

## Phase Diagram and Optimal Information Use in a Collective Sensing System

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We consider a population of individuals living in an uncertain environment. Individuals are able to make noisy observations of the environment and communicate using signals. We show that the model shows an order-disorder transition from an ordered phase in low communication noise in which a consensus about the environmental state is formed to a disordered phase in high communication noise in which no consensus is formed. There are different consensus states: informed consensus in which consensus on the correct belief about the environmental state is formed, and misinformed consensus in which consensus on a wrong belief is formed. Based on the consensus state reached, the ordered phase is decomposed into multistable states separated by first order transitions. We show that the inference capability of the population in a changing environment is maximized on the edge of bistability: on the border between an informed consensus phase and a bistable phase in which both informed and misinformed consensuses are stable. In addition, we show that an optimal level of noise in communication increases the responsiveness of the population to environmental changes in a resonancelike phenomenon. Furthermore, the beneficial effect of noise is the most crucial in a fast changing environment.

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*Introduction.*—Survival in an uncertain environment necessitates biological populations infer information about environmental conditions and environmental changes [1–5]. Collective sensing mediated by communication between individuals is one of the most important mechanisms evolved to accomplish this task [5–8]. Examples are found all over the biological world from quorum sensing in bacteria [9,10] to communication between cells in multicellular organisms [11], communication between insects (for instance, in eusocial insects [12,13]), communication between large animals living in groups [14], and finally human language [15,16]. Given the prevalence of such collective sensing populations, an important challenge is to understand the mechanism and the optimal conditions by which collective sensing enables a population to collectively extract information about the environment. To tackle this challenge, we consider a model of collective sensing in which individuals in a population, who live in an uncertain environment, are able to make noisy observation of the environment and communicate by production and comprehension of signals [7]. By developing a mean field theory and using agent based simulations, we extend a previous study [7] by deriving the full phase diagram of the system. The model shows an order-disorder transition from an ordered phase in low communication noise to a disordered phase in high communication noise. In the ordered phase, consensus happens either on the correct belief about the environmental state, which we call informed consensus, or on a wrong belief, which we call misinformed consensus. Based on the type of the consensus, the ordered phase is decomposed into different multistable phases separated by

discontinuous transitions. Given that different consensus states are possible, an important question is the following: Under what conditions does the population make optimal use of information and form a desirable consensus state? We show that the inference capability of a collective sensing population in a changing environment is maximized on the edge of bistability: That is on the border between a monostable informed consensus phase and a bistable phase in which both informed and misinformed consensuses are stable.

In addition, we show that, although some amount of noise in communication is beneficial by increasing the speed by which the population responds to environmental changes, too much noise is detrimental by decreasing the decision making accuracy. The optimal speed-accuracy trade-off is reached on the edge of bistability in a resonancelike phenomenon. Furthermore, we show that the constructive role of noise is the most crucial in fast changing environments.

*The model.*—We consider a population of individuals living in an environment that can take one out of  $n$  possible states. Individuals have access to  $n$  representations. Each representation corresponds to one of the environmental states. In addition, in order to communicate their representations, they can produce and comprehend  $n$  signals: each corresponding to one of the representations. In the following, after explaining how observation, signal production and comprehension, and belief formation are performed, the dynamics of the model is described.

In order to make observations, each individual is equipped with an observation channel  $\gamma_R^{r,e}$ . This is a probability

transition matrix such that the result of an observation in environment  $\epsilon$  is representation  $r$  with probability  $\gamma_R^{r,\epsilon}$ . Individuals communicate by production and comprehension of signals. For this purpose, each individual is equipped with a production channel  $\gamma_G^{\sigma,r}$  such that it produces signal  $\sigma$  for representation  $r$  with probability  $\gamma_G^{\sigma,r}$ . Similarly, individuals have a comprehension channel  $\gamma_C^{\sigma}$  such that representation  $r$  is comprehended for signal  $\sigma$  with probability  $\gamma_C^{\sigma}$ . To implement the fact that the observation, production, and comprehension of signals are subject to noise, we parametrize these matrices by a single noise parameter  $\eta_x$ , such that  $\gamma_x^{a,b} = 1 - \eta_x$  if  $a = b$ , and  $\gamma_x^{a,b} = \eta_x/(n-1)$  otherwise. Here,  $x$  can be  $R$ ,  $G$ , or  $C$ , referring to the different channels.

As a result of observation and communication, an individual  $i$  reaches an internal state  $\mathbf{r}_i = \{r_i, \mathbf{r}'_i\}$ . Here,  $r_i$  is the result of observation of individual  $i$  in case it has made an observation, and  $\mathbf{r}'_i$  is the set of representations the individual has formed by comprehending the signals it has received from others. Each individual  $i$  needs to form a belief  $Z_i$  about the environmental state based on its information  $\mathbf{r}_i$ .  $Z_i$  can be either of the  $n$  representations. For example,  $Z_i = b$  means individual  $i$  believes the environment is in state  $b$ . To form beliefs, individuals use a decision rule. We consider a noisy weighted majority rule. In this decision rule, individuals count their representations, weighting their personal observation by a weight factor  $\omega_R^0$ , and form belief  $a$  with a probability proportional to the exponential of a decision accuracy parameter  $\beta_0$  times the weight of representation  $a$ . That is,

$$P(Z_i(t+1) = a) = \frac{\exp\{\beta_0[\omega_R^0 X_i^a(t) + Y_i^a(t)]\}}{\sum_a \exp\{\beta_0[\omega_R^0 X_i^a(t) + Y_i^a(t)]\}}. \quad (1)$$

Here,  $t$  refers to time,  $Y_i^a$  is the number of representations  $a$  that individual  $i$  has received due to communication, and  $X_i^a$  is a random variable that is equal to one if individual  $i$  obtains representation  $a$  as a result of an observation; and it is zero otherwise.

The dynamics of the model is as follows: We assume individuals reside on a communication network (which we take to be a fully connected network) such that, when an individual intends to signal others, transmits its signal to all its neighbors. At each time step, each individual makes an observation with probability  $h$  using its observation channel. In addition, each individual receives a set of signals from its neighbors and comprehends these signals using its comprehension channel  $\gamma_C^{\sigma}$ . As a result of observation and communication, each individual  $i$  reaches an internal state  $\mathbf{r}_i = \{r_i, \mathbf{r}'_i\}$  and forms a belief  $Z_i$  using its decision rule. Forming belief  $Z_i$ , the individual produces a signal  $\sigma$  using its production channel  $\gamma_G^{\sigma,Z_i}$  and transmits the signal to all its neighbors.

We begin by deriving the phase diagram of the model. Then, we study the dynamics of the model in a changing

environment by assuming that each environmental state lasts for  $\tau$  time steps; after which, the environment changes to a new state chosen uniformly at random.

*Mean field equations.*—To derive a set of mean field equations, we define  $\rho_G^a$ ,  $\rho_C^a$ , and  $\rho_B^a$  as, respectively, the densities of signal  $a$ , representation  $a$  resulting from comprehending signals, and belief  $a$  in the population. An individual has belief  $b$  with probability  $\rho_B^b$ ; in which case, it produces signal  $a$  with probability  $\gamma_G^{a,b}$ . Summing over  $b$ , we have for the mean field evolution equation for the density of signals

$$\rho_G^a(t+1) = \sum_b \gamma_G^{a,b} \rho_B^b(t). \quad (2)$$

Similarly, we can write for the density of representations resulting from comprehending signals

$$\rho_C^a(t+1) = \sum_b \gamma_C^{a,b} \rho_G^b(t). \quad (3)$$

In general, we have for the time evolution of the density of beliefs

$$\rho_B^a(t+1) = \langle P[Z_i^a(t+1)] \rangle_i. \quad (4)$$

where  $\langle \cdot \rangle_i$  denotes an overage over the population. We make the mean field assumption by replacing the random variables  $X_i$  and  $Y_i$  in this expression with their mean. This gives

$$\rho_B^a(t+1) = \frac{\exp[\beta(\omega_R h \gamma_R^{a,\epsilon} + \rho_C^a(t))]}{\sum_a \exp\{\beta[\omega_R h \gamma_R^{a,\epsilon} + \rho_C^a(t)]\}}. \quad (5)$$

Here, we have defined  $\beta = \beta_0 \langle k \rangle$ ,  $\omega_R = \omega_R^0 / \langle k \rangle$ , and used the following equation for the averages of  $X_i^a$  and  $Y_i^a$ :

$$\begin{aligned} \langle X_i^a(t) \rangle &= h \gamma_R^{a,\epsilon}, \\ \langle Y_i^a(t) \rangle &= \langle k \rangle \rho_C^a(t). \end{aligned} \quad (6)$$

where  $\langle k \rangle$  is the mean connectivity of the communication network. Equations (2), (3), and (5) constitute the set of mean field equations for the model. In the following, we derive the phase diagram of the system based on these equations and using agent based simulations.

*Phase diagram.*—We begin by setting  $\eta_G = 0$  and considering the comprehension noise. Production noise leads to qualitatively similar phase diagrams. In Figs. 1(a) and 1(b), we sketch the phase diagram of the model in, respectively,  $\omega_R - \eta_C$  and  $\omega_R - \beta$  planes. Here,  $h = 1$  and  $\eta_R = 0$ . In Fig. 1(a),  $\beta = 50$ ; and in Fig. 1(b),  $\eta_C = 0$ . Blue dots (which appear as lines) denote mean field solutions, and red markers indicate agent based simulation results. Different phases are abbreviated by letters. Blue letters denote phases resulted from mean field solutions, whereas red letters indicate simulation results. For other parameter values, the model shows qualitatively similar phase diagrams

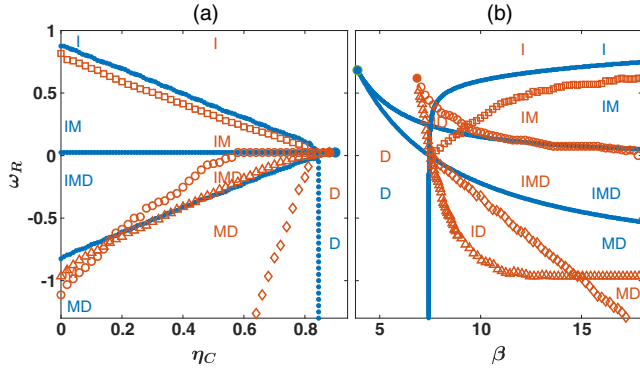


FIG. 1. Phase diagram of model in (a)  $\omega_R - \eta_C$  plane and (b)  $\omega_R - \beta$  plane. Blue dots denote mean field predictions, whereas red markers indicate agent based simulation results. Different phases are abbreviated in figures.  $I$  stands for informed consensus,  $M$  for misinformed consensus, and  $D$  for disordered phase. Here,  $h = 1$ ,  $\eta_R = 0$ ,  $n = 100$ , and  $\eta_G = 0$ . Other parameter values result in similar phase diagrams.

(see the Supplemental Material [17]). Here, and in the following, agent based simulations are performed on a fully connected network of size  $N = 100$ .

We begin by the phase diagram in the  $\omega_R - \eta_C$  plane, in Fig. 1(a). For large noise levels, a disordered phase (indicated by  $D$  in the figure) occurs, in which each individual forms a random belief independently of others. At each fixed  $\beta$  (large enough) and  $\omega_R$  (small enough), by decreasing the noise level  $\eta_C$ , the model shows an order-disorder transition. In the ordered phase, a consensus is formed. However, the nature of the consensus depends on  $\omega_R$ . For large  $\omega_R$ , the system has only one stable phase, which we call the informed consensus (denoted by  $I$ ). By decreasing  $\omega_R$ , in a value of  $\omega_R$  that depends on  $\eta_C$ , the system becomes bistable and a new consensus state, called misinformed consensus, appears in which the consensus on a wrong belief is formed. Consequently, we have a coexistence of informed and misinformed consensuses (denoted by  $IM$ ). By further decreasing  $\omega_R$ , yet another bifurcation happens: for smaller  $\omega_R$ , the system shows three stable solutions: the informed consensus, misinformed consensus, and disordered phase (denoted by  $IMD$ ). By further decreasing  $\omega_R$  in the negative range, another bifurcation happens; below which, the informed consensus becomes unstable. According to the simulations in this region, for small noise levels, only the misinformed consensus exists (denoted by  $M$ ). On the other hand, for larger noise levels, both the misinformed consensus and the disordered phase are stable (denoted by  $MD$ ). However, mean field solutions do not predict the existence of a monostable misinformed consensus phase. Finally, by further decreasing  $\omega_R$ , a final bifurcation happens; below which, the only stable phase is the disordered phase.

The  $\omega_R - \beta$  phase diagram, presented in Fig. 1(b), shows similar phases. For large  $\beta$ , as  $\omega_R$  decreases, the

model successively shows transitions from the monostable informed consensus to the bistable informed-misinformed consensus, the multistable informed-misinformed-disordered state, the bistable misinformed-disordered state, and the disordered phase. In addition to these phases, the model shows an informed consensus-disordered bistable phase, the size of which increases with decreasing  $\beta$ , denoted by  $ID$  in Fig. 1(b) [a small region to the left of the filled circles in Fig. 1(a) (not annotated)].

We note that, although for small  $\omega_R$  the order-disorder transition shows bistability and is discontinuous, as  $\omega_R$  increases, both the mean field theory and simulations show this transition becomes continuous at a single point (shown by filled circles) in the  $\omega_R - \eta_C$  plane for each fixed, large enough  $\beta$  (and at a single point in the  $\omega_R - \beta$  plane for each fixed, small enough  $\eta_C$ ), where  $IM - IMD$  (circles) and  $IMD - MD$  (triangles) bifurcation lines meet. For larger  $\omega_R$ , as the noise level increases, the system moves from the ordered to the disordered phase gradually without passing any phase transition [17].

The different phases of the system can be distinguished by two order parameters. These are the size of the majority group defined as

$$m = \max_b \frac{N(b)}{N}$$

and the fraction of informed individuals

$$\mu = \frac{N(\epsilon)}{N}.$$

Here,  $N(b)$  is the number of individuals with belief  $b$ . The phase diagram of the model can also be studied based on the probabilities that these order parameters take different values belonging to different phases starting from a generic (random) initial condition. This is done in Figs. 2(a) and 2(b) in, respectively,  $\omega_R - \eta_C$  and  $\omega_R - \beta$  planes. The upper panels show the contour plots of the probability that  $m$  takes a large value  $P(m > 0.9)$  belonging to the ordered phase, and the lower panels show  $P(\mu > 0.9)$  belonging to the informed consensus phase.

*Inference capability maximized on edge of informed-misinformed bistability region.*—The fact that the system can be found in different phases raises the following important question: Under what conditions does the population achieve the highest capability to collectively infer and represent the environment? To answer this question, we assume the population lives in a changing environment in which each environmental state lasts for  $\tau$  time steps; after which, the environment changes. We define the inference capability of the population as the average fraction of the individuals who infer the correct environmental state by the end of an environmental state. This is plotted in color in Fig. 3. In Fig. 3(a) [Fig. 3(b)],  $\eta_G = 0$  ( $\eta_C = 0$ ) and the inference capability in the  $\omega_R - \eta_C$  ( $\omega_R - \eta_G$ ) plane is

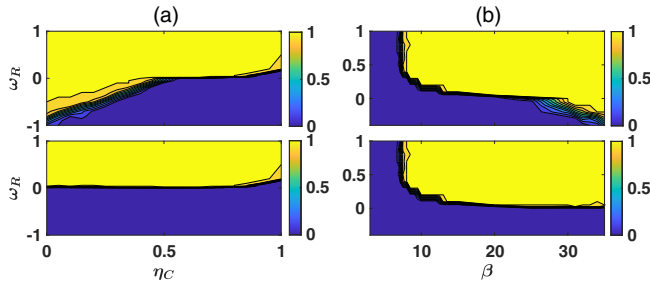


FIG. 2. Probabilities that order parameters take values belonging to different phases. Up  $P(m > 0.9)$  and down  $P(\mu > 0.9)$  in (a)  $\omega_R - \eta_C$  and (b)  $\omega_R - \beta$  planes, starting from a random initial condition. Here, a sample of 20 simulations run for  $T = 500$  time steps are used to calculate probabilities. Here,  $h = 1$ ,  $\eta_R = 0$ ,  $n = 100$ , and  $\eta_G = 0$ .

plotted. Here, the simulation is run for  $T = 5000$  time steps and  $\tau = 500$ .  $T$  is an averaging parameter and does not affect the results.

In a changing environment, the population needs to constantly respond to environmental changes by updating its collective belief. This is not achieved in the misinformed-informed bistable phase because, in this phase, the population is susceptible to a misinformed consensus. On the other hand, for large  $\omega_R$  such that the system is well into the informed consensus phase, individuals put a high weight on their personal observation. Because the observation is noisy, this decreases the inference capability by suboptimal use of the information provided by communication. The optimum inference capability, in which the population optimizes its use of social and personal information, is achieved in between these two extremes. Interestingly, this is exactly the boundary of the monostable informed consensus and the bistable informed-misinformed consensus phases (indicated by red circles in Fig. 3). In this region, the population is responsive enough to not get

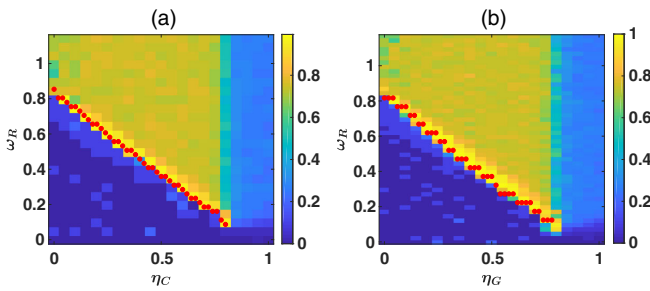


FIG. 3. Inference capability maximized on edge of bistability. Color plot of inference capability, defined as fraction of individuals who infer the correct environmental state, in (a)  $\omega_R - \eta_C$  and (b)  $\omega_R - \eta_G$  planes. Boundary of monostable informed consensus and bistable informed-misinformed consensus phases is indicated by red circles. For both (a) comprehension and (b) production noise, the inference capability is maximized on the edge of bistability. Here,  $h = 0.5$ ,  $\eta_R = 0.5$ ,  $n = 100$ , and  $\tau = 500$ . In Fig. 3(a),  $\eta_G = 0$ ; and in Fig. 3(b),  $\eta_C = 0$ .

trapped in a misinformed consensus (as happens for small  $\omega_R$ ) and, at the same time, is not too fast in responding before taking the social information into account (as happens for large  $\omega_R$ ).

*Noise increases adaptation to changing environment.*—As can be seen in Figs. 3(a) and 3(b), noise can be beneficial; for a fixed  $\omega_R$ , the inference capability is maximized for a finite noise level. To see how this happens, in Fig. 4(a), we plot the fraction of informed individuals as a function of time for  $\omega_R = 0.25$  and three different noise levels. Here,  $\tau = 50$ . For a too small noise level (red), it may take too long for the population to update its belief in response to environmental change, or it may even fail to do so. Increasing noise (orange and blue) by facilitating switching between different consensus states decreases the response time of the population. However, too much noise (blue) decreases decision making accuracy by decreasing the fraction of informed individuals. Thus, there is a speed-accuracy trade-off associated with increasing the noise, and the inference capability of the population is maximized at an optimal noise level that obtains the optimal trade-off (orange). This can be seen to indeed be the case in Fig. 4(b), where the inference capability as a function of noise is plotted. This shows that noise in communication can increase the inference capability of the population by increasing its responsiveness to environmental changes in a resonancelike phenomenon. Interestingly, as shown, the resonance coincides with the edge of bistability.

We note that the benefit of noise is the most crucial in fast changing environments. This can be seen in Fig. 4(c), where the inference capability is plotted in color in the  $\omega_R - \eta_C$  plane for  $\tau = 25$ . Whereas in a slowly varying

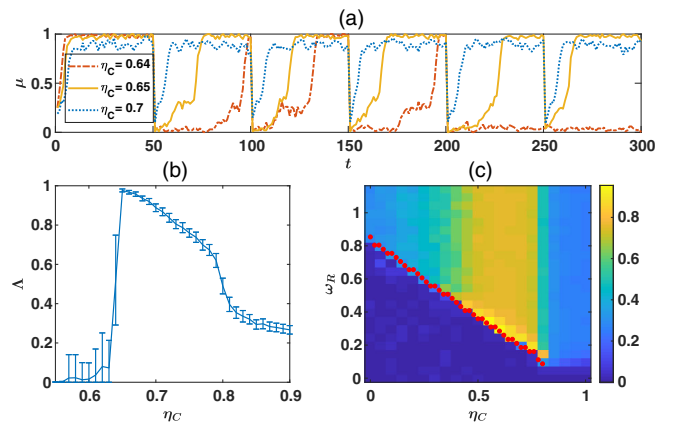


FIG. 4. Benefits of noise. (a) Fraction of informed individuals  $\mu$  in a fluctuating environment ( $\tau = 50$ ) for  $\omega_R = 0.25$  and three different noise levels. A higher noise level increases decision making speed while lowering its accuracy. (b) Optimal speed-accuracy trade-off occurs in a resonancelike manner ( $\tau = 50$  and  $\omega_R = 0.25$ ). (c) In a fast changing environment ( $\tau = 25$ ), a high level of noise is necessary for the population to extract information. Here,  $h = 0.5$ ,  $\eta_R = 0.5$ ,  $n = 100$ , and  $\eta_C = 0$ .

environment [such as  $\tau = 500$  in Fig. 2(a)], the population can reach a high inference capability, even for small noise levels, by choosing a proper weight of personal information with respect to social information (i.e.,  $\omega_R$ ); in a fast changing environment where the decision making speed is of higher importance, this is not possible, and information use can only be optimized for large noise levels (see the video in the Supplemental Material for a visual manifestation [17]). This finding predicts that communication systems operating in fast fluctuating environments must have evolved to incorporate the higher amount of noise.

In the Supplemental Material [17], we establish the robustness of our findings by showing their validity for other parameter values and different communication network structures.

*Discussion.*—We have shown that a simple model of collective information acquisition shows a rich phase diagram with different consensus states. This raises the following important question of how, by optimal use of information, the population manages to avoid getting trapped in a disadvantageous physical phase. It is argued that this can happen by excessive use of social information [18,19]: for instance, in social systems such as financial markets [20]. In this regard, we have shown that information use is optimized on the edge of bistability, where misinformed consensus is barely stable. This boundary is akin to a first order transition and is different from a critical transition. Thus, this optimality condition contrasts with many arguments that biological functions, such as the information acquisition capability, are optimized at criticality [21–30]; and it introduces an alternative way in which biological populations can optimize their information use. This seems to parallel some critiques of the so-called criticality hypothesis [31]. We have also shown that noise is beneficial for a communicating population by increasing its responsiveness to environmental change in a resonancelike phenomenon. In addition, the constructive role of noise is the most pronounced in fast changing environments. These findings can explain why, most often, communication systems incorporate a large amount of noise [14] and predict conditions over which a higher amount of noise is observable in such systems.

The resonancelike phenomenon, through which the right amount of noise optimizes the inference capability of a population, is reminiscent of stochastic resonance [32], through which it is shown that noise can serve a positive role by increasing the information processing capability: for instance, in neural systems [33–36]. As we have shown, a similar phenomenon can be at work in collective information acquisition, where the optimal solution to the speed-accuracy trade-off and the trade off between the use of social and personal information is achieved through a resonancelike phenomenon at the edge of bistability.

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- [1] G. Tkacik and W. Bialek, Information processing in living systems, *Annu. Rev. Condens. Matter Phys.* **7**, 89 (2016).
- [2] E. Kussell and S. Leibler, Phenotypic diversity, population growth, and information in fluctuating environments, *Science* **309**, 2075 (2005).
- [3] G. De Luca, G. Mariani, P. MacKenzie, B. R. MacKenzie, and M. Marsili, Fishing out collective memory of migratory schools, *J. R. Soc., Interface* **11**, 20140043 (2014).
- [4] I. D. Couzin, J. Krause, N. R. Franks, and S. A. Levin, Effective leadership and decision-making in animal groups on the move, *Nature (London)* **433**, 513 (2005).
- [5] S. R. Dall, L. A. Giraldeau, O. Olsson, J. M. McNamara, and D. W. Stephens, Information and its use by animals in evolutionary ecology, *Trends Ecol. Evol.* **20**, 187 (2005).
- [6] M. Salahshour and S. Rouhani, Evolutionary value of collective sensing, *arXiv:1802.03524*.
- [7] M. Salahshour, S. Rouhani, and Y. Roudi, Phase transitions and asymmetry between signal comprehension and production in biological communication, *Sci. Rep.* **9**, 3428 (2019).
- [8] L. Conradt and T. J. Roper, Consensus decision making in animals, *Trends Ecol. Evol.* **20**, 449 (2005).
- [9] C. M. Waters and B. L. Bassler, Quorum sensing: Cell-to-cell communication in bacteria, *Annu. Rev. Cell Dev. Biol.* **21**, 319 (2005).
- [10] R. Popat, D. M. Cornforth, L. McNally, and S. P. Brown, Collective sensing and collective responses in quorum-sensing bacteria, *J. R. Soc. Interface* **12**, 20140882 (2015).
- [11] U. Alon, *An Introduction to Systems Biology: Design Principles of Biological Circuits* (Chapman and Hall/CRC, London, 2006).
- [12] S. D. Leonhardt, F. Menzel, V. Nehring, and T. Schmitt, Ecology and evolution of communication in social insects, *Cell* **164**, 1277 (2016).
- [13] V. Tereshko and A. Loengarov, Collective decision making in honey-bee foraging dynamics, *Comput. Inf. Syst.* **9**, 1 (2005).
- [14] H. Brumm, in *Animal Communication and Noise*, edited by V. M. Janik, and P. MacGregor (Springer-Verlag, Berlin, Germany, 2013), Vol. 2.
- [15] M. A. Nowak and D. C. Krakauer, The evolution of language, *Proc. Natl. Acad. Sci. U.S.A.* **96**, 8028 (1999).
- [16] M. A. Nowak and N. L. Komarova, Towards an evolutionary theory of language, *Trends Cognit. Sci.* **5**, 288 (2001).
- [17] See Supplemental Material at <http://link.aps.org/supplemental/10.1103/PhysRevLett.123.068101> for the phase diagram of the model for different parameter values, a discussion of the nature of the phase transitions, and the validity of the results for different parameter values.
- [18] C. J. Torney, T. Lorenzi, I. D. Couzin, and S. A. Levin, Social information use and the evolution of unresponsiveness in collective systems, *J. R. Soc. Interface* **12**, 20140893 (2015).
- [19] G. Rieucau and L. A. Giraldeau, Persuasive companions can be wrong: The use of misleading social information in nutmeg mannikins, *Behav. Ecol.* **20**, 1217 (2009).

- [20] D. Tuckett, Addressing the psychology of financial markets, *Economics* **3**, 1 (2009).
- [21] T. Mora and B. William, Are biological systems poised at criticality, *J. Stat. Phys.* **144**, 268 (2011).
- [22] J. Hidalgo, J. Grilli, S. Suweis, M. A. Munoz, J. R. Banavar, and A. Maritan, Information-based fitness and the emergence of criticality in living systems, *Proc. Natl. Acad. Sci. U.S.A.* **111**, 10095 (2014).
- [23] J. M. Beggs and P. Dietmar, Neuronal avalanches in neocortical circuits, *J. Neurosci.* **23**, 11167 (2003).
- [24] M. Nykter, N. D. Price, M. Aldana, S. A. Ramsey, S. A. Kauffman, L. E. Hood, O. Yli-Harja, and I. Shmulevich, Gene expression dynamics in the macrophage exhibit criticality, *Proc. Natl. Acad. Sci. U.S.A.* **105**, 1897 (2008).
- [25] T. Petermann, T. C. Thiagarajan, M. A. Lebedev, M. A. L. Nicolelis, D. R. Chialvo, and D. Plenz, Spontaneous cortical activity in awake monkeys composed of neuronal avalanches, *Proc. Natl. Acad. Sci. U.S.A.* **106**, 15921 (2009).
- [26] X. Chen, X. Dong, A. Beer, H. L. Swinney, and H. P. Zhang, Scale-Invariant Correlations in Dynamic Bacterial Clusters, *Phys. Rev. Lett.* **108**, 148101 (2012).
- [27] W. Bialek, A. Cavagna, I. Giardina, T. Mora, E. Silvestri, M. Viale, and A. M. Walczak, Statistical mechanics for natural flocks of birds, *Proc. Natl. Acad. Sci. U.S.A.* **109**, 4786 (2012).
- [28] A. Haimovici, E. Tagliacuzzi, P. Balenzuela, and D. R. Chialvo, Brain Organization into Resting State Networks Emerges at Criticality on a Model of the Human Connectome, *Phys. Rev. Lett.* **110**, 178101 (2013).
- [29] A. Gelblum, I. Pinkoviezky, E. Fonio, A. Ghosh, N. Gov, and O. Feinerman, Ant groups optimally amplify the effect of transiently informed individuals, *Nat. Commun.* **6**, 7729 (2015).
- [30] H. Chaté and M. A. Muñoz, Insect swarms go critical, *Physics* **7**, 120 (2014).
- [31] M. Marsili, I. Mastromatteo, and Y. Roudi, On sampling and modeling complex systems, *J. Stat. Mech.* (2013) P09003.
- [32] P. Hänggi, Peter. Stochastic resonance in biology how noise can enhance detection of weak signals and help improve biological information processing, *ChemPhysChem* **3**, 285 (2002).
- [33] M. D. McDonnell and M. Ward Lawrence, The benefits of noise in neural systems: Bridging theory and experiment, *Nat. Rev. Neurosci.* **12**, 415 (2011).
- [34] J. K. Douglass, L. Wilkens, E. Pantazelou, and F. Moss, Noise enhancement of information transfer in crayfish mechanoreceptors by stochastic resonance, *Nature (London)* **365**, 337 (1993).
- [35] J. E. Levin and J. P. Miller, Broadband neural encoding in the cricket cercal sensory system enhanced by stochastic resonance, *Nature (London)* **380**, 165 (1996).
- [36] F.-G. Zeng, Q.-J. Fu, and R. Morse, Human hearing enhanced by noise, *Brain Res.* **869**, 251 (2000).