

Dynamics of social interaction: Modeling the genesis of scientific collaboration

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Collaboration plays a key role in physics and in the broader scientific enterprise. Here we develop a mathematical model for predicting new collaborations. We demonstrate that a simple ordinary differential equation model is a good fit to a data set that tracks collaborations resulting from four series of annual conferences on diverse scientific topics, 12 conferences in total over a period of five years. The model, inspired by the physics of catalysis, attempts to quantify the time-varying probability that any pair of individuals will initiate a new collaboration. It takes as input the pair's prior familiarity with one another as well as their pattern of interaction over time, and incorporates the effect of temporally decaying memory. This model accurately reproduces the collaborations formed across all first-year conferences in the four series and outperforms seven other candidate models. We also find evidence that prescribed interaction can lead to novel team formation, with observed collaboration probabilities increased by almost an order of magnitude. These results suggest that encounters among individual researchers at conferences, including encounters engineered by organizers, play an important role in shaping the future of science.

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I. INTRODUCTION

Physics-based models for social phenomena have had significant success in recent years (see, e.g., Refs. [1–6] and review papers [7–9]). In particular, the tools of statistical mechanics and nonlinear dynamics have been usefully applied to a wide range of phenomena from political polarization to team decision making to human activity prediction. In this work we attempt to develop a physical model for the catalysis of new collaboration¹ formation among scientists attending conferences.

The scientific enterprise has increasingly become a team effort [10–13]; the typical number of coauthors on physics papers has increased drastically since the 1960s [14]. Some evidence also suggests that multiauthor teams are more productive and do work that is more novel [15,16]. There are, however, intellectual, technical, and logistical obstacles, which impede the formation of new teams [17]. In particular, research has shown that geographical proximity is a

factor in team assembly [18]. Conferences can help overcome these barriers and are one of the main catalysts for the formation of new scientific collaborations. However, convening conferences is expensive in terms of organizational, travel, environmental, and opportunity costs; the direct monetary cost for academic meetings alone is estimated at multiple 10^9 of US dollars each year [19,20].

Past research has mostly focused on measuring or modeling various aspects of scientific collaborations (understood as coauthorship on publications) once formed [21–23] and the makeup of successful teams (including, e.g., metrics such as the number of institutions present [24], team size [16], and team freshness [25]). There have been some efforts to study scientific team assembly (see, e.g., Refs. [12,17,26,27]), but little is still known about the impact of conferences on collaboration initiation. Some limited evidence, however, demonstrates that increased interaction among potential members raises the likelihood of team formation [28–30].

Here we present evidence that properly engineered interaction leads to collaboration, and we go beyond empirical observation by proposing a mathematical model for the origin of this phenomenon. Such a model has the potential to allow for optimization of conference design to promote collaboration.

II. NOVEL DATASET

We constructed a longitudinal data set derived from a diverse set of conferences known as “Scialogs” [31]. Organized by the nonprofit funding agency Research Corporation for

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¹We use the terms “collaboration,” “team formation,” and “team assembly” interchangeably, as these terminologies can all be found in the literature designating the same phenomenon.

TABLE I. Conference statistics.

Conference	Year	Topic	Part.	Fellows	Pairs of Fellows
A	2015	Molecules Come to Life	64	52	1326
B	2015	Time Domain Astrophys.	59	49	1176
C	2017	Advanced Energy Storage	71	60	1170
D	2018	Chem. Machin. of the Cell	60	50	1225

Science Advancement (RCSA), these conferences seek to accelerate the work of science through research, intensive dialog, community building, and by catalyzing new scientific collaborations on challenges of global significance. Scialog conferences last three days and have an interactive format, with the participation of around 50 fellows, who are invited early-career scientists, and around ten facilitators, who are more senior scientists. Participants are assigned to small- (three to four people) and medium-sized (eight to ten people) sessions and self-assemble into teams at the end of the conference to submit proposals, five to eight of which are funded. For each conference, we have detailed records including: how well each participant knew the other participants before the conference (prior knowledge K_0), which sessions they attended [this defines the pairwise interaction profile $I(t)$], and with whom they wrote proposals (collaborated). Although Scialog conferences are multiyear initiatives, we focus here on the first year to omit effects of repeated participation. See Table I for conference statistics.

III. EMPIRICAL RESULTS

We first tested whether pairs who collaborated were different from pairs that did not in terms of total effective interaction I_{tot} , proportional to the time spent in a session and inversely proportional to its size (see Supplemental Material (SM) [32]). To do so, we employed the Mann-Whitney U test [33]; metrics were computed for each conference individually as well as aggregations of the conferences. All metrics indicate that collaborators have significantly more interaction than noncollaborators (see Fig. 1). The right panel of Fig. 1 shows that collaborators spent 63% more total effective time together than noncollaborators on average across all conferences. This is equivalent to being in a group of 12 people for an extra 45 m (60% of the duration of a topical discussion session) or being in a group of four people for an extra 15 m (50% of the duration of a small group session).

To disentangle causality from correlation for the effect of interaction on collaboration initiation, we performed a test based on 2500 counterfactual schedules for one of the conferences (see SM for details). For each counterfactual schedule, we computed the mean interaction² for all pairs that, in the actual conference, ended up collaborating, denoted $\bar{I}_{\text{CF}}$. We found that the mean interaction at the actual conference $\bar{I}_A$ was nearly always much greater; this was true for more than 99% of the counterfactual schedules. The only cases

where $\bar{I}_{\text{CF}}^i > \bar{I}_A$ was observed corresponded to counterfactual scenarios sharing the same exact small-group session assignments but with variations in the larger topical discussion session assignments. Note that this method enabled us to blindly recover the small-group assignments knowing only which pairs ultimately collaborated, which strongly suggests a causal connection between intense interaction in a small-group setting and team formation. To quantify the statistical significance of this result, we performed a Wilcoxon signed-rank test [34]. The null hypothesis that the distribution of $\bar{I}_A - \bar{I}_{\text{CF}}$ has zero median is rejected at the 10^{-5} level of significance. See Fig. 2 for a graphical display of this result.

In addition to showing that interaction has a statistically significant effect on collaboration probability, we also wish to know the size of the effect. To evaluate that, we restrict our data to pairs with prior knowledge $K_0 = 0$ ($N = 984$) and used bootstrap statistics to estimate the odds of collaboration for pairs who coattended one minisession (0.15, 95% CI [0.10 0.21]) and those who did not coattend any minisession, but could have in one of the 2500 counterfactual scenarios (0.017, 95% CI [0.0085 0.028]). In this case, coattending a minisession multiplied the chance of a pair collaborating by 8.7.

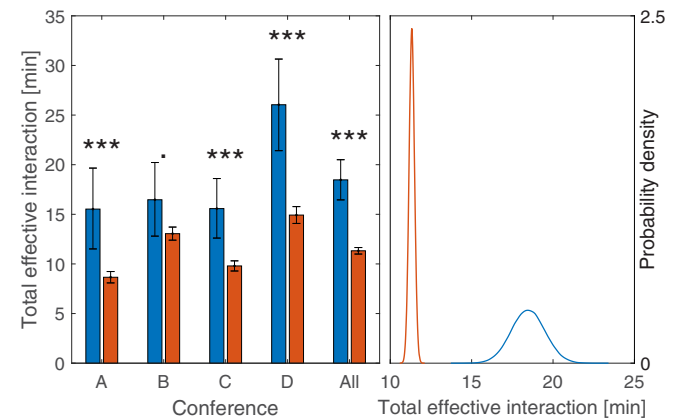


FIG. 1. Effect of interaction on collaboration. Left: Blue (left) and red (right) paired bars show bootstrap estimates for mean total effective interaction time for collaborators and noncollaborators, respectively. Paired bars are shown for each conference analyzed (A–D) as well as the combined data set of all conferences (All). p values of the Mann-Whitney U test for A: 6.0×10^{-4} , B: 6.3×10^{-2} , C: 1.4×10^{-4} , D: 7.7×10^{-6} , All: 1.0×10^{-12} . Error bars show mean values of the bootstrapped data with 95% confidence intervals. Right: kernel density estimates showing bootstrapped mean total effective interaction time distributions for collaborators (blue, right) and noncollaborators (red, left) for combined data set of all conferences.

²Here for brevity and clarity we use the word “interaction” to mean total effective interaction over the course of the conference.

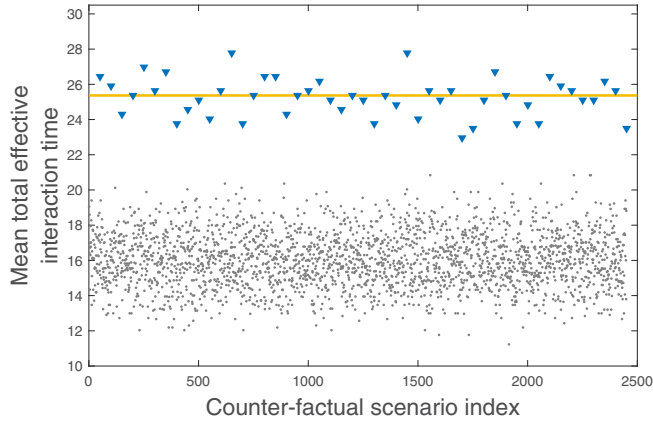


FIG. 2. Mean total effective interaction of collaborators. Yellow line represents the actual conference, blue inverted triangles are the counterfactual conference solutions where the collaborators were in the same small groups as in the actual conference. Gray points are the other counterfactual conference solutions.

IV. MODEL

Beyond empirical observations, we develop a mechanistic model for the dynamics of team formation at conferences. In 1996, the physicist Serge Galam wrote: “Do humans behave like atoms?” [35]. The model we present is based on the idea that scientists at a conference behave like molecules in a solution, where formation of a collaboration is analogous to undergoing a chemical reaction. The conference itself acts as a catalyst by lowering the barriers to collaboration and creating more productive collisions among the scientists who participate. The model takes as input the pairwise levels of interaction $I(t)$ among conference participants as well as their prior knowledge K_0 of one another, and estimates the probability $P(t)$ that any pair of participants will subsequently form a collaboration.

As a first simple model, consider a pair of attendees at a conference. We assume that collaboration probability $P(t)$ rises for nonzero interaction intensity I between participants, and when interaction ceases, probability of a collaboration forming decays. For simplicity we assume linear growth and decay processes, leading to the following ordinary differential equation (ODE) governing the change in collaboration probability over time:

$$\frac{dP}{dt} = \underbrace{S \frac{I}{I_{\max}} (1 - P)}_{\text{strengthening}} - \underbrace{WP \left(1 - \frac{I}{I_{\max}}\right)}_{\text{weakening}}. \quad (1)$$

To understand the changes in collaboration probabilities that may occur during the course of a conference, we focus on the case where $I = I(t)$ is not constant, representing the time-varying strength of interaction between two individuals. Figure 3(a) shows a realistic looking example for a two-day conference, with three sessions of different lengths and intensities, one small (four people) and two larger (12 people) in this example. Note that $I(t)$ is a dimensionless quantity; for more details on how $I(t)$ was constructed from data, see SM.

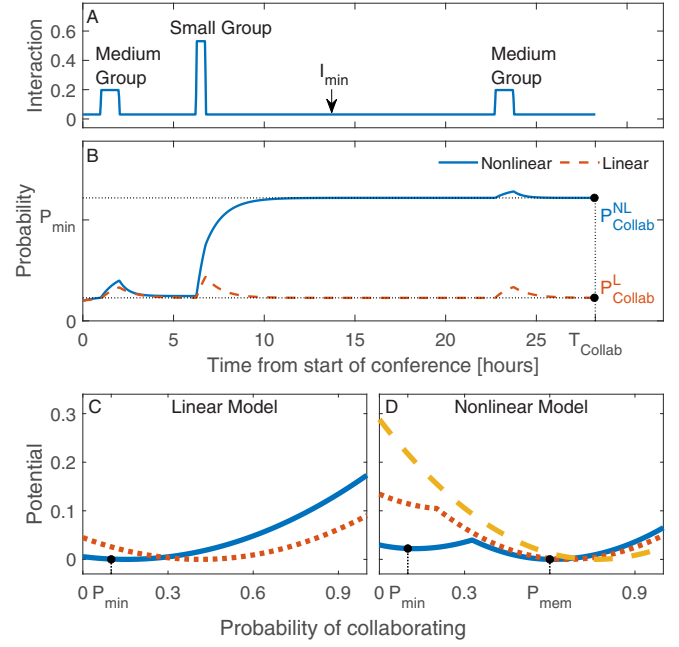


FIG. 3. Model examples. (a) Effective interaction $I(t)$ and (b) corresponding probability of collaboration as a function of time for a single pair of participants at a realistic conference. Example potential for (c) linear model, and (d) nonlinear catalysis model. In (b), solid blue curve shows the probability for the nonlinear catalysis model and dashed red curve shows the probability for the linear model. T_{Collab} is the time at which teams of participants are formed, $P_{\text{Collab}}^{\text{NL}}$ ($P_{\text{Collab}}^{\text{L}}$) is the probability at this time for the nonlinear (linear) model. In (c) and (d), solid blue curve shows potential for minimal interaction, dotted red curve shows potential for medium interaction (medium group), and in (d) dashed yellow curve shows potential for high interaction (small group). Parameter values are the same for linear and nonlinear models where applicable, selected for illustrative purposes ($a = 0.02$, $I_c = 0.1$; $I_{\max} = 0.6$; $P_{\min} = 0.1$; $P_{\text{mem}} = 0.6$; $P_{\max} = 0.9$; $W = 1$; $S = 0.5$).

We can express the right-hand side of Eq. (1) as the derivative of a potential function $V(P)$:

$$\frac{dP}{dt} = -\frac{\partial V}{\partial P}, \quad (2)$$

where the minus sign implies that stable equilibria occur at potential minima. Since Eq. (1) is linear, the resulting potential is quadratic, with a local minimum somewhere in $0 \leq P \leq 1$ (depending on I). Figure 3(c) shows examples of such potentials.

We expect the linear model described above to capture some of the dynamics of formation of new scientific collaborations during conferences. One major limitation, however, is that the linear model relaxes to zero after interaction has ceased, which implies that participants completely forget one another. For a more realistic generalization, we wish to allow scientists who have interacted sufficiently to remember one another long after the interaction has ceased. To implement this, we modify the potential landscape for a new nonlinear model as shown in Fig. 3(d).

When interaction $I = 0$, there are two stable equilibria, one at the minimum probability $P_{\min}$, and the other at memory

TABLE II. Model selection.

Conf.	Nonlinear Model AIC	Next Best Model AIC	Next Best Model	Relative Likelihood
A	375.88	385.62	$aK_0 + bI_{\text{tot}} + c$	0.0077
B	337.02	340.79	$aK_0 + b$	0.15
C	522.91	541.64	$aK_0 + bI_{\text{tot}} + c$	8.6e-05
D	407.96	430.53	$aI_{\text{tot}} + b$	1.3e-05

state P_{mem} , with an unstable equilibrium in between. As the interaction increases, it acts as a catalyst by changing the shape of the potential function and reducing the barrier between the two stable states. At a critical value of the interaction I_c a bifurcation occurs and the barrier disappears, leaving only a single stable equilibrium. If the system gets sufficiently close to that new equilibrium before interaction ceases, the probability will remain permanently in the higher memory state P_{mem} . See SM for exact form.

V. MODEL SELECTION

We validate the nonlinear catalysis model by testing how well it explains which pairs of participants ultimately collaborated. The probability of collaborating is the output of the model at time $t = T_{\text{Collab}}$ (see Fig. 3), the start of the period allocated for team formation and proposal writing at the end of the conference. We compared the quality of the nonlinear catalysis model to seven null models by computing the Akaike information criterion (AIC) [36] and relative likelihood for each one. Table II shows that the AIC of the nonlinear catalysis model is lower compared to the next best model for conferences A, B, C, and D, indicating that it is the preferred model for all four conferences.

VI. DISCUSSION

Our analysis is predicated on the quality of interpersonal interactions as well as their quantity. Impromptu meetings around the coffee maker may differ from those at a conference where participants were encouraged to have a specific conversation and incentivized to form teams through a grant-awarding process, as was the case in the data set analyzed here. Another limitation of this proposed model is that we do not explicitly account for many issues likely affecting team assembly such as personality characteristics, homophily, and distance between research areas. However, our approach implicitly incorporates these to some extent through its prob-

abilistic nature. They could also be explicitly incorporated in a more complex future model, but we see the success of the nonlinear catalysis model as remarkable precisely because of its simplicity.

The nonlinear catalysis model is not necessarily limited to scientific conferences and collaboration; we speculate that it may also have applicable extensions in other areas where matches between individuals within a network are sought. For example, in business settings, employers may wish to promote organic team building through prescribed sessions among employees. In romantic contexts, a model could inform online dating algorithms and approaches to social interaction. In pedagogical settings, educators might use in-class prescribed group exercises to promote formation of student study groups or teams for collaborative assignments.

VII. CONCLUSIONS

Scientific conferences play an important role in the diffusion of knowledge and generation of novel ideas. We have shown that properly engineered interaction at conferences induces the formation of new scientific collaborations. Our model helps to illuminate the mechanism by which this occurs, and we hope that it will play a role in designing more efficient future conferences to maximize their benefit for physics and science in general. A web application that allows users to interactively explore the model can be found at [37].

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