Model-based characterization of text discourse content to evaluate online group collaboration

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Abstract. This paper presents a model that characterizes textual discourse contents of online groups and provides a visualization of the level of collaboration within groups. This approach is envisioned to provide an insight into a real-time intervention to scaffold collaboration within online learning groups.

Keywords: joint problem-solving · discourse content · online groups

1 Introduction and related work

Online group learning involves virtual access to education without limitation of geographical location and a collaborative environment that provides cognitive benefits attributed to group learning as established in literature [22,10,15,17,21]. However, all *learning groups* do not automatically collaborate well [19], thus the rationale to support groups for optimal collaboration.

In this context, groups interact either through verbal or text-based discourse; both have been posited in existing work to be similar in collaborative effect during joint problem solving (JPS) and that they can be juxtaposed in context [6,4,7,14,8,16,20,18]. This paper improves upon the work by Schwarz & Asterhan [18] to provide a simpler computational mechanism to visualize (1) group collaboration compared to their social network based evaluation of group collaboration, and (2) individual participation compared to their many bars representing each individual's *variables of participation*, and individual participation measures, which is cumbersome and hard to base a real-time intervention on.

2 Study design and procedure

Demographics of participants: A convenience sample of twenty students participated in this study, randomly grouped into teams of 4 members (Group G1: 3 male, 1 female, all aged 18-25; G2: 3 male, 1 non-disclosed; all 18-25; G3: 2 male, 2 female; all 18-25; G4: 4 male, all 26-35; G5: 4 male, 3 aged 26-35, 1 aged 36-45).

The learning task and context provides each group with a joint task to solve; we adopted the "NASA man on the moon task" [1] for this study; a scenario of a space crew on the moon that needs to vacate a faulty spaceship to

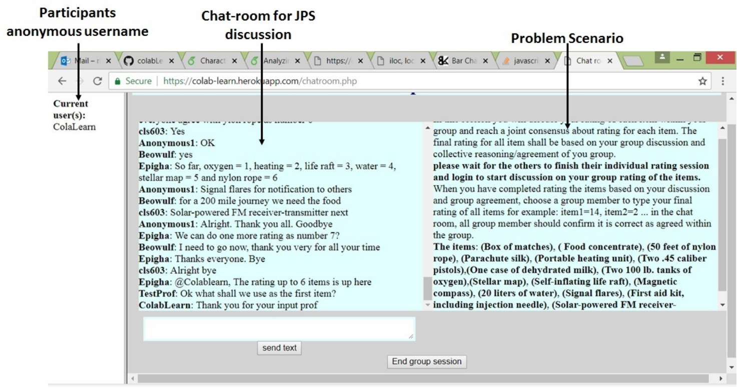


Fig. 1: Chat-room for groups' JPS discussion

another one 200 miles away, with the group needing to rate 15 items in order of priority to take along [1]. The task meets Cohen's recommendation [5] of a group task with respect to complexity and being open ended.

System design for data collection: We designed a JPS-discourse (JPSD) chat-room shown in Figure 1, an environment for online groups similar to *AcademicTalk* [14], *specialized work space* [20], *discussion tool for education* [16], *web interface* [9] and *e-argumentation* [18]. JPSD chat-room collects text-based interaction data as input to our model, to provide a simplified visualization of the individual participation and group collaboration level.

2.1 Data model

Gini-coefficient measure of symmetry *(GCMS)* used in Adeniran et al. [3,13] is adapted to capture variables on interaction within online groups based on of their textual discourse content. The model adaptation is as follows:
A member i's sequential text contribution at different time intervals is a collection of statements given by $\overrightarrow{S}_1, \overrightarrow{S}_2, ..., \overrightarrow{S}_m$, which we call $\overrightarrow{k}_i$. So, member i contributes $\mid \overrightarrow{k}_i \mid$, to the group's discussion. GCMS of $\mid \overrightarrow{k}_i \mid$ within groups represents a measure of group interaction quality [2,11]; this is computed as follows: the mean of $\mid \overrightarrow{k}_i \mid$ for a group is calculated as shown in Equation 1:

$$k_{mean} = \frac{1}{n} \sum_{i=1}^{n} \mid k_i \mid \tag{1}$$

The GCMS of contributions within a group is as shown in Equation 2:

$$G_c = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |k_i - k_j|}{2n^2 k_{mean}} \tag{2}$$

G_c ranges from 0-1: 0 for perfect symmetry and 1 for perfect asymmetry. We assume that an indication of good collaboration is proportional to $\frac{1}{G_c}$.

Word-count of contribution within a group is considered for a more robust metric of collaboration. We found in literature that, *"the more collaborative groups had higher levels of verbal activity"* [12] and that elaborated discussion through explanation is an indicator of group collaboration and this results in the generation of volume of text in a textual discussion [6]. Evidence of collaborative skills [19] and its indicators during JPS [3,2], all involves generating a volume of text when JPS discourse is text-based. Hence, we use the volume of text contributions to measure collaboration when a group discussion is text-based. The overall word-count of contributions by member i is derived from their text contributions, $\overrightarrow{k}_i$. Each statement $\overrightarrow{S}_j \in \overrightarrow{k}_i$ is a sequence of words. The total word-count of all contributions by member i is:

$$w_{ct}^{i} = \sum_{j=1}^{m} \mid \overrightarrow{S_j} \mid, where\, m = \mid \overrightarrow{k}_i \mid \tag{3}$$

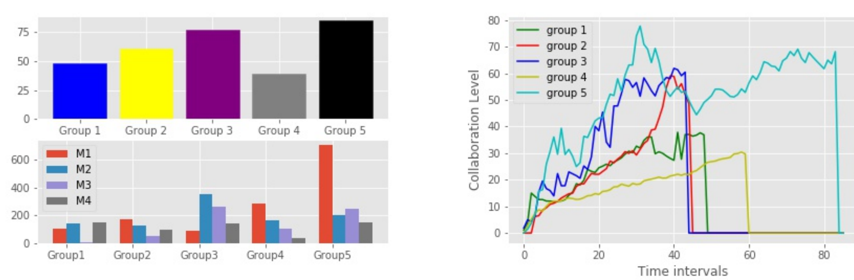
However, a group may contain a highly extrovert member who contributes unnecessarily long texts or an extremely introvert member who contributes short texts. Therefore, we compute the median:

$$G(w_{ct}) = median(w_{ct}^{1}, w_{ct}^{2}, ..., w_{ct}^{n}), where\, n\, is\, the\, group\, size \tag{4}$$

We combine $G(w_{ct})$ and G_c to obtain a more sensitive measure of collaboration based on discourse called **WC/GCMS metric of collaboration within a group** as shown in Figure

$$G_{cl} = \frac{G(w_{ct})}{G_c} \tag{5}$$

Figure 2a(*top*) shows the relative value of G_{cl} between the study groups.



(a) Collaboration measure (top), and individual participation within groups (bottom).

(b) Simulated real-time collaboration level between groups with sequence of contributions at discrete time intervals

Fig. 2: Collaboration measures

2.2 Validating WC/GCMS model & Visualization output

Real-time visualization of group collaboration level: Figure 2a shows the output of our collaboration metric model based on each group's total discourse. Groups G3 and G5 collaborated more; this is corroborated by the real-time simulation (Figure 2b) as G3 and G5 collaborated better, throughout JPS.

Evaluation of models' output and the visualization: We triangulate the output measures (as shown in Figure 2), with qualitative data of the group discourse, considering the collaboration indicators/inhibitors identified in [2,19]:

The discourse in G3 & G5 shows evidence of collaborative skills [3,19] with cognitive elaboration during JPS [22], whilst the other groups' discourse contains mainly *suggested solutions* which are mostly erroneous and blind agreements[3]. The latter groups' discourse is similar to what Webb [22] refers to as "giving and receiving non-elaborated help", i.e. unexplained solutions to the JPS task. Such statements provide no cognitive benefit to the giver of the information nor to other members. In G1,2,4 many of these *unexplained solutions* are wrong.

Individuals' participation level influences the measure of group collaboration and there is evidence of non participating members in G1 and G4, members m3 in G1 and m4 in G4 respectively as shown in Figure 2a(bottom) with "bar3" of G1 and "bar4" of G4, thus justifying the low collaboration measures for G1 and G4 shown in Figure 2a (top).

Quality of contribution and knowledge level of context (in this case the environment of the moon) is evident in the discourse of groups G3 & G5 contrary to what we have in G1,2 & 4. This justifies higher measures of collaboration in the former inline with the effect of knowledge level during JPS as presented in [2] and *Vygotskian perspective* mentioned in [22], which states that collaboration provides cognitive benefits when "a more expert member helps less-expert ones".

3 Conclusions

Studies exist that have explored similar ideas as presented in this study; ours however adds to the existing knowledge to provide an easily interpretable visualization, based on a *scalable* and *generic WC/GCMS* model to evaluate the participation and collaboration level within online groups. Whilst the indicators of JPS collaboration exceed the characteristics of the text discourse content used in this paper, the WC/GCMS model is sensitive enough to serve as a proxy-effective metric of collaboration and participation within online groups. However, whilst we gained valuable insights from our study, we would like to run a larger scale study to further investigate the indicators, factors and models presented. We will also investigate the use of our metrics and visualizations to provide real-time feedback to learners to scaffold collaboration, and measure both quantitatively and qualitatively the effect of such feedback on JPS. We further aim to develop algorithms for a computer agent (taking our models as input) to stimulate participation and consequently scaffold collaboration.

[3] For complete group discourse see colab-learn.herokuapp.com/modelVS/groupX.php replacing X with the group number

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