9^{th} International Conference on Computational Social Science IC^2S^2
July 17-20, 2023, Copenhagen, Denmark

Saying the Right Thing at the Right Time: Task-Sensitive Theories of Team Communication Processes

Keywords: teams, groups, communication process, performance, tasks, generalizability

Extended Abstract

Over the decades, a question of perennial interest is what drives team performance: is it the right task design, the right member characteristics, or the right interactions (that is, the "communication process?") Among these factors, the communication process is a uniquely important ingredient because it is one of the team's most easily mutable elements. The task and member composition may not be changeable; for example, a newly-hired manager, brought on to launch a product, is given an existing team and a predetermined goal, and it is expensive to replace a team member or to initiate a major project pivot. On the other hand, it is much simpler and cheaper to adjust one's way of interacting with teammates. Thus, the ability to change a team's communication patterns can be a powerful tool for supercharging team performance.

But how, exactly, should one improve a team's communication patterns? Scholarship on teams offers an almost overwhelming set of options, including *balance in contributions* [4], *information exchange* [1], *positivity* [6], the *rhythm* and *tempo* of communication [5], and more (see reviews by Matthieu, et al., 2017 [3] and Marks et al., 2001 [2]). Further complicating matters, these communication features are often studied within the context of different focal tasks, and the relative importance of features may vary depending on the task at hand. For example, having balanced contributions may be more likely to help a brainstorming team succeed (since it would elicit a greater number and variety of ideas) than to help a trivia team succeed (since the team can perform well even if just one person knows all of the answers).

In this ongoing research, we answer the question, "what types of team communication processes are most beneficial for teams in different task contexts?" Specifically, we analyze empirical data from teams collaborating on various online tasks. During each interaction, teams communicate via chat (our source of the teams' communication process) while completing a task for evaluation (our dependent variable). We then use Natural Language Processing techniques to extract features from the teams' chat data corresponding to elements of team communication that appear in existing theories of team performance (such as balance in contributions, information exchange, positivity, and the other features named above). Finally, we use these features to identify how team communication patterns shift with task context — as well as to build predictive models for when a particular style of communication may be most effective.

As an illustration of our approach, in Figure 1, we present data from online experiments using two tasks: $N = 435$ teams completing a Room Assignment Task (also known as a Constraint Satisfaction and Optimization Problem, or CSOP) and $N = 348$ teams completing a Jury Deliberation Task. For CSOP, we measure performance using *efficiency* (defined as the team's score divided by time elapsed, which balances the dual goals of scoring high and working quickly), and for Jury Deliberation, we measure performance by the *size of the majority faction* (defined as the percentage of participants who agreed with the final verdict, as the task's goal was to persuade others). Both dependent variables were standardized and converted to binary variables — that is, teams were divided into those scoring either above or below the 50th percentile.

Next, we generate 18 features for each conversation (examples include the Gini coefficient, which measures balance in contribution, a feature measuring information exchange, and the quantities of words, messages, and characters). In Figure 1, we present a two-dimensional projection, using PCA, of the team conversation features across the two tasks. Notice that the data naturally separates into two clusters, suggesting that those participating in CSOP and those participating in the Jury Deliberation Task communicated in very distinct ways.

We also plot team performance: high-performing teams are represented with a filled circle, and low-performing teams with an empty triangle. Notably, high-performing teams in the CSOP task are all clustered in a similar region, whereas high-performing Jury teams are scattered throughout the space. Therefore, we anticipate that the chat features in our model will be more predictive of performance in CSOP compared to performance in the Jury Task.

This is indeed the case: a Random Forest model (using n = 500 trees and 4 variables at each split) for the CSOP data achieves an out-of-sample F1 score of 0.876 and an out-of-bag error of 23.95%, while a Random Forest model for the Jury data achieves an out-of-sample F1 score of only 0.538 and an out-of-bag error of 47.76%. By measuring variable importance using the mean decrease in Gini, we find that, for CSOP, the average word count across team members and the number of words spoken by the most talkative member were the two most predictive features. In contrast, these features were not predictive for the Jury Task. Further exploration of the CSOP model using logistic regression shows that, while the coefficient for average word count is negative, the coefficient for the words spoken by the most talkative member is positive. In other words, the data suggest that teams completing the CSOP task tend to perform better when a *single individual communicates more, while the team as a whole communicates less*. However, this strategy would not be effective for teams completing the Jury Task.

In this way, we produce a task-sensitive model of team performance, and we use it to predict when a style of communication would be effective (CSOP) and when it would be ineffective (Jury Deliberation). Our continued work includes greatly expanding the number of chat features, expanding the number of tasks, and ultimately building a more comprehensive theory about when different communication strategies will be useful under a variety of task circumstances. As we build this theory, we aim to conduct *de novo* experiments to validate our predictions on entirely new teams, both in the lab and in the field. Through this work, we hope to produce an "engine" that learns which team processes are important under a given circumstance, and ultimately refines our understanding of the ingredients for team success.

References

[1] Vicente González-Romá and Ana Hernández. Climate Uniformity: Its Influence on Team Communication Quality, Task Conflict, and Team Performance. *JAP*, 99(6):1042, 2014.

[2] Michelle A Marks, John E Mathieu, and Stephen J Zaccaro. A Temporally Based Framework and Taxonomy of Team Processes. *AMR*, 26(3):356–376, 2001.

[3] John E Mathieu, John R Hollenbeck, Daan van Knippenberg, and Daniel R Ilgen. A Century of Work Teams in the Journal of Applied Psychology. *JAP*, 102(3):452, 2017.

[4] Vlad Niculae and Cristian Danescu-Niculescu-Mizil. Conversational Markers of Constructive Discussions. *arXiv preprint arXiv:1604.07407*, 2016.

[5] Martina Oldeweme, Udo Konradt, and Max Brede. The Rhythm of Teamwork: Discovering a Complex Temporal Pattern of Team Processes. *Group Dynamics*, 2021.

[6] Yla R Tausczik and James W Pennebaker. Improving Teamwork Using Real-Time Language Feedback. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 459–468, 2013.

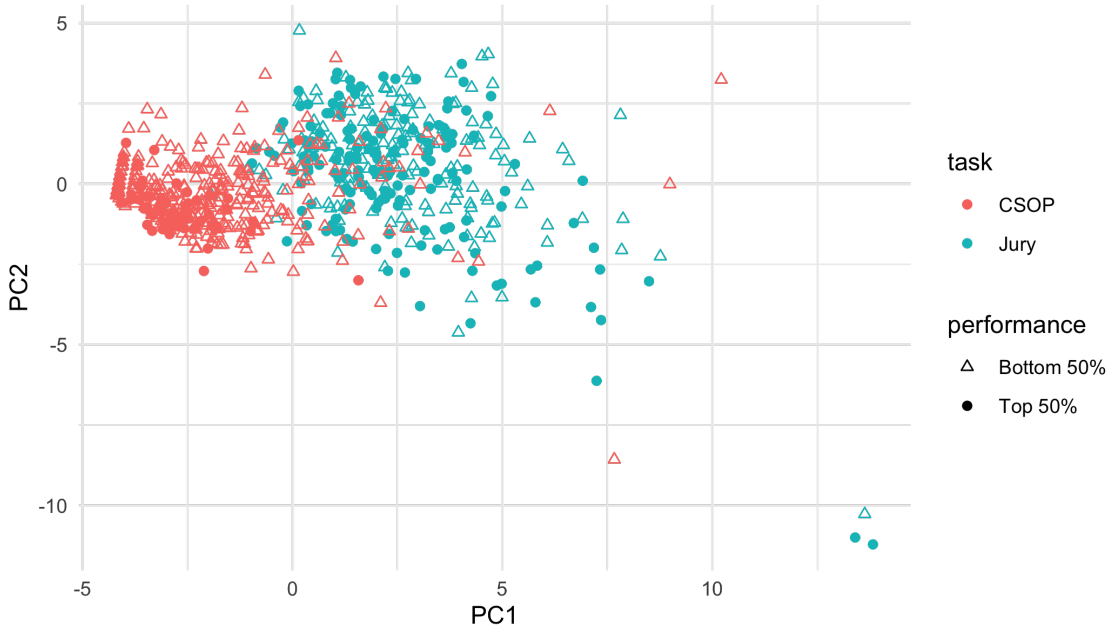

Figure 1: A two-dimensional projection, using Principal Component Analysis (PCA), of the $N = 435$ CSOP teams and $N = 348$ Jury Deliberation teams across 18 chat features. The CSOP teams are shown in red-orange, while the Jury teams are shown in blue. The distinct separation clusters of clusters by color suggest that teams performing the two types of tasks communicated in very different ways. Specifically, an exploratory interpretation of the first Principal Component (the x-axis) suggests that jury teams tend to have a much higher word and message count (unsurprising, since the task is focused around group discussion), and that contributions tend to be more egalitarian (e.g., team members participate more equally).

Further, teams performing in the top 50% are shown with a filled circle, and teams performing in the bottom 50% are shown with an empty triangle. Observe that filled circles tend to be clustered in one corner for CSOP teams, whereas filled circles are distributed more evenly for Jury Deliberation teams. This pattern suggests that the 18 chat features currently included in the model are more predictive for CSOP teams than Jury Deliberation teams.

These patterns are also reflected in our computational model, in which a CSOP team is predicted to perform higher if the team overall speaks less, but a single talkative individual speaks more.