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Measuring emergent behaviors in a mixed competitive-cooperative environment

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Abstract: A fundamental challenge in evolutionary theory is explaining the evolution of cooperative (or altruistic) tendencies despite local competition among agents can limit cooperative benefits. In this paper, an agent-based model is developed that combines network evolution strategies with conflicting pressures to induce cooperation as an emergent behavior. Thoroughly, we define a model of two agents able to evolve cooperative actions in a mixed competitive-cooperative environment. Specifically, two simulated E-puck robots are put inside an arena filled with diverse kinds of food items (i.e., *individual, social*). The goal is to survive as long as possible by eating food to contrast energy consumption. Robot controllers, which determine the agent's interaction with other agents, are evolved by using a genetic algorithm. Simulation results suggest that by side with expected behaviors, a new strategy emerges without any external pressure. Outcomes allow conclusions about the feasible cooperation choices individuals should make when participating in complex mixed cooperative-competitive scenarios. In particular, we observe a natural emergence of opportunistic behaviors in agents when such strategies can lead to the team's success.

Keywords: Agent-based model, Multi-agent systems, Genetic algorithm, Competition, Cooperation

I. Introduction

Agent-based modeling (ABM) [1] is a method of computational simulation technique with many applications. It works at a microscopic level, that is it concerns the control and the interactions of single autonomous agents. In the last decades, simulation modeling techniques have been largely applied in many disciplines, including social sciences research [2, 3]. Typically, ABM is mainly focused on exploring insight into the collective behavior of agents, which emerges from simple rules, such as in natural systems. Alongside this aspect, the multi-agent systems (MAS) [4] paradigm represents an interdisciplinary approach and a fruitful ground for interaction between different disciplines [5], such as Robotics [6], Game Theory [7] and Artificial Intelligence [8]. MAS are systems that intrinsically contain two levels: a "microscopic" level

(i.e., the agent's point of view) and a "macroscopic" level (i.e., the system as a whole). Differently from ABM, the goal of multi-agent systems is to design agents able to solve problems for specific applications [9]. Despite the large amount of work in this field, MAS still present several challenges, like coordination control and fault detection [10]. A possible solution to address some of them is the use of genetic algorithms [11, 12], namely techniques mimicking biological evolution according to Darwin's theory of adaptation and survival of the fittest. Genetic algorithms have been widely employed to evolve controllers for MAS [13, 14, 15, 16, 17, 18]. For example, in [19] a genetic algorithm is applied in a satellite formation flying. The authors show how this technique allows to effectively solve the task and, at the same time, deal with the consensus issue. In [20], a genetic algorithm to evolve controllers for MAS is proposed, in which agents must accomplish an object-sorting task requiring coordination between robots. In [21], swarm robotics is used to perform marine environmental monitoring missions. The authors employed a genetic algorithm and demonstrated the capability of the swarm to solve the problem in terms of coverage. Furthermore, they proved the swarm's robustness to faults of single units.

Scientific research in multi-agent systems primarily focuses on modeling agents that are able to interact so that they achieve specific goals. In designing such systems, the most challenging problem is how to induce the agents to cooperate in order to get the best strategy for the whole system. In that respect, the concept of individual rewards has been replaced by a more complex global function that includes other agents' actions. In particular, an asymmetric environment (e.g., a *common-pool resource dilemma*) and time pressures could lead to promoting agents' opportunistic propensity. Opportunism, in fact, can be seen as an intentional choice that takes advantage of self-interest and relevant knowledge asymmetry [22]. Generally, it is crucial to minimize such behaviors, as they produce undesirable results. Conversely, in the presented work it might be the preferred solution. In multi-agent systems, the knowledge is shared among participants and this aspect may create an opportunistic propensity. In contrast, here agents have only partial knowledge about the environment and other agents' actions, but the imposed

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task rules raise pressure on selfish strategies, so the ability to behave opportunistically might be crucial to guarantee efficient solutions. We state that individuals in our population have a higher chance to be selected in the evolutionary cycle when a cooperation strategy has been performed by the participants, which causes their behavior to spread to future generations. This assumption takes inspiration from Evolutionary ethics [23, 24], which aims to blend natural sciences with philosophy and states that individuals in a society will have a higher survival rate when their actions are based upon good morals. Moreover, according to the theory of evolution, the primary goal of an organism is to enhance its own fitness in order to guarantee its survival. Curiously, in situations where an organism has to select between a selfish or an altruistic choice, often organisms try to enhance the fitness of the whole group, especially if members are similar (i.e., same species). This is a famous paradox (i.e., *paradox of altruism*), a long-contested problem, extensively studied by Evolutionary ethics and proved by empirical studies [25, 26]. In this regard, agent-based modeling and multi-agent systems gave a significant contribution to the growth of these ideas. Aiming at verifying our assumptions, we allowed the population to evolve in certain coordinated behaviors and diverse generations were examined. Thus, the resulting behaviors can have an egoistic or altruistic nature, but there might be a specific combination of them allowing the agents to survive. We interpreted the different behavioral strategies by using some adjusted metrics.

In particular, we focus both on the local interactions between evolving agents at a microscopic level and the quality of the final population. Specifically, we investigate whether and how external contingencies may drive agents toward cooperation or competition. The goal of this paper is to explore the impact of environmental constraints (i.e., competitive vs. cooperative) on influencing the emergence of interdependency strategies among individuals. Simulations produce consistent results regarding the adherence to reality, in terms of plausible social behaviors, and reveal the complexity of cooperative scenarios where agents operate under opposing rules.

II. Background

A. Agent-based modeling of social behaviors

Agent-based modeling (ABM) [1] is used as a computational approach to study complex systems, including social behaviors. It represents individuals (referred to as *agents*) and their interactions as the basis for understanding and predicting collective behavior. Creating agent-based modeling systems to simulate real systems – partially or in whole – in order to investigate emergent behaviors is a challenging problem. In that respect, agent-based modeling has become increasingly popular because it permits to model the individual heterogeneity by focusing on agents' interactions and decisions [27]. Thus, these models can help analyze the emergent dynamics, arising from strict interactions between agents, by using a bottom-up approach and incorporating individual variability or stochastic events. In such a sense, multi-agent systems (MAS) [28] can be seen as a specific type of ABM, where the agents are implemented as simulated units that in-

teract in a predefined environment. Truly, there is no general agreement on the definition of what an agent is and, for this reason, the ideas about the origins of agent-based modeling differ in the specialists' community [28, 29]. Specifically, here, ABM enhances our capacity to model competitive and cooperative behaviors at both the individual and population levels of analysis. In this study, in fact, we show how competition and cooperation may generate populations that manage different strategies at both the group and individual levels. Indeed, mixed cooperative-competitive environments can be hard for optimization problems because each agent needs to coordinate with others (seen as teammates) while competing with others for resources (seen as opponents). With our simulated model, we aim to investigate what kind of behaviors agents – acting in a resources dilemma problem – will develop to allow the team to thrive. We are particularly interested in the analysis of cooperative emergent behaviors.

B. Cooperation vs. Competition

Cooperation and competition are two important concepts in the context of agent-based models and multi-agent systems. They describe the ways in which agents can interact with each other and, usually, the interplay between these two behaviors can have a significant impact on the emergent dynamics of the system. Specifically, *Cooperation* refers to the behavior of agents working together to achieve a common goal. In this scenario, the agents coordinate their actions and share resources in order to achieve the desired outcome. It can be beneficial in situations where the agents can achieve more together than they could individually, such as in collective problem-solving, resource-sharing, or decision-making tasks. Conversely, *Competition* refers to the behavior of agents working against each other to achieve their individual goals. In these scenarios, the agents compete for limited resources or strive to be the best at a task or goal.

The study of cooperative and competitive behaviors is one of the most fascinating and debated topics in research communities, like psychology and social sciences [30, 31, 32, 33, 34, 35], economics [36, 37] and sports [38]. Cooperation and competition are typically the results of social interactions between at least two elements, no matter whether they are individuals, groups or companies. Generally, they can be observed in groups of individuals. Broad research about the group dynamics was conducted by Kurt Lewin. In [39], Lewin stated that the group has properties differing from both the characteristics of single individuals/entities and the sum of them. According to [39], the group is considered the result of the interdependence among its members. In this respect, cooperative and competitive behaviors are tightly dependent on the individual's inclinations.

A pioneering work in this area is that of Deutsch [32], where a new theory of cooperation and competition was proposed. Specifically, the proposed model distinguishes the two types of behavior based on the different goal regions. In a cooperative situation, an agent obtains the goal if all other individuals get the goal too. Instead, in a competitive situation, when one or few individuals obtain the goal, others cannot (see also [40]). In other words, competition is characterized by positively interdependent goals between individuals, whereas individual goals conflict with each other in competition.

However, it has been observed how competition between groups can foster the development of cooperative behaviors within group members under specific conditions [41].

Usually, cooperation and competition have been studied by observing behaviors in human subjects [42, 43, 44, 45]. In [46], an analysis of cooperation and competition with relatives is reported. Authors claim that competition can delete the natural tendency to altruism towards relatives when part of them see a benefit increase that is achieved by damaging other relatives. These results contrasted with Hamilton's theory of genetic evolution of social behavior [47, 48, 49]. Coherently with the previous outcomes, a study on coalitions of male lions [50] demonstrated that the emergence of cooperation cannot be ascribed to genetic similarity.

A different approach is the one reported in [51], in which the authors analyzed competition in a Human-Robot Interaction framework. Their findings seem to indicate that groups of humans compete with robots more than single individuals. Moreover, the level of competition increases when the size of the robot's group matches that of the human's one.

Cooperative and competitive behaviors might also display macroscopic differences at the level of individual action. A study on the kinematic patterns of reach-to-grasp movement revealed correlations between the prior intention of the subjects and the sequence of movements they perform [52]. Hence, the authors concluded that there could exist motor patterns associated with social behavior.

Despite the cross-cutting interest in different research fields, identifying the emergent dynamics of a system in a mixed cooperative/competitive framework is far from trivial. Attempting to shed the light on this issue, our model aims at providing insights into the agent's adaptation to environmental pressures. Moreover, we investigate the importance of situational circumstances (e.g., the nearby availability of resources) and to what extent these affect the individual's behavioral strategies.

C. Genetic algorithm

Genetic algorithms (GAs) [11, 12, 53] have been developed in the early 70s by Holland and colleagues. The original aim was to study and reproduce adaptation as it occurs in natural organisms [12]. However, these techniques were successfully used in many domains [54, 55, 56, 57, 58]. Examples of application include robot navigation [59, 60, 61, 62, 63], swarm robotics [64, 65, 66, 67], optimization problems [68, 69, 70, 71], classic control problems such as the pole balancing task [72, 73], computer games [74, 75, 76], path planning for robotic arms [77, 78, 79], multi-objective optimization [80, 81, 82], game theory problems like the Prisoner's dilemma [53, 83, 84], analysis of the emergence of basic emotions in virtual agents [85] and combinatorial problems like the Traveling Salesman problem [54, 55] and the Knapsack problem [55]. Genetic algorithms were also applied in completely distant fields of research like economics [86, 87], medicine [88] and cosmology [89].

From the 90s onwards, genetic algorithms have been widely employed in combination with neural networks [62, 63, 90]. There are many examples demonstrating how GAs have been successfully used to evolve neural network controllers for autonomous robots [62, 63, 91, 92, 93, 94]. The success of

GAs paved the way to the development of a wide variety of methods attempting to outperform the classic version of the genetic algorithm [72, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106]. As a consequence, a huge amount of comparative studies was produced [72, 76, 97, 104, 107, 108], which aimed at identifying those features resulting in the superiority of one technique over the others. However, these algorithms are generally not biologically plausible and quite distant from the original aim of Holland and colleagues. Put in other words, these techniques lack any interest in modeling biological aspects of evolution and adaptation.

The operation of a genetic algorithm can be sketched in the next steps:

1. an initial population is created and its members (termed as *chromosomes* or *genotypes*) are typically filled with random values. Each individual is a possible solution for the problem;
2. individuals are evaluated and a score (usually called *fitness*) is assigned to them;
3. selection takes place and the best individuals are allowed to reproduce;
4. new individuals are generated through mutation and/or recombination operators;
5. the process iterates until a certain number of generations is reached or an optimal solution to the problem is found.

Genetic algorithms operate at a generation level, thus determining changes in the long term. The key elements are the evaluation, the selection and the reproduction processes. The way they work allows discriminating between different implementations of the algorithm [56, 109, 110, 111, 112]. Another worthwhile feature is the genetic encoding, i.e., how genes define the properties of the evolving individuals. The NEAT algorithm [104] allows to vary the controller of the evolving agents. To do this, genes encode structures defining neurons and connections (with associated weight values), along with other information useful for the operation of the whole method. In [98] a cellular encoding is introduced, where genes represent possible neural networks able to solve boolean functions. Other techniques evolve genotypes whose genes simply encode the connection weights of the neural network controller [72, 99, 105].

The approach here presented follows a phylogenetic evolution strategy, but there are different approaches adopting more ontogenetic paradigms. The latter implies that modifications in the genetic structure are applied to the specific agent and learning improves the agent's capabilities through changes in its neural network. This strategy is mostly used to obtain an optimized adaptation and task specialization in groups of robots with no starting knowledge, as shown in [113, 114, 115, 116].

In this work, we used the Generational Genetic Algorithm (GGA) [117, 118, 119], which constitutes a variant of the genetic algorithm developed by Holland. In the version used to run the experiments, no crossover is possible between the population members. Moreover, we kept the best-reproducing individuals in the population in order to re-

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1: initialize NGenerations, PopSize, NReproducing, NOffspring, Pop(0)
2: for gen <- 0 to NGenerations do
3:   for p <- 0 to PopSize do
4:     Fitness[p] <- evaluate (p)
5:   done
6:   selectBestReproducing(Fitness, NReproducing)
7:   Pop(gen + 1) = generateOffspring(NReproducing, NOffspring)
8: done

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Figure. 1: Pseudo-code of the Generational Genetic Algorithm.

tain adaptive traits that might be beneficial for the discovery of effective solutions. We refer to this feature as *elitism* [120, 121, 122, 123]. In our GGA, genotypes encode the connection weights of neural network controllers as integer values. The mapping between genes and connection weights is provided in Eq. 1:

$$w = w_{range} - \frac{g}{MAX_G} * w_{range} * 2.0 \quad (1)$$

where g is the generic gene value (integer), MAX_G is the maximum gene value and w_{range} represents the weight range. As described in section III, the variable w_{range} is set to 5.0, while the value of MAX_G is set to 255. Therefore, in our GGA the mapping is quite trivial.

The GGA works as follows:

1. a population of individuals is randomly initialized;
2. each individual is evaluated and receives a fitness score indicating its ability in solving the task;
3. after all individuals have been evaluated, the best individuals are selected for reproduction;
4. each selected individual generates a given number of offspring, which represent mutated copies;
5. the process is repeated until the total number of generations has been reached.

The pseudo-code of the GGA is provided in Fig. 1. We chose the GGA algorithm since we are mainly interested in analyzing the behavioral strategies discovered by evolving agents rather than finding optimal solutions to the problem. Moreover, the evolutionary task (see Section III) can be efficiently solved with no need for more sophisticated strategies like CMA-ES [99, 124], OpenAI-ES [103, 108, 125] or xNES [105, 126]. Finally, as we already discussed above, we want our method to maintain some form of biological plausibility.

III. Materials and Methods

A. Experimental setup

We design a cooperative/competitive simulated task in which two E-puck robots [127] are put inside a squared arena of $2m \times 2m$, surrounded by walls, filled with 5 food items. The goal is to survive as long as possible. To do this, robots should learn to eat food tokens. We define two food classes:

1. *Individual food*: it can be eaten by a single robot by itself;
2. *Social food*: only two robots together may eat this food item.

The environment contains 4 individual foods and only 1 social food. An example of environmental setup is displayed

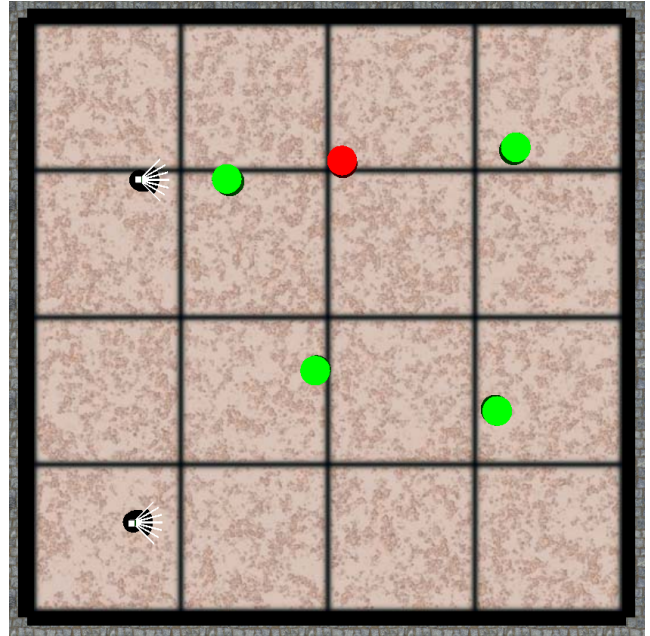


Figure. 2: Environmental setup. Both robots and food items are randomly placed within the arena. Green cylinders represent the individual food items, while the red object is the social food item.

in Fig. 2. Agents have an energy tank that can be increased by eating food items. The tank is set to 5.0. Robots start with an energy of 1.0 (corresponding to the 20% of the tank capacity), which constantly decreases during an evaluation episode. The energy loss is constant and set to 0.005 at each step of an episode. Once the robot's energy is 0, the robot cannot move anymore and "dies". Depending on the type of food, the robot receives different amounts of energy: the individual food item provides the robot with an energy equal to 1.0, while the social food item gives each robot an amount of energy equal to 4.0, i.e., four times the energy of the individual food item. This implies that, from the robot's point of view, there exist two equivalent alternative strategies:

1. eating all the individual food items individually, without caring about the other agent (*Egoistic behavior*);
2. eating the social food item with the other peer (*Altruistic behavior*).

It is worth noting that, once a food item is eaten, it disappears from the environment. Moreover, when the social food item is eaten, also the individual food items are removed from the arena, while the contrary is not true. In fact, eating the social food item is sufficient to stay alive until the end of the evaluation episode. This particular setup creates a group dilemma (or tragedy of the commons) in agents since they could work together to obtain higher performance (i.e., the higher energy of social food), despite a built-in incentive to be selfish (i.e.,

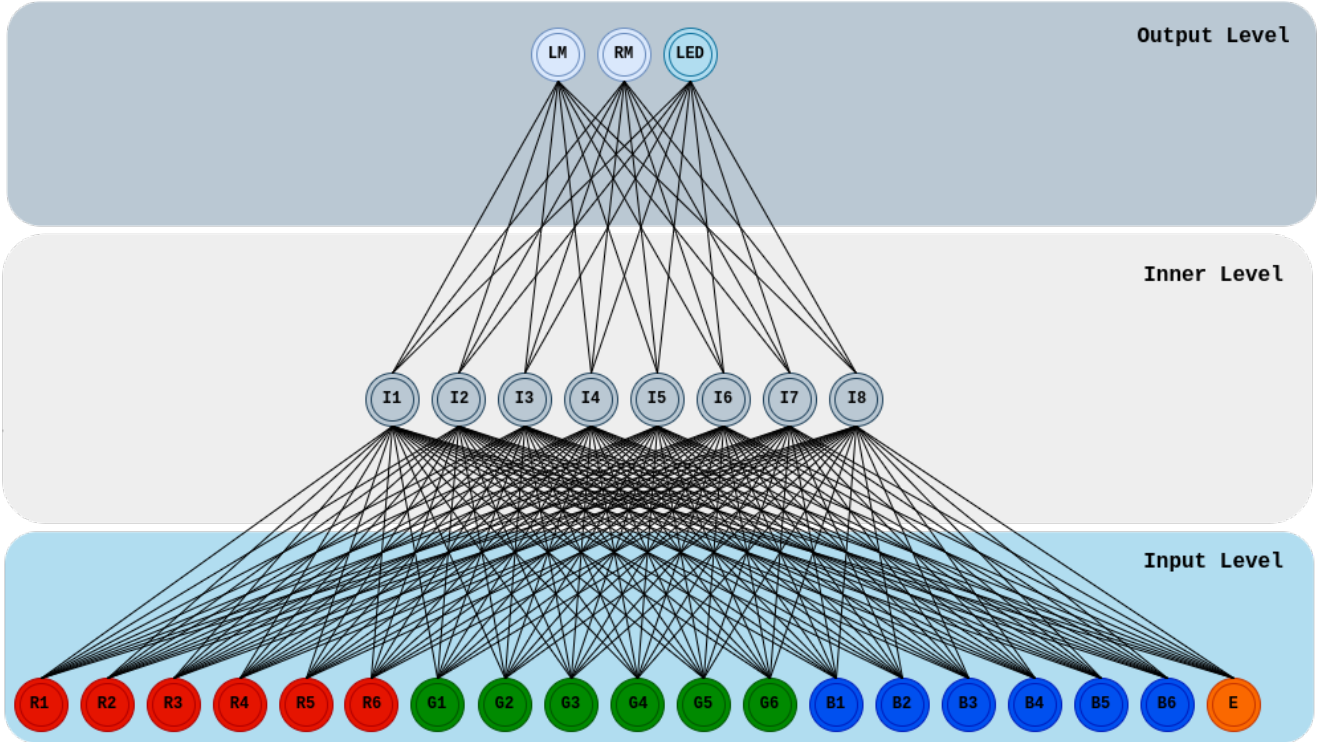


Figure 3: The neural network used as robot’s controller. The Input layer contains colored receptors neurons, respectively, Red (**R1...R6**), Green (**G1...G6**) and Blue (**B1...B6**) vision sensor signals for a total of 18 neurons; **E** is the Energy control neuron. The Inner level contains 8 inter-neurons (**I1...I8**) that act on the motor neurons (i.e., left and right motor speed, **LM/RM**) and on the **LED** output sensor.

energy consumption). Thus, if an agent is fully egoistic, it can maximize its own energy, but the couple (including itself) will be penalized in terms of long-term survival. The evolutionary task has been simulated by using FARSA [128, 129], an open-software tool that has been successfully used in various experimental settings [130, 131, 132].

B. Evolutionary parameters

The experiments have been repeated 30 times. Robot controllers have been evolved by using the GGA, previously described in Section II-C. Specifically, we set the number of generations to 400, the population size to 100 and the number of reproducing individuals to 10. According to *elitism*, the best-reproducing individuals are retained in the population for the next generation, and each one generates 9 offspring. In addition, the mutation rate has been set to 0.01. Individuals in the population are randomly initialized with genes drawn from a uniform distribution in the range [0, 255]. The full list of experimental parameters is summarized in Table 1.

C. Robot controller and Performance measures

As pointed out in Section II-C, a worthwhile component of a genetic algorithm is the evaluation of the individuals. This is made by assigning them a fitness value rating to what extent agents are able to cope with the evolutionary task. In our experiments, robots are rewarded with the following fitness function (Eq. 2):

Experimental parameter	Value
# of replications	30
# of evaluation Episodes	5
# of episode Steps	2000
# of generations	400
Population size	100
# of reproducing individuals	10
# of offspring	9
Mutation rate	0.01
Gene range	[0, 255]

Table 1: Experimental parameter settings.

$$F = \frac{1}{N_{episodes}} \sum_{i=1}^{N_{episodes}} \frac{NS_{steps}}{N_{steps}} \quad (2)$$

where NS_{steps} represents the number of steps a robot survives, N_{steps} is the number of steps of each evaluation episode and $N_{episodes}$ is the number of evaluation episodes. In our setting, agents are evaluated in 5 episodes, each one lasting 2000 steps (see Table 1).

Robots are equipped with a linear camera, whose field of view (FOV) is set to 90 degrees, which permits them to detect colored objects. The camera’s FOV is split into 6 sectors of 15 degrees each, and each sector has a receptor for 3 basic colors (i.e., red, blue and green). Furthermore, agents have an additional sensor to control the energy level. Motors include the two speeds of the robot wheels and an additional output allowing robots to turn on/off a colored LED. In this

way, robots can create a communication mechanism similar to those found in [76, 133, 134].

The robot's controller is a feed-forward neural network with 19 inputs, 8 internal units and 3 outputs (see Fig. 3). The activation function of the neural network is the logistic function. The connection weights of the network are bounded in the range $[-5.0, 5.0]$ and are derived from the corresponding genotypes.

D. Emergent Behaviors

Emergent behavior can be defined as a behavior that is not directly programmed in individuals but emerges from agents' interaction with each other and with the environment. In this scenario, the mixed cooperative-competitive setup might cause instability in cooperative strategies since individual rewards induce agents to act in a selfish way, opposite to the collective good. Thus, we expected that evolved agents can be split into three main behavioral classes:

1. *unable*: robots that do not learn the evolutionary task;
2. *egoistic*: robots solving the problem by eating individual food items and ignoring the other peers;
3. *altruistic*: robots addressing the problem by cooperating with others, thus eating the social food token.

The presence of unable robots in the final population is not surprising given the operation of the GGA. Indeed, it is not guaranteed that the offspring derived from the best-selected individuals represent effective solutions to the problem. Mutations are stochastic and can generate poor individuals.

E. Metrics

Hamming metric [135] is widely used in information theory to measure how two strings of symbols differ from each other. The Hamming distance generally counts the number of symbols that must be changed to produce two identical strings.

For example, if we consider the following two bit-strings: $a = [1\ 0\ 0\ 1\ 0\ 1]$ and $b = [1\ 1\ 0\ 1\ 0\ 0]$, the Hamming distance is 2 since we must change two symbols in string b to obtain the string a . This simple metric can be adapted to take into account the genetic diversity among individuals in a population [136, 137]. In particular, the Hamming distance – here seen as a chromosome distance – counts the population diversity and it can be defined as the sum of the Hamming distances between all possible pairs of chromosomes.

Following this definition, we compute the average Hamming distance between all pairs of individuals in the population using the Eq. 3:

$$H = \frac{1}{N_{pairs}} \sum_{j=i+1}^{N_{pairs}} \sum_{i=1}^{N_{pairs}-1} \frac{N_{diffgenes}}{N_{genes}} \quad (3)$$

where $N_{diffgenes}$ indicates the number of different genes between two individuals, N_{genes} represents the number of genes encoding the individuals and N_{pairs} is the number of pairs of individuals to be evaluated (Eq. 4):

$$N_{pairs} = \frac{N_{individuals} * (N_{individuals} - 1)}{2} \quad (4)$$

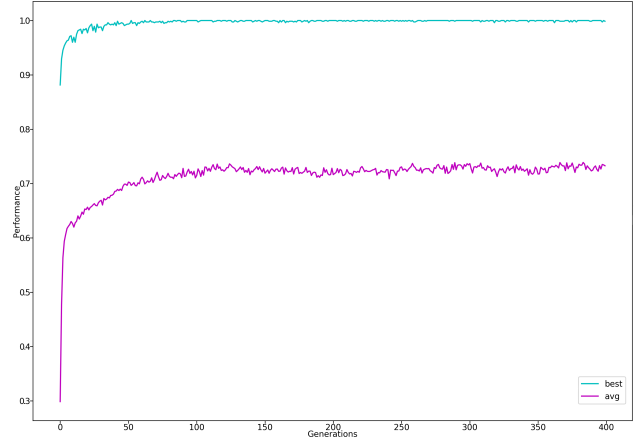


Figure. 4: Performance of the evolved controllers during evolution. Purple curve indicates the average performance of the population. Light blue curve represents the performance of the best controller within the population. Data have been obtained by averaging 30 replications of the experiment.

In the above formula, $N_{individuals}$ corresponds to the number of individuals in the population. Thus, the distance H is a quantity bounded in the range $[0,1]$, where 0 means identical individuals, while 1 indicates completely different ones.

A second metric we used is Cooperation Efficiency (CE), which inspires by the Collaboration Efficiency measure defined in [138]. Specifically, CE is defined as:

$$CE(sp) = \frac{N_{cooperative_interactions}(sp)}{N_{interactions}} \quad (5)$$

The variable $N_{cooperative_interactions}$ indicates the number of times an agent cooperates with a peer altruistically, while $N_{interactions}$ refers to the overall number of interactions. A noteworthy aspect is that the number of interactions is computed at a population level, whereas the number of cooperative interactions is calculated at species (sp) level (i.e., egoistic, altruistic, etc.).

IV. Results and Discussion

A. Data Analysis

Data analysis allowed us to assert that evolved controllers are able to effectively solve the problem. The average fitness over the 30 replications is 0.733 (Fig. 4, purple curve) with a standard deviation of 0.032. The best fitness is 0.999 (Fig. 4, light blue curve).

By analyzing the evolved strategies, we see that evolution discovered a fourth behavior: the *opportunism*. It consists in eating at least one individual food item, in order to extend the agent's chance to survive, and then cooperating with the other peer and eating the social food item. This emergent property becomes predominant in the population as shown in figures (Fig. 5, Fig. 6 and Fig. 7).

B. Behavioral Analysis

Fig. 5 displays the individual preference, defined as the probability of belonging to a specific behavioral class. At the beginning of the evolutionary process, the population mainly

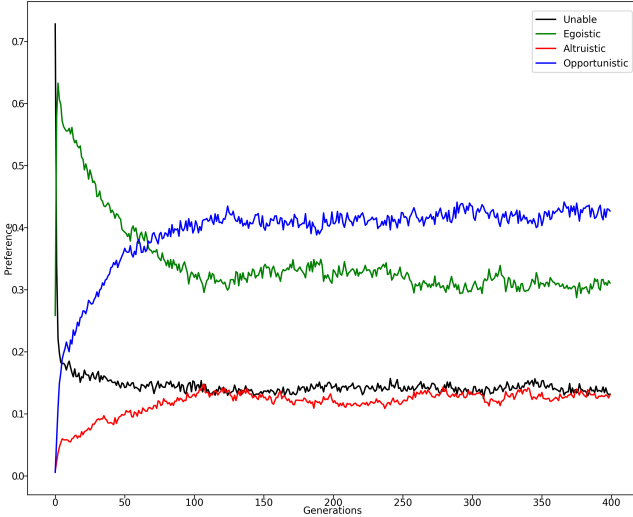


Figure 5: Preference of the evolved controllers defined as the probability of belonging to a specific behavioral class. The probability is calculated by measuring the number of times a specific strategy (i.e., *egoism*, *altruism*, *opportunism*) is performed by an agent. The value is averaged over the 5 evaluation episodes. Curves are the mean values over the 30 replications.

consists of unable individuals and only a few ones manage to eat the individual food item, which represents the easiest solution to the problem and can be done independently of the peer. The probability to eat the social food item is around 0% since this behavior requires either the coordination between the two robots or the tendency to reach the social food alone and wait for the other peer. Consequently, in the early generations, egoistic individuals are more likely to reproduce. This in turn triggers competition between agents, which is not effective in the long term. Indeed, fighting for resources significantly reduces the chance of survival. The presence of an energy level constantly decreasing during an evaluation episode produces a switch in the behavioral attitude of the agents, where selfish strategies are no longer efficient. This is why some sort of cooperation emerges, because the robots start going towards social food. Differently from what we expected, the most widespread strategy consists in eating at least one individual food, so to increase the robot's survival possibility, and only later moving toward social food.

Indeed, the presence of individual foods creates a common pool resource dilemma because these foods disappear when eaten, thus inducing agents to limit their selfish tendencies and to consume social food with others by reaching team-optimal behaviors.

If we examine the preferences of the best-reproducing individuals (see Fig. 6), it is clear how the opportunistic strategy emerges in the very early stages of the evolutionary process (approximately at generation 20). Interestingly, we observe a similar number of egoistic and altruistic individuals among the best-reproducing ones starting from around generation 70. Nevertheless, this does not correspond to a similar amount of egoistic and altruistic individuals in the population (see Fig. 5).

This can be explained by considering that *opportunism* is characterized by a selfish initial behavior. The gap between

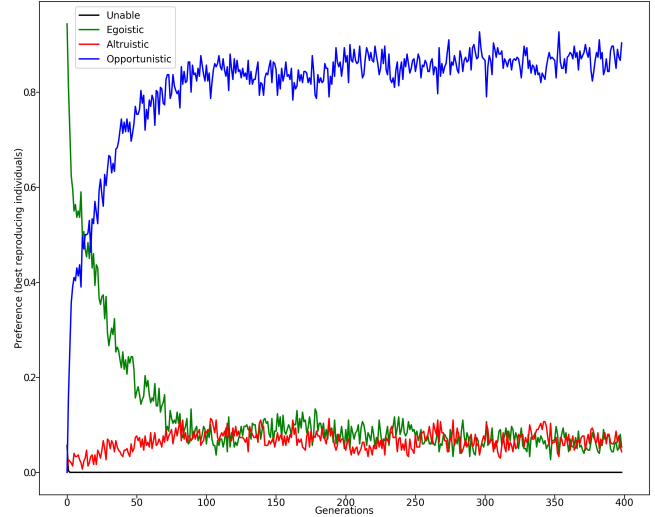


Figure 6: Preference of the best reproducing individuals defined as the probability of belonging to a specific behavioral class. Curves are the mean values over the 30 replications.

these two strategies is quite low, as can be seen by looking at the following examples (see Box 1) in which we indicate the sequence of food items eaten by an egoistic and an opportunistic individual (the 0 indicates the individual food item, while the 1 indicate the social food item):

Example 1	Example 2
egoistic: [0 0 0]	egoistic: [0 0]
opportunistic: [0 0 1]	opportunistic: [0 0 1]

Box 1: Two examples of egoistic and opportunistic behaviors. The values indicate the type of eaten food item (0: individual; 1: social).

These two simple examples demonstrate that egoistic and opportunistic behaviors differ only for the last food item eaten. Consequently, opportunistic individuals are more likely to produce egoistic offspring rather than altruistic ones, which simply go towards and eat the social food item.

The prevalence of opportunism is even clearer if we look at Fig. 7(b). Indeed, almost half of the evolved individuals display an opportunistic tendency. Egoistic agents represent around a quarter of the entire populations. Noticeably, a significant part of individuals does not exhibit any specific preference (Fig. 7(b), yellow slice). These agents belong to the class *indifferent*. Put in other words, *indifferent* individuals can arbitrarily behave as either *egoistic* or *altruistic* or *opportunistic*. Finally, the altruistic class is the smallest one (Fig. 7(b), red slice).

In order to quantify the similarity in the evolved population, we analyze the genetic difference among the evolved controllers by computing the Hamming distance (see Eq. 3). Fig. 8 shows how individuals vary among themselves during evolution.

At the beginning of the evolutionary process, individuals are randomly initialized, thus the Hamming distance is around 1.0. As stated in Section III, this means that individuals are completely different from each other. The Hamming distance

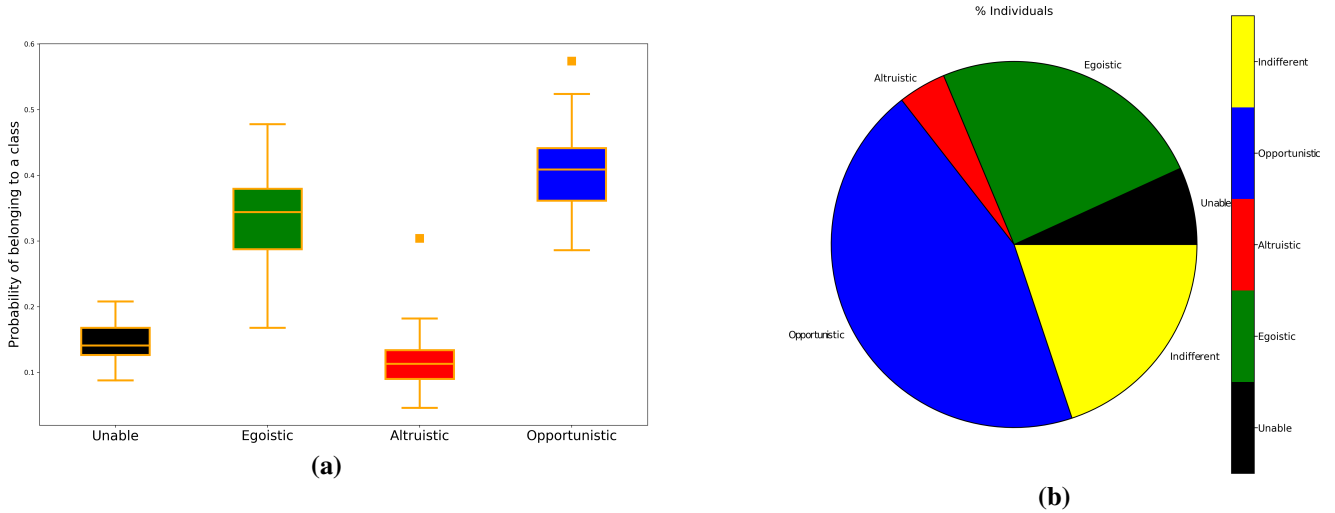


Figure 7: (a) - Probability of belonging to a specific behavioral class. Box represents the inter-quartile range of the data and the horizontal line inside the box marks the median value. The whiskers extend to the most extreme data points within 1.5 times the inter-quartile range from the box. Data are obtained by replicating the experiment 30 times. (b) - Percentage of individuals belonging to each behavioral class. Data refer to the individuals, evolved in 30 replications of the experiment.

then reduces across generations since the best individuals reproduce, generating offspring that are very similar to their parents. The Hamming distance stabilizes around 0.5, which represents an intermediate value of genetic difference, from generation 50 and reaches a final value of 0.492.

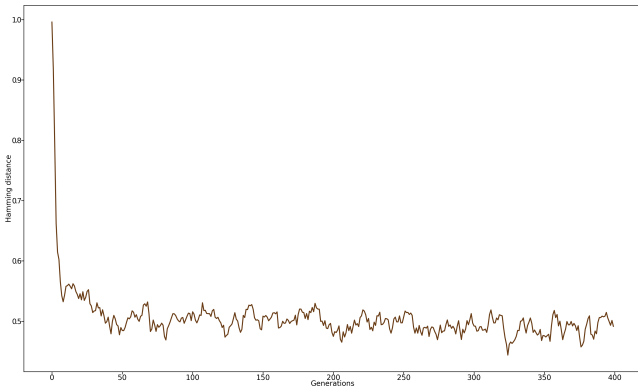


Figure 8: Hamming distance (genetic diversity) of the evolving population measured during evolution. Data are the mean value over the 30 replications.

We also measured the Cooperation Efficiency (CE) of the different groups/species we identified in the experiments. This allows us to estimate the percentage of altruistic interactions within each species. Fig. 9 shows the CE during evolution. As we pointed out in Section III, CE computes the number of altruistic interactions within a species normalized by the overall number of interactions at a population level. If we look at the different curves, we can see that opportunistic individuals are those involved in the highest number of cooperative interactions, followed by indifferent ones. The limited number of altruistic individuals in the population (see Fig. 5 and Fig. 7) explains why they are involved in very few interactions (red curve in Fig. 9).

The way input signals propagate through the agent's network controllers has been investigated by analyzing the size of weights connecting camera inputs (Fig. 3, inputs R1-R6,

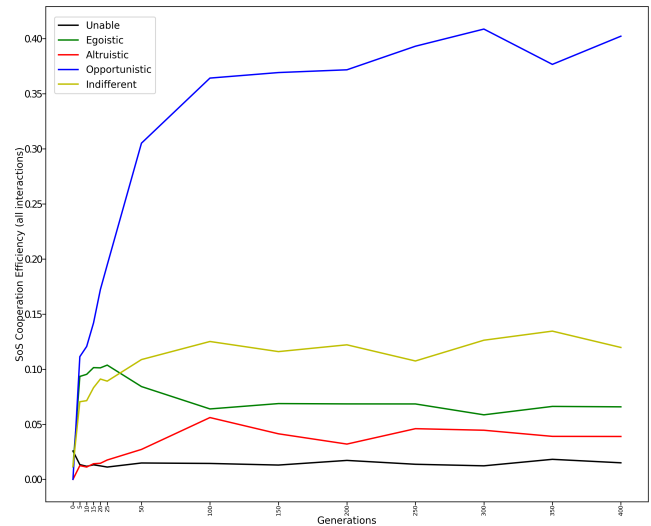


Figure 9: Cooperation Efficiency (CE) during evolution. Data are the mean value over the 30 replications.

G1-G6 and B1-B6) with the inner neurons (Fig. 3, neurons I1-I8). Data have been collected for each behavioral class. Results are reported in Fig. 10. Noticeably, there are no clear differences among the evolved controllers. This is not surprising given the operation of our GGA (see Section III). In fact, only 10 individuals reproduce in each generation. Moreover, the mutation rate has been set to 0.01 (i.e., 1%). This implies that the genetic diversity of the population is moderate, as we already showed in Fig. 8. Despite these limitations, altruistic individuals are characterized by a higher size of weights connecting blue inputs with internal neurons (Fig. 10, top-right colormap). The difference is statistically significant (Kruskal-Wallis H test, $p < 0.05$).

In order to have a better idea of the behavioral strategies discovered by the evolved agents, we analyzed the percentage of times a specific food item (either *individual* or *social*) is chosen. Specifically, in Fig. 11 we plot how many times a food item is eaten as i -th item, with $i = 1, \dots, 5$. As it can be

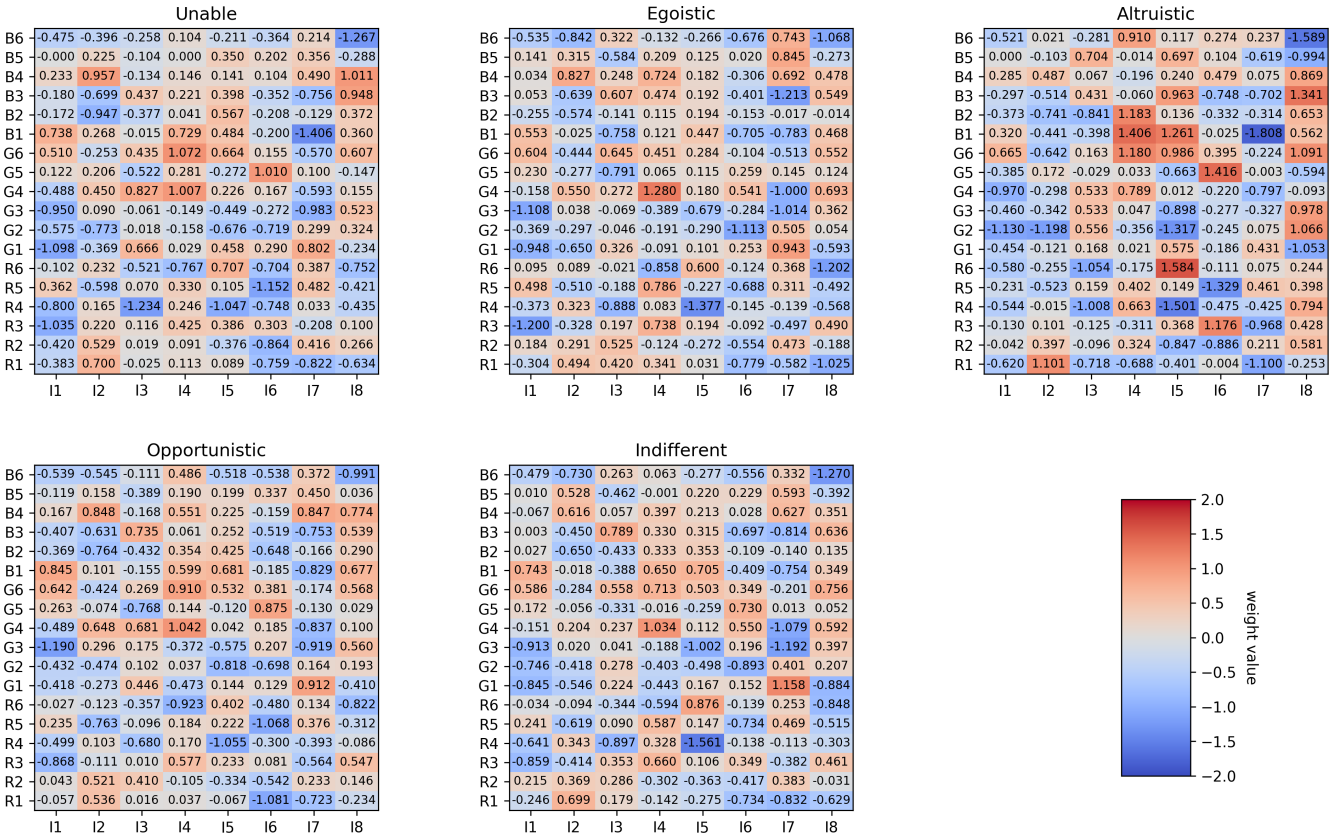


Figure. 10: Connection weights between the input and hidden layer. Colormaps represent the average value of weights connecting camera inputs with inner neurons for each behavioral class. Data have been obtained by replicating the experiment 30 times.

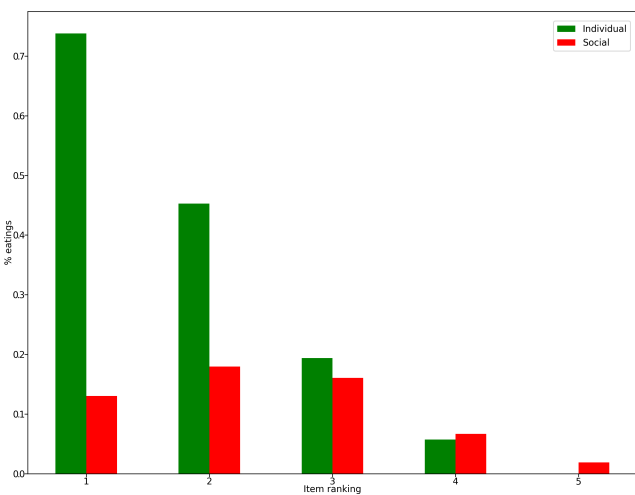


Figure. 11: Percentage of times a food item is chosen. The green bars refer to the individual food items, whereas the red bars to the social ones. Average data obtained by replicating the experiment 30 times.

observed, the individual food item is eaten as the first item more than 70% of times, whereas the social food item is chosen only around 10% of times. The ratio between the two types of food decreases to 2 – 2.5 when we look at the percentage of times a food item is eaten as a second item. Then, the two values become almost identical. The figure clearly demonstrates how opportunistic behavior is the most widespread strategy in the population. Indeed, typically individuals eat at least one individual food item before eventually moving to the social food item. This behavioral strategy enhances the agents’ ability to survive and increases the chance to cooperate with peers. We want to underline that, given the experimental setting, only the social food can be eaten as the fifth item (see description of the experiment in Section III). Nonetheless, this happens very rarely. Overall, this analysis reveals that opportunistic individuals typically eat at most one/two individual food items before moving to the social food item.

Finally, aiming at investigating the role of communication between robots, we analyzed the average LEDs activation. Fig. 12 shows the trend of LEDs activation during evolution, which starts at an intermediate value of 0.5. This is due to the random initialization of the population. Indeed, controllers consisting of random uniform weights are more likely to make half of the individuals turn their LED on, on average. Soon after the first generation, the LEDs activation suddenly decreases reaching a minimum of around 0.3 and later raises and oscillates around a value of 0.55 starting from generation 100. The initial fall of the LEDs activation can be

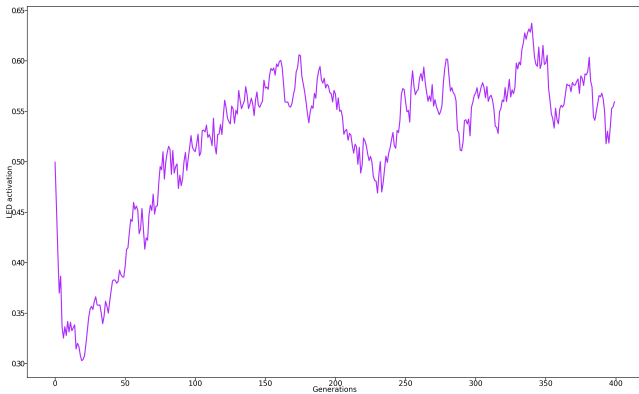


Figure 12: LEDs Activation rate. Average data obtained by replicating the experiment 30 times.

explained by considering that, during the early generations, most of the individuals in the population are egoistic, i.e., they do not care about the other agent and are not interested in communicating with it. Consequently, they do not need to turn their LED on. In order to develop effective strategies in the long term, an initial phase (around 100 generations, see Fig. 12) is required to make robots understand the importance of interacting with the other peer so as to increase the chance of survival. Overall, the curve demonstrates that robots do communicate with each other as similarly reported in [76, 133, 134].

The role of LEDs has been further investigated by analyzing the correlation between the number of individuals evolving a specific behavioral strategy and the average LEDs activation. We found a strong positive correlation in the case of altruistic individuals (Pearson correlation, $r = 0.936763$ significant at $p < 0.01$) and a positive correlation regarding the opportunistic individuals (Pearson correlation, $r = 0.487229$ significant at $p < 0.01$). Conversely, there is no correlation with respect to egoistic individuals (Pearson correlation, $r = -0.027907$). These outcomes imply that altruistic (and, to a lesser degree, opportunistic) individuals turn their LED on in order to become visible to their peers. On the contrary, egoistic individuals are not interested in communicating with others. These results are coherent with previous analyses of the evolved strategies.

Fig. 13 displays the average LEDs activation of each behavioral class. As can be seen, altruistic individuals tend to turn their LED on in order to be perceived by their peers more frequently than other groups (Kruskal-Wallis H test, $p < 0.05$). Instead, the LEDs activation of egoistic individuals is inferior to that of other classes (Kruskal-Wallis H test, $p < 0.05$). Finally, similar trends can be observed for unable, opportunistic and indifferent individuals (Kruskal-Wallis H test, $p > 0.05$).

The individual propensity to be either egoistic, altruistic, or opportunistic has been further analyzed in a post-evaluation phase, in which we placed two agents of the same species (for example, two altruistic individuals) in a laboratory environment filled with one individual food item and one social food item. The goal is to investigate whether the agent's attitude changes when it interacts with a similar peer. Put in other words, we are interested in identifying the effect of situational circumstances on the agent's strategy and whether

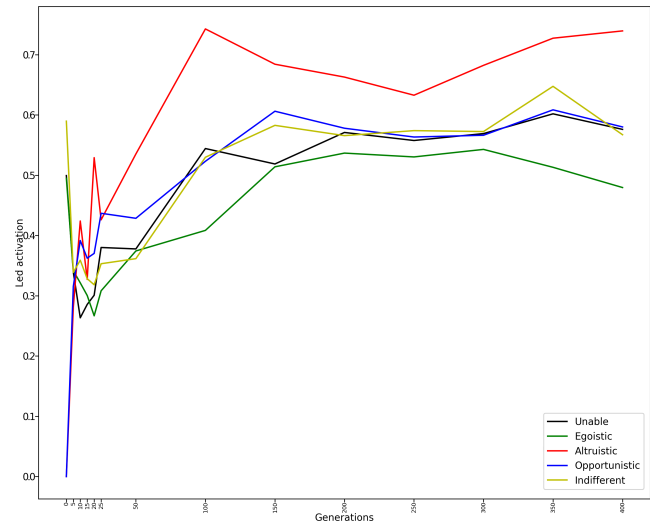


Figure 13: Average LEDs activation of the individuals belonging to a specific behavioral class. Average data obtained by replicating the experiment 30 times.

particular conditions might produce behavioral changes. The post-evaluation test consists of 4 evaluation episodes in which robots experience different relative positions of the other elements. An example of a test episode is provided in Fig. 14.

At each evaluation episode, we measured the item(s) reached by each agent, so to quantify the robot's propensity. The results of the post-evaluation test are provided in Fig. 15, Fig. 16 and Fig. 17. Now, it should be mentioned that the low number of altruistic individuals, belonging to the evolved population, remarkably limits the number of tests compared to the other two species.

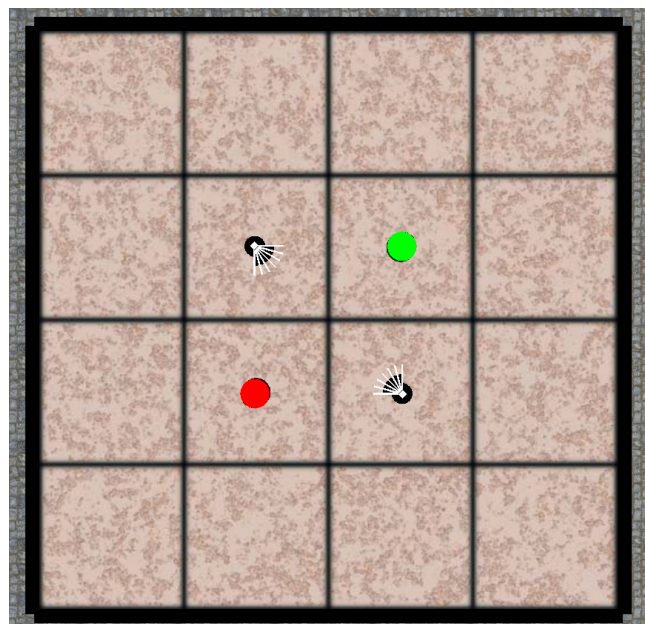


Figure 14: Example of test episode. Robots are initially placed in front of each other and both of them see food items.

As it can be seen, the test reveals that individuals adapt their strategy to both their peer's behavior and the environmental circumstances. In fact, altruistic individuals might some-

times behave either egoistically (Fig. 15, bars 3, 13 and 14) or opportunistically (Fig. 15, bars 1, 18 and 23). Similar tendencies can be observed by considering some of the test outcomes about opportunistic (see Fig. 16) and egoistic individuals (see Fig. 17). We can argue that situational conditions affect the agent’s propensity and drive towards behavioral modifications with respect to the evolved strategies. Namely, the individual’s behavioral strategies are situational responses rather than intentional actions.

Overall, these data indicate that robots exhibit a tendency to behave in a preferred way, but they are capable of adjusting their strategy to fit better with the specific environmental condition they experience. However, there are some differences between evolved species: opportunistic and egoistic individuals preferentially behave according to their tendency as can be seen by looking at Fig. 16 and Fig. 17, respectively. This can be explained by considering that these two species become predominant since the early generations of the evolutionary process. The strategies adopted during the test phase do not differ from those observed during evolution, where the chance to be evaluated with a peer of the same species is high. The little variability in some replications may be ascribed to specific counter-behaviors performed as a result of the interaction with the peers. In addition, as we stated above, agents are reactive and adapt to both the particular environmental condition and the strategy of other peers. Conversely, altruistic individuals change their behaviors very frequently across the different replications. This result is only partially surprising: first, the number of evolved altruistic individuals is significantly inferior to the other species (Kruskal-Wallis H test, $p < 0.05$). Furthermore, it is highly unlikely that an altruistic individual has been evaluated with a peer of the same species during evolution. Consequently, altruistic agents are tested under not experienced environmental circumstances, and the exhibited behaviors are unpredictable a priori.

V. Conclusions

Cooperation and competition are two well studied behaviors that can be observed in a wide range of real-life situations, including human relationships, economics, games, etc. One does not exclude the other. Instead, their interplay can result in the emergence of complex strategies, whose identification is far from trivial. In general, competitive scenarios may involve either two groups competing against each other (for example, a predator-prey scenario) or members of a group fighting for limited resources. On the other hand, cooperation emerges when individuals cannot cope with a specific situation by themselves or share a common goal.

In this work, we investigated the emergence of cooperation and/or competition in a group of two robots. From a robot’s point of view, alternative behaviors are equivalent since they represent identical suitable solutions to the evolutionary problem. In this scenario, a higher level of cooperation is required. Indeed, the presence of diverse possible strategies could induce agents to select an optimal policy where a fully altruistic behavior should be combined with a more egoistic one to produce the best strategy for their common goals. Nonetheless, evolved agents discovered another behavioral strategy, the *opportunism*, which is the most diffused behavior in the population evolved with the GGA. This

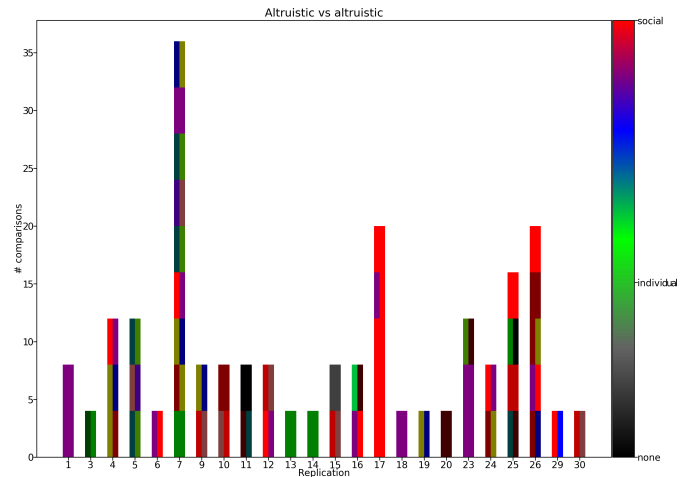


Figure 15: Post-evaluation test of altruistic individuals. Missing replications depend on the few numbers (< 2) of altruistic individuals in the final population. Colors code the two possible types of items reached by agents during the episode: (*green*) individual food, (*red*) social food. The obtained color map depicts the type of action: from an egoistic choice (*light green*) to an altruistic propensity (*light red*) passing through an opportunistic behaviour (*violet*). The adjacent bars represent, for each agent in the tested couple, the mean color obtained from the sequence of reached items following the just defined color map.

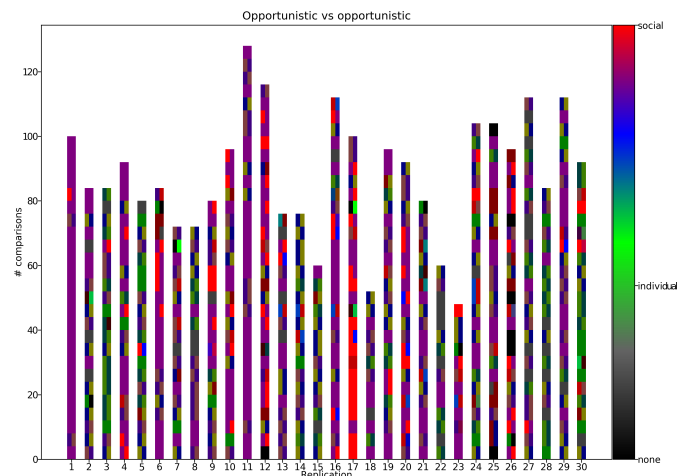


Figure 16: Post-evaluation test of opportunistic individuals. Colors code the two possible types of items: (*green*) individual food, (*red*) social food. Each comparison’s color is obtained by averaging the sequence of reached items. Here, the prevalence of violet confirms the opportunistic tendency of the agents.

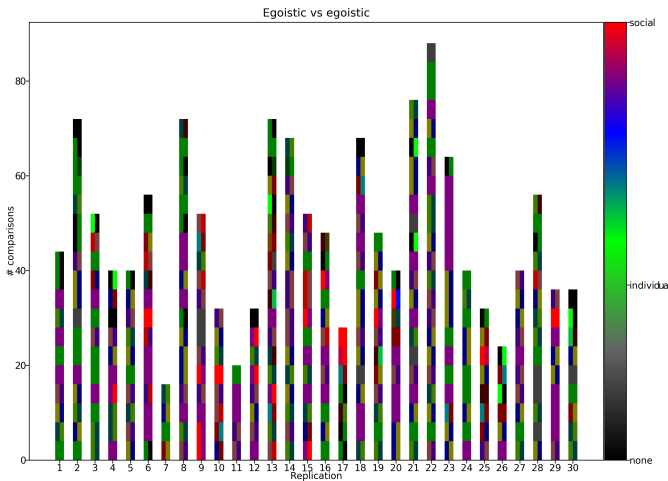


Figure 17: Post-evaluation test of egoistic individuals. Colors code the two possible types of items: (*green*) individual food, (*red*) social food. The mean value tends to green color combinations, which attests to a greater egoistic tendency of the couple.

emergent property permits the robots to stay alive longer and adapts better to external constraints. Noticeably, the spread of such behavior in the population comes only from the evolutionary process. In fact, the experimental setup we choose does not drive agents toward a preferred solution, since there is no global incentive to cooperate or compete. Instead, robots are left free to explore and behave according to the environmental conditions they experience. As we showed in the post-evaluation test, agents adapt to situational circumstances and may change their propensity depending on the particular situation. This demonstrates that the designed scenario does not limit individual choices, but rather fosters the emergence of a wide variety of behavioral opportunities that cannot be predicted. In particular, we show that cooperative behaviors can be naturally evolved in a population of agents when such behaviors can lead to the team's success.

Emerged strategy implicitly includes selfish sub-tasks if the coordination within a team proves complex. As we stated above, opportunistic behavior has not been explicitly induced but can arise if highly beneficial to the system.

The setup we define is challenging since robots are endowed with a limited amount of energy at the beginning of an evaluation episode. Indeed, their energy level is only 20% of the tank capacity. Moreover, energy constantly decreases during the episode, regardless of the agent's behavior. Consequently, robots must explore the environment as quickly as possible so as to have a chance to eat food items and live longer. Cooperation and competition mechanisms arise, and opportunism becomes prevalent in the evolved population. However, we cannot guarantee that similar results still hold when initial conditions vary. For example, evaluating robots with a full initial energy level may result in a completely different system dynamic, with unpredictable behavioral strategies. Alternatively, changing the number of foods – individual or social – and/or the ratio between the energy they provide to the robots might generate different outcomes. Future analysis will be devoted to investigating the impact of

different environmental conditions on the agent's behaviors and interactions.

Lastly, as future research directions, we plan to investigate what kind of behavioral strategies emerge when the number of robots increases and, in particular, to extend the analysis to swarms of agents that should take a collective decision, as shown in [133, 134]. In these scenarios, agents must work in conjunction with teammates and compete against the other teams' members, so challenges get increasingly complex. The larger the size of the group, the higher the number of possible interactions.

Acknowledgments

The authors would like to dedicate this work to the memory of Dr. Domenico Parisi. This research originates from his curiosity and interest in Robotics and Social Sciences, among others. Domenico Parisi was an incredible source of ideas and undoubtedly inspired our past and current research activity.

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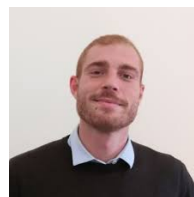
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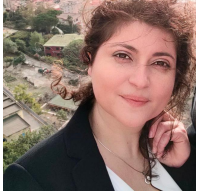
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