From Touches to Teamwork Constructs: Towards Automatically Visualising Collaboration Processes

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Figure 1. Team members engaged face-to-face in a collaborative problem-based activity consisting in integrating three different perspectives to the same question represented via concept maps.

ABSTRACT
This paper presents a rule-based approach to automatically associate low-level actions of team members -performed on a tabletop-based open-ended concept mapping application- with higher order sub-processes. We illustrate the approach by presenting and discussing two versions of the same visual representation of the identified sub-processes: visualisations completely crafted by humans versus those automatically crafted by our rule-based algorithm. We describe our lessons learnt and discuss the potential of our approach, challenges encountered and possible avenues for future work.

Author Keywords
CSCW; visualization; tabletop; collaboration; analytics

ACM Classification Keywords
H.5.3 [Group and Organization Interfaces]: CSCW.

INTRODUCTION
Developing effective teamwork skills is critical for the 21st century life-long learner [2]. However, for students and professionals to learn to collaborate with other people may be challenging [3]. Teamwork activity is complex, as it features concurrent mechanisms in at least four realms: social (e.g. roles, relationships of power), the set (tools used and the space where the activity unfolds), epistemic (ways in which team members address their tasks) [8] and affective (motivation, mood, feelings and attitudes at individual and group levels) [13]. Given this complexity, people often needs coaching to develop the skills needed for them to contribute to their team effectively [3].

In the Computer-Supported Cooperative-Work (CSCW) field, developing teamwork skills has been considered as an ongoing learning process (e.g. see foundational work connecting learning and CSCW by Engeström in [5]). As such, metacognitive processes and support tools can be critical for solo individuals and teams to reflect on their products and operations for enhancing future team activities

There has been a growing interest to provide people with tools that can help them enhance their awareness during teamwork (see recent work in [6; 11]). These tools are aimed at leveraging the digital traces that team members leave while interacting, either face-to-face, or while collaborating through computer interfaces (e.g. online systems) [4]. However, a recent review of the past 10 years in the area of CSCW concluded that most awareness tools are limited to facilitate communication flow, shared storage and synchronisation [10] rather than supporting metacognition or reflection based on teamwork evidence. There has also been a growing interest in HCI in mining interaction logs (e.g. clickstreams) to gain understanding of user's behaviors (e.g. [1], [7]) but results commonly cannot easily be presented to users. Some work has attempted to visualise aspects of collaboration based on team members' individual interactions. For example, Tang et al. [15] built a tool to visualise the touches made on a tabletop as a proxy of collaboration. However, presenting logged touches (or clicks) without any contextual information, do not tell much about higher order collaboration processes, hence they would hardly serve as a basis for supporting reflection. Other work by Martinez-Maldonado et al. [12] made use of machine learning techniques to find patterns of interaction from touch and click streams. Again, it was challenging for authors to articulate the meaning of such patterns and translate them into recommendations that team members could understand. A similar situation has been highlighted by Buckingham Shum [14] in non-collocated environments.

In sum, there is a lack of work focused on modelling and visualising higher level collaboration processes in open-ended tasks (tasks where collaborators can perform fluid interactions without limitations imposed to model the collaboration processes), particularly in collocated settings.

We build on our previous work [9] where we manually associated groups of low level interactions (e.g. generate idea, connect ideas, move window) with higher order collaboration concepts (e.g. brainstorming, sharing ideas, revisions). We present our initial steps towards automating this process by proposing a rule-based approach to associate low-level actions with higher order collaboration sub-processes in collocated team situations. We illustrate this in the context of an open-ended task where twenty teams worked together around an interactive tabletop after individually tackling the problem. We compare and discuss two versions of the same visual representation of collaboration sub-processes: one completely crafted by humans, and the second automatically generated by our rule-based algorithm.

CONTEXT OF THE STUDY

A total of 60 university students participated in our study. Students were grouped in teams of three members. The experimentation took place in a controlled environment (see Figure 1). Each team member was asked to provide an answer to a focus open-ended question about their interpretation of the Australian Dietary Guidelines (a topic in the area of Nutritional Science), They were asked to perform two tasks: 1) Individual phase: each team member would build an individual concept map in private, using a personal computer, giving a compelling response to the focus question (using an editor called CMapTools); and then 2) Team phase: the team would build one concept map at a multi-touch interactive tabletop (using a collaborative tool called CMate) by aligning their three different perspectives. In this paper, we focus on the latter. Each team session lasted between 30 and 35 minutes. Team members had on-screen access to their individual maps created in the individual phase (see Figure 1, centre) to either show to the other team members or just to recall what they previously did. The multi-touch tabletop was linked to the Collaid sensing system that can automatically collect differentiated touch activity (e.g. identifying who added a concept or created a link). Additionally, each session was video recorded. Further details about the dataset and associated technologies can be found in [12].

APPROACH

In [9] we proposed a coding scheme to identify critical concept mapping sub-processes based on observations conducted by two human observers who evaluated the 20 sessions in detail. The coding scheme focused on the possible actions performed by team members using the concept mapping tabletop application. The coding scheme included the following six task-related teamwork sub-processes:

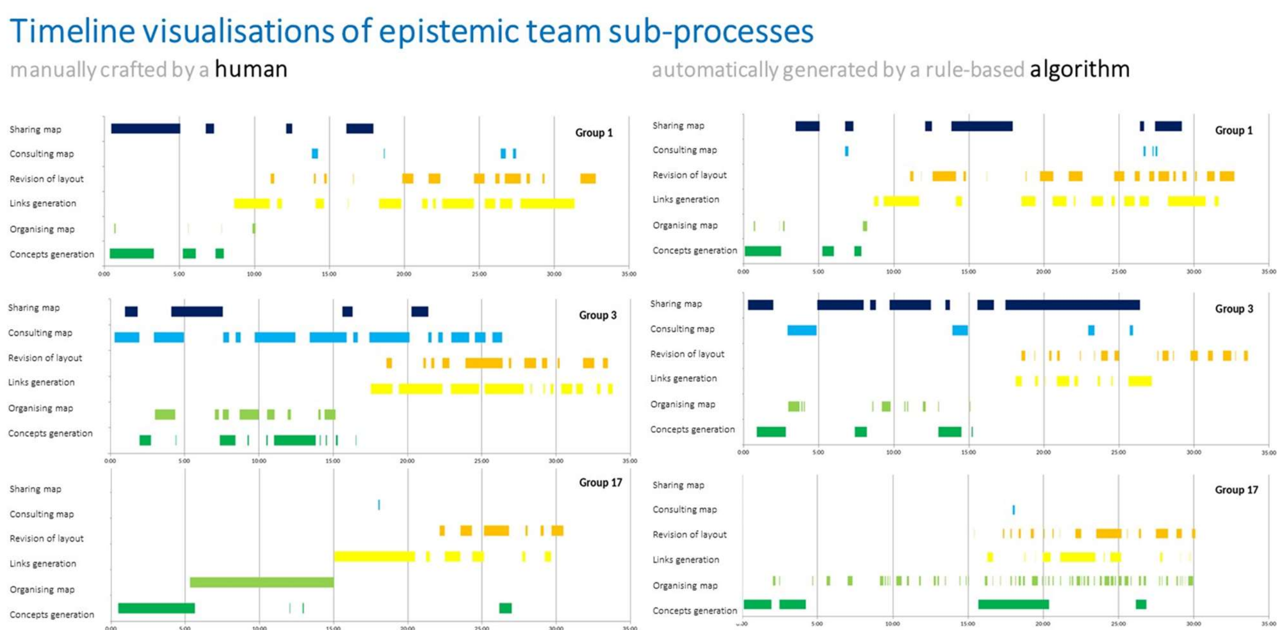

Figure 2. Example visualisations for three teams. Left: Visualisations crafted by human observers identifying critical sub-processes in teams' activity. Right: Equivalent visualisations automatically crafted based on our rule-based algorithmic approach.

1. **Sharing individual map**: when any team member opened their map(s) and explicitly shared it with others in the team. The map could be enlarged, minimised, and moved towards others.

2. **Consulting individual map**: when any team member consulted their own individual map but did not explicitly shared it with others.

3. **Generation of concepts**: when team members added concepts on the map from a list of the concepts they created in the individual phase, or when they typed a new concept from scratch (using an on-screen individual keyboard).

4. **Organisation of concepts**: when team members focused just on changing concepts' position in the interactive surface, deleting redundancies, creating groups or subgroups of concepts, emphasising hierarchies, or adding one or two missing concepts. If team members added several new concepts, then they were involved in the sub-process "3-Generation of concepts".

5. **Generation of links**: when team members created links between two or more concepts, choosing the direction of the arrow and the linking word.

6. **Revision of layout**: when team members focused on revising the map, making small changes (e.g. creating one or two more links or editing linking words). This sub-process usually emerged as an iterative sub-process after "5-Generation of links"

Automated rules description

We produced a set of rules to automatically associate sets of logs with the sub-processes presented above. For example, for the 'Sharing individual map' sub-process, the rule was as follows: *If the team member opens his individual map and moves it to the centre of the table and expands it (more than two "move" logged events detected) times, store the opening and closing times as the beginning and end of the sharing sub-process.* If the team member just opens and closes their individual map, then, it would be associated with the 'Consulting individual map' sub-process. More complex rules were generated to identify other sub-processes. A full description of each rule can be found in this link. Our algorithm consists of the following steps:

1. Pre-process the multimodal dataset generating one long sequence of logged events per person within each team to easily identify patterns.

2. Look for patterns in each user sequence that matches the rules (e.g. a "maximise keyboard" logged action followed by a series of "key entered" logged actions would be associated with a team member editing a concept or a linking word).

3. Store in two dynamic lists the start and end times (forming a sub-process block) of the set of actions that satisfy a given rule (this can be further used to calculate the duration of a sub-process).

4. Repeat steps 2 and 3 for each user, sorting all blocks in an ascending order.

5. Merge blocks that are close to each other into a single time interval and also merge overlapping time intervals

For step 5 we defined a parameter called "*time tolerance*". This parameter allows us to merge blocks of actions that are similar to consider multiple small blocks as a single team sub-process. For example, events such as adding concepts and links commonly occurred in a specific point in time. Team members did not add concepts continuously without stopping, but often took time thinking which concept will be added, searching for them in their menu (see Figure 1, right). As a result, sub-processes such as 'Generation of concepts' and 'Generation of links' had larger time tolerances (up to thirty seconds) to be able to consider larger blocks of activity. Other events such as 'Organise concepts' and 'Revision of layout' have smaller time tolerances (3 and 15 seconds respectively), since moving a concept or a link is less time demanding than thinking which concept to add. Since this parameter can change the length of the sub-processes, exploring different calibrations of this parameter based on heuristics should be considered for future work.

Resulting visualisations

By applying the algorithm described above on the data from the 20 teams, we were able to generate visualisations such as the ones in Figure 2. At the left of the figure, we present three examples crafted by humans for groups 1, 3 and 17. At the right, we present the equivalent visualisations automatically crafted by our algorithm. We selected these because they feature team situations and anomalies that illustrate the potential and the challenges in associating low level logs with higher order sub-processes. Each of the six lines in the visualisations corresponds to a subprocess. The horizontal axis represents the duration of the session (maximum 35 minutes). The horizontal bars represent a block of activity associated with each sub-process.

By comparing the first set of visualisations for Team 1 (Figure 2, top) we can see that there is some matching between the blocks identified manually (left) and those identified by our algorithm (right). Members of this team started brainstorming concepts (see blocks at the bottom line 'Concepts generation' of each visualisation starting from minute 0); then shared their individual maps (see short blocks in the line 'Sharing map') combined with bursts of activity in the lines 'Links generation' and 'Revision of layout'. By contrast, the visualisations for Team 3 (Figure 2, middle) show that members in this team started by sharing their individual maps before adding any concepts (see blocks at the line 'Sharing map' or 'Consulting map' starting from minute 0). Our algorithm associated logs with the sub-process 'Sharing map' whilst the human observer recognised that team members were not sharing their maps (see more presence of blocks in the 'Sharing map' line in the graph at the right, and more blocks for 'Consulting map' in the visualisation at the left). Besides this major mismatch, both visualisations look similar in terms of the other four sub-processes. For Team 17, the visualisations (Figure 2-bottom) show that in this team people never looked at or shared their individual maps (no blocks in the first two lines). They rather followed a waterfall approach. The visualisation crafted by the human (left) shows that the team moved from one subprocess to the other in sequence. By contrast, the visualisation produced algorithmically did not depict a similar process and missed some blocks (particularly those related with 'Organising map'). In sum, by comparing the visualisations produced by humans and by the machine we can see that they differ in some details, but some general sub-processes can be identified.

DISCUSSION AND CONCLUSION

We presented a rule-based approach to automatically associate low-level actions of team members with higher order sub-processes. We illustrated the potential of the approach in the context of a problem-solving, open-ended task where 20 teams worked around an interactive tabletop to build a concept map. We showed three sets of visualisations that highlighted both the potential to generate graphs similar to those that a human would craft. However, we also showed the limitations of the rules to capture the intentions of the team members. We noticed for example that a human can easily differentiate whether a team member opened their individual map for sharing or just for personal consumption. This means the algorithm can be further improved by using more sophisticated machine learning approaches or considering other sources of data.

We faced some challenges. First, the generation of rules was not an easy task. Lax rules can result in false positives whilst very strict rules may identify only a small portion of sub-processes. It was also challenging for simple rules to capture the intent of the team members. For example, sometimes they added concepts by mistake, which were deleted immediately, or added two concepts consecutively, which get overlapped and were moved to be read. Another challenge was the ambiguity of the human classification, e.g. sometimes two identical patterns were identified in the dataset as being associated with two different sub-processes by humans. In short, a perfect match between the human and computer-generated graphs cannot be expected. Our next steps will involve the validation of the visualisations by assessing their usefulness when shown to different stakeholders with specific purposes (e.g. to a teacher attending multiple teams in a classroom) and to implement a scale to measure the correlation between human and computer-generated visualisations.

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