Reyes P., Tchounikine P. (2005), *Mining learning groups' activities in Forum-type tools*, In: CSCL'2005 (Computer Supported Collaborative Learning), Taipei (Taiwan).

Mining learning groups' activities in Forum-type tools

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Abstract. Mining data produced by students involved in communication through forum-like tools can help revealing aspects of their communication. In this paper we propose an approach to the construction of models to highlight structural properties of learning groups based on a relational perspective (analysis of chains of references) and the use of Social Network Analysis techniques. These models can be useful both for the tutor and the participants. We begin by introducing the overall approach, then we describe how the models are constructed and finally we present preliminary results from the integration of these ideas in a forum-type tool.

Keywords: Link analysis, peer-to-peer support, social network analysis.

INTRODUCTION

Network technologies have enabled web-learning activities such as learning groups and e-communities that can take place in e-learning platforms. Current e-learning tools and approaches can be roughly classified into four main categories (IBM, 2002): Tools dedicated to information transfer (support and reference materials), tools to allow interaction (interactive simulations and games), tools to allow collaboration (collaborative learning strategies) and tools to allow collocation (experience based learning tools). Various Computer Aided Learning systems (CAL systems) have been implemented for each of these layers, which can be seen as a key element to support web-learning activities.

In this paper we are interested by CAL systems in the collaboration layer. We introduce CAL strategies to support collective activities taking place in learning groups based on a relational model of messages exchanged among participants in a *forum-type tool* (FTT). The FFT describes a mainly text-based and asynchronous electronic conferencing system that makes use of a hierarchical data structure of enchained messages, called *threads*. The FFTs is an important tool to carry out collective activities.

We model the message exchanges as a graph where the vertices are the participants of a group and the links are the exchanges among them. This is a basic model broadly used for modeling relationships among users from a social networks analysis point of view. Several procedures have been developed to detect structural regularities and to analyze the implications of structural patterns in the members' behavior. We exploit the link structure to improve information retrieval. In order to contribute to a comprehensive understanding of the group activities we use models that deal with relational data, the relations among different entities being of a central importance. This contrasts with data analysis based on propositional data, where the analysis is based on the individual attributes of each entity.

In this article we propose the use of two models to gather information about group activity from a relational perspective. Each of these models corresponds to a different granularity of the analysis. The first model denotes properties of the group as a whole; the second denotes properties of the individuals in relation with the group to which they belong. Our algorithms construct indicators that allow characterizing the collaboration process, which can be useful for both tutors and students.

The article is organized as follows. First, we describe the idea of mining group activities and their use in a CAL context. Then, we propose and describe two models to gather different characteristics of a group. Finally, we present preliminary results from an empirical study that illustrates the use of our models.

MINING GROUP ACTIVITIES

Mining group activities in a learning context

Mining group activities is an active line of research. Current research is mainly focused on the construction of indicators of collaborative group's activities aiming at a theoretical or ethnographic analysis of the group (e.g., (Reffay & Chanier, 2002), (Martínez et al., 2002) or (Butts, 2001)) and other social networks works). Nevertheless, these analyses are rarely used to support online collective learning activities.

The use of mining strategies can be an important element in educational contexts. Mining group activities in a learning context provides quantifiable profiles of the groups, which allows to (1) evaluate the collaborative activity that the participants carry out, (2) analyze the link structure of the group, (3) compare the collaborative performance among different groups and (4) predict behaviors, discover link patterns (Getoor, 2003) and collaboration trends. This knowledge can be used and applied directly to support the collaborative activities. In this sense, link models can be an element that helps the tutor in his tasks of collaboration management and that scaffolds the collaborative learning among the participants.

The link analysis approach can be meaningful for three types of users: the external analyst, who analyses the group interactions from a theoretical or ethnographic point of view; the tutor, who uses the link analysis results to orient his pedagogical strategies and to track the structural properties of his group; and the participants of the group (the students), who use link analysis to discover the structural features or activities of their group (what has been termed structural awareness (Gutwin, Greenberg, & Roseman, 1996)).

Link analysis provides a new role for tutors in collaborative environments. Instead of their traditional role in the "transfer of information", the role of tutors is shifted to that of establishing the appropriate conditions to allow the students to get connected to the group (the set of relations) through participation (e.g., as part of a community of practice) in the service of an intention (Barab et al., 1999). Consequently, “ (in a) collaborative environment, the instructor must re-conceptualize his or her role as a 'teacher' and create a set of opportunities and reward structures that encourage students to look upon their interactions with their peers as valuable resources for learning (…)” (Hiltz & Benbunan-Fich, 1997). The structural models that we propose make salient certain profiles of the groups and their participants which can help to be aware of the group activities and can help orienting the pedagogical strategies. The characterization of the group's activity by a set of indicators can be an important tool for the analysis of the collaborative activities without need for an extensive review of each group's interactions.

Structural models can help participants of a group to create macro-micro links and facilitate peer-to-peer learning. The concepts of peer-to-peer learning and the macro-micro link underline the importance of the structure of interactions as a means to reveal activities and situations that take place in a group. The concept of peer-to-peer learning refers to a situation where students learn one from another without any one of them having an a priori authority over the others. This has been expressed by the tenet “Students learn a great deal by explaining their ideas to others and by participating in activities in which they can learn from their peers” (Boud, 2001). The macro-micro link is a sociological concept that establishes the theoretical foundations for the influence of interaction structure of a community (macro level) with the local interactions among the participants (micro level). We found an example of this type of influence in the works of Pierre Bourdieu (Bourdieu, 1988), which explain the effect of societal structures on the behavior of individuals and vice versa. The concept of macro-micro link allows us to focus on the interdependency of the structural regularities of the group with the activities of the participants. Indeed, several learning theories emphasize the influence of social interactions on the individual learning. In the perspective of the communities of practice, for example, it has been stated that sharing and interacting are the fundament of learning in these communities (Lave & Wenger, 1991). Learning changes "(…) from the individual as learner to learning as participation in the social world" (Lave & Wenger, 1991).

The social constructivist point of view highlights also that knowledge is socially constructed by interactions among individuals (McCarthey, 1992). Learning can be regarded as a result of internalization of such social interactions (Vygotsky, 1986). Indeed, the theory of learning of Piaget (Piaget, 1926) states as a fundamental assumption that the interaction among peers while performing tasks facilitates the learning of concepts. By making salient the structure of interactions in a group we allow the participants to be aware of an important element of learning.

Techniques for mining group activities in a relational perspective

The mathematical tools we use for mining group activities come from the Social Network Analysis (SNA) models. Many methods have been proposed in this field to obtain knowledge about the group from its relational ties. In essence, the SNA models are based on the idea that the social environment can be expressed by the patterns of relations of its interacting units (Wasserman & Faust, 1997). The SNA uses as data the connections among units, which relates them in a system. Relations are not the properties of the units, but of systems of units; these relations connect units into large relational systems.

The three principal mathematical approaches used to analyze the networks are graph theory, statistical models and algebraic models. These approaches are employed to develop a group of metrics which can capture properties of the participants in a network (e.g., connectivity, prestige or centrality of a participant), dyads (e.g., reciprocity or symmetry), triads (e.g, transitivity) as well as global characteristics of a whole network (e.g., density, heterogeneity or centralization of network). We use a graph theory approach to mining group activities by analyzing the *sociograms* associated to a given group. In FTT a sociogram is a graph where the participants are represented as vertices and the messages that they exchange are represented as the links of the graph. Sociograms can be handled as sociomatrices which are the matricial representation of the graph (more information on the construction of sociograms and sociomatrix can be found in (Wasserman & Faust, 1997)).

PROPOSED MODELS FOR SOCIAL INTERACTIONS

We model two characteristics of social interactions: the status of participants and group cohesion. These models gather information about the group activity at different granularity levels.

The status belongs to a family of models that reveal the role of a given participant in the group. The cohesion belongs to a family of models that reveal structural properties of groups: it provides information about the group and not about the participants of the group.

Status

Status definition

In a community, the concept of status represents the “prestige” of a specific participant. The status of a participant is related to his participation in a community as well as the status of the participants which s/he communicates with (Wasserman & Faust, 1997). This concept is not a simple account of the number of user interventions, because it also considers the prestige of his entire neighborhood.

Starting from the participant’s status we can find the each participant position in relation to the whole community, and the social structure of this community. Moreover, this indicator is related to a concept of learning in the communities of practice (Lave & Wenger, 1991), where learning is conceived in terms of participation. In the context of the communities of practice, learning can be interpreted as an evolution of the status of a participant from a peripheral participation (low status) towards a central participation (high status) within its community. Through the status indicator, we can measure these evolutions. This model gives participants and tutors an element for comparison among their position in the group and a quantitative measure of their evolution.

Status model

There are several models to obtain the status of participants in a group, each of them is based on a different notion of status. The *Betweenness-centrality* model takes into account the degree of dependence of a given vertex and the other vertices, quantifying how much a vertex acts like a “bridge” for subgroups of vertices (Wasserman & Faust, 1997). Here, the important idea is that a participant is central (high status) if it is *between* many participants.

The *Closeness-centrality* model, is based on the vertex distance, and focuses on how near a participant is to the others. Here, a participant is central if s/he can quickly interact with the rest (Wasserman & Faust, 1997).

The *Degree-centrality* model takes into account the direct relations between two participants. In this type of measure, a participant is central if s/he has many links with the remaining participants (Wasserman & Faust, 1997).

The *Eigenvector-centrality* model is more refined than the others, and considers not only the associations with the adjacent vertices, but also the status of these vertices. Consequently, “an actor’s status is increased more by nominations from those who themselves have received many nominations” (Bonacich & Lloyd, 2001). From its structural nature, one says that the eigenvector-centrality measures the “prestige” of participants.

Here, we will concentrate on the *Eigenvector-centrality* model because it is the only status model that establishes the value of a participant prestige taking into account the other participant’s status. In addition, this model can take advantage of many numerical methods existing to obtain the eigenvectors from a matrix.

For a sociomatrix A of size n (n participants) that represents the interactions among the participants of a specific group, A^t is the transposed matrix of A, and λ are the eigenvalues of A. In the equation (1) the vector c corresponds to an eigenvector of the sociomatrix A. Each component of this eigenvector c corresponds to the prestige of each participant. That is, if $c = (c(v_1), c(v_2),...., c(v_n))$, the status of participant i is $c(v_i)$.

$$A^T c = \lambda c \quad (1)$$

In spite of the precision of this method to obtain the status values of participants in a group, it makes sense only for the symmetrical sociomatrices ($A \rightarrow B \equiv B \rightarrow A$, for example, somebody's brother is a symmetrical relation). In our case, the matrices of interactions in the FTT are asymmetrical ($A \rightarrow B \neq B \rightarrow A$, answering a message is an asymmetric relation). The alpha-centrality model introduced by Bonacich (Bonacich & Lloyd, 2001) presents a generalization of the eigenvectors' model for asymmetrical matrices. Bonacich makes the assumption that the status of a participant depends on two parameters: the external initial status of a participant and the status that is formed starting from the interactions among the participants. By adding the external idea of status to the traditional concept of eigenvectors (based on equation (1)), we obtain equation (2). The complete description of this method is found in (Bonacich & Lloyd, 2001).

$$c = \alpha A^T c + e \quad (2)$$

In this equation A is a sociomatrix. c is a vector of participant's status, and α is a parameter which reflects the relative importance of the external status versus the internal status to determine the final status. We can also interpret α as the status degree of transference from one person to another. The solution of the equation (2) for c gives us the vector c, which indicates the each participant status for the asymmetrical relations.

Among the outstanding characteristics of this indicator we emphasize: first, the status is not related to participation (e.g., in the star graph (figure 2), the most central participant has the greatest value of status and s/he has never participated), the status is associated with the impact of the interventions of a specific participant on the activity of the group (participant's visibility); second, this index can be dichotomized as follows: "one part due to the status that an actor gets from another actor, and one due to the status that comes back to the original actor after being initially sent to the other actor" (Wasserman & Faust, 1997).

Cohesion

Cohesion definition

Cohesion is a concept related to the diffusion of information in a group (Wasserman & Faust, 1997). In a cohesive group the information is extremely likely to be distributed for the entire group. This fact improves the communication, the coordination and the influence within the group. This indicator is also associated to the concept of solidarity in a group. Analytically, the solidarity includes two components (Moody & White, 2000): an ideational component which is related to the psychological identification of the community members, and a relational component concerning the connections between the community members. Cohesion corresponds to the relational dimension of solidarity. This indicator gives a measure of how strong the social relations are in order to maintain the group together.

From this indicator, users can perceive the group solidarity level, manifested by the ability of the group to hold their members. A group with a high value of cohesion is a group that holds social relations among almost all participants. Consequently, the group could face the departure of some of its participants without destroying it.

Cohesion model

There are several models to obtain the degree of cohesion of a group (Wasserman & Faust, 1997). Bock and Husain propose to iteratively build sub-groups so that the proportion between the number of links in the sub-group and links between the sub-groups does not decrease with the addition of new members. The model is composed of two components (Wasserman & Faust, 1997): the measurement of the group cohesion (centripetal property), and the measurement of the links dispersion towards the participants outside the sub-group (centrifugal property). Reffay and Chanier (Reffay & Chanier, 2002) obtain the group cohesion by measuring the degree of reciprocal relations that take place in a forum among participants.

James Moody and White (Moody & White, 2000) introduce another concept of cohesion, which is defined as the minimal number of participants who, if removed from the group, would disconnect it. This approach led to obtain hierarchically nested groups, where highly cohesive groups are built over less cohesive ones. We seek to make salient this notion, which corresponds to the definition of k-connectivity (a graph is k-connected if there are at least k independent paths connecting every pair of participants in the graph) in the graph theory. This

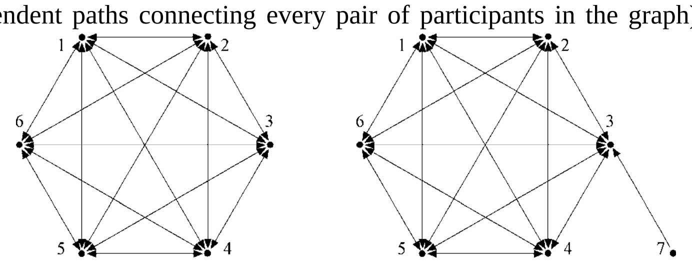


Figure 1. Issues with slightly connected participants on the cohesion value

indicator expresses the property of certain groups to hold their members. Yet, this model of cohesion is very sensitive to participants slightly connected in the group. For example, a group with a complete network configuration (see figure 1) with 6 participants have k-connectivity value equal to 5. Nevertheless, if we add another participant to this group (participant nº 7 in figure 1) with only one link, the k-connectivity value decrease to 1, i.e, a very low cohesion degree for a highly connected group, So, the real group cohesion is hidden.

We consider that a cohesion model must take into account the group structure as a whole. Thus, we modify the original cohesion model (the minimal number of participants who, when removed from the group, disconnect it) in favor of a concept of cohesion as the minimal number of participants who when removed from the group, disconnect it completely. This model provides a more robust measure of cohesion, even for groups with weakly connected participants.

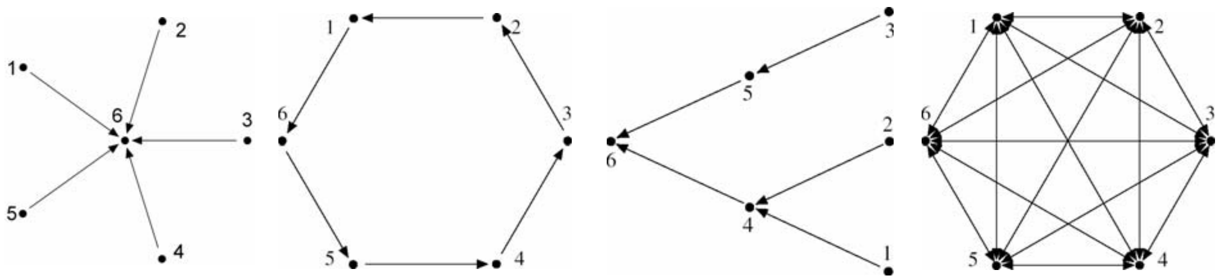
To calculate cohesion, we apply the original algorithm in an iterative way to the groups that remain connected. The summa of the values of the k-connectivity of each iteration will give the final measurement of cohesion. In order to compare the cohesion values for groups of different sizes and structures of participants, these values are normalized. Two normalization methods are necessary: first, in relation to the number of iterations executed in the algorithm (i.e., the number of iterations to obtain a group completely disconnected). Second, a normalization regarding the number of participants. The maximum value for the cohesion is produced by the complete graph. Thus, for a complete graph composed by n participants (K_n) the cohesion of a group ($C(K_n)$) is $n-1$ and we obtain a graph completely disconnected after j iterations. We will assign to this graph structure a value of cohesion equal to 1. Then we divide this value, the maximum value for the cohesion and the number of iterations. Equation (3) shows the normalized cohesion value:

$$\overline{C}(G_n) = \frac{C(G_n)}{(n-1) * j} \tag{3}$$

Hypothetical social networks

Figure 2 illustrates six hypothetical social networks with six participants each, and the associated status values for each participant ($c = \{c(v_a), c(v_b), ..., c(v_f)\}$), where $c(v_i)$ is the status of participant i. For simplicity, participants in all these social networks, have the same initial status, that is, e is a vector of '1'.

In the star network we can observe the central position of participant "6" in it. This fact is reflected by his/her high status value. The same result is obtained in the hierarchical network. Nevertheless, the low value of cohesion of the star graph structure allows us to suppose that it is fragile, given that all interactions pass through participant "6". In the circular network, all participants have the same status values because each of them has the same link number and structure. The highest cohesion value is obtained for a complete graph. This fact represents a group highly robust, with multiple channels of communication among participants.



Star network
Status = {1,1,1,1,1,3.5}
Cohesion = 0.2

Circular network
Status = {2,2,2,2,2,2}
Cohesion = 0.3

Hierarchical network
Status = {1,1,1,2,1.5,2.75}
Cohesion = 0.2

Complete network
Status = {5,5,5,5,5,5}
Cohesion = 1

Figure 2. Hypothetical social networks

INTEGRATION OF COHESION AND STATUS IN A FTT

The results of the proposed structural models are integrated in a FTT called "Mailgroup" (figure 3). In this environment, the participants can maintain a discussion by exchanging messages. MailGroup has been designed according to the objective of supporting learning conversations taking place in forums (Reyes & Tchounikine, 2003). A study of usual FFT allowed highlighting two situations which discourage the emergence of the learning conversations. First, “interactional incoherence”: threads of messages only denote the relation between the messages, without taking into account the “topics” that correspond to the parts of the message selected by the student that respond to the message. Second, “sequential incoherence”: there is a dissociation between the temporal order and the thread order of the messages (Butts, 2001). MailGroup proposes mechanisms which intend to surmount these incoherencies: first, the localization of topics in a message, based on the “*what you answer is what you link*” criteria (Reyes & Tchounikine, 2003); and second, visualization that allows merging in a single view the time order and the thread order of the messages.

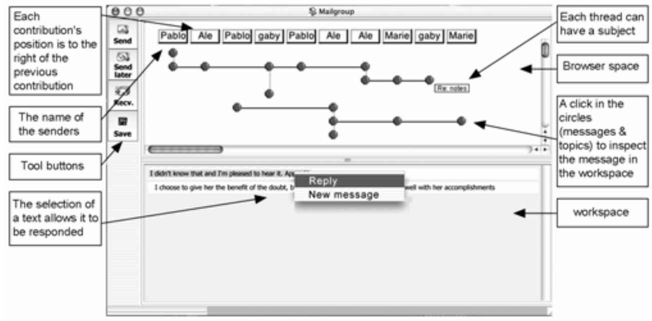


Figure 3. General overview of the MailGroup FFT

The support provided by such a FFT tool can be enhanced by allowing the participants and the tutor to access at any time, through a menu item, to the values of status and cohesion. Values are shown as bar graphs. Mailgroup shows a single bar representing the group cohesion (group-level indicator), and individual bars representing the each participant status value (participant-level indicator).

EMPIRICAL STUDY AND RESULTS

An empirical study was designed in order to collect feedback on the actual characteristics of the group models from the user's perspective. In this study, 15 participants were recruited. The participants were teachers who, during one and a half months, carried out a distance collaborative activity as part of training course on ICT. During the study, they used Mailgroup as medium of communication and discussion (Reyes & Tchounikine, 2003). The goal of the activity was to carry out a collaborative analysis of the integration and utilization of ICTs in education.

In a first stage of experimentation, indicators are showed only to the monitor of this activity in order to test out the validity of SNA models used in these indicators. Yet, the tutor was able to use these indicators to gather information about the groups' activities. Table 1 shows values of cohesion and status obtained in some real conversations that took place in the carried out experience in Mailgroup.

Conversations	Cohesion	Status
1	9%	(12, 1, 13, 9, 1, 11, 14, 1)
2	56%	(17, 12, 6, 3, 8)
3	13%	(5, 11, 1, 4, 4, 17, 8)

Table 1. Values of cohesion and status.

For example, from the analyses of indicators of conversation number 3, the tutor saw as an outstanding fact the low value of the cohesion indicator. Analyzing the status of participants we can deduce that there is an unbalanced participation since two users carry out almost the whole conversation. Their participation and central position (High status value) indicate that they lead the conversation. A potential absence of these participants can imply the ending of this conversation or a radical change of interaction structures. This way, both indicators indicate to a tutor (or to users) that it is necessary to change their current social structure: based on the indicators provided by Mailgroup, the tutor might introduce different strategies in order to orient the group towards a more reliable structure, with a more important and balanced implication of the participants in the common task.

DISCUSSION

The use of models for mining group activities is an active line of research. In this paper we have presented how we have adapted them for their use for pedagogical purposes: The tutor management and orientation of participant exchanges that take place in a learning group through the tracking of its structural properties.

The pedagogical use of these models is inspired by learning theories and models that emphasize the importance of peer-to-peer interactions and the social structure that they generate. These models can facilitate and even automate the work of tutors in tracking the group activities, helping in focus the attention of the tutor in groups with low levels of cohesion or unbalanced structures of participation. These models indicate, in a compact way, the social situation of a group.

In this article we have presented two methods for mining group activities based on models for status and cohesion inside a group. The new cohesion model that we have introduced takes into account the general structure of a group, thus overcoming the problem of sensitivity to groups with weakly connected participants. We consider these models as complementary given that they focus on different levels of granularity in the analysis: the group-level in the case of cohesion and the participant-level in the case of status. We think that mixing both models allows analyzing and mining information about the groups in a complementary way: while one indicator denotes the profile of structural regularities the other helps to find explanation about this behavior.

We showed the results of a test that aimed to corroborate the proposed link models. Indeed we showed these models to a tutor as a first stage before giving these indicators to students. We obtained that these models describe certain structural properties of a group. Moreover, for the tutor this information can be an element that improves the effectiveness of its pedagogical strategies that to be implemented on the group.

Finally, we think that socioconstructivist approach and other views of learning that emphasize the knowledge is socially constructed by interactions among individuals orient the new trends in education to a peer-to-peer learning. These trends require: (a) a new role of tutors where they “create a set of opportunities and reward structures that encourage students to look upon their interactions with their peers as valuable resources for learning (…)” (Hiltz & Benbunan-Fich, 1997). (b) new methods to support learning must be proposed. In particular, we should do not seek to build a system that intervenes on the actors, but a system that gives them the means for intervening by themselves. In this context, support notion goes in hand with the peer-to-peer support approach.

Finally, the models presented in this work are implemented as a part of a peer-to-peer support system: “Structural awareness”. The objective of structural awareness is to make salient the structural properties of a group to its participants in order to promote collaborative interactions and allowing tutors the management of learning interactions and tracking collaborative processes.

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