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The Impact of Learning Styles on Student Grouping for Collaborative Learning: A Case Study

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Abstract.
Learning style models constitute a valuable tool for improving individual learning by the use of adaptation techniques based on them. In this paper we present how the benefit of considering learning styles with adaptation purposes, as part of the user model, can be extended to the context of collaborative learning as a key feature for group formation. We explore the effects that the combination of students with different learning styles in specific groups may have in the final results of the tasks accomplished by them collaboratively. With this aim, a case study with 166 students of Computer Science has been carried out, from which conclusions are drawn. We also describe how an existing web-based system can take advantage of learning style information in order to form more productive groups. Our ongoing work concerning the automatic extraction of grouping rules starting from data about previous interactions within the system is also outlined. Finally, we present our challenges, related to the continuous improvement of collaboration by the use and dynamic modification of automatic grouping rules.

Keywords: learning styles, group formation, user modeling, adaptation, CSCL

1. Motivation

The capacity of the Internet for delivering information has given rise to different approaches to support e-learning, ranging from web-based individual learning environments (Brusilovsky et al., 1996a) (Carro et al., 1999b) to collaboration workspaces in which students can learn together (Barros and Verdejo, 1998) (Dillenbourg, 1999). In the educational area, adaptive hypermedia plays a significant role, since it supports the adaptation of the educational resources to each student (Brusilovsky, 2001). Students can be individually guided and their specific needs can be fulfilled during the learning process. In order to do that, it is necessary for adaptive systems to store information about each user that is considered relevant for the adaptation process (i.e., the student personal features, preferences or actions) (Kobsa, 2001). This information constitutes the user model, which is stored by the system and used for adaptation purposes during the whole learning process.

Among the user features considered in user models, learning styles constitute a valuable tool for improving individual learning, as stated by (Stern and Woolf, 2000), (Grigoriadou et al., 2001), (Paredes and Rodríguez, 2002a), (Triantafillou et al., 2002), (Wolf, 2002), (De Bra et al., 2003), (Brown and Brailsford, 2004) and (Stash et al., 2004).

Yet not only can the students learn from their individual interactions with educational resources, but also they can acquire knowledge during the accomplishment of activities in collaboration with others. Collaborative activities have been used with educational purposes in traditional classrooms since the 70s (Vygotsky, 1978), and it has been widely postulated that the realization of this type of activity has a great impact on learning (Dillenbourg, 1999). It also helps the students to develop social, cognitive and reasoning skills such as thinking, making ideas explicit, communicating ideas, being responsible and cooperating with others (Schlichter, 1997)(Barros and Verdejo, 1998).

One of the recent works of our research group concerns the development of mechanisms to support and enhance learning through the Web by providing both adaptation to individual students (considering, among other student features, their learning styles) and a framework for collaborative learning. Students can profit from the collaborative experience without losing the benefits that a personalized experience can provide. Moreover, they can benefit not just from adaptation and collaboration independently, but also from their combination, since adaptive hypermedia techniques are also used for the adaptation of collaboration-related aspects (Carro et al., 2003a).

In collaborative learning, the way in which students are grouped may affect the results of the learning experience. A wrong selection of colleagues can turn a positive learning experience into a negative one. According to (Johnson and Johnson, 1975), when students group themselves they have a tendency to gather with other students with similar features and skills. Nevertheless, it is not clear whether homogeneous groups, with respect to learning styles, perform better than heterogeneous ones.

In this direction, grouping students according to both their individual features and the synergy that the combination of these features can achieve may constitute a good opportunity to improve the results of the learning process. This motivates us to find out, firstly, the influence of learning styles on the outcome of collaborative work developed by self-selected groups, if any; and secondly, the way this knowledge can be used for grouping students automatically in adaptive e-learning systems. These are the aims of the case study we have developed with real students, which is explained in detail in this paper.

The results of this study are expected to bring more insight into the role learning styles play in collaborative learning. The importance of users' learning styles for the success of collaborative work may have important implications for user modeling and collaboration support. Therefore, the results obtained can be of interest for the research communities involved in user modeling, collaborative learning, adaptive hypermedia and artificial intelligence in education, among others.

The rest of the paper is organized as follows: section 2 describes the state of the art, concerning the relevant aspects for our work, of adaptive hypermedia, user modeling, learning styles and collaborative learning. In section 3 the case study is described, including its goals, assumptions, set up and results. Section 4 deals with the application of the results observed. It also includes a description of TANGOW, a system in which the results can be applied. Finally, in section 5 conclusions are drawn and future work is outlined.

2. State of the art

The number of people that use the Internet as a source of information increases continuously, either for working or for personal purposes. It is evident that the Internet provides users with a great quantity of information, which is available from almost every place at any time. This makes it possible to complement the training of the users in a flexible way.

However, not all the users have the same goals, background, interests and needs. A given web-based learning resource can be easy to understand for some users and, at the same time, pretty complicated for others. Some users can feel disoriented or overloaded in the information space, while others can feel comfortable in the same hyperspace. Therefore, there is a need to guide the users during the learning process, so that the hypermedia presented to each of them is adapted by considering their personal features and needs. The development of Adaptive Hypermedia Systems can be traced back to the early 1990s. These systems are based on hypertext or hypermedia, store a user model and adapt the hypermedia to this user model (Brusilovsky, 2001).

In the context of e-learning, adaptive systems focus on the adaptation of learning resources to each student. It also deals with the way in which knowledge is learned by the students and takes into consideration the learning activities, the cognitive structures and the context of the learning material. According to Stoyanov and Kirschner (Stoyanov and Kirschner, 2004):

> An adaptive e-learning system is an interactive system that personalizes and adapts e-learning content, pedagogical models, and interactions between participants in the environment to meet the individual needs and preferences of users if and when they arise.

Many relevant adaptive educational hypermedia systems were developed during the 90s, such as ELM-ART (Brusilovsky et al., 1996a) used for teaching real university course based on LISP programming language, InterBook (Brusilovsky et al., 1996b) a tool for authoring and delivering adaptive electronic textbooks on the World Wide Web, DCG (Vassileva, 1997) which use a classical mechanism for planning in an AND/OR-graph representation of the domain concepts for automatic generation of a content plan of a course, AST (Specht et al., 1997) based on a conceptual model of the domain of introductory statistics, ADI (Schöch et al., 1998) added the inspectable and editable user model, AHM (Pilar da Silva et al., 1998) that implements the dynamic drawing of local overview diagrams or concept maps, MetaLinks (Murray et al., 1998) a computer program and a design framework for electronic text books, CHEOPS (Negro et al., 1998) is a system that makes it easy for a designer to add adaptivity to a hyperdocument in a modular way, RATH (Hockemeyer et al., 1998) that develops a mathematical model for the structure of hypertext which can be applied practically for obtaining an adaptive tutoring hypertext system, CAMELEON (Laroussi and Benahmed, 1998) that uses a mechanism based on matrix products using representations of users and contents by means of boolean vectors, Multibook (Seeberg et al., 1999) uses standardized content relations and meta-information to adaptively compile a selection from the set of available information units, ACE (Specht and Oppermann, 1998) a WWW-based tutoring framework which combines methods of knowledge representation, instructional planning, and adaptive media generation to deliver individualized courseware via the WWW, KBS-Hyperbook (Henze et al., 1999) is a system which uses explicit conceptual models and meta data to structure and connect external data such as pages on the www.

Some recent examples of the relevance and productivity of this area are: TANGOW (Carro et al., 2002) that is explained in more detail later, AHA! (De Bra et al., 2002) a simple Web-based adaptive hypermedia system, OntoAIMS (Aroyo et al., 2003) an ontological approach to courseware authoring, The Personal Reader(Dolog et al., 2004), an experimental environment supporting personalized learning based on semantic web technologies that integrates closed corpus adaptation and global context provision, and ACCT (Dagger et al., 2005) a design-time tool which allows the course developer to create adaptive and non-adaptive activity-oriented courses, among others.

In order to provide individual adaptation it is necessary to store the information about the users (goals, preferences, knowledge, etc.) to be used for adaptation purposes. This information constitutes the user model, which is stored and maintained by the system (Kobsa, 2001). With no knowledge about the user, a system would perform in exactly the same way for all users. Koch (Koch, 2000) describes the application of user models as follows:

> Users are different: they have different background, different knowledge about a subject, different preferences, goals and interests. To individualize, personalize or customize actions a user model is needed that allows for selection of individualized responses to the user.

Different types of applications can benefit from user models, such as search engines, recommender systems or help systems. In general, the adaptation process can be described by three stages: retrieving the information about the user, processing the information to initialize and update a user model, and using the user model to provide the adaptation (Brusilovsky and Maybury, 2002). The information about the users that is more commonly considered in existing user models include the users' goals, knowledge, background and preferences (Kobsa, 2001). Additionally, recent user models also store the interests and individual traits. Individual traits include personality, cognitive factors and learning styles, but they are not easy to extract from the users (Fröschl, 2005).

Before a user model can be used it has to be constructed. There are several methods that can be applied for its construction, such as stereotype methods (Kay, 2000), overlay methods (Conlan et al., 2002), machine learning methods (Webb et al., 2001) or Bayesian methods (Li and Ji, 2005) (Suebnukarn and Haddawy, 2006). The initialization of a learner model represents the process of gathering information about the learner and transferring this information into the model. According to (Self, 1994), a learner model can be initialized in three ways: through explicit questions, initial testing or by stereotyping. In order to keep the information about the learner up-to-date, it is necessary to provide mechanisms able to dynamically change the information stored about the learner.

One of the student features that can be part of the user model is their learning style. A learning style is defined as characteristic strengths and preferences in the ways people take in and process information (Felder, 1996). Each student has his/her unique way of learning. In recognition of the fact that individuals learn in different ways, a body of research and techniques has been developed, which attempts to categorize individual variations while satisfying different learning style preferences. A recent report suggested there may be as many as 71 learning style models currently in use (Coffield et al., 2004), although many of them suffer from low internal reliability and a lack of empirical evidence (Brown et al., 2005).

Many researchers have attempted to construct overviews of learning styles, such as Rayner and Riding (Rayner and Riding, 1997), de Bello (De Bello, 1990), Swanson (Swanson, 1995), Cassidy (Cassidy, 2004) and Coffield et al (Coffield et al., 2004). In past decades, researchers from different disciplines have intended to define and classify learning styles. For example, the Myers-Briggs Type Indicator (MBTI) places people on a scale based on the qualities of extrovert/introvert, thinking/feeling, sensation/intuition, and judgment/perception (Briggs and Myers, 1977). Kolb's learning style model describes students as divergers (concrete experience, reflective observation), assimilators (abstract conceptualization, reflective observation), convergers (abstract conceptualization, active experimentation), and accommodators (concrete experience, active experimentation) (Kolb, 1984). Herrmann Brain Dominance Instrument (HBDI) is based on four different task-specialized quadrants of the brain and students could be Quadrant A (left brain, cerebral), Quadrant B (left brain, limbic), Quadrant C (right brain, limbic), and Quadrant D (right brain, cerebral) (Herrmann, 1990). The Felder-Silverman Learning Style Model used in this work builds on Jung's theory of psychological types (Jung, 1976), as well as on the information processing theory used by Kolb. This model classifies students' preferred learning style on five dimensions. Each individual can be classified into a selected learning style in every dimension (active/reflective, sensing/intuitive, visual/verbal, sequential/global, and inductive/deductive) (Felder and Silverman, 1988).

Only a few systems that attempt to adapt to learning styles have been developed, and it still is unclear which aspects of learning styles are worth modeling, and what can be done differently for users with different learning styles. The system developed by Carver et al. (Carver et al., 1999) is based in two concepts: firstly, the idea of the development of hypermedia courseware and, secondly, the development of an interface that provide dynamic tailoring of the presentation of course material based on the individual student's learning style. The Arthur system (Gilbert and Han, 1999) defines different styles of instruction from several instructors and makes them available to each learner depending on their learning style. Hong and Kinshuk (Hong and Kinshuk, 2004) extend the adaptation developed by Paredes and Rodriguez (Paredes and Rodríguez, 2002b) from two to four dimensions of Felder-Silverman learning style theory. Other examples are: MANIC (Stern and Woolf,

2000) applying preferences for graphic versus textual information; INSPIRE (Grigoriadou et al., 2001) and MOT (Stash et al., 2004), using Kolb's theory of experiential learning (Kolb, 1984); AES-CS (Triantafillou et al., 2002) using Witkin's field dependence/independence (Witkin and Goodenough, 1981); iWeaver (Wolf, 2002) using Dunn and Dunn's learning style model (Dunn and Dunn, 1978); AHA! (De Bra et al., 2003; Stash et al., 2004) using Honey and Mumford's Learning Styles Questionnaire (Honey and Mumford, 1992); and WHURLE (Brown and Brailsford, 2004) using Felder-Soloman Inventory of Learning Styles (Felder and Soloman, 2004).

Individual learning can be enriched by means of collaborative activity realization, which contributes to the development of personal and social skills that otherwise could remain underdeveloped. Collaborative tools have been used in educational contexts to reduce student isolation, and to contribute to the development of both personal skills, such as thinking, reasoning or knowledge constructing (Bruner, 1966) (Barros and Verdejo, 1998), and social skills, such as working in groups (Johnson et al., 1984), (Panitz, 1999). The Internet gives students the opportunity to interact with other learners online, at their own time and from different places. Thanks to the development of the communication infrastructure, to the results obtained in collaborative traditional environments (face to face) and to the creation of collaborative tools that support group work (email, forum, shared editors, etc), a new area of study emerged in the 80s (Slavin, 1980): *Computer-Supported Collaborative Learning (CSCL)*.

CSCL is based on several theories (Koschmann, 1996) such as *Sociocultural Theory* (Vygotsky, 1978) (Kuutti and Arvonen, 1992) (Engeström, 1987), *Constructivism Theory* (Bruner, 1966) and *Situated Cognition* (Brown et al., 1989). All these theories assume that individuals are active agents that are seeking and constructing their knowledge within a meaningful context and that the knowledge is evolving continually.

CSCL is used for: supporting students in the comprehension of new information and for the connection of that new information with previously acquired knowledge; providing feedback; motivating the students; and offering communication tools in order to facilitate the collaboration among learners.

Nowadays, collaborative hypermedia-based systems are used in different areas. Some of the systems used for teaching and learning are: SNS (Gottdenker et al., 2002), a web-based CSCL environment to support the implementation of a learning community, wherein teachers, parents and students use tools for representing, organizing and sharing knowledge; DEGREE (Barros and Verdejo, 2000), which supports the accomplishment of a variety of learning tasks in small groups of students in a asynchronous way as well as their evaluation; and Kükäkükä (Suthers and Xu, 2002), which supports referencing, manipulating and discussing about external artifacts (sketches, pictures and objects) involving students in online learning. In (McLaren and Sewall, 2006), the authors present a methodology to learn from the results obtained by the students in order to improve the collaborative learning system.

As has been said before, the main goal of adaptive educational systems is to satisfy the needs of each individual. Concerning collaboration, the students should feel comfortable within an environment that favors communication, the exchange of ideas and the visualization of the work performed by their classmates. It should be taken into account that the interaction between distance learners and the way in which it is supported is different from that of face-to-face learners. Interaction of e-learners depends on the features and capabilities of the available tools. The needs and preferences of students concerning collaborative tools can vary from one student to another. Consequently, it is convenient to adapt the collaborative issues according to the student's features, needs or even affective state (Masthoff and Gatt, 2006).

Some existing collaborative systems that include adaptation with respect to collaboration activities are: EPSILON (Soller, 2001), WebDL (Gaudioso and Boticario, 2002), COALE (Furugori et al., 2002),TANGOW (Carro et al., 2003a) and SMART-Learning (Benkiran and Ajhoun, 2002). In (Cheng and Vassileva, 2006) adaptive incentives are given to the students according to the suitability of their contributions with respect to the needs of the learning community.

A relevant aspect for collaborative work is the group formation. The group's productivity is determined by how well the members work together. There are some studies regarding group formation and how it influences group performance in traditional classrooms (Johnson and Johnson, 1975). In these studies it is stated that homogeneous groups (formed by students with similar abilities, experiences and interests) tend to be better at achieving specific aims. However, when heterogeneous groups are analyzed, they outperform homogeneous groups in a broader range of tasks. If the students organize themselves, they usually form homogeneous groups. Instead, if teachers are responsible for group formation, they can select whether the groups will be homogeneous or heterogeneous.

Until recently, most support for group formation in CSCL systems was based on learner profile information such as gender, class, and so forth. There are also more sophisticated approaches based on complementary or overlapping knowledge and competences (Muehlenbrock, 2006). With respect to the consideration of the students' features for grouping, there are two different approaches:

– Given a number of students working on comparable problems, find pairs of students that could potentially benefit from cooperation in a joint session taking into account criteria such as complementary or competitiveness;

– Given a group of students, select or generate a problem that forms an adequate challenge for the group as a whole.

When a specific group is constituted, the students can be informed about their belonging to a concrete group or asked if they desire to be members of this group (Wessner and Pfister, 2001). In traditional classrooms, teachers group students in work teams, but in CSCL systems, group formation can be performed either by the teacher (in classroom or using the information stored in the system) or automatically by the system (Carro et al., 2003a). If the group formation is done by the system, it can be done randomly or by taking into account personal features included in the user and group models (Read and Pancorbo, 2006).

In some systems students are grouped according to their learning styles, such as in (Martín and Paredes, 2004) and (Deibel, 2005). These papers deal with the combination of students in groups considering some dimensions of Felder-Silverman Model(Felder and Silverman, 1988). In (Deibel, 2005), groups are formed by combining students according to two learning style dimensions: active/reflective and sequential/global. The members of the same group should have similar values for these two dimensions. In (Martín and Paredes, 2004), the default criteria for group formation consist of combining active students with reflective ones in similar percentages. In that work, students with a moderate or strong tendency to either visual or verbal styles are grouped with similarly rated students, so that the collaboration workspace interfaces can be adapted accordingly. In any case, it is possible for the course responsible to change grouping criteria.

3. The Case Study

With the aim of obtaining information about the impact of learning styles on the success of collaborative work, we have designed a case study, which is described in the next subsections. First of all, its goals are specified. Then, the assumptions that motivated it are presented. Afterwards, the case study itself is described. And finally the results obtained are reported.

3.1. Goals

The main goal of this study is to gather information about whether the learning styles of several students working together may influence the outcome of their collaborative work and, if so, which are the relevant features that may affect the success of the learning experience. In particular, the study is oriented to find out information that can be used in e-learning to support automatic grouping of students starting from the information stored in the corresponding user models. Providing automatic grouping is specially useful in the case that the students do not know each other and also in the case that the students tend to group themselves in a way that does not lead to a fruitful collaboration. In this direction, the study is also oriented to determine patterns of grouping when the students are free to organize themselves, so as to know whether the effort of grouping them automatically is worthwhile in this case.

Specifically, the questions the study is intended to answer are:

- Do learning styles affect the performance of the students in collaboration?
- Is any dimension of the learning styles more relevant than the others with respect to the outcome of the collaborative task?
- Do heterogeneous groups (formed by students with different learning style) work better than homogeneous groups?
- Is there any correlation between any two dimensions of learning styles?
- When students are allowed to group by themselves, do they tend to join classmates with similar learning styles or do they prefer to join students with different ones?
- Which are the predominant learning styles of the students, if any?

3.2. Assumptions

The assumptions that motivated and, to some extent, guided the design of the case study are:

- People with different learning styles generate different perspectives on effective strategies for dynamic group interactivity (Kolb, 1999). As a consequence, the learning styles are expected to have an impact on how a collaborative task is developed.

- Some dimensions of learning styles have more effect on the collaborative work than others. Considering the learning style model used in this work (explained in detail in next subsection), the active-reflective dimension has more chances to influence the outcome of the collaboration. As (Felder and Silverman, 1988) says,

  > the complex mental processes by which perceived information is converted into knowledge can be conveniently grouped into two categories: active experimentation and reflective observation. Active experimentation involves doing something in the external world with the information, discussing it, explaining it or testing it in some way, and reflective observation involves examining and manipulating the information introspectively. A class in which students are always passive is a class in which neither the active experimenter nor the reflective observer can learn effectively.

  The same reasoning is useful in group formation.

- We think that the outcome of the study may vary depending on the subject area. This paper presents the results obtained for one course of a Computer Science degree, although the results may prove to remain true even when considering other domains.

3.3. Learning style modeling

In order to model the student learning style, the Felder and Silverman model (Felder and Silverman, 1988) was used. This model categorizes a student's preferred learning style along a sliding scale of five dimensions: sensing-intuitive (how information is perceived), visual-verbal (how information is presented), inductive-deductive (how information is organized), active-reflective (how information is processed) and sequential-global (how the information is understood)

- Active/Reflective: active learners prefer to learn by trying things out and doing something beyond listening and watching (e.g., discussing, questioning, or arguing). Reflective learners prefer observation rather than active experimentation.

- Sensing/Intuitive: sensing learners prefer learning first concrete and practical information oriented toward facts and procedures. Intuitive learners prefer conceptual and innovative information oriented toward theories and meanings.

– Visual/Verbal: visual learners obtain more data from visual representations as graphs, charts, pictures, and diagrams. Verbal learners are more comfortable with verbal information such as written texts or lectures.

– Sequential/Global: sequential learners prefer to access well structured information sequentially, studying each subject step by step, while global learners prefer to build a knowledge map from the exploration of the information by having a look at the whole information space in a more flexible way.

– Inductive/Deductive: inductive learners like concluding principles and theories by inference from specific cases. Deductive learners prefer deducing effects and uses from general axioms.

One of the reasons why the Felder-Silverman model was chosen among the existing learning style models is because it has been successfully used in previous works for individual adaptation of e-learning material (Paredes and Rodríguez, 2004) (Hong and Kinshuk, 2004) (Brown and Brailsford, 2004). One of the advantages of this model is that the sliding scales support a classification of student's style richer and more flexible than bipolar models. Moreover, this model is based on dimensions that give us information suitable and feasible of being used with adaptation purposes.

In order to classify the students according to their learning style, the Index of Learning Styles (ILS) questionnaire (Felder and Soloman, 2004) was used. This questionnaire was developed by Felder and Soloman based on the Felder-Silverman model and its objective is to establish the dominant learning styles of each student. The ILS questionnaire is formed by 44 questions with two possible answers, *a* or *b*. These questions are separated into four groups, with eleven questions each. These groups correspond to four of the five dimensions in the classification of Felder and Silverman. The authors do not take into account the inductive-deductive dimension for pedagogical reasons. They state that many or most students would say that they prefer deductive presentation because they are used to it. Even so, inductive learning is the best method of teaching.

The score for each dimension is obtained by subtracting the number of answers related to one category from the number of answers related to the opposite category. In this way, the final results from the test are four scores (odd numbers between -11 and 11), one for each dimension. Generally, scores are referred by their absolute values together with the associated category. For example, if a student has four answers indicating a *sequential* preference and seven indicating a *global* one, his/her preference is said to be -3 in the *sequential-global* dimension or, in other words, *global* with a score of 3.

If a student gets a score from 1 to 3 in any dimension, he/she has a mild preference but his/her learning style is well balanced. Differently, if the score is from 5 to 7, the student has a moderate preference and he/she will learn more easily in teaching systems that favor that dimension. Finally, if the student scores from 9 to 11, he/she could have difficulties when learning through a system which does not support this preference.

Measurements of reliability and validity of ILS scores have been carried out by Livesay et al. (Livesay et al., 2002), Seery et al. (Seery et al., 2003), and Zywno (Zywno, 2003), showing that the current version of the instrument may be considered reliable, valid, and suitable.

3.4. Case study set up

The study was carried on with 166 students from a course on *Theory of Computation*, whose contents include finite automata, regular expressions, pushdown automata, grammars and Turing Machines. The course is mandatory in the Computer Science degree at the Universidad Autonoma de Madrid.

Firstly, the students were required to fulfill the ILS questionnaire to determine the learning style of each one. The questionnaire was available during the first two weeks of that semester through the Internet and students could fill in the questionnaire whenever they want.

Secondly, the students were asked to solve two programming exercises in groups. The first one consisted of implementing finite automata (FA), answering questions about the language accepted by some FAs, FA minimization, and doing conversions between deterministic and non-deterministic automata. In the second exercise they ought to implement a command line interpreter with the capability of doing a morphological and syntactical analysis of the sentence written by the user. Optionally, they could also use a graphical library to show pictures, to enlarge and reduce them, and to go back and forward through an album of pictures.

They were allowed to group themselves in pairs, with no instruction given about who their partners should be. Most of them decided to work with friends, and many of them had already worked in previous courses with the selected partner. Regarding the number of components of each group, two is the usual number for collaborative work in laboratories in the Higher Polytechnic School.

Finally, the teacher (the same one for all the groups) evaluated the exercises, and the work of each pair was marked with a score between 0

Table I. Characteristics of the distributions of the four learning styles considered, for the students in the course.

Dimension	Mean	Std.dev.	Median	1^{st} quartile	3^{rd} quartile
Active-reflective	1.52	4.52	3	-1	5
Sensing-intuitive	3.41	5.06	3	1	7
Visual-verbal	4.95	4.12	6	3	7
Sequential-global	1.69	3.90	3	-1	5

and 10. Almost all the students that handed in the exercises obtained at least a score of 5 (passed the practical work). There were very few exceptions that made some serious mistakes. Those students that were not able to complete the work obtained score of 0.

The students were highly motivated for delivering a good work, as this mark was part of the evaluation criteria for the course. Regarding the case study, the mark obtained was also used to measure the success of the collaborative task.

3.5. Results obtained

The following subsections show the results obtained from the case study and try to find the answer to the questions posed above by analyzing these results.

3.5.1. *Descriptive statistics of the students*

Figure 1 shows the histograms for each of the four learning style dimensions considered, and Table I shows some characteristics of the distributions. As it can be seen, the distributions of the active/reflective and the sequential/global dimensions are more centered, as there are both many positive and negative values, with a slight skewness towards the positive values. In contrast, in the sensing/intuitive dimension there are more positive than negative values, with a mean value of 3.41. This shows that there are more intuitive than sensing students in our course in Computer Science. Finally, the asymmetry is much more evident in the case of the visual/verbal dimension. Nearly two thirds of the students have a value higher or equal to 5, which means that most of them are strongly visual learners.

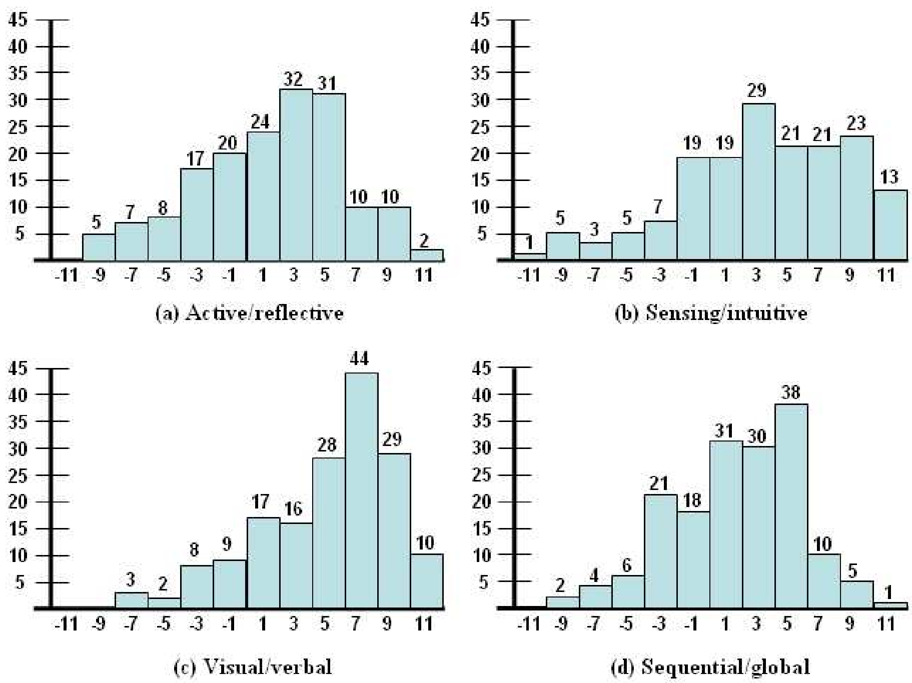

Figure 1. Histograms of the four dimensions.

Table II. Correlations between the four dimensions.

	Active Reflective	Sensing Intuitive	Verbal Visual	Sequential Global
Active-reflective	-	0.07	0.21	0.10
Sensing-intuitive	-	-	0.19	0.25
Visual-verbal	-	-	-	0.00
Sequential-global	-	-	-	-

3.5.2. *Relations between the dimensions*

A question that can be answered at this point is whether there is any correlation between any two dimensions. To answer this, the correlations of the dimensions are calculated, two by two, for all the students. The results are displayed in Table II. It can be seen that the correlations are small in all the cases.

3.5.3. *Descriptive statistics of the groups*

As the students have grouped together in pairs, we are interested in knowing whether they tend to group with others with similar learning

Table III. Characteristics of the distributions of the marks obtained by the pairs.

	Mean	Std.dev.	Median	1^{st} quartile	3^{rd} quartile
Euclidean distance	10.95	4.23	10.2	7.48	13.78
Active-reflective	5.18	3.60	4.0	2	8
Sensing-intuitive	5.15	3.60	4.0	2	7
Visual-verbal	3.87	3.52	2.0	2	6
Sequential-global	4.60	3.16	4.0	2	6

styles, or if there is any tendency to collaborate with classmates with different learning styles.

In order to measure the similarity or dissimilarity between the two students in a pair, the Euclidean distance between their learning profiles has been used. Pairs with a small distance are formed by alike students, and pairs with a large distance are constituted by different students.

It might be the case that only one or two dimensions affect the way the students group together, or their final performance. Thus, we also measured, for each pair and for each of the four dimensions, separately, the distance between the values of the two members in the pair.

The results obtained are described in Table III. The mean Euclidean distance between the two members in a pair is 10.95, and the mean distance for each of the four dimensions ranges between 3.87 and 5.18. Expectedly, the distance in the visual-verbal dimension is the lowest one. Because most of the students have similar values along this dimension (between 5 and 9), it is easier that, just by chance, the two members in each pair have similar values. The second dimension with the smallest distance is the sequential-global dimension, which was the one with the smallest standard deviation.

In order to study the different possible pairs of students, we have grouped them, for each dimension, in three separate categories:

- **Positive (Pos)**: students that have a value higher or equal to 5, which indicates that they belong to the first extreme in the dimension (active, sensing, visual or sequential, respectively).

- **Medium (Med)**: students that have a value between -3 and 3, which indicates that they are either centered or they just have a mild tendency towards one of the sides.

- **Negative (Neg)**: students that have a value less or equal to -5, which indicates that they can be clearly classified as belonging to

Table IV. Different types of pairs depending on the profile of the two members, for each of the four dimensions.

	Pos-Pos	Neg-Neg	Pos-Neg	Pos-Med	Med-Neg	Med-Med
Active-reflective	4	0	6	26	14	33
Sensing-intuitive	15	2	2	36	8	20
Visual-verbal	32	0	1	31	4	15
Sequential-global	4	0	3	26	9	41

Table V. Expected numbers of pairs for each possible kind, and for each dimension, if the students grouped randomly.

	Pos-Pos	Neg-Neg	Pos-Neg	Pos-Med	Med-Neg	Med-Med
Active-reflective	4.82	1.20	4.82	25.54	12.77	33.84
Sensing-intuitive	13.93	0.59	5.73	34.41	7.08	21.25
Visual-verbal	27.76	0.08	2.89	37.59	1.96	12.73
Sequential-global	4.12	0.43	2.67	26.07	8.46	41.23

the second extreme in the dimension (reflective, intuitive, verbal or global, respectively).

Table IV shows how the students grouped themselves in pairs and Table V shows the expected number of cases of every possible combination if the students had twined randomly. There is, therefore, a high confidence in the fact that the students are grouping randomly with respect to any of the four dimensions (the p-values for the dimensions are, respectively, 0.88, 0.29, 0.34 and 0.99).

3.5.4. *Relation between the learning styles and the mark obtained*
In order to know whether students with similar learning styles performed better than mixed pairs or the other way around, it is necessary to explore whether there is any particular combination of learning styles that resulted in a better work performed.

Figure 2 shows the results obtained by the pairs. Most of the students that finished the practical work obtained a score between 7 and 8 out of 10, being the next most popular scores between 6 and 7, and between 8 and 9. Note that more than 20 students were not able to complete the task and got a 0. Table VI shows some characteristics of the distribution of these scores.

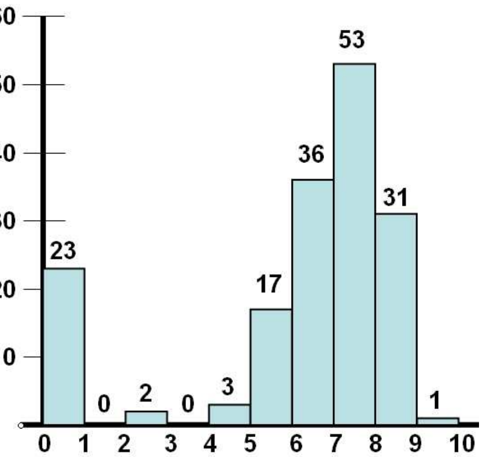

Figure 2. Histogram of the marks obtained.

Table VI. Characteristics of the distributions of the marks obtained by the students.

	Mean	Std.dev.	Median	1^{st} quartile	3^{rd} quartile
Practicals	6.13	2.70	7.09	5.70	7.76

Table VII shows the mean score obtained for each type of pairs, considering each dimension separately. It is important to note that the number of students is too small to consider any of these differences as statistically significant. However, there are some differences between the groups that may be hinting possible tendencies:

– In the active-reflective dimension, the best result has been obtained with a mixed pair containing an active and a reflective student. Mixed pairs also provide reasonably good results in the visual/verbal and in the sequential/global dimensions.

– The mixture of a student of any category with a medium does not give bad results in any dimension.

A similar analysis was done by classifying the pairs of students according to the numeric distance between the members of the pairs. Concerning the Euclidean distance, the pairs have been divided in those whose distance is below the mean (10.95), and those whose distance is over it. Now the mean score of the two groups can be calculated to guess whether pairs with different students have performed better than pairs with alike students, or the other way around. The same has been

Table VII. Mean score for each possible type of pair.

	Pos-Pos	Neg-Neg	Pos-Neg	Pos-Med	Med-Neg	Med-Med
Active-reflective	4.44	-	7.22	5.70	6.28	6.41
Sensing-intuitive	6.32	3.63	5.59	6.36	6.93	5.54
Visual-verbal	5.62	-	6.97	6.28	7.06	6.58
Sequential-global	7.06	-	6.28	5.78	6.62	6.14

Table VIII. Mean score for each possible type of pair according to the distance between its members. Five different distance metrics have been considered.

	Below the mean	Over the mean
Euclidean distance	5.81	6.50
Active-reflective	5.91	6.40
Sensing-intuitive	5.94	6.34
Visual-verbal	6.10	6.15
Sequential-global	6.15	6.09

repeated for the distances in each of the four dimensions. Table VIII shows the results. Interestingly, the mean is slightly higher for pairs with different members considering the Euclidean distance, and that result reproduces itself if we focus on the first two dimensions: active and reflective students may work better, and sensing and intuitive students as well.

Apparently, there is no much difference if we group together different students or alike students in the dimensions visual-verbal and sequential-global.

3.5.5. *Discussion*

Some conclusions that can be extracted from the previous results are:

– Learning styles seem to affect the performance of the students when working together, since there are some differences in the scores for the different groups, although not being statistically significant.

– The tendency seems to be that mixed pairs (pos-neg, pos-med and med-neg) in the active/reflective and the sensing/intuitive dimensions work better.

- It also seems that heterogeneous groups, when considering Euclidean distance, get better results.
- There is not any clear correlation between the dimensions.
- The students seem to group themselves randomly, according to no pattern with respect to their learning styles.
- There are far more visual students than verbal ones in Computer Science. There are also more intuitive than sensing students. The other two dimensions seem to have a more symmetrical distribution.

4. Application

The results of this case study give clues about the influence of learning styles in collaborative learning. This information can be used with adaptation purposes in educational hypermedia and collaborative systems. The TANGOW system will be used as an example of the application of this information, since it supports the creation and delivery of adaptive web-based hypermedia, collaborative learning and dynamic group formation. The bases of the TANGOW system are presented next, whereas the application of the results obtained from the case study are explained afterwards.

4.1. The TANGOW system

TANGOW (Task-based Adaptive learNer Guidance On the Web) is a system for web-based learning that supports the accomplishment of both individual activities (Carro et al., 1999b) and collaborative activities (Carro et al., 2003a). This system is based on a formalism (Carro et al., 2003b) that supports the specification of teaching tasks (activities that the students can perform), and teaching rules, which specify the way these tasks are adapted to each student by taking into account information about their personal features, including learning styles, as well as their actions while taking the course. This information, which is stored in the user model, is used with adaptation purposes in the rule conditions.

4.1.1. *First stage: Individual adaptation*

In the first version of the system (Carro et al., 1999b), adaptation techniques were used for the personalization, to each student while learning individually, of the following:

- Presence or absence of tasks: A specific task can be proposed to a given student when taking a course, while it can be omitted for other student while taking the same course.

- Organization of tasks: A given task can be presented to different students in different points of the course, that is, at different times with respect to the course evolution. This gives rise to different final course structures for distinct students.

- Previous requirements: Given a set of tasks, dependencies between them (so that if the earlier tasks have not been performed, the access to the later ones is not allowed) can be established in distinct ways. Different prerequisites can be established for different students by including conditions related to the characteristics of each student and also to their actions.

- Flexibility of the navigational guidance: A task can be divided into subtasks, and there are several possibilities to establish the order of their accomplishment. It is possible either to establish a specific order among them (this has been called AND sequencing), to let students choose the order of their execution (ANY sequencing), or to let them choose between different subtasks with the same goal (OR sequencing). On one hand, different sequencing modes for the set of subtasks which compose a task can be specified for distinct types of students. On the other hand, the order among tasks when guiding the students directly (AND sequencing) can also be different depending on the type of student.

- Contents: The pages showed to the students by TANGOW are dynamically generated starting from content fragments. Fragment variations (including different multimedia elements) can be provided for specific tasks, so that the most appropriate explanations, examples or problem statements can be built for each student at runtime. Fragment variation also supports multilingualism.

These adaptation capabilities were specified (and are also specified in the current version of the system) by means of a rule-based formalism that allows the course creators to describe adaptive courses. The adaptation itself is performed by a mechanism that processes the corresponding rules at runtime in order to obtain the most suitable set of tasks to be available for every specific student at each step and generates the web pages accordingly.

The use of a single set of tasks and rules allows the description of completely different courses for distinct students without specifying a new course structure for each variation desired. Notice that the adaptation is decided by the persons in charge of the course. They can specify the adaptation rules according to the needs of their students and can extend the courses already developed by adding new contents/tasks and adaptation rules. More details about this can be found at (Carro et al., 1999a).

In order to achieve this adaptation, user models are created to store the data about the students to be processed at runtime by the system. Information about both static and dynamic features is stored. In the courses we have developed with TANGOW, the user model contains personal features such as age, language, information preferred (general/detailed), previous knowledge about the subject and learning strategy (theory before practice or the other way round). It also contains the actions performed by the students when interacting with the courses (pages visited, exercises done, scores obtained in exercises). In fact, the formalism used for the description of courses in TANGOW supports the specification of any feature that is considered as relevant by the course responsible. The only requirement is that its potential values are suitable of being represented by means of a set of either discrete values or continuous intervals.

The user model is constructed by gathering information about each student from two sources. On one hand, personal features, preferences, goals and learning styles are obtained directly from the student through a test shown the first time the student enters the system. On the other hand, all the actions performed by the student when interacting with the educational materials are also stored in the user model.

4.1.2. *Second stage: Learning styles*

In a second stage of this work it was broached how learning styles can determine the way each student learns and, therefore, can influence his/her success when interacting with educational materials (Paredes and Rodríguez, 2002a). The possibility of extending the adaptation supported by TANGOW by considering learning styles arose, so that students could benefit from learning materials adapted to their particular learning style.

Yet the aim was not only to include learning styles as new features of the user model to be included in rule conditions by the course designers, but also to modify the rules automatically depending on the student learning style, so that course developers would not need to specify this adaptation too (Paredes and Rodríguez, 2002b).

With this purpose, a mechanism to support the dynamic adaptation of the rules was incorporated within the system, and learning styles were included in the user models from then on.

The adaptation performed in this sense starts from the rules specified by the course designers and also from the information about the student learning style. Rules are modified for students with a strong preference concerning a specific learning style in the following way:

- Sequential/Global adaptation: Sequential learners should be more directly guided through the learning materials, since global learners should be able to have a look at the whole course before studying specific subjects. Therefore, the sequencing of specific rules can be changed from ANY to AND for the former students, and vice versa for the later.

- Sensing/Intuitive adaptation: Sensing students tend to prefer to observe and interact with examples before studying theoretical concepts or procedures, while intuitive learners usually prefer the other way round. In this case, when both exposition and exemplification tasks are available for a specific learning unit, sensing learners are presented with the exemplification task first, while the theoretical task will be proposed to the other ones at the beginning.

Taking into account these two dimensions (sequential/global and sensing/intuitive), the courses can be automatically adapted to the four possible combinations: global-sensing, global-intuitive, sequential-sensing and sequential-intuitive, so as to guide the students through the tasks in accordance with their personal learning style.

4.1.3. *Third stage: Collaboration*
In a third stage we reflected on the benefits of collaboration in e-learning, which have already been mentioned in section 2, and also on the potential advantages of merging adaptation techniques and collaboration activities, so that students can benefit not only from both of them separately but also from their integration. That reflection led to the current version of the system, in which, on one hand, collaboration tasks have been incorporated and, on the other hand, adaptation techniques are used for the adaptation of the following aspects regarding this type of activities:

- Proposition of collaboration tasks: It may make sense for a certain student to engage in collaboration activities during the learning process, while it may not be appropriate to propose this type of activities to a different student when taking the course (i.e., if the student's preferences indicate that he/she just wants to have a look at the course contents in general).

- Collaboration activities: The adaptation mechanisms makes it possible for some groups of students to be proposed with collaboration tasks that will not be available for other groups, which will be encouraged to perform other collaboration tasks. Note: a collaboration task includes information about a subject to work on (i.e., collaboration task about digital circuits), but it does not include the specific problem to be solved.

- Time of presentation: Whereas it may be convenient for some students to be presented with a collaborative task at a certain point of the learning process, it may be considered more appropriate to propose the same task to other students at a different point of the course, leading to distinct curricula for each of them.

- Activity prerequisites: the requirements for a group of students to broach a collaboration task can be established in different ways for each of them.

- Problem statements: Although related to the same subject, the specific problem to be solved collaboratively or the subject for the discussion to be undertaken can be selected for each particular group among those related to the corresponding task.

- Collaboration workspaces: These spaces are built at runtime. In the cases that the set of tools that support collaboration among students when working on a collaboration task is not strictly dependant on the specific problem to be solved, the most suitable tools for each group can be selected according to specific features of the students (i.e., according to their learning style, visual learners would use graphical editors while textual learners would use text editors). These tools are presented as part of the main interface, and additional tools are available from this interface. The goal here is to create collaborative workspaces in which each group can feel comfortable.

In order to support this adaptation, the existing rule-based formalism was extended to include collaboration activities as well as information about collaboration workspace adaptation (Carro et al., 2003b). Collaboration tools are offered and course developers can specify the way they should be combined for the different types of groups.

Concerning the formation of groups for collaboration, there exist three possibilities:

- Students can group themselves.

- Teachers can specify the way the students will be grouped. They can combine students with same abilities and styles (homogeneous groups) or form heterogeneous groups.

- The system forms the groups automatically according to grouping rules that are either specified by the course responsible or included by the system by default. In this case, the student's features and preferences, as well as their performance before the time at which they are grouped, are considered by the system for the group formation, in the way specified in the rules.

The automatic grouping is carried out in two phases (Carro et al., 2003a):

- In the first one, grouping rules determine the group composition regarding the personal features and preferences of the students. Rules by default are provided, and the course designer can define rules with different criteria to form the groups, either specifically for certain collaborative tasks or for the whole course.

- In the second phase, for each collaboration task, as soon as it is available to a minimum number of persons belonging to the same group (which is configurable too), subgroups are formed and users can initiate the cooperation. During this second grouping phase, their opinions and preferences based on previous collaboration experiences are also considered (i.e., other users they do not wish to interact with again).

4.2. Application of learning styles for automatic grouping

The results of the case study presented in section 3 seem to indicate that there exist a relationship between the way in which students group themselves with respect to their learning styles and the results obtained by them when performing collaborative tasks. Although more experimentation is needed in order to obtain more data, the results obtained suggest the possibility of taking this information into account for the automatic grouping supported by TANGOW.

The immediate application consists of using this information to create new rules for grouping students for subsequent editions of the same subject, with the aim of maximizing the possibility of their success during the realization of collaboration tasks. These rules can either be applied directly by teachers for lab work or be incorporated in TANGOW, so that the students entering the system for the execution of the collaborative activities related to this subject can be grouped automatically.

Other application of the previous results, in which we are currently working on, concerns the development of a mechanism that, starting from data about a certain course already taken by the students (activities, student's learning styles and performance, etc.), establishes, for each group of students, the relationship between the way they were grouped with respect to learning styles and the student performance. The main aim is that the mechanism infers a good set grouping rules, so that grouping rules are automatically generated and applied for student grouping in subsequent editions of the course.

This mechanism should be able not only to infer new rules but also to modify the existing ones according to the analysis of new data. In such a way, the set of rules previously used for group formation in a given course would be automatically modified for the next time the course is taken, which is expected to lead to better student performance (what we plan to check with the corresponding experiments). The automatic student grouping would be continuously improved for each course, what would give rise to a continuous evaluation and improvement of our courses, which is, in fact, other of our research aims (Ortigosa and Carro, 2003).

5. Conclusions and Future work

The effect of taking into account information about learning styles for grouping students for collaborative learning activities in the context of a course on Theory of Computation was analyzed in this paper.

With the goal of studying the impact of learning styles and group homogeneity/heterogeneity on the results obtained by students in collaborative tasks, a case study with 166 students of Computer Science was carried out, and its results have been presented in the paper. From this case study, it can be concluded that some dimensions of the learning style model, namely active-reflective and sensing-intuitive, seem to affect the quality of the resulting work.

These results suggest the possibility of improving collaborative learning by grouping students in specific ways. This can be of interest for collaborative learning systems such as TANGOW, which has been used as an application example. TANGOW delivers adaptive courses including collaboration activities. It supports automatic grouping of users. Therefore, it is suitable of using this knowledge to improve the way students are grouped for solving collaborative activities related to the subject presented in the case study. With this aim, new grouping rules have been incorporated in TANGOW to be used in the corresponding courses.

Currently we are working on a mechanism for establishing relationships between learning styles plus group formation and the student performance, in order to infer rules that can be applied for subsequent groupings, as it has been explained in section 4.2.

The next step is to carry out similar experiments on different subjects, in order to get information about this type of correlations, to infer conclusions for different disciplines starting from the observation of student behaviors.

It must be mentioned that there will probably be no "absolute best rules" for a course. Variations may occur from one course edition to another and the students may be pretty different each time. This may make difficult to compare their results with that obtained when using different grouping rules. Yet the aim here is to evaluate whether it is really possible to find "a good set of rules" for each course and to use it for grouping students.

The set of good rules for grouping students according to their learning style and previous actions could be different for distinct disciplines (even for different subjects related to the same discipline). Therefore, the need of analyzing new data and inferring the rules for grouping is clearly there, and the possibility of doing it automatically would be an important step forward.

It is expected that similar experiments with different subjects will allow us to contrast the results and to extract more general conclusions. Other variables such as the student performance in other courses would be considered during the analysis of the data obtained from these experiments. We expect that future studies, as a follow-up to this one, can throw light on the nuances discovered in this paper.

We find this field promising and our challenge is to bring more insight about the role of learning styles in collaborative learning, which can have an impact on research fields such as user modeling, collaborative learning, adaptive hypermedia and artificial intelligence in education, among others.

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