Modelling Symmetry of Activity as an Indicator of Collocated Group Collaboration

Roberto Martinez[1], Judy Kay[1], James R. Wallace[2], and Kalina Yacef[1]

[1] School of Information Technologies, J12, University of Sydney, 1 Cleveland St. NSW 2006, Australia
{roberto,judy,kalina}@it.usyd.edu.au
[2] Department of Systems Design Engineering, University Waterloo, 200 University Ave. West, Waterloo, Ontario, Canada N2L 3G1
jrwallac@uwaterloo.ca

Abstract. There are many contexts where it would be helpful to model the collaboration of a group. In learning settings, this is important for classroom teachers and for students learning collaboration skills. Our approach exploits the digital and audio footprints of the users' actions at collocated settings to automatically build a model of symmetry of activity. This paper describes our theoretical model of collaborative learning and how we implemented it. We use the Gini coefficient as a statistical indicator of symmetry of activity, which is itself an important indicator of collaboration. We built this model from a small-scale qualitative study based on concept mapping at an interactive tabletop. We then evaluated the model using a larger scale study based on a corpus of coded data from a multi-display groupware collocated setting. Our key contributions are the model of symmetry of activity as a foundation for modelling collaboration within groups that should have egalitarian participation, the operationalisation of the model and validation of the approach on both a small-scale qualitative study and a larger scale quantitative corpus of data.

Keywords: tabletop, group modelling, groupware, collaborative learning, collocated collaboration, clustering.

1 Introduction

There are important reasons for building effective models of the collaborative process of small teams of people who are using electronic tools as part of collocated activities. This is particularly important in those educational contexts where the goal of the learning activity is to develop learners' collaboration skills. If we can build accurate models which reflect the levels of key aspects of collaboration, this can be valuable for teachers, learners or learning management systems to improve the learning process. There are many situations where people need to work collaboratively in small groups, both at the workplace and informal settings. In many cases, all members of the group should be active in the collaboration: for example, to draw upon the different expertise and background of each member or to find solutions to problems by negotiation and discussion of competing possibilities.

Joseph A. Konstan et al. (Eds.): UMAP 2011, LNCS 6787, pp. 207–218, 2011.

This makes it important to be able to build models that indicate whether a group is collaborating effectively. Emerging technologies that can support small groups have the potential to provide the data that could be used to create such group models of collaboration. Previous work in user modelling research has articulated the importance of capturing a user model according to the users' interactions around the tabletop in order to adapt and improve the support to the group activities [1].

Drawing on the considerable work on collaborative learning theories [2] and collaborative learning supported by desktop computers [3], an objective and useful indicator of collaboration is the notion of *symmetry*. We build upon that work, and constructivist theories of *group cognition* [4] to create a theoretical model of *symmetry of activity* of the group in small collocated settings, such as at interactive tabletops. We argue that the measure of the symmetry of participation of collocated group members can provide insights into the extent of collaboration of the group, and that this measure can be extracted automatically from log and audio traces. This paper describes our exploration of ways to create helpful models of collaboration based upon indicators of symmetry.

We begin by describing some theoretical foundations and outlining important elements of the collaboration model. We then describe our model in terms of our exploratory study based on concept mapping at the tabletop and show how we have implemented it by defining measures of symmetry of activity. We then evaluate the model using a larger scale trial drawing on a corpus of coded data from a multi-display groupware collocated setting based on a problem-solving activity.

The remainder of the paper is organised as follows. The next section presents a short overview of related work. Next, we describe our exploratory study in terms of the collaborative learning theory Afterwards, the extraction of the model is presented, with Section 4 describing the creation of our model of symmetry, and Section 5 presenting the clustering work to validate such a model. Then, we discuss the results of the analysis with reflections on how the indicators of symmetry ought to be included in the learner model of the group to improve teaching and learning. Finally, we conclude with the discussion and future work.

2 Related Work

There has been relatively limited research exploring how to make use of the digital footprints of the learners' activity to infer indicators that could help build models of collocated collaboration; these could be used in many ways to help groups to learn work more collaboratively and effectively. Previous work in this area has focused mostly on supporting group collaborative tasks within e-learning systems.

The Narcissus system [5] gives support to groups working collaboratively through the Trac[1] web-based collaborative system. It allows teams to interact with their group model of activity, helping learners and their tutors gain insights on how the group has operated. Anaya and Boticario [6] described a domain-independent collaborative learning modelling method based on statistical quantitative data. This was evaluated using two data mining techniques, clustering and decision trees. This approach aims to classify and group individuals according to their collaboration level. Perera et.al.

[1] Trac Open Source Project: `http://trac.edgewall.org/`

[7] also modelled key aspects of teamwork and collaboration, using machine learning techniques but focusing on clustering groups according to various indicators of collaboration and exploring the sequential patterns of interaction. Soller and Lesgold [8] modelled the *process* of collaborative learning supported by an online shared workspace. They presented a modelling approach based on Hidden Markov Models to recognise the communication networks within groups classifying the sequences of interaction that distinguish the effective sharing knowledge episodes. Casillas and Daradomius [9] described another approach for extracting and modelling behavioural patterns in collaborative settings building on Social Network Analysis.

3 Theoretical Foundations: Group Cognition and Symmetry of Action

Group cognition theory builds upon many other theories based on the concept of constructing meaning through language and social interactions [10]. According to these theories, a group of people working collaboratively externalise and negotiate their different viewpoints. Sometimes the flux of interactions results in the creation of external artefacts such as texts, conceptual maps, diagrams, sculptures and other objects. These social artefacts embody the group's understanding. Figure 1 depicts the elements in the process of group cognition starting with the personal understanding cycle (1), which occurs inside individuals' minds, and the social knowledge building cycle (2), which includes all the sub-processes that may be present when building shared understanding. In face to face interactions, these sub-processes can generate a huge quantity of cognitive artefacts in short periods of time. Group members have to articulate their thoughts to convince others or to explain their point of view. They negotiate, share, revise and externalise their standpoints to other participants, leaving more digital evidence of the collaboration process than in individual learning settings. These are the digital tracks of the process of the interaction that we aim to exploit.

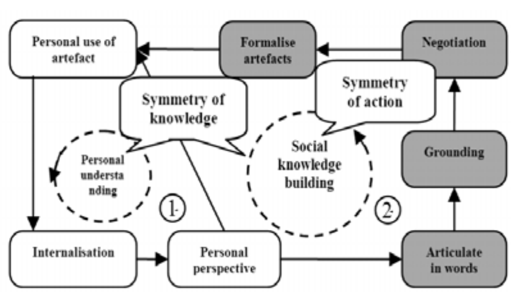

Fig. 1. Simplified model of collaborative knowledge building adapted from [10]

Dillenbourg [2] points to the importance of high levels symmetry of action, knowledge and status for successful collaboration in learning contexts.. Symmetry of action is the degree to which users perform the same level of activity; we can capture this aspect from actions at a tabletop or at a multi-display setting. Symmetry of knowledge refers to the extent to which users have the same level of skills and knowledge. In Figure 1 we depict these two dimensions of symmetry as related directly to the collaborative process. Finally, the symmetry of status is associated with the relative position that each user has in their community.

We investigate whether assessing key aspects of the *symmetry of action* in group's logs and audio traces can determine important aspects of collaboration in the group. Key features of this symmetry can easily be captured, whereas the symmetry of knowledge is highly domain dependent and therefore difficult to assess in a generic way. Similarly, the symmetry of status is a complex social phenomenon that cannot be entirely tackled from a quantitative perspective.

We collected data from two sources: the logs of interactions (touches on the tabletop or clicks in a multi-display setting), obtained directly from the application, and the audio traces, obtained using microphones [11]. From these two sources of data, we identified four measures of action that we aim to use to model the degree of symmetry of action: the number and total duration of verbal interventions, and the number and total duration of physical interaction with the system.

In addition to these measures, we used the *Gini Coefficient* [12], a measurement of statistical dispersion which has been successfully used to estimate equity of participation of students in learning environments [13] and also for measuring levels of participation at multi-touch devices [14]. The Gini Coefficient (*G*) is an indicator of dispersion that ranges between 0 and 1. A coefficient value of 1 indicates total asymmetry or dispersion and 0 indicates total symmetry or perfect equality.

This indicator can be defined as the mean of the difference between every pair of participants (n= 3 or 4 in this study), divided by the mean size μ (1). In essence, our approach requires a way to translate the logs of interactions into Gini coefficients for representing symmetry of activity.

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2\, n^2 \mu} \qquad (1)$$

Our methodology consists of, first, conducting a qualitative and statistical exploration in a small study to refine a model of group collaboration based on these measures (in the form of rules), and then, evaluating this model through a large-scale study.

4 Model of Symmetry

4.1 Context of the Study

We designed a case study on a multi-touch tabletop interface. Multi-touch tabletops offer the promise of supporting rich face to face collaboration. Importantly, they can capture digital footprints of the users' activity.

Groups were recruited for the first part of the analysis to build an artefact collaboratively at the tabletop using Cmate, as shown in Figure 2. Cmate is a tabletop application designed for collaborative *concept mapping* [15]. One of the advantages of the concept maps is that through these tools learners can construct understanding in their own terms, discuss relationships between concepts and reflect on alternative perspectives. The implementation of the Cmate interface is described in detail in [16].

Task. In the first part of the experiment, participants were asked to create an individual concept map, capturing their own understanding of a topic using their own concept set. After studying the same text titled: *Recycling, cost-benefit analysis,* participants were requested to draw maps answering the focus question: *does recycling help the environment?* These initial individual artefacts were built on desktop computers, using CmapTools[2], and preloaded into the tabletop. In the second (and collaborative) part of the experiment, each group was asked to build a common group concept map at the tabletop. After the group had discussed their individual maps, participants could use Cmate to perform basic actions such as adding concepts, creating directed links between two concepts, moving and deleting concepts/links, and editing node words by double tapping a node and modifying the word using a virtual keyboard, all these with the purpose of creating a combined group map.

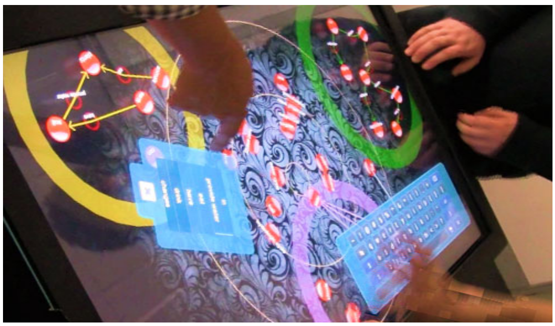

Fig. 2. Our tabletop application being used to build group concept maps

Population and data collection. Every touch on the tabletop was logged, along with the user who made it, and all sessions were video recorded. Sound was recorded with individual microphones worn by each participant. The study involved five groups, each of 3 or 4 participants, for a total of 18 participants. They were students predominantly enrolled in engineering courses and were aged between 20 and 27. Group members were familiar with one another. Each group had thirty minutes to build the concept map and five additional minutes to discuss the ideas and formalise which propositions should remain in the final map. Groups performed between 1450 and 2360 actions per session, for 8500 recorded touches. We also obtained a total of 6296 seconds of active verbal participation.

In Table 1 we present two example excerpts from group session logs. The fragment at the left corresponds to a collaborative group. In this case students combined talking with actions at the tabletop, dedicating some time to discussion before making changes. A different group, non collaborative this time, is shown in the excerpt at the right; this group dedicated most of the time to perform physical actions rather than discussing their ideas. Both fragments where extracted from the starting part of their respective sessions to illustrate the nature of the available data.

[2] Institute for Humans and Machine Cognition. CmapTools: `http://cmap.ihmc.us/`

Table 1. Simplified fragments of the combined log (application log + audio log). Left: collaborative group. Right: Non-collaborative group.

		Collaborative group			Non-collaborative group
Author	Time	Log	Author	Time	Log
2	5:59:13	audio participation 4 sec	4	2:49:06	app “add concept” 32 "production"
1	5:59:15	audio participation 4 sec	4	2:49:07	app “move concept” 32 " production "
4	5:59:16	audio participation 1 sec	2	2:49:06	app “scroll menu m44
1	5:59:18	app "scroll menu" m9	3	2:49:10	app “move concept” 32 "production"
3	5:59:18	app "move menu" m10	3	2:49:15	app “add concept” 33 "consumption"
4	5:59:19	app "add link " 1 "waste"	4	2:49:16	app “delete concept” 32 "production "
1	5:59:20	app "scroll menu" m10	3	2:49:16	app “move concept”33 "consumption "
3	5:59:24	app "scroll menu" m11	2	2:49:17	app “scroll menu m44
4	5:59:29	audio participation 2 sec	2	2:49:18	app “add link" 35 "is"
3	5:59:31	app "move menu" m11	3	2:49:20	audio participation 1 sec
4	5:59:35	audio participation 2 sec	4	2:49:21	audio participation 2 sec
3	5:59:36	app "add concept gesture" m12	3	2:49:26	app “edit concept” 33 "consumption "

4.2 Model of Symmetry as an Indicator of Collaboration

In this section, we describe the statistical and qualitative approach to obtain the measurements of symmetry. Before any quantitative technique was performed, the data and video recordings were examined to see whether any simple statistics could discriminate symmetric groups in terms of their collaborative behaviour. We could observe that a couple of groups were highly collaborative. They were distinguished from others in terms of their consistent verbal communication and awareness of others’ physical actions, discussing most of the actions each group member intended to perform. The other three groups displayed behaviour that ranged from moments of collaboration to periods of partial or non-existent communication. Most of the time, these participants worked individually, either not communicating with others or involving just a couple of participants in the discussion, leaving others working independently with the tabletop interface in a small region.

During the non-collaborative moments, participants split the work and worked in their personal space without awareness of others actions. These moments were characterised by high amounts of physical activity with each participant performing similar amount of actions, but low levels of verbal communication in very irregular amounts. This means that we expect the Gini coefficient in the physical dimension to be quite low (reflecting symmetry) whereas in the audio dimension it should be high (reflecting asymmetry). By contrast, the collaborative periods, especially for the groups that were generally collaborative, were characterised by high levels of verbal communication with a somewhat egalitarian distribution of participation in this dimension (hence a low Gini coefficient). However, as they were focused on the discussion and observing others’ actions, the level of physical actions was lower compared with the non-collaborative groups. We could additionally observe that in some groups participants were keen to partially collaborate, leaving one or two members as spectators, or, at the extreme, one participant tended to do all the work by himself (hence a high Gini coefficient).

Another way to explore the symmetry of activity was to examine the *radars of activity* [17], giving a more summarised view of the activity. We generated a pair of radars, one for the physical events on the tabletop, measured in terms of the quantity of touches; and time of verbal participation, measured in seconds. For this study the time window for each visualisation was 90 seconds. Figure 3 shows three pairs of radars of a collaborative group (left) and a non collaborative group (right). Each coloured circular marker corresponds to one learner at their circular personal space: orange, yellow, green and purple for participants 1, 2, 3 and 4 respectively. The position of these markers indicates the level of participation: the closer the marker is to the centre, the less active they were in that period of time. The shape of the radars gives an indication of the symmetry of activity. Through these visual aids, we confirmed what we had observed from the videos. The collaborative group had more verbal participation but a low level of physical actions at the tabletop (see pairs of radars 1, 2 and 3 at the left of the figure). By contrast, the members of the non collaborative group performed high amounts of physical actions without externalizing their thoughts too much.

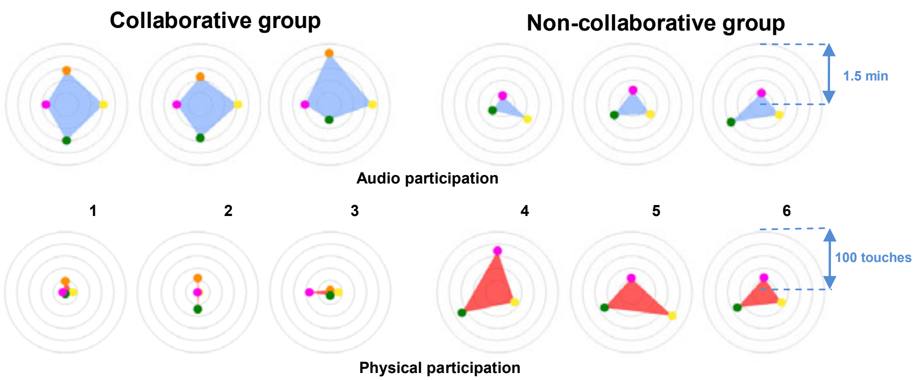

Fig. 3. Radars of activity for three different episodes, for both a collaborative and a non very collaborative group. They illustrate the symmetry and amount of audio (radars at the top of the figure) and touch participation (radars at the bottom).

These visualisations helped to assess whether groups were collaborating or not relying not just on the symmetry of groups but also in the extent of their participation (verbal and physical). In fact, our approach aims to quantify this information so that it can be incorporated and exploited in a group model. The quantitative information needed to draw these radars corresponds to the metrics we are evaluating as indicators of symmetry. Table 2 shows these measures for the episodes shown in Figure 3. They are: talking time, Gini coefficient of verbal participation, number of touches and the Gini coefficient of the quantity of touches.

Our initial analysis indicated that our metrics of symmetry can model facets of group collaboration. Based on the observations offered by this dataset, we hypothesise a set of rules, in terms of numeric metrics, as follows:

$$(low)P_{talk} + (high)G_{talk} + (high)P_{physical} + (low)G_{physical} \rightarrow Non\ Collaborative\ situations \tag{2}$$

$$(high, medium)P_{talk} + (high)G_{talk} + (high)P_{physical} \rightarrow Partial\ collaboration \tag{3}$$

$$(high)P_{talk} + (low)G_{talk} + (low)P_{physical} + (high, med)G_{physical} \rightarrow Collaborative\ situations \tag{4}$$

Table 2. Tabletop data log grouped in pieces of 90 seconds. These values correspond to the visualisations showed in Figure 2.

Attribute	Collaborative group			Non-collaborative group		
Radar #	1	2	3	4	5	6
P_{talk} (seconds)	53	51	56	21	23	28
G_{talk} (Gini coeff.)	0.131	.132	0.315	0.400	0.129	0.347
$P_{physical}$ (touches)	17	24	25	72	69	47
$G_{physical}$ (Gini coeff.)	0.488	0.678	0.587	0.214	0.357	0.242

where P_{talk} corresponds to verbal participation, $P_{physical}$ to physical participation (touches, clicks), G_{talk} to the Gini coefficient as indicator of symmetry of talk and $G_{physical}$ as an indicator of symmetry of physical actions.

Indeed, after inspecting the correlation between these metrics of symmetry we found interesting relationships. There was a negative correlation between physical and verbal participation – corr. -0.441, (see chart at the left of Figure 4) and a stronger negative correlation between physical participation and the Gini coefficient of physical action - corr, -0.611 (Figure 4, right). In other words, when groups talk they do not perform many actions and, additionally, when they perform many actions, this physical activity is more egalitarian. However, in order to confirm that these observations are valid across collocated domains, and that the metrics are correlated with the extent of collaboration of the group, we used a second large-scale dataset based on a corpus of coded data.

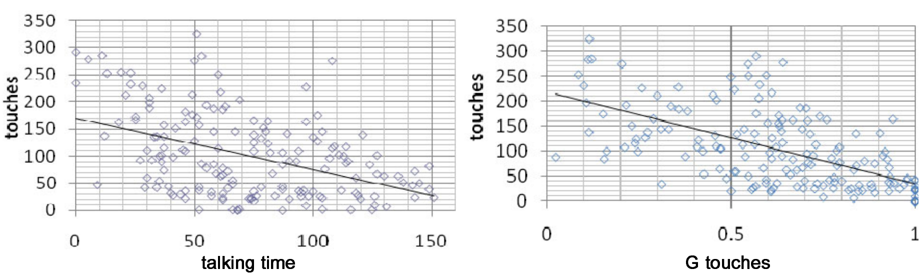

Fig. 4. Left: Scatter plot of physical and verbal participation. Right: Scatter plot of number and the Gini coefficient of physical participation.

5 Evaluation

5.1 Experiment and Data Collection

We evaluated the rules described in the subsection 4.2 using a dataset from groups performing a Job Shop Scheduling (JSS) task, an optimisation problem previously used for evaluating group interactions [18]. In this case, participants have to optimise the scheduling of six jobs, each one composed of six operations. These operations require the use of six resources that cannot be used by two or more operations at the same time. Participants modify the schedule by arranging the position of the resource pieces with the purpose of setting up the completion of all six jobs in the minimum time. A detailed description of the implementation of the interface can be found in [19]. The physical setting for these trials included a large shared display projected on a nearby wall and personal laptops with external mice for each participant, through which they could perform individual actions. Data from 19 trials were considered. The participants were students aged between 18 and 27 years. Groups of three were formed for each trial. Each group performed between 100 and 600 actions per solution, for a total of 9800 recorded interactions with the JSS software. The actions corresponded mostly to dragging resource pieces into position. In addition to the application data, we also transcribed verbal communication for each trial from video recordings. These transcripts included a total of 4836 utterances.

The video recordings of each trial were observed and coded manually. A coding label was assigned to each 90 seconds block of activity for each group. These time frame size was chosen based on the observations of the videos of the sessions in a parallel study [20]. Each block of activity was coded as corresponding to one of three possible values, according to the following guidelines. A block was labelled *collaborative* (C) if all participants participated to some extent and were aware of their peers' actions during that period of time. *Medium collaboration* (M) was used if one or two members of the group were unaware of their peer's actions and the group communication was partial. Finally, a block was labelled *non-collaborative* (NC) if the group split the task, working separately without awareness of each other. Three raters, including a domain expert, coded the blocks according to the descriptions detailed above. Inter reliability was tested on 15% of the sample (Cohen's, k = 0.69). This dataset is very similar, in terms of definition of data, to our tabletop dataset (see Table 2). Therefore, we grouped the log lines and calculated the same attributes we used for the first dataset. In this case, the difference is that we have an additional label for each 90 seconds of activity block. This additional information and the larger size of the dataset served to apply our unsupervised machine learning techniques and supervise the results to validate the hypotheses posed in the previous section.

5.2 Clustering Group Interactions According to Their Collaboration and Symmetry

We used a clustering machine learning technique to reveal the relationship between the rules of our model described in the previous section and the extent of collaboration of the groups. The features used were verbal participation ($\boldsymbol{P_{talk}}$), physical participation ($\boldsymbol{P_{physical}}$, number of clicks) and Gini coefficients as indicators of symmetry of talk (G_{talk}) and symmetry of physical actions ($\boldsymbol{G_{physical}}$). Clustering has been used in a collaborative learning setting such as in [21], where authors aimed at grouping students according to their individual collaboration within their groups. In contrast, we use clustering to assess whether our rules can be applied to other domains with the aim of obtaining meaningful information about the symmetry and collaboration of collocated groups. It is important to highlight that in our approach we cluster segments of activity rather than the entire groups.

We used the clustering algorithm k-means with Euclidean distance measure. This algorithm is simple and effective if the number of clusters is previously known. However, k-means is sensitive to the initial seed. To mitigate this limitation we ran k-means 10 times using the 4 attributes specified in the rules of our model. Additionally, we also ran a secondary algorithm, the Expectation Maximisation (EM), using the same settings (k=3 clusters), obtaining similar results as with k-means (see Table 3). After the clusters from both algorithms were obtained, we compared the presence of collaborative, non- collaborative or moderately collaborative blocks in each cluster. The results of this comparison defined cluster 0 as the group with more collaborative blocks, cluster 1 as medium collaboration blocks and cluster 2 with the non collaborative blocks. The percentage of correct grouping was around 60% for both algorithms. This indicates that our clusters are not excellent classifiers but classification is not the purpose of our approach this time.

Table 3. Clustering results. Cluster-0 (C), Cluster-1 (M), Cluster-2 (NC).

Attribute	Clusters running 10 times k means				Clusters running EM			
	Full data	Cluster-0	Cluster-1	Cluster-2	Full data	Cluster-0	Cluster-1	Cluster-2
P_{talk}	28.668	**32.524 (h)**	34.999 (h)	**17.231 (l)**	28.668	**29.719 (h)**	37.099 (h)	**11.233 (l)**
G_{talk}	0.5304	**0.359 (l)**	0.610 (h)	**0.694 (h)**	0.5304	**0.444 (l)**	0.592 (m)	**0.753 (h)**
$P_{physical}$	36.714	**33.787(l)**	30.680 (l)	**46.25 (h)**	36.714	**37.691 (1)**	27.741 (l)	**47.463 (h)**
$G_{physical}$	0.3502	0.305(m)	0.528 (h)	**0.246 (l)**	0.3502	0.267 (l)	0.586 (h)	**0.284 (l)**

6 Discussion

The comparison of Table 3 with the rules posed in section 4 revealed that every cluster formed by the second dataset followed similar numerical behaviour than the tabletop dataset. The rules (2), (3) and (4) presented in the previous section are defined in non numerical terms (high, low, medium levels of participation and Gini coefficients). For the Gini coefficient attributes (G_{talk} and $G_{physical}$) the quantitative equivalent to *low* and *high* can be translated into the quantitative equivalences *below 0.5* (more symmetric) and *above 0.5* (less symmetric). But for the numerical attributes (P_{talk} and $P_{physical}$) the parameter to define the terms *low* and *high* are the correspondent average of the attributes across the complete dataset (P_{talk} =28.668, and $P_{physical}$ = 36.714, see columns *Full data* in Table 3).

$$(low)P_{talk} + (high)G_{talk} + (high)P_{physical} + (low)G_{physical} \rightarrow Non\ Collaborative\ situations.$$

We found that all parts of the rule are confirmed by the clustering information obtained from the two algorithms (see columns *Cluster-2,* Table 3). The non collaborative situations are characterised by low level of talk, asymmetry in the conversation and high levels of physical action compared with the average across groups. Therefore, we can accept the rule hypothesised in (2).

$$(high,medium)P_{talk} + (high)G_{talk} + (high)P_{physical} \rightarrow Partial\ collaboration\ .$$

In educational terms is not easy to define when a group is collaborating, even if experts observe directly the activity of groups. Even though, we observed that when a partial collaboration within the group exists it is because one or two members “leaded” the activity in both physical and verbal participation. However, even when the clustering results for partial collaboration (see columns *Cluster-1,* Table 3) shows high levels of asymmetric verbal participation, it is hard to define what happened with the physical dimension, obtaining low level of physical actions and undefined symmetry ($G_{physical}$ around exactly 0.5). Therefore, we cannot accept the rule hypothesised in (3) as is.

$$(high)P_{talk} + (low)G_{talk} + (low)P_{physical} + (high)G_{physical} \rightarrow \textit{Collaborative situations}.$$

In this case the major part of the rule is confirmed by the clustering information obtained from the two algorithms (see columns *Cluster-0,* Table 3). Collaborative situations are characterised by high levels of symmetric conversation and less physical actions compared with the average across groups. We were expecting more asymmetry in the physical actions caused by the variable flux of the conversation. We learnt from this rule that collaborative moments tend to be symmetrical in both the physical and verbal layers. Thus, even when the hypothesised rule was not perfectly matched, most of its factors were present. Then, we can accept the rule hypothesised in (4).

7 Conclusions and Future Work

We have presented our research to validate the significance of the notion of symmetry of activity for modelling the presence of collaboration within small groups of people. We illustrated how the theoretical model we built upon and our methodological basis can give insight on the groups' collaborative process, first, with a small-scale qualitative study at the tabletop, and then, evaluating in a larger dataset of collocated interactions. Our approach applies qualitative assessment, statistical analysis for the formulation of the model and machine learning techniques for the evaluation.

Our evaluation demonstrates that both amount and symmetry of verbal and physical participation are good indicators of collaborative and non-collaborative moments. The symmetry of participation is just one dimension of the complex collaborative process; however, it provides useful information that would be an essential part of the group model. In order to asses collaboration in a more effective way, the future research agenda of this project includes evaluating the indicators of symmetry of knowledge and enriching the group model by including the different facets of the collaborative process besides the levels of interactions.

References

1. Martín, E., Haya, P.A.: Towards Adapting Group Activities in Multitouch Tabletops, in adj. In: De Bra, P., Kobsa, A., Chin, D. (eds.) UMAP 2010. LNCS, vol. 6075, pp. 28–30. Springer, Heidelberg (2010)
2. Dillenbourg, P.: What do you mean by 'collaborative learning'? In: Collaborative Learning: Cognitive and Computational Approaches, pp. 1–19. Elsevier Science, Amsterdam (1998)
3. Jeong, H., Hmelo-Silver, C.E.: An Overview of CSCL Methodologies. In: Proc. ICLS 2010, Chicago, USA, pp. 920–921 (2010)
4. Stahl, G.: Collaborative learning through practices of group cognition. In: Proc. CSCL 2009, pp. 33–42 (2009)
5. Upton, K., Kay, J.: Narcissus: Group and individual models to support small group work. In: Houben, G.-J., McCalla, G., Pianesi, F., Zancanaro, M. (eds.) UMAP 2009. LNCS, vol. 5535, pp. 54–65. Springer, Heidelberg (2009)

6. Anaya, A., Boticario, J.: Content-free collaborative learning modeling using data mining. User Modeling and User-Adapted Interaction 1(20), 1–36 (2010)
7. Perera, D., Kay, J., Koprinsca, I., Yacef, K., Zaiane, O.: Clustering and Sequential Pattern Mining of Online Collaborative Learning Data. IEEE TKDE 21, 759–772 (2009)
8. Soller, A., Lesgold, A.: Modeling the process of collaborative learning. The Role of Technology in Proc. CSCL 2007, 63–86 (2007)
9. Casillas, L., Daradoumis, T.: Knowledge extraction and representation of collaborative activity through ontology based and Social Network Analysis technologies. J. Business Intelligence and Data Minining 4(2), 141–158 (2009)
10. Stahl, G.: Group Cognition: Computer Support for Building Collaborative Knowledge. MIT Press, Cambridge (2006)
11. Bachour, K., Kaplan, F., Dillenbourg, P.: An Interactive Table for Supporting Participation Balance in Face-to-Face Collaborative Learning. IEEE Transactions on Learning Technologies 3(3), 203–213 (2010)
12. Thomas, V., Wang, Y., Fan, X.: Measuring Education Inequality: Gini Coefficients of Education (2000)
13. Belgiorno, F., Ilaria, M., Giuseppina, P., Vittorio, S.: Free-Riding in Collaborative Diagrams Drawing. In: Sustaining TEL: From Innovation to Learning and Practice, pp. 457–463 (2010)
14. Harris, A., Rick, J., Bonnett, V., Yuill, N., Fleck, R., Marshall, P., Rogers, Y.: Around the table: are multiple-touch surfaces better than single-touch for children's collaborative interactions? In: Proc. CSCL 2009, pp. 335–344 (2009)
15. Novak, J.: Concept maps and Vee diagrams: two metacognitive tools to facilitate meaningful learning. Instructional Science 19(1), 29–52 (1990)
16. Martinez, R., Kay, J., Yacef, K.: Collaborative concept mapping at the tabletop. In: Proc. ACM ITS, p. 207 (2010)
17. Martinez, R., Kay, J., Yacef, K.: Visualisations for longitudinal participation, contribution and progress of a collaborative task at the tabletop, pp. 2–11 (2011)
18. Tan, D., et al.: Using job-shop scheduling tasks for evaluating collocated collaboration. Personal and Ubiquitous Computing 12(3), 255–267 (2008)
19. Wallace, J., Scott, S., Stutz, T., Enns, T., Inkpen, K.: Investigating teamwork and taskwork in single-and multi-display groupware systems. Personal and Ubiquitous Computing 13(8), 569–581 (2009)
20. Martinez, R., Wallace, J., Kay, J., Yacef, K.: Modelling and identifying collaborative situations in a collocated multi-display groupware setting. In: Proc. AIED 2011 (2011)
21. Anaya, A., Boticario, J.: Clustering learners according to their collaboration. In: Proc. CSCWD 2009, pp. 540–545 (2009)