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Original citation:
Medina, E. , Vega, D. , Meseguer , R. , Medina, H. , Ochoa, S.F. and Magnani, M. (2016) 'Using indirect blockmodeling for monitoring students roles in collaborative learning networks' in Weiming Shen, Xiaoping Liu, Chunsheng Yang, Jean-Paul Barthès, Junzhou Luo, Limin Chen, Jianming Yong (Ed). IEEE 20th International Conference on Computer Supported Cooperative Work in Design (CSCWD) (pp: 164-169). IEEE. DOI: 10.1109/CSCWD.2016.7565982

http://ieeexplore.ieee.org/document/7565982/

Using Indirect Blockmodeling for Monitoring Students Roles in Collaborative Learning Networks

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***Abstract*— Collaborative learning activities have shown to be useful to address educational processes in several contexts. Monitoring these activities is mandatory to determine the quality of the collaboration and learning processes. Recent research works propose using Social Network Analysis techniques to understand students' collaboration learning process during these experiences. Aligned with that, this paper proposes the use of the indirect blockmodeling network analytic technique for monitoring the behaviour of different social roles played by students in collaborative learning scenarios. The usefulness of this technique was evaluated through a study that analysed the students' interaction network in a collaborative learning activity. Particularly, we tried to understand the structure of the interaction network during that process. Preliminary results suggest that indirect blockmodeling is highly useful for inferring and analysing the students' social roles, when the behaviour of roles are clearly different among them. This technique can be used as a monitoring service that can be embedded in collaborative learning applications.**

Keywords*— *Indirect blockmodeling, collaborative learning, learning monitoring, role detection, social network analysis.

I. INTRODUCTION

The monitoring and analysis of collaboration processes get the interest of many researchers in Computer-Supported Collaborative Learning [1, 2]. These activities usually consist on capturing, analysing and visualizing different types of interactions among people, in order to identify and understand individual and collective behavioural patterns of participants in a collaboration process. In the specific case of learning scenarios, the monitoring information helps instructors (and also students) make reasonable inferences about the learning process that are being carried out. These inferences can then be used to foster collaboration during the learning activity; e.g., by providing feedback that allows students to reflect on their own learning practices, and based on that, to adapt their individual and collective attitude accordingly. Instructors can also profit from these results by using them to inform the design of collaborative learning activities.

Recent researches advocate for the use of Social Network Analysis (SNA) techniques for modelling and monitoring collaboration [3, 4], highlighting the importance that the interaction patterns among participants and the social structures have in the collaboration outcomes and people performance [5, 6, 7]. The use of these techniques also applies to learning environments [8, 9, 10, 11].

Previous studies, that use SNA in learning scenarios, stress the importance of identify *behaviour patterns* [12] and *social roles* [10, 13], in order to understand their impact on the collaboration process and the learning outcomes. Taking this into consideration, this paper proposes the use of *indirect blockmodeling* [15, 16] to monitor the behaviour of different students' roles, exploring how these social roles are represented in the network structure. Particularly, this technique is used to identify *structural roles* and *positions* within a network.

Structural roles – based on how specific individuals are connected to others – and *social roles* are not the same concepts. Therefore, a particular social role might not correspond to the same type of structural role. Provided that both structures are built upon long-term interactions, it could be appropriate to use analysis methods to identify the former type of roles – *structural* – and also to infer the actual "social roles" present in a collaboration process. This represents a hypothesis since the use of indirect blockmodeling techniques (or variants of it) has not been previously used to monitor the social roles in a collaborative learning environment.

In order to explore the usefulness of such an alternative, we report its application for monitoring students in a university collaborative learning scenario. This process was conducted with students from the Universitat Politècnica de Catalunya, Spain. This evaluation allowed us explore the suitability of the indirect blockmodeling for roles and positions detection, and also for analysing the collaboration processes and activities of the different social roles played by the students. Although the study results are still preliminary, they show that this technique is useful to characterize the behaviour of the different social roles present in a learning context, and also to represent how these roles are related to the social structure.

Next Section introduces the main SNA and blockmodeling concepts, particularly those used in this paper. Section III describes the experience of using the technique for monitoring students. Section IV reports and discusses the study results. Finally, Section V presents the conclusions and the future work.

II. Background

An evident human behaviour is the ability to form social norms and structures, in order to share responsibilities of key functions and collaborate to achieve objectives or endeavours not possible for a single individual to accomplish. Nowadays, the advancement of communication technologies had led to a paradigm shift, in which individuals belonging to the same social group do not need to be located in close proximity. For instance, within an educational context, students may be formally grouped together by the instructor or tutor, in order to deliver a project or accomplish a given task. However, once the group has been created the students typically collaborate and interact using a range of communication software platforms (e.g., virtual learning environments, social networking services, or email/videoconference systems). Whilst these collaboration interactions can be effective, they can be hardly monitored by instructors or tutors, and therefore incorporated into formal and informal assessments.

Consequently, the use of SNA techniques becomes attractive, as they have the potential to facilitate the identification and monitoring of the students' collaboration interactions. The structural analysis of social networks aims to capture and interpret how actors of a social network (e.g., students) interact with each other, by analysing the network topology. This information helps identify key individuals or groups whose participation influences the dynamics and structure of the social network. Moreover, the structural analysis of these networks can occur at two levels: (i) at macroscopic level, the analysis is focused on the identification of *communities*, and (ii) at microscopic level, to identify *structural roles* and *positions* of actors into the network.

A community is identified by a set (or sets) of actors with more connections inside the set than outside of it. The methods for the analysis of such structures focus on assigning nodes to sets based on either density, cohesion, proximity and/or closeness. However, structural roles and positions are distinguished based on the notion of similarity or equivalence (i.e., based on similar connection-structure-position relationships identified within the set). That is, solely on the similarity of structural patterns. This represents a challenge for the identification of the collaborative actions that individuals perform in a learning environment in favour of their communities.

A popular approach that helps analyse macro social network structures is blockmodeling [17, 18]. In the context of this work, we have used a specific method, called indirect blockmodeling [15, 16], to identify the structural role and position of the students. Thus, we can determine their social interactions and the roles played during a certain collaborative learning process.

Although there are several definitions of roles and positions, for the purpose of this work we will adopt the interpretation provided by Wasserman and Faust [18]. Particularly, *position* is used to identify a collection of actors, individuals or companies, which are *similarly* embedded within other actors of the network, and it does not necessarily imply connectivity – i.e., members or individuals with the same position may or may not be connected. On the other hand, role refers to patterns of interconnectivity and collaborative relations between individual members or positions. In this regard, the definition of role includes the notion of functionality or function of a given actor. The concepts of position and role serve as the basis to use the indirect blockmodeling technique; particularly to perform structural analysis at a micro level in computer-supported collaborative learning networks.

A simple example that can be useful to better understand the differences between the concepts of *community*, *structural role* and *position* is depicted in Fig. 1. This figure shows a hierarchical network graph that has a root node, three nodes in the second level, and five leaf nodes. At the second level, we can observe that the three nodes were classified in three different positions and two different roles (two nodes share the same role). In addition, the figure highlights that one second-level node belongs to a community that also includes other network nodes (the last two leaf nodes).

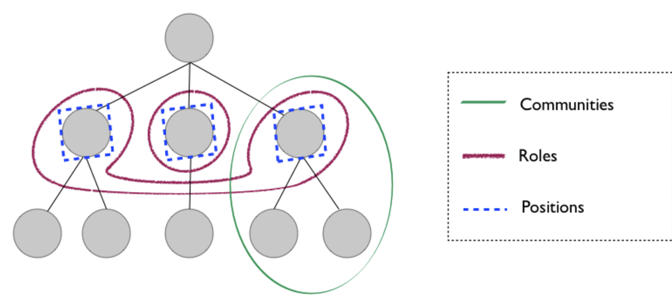

Fig. 1. Examples of community, role and position in a network structure

III. Experimentation Methodology

In order to explore the suitability of the indirect blockmodeling technique, we used it to monitor students' roles in a collaborative learning activity. Next we present the details.

We collected data from 21 undergraduate students enrolled in the "Design of Applications and Services (DSA)" course, held at the Castelldefels School of Telecommunications and Aerospace Engineering of the Universitat Politècnica de Catalunya (UPC), Spain. The traces were collected from the students' interactions during an 8-week software development project, which involved collaboration and teamwork. We explored the students' face-to-face and online collaboration activities, as well as their online interactions with forums, learning materials, assignments, and self-assessment tasks. As sources for data collection we used (i) collaboration questionnaires filled by students and lectures to keep record of every collaborative interaction between students, (ii) software logs from the students' actions in the Moodle Learning Environment (used to support for the course activities), and (iii) a detailed record of the lecturers' observations about the behaviour, engagement and performance of the students.

From these sources we only gathered information related with the students' actions performed within the context and duration of the project. Although we collected data from 21 students, only 18 of them were considered in the analysis, since three students did not interact with their peers. Then, we used the data traces from the collaboration questionnaires to create a network graph of the students' social interactions.

Considering the 18 students, we used indirect blockmodeling to identify the *structural roles* and positions existing within the collaboration network. This technique allows us analyse the influence of social roles or behaviour patterns in interaction networks, based on several similarities, like *structural* and *automorphic equivalence* of the individuals.

Blockmodeling is, to our knowledge, the most used and explored technique to detect roles and positions in social networks and, more generally, in any system that can be modelled mathematically using a graph. In blockmodeling, actors are grouped into blocks – positions or roles – based on a similarity or dissimilarity measure. The *indirect blockmodeling* techniques differs from other variants as they are based on unsupervised clustering methods.

The literature reports several clustering algorithms that can be used to make the assignment between actors and structural positions or roles. For the purposes of this work, we first generate a matrix by computing the Euclidean distance between actors' similarities, and then we perform a hierarchical clustering using the Ward [14] cluster similarity function.

Structural and *automorphic equivalences* are two different mathematical properties of sets of vertices in a graph. According the definition, two nodes are *structurally equivalent* if, and only if they have identical relational ties to and from all other actors in a network (see positions in Fig. 1). Instead, two nodes are considered automorphic equivalent if we can permute the graph in such a way that exchanging the two actors has no effect on the distances among all actors in the graph (see roles in Fig. 1).

Finally, in order to examine the particular behaviour of different students' roles, we performed a statistical analysis to the data traces from the students interactions in the Moodle platform. This analysis was useful to correlate such interactions with particular behaviour patterns that are expected for the mentioned social roles.

As a ground truth, we used the classification of roles provided by [13], where the authors proposed seven different roles. Due to the fact that our data sample is relatively small and we have a reduced number of students, we decided to simplify such classification into five roles: *leader*, *coordinator* (coordinator and animator in the original classification), *active*, *peripheral* and *missing* (corresponding to missing and quiet). We consider these roles to be complex social roles, since they have very specific characteristics that define them. However, some complex roles could look similar when we analyse them, and therefore, they can be difficult to differentiate. For that reason, we also defined two coarse categories, transversal to the previous ones, named *basic social roles*. These basic roles make possible to distinguish between average students (workers) and those students who play a more active part in the coordination and organization of the collaborative activities (managers). Lecturers in charge of the course used their observations to classify the students according to the taxonomy established by complex and basic roles and also to provide the ground truth for the experimentation.

IV. Experimental Results

We discuss the results of this study from three perspectives: group formations, simple social roles and complex social roles. Thus, we explore the suitability of the proposal to monitor these three aspects of the collaborative learning process.

A. Analysis of group formations

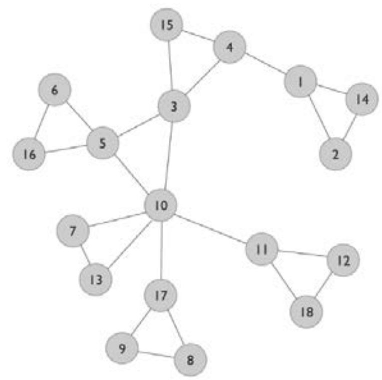

Fig. 2. Students' social network

Based on the data collected through the questionnaires, we built a graph of the students' interactions (Fig. 2). Notice that each student is represented by a numbered node and the connection lines represent the interactions among them. We used the lecturers' observations about the actual members of the different group formations, and correlated this information with the results obtained when applying the indirect blockmodeling analysis to the students social network. In this case, we used an analysis based on structural equivalence. Provided that we knew that the students were arranged in six different groups, we specified that we wanted to detect six blocks. Figure 3 depicts the result of applying the 6-blocks indirect blockmodeling analysis to the network graph of the students' interactions. It provides an alternative representation of the resulting graph using an adjacency matrix.

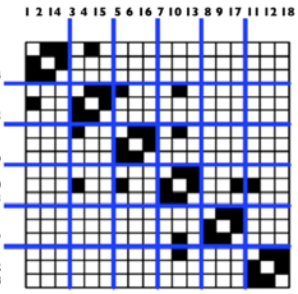

Fig. 3. Example of indirect blockmodeling for six blocks

This matrix has been calculated arranging the different students (i.e., rows and columns) in a way that gathers the highest possible number of interactions (indicated as black cells) in six different blocks. Notice that the arranging method is based on the equivalence between nodes. In this case, we use *structural equivalence* as explained previously. The percentage of possible errors reported by the arranging method was 3.74% (black cells in zero-blocks or blocks with no ties in Fig. 3).

Fig. 4 shows more clearly the groups identified by the indirect blockmodeling technique. The group arrangements detected by this technique correspond to the actual group formations as recorded in the lecturers' observations. These results indicate that using this method properly, we can successfully detect different group formations in a collaborative learning setting. However, further studies are necessary to confirm this claim, since the data sample that we used was small and only included homogeneous groups of three students. It would be also useful to study the effect that the group size has on the resulting collaboration process.

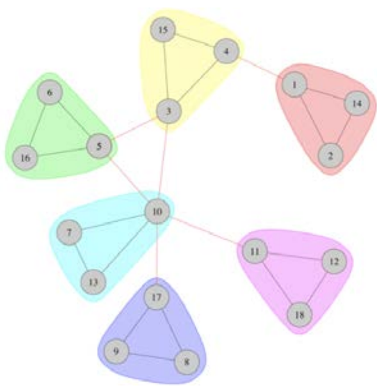

Fig. 4. Students groups detected using 6-blocks indirect blockmodeling based on structural equivalence

B. Analysis of basic social roles

The next objective was to understand how the indirect blockmodeling technique can help identify basic and distinct social roles played by students during a collaborative process. In a first stage, the lecturers in charge of the course used their observations to classify their students into the two basic social roles; i.e., managers and workers. Then, we used *automorphic equivalence* to do the same task (Fig. 5). Fig. 5(a) shows the results when we establish 7 predefined blocks. The most noticeable thing is that most students that play a manager role were detected correctly. However, the student number 1, despite being a manager, was classified in the same block than other two students that acted as workers.

Similarly, Fig. 5(b) depicts the results when applying an indirect blockmodeling considering 8 blocks. In this case, we obtained similar results, but now all the students behaving as workers were classified correctly, and the student number 1 was considered as the only member of a block.

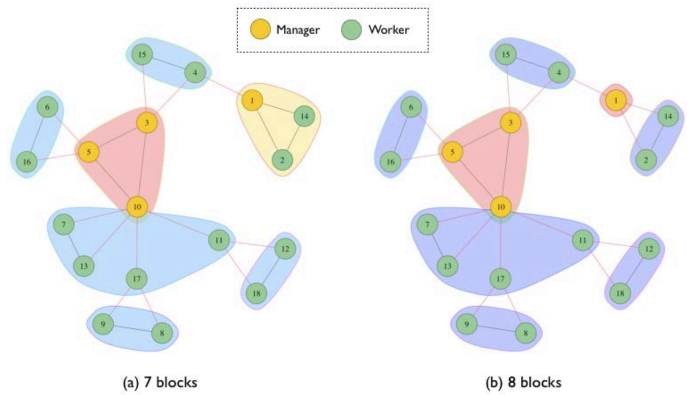

Fig. 5. Detection of basic students' roles using indirect blockmodeling based on automorphic equivalence

Both figures suggest that the results of applying the indirect blockmodeling technique are correlated with the actual students' roles as classified by the lecturers. Nevertheless, due to the fact that we wanted to detect only two basic roles, the ideal result would be obtaining only two blocks (one per role). In our case, because we were able to detect these basic roles but using a higher number of blocks, it would be necessary some kind of human intervention to obtain the ideal classification. Anyway, despite not being ideal, the automatic classification is quite accurate, therefore it could be used (without human intervention) to monitor the students.

C. Analysis of complex social roles

Provided the main study goal was to monitor the behaviour of several students' roles in collaborative learning processes, in this section we analyse the complex social roles we have identified. First, we explored the usefulness of the indirect blockmodeling to analyse the collaboration interactions of these social roles. Second, we performed a statistical analysis to the students interactions traces, recorded in the Moodle platform with the purpose of understanding the specific behaviour of each role when interacting with this learning platform. Finally, we will provide the relationship between these roles and students performance. Once again, we lie on lecturers' observations to classify the students.

SNA Analysis. This analysis intended to identify different complex roles using information about the students' collaboration interactions. Similar to the case of the basic role analysis, the students' collaboration questionnaires were used to generate a graph representing the interaction network. Moreover, 7-blocks and 8-blocks indirect blockmodeling analysis, based in *automorphic equivalence*, was performed to classify the network nodes into the five complex social roles. For that reason, the ideal result would be detecting them – if they are present in the experiment – by fixing the number of blocks to 5. In this case, it was not possible, therefore we used a higher number of blocks to improve the final results (Fig. 6).

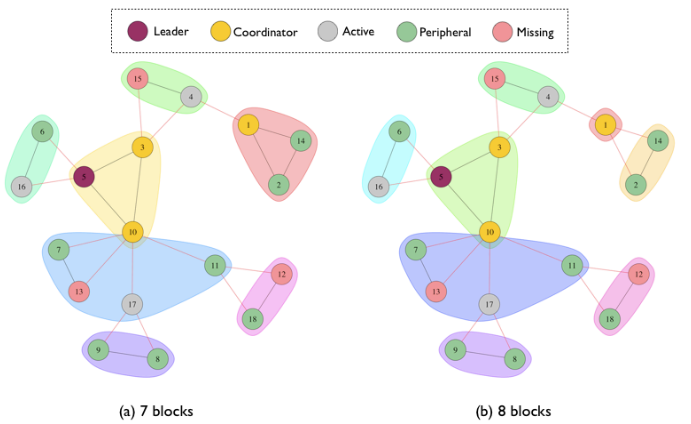

Fig. 6. Detection of students' roles using indirect blockmodeling based in automorphic equivalence

Fig. 6(a) shows the results of the 7-blocks indirect blockmodeling analysis. As we can observe, most blocks combine several roles. This means that this blockmodeling technique is not accurate for detecting our complex social roles. Also, notice that there is a block that contains two coordinators (students 3 and 10) and the only student of the dataset acting as leader (student 5). This is interesting if we compare the result with the analysis of simple roles performed in the previous section, where these same students were detected correctly as managers. Therefore, the technique was able to detect the students' basic roles, but it has some limitations to determine the complex roles played by them. Furthermore, it seems that the active, peripheral and missing roles are classified indistinctly.

Fig. 6(b) depicts the results of the 8-blocks indirect blockmodeling. The only difference with the previous analysis is that, in the same way as in Fig. 5, the student number 1 (behaving as coordinator) is now separated from the students 2 and 14 (acting as peripheral).

The results from the analysis of the complex social roles were not as expected because the technique was not accurate enough to detect complex roles based on the students' network of collaborative interactions. We have three different hypotheses that could explain these facts: (1) the collaborative interactions considered in this study were very similar for most complex roles, (2) our interaction dataset was too small to detect patterns and distinguish between roles, and (3) the indirect blockmodeling technique is not useful to differentiate the details that exist between complex roles. Discarded the actual reason for the mismatching would require extra analysis.

Statistical Analysis. This analysis was used to correlate the students' behaviour, with their academic achievements. Based on the lecturers' roles classification, we performed a statistical analysis considering the students' interactions with the learning materials and forums, as well as their submissions of course assignments and self-assessments questionnaires.

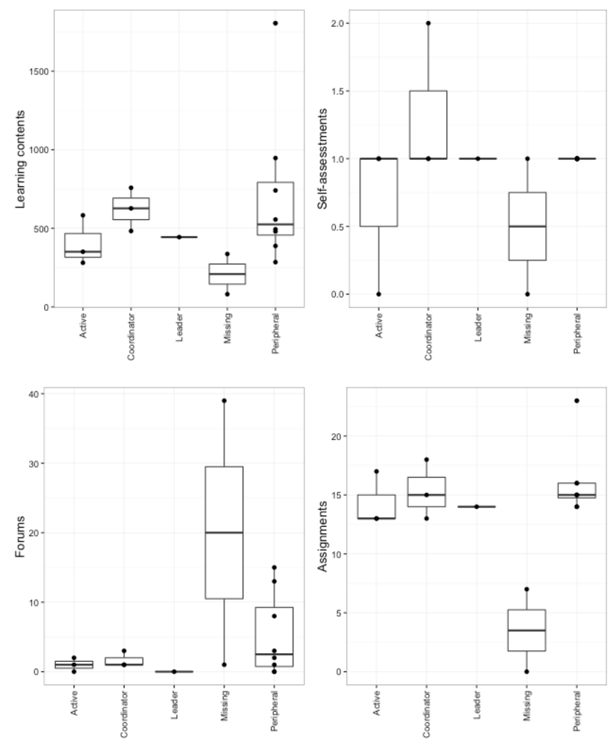

Fig. 7. Behaviour of the different students' roles in Moodle

Fig. 7 compares some results from this analysis of the five complex roles considered. It is interesting to note that students behaving as missing are very passive regarding access to the course contents, assignments and self-assessments submissions. By contrast, they are significantly active in the forums, which can be an indicator that they try to compensate their lack of activity following discussions about the course and the project. The leader, coordinator and active roles have similar behaviour. The main difference among them is that the coordinators are the most active in self-assessment submissions. This suggests that they are organized and reflective, monitoring and evaluating their own activities. On the other hand, peripheral students have a high dispersion of values for interactions with contents and assignments submissions.

The results of the statistical analysis indicate that there are some correlations between the behaviour of the different student roles. However, some of these differences are not statistically significant. Thus, although intuitively we can observe some patterns of behaviour and some differences between roles, we cannot unequivocally confirm this claim.

Figure 8 shows the statistical analysis of the final grades of the course, for each one of the students' roles. The student behaving as leader obtained the highest mark, whereas missing students had the lowest. This was expected, since they either dropped the course or worked too little. On the other hand, active and coordinator roles have similar marks. Once more, peripheral students showed a high dispersion of values for the final marks. Mainly, active, coordinator and leader roles are the ones passing the course.

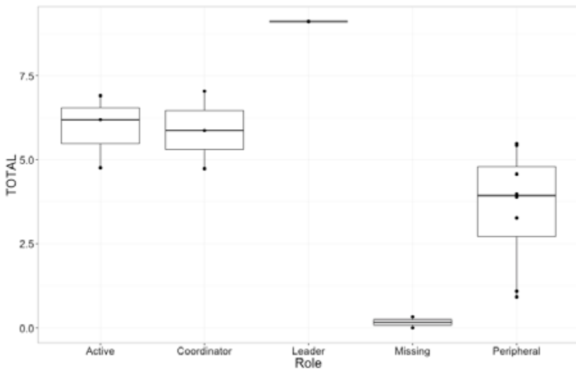

Fig. 8. Final grades for the different student's roles

V. CONCLUSIONS AND FUTURE WORK

This work proposes the use of indirect blockmodeling technique, as well as statistical analysis to monitor the students' behaviour and performance in collaborative learning settings. In order to determine the usefulness of this proposal, we performed a study that explored how different social roles affect the structure of the network of students' interactions in a collaboration process. The obtained results show that this indirect blockmodeling technique is an appropriate alternative for role detection and monitoring in educational contexts, when people playing these roles behave clearly different to other roles. However, the effectiveness of this technique is limited when the roles show a similar behaviour.

An interesting benefit of using indirect blockmodeling with these purposes is that the analysis strategy can be systematized and implemented as a software service. Therefore, it can be embedded in collaborative learning applications and reused by the developers. Thus, it is possible reduce the risk and effort of implementing this service, and also provide an interesting supporting tool for instructors and students.

Future work should be focused on two directions: (i) expanding this work with further experiments, using a larger dataset, and (ii) including different kinds of interactions, not only interactions between students.

ACKNOWLEDGMENT

This work has also been partially supported by Spanish goverment under contract TIN2013-47245-C2-1-R.

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