

# The destructive effect of human stupidity: a revision of Cipolla's fundamental laws

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**Abstract.** In this work, we analyze an evolutionary game that incorporates the ideas presented by Carlo Cipolla in “The fundamental laws of human stupidity”. The game considers four strategies, three of them are inherent to the player behavior and can evolve via imitation dynamics, while the fourth one is associated with an eventual behavior that can be adopted by any player at any time with a certain probability. This fourth strategy corresponds to what Cipolla calls a stupid person. The probability of behaving stupidly acts as a parameter that induces a phase transition in the steady distribution of strategies among the population.

## 1 Introduction

In 1988, Carlo Cipolla presented an essay entitled The fundamental laws of human stupidity [1]. The structure of this essay consisted of several chapters with some of them intended for the introduction and discussion of each of the five fundamental laws that according to Cipolla rule the human stupidity.

As the concept of stupidity can be ambiguous it is important to properly frame the meaning we embrace here. A stupid person is someone given to unintelligent decisions or acts and here we consider those acts within a social context. Stupidity should not be understood as the opposite of intelligence. In fact, according to some of the ideas of Cipolla, none of us gets rid of or will never get rid of a brief moment of stupidity.

The association of stupidity to a source of collective troubles and nuisance and to the origin of social scourges has been manifested through history in several nowadays popular quotes. Among them, it is worth citing a phrase credited to A. Dumas: “One thing that humbles me deeply is to see that human genius has its limits while human stupidity does not” [2]. B. Russell, in his essay *The triumph of stupidity*, wrote: “The fundamental cause of the trouble is that in the modern world the stupid are cocksure while the intelligent are full of doubt” [3].

Cipolla starts his work by warning us about the silent social danger of stupidity in the first law that affirms that detecting a stupid person is a hard task. This law states

that always and inevitably everyone underestimates the number of stupid individuals in circulation.

While it could be tempting to associate stupidity with a lack of education or training, Cipolla affirms that the probability that a certain person be stupid is independent of any other characteristic of that person. This is the content of the second law. This somehow suggests that there is a natural stupidity, which is shielded against academic training.

As mentioned before, we are here interested in an operational definition of stupidity, the one that is dangerous for others, an idea that can be summarized by a quotation from one of M. Atwood novels, [4]: “Stupidity is the same as evil if you judge by the results.” A similar concept is expressed in Cipolla's third law: A stupid person is a person who causes losses to another person or to a group of persons while himself deriving no gain and even possibly incurring losses.

This law also suggests the definition of three other phenotypes that complement the stupid group (S). These three groups, according to Cipolla, are the intelligent people (I), whose actions benefit both themselves and others, the bandits (B), who benefit themselves at the expense of others, and finally the helpless or unaware people (U), whose actions enrich others at their own expense.

Stupid people are dangerous and damaging because their behavior is hard to understand and predict from a rational point of view. The bandit's actions, while producing some damage, obey a predictable pattern of rationality. The possibility to foresee the behavior of a bandit can help an individual to build up defenses. On the

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contrary, when facing a stupid person this is impossible. So, while most of the time the evil has a clear face and is easily identifiable, stupidity is not. This biased evaluation is what is considered in the fourth law: non-stupid people always underestimate the damaging power of stupid individuals. In particular, non-stupid people constantly forget that at all times and places and under any circumstances to deal and/or associate with stupid people always turns out to be a costly mistake.

The effect of stupidity and the difficulty to recognize it is what leads us to the fifth law: a stupid person is the most dangerous type of person; and its corollary: a stupid person is more dangerous than a bandit.

Cipolla characterized the four groups in terms of two parameters: the own gains or losses  $p$ , and the gains or losses that an individual inflicts on others,  $q$ . The payoff resulting from the interaction between two persons can be defined by these quantities associated with the membership of the participants to one of the four defined groups. These four groups can then be characterized by the range of values adopted by  $p$  and  $q$  as follows:

$$\begin{aligned} S &: p_s \leq 0 \text{ and } q_s < 0 \\ U &: p_u \leq 0 \text{ and } q_u \geq 0 \\ I &: p_i > 0 \text{ and } q_i \geq 0 \\ B &: p_b > 0 \text{ and } q_b < 0. \end{aligned}$$

In a previous work [5] consisting of agent-based simulations, the authors tested the results derived from an evolutionary dynamics to explore the emergence of behavioral profiles that were in agreement with Cipolla's idea. The agents' behavior was characterized by several parameters linked to the four groups defined by Cipolla and by others associated with the tendency of the players to protect themselves from bandits. The authors showed that there was a range of parameter values that lead to results supporting Cipolla's conclusions.

In the present work, we want to mathematically verify the central ideas of Cipolla's work, namely the destructive effect that human stupidity has on the wealth of a society. In a previous work [6], we settle the basis for that by formulating of a four-strategy game and presenting the corresponding payoff matrix.

$$A = \begin{pmatrix} p_s + q_s & p_s + q_u & p_s + q_i & p_s + q_b \\ p_u + q_s & p_u + q_u & p_u + q_i & p_u + q_b \\ p_i + q_s & p_i + q_u & p_i + q_i & p_i + q_b \\ p_b + q_s & p_b + q_u & p_b + q_i & p_b + q_b \end{pmatrix}.$$

The payoff of the strategies is defined by the values of  $p$  and  $q$ . The results found in [6] supported the validity of the laws enunciated by Cipolla regarding the dangerousness of the presence of stupid people. In this work, the evaluation of the effect of the actions of a stupid player was done by calculating the total wealth of the population in the steady state resulting from an evolutionary game. The presence of stupid people not only undermined the total wealth but also promoted the inhibition of cooperative behaviors represented by intelligent and unaware people.

However, one of the unavoidable questions derived from Cipolla's law remains unanswered. The first law warns us about the difficulty of assessing the number of stupid

**Table 1.** Chosen values for the payoff matrix.

$p_i$	$p_b$	$p_u$	$p_s$	$q_i$	$q_b$	$q_u$	$q_s$
1	[1,1,2]	[-2,-1]	[-2,-1]	1	-1	1	-1

individuals in circulation. Even though, it will be interesting to know whether there is a critical fraction of stupid individuals above which their presence dominates the dynamics and that separates the behavior of the system into two different regimes.

To test this possibility, we consider that the players will normally choose between three of the strategies of the game, (I), (B), and (U), but eventually some of them may behave like a stupid person and this occurs with a given probability  $\rho_s$ . This probability is the parameter that will govern the number of people behaving stupidly at each time.

This means that being stupid will not be a permanent state by an occasional state accounting for the possibility that at any time any individual can be momentarily stupid. In the following sections, we present a more thorough description of the model and the numerical results.

## 2 The model

In the present work, we consider an evolutionary game, with four strategies though one of them, the (S), differs from the others in the sense that it is not durable. Any individual can be stupid at any time and during one-time step with probability  $\rho_s$ . Longer stupid behavior events are not forbidden but are governed by the same probability.

While stupidity is not a permanent condition on this version of the game, we still need to define the payoff of each of the three strategies when playing between them and when occasionally confronting a stupid person. We also need to define the payoff that an eventual stupid player may receive. This information is given by the matrix  $A$ .

We will adopt the values in Table 1 for the payoffs. These values define a social dilemma with a single Nash equilibrium, (B). In the absence of the strategies (U) and (S), we are in the presence of a usual Prisoner dilemma [6]. The ratios between the payoffs of (B) and (I) warrant that despite being (B) the unique Nash equilibrium, the topological effects induced by the underlying network can lead to the survival and emergence of cooperation, linked in the present work to (I) [8]. Note should be taken that if the ratio between payoffs cannot allow the (I) players to get some profit from mutual cooperation, the system will converge to a trivial state dominated by (B).

We are not considering a fully mixed population but players located on top of a network defining their neighborhoods. In each round, a randomly chosen player will play with each of the members of its neighborhood and in turn, each of the neighbors plays with the members of their own neighborhoods. The only Nash equilibrium of this game is the strategy (B), thus any payoff monotonic dynamics described by mean field differential equations

will have only one steady state. However, when considering a spatially extended game with players located on top of a network, the steady state can converge to a different configuration. Previous works have shown the relevance of the topology of the network in the evolution of strategies in several non-cooperative games [7–10].

Here we locate the players on top of a particular family of regular networks, i.e. with all the nodes having the same degree, but with a tunable degree of disorder. These networks, described in [12], present a topology that varies according to a disorder parameter  $\pi_d$ . Starting from an ordered ring network, where each node is connected to its  $k$  first neighbors, we built the disordered networks by taking  $\frac{\pi_d k N}{2}$  pairs of links and exchanging an adjacent node of each one. Care is taken to avoid double and self-connections and thus preserving the total number of links and the regularity of the resulting network.

The evolutionary dynamics is ruled by an imitation process. Players will adapt their chosen strategy according to their own performance and the yield of its neighbors. Here, we adopt a simple deterministic imitation dynamics to reduce to a minimum the number of parameters. As mentioned before, in each round, a selected player plays with all its neighbors. In turn, these neighbors do the same with their own. After that, the selected player analyses its performance or earnings and compares them with that of its neighbors. Then, it adopts the strategy of the player with the highest gain, which eventually can be its own one. In the case of a tie, the choice is decided at random. This update dynamics is the simplest one, representing a deterministic imitation and closely linked to the replicator dynamics [11].

In principle, players play according to their chosen strategy, that can be (I), (B), or (U) but at any time, any player can adopt the strategy (S) with probability  $\rho_s$ . This choice will not be permanent, will last only one-time step (there is always a probability  $\rho_s^n$  of adopting the (S) strategy during  $n$  consecutive steps) and after that, the player will adopt the original behavior or change it to imitate the neighbor with the highest payoff. The payoff of the strategies prevent the (S) behavior from being imitated as, under no circumstance, a player adopting the (S) strategy will obtain the higher payoff. The fact that there is a probability  $\rho_s$  of adopting the strategy (S) means that at each time step there is a mean effective population of  $\rho_s N$  stupid players, where  $N$  is the total population size. We are going to characterize the state of the system by the fraction of (I) players  $\rho_i$  and the mean gain of the population  $\langle \epsilon \rangle$ .

### 3 Results

For each simulation, we consider  $10^3$  networks of  $N = 10^4$  nodes. The system evolves until reaching a steady state that is detected by controlling the change in the values of the quantities that we measure to characterize the state of the system between consecutive time steps.

The degree of disorder  $\pi_d$  and the probability of adopting the (S) strategy at each time step,  $\rho_s$ , are the parameters changing between different realizations.

The results are shown in Figure 1, where the steady fraction of (I) players  $\rho_s$  and the mean gain of the population  $\langle \epsilon \rangle$  are shown as a function of  $\rho_s$  and for different values of  $\pi_d$ . The mean gain is calculated as the mean value of the payoffs of each player when playing with all the members of its neighborhood.

We observe that the topology of the network has a subtle effect on the evolution of the strategy profile of the population. On the contrary, the probability of adopting the (S) strategy plays a crucial role. The system shows the existence of two different regimes. For low values of  $\rho_s$  the dominating strategy is (I) while for higher values, (B) dominates. This is clearly reflected in the left panel of Figure 1 showing the fraction of (I) in the steady state and also in the right panel showing the mean gain of the population. Clearly, the prevalence of (B) attempts against the wealth of the population, and this prevalence is promoted by the sporadic appearance of the (S) behavior. The presence of a crossover between a cooperative and defective steady state was not observed in [6].

To understand the relevance of this result, we refer to previous results involving evolutionary games. There are several examples of the effect of locating the players on networks with different topologies [7,8,12–22]. These works show that the evolutionary behavior of the strategies might be affected by the underlying topology of links between players, sometimes promoting cooperative states even when the Nash equilibrium is the defective strategy. In these examples, the topology of the network is the factor responsible for different regimes. Here we show that while the topology of the networks plays a nonnegligible role, the most important parameter is the probability of a player to adopt the (S) strategy.

The results show that as  $\rho_s$  increases there is a change from a scenario where (I) is prevalent to another one where most of the population behaves as (B). The crossover is sharper for highly ordered networks and turns smoother as  $\pi_d$  increases. We cannot clearly find the critical value at which this transition occurs, but we can find the value of  $\rho_s$  at which  $\rho_i = 0.5$ , which we call  $\rho_s^{0.5}(\pi_d)$ . Also we can measure the width of the interval  $[\rho_s^{0.1}, \rho_s^{0.9}]$  for each value of  $\pi_d$ , and call it  $w_f(\pi_d)$ . We observe that both increase with  $\pi_d$ .

For convenience, we define

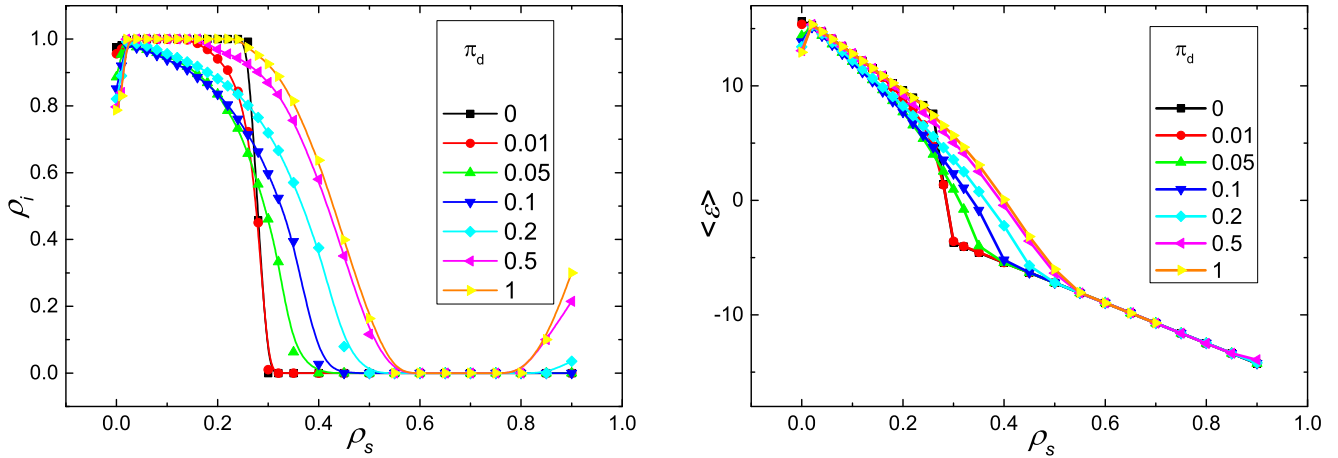
$$w_r^{-1}(\pi_d) = \frac{w_f(0)}{w_f(\pi_d)}.$$

We have fitted the curves associated with each quantity obtaining the following fits.

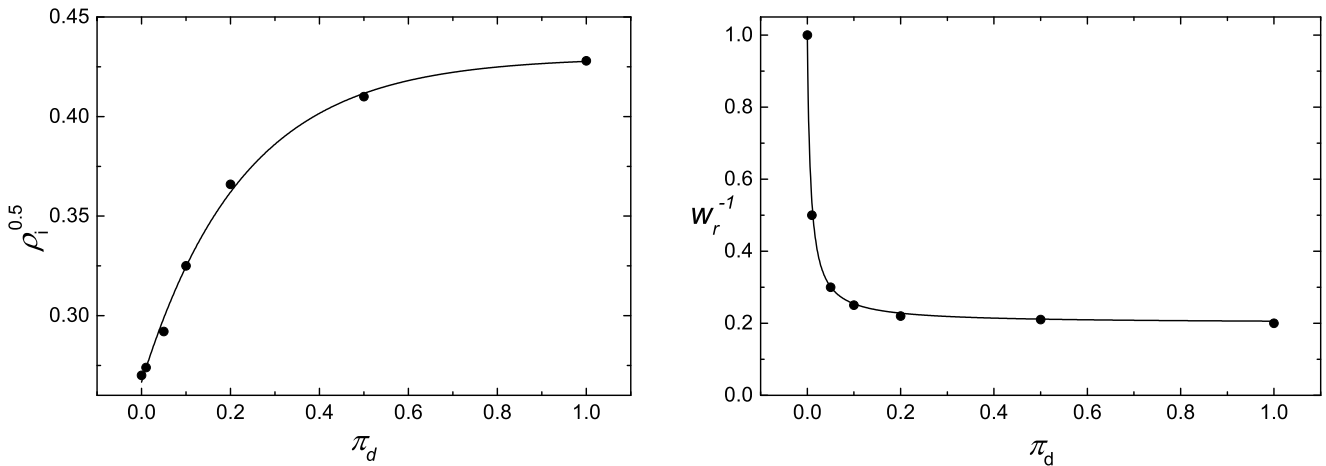
$$\rho_s^{0.5}(\pi_d) = 0.429 - 0.163 \exp(-4.996\pi_d) \quad (1)$$

$$w_r^{-1}(\pi_d) = 0.2 + \frac{5.810^{-3}}{7.310^{-3} + \pi_d}.$$

The results are shown in Figure 2, where the values of  $\rho_s(0.5)$ ,  $w_r^{-1}$  and the corresponding fits are displayed as a function of  $\pi_d$ .



**Fig. 1.** This plot shows the fraction of (I) individuals  $\rho_i$  (left) and the mean gain of the population in one round  $\langle \epsilon \rangle$  (right) as a function of  $\rho_s$ . All the curves correspond to the steady state.



**Fig. 2.** This plot shows the value of  $\rho_s^{0.5}$  (left) and  $w_r^{-1}$  as a function of  $\pi_d$ . The curves are the fittings shown in the text.

Considering the function

$$\xi(\rho_s, \pi_d) = w_r(\pi_d)(\rho_s - \rho_s^{0.5}(\pi_d)).$$

We renormalized the curves, obtaining what is shown in Figure 3. We point out that the scaling was used by analyzing the plot corresponding to the fraction of (I) players in the steady state but it also works for the mean gain.

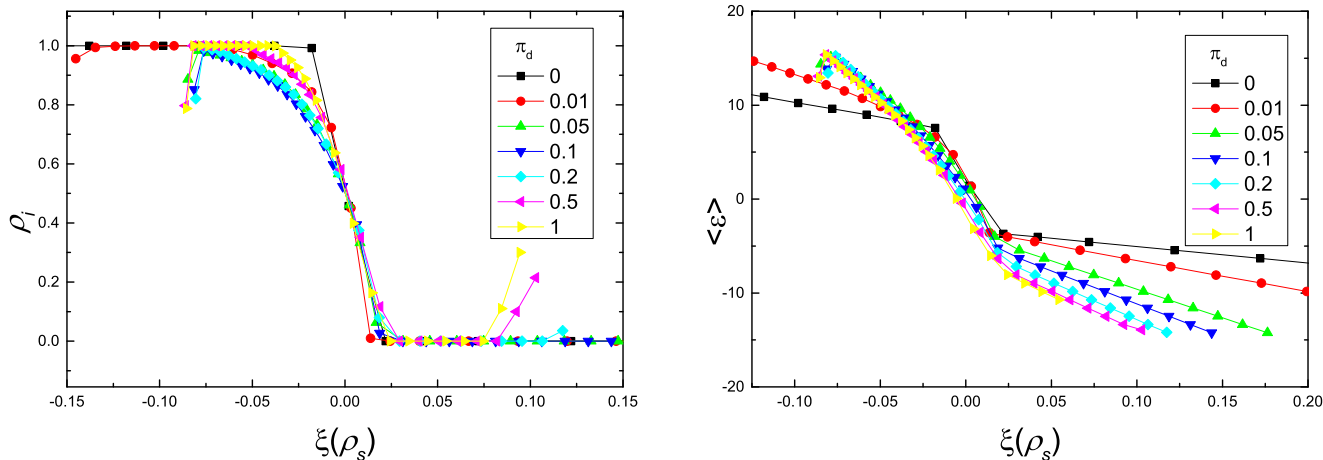
The anomalous behavior at the extremes of the ranges of values of  $\rho_s$  responds to different causes. For small values, there is a small fraction of realizations where the (B) strategy can thrive. Statistically, this contributes to making the fraction of (I) players smaller. This effect has been previously observed in a similar system when the same family of networks was adopted as substrate [8]. The rise of the population of (I) players for a mean high fraction of (S) players responds to a different phenomenon. The existence of many (S) players prevents the (I) players from the interaction with (B) players and makes them face an alternative strategy, the (S), that is not appealing, and so encouraging them to preserve their original strategy. We recall that originally, the strategies are uniformly assigned,

so the increase in the fraction of (I) should not be understood as a result of imitation but as a result of survival of the original (I) players.

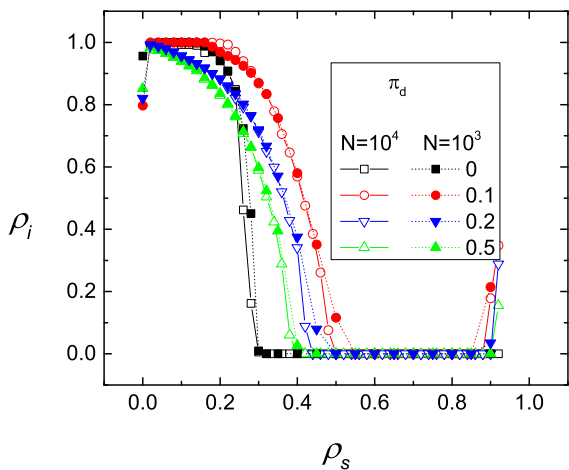
In order to check the presence of size effects in our results we have considered a system 10 times smaller, i.e.  $N = 10^3$ . Figure 4 compares the curves corresponding to Figure 1a both system sizes. We can observe that the effect due to the size of the system is almost negligible, as the curves almost overlap in all cases.

## 4 Conclusions

As we stated in the introduction, the work by Cipolla should be understood as a cartoonish representation of some disruptive social behaviors. Nevertheless, it implies certain facts that deserve to be taken into consideration. It is in this spirit that we analyzed the work by Cipolla and the results that can be obtained by translating these ideas into a mathematical model. Let us start with the first law. It affirms that we always underestimate the number of stupid individuals in circulation. Inspired by this statement we wonder whether despite the density of



**Fig. 3.** This plot shows the fraction of (I) individuals  $\rho_i$  (left) and the mean gain of the population in one round  $\langle \epsilon \rangle$  (right) as a function of  $\xi(\rho_s)$ . All the curves correspond to the steady state.



**Fig. 4.** This plot compares the results obtained for the fraction of (I) individuals  $\rho_i$  as a function of  $\xi(\rho_s)$  for two system sizes,  $N = 10^4$  and  $N = 10^3$ . The curves almost overlap.

stupid is impossible to calculate there is a critical density that might separate two different scenarios or not. We mean by this to evaluate the possibility that only by reaching a threshold density, the group of stupid people can inflict considerable harm to the entire population. For that, we proposed a model in which any individual is susceptible to behaving stupidly at any time and with a certain probability. Our results show the existence of a crossover between two regimes. The transition from the cooperative regime to the defective one is only sharp for slightly disordered networks, turning smoother as the disorder increases. Also, the increasing disorder produces a displacement of the values of  $\rho_s$  promoting the cooperative behavior to higher values.

Still, there is a less apparent effect. The curves show that while for low values of  $\rho_s$  the disorder attempts against (I), the situation is reversed for the highest degrees of disorder. These results agree with those obtained in [6] for the case when the fraction of (S) individuals

remains constant throughout the whole simulation. This phenomenon can be attributed to a screening effect played by the (S) population. Despite the fact that the (I) players are not clustered, they are surrounded by (S) players, that perform worse than them under any condition. Thus they are not affected and tempted by the presence of (B) ones and continue to adopt the (I) strategy. This screening effect is not present in highly ordered networks as in that case both (I) and (B) are more clustered and the isolation of (I) players is unlikely.

The traditional game of PD has been expanded in previous works by considering a third strategy associated with the possibility of a player abstaining from participating [23–27]. This version, sometimes referred to as the Prisoner’s Dilemma Game with Voluntary Participation assigns the abstaining player and the eventual but frustrated opponent the same payoff  $L$ , called the lonely reward. Its value is such that it maintains the structure of the social dilemma ( $T > R > L > P > S$ ) but its presence leads to different results and under certain conditions it promotes cooperation. The new strategies included in the present work do not play the same role, so a question remains open about the effect of abstention in the game presented here. It would be certainly interesting considering the not only a probability of playing the S strategy but also a chance of abstention that could be affected or not by the previous experience of the players.

### Author contribution statement

J.K. and M.K. conceived the project. D.B. and M.K. developed the programs and run the numerical calculations. All authors contributed to the discussion and analysis of the results. M.K. prepared the manuscript with inputs from all co-authors.

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