'Artificial Intelligence', credit: 3})
CREATE (gustavoM: Student {name: 'Marquina'})
CREATE (lourdesB: Student {name: 'Benavides'})
CREATE (gianP: Student {name: 'Paima'})
CREATE (edwardF: Student {name: 'Flores'})
CREATE (joseS: Student {name: 'Sotelo'})
CREATE (ricardoC: Student {name: 'Centurion'})
CREATE (joseB: Student {name: 'Burgos'})
CREATE (arturoP: Student {name: 'Paz'})
CREATE
(gustavoM)-[:ENROLLED-IN]->(AI)
(lourdesB)-[:ENROLLED-IN]->(AI),
(gianP)-[:ENROLLED-IN]->( AI),
(edwardF)-[:ENROLLED-IN]->(AI),
(joseS)-[:ENROLLED-IN]->(AI),
(ricardoC)-[:ENROLLED-IN]->(AI),
(joseB)-[:ENROLLED-IN]->(AI),
(arturoP)-[:ENROLLED-IN]->(AI)
RETURN AI; ;********************************
```

(b)

Fig. 3. Part (a) Social network generated by relationship "enrolled-in". Part (b) Portion of the graphical data base in Neo4j.

Artificial-Intelligence, Seminar-Thesis, Complex-Systems, Data-Mining} of Fig. 3, Part (b).

Step2. Neography [37] retrieves the database Neo4j *"DataBase_description.txt"* using a REST API and returns it as "JSON response".

Step3. The information retrieved is processed by VivaGraphJS library [38]—incorporating the tracing algorithm $FR(GraphG)$ [39]—for visualization as graph. [32].

Analytics based on Social Network Analysis (SNA). The structural measures and indices of centrality of SNA allow us to understand and measure the performance of students in their learning relationships [40].

Definition 4.—Any of the relationships E = "shared-in" ("friend-of" and "shared-in") that establish the students $s \in N$ = {Marquina, Benavides, ...} each other in a collaboration session Γ on social learning environment $\xi = (N, E, L_n, L_E, \tau, \nu, \epsilon)$ can be described by a simple graph $G = (N, E)$ and the *centrality indices* of a node $\nu \in N$ are interpreted as the role that students have in the social structure. They are calculated by:

$$C_C(\nu) = \frac{1}{\sum_{t \in \nu^d G^{(\nu,t)}}} (Closeness) \quad (1)$$

$$C_G(\nu) = \frac{1}{max_{t \in \nu} d_G(\nu, t)} (Degree\ Centrality) \quad (2)$$

$$C_S(\nu) = \sum\nolimits_{s \neq \nu \neq t \in V} \sigma_{St}(\nu) (Stress\ Centrality) \quad (3)$$

$$C_B(\nu) = \sum\nolimits_{s \neq \nu \neq t \in V} \frac{\sigma_{st(\nu)}}{\sigma_{st}} (Betweenness) \quad (4)$$

Where:

$d_G(s, t)$: Is the minimum length of any path connecting s and t in G. It defines the distance between the vertices corresponding to the students s and $t \in N$, with $d_G(s, t) = d_G(t, s)$ and $d_G(s, s) = 0$. Let σ_{st} be the number of shortest paths from $s \in N$ to $t \in N$, such that $\sigma_{st} = \sigma_{ts}$ and $\sigma_{ss} = 1$. Let $\sigma_{st}(\nu)$ denote the number of shortest paths from s to t for any node $\nu \in N$ that lies in the path between s and t.

In order to implement centrality indices -*Betweenness* $-$ *Centrality*$(\nu \in N)$- we chose algorithms with temporal and spatial complexity $O(n + m)$ and $O(nm + n^2 * Log(b))$ for n and m number of nodes and number of links [41].

As an application of the "framework of learning environment with learning analytics" the prototype SGroupMeeting (Social Group Meeting) is being

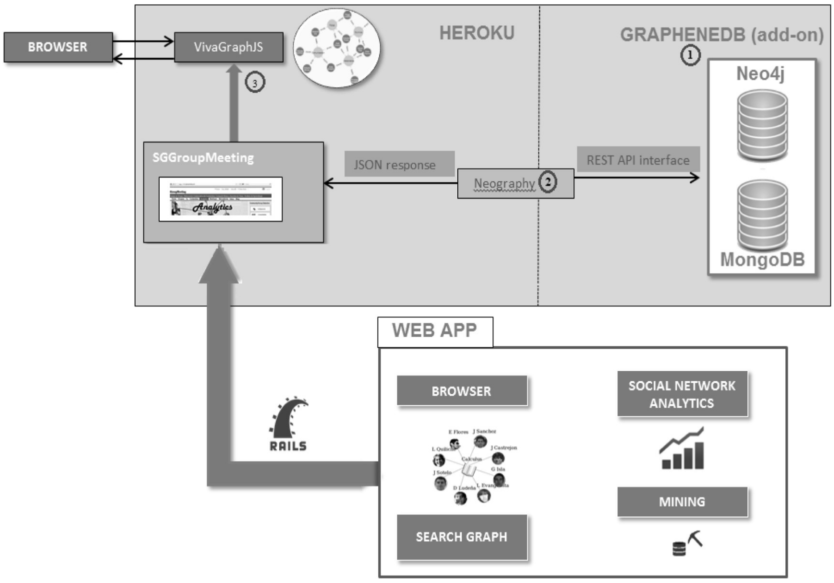


Fig. 4. Process of retrieval & deployment of graphic databases to visualize information from the social networks formed by the different relations.

developed as a software prototype that implements the features outlined in Section 3.1 to test the present work. SGroupMeeting aims to implement: a) the educational social network [42] with purposes of informal learning support and share documents of educational activities (reports, class notes, etc.), b) learning analytics functionalities with the "Analytical Educative" engine, which presents a viewfinder of indicators of centrality of the students social network, as well as the assessment, c) functionalities of educative mining as reputation, clustering, association and recommendation, d) Search graph and graphic database, tracing and visualization.

4. Results

"Analytical Educative" is an assessment tool of the prototype of learning environment SGroupMeeting that we are developing. It implements some of the social network analysis and educational data mining techniques, as learning analytics capabilities, level indicators and metrics for student assessment [43].

"Analytical educative" presents a summary of: (a) *Data of student node*—attributes of node in the current network; (b) *Information of the linked data* between nodes in the social network; (c) *Data of e-Activity*: working papers, study notes, notes of course—associated with the current subject and the relations of collaborations; (d) Mining *data*: reputation and recommendation; (e) *Social network analysis data:* Centrality—betweenness, closeness, degree —and cohesiveness—; (f) Student *Centrality-based assessment*

Viewfinder (the left side of Fig. 5) shows the analytical data of the student Paima G. and his assessment in the development of assignment#2-AI, in a typical scenario of collaborative relationships in the learning social network of the group of students {Marquina, Benavides, Paima, Flores, Sotelo, Centurión, Burgos, Paz} (right side of Fig. 5). The assessment is calculated as follows:

$$ASSESSMENT(S_i) = \frac{40 * NormCloseness + 20 * NormBetweenness + 20 * NormGrade}{100} + 0.2 * NormRank(S_i) \quad (5)$$

Where: $NormRank(s_i)$ are the normalized values of students ranking $S_i, i = 1, n$ authors of the documents d that they share in the assignment. *NormGrade*, *NormCloseness* y *NormBetweenness*, are the normalized values of Grade, Closeness y Betweenness of the students in the scale [0.0 – 5.0] (explained in the next section) by:

$$minNew + \frac{X - minOld}{maxOld - minOld}(MaxNew - minNew).$$

"Analytical educative" has been tested in the Faculty of Engineering at the Antenor Orrego University of Trujillo. The data for this study was obtained during the first semester of the academic year 2014 from students of the Software Engineering course. We took a sample of 40 students (both male and female), structured into 5 groups of 8 students each enrolled in the subject 'Artificial Intelligence'—the number of students per group has been determined based on recommendations given for collaborative learning techniques. The results obtained were similar between the different

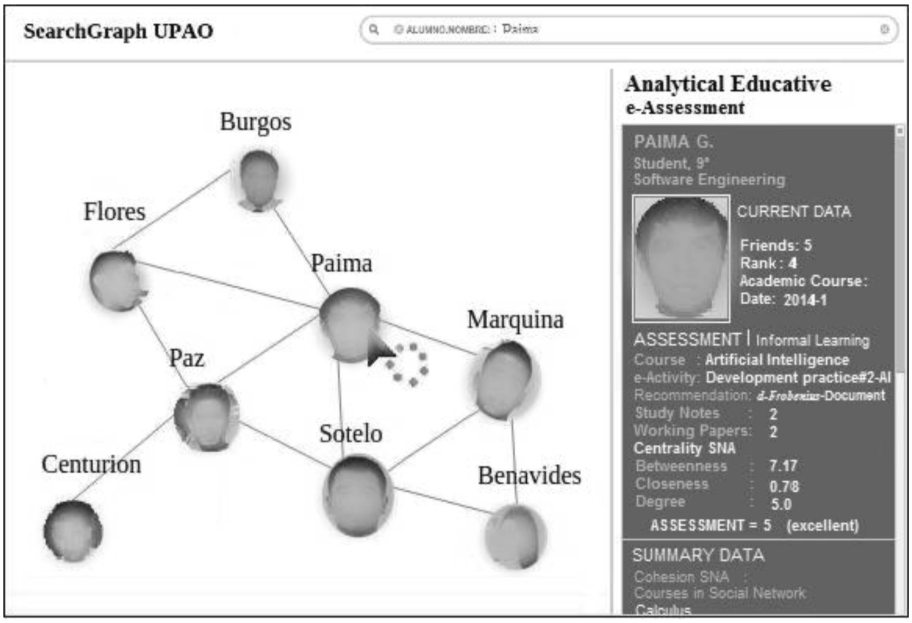


Fig. 5. Snapshot of viewfinder of the data analytic of the student Paima.

Table 1. Indexes centrality of the social network of students (right side of Fig. 5) from the chosen group

Group G Student	Degree	Norm Degree	Close ness	Norm Close	Betwee nness	Norm Betwee	Rank	Norm Rank	Assessment
Marquina	3	2.50	0.58	2.13	1.33	0.93	2	1.67	1.87
Benavides	2	1.25	0.47	0.43	0.00	0.00	2	1.67	0.75
Paima	5	5.00	0.78	5.00	7.17	5.00	4	5.00	5.00
Flores	3	2.50	0.58	2.13	1.00	0.70	2	1.67	1.83
Sotelo	4	3.75	0.70	3.85	4.67	3.26	3	3.33	3.61
Centurion	1	0.00	0.44	0.00	0.00	0.00	1	0.00	0.00
Burgos	2	1.25	0.50	0.91	0.00	0.00	1	0.00	0.61
Paz	4	3.75	0.70	3.85	6.83	4.77	4	5.00	4.24

groups. For illustrative purposes we will show the results of the group previously chosen in Table 1. It corresponds to the social network of students G = {Marquina, Benavides, Paima, Flores, Sotelo, Centurion, Burgos, Paz}. Fig. 5 shows centrality indices (and normalization) – obtained by equations 1, 2 and 4 of Definition 4, of the Behavior of students in the group to determine the assessment. In this way we were able to validate the results obtained by the viewfinder of the Analytical Educative.

Table 1 shows that the leadership provided by the indicators of Closeness and Betweenness has been attributed a greater weight for the calculation of the $ASSESSMENT(s_i)$, because they work as a bridge of connectivity between students and between clusters or communities of learners. Furthermore, we consider that the indicator of Degree can be discriminated for being an egocentric local measure. However, we consider that the criteria for assigning weights to centrality indicators must be a configurable option, so users can assign weights according to the indicator they want to highlight.

5. Discussion

We seek to verify the **hypothesis** [44]: "the assessment based on learning analytics is as reliable and robust than that done by traditional methods" in the context of this work. Expressed in terms of **statistical hypothesis,** it could be stated as **H**: "that the proposed assessment system with learning analytics is equal to or better than the current traditional evaluation system in use".

For the verification we developed a test with the current group G of students, observing and evaluating the results of the development of practice#2-AI in the course of Artificial Intelligence from Fig. 5 and Table 1 of the previous section. We configured the data collection into two stages: First a Pre-Test mode $\mu 1$, that involves taking the data of evaluation at the Group G using the "evaluation traditional"; and after a Post-Test mode $\mu 2$, that consists of evaluating the Group G applying the new proposed learning analytics system (i.e. with the analysis of the relations of cooperation and collaboration over

G-Student Practice#2-AI	Post-Test Assessment	Pre-Test Evaluation	Dif. D
Marquina	1.87	1.50	0.37
Benavides	0.75	0.40	0.35
Paima	5.00	4.50	0.50
Flores	1.83	1.00	0.83
Sotelo	3.61	2.80	0.81
Centurion	0.00	0.50	-0.50
Burgos	0.61	0.90	-0.29
Paz	4.24	3.10	1.14
Standard deviation	0.560		

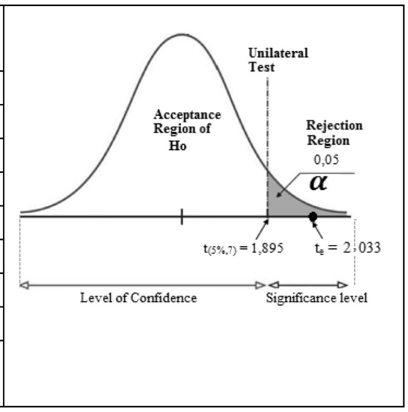


Fig. 6. Comparison of means for dependent observations, with Student's t-Dist.

an on-line learning environment). The objective is to evaluate the variable "learning analytics" in an environment of on-line learning and its relation with the assessment.

The evaluation indicators of academic performance that we used are those of the relationship Value-range: Sufficiency-Indicator ([0.0 - 0.75]: Disapproved, <0.75 – 1.5]: Regular, <1.5 – 2.25]: Approved, <2.25 – 3.25]: Outstanding, <3.25 – 5.0]: Excellence). The average values of evaluation of Pre-Test and Post-Test raised by the subject teacher of Artificial Intelligence in the practice#2-AI respectively, are described on the left side of Fig. 6.

Likewise, for the hypothesis **H**, the statistical hypotheses referred [44, 45] are; the null hypothesis **H0**: The current (or traditional) evaluation system is better than the proposed system with learning analytics (**H0**: $\mu 1 – \mu 2 \geq 0$), and the alternative hypothesis **H1**: The proposed system of assessment with learning analytics is better than the traditional system (**H1**: $\mu 2 – \mu 1 > 0$).

To verify whether the **H** hypothesis is accepted or rejected [45, 46], using data from the table above, we used the Student's t-Distribution, which is a probability distribution that arises of the problem of estimating the average of one normally distributed population when the size of the sample n is small. The parameter $n - 1$ is the number of degrees of freedom.

Since the conclusions we reached are based on a sample, it is possible they may be mistaken and therefore, we may take the wrong decision "reject the null hypothesis **H0** when it is true"; statistically it is said to be an error of type 1. The probability of making an error of type 1 is known as "significance level" (size of the rejection region), and the complement of the rejection region is called "level of confidence". In Student's-t distribution of Fig. 6, the graphic to the right illustrates the data applicable to this case. The rejection region is the set of values such that if the statistical test falls within this range, we decided to reject the null hypothesis **H0**.

For the data of Fig. 6, with $n = 8$, and standard deviation $\sigma_D = 0.560$, taking a significance level of $\alpha = 0.05$ (size of the rejection region) and degrees of freedom $(n - 1) = 7$, the critical value in the **table t-student** is $tt = 1.895$, as shown in the graphic to the right of the Fig. 6.

The calculation of the test statistic t-student, is

$$t_e = \frac{\bar{D}}{\sigma + D\sqrt{n}} = 2.033.$$

Where it is observed that $t_e = 2.033 > 1.895 = tt$, i.e. the statistic test has fallen within the rejection region shown in the graphic of the Student's t-distribution of Fig. 6 and therefore we conclude that "there is sufficient statistical evidence to infer that the null hypothesis **H0** is false" and thus take the alternative hypothesis **H1**: "The proposed system of assessment with learning analytics is better than the traditional system" as true.

Consequently, we accept the hypothesis "the assessment based on learning analytics is as reliable and robust than that done by traditional methods" posed at the beginning of this section.

6. Conclusions

This work suggests that it is possible to adapt the educational functionalities or services of each student. Not only to support content delivery, but also into something that is very sensitive: assessment.
Methods and technologies of the learning analytics framework presented in this paper sustain that the assessment of each student responds to their performance and individual characteristics and it is possible, without disregarding the relationship with their peers from group or his current educational network companions.

A restriction of this work is that the assessment results are preliminary, based only on indicators of centrality, cohesion and reputation of the students in the current social network and it lacks to unify academic and pedagogical criteria, of traditional assessment—formative, summative—, data mining, types of assessment–peer, self and e-Assessment—and centrality-based assessment and combining all these data, in formulae of dispersion measures, adjustment data and normalization to pass toward indicators of assessment.

The data shown in Section 5 for verification and testing are referred to a single test group, the data from the other 7 groups that were sampled, also threw similar results, hence it is still working on the implementation, monitoring and analysis of other students groups, diversifying the relations of the social network and the types of assessment. However, these tests provide an important fact, that using Student's t-Distribution, allows us to infer population mean results from the analysis of sample mean. Consequently, it can be established that the assessment with learning analytics is more reliable than traditional assessment for the entire student population of the subject or course within a learning environment. Therefore it can be concluded that learning analytics is a reliable element and may be included in the practices of technology-enhanced assessment.

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Teobaldo Hernán Sagastegui Chigne, PhD Student at Computer Science Department, University of Oviedo. He is an Associate Professor at the School of Computer and Systems Engineering in Antenor Orrego University of Trujillo — UPAO-(Peru). His research interests include Social Computing, Usability and Accessibility in Social Semantic Web-based Educational Systems, Educational Data Mining & Learning Analytics.

Jose Emilio Labra Gayo is an Associate Professor at the University of Oviedo, Spain. He is the main researcher of the WESO research group (Web Semantics Oviedo). The group develops practical applications of semantic web and linked open data and has been involved in several projects with industrial partners and public administrations. His research interests are Semantic Web technologies, Declarative Programming Languages and Web Engineering.

M. Elena Alva Obeso is Ph.D. in Computer from the University of Oviedo and Master in Information System (UPAO-Peru & I.T.S.M-Mexico). She was professor at the Programming Languages in the Engineering Faculty of the U.P.A.O University in Peru (1990–2005). From 2007 she is a Professor at the Languages and Computers Systems area in Oviedo University. Her research interests include Human–Computer Interface, Usability, Accessibility, and Learning Environment

Patricia Ordóñez de Pablos is a Professor in the Department of Business Administration in the Faculty of Economics and Business at the University of Oviedo, Spain. Her teaching and research interests focus on the areas of strategic management, knowledge management, intellectual capital, organizational learning, human resources management, information technologies, semantic web, Asia (Bhutan, China, Myanmar), higher education and mobile and distance education.

Juan Manuel Cueva Lovelle is a Ph. D. from Madrid Polytechnic University, Spain (1990). He is Mining Engineer from Oviedo Mining Engineers Technical School in 1983 (Oviedo University, Spain). Since 1985 he is a Professor at the Languages and Computers Systems Area in Oviedo University (Spain). ACM and IEEE voting member. His research interests include Object-Oriented technology, Language Processors, Human-Computer Interface, Web Engineering, and Modeling Software with BPM, DSL and MDA.