Collaborative work has emerged as a hot research topic in Virtual Learning Communities since it may considerably improve the knowledge quality and experience of students. However, this novel approach makes the assessment process challenging (i.e., interactions between virtual students, their achievements, and their profiles have to be properly addressed). The purpose of this paper is to propose a comprehensive Intelligent Tutoring System for Virtual Learning Communities that relies on artificial intelligence techniques which are able to manage the specificities of the collaborative working groups that arise in this domain. These specificities can be summarized in the following four goals: 1) conduct an individualized tracking of every student upon the collected data from his/her profile and daily work, 2) configure the classroom to maximize the performance of all its members, 3) automatically obtain the teacher’s feedback about the class operation and possible anomalies, and 4) monitor the working groups behaviour and achievements automatically to redirect their operation when necessary. The framework of the proposed system is described, a proof of concept is presented, and a new virtual student profile, named as bystander, is identified in preliminary experimentations.

Keywords: Intelligent tutoring systems; collaborative learning; virtual learning communities; Web 2.0; constructivism; artificial intelligence; bystanders

ACM Classifications: K.3.1 – Computer Uses in Education; K.3.2 – Computer and Information Science Education; I.2.6 – Learning

1. Introduction

Over recent years, learning and knowledge acquisition techniques have experienced considerable progress and development. Such advances have been mainly fostered by the constant incorporation of several theories which have emerged in the domain of Psychology and which tend to be targeted at the portrayal and analysis of the mental phenomena involved in the learning process. Therefore, current learning theories in Pedagogy are based on conceptual systems that describe how individual brains acquire knowledge.

As far as the learning theory is concerned, two major thinking trends can be distinguished in the Pedagogy field: instructivism and constructivism. Although both paradigms refer to the degree of involvement of the formative influence agent during the educational process and assess up to
what extent students have the flexibility to exploit their own resources in order to achieve specific learning aims, there are important differences between them that should be noted.

Instructivism leaves the learning objectives and definition of strategies exclusively to the teacher (also referred to as educative entity). Therefore, instructivist theories foster instructor agents to predefine the student’s learning goals, methodologies, and pace. Hence, this approach, which entails a unique teaching pattern for all students, does not consider their individual specificities. This situation might create a significant issue in the development of the learning process that should be addressed properly.

From the instructivist point of view, knowledge exists independently from the student. According to this approach, the main goal of students is to passively accept the information transmitted by the teacher, which is known as the Teacher-centred model. Contrary to this perception of education, there is another trend which confirms that there are students who are capable of building their own knowledge on their own. Actually, this hypothesis is the backbone of what is known as the constructivist learning approach, and leads to what has been coined as the Student-centred model.

Indeed, constructivist theories focus on the individual context of every student and establish a conceptual framework of the individual as the starting point in the learning process. Thus, according to this idea, educative agents advise students during their learning process although they do not exclusively and rigidly define their specific progression. This advisory task aims to assist students by emphasizing personal experiences, managing the capabilities developed up to date, and providing them with the necessary tools to achieve the proposed learning outcomes. Thereby, with the utilization of this novel paradigm – aimed at fostering the student’s personal abilities – the educator becomes a facilitator (Stephenson and Sangrà, 2012) rather than an instructor.

Hence, the constructivist natural learning process consists of inviting individuals to analyze a new environment or landscape, and later requesting them to compare their new findings with previously gained knowledge and experiences. In this way, with the proper guidance provided by the teacher, the students are able to develop a unique and personalized knowledge model, potentially different from the one built by their peers, and moulded according to their individual competencies.

The purpose of this paper is to make headway on constructivist techniques applied in the educational field. More specifically, it presents a novel technological framework that integrates an intelligent tutoring system with a collaborative learning environment. Preliminary obtained results with this approach have permitted the early identification of a new conflictive student profile. The consequent rapid correction of these situations has encouraged practitioners to work in this direction.

The remainder of this paper is organized as follows. Section 2 stresses the advantages of applying technology to the educational domain and it also highlights the major lessons extracted from existing collaborative learning environments. Section 3 reviews the key concepts of tutoring systems, and Section 4 presents the proposed system. Then, Section 5 details some experiences collected on its implementation on a pilot course. Finally, Section 6 ends the work with some conclusions.

2. ICT and Collaborative Learning Environments

In recent years, society has incorporated a considerable number of new technologies that have provided new forms of interactions and development. This has become particularly relevant in the educational field, where the introduction of Information and Communication Technologies (ICTs)
has leveraged a constructivist view of education and fostered the idea of collaborative learning. This section reviews the influence of ICTs in education and how their application has led to virtual learning communities. In addition, the main characteristics that these virtual learning environments must have in order to successfully carry out collaborative work are detailed.

### 2.1 ICT in Education

In the last decades of the twentieth century, Information and Communication Technologies (ICT) were included in every area of society. Along with the phenomena of globalization, the incorporation of ICTs has led to a global reshape of the educational system and, thus, to the concept of education.

While in the past, education was conceived as an act of instruction, aimed at homogeneously training individuals according to a specific set of cultural values, nowadays this idea has evolved considerably. Certainly, the continuous introduction of ICTs in this field has aligned the educational paradigm with the society in which it is integrated. Hence, these technological tools have assisted, and actually facilitated, the introduction of useful concepts, such as experimentation or socialization, in classrooms.

However, despite the several relevant advances that have emerged so far, such developments have been mainly focused on improving the teaching materials rather than enhancing the teaching model itself. In fact, a wide variety of ICT-based tools have been proposed in the literature, which have been integrated in instructivist educational systems. However, most of them fail to fully exploit their potential since they find themselves strictly constrained by the educational system model. Recent contributions on this area (Vernet et al., 2012), envisage that the main reason for such issue relies on the fact that they are considered as mere training supplements instead of useful paths to acquire new knowledge.

In addition, from the educational model point of view, it is worth mentioning the rising interest in the application of the constructivist theories in educative domains. Nevertheless, there is still a latent difficulty in adapting both methodologies and trainers to these novel ideas, which makes their implementation difficult.

Certainly, the instructivist approach has been broadly deployed in the educational field so far. Actually, there are very few organizations that still support constructivist theories nowadays. Accordingly, most of the tools provided by Knowledge and Information Technologies applied to the educational field are targeted at emulating the instructivist learning approach by modeling the traditional in-person teaching model. Therefore, most of the cutting-edge technological tools developed in recent years, such as tutoring systems, literally translate the traditional instructivist educative model and ignore the appealing features that these new technologies may bring to the constructivist field which would enable it to take advantage of such advances.

Certainly, the integration of ICT in the educational domain forces practitioners to reformulate the concept of learning and its execution. Indeed, these new technological tools based on ICTs that support and enrich the learning process have opened a new way to conceive the learning process referred to as e-learning, which is different from the traditional learning approach. As García Peñalvo (2008) defined, e-learning is a process aimed to ensure that a set of competences are obtained by students using today’s technologies, specially the web-based ones. In addition to technology, other facets have to be properly addressed in this new educational model in order to guarantee its success. These include structured contents, an assessment method able to cope with
the specificities of this new learning paradigm and an effective collaborative environment to offer appropriate services.

In fact, e-learning is also in line with constructivist theories that suggest the creation of learning groups in order to achieve a comprehensive learning experience. Thanks to the ICT-based tools encompassed by e-learning, traditional group learning strategies have found fundamental support for their implementation and development. These have been coined as Collaborative Learning Environments. Considering their importance in the current context, their main characteristics are detailed in what follows.

2.2 Collaborative Learning Environments

From a sociocultural perspective, the emergence of ICT in education has led to a reformulation of the learning concept. In fact, today’s society is based on the interaction between individuals, which results in an interleaved set of knowledge networks (Martín-Moreno, 2004). In the same way, educational communities have integrated the concept of social networks in their methodologies, which has led to the concept of collaborative learning.

In recent years, internet has become a platform for mediation (Sotomayor, 2010) where geographically distanced people share and exchange knowledge. Similarly, existing learning environments have integrated some tools commonly found on the Web 2.0, such as social networks or negotiation and debate instruments into their frameworks. These tools facilitate the conception of a new form of social network, coined as alumni network, as a collaborative learning environment.

Virtual learning communities base their operations on the principle of collaboration – which should be distinguished from cooperation. Although the terms collaboration and cooperation are often randomly exchanged to designate the type of interaction, there are several authors (Dillenbourg, 1999; Panitz, 2012) that clearly differentiate these two concepts in the sense that they differ in regards to how the task is being carried out. In fact, although both approaches agree with two or more individuals solving an activity together, cooperation involves a division, a distribution, and a subsequent assembly of content portions, while collaboration entails a joint construction of the final content, which forces members to trade information and thus requires specific platforms for discussion.

Generally speaking, a collaborative learning environment can best be seen as a virtual space where a group of individuals interact and develop a joint activity. Typically, this interaction is conducted through two modules – considering the nature of the support (i.e., internet) more modules might be developed. These modules are devoted to performing specific functions that provide the collaborative learning environment with enhanced tools to achieve its goal. The two main modules are detailed below and depicted in Figure 1.

2.2.1 Working Platform

This is a mandatory module that must exist in any collaborative environment. This platform enables students to interact with each other and build their own knowledge upon what they are currently learning. There are several virtual working platforms in use, such as the so-called Learning Management Systems (also referred to as LMS).

On the contrary, other working platforms are used as data repositories, which enable students to have a place to post their progress and share it with the rest of the group. These tools range from Portfolio systems (e.g., Mahara) to Version Control Systems (also referred to as VCS) which are used when a group is involved in a progressive project.
Note that in order to take full advantage of the versatility featured by these working platforms, an advanced proficiency and a deep knowledge of them is required. In general terms, this issue does not entail an additional difficulty in the learning process since (1) most of the students already have them or (2) can rapidly catch up with them thanks to their predisposition in the digital environment.

### 2.2.2 Discussion Space

The existence of a discussion space in a collaborative learning environment is essential: this module enables students belonging to the same group to exchange their views and ideas. Fortunately, the aforesaid Web 2.0 provides several solutions to achieve such commitment: social networks (e.g., Facebook, Twitter, Google+), electronic mail, or even some mechanisms which have already been implemented in the working platform.

It has been previously shown that the usage of collaborative learning communities entails a significant advance towards the constructivist paradigm, since the student gains a better control of the learning process.

### 3. Tutoring Systems

Recent progress on the integration of ICT tools in the educative field has eased the development of what have been coined as tutoring systems. As a part of an ever changing and evolving technology, this kind of student-aid instrument has benefited from the latest improvements in this area, such as the application of artificial intelligence (Pao-Hua et al., 2009). As detailed below, the provision of certain capabilities to tutoring systems has led to qualitative improvements. In addition, it can be noted that such enhancements have led to an opening of the traditional educative method, thus enabling a teaching model conception which is more consistent with the current social moment.
This section reviews such advances by (1) describing the concept of traditional tutoring systems and (2) analyzing the main features of intelligent tutoring systems.

3.1 Traditional Tutoring Systems

Traditional tutoring systems are aimed at helping students during the learning process. This is achieved by the educative agent giving them a structured and predefined guidance on the knowledge acquisition phase. In fact, it is commonly considered that ICT-based tools applied to the educational area are merely complementary instruments of the master class, which is generally carried out on a face-to-face basis. Therefore, these tools are generally considered as a small portion of this technology.

In fact, migrating instructivist procedures into the technology-based educational tool spectrum implies a limitation of the capabilities of the resulting system: the potential provided by these tools remains unexplored because of the excessive rigidity of these traditional education methods. Hence, common teaching practices, such as sequentially delivering rigid contents following a predefined order – determined by either the designer or the lack of personalized interaction – drive most of the ICT tools applied to the educational area to behave as secondary teaching complements that poorly help the learning process (Pérez et al., 2001).

3.2 Intelligent Tutoring Systems

In the specific field of tutoring systems, the conversion of the instructivist paradigm to that of constructivism has been achieved mostly thanks to the application of artificial intelligence techniques (Hung et al., 2003). This has led to the emergence of a novel approach in education that has been recently coined as intelligent tutoring systems. These ICT-based systems are targeted to guide every student throughout their learning process, as a physical tutor would do (Brusilovsky and Peylo, 2003), but accurately adapting themselves to the specific characteristics of every individual. Indeed, these techniques have provided a significant degree of personalization to the tutoring systems, permitting a better adaptability in terms of behaviour and supplying them with enough capabilities to assess the specific characteristics of the student they are interacting with.

Typically, these systems are composed of five modules (Self, 1990), whose interactions are depicted in Figure 2. Although the most interesting modules are the first two, every module is described in what follows:

1. Student module. It is devoted to collecting all the historic data concerning the student’s grades and characteristics. In this module all the information related to the person, referring to either academic outcomes or aptitude/competence assessment, is stored. The more data the system has on the student the better it may perform.

2. Pedagogical module. It is able to forecast the student’s evolution and infer a possible set of alternatives to compensate for the deficiencies observed. Actually, significant improvements have been made towards this goal in previous works (Vernet et al., 2001; Vernet et al., 2010; Golobardes et al., 2000) using artificial intelligence.

3. Communication module. It is aimed at connecting the student, the teacher, and the system through a user interface.

4. Domain knowledge module. It is targeted at collecting all the information and available resources concerning the subject or course to be taught (e.g., syllabus, assignments, exercises, schemas, diagrams, exams). The storage technique used to efficiently manage all this information has been discussed already (Vernet et al., 2010).
5. Expert module. It is able to process the answers that every student has delivered to the system and verify whether they are correct or wrong.

Certainly, intelligent tutoring systems are amazingly effective tools to perform personalized student education since they are based on the continuous analysis of student evolution and thus can select the learning methodology that best fits the learner. Although the aforementioned adaptability of these systems plays a key role from the constructivism point of view, they fail to obtain the maximum performance of this paradigm. Specifically, according to the current social moment, they are unable to equally integrate the student’s abilities and the learning outcomes that he or she could reach if interaction with other individuals was considered (Johnson and Johnson, 1986), which is actually one of the goals of the constructivist paradigm (Wilson, 1998). Hence, if intelligent tutoring systems symbolize highly personalized technological teaching tools – and thus individualized – then, collaborative learning environments promote a new learning model based on a system of sharing and exchanging.

4. An ITVLC System

It is quite clear that the interaction with other like-minded individuals envisages a great chance to build specific knowledge networks. However, some challenging questions arise from this statement: How are the networks organized so that the knowledge gained is optimal? How does an individual select a given set of partners from the virtual community in order to efficiently improve their knowledge and/or skills? Can artificial intelligence somehow help to determine this choice?

These questions have been behind the need to converge the two most relevant educational technologies proposed so far: intelligent tutoring and collaborative learning environments. This union might provide virtual communities with specific tools to improve their performance and orientation. Therefore, the aforesaid intelligent tutoring systems are no longer confined to overseeing and guiding the education of a single student, but extend their domain to all the individuals of a community and the relationships established between them.

The purpose of this section is to present a novel intelligent tutoring system of virtual learning communities to exploit this idea. First, a system description is provided and later, its technical features are analyzed.

4.1 Challenges

The intrinsic gap between teachers and students found in virtual learning communities opens new
challenges in terms of learning monitoring. Despite the latest efforts in this field to include new technologies to reduce this gap, they have not generally led to an automated management of virtual classrooms.

Hence, the success of this type of virtual learning relies not only on obtaining the maximum amount of information about the classroom, but on effectively processing this vast amount of data as well. This information becomes especially relevant when 1) configuring the working groups and 2) conducting corrective measures when faults are detected.

The system proposed herein is designed to cope with the following needs which have been broadly detected in the e-learning domain:

1. Students’ intelligent monitoring.
2. Classroom’s intelligent tracking.
3. Teacher’s feedback inclusion.
4. Working groups’ optimal configuration to make their control and supervision possible.

In what follows, each one of these challenges is elaborated and different techniques are proposed to face them, which may result in future lines of work.

### 4.2 System Description

As already mentioned, the proposed tutoring system covers not only the individual’s personalized learning, but aims to go further and give individual attention to students in relation to the other members of the virtual community. That is, the system is aimed at tutoring the student considering that the collaboration with other members of the classroom may help him or her to reach the proposed learning objectives efficiently.

The proposed system conceives virtual communities as classrooms where different working groups of several students may cohabit, which allows for the performance of intelligent tutoring in three key elements: the class, the group, and the student. That is, in the same way that the community can support the development of individual training, the student may have a positive influence on the acquisition of skills and development process of other partners, and by extension, the entire class.

Moreover, thanks to the intelligent tutoring, the system is able to monitor and assess both the performance and the operation of the class, so that the teaching staff can track the progress of their students at anytime. Indeed, this represents a significant difference with existing approaches because educational technology no longer operates as a mere complement to traditional education. In this system, collected data are used to dynamically reformulate the contents of the lectures at anytime, which permits their adaption to the specific needs of the class and its members.

Figure 3 depicts a general layout of the proposed system. It can be seen that this approach integrates concepts from both intelligent tutoring systems and collaborative learning. This integration permits the usage of Web 2.0 techniques to effectively collect and analyze data. In this way, this data will be used to extract valid conclusions and ease the teaching entity to apply changes in different facets of the class, either individually or within a community scope.

In a virtual learning environment, guiding alternatives are dramatically increased: teachers no longer have to closely monitor each member of the class – which is time consuming and thus unfeasible given the overcrowding experienced nowadays – since software agents are responsible for monitoring both student progression and the role it plays in a group context. Obviously, early
detection is essential to correct any deviations or problems arisen. However, is it possible to detect these problems before they occur?

From the perspective of the human brain, it is extremely difficult to detect whether and when a student’s path may be truncated if we rely solely on the knowledge that teachers have concerning the student’s academic history, personality, or academic results pattern. Hence, a higher degree of analysis and prediction can be reached if all this information is effectively processed through a computer with artificial intelligence support.

From a pragmatic point of view, early detection of possible patterns indicating a decrease in the academic performance may be of great interest to correct the behaviour of a student in time. Furthermore, the following question arises: can it be useful as a guide for the overall trend of class performance as well? Intuitively, the answer seems to be positive. Just as an intelligent tutor can detect incorrect behavioural patterns in individuals or groups, it could also analyze the personal profiles of students belonging to a community and propose associations which, based on the knowledge gained from past experience with successful outcomes, could be more productive and beneficial to the class as a whole.

The following sections describe the basic characteristics of the proposed system in detail.
4.2.1 Intelligent Monitoring of the Student
The fundamentals of the aforementioned individualized tutoring system are not lost when it is applied on a global scale. Although the primary target is focused on improving the global performance of the group, individualized tutoring is still important and it is feasible to reach such commitment. Therefore, the proposed system permits both individual student tutoring and an accurate tracking of the degree of skills of the student.

The student module housed in our system collects the information regarding every student. This information is constantly processed by the teaching module, which will be responsible – through the usage of artificial intelligence techniques – to infer the most effective and relevant actions (e.g., provide specific exercises to reinforce the knowledge concerning some topics, reallocate students in a group whose members can better complement their shortcomings, publish the assessment results or forecast them to the teaching staff to help with personal tutoring).

4.2.2 Intelligent Monitoring of the Class
Symmetrically to the student element, the tutoring system internally monitors the student groups operation as well. Hence, it continuously tracks and analyzes the interaction between individuals and evaluates the progression of their collective work. According to such analysis, it proposes specific strategies to correct a malfunctioning group.

These strategies range from assigning reinforcement collective tasks to breaking up a given group, including the reallocation of a student to another group if it is found that this change may improve the work performance of the whole class.

4.2.3 Teacher’s Feedback
The proposed tutoring system is able to periodically provide the teaching entity with comprehensive data that reflects the operation of key elements in this learning environment: the class as a whole, the groups, and the individuals. Such statistics permit validating the correct execution of collaborative learning, locating those elements with a divergent behaviour, and the detection of possible conceptual shortcomings in a general perspective. In this way, the teaching entity can reformulate the strategies to be used in their lectures.

4.2.4 Creating Working Groups
One of the most appealing novel features of this system is the fact that, by taking the individual profiles of each student, the system is able to autonomously propose the student groups or associations that would maximize the chance of overall success. The creation and design of these groups is not only intended to optimize their individual performance, but also to ensure that the other groups operate properly, which increases the performance of the class as a whole.

4.3 Technical Features
After overviewing the general features of the proposed system, a technical description of the system deployment is provided. Taking into account the nature of the context in which the interaction takes place, the tutoring system has been implemented in a web environment, thus taking benefit from the in-built tools of such framework.

The main module that manages the whole system has been named the teaching module. It contains the tracking system and detects all the possible situations that may happen in the classroom. Note
that it is strongly related to the student and group modules, where the knowledge acquired concerning these elements is stored.

This module uses artificial intelligence techniques to cover both student and group entities in order to provide the aforementioned facilities. More specifically, the system applies these techniques in the following cases: student type elements, group type elements, and interactions between these modules and the teaching staff. Although presenting the teaching module is not the main objective of this article, it forms a fundamental part of the system. Its main features are detailed in the next section.

4.3.1 Relationship to the Student Model

In this first case, the student module collects all available individual information from every student and generates a data set to compare each profile.

The teaching module manages this profile using an artificial intelligence technique called Case-Based Reasoning (also referred to as CBR) (Riesbeck and Shanck, 1989). This technique is aimed at solving problems using the analogy concept, i.e., comparing the new problem with other ones previously solved in order to apply a solution that already worked in the past. Recall that these previously solved problems are stored in a case base at an earlier stage (also referred to as CB or case memory), which hosts the system experience.

The Case-Based Reasoning follows the lifecycle (Aamodt and Plaza, 1994) shown in Figure 4. The major goals of each step of CBR are briefly detailed as follows:

a) Retrieval phase. Given a new case, all cases stored in the case base are reviewed; the ones sharing the most similarities with the new case are retrieved. In the context of this paper, a case is referred to as either a student or a group.

b) Reuse phase. It is aimed at adapting the set of cases, which the retrieval step has selected, to the new scope and demands. Recall that with traditional pure classification problems, this step is

![Figure 4: Case Based Reasoning traditional lifecycle](image-url)
not necessary since the previous phase has provided a set of possible final solutions. However, in this case this step cannot be ignored due to the fact that the retrieved cases must be adapted to the new situation challenged by the new case.

c) Review phase. It is devoted to assessing whether the proposed solution is valid or not for the new case. Usually, such achieved decision is taken with the interaction of a human expert. However, if the expert is not available, this step can be carried in an automatic fashion. In the proposed system, the human expert is expected to be the teacher whose expertise is used to review the proposals suggested by the system.

d) Retain phase. This phase implements the system’s learning process. That is, it decides whether the proposed solution has to be stored in the case base for future cases or not. That is, every time the system discovers a new student with novel features, it stores their associated information to the case memory in order to boost the performance of the system in further situations.

4.3.2 Relationship to the Group Module

In this second case, the module collects group information concerning the class. From a technical perspective, this data is processed with clustering techniques. So far, practitioners have developed an overwhelming amount of clustering techniques which are suitable for each situation according to the data nature they are classifying (Han and Kamber, 2006).

The proposed Intelligent Tutoring for Virtual Learning Communities (ITVLC) system uses a modified version of the MKM technique, already presented in Vernet and Golobardes (2003), in order to run the clustering process. The key to success in the use of this strategy is to come up with an efficient way to compute the similarity of two of the input elements. Although several similarity functions have been broadly explored in the literature for general data, very few of them fit with the concrete specificities of the educational context. In fact, this distance function has to consider all these concrete attributes that are related to the teaching domain and with the particular features of students.

More specifically, from the educational point of view, it can be concluded that there are three key metrics that enable the reliable computation of the distance (i.e., similarity) between two students: the social profile, the academic profile, and the learning profile. Each one of these parameters is elaborated in the next section.

Social distance takes into account the proximity of two individuals given their personal interests, knowledge, and profile within society. Hence, this metric is aimed at promoting the cohesion and collaboration between the members of a group. Note that although this distance parameter can drive a group composition that promotes the interaction between group members, it is still unable to ensure an overall performance since it ignores some of the relevant knowledge acquisition parameters of every member.

Therefore, the second distance metric is introduced: the academic profile, which is devoted to covering the aforementioned issue. This parameter embraces all grades, competencies, and objective academic data of each student collected during previous periods. Hence, from the distance point of view, this metric emphasizes those students with similar academic profiles. Taking such information into account, the system ensures that the preliminary knowledge contribution of every group member when facing a given assignment will be pretty similar, thus minimizing the risk of finding important performance differences among them. However, this might derive on an unfavourable outcome: since all similar academic profiles are grouped together, heterogeneous
clusters are inexistent and thus, groups with lower academic profiles increase their chances of failure substantially.

In order to correct this negative effect, it is still mandatory to consider all the specific strategies used by each student to acquire knowledge, which is known as the learning profile (also referred to as learning style). In fact, several learning profiles can be identified through the Felder-Silverman Learning Style Model (FSLSM) (Felder and Silverman, 1988). Therefore, after discovering the profile corresponding to every student through the Soloman questionnaire (Soloman and Felder, 2005) the Group Module of the presented ITVLC system suggests several student combinations according to these new findings (i.e., student profiles). Note that this strategy has already been shown to be successful in the past (Peña et al, 2002; Hong and Kinshuk, 2004).

To summarize, the profiles provided by this model are elaborated in what follows:

a) Reflective student vs active student: It distinguishes those students that are more involved in the class from the ones that tend to have reflective and introspective behaviours.

b) Inductive student vs deductive student: It has to do with the information acquisition process and classifies students according to the type of reasoning used to reach a particular goal: either induction or deduction.

c) Visual student vs verbal student: It differentiates students according to their sensitivity to the different modes of presenting information.

d) Sensorial student vs intuitive student: It identifies students according to how they perceive information: either through their senses or reasoning themselves.

e) Sequential student vs global student: It classifies students according to their knowledge acquisition process: through a sequential procedure that requires a logical progression of small incremental steps or through a comprehensive understanding that requires a holistic view.

The combination of different distance metrics enables the fine creation of different group types with different mixes of student profiles. In this way, a greater heterogeneity on the learning styles is obtained, which ensures a better coexistence of different strategies in order to reach a common goal.

4.3.3 Relationship with the Teaching Staff

As far as the relationship with the teaching staff is concerned, the proposed ITVLC system provides two types of information: relative to the initial group configuration and relative to the academic paths, either from individuals or groups. Each information type is elaborated in what follows.

On the one hand, the Pedagogical Module provides the best initial group configurations which maximize the performance of the whole class based on the groups proposed by the ITVLC system and using the aforementioned clustering techniques. Note that one of the most appealing features of the MKM technique is that it allows the configuration of the default number of groups in the class and thus, the amount of students belonging to each group. In addition, while new data is added to the system, it is continuously verifying that the current group configuration still matches the selected optimal criteria, which enables the teaching staff to keep track of the groups’ evolution and reorganize them if necessary.

On the other hand, the teaching staff are periodically informed by the system of some actions concerning the groups’ arrangement in order to correct the poor record of a given group, or maximize once again the overall performance of the class.
Although this continuous assessment and revision of groups’ configuration provides a considerable degree of robustness in the learning achievement, some challenging questions arise concerning the groups’ loyalty: how often should the recommendations provided by the system concerning groups’ reconfiguration be considered? What should be the response time for a group to correct deficiencies in their working strategy? And last but not least, from an individual perspective, is it positive for a student to deal with different partners throughout the learning process? Indeed, answers to these questions are still open research lines nowadays. After conducting some previous experimentation using the proposed ITVLC system, we have seen that this tool successfully contributes to the improvement of group performance and effectiveness and thus, may help with the resolution of these questions. The following section describes our new findings in these preliminary experiences and elaborates some near-future directions based on this approach.

5. On the Application of the ITVLC System in Groups’ Management

In fact, the proposed ITVLC system unveils a broad range of hypotheses concerning the tutoring of virtual learning communities that may lead to years of complex experimentation in order to obtain relevant results. Nevertheless, some initial trials have already been carried out concerning the group management in virtual learning communities.

As stated by Yang and Zhang (2010), the effectiveness of working groups is directly based on the outcome of the following strategies:

a) Setting up a study group properly.

b) Establishing clear cooperative learning goals and responsibilities.

c) Developing a sense of community and cooperation skills among group members.

d) Choosing the right learning content for the team.

e) Establishing a rational cooperative learning evaluation mechanism.

According to these indications, the purpose of this section is to detail up to what extent previous experiences using the herein presented ITVLC system – aimed at improving the global performance of the class – have met these guidelines.

As far as the global performance of the class is concerned, it is worth mentioning that critical problems might be encountered when the tasks are not uniformly distributed among the group members. After applying our ITVLC system in some virtual communities, we have detected a new odd category of student: behind an apparently shy appearance, these students remain unnoticed and do not actively participate in the collective task resolution, shifting their burden to other members. Fortunately, the psychology domain has already detected this profile, and labeled such students as bystanders. However, this student category is very difficult to identify in Virtual Communities since its detection demands a deep and accurate group activity tracking analysis.

However, the bystander effect has been successfully detected by the proposed ITVLC system as mentioned above. More specifically, we have run it over the last years on the subject “Web Projects” of the Computer Engineering Degree in which students are assigned a task to be solved in groups of three using a framework with version control as Working Platform. Our prototype version of the ITVLC system has found that, on average, 33% of groups have at least one bystander.

Indeed, the proposed ITVLC system successfully detects such challenging profiles from the academic records and learning profiles. We have seen that the above information delivered to the teaching staff, especially that which refers to the reallocation of a student to another group based
on an accurate selection process, is surprisingly valuable (i.e., it includes enough objective arguments) when considering whether to accept the suggestions provided by the system.

Although these experiments are aimed at assessing the management of working groups, we have already seen that the usage of the proposed ITVLC system successfully meets strategies a) and c) proposed by Yang and Zhang (2010).

Note that, after this initial success, a further experimentation might be required in order to explore the ability of this ITVLC system to meet the remaining strategies. However, the positive experiences described herein envisage the goodness of our approach and encourage practitioners to work towards this direction.

6. Conclusions

This paper introduces the concept of intelligent tutoring of virtual learning communities. The proposed approach combines the power of intelligent tutoring systems with the educational learning process by using new technologies and Web 2.0 features.

The presented system enables the teaching staff not only to monitor each student individually, but also to boost group performance. In fact, most existing intelligent tutoring systems that consider group interactions are focused on the individual behaviour of each member, rather than addressing the effect of individual student’s profiles on other classmates as our system does.

We have found that it is very important to consider the different student profiles in order to properly build the working groups. Therefore, it is mandatory to take into account not only previous academic records, but also student learning and social profiles.

Overall, this paper has addressed four key aspects to manage a virtual learning community: 1) a smart student monitoring, 2) an intelligent classroom tracking, 3) an automated feedback system for the teaching staff, and 4) an exhaustive control of the group performance in order to adjust groups and detect possible faults.

Additionally, the proposed system poses new research challenges: firstly to improve the overall classroom performance as well as that of each individual student and, secondly, to achieve the total integration of all the students working in a group and to avoid the “bystander” scenario.

Nowadays, beyond the proof of concept explained in this paper, a physical system is being developed based on the modules herein described in pursuit of this novel concept.

References


**Biographical Notes**

**David Vernet** is a researcher and he is developing his work at La Salle in Barcelona, Spain (Ramon Llull University). He is currently the Program Coordinator of the computer science degree and he teaches programming methodology and web programming in this faculty. His main research interests are artificial intelligence, intelligent tutoring systems and learning communities, and he has numerous important publications that support his work in this field. He holds a BSc and an MSc degree in computer science from Ramon Llull University and he is currently a PhD candidate in the same university.

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Joan Navarro received the MSc graduate degree in telecommunications engineering in 2008 and the BSc in telematics engineering in 2006 from the Universitat Ramon Llull, Barcelona, Spain (URL). He is currently an Associate Lecturer and PhD student and member of the “Grup de Recerca de Sistemes Distribuïts i Telemàtica” at the same university. His main research interests are focused on the area of distributed systems and data management specifically in the context of Big Data and cloud computing. Throughout these years, he has participated in many public and private funded R&D projects and contributed to several conferences.

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