# The selfish vaccine Recipe: A simple mechanism for avoiding free-riding

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# THE SELFISH VACCINE RECIPE: A SIMPLE MECHANISM FOR AVOIDING FREE-RIDING

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## ABSTRACT

Social loafing and free riding are common phenomena that may hinder crowdsourcing. The purpose of this work is to identify the minimum conditions that can promote cooperation and group problem solving avoiding free riding and social loafing. We assume two kinds of scenarios (Recipe A, free riders have access to benefits produced by groups and Recipe B, the benefit produced by groups are shared only within the group) and then we investigate the relationship among the tendency to cooperate, group sizes, and difficulty of the task by means of numerical simulations. Results indicate that in the Recipe A world, collective intelligence and crowdsourcing are generally less efficient compared to what observed in the Recipe B world. Indeed, in the latter cooperation appears to be the optimal strategy for the progress of the world. Given the social importance of crowdsourcing, we discuss some useful implications of our results on crowdsourcing projects.

## 1 INTRODUCTION

Since ancient times, humans have shown the tendency to aggregate, and therefore to rely on each other, to solve complex problems, first of all the one about their own survival. The first members of our kind, traditionally identified with Homo rudolfensis and Homo erectus which lived around 1.8 million years ago, shown a significant expansion of the brain (Dean 1990). According to some authors (Bogin and Smith 1996; Key 2000), such brain expansion is a reliable signal of the beginning of an enlarged social cooperation. Indeed, the increasing brain size could never have happened in the absence of a context characterized by a wide social support. The capability defined as Collective Intelligence (Pierre 1990; Singh 2011), that is a form of intelligence that emerges from collaboration and coordinated efforts of many individuals, is an ability that we share with other social species (e.g., social insects, birds). However, as claimed by Dunbar (2004), there is a relationship between the possibility of socialization and the size of a group. The typical capability of humans to exchange information in a complex way (i.e., language) allowed a significant increase in group size (Dunbar and Bickerton 1996) and therefore an easier access to forms of Collective Intelligence. The ability of groups to show greater intelligence than its individual members has in humans its highest expression. Our social system is strongly pervaded by Collective Intelligence. The development of collective knowledge (Carpendale et al. 2014), the emergence of social norms (Kenrick, Li, and Butner 2003), the adoption of a common language (Loreto and Steels 2007), and thus ultimately the very same human society (Durkheim 1912), could be considered the product of Collective Intelligence. Taking into account the unprecedented predisposition of human beings to rely on others to produce better solution to problems, one of the challenges of our contemporary world consists precisely in exploiting this capability. For example, the attempt to involve a large number of people in solving problems or in generating ideas. This approach, characterized by a widespread problem solving, is defined Crowdsourcing (Howe 2006; Surowiecki, Silverman, et al. 2007). Surprisingly, the ability of individuals to obtain good performance by working in groups on a wide variety of tasks, it is not strongly linked to maximum or average intelligence of its members, but rather to social skills (i.e., the average social sensitivity of group members or the equality in distribution of conversational turn-taking) (Woolley, Chabris, Pentland, Hashmi, and Malone 2010). The same production of knowledge seems to emerge by coordinated interactions among actors whose individual expertise is limited (Dankulov, Melnik, and Tadić 2015).

The rise of new information technologies has greatly expanded the number of people that can be reached. Nowadays, information and communication technologies connect people around the world, allowing them to interact across geographical boundaries. These new opportunities for large-scale interaction, as well as the bi-directionality offered by these means (Dellarocas 2003), allow immediate access to the collective knowledge produced and to quickly generate new one (e.g., Google, Wikipedia). The crowdsourcing has obviously benefited from these new opportunities. Many scientific studies have indeed took advantage from the involvement of a wider pool of people, whose expertise was limited, in the resolution of complex problems. In the EteRNA project 37,000 non experts volunteers playing with simulated RNA design puzzles, discovered several previously unrecognised rules, significantly outperforming prior algorithms and improving the experimental accuracy of RNA structure designs (Lee, Kladwang, Lee, Cantu, Azizyan, Kim, Limpaecher, Yoon, Treuille, and Das 2014). Other important scientific discoveries were made possible by crowdsourcing, for example new classes of galaxies in the project Galaxy Zoo (Cardamone, Schawinski, Sarzi, Bamford, Bennert, Urry, Lintott, Keel, Parejko, Nichol, et al. 2009), and the structure of proteins relevant for the transmission of HIV in the project Foldit (Khatib, DiMaio, Cooper, Kazmierczyk, Gilski, Krzywda, Zabranska, Pichova, Thompson, Popović, et al. 2011). Crowdsourcing has proved to be a successful approach, even in areas other than science. For example, the Soylent project allowed to develop a word processing interface that utilizes crowd contributions, able to carry out complex tasks of correction and editing of a text (e.g., text shortening without changing the meaning of the text, formatting citations, finding appropriate figures, spelling and grammar checks) (Bernstein, Little, Miller, Hartmann, Ackerman, Karger, Crowell, and Panovich 2015). In the latest years, an increasing interest is devoted in particular toward practical mechanisms (i.e., algorithms) dedicated to the aggregation and ranking of crowdsourcing contributions (Raykar and Yu 2012), as well as to their quality (Chen, Bennett, Collins-Thompson, and Horvitz 2013; Davtyan, Eickhoff, and Hofmann 2015).

Since its beginnings, social psychology has focused on the effects that group membership has on individual performance. The pioneering work of Ringelmann (1913), conducted between 1882 and 1887, can be considered the first social psychology experiment. Although the comparison of individual and group performance was only a secondary interest in his report, he noticed that the performance decrease in relation to the increase of the group size (i.e., Ringelmann effect). This effect has been taken up and expanded by later authors (Latane, Williams, and Harkins 1979) under the name of social loafing (i.e., decrease in individual effort when performing in groups as compared to when they perform alone). Such behaviour has shown itself robust across gender, cultures, and tasks (Karau and Williams 1993) impairing the ability of human beings to create Collective Intelligence.

Another problem associated with the increase of the group size is free-riding (i.e., the exploitation of others' cooperation). Social dilemmas have been defined by Dawes (1980) as situations in which each person has available a dominating strategy, (i.e., one that yields the person the best payoff in all circumstances) and the collective choice of dominating strategies results in a deficient outcome (a result that is less preferred by all persons than the result that would have occurred if all had not chosen their dominating strategy). In social dilemma, there are strong incentives to act selfishly, but the highest profit can be achieved only when everybody cooperates (e.g., creation of a public good, sustainable use of a common resource). In such kind of context, it's frequent to observe free-riding behaviour. Within social dilemma games when the contributions of individuals can not be identified, the donations appear to be lower (Small and Loewenstein 2005). Some individuals tend to shirk, determining an inefficient public good (Volk, Thöni, and Ruigrok 2012). When the group increases in size, the ability to identify who contributes decreases, as well as the probability that all the others cooperate ensuring the greatest possible profit. In this case, free-riding on the actions of others is the most profitable strategy. Other examples of this behaviour are observed within innovation contest communities, which are used by companies to integrate knowledge and creativity of external people. Free-riders receive comments and feedback on their ideas from the other members of the virtual community, but they do not concede in turn indications to improve others' proposals, thus increasing their chances of winning the contest (Kathan, Hutter, Füller, and Hautz 2015). The same crowdsourcing platforms mentioned earlier are not immune to these effects. Analyzing the contribution patterns in seven different crowd science projects, Sauermann and Franzoni (2015) noted that most of the participants contribute only once and with little effort. Indeed, only about the 10% of the collaborators accounted for almost all the work. The same use of a network dedicated to Peer to Peer file sharing such as Gnutella, is strongly affected by free-riding behaviour. Almost 70% of Gnutella users share no files (Adar and Huberman 2000). The decrease in cooperative behaviour with the increase of group size, has found further confirmation in the simulations conducted by Guazzini and colleagues (Guazzini, Vilone, Donati, Nardi, and Levnajić 2015). When the tasks are not particularly demanding, the authors have observed that very large groups tended to have a minor fitness (i.e., score) compared to smaller groups. This is due to the excessive presence of free riders that hinder the generation of new knowledge.

The present study is an exploratory evaluation of the factors affecting the probability of cooperation and the fitness of the agents. Its purpose is therefore to hypothesize the minimum conditions that can promote cooperation even in large groups without incurring in phenomena such as social loafing and free riding, thus offering new and valuable indications for more efficient and effective crowdsourcing platforms and applications.

## 2 MODEL DESCRIPTION AND PARAMETERS SETTINGS

We consider a population of $N$ players divided into $n$ groups with fixed size $S$ (where $S = \frac{N}{n}$). We take a single value of N ($N = 128$), and seven values of $S = 2, 4, 8, 16, 32, 64, 128$.

The measure of player's the propensity to work collectively as opposed to individually (in other terms, the tendency to collaborate with other group members when solving a certain task) was labelled as $p_i$. We generated the value of $p_i$ following a uniform distribution (between 0 and 1) to each player $i$ in each group. Such value $p_i$ does not change over time and thus it is characteristic for each player. Then, the algorithm assigned a task to each group according to the following:

- A task (of a given value $R$ of simplicity) is assigned to each group where the value $R$ is chosen randomly from 13 values ($R = 0.0001, 0.001, 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1$).
- Each of $n$ groups worked in parallel to a task with the same-simplicity $R$.
- A sequence of games was run for each combination of size group $S$ and task simplicity $R$.

Each iteration was divided in three steps:

- Each individual $i$ has a probability $p_i$ of joining the collectivist group, if not, the person plays alone (i.e., individualist player).
- If the player choose to cooperate the expected gain of the player $i$ ($G_i$) is fixed at $G_i = C_j + 1$, with $C_j$ representing the group's collective knowledge (see below). It represents the "experience" of the groups, in other terms the level of knowledge reached by the group during the previous turns. Conversely, if the player $i$ adopts an individualistic strategy, the gain $G_i$ is chosen uniformly (between 1 and 10). Larger $G_i$ means smaller probability to solve the task but with potentially bigger gain in case of a positive resolution of the task.
- The algorithm determines whether the task is actually solved by the collectivist player (with probability $R$) and by each individualist player (with the probability $R^{G_i}$; since $R \leq 1$, larger $G_i$ means smaller chance of problem solving).

So, we assume that, when a group is facing a problem in a cooperative way, it will exploit its previous knowledge (e.g., solving a difficult mathematical problem given some fundamental theorem previously discovered). On the contrary, a non cooperative subject would try to force the solution alone without any advantage given by the group's knowledge. As a consequence, the chance of solving a task by an individual player should depend on the gain, while it does not depend on the gain for a group of players. Indeed, a cooperative group can be thought as always solving a relative simple task (i.e., just a one step procedure). Conversely, a selfish agent trying to jump without any help by the group to the same gain should pay the entire effort (i.e., $R^G$) in order to obtain it.

Regardless of its iteration-dependent divisions into collectivists and individualists, each group was indexed with $j$ to differentiate from the $i$ index which indicate players within a group. Given the winners and losers for a given iteration, the algorithm assigns a set of scores.

The Capacity $C_j$, that is the group's capacity to solve tasks (e.g., the collective knowledge of a group), is an integer value equal to the number of iterations in which one collectivist has solved the task, regardless of $R$. At the beginning it is set for all groups to the value $C_j = 0$ and it's updated $C_j \to C_j + 1$ each time one player playing as a collectivist solves the task.

Within such a framework we designed two different scenario, with respect to the pay off dynamics, representing two interesting set of norms that can be used within a real social system. The two "norm systems" are indicated as A (i.e., numerical recipe A) and B (i.e., numerical recipe B), and substantially affecting the "free ridings" advantages of the agents.

### 2.1 Recipe A

In the recipe A the potential benefits for free riders are maximized: in case of a failure to solve the task by a collectivist or an individualist, nothing happens. On the contrary, If a collectivist solves the task, it contributes to each player in the group (collectivists and individualists). Such contribution is quantified by the additional fitness $G_i = \frac{C_i+1}{S}$, where $C_i$ is the capacity of the group in which operates $i$, and $S$ is the group size. And consequently the gain of $i$ is reduced to the same quantity $G_i$. Crucially, an individualist who solves the task gains additional fitness $G_i$ but there is no other contribution to other players. However, individualist always gain $\frac{C_i}{S}$. Such model of pay-offs tries to represent the idea that collectivists distribute new knowledge both to themselves and to all others, while individualists keep it for themselves. However, collectivists face with easier tasks since they work together, but with potentially lesser new knowledge (fitness) for each of them separately. In contrast, by working alone, individualists face with harder tasks but learn much more when they actually solve them, but they avoid to share this new knowledge with others.

### 2.2 Recipe B

In the recipe B the potential benefits for free riders are minimized. As in the recipe A, in case of a failure to solve the task by a collectivist or an individualist, nothing happens. On the contrary, If a collectivist solves the task, it contributes to each player in the group was been a collectivist the turn before (i.e., the other collectivists). Such contribution is quantified by the additional fitness $G_i = \frac{C_i+1}{S_c}$, where $C_i$ is the capacity of the group in which operates $i$, and $S_c$ is number of agents that cooperated in the previous turn. In this case the gain of $i$ is again reduced to the same quantity (i.e., $G_i$). Again an individualist who solves the task gains additional fitness $G_i$ without gifting any contribution to other players. In this recipe individualists do not receive the cooperators contribution. Such model of pay-offs tries to represent a system where collectivists would distribute new knowledge only to themselves and to all others who have contributed before (i.e., so without share any benefits with those who were individualist).

### 2.3 Numerical simulation

The simulation involved $n$ groups of size $S$ simultaneously for a given $R$. After 1000 iterations (a round) the simulation is interrupted. The systems adapts over 2000 rounds (a game) with evolutionary selection being applied at the beginning of each round (the numbers of iterations and rounds were sufficient for reaching a stable configuration). We computed the mean fitness $\bar{\pi}$ of all players (regardless the group they belong to) removing at random 20% of players whose fitness is below $\bar{\pi}$ (i.e., such players are replaced by new ones whose $p_i$ are drawn again, so that the groups' sizes $S$ are preserved). From one round to another, the value $R$ remains the same (the only thing that has changed from one round to another is the structure of groups in terms of players' $p_i$, i.e., the distribution of $p_i$ within each group) but all groups' capacities $C_j$ and all players' fitnesses $\pi_i$ are reset to 0. Better fit players are kept in the game, in addition to 80% of lesser fit players. It is the player's $p_i$ and its relation with other player's $p_i$-s that dictates the player's overall performance in any game. We run different series of simulations in order to test the effect of the adopted social recipe.

## 3 NUMERICAL RESULTS

The numerical simulations tested the effects of the factors: group size, and difficulty of the task, on the final degree of cooperation, agents' fitness and collective knowledge of the group at the equilibrium. i.e., in the most "stable" state reached by the system after the adaptation.

The results allow to compare the order parameters of the system at the equilibrium, with respect to the "recipes" adopted to mimic the human dynamics properly. In particular within this study are compared two different numerical approximation of real social systems, in terms of shared social norms (i.e., here respectively indicated as A and B.

### 3.1 Final density of "Cooperation"

The first order parameters taken into account has been the average probability of observing a cooperative act from an agent belonging to the system at equilibrium. Such a quantity was derived through numerical simulation with respect to the Group Size and to the Difficulty of the task (Figure 1).

The order parameter *density of cooperation* at the equilibrium, is represented respectively: on the left Figure with respect to the group size, and on the right Figure with respect to the "difficulty of the task". While the Recipe *A* produces systems showing the well know "Social Loafing effect", i.e., the tendency to reduce the cooperative behaviour frequency at the increasing of the group size. At the contrary the Recipe *B* determines systems where the average agents' tendency of cooperation increases with the increasing of the group size. (i.e., large groups induce a greater density of cooperation between agents). A different representation of the numerical results is reported in Figure 2, which shows the final density of cooperators for the recipes A and B.

The inspection of the Figure 2 evidences how the cooperation rate is always greater in the world shaped by the Recipe B (on the right Figure). Within such a world the cooperation rate is always greater than chance level (i.e., 0.5), approximating such a value only for challenging problems (i.e., low simplicity task, $R \approx 0$). Notably the "Social Loafing effect" can be clearly detected in the Figure on the left, as well as it is absent in the right Figure.

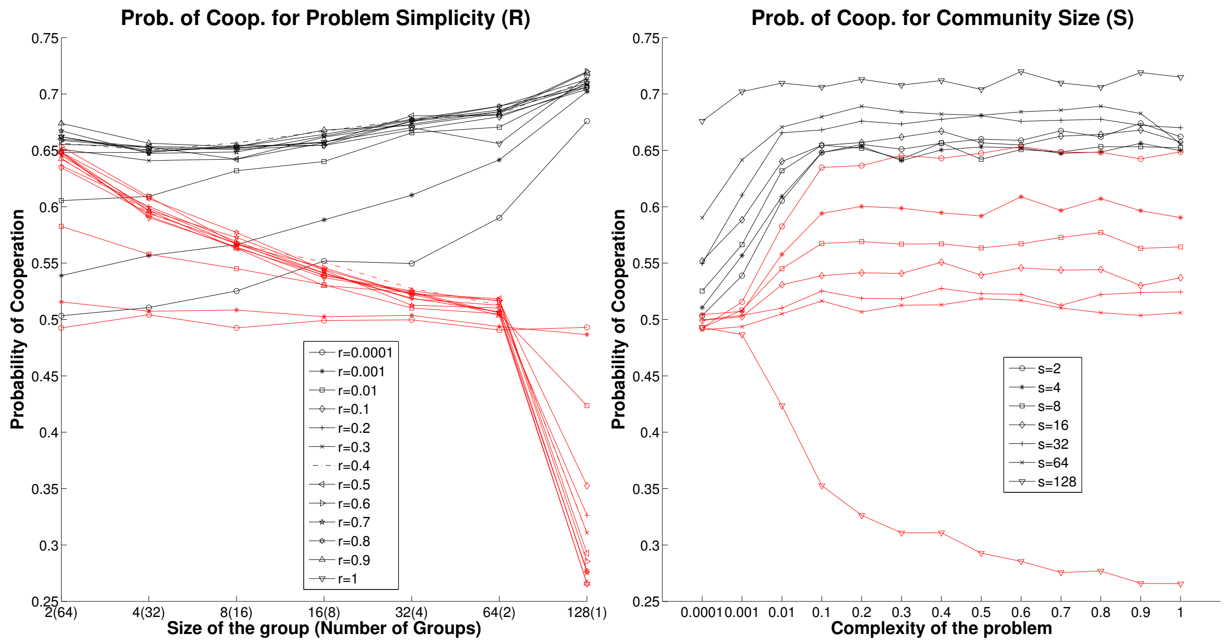


Figure 1: Final probability of cooperation in the two systems respectively the "Recipe A" in red, and the "Recipe B" in black.

### 3.2 Agents fitness and Collective Knowledge

Interesting effects are revealed by the numerical data even on different order parameters. The final average fitness of the agents, and the final average level of collective knowledge within the groups, show the difference between the recipes A and B (Figure 3).

The logaritm of the final quantities of the variables "Agent Fitness" and "Collective Knowledge", allow to appreciate the differences between the recipe A (black) and the recipe B in red, with respect to the size of the group and to the difficulty of the task. Always the recipe B performs better than the recipe A.

## 4 DISCUSSION

Through a simulation approach two systems were identified. In both systems, the population of agents was composed by cooperative and competitive individuals. As it happens in reality, these types of subjects lived side by side. What distinguishes the two systems is the different access to the benefits given by cooperation (i.e., the attainment of the Collective knowledge produced by groups). Indeed, in the first system the profits gained by cooperators were also shared with those who did not cooperate (i.e., free-riders). Instead, in the second system, the advantage resulting from the common work was shared only among those who actively took part in the group. A first difference between the two systems concerned the tendency to cooperate with the increasing of the group size. In the Social Recipe *A* a greater number of individuals within a group determined a decrease of the cooperative behaviours. The opposite is true for the second system (i.e., Social Recipe *B*). Individuals showed a greater propensity to cooperate between themselves when the group size raised. This relationship occurred independently from the difficulty of the problem that agents had to solve.

A trend was also observed between the two systems regarding the relationship between the difficulty of the problem and the size of the group. In the world defined by the Recipe *B*, the tendency to cooperate grew up in relation to the simplicity of the tasks, reaching the maximum in the group defined by the totality of

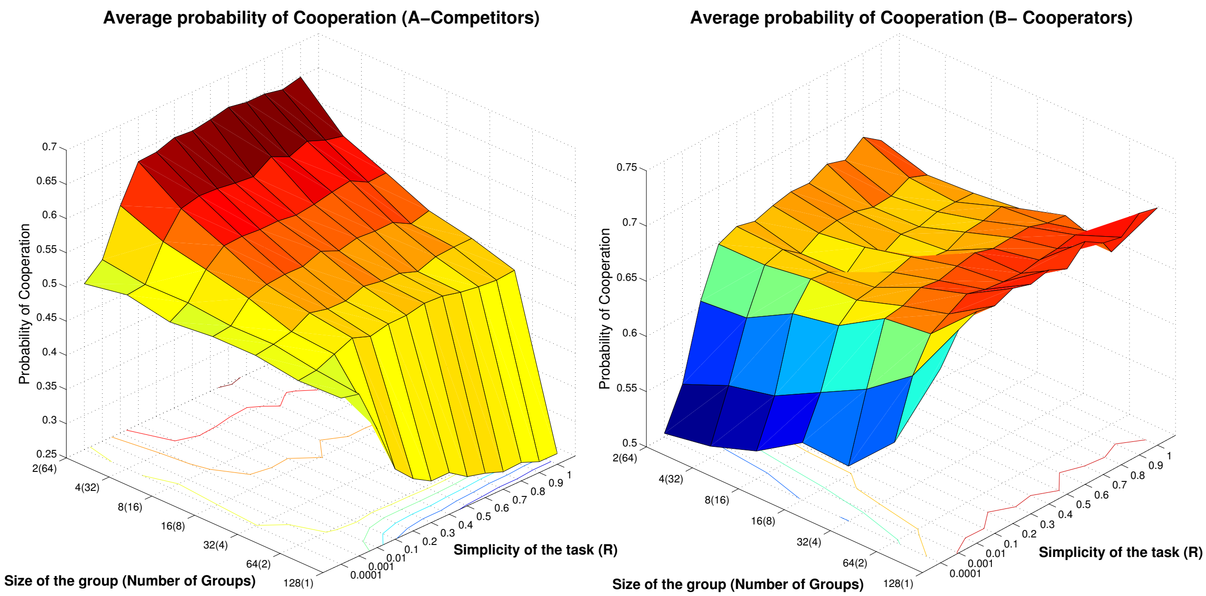


Figure 2: Final probability of cooperation in the two systems respectively the recipe "A" on the left and recipe "B" on the right.

the agents (i.e., the more the problem was easier to solve, the more cooperative behaviours were observed). Instead, the opposite happened in the Recipe *A*. In the "aggregated condition" (i.e., with only one group composed by the whole community), with the increase of the ease of the task, the individuals cooperated less. While in other contexts, defined by a different amplitude of the group, there was a weak trend towards cooperation. The two identified systems also differed according to the average gain for the individual agent and for the world defined by the system itself. Indeed, the Recipe *B* provided the greatest benefits for the agents that compose it (i.e., cooperation as evolutionarily stable strategy) and allowed the greater production of Collective Knowledge. An apparently minimal factor such as the different accessibility for the selfish individuals to the benefits produced by the collectivity, can lead to two very different realities. Within the Recipe *A* the small groups are those with the greatest tendency to cooperate. However, this types of groups are characterized by a weaker knowledge and by a minor ability to resist to dispersion (Derex, Beugin, Godelle, and Raymond 2013). On the other hand, in large groups the indiscriminate distribution of benefits among cooperators and free-riders, hinders the build process of the Collective Knowledge, with obvious repercussions on the progress of the world defined by Recipe *A*. Instead, in the Recipe *B* the ability to share the benefits gained by working together with members who have actually made a contribution to the resolution of the problem, appears to determinate more efficient and effective social dynamics. In these circumstances, the cooperation appears as the optimal strategy for themselves and for the world progress (i.e., allowing the resolution of complex problems).

A limit of this work is that the proposed model is not grounded in an established mathematical modeling techniques such as game theory. In particular, within game theory, there have been developed reputation and incentives-based models able to address the free-riding problems (Miller, Resnick, and Zeckhauser 2005). Future works should integrate such results with the simulations proposed here in order to obtain a better understanding of the phenomenon.

Despite the present model has not been validated, relying on the findings from the this study we could deduce some useful indications for the optimization of crowdsourcing projects. As mentioned above, crowdsourcing is one of the most promising means to generate innovative solutions to the problems of our society. However, it suffers from free-ridings and social loafing dynamics. As we have seen, it is possible to obtain an effective large-scale cooperation as long as free-riders are induced to adopt new and

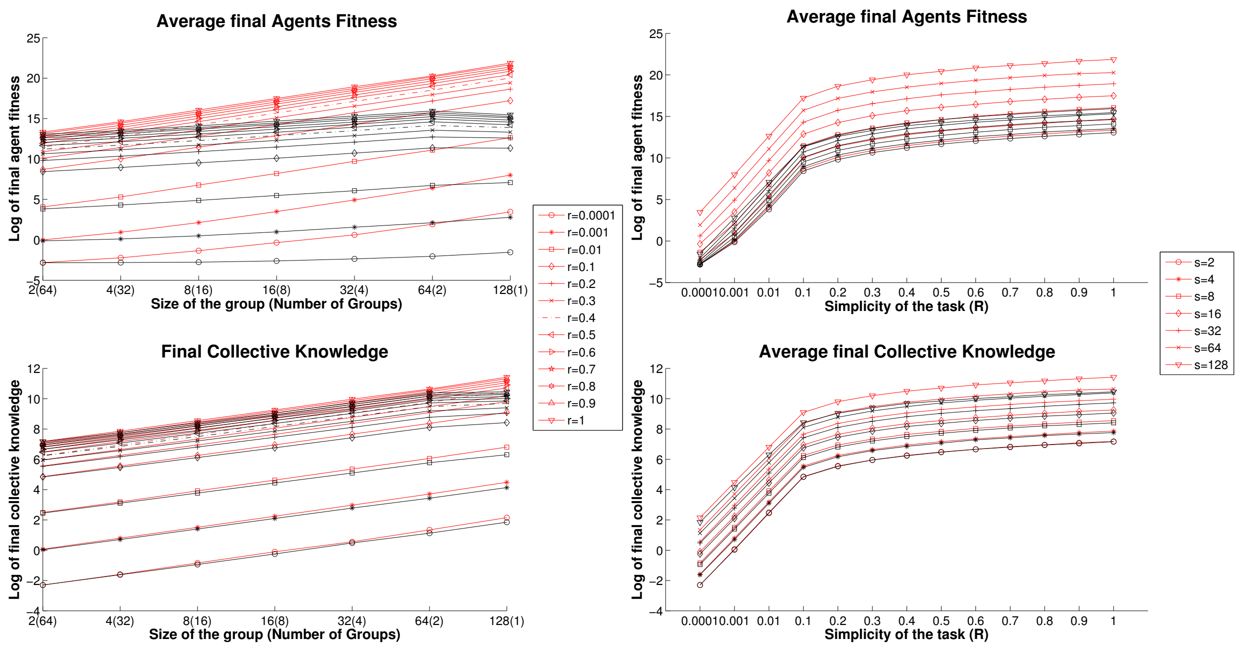


Figure 3: The final "Average agent fitness", is shown in the upper part of the Figure, while the final average collective knowledge of the system at the equilibrium is presented in the lower part, all the graphs report on the y-axis the logaritm of the final quantities (black lines: Recipe A, red lines: Recipe B).

cooperative behaviours. This change is possible when the selfish behaviour of free riders is deprived of its gain. Indeed, the selfish individuals rely on the earnings of co-operators to get a higher personal gain. Trying the personal gain to the achievements of the extended community, ensuring the gains of working together only to the cooperative members of the group, appears to be effective in discouraging free-ridings. The practical application of what has been described is obviously not trivial. Each crowdsourcing project shows particular characteristics and dynamics. So, technical recipes to achieve an environment similar to the one described by Recipe *B* may be different.

Notably, the Recipe A corresponds to already existing services and projects such as Linux, Wikipedia, Google, which, as we have shown, are greatly affected by free-riding and social loafing. Differently, Recipe B, would provide a different approach. Within such systems subjects should receive back from others as a function of what they give.

Nevertheless, even if the limitation of the access to results of knowledge to cooperative workers only could be challenging, possible solutions could be designed using reputation or access constraints mechanisms. For instance, allowing full or partial access to shared resources (e.g., to the abstracts or to the full papers) depending on the degree of efforts spent by the actors to participate within a certain platform. Some modelling studies (Nowak and Sigmund 1998; Ohtsuki and Iwasa 2004) support the role of reputational systems in inducing and maintaining cooperation among humans. Also, empirical evidences seem to go in the same direction (Small and Loewenstein 2005; Piazza and Bering 2008). Indeed, reputation allows identifying the cooperators and, at the same time, to exclude non-cooperators through social control (Giardini and Conte 2012). Properly calibrated reputation may be a promising way to create a new crowdsourcing system capable of keeping track of people's behaviour, therefore contributing to the flourishing literature about practical algorithms for ranking crowdsourcing work results. Provided with this information, the system could act according to it. For example, denying the access to the individuals with bad reputation (obtained by free-riding in previous interactions) to the common gain of the group.

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