Formation of Learning Groups by using Learner Profiles and Context Information

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Abstract. An important but often neglected aspect in Computer Supported Collaborative Learning is the intelligent formation of learning groups. Until recently, support for group formation was mostly based on learner profile information. However, the perspective of ubiquitous computing and ambient intelligence allows for taking a broader view on group formation, extending the range of features to include learner context information such as sensor-derived activity and availability. A probabilistic approach has been developed that automatically learns individual characteristics and indicates relevant situations, and which has been tested in a set of experiments.

1. Introduction

An important but often neglected aspect in Computer-Supported Collaborative Learning is the formation of learning groups. Most CSCL systems focus on mediating and supporting collaborative learning while the activity is going on, or after the activity has ended, by proving system functionality ranging from mirroring to guiding [6]. Moreover, if support could also be given prior to the actual collaborative learning activity by suggesting appropriate group arrangements, many problems might be solved even before they arise, and beneficial group processes might be boosted.

Until recently, most support for group formation was based on learner profile information such as gender, class, etc., including more sophisticated information such as the complementarity or overlapping of knowledge and competencies. Such an approach will be described in the following section. In addition, the perspective of ubiquitous computing and ambient intelligence allows for a wider perspective on group formation, broadening the range of addressed features to include learner context information such as location, time, and availability. This new perspective will be addressed in the third section.

1. Group Formation based on Learner Profiles

A general conceptual and formal framework for student model integration has been introduced in [3] under the notion of multiple student modelling, and has been extended in [10] for open distributed learning environments. The general premise is that individually assessed learner models can be used to support the configuration or parameterization of collaborative learning settings. These are prototypical cases:

- Given a number of students working on comparable problems in an open learning network, find pairs of students that could potentially benefit from cooperation in a joint

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session. The selection can be based on such criteria as complementarity or competitiveness.
- Given a group of students, select or generate a problem that forms an adequate challenge for the group as a whole. The problem should not be solvable by one student's knowledge alone, but rather through the union of all the students' individual knowledge bases. In this case, the challenge for the group consists in knowledge exchange and integration.

Selection criteria for these prototypical cases can be formulated on the basis of general modelling primitives such as *knows(Student, Topic)* or *has_difficulty(Student, Topic)*, which can be inferred from different standard types of student models. A simple case of knowledge integration is exemplified by the rule

can_help(Student1, Student2, Topic) ←
knows(Student1, Topic) & has_difficulty(Student2, Topic).

Interestingly, there is a wide range of different support functions that can be implemented based on such a rule and further extensions:

- **Intelligently mediated peer help:** The individually assessed learner models are used to match pairs of learners that should maximally benefit from each other when working together. The prediction can be based on different criteria such as complementarity of skills/knowledge or competition.
- **Intelligently mediated expert tutoring:** Formally, this case can be considered as a specialization and simplification of matching peer learners, since only one of the models (the learner's) has to be dynamically assessed, whereas the tutors' profiles may be predefined.
- **Teacher/tutor support for supervising individual exercises:** Essentially a decision support function for the teacher. To achieve this it is sufficient to aggregate the individual learner models in a form that allows for filtering out specific features, e.g. frequent problems. The support mechanism can also actively inform the teacher if adequate.
- **Group formation around given problems:** This is a generalization of mediating peer help in that the number of group members is not restricted to two. Also the problem requirements must be analytically specified.
- **Selection of adequate problems for a given group:** A problem is e.g. selected or generated in such a way that it could serve as a challenge to the group as a whole but should still be feasible if the group were able to combine individual strengths.

This framework has been used in different learner grouping scenario. For instance, see figure 1 for a user interface that proposes peer helpers for a learning task in mathematics. In the context of group learning, the individual student models are accumulated and integrated to derive a model of group problem solving that initiates and supports remedial activities. The underlying distributed architecture of the intelligent subsystem must allow for combining elements from different individual student models, as has been described in [10].

Massive practical applications of group formation based on similar principles as described here have been reported by [7]. An ontology-based representation of group formation principles has been proposed by [5].

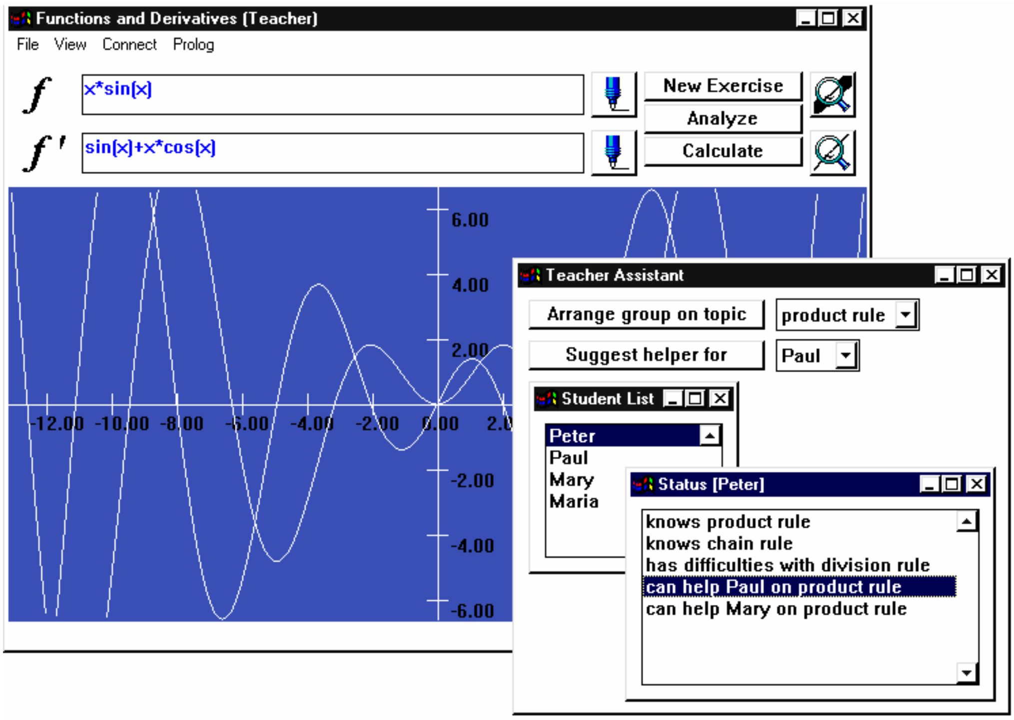

Figure 1. User interface for the formation of learning groups including peer helper suggestion and topic selection.

3. Group Formation based on Learner Context

The concept of ubiquitous computing envisions a new computing era where computational and communication power is available in devices and objects of every size and purpose [12]. One of the biggest challenges in ubiquitous computing is the automatic detection of a user context [11]. A typical contextual variable of a user that is frequently addressed is location, driven by many advances in device and sensor technology. Further interesting context features of a user and in a user's environment include among others activity, availability, stress and emotional parameters as well as temperature, noise, weather, co-location of other people, and availability of devices, respectively. For learning group formation, these contextual features provide an additional source of learner information, which could help in improving the quality of the grouping.

Using a networked infrastructure of easily available sensors and context-processing components, an application has been developed for peer helper suggestion and opportunistic group formation based on contextual parameters such as location, activity, and availability [9]. These notions of location, activity, and availability have both been detected automatically based on sensor information and learnt automatically based on users' feedback to the system.

In order to detect a person's location, activity, and availability, different sensing techniques have been used in a prototypical application. All these sensors are already available in many environments or can be installed without much effort, such as

- **PDA location:** Determination of the location of user's PDA (personal digital assistant) by using a wireless network. Wireless LANs are becoming more and more widespread, and a location system can be obtained as a by-product of the wireless LAN by triangulating the radio signal [2]. Places are first identified by their radio characteristics such as signal strengths in a calibration phase. Afterwards a device can locate itself by measuring the current radio characteristic and comparing it with calibration data, resulting in a localization reliability of about 80% according to our experience [1].

- **PC usage:** Detection of users' keyboard and mouse activity on personal computers. Sensing the user activity level on a personal computer is an important and easy source of information. The PC usage is detected by a demon that runs on the PCs and monitors typing and mouse movements.
- **PDA ambient sound:** Detection of ambient sound in the PDAs' vicinities. Each PDA is equipped with a microphone that is used to record several sound samples in a minute. These sound samples are compared to a sample of those situations with the lowest sound level encountered so far, defining a reference point for the no-ambient-sound situation.
- **PDA user feedback:** Explicit feedback on some context variables provided by the users. A user interface has been developed for the PDA that prompts the user for information on his context in a regular fashion. This user information is used to label situations in order to create a set of training data for calibrating the context sensing system to individual characteristics. The user is asked to provide explicit feedback on a number of context variables. These include his location, the co-location with other people, which could be either people identified to the system or just the number of people present, activity and availability (see figure 2).

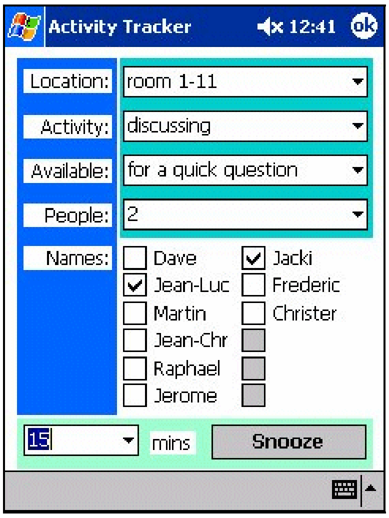

Figure 2. PDA user interface for context feedback.

The various sensors send their information to a database residing on a server that can be accessed from both the wired and the wireless networks (see figure 3). The database contains static profile data as well as the dynamic event data. The static profile data may vary over time, e.g. if someone is allocated a new PC or changes office, but comparatively slowly compared to the event data. The profile data names the entities, i.e., people and devices, and places that are referred to by the dynamic event data. Furthermore the profile establishes links between devices and places and people. For example the profile indicates that particular computers, PDAs and phones are associated with a particular user and that a user has his office in a particular place. It also indicates the normal function of places so that our software can find out if a user is in a place that is someone's office or in a public space such as a meeting room or coffee area. The tables associated with the dynamic event data store information about events generated by the sensors as well as the events generated by higher-level components predicting activity and availability.

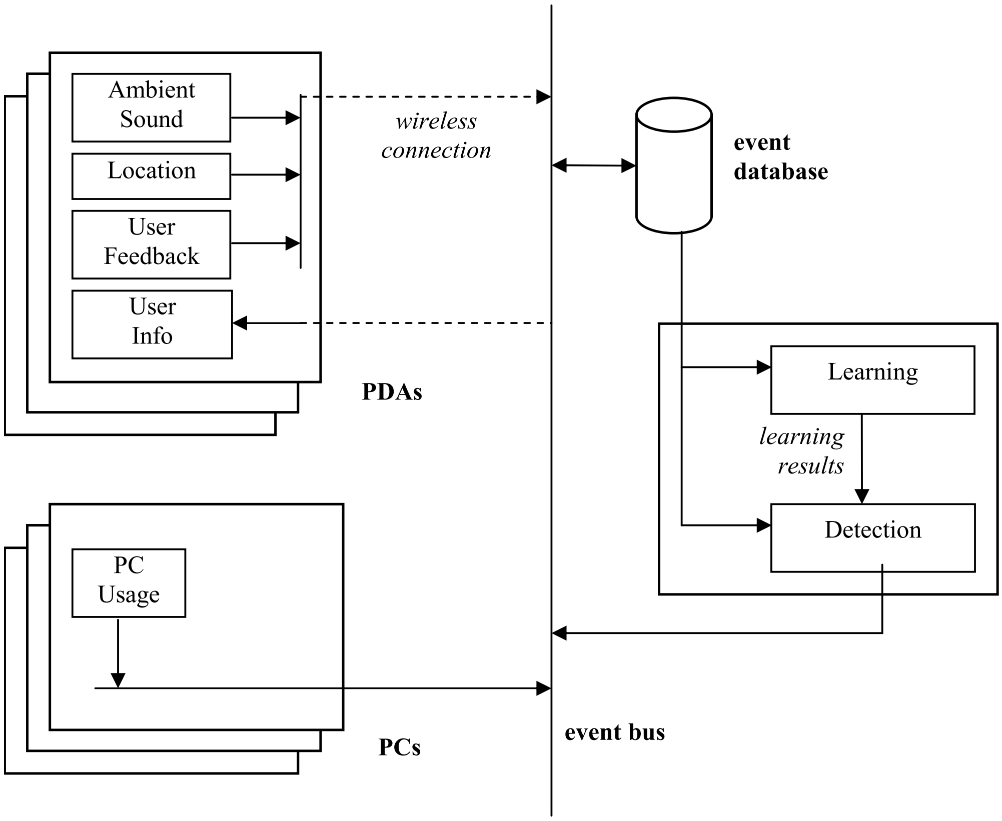

Figure 3. System architecture.

The context processing consists of combining information from different sources and deriving an estimation of the users' situation. Of particular interest for the application are the activities and availabilities of the users. The set of relevant activities is comprised of single-person activities like using a PC, using a PDA, and working on the desk, multi-person activities such as phoning, discussing, or being in a meeting, and intermediate activities like walking from one place to another, which result in a drastic change of context. These activities are assumed to have a major influence on the level of a person's availability. Relevant classes of availabilities that are considered to be useful are being available for a quick question, being available for a longer discussion, being available soon, or not being available at all. By using machine-learning methods the system is to find a connection between sensed information and situations as perceived by users, including also information on people's habits.

On the basis of labeled sensor data, probabilistic classifiers for relevant user activities and availabilities are learnt. As can be seen in figure 4, user activity is related to the PDA location, the PC usage, the ambient sound, the PDA co-location, and the time of day, whereas user availability is related to PDA location, activity, and time of day. A Bayesian approach is used to determine the activity with the maximum a posteriori probability. The simplifying assumption is made that all sensor values are conditionally independent (Naïve Bayesian classifier). The estimation of the prior probabilities for the Bayesian learning is based on the number of occurrences of each activity in the user feedback with and without the respective sensor value being detected as well as on the sum of probabilities of rooms in the user feedback where an activity was indicated. In order to get more reliable probability values, especially in the case of missing user feedback, a simple LaPlace smoothing has been used. Similarly, probabilistic classifiers for users' availabilities are derived.

The results of the learning of activity and availability notions are automatically included in a detection component, which is constantly monitoring the most recent events in the event database. For each user the detection component derives an up-to-date context description

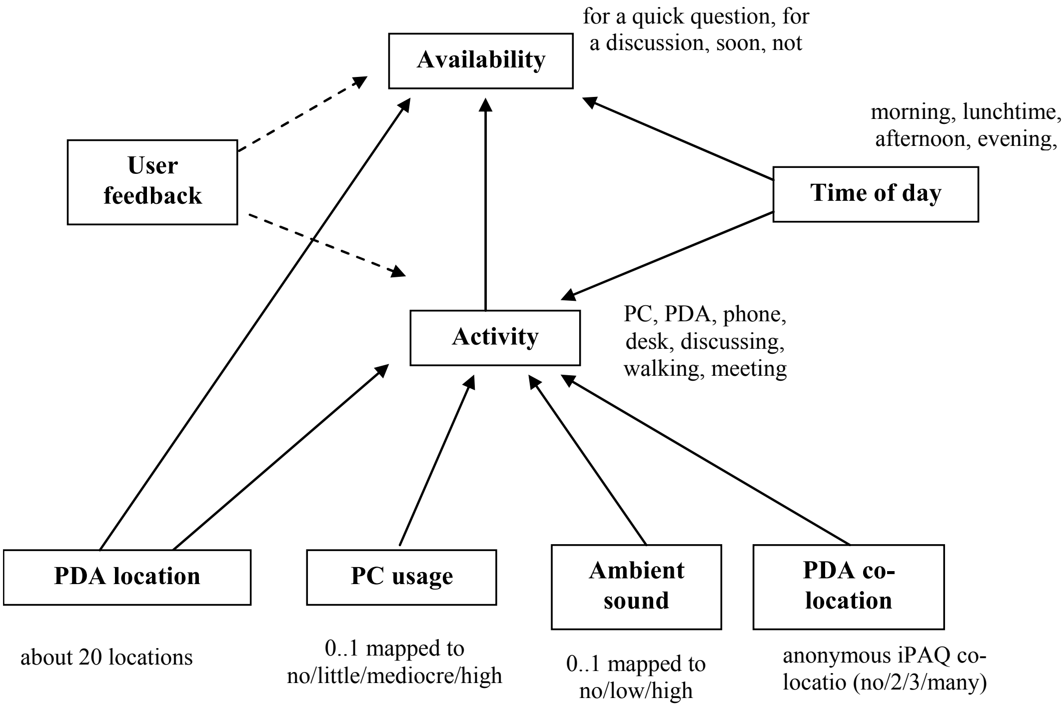

Figure 4. Learning dependencies.

based on the most reasonable situation estimation (see figure 3). The application is also adaptive to changes in a user's environment and habits. Whenever the user provides to the system new samples of information about his activity and availability using the context feedback application, the system can automatically adapt the context estimators and update its situation estimation.

In order to investigate the quality of the situation estimation and to test the sensing infrastructure, several one-day experiments have been conducted with different sets of users, including typical user situations such as PC work, discussing, meeting, etc. After having collected characteristic data during one day, we tried to classify new user-labeled situations the following day. Table 1 and Table 2 show the results of the activity and the availability detection in form of confusion matrices. Each matrix element shows the number of test examples for which the actual class is the row and the predicted class is the column. The training and test sets are comprised of 62 situations (day 1) and 27 situations (day 2), respectively. All situations included the activities "PC, "desk" or "discussing".

The results of the detection of the activities "PC" and "discussing" were very good, because they rely directly on sensor information (PC activity and ambient sound). As the PC activity sensor smoothes its values, it does not immediately return to zero when the user stops working on PC and begins working on desk. That is why there is a quite high detection rate of the activity "PC", even though the user labeled it "desk". The results of the detection of the availabilities "for a discussion" and "not at all" are excellent due to the fact that the users linked these availabilities especially to the time of day during the experiment. Many of them did not want to be contacted in the morning most of the time, but were available for a discussion in the afternoon to a large degree. Furthermore, in the experiments it turns out that a user's location is a strong indicator for his activity. This seems reasonable since in his own room a user typically would be doing PC and desk work, whereas in his colleagues' rooms and meeting rooms he would usually be discussing or meeting, respectively.

	PC	Desk	Discussing
PC	0.74	0.05	0.16
Desk	0.33	0.67	0.00
Discussing	0.00	0.00	1.00

Table 1. Confusion matrix for activity.

	For a quick question	For a discussion	Soon	Not at all
For a quick question	0.50	0.50	0.00	0.00
For a discussion	0.00	1.00	0.00	0.00
Soon	0.00	0.09	0.91	0.00
Not at all	0.00	0.00	0.00	1.00

Table 2. Confusion matrix for availability.

The automatic generation of probabilistic models of human behavior has also been done in other projects. Bayesian learning has extensively been used in the Microsoft Coordinate project for instance to predict peoples' presence at their desks or their interruptibility while being in a meeting [4]. In addition to Bayesian learning, other probabilistic methods have been used to learn and detect human activity, such as an approach based on hierarchical hidden Markov models to learn the hierarchical structure of sequences of human actions [7], although with a different objective, i.e., the extension of the functional capability of the elderly.

4. Summary

The combination of learning group formation based on information from learner profiles and information on the learner context has a potential of improving the quality of the grouping. It allows for the ad-hoc creation of learning groups, which is especially useful for peer help for immediate problems, by reducing the risk of disruptions. It also leverages the forming of face-to-face learning groups based on the presence information. The context sensing has been tested with a set of experiments, and a distributed application has been developed that helps teachers to form learning groups.

Potentially, other context information can be used to improve the group formation than the one that has been considered here, such as agenda information from personal calendars, or the availability of preferred communication channels. The building of learning groups could also be enriched by information available on the experience from past collaborations, which could be provided by peers but also from a teacher if available. Furthermore, in addition to the topic of the collaboration, the group formation could include information on the type of support needed, among others.

Acknowledgement

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References

[1] Andreoli, J.-M., Castellani, S., Fernstrom, C., Grasso, A., Meunier, J.-L., Muehlenbrock, M., Ragnet, F., Roulland, F., & Snowdon, D. (2003). Augmenting offices with ubiquitous sensing. In *Proc. of Smart Objects Conference SOC-2003*, Grenoble, France, May.

[2] Bahl P. & Padmanabhan, V. N. (2000). Radar: An in-building RF-based user location and tracking system, In *Proc. of the IEEE Infocom-2000*, Tel-Aviv, Israel, vol. 2, Mar. 2000, pp. 775-784.

[3] Hoppe, H. U. 1995, The use of multiple student modeling to parameterize group learning, In J. Greer (Ed), *Proceedings of AI-ED 95*, Washington D.C., USA.

[4] Horvitz, E. Koch, P. Kadie, C.M., Jacobs, A. (2002) Coordinate: Probabilistic Forecasting of Presence and Availability,. In *Proceedings of the Eighteenth Conference on Uncertainty in Artificial Intelligence*, Edmonton, Alberta, Aug.

[5] Inaba, A., Supnithi, T., Ikeda, M., Mizoguchi, R., & Toyoda, J. (2000). How Can We Form Effective Collaborative Learning Groups?, *Proceeding of ITS 2000*, 282-291, Montreal, Canada.

[6] Jermann, P., Soller, A., & Mühlenbrock, M. (2001). From mirroring to guiding: A review of the state of art technology for supporting collaborative learning. In P. Dillenbourg, A. Eurelings, & Kai Hakkarainen, editors, *Proceedings of the European Conference on Computer-Supported Collaborative Learning, EuroCSCL-2001*, p. 324-331. Maastricht, The Netherlands, March.

[7] Lühr, S., Bui, H.H., Venkatesh, S., West, G.A.W. (2003) Recognition of Human Activity through Hierarchical Stochastic Learning. In *Proceedings of the First IEEE International Conference on Pervasive Computing and Communications PerCom-03*, 416-421. Fort Worth, Texas, USA

[8] McCalla, G. I., Greer, J. E., Kumar, V. S., Meagher, P., Collins, J. A., Tkatch, R. Parkinson, B., 1997, A peer help system for workplace training, In Boulay & Mizoguchi, editors, *Proceedings of the Conference on Artificial Intelligence in Education AIED 97*, pages 183-190, Kobe, Japan.

[9] Mühlenbrock, M., Brdiczka, O., Snowdon, D., and Meunier, J.-L. (2004). Learning to detect user activity and availability from a variety of sensor data. In *Proceedings of the Second IEEE Conference on Pervasive Computing and Communications*, Orlando, FL, March.

[10] Mühlenbrock, M., Tewissen, F. & Hoppe, H. U. (1998). A framework system for intelligent support in open distributed learning environments. *International Journal of Artificial Intelligence in Education*, 9, 256-274.

[11] Salber, D., Dey, A., and Abowd, G. (1999). The Context Toolkit: Aiding the Development of Context-Enabled Applications. In *Proceedings of the 1999 Conference on Human Factors in Computing Systems CHI 99*, pages 434-441, Pittsburgh, PA, May.

[12] Weiser, M. and Brown, J. S., *Designing Calm Technology*, 1995.