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An agent-based model for the formation of common ground

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Abstract: Common ground is the shared meaning and understanding between a group of people, and is required for communication and information exchange. We present a novel agent-based model to describe how common ground forms through repeated interactions between a sender and a receiver. Simulations reveal a range of emergent phenomena, including a global common ground or clusters of different common ground in the same network, depending on the interaction environment and the amount of information available for communication.

Keywords: *Psycholinguistics, social psychology, complex networks, social dynamics, information environment*

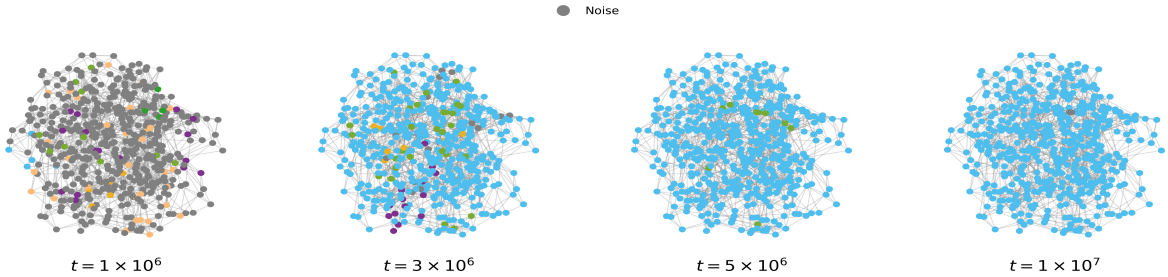
1 INTRODUCTION

Information sharing is a fundamental process in society (Kashima et al., 2019). It can allow knowledge propagation across groups and generations, preserving or changing culture through the rejection or adoption of new norms and practices. It can also bring harm through the spread of mis/disinformation, hate speech and other extremist ideologies. In order for the shared information to have meaning, a common ground must exist among the people. Common ground is a set of shared understanding, a resource that enables words and actions to be interpreted and translated into useful information between those who are interacting (Kashima, 2014). To date, literature from the linguistics and behavioural science communities has theorised on the nature of common ground (Shteynberg et al., 2020). In this abstract, we introduce a novel agent-based model that captures how agents (people) in a network share information with one another and, through this process, can develop a common ground. Crucially, the model focuses on the sender-receiver interaction sequence identified as a key micro-level interaction mechanism. As a result, the subsequent macro-level cultural dynamics observed in the simulations can be directly linked to the micro-level interactions, providing mathematical insights on the existing literature (Kashima et al., 2019).

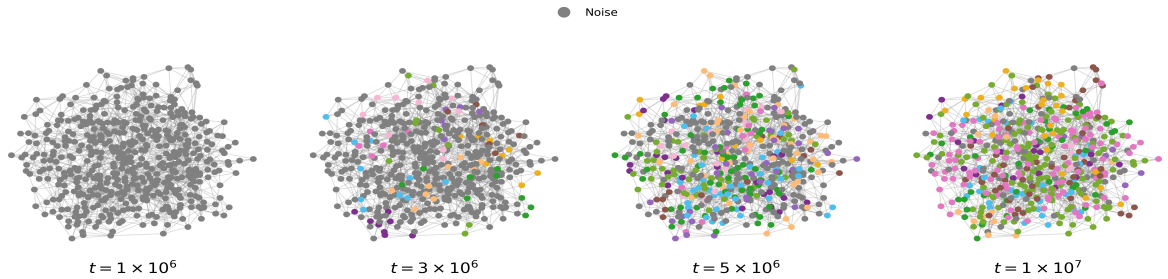
2 MODEL AND RESULTS

Model. The model consists of a population of n agents (individuals) connected over a fixed undirected network, who interact over discrete time steps $t = 0, 1, 2, \ldots$ in order to communicate about m pieces of information. Each agent i has a state vector $x_i(t) \in \mathbb{R}^m$, with kth entry being $x_i^k(t) \in [-1, 1]$. This entry captures agent i's certainty that the kth piece of information belongs to the common ground, with $x_i^k(t) = -1$ and $x_i^k(t) = 1$ meaning maximal certainty the information does not belong and does belong, respectively. At each time step, one agent is selected uniformly at random to be the sender. The sender selects a receiver uniformly at random from their network neighbours, and the pair then engage in a "grounding attempt": the sender selects a piece of information to share, and the receiver decides to accept or reject the information, before relaying this decision back to the sender. These actions are modelled using bounded rationality-type stochastic processes. Both the sender (say agent i) and receiver (say agent j) then update their certainty on the information that was shared, while certainty on information not shared decays. E.g. if the kth information was shared, then $x_i^k(t)$ and $x_j^k(t)$ are updated.

Among the various parameters in the model, we highlight two. The parameter $\epsilon \in [0, 1]$ captures the probability that the accept/reject decision from the receiver fails to reach the sender. If said decision never reaches the sender, then $\gamma \in [-1, 1]$ describes how the sender reacts, from reacting as if it was an actual rejection ($\gamma \to -1$) to as if it was an actual acceptance ($\gamma \to 1$). Pairs of (ϵ, γ) allow for abstract representations of different types of interaction environments. For example, with $\epsilon = 0.1, \gamma = -1$, the sender almost always receives the receiver's decision, and no reception is taken as a rejection. This might occur in a face-to-face conversation, where the sender can closely observe the receiver and the lack of a response creates a strong discomfort. Compare this to an online forum, where a user may post comments and often receive no reply, but is untroubled by this; this is captured by $\epsilon = 0.5, \gamma = 0$.



(a) Offline setting



(b) Online setting

Figure 1. Example simulations of an offline and online information environment, in Panel (a) and (b), respectively. Snapshots of the network at different time steps are shown, with different colours corresponding to different clusters identified using DBSCAN. Grey nodes are those identified as noise, i.e. are not assigned to any cluster.

Results. Fig. 1 showcases two exemplar simulations, on a Watts–Strogatz network with $n = 500$ agents, who can select from $m = 16$ pieces of information. In Fig. 1a and Fig 1b, we set $\epsilon = 0.1, \gamma = -1$ and $\epsilon = 0.5, \gamma = 0$, respectively. These capture the offline and online environments described above. Each panel shows a snapshot of the network at a time step in the simulation. The DBSCAN algorithm is used to identify clusters of agents who have similar state vectors $x_i(t)$ (we use Euclidean distance to compute similarity). Agents (nodes) belonging to the same cluster are given the same colour, while those identified as noise by DBSCAN are coloured grey (these agents do not belong to any cluster). We say that agents in the same cluster share a common ground, because the entries of $x_i(t)$ correspond to agent i's certainty of different pieces of information belonging to the common ground. In the offline setting, we observe that over time, the noise dissipates and different clusters disappear until a single global common ground forms across the entire network. In other words, there is a consensus among all agents on what pieces of information are part of the common ground. In the online setting, the decrease in noise is slower and over a much longer period. At the end of the simulation, there are several clusters in the network but little noise, indicating the existence of several different common ground. Within a cluster, agents share a common ground, but the common ground between clusters is different. Currently, we are conducting extensive Monte Carlo simulations to explore the impact of m, γ and ϵ on how clusters (common ground) evolve over time.

3 CONCLUSIONS

We proposed an agent-based model to study common ground formation and evolution in a group of people interacting over a network. Our initial results highlight the role that different information environments, such as online vs. offline communication, can play in the speed of common ground formation, as well as the diversity of the common ground. Future research will focus on the effect of biases, such as content bias (some information are more interesting or shareable) or personal biases (some agents are more impacted by rejection). Ultimately, we hope this model can be used to test hypotheses and theories from the field of pyscholinguistics, cultural dynamics, especially in exploring how individual-level mechanisms and factors lead to emergent population-level phenomena.

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