Incentivizing social diffusion on networks using a novel game-theoretic model

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Introduction — Social diffusion is a key phenomenon in human societies through which social conventions, such as greetings or grammatical rules in languages, change and evolve. In a population universally supporting a status quo convention, diffusion often begins through a stubborn committed minority introducing a novel alternative convention. If this alternative is then adopted by part of the uncommitted population, a critical mass may be reached to unlock social diffusion. In order to better model this phenomenon, it is important to understand the complex behavioral mechanisms that govern the human decision-making process behind adoption of the alternative. Agent-based models, in particular those based on game theory, are strongly suited to this task. In particular, coordination games have been used to capture the mechanism of *social coordination* [4, 3]. However, these models do not capture key recent developments from the social psychological literature, which suggest that *inertia* and *trend-seeking* are behavioral mechanisms that also feature in key roles during social diffusion [6, 7]. The former refers to the inclination of an individual to be consistent with previous choices [6], while the latter refers to an individual being influenced by dynamic trends of changes seen in the population [7]. Part of the work presented here is based on [8].

Experiment — We design and conduct an online experiment involving a multi-round game to unveil the role of inertia and trend-seeking in shaping social diffusion. Partially inspired by the work in [2], the experiment requires a group of players to reach a consensus over a binary choice through repeated revised decisions. A committed minority (comprised of computer bots) first enforces a *status-quo* majority, and then starts promoting the *alternative*. More details on the design of the experimental paradigm can be found in [5, 8]. The experiment provides statistically significant evidence that social coordination, inertia, and trend-seeking are all present and important in each participant's decision-making process during social diffusion [8]. Moreover, our experimental data highlights some key features of social diffusion. At the population level, we observe that diffusion may not always occur and, even if it does, its take off may be strongly delayed due to the presence of inertia. However, if a tipping point is reached, then the innovation explosively diffuses within a few rounds, under the impact of trend-seeking (see Fig.1a). At the individual level, we observe a moderate and heterogeneous rate of changing choice due to the participant population having heterogeneous susceptibility to the two behavioral mechanisms.

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LZ and MC are supported in part by the European Research Council (ERC-CoG-771687). MY is supported in part by the Western Australian Government, under the Premier's Science Fellowship Program.

Model — Based on the experimental evidence described in the above, we propose an agent-based model that encapsulates these three behavioral mechanisms. Consider a set $\mathcal{V} = \{1, ..., n\}$ of $n \geq 2$ individuals interacting on an undirected network $(\mathcal{V}, \mathcal{E})$, where $\mathcal{N}_v := \{j : (ij) \in \mathcal{E}\}$ is the set of neighbors of individual v and $d_v := |\mathcal{N}_v|$ its degree. Individuals are partitioned into committed minority $\mathcal{C}$ and uncommitted population $\mathcal{U}$. Each individual $v \in \mathcal{U}$ can choose between two strategies: the status quo (0) and the alternative (1). At each discrete time-step, each uncommitted individual $v \in \mathcal{U}$ revises their strategy (denoted by $x_v(t)$) according to log-linear learning dynamics [1]:

$$\mathbb{P}[x_v(t+1) = x] = \frac{\exp\{\beta_v \pi_v^1(t)\}}{\exp\{\beta_v \pi_v^0(t)\} + \exp\{\beta_v \pi_v^1(t)\}}, \tag{1}$$

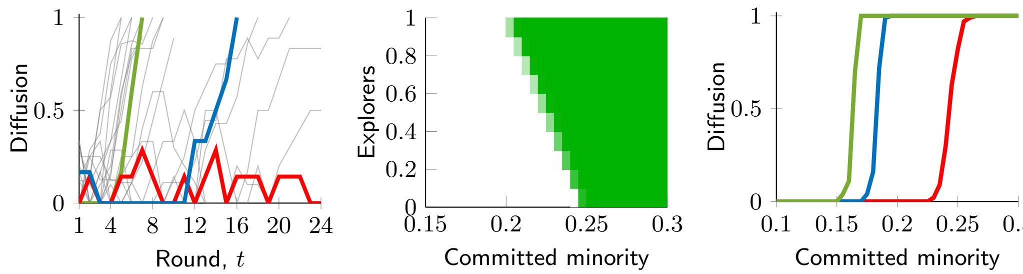
where $\beta_v \geq 0$ is a measure of the *rationality* of individual v. The function $\pi_v^1(t)$ is the payoff of $v \in \mathcal{V}$ for adopting the alternative (1) at time t, and is given by

$$\pi_v^1(t) = b_v \frac{1}{d_v} \sum_{w \in \mathcal{N}_v} x_w(t) + k_v x_v(t) + r_v \hat{x}_v(t)\,, \tag{2}$$

where b_v, k_v, r_v are non-negative scalar constants such that $b_v + k_v + r_v = 1$ for all $v \in \mathcal{U}$ and $\hat{x}_v(t) = \frac{1}{2}[1 + \frac{1}{n-1} \sum_{w \in \mathcal{V} \setminus \{v\}} (x_w(t) - x_w(t-1))]$. The payoff for adopting the status quo, $\pi_v^0(t)$, is defined in a similar fashion (see [8]). The payoff is a convex combination of three separate terms: the first being a standard social coordination term [4, 3] that captures the individual's desire to coordinate strategy with their neighbors; the second one captures inertia by increasing the payoff for sticking with the current strategy; the third one encapsulates trend-seeking, providing an increased payoff for choosing the strategy whose popularity has increased in the previous time step. The decisions of the committed minority $v \in \mathcal{C}$, instead, can be designed as an a control input for the system.

Using the Model to Study Social Diffusion — First, we parametrize the model using our individual-level experimental data, identifying two different types of individuals: *explorers*, who are highly sensitive to trends (large r_v), and *non-explorers*, who are more grounded by inertia (large k_v). Second, we verify that the model reproduces the population-level patterns of social diffusion observed in the experiment (in contrast to models that do not incorporate all three behavioral mechanisms, cf. [8]). Finally, we utilize the model to perform Monte Carlo simulations to explore the system dynamics beyond practical experimental limitations. We examine the effects of inertia and trend-seeking on large-scale populations and over arbitrary interaction networks, in contrast to the experiment involving small groups and all-to-all communication. As an example, Fig. 1b shows how the size of the committed minority stubbornly supporting the alternative and the characteristics of the population (ratio of explorers vs non-explorers) can determine whether social diffusion occurs.

Unlocking Social Diffusion on Networks — The calibrated model can then used to assess different strategies to incentivize social diffusion on networks. A key question to address is *where and when should we introduce a finite number of committed minority into the network to facilitate social diffusion?* In a preliminary analysis, reported in Fig. 1c, we numerically compare three strategies for introducing committed minority (CM) individuals



(a) Experimental results (b) Social diffusion (c) Incentivization

Fig. 1: (a) Patterns of social diffusion observed in the experiment. (b) The color intensity represents the fraction of successful diffusions over 100 independent runs (green: diffusion occurred; white: no diffusion), for different size of committed minority and fraction of explorers in a fully-connected network. (c) Fraction of successful diffusions over 100 runs in scenarios i) (red), ii) (blue), and iii) (green). (a) and (b) are from [8].

on an Erdos-Renyi random graph: i) introducing all CM individuals at time $t = 1$ in randomly chosen nodes; ii) introducing all CM individuals at $t = 1$ at the nodes with highest (Bonacich) centrality of the network; and iii) introducing CM individuals at the nodes with highest centrality, gradually over 20 time steps. The results suggest that both the position and timing are important: placing CM individuals in central nodes makes them more influential thanks to the role of social coordination, introducing them over time simulates a trend, to which individuals are sensitive. Hence, strategy iii) outperforms the others in terms of favoring social diffusion. Ongoing research aims at considering more complex network structures, toward understanding how other features (e.g., presence of clusters, assortativity) can be exploited to facilitate social diffusion.

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