Analyzing Groups' Problem-solving Process to Characterize Collaboration within Groups

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Abstract. Collaborative learning has gained much research attention in the past few years given the cognitive benefits attributed to it. We are investigating automatic adaptive support to groups in a computer supported collaborative learning (CSCL) system. In this paper, we report a study in which we observed the joint-problem solving processes of a teams of three learners. We adopted a Sudoku puzzle as our learning task. We analyze data collected from groups' problem-solving to identify different states of individuals' participative activities within groups. We also determine indicators, activators and inhibitors of collaboration during joint problem-solving (JPS) to characterize group learning activities. Our findings together with the related work provide a foundation for further studies that will design an appropriate technological solution for a shared-activity group environment. This environment will be enhanced to gather collaboration data, evaluate the level of group interaction, determine the need and kind of support to groups and finally, provide real-time adaptive support to learning groups for enhanced collaboration.

Keywords: Collaborative learning, joint problem-solving, shared-activity environment, collaboration, adaptive support.

1 Introduction

Analyzing groups' joint-problem solving (JPS) processes can provide insights into requirements for a computational model of a collaborative learning process. It can help to determine indexes, factors and methods to evaluate collaboration within learning groups, which can inform design of a real-time support mechanism to aid collaborative learning [1]. A model of the JPS process of a group will help to define finite possible activity-states during collaborative learning and to determine how participative activities of learners transit among these states during JPS. Such a model may provide enough information to characterize group collaboration and advise the design of an environment that aids groups to collaborate optimally [1].

Collaborative learning involves "two or more people" learning or attempting to learn something "together" [2, 3]. Its cognitive advantages have been established [4]. However, only a functional group (which interacts well) can benefit from collaboration [5]. When students are made to solve a learning task jointly, it does not automatically imply *collaborative* problem solving [5]; an effective computer-supported collaborative learning (CSCL) system should be able to monitor, understand and support groups to collaborate.

This paper presents a study of a face-to-face JPS process of groups. We hypothesize activity-states involved in JPS and observed individuals participative activities in a group as it transits between states progressively towards JPS [6]. We envision a computational model to evaluate collaboration within groups and indicate inhibitors/activators to cognitive interaction during JPS [5].

2 Review of related work

Theories such as *cognitive load theory* [7, 8] and *Vygotsky*'s *Zone of proximal development (ZPD) theory* [9, 10] explain how group learning is impacted by task difficulty and relative knowledge levels. Many studies have been done to show that collaboration aids learning [11–15]. Together these studies and theories attribute cognitive advantages to collaboration, and justify exploration of group learning. Recent studies have shifted focus from designing an enabling environment for groups [16–19], to analyzing group interaction and investigating computational methods to support groups for optimal collaboration. This trend prompts investigation towards extracting and analyzing group JPS data, to provide a factual basis for designing and developing systems that support group collaboration [20].

In a related study by Martinez and colleagues [21], they categorized a group JPS process into collaborative, non-collaborative and somewhat collaborative. They coded audio and the application log trace of group JPS using these categories and cross validated this with observations in video-recordings of group- work processes [21]. A model was presented, to provide both teachers and learners with an awareness of the level of collaboration within a group.

Roberto Martinez [22] in a similar study, explored a log of learners' touches working around an enhanced tabletop, and their detected speeches. They employed a classification model, sequence mining and hierarchical clustering to distinguish patterns of group collaboration and determine high, medium and low collaborative groups based on these patterns.

A similar study was conducted by Cukurova and others [20], where hand positions and head directions of students during JPS were explored to evaluate collaboration. Data was collected through a multi-modal learning analytic system and a framework termed "Nonverbal Indexes of Students' Physical Interactivity" (NISPI) was presented to evaluate participation in groups' JPS [20]. Other works on group collaboration detection include [23–25].

The related work discussed above explored group-work processes, as well as suggested indicators and models to evaluate collaboration during JPS. However, most of these works targeted manual support for groups. The authors' proposals for data extraction, analysis and inference on causes and effects during group JPS were not easily resolvable to computational variables (such as sentence openers, button clicks or check boxes). Resolving these JPS data to such computational variables could aid real-time evaluation and support for groups as proposed in this research. We aim to advance existing work and provide groups' JPS data that can inform a computer algorithm to automatically evaluate group collaboration and lend support to groups for enhancement/optimization of group collaboration.

3 Study Objectives, context, procedure, data collection and exploration

This study aims to: (1) investigate finite states of collaborative activities during JPS and (2) investigate how the distribution of these states differentiates individuals within a group and how it differs between groups.

3.1 Context of study

Participants are recruited among postgraduate students and aged 18-40 years. Four groups were used of three participants each (11 male and 1 female). Each group solved a Sudoku puzzle jointly in an unstructured interactive face-to-face environment. The triads were formed randomly. The Sudoku puzzles used in this experiment were extracted from an on-line Sudoku puzzle solver website [26]. The author of the site categorized the puzzles into simple, easy, medium and hard categories. We verified the difficulty variations of the puzzles in a pre- study experiment and could confirm the difficulty level gradient of the puzzles based on our findings.

For the JPS of the Sudoku puzzle, groups 1 and 2 solved the puzzle in Figure 1b, which is a more difficult puzzle. Our observation of how difficulty level of the puzzle inhibited the interaction within the groups prompted us to change the puzzle to another of lower difficulty level for groups 3 and 4. Our decision was corroborated by an observable difference in interaction within groups 3 & 4, we explain this observation further in Section four bellow.

3.2 Data collection

A Video recording of the JPS process of all groups was collected. This provides data of verbal interaction, as well as the gesture and problem solving action of individual learners during problem solving (see Figure 2).

3.3 Data exploration

We defined states of JPS activity based on "the collaborative learning conversation skill taxonomy" presented by Soller [5] (See Table 1). We observed (watched) and annotated video of each group coded with our defined states of activities using The Anvil video annotation research tool [27], (see Figure 2). This classification is based on researchers' perception of individuals and group activities with inferences from literatures on small group communication during JPS.

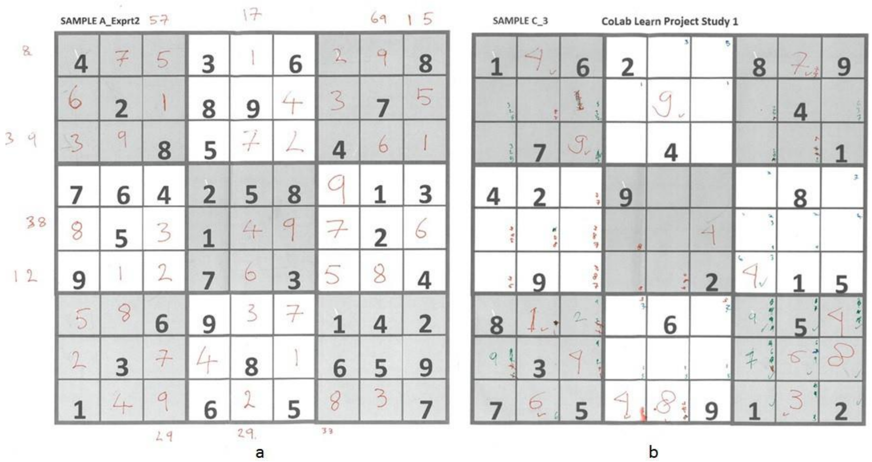

Fig. 1: Sudoku puzzle solved by groups: (a) More difficult puzzle solved by group 1 and 2, (b) Easier puzzle solved by groups 3 and 4

Fig. 2: Group Joint Problem-solving (JPS) Experiment

For our experiment, the groups' affective state during JPS was color-coded using ANVIL "spec". We adapted "example-step-3" xml code in anvil to capture our idea of collaborative activity-states in different colors. The groups JPS process video was observed and annotated using the color code to determine time interval of collaborators in different activity-state at instances during JPS. The unit of time is in "Frame" of anvil media such that $1 Frame \approx 0.04 s$ by calculation.

Fig. 3: Annotating Group's JPS process with ANVIL

Table 1: Finite activity-state in the JPS process adapted from the taxonomy of collaborative skill present in Soller's [5] study.

JPS states	State components	Sentence opener/gesture examples
Task	Coordinate Request focus change Summarize information End participation	"Ok lets move on", "are you ready" "let me show you" "to summarize" "I am off here"
Maintain	Listening	Listening gesture/posture
Acknowledge	Appreciative Accept/confirm Reject	"Yeah I get it now", "thank you". "Ok", "Yes" "No"
Request	Information Elaboration Justification Opinion Illustration	"Do you know" "Do you mean that" "Why do you think that" "Do you think" "Please show me"
Inform	Lead Rephrase Elaborate Suggest Explain/clarify Justify Assert	"I think we should" "In other words" "Also.." "I think" "Let me explain" "This is because.." "Sure!", "I am reasonably sure"
Motivate	Encourage Reinforce	"very good", "good point" "That is right", "correct"
Argue	Conciliate Agree disagree offer alternative Infer Suppose Propose exception Doubt	"We are both correct" "I agree because" "I disagree because" "Alternatively" "Therefore ..", "so .." "If...then..." "But" "I'm not so sure"
Internalize	Quiet/exhaustion	"sigh..", "quiet", "we need help"

4 Group JPS Data Analysis, visualization, presentation and Observation

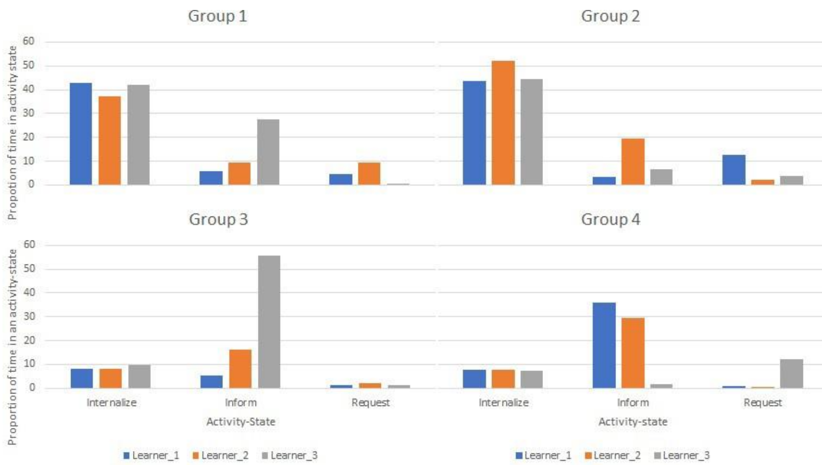

Fig. 4: Activity-state comparison 1

Figure 4 describes the proportion of time that each individual assumed a particular activity-state during JPS. As each triad spent varying amount of time for the experiment, we used proportion of time for the graph and analysis. The vertical axis indicates the proportion of time that an individual in the group assumed a particular activity-state during JSP and the horizontal axis shows different activity states. Individual learners are represented with different colors of bars in the graph.

Groups 1 and 2 were made to solve a more difficult puzzle compared to Groups 3 and 4. We observed a clear distinction comparing 1 and 2 versus 3 and 4 based on the proportion of time that members assumed Internalize and Inform states. In Groups 1 and 2 members assumed Internalize state for an average of 40 and 47 percent respectively during JPS, while Groups 3 and 4 members assumed the same state of activity for an average of only 8.6 and 7.6 percent respectively during JPS. Conversely Groups 1 and 2 members assumed an inform-state for an average of 14.1 and 9.8 percent of time during JSP, while Groups 3 and 4 assumed an inform-state for an average of 25.7 and 22.2 percent of time.

Figure 5 shows the percentage distribution of activity-states within groups. From this, it is observed that the proportion of internalize-state is evenly distributed within all groups. We can also observe that the inform-state and request- state distinguish individuals within groups more clearly than other states. A correlation measure, between the two states indicates a weak downhill linear correlation (value=-0.391; not significant given small group number) between Inform and Request activity states across all the groups.

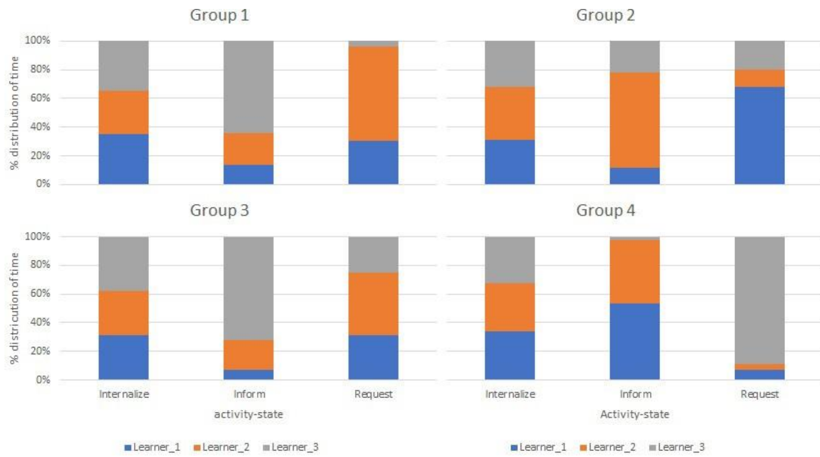

Fig. 5: Activity-state comparison 2

5 Conclusion, Application and Future work

5.1 Conclusion

Based on our findings in this study, we present the following inferences and identify clues for further exploration:

Inform and Request are the most influential participative activity-states within a group. Based on this preliminary conjecture, we adapt the concept presented by Roberto Martinez and colleagues [21] to measure of symmetry of participative activities of individuals within a group, applying it specifically on Inform and Request states. *The Gini coefficient* was employed to indicate dispersion of an activity-state within groups, the measure results in ranges between 0 and 1. 1 indicates total asymmetry and 0 indicate total symmetry. Symmetry of participative activity within a group is an indication of collaboration level, according to Martinez et al., [21], the more symmetrical the more collaborative. The Gini coefficient measure of symmetry is given by:

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

n= the number of participants in a group
x_i= the value of a participant i (e.g. amount of time spent in request state)
μ= mean of the value distribution within the group.

We calculated G_{inform} and $G_{request}$ and considered the resultant Gini coefficient value as given by:

$$G_{av} = \frac{G_{inform} + G_{request}}{2} \quad \text{equation (2)}$$

Groups	G(inform)	G(request)	G(average)
1	0.170	0.207	0.188
2	0.183	0.186	0.184
3	0.217	0.063	0.140
4	0.171	0.285	0.228

Fig. 6: Gini coefficient measure of symmetry within the group

Symmetry of individual participative activity. Based on our preliminary conjecture that Inform and Request states are the most discriminating states of activity within a group, we measure symmetry of Inform and Request states within a group [21] for all groups. Our measure shown in Figure 5 describes Group 3 as the most collaborative group and Group 4 as the least collaborative group. Our qualitative observation of JPS video of the groups agrees with the Gini coefficient results in Figure 5. It was clearly observable that members of Group 3 seemed enthusiastic and motivated throughout the duration of the JPS. Contrarily an extraction of Group 4's discussion shown below will give an indication of the lack of team work within that group. In this case, the lack of teamwork seemed partially due to too large a gap in knowledge between group members. The language used by group members somewhat hostile may also have had an impact.

Extracted transcript of Group 4 discussion:

Learner 1: What is missing here, hmm I think 9.
Learner 2: Yes, that will be 9.
Learner 3: Hmmm I think we should start off by introducing steps to solve this puzzle.
Learner 1: This is a game of solving puzzle.
Learner 3: But you understand the game but I don't.
Learner 1: That was why we started by explaining the rules to you.
Learner 3: No make it step-by-step
Learner 1: Ok. Let me explain the rule to you again
...
Learner 3: It appears that you are an expert in this game.
Learner 1: Nooo it's a game.
Learner 3: I know it's a game but we need to be more interactive. You are the only one talking here.
Learner 3: If you can slow down a little bit at least for others.
Learner 1: Open your eyes, you will see how. Do you know how to play draft?
Learner 2: Yeah but let's be more interactive you know.

Effect of task difficulty. Task difficulty impaired collaboration within Groups 1 and 2, it forced the group into the Internalize state for a longer period and thus hindered communication during JPS. This observation is corroborated by *cognitive load theory*, where cognitive load imposed by collaborative learning is decomposed into [7]:

Intrinsic load, In_L: load required to solve the learning task,
Extraneous load, Ex_L: load imposed by non-cognitive interaction within group,
Germane load, Ga_L: load imposed by collaborative learning, information flow and knowledge sharing that foster problem solving.

A group has a *working memory, W_m* that combines all working memory of its members, i.e. knowledge levels and capacity to solve given tasks [7], thus provides the distributive advantage of group learning [7]. Effective collaboration occurs when $W_m > In_L + Ex_L + Ga_L$. However, it should be noted that if $W_m >>> In_L + Ex_L + Ga_L$ (i.e. much larger than), collaboration becomes inefficient [7] as the task could be easily and more efficiently solved by an individual learner. The tasks difficulty for Group 1&2 is observed to have imposed a high In_L that made the W_m of the groups not enough to cope with Ex_L and Ga_L, thus resulting in members going to Internalize state more often during JPS.

Knowledge level threshold. There is a threshold of knowledge level that will promote collaboration within a group. Homogeneous groups with respect to knowledge level will exploit benefits of collaboration as advocated in ZPD theory [10]. However, a threshold of knowledge that shows understanding of both syntactic and semantic knowledge of a learning task is required for a group to collaborate cognitively well. Group 2 in our study is below such a threshold. The JPS process within the group was hindered by lack of knowledge.

Coordination and leadership. We observed that every group had one member who assumed the coordinator and leadership role in the group. We thus inferred that the coordination and leadership role in a group initiates and moderates collaboration. The member that assumed the leadership role in each of these groups (as observed in the video) was found to assume the Inform state most within the groups (Figure 3).

5.2 Application

The broad idea is based on the literature that collaboration aids learning; we thus infer that if collaboration is maximized during JPS, optimal cognition will be experienced by learners. However, it is often said that “we can’t manage what we don’t measure” [28], thus justifying the investigation of how to evaluate and represent collaboration in a quantitative and computable manner.

To this end, activity-state during JPS as defined in this study when further validated and re-defined will provide a set of inputs that will inform an algorithm to train the model for evaluating the level of collaboration as presented in this study. A diagram of the system layers of our research scope is shown in Figure 7.

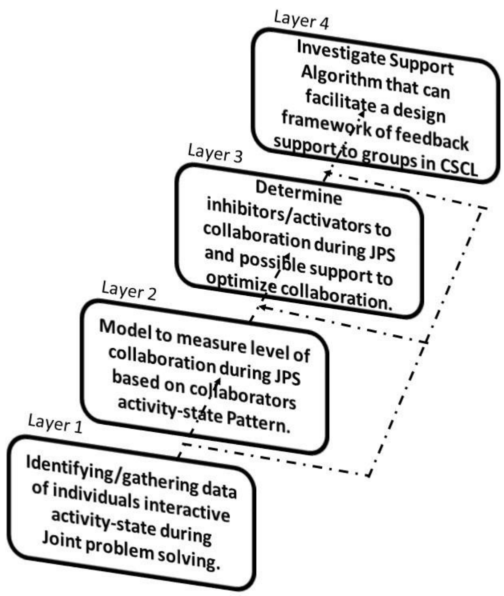

Fig. 7: Layered Framework of research scope

5.3 Future work

For future work, we will re-define and validate collaborative activity-states during JPS. We will advance the study to validate our preliminary conjecture from this study using feedback from participants, pre- and -post repeated measures to evaluate cognitive impact of collaboration to determine the most effective indicators/factors and the best model to evaluate group collaboration. Our intension is to resolve inputs of such a model of evaluating collaboration into computational variables like button clicks and sentence openers. This will inform a computer algorithm for automatic evaluation of groups in a computer supported collaborative learning system.

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