First Steps Toward a Swarm Robotics Model of Self-Domestication and Language Evolution

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Abstract

Swarm Robotics, which studies collective behaviors of large populations of interacting robots with simple embodied cognition, is an ideal testbed for studying the cultural evolution of language. Our goal is to expand existing simulations in order to explore a dominant theory in evolutionary linguistics—the self-domestication hypothesis—which suggests that increased prosociality led to the sophistication of the cultural niche, enabling the complexification of languages. In our model, robots in multiple nests are engaged in a foraging task (i.e., gathering resources in their environment) while playing a language game. Crucially, we include two novel features: (1) robot individuation: robots have a partner-specific memory, keeping track of the outcomes of past interactions with specific robots; (2) parameterizable prosociality: robots' tendency to interact is based on experience: successful communication between robots reduces their aggression toward each other and increases their chances of interacting again. First, we show that these manipulations lead to the formation of a classic "in-group bias" where robots favor interaction with some robots over others - a bias which is highly common in social animals in nature but that was so far absent from swarm robotics models. Second, we observe that higher prosociality values result in the collection of more resources, potentially indicating an evolutionary advantage. Finally, we show that prosociality modulates the effect of physical distance on lexical convergence, such that low values of innate prosocially lead to more stable sub-swarm divergence, even in relative proximity (i.e., different nests robustly converge on different lexical variants despite being close to each other).

1 Introduction

Swarm robotics is an approach to the study of multi-robot systems that aims at designing complex collective behaviors by means of relatively simple robots. A key factor in the design of robot swarms is self-organization, which results from the numerous local interactions among robots and between robots and their environment (Kube and Bonabeau, 2000). These local interactions, along with other features of robots' behavior, are often modeled after natural systems—with animal societies being the most relevant source of inspiration (Brambilla et al., 2013).

Beyond simple communication processes, past experiments in swarm robotics have explored the potential of language games in an embodied agent context (Trianni et al., 2016; Cambier et al., 2017, 2018; Miletitch et al., 2019). A language game is defined as a turn-based game played between agents/robots with the purpose of mimicking real-world dynamics leading to the emergence of a structured language. Previous studies showed that the naming game, a variation of language games whereby agents must name topics (Baronchelli et al., 2008), yields an early explosion of words followed by an increasingly fast reduction in word variation, and the ultimate convergence on one single word throughout the entire population (Baronchelli et al., 2006). This pattern has also been observed in dynamic swarms where robots communicate with a varying set of agents (Trianni et al., 2016), although collision between robots and the ensuing clustering led to a reduced interaction rate in the population and a slower convergence with respect to simulated agents.

Building on this work, later swarm robotics studies used the naming game to create a naming system that adapts to the features of the environment as well as to the way in which the task is performed by the swarm. Such work observed the creation of words corresponding to local clusters in self-organized aggregation (Cambier et al., 2017), as well as food sources for foraging tasks (Miletitch et al., 2019). In (Cambier et al., 2018), a further interaction was considered; The parameters of an aggregation controller were encoded as words exchanged in the naming game, which enabled the cultural evolution of an aggregation behavior.

The goal of the current project is to expand these existing simulations in order to explore a dominant theory in evolutionary linguistics, namely, that the evolution of present-day languages might have resulted in part from the self-domestication of the human species (Thomas and Kirby, 2018; Benítez-Burraco and Progovac, 2020). According to this human self domestication (HSD) hypothesis, humans' distinctiveness is, to a large extent, the outcome of an evolutionary process similar to animal domestication (Hare, 2017). At the heart of this view lies the idea that HSD resulted in less aggressive individuals, who are more prone to interact with others (and particularly, with their kin, but also with strangers). This increased prosociality and reduced aggressiveness would have in turn promoted more social contacts within a community, and supported the emergence of more sophisticated forms of language (Tamariz and Kirby, 2016; Steels, 2017). Our goal is to model this process of self-domestication and language evolution using swarm robots, testing the effect of increased socialization patterns on the formation of language.

Current swarm robotics models, however, lack several crucial features that are considered prerequisites for this process. Swarm robots are typically collaborative, but homogeneous, and have little to no memory, not to mention social memory (who did what to whom). In order to mimic the effects of self-domestication properly, an evolutionary advantage for prosociality first needs to be introduced, and robots need to be treated as distinct individuals. To this end, we designed a novel version of the naming game with swarm robots, which includes two crucial modifications: robot individuation and procosicality.

Specifically, robots engage in a classic naming game, but the likelihood of future interactions with a given robot depends on the prosociality values associated with each individual: robots with higher prosociality values toward each other are more likely to interact again, while robots with low prociality values toward each other are more likely to reject the interaction and avoid each other. All robots start out with a baseline prosociality value, which they then update on an individual basis for each robot in the swarm based on their interaction experience (i.e. previous naming games).

As we are aiming to develop agents that create a language interwoven with an activity (Wittgenstein, 1953), our model involves a foraging task whereby robots, separated into two sub-swarms, look for resources to bring back to their nest (one per sub-swarm). Foraging is a typical animal activity, which has been widely studied in the field of swarm robotics (Bonabeau et al., 1996; Krieger et al., 2000; Liu et al., 2007; Miletitch et al., 2018), and is also observed in primates (Garber, 1987; Janson and Goldsmith, 1995). Moreover, such tasks drive a swarm's topology towards segregated communication networks which only interact in a few points. This ensures that, conversely to the naming game influencing the swarm behavior (failure increases aggression, which leads robots to flee), the latter also influences the former. Finally, resource collection constitutes an obvious marker of evolutionary fitness, which is highly relevant to an investigation of the HSD, an evolutionary hypothesis.

Our goal is to examine the evolution of communicative alignment and foraging behavior within and between nests as a function of prosociality and geographic distance, which are two key factors accounting for language diversity and impacting on language complexity (Padilla-Iglesias et al., 2020; Bickel and Nichols, 2009). First, we ask whether increased prosociality leads to more efficient foraging, and whether this pattern is affected by the geographical proximity of nests (seeing as closer nests result in more competition over the same resources). Second, we ask whether our manipulation of initial prosociality affects classic convergence patterns (i.e., where all robots end up aligning on the same word variant), leading to differential divergence depending on nest and past history. That is, does initial prosociality affect the degree and/or speed of convergence within and between nests, and does it result in a distinction between in-group robots (belonging to the same nest) and out-group robots (belonging to different nests)?

This investigation thus consists in a first step toward modeling and understanding the potential effects of self-domestication on language formation, introducing a novel modification of individuation to classic swarm robotics models. We discuss subsequent steps and future extensions of this basic model in the discussion.

2 Model and Implementation

In our setup, the agents are distributed in two nests (marked on the floor as grey disks). In their environment, resource items are uniformly distributed. The robots goal is to search for these items and bring them back to the nest. Once an item is brought back to the nest, another one randomly appears in the environment.

2.1 Foraging

We implemented a probabilistic finite state machine (PFSM), shown in Figure 1, which guides the robots' behavior. This PFSM is composed of three states:

- **Exploring** the robot follows a random walk.
- **Going to nest** the robot moves toward the position of its nest.
- **Going to resource** the robot moves toward the position of the last resource item found.

Notably, this PFSM requires the robot to remember landmark positions and to home in to them. This can be achieved through odometry with reasonable accuracy, particularly when using social feedback in a dense swarm (for exemple with social odometry (Gutiérrez et al., 2009b; Miletitch et al., 2013)), as we are considering here.

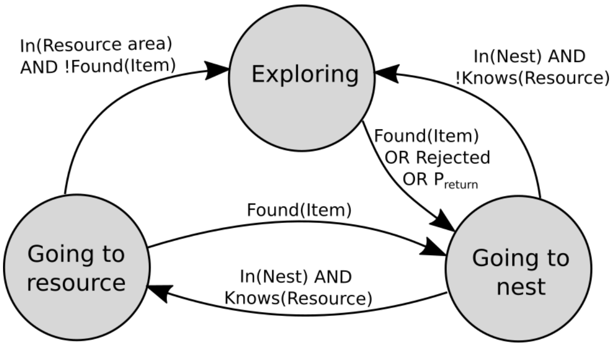

Figure 1: Probabilistic Finite State Machine which guides the foraging behavior of our robots.

From a foraging point of view, an exploring robot has two reasons to go back to the nest: either because it has found an item and is therefore bringing it back, or because the transition between the two states was triggered according to a probability $P_{return} = 0.0004$. Once the robot has reached its nest, it can either start to explore again if it does not know of a resource position, or go directly to the resource if it knows of one (i.e. it came back because it found an item). If the robot encounters a resource on its path towards the resource position, it picks it up and immediately brings it back to the nest. Otherwise, it switches to the exploring state once it has reached the resource position. In such a case, the robot also forgets the resource position as it is no longer relevant.

2.2 Minimal Naming Game

In parallel to foraging, the robots are playing a Minimal Naming Game (MNG) (Loreto et al., 2010) with local neighbours according to a dynamic and individual prosociality factor.

The MNG is a category of language games, which are models of the cultural evolution of language in populations of agents (Steels, 2011). In such games, a language is represented as a lexicon (a list of words, represented here as a vector of 8-bit unsigned numbers), which is specific to each and every agent. The goal of the MNG is to converge on a single word to name a given topic, i.e. to reduce the lexicon to a single word, which is the same for every agent. This topic, as is our case here, can be purely abstract and does not need to be a physical object. To reach such an agreement, the agents take either of two roles: speaker or hearer.

The speaker starts a game by selecting a random word from its lexicon (if the lexicon is empty, it creates a word first) and sending it to the hearer. Upon receiving the word, the hearer compares it to the content of its lexicon. If the word is already in the lexicon, the game is won, and the hearer deletes any other word from the lexicon. If, on the contrary, the word is not already in the lexicon, the game is lost, and the hearer simply appends the word to its lexicon. Finally, the hearer signals whether the game was won or lost to the hearer who, in the former case, also deletes all the words in its lexicon, with the exception of the word it had selected.

The novelty of our approach in this paper is that we introduce a prosociality factor, which can modulate the communications between agents such that sub-swarms can stop communicating almost entirely, and therefore hinder the potential for convergence between nest populations, as can be observed in human populations (Bickel and Nichols, 2009).

2.3 Prosociality

Notably, swarm robotics is predicated on homogeneity in agents communication (Brambilla et al.,

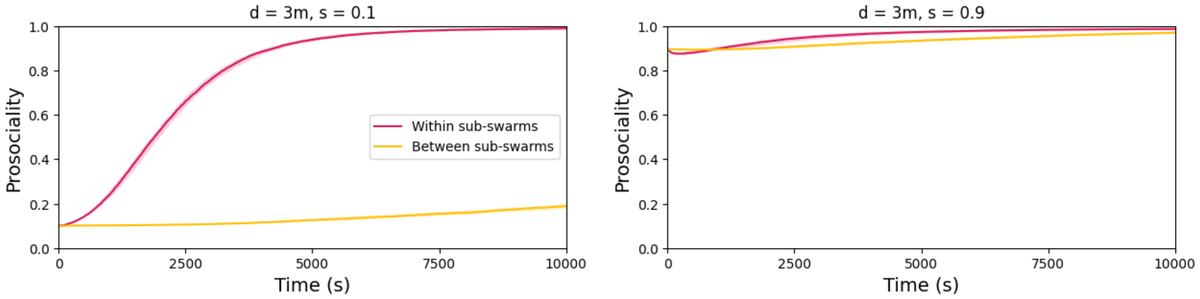

Figure 2: Evolution of the prosociality over time. Left: distant nests and low prosociality. Right: distant nests and high prosociality.

2013) (though not necessarily in the agents themselves (Kengyel et al., 2015)). This is very different from primate populations (Roberts and Roberts, 2017) which, by the very nature of our goal, we need to emulate. We therefore introduced two novel cognitive abilities to our robots, in order to bring them closer to the primate population we eventually aim to study. The first feature is robot individuation: robots have a partner-specific memory, keeping track of the outcomes of past interactions with specific robots. The second features is parameterizable prosociality: robots' tendency to interact is based on experience, such that successful communication between robots reduces their aggression toward each other and increases their chance to interact again.

Formally, we defined prosociality as a probability to interact s_{ij}, where i and j are two distinct robots. Any agent i computes s_{ij} according to previous interactions with j and Equation 1:

$$s'_{ij} = k_{ij} * \frac{MNG^{ij}_{win}}{MNG^{ij}_{win} + MNG^{ij}_{lost}} + (1 - k_{ij}) * s_{ij} \tag{1}$$

where $MNG^{ij}_{win/lost}$ is the quantity of games played between i and j that were won/lost. Equation 1 requires an initial value s for s_{ij} which is our initial prosociality parameter. k_{ij} is the weighing factor and is given by Equation 2:

$$k_{ij} = min\{1, \frac{MNG^{ij}_{win} + MNG^{ij}_{lost}}{MNG_{ref}}\} \tag{2}$$

with $MNG_{ref} = 10$ in our experiments, allowing for a slow transition from the initial prosociality to the acquired one.

As $MNG^{ij}_{win/lost}$ is identical to $MNG^{ji}_{win/lost}$, and given Equations 1 and 2, $s_{ij} = s_{ji}$.

The prosociality s_{ij} dictates robot i's behavior upon receiving a word from an exploring robot j. With a probability equal to s_{ij} , it hears the word, plays the naming game normally, and updates s_{ij} accordingly. Otherwise, it rejects the interaction and "attacks" robot j to mark its territory, causing robot j to return to its nest (see Figure 1). Our hypothesis is that, since robots meet robots from their own nest more often, their vocabulary will converge over time and their prosociality will therefore increase faster than with robots from the other nest. This would increase rejections of the latter and eventually lead to territoriality and a rupture of contact between nest populations.

2.4 Experimental Setup

In order to test our hypothesis, we set up an arena of 10x10m with two nests, and manipulated two parameters: the initial prosociality s and the distance between the nests d (in meters). We selected three settings for both of these parameters and recorded 100 runs for each of the 9 combinations of settings. The parameter values we selected were $s = \{0.1, 0.5, 0.9\}$ and $d = \{0, 1.5, 3\}$. As robots are unable to distinguish between robots from their nest and from other nests, we expect $d = 0$ to yield homogeneous dynamics, whereas, with other settings of d, we expect robots to differentiate their kin from strangers.

Our experiments were carried out with ARGoS3 (Pinciroli et al., 2012), a physically realistic simulator made for swarm robotics experimentation, with a simulation rate of 10 ticks per second. We simulated 50 e-puck robots (Mondada et al., 2009; Garattoni et al., 2016), such that 25 robots were attributed to each nest. The e-puck uses a range-and-bearing system to communicate locally (Gutiérrez et al., 2009a). 50 resource items were distributed uniformly in the environment, and reappeared in a different place after they were consumed (i.e. brought back to a nest).

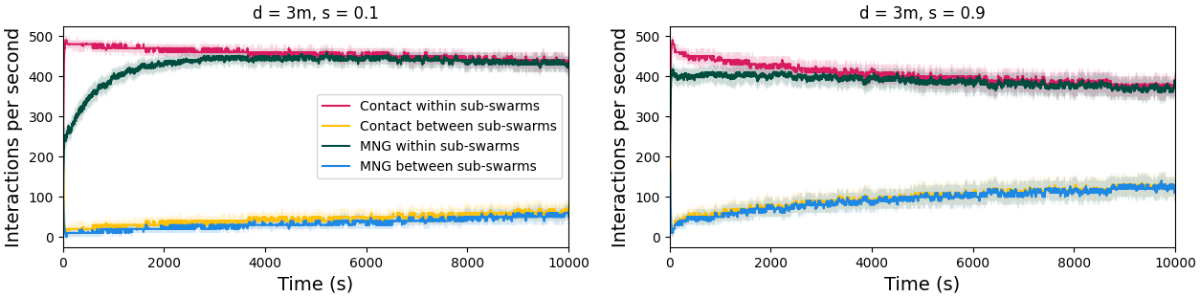

Figure 3: Evolution of the number of interactions (resulting in MNG games or not) over time. Left: distant nests and low prosociality. Right: distant nests and high prosociality.

3 Results

The resulting dynamics of the swarm can be separated in three categories. First is the evolution of prosociality, which is determined by how often robots interact with each other. Second is social dynamics; interactions that lead to a MNG, and how each robot's and sub-swarm's vocabulary evolve over time. Last is foraging dynamics and is characterized by the reach of the robots, which is impacted by the prosociality and the social dynamics.

3.1 Evolution of Prosociality

As seen in Figure 2, the average prosociality of robots toward their kin increases over time in a quicker fashion than it does for robots attached to the other nest. This is caused by the proximity of kindred robots: more occasions to communicate allow for a quicker dynamic. As the sub-swarm's vocabulary converges over time, more interactions are validated and prosociality grows.

Here two dynamics interlock: the evolution of prosociality and the convergence of the vocabulary. If the former is faster than the latter (right side of Figure 2), prosociality falls at the beginning of the experiment because few robots in their sub-swarm agree on a specific vocabulary which leads to a higher rate of failed interactions. However, in both cases, robots eventually start having more successful interactions MNG (because they are initially forced to remain in/return to the nest as they receive rejection even from their kin) and the prosociality within sub-swarms quickly converges toward 1.

3.2 Social Dynamics

We introduced a social aspect on top of the naming game in order to generate novel dynamics while retaining the *well mixed population* constraint. Figure 3 is a comparison of that dynamic between low and high initial prosociality (a prosociality of 1 would be equivalent to discarding the social layer in the behavior). When the initial prosociality is low, it slows the language dynamic down (as MNG are rarely played) at the beginning of the experiment. Once the prosociality reaches a higher level (or if it is at such levels from the start), most interactions result in an MNG, at the cost of a decrease in the total quantity of contacts within the sub-swarm (as seen in the decrease of the red curve). This happens because, as the prosociality increases, the robots are rejected less and can therefore stray further away from their nest, in areas were they encounter less robots.

The evolution of prosociality is determined by how often the MNG being played results in success or failure. Once a sub-swarm converges on a vocabulary, all interactions between robots within this sub-swarm increases the prosociality. On the other hand, as long as the two sub-swarms keep a different vocabulary, most of their interactions lead to a decrease in prosociality. Figure 4 displays the time of convergence both for sub-swarms and for the global swarm. On the left ($d = 0m$), both the sub-swarms and the global swarm behave in a similar way as they share the same nest. The further apart the nest are, the less time it takes for the sub-swarms to agree on a shared vocabulary, except for $s = 0.9$. The former phenomenon is explained by the fact that, as the distance increases, robots from different sub-swarms interact less, which means that, as less new words are introduced to a given sub-swarm, said sub-swarm can converge to a single word faster. In the case of $s = 0.9$, however, robots continue to play a significant amount of MNG with the other sub-swarm (around a hundred per second according to Figure 3), which constantly introduces new words into the robot's sub-swarm and therefore slows the language dynamics down.

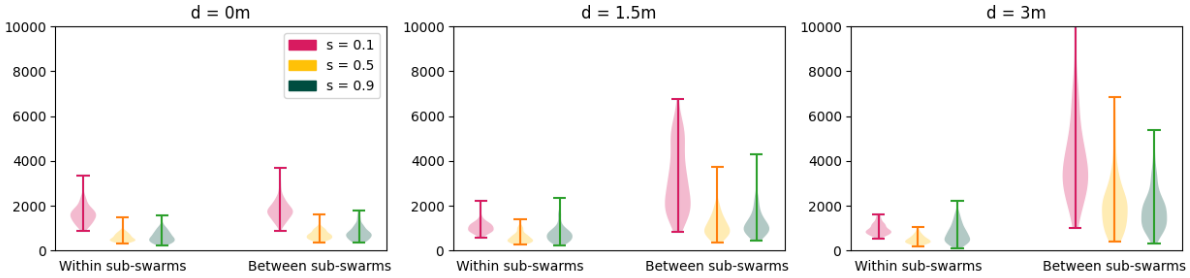

Figure 4: Violin plots of the time for the first sub-swarm to converge (within swarms, left side of graphs), and for the complete swarm to converge (between swarms, right side of the graphs), to a single word. Plots show different nest distance (left to right), and initial prosociality values (color). The case s=0.1, d=3 for convergence between swarm peaks at 16000s, left out of the graph for readability.

At the global scale, distance predictably increases the convergence time as sub-swarms have less opportunity to play, which creates a bottleneck in the communication network.

With respect to the prosociality, we observe that a very low initial prosociality results in a higher convergence time (both within and between sub-swarms) but that there is no consistent difference between medium or high initial prosociality. In other words, only very low initial prosociality values can consistently hinder the word convergence.

3.3 Foraging Dynamics

Our results (Figure 5) show that increased prosociality leads to more efficient foraging behavior: across all nest distance configurations, higher prosociality values were associated with a higher number of collected resources over time. This is explained by our rejection mechanism by which lower prosiocality leads to rejection and forces robots to return to their nest. Therefore, as prosociality increases, robots become more free to explore far away from their nest (this is the same dynamic as the one discussed in Section 3.2) and to find resources.

When the initial prosociality is high, the rate of exploitation is constant. A lower initial prosociality introduces a transitory dynamic, which, as the individual prosociality increases, approaches (and eventually overlaps) the collection rate of higher initial prosociality values.

4 Discussion

In this paper, we introduced a new swarm robotics framework for the study of linguistics hypotheses, and more specifically human self-domestication. This framework consists in two novel features: robot individuation and parameterizable procosicality. In other words, our robots remember their history with each individual robot, in the form of a dynamic prosociality value (whose initial value can be set), and this value changes the behavior of the robot towards others.

We devised an experimental setting whereby robots, which are separated into two nests, must simultaneously communicate through language games and find resource items distributed into the environment. Our goal was to determine whether prosociality could trigger kin recognition and how this would affect both the social and foraging dynamics.

Our experiments showed an emergence of an in-group bias, namely, communicating with robots from the same nest but rejecting others, with prosociality within and between nests having radically different dynamics (although they might converge asymptotically). Furthermore, prosociality affects linguistic convergence as a more agressive behavior (i.e. low prosociality) delays word convergence on the global scale. With a large geographic distance, aggressivity can even accelerate between-nest divergence, amplifying the in-group bias and promoting word convergence at the nest level rather than the swarm level, and could therefore be useful in maintaining name distinction for landmarks in the continuation of previous works (Cambier et al., 2017; Miletitch et al., 2019). Conversely, higher prosociality leads to slightly less contacts within the nest and a more efficient foraging, which are both explained by the exploration enabled by a decrease in aggressive behaviors (as rejections cause the robot to return to its nest) from kin and strangers alike. This difference is more marked as nests get closer, presumably because of competition over resources.

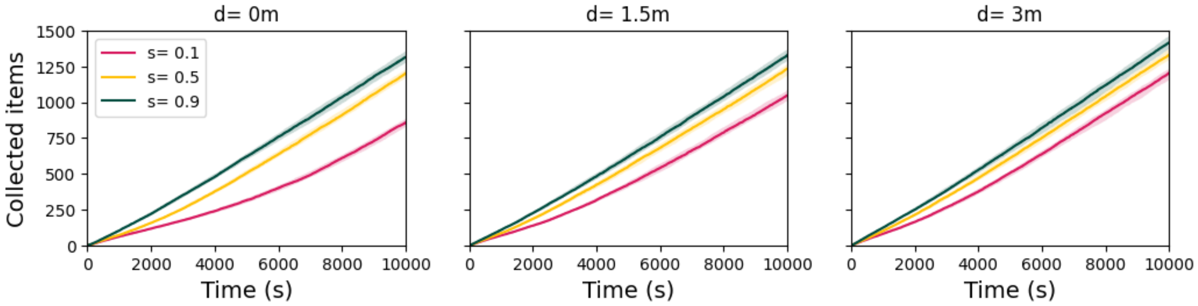

Figure 5: Evolution of the number of collected resource items over time for different nest distances (left graph to right), and initial prosociality (color).

We reckon that our model requires three more essential components in order to properly test the self-domestication hypothesis.

First, we aim to create emergent meaning by associating a word to experiences of the real world. Robots can experience the environment from different points of view, so that the sensory data they associate with a shared word is usually not exactly the same. How to make this association is called the symbol grounding problem (Harnad, 1990) and is achievable by the consensus dynamics of language games (Steels and Loetzsch, 2012), even if each robot has its own internal representation of each word's meaning. When robots are equipped with visual and other complex sensors, this mechanism can require complex technologies involving computer vision and sensor aggregation algorithms (Ganz et al., 2014), which are extremely demanding in terms of computational resource and therefore, inoperable on most swarm robots. However, in our model, the only representation of the world a robot is currently able to perceive is its position. As a first step, we will therefore attach the meaning of words to the position of the robot when playing a MNG, ensuring a straightforward but efficient grounding of the words in environmental cues.

Second, prosociality is an important factor in the development of natural languages because it enables play and teaching among kin (Benítez-Burraco and Progovac, 2020). One way to implement the notion of play in our model is to include random innovation protocols for new words and/or slight modifications and tweaks to existing words, be it in their form or in their associated meaning. As for teaching, we aim to implement an additional communication protocol which captures a learning scenario. For example, a given robot can choose to only demonstrate its word repertoire to another robot, without that interaction resulting in a failure.

Finally, in the human self-domestication hypothesis both biological and cultural evolution are present via niche construction. Genes that have been positively selected in our species are enriched in candidates for mammal domestication (Theofanopoulou et al., 2017). We have already gained some insight to this dynamic by studying different values of the innate behaviors (in this case, prosociality s), yet subsequent improvements of our model should use food consumption as a fitness evaluator for underlying biological evolution. As a first step, we intend to use relatively simple optimization algorithms that will act as an underlying "biological evolution" (López-Ibáñez et al., 2016). Then, we will turn our attention toward genetic algorithms typical of swarm robotics (Trianni, 2008; Bredeche et al., 2018). Notably, new robots can inherit the mean prosociality value of their ancestors, and mutations on innate prosociality can also be introduced.

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