The Role of Information in Group Formation

Stefano Bennati, Leonard Wossnig and Johannes Thiele
Chair of Computational Social Science, ETHZ, Clausiusstrasse 50, 8092, Zürich, Switzerland

Keywords: Group Behavior, Swarming, Information, Simulation.

Abstract: A vast body of literature studies problems such as cooperation and coordination in groups, but the reasons why groups exist in the first place and hold together are still not clear: in presence of within-group competition, individuals are better off leaving the group. An environment that is advantageous to groups, e.g. better chances of succeeding at or escaping from predation, seems to play a key role for the existence of groups. Another recurrent explanation in the literature is between-group competition. We argue that information constraints can foster sociable behavior, which in turn is responsible for group creation. We compare, by means of an agent-based simulation, navigation strategies that exploit information about the behavior of others. We find that individuals that have sociable behavior have higher fitness than individualistic individuals for certain environmental configuration.

1 INTRODUCTION

We study the emergence of sociable behavior from a population of zero-intelligence autonomous agents.

We define sociable behavior as taking into consideration the behavior of alter, without any implication about its effects on ego and alter.

Sociable behavior does not require any intelligence as it can be purely reactive, for example bacteria moving in response to a chemical stimulus (Chemotaxis).

The question we want to address is whether information can be the driver of group creation in environments that incentivize selfish behavior.

Information plays a key role in evolution: information exchange is crucial for group behavior (Skyrms, 2010) and collective intelligence (Garnier et al., 2007), as well as for the evolution of the complexity that supports them.

The seminal paper of Szathmary and Smith (2000) argues that changes in transmitting information are the reason why evolution favored increase in complexity. The paper explains, for example, the transition from protists to animals by the change of what information is heredited during cell duplication, which enabled cell differentiation. Quoting Szathmary "transitions must be explained in term of immediate selective advantage to individual replicators" and this transition is explained by division of labor: multicellular organisms with specialized cells are more efficient than a comparable colony of unicellular organisms.

The existence of multicellular organisms is hypothesized to be an effect of symbiosis, either of organisms of different species or of similar organisms. In the former case division of labor provides an evolutionary advantage by increasing efficiency and allowing cells to reduce in size. In the latter case the advantage comes from reproduction as colonies produce more offspring than single cells of similar size (Szathmary and Smith, 2000). These advantages are generated by increased efficiency at the individual level, this increase is independent of the environment.

The next transition in evolution goes from single individuals to groups. Similarly to the previous case, groups are supported by division of labor, with (e.g. bees) or without (e.g. humans) individual specialization.

Although symbiosis is able to sustain the formation of heterogeneous groups, because of an individual advantage given by exchange of services or resources, it is not able to explain formation of heterogeneous (social) groups in presence of within-group competition.

Between-group competition, as well as other favorable environmental factors, might support the formation of homogeneous groups when there is within-group competition: for example schools of fish form groups to increase their chance to escape predation, similarly predators hunt collectively to increase their

Bennati, S., Wossnig, L. and Thiele, J.
The Role of Information in Group Formation.
DOI: 10.5220/0005751802310235
In *Proceedings of the 8th International Conference on Agents and Artificial Intelligence (ICAART 2016) - Volume 1*, pages 231-235
ISBN: 978-989-758-172-4

ability to capture prey (Dawkins, 2006).

As opposed to the previous transition, the environment seems to play a key role for emergence of groups.

We argue that group creation can be supported also in an environment that does not favor groups and in presence of within-group competition. In this case the driver of group creation is sociable behavior, that individuals develop in response to (lack of) information in the environment.

2 METHODS

Group formation is all about interactions, and it is an extremely difficult problem to capture its dynamics in a mathematical model. For this reason we study this problem by means of a computer simulation which is able to reproduce a vast range of dynamics.

We design an environment that does not give an advantage to group behavior as every agent competes for the same resources, which in our case is food.

The simulation environment is a squared grid with circular boundary conditions, each cell can contain a variable number of food units and agents. The number of cells containing food is defined by a parameter and remains constant during the simulation: anytime a food source is depleted, a new food source is spawned at a random location. The continuous respawning of food sources is the mechanism that tests the quality of an agent's foraging strategy. The food source capacity (i.e. the maximum number of food units that a cell can contain) is set to a value, sufficiently high to avoid that a single agent could exaust it before any other agent can find it. We will discuss in the next section the effects of this parameter on our findings.

Agents are initially randomly placed in the grid. Agent perceptions include the food in the current cell and the agents in the surroundings. The perception mechanism mimics the working of the retina in fish (Strandburg-Peshkin et al., 2013): perceptions indicate the number of agents in every of the cardinal directions, but it is not refined enough to tell the exact number of agents in a specific cell, nor distinguish between stationary and moving targets. Available actions are foraging and moving of one cell in one of the four cardinal directions.

At every simulation step agents activate in a random order and execute one action based on their perception. The order of play is crucial as agents compete for the same resources with a first-come first-served policy. Whenever an agent depletes a source of food, a new source is immediately created somewhere else. Any other agent in that cell that is still waiting in queue would have now to look for a new source, the strategy they use to look for new sources of food makes the difference for their performance.

Agent decisions are based on the output of a simple neural network that transforms a vector in the perception space to a vector in the action space. The agent executes the action that corresponds to the highest value of the output vector (see Figure 1). At this stage the learning is disabled, so the weights of the network remain constant for the whole simulation.

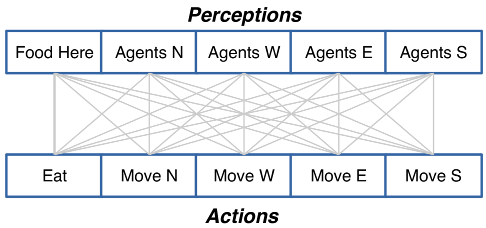

Figure 1: Diagram of the decision system. The weights associated to each connection produce a vector of output values, the action with the highest value is executed.

An important assumption is that location of food is unknown and is disclosed to one agent only upon entering its location. This assumptions makes the task not-trivial: being unable to perceive food in a distance, the only chance to improve over a random walk is to find a foraging strategy that exploits a proxy for food location. The intuition is that, assuming all agents stop to eat whenever they encounter a food source, cells with more agents are more likely to be food sources. We call a strategy, exploiting the signal of position of others, "sociable". Sociable strategy interprets the presence of agents as increasing the likelihood of food

In our simulation we define two types of agents: random and sociable (SAs). Random agents, as the name suggests, walk randomly in the environment searching for food, independently of where other agents are. Their behavior is determined by random noise, added to the randomly initialized weights. Sociable agents like company: they favor going towards where other agents are. For example if their perception shows the majority of agents to the east, the agent will move to the east. They are generated from a random agent, by increasing the weight that connect a specific input value to a desired action. The only difference between types of agents is the average value of the weights. All agents are initialized to have a very high weight on the edge that connects perception "food in the current cell" to action "forage", this makes sure that agents will always forage when given the opportunity. This assumption does not remove generality as, in an evolutionary perspective, it is expected that agents forage whenever possible.

3 LITERATURE

A vast body of literature applies Agent Based Modeling to study group and societal issues. Most Agent Based Models of society concentrate on the problem of cooperation (Helbing and Yu, 2009) or coordination (Mäs et al., 2010). Our model is designed in a way that neither cooperation nor coordination are required to be successful: we created a foraging task whose outcome does not depend on interactions between agents.

Our approach is similar to models of Natural Selection, e.g. (Grund et al., 2013), where different groups obtain different fitness due to their characteristics. Unlike most natural selection models, in our simulation the size of the groups remains constant. Our simulation models a snapshot of a natural selection process, where the lifetime of every single agent is much longer than the simulation length. Fitness is used to evaluate one group versus the others at the end of the simulation.

Our design has been inspired by biological systems, in particular schooling fish. The computational model of fish behavior developed by Strandburg-Peshkin et al. (2013) is able to reproduce group movement as a simple reaction to changes in visual perception, proportional to the size of the retina covered. Similarly our agents react to changes in quantity in their visual perceptions.

Some assumptions are quite common in the literature, and most models rely on at least one of them to produce their results. As opposed to previous work, we relax the following common assumptions:

- The environment favors cooperation, as in (Montanier and Bredeche, 2013). In our model an agent has the same payoff whether it is in a group or by itself. We could say that the environment actually favors individuals because a higher number of agents using a resources would lead to its faster depletion.
- Spatial dispersion is imposed, as in (Grund et al., 2013). Agents are randomly placed and there is no mechanism that keeps agents of the same kind close together. Similarly food is created randomly in the grid, so there is no incentive to stay close to an empty food source.
- Kin selection is possible, as in (Smith, 1964). Agents do not have any visible characteristic that make them recognizable as members of a group (e.g. Green Beard (Hamilton, 1964)) so they cannot develop mechanisms that favor kin.
- Agents are able to learn, as in (Duan and Stanley, 2010). Although equipped with a neural network, learning algorithms are not implemented. Every agent behaves consistently for the whole simulation.

4 RESULTS

We expect that, for some environment settings, sociable strategy achieve the highest performance.

Being driven by other agents, sociable agents (SAs) cannot explore the environment as efficiently as others, but are are able to use the information about the behavior of other agents to better exploit the environment.

When perception of food is restricted, the behavior of others is the only proxy to food location, rendering sociable behavior advantageous with respect to random walk.

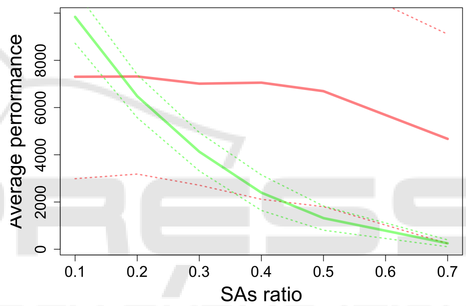

Figure 2: Performance varying population composition. Performance of SA decreases with increasing percentage of SAs. Legend: Red is Random, Green is SA.

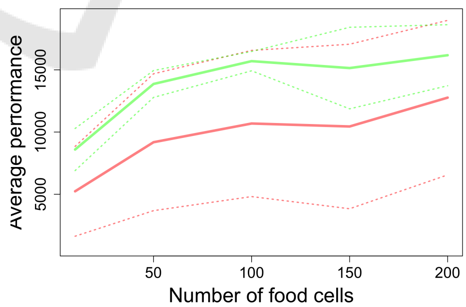

Figure 3: Performance for 10 agents and food stack size 200. SA are outperforming random agents for any number of food sources. Legend: Red is Random, Green is SA.

The results presented here are the average of 24 simulations of length 2e+4 timesteps. Performance is defined as the number of foraging actions an agent takes during the whole simulation. Group performance is the average of group members' performance. Our first result is that performance of sociable

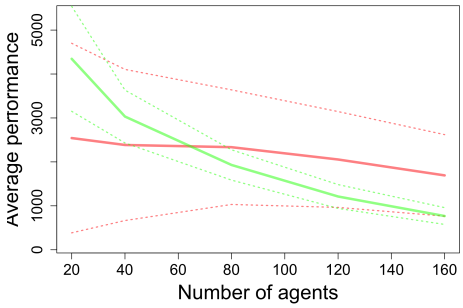

Figure 4: Performance varying population size. For 10 food sources of size 200. Performance of SAs decreases with increasing population size. Legend: Red is Random, Green is SA.

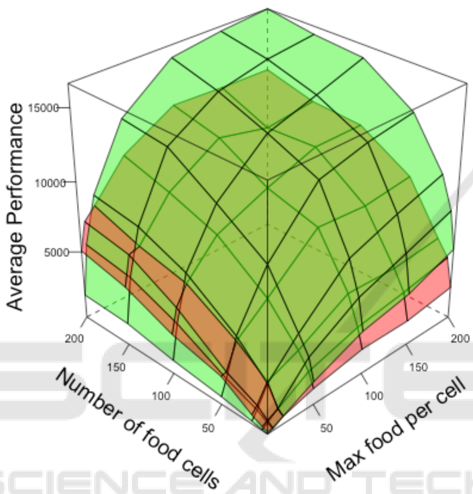

Figure 5: Effect of food scarcity on performance, for 10 agents. SAs outperform random agents for any food concentration and any stack size greater than 20. Legend: Red is Random, Green is SA.

agents decreases with an increasing share of sociable agents in the population (Figure 2).

This result is partly expected as SAs are exploiters, so they need other agents to perform exploration. Our second result is that, given the optimal population composition, SAs can significantly outperform the other agents for any food concentration, as long as the number of agents is low (Figure 3).

The reason for the performance decrease with an increasing number of agents (Figure 4) could be that SAs are not able to efficiently spot food sources anymore. If the grid is too crowded, a region with many moving agents could appeal more than a region with few stationary agents, leading the agent away from a possible food source.

The success of SAs is driven by the scarcity of food sources: if the source does not contain enough units of food, SAs will not be able to reach it before it gets depleted. We explore the effect of this parameter in Figure 5, we see that the stack size is less than 20 units (that is an average stack size of 10), random agents are able to outperform the other strategies. The number of food sources does not seem affect the performance of SAs.

5 DISCUSSION

In their seminal paper, Szathmary and Smith (2000) argue that information played a key role in building the first multicellular organisms, as well as human society. Although having convincing explanations for the early and late stages of evolution, it lacks a complete explanation for the emergence of groups. Our preliminary findings build on and complement this argument by finding evidence for a role of information in group formation: sociable behavior would emerge as a selfish response to limited information about the environment, leading to formation of groups, which would enable altruistic behavior such as cooperation.

Our results speak for studying more deeply the role of information in evolutionary biology and social science.

The work is far from complete. The next step is to look for emergence of group behavior. So far we have concentrated on performance of groups. More interesting is group behavior after a food source is depleted: agents will move away, driven by the agents surrounding them, which are most likely of the same type. We expect SAs to show some group behavior while looking for the next food source.

We will also study the evolutionary stability of the strategies, of particular interest in the dynamic of the evolution as the population's composition varies over time. We expect to find that changes in the population composition, driven by natural selection, will destabilize the population of SAs leading it, in the majority of cases, to extinction. We also want to investigate what happens if group cooperation makes foraging more efficient.

Another interesting addition to the model would be learning, in particular when compared to, or alongside to an evolutionary process. We expect to see a faster adaptation to the environment and the emergence of more complex group dynamics.

REFERENCES

Dawkins, R. (2006). *The selfish gene*. Number 199. Oxford university press.

Duan, W.-Q. and Stanley, H. E. (2010). Fairness emergence from zero-intelligence agents. *Physical Review E*, 81(2):026104.

Garnier, S., Gautrais, J., and Theraulaz, G. (2007). The biological principles of swarm intelligence. *Swarm Intelligence*, 1(1):3–31.

Grund, T., Waloszek, C., and Helbing, D. (2013). How natural selection can create both self-and other-regarding preferences, and networked minds. *Scientific reports*.

Hamilton, W. (1964). The genetical evolution of social behaviour. i.

Helbing, D. and Yu, W. (2009). The outbreak of cooperation among success-driven individuals under noisy conditions. *Proceedings of the National Academy of Sciences*, 106(10):3680–3685.

Mäs, M., Flache, A., Helbing, D., and Bergstrom, C. T. (2010). Individualization as driving force of clustering phenomena in humans. *PLoS Comput Biol*, 6(10):e1000959–e1000959.

Montanier, J.-M. and Bredeche, N. (2013). Evolution of altruism and spatial dispersion: an artificial evolutionary ecology approach. In *Advances in Artificial Life, ECAL*, volume 12, pages 260–267.

Skyrms, B. (2010). *Signals: Evolution, learning, and information*. Oxford University Press.

Smith, J. M. (1964). Group selection and kin selection. *Nature*, 201:1145–1147.

Strandburg-Peshkin, A., Twomey, C. R., Bode, N. W., Kao, A. B., Katz, Y., Ioannou, C. C., Rosenthal, S. B., Torney, C. J., Wu, H. S., Levin, S. A., et al. (2013). Visual sensory networks and effective information transfer in animal groups. *Current Biology*, 23(17):R709–R711.

Szathmary, E. and Smith, J. M. (2000). The major evolutionary transitions. *Shaking the Tree: Readings from*, pages 32–47.