# Model-based characterization of text discourse content to evaluate collaboration within online groups

Author[1], Author[2], and Author[3]

Institution
`autor1email`

**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 learning can provide education to geographically dispersed learners that might otherwise be limited in accessing a traditional classroom [2]. This paper investigates a model-based characterization and analysis of textual discourse content of online groups, providing a computational framework to enable a computer agent to monitor, evaluate and scaffold collaboration within groups during joint problem solving (JPS).

### 1.1 Collaborative learning

In *collaborative learning* a learning task is solved *synchronously* and *interactively* by two or more learners [7]. During collaboration, learners elaborate on their thoughts while trying to explain learning material to others in a group, reorganize their own knowledge, “fill in the gap” in their own understanding, connect new information to what they already know, which helps internalization and production of new knowledge [25]. Research showing that collaboration aids learning is ubiquitous, e.g., [13,17,20,24], however studies also established that all *learning groups* do not automatically collaborate well [22] providing the rationale for studies on how to support groups during JPS and scaffold collaboration.

### 1.2 Scaffolding collaboration

Existing studies indicate support needs and possible intervention roles, either by a *remote human teacher* or through an *adaptive support agent* to aid collaboration within online groups during JPS. Collaboration can be scaffolded through:

*(a) Explanation prompts* in real-time during JPS to help learners to construct their explanation, find patterns in their inquiries, justify answers and beliefs and relate prior knowledge to the group task [25]; *(b) Cognitive role specialization* in which learners are assigned roles based on an evaluation of their contribution, e.g. group leader, active listener, peer tutor, next contributor, explainer of an earlier contribution [25]; *(c) Feedback for group processing*, as social psychology maintains that if group learners get feedback on how they participate as individuals and together as a group, it improves collaboration [19,25].

As regards to how to determine the need for intervention, Ding et al [9] presented three conditions that indicate this during JPS. First, *when no group member can answer or solve the task*; this was identified as *knowledge level and task difficulty* inhibiting group collaboration in [4], and signaled by a long *internalization* period (i.e. the group keeping quiet for a long time) or *suggestion and blind acceptance of erroneous solutions* [4]. Second, *when there are communication problems between the learners*, Third, *when one member dominates solving the joint task*, without allowing others to contribute [4,8].

### 1.3 Collaboration in verbal versus textual discourse

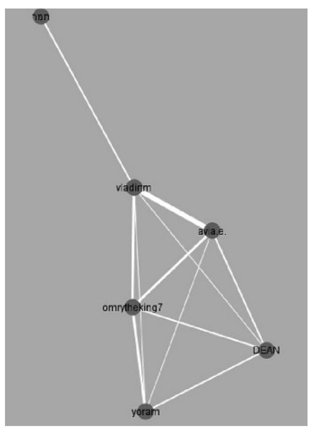
Comparative studies between *text-based* versus *face-to-face* (F2F) verbal discourse attests to similarities in both, despite a lack of facial expressions and gestures in text-based virtual group discourse [5]. Features such as *frequency of agreement or disagreement*, *use of negative affect terms* and *frequency of punctuation use* in text contributions reveal emotions of discussants via text, which is similar to facial expressions and gestures in F2F verbal discussions [11].

Curtis [7] posits that online discussion provides evidence of collaboration as seen in *F2F*, although this evidence has different representations in both, meaning text or verbal information containing the same content provides the same emotional or cognitive effect although they are processed differently. Going by testimony in existing work in this line of thought, we assume that text-based dialogue is close to spoken conversation [5,10,16,11] and based on this assumption we extrapolate findings from our previous investigations [3,4] and established in other existing studies evaluating collaboration in *F2F groups* [15,22] to explore *online groups* using their *textual discourse content.*

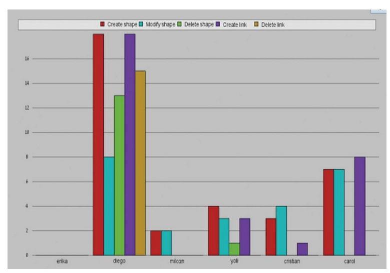
### 1.4 Evaluating collaboration based on textual discourse content

Related studies, e.g. [16,18,23,21], have also explored either text discourse or another form of joint activity of online groups, to research characteristic features of JPS within groups. We will elaborate on Schwarz & Asterhan's work [21], because they evaluate and visualize individual participation and group collaboration in real-time, unlike others where group activity was only analyzed after it had ended. We aim to improve on their work in two respects. First, Schwarz & Asterhan [21] applied a social network (SN) to evaluate group collaboration (see Figure 1a). The SN describes "who" talks to "whom" within a group, indicating *connection* rather than *collaboration* and does not fit well to evaluate collaboration in small groups' synchronous discussion, where every contribution is directed to all members. Second, the SN diagram does not provide a clear and actionable insight of *which* group or *whom within* a group requires support to encourage participation and improve collaboration. Their individual participation measure (Figure 1b) is also cumbersome and hard to base a real-time intervention on, noting the many bars representing individuals' *variables of participation.*

To improve on these, this paper presents a real-time visualization of the relative *collaboration level between groups* and *participation level within groups* that is concise, adjudged informative to a computer agent (or remote teacher), and able to provide insights for appropriate support and intervention to scaffold collaboration. The remainder of this paper describes a model-based computational mechanism to evaluate/visualize the level of collaboration in real-time, within online groups that interact through text, as well as an evaluation of the output from this mechanism based on a qualitative analysis of groups' discourse content.




(a) Group collaboration measure with Social network




(b) Individual group members' activities

Fig. 1: E-moderation of online group collaboration, Schwarz & Asterhan [21]

## 2 Study design and procedure

A convenience sample of twenty students participated in this study, randomly grouped into teams of 4 members (Group1: 3 male, 1 female, all aged 18-25; Group 2: 3 male, 1 non-disclosed; all 18-25; Group 3: 2 male, 2 female; all 18-25; Group 4: 4 male, all 26-35; Group 5: 4 male, 3 aged 26-35, 1 aged 36-45). Each group jointly tried to solve a learning task. Applying problem-based learning, we adopted the "NASA man on the moon task" [1] for this study. This provides

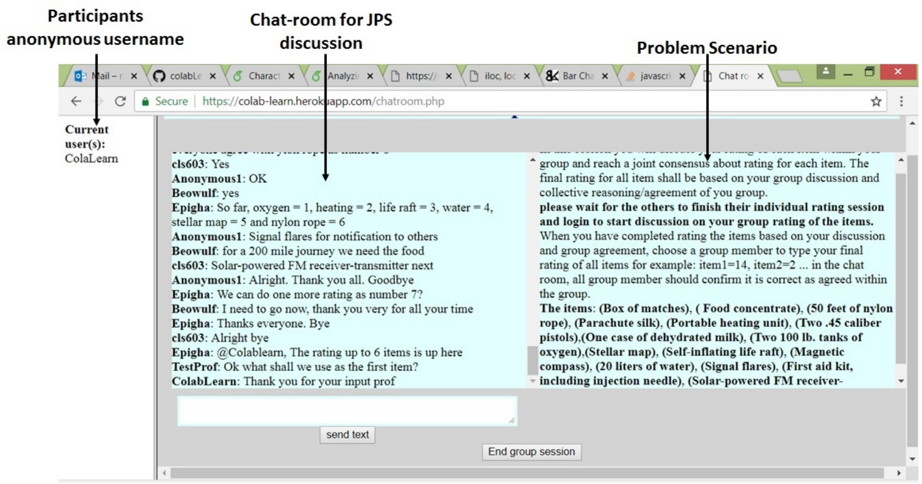



Fig. 2: Chat-room for groups' JPS discussion

a scenario of a space crew on the moon that needs to vacate a faulty spaceship to another one 200 miles away, with the group needing to rate 15 items in order of priority to take along [1]. This task meets Cohen's recommendation [6] of a group task, i.e. "*complex enough or open ended problem without clear cut answers or one that has procedures that are difficult to complete individually or require combined expertise of every member of the group*". Participants interacted using text via an on-line chat-room (Figure 2) designed to capture the group discourse, including who contributed what. This data was used for our model and analysis.

**Research questions:**

- Can we quantify and visualize the level of individual participation and group collaboration in real-time during on-line JPS based on the textual discourse?
- How valid are the conclusions we draw from this model with respect to what actually happens within groups during JPS?

**System design for data collection:** We designed a JPS-discourse (JPSD) chat-room hosted on the Heroku platform to capture the text discourse content of the studied groups. JPSD resembles *AcademicTalk* [16], *specialized work space* [23], *discussion tool for education* [18], *web interface* [12] and *e-argumentation* [21]. The interface and data capture design in JPSD was improved to integrate a mechanism for the real-time evaluation of group collaboration and provide a simplified visualization of the individual participation and group collaboration level that can be easily interpreted. It provides a generic framework for online JPS that can be extended to capture more collaboration indicators and include other context of online JPS e.g. online verbal discussion or group project work.

## 3 Data model, analysis and results

### 3.1 Word-Count/Gini-coefficient measure of symmetry

The Gini-coefficient measure of symmetry (GCMS) used in Adeniran et al. [4] to study F2F groups is adapted in this study to capture variables in textual discourse of *online groups*. Originally GCMS was introduced by Martinez-Maldonado [15] to evaluate collaboration of a group working around a tabletop. Our adaptation of this model for online groups in this paper results in a hybrid word count and GCMS model (*WC/GCMS*), producing a real-time measure of participation within and relative collaboration between groups. *WC/GCMS* and its components based on a group's *textual discourse* are explained below.

***Individual group members' participation:*** We modeled individual participation as the total number of text contributions by each individual within the group. Each member $i$ contributes a sequence of statements at different time intervals $\overrightarrow{S}_1, \overrightarrow{S}_2, ..., \overrightarrow{S}_m$, which we call $\overrightarrow{k}_i$. So, member $i$ contributes $\mid \overrightarrow{k}_i \mid$, to the group's discussion.

***Gini-coefficient measure of symmetry (GCMS) adapted for online groups' text-based discussion:*** The GCMS for online groups based on their text discourse content is described in Equations 1 and 2. The number of text contributions is similar to the frequency of touch by individuals on the tabletop interface in [14] or how often a group member speaks in [4]. The mean of these values per group is calculated:

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

The symmetry of the text contributions within a group (i.e. GCMS) is:

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

$G_c$ ranges from 0-1; 0 for perfect symmetry and 1 for perfect asymmetry. Assuming that an indication of good collaboration is proportional to $\frac{1}{G_c}$, Figure 4 visualizes $\frac{1}{G_c}$ as we simulate its real-time values for the 5 groups studied.

***Word-count of contribution within a group**:* For a more robust metric of collaboration and based on a comment in [14] that *"the more collaborative groups had higher levels of verbal activity"*, Curtis [7] also opined 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. Furthermore requesting, arguing, acknowledging, agreeing/disagreeing, informing and coordinating, which were identified as evidence of JPS collaboration [3,4,22], all result in 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:

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

This measure represents the participation level within the group plotted in Figure 3 (*bottom*). 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:

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

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

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

Figure 3(*top*) shows the relative value of $G_{cl}$ between the groups in our study.

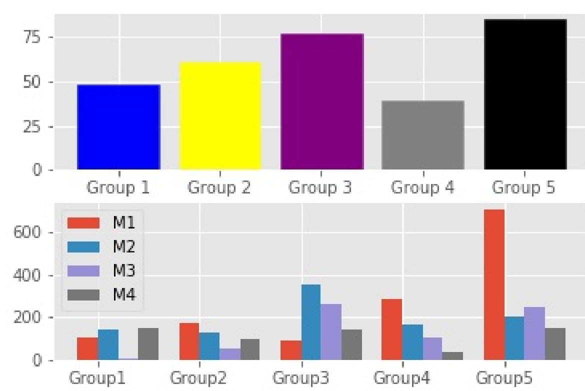
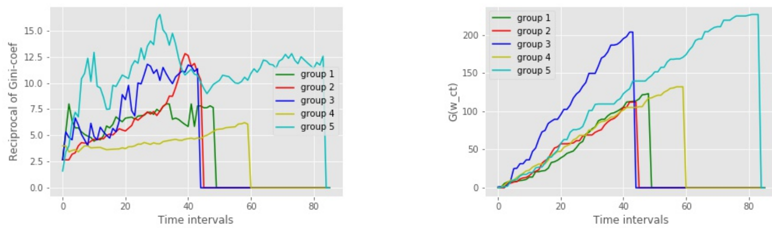



Fig. 3: Final collaboration measure between groups based on discourse content (top), and individual participation measure (of members M1-M4) within groups based on the number and word count of contributions (bottom).

### 3.2 Real-time visualization of group collaboration level

Figure 3 shows the collaboration metrics based on each group's total discourse. Groups 3 and 5 collaborated more; this is corroborated by the real-time simu-




(a) $1/G_c$ measure between groups (b) $G(w_{ct})$ measure between groups

Fig. 4: Components of Collaboration-metric model

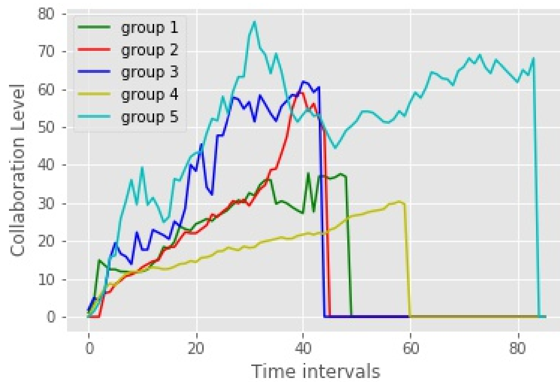



Fig. 5: Discrete time-series view using gradual sequential extraction of group discourse content at time intervals

lation (Figure 5) as Groups 3 and 5 collaborated more throughout JPS. Comparing Groups 3 and 5, although Group 3 generated more text (Figure 4b), the distribution of contributions was more symmetrical within Group 5 during JPS (Figure 4a), explaining the higher collaboration measure (Figure 3 top). The collaboration level drops to 0 in all groups as JPS ends (Figures 4 and 5).

## 4 Evaluation of model and result of analysis

We evaluate our model's output through a qualitative analysis of the groups' discourse with respect to the indicators of collaboration identified in [4].

***Evidence of collaborative activity-states:*** Certain group discourse features, e.g. *inform*, *argue*, *agree/disagree*, and *coordination*, are evidence of collaboration [4,22]. The discourse of Groups 3 and 5 shows most of these features, whilst the other groups' discourse contains mainly *suggested solutions* which are mostly erroneous and blind agreements (See extracts in Table 1). The latter groups' discourse is similar to what Webb [25] 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 the case of Groups 1,2,4 many of these *unexplained solutions* are wrong. Cognitive elaboration is evidence of collaboration [25]. This is grossly lacking in the discourse of Groups 1,2,4 and more evident in Groups 3,5, thus validating the output of our collaborative metric as seen in Figures 3 (top) and 5.

***Measure of individuals' participation:*** In Group 1, a member ("charis") did not contribute to the group discussion, only contributing once in the chat-room throughout the discussion. Similarly in Group 4, a member ("the unknown") joined the chat towards the end of the discussion. This visible in Figure 3(bottom) as "bar3" of Group 1 and "bar4" of Group 4, thus justifying the low collaboration measures for Groups 1 and 4 shown in Figure 3 (top).

***Quality of text contribution and knowledge level:*** The discourse shows that members of Groups 3 and 5 contribute based on logical reasoning about the JSP scenario; their discussion conveys knowledge of context (in this case the environment of the moon) contrary to what we have in Groups 1,2, & 3 (see extracts in Table 1). The better collaboration we found in Groups 3 and 5 is in line with the *Vygotskian perspective* to group learning as mentioned in [25], which states that collaboration provides cognitive benefits when "a more expert member helps less-expert ones". It is also inline with the findings in Adeniran et al [4] about the *knowledge level* effect on collaboration, that there is a *knowledge level threshold* with respect to a task, that can foster good JPS collaboration during. Below this threshold, a group will not make a solution attempt at all or suggest unexplained erroneous solutions which hinders collaboration and cognition.

## 5 Conclusions

Few works have proposed a real-time approach to evaluate and monitor collaboration within online groups. We add 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 visualisations to provide real-time feedback to learners to scaffold collaboration, and measure both quantitatively and qualitatively the effect of such feedback on JPS.

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

Table 1: Extracts from group discussions[1]

Group 3:

```
Beowulf: Good Morning everybody
Epigha: What item do we think should have the highest ranking of 1?
        I suggest oxygen
Epigha: Any other suggestion?
Anonymous1: I think safety is most important, so life raft is my suggestion
Beowulf: My ratings were based on a few things know about the moon.
        // First: there is no atmosphere
        // Second: It is very cold
        // Third: there is no magnetic field
Epigha: If there is no atmosphere, how can you breathe without oxygen?
        I think you need to breathe before considering safety
```

Group 1:

```
Lucas: I think water should be 2
Ranco: Ok....same here...good
Lucas:Ranco, Any suggestion for 3?
Ranco: One case of dehydrated milk
...
United:Then the stellar map
United: As 4
Ranco: I think Magnetic compass 3
Ranco: Stella map 4
```

Group 2:

```
Carbon: Item 1= oxygen Item 2 = first aid
smith:I agree with this
oluwalonimi: 1. oxygen2. first aid3 self -inflating life raft
Carbon:Parachute kit no 3
oluwalonimi: 4. Parachute kit
Arrival: first aid, oxygen, water, milk, food, heat for warm up
then map to find yourself back to your original habitat
Carbon:I support arrival idea
Carbon:That means the order should be health, food then navigation
...
Arrival:parachute before water then the rest can follow
oluwalonimi:6 water
smith: item 5-water
Arrival:but I was thinking the parachute should be part of
the first aid
smith:6 dehydrated milk
oluwalonimi:ok 5 water6 milk
oluwalonimi: 7 map8 compass9 solar
```

Group 5:

```
Cg:I can write these down, I will do it in one line
    (and keep it in a text editor so it is not lost)
Cg: TestTest
...
Mide:YES, OXYGEN 1
Mide: 2, PARACHUTE
Cg: After that I think water. You will die from lack of
    air, water, food in that order. The cold may also kill
    you although not enough information is provided on your
    space suit or other things.
Cg:Why 2 parachute?
sir D:no to parachute
sir D:u r in space, so u wont be landing
Cg:The parachute is useful in that it is a large piece of material.
    But I do not think that high
sir D:no gravity
Cg:It can be used for things other than its intended use.
Cg:There is gravity but no atmosphere.
...
Ku: The main objective is to get to the mother ship
...
Cg:The main objective is to not die in a hostile environment.
    You could get on the life raft and have some way to push
    it off such that it eventually gets to the mothership
    but that is no use if you are dead.
```

Group 4:

```
Swift:Obviously, first place important thing is oxygen
Swift:Then water, followed by food
Swift:What do you think?
smart:Yes, oxygen... Correct
smart:Yes.. In that order
smart:Without it
smart:All those in order,
Swift:So, what do you think should be the next?
smart: A feel a magnetic compass
smart:Cos they would have to knw
smart:Where they wanna go
Swift: Yeahh...I agree
...
jade: followed by first aid
Swift:The matches come before the heating unit
...
jade: then the food
Swift: So what should be next after heating unit
```

We further aim to develop algorithms for a computer agent (taking our models as input) to stimulate participation and consequently scaffold collaboration.

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