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A Method for Supporting Heterogeneous-Group Formation through Heuristics and Visualization

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Abstract: Group formation is a key issue in e-learning environments that make use of collaborative work to enhance student performance. While there are many ways to arrange students to work in cooperative groups, recent works have shown that learning styles offer good opportunities to organize students. Particularly, it seems the case that regarding learning styles, heterogeneous groups tend to perform better than groups formed by students with similar characteristics. This work addresses the issue of supporting the authors' task of forming effective learner groups to improve student and group performance. This support is provided through a supervised method which, backed by a visualization tool, is able to produce groups with a good level of heterogeneity. Moreover, this method is not time-consuming for teachers.

Keywords: Authoring Tool, Collaborative Work, Group Formation, Learning Styles
Categories: L.3.3, L.3.6, L.6.2

1 Motivation and Antecedents

Cooperative learning has been one of the many instructional techniques described in the academic literature to enhance student performance [Dansereau, 94]. Some researchers suggest that performance on a subject is enhanced when an individual learns information with others as opposed to when she or he studies alone. Students who work in groups are observed to develop an increased ability to solve problems, to show greater understanding of the subject being taught, and to retain it longer than when the same content is presented in other instructional formats (such as individualized instruction). Further, several works reported that students were more likely to acquire critical thinking skills and meta-cognitive learning strategies, such as learning how to learn, in small group cooperative settings as opposed to listening to lectures [Dishon, 84][Johnson, 90].

Although the advantages of cooperative learning are well documented, group productivity or improvement in individual performance is very much determined by how well members work together. In this sense, group formation is a key issue in order to provide a successful collaborative experience. However, group formation is usually delegated to the teacher, a solution that does not scale, or randomize, a solution that may not yield to satisfactory pedagogical results. In this sense, availability of classification criteria, algorithms and tools able to support group formation is a significant issue.

While there is no “one right way” to allocate students into groups, there exist a number of practices in use. Most of these practices depend on forming the groups based on the ability or the performance level of each student in the class. For instance, teacher-formed groups based on pre-test scores are common. Researchers in the area [Martin, 04][Rommey, 96] suggested that in addition to performance levels, attributes such as gender, family and school background of the student, instructional language proficiency, ethnic background, motivations, attitudes, interests, and personality (argumentative, extrovert, introvert, etc.), should be given due attention in the process of forming groups.

In general, it has been observed [Martin, 04][Nijstad, 02] that while homogeneous groups are better at achieving specific aims, heterogeneous groups (that is, when students with different abilities, experience, interests and personalities are grouped) are better in a broader range of tasks. Heterogeneous grouping works with the assumption that groups work better when the members are balanced in terms of diversity based on functional roles or personality differences.

For example, James Surowiecki in his book “The Wisdom of Crowds” states that “... the simple fact of making a group diverse makes it better at problem solving” and “groups that are too much alike find it harder to keep learning, because each member is bringing less and less new information to the table” [Surowiecki, 04].

In this context, a case study was developed during the 2005 academic year [Alfonseca, 06] with the aim of evaluating the effects that the combination of students with different learning styles in specific groups may have in the final results of collaborative tasks. This case study analyzed the relationship between the learning styles of group members and the final score assigned to each group by the teachers.

With this goal, the learning style of each student was classified following the Felder and Silverman model [Felder, 88], categorized accordingly to the Index of Learning Styles (ILS) questionnaire [Felder, 04]. This model was selected because it provides a numerical evaluation of the LS of each student along each dimension. This questionnaire categorizes a student's preferred learning style along a sliding scale of four dimensions: sensing-intuitive (how information is perceived), visual-verbal (how information is presented), active-reflective (how information is processed) and sequential-global (how the information is understood). The goal of ILS is to establish the dominant learning styles of each student and it is formed by 44 questions with two possible answers: a or b. These questions are separated into four groups (one for each dimension), with eleven questions each. 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.

The study was carried out with 166 students from a course on Theory of Computation. The students were required to group in pairs (83 groups) and work together during the semester. At the end of the course, the teachers graded the work of each group. The conclusions that can be extracted from this case study are:

- learning styles seem to affect the performance of the students when working together
- the tendency seems to be that mixed pairs in the active/reflective and the sensing/intuitive dimensions (that is, heterogeneous groups regarding to these two dimensions) work better
- the students seem to group themselves randomly, following no pattern according to their learning styles.

This study motivates the research for mechanisms supporting the automatic or semi-automatic formation of heterogeneous groups, and more specifically, mechanisms supporting the creation of groups where their members have different learning styles. These mechanisms are the focus of this paper.

Mechanisms supporting group formation could be especially useful in contexts where the students do not know each other, as is the case of some e-learning environments providing support to collaborative activities through the Web. In this context we propose to design grouping mechanisms that take into consideration the students' learning styles to build groups with better chances to enhance student performance. Specifically, considering the results of the study described above, we propose to design mechanisms oriented to build heterogeneous groups regarding learning styles, that is, groups where the learning styles of their members are as different as possible from each other.

These mechanisms can be integrated into e-learning systems with support for collaborative activities. For example the collaborative version of the TANGOW system [Carro, 03] provides adaptive collaborative Web-based courses. Based on each student profile, this system selects the most suitable collaborative tasks to be proposed, the moment at which they are presented, the specific problems to be solved, the most suitable partners to cooperate with and the collaborative tools to support the group cooperation. In this context, the mechanism proposed in this paper can support TANGOW's decision when building groups.

Nevertheless, even with the well-defined goal of building heterogeneous groups, implementing effective mechanisms for forming the groups given a set of students is far from easy. An algorithm trying to find out the optimal division of students into groups would require a criterion for comparing candidate solutions. In terms of our problem, there are no clear criteria for deciding, given two collections of groups, which one is the best of them.

In order to provide practical techniques for integrating grouping mechanisms into e-learning environments, we propose a solution based on two complementary components: i) a supervised algorithm for group formation named Faraway-so-close, and ii) a tool, named TOGETHER, that supports the teacher on applying the algorithm with different configurations and selecting a suitable assembling, accordingly to his or her opinion and interests. The goal of this paper is to present both the Faraway-so-close Algorithm and the TOGETHER visualization tool.

2 Related Work

To determine the conditions under which collaborative learning is effective, one could vary the composition of the group, the features of the task, the context of collaboration, or the ways of communication [Dillenbourg, 96]. Regarding the composition of the group, parameters that can be considered are the number of members, their gender and the differences between them. We restrict ourselves here to differences between members of the group. Some of the research carried out taking into account personal differences is detailed below.

Romney [Rommey, 96] has employed a collaborative learning method to a French translation course in Canada. According to her, the groups, made up of five students, were formed by taking the following factors into account: gender, language proficiency in both English and French, personality, age, work and life experience. The resulting groups were as heterogeneous as possible so as to expose students to a variety of opinions. Results show definite gains on an academic level.

Bradley and Herbert [Bradley, 97] carried out a study on the effect of individual personality differences on the productivity of a group. Among the preference alternatives in the behavior of individuals there were how a person was energized - designated by extrovert against introvert. The extroverts referred to behavior of individuals who were energized by interacting with other members of the team as compared with the introverts who prefer to be by themselves. As such, when considering leadership in a group, the best leader should, besides showing good judgment and deep thinking, be an extrovert with the traits of sensing or introvert with keen intuition.

In relation to grouping based on ability, Stepaneck [Stepaneck, 99] argued that ability grouping was a complex and often divisive issue in education. Heterogeneous grouping is necessary in order to ensure equal opportunities for all students. Students who get stuck in low-level tracks are deprived of opportunities to develop higher-level skills and study richer content [Oakes, 90].

In addition, a key issue is how groups are built. Students are either asked to group themselves or they are informed about their belonging to a concrete group [Wessner, 01]. Regarding the second case, while teachers use to group students in traditional classrooms, in Computer-Supported Collaborative Learning (CSCL) systems group formation can be performed either by the teacher or automatically by the system [Carro, 03]. Automatic group formation can be done randomly or taking into account personal features included in the user and group models [Read, 06][Zurita, 05]. In some systems students are grouped according to their learning styles [Martin, 04], but most of the times they are teamed with similar ones [Deibel, 05].

3 Faraway-so-close Algorithm for Supporting Supervised Group Formation

In order to build a mechanism for group formation based on heterogeneity, it is necessary to formalize the concept of group heterogeneity. The first step is to define which attribute(s) of the students will be used to compare the groups. The only requirement of the proposed method is to use numerical attributes. Because our previous results are related to learning styles, the next subsection describes some of the equations used to evaluate how similar (or dissimilar) some students are regarding their learning styles. These equations assume the information about the student learning styles comes from the ILS questionnaire, described in the previous section.

After introducing the equations used to measure group similarity, aspects of an optimal algorithm for building groups based on these concepts are presented.

3.1 Similarity Measuring

Student learning style representation: a student learning style, S_i, is represented by a tuple, which corresponds to the values for the four dimensions used in the Felder-Silverman Learning Style Model (FSLSM).

$$S_i(Dim_1, Dim_2, Dim_3, Dim_4) \tag{1}$$

where

$$-11 \le Dim_i \le 11$$

Depending on the context, each student can also be represented by the projection of this vector on one, two, three or four dimensions. For this reason, next equations depend on the actual number of dimensions (n).

Figure 1 shows an example of the visualization of two students accordingly to their respective values in two dimensions on the FSLSM. Values in x and y axes represent the students' scores in each dimension through the ILS questionnaire (odd numbers between -11 and 11).

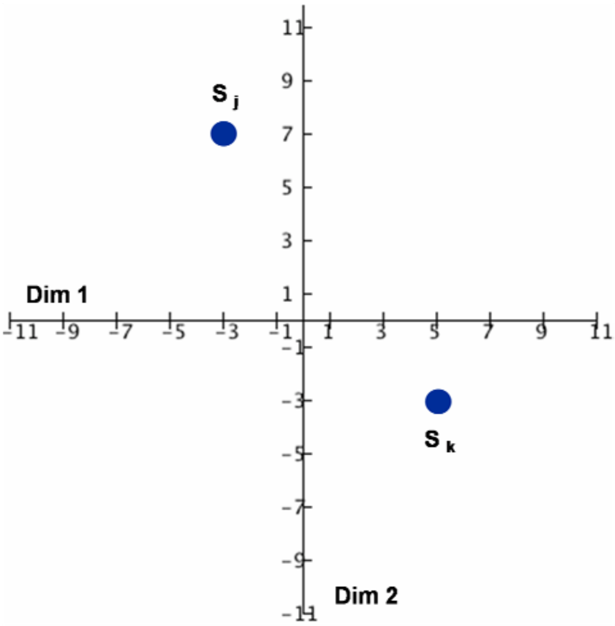

Figure 1: Representation of two students taking two dimensions into account

Distance between two students S_j and S_k: the similarity of two students is evaluated through the distance between the vectors representing the students. Applying the Euclidean distance, this becomes:

$$D(S_j, S_k) = \sqrt{\sum_{i=1}^{n} (Dim_i(S_j) - Dim_i(S_k))^2} \tag{2}$$

where n is the number of dimensions. Graphically this distance (in two dimensions) is represented in figure 2.

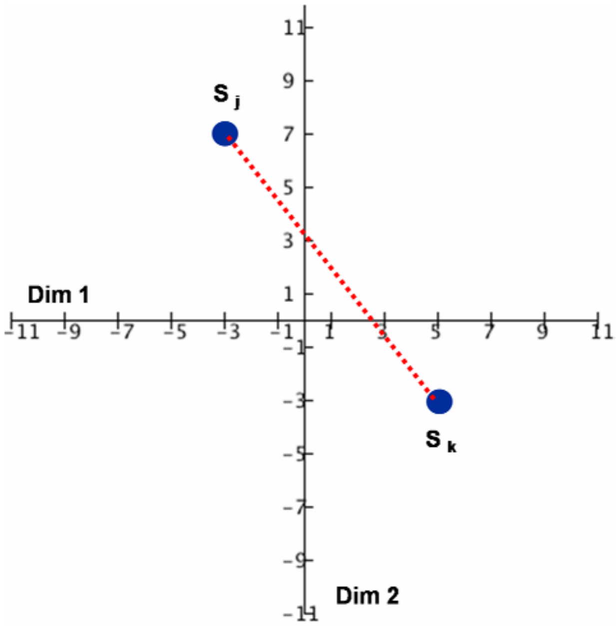

Figure 2: distance between two students considering two dimensions.

Average distance between students: arithmetical mean computed from student distances

$$AD = \frac{\sum_{j=1}^{m-1}\sum_{k=j+1}^{m}\sqrt{\sum_{i=1}^{n}(Dim_i(S_j) - Dim_i(S_k))^2}}{\frac{m(m-1)}{2}} \tag{3}$$

where m is the number of students and n the number of dimensions

Group average distance: the previous equation applied to the members of a group

$$GA(S_1,...S_m) = \frac{\sum_{j=1}^{m-1}\sum_{k=j+1}^{m}\sqrt{\sum_{i=1}^{n}(Dim_i(S_j) - Dim_i(S_k))^2}}{\frac{m(m-1)}{2}} \tag{4}$$

where m is the size of each group and n the number of dimensions

Internal Euclidean distance: it results from adding all the students' distances in a group. It is the previous equation without the divisor.

$$IED(S_1,...S_m) = \sum_{j=1}^{m-1}\sum_{k=j+1}^{m}\sqrt{\sum_{i=1}^{n}(Dim_i(S_j) - Dim_i(S_k))^2} \qquad \textbf{(5)}$$

3.2 Optimal Group Formation

In order to design an algorithm capable of building the best possible groups given a set of students, it is necessary to define what "best group composition" is. For example, given a set of six students (S1 ... S6), and two alternative divisions on groups of three members each

Alternative 1: G1=(S1, S2, S3), G2=(S4, S5, S6)

Alternative 2: G1=(S1, S5, S6), G2=(S2, S3, S4)

Which alternative is the best, if the goal is to build groups as much heterogeneous as possible?

Given the equations of the previous subsection, the obvious choice is that two students are as different as their Euclidean Distance (equation 2) is. Even so, there may be cases where the answer is not so clear. For example, consider three students, each student described by his or her learning style representation:

S1(-3,3,5,-1), S2(11,3,-9,-1), S3(3,5,-1,9)

Applying equation 2 the distance can be calculated, for example, between student 1 and student 2, and between student 1 and student 3.

D(S1,S2) $\approx$ 19.8
D(S1,S3) $\approx$ 13.27

The distance between S1 and S2 is greater than the distance between S1 and S3. However, it must be observed that S1 and S2 have the same value for two learning style dimensions. Arguably, S3 may be considered a better partner for S1, as in some regards is more different from S1 than S2, against the Euclidean Distance criterion.

When comparing groups, it is possible to decide that the most heterogeneous group is the one with the greatest Internal Euclidean Distance (equation 5) or equivalently, the one with the greatest Group Average Distance (equation 4). Nevertheless, this criterion can select a group where two students have the same values for the n dimensions and the third member is very different from them over a group where its three members are (approximately) equally far away one from the other. Again, it may be argued that a different measure would work better.

The problem is still more significant when comparing collections of groups. For example, it is possible to calculate the arithmetical mean of the Internal Euclidean Distance (equation 5) for each collection, and to select the collection with the greater value. Again, a good value on the average does not preclude the existence of some groups with very similar students. Even if most of the groups are "good" (mostly heterogeneous), this fact will not improve the situation for the members of "bad" (mostly homogeneous) groups. Once again, it may be preferable to get a solution where all (or at least most) of the groups are reasonable balanced to a solution obtained through the optimization of some parameter.

Therefore the problem is the lack of an absolute criterion for determining which the optimal group collection is from a given set of students. With the aim of overcoming this problem, this paper proposes a supervised method for building groups made up of two complementary components: the Faraway-so-close supervised algorithm and the tool supporting its application through visualization techniques, which is presented in the next section.

3.3 Algorithm Steps

We propose to form well-balanced heterogeneous groups by means of a supervised method. This method, based on the Faraway-so-close Algorithm, finds out different group configurations based on four parameters: the collection of students (represented as stated in equation 1), the number of students in each group, the pair threshold and the group threshold.

The pair threshold is the intended lower bound for the distance (equation 2) between any two students in the same group, while the group threshold is the intended lower bound for each group average distance (equation 4). The idea is for the teacher to provide the algorithm with different values for these last two parameters and compare the solutions the algorithm produces, looking for a solution containing the most heterogeneous groups; the tool introduced in the next section supports this process of trial-and-error.

The algorithm works on two sets:

- The G set of completed groups, initially empty.
- The S set of not grouped students, initially containing all the students.

At the end of the algorithm, the G set will contain M groups with all the students originally in S, while S will be empty.

Four steps compose the algorithm. Steps 1 and 4 are mandatory, while steps 2 and 3 can be skipped. Nevertheless, most of the times skipping them is not recommended, as they contribute to enhancing the final solution (that is, to increase the heterogeneity of proposed groups).

Step 1. The first student in S is selected to serve as a group pivot, removed from S and assigned to group G1. Then all the other students from S are compared with the group pivot to decide their assignment to G1, using the distance between them (equation 2). This distance must be greater than or equal to the pair threshold parameter.

$$D(S_1, S_j) \geq \text{pair threshold} \qquad \textbf{(6)}$$

The algorithm also verifies that the group average distance value (equation 4) is at least as big as the value of the group threshold parameter.

$$GA_1 \geq \text{group threshold} \tag{7}$$

If a given student data fulfil equations 6 and 7, he or she is added to G1 and removed from S. This process continues until the first group is completed (and added to the assemble G) or all the students on S were checked. The whole step is then repeated for the second and successive groups with the students still in S, until all these students have been considered. At the end of this step, G will contain M groups, some of them incomplete, while S will contain the students without group.

Step 2. The second step tries to complete incomplete groups.

Step 2 phase 1. In step 1 the first student included in each group was used as pivot, a reference to decide if new students were added to the group. In this first phase of step 2 the algorithm tries other members of the group as pivots. To this end, the algorithm sequentially takes a student from S and it selects a group from G that is not yet completed. It then applies the distance measure on that student and every member from the group. If the distance is greater than the pair-threshold for at least one of the students in the group and the average distance of the group is greater than the group threshold, then the student is included in the group and removed from S. If the student's parameters do not fulfil the constraints, the algorithm tries with every incomplete group in G.

This phase is repeated with all the students in S. Eventually, some of the students of S would be incorporated to the incomplete groups of G.

Step 2 phase 2. In this second phase, the algorithm takes the first incomplete group in G, undoes it and tests its student/s, trying to put them into the remaining incomplete groups, using again equations 6 and 7. This phase is repeated until there are no more incomplete groups.

At the end of this phase, G has a number of complete groups and S has the students not assigned to a group yet.

Step 2 phase 3. The students in S can be divided into students who have already been used as pivots and others who have not. In this third phase, the system tries to form new groups using as pivots students who have not been used yet.

Step 3. The third step performs a trial-and-error process on the groups in G. Firstly, these groups are sorted taking into account its Internal Euclidean Distance (equation 5), greatest value first. The algorithm temporarily removes a student from the first group and replaces him or her by a student in S. It then checks if the new student fits the join-constraints (equations 6 and 7). If he or she fits, the exchange is kept, otherwise it is undone and the algorithm tries with the next student in S.

This step is repeated for all the groups in G. At the end, G has a number of complete groups and S has the students without a group.

Step 4. The fourth step sequentially assigns students to incomplete and new groups without checking the join-constraints, until S contains no more students.

The algorithm would stop before any step if the previous one reached the goal of placing every student of S into G. An important assumption of the current version of the algorithm is that the total number of students is divisible by the number of members of each group; in other words, at the end all the groups will have the same number of members.

It is also important to highlight that the Faraway-so-close Algorithm does not look for an optimal solution given certain criterion (for example, the assemble maximizing the sum of Euclidean Distance of each group). That is to say, it does not look through the whole space of solutions, but it uses heuristics to approximate a good one. The reason to select this approach was the difficulty to build an optimizing algorithm when no absolute criterion can be chosen for selecting the best group. However, repeatedly applying the algorithm with different configurations and selecting the best solution found can achieve good results. Supporting this iterative process is the goal of the TOGETHER tool, presented in the next section.

4 TOGETHER Visualization Tool

Given the straightforward nature of the Faraway-so-close Algorithm, it can produce very different results depending on the pair and group thresholds and even the order in which students are considered. For this reason, a tool name TOGETHER was developed, with the goal of supporting the application of the Faraway-so-close Algorithm with different configurations and contrasting the results. The tool can also reduce the impact of the student initial order on the final result by executing the algorithm repeatedly, starting from different initial configurations.

This method requires choosing, from a set of candidate group collections, the best one. However, as it was explained in the section “Building heterogeneous groups”, there is not an absolute criterion for comparing two or more collections of groups. Consequently, TOGETHER proposes a visualization technique for supporting the teacher on picking the best grouping accordingly to her criterion, which is explained in the next subsection.

In this context, TOGETHER provides two main alternatives of execution, both based on executing repeatedly the Faraway-so-close Algorithm:

- Choosing every time a different starting student, considering the student list as a circular array.
- Using every time a randomly chosen student ordering.

In both cases, the user can specify the number of executions and the tool automatically shows the best result obtained among all the alternatives considered. Table 1 shows the time spent for TOGETHER when grouping different number of students into teams of three people with different number of iterations. These examples are generated with synthetic data.

Again, because of the impossibility of choosing the best alternative, the tool provides a pool of criteria for selecting candidate solutions. The user can select the preferred criterion, as explained in subsection “Criteria for choosing a solution”.

Iterations	300 students	600 students	900 students
100	<1 sec.	3 sec.	6 sec.
1000	8 sec.	25 sec.	50 sec.
10000	80 sec.	240 sec.	467 sec.

Table 1: Time spent to group students into teams of three people

The whole idea is for the user to try with different configurations, initial parameters and evaluation criteria. He or she can even choose not to apply one of the steps of the Faraway-so-close Algorithm, as step 2 and 3 are optional. In this way the user can approach, almost by trial-and-error, an appropriate solution. The solution is selected using the visual representation provided by TOGETHER as it is explained in the next section.

4.1 Visualizing Solutions

When designing TOGETHER, the first concern was how to visualize the result of the algorithm so that the teacher can evaluate the proposed group collection. In this sense, it was decided to focus the student grouping considering two out of the four dimensions proposed by Felder and Silverman [Felder, 88], namely active-reflective and sensing-intuitive. The reason to choose these dimensions is that they have shown to have the biggest impact on group performance, as it was explained in section “Motivation and Antecedents” [Alfonseca, 06].

However, it is important to highlight that the Faraway-so-close algorithm is not restricted to any number of dimensions.

This reduction of dimensions is made only for visualization purposes and, as a consequence, TOGETHER takes advantage of it, as it is much simpler to show information in two dimensions. Therefore, reducing the number of dimensions makes it possible to build a graphical representation that provides a very simple and intuitive way of comparing different aggregations. In this way the teacher can select the best (at least accordingly to his or her criterion) collection of groups.

TOGETHER diagrams (figure 3) are built in the following way: the x-axis represents values on the active-reflective dimension, while the y-axis represents values on the sensing-intuitive dimension. For each group, the sum of internal distances on each dimension is calculated, following the equation:

$$Dim_x value = \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} \left| (Dim_x(S_i) - Dim_x(S_j)) \right| \quad \textbf{(8)}$$

where m is the size of each group.

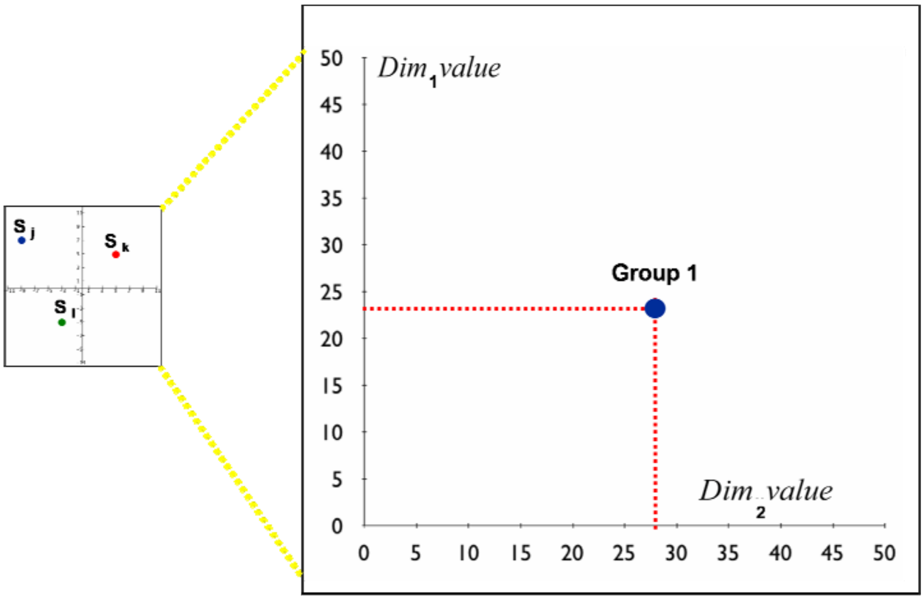

Figure 3: from students to group representation.

A dot is drawn for each group, using the value of each dimension provided by the equation. Considering the goal of building heterogeneous groups, the further a given dot is from the coordinate origin, the better the group is. Besides, the color of each dot represents how many groups share the same values for both axes, accordingly to a scale dynamically calculated that ranges from blue to red.

All the figures of this section are actual screenshots from TOGETHER, using data from real students. The scale from 0 to 50 is dynamically generated based on the maximum values that the sample to be represented has. It facilitates the visualization of the graph, and can zoom in the display when the values are small and expand it when they are bigger. Using this visualization the teacher can compare different collections of groups and select the appropriate ones.

4.2 Criteria for Choosing a Solution

As it would be impossible for the teacher to compare thousands of candidate solutions, TOGETHER uses some general criteria for selecting the candidate solutions that will be proposed to the teacher. These criteria are just approximations to good solutions, and the teacher can choose which criterion to use in any moment:

- Mean Euclidean Distance: the mean value of the Internal Euclidean Distance calculated for every group, as defined by equation 5.
- Minimum Euclidean Distance among all members: minimum value calculated for the Internal Euclidean Distance of every group (equation 5).

- Minimum Euclidean Distance between pair of students belonging to the same group: for every group, equation 2 is applied between every pair of students, and the minimum value calculated is returned.

Each criterion tries to optimize the group formation in a given direction. Criterion 1 (Mean Euclidean Distance) tries to improve the global "look" of the groups, producing most of them in a central zone of the graphic.

Criterion 2 intention (Minimum Euclidean Distance among all members) is to avoid "bad" groups, that is, groups where students are too similar one to the other; in that sense, it does not produce the nearest groups to the coordinate origin produced when using criterion 1.

However, none of the above criteria avoids the situation in which two students are very close while the third is far away from them. The purpose of the third criterion (Minimum Euclidean Distance between pair of students belonging to the same group) is to try to avoid this situation. Left side of figure 4 shows a "good" group, where every member is relatively far away from the others in the representation of their learning styles. On the contrary, right side depicts a "bad" group, because two of its members are located almost at the same position, even if the constraints for group creation are fulfilled.

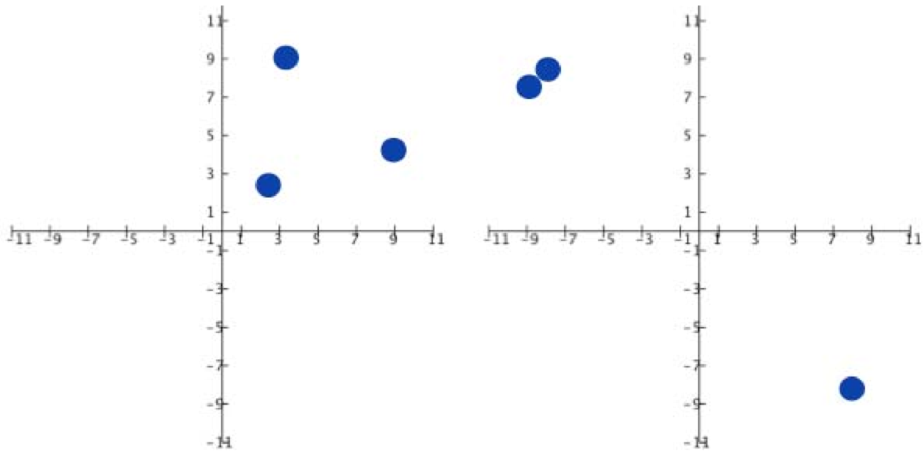

Figure 4: Visualizing individual groups. Each chart shows information about one group and each dot represents a student. Axes represent the actual value of each student in both LS dimensions considered.

4.3 Using Visualization to Select Algorithm Parameters

Depending on the set of students to be grouped, the pair and group threshold parameters can affect to a large extent the type of solutions found by the algorithm.

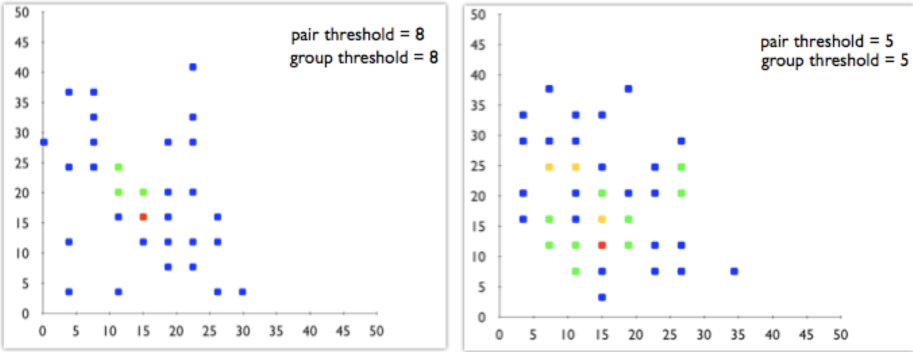

Figure 5: Comparing solutions with different thresholds. In both charts dots represent groups, while axes represent the result of equation 8 for each group, considering the active-reflective dimension (axis x) and the sensing-intuitive dimension (axis y).

Figure 5 shows two solutions generated from the same set of students with different parameters (in this figure each dot represents a group). The graphic on the left side shows the groups generated with pair threshold = 8 and group threshold = 8. These two values are initially established as the average distance between the whole set of students (equation 3). The graphic on the right side shows an example of results when relaxing the constraints, using in this case pair threshold = 5 and group threshold = 5. It is possible to see that this second solution produces groups farther from the coordinates origin (that is, more heterogeneous). In other words, sometimes decreasing the values of the parameters (that is, reducing the constraints on group formation) can lead to a better general solution. The reason for this behavior is that student population may not be large enough or may have an irregular distribution (with many students with similar scores and a few very remote from the rest) to satisfy hard constraints. Accordingly, maybe a better overall solution is obtained when weaker constraints are required.

5 Using TOGETHER in real scenarios

This section is aimed at showing some experiences already carried out in order to test the usefulness of the method we present. At present, we have conducted two kind of experiences, being one of them student centered and the other one teacher centered. More information about these experiences can be found at [Paredes, 08].

5.1 Student centered use

The student centered experience carried out, aimed to test the advantages of heterogeneous groups, created by means of the method we propose, when facing collaborative tasks. As mentioned above, those groups were supposed to obtain better results at collaboration than other groups where diversity, in this case, with respect to learning style, was not a key fact.

For the purpose of this experience, two sets of students were selected, summing up 130 students. 42 out of them were secondary school students, corresponding to two whole classes. The remaining 81 were post-secondary school ones, concretely from a Vocational School where they specialized in audio-visual technology. In this last case, the number of classes involved was four. Both secondary and post-secondary classes were standard ones, and no biases were reported by teachers about differences between them.

Given that this experiment involved six whole classes, it was thought to proceed by grouping with TOGETHER the students of half of the classes, while allowing the students of the remaining ones to group by themselves, acting as control. The number of students per group was set to three. It is worth mentioning that the number of students fit this grouping in every class. It was not the case, we had to adjust the grouped ones, and left the one or two remaining students apart, given that in this version no impairment is considered.

As for the experiment itself, firstly, all the students were required to fulfil the ILS questionnaire in order to determine their learning style. Afterwards, the grouping took place: half of the classes by means of TOGETHER and the rest by themselves. Finally, the students were asked to carry out a collaborative task consisting of solving a logic problem. We provided each member of the group with a piece of information (premises) and the group had to give a joint solution to the problem. The joint solution of each group was evaluated by a set of 10 questions that should be answered. For each question, there was only a right answer.

Table 2 shows the results (right answers) obtained on the average by the groups built by TOGETHER versus the results obtained by random groups. It is possible to see that, on the average, TOGETHER groups got 1.25 more right answers. Whilst these results indicate a potential difference between these two groups is not enough data to draw any firm conclusions, further experimentation will examine this.

	Mean	Std.dev
TOGETHER	7.86	2.48
Random	6.61	3.03

Table 2: Mean number of right answers and standard deviation for groups grouped with TOGETHER and by themselves

Figure 6 shows the distribution of the number of groups according to the number of right answers. For example, 44% of the groups built by TOGETHER answered 10 questions correctly, and none of them failed more than 6.

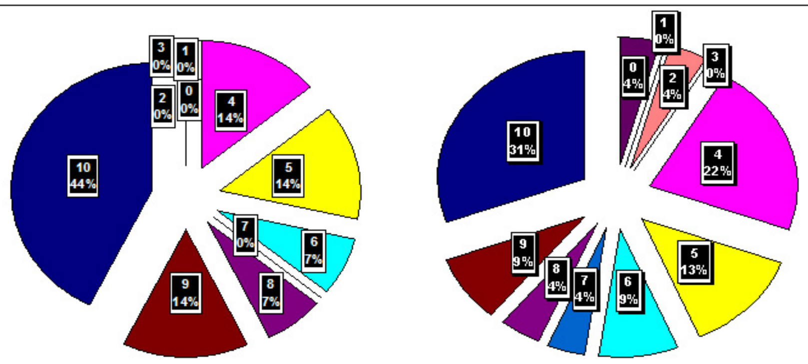

Figure 6: Number of right answers for each TOGETHER group (left side) and number of right answers for each random group (right side).

5.2 Teacher centered use

In the previous experience, student centered, the grouping by means of TOGETHER was made directly by us, from the data about students' learning styles previously collected.

However, as one of the goals of this work was to support teachers on the formation of heterogeneous groups, it was also important to test teachers' opinion. In this sense, in order to get feedback from potential real users, TOGETHER was tested with a group of 10 teachers from the Department of Computer Science, UAM. They used the tool during 30 minutes and filled in a questionnaire about its usability. This questionnaire is formed by 9 questions and targeted mostly issues such as understanding of how the system works, and satisfaction with the resulting presentation. First four questions are 5 point scale, while the others are open questions.

It was not intended to provide a detailed analysis of the tool usability, which only would make sense when the tool is integrated on the framework of an e-learning system. Instead, the goal was to poll teachers' opinion on their first use of the tool.

Figure 7 depicts the teachers' general impression of the first time they used TOGETHER. The score of each question goes from 1 to 5, being 1 the worst answer and 5 the best.

• Question 1 is related to how easy to use is TOGETHER. Mean score is 3,29, and main objection is that sometimes they need more explanations about the functionality of controls and meaning of colours.

• Question 2 asks whether TOGETHER covers the necessity of a tool for group formation or not. Teachers considered the implementation of TOGETHER and visualization of results useful for group formation (4,29 mean score).

• Question 3 refers to pleasant of the interface. Reorganization of some data is needed to improve the interface (3,57 mean score).

• Question 4 analyzes the time spent by TOGETHER. The results show that TOGETHER is very fast and finds out a good solution in reasonable time (4,57 mean score) in the opinion of the teachers who tested the tool. Objective information can be found in Table 1.

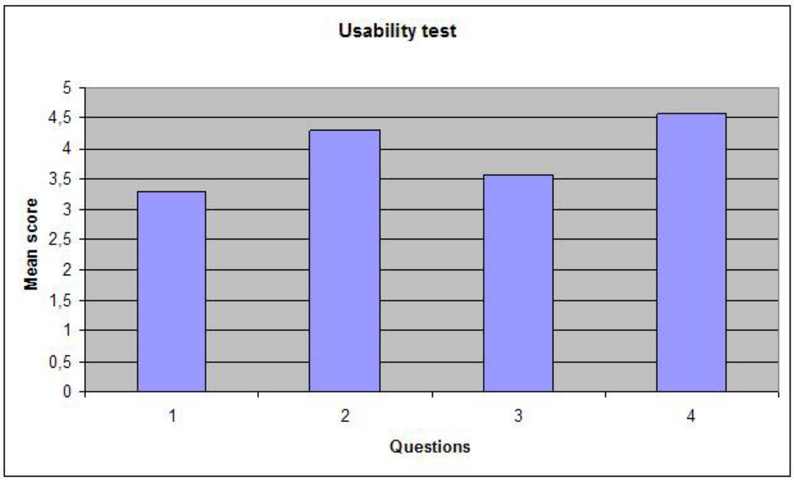

Figure 7: Mean score of the four questions.

Even if the number of interviewed teachers is not big enough to extract firm conclusions, it is clear that most of them found the tool useful for the task at hand. Another important conclusion drawn from open-ended questions is that all of them took for granted the convenience of tools providing grouping support.

6 Conclusions and Future Work

Nowadays there is a clear need for tools able to automatically group students, taking into account their personal features, such as learning styles. Moreover, groups formed by heterogeneous/diverse students are better in a broader range of tasks [Nijstad, 02]. These tools should be flexible enough to fit the different teacher requirements and preferences. The tool presented, and the underlying algorithm, try to fulfil these needs. Our method uses a supervised approach for looking for a good enough solution to the student grouping problem. The user can adjust the algorithm behavior through several parameters resulting in a mechanism that is both flexible and not time-consuming.

Even if the teacher is responsible for group formation, the tool should help make it possible to manipulate data about large student populations with little effort, providing an effective support for building groups according to different criteria.

Our algorithm and the visualization tool can be of interest for collaborative learning systems such as TANGOW [Carro, 03]. These e-learning environments deliver adaptive courses including collaboration activities and our tool could support supervised grouping of users.

It is clear that the performance of the Faraway-so-close algorithm depends heavily on the particular set of data. However its simplicity enables to try different configurations with little effort and the use of the visualization tools makes it possible to select good results quickly.

The results obtained in our experiences with students and teachers are quite promising, and will be taken into account for the new version of the tool that supports the method.

Regarding the group size, our case studies provide us with data about small groups (two or three students). Further experiments are needed in order to test TOGETHER with larger groups.

Other additional ILS dimensions can be included in the tool and taken into account when calculating distances among students for grouping purposes. However, at present the visualization mechanism makes use of two-dimension axes. If three dimensions were to be considered simultaneously, a spatial representation would be necessary. More than three dimensions would be easy to deal with from the algorithm point of view, but the visualization phase should be re-visited. In fact, any other characteristics could also be eventually considered. The only restriction is that features must be expressed as numbers.

With the aim of improving the algorithm, our future work will consist in testing other metrics for the distance between two students (such as the Huffman distance) and improve step 4 by removing the pair threshold and the group threshold in separate steps.

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