Strategic Collaboration Support in a Web-based Scientific Inquiry Environment

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Abstract. This paper describes our work-in-progress toward developing indirect, strategic support for collaborative learners in a web-based scientific inquiry environment. Using the distribution of students' current problem solving strategies and their most likely predicted future behaviors, we plan to strategically construct collaborative learning groups containing heterogeneous combinations of various behaviors such that students with less efficient strategies will likely adopt the strategies of their more efficient peers. The objective of this research is to explore the possibility of facilitating peer interaction through strategic pairing and facilitation, with a minimal amount of direct instructional intervention.

1 INTRODUCTION

The strategies students use in solving scientific inquiry problems, in which they must search for and evaluate the quality of information, draw inferences, and make quality decisions, provide evidence of their knowledge and understanding of the domain [10]. Previous research has shown the utility of artificial intelligence methods, in particular Neural Networks and Hidden Markov Models, for automatically identifying students' individual problem solving strategies, and predicting their future strategies [16]. This research suggests that we may be able to determine (with over 90% accuracy) whether or not a student is likely to continue applying an inefficient problem solving strategy, and hence likely to need help and guidance in the near future. If so, help might be provided through direct intervention by a teacher or computer-based coach, or indirect intervention by strategically setting up and mediating peer collaboration situations.

In this paper, we describe our work-in-progress toward developing a new approach to indirect, but targeted collaboration learning support. Using the distribution of students' current problem solving strategies and their most likely predicted future behaviors, we plan to strategically construct collaborative learning groups containing heterogeneous combinations of various behaviors such that students with less efficient strategies will likely adopt the strategies of their more efficient peers. The objective of this research is to facilitate peer interaction through strategic pairing, with minimal direct instructional intervention. We also explore the possibility of providing a limited amount of direct facilitation though mouse control and sharing schemes. The next section briefly describes our web-based multimedia collaborative inquiry learning platform, and previous research in automatically identifying individual problem solving strategies. We then discuss our work-in-progress for providing strategic collaboration support in this problem solving environment.

2 THE IMMEX ONLINE LEARNING ENVIRONMENT

IMMEX™ (Interactive Multi-Media EXercises) is a web-based multimedia learning environment that runs within students' web browsers. The single-user version was developed at the University of California, Los Angeles, has been used in science classes across middle and high schools, universities, and medical schools in the U.S. over the past 12 years, and has logged over 250,000 student problem solving performances [15]. A rich portfolio of over 100 problem sets in various disciplines has been developed, and is available online at http://www.immex.ucla.edu.

IMMEX Collaborative (shown in Figure 1), which was developed at the University of Trento, Italy, also includes general purpose collaborative web navigation and synchronization facilities, and a structured chat interface [4]. The IMMEX Collaborative environment is designed to help groups of students learn how to elaborate hypotheses and analyze laboratory tests while solving real-world problems. For instance, in the *Hazmat* problem, students must discover the composition of a substance resulting from a chemical spill to determine if it is dangerous. The students use scientific inquiry skills to frame the problem, judge what information is relevant, plan a search strategy, select the appropriate physical and chemical tests to solve the problem (e.g. litmus, conductivity), and eventually reach a decision that demonstrates understanding. As the students work through the problems, the system logs their chemical and physical test selections, browser navigation actions, and chats. These actions then serve as the input vectors to self-organizing artificial neural networks (SOMs) [8] that are trained to recognize student problem solving strategies (described in the next section).

The IMMEX Collaborative client interface is divided into three portions. The main window is a shared workspace dedicated to the collaborative navigation of the IMMEX multimedia web pages. Actions taken by students in this frame are automatically reflected on the other group members' screens. The vertical frame on the left side shows the structured chat interface, and the horizontal frame along the bottom shows a graphical representation of the service and synchronization facilities, which are used to manage the flow of action and control in the collaborative space. The mouse image moves over the name of the student who has control of the workspace, as if the members were seated in front of the same monitor, passing the mouse among each other.

The client runs in any browser, and is managed through Java applets, which communicate with the IMMEX Collaboration Server (see Figure 2). The collaboration server is an http server acting as a proxy, that filters, edits, and synchronizes the IMMEX HTML pages through JavaScript, and sends them to the clients [4].

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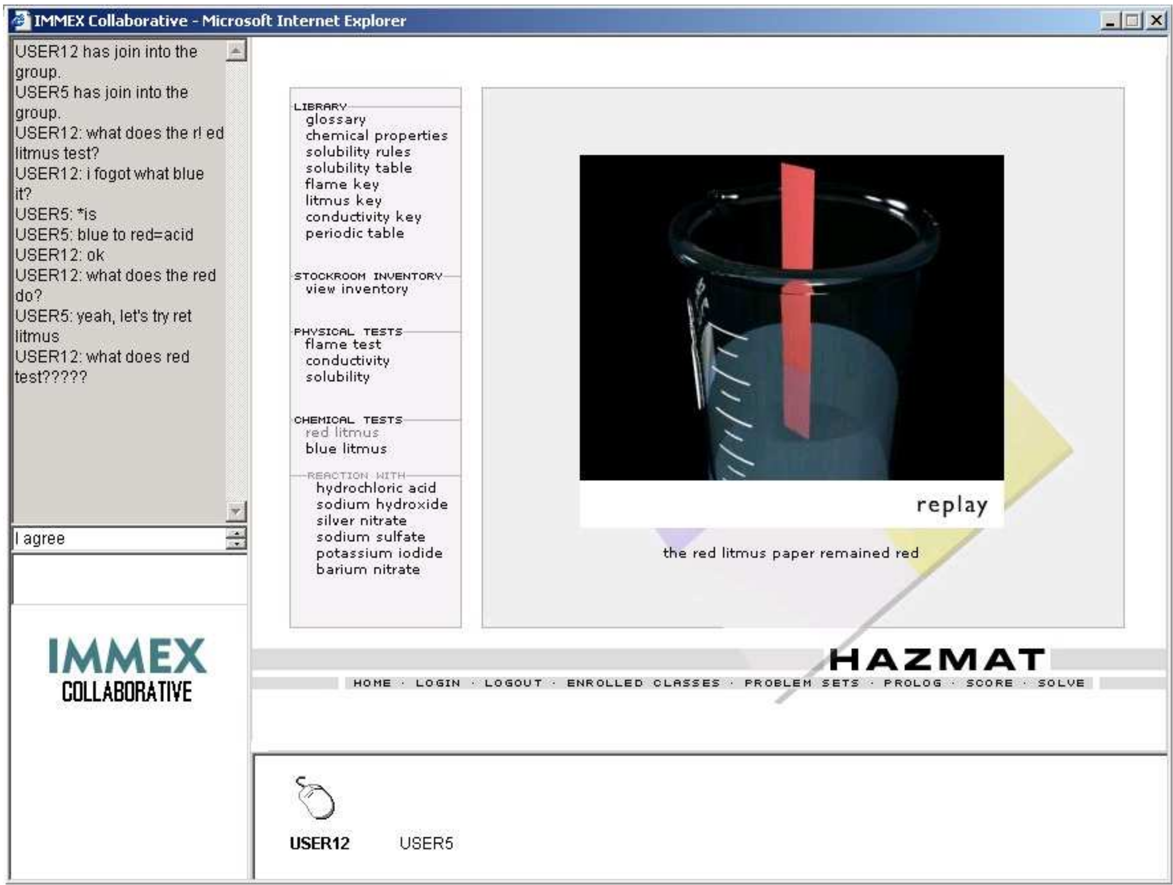

Figure 1. The IMMEX Collaborative interface showing a sample screen from the Hazmat problem set.

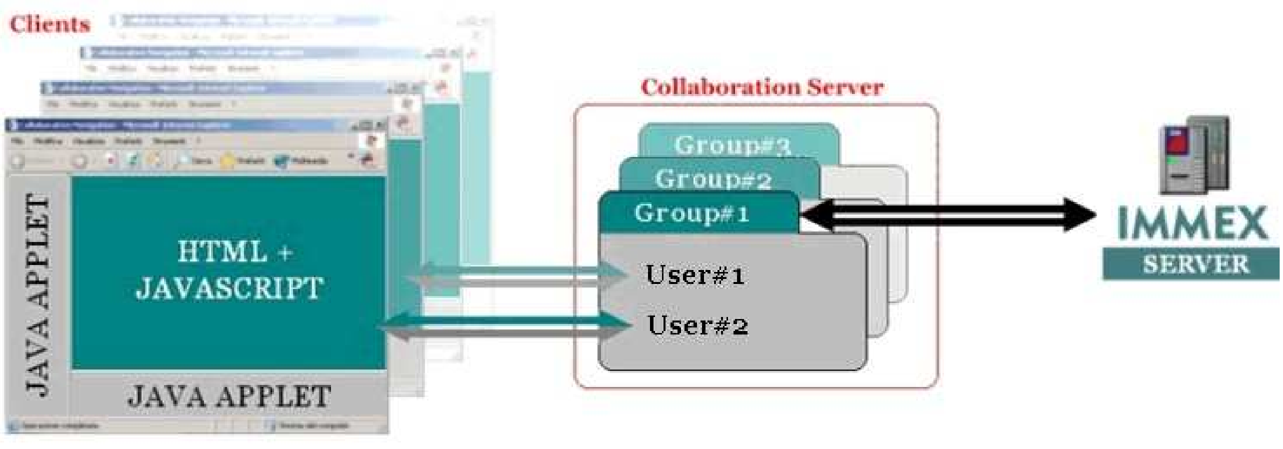

Figure 2. IMMEX Collaborative Architecture

3 PREDICTING INDIVIDUAL PROBLEM SOLVING STRATEGIES AND FUTURE BEHAVIORS

Statistics for over 5000 individual problem solving performances collected by the IMMEX system were used to train competitive, self-organizing artificial neural networks (SOMs), producing maps of common problem solving strategies used by high school chemistry students [8] [15]. The neural network input vectors described sequences of individual student actions during problem solving (e.g. Run_Blue_Litmus_Test, Study_Periodic_Table, Reaction_with_Silver_Nitrate) [18]. The training resulted in a topological ordering of neural network nodes according to the structure of the data, such that the distance between the nodes described the similarity of the students' problem solving strategies (see Figure 3). For example, the neural networks identified situations in which students applied ineffective strategies, such as running a large number of chemical and physical tests, or not consulting the glossaries and background information, effective strategies such as balancing test selection with searching for background information, or problem-specific strategies such as repeatedly selecting specific tests (e.g. flame or litmus tests) when presented with compounds involving hydroxides [16].

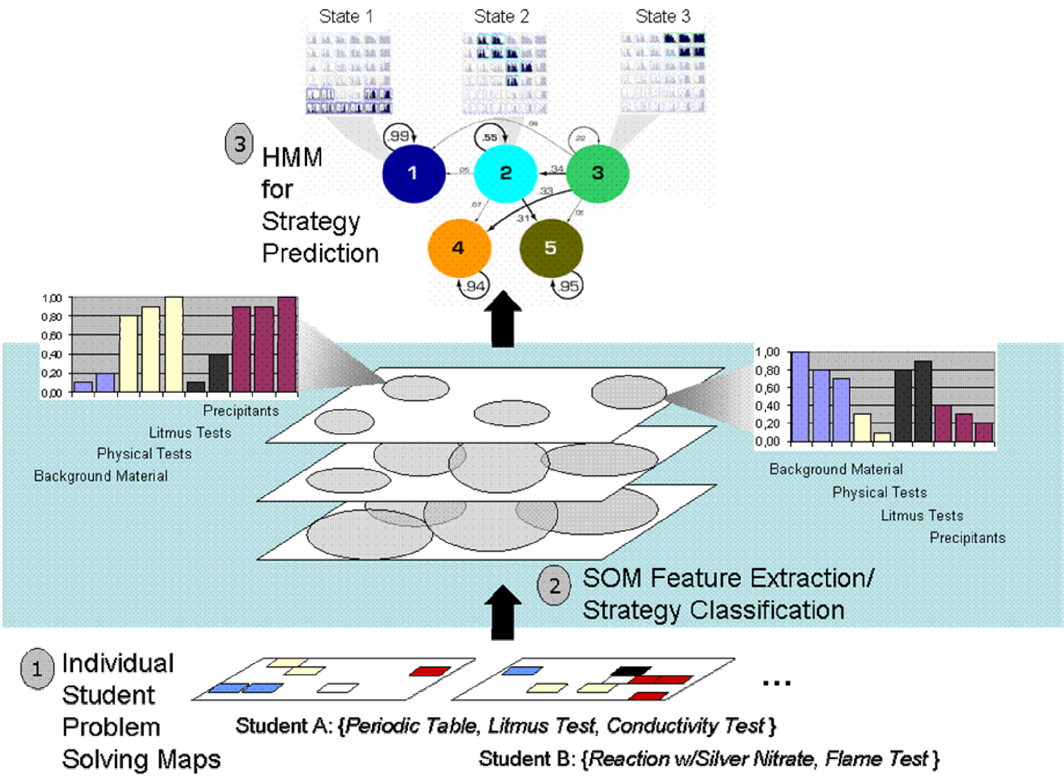

Figure 3. Individual Problem Solving strategies are identified by self-organizing Artificial Neural Networks, and then input into an HMM to predict learning trajectories.

The artificial neural network analysis provided point-in-time snapshots of student problem solving, and has been found useful for providing feedback to students and teachers [15] [18]. Stevens, Soller, Cooper, & Sprang [16] also found that sequences of these neural network models, trained across several problem sets, represented strategy trends over time, and could be used to train Hidden Markov Models [12] to characterize student learning trajectories. The trained Hidden Markov Models described patterns of students strategy shifting over time, and could be used to describe and explain learning trajectories, and predict future problem solving performances. The models performed at over 90% accuracy in predicting the students' next most likely problem solving strategies, described by a suite of five neural network maps.

Interestingly, this analysis showed that without intervention, individuals learning alone generally tended not to switch their strategies, even when their strategies were ineffective in solving the problems. When the individuals were working with partners, however, their problem solving performance increased from a 51% solve rate (for individuals) to a 63% solve rate (for the students in groups). Although performance increases for collaborative learners are not unusual, they are sometimes difficult to predict and explain [2]. The type of performance increase that we saw might be explained by the Hidden Markov Model learning trajectories, which showed that the collaborative learners established stable patterns of problem solving more rapidly than the individual learners [16]. This hypothesis makes sense if group interaction indeed helps students see multiple perspectives and reconcile different viewpoints, such that they are more likely to overcome impasses and adopt more efficient problem solving strategies [3] [9].

The Hidden Markov Model analysis provides information about whether or not a student is likely to continue to use an inefficient problem solving strategy, enabling us to better assess whether or not the student is likely to need help in the near future. Perhaps more intriguing, however, is the possibility of using the distribution of students' current problem solving strategies, and most likely future behaviours, to strategically construct collaborative learning groups containing heterogeneous combinations of various behaviors, such that intervention by a human instructor is required less often. We consider this possibility in the following section.

4 METHODS TOWARD STRATEGIC PAIRING AND FACILITATION

Two fundamental approaches have been applied toward promoting effective learning group interaction. In the first approach, a (human or computer) facilitator constructs the learning group by selecting members with the most compatible knowledge, skills, and behaviors in anticipation that this will create the dynamics needed to produce effective learning. Although small group research has suggested that individual characteristics are generally poor predictors of group learning performance [10] [19], we have not yet seen the potential of using predictive analysis to project the effects of individual tendencies in group learning situations. In the second approach to promoting effective learning group interaction, a facilitator analyzes the group interaction after the students have begun problem solving, and dynamically attempts to either facilitate the group interaction, or modify the learning environment appropriately. This research aims to apply a strategic combination of both these approaches by first, pairing students based on their current problem solving strategy, and predicted future strategy use, and second, mediating the group interaction by facilitating the collaboration management and control.

Figure 4 shows the possible student partnering combinations based on their current and future strategy predictions. For example, we might recommend that a student who is using an ineffective strategy (and whom we predict will continue to use the ineffective strategy) partner with another student who has adopted an efficient strategy. Or, we might recommend that two students work together if they are both using less effective strategies, but show a high tendency to shift their strategies on the following problem set. Once a group is strategically constructed and begins a collaborative problem solving session, the IMMEX neural network-based modeling software begins to automatically predict the new group problem solving strategy. This analysis is done by examining the sequence of student actions, in the same way as was done for the individuals. In the future, a more finer-grained analysis of student actions will be performed, accounting for which students took which actions [11] and made which conversational contributions [14].

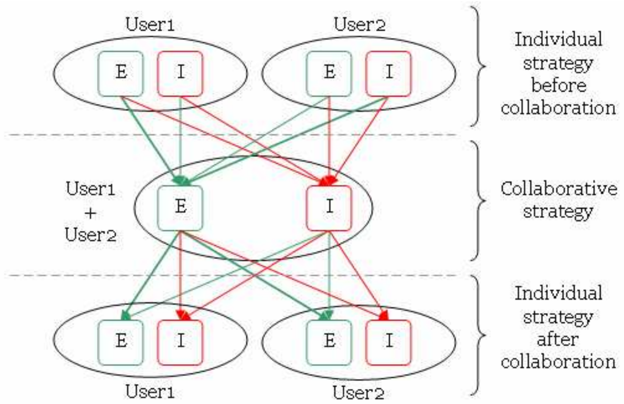

Figure 4. Student partnering possibilities based on current and future ("E" – effective, and "I" – ineffective) strategy predictions, and the possible outcomes based on the pairing and collaborative performance.

The group strategy provides some indication of how the group problem solving is proceeding, however it may provide little information about the individuals' learning. For example, the student with the efficient strategy may solve the problem alone without explaining his actions to his partner, or he may instead give instructions to his partner on what to do, and his partner may simply follow these instructions without question. In both cases, the overall group problem solving strategy will be recognized as efficient, however the individual outcomes will not reflect the group activity. Whether or not the individual with the less efficient strategy adopts a more efficient problem solving method depends on both the combination of prior individual strategies, and the development of the collaborative learning process. It is also possible for the student with the more efficient strategy to regress. For this reason, it is important to *monitor* and *facilitate* the collaborative interaction.

Monitoring and assessing collaborative interaction might be done similarly to Soller's [14] approach, in which sequences of student conversation acts (given by sentence openers as in Figure 5) and actions are analyzed using Hidden Markov Models (also see [5]). This approach was shown to accurately predict the effectiveness of student knowledge sharing interaction. In this research, a similar approach might be used to determine whether or not students are helping each other adopt more efficient problem solving strategies. For example, the structure of the student discussions in our chemistry environment might reflect the structure of their decision processes in selecting and explaining the results of various physical and chemical tests. Student strategy shifts might then be recognized by modeling and characterizing interaction patterns in the contexts of various known strategy applications.

Situations in which the student interaction is less likely to produce problem solving strategy shifts might be facilitated by targeted mouse control schemes. Previous research has shown that mouse control schemes, that change the way in which group members share their access to the learning environment, can have significant effects on student learning [6] [17]. For example, Chiu [1] studied the effect of 4 different schemes on student performance: *assign*, in which one student was assigned exclusive control of the workspace; *rotate*, in which control automatically shifted to the next student every 3 minutes; *give*, in which the student currently controlling the workspace decided when and to whom to relinquish control; and *open*, in which any member could take control at any time. The results of the study suggested that when one student is assigned control of the workspace such that the other group members cannot anticipate attaining control at some future time, they not only perform better, but also engage in more task-oriented dialog. It seems that the inability to directly control the workspace may encourage students to express and justify their ideas in words, rather than waiting for their turn to take actions.

Learning achievement in different mouse control conditions may also be gender dependent. Inkpen, McGrenere, Booth, and Klawe [6] showed that male pairs who operated under a protocol where they could steal the mouse from their partner tended to exchange control of the mouse more often than pairs who were required to explicitly pass the mouse to their partner. This higher tendency to share control of the workspace, at least for boys, meant a more equal distribution of the amount of time that each partner could take actions, which correlated with the boys' subsequent individual achievement.

Our proposed research intends to build upon these findings through the development of a dynamic assignment mouse control scheme in which the selection of a control exchange policy is guided by both the dynamic analysis of the student dialog, and the students' predicted strategy shifting tendencies. We expect that such a scheme might encourage students to take turns, spending an equal amount of time selecting physical and chemical tests, and explaining the results of each other's tests.

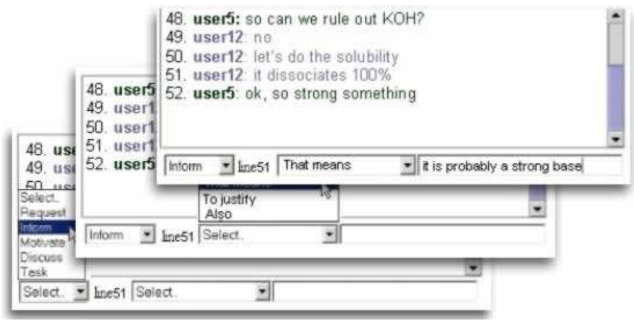

Figure 5. User5 explains the results of a solubility test by selecting the sentence opener, "That means…"

5 FUTURE WORK

We are preparing to run experiments in which we strategically construct student pairs based on their individual prior problem solving strategies, and predicted future problem solving strategies. Then, based on an analysis of the ongoing collaborative learning process, we will decide whether or not to introduce a cyclic or assignment-oriented mouse control scheme. The results of this experiment should provide across-group knowledge of whether or not it is possible to monitor and facilitate collaborative learning interaction through such strategic pairing and facilitation.

The purpose of the planned experiment and analysis is to determine the conditions under which collaborative learners with less efficient strategies adopt more efficient problem solving strategies. We expect to find correlations between students' prior individual strategies, interaction dynamics, and individual post-collaboration strategies. These correlations could be used to design an intelligent coaching agent that strategically recommends student partners and mediates the learning groups.

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