An automatic approach for mining patterns of collaboration around an interactive tabletop

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Abstract. Learning to collaborate is important. But how does one learn to collaborate face-to-face? What are the actions and strategies to follow for a group of students who start a task? We analyse aspects of students' collaboration when working around a multi-touch tabletop enriched with sensors for identifying users, their actions and their verbal interactions. We provide a technological infrastructure to help understand how highly collaborative groups work compared to less collaborative ones. The contributions of this paper are (1) an *automatic approach* to distinguish, discover and distil salient common patterns of interaction within groups, by mining the logs of students' tabletop touches and detected speech; and (2) the *instantiation* of this approach in a particular study. We use three data mining techniques: a classification model, sequence mining, and hierarchical clustering. We validated our approach in a study of 20 triads building solutions to a posed question at an interactive tabletop. We demonstrate that our approach can be used to discover patterns that may be associated with strategies that differentiate high and low collaboration groups.

Keywords: Data Mining, CSCL, Face-to-face Collaboration, Tabletops

1 Introduction

When students collaborate on a task, the triggering of specific cognitive mechanisms, such as argumentation, debating and building of shared understanding, increases the likelihood that learning may occur [2]. Developing skills for effective collaboration is crucial not only in educational settings but also to meet other real-world challenges [17]. In particular, face-to-face collaboration skills provides benefits that are not easy to find in other forms of group work [5]. Without adequate support, however, group members do not always naturally collaborate to complete their joint task or they may find out that it requires too much time and additional effort [2]. This means that in collaborative learning environments, it is important for the teacher to be aware of students' collaboration in order to provide this support [14].

New technologies can provide meaningful collaborative learning experiences for students but also open new ways to help teachers enhance their awareness of students' collaborative processes and potential group issues. We use two emerging technologies in order to *automatically* capture and analyse students' collaborative interactions: multi-touch tabletops and data mining. We argue that enriched interactive tabletops

adfa, p. 1, 2011.

have the potential to capture students' verbal and touch activity that can be analysed using data mining techniques to discover effective group collaboration strategies.

This paper describes the design of an automatic approach to distinguish, discover and distil patterns of interaction that can be associated with groups' strategies. We apply three data mining techniques: a classification model to detect periods of collaboration; sequential pattern mining, to find sequences that differentiate groups; and hierarchical clustering. We demonstrate our approach with a study involving 20 triads of students building a shared artefact at an enriched tabletop that can automatically and unobtrusively capture students' activity. The main contribution of the paper is our approach to automatically discover patterns of verbal interactions between peers and touch actions on the shared device, which can be associated with strategies that distinguish high from low collaboration groups.

The paper is organised as follows. First, we describe a summary of research at the intersection of educational data mining and interactive tabletops. Then, we outline the context of the study and the software and hardware used. Section 4 describes the data mining approach. Section 5 presents the results found in our study and Section 6 concludes with a discussion of the results and future research directions.

2 Related Work

There has been little prior research on using Artificial Intelligence (AI) techniques for collaborative learning through a shared device. In previous work, we introduced a semi-supervised technique to mine frequent students' actions using a pen-based tabletop [11]. However, that work did not consider verbal activity, an essential aspect of face-to-face collaboration. By contrast, Roman et al. [16] explored patterns of collaborative conversation at a non-interactive table. Even without AI techniques, they showed that simple measures of speech presence can help distinguish outstanding groups in terms of collaboration. In a similar setting, we proposed a technique to detect periods of collaboration at a multi-display setting using classification algorithms and taking into account the aggregation of both manually captured verbal utterances and actions performed on personal computers [10]. However, no previous work in the area has explored the fine-grained interweaving of students' speech and touch activity when working at an interactive tabletop.

A number of research projects have used AI techniques in networked collaborative settings. For example, Anaya et al. [1] presented an approach to cluster and classify students according to their collaborative activity. Duque et al. [3] proposed a fuzzy model that generates rules to classify the different forms of collaboration that leads to solutions of a certain quality. Soller et al. [18] used Hidden-Markov Models to identify moments of knowledge sharing at a constrained and scaffolded interactive networked system. In these three projects, the learning setting was such that all communication during the learning task was mediated by the system, making it possible to automatically log all the students' actions compared with face-to-face environments, where communication occurs simultaneously also verbally.

3 Context of the Study

A total of 60 students, mostly enrolled in science courses, participated in the study. Their learning goal was to enhance and share their understanding of the types of food that should be included in a balanced diet, as recommended by the Dietary Guidelines 2011 published by the National Health and Medical Research Council of Australia. First, each student read the guidelines and then created a *concept map* to represent their understanding. A concept map is a directed graph in which nodes represent the main *concepts* of a given topic and the edges are labelled with a linking word to form a meaningful statement called *proposition* [13]. These maps were first built individually, using a desktop editor called CmapTools. For this, they were provided with an informative text and received basic training in building concept maps. Then, students were organised into groups of three and were given 30-35 minutes to build a joint concept map at a tabletop. Next, we describe the tools the students used to create a group concept map and, simultaneously, capture information of their interactions.

Fig. 1. Interactive tabletop learning environment for collaborative concept mapping.

3.1 Collaborative Learning Tabletop Environment

We used Cmate [9], a tabletop application that allows learners to represent their collective understanding of a topic in the form of a concept map (Figure 1). Cmate provides students with personalised menus to add the concepts or linking words they used in their individual concept map created with CmapTools. At any time they can create new concepts and links. Students can also have access to a screenshot of their individual map to recall or share it with others. Students can decide to collaborate, work separately, build upon their previous maps or create a totally new group artefact.

To capture students' differentiated verbal and touch activity, we used Collaid [7]. Collaid extends ordinary interactive tabletop hardware to unobtrusively differentiate students' input by associating each touch performed on the interactive surface with a specific student tracked through an overhead depth sensor[1]. Additionally, we capture the presence of verbal participations by each learner and verbal turn-taking through an array of microphones[2] situated on one of the edges of the tabletop.

1 http://www.xbox.com/kinect
2 http://www.dev-audio.com

3.2 Qualitative assessments

The 20 groups were assessed by an external observer, following the method proposed by Meier et al. [12] which quantifies nine qualitative dimensions of collaboration. These are: mutual understanding, dialogue management, information pooling, consensus, task division, time management, technical coordination, reciprocal interaction and task orientation. Each dimension is quantified with a number between -2 (very bad) and 2 (very good). We summed the nine dimensions to obtain a single score. Groups with an overall negative score were considered as having low collaboration (10 groups had scores ranging from -10 to 0). Groups with positive scores were considered as having high collaboration (10 groups had scores ranging from 5 to 19).

3.3 Research question of the study

In this study, we aimed to address the following research question: *can we distinguish high from low collaboration groups by identifying patterns of interaction, based on their interwoven verbal and touch actions*? Addressing this question can help build a system that may automatically provide information to classroom teachers about multiple groups, enabling them to decide which group most needs attention.

4 Approach

We describe our approach to *distinguish* which groups of students show high or low levels of collaboration; *discover* patterns of verbal and touch activity that differentiate these groups; and *distil* these patterns of interaction by associating them with groups' strategies. Verbal and physical actions are captured through our environment. The analysis is based on three data mining techniques. First, a classification model detects periods of collaboration within each group to generate two datasets of high and low collaboration. We aim to obtain group assessments similarly to the one described in section 3.2 with no human intervention. Second, a sequential mining technique extracts patterns more frequently found in either high or low groups. Finally, hierarchical clustering is used to group similar patterns and facilitate their interpretation. Next, we describe the details of each technique in the context of our research question.

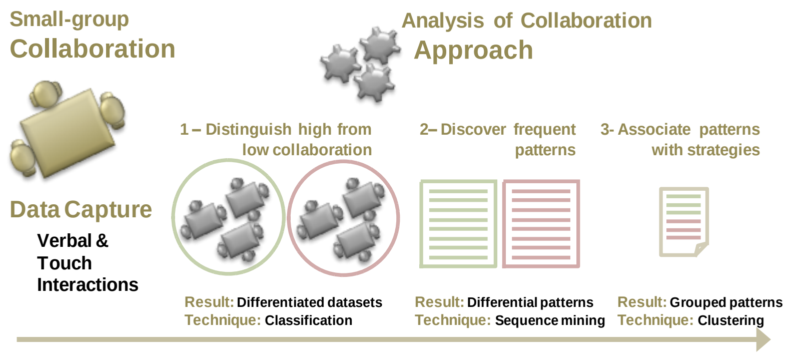

Fig. 2. Analysis of collaboration approach using three data mining techniques.

4.1 Distinguishing from groups' high and low collaboration

To determine the level of collaboration we implemented a method proposed by Martinez-Maldonado et al. [8]. This begins by splitting the continuous group session into blocks. Then, a Best-First decision tree is produced and used to classify each period of group work according to a set of features of verbal and physical activity. It was implemented as follows: 1) the audio and touch actions of each triad are grouped in *blocks* of period of time *t* (*t*=30 seconds as recommended by [8]); 2) a defined set of indicators of interaction are calculated per block, including: *total time* of all learners' speech, total number of *utterances*, distribution of verbal participation among the students measured with the Gini coefficient [10] (*symmetry of speech)*, total number of *touch actions* and *symmetry of these actions*; 3) the algorithm generates a decision tree based on these features to classify each block as matching one of three possible values: *high (H)*, *medium (M)* or *low (L)* collaboration; finally, 4) the group is labelled overall as having either high or low collaboration based on the proportion of blocks that appears more often.

This method was trained on a dataset captured from a multi-display setting where learners had the same opportunities of participation and no roles assigned. The approach was further extended to multi-touch tabletop systems [10]. This work explored a few tabletop sessions and proposed the description of this model in terms of simplified rules. They report that highly collaborative groups are characterised by high levels of symmetric conversation, fewer physical actions and some asymmetry in touch activity. By contrast, low collaboration groups present low levels of talk, asymmetry in the conversation and more physical actions.

4.2 Discovering Frequent Patterns

One technique that takes account of the order of system's events and that has been used to identify patterns differentiating students' behaviours in groups is sequential pattern mining. Perera et. al. [15] analysed teamwork interactions through an online management system by proposing a series of alphabets to represent sequential events. Martinez-Maldonado et al. [11] also extracted sequential patterns of physical actions at a pen-based tabletop and mapped similar patterns to group strategies. Kinnebrew et al. [6] presented the *differential sequence mining* (DSM) technique which looks for patterns that differentiate two datasets. These authors also included contextual data of the actions in the sequence mining algorithm. We implemented a mixed technique by using the DSM algorithm [6] and designing our own alphabet that considers verbal and touch actions performed by multiple students [11, 15].

Alphabet definition. The DSM algorithm works on encoded students' actions that contain contextual information as defined by an alphabet. The *initial raw data* of each group consists of two long sequences of actions: verbal and touch, defined as: {*Resource, ActionType, Author, Time, Duration*}, where ActionType can be: *Add* (create a concept or link), *Del* (delete), *Mov* (move), *Chg* (edit), *Open* or *Close* (an individual map). Resources can be: *Conc* (concept), *Link* (proposition), *Indmap* (individual map) or *Speech* (utterance). Author is the learner who performed the action, Time is the timestamp when the action occurred, and Duration is the time taken to complete it.

Then, we encode each action using the alphabet in Table 1. The coding for a touch action has *one keyword from each level*. The first two levels correspond to *Resource* and *ActionType*. Levels 3 and 4 add contextual information. First, we inspect the important aspect of speech flow between students. Level 3 indicates whether there was speech occurring with touch actions. It includes the next keywords: *Sauthor*, which indicates that the same learner was talking and performing the touch action; *Sother*, when another learner was talking while the author was performing the action; and *Nospeech*, when the action was performed with no speech from any learner. Then, we focus on *touch actions*, taking into account the time, order and author of each touch to explore if only one student was building the solution or if their individual work was more reciprocal (by either taking turns or modifying the solution in parallel).

Table 1. Alphabet

Alphabet: Touch-Verbal participation				
Level 1: Resource	**Level 2: Action type**		**Level 3: Speech during touch**	**Level 4: Previous action**
Link	Add	Rem	Nospeech	Tsame
Conc	Chg	Mov	Sauthor	Tother
Indmap	*Open	*Close	Sother	Tparallel
Speech	Shrt	Full		

* Applies to INDMAP object only

Level 4 distinguishes the learner who performed the previous touch action and possible parallelism. It includes the next keywords: *Tsame*, when the previous action was performed by the same learner; *Tother*, when the previous action was performed by a different learner; and *Tparallel*, when the previous action was performed by a different learner less than one second earlier. The utterances (*Speech*) that did not happen in parallel with any touch actions are coded in the same sequence, with 2 keywords: *Shrt* and *Full* for utterances shorter or longer than u seconds respectively (u=2). Some examples or encoded actions are: {*Conc-Add-Tother-Sother*} for an *add a concept* action performed while another learner was talking; {*Link-Add-Tsame-Sauthor*} if the same learner who performed the previous action added a link while speaking; and {*Speech-Full*} if one of the learners starts speaking while none of learners interact with the tabletop. The sequence obtained for each group contained from 434 to 1467 *physical actions* and from 83 to 627 *utterances*.

The algorithm. In order to extract patterns of activity that differentiate high from low collaboration groups, we applied the DSM algorithm [6] on our encoded datasets. A sequential pattern is a consecutive or non-consecutive ordered sub-set of a sequence of events that is considered frequent when it meets a minimum support criteria [4]. For DSM this is called sequence-support (*s-support*) and corresponds to the number of sequences in which the pattern occurs, regardless of how often it appears within each sequence. For this study, we set the *s-support* to 0.5 (similarly to [6]). The algorithm also calculates repeated patterns within the dataset of sequences. This is called instance support (*i-support*). We also set the error threshold to 1 to allow the matching of patterns with up to one action different (similarly to [6, 11]). The output of this algorithm is a list of frequent patterns in each dataset that distinguish high from low collaboration groups based on their *i-support* ($p<0.1$).

4.3 Clustering Frequent Patterns

As a result of applying the DSM technique it may be possible to find *too many* differential patterns or some that are very *similar*. Therefore, it may not be simple to determine the higher level meaning of such findings without further processing. To alleviate these redundancy and dimension issues, we clustered the resulting patterns based on their *similarity,* as we did in [11]. We designed a modified version of the Agglomerative Nesting (AGNES) hierarchical clustering algorithm. It was implemented as follows: 1) Due to the multi-dimensionality of each sequence item, (each item can have up to 4 keywords) we define a *similarity criterion* to drive the clustering. This is performed by configuring the level of keywords that will be used to measure the similarity between 2 patterns. We explored two similarity criteria: i) focused on speech (*speech*, *nospeech*, *sauthor* and *sother* keywords), or ii) focused on touch (*tsame*, *tother* and *tparallel* keywords). 2) The hierarchical clustering step is performed in an iterative process that starts by considering each single pattern as a cluster. Then, a similarity matrix among clusters is generated by calculating the average average-link inter-clustering distance between sequences of each pair of clusters focusing on the keywords selected in the previous step. The algorithm merges the most similar clusters into new clusters recalculating the similarity matrix and continuing with the process until it produces one single cluster that contains all the sequences in the dataset. 3) To choose an *adequate* number of clusters we stop the iterations when their number matches the max threshold (parameter $m<=10$). The clusters that are still similar are merged (only if the intra-clustering distance of the new cluster is not higher than the maximum internal distance of the largest cluster). 4) For each cluster, the sequence that has an *average length* and contains the *majority of the top keywords* found within each cluster is chosen as the *representative sequence* of the cluster. Clusters with only one sequence are not included in the results. The result is a short list of clusters of sequences within each dataset (high and low collaboration).

5 Study Results

Detecting Level of Collaboration. The classification model to detect blocks that are collaborative was trained on an external dataset [8] and then applied to each of the half a minute blocks of tabletop activity. This dataset included audio and activity logs captured from a multi display collaborative environment. As a result, 17 out of the 20 (85%) group sessions were correctly identified as either highly or not very collaborative according to the aggregation of their classified blocks (around 60-70 in each group) and the qualitative assessment described in Section 3.2. Table 2 presents the distribution of blocks according to groups’ collaboration. We can observe an increasing trend to highly collaborative blocks in the high collaboration groups (30, 17 and 12 blocks classified as high, medium and low collaboration). Groups with low collaboration levels presented more medium than low collaboration blocks, but very few highly collaborative blocks (H=8, M=35, L= 29). Some of the indicators of *quality of collaboration* are not easy to determine even through human judgment, and in consequence more challenging to measure automatically. These results show that it is possible to approximately detect the overall level of collaboration with simple rules using only quantitative indicators.

Table 2. Average number of classified blocks for high and low collaboration groups

Mean proportions of collaborative blocks			
Collaboration	**High**	**Medium**	**Low**
High	30 s=10	17 s=6	12 s=4
Low	8 s=4	35 s=9	29 s=10

Differential sequence mining and clustering. Then, the DSM algorithm was applied on the dataset of high and low collaboration groups that was originally assessed *qualitatively.* The result of this process was a total of 453 and 88 frequent patterns respectively that were differential (p<0.1). The next step was to cluster similar patterns using the AGNES clustering technique described above. Table 3 shows the resulting clusters using two similarity criteria: i) focused on speech, and ii) focused on parallelism and turn taking. First, regarding the role of speech in learners' strategies at the tabletop, highly collaborative groups had two main clusters: cluster-c1 that contains sequenced speech actions (utterances, highlighted in Table 3) and cluster-c2 that shows an interweaving of physical actions with speech performed by other learners (*Sother* keyword). For low collaboration groups, the clusters were: c3 that contains mostly sequences of touch actions without speech (*Nospeech*, highlighted in Table 3) and, to a much lesser extent compared with the highly collaborative groups, clusters

Table 3. Clusters generated

Clusters: focused on speech			
High collaboration	Representative sequences	Strategy	#
C1-{Con-Mov-Sother}>{**Speech**}>{**Speech**}>{**Speech**}>{**Speech**}>{**Speech**}		Chain of conversation	269
C2-{Speech}>{Speech}>{Con-Mov-**Sother**}>{Link-Add-**Sother**}		Actions and others' speech	144
Low collaboration			
C3-{Con-Mov-**Nospeech**}>{Link-Add-**Nospeech**}>{Con-Mov-**Nospeech**}		Actions with no speech	72
C4-{**Speech**}>{**Speech**}>{Con-Mov-**Nospeech**}		Speech and actions	9
C5-{Con-Mov-Sauthor}>{**Speech**}>{**Speech**}>{**Speech**}>{**Speech**}		Chain of conversation	4
C6-{Con-Mov-**Sother**}>{Con-Mov-**Sother**}		Actions and others' speech	3
Clusters: focused on turn-taking and parallelism			
High collaboration	Representative sequences	Strategy	#
C7-{Speech}>{Speech}>{Speech}>{Speech}>{Speech}>{Speech}>{Speech}		Long conversation	246
C8-{Speech}>{Con-Mov-Tsame}>{Speech}>{Speech}>{Speech}		Chain of conversation	145
C9-{Con-Mov-**Tsame**}>{Link-Add-**Tsame**}>{Link-Chg-**Tsame**}		1 learner actions	36
C10-{Speech}>{Con-Mov-Tsame}>{Link-Add-Tsame}>{Speech}>{Speech}		1 learner actions and speech	20
C11-{Link-Add-**Tsame**}>{Con-Mov-**Tother**}>{Link-Mov-**Tother**}		Turn-taking	6
Low collaboration			
C12-{Con-Mov-**Tparallel**}>{Link-Mov-**Tother**}>{Con-Mov-**Tparallel**}		Parallelism	34
C13-{Con-Mov-**Tother**}>{Con-Mov-**Tother**}>{Link-Add-**Tsame**}		Turn-taking	27
C14-{**Speech**}>{Con-Mov-**Tparallel**}>{**Speech**}		Speech and parallelism	5
C15-{Con-Mov-Tother}>{Speech}>{Speech}>{Speech}>{Speech}		Chain of conversation	4

number of frequent patterns included in the cluster

that can be associated with conversational patterns and interweaving of actions with some speech (c5 and c6). In the case of clusters obtained by focusing on the sequence and authorship of touch actions, we found 5 clusters for the highly collaborative groups (c7-11). Similarly to the previous case, the two larger clusters are associated with long chains of conversation (c7) or conversation accompanied with some touch actions (c8). Clusters c9 and c10 show chains of actions performed by the same learner in a row. This information is shown by the presence of the keyword *Tsame* (highlighted in Table 3) in the sequences. The smaller cluster is c11 that shows sequences of actions performed by different learners; an indication of what we call *turn-taking* (*Tother* keyword). In the case of low collaboration groups the size of the clusters had the opposite order compared to highly collaborative groups. The largest clusters mostly contain sequenced actions with the keywords *Tparallel* and *Tother* (c12 and c13), pointing to the presence of more parallelism and turn-taking in low collaboration groups than in highly collaborative groups. Cluster c-15 shows some conversational patterns in these groups.

6 Discussion and Conclusions

We presented the design of our approach for *automatically* distinguishing groups according to their level of collaboration, mining the frequent sequential patterns that differentiate these, and then grouping the patterns to associate them with higher level strategies. We implemented this process by analysing the *verbal and touch traces* of learners' interaction at an interactive tabletop. We validated our approach through a study that involved the participation of 20 triads building concept maps on a tabletop.

We used a decision tree to classify blocks of activity based on quantitative indicators of verbal and touch actions and how symmetric these were. This method proved effective in identifying the level of collaboration of 85% of the triads. The classification was not infallible but had an acceptable rate, suggesting a reasonable method for automatic differentiation of groups' activity. We applied the DSM [6] technique which generated a large number of patterns, especially for the highly collaborative groups. Our AGNES hierarchical clustering algorithm served to analyse the relationship of speech and touch and address our research question. We found some strategies that differentiate groups based on the sequences of actions of speech with *and* without physical activity, which characterised the highly collaborative groups. On the other hand, we found that the sequenced actions with higher rates of parallelism, turn taking and touch activity with less speech characterised the low collaboration groups.

Our approach can serve as a basis for the implementation of a system that can automatically and unobtrusively capture verbal and physical activity at the tabletop in order to alert teachers of possible issues in small-groups activities. It can provide them with key information to enhance their awareness of and highlight good collaboration practices. Our future work includes the design of the presentation layer for a teachers' dashboard displaying a suitable form of this information. We also plan to include different contextual information in the data analysis, for example, indicators obtained from the group artefact and the content of the learners' utterances.

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