Eliciting fairness in N-player network games through degree-based role assignment

Andreia Sofia Teixeira1,2,3,6,* , Francisco C. Santos2,6, Alexandre P. Francisco2, and Fernando P. Santos4,5,6

1Hospital da Luz Learning Health, Luz Saúde, Lisboa, Portugal
2INESC-ID and Instituto Superior Técnico, Universidade de Lisboa, R. Alves Redol 9, 1000-029 Lisboa, Portugal
3Indiana Network Science Institute, Indiana University, 1001 IN-45 Bloomington IN, USA
4Informatics Institute, University of Amsterdam, Science Park 904, 1098XH Amsterdam, The Netherlands
5Department of Ecology and Evolutionary Biology, Princeton University, Princeton, NJ 08544, United States
6ATP-Group, IST-Taguspark, Porto Salvo, Portugal
*Correspondence should be addressed to Andreia Sofia Teixeira: steixeira@inesc-id.pt

Abstract

From social contracts to climate agreements, individuals engage in groups that must collectively reach decisions with varying levels of equality and fairness. These dilemmas also pervade Distributed Artificial Intelligence, in domains such as automated negotiation, conflict resolution or resource allocation, which aim to engineer self-organized group behaviors. As evidenced by the well-known Ultimatum Game — where a Proposer has to divide a resource with a Responder — payoff-maximizing outcomes are frequently at odds with fairness. Eliciting equality in populations of self-regarding agents requires judicious interventions. Here we use knowledge about agents’ social networks to implement fairness mechanisms, in the context of Multiplayer Ultimatum Games. We focus on network-based role assignment and show that attributing the role of Proposer to low-connected nodes increases the fairness levels in a population. We evaluate the effectiveness of low-degree Proposer assignment considering networks with different average connectivity, group sizes, and group voting rules when accepting proposals (e.g. majority or unanimity). We further show that low-degree Proposer assignment is efficient, not only optimizing individuals’ offers, but also the average payoff level in the population. Finally, we show that stricter voting rules (i.e., imposing an accepting consensus as a requirement for collectives to accept a proposal) attenuates the unfairness that results from situations where high-degree nodes (hubs) play as Proposers. Our results suggest new routes to use role assignment and voting mechanisms to prevent unfair behaviors from spreading on complex networks.

Keywords— Modeling and Simulation; Social networks; Evolutionary Game Theory; Population dynamics; Complex Systems; Fairness; Wealth inequality
1 Introduction

Fairness has a profound impact on human decision-making and individuals often prefer fair outcomes over payoff maximizing ones [10]. This has been evidenced through behavioral experiments, frequently employing the celebrated Ultimatum Game (UG) [14]. In the UG, one Proposer decides how to divide a given resource with a Responder. The game only yields payoffs associated with the proposed resource allocation to the participants if the Responder accepts the proposal. Human Proposers tend to sacrifice some of their share by offering high proposals and Responders often prefer to earn nothing rather than accepting unfair divisions. These counter-intuitive results motivated several lab experiments and theoretical models that aimed at justifying, mathematically and empirically, the emergence and maintenance of fair intentions in human behavior [5, 25, 23, 7, 32].

Most of these works, however, have neglected the fact that, in many situations, offers are made in the context of groups, instead of simpler pairwise interactions. This is the case in the negotiation of collective work contracts, environmental coalitions and policy making [2], human rights conventions, collective insurance [40], adoption of regulatory frameworks (e.g., in the use of technology [15]), exchange of flexibilities between local energy communities [35], or the simple act of scheduling a meeting with several participants, among other possible scenarios. Fairness and bargaining dilemmas occur within groups, in which group decisions emerge from the combination of each individual’s assessment of what is perceived as a fair offer. Similarly, in engineering applications grounded on Artificial Intelligence and Multiagent Systems, fairness concerns are important in domains that go beyond pairwise interactions. Autonomous agents have to take part in group interactions that must decide between outcomes that may each favour a different part of the group. Examples of such domains are automated bargaining [18], conflict resolution [29] or multiplayer resource allocation [6].

To capture some of the dilemmas associated with fairness versus payoff maximization in these group interactions, one may resort to multiplayer extensions of the Ultimatum Game [36] (MUG) (see Figure 1). Here, a proposal is made by a Proposer to a group of \( N - 1 \) Responders that, collectively, decide to accept or reject it. As in the pairwise UG, the strategy of a Proposer, \( p \), is the fraction of resource offered to the Responders; the strategy of each Responder \( i \), \( q_i \), is the personal threshold used to decide between acceptance or rejection [23, 25]. Groups decide to accept and reject a proposal through functions of the individual acceptance thresholds, \( q \). Group acceptance depends on a decision rule: if the fraction of acceptances equals or exceeds a minimum fraction of accepting Responders, \( M \), the proposal is accepted by the group. In that case, the Proposer keeps what she did not offer \((1 - p)\) and the offer is divided by the Responders — each receiving \( p/(N - 1) \). If the fraction of acceptances remains below \( M \), the proposal is rejected by the group and no one earns anything. As in the UG, the sub-game perfect equilibrium of MUG consists in a very low value of proposal \( p \) and very low values of threshold \( q \) [37].

Previous studies with the UG [25, 23, 7, 32, 17] and the MUG [36, 45, 39], assume that the roles of Proposer and Responder are attributed following uniform probability distributions:
Figure 1: Setting of the Multiplayer Ultimatum Game. After a Proposer is selected, a proposal $p$ is made to a group of $N - 1$ Responders. Each responder will compare its strategy $q$ (translating the minimum acceptable offer) with the expected value to be received, $p/(N - 1)$. For a given $M$, the proposal will be accepted if at least that fraction of responders accepts the proposal.

each agent has the same probability of being selected to play as Proposer. These assumptions are naturally at odds with reality. In real-life Ultimatum Games, being the Proposer or the Responder depends on particular agents’ characteristics. Proposers, such as employers, investors, auction first-movers or rich countries, are in the privileged position of having the material resources to decide upon which proposals to offer. This advantageous role is notorious if, again, one considers the theoretical prediction of payoff division in the UG (subgame perfect equilibrium) posing that Proposers will keep the largest share of the resource being divided. The benefits of Proposers are more evident when proposals are made to groups, as Responders need to divide the offers — thus increasing the gap in gains between the single Proposer and the Responders. In this multiplayer context, punishing Proposers becomes harder: any attempt to punish unfair offers is only effective if there is a successful collective agreement — amongst Responders — to sacrifice individual gains and reject an offer. Asserting that these two roles are asymmetric, so should be the criteria to assign them, leading us to two main questions:

- How should a Proposer be selected within a group, in multiplayer ultimatum games, to guarantee efficiency and fairness?

- The fact that individuals are often embedded in networks makes it important to understand to which extent the network ties and the way groups are assembled influence overall fairness, exchanges, and cooperation. Given this networked context, which network-based role assignment criteria can be used to maximize long-term efficiency and fairness?


Here we introduce a model, based on evolutionary game theory (EGT) [48, 47] and complex networks, to approach the previous questions. We analyze multiplayer ultimatum games in heterogeneous complex networks through network centration-based role assignment. The fact that networks are heterogeneous allows us to test several node properties and centrality measures as base criteria for defining how to select Proposers in a group. We focus on degree centrality. We find that selecting low-degree Proposers elicits fairer offers and increases the overall fitness (average payoff) in a population.

1.1 Related Work

The questions we address in this work — and the model proposed to tackle them — lay on the interface between mechanisms for fairness elicitation in multiagent systems, multilayer bargaining interactions, dynamics on complex networks and network interventions to sustain socially desirable outcomes.

Some of the most challenging contexts to elicit fairness involve the tradeoff between payoff-maximizing outcomes and fair outcomes. As stated, the UG [14] has been a fundamental interaction paradigm to study such dilemmas. In this context, reputations [23] and stochastic effects [32] were identified as mechanisms that justify fair behaviors. Page et al. found that, in a spatial setting, fairer proposals emerge as clusters of individuals proposing high offers are able to grow [25]. Also in the realm of interaction networks, De Jong et al. concluded that scale-free networks allow agents to achieve fairer agreements; rewiring links also enhances the agents’ ability to achieve fair outcomes [7]. A game similar to the UG assumes that Responders are unable to reject any proposal and Proposers unilaterally decide about a resource division. This leads to the so-called Dictator Game. In this context, reputations and mechanisms based on partner choice were also identified as drivers of fair proposals [50].

The previous works assume that all agents have the same probability of playing in the role of Proposer or Responder. Going from well-mixed (i.e., all individuals are free to interact with everyone else) to complex networks, however, provides the opportunity to implement network-based role assignment that considers network measures. In this context, Wu et al. studied the pairwise UG in scale-free networks, with roles being attributed based on network degree. The authors show that attributing the role of Proposer to high-degree nodes leads to unfair scenarios [49]. Likewise, Deng et al. studied role assignment based on degree, concluding that the effect of degree-based role assignment depends on the mechanism of strategy update [8]. When considering a pairwise comparison based on accumulated payoffs and social learning (as we do in the present work), the levels of contribution in the population increase if lower-degree individuals have a higher probability of being the Dictators. Both works consider the pairwise Ultimatum Game.

In this work we use a multiplayer version of the UG (MUG) proposed in [36]. Other forms of multiplayer ultimatum games can be found in [11, 13, 45]. Santos et al. studied this game in the context of complex networks, showing that fairness is augmented whenever the networks,
upon which the game is played, allow agents to exert a sufficient level of influence over each other, by repeatedly participating in each others’ interaction groups. The authors also find that stricter group decision rules (i.e., high $M$ in MUG) allow for fairer strategies to evolve under MUG. Here we use networks to define group formation as suggested in the previously mentioned work (originally in [42]) and as exemplified in Figure 2.

Departing from previous works that study degree-based role assignment in pairwise Ultimatum Games [49, 8], we focus on a multiplayer game. As mentioned, this version highlights the asymmetries between the Proposer and Responder roles. By comparison with the UG, MUG Proposers are likely to receive an even higher share of payoffs than each Responder as the latter must divide any accepted offer between themselves. Moreover, in order to punish unfair MUG Proposers, Responders must act as a group which may naturally may call for extra coordination mechanisms. Also, in contrast with [49, 8], here we combine the study of network-based role assignment with consideration of different voting mechanisms; we show that, whenever highly connected nodes are the natural candidates to play in the role of Proposer, stricter voting rules (i.e., imposing an accepting consensus as requirement for collectives to accept a proposal) attenuates the emergent level of inequality.

Finally, the approach we follow in this work is akin to testing network interventions for social good. Several works study social dilemmas on top of complex networks and stress the conditions leading, in this context, to socially desirable outcomes [33, 30, 34, 27]. In this realm, we shall underline a recent work that employs EGT — as we do in the present paper — to study interventions that aim to sustain cooperation in complex networks [20]. The authors conclude that local interventions — i.e., based on information about the neighborhood of the affected node — outperform global ones. A similar conclusion is presented in [27].

Materials and Methods

Here we detail the proposed evolutionary game theoretical model to evaluate the effect of degree-based role assignment on fairness under MUG. We start by providing details on the payoff calculation under MUG.

Multiplayer Ultimatum Game

In the 2-player UG, a Proposer has a resource and is required to propose a division with a Responder. The game only yields payoff to the participants if the Responder accepts the
Figure 2: Example of group formation and Proposer selection based on degree. Each node and its neighborhood define an interaction group. In the figure, node $A$ plays in 5 groups and its fitness results from the payoff sum after playing in all those groups. In general, a node plays in a number of groups equal to its degree plus one. For each group, the payoff is calculated after one individual is selected to be the Proposer. Proposer selection depends on the degree of each individual in the group, and a parameter $\alpha$ controls this dependence (see Methods section). To exemplify this process, the inset graph represents the probability of each individual — $A$ (high-degree), 1 (medium-degree) and 2 (low-degree) — to be selected as a Proposer when playing in the group centered on $A$, as a function of $\alpha$.

Proposal [14]. Given a Proposer with strategy $p \in [0, 1]$ and a Responder with strategy $q \in [0, 1]$, the payoff for the Proposer yields

$$\Pi_P(p, q) = \begin{cases} 1 - p, & p \geq q \\ 0, & p < q \end{cases},$$

and for the Responder

$$\Pi_R(p, q) = \begin{cases} p, & p \geq q \\ 0, & p < q \end{cases}. \tag{2}$$

In the MUG, proposals are made by one Proposer to the remaining $N - 1$ Responders, who must individually reject or accept it [36, 39]. Since individuals may act both as Proposers and Responders (with a probability that will depend on node characteristics), we assume that each individual adopts a strategy $(p, q)$. When playing as Proposer, individuals offer $p$ to the Responders. Responders will individually accept or reject the offer having their $q$ as a threshold: if the share of an offer $p$ is equal or larger than $q$ (i.e., $\frac{p}{N-1} \geq q$) the individual
accepts the proposal. Otherwise, the Responder rejects that proposal. We can regard $q$ as the minimum fraction that an individual is willing to accept, relative to the maximum to be earned as a Responder in a group of a certain size. Alternatively, we could assume that individuals ignore the group size and as such, when faced with a proposal, they must judge the absolute value of that proposal (an interpretation that also holds if we assume that individuals care about the whole group payoff).

Overall group acceptance will depend upon $M$, the minimum fraction of Responders that must accept the offer before it is valid. Consequently, if the fraction of individual acceptances stands below $M$, the offer will be rejected. Otherwise, the offer will be accepted. In this case, the Proposer will keep $1 - p$ to himself and the group will share the remainder, that is, each Responder gets $p/(N - 1)$. If the proposal is rejected, no one earns anything. All together, in a group with size $N$ composed of 1 Proposer with strategy $p \in [0,1]$ and $N - 1$ Responders with strategies $(q_1, ..., q_{N - 1}) \in [0,1]^{N-1}$ the payoff of the Proposer is given by

$$
\Pi_P(p, q_1, ..., q_{N-1}) = \begin{cases} 
1 - p, & \sum_{i=1}^{N-1} \Theta(p_{N-1} - q_i)/(N - 1) \geq M \\
0, & \text{otherwise}
\end{cases}, \quad (3)
$$

where $\Theta(x)$ is the Heaviside step function, that evaluates to 1 when $x \geq 0$ and evaluates to 0 when $x < 0$. The payoff of any Responder in the group yields,

$$
\Pi_R(p, q_1, ..., q_{N-1}) = \begin{cases} 
\frac{p}{N-1}, & \sum_{i=1}^{N-1} \Theta(p_{N-1} - q_i)/(N - 1) \geq M \\
0, & \text{otherwise}
\end{cases}. \quad (4)
$$

We assume that MUG is played on a complex network, in which individuals are assigned nodes and links define who can interact with whom. Following [42, 38], every neighborhood characterizes a N-person game, such that the individual fitness (or success) of an individual is determined by the payoffs resulting from the game centered on herself plus the games centered on her direct neighbors. We provide a visual representation of such group formation in Figure 2. Degree heterogeneity will create several forms of diversity, as individuals face a different number of collective dilemmas depending on their degree (and social position); groups where games are played may also have different sizes. Such diversity is introduced by considering two types scale-free networks. One is generated with the Barabási-Albert algorithm (BA) of growth and preferential attachment [1] leading to a power-law degree distribution, high correlation in the degrees of neighboring nodes and a low clustering coefficient. The clustering coefficient offers a measure of the likelihood of finding triangular motifs or, in a social setting, the likelihood that two friends of a given node are also friends of each other, a topological property of relevance in the context of fairness and N-person games [38]. In the second case, we consider the Dorogotsev-Mendes-Samukhin (DMS) model [9], exhibiting the same power-law degree distributions, yet with large values of the clustering coefficient.
Networks generated

In the BA model [1], at each time step, the network grows by adding a new node and connecting it to \( m \) other nodes already in the network. These connections are probabilistic, depending on the degree of the nodes to be connected with: having a higher degree increases the probability of gaining a new connection. This process results in heterogeneous degree distributions, in which older nodes become highly connected (creating so-called hubs). This is the combination of two processes – growth and preferential attachment. In the DMS model [9], at each time step, a node is added; instead of choosing other nodes to connect with, it chooses one existing edge randomly and connects to both ends of the edge. The networks generated by the DMS model have higher cluster coefficient than those with BA model, combining the high-clustering and high-heterogeneity that characterizes real-world social networks.

Network based role selection

Previous works show that anchoring the probability of nodes being selected for the role of Proposer or Responder on their degree has a sizable and non-trivial effect on the evolving magnitude of proposals in traditional two-person Ultimatum Games [49, 8]. Considering multiplayer ultimatum games, however, opens space to study the interplay between group characteristics (such as group sizes) and network-based criteria to select Proposers in completely unexplored directions. So far, we assume that nodes are selected to be Proposers based on their degree. As such, in a group with \( N \) individuals, where each individual \( i \) has degree \( k_i \), the probability that \( j \) is selected as Proposer is given by

\[
p_j = \frac{e^{\alpha k_j}}{\sum_i e^{\alpha k_i}},
\]

where \( \alpha \) controls the influence of degree on role selection. One node is selected as Proposer and the remaining \( N - 1 \) play as Responders.

Evolutionary Dynamics

We simulate the evolution of \( p \) and \( q \) in a population of size \( Z \), much larger than the group size \( N \). Initially, each individual has values of \( p \) and \( q \) drawn from a discretized uniform probability distribution in the interval \([0, 1]\). The fitness \( f_i \) of an individual \( i \) of degree \( k \) is determined by the payoffs resulting from the game instances occurring in \( k + 1 \) groups: one centered on herself plus \( k \) others centered on each of her \( k \) neighbors (see Figure 2). Values of \( p \) and \( q \) evolve as individuals tend to imitate (i.e., copy \( p \) and \( q \)) the neighbors that obtain higher fitness values.

The numerical results presented below were obtained for structured populations of size \( Z = 1000 \). Similar results were obtained for \( Z = 10000 \). As already mentioned, we consider networks generated with both BA and DMS algorithms, with average degree \( \langle k \rangle = \{4, 8, 16\} \).
Initialize all \( p_i, q_i = X \sim U(0, 1), i \in \{1, ..., Z\} \)

for \( t \leftarrow 1 \) to \( \text{Gens} \) do Main cycle of interaction and strategy update:

for \( j \leftarrow 1 \) to \( Z \) do Select agent to update:

// Sample two neighbors of the population

\( A \leftarrow X \sim U(\{1, ..., Z\}) \) (agent to update)

\( B \leftarrow Y \sim U(\text{neighbours}(A)) \) (agent to be imitated)

if \( X \sim U(0, 1) < \mu \) then Mutation:

\( p_A \leftarrow X \sim U([0, 1]) \)

\( q_A \leftarrow X \sim U([0, 1]) \)

else Imitation:

\( f_A \leftarrow \text{fitness}(A) \)

\( f_B \leftarrow \text{fitness}(B) \)

\( \text{prob} \leftarrow 1/(1+e^{-\beta(f_B-f_A)}) \)

if \( X \sim U([0, 1]) < \text{prob} \) then

\( p_A \leftarrow p_B + \text{imitation error} \sim U([-\varepsilon, \varepsilon]) \)

\( q_A \leftarrow q_B + \text{imitation error} \sim U([-\varepsilon, \varepsilon]) \)

Simulations take place for \( 2 \times 10^5 \) generations, considering that, in each generation, all the individuals have (on average) the opportunity to revise their strategy through imitation once.

At every (discrete and asynchronous) time step, two individuals \( A \) and \( B \) (neighbors) are selected from the population. Given the group setting of the MUG, \( B \) is chosen from one of the neighbours of \( A \). Their individual fitness is computed as the accumulated payoff in all possible groups for each one, provided by the underlying structure (in each group the role of Proposer or Responder is selected following the section below); subsequently, \( A \) copies the strategy of \( B \) with a probability \( \chi \) that is a monotonic increasing function of the fitness difference \( f_B - f_A \), following the pairwise comparison update rule: \( \chi = \frac{1}{1+e^{-\beta(f_B-f_A)}} \) [46].

The parameter \( \beta \) specifies the selection pressure (\( \beta = 0 \) represents neutral drift and \( \beta \rightarrow +\infty \) represents a purely deterministic imitation dynamics). Imitation is myopic: the value of \( p \) and \( q \) copied will suffer a perturbation due to errors in perception, such that the new parameters will be given by \( p' = p + \zeta_{p,\varepsilon} \) and \( q' = q + \zeta_{q,\varepsilon} \), where \( \zeta_{p,\varepsilon} \) and \( \zeta_{q,\varepsilon} \) are uniformly distributed random variables drawn from the interval \([-\varepsilon, \varepsilon]\). This feature not only i) models a slight blur in perception but also ii) helps to avoid the random extinction of strategies, and iii) ensures a complete exploration of the strategy spectrum. To guarantee that new \( p \) and \( q \) are not lower than 0 or higher than 1, we implement reflecting boundaries at 0 and 1. Alternative options of mutation operators to test in the future include drawing mutations from normal distributions of considering absorbing boundaries [4].
Figure 3: The average proposal played by agents in a population, \( \langle p \rangle \), decreases with \( \alpha \). This means that attributing the role of Proposer to high-degree nodes reduces the overall fairness level in a population. We present results for BA and DMS networks with average degree \( \langle k \rangle = 4 \). We verify that low-degree Proposer assignment maximizes \( \langle p \rangle \) for different group decision rules, \( M = \{0.1, 0.5, 0.9\} \), i.e., the fraction of Responders that needs to accept a proposal for it to be accepted by the group.

Furthermore, with probability \( \mu \), imitation will not occur and the individual will adopt random values of \( p \) and \( q \), drawn from a uniform distribution over \([0, 1]\). This can either represent the adoption of a random strategy by an individual or a low rate of existing players being replaced by new naive players. We use \( \mu = 1/Z, \beta = 10 \) and \( \varepsilon = 0.05 \) throughout this work. The effect of varying \( \mu \) is similar to the one verified when changing \( \varepsilon \): an overall increase of randomness leads to higher chances of fairer offers (as in [32, 36]). For each combination of parameters, the simulations are repeated 100 times (10 times using 10 different networks from each class studied), whereas each simulation starts from a population where individuals are assigned random values of \( p \) and \( q \) drawn uniformly from \([0, 1]\). We provide a summary of the algorithm used to revise agents’ strategies in Algorithm 1. The average values of \( p \), \( q \) and \( f \) (denoted by \( \langle p \rangle \), \( \langle q \rangle \) and \( \langle f \rangle \)) are obtained as a time and ensemble average, taken over all the runs (considering the last \( 10^5 \) generations, disregarding an initial transient period).

Results and Discussion

We run the proposed model and record the average strategies played by the agents over time and over different runs (starting from different initial conditions, see Methods). We find that attributing the role of Proposer to low-degree nodes (or low-degree Proposer assignment) increases the average level of proposal, \( p \), adopted in the population of adaptive agents. This means that the payoff gap between Proposers and Responders is alleviated. Figure 3 shows that, for low \( \alpha \) (\( \alpha < 0 \)), we obtain higher levels of average proposal when considering both...
Figure 4: On top of decreasing the average level of proposal in the population, $\langle p \rangle$, we found that attributing the role of Proposer to highly connected nodes decreases the level of fairness and equality within the population. Here we use scatter plots to observe the average payoff obtained per game, $\langle \Pi \rangle$, for individuals with a certain degree (horizontal axis). The left panels, a) and d), represent a low-degree Proposer assignment scenario ($\alpha = -2$); the center panels, b) and e), represent random — and degree-independent — role attribution ($\alpha = 0$); the right panels, c) and f), represent a high-degree Proposer assignment scenario ($\alpha = 2$). Each gray cross represents a node in a degree-$(\Pi)$ space; the orange line represents the mean taken over all nodes with a certain degree. Top panels represent $M = 0.1$ and bottom panels $M = 0.9$. High $\alpha$ — i.e., high-degree Proposer assignment — implies that highly connected nodes earn (approximately) five times more payoff per game than low-connected nodes (top-right panel). This effect is alleviated for higher $M$; for $M = 0.9$, highly connected nodes earn (approximately) three times more payoff per game than low-connected nodes (bottom-right panel).

We also confirm that high-degree Proposer assignment leads to unequal (unfair) results within a population. Figure 4 depicts the average payoff gains for individuals with a certain degree. We can observe that, for $\alpha = 2$, high-degree nodes obtain much higher values of payoff than low-degree nodes. This situation is ameliorated if individuals with lower degree are given a higher chance of becoming Proposers (lower $\alpha$) and, to a lower extent, if more Responders are required to accept a proposal in order for it to be accepted (higher $M$, bottom panels in Figure 4).
Figure 5: Selecting high-degree nodes as Proposers increases unfairness. Here we represent the so-called Lorenz curves, often used to compute the Gini coefficients—a typical measure of income inequality. Each curve is generated by ordering individuals by increasing value of income and plotting the corresponding cumulative distribution. Curves closer to the perfect equality line (45 degree line) represent more egalitarian outcomes. Here we observe, yet again, that assigning the role of Proposer to high-connected nodes ($\alpha = 2$) yields unfair outcomes (orange line). While this is evident for soft (panel a, $M = 0.1$), medium (panel b, $M = 0.5$) and strict decision rules (panel c, $M = 0.9$), we also verify that whenever hubs are the Proposers ($\alpha = 2$), having strict decision rules (high $M$) reduces unfairness. In all cases, random Proposer assignment leads the most egalitarian outcomes.

Figure 6: Low-degree Proposer assignment maximizes the average fitness (i.e., sum of payoffs taken over all games, see Figure 2) in a population. Here we observe that the average fitness, $\langle f \rangle$, increases as $\alpha$ decreases. We show results for BA networks with different values of $\langle k \rangle$ and $M$. A similar conclusion is obtained when considering DMS networks with the same parameters as Figure 3 and 6. Note that, increasing $\langle k \rangle$ implies that the average group size to play MUG also increases, which leads offers to be divided by larger groups (hence contributing to lower values of average payoff per game). On the other hand, increasing $\langle k \rangle$ means that more games are played, thus contributing to an increase in accumulated fitness (taken as the sum of payoffs in all games played).

We can further verify the effect of $\alpha$ on fairness through the so-called Lorenz curves [19], often used to compute the Gini coefficients [12] that quantify income inequality. In Figure 8 we represent the Lorenz curves associated with different role-assignment rules ($\alpha$) and voting rules, $M$. Each curve is generated by ordering individuals by increasing value of income.
Figure 7: We confirm that low-degree Proposer assignment maximizes populations’ average level of proposal, $\langle p \rangle$, for both BA and DMS networks with higher average degree ($\langle k \rangle = 8$, panel a, and $\langle k \rangle = 16$, panel b). For networks with higher $\langle k \rangle$ — leading to MUGs played in larger groups — and low $M$, random role attribution ($\alpha = 0$) configures the worst scenario in terms of fair proposals.

plotting the corresponding cumulative distribution. A curve closer to the perfect equality line ($x = y$) represents a more egalitarian distribution of resources and a lower Gini coefficient.

As we verify in Figure 8, the most unequal outcomes (higher Gini) are obtained for higher $\alpha$. We further verify that, when fixing $\alpha = 2$, having stricter voting rules (high $M$, in this case $M = 0.9$) attenuates the unfairness associated with having hubs being the Proposers.

Not only does low-degree Proposer assignment reduce unfairness, it also sustains more efficient outcomes — taken as higher values of average fitness observed in the population. In Figure 6 we confirm that low values of $\alpha$ maximize the average fitness of populations. This occurs when considering heterogeneous networks with different average degrees ($\langle k \rangle$) and group decision rules ($M$). This effect is more evident when considering less strict group decision rules (that is, lower $M$, meaning that less Responders are required to accept a proposal for the group to accept it) and networks with higher $\langle k \rangle$.

Finally, we confirm that low-degree Proposer assignment maximizes the average proposal played in the population (and thus fairness) when considering networks with higher $\langle k \rangle$ and, as a result, larger average group sizes. As Figure 7 conveys, the higher values of average proposal, $\langle p \rangle$ are obtained for $\alpha < 0$. Notwithstanding, we are able to find parameter spaces where the dependence of $\langle p \rangle$ on $\alpha$ is seemingly affected by i) the average connectivity of the network — and thus on the average size of the groups in which MUG is played — and ii) particular values of $M$. Also, we confirm that increasing $M$ increases $\langle p \rangle$ for all values of $\alpha$. Our results suggest that offering the first move to low-degree nodes balances the natural power of highly connected nodes in scale-free networks, leading to a significant increase in the global levels of fairness. Interestingly, we also find that particular voting rules ($M$) are able to attenuate the negative effect of high $\alpha$ (i.e. privileged high-degree nodes being selected to be Proposers) on fairness.
Figure 8: Dynamics of fairness on two stars, centered in hub-nodes $H_1$ and $H_2$, characterized by values of proposal $p_h$ and $p_l$. In Box 1 we present the total fitness of $H_1$ and $H_2$ ($f_h$ and $f_t$, respectively) assuming that $\alpha$ is high and hubs play as Proposers. In Box 2 we present the total fitness assuming that $\alpha$ is low and hubs play as Responders. In both cases we assume that proposals are always accepted. Assuming that $H_1$ is a fairer node ($p_h > p_l$) we can conclude that $H_1$ is likely to be imitated for low $\alpha$ and $H_2$ is likely to be imitated for high $\alpha$.

One can reach an additional intuition for the increase of fairness through the attribution of the role of proposer to low degree nodes if we approximate scale-free networks to a collection of heterogeneous star-like structures [42]. For simplicity, let us consider two hubs ($H_1$ and $H_2$, both with degree $k$) at the center of two stars, each with a two prevalent $p$ values (high $p_h$ in the green star, around $H_1$, and low $p_l$ in the blue star, around $H_2$). Under this configuration we may ask which strategy ($p_h$ or $p_l$) will prevail. For that, we note that, within each star, the strategies of the hubs are likely to locally prevail and thereby we focus on strategy invasion along the edge connecting both hubs (red/thick link); we further assume that $H_1$ is characterized by a higher value of $p$ than $H_2$ ($p_h > p_l$). The question is: will $\alpha$ impact the total payoff of $H_1$ and $H_2$ ($f_h$ and $f_t$, respectively) such that under high $\alpha$ $H_1$ is likely to be imitated by $H_2$ ($f_h < f_t$) and under low $\alpha$ $H_2$ is likely to be imitated by $H_1$ ($f_h < f_t$)? The answer is yes: If high-degree nodes are preferentially selected as Proposers (high $\alpha$), the total payoffs of $H_1$ and $H_2$ decrease with the value of $p$ characterizing their stars — $p_h$ and $p_l$, respectively. As a result, if $p_h > p_l$, it is likely that $H_2$ gets imitated by $H_1$ which contributes to decrease the average value of $p$ in both stars (Box 1). Conversely, if high-degree nodes are preferentially selected as Responders (low $\alpha$) the fitness of $H_1$ and $H_2$ will increase with $p_h$ and $p_l$, respectively. As a result, the hub associated with the star revealing a higher $p$ is likely to be imitated which, if $p_h > p_l$, implies that $H_1$ will tend to be imitated by $H_2$;
the average value of $p$ in both stars thereby increases (Box 2). This intuition hinges on the assumption that all offers are accepted, which is only true for $M = 0$ or $p \geq q$ for all nodes. If $M$ increases, it is harder for low proposals to get accepted as they require a higher number of accepting Responders to be validated which contributes for $p$ to increase overall and to fairer proposals [38, 36]. This intuition remains valid if such heterogeneous structures portray a high clustering coefficient (e.g., when leaves of each star-like community are linked to each other), offering an additional intuition on why the DMS and the BA network models offer similar results.

**Conclusion**

In this paper we address the general problem of 1) deciding how to attribute bargaining roles in a social network and, in particular, 2) understanding the impact of different criteria on the emerging levels of fairness in Multiplayer Ultimatum Games. We verified that attributing the role of proposer to low degree nodes boost both fairness and overall fitness. This conclusion remains valid for different network structures (BA and DMS networks with average degrees ranging from 4 to 16) and interaction scenarios (in terms of group sizes and group decision rules).

We also find that the perils of having high-degree Proposers can be softened with strict group decision rules. This means that, whenever $\alpha$ is high can default and cannot be lowered (e.g., hubs by having the needed resources to be the first movers in a bargaining situation) unfairness can be reduced by imposing that proposals need to be validated by a large fraction of Responders. The effect of $M$ on eliciting fairer offers is similar to that found in recent literature [36, 39]. By considering a higher $M$, more accepting Responders are required in order for a proposal to be accepted; as a result, it is harder for unfair Proposers (i.e., adopting lower $p$) to have their proposals accepted and increase their payoffs by keeping the largest sum of the initial endowment to themselves. As a result, there is a tendency for the average offer in the population, $p$, to increase. Also, our results are in line with works showing that selecting low-degree Proposers maximizes fairness in the context of pairwise Ultimatum Games [49] and Dictator Games [8]. Here we confirm that the mechanisms contributing for fairness through adaptive role-assignment in the pairwise UG are likely to extend to Multiplayer Ultimatum Games, a setting where (as discussed in Related Work) the asymmetry in payoffs between Proposers and Responders is exacerbated; extending the analysis of role-assignment in MUG allows one to cover N-person interactions and, importantly, to test how voting mechanisms can curb the effects of particular role-assignments.

This work can underlie several extensions of interest for social and engineering sciences. Here we consider that role assignment is endogenously imposed. In reality, the tendency for certain nodes to be allocated particular roles is likely to evolve side-by-side with individual strategies, being another self-organized property of the system, like fairness and wealth distributions. Other sources of heterogeneity known to influence the propensity to be fair — such as cultural
[24] and socio-economic [26] settings, or individuals’ engagement in institutions [16] — may further influence how roles and power-dependencies [21] are assigned. Moreover, the fact that network-based role assignment elicits fairness in rather complicated scenarios — as multiplayer bargaining games — suggests that such an approach could also be used within the broader context of active interventions aiming at fostering fairness in hybrid populations comprising humans and machines [39, 43, 31, 44]. In this context, it would be relevant to assess — both experimentally and through numerical simulations — the impact on human decision-making of having virtual regulators dynamically deciding the role to adopt by their group peers, depending on their position in the interaction structure.

Finally, we note that, while here we consider static networks, it is likely that dynamic networks [41, 3, 22, 28] can offer extra means for degree and roles to become correlated over time. For example, if fair Proposers (or lenient Responders) attract a higher number of neighbors, their degree will increase as a by-product of their role and strategy, which may imply that effective values of $\alpha$ may emerge from the co-evolution of strategies and social ties.

Despite these open questions, our present work already suggests that carefully selecting the role of each agent within a group — depending on their social position and without limiting their available options — can offer a long-term social benefit, both in terms of the overall levels of fairness, wealth inequality, and global wealth of a population comprised by self-regarding agents.

Data Availability

The methods to produce the data that support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

This work was partially supported by FCT-Portugal (UIDB/50021/2020, PTDC/MAT-APL/6804/2020, and PTDC/CCI-INF/7366/2020). F.P.S. acknowledges support from the James S. McDonnell Foundation Postdoctoral Fellowship Award. A preliminary version of this work was presented in Abstracts from the Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021).
References

[1] Albert-László Barabási and Réka Albert. Emergence of scaling in random networks. *Science*, 286(5439):509–512, 1999.

[2] Scott Barrett. *Environment and statecraft: The strategy of environmental treaty-making*. OUP Oxford, 2003.

[3] John Bryden, Sebastian Funk, Nicholas Geard, Seth Bullock, and Vincent AA Jansen. Stability in flux: community structure in dynamic networks. *Journal of the Royal Society Interface*, 8(60):1031–1040, 2011.

[4] Seth Bullock. Smooth operator? understanding and visualising mutation bias. In *European Conference on Artificial Life*, pages 602–612. Springer, 2001.

[5] Colin F Camerer. *Behavioral game theory: Experiments in strategic interaction*. Princeton university press, 2011.

[6] Yann Chevaleyre, Paul E Dunne, Ulle Endriss, Jérôme Lang, Michel Lemaitre, Nicolas Maudet, Julian Padget, Steven Phelps, Juan A Rodriguez-Aguilar, and Paulo Sousa. Issues in multiagent resource allocation. *Informatica*, pages 3–31, 2006.

[7] Steven De Jong, Simon Uyttendaele, and Karl Tuyls. Learning to reach agreement in a continuous ultimatum game. *J. Artif. Intell. Res.*, 33:551–574, 2008.

[8] Xinyang Deng, Qi Liu, Rehan Sadiq, and Yong Deng. Impact of roles assignation on heterogeneous populations in evolutionary dictator game. *Sci. Rep.*, 4:6937, 2014.

[9] S. N. Dorogotsev, J. F. F. Mendes, and A. N. Samukhin. Size-dependent degree distribution of a scale-free growing network. *Phys Rev E*, 63, 2001.

[10] Ernst Fehr and Urs Fischbacher. The nature of human altruism. *Nature*, 425(6960):785, 2003.

[11] Ernst Fehr and Klaus M Schmidt. A theory of fairness, competition, and cooperation. *Q. J. Econ.*, 114(3):817–868, 1999.

[12] Corrado Gini. Measurement of inequality of incomes. *The economic journal*, 31(121):124–126, 1921.

[13] Veronika Grimm, Robert Feicht, Holger Rau, and Gesine Stephan. On the impact of quotas and decision rules in ultimatum collective bargaining. *Eur. Econ. Rev.*, 100:175–192, 2017.

[14] Werner Güth, Rolf Schmittberger, and Bernd Schwarze. An experimental analysis of ultimatum bargaining. *J. Econ. Behav. Organ.*, 3(4):367–388, 1982.

[15] The Anh Han, Luis Moniz Pereira, Francisco C Santos, Tom Lenaerts, et al. To regulate or not: A social dynamics analysis of an idealised ai race. *Journal of Artificial Intelligence Research*, 69:881–921, 2020.
[16] Joseph Henrich, Jean Ensminger, Richard McElreath, Abigail Barr, Clark Barrett, Alexander Bolyanatz, Juan Camilo Cardenas, Michael Gurven, Edwins Gwako, Natalie Henrich, et al. Markets, religion, community size, and the evolution of fairness and punishment. *Science*, 327(5972):1480–1484, 2010.

[17] Genki Ichinose and Hiroki Sayama. Evolution of fairness in the not quite ultimatum game. *Scientific Reports*, 4(1):1–4, 2014.

[18] Nicholas R Jennings, Peyman Faratin, Alessio R Lomuscio, Simon Parsons, Carles Sierra, and Michael Wooldridge. Automated negotiation: prospects, methods and challenges. *Group Decis Negot*, 10(2):199–215, 2001.

[19] Max O Lorenz. Methods of measuring the concentration of wealth. *Publications of the American Statistical Association*, 9(70):209–219, 1905.

[20] Simon Lynch, Long Tran-Thanh, Francisco C Santos, et al. Fostering cooperation in structured populations through local and global interference strategies. In *Proc of IJCAI’18*, 2018.

[21] Linda D Molm. Affect and social exchange: Satisfaction in power-dependence relations. *American Sociological Review*, pages 475–493, 1991.

[22] Joao A Moreira, Jorge M Pacheco, and Francisco C Santos. Evolution of collective action in adaptive social structures. *Scientific Reports*, 3(1):1–6, 2013.

[23] Martin A Nowak, Karen M Page, and Karl Sigmund. Fairness versus reason in the ultimatum game. *Science*, 289(5485):1773–1775, 2000.

[24] Hessel Oosterbeek, Randolph Sloof, and Gijs Van De Kuilen. Cultural differences in ultimatum game experiments: Evidence from a meta-analysis. *Experimental Economics*, 7(2):171–188, 2004.

[25] Karen M Page, Martin A Nowak, and Karl Sigmund. The spatial ultimatum game. *Proc R Soc B*, 267(1458):2177–2182, 2000.

[26] Paul K Piff, Michael W Kraus, Stéphane Côté, Bonnie Hayden Cheng, and Dacher Keltner. Having less, giving more: the influence of social class on prosocial behavior. *Journal of Personality and Social Psychology*, 99(5):771, 2010.

[27] Flávio L Pinheiro and Fernando P Santos. Local wealth redistribution promotes cooperation in multiagent systems. In *Proc of AAMAS’18*, pages 786–794, 2018.

[28] Flávio L Pinheiro, Francisco C Santos, and Jorge M Pacheco. Linking individual and collective behavior in adaptive social networks. *Physical Review Letters*, 116(12):128702, 2016.

[29] Amy R Pritchett and Antoine Genton. Negotiated decentralized aircraft conflict resolution. *IEEE T Intell Transp*, 19(1):81–91, 2017.
[30] MA Raghunandan and CA Subramanian. Sustaining cooperation on networks: an analytical study based on evolutionary game theory. In Proc of AAMAS’12, pages 913–920, 2012.

[31] Iyad et al. Rahwan. Machine behaviour. Nature, 568(7753):477–486, 2019.

[32] David G Rand, Corina E Tarnita, Hisashi Ohtsuki, and Martin A Nowak. Evolution of fairness in the one-shot anonymous ultimatum game. Proc. Natl. Acad. Sci. USA, 110 (7):2581–2586, 2013.

[33] Bijan Ranjbar-Sahraei, Haitham Bou Ammar, Daan Bloembergen, Karl Tuyls, and Gerhard Weiss. Evolution of cooperation in arbitrary complex networks. In AAMAS’14, pages 677–684, 2014.

[34] Norman Salazar, Juan A Rodriguez-Aguilar, Josep Ll Arcos, Ana Peleteiro, and Juan C Burguillo-Rial. Emerging cooperation on complex networks. In Proc of AAMAS’11, pages 669–676, 2011.

[35] Fernando P Santos and Daan Bloembergen. Fairness in multiplayer ultimatum games through moderate responder selection. In Proc of ALIFE’18, pages 187–194. MIT Press, 2019.

[36] Fernando P Santos, Francisco C Santos, Ana Paiva, and Jorge M Pacheco. Evolutionary dynamics of group fairness. J Theor Biol, 378:96–102, 2015.

[37] Fernando P Santos, Francisco C Santos, Francisco S Melo, Ana Paiva, and Jorge M Pacheco. Dynamics of fairness in groups of autonomous learning agents. In AAMAS’16 Workshops, Best Papers, pages 107–126. Springer, 2016.

[38] Fernando P Santos, Jorge M Pacheco, Ana Paiva, and Francisco C Santos. Structural power and the evolution of collective fairness in social networks. PloS ONE, 12(4): e0175687, 2017.

[39] Fernando P Santos, Jorge M Pacheco, Ana Paiva, and Francisco C Santos. Evolution of collective fairness in hybrid populations of humans and agents. In Proc of AAAI’19, volume 33, pages 6146–6153, 2019.

[40] Fernando P Santos, Jorge M Pacheco, Francisco C Santos, and Simon A Levin. Dynamics of informal risk sharing in collective index insurance. Nature Sustainability, pages 1–7, 2021.

[41] Francisco C Santos, Jorge M Pacheco, and Tom Lenaerts. Cooperation prevails when individuals adjust their social ties. PLoS computational biology, 2(10):e140, 2006.

[42] Francisco C Santos, Marta D Santos, and Jorge M Pacheco. Social diversity promotes the emergence of cooperation in public goods games. Nature, 454(7201):213, 2008.

[43] Hirokazu Shirado and Nicholas A Christakis. Locally noisy autonomous agents improve global human coordination in network experiments. Nature, 545(7654):370–374, 2017.
[44] Hirokazu Shirado and Nicholas A Christakis. Network engineering using autonomous agents increases cooperation in human groups. *Iscience*, 23(9):101438, 2020.

[45] Hirofumi Takesue, Akira Ozawa, and So Morikawa. Evolution of favoritism and group fairness in a co-evolving three-person ultimatum game. *Europhysics Letters (EPL)*, 118(4):48002, 2017.

[46] Arne Traulsen, Martin A Nowak, and Jorge M Pacheco. Stochastic dynamics of invasion and fixation. *Phys Rev E*, 74(1):011909, 2006.

[47] Karl Tuyls and Simon Parsons. What evolutionary game theory tells us about multiagent learning. *Artif. Intell.*, 171(7):406–416, 2007.

[48] Jörgen W Weibull. *Evolutionary game theory*. MIT press, 1997.

[49] Te Wu, Feng Fu, Yanling Zhang, and Long Wang. Adaptive role switching promotes fairness in networked ultimatum game. *Sci. Rep.*, 3:1550, 2013.

[50] Ioannis Zisis, Sibilla Di Guida, TA Han, Georg Kirchsteiger, and Tom Lenaerts. Generosity motivated by acceptance-evolutionary analysis of an anticipation game. *Sci. Rep.*, 5:18076, 2015.