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A cognitive model of social preferences in group interactions

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Abstract. Modeling the interactions in groups is becoming increasingly important in many application domains such as the design of interactive systems and social robots. Since human interactants do not always make rational choices, a good model of their social motivations is needed to explain the strategies of the interactants that are often influenced by social factors and preferences, the feeling of fairness and understanding the need for cooperation. We propose a cognitive model of social preferences of three or more interactants that are engaged in a collaborative game. The game strategies of the interactants are modeled with cooperation ratios and utility functions. We developed a new generalized utility-based approach to model the cooperation and fairness in multiplayer interactions, which uses three utility parameters. In two-person games, as it has been investigated by others, it is impossible to distinguish between fairness and cooperation in the decisions of a given player. We show that in n-person games ($n > 2$), and with the use of the proposed utility-based approach, it is possible to distinguish between fairness and cooperation. This makes the proposed approach suitable for more detailed analysis of group interactions in a game setting, which can better explain the social motivation of the interactants, than existing utility models and models that utilize on cooperation ratios. We show that the proposed generalization makes the newly proposed utility function less sensitive to the payoffs of one player if the size of the group grows, and test it with data from the MARS-500 isolation experiment.

Keywords: Monitoring social behavior, games, group interactions, subjective factors in decision making, space technologies

1. Introduction

Cognitive models of decision making in group interactions have been proposed in economics, sociology, game theory and biology, based on the assumption that interactants are egoistic subjects/agents that are driven by the motivation to maximize their own benefit/payoff. Recent studies demonstrated that these models cannot adequately explain many experimental findings and that humans often are also motivated by social factors and preferences, the feeling of fairness and by understanding the need for cooperation. People choose actions that do not maximize their own payoff when those actions affect the payoffs of other individuals.

Empirical evidence of such altruistic behavior have recently inspired development of models of "social preferences" that assume that subjects are self-interested, but also are concerned about the effect of their decisions on others. These models try to capture phenomena as altruism [17], trust [6,26,29], cooperation [18], to account for fairness, reciprocity, and ethics in decision making [30]. In emerging applications of human-computer and human-robot interaction, it is becoming increasingly important to understand and model the "irrational" behavior of the participants in group interactions with the aim to ground these in agent's behavior [2,20,30].

Among the models designed to capture the social (no self-interested) behavior, three classes can be distinguished. The first class includes models that are based on the fairness of the distribution of resources, in particular, the fairness of the distribution of effort and wage [1,10], equity of distribution and competition [4], distribution determined by exchange and com-

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petition [11], the role of envy in the distribution [19]. The second class of models are driven by a concern for reciprocity, including sequential reciprocity [8], also tested in interaction between artificial agents [16] and in human-robot interaction [2], and the impact of social preferences on reciprocity [22]. The third group of models combine elements of both approaches [5,7,12].

The first two groups of models introduce a distributional or reciprocal component in the utility (to explain these aspects in the strategy of the agent). The impact of the distributional or reciprocal component depends on the type of the situations that has to be modeled. There are cases in which reciprocity cannot be neglected. For instance, in proposer-responder type of games, the responder needs to make a decision given the decision of his/her co-player, who makes a proposal. In this case, the kind/unkind actions of the proposer are usually reciprocated by a reward or punishment of the responder. To model the reciprocal behavior of the responder, the following factors have to be taken into account: the options available to the responder, the option proposed by the proposer, the options that could be proposed by the proposer and beliefs of the responder about the intentions of the proposer.

There are also situations in which the reciprocal behavior is not feasible. For instance, for the person who makes the very first move in the game, the attractiveness of the options depends solely on the benefits/payoffs associated with the option itself. In this case, only the distributional factors matter. Even for this simple case, there is no consensus in the existing models about what is the correct way to model preferences of the interactants. In the literature, several alternative types of models have been proposed. For instance, the *difference-aversion models* assume that subjects are motivated to increase their personal benefit and also to reduce the difference between their and others' payoffs, as proposed in the study of Fehr and Schmidt [12].

In contrast, the *social-welfare models* assume that subjects' preferences consist of three components: (1) a component responsible for an egoistic behavior, (2) Hicks optimality component which is responsible for a cooperative behavior, and (3) a fairness component [5].

Although the inequity-aversion and social-welfare utilities are based on different assumptions, it has been shown in the literature that for the case of two subjects they can be represented by the same simple equations and the difference between the utilities appears only because of different values of the utility parameters as proposed by Charness and Rabin [5].

In this paper, we model the case of multiple (more than two) interactants and show that for this case the inequity-aversion and social-welfare utilities are different. We argue that the form of utility that we propose has several advantages in comparison with the earlier proposed ways to describe the strategies of the interactants. Moreover, we introduce an additional fairness term. The purpose of this term is to model the decision making process of the proposers if the proposition is rejected. We argue that this additional fairness terms is important part of an adequate model of the proposers' behavior.

The construction of the proposed utility function was driven by practical need to describe behavior of the participants in a game used in the MARS-500 experiment [3,15,24] to monitor interpersonal relationships and eventual conflicts by astronauts that were a part of this experiment [3,15,16,31].

2. Modelling proposer-responder behavior

To facilitate group interactions, we conducted the following experiment, which was part of MARS-500 experiment [15,24,25,27]. MARS-500 was conducted by the Institute for Biomedical Problems (IBMP) in Moscow and the European Space Agency, performing a full-scale ground-based simulation of a manned mission to Mars. Such a full-scale mission requires from 520 to 700 days of isolation. All key features expected in such a flight were present, which ensured that the psychological and physiological impacts of isolation through such an extended period were simulated with high fidelity.

To monitor the developments in the social relations through games, we designed a modified version of the Colored Trails (CT) game [15], to the original CT game that was developed at Harvard University [14]. CT is a computer version of multiplayer negotiation board game that combines social skills as negotiation and logical reasoning. It creates situations in which people have different goals and insufficient resources to reach these goals. At the start of each game players are in different situations (starting positions on the board and possession of chips) and, as a consequence require different resources to reach their goals. To come up to the new resources, the players can redistribute these resources through negotiations with other players. The game supports the analysis of the development of social relations since it contains both competitive and collaborative components. A snapshot of the game is shown in Fig. 1.

The game is played by three persons in the way explained in the caption of Fig. 1. Players can move their chips horizontally or vertically to one of the neighboring squares if they have a chip of the same color as the new square. The player than surrenders a chip of that color. The goal of the player is to move as close as possible to the goal-square, spending a minimum number of chips.

Before making their moves, players are allowed to exchange some of their chips with another player if both participants agree. For the Mars-500 experiment, we proposed a generalization of the CT negotiation scheme. In the generalized version of the CT game, each player can take the role of a proposer and can choose to whom to make a proposition. These modifications provide several advantages that makes possible to generate more data from the same number of games. An additional consequence from the changes is that we increased the variety of situations in which responders can be. This yields additional information about the social preferences in the group. Every player can potentially receive a proposition and play the role of a responder. The responders can have up to three propositions and, in this way, they experience a broader range of situations in comparison to the original version of the game. Also, we added a phase to the game, that is aimed to assess irrational preferences of the players.

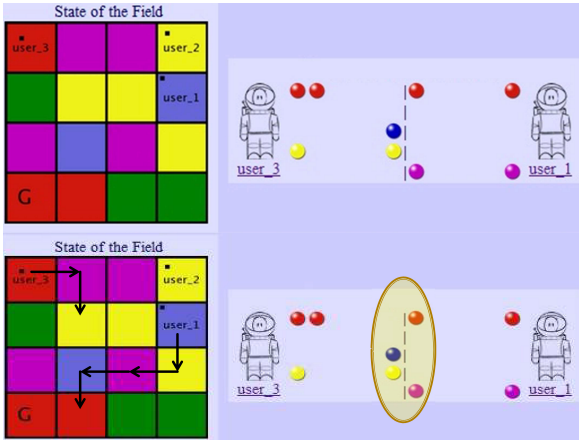

Fig. 1. A snapshot of the colored trails game. Three players' form a partner network are assigned to different squares of a colored board. If a player has the chip with the same color as a neighboring square on the board, then he can move to this square. Each player aims to get as close as possible to the GOAL square. Every player can be a proposer or responder – i.e., offer chips or ask for chips. On the upper plot are shown the chips of two of the three players. If Player 1 receives blue and yellow chip from Player 3, he can move closer to the goal state G, as visualized in the lower plot with arrows. Player 3 can help by exchanging these chips.

3. Experimental setting for group interactions

3.1. Assumptions

We assume that proposers and responders value options based on the payoffs associated with each option provided by the game setting. Expressed in different words, we assume that there is a utility function u that is used by the players (explicitly or implicitly) to estimate the attractiveness of different game options. The proposer-responder interaction is therefore modelled by a utility function. In the proposal phase, the proposer chooses one option from a set of available options. Every option is characterized by two numbers: p and r that represent the payoffs of the proposer and responder, respectively. We assume that proposer uses a utility function u that depends on p and r to estimate the attractiveness of every option: $u = u(p, r)$. We also assume that the attractiveness of the options depends on the default payoffs of the proposer and responder p_0 and r_0 (payoffs that will be given to the proposer and responder in the case of no exchange): $u = u(p_0, r_0, p, r)$. In the case of egoistic proposition, which tries to optimize only the payoff of the proposer, the utility function is given by the following simple expressions: $u(p_0, r_0, p, r) = p$. The above egoistic utility function is too simple to describe the behavior of the proposer adequately. For example, the attractiveness of an option to the proposer might depend not only on the payoff provided by the option to the proposer but also on the probability that the considered option will be accepted by the responder and this probability, in its turn, depends on the payoff of the responder.

To describe preferences of subjects in simple test games different utility functions have been proposed. In this study we will consider simple utilities, the first one is the *inequity-aversion utility* [12]. This model assumes that subjects are motivated to increase their own benefit while at the same time they are motivated to reduce the difference between their own and others payoffs. The second utility we consider is called the *social-welfare utility* [5]. It assumes that the interactants are motivated to increase their own benefit as well as the social benefit, caring especially about helping those individuals who have a low payoff.

The utility based approach is more suitable for modeling decisions in the proposition phase since in this case the attractiveness of every option is completely characterized by the payoffs associated with it. The decisions of the responder are not entirely character-

ized by the payoffs associated with the available options (for example accept and reject), so utility function alone cannot model well the behavior of the responder. In addition to the payoffs associated with different options, the responder is more likely to also take into account the payoffs of the options that could be proposed by the proposer. For example, a responder might want to reward or punish proposer depending on what proposals he/she made (good one or bad one). This kind of behavior is known as reciprocity and has been considered by many researchers [4,7–9].

3.2. *Utility functions for two interactants for both utilities*

3.2.1. *The inequity-aversion utility*

For the case of two players it has the following simple form:

$$U_{ia}(p,r) = p - \alpha \max(r-p,0) - \beta \max(p-r,0) \quad (1)$$

This utility function has a simple interpretation. The first term represent egoistic preferences of the players. It was assumed that people do not like situations in which one of the players receives more than another one, i.e., do not like unequal distribution of the payoffs and have aversion to inequality. The second and third term, therefore, model this inequity aversion [12]. It was also assumed that the degree of the dislike of an inequity depends not only on the amount of the inequity but also who is receiving more (me or my co-player). The last assumption explains why the utility function has two terms in addition, compared to the egoistic utility.

3.2.2. *The social-welfare utility*

Charness and Rabin [5] proposed the social-welfare utility function which, for the case of two subjects, has the following form:

$$U_{sw}(p,r) = (1-\lambda)p + \lambda[(1-\delta)(p+r) + \delta \min(p,r)] \quad (2)$$

As can be seen in Eq. (2), the social-welfare utility combines the egoistic preferences (the first term) with the social preferences (the second term). If the parameters λ is equal to zero, the subject is absolutely egoistic. If λ is equal to one, then the subject cares only about fairness, i.e., the social utility. The social term, in its turn, consists of the Hick optimality term and the maximin fairness. The Hick optimality corresponds to the maximization of the total benefit while the maximin fairness motivates the subject to increase the lowest payoff.

We can show that the inequity-aversion utility (1) coincides with the social-welfare utility (2) for the case of two subjects. For that, we need to find an explicit relation between the parameters of the inequity aversion (1) and social welfare (2) utility functions written for two subjects. To accomplish that we need to ensure that both utility functions are "normalized" in the same way. In other words, we need to remove the ambiguity in the definition of a utility function that can arise from the fact that a decision maker is invariant with respect to the multiplication of the underlying utility by a positive number. To do that we consider both utilities for the case $p = r$. In this case, the inequity aversion utility is equal to p while the social-welfare utility is equal to $p(1+\lambda-\lambda\delta)$.

In this form the two considered utility functions are different. We can easily see that this difference can be removed if we slightly modify the original social welfare utility function in the following way:

$$U_{sw}(p,r) = (1-\lambda)p + \lambda\left[\frac{1}{2}(1-\delta)(p+r) + \delta \min(p,r)\right] \quad (3)$$

The term representing the Hick optimality (cooperative term) is divided by two, and with this modification, the social-welfare utility function will be equal to p for $p = r$. This modification can be done by redefinition of the parameters λ and δ in the expression, and it does not change the meaning of the parameters. As before, λ represents the portion of the egoistic and social terms in the utility. The λ equal to 1 represents a subject who does not care about the personal benefit. In contrast, λ equal to 0 represents the totally egoistic subject. The δ gives the balance between the Hick optimality and maximin fairness. The meaning of δ equal to 1 is that the player does not try to cooperate and cares only about the fairness of the outcome. The δ equal to 0, in contrast, represents cooperative players who do not care about the fairness of the outcome.

To demonstrate that the utilities (1) and (3) are the same we will analyze them for two different cases: $r < p$ and $r > p$. For the $r > p$ the inequity aversion and the modified social welfare functions are equal:

$$U_{ia}(p,r) = p(1+\alpha) - \alpha r \quad (4)$$

$$U_{sw}(p,r) = \left[1 + \frac{\lambda}{2}(\delta - 1)\right] p - \frac{\lambda}{2}(\delta - 1) r \quad (5)$$

For the case of $r < p$ we have the following expressions for the two utility functions:

$$U_{ia}(p,r) = p(1-\beta) + \beta r \quad (6)$$

$$U_{sw}(p,r) = \left[1 + \frac{\lambda}{2}(\delta + 1)\right] p + \frac{\lambda}{2}(\delta + 1) r \quad (7)$$

The relation between the inequity-aversion and the social-welfare utilities is easy to be seen if both utilities are represented by two linear functions one of which is valid for the region $r \geqslant p$ while the one is valid for the region $r \leqslant p$. It means that both utilities can be written in the following form:

$$U(p,r) = (1-\sigma)p + \sigma r \quad \textit{if} \quad r \geqslant p,$$
$$U(p,r) = (1-\rho)p + \rho r \quad \textit{if} \quad r \leqslant p, \quad (8)$$

where σ and ρ are some real constants. This way of representing the utility functions was proposed by Charness and Rabin [5]. In this form, the utility function has a clear interpretation, and the different types of the utility functions correspond to different ranges of the parameters σ and ρ. The inequity-aversion utility is valid in the range: $\sigma < 0 < \rho < 1$, while the social-welfare utility corresponds to the following range of the parameters: $1 \geqslant \rho \geqslant \sigma > 0$.

A competitive player will have ρ in the range: $\sigma \leqslant \rho \leqslant 0$. This implies that this player always optimizes own profit. A graphical representation of the relations between the parameters σ and ρ is given in the Fig. 2.

In Fig. 2, in addition to the regions corresponding to the three classes of the utility functions are seen four points corresponding to the four special utility functions. The left most point corresponds to the egoistic utility which describes subjects who care only about their own benefit. The cooperative utility corresponds to the subjects who are equally concerned about the payoff of each player. These players try to maximize the total benefit. The sacrificing utility corresponds to an altruistic player, who cares only about the payoff of another subject. And finally, the maximin fairness utility describes subjects who care only about the fairness of the outcome.

3.3. Utility functions for more than two interactants

The generalization of the utility functions for more than two subjects has been already studied by other

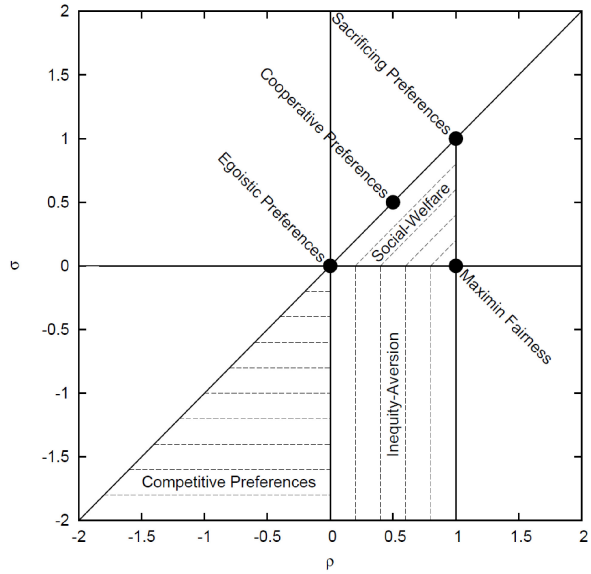

Fig. 2. Regions of the parameters σ and ρ corresponding to different classes of the utility functions.

researchers. In particular in the work of Fehr and Schmidt [12] which introduces the inequity aversion utility function (1), a form applicable to more than two players is:

$$U_i^{ia} = x_i - \frac{\alpha}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^{n} \max(x_j - x_i, 0) - \frac{\beta}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^{n} \max(x_i - x_j, 0) \quad (9)$$

Charness and Rabin [5], who introduce the social-welfare utility function, also give the generalization of the function in the case of more than two players:

$$U_i^{sw} = (1-\lambda)x_i + \lambda \left[(1-\delta) \sum_{i=1}^{n} x_i + \delta \min(x_1, x_2, \ldots, x_n) \right] \quad (10)$$

As we have demonstrated, in the case of two subjects the inequity aversion and social-welfare utility functions coincide but it is not clear if they are generalized to the case of many players in the same way. We will propose a way to make this generalization that provides a more adequate description of the behavior of the players. First, we formalize the procedure that is used to generalize the inequity aversion function. Second, we apply this procedure to the social-welfare utility

function for two subjects to make it more obvious that the many-subjects inequity aversion utility functions differs from the many-subjects social-welfare function. Third, we examine the logic behind the two ways to make the generalization to the many-subjects case and present a new way to make this generalization that does not suffer from the above mentioned drawback.

To demonstrate that inequity aversion utility function for multiple interactants (Eq. (9)) can be obtained from the two-subjects utility function (Eq. (1)), we use the following generalization to multiple players:

$$U_{ia}^{(n)}(x_1,\ldots,x_i,\ldots,x_n) = \frac{1}{n-1}\sum_{\substack{j=1\\ j\neq i}}^{n} U_{ia}^{(2)}(x_i,x_j) \tag{11}$$

If we apply this procedure to the modified social-welfare utility function (Eq. (3)), we will get the following equation:

$$\begin{aligned}&\frac{1}{n-1}\sum_{\substack{j=1\\ j\neq i}}^{n}(1-\lambda)x_i+\lambda\left[\frac{1}{2}(1-\delta)(x_i+x_j)\right.\\&\left.+\delta\min(x_i,x_j)\right] = (1-\lambda)x_i+\frac{\lambda(1-\delta)}{2}x_i \\&+\frac{1}{n-1}\frac{\lambda(1-\delta)}{2}\sum_{\substack{j=1\\ j\neq i}}^{n}x_j+\frac{\lambda\delta}{n-1}\sum_{\substack{j=1\\ j\neq i}}^{n}\min(x_i,x_j)\end{aligned} \tag{12}$$

The structure of the above Eq. (12) is different from those of the social-welfare function proposed by Charness and Rabin [5], in spite of the fact that we started from the two-subjects social-welfare function (Eq. (3)).

The difference between the above Eq. (12) and the many-subject social-welfare function Eq. (10) is as follows. The utility function Eq. (12) is very similar if the inequity aversion utility is written in a different way, does contain some terms that could be associated with the egoistic preferences, Hick optimality (cooperativeness) and the maximin utility. However, there are some differences; the first one is that the cooperative term (the third term) in the Eq. (12) does not contain the contribution from the subject for whom the utility is given. Moreover, it is divided by the number of interactants. In other words, the above inequity aversion utility function uses the average payoff of the players while the social-welfare utility uses the total payoff of the players. To make the above expression closer to the social-welfare function we will remove the $n-1$ term from the expression. In this case the second term can go under the sum of the third term and we will get the same Hick optimality terms as in the social-welfare utility function:

$$(1-\lambda)x_i+\lambda\left[\frac{1}{2}(1-\delta)\sum_{j=1}^{n}x_j+\delta\sum_{\substack{j=1\\ j\neq i}}^{n}\min(x_i,x_j)\right] \tag{13}$$

The Eq. (13) is similar to the original social welfare utility function Eq. (10). The 1/2 coefficient in the front of the Hick optimality term is there just because we used the modified version of the social-welfare function Eq. (3) instead of the original one Eq. (2).

3.4. Alternative generalization procedure

The only difference between the last expression Eq. (13) and the original social-welfare function is the maximin fairness term. In the case of the social- welfare function the fairness is calculated as the minimal payoff in the group. In Eq. (13) a player compares himself with all other subjects in the group and for every comparison, the fairness is calculated and is added to the total fairness. This difference demonstrates that there could be different ways to calculate the total fairness, i.e., there could be different ways to generalize the maximin fairness from the two-subjects case to the more than two-subjects case. We argue that using the term proposed in the original social-welfare function is problematic. This can be illustrated with the following example. A player needs to choose between two situations. In the first situation, 50 subjects get 11 points, other 50 subjects get 9 points, and 1 subject gets 7 points. In the second situation, 50 subjects get 12 points, other 50 subjects get 8 points, and one subject gets 7 points. Transition from the first case to the second one seems to make the distribution of points less fair since the rich subjects start to get even more and poor subjects start to get even less. However, according to the expression used in the social-welfare function, the fairness of both situations is the same (it is equal to 7, the minimal payoff in the group). To resolve this problem, we propose to calculate the fairness of the payoffs distributions for all possible pairs of players and sum the values up:

$$\sum_{\substack{k,l=1\\ k\neq l}}^{n}\min(x_k,x_l) \tag{14}$$

In addition, we have to decide how the weighting factor in front of this expression should depend on the number of the interactants in the group. This is challenging since in the Hick optimality terms there are n summands while in the maxim in that we have just introduced the number of terms is n square $-n$. As a result, the fairness terms will dominate the cooperation term if n is large enough. To resolve this problem, we propose to calculate the average fairness. For that, we divide the total fairness by number of terms under the sum $n(n-1)$. This quantity should not grow as n grows. Since the Hick optimality is proportional to n, we multiply the average fairness of the distribution by n. This way to combine the maximin fairness and Hick optimality ensures that none of this terms will dominate another one for large n. In summary, we propose to use the following utility function for the case of more than two subjects:

$$U = (1-\lambda)x_i + \lambda\left[\frac{1}{2}(1-\delta)\sum_{j=1}^{n} x_j + \frac{1}{2}\frac{\delta}{n-1}\sum_{\substack{k,l=1\\k\neq l}}^{n}\min(x_i, x_j)\right] \tag{15}$$

For the two players, the above utility function is the same as the *inequity-aversion* and the *social-welfare* utilities functions. For the case of more than two players, all the three utilities functions are different.

In the proposer-responder settings, the decisions of the proposer (which option will be proposed) depend not only on the payoffs of the options but also on the payoffs of the default option [21]. By the default option, it should be understood the option which will be implemented if proposer did not propose anything or if the responder rejects the proposed option. In particular, we can assume that the subjects care not only about the absolute payoffs associated with the options but also about the gain in the payoff that an option provides in addition to the default score. In other words, we assume that the subjects perceive the payoffs of the default option as something that they already have since the proposer and the responder can always get the default option, if they want, independently of the actions of the co-player. As a consequence, we could assume that the players judge all other options by the amount of points that these options give in addition to what they already can gain from the default option. We will call this amount *gain from the option*. By introducing this gain, we can assume that it is treated in the same way as the absolute payoff of the option, i.e., that the players might want to maximize their own gain or the total gain of all the players. However, utilities of this kind do not add anything new to the above considered utilities since a maximization of their gain is equivalent to the maximization of the absolute payoff. The same is valid for the total gain and the total absolute payoff. In contrast, the maximum fairness of the gain is not identical to the maximin fairness calculated for the absolute score. This means that the extended social-welfare utility function taking into account *gains from the options* can be written in the following way:

$$U_{4w}(p,r) = p + w_c(p+r) + w_f\min(p,r) + w_g\min(p-p_0, r-r_0) \tag{16}$$

where w_c, w_f, and w_g, are weighting factors that represent the importance of cooperation and the two different kinds of fairness to the given player, respectively. The first term p models the egoistic preferences. It has no coefficient (weighting factor) in front because the utility function is invariant with respect to a positive scaling factor and, as a consequence, we can always choose such a scaling factor that makes the coefficient in front of the egoistic term equal to zero. This normalization is convenient since in this case the importance of other factors will be defined relative to the importance of the own benefit of the player.

3.5. Fair gain and more than two interactants

The above proposed utility models make it possible to calculate fairness with respect to the final score. It is possible that the decisions of the players are based on how a certain choice is better than the one that the player will have by the default option. To generalize the above function to include fairness with respect to the gain we need to add one more term to the utility function:

$$\sum_{\substack{k,l=1\\k\neq l}}^{n}\min(x_i - x_i^d, x_j - x_j^d), \tag{17}$$

where x_i^d denotes the default score of the player i. This generalization will introduce ambiguity to the utility function, meaning that different values of the utility parameters could give the same utility function. To resolve this problem, we should take the two-subjects utility function with the removed ambiguity and generalize it to the case of more than two players. To do so we have to formalize the generalization procedure – we have to find the procedure that transforms the *modified social welfare utility* (3) to the *desired many-subject*

utility functions Eq. (14). After we find this procedure, we can apply it to the two-subjects utility with removed ambiguity and, in this way, we should obtain the many-subject utility without ambiguity.

Let us first take the two-subject utility (3) and sum it up for all possible pairs of subject and then divide by the number of the considered pairs:

$$\frac{1}{n(n-1)} \sum_{\substack{k,l=1 \\ k\neq l}}^{n} \Big\{ (1-\lambda)x_k + \lambda \left[\frac{1}{2}(1-\delta)(x_k + x_l) + \delta \min(x_k, x_l) \right] \Big\} \tag{18}$$

The above equation can be transformed to the following form:

$$(1-\lambda)x_i + \lambda \left[(1-\delta)\frac{1}{n}\sum_{j=1}^{n} x_j + \frac{\delta}{n(n-1)} \sum_{\substack{k,l=1 \\ k\neq l}}^{n} \min(x_k, x_l) \right] \tag{19}$$

If we compare the above Eq. (19) and the earlier proposed Eq. (15), we can see that the Eq. (15) can be obtained from the Eq. (18) if the following substitution $\lambda \to \lambda n/2$ before the social term is used. In other words, the generalization of the two-subject case (3) can be done if we replace λ by $n\lambda/2$ and average this two-subjects utility for all possible pairs of players. Now we can apply this procedure to the two-subjects utility which incorporates the two kinds of fairness and in which the ambiguity in the parameters is removed, by unifying the parameters for cooperation and different kinds of fairness and cooperation and expressing these through ω.

$$\begin{aligned} U_{3r}(p,r) = p - \tfrac{1}{2(n-1)} \sum_{\substack{k,l=1 \\ k\neq l}}^{n} [(w+f)\max(p-r,0) \\ +(w-f)\min(p-r,0)] - \tfrac{1}{2(n-1)} \\ \sum_{\substack{k,l=1 \\ k\neq l}}^{n} [(w+g)\max(\Delta p - \Delta r, 0) \\ +(w-g)\min(\Delta p - \Delta r, 0)] \end{aligned} \tag{20}$$

4. Testing the method in real-world interactions within MARS-500 and an online game

We showed that in group interactions we can distinguish between fairness and cooperation-motivated behaviors of the players. In this section, we will briefly show how to apply this method for analyzing the interactions and therefore show its validity.

4.1. Evolutionary algorithm for choosing games with the desired properties

To apply this method to real-world problems we need to generate games in the way that the participants will be forced to make the decisions that will expose their motivation to behave in a certain way. Because of that, we use an Evolutionary algorithm to generate the optimal sequences of games. There are other possible methods to find the optimal sequence of games, however, the choice of the method cannot impact the answer of the main research question of this paper.

We want to use games in which the sets of the payoff options, corresponding to different predefined strategies, do not overlap with each other. This property allows us to derive a strategy from the decisions of the players. We have found that only a very small percentage of games have such property. A random search for the games with this property would be too time-consuming.

To overcome this problem, an evolutionary search was performed. We needed to create games with several restrictions: (1) the chips of the game should stay on relatively small field; (2) two players were not allowed to occupy the same square; (3) the number of chips owned by one player should be between three and five; (4) the game should remine interesting for all players independent of who negotiates with whom. Because of the first two restrictions cross-over operations will be less efficient than mutations with one position or change to another color from the few options.

We started from a randomly generated game. Each game was generated for 3 players. The state of the field, the positions of players and the goal, as well as redistribution of chips, was done randomly. The only restriction that was applied is that every player can have from three to five chips. Then we started an iterative process in which either the state of the field or the position of the player or the location of the goal, or the set of the chips was modified. During the modification of the field, we randomly changed the color of a randomly chosen square. Changing a position of a player or of the goal we made one horizontal or vertical step to one of the neighboring squares (under the obvious restriction that the chips in the game should stay on the field). In addition, two players were not allowed to occupy the same square. By modifying the set of chips, a player was chosen at random, and for this player, a chip of a randomly chosen color was added or removed. Doing that, we kept the restriction that the number of chips owned by one player should be between three and five.

On every step, we calculated the overlap between sets of options representing different strategies. The size of the overlap was calculated for every potential pair of players, and the total size of the overlap was taken into account. In this way, we could guarantee that the game will be interesting independent of who negotiates with whom. A considered mutation was accepted only if it decreases the overlap. The mutation process was continued until no overlaps were found for any pair of players.

4.2. Analysis of the decisions of the players

In this Section, we apply the model-based approach to calculate the utility parameters of different participants based on their proposals made in the CT game.

The data were collected during two game interactions: an online (web based) experiment as reported in [15] and the dataset that we collected during MARS-500 isolation experiment. We collected three kinds of data: behavior in a cooperative computer game, self-assessment questionnaires, and video records of facial expressions during game play [3]. In the web based experiment, 27 participants took part. Nine teams consisting of 3 players were formed. The teams played different numbers of games (ranging from 4 to 18). In total 93 games were played. The second data set was collected during the Mars-500 isolation experiment from six participants over a period of 520 days. Every second week, the participants were required to interact with each other through a computer environment for approximately 30 min as a part of our experiment. They played 65 games in total during these sessions; the participants were seated in front of the computers, performing different learning tasks and playing the modified CT game with each other [3].

We have calculated the utility parameters of 21 players (7 teams including 2 teams from the MARS-500 experiment). Two teams from the online experiment were discarded since the players performed too few games. In the Figs 3–5, we show the calculated utility parameters. Since every utility function is given by three utility parameters (ω, f, and g), the utility function of each player can be presented as a point in the 3D space of the utility parameters. To present the utility parameters of the considered players we use 3 different 2D projections of the 3D utility space – we project the points into the (ω, f), (ω, g) and (f, g) subspaces.

In Figs 3–5 we can see the following properties of the utility parameters. First, the values of the utility parameter ω, which is responsible for the cooperation, are distributed around the value corresponding to optimal cooperation (0.25).

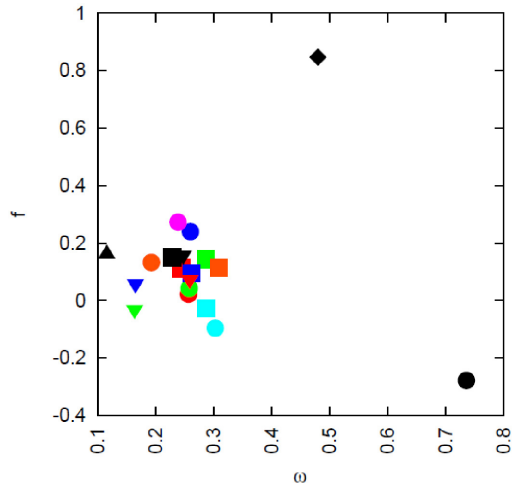

Fig. 3. Utility parameters of players shown in terms of the cooperativeness ω and fairness with respect to the final score f. This is a plot of 2 out of the 3 dimensions for these participants. Each participant is visualized with a different figure (color or shape). The smaller values of ω indicate that a subject cares more about his/her own benefit than the benefit of his/her opponent.

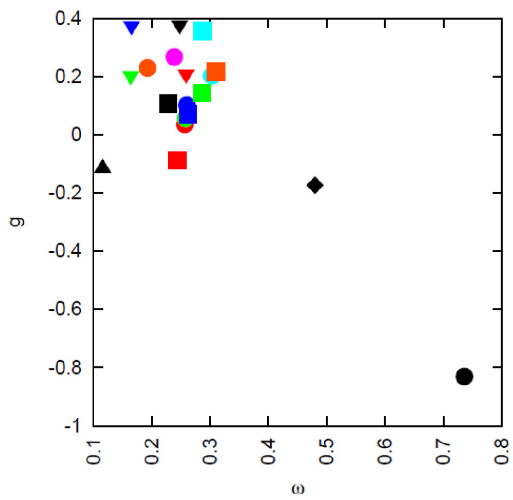

Fig. 4. Utility parameters of players shown in terms of the cooperativeness ω and fairness with respect to the gain g. Each participant is visualized with a different figure (color or shape). The parameter ω close to zero means an absolutely egoistic player, who does not care about payoff of his/her opponent at all. $\omega \geqslant 0.5$ which corresponds to an absolutely altruistic player who cares only about payoff of his/her opponent and does not care about his/her own payoff.

The smaller values of ω indicate that a subject cares more about his/her own benefit than the benefit of his/her opponent. The values which are larger than 0.25 mean that subject cares more about the benefit of the opponent than about his/her own benefit. The parame-

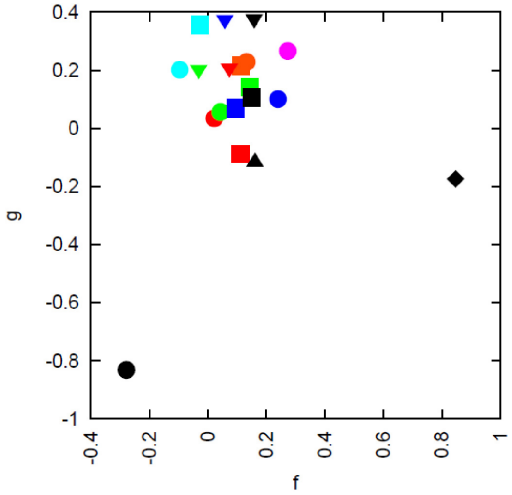

Fig. 5. Utility parameters of players shown in terms of the fairness of two different types (f and g). Mostly, the value of the parameters corresponding to the two different kinds of are larger than zero, which means that most of the players do care about fairness of the proposals.

ter ω equal to zero means an absolutely egoistic player, who does not care about payoff of his/her opponent at all. Another extreme case corresponds to $\omega = 0.5$, which corresponds to an absolutely altruistic player who cares only about payoff of his/her opponent and does not care about his/her own payoff. In this context, it is interesting to notice that in all cases ω was larger than 0.1 and in most of the cases it was smaller than 0.35.

This means that most of the players balance between their own payoffs and payoffs of their opponents. The two exceptions, corresponding to extremely large values of omega are most likely to be explained by inaccuracy of the values of the parameters. Another observation is that in most of the cases the value of the parameters corresponding to the two different kinds of fairness (f and g) are larger than zero. It means that most of the players do care about fairness of the proposals. It is also interesting to notice that players tend to care about fairness of the gain slightly more than about fairness of the final score. For such players, it is less important how much everyone will have after an exchange. For them, it is more important how much everyone gets in addition to what everyone already had before the exchange. Finally, it should be noticed that the range of the distribution for all three parameters is approximately the same (about 0.5).

As can be seen in the Figs 3–5 the values of the utility parameters form a quite homogeneous cluster. In particular, a clear relation between the utility parameters cannot be seen. For example, it cannot be said that a cooperative player tends to care about fairness less. This distribution of the values, as well as a rather small number of games per player, raises the question if the observed difference between the utility parameters of the players is statistically significant or if it is just noise.

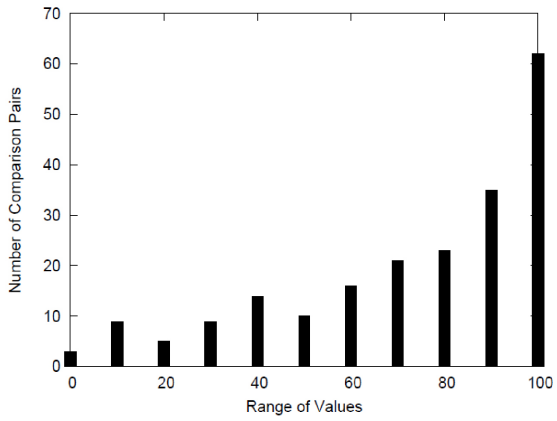

Fig. 6. Distribution of the percentage of cases in which the distance between the fake utility parameters has been smaller than the distance between the real utility parameters of two given players.

To answer this question, a pair-wise comparison of all players has been made. For every pair of players, the difference between the utility parameters that describes their play behavior have been calculated. The difference has been calculated as Euclidian distance between the two points representing the utility parameters of two players in the 3D utility space. After that, for a given pair of players, their decisions have been put in one set, shuffled these decisions and split the combined set into two subsets of the same sizes as the original two subsets. For the two new subsets of decisions, the utility parameters, as well as the difference between them, have been calculated. For a given pair of players, this procedure was repeated many times to find out in what percentage of cases the difference between the two "fake" utility parameters is smaller than the original distance between the real utility parameters of the two considered players. This percentage has been calculated for all possible pairs of players. The distribution of the values of these percentages is shown in Fig. 6.

As we can see from the distribution shown in Fig. 6, the larger values of the percentage are populated more than the smaller values. It means that there is a tendency for the pairs of the real utility parameters to be more distant from each other than pairs of fake utility parameters. In case if there is no difference be-

tween the players regarding the utility parameters the distribution shown in Fig. 6 has to be homogeneous. To draw a solid conclusion, we have calculated the p-value of the null hypothesis assuming that the players are not distinguishable in terms of the utility parameters and the given deviation of the distribution from the homogeneous one is obtained just by chance. The calculated p-value was found to be extremely small (less than 10^{-10}). From that outcome, we can conclude that players differ from each other regarding the utility parameters that characterize their play behavior.

Finally, we would like to emphasize that the difference between the players, for which the statistical significance has been calculated, is cumulative. In other words, we have calculated the p-value of null hypothesis assuming that all the players are the same. If we, instead, try to compare a pair of players, we will find out that in many cases the difference between them is statistically insignificant. We can see this from the distribution in Fig. 6. For a larger portion of the pairs of players, the distance between their utility parameters can be as large as it is (or even larger) just by chance.

5. Conclusions

This work reports the development and validation of a cognitive model of social preferences of three or more interactants that are engaged in a collaborative game. We hypothesized that the proposed new generalized utility-based approach would model the cooperation and fairness in multiplayer interactions, and thus will give a better understanding of the motivation of the players. In this way, it might help monitoring the long-term interactions between individuals for monitoring of the interpersonal relations in isolated, goal-oriented teams. The interpersonal relations are inferred from measuring fairness and cooperation in game behavior. In two-person games, as it has been investigated by others, it is impossible to distinguish between fairness and cooperation in the decisions of a given player. Although the existing approaches could explain some experimental data from real-life experiments, we provide a model for analyzing when the person in a group interaction was motivated by its feeling of fairness or the rules of cooperation. In this work, we have compared the inequity-aversion and social-welfare utility functions.

We have demonstrated that, despite the fact that the two considered utility functions are identical for the case of two subjects, their generalizations to the case of more-than-two subjects are different.

The generalization procedures have been compared and analyzed. As a result, we have proposed a new generalization procedure that is different from the generalization procedures applied to the inequity-aversion and social-welfare utility functions. The proposed way to generate utility functions for more than two subjects provides several advantages. First, the fairness of the payoff distributions is calculated by considering all possible pairs of interactants. This is different from the calculation of fairness prescribed by the inequity-aversion functions in which only pairs containing the decision-making subjects are considered. Second, the importance of the social contribution to the utility functions, as compared to the egoistic contribution, grows as the size of the group grows. The inequity-aversion utility does not have this property. Third, the utility proposed for the case of more-than-two subjects becomes less sensitive to the payoff of a single subject as the size of the group grows. This is different from the social-welfare utility which could be very sensitive to the payoff of one player even for huge groups. Finally, we have proposed an additional max-imin fairness term to the utility function to capture the fact that proposers can behave differently depending on how many points the default option gives to the proposer and responder. In summary, we have proposed a many-subjects utility function that can explain egoistic, cooperative and fair behavior of different kinds in the proposer-responder setting.

The main conclusion of applying the method is that the values of the utility parameters of any two players are not accurate enough to be compared with each other and analyzed in detail. However, the accuracy is good enough to draw conclusions about collective properties (distribution) of the values for the considered group of players. In particular, we can get a good idea about the expected values of the utility parameters as well as how broadly they are distributed and what is the shape of the distribution. Moreover, we have a convincing reason to believe that players differ from each other in terms of their utility parameter and, as a consequence, these parameters can be used to characterize players in a meaningful way.

For a practical application of this model in real life scenarios, we need to consider several factors, such as working with unbalanced datasets [13] and using an evolutionary strategy to generate sequences of games in which the social motivation of the interactants will be quickly captured. We showed how the proposed model can be applied to real-life data from MARS-500 experiment.

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