Insights into the Emergence of Convergence in Group Discussions

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Abstract: Understanding how complex group discussions converge presents a major challenge for collaborative problem-solving research (Fischer & Mandl, 2005). From a complex systems perspective, convergence in group discussions is an emergent behavior arising from the transactional interactions between group members. Leveraging on the concepts of *emergent simplicity* and *emergent complexity* (Bar-Yam, 2003), a set of theoretically-sound yet simple rules was hypothesized: Interactions between group members were conceptualized as goal-seeking adaptations that either help the group move towards or away from its goal, or maintain its status quo. Operationalizing this movement as a Markov walk, we present quantitative and qualitative findings from a study of online problem-solving groups. Findings suggest high (low) quality contributions have a greater positive (negative) impact on convergence when they come earlier in a discussion than later. Significantly, convergence analysis was able to predict a group's performance based on what happened in the first 30-40% of its discussion.

Introduction

One of the major challenges facing collaborative problem-solving research is to understand the process of how groups achieve convergence in their discussions (Fischer & Mandl, 2005). Roschelle (1996) argued that convergence, as opposed to socio-cognitive conflict, is more significant in explaining why certain group discussions lead to more productive outcomes than others (Barron, 2003). Therefore, understanding the process of how multiple actors, artifacts, and environments interact and evolve in space and time to converge on an outcome is critical (Barab, Hay, & Yamagata-Lunch, 2001). Yet, generally speaking, measures and methods for conceptualizing the evolution of collaborative problem-solving processes as well as the emergence of learning remain lacking (Barab et al., 2001; Collazos, Guerrero, Pino, & Ochoa, 2002).

Increasingly, a realization of the inherent complexity in the interactional dynamics of group members (or agents) is giving way to a more emergent view of how groups function and perform (Arrow, McGrath, & Berdahl, 2000; Kapur, Voiklis, & Kinzer, 2005; Stahl, 2005). However, the use of complex systems in the learning sciences is relatively sparse, but gaining momentum (for a fuller review and treatment, see Jacobson & Wilensky, in press). A major thrust of such research is on the curricula, teaching, and learnability issues related to complex systems, and how they influence learning and transfer. However, complex systems also offer important theoretical conceptions and methodologies that can potentially expand the research tool-kit in the learning sciences (Jacobson & Wilensky, in press). Our proposal leverages on this potential to better understand how convergence emerges in group discussions. From a complex systems' perspective, convergence in group discussions can be seen as an emergent behavior arising from the local interactions between multiple actors, and mediated by tools and artifacts. But before delving any deeper, we discuss the concept of emergent behavior, particularly the distinction between *emergent simplicity* and *emergent complexity*; a distinction that is central to our proposal.

Emergent Simplicity versus Emergent Complexity

Central to the study of complex systems is how the complexity of a whole is related to the complexity of its parts (Bar-Yam, 2003). The concept of emergent behavior—how macro-level behaviors emerge from micro-level interactions of individual agents—is of fundamental importance to understanding this relationship. But, emergent behavior can be of different types. For many complex systems, their agents are themselves complex, and it is only intuitive to expect complex agents to result in a complex whole. But, is it possible for a system of complex agents to exhibit simple behavior? Although counter-intuitive, the answer is "yes." For example, a neuron comprises complex, autocatalytic, chemical systems. Yet, its behavior as a whole in interacting with other neurons is simple, often conceptualized as simple binary synapse. This type of emergent behavior, when complexity at the micro-level results in simplicity at the macro-level, is called *emergent simplicity* (Bar-Yam, 2003).

One must also consider the other possibility, in which a system of simple agents (or agents that exhibit simple behavior) may, as a whole, behave in a complex manner. For example, consider the brain as a system of neurons (agents). These neurons are complex themselves, but exhibit simple behavior in their synaptic interactions. Yet, these simple interactions between neurons collectively give rise to complex brain "behaviors"—memory, cognition, etc.—that cannot be seen in the behavior of individual neurons. This type of emergent behavior, when simplicity at the micro-level results in complexity at the macro level, is called *emergent complexity* (Bar-Yam, 2003).

The distinction between emergent simplicity and complexity is critical, for it demonstrates the possibility that a change of scale (micro vs. macro level) can be accompanied with a change in the type (simplicity vs. complexity) of behavior. In this paper, we use notions of emergent simplicity and complexity to conceptualize a group of individuals (agents) interacting with each other as a complex system. The group, as a complex system, consists of complex agents, i.e., just like the neurons, the individuals themselves are complex. Again, it is only intuitive to think that their behavior can be anything but complex and any attempt to model it via simple rules is futile. However, emergent simplicity suggests that this is not an ontological necessity. Their behavior may very well be modeled via simple rules. Further, emergent complexity suggests that doing so may reveal critical insights into the complexity of their behavior as a collective. It is this possibility that we explore and develop in this paper.

Purpose

We describe how convergence in group discussions can be examined as an emergent behavior arising from theoretically-sound yet *simple* teleological rules to model the collaborative, problem-solving interactions of its members (agents). We support our view empirically, through findings from a study of in-situ groups solving problems in an online, synchronous, chat environment.

Methodology

Research Context and Data Collection

Participants included sixty 11th-grade students (46 male, 14 female; 16-17 years old) from the science stream of a co-educational, English-medium high school in Ghaziabad, India. They were randomized into 20 triads and instructed to collaborate and solve either well- or ill-structured problem scenarios. Both ill- and well-structured groups were presented with an authentic car accident scenario that required the application of concepts in Newtonian kinematics. The study was carried out in the school's computer laboratory, where group members communicated with one another only through synchronous, text-only chat. The 20 automatically-archived transcripts, one for each group, contained the group discussions as well as their solutions, and formed the data used in our analyses.

Hypothesizing Simple Rules

The concept of *emergent simplicity* was invoked to hypothesize a set of simple rules. In other words, despite the complexity of the individual agents in the group, the impact of their interactions was conceived to be governed by a set of simple rules. As such, group members were conceived as transactionally interacting with one another in a goal-directed manner toward solving a problem (Barab et al., 2001). Viewed *a posteriori*, these transactional interactions seemed to perform a telic function, i.e., they operated to reduce the difference between the current problematic state of the discussion and a goal state. Thus, local interactions between group members can be viewed as operators performing a means-ends analysis in the problem space (Newell & Simon, 1972). From this, a set of simple rules follows naturally: Each interaction has an impact that:

i. moves the group *towards* a goal state, or
ii. moves the group *away* from a goal state, or
iii. *maintains* the status-quo (conceptualized as a "neutral impact").

Then, convergence in group discussion was conceived as an *emergent complexity* arising from this simple-rule-based mechanism governing the impact of individual agent-based interactions.

Operationalizing Convergence

Concepts from the statistical theory of Markov walks were employed to operationalize the model for convergence (Ross, 1996). First, quantitative content analysis (QCA; Chi, 1997) was used to segment utterances into one or more interaction units. The interaction unit of analysis was semantically defined as the impact(s) that an utterance had on the group discussion vis-à-vis the hypothesized simple rule. Two trained doctoral students independently coded the interactions with an inter-rater reliability (*Krippendorff's alpha)* of .85. An impact value of 1, -1, or 0 was assigned to each interaction unit depending upon whether it moved the group discussion toward (impact = 1) or away (impact = -1) from the goal of the activity—a solution state of the given problem, or maintained the status quo (impact = 0). Therefore, each discussion was reduced to a temporal string of 1s, -1s, and 0s.

More formally, let n_1, n_{-1}, and n_0 denote the number of interaction units assigned the impact values 1, -1, and 0 respectively up to a certain utterance in a discussion. Then, up to that utterance, the convergence value was,

$$C = \frac{n_1 - n_{-1}}{n_1 + n_{-1}}.$$

For each of the 20 discussions, convergence values were calculated after each utterance in the discussion, resulting in a notional time series representing the evolution of convergence in group discussion.

Results

Plotting the convergence value on the vertical axis and time (defined notionally with utterances as *ticks* on the evolutionary clock) on the horizontal axis, one gets a representation (also called a fitness curve) of the problem-solving process as it evolves in time. Figure 1 presents four major types of fitness curves that emerged from the discussion of the 20 problem-solving groups in our study. These four fitness curves contrast the high- with the low-performing groups (group performance is operationalized in the next section) across the well- and ill-structured problem types.

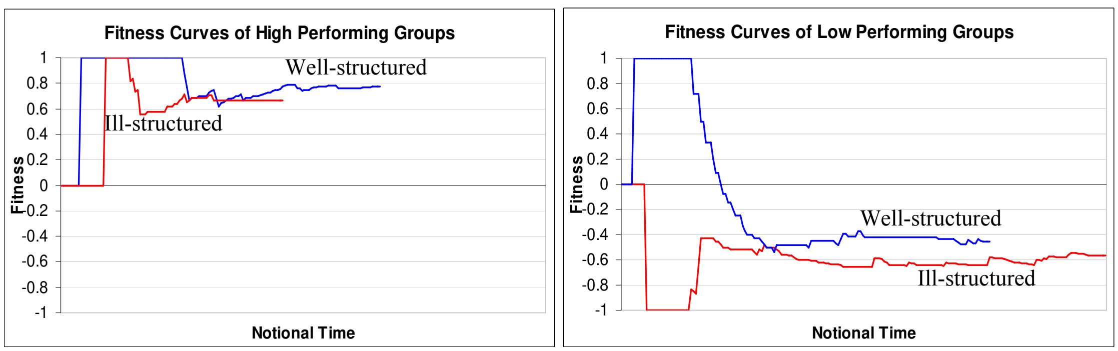

Figure 1. Fitness curves of high and low performing groups across problem types

Interpreting Fitness Curves

It is easy to see that the convergence value always lies between -1 and 1. The closer the value is to 1, the higher the convergence, and the closer the group is to reaching a solution. The end-point of the fitness curve represents the final fitness level or convergence of the entire discussion. From this, the extent to which a group was successful in solving the problem can be deduced. Furthermore, one might imagine that an ideal fitness curve is one that has all the moves or steps in the positive direction, i.e., a horizontal straight line with fitness equaling 1. However, the data suggests that, in reality, some level of divergence of ideas may in fact be a good thing (Schultz-Hardt et al., 2002), as can be seen in the fitness curves of both the high-performing groups.

The shape of the fitness curve, therefore, is also informative about the paths respective groups take toward problem solution. For example, in Figure 1, both the low-performing groups converged at approximately the same (negative) fitness levels, but their paths leading up to their final levels were quite different. The well-structured group showed a sharp fall after initially moving in the correct direction (indicated by high fitness initially). The ill-structured group, on the other hand, tried to recover from an initial drop in fitness but was unsuccessful, ending up at approximately the same fitness level as the well-structured group. Further, comparing the high-performing with the low-performing groups, one can see that the discussions of high-performing groups had fewer utterances, regardless of problem type. Finally, all fitness curves seemed to settle into a *fitness plateau* fairly quickly. What is most interesting is that this descriptive examination of fitness curves provides a view of paths to a solution that are lost in analysis systems that consider only a given point in the solution process, thus assuming that similar behaviors or states at a given point are arrived at in similar ways. As different paths can lead to similar results, unidimensional analyses that consider only single points in time (often only the solution state) are not consistent with what this study's data suggest about problem-solving processes.

Most important is a mathematical property of convergence. Being a ratio, convergence is more sensitive to initial contributions, both positive and negative, than those made later in the process. This can be easily seen because with each positive (or negative) contribution, the ratio's numerator is increased (or decreased) by 1. However, the denominator in the ratio always increases, regardless of the contribution being positive or negative. Therefore, when a positive (negative) contribution comes earlier in the discussion, its impact on convergence is greater because a unit increment (decrement) in the numerator is accompanied by a denominator that is smaller earlier than later. Said another way, this conceptualization of convergence allows us to test the following hypothesis: *"good" contributions made earlier in a group discussion, on average, do more good than if they were made later. Similarly, "bad" ones, on average, do more harm if they come earlier than later in the discussion*. To test this hypothesis, the relationship between convergence and group performance was explored by running a temporal simulation on the data set.

Exploring the Relationship between Convergence and Group Performance

The purpose of the simulation was to determine if the level of convergence in group discussion provided an indication of the eventual group performance. Group performance was operationalized as the quality of group solution, independently rated by two doctoral students on a 9-point rating scale with an inter-rater reliability (*Krippendorff's alpha*) of .95. The discussions of all 20 groups were each segmented into 10 equal parts. At each tenth, the convergence value up to that point was calculated. This resulted in 10 sets of 20 convergence values; the first set corresponding to convergence in the discussion after 10% of the discussion was over, the second after 20% of the discussion was over, and so on until the tenth set, which corresponded to the final convergence value of the discussion, i.e., after 100% of the discussion had occurred. A simulation was then carried out by regressing group performance on convergence values at each tenth of the discussion (hence, a temporal simulation), controlling for problem type (well- or ill-structured) each time. The *p*-value corresponding to the statistical significance of the predictive power of convergence at each tenth of the discussion on eventual group performance was plotted on the vertical axis (see Figure 2).

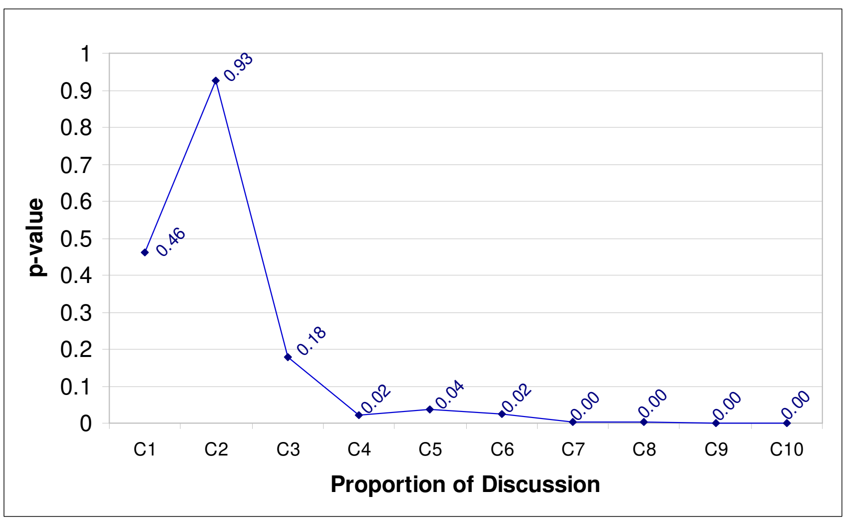

Figure 2. Simulation of the significance of convergence in predicting group performance

C1 through C10 denote the 10 equally spaced instances in each discussion at which the convergence values were calculated. The simulation suggested that, on average, at some point after 30% but before 40% of the discussion is over (i.e., between C3 and C4 in Figure 2), the convergence value is able to predict eventual group performance at the .05 level of significance or better. This shows that convergence is a powerful measure that is able to model the impact that early contributions have on eventual group performance. This insight bears important implications for scaffolding group discussions to achieve optimal outcomes. For example, if one's interest is primarily in maximizing group performance, the insight suggests a need for scaffolding early in the discussion, since the impact of early interactional activity on eventual group performance seems to be greater. Scaffolding earlier parts of a group discussion may increase its likelihood of settling into higher fitness plateaus; the higher the fitness plateau, the better the group performance, on average. This insight is in and of itself a significant finding, but since participation in high-performing groups is consistently (and not surprisingly) a strong predictor of subsequent individual learning gains (e.g., see Barron, 2003; Cohen et al., 2002), we believe it makes it all the more significant, for it demonstrates strong connections to group and individual learning.

To delve deeper into what makes convergence a powerful measure, micro-analytical interactional analysis sheds more light. Given the constraints on the page limit, we present a very brief analysis of the following excerpt containing an exchange between group members S1 and S2.

S1 > *are we going to apply frictional retardation for the reaction time also?*	-1
S2 > *no, because reaction time is the time between watching the boy and applying the brakes so in this time car must be accelerating*	1, 1
S1 > *but I think we must not forget that the car is moving on the same road on which the incident occurs and the road is providing the retardation*	-1, -1
S2 > *but maximum speed is at the instant when he applied the brake*	1
S1 > *but earlier you said that the car will accelerate after perceiving the boy*	-1
S2 > *I said so because his foot must be on accelerator during reaction time*	1
S1 > *Now I understand… please proceed to write your answer*	1, 1

Recall that the problem involved a car-accident scenario. In this excerpt, S1 and S2 are trying to decide whether or not reaction time of the driver of the car that was involved in the accident should factor into their calculations. The excerpt starts with S1 asking a question about applying frictional retardation during reaction time of the driver. Being a misconception, it was rated as having a negative impact (-1). S2 evaluates S1's question and says '*no*,' attempting to correct the misconception. Hence, its positive (+1) impact rating. In the same utterance, S2 elaborates why frictional retardation should not to be applied, further positively impacting the group's progress. The argument continues with S1 persisting with the misconception (assigned negative impacts) until S2 is able to convince S1 otherwise (assigned positive impacts), thereby converging on a correct understanding of this aspect (dealing with friction during reaction time) of the problem given to them. Note that had S2 wrongly evaluated and agreed to S1's misconception, the impact ratings would have been negative, which, without any further correction, would have led the group to diverge from a correct understanding of that very aspect of the problem.

This analysis, albeit brief, shows that impact ratings are meaningful only in relation to preceding utterances (Bransford & Nitsch, 1978) and take into account the sequence and temporality of collaborative interactions (Kapur et al., 2005). Other examples of highly convergent discussion episodes would include agreement with and positive evaluation and development of correct understandings of the problem, solution proposals, and problem solving strategies. As a result, despite the groups solving different types of problems (well- or ill-structured), their performance depended mainly upon the convergence of their discussions. Because convergence takes into account both the number as well as the temporal order of the units of analyses, it utilizes a greater amount of information present in the data. This makes convergence a more powerful measure, both conceptually and statistically, than existing predictors that do not fully utilize the information present in interactional data. If this is the case, then the following hypothesis should hold up: *convergence is a more powerful predictor of group performance than existing, commonly-used interactional predictors*.

Comparing Convergence with other commonly-used Interactional Predictors

Many studies of collaborative problem solving, including this one, use QCA to operationalize measures for problem-solving processes. These measures typically result in data about the frequency or relative frequency of positive indicators (e.g., higher-order thinking, questioning, reflecting, etc.), or negative indicators (e.g., errors, misconceptions, lack of cooperation, non-task, etc.), or a combination that adjusts for both the positive and negative indicators (e.g., the difference between the frequencies of high- and low-quality contributions in a discussion). In this study, we operationalized three measures to represent typical measures:

i. Frequency (n_1 : recall that this is the number of interaction units in a discussion with impact = 1),

ii. Relative Frequency ($\frac{n_1}{n_1 + n_0 + n_{-1}}$), and

iii. Position ($n_1 - n_{-1}$).

Convergence ($\frac{n_1 - n_{-1}}{n_1 + n_{-1}}$) formed the fourth measure.

Multiple linear regression was used to simultaneously compare the significance of the four measures in predicting group performance, controlling for problem type in each case. The overall model was significant (*F* =

6.391, p = .003). Results in Table 1 suggest that, of the four predictors of group performance, convergence was the only one significant (t = 2.650, p = .019), thereby supporting our hypothesis. In other words, consistent with our hypothesis, convergence seems to be a more powerful predictor of problem-solving performance when compared to existing, commonly-used predictors.

Table 1. Regression Parameter Estimates of the Interactional Variables & Problem Type

	B	**SE**	**Beta**	***t***	***p***
(Constant)	-1.778	1.693	.	-1.051	.311
Frequency	.006	.021	.239	.268	.793
Relative Frequency	1.541	2.792	.116	.552	.590
Position	-.012	.024	-.446	-.513	.616
Convergence	5.338	2.014	.839	2.650	.019*
Problem Type	-.050	.544	-.021	-.092	.928

Implications and Future Directions

Leveraging on the concepts of emergent simplicity and emergent complexity, this study hypothesized a set of theoretically-sound yet simple rules to model the micro-level problem-solving interactions between group members, and then examined the resulting emergent behavior (convergence in their discussion). Insofar as we are aware, the analysis revealed novel insights into the process of collaboration. The first insight concerned the differential impact of contributions in a group discussion—high (low) quality contributions have a greater positive (negative) impact on the eventual outcome when they come earlier than later in a discussion. A corollary of this finding was that eventual group performance could be predicted based on what happens in the first 30-40% of a discussion because group discussions tended to settle into fitness plateaus fairly quickly. Finally, convergence was shown to be a more powerful predictor of group performance than some existing, commonly-used measures. These insights are significant, especially since participation in high-performing groups is a strong predictor of subsequent individual learning gains (e.g., see Barron, 2003; Cohen et al., 2002). In other words, this conceptualization and analyses of convergence demonstrates strong connections to group performance and individual learning.

At a more conceptual level, the idea that one can derive meaningful insights into a complex interactional process via a simple rule-based mechanism, while compelling, may also be unsettling and counter-intuitive. Hence, a fair amount of intuitive resistance to the idea is to be expected. For instance, it is reasonable to argue that the extreme complexity of group interaction—an interweaving of syntactic, semantic, and pragmatic structures and meanings operating at multiple levels—make it a different form of emergence altogether and, therefore, insights into complex interactional processes cannot be gained by using simple-rule-governed methods. However, a careful consideration of this argument reveals an underlying ontological assumption that complex behavior cannot possibly be explained by simple mechanisms. Saying it another way, some may argue that *only* complex mechanisms (e.g., linguistic mechanisms) can explain complex behavior (e.g., convergence in group discussion). Of course, this is indeed a possibility. But, notions of emergent simplicity and emergent complexity suggest that this is not the "only" possibility (Bar-Yam, 2003), especially given our knowledge of the laws of self-organization and complexity (Kauffman, 1995).

It is noteworthy that emergent complexity is also integral to the theory of dynamical minimalism (Nowak, 2004) used to explain complex psychological and social phenomena. Dynamical minimalist theory attempts to reconcile the scientific principle of parsimony—that simple explanations are preferable to complex ones in explaining a phenomenon—with the arguable loss in depth of understanding of that phenomenon because of parsimony. Using the principle of parsimony, the theory seeks the simplest mechanisms and the fewest variables for explaining a complex phenomenon. It argues that this need not sacrifice depth in understanding because simple rules and mechanisms repetitively and dynamically interacting with each other can produce complex behavior: the very definition of emergent complexity. Thus, parsimony and complexity are not irreconcilable, leading one to question the assumption that complex phenomena necessarily require complex explanations.

Therefore, the conceptual and methodological implication from this study is not that complex group behavior ought to be studied using simple-rule-based mechanisms. It is more that exploring the possibility of modeling complex group behavior using simple-rule-based mechanisms is a promising and meaningful endeavor. Leveraging on this possibility, this study demonstrated one way in which simple-rule-based mechanisms can be used to model convergence in group discussion, in turn revealing novel insights into the collaborative process. The proposed measures of convergence and fitness curves have been intentionally and conceptually designed to be generic and can, therefore, easily be applied to other problem-solving situations. Hence, they also provide a platform for the development of more sophisticated measures and techniques in the future.

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