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Identifying patterns of human behavior: an analysis on experimental data of the Public Goods Game

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Abstract

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by Ferran ESPAÑOL

The cooperation capacity among different people or countries is nowadays essential to meet certain collective objectives such as undergo a climate action, solve the pollution of the seas, or in general initiate a collective action where everybody has to contribute. Public Goods and Collective Risk Dilemmas (CRD) games have been widely used to analyse these problematics, trying to understand which is the kind of contribution of all actors engaged. In this report we add new perspectives to the debate by analysing one of the largests samples that has been used. This analysis is done by means of Machine Learning (ML) techniques which suppose a new way of addressing the identification of patterns in CRD data. In terms of the game theoretical analysis we found that an unequal distribution of resources at the beginning of the game ends up causing imbalances, mainly in the distribution of costs, which has important implications in terms of climate justice.

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Chapter 1

Introduction

1.1 Objectives

The fundamental objective of this work is the identification of behavior pattern of participants in a collective risk dilemma by means of data science methodologies. To fulfill this objective we propose the use of Machine Learning (ML) techniques to improve the identification of these patterns based on the characterization of groups of players that acted in much the same way. These situations have been generally analysed following a pure game-theoretical approach using, only, the classical statistical tools. With ML we add new possibilities that allows to identify patterns not based on predefined and well-known strategies (free-rider, conditional cooperation,...) but on groups of players that can be clustered together.

With this rather new approach, the analysis must be focused on the characterization of these groups and identify why they are closer to some players and not to others. The application of ML models to this particular data is something not totally new (Vicens et al., 2017) but still is not broadly used for the community on behavioural sciences. In this context the current work also represents an exercise to explore whether ML techniques are meaningful in the analysis of behavioural data, and also, to identify the most relevant ML techniques that can be useful to study collective risk dilemmas and serve as part of the palette of tools to obtain relevant knowledge.

1.2 Game Theory

1.2.1 Game theory background

The use of Game Theory (GT) to study human behavior has a long academic tradition. The formalism allows to study quantitative aspects of human relations that could help to understand in a deeper way our relations as a society. As in many problems of Physics or Economics, the objective of GT is to find stable equilibriums which corresponds to particular behaviors in the game. John von Neumann became the father of this discipline at 1944 with the publication of "Theory of Games and Economic Behavior" with Oskar Morgenstern. It was not until the late seventies that GT started to be more widely used. In terms of the number of publications there was a progression from 50 articles published annually at 1982 to 200 at 1998. The objective in Economics is one of the disciplines that have somehow adpoted this approach to understand how agents behave and trade. In terms of experimentation allowed the recreation of economic situations controlling the most important variables as budgets, prices or information, which implied for economics being therefore also closed to the scientific method in physics.

However, in social experimentation the individuals who participate in a laboratory are influenced by many more variables than the pure monetary restrictions. The most important ones according Steven D Levitt and John A List, 2007 are: *"1) the presence of moral and ethical considerations; 2) the nature and extent of scrutiny of one's actions by others; 3) the context in which the decision is embedded; 4) self-selection of the individuals making the decisions; and 5) the stakes of the game"*. Those variables have important implications because what we can be measuring in the laboratory are not only the responses to the incentives established by the experiment but also behaviors related with the distortions we mentioned.

All these interferences to the experimental incentive structure questioned what was called the generalizability of the results, that is, the capacity to translate the conclusions found in an experiment to the real world situation. The generalizability problem has concerned many scholars and publications, in Steven D. Levitt and John A. List, 2007 we can find some examples of it. They mentioned Pruitt and Kimmel 1977 which talked about the problem of the external validity of laboratory experiments, or Rapoport 1970 that criticized severely the generalizability of field experiments (field in the sense of out of the laboratory). More example would be Mook 1983, Schram 2005 or Bardsley 2005 that tried to find those cases where generalizability would not be a problem. Generalizability is still an open debate and has important implications for all the experiments done in experiments related with GT.

Returning to the object of study of this thesis. The game we focus in this study is called the Collective Risk Dilemma (CRD), that is, an adaptation of the traditional Public Goods Game (PGG). We will see later the particular characteristics of the CRD experiments but let's start with PGG. In a broad sense PGG traditionally was used to study the level of cooperation of a certain amount of people to provide a public good. This schema works well for a very wide range of problems and real situations like climate change or pollution in general, military projects or space missions. As it is defined in Steven D Levitt and John A List, 2007 we can see the PGG as a generalization of the famous prisoners dilemma game. In this case a group of n persons decide simultaneously how much to invest in a public good. The contributions return is explained with a payoff function that has the form $P_i = e - g_i + \beta \sum_n g_j$ where e is the initial endowment, g_i is the level of contribution that subject i does for the public good, β is the marginal payoff of the public good (with a range $0 < \beta < 1 < n\beta$) and $\sum_n g_j$ the contributions of the rest of individuals. Once we have the formalism, which are the expected solutions in a PGG?

In the introduction of the book "Public Goods: A Survey of Experimental Research" written by John O. Ledyard the author explains the two big theories about the optimal answer of the PGG experiment. First, the game-theoretical prediction says that the optimal strategy is to play as a free-rider (invest in the private project) because the immediate return is bigger for the investment in the private project than in the public one (independently that what others do). As it is expected that everybody follows the same reasoning, the result is that nobody contributes to fund the public good and the final outcome is not the maximum profit situation and eventually everybody losses. The second theory explained in Ledyard, 1995 is the one given by the sociologic-psycologic prediction that is that everybody will contribute part of it.

Both predictions seems to be coherent in terms of theory but experiments have shown that people follow a wider range of strategies and much more complex in terms of patterns. The results shows that pure strategies are hardly used and people change their actions according many stimulus as, for example, other player contributions or the round he or she is playing. Then, again, the generalizability problem arise, can we ensure that we are measuring the effects we are expecting or previous behavior is determinant?. Ledyard also identified this problem and understood that the answer was in the experimentation methods and specially in the need of add treatment groups to control behavioral biases. This way of thinking "social experimentation" was used as a reference for further studies in this field.

At Ledyard, 1995 the experimental evidence already showed that the people contribute at least the 40% of their endowment to public goods and denied the theoretical predictions mentioned above. Also it was identified that the contributions tend to decrease after some iterations in the PGG experiment (our experimental data have the same pattern but for the threshold objective effect, when most of the people reaches the objective immediately stops contributing). When he revises the homogeneity in the public goods he said: *"There is now reason to believe that such homogeneity in the environment [same preferences and endowments] has a positive effect on contributions."*. This will be important because recent experiments in the CRD reopens this debate with opposite findings.

Let's see in more detail some classic papers analysing the PGG experiments that had been useful as a base for this study. For example, for the important paper of Fischbacher, Gächter, and Fehr, 2001 they used a single PGG to identify the conditional cooperation of individuals by asking them how much they were willing to contribute to a common fond according the contributions of the rest of hypothetical participants. Conditional cooperators are those players that will contribute according what others do, if other players contribute more they also contributes more (and vice versa). As a result they identify that a 50% of people behave as a conditional cooperator and the 30% as a free-riding. These results are useful as a reference and we will be able to compare our findings with this classic of the academic literature.

Claudia Keser and Frans van Widen identified in Keser and Winden, 2000 the consequence of being partners or strangers in a PGG in terms of cooperation, finding that cooperation in partners treatment is higher, and from the beginning of the game, compared to the strangers games. Authors also used pre-defined strategies to analyse the behavior or the participants. They used conditional cooperation (reactive and future oriented), free-rider (strong or weak if they contribute 0 at all rounds or not) or altruist (strong or weak). These categories allows to see important characteristics of your players in an easy way. The results were that 33% of partners were free-riders (weak or strong) and 55% of subjects for the strangers conditions. According to their experimental design being a free rider means that in 25 decisions they contribute only to ensure their own benefit and not the public one (which is the one that can give the maximum benefit).

Posterior literature as Bardsley and Sausgruber, 2005 tried to isolate reciprocity and conformity as two different behaviors to explain the crowding-in effect (people contributes more when they see other people contributing). More recent studies has focused on the CRD. We will see what characterize them in more detail and the debate it has generated in the next section. Before that, there has been other literature which has applied ML in game theoretical fields. It is the case of Macy and Flache, 2002 which elaborate a learning model for the dynamics of cooperation in different games or Sandholm and Crites, 1996 which design a multiagent reinforcement learning model for an iterated Prisoner's Dilemma game.

1.2.2 Collective risk dilemmas and the analysis of climate change

In recent years some researchers adapted the PGG to simulate in a more proper way problems related with what is called a Collective-Risk. It consists in a collective having to solve, together, a risk by attaching a certain goal, if they do not success in this task they lose everything they have earned. The individuals in the CRD do not know a priori which strategy can be the best one to finally keep the maximum profit. Individuals are responsive to other players contributions and define their strategies according to that. This schema fits very well in the analysis of the political relations to paliate climate change or any other collective conflict were an objective has to be fulfilled. This new PGG has been called Collective-Risk Dilemma game (CRD) and the referential design was done by Manfed Milinski et al., 2008 which designed the basic experiment from which other researches has enriched with more complexity.

The basic treatment cases in the CRD were created introducing inequalities in the model to simulate in a more realistic way the nowadays tensions between countries in the common fight against climate change. Recent events as the publication of Core Writing Team and (eds.), 2014 or the Paris Agreement of 2015 have boost the worry for this topic. Also, Paris Agreement has been taken for literature as a way of testing the generalizability of the results found in CRD. Another important reference that justified the use of loss treatments was Mendelsohn, Dinar, and Williams, 2006 which talked about the unequal distribution of the impact of climate change. Poor countries are the ones that suffer the more severe consequences and at same time they also have less means to fight against it.

By now the basic two inequalities used as treatment groups are focused on the endowment heterogeneity (rich and poor) and also the to the loss in case of not fulfilling the objective (poor countries suffer more for climate change than rich ones). The references we took to design our treatment structure are the following: Manfed Milinski et al., 2008, Tavoni et al., 2011, Manfred Milinski, Röhl, and Marotzke, 2011, Burton-Chellew, May, and West, 2013, Brown and Kroll, 2017 and Waichman et al., 2018.

As we have said, Manfed Milinski et al., 2008 presented the basic experimental procedure that influenced the design of our own experiments. They used the loss rate to create three treatment groups. They found that games with a high loss rate performs better in terms of success rate (games succeding in fulfilling the objective over the total number of games) and at same time less people played free rider strategies. Tavoni et al., 2011 include the homogeneous and heterogeneous treatment groups but not the loss risk in case of being rich or poor. Manfred Milinski, Röhl, and Marotzke, 2011 neither include an homogeneous/egalitarian group to control the heterogeneity nor risks for rich and poor (treatment for the loss) in case the objective was not fulfilled. However, it has been useful to compare classical statistical results as the evolution of the average contribution. Burton-Chellew, May, and West, 2013 did several critics to Manfred Milinski, Röhl, and Marotzke, 2011 for not controlling homogeneous games and not adjusting the required spending threshold accordingly to their treatment groups (rich, poor and mix). We have to take into account these issues to carefully compare, if it is possible, our results.

The most relevant result found by Waichman et al., 2018 was that groups under loss heterogeneity are the ones which have better success rates and also that the burden sharing in the asymmetry endowment case is proportional to the initial endowment of each subject. We will see in Chapter 3 that our finding is actually the opposite. In the inequality situation the poorest individuals tended to contribute proportionally more than the rich ones. Other results from Waichman et al., 2018 related with the dynamic patterns of the data are going to be commented, also, in the Chapter 3.

All these papers try to answer the same questions, that is, which context (heterogeneous or homogeneous) is better to fulfill common objectives in a collective dilemma?. Results obtained by now give two opposite answers. The first one is that homogeneous games (situations were all participants have equal initial endowment) has a higher success rate than the heterogeneous games. Tavoni et al., 2011 and Burton-Chellew, May, and West, 2013 are agree with this result. The second one is the opposite to the first, Brown and Kroll, 2017 and Waichman et al., 2018 defend that heterogeneities can gives better results in terms of success rate and cooperation in the games.

The conclusions of this review that we are particularly interested in are the following: 1) at this moment there is no agreement in CRD experimental data about which context is best to face a collective dilemma, and 2) ML tools are not used by the most related literature.

1.2.3 Mathematical formalism

To give some insights about the mathematical formalism behind the CRD we can look at the definition of Waichman et al., 2018. For homogeneous games we have n players ($n = 6$ in our experiments), which receive an equal initial endowment a ($a = 40$ MU). The game is played T (=10) rounds. The contribution of each player is defined as c_{it}, that is, the contribution of subject i ($i = 1, \ldots, n$) at round t. The contribution vector is build as $c_i = (c_{i1}, \ldots, c_{iT})$ and the total contribution profile as $c = (c_1, \ldots, c_n)$. $\tilde{c}_i = \sum_{t=1}^{t=T} c_{it}$ is the total contribution of each individual. We use p to denote the probability of a loss occurring if total contributions fall short of a particular threshold $A\frac{n}{2}a$, and q to denote the loss rate of the subjects' fianl wealth if a catastrophe occurs. With these information we can define that at the end of the game, player i's expected earnings will be $p(1-q)(a-\tilde{c}_i) + (1-p)(a-\tilde{c}_i) = (1-pq)(a-\tilde{c}_i)$ if total contribution fall short of threshold A.

Let's see the utility analysis that did Waichman et al., 2018. If y_i is the final monetary payoff of player i's the utility is denoted by $U(y_i)$. But, if we take into account the strategy profile c then utility is $U_i^{\sim}(c)$. Then, player i's expected utility is then:

$$\tilde{U}_i(c) = \begin{cases} U(a-\tilde{c}_i) & \text{if } \sum_{i=1}^{n} \tilde{c}_i \geq A \\ (1-p)U \quad (a-\tilde{c}_i) + pU((1-q)(a-\tilde{c}_i)) & \text{if } \sum_{i=1}^{n} \tilde{c}_i \leq A \end{cases}$$

There are several equilibrium in this game. The first to mention is the non contribution equilibrium and it is because $a < \frac{n}{2}a = A$ for $n > 2$. The expected utility in this case is:

$$U_i(0, \ldots, 0) = (1-p)U(a) + pU((1-q)a)$$

But there can be many other equlibria. As it is exposed by Waichman et al., 2018 a *catastrophe prevention equilibrium* is a contribution profile c^* for all participants in the game that what follows holds:

$$0 < c_{it}^* \leq \frac{a}{T} \tag{1.1}$$

$$\sum_{t=1}^{n} \tilde{c}_t^* = \frac{n}{2}a \equiv A \tag{1.2}$$

$$U(a - \tilde{c}_t^*) \geq (1-p)U(a) + pU((1-q)a) \tag{1.3}$$

which means that the certain utility from contributing c_i^* within the T rounds is at least as large as the expected utility of not contributing anything. This would be the situation for the homogeneous games but let's see how change the formalism adding endowment heterogneity.

In our case we have n = 6 players were two has an initial endowment of 40 MU and the rest can have an initial endowment of 20, 30, 50 or 60 MU. In terms of the formalism we defined as a_L the initial budget of these subjects with an initial endowment of 20 or 30 MU, a_M for these with 40 MU, and a_H for the ones with 50 or 60. Let $j(i)$ represent the type (L, M or H), then utility $U_{i,j(i)}(\tilde{c})$ is the utility of player i being of type $j(i)$ under contribution profile $\tilde{c}$. In this case we can asume that to succeed in the CRD, on average half of he endowment will be spent by all players. The utility then it's defined:

$$U_{i,j(i)}(\tilde{c}) = \begin{cases} U(a_{j(i)} - \tilde{c}_i) & \text{if } \sum_{i=1}^{n} \tilde{c}_i \geq A \equiv \frac{n/2}{3}(a_L + a_M + a_H) \\ (1-p)U & (a_j - \tilde{c}_i) + pU((1-q)(a_j - \tilde{c}_i))\text{if } \sum_{i=1}^{n} \tilde{c}_i < A \end{cases}$$

In this case, again, the non contribution equilibrium holds. The utility is given by:

$$U_{i,j(i)}(0, \ldots, 0) = (1-p)U(a_{j(i)}) + pU((1-q)a_{j(i)})$$

The catastrophe prevention equilibrium has a profile c^* that holds for the following equations:

$$0 < c_{it}^* \leq \frac{a_{j(i)}}{T} \tag{1.4}$$

$$\sum_{t=1}^{n} \tilde{c}_t^* = \frac{n}{6}(a_L + a_M + a_H) \equiv A \tag{1.5}$$

$$U(a_{j(i)} - \tilde{c}_t^*) \geq (1-p)U(a_{j(i)}) + pU((1-q)a_{j(i)}) \tag{1.6}$$

This would be in schematic terms the mathematical oriented approach behind the experiments we are analysing.

1.3 Data Presentation

The data used in this study is experimental data obtained from three experiments organized by the UB Physics group OpenSystems. All the experiments were designed following the structure of the CRD first defined in Manfed Milinski et al., 2008. On top of that, they used what is called a lab-in-field experimental procedure to avoid the restriction that suppose the social experimentation with undergraduate students. In this case participants are also recruited where they generally take decisions. In this way, it is expected they will behave more in accordance to their interests and expectations concerning their neighborhood or city. We are going to

TABLE 1.1: Total number of participants in related literature

Publication	# of participants
Manfed Milinski et al., 2008	180
Manfred Milinski, Röhl, and Marotzke, 2011	342
Burton-Chellew, May, and West, 2013	192
Brown and Kroll, 2017	378
Waichman et al., 2018	510
Current work	612

see in more detail the characteristics of the data and the procedure followed in the next chapter.

In terms of the total amount of participants this study has the privilege of being one of the largest samples analysed in the social experimentation framework. There is a total amount of 612 subjects splitted in two treatment games (homogeneous and heterogeneous games). Table 1.1 shows the total amount of participants in other experiments done with the collective risk dilemma structure for climate change.

Moreover, these experiments designed from three to four treatment groups so our groups are bigger in comparison with the rest.

The basic information of a CRD are the contributions done by al players along the T rounds of the game. Contribution are numeric discrete data. All participants were asked for basic socio-demographic information and also the answer to a few questions related with the topic of study. For DAU and STREET datasets the frame of the game was the climate change so the questions done were related about basic knowledge about climate change and also about their expectations with the game. For the VIL dataset the experiment was focused on the capacity of local people to protect a local space in Viladecans as it is "la Rambla". The questions were related with this issue instead of climate action.

1.4 Hypothesis and Questions

The fundamental question we want to answer is, can Machine Learning techniques help to analyse experimental CRD data?. Most recent experiments are starting to have relevant amount of data (510 individuals and 5100 actions) thus allowing to get more insights in relation to existing behavioural patterns. Machine Learning thus becomes an attractive option. The main abilities of ML techniques are 1) do groups based on the data, 2) classify individuals according a target. Both mechanisms fits good for the task of identifying common patterns of individuals that participates in a CDR. We expect that using these tools for the analysis and identification of groups based on the distances between their contributions will show new patterns in the study of this experimental data.

In this situation more questions arise, which kind of ML tools are potentially good?. Why?. And what for?. Both, unsupervised and supervised learning algorithms are potentially good methods to identify groups of individuals that follows common behaviors. Unsupervised learning allows to infer a classification for individuals without the need of a target variable for our data. This is the best method to address our problem in a first approximation. In case we have had a more balanced success rate of the games we would have been able to apply in a more extensive way other classification algorithms. In any case, we put more attention to the unsupervised learning family.

As we have said supervised learning algorithms can be useful as a tool of prediction but in this study it is just presented a simple exercise. We use gender as a target variable to evaluate the predicting capacity of the contributions. A priori we dont expect to found any specific pattern. Go deeper in the use of supervised learning for studying CRD will be discussed in Chapter 5.

At same time we also want to contribute to the game theoretical debate related with the CRD. We will focus our attention on which kind of treatment (homogeneous or heterogeneous) does better in terms of overcoming collective dilemmas as it coud be climate action.

There are two frameworks or contexts according the experiment. As we have seen in last section at DAU and STREET the context was the climate action dilemma while in VIL was focused on the protection of a public place in Viladecans. Our aim is to find the general patterns that can develop in a CDR independently of the contexts it has.

However, to be able to make comparable our results with the ones of the literature, we are going to specially focus on the climate change framework. The main debate is which treatment favors a better cooperation and perspective of fulfilling common objectives. By now the results are not determinant and the contribution with more data to the debate can be interesting.

We also think that it is relevant at which round the objective was fulfilled. Allows to differentiate two pictures of the data, that is, what happens before and after that moment in the game. Comparing the results obtained in both situations we expect to gain clear information about the endogenous evolution of clusters.

This study is organized as follows. In Chapter 2 we are going to see the methodological structure we have used in the analysis. Chapter 3 is devoted to the exploratory analysis of the data. A review of the classical statistics results and the ones obtained using ML are presented in Chapter 4. This study is closed with Chapter 5 with the discussion and conclusions.

Chapter 2

Methodology and data review

The methodology section has the objective of providing enough tools and procedures to answer the questions asked in Chapter 1. It is designed to do a two level analysis with the game theoretical approach in one side, and the clustering analysis on the other. Both approaches will be complementary at some point to explain in a clearer way the groups we found.

This chapter is organized as follows: 1) review of the data and the experimental procedure, 2) reorganization of data based on treatment groups, and 3) methodologies used at each block of analysis to extract the relevant information we expect. In this last section we include the information related with unsupervised and supervised tools we have used for the analysis.

2.1 Data Review and Experimental procedure

2.1.1 Experimental procedure to obtain the data

All datasets are generated using experiments that follow the lab-in-the-field experimental guidelines established in Sagarra et al., 2016. The objective of this experimental procedure is that general audiences participates in the generation of data, and not only the classical academic experiments with undergraduate students. With a more heterogeneous audience (in terms of age and education) we avoid the problems of generality and bias of the sample.

The experimental setting followed in the experiments was a traditional CRD. The game was done by six players who simultaneously chose a contribution selection (from 0 to 4 MU) which was given to a common fund. As in Manfed Milinski et al., 2008 the objective was established at 120 MU and the initial endowment distributed among the players was 240 MU. All participants did the experiment through a tablet and communication was not allowed between them. At the beginning of the process they received the instructions of the game with the support of the experimenters to make sure that everybody understood the game before start. All individuals had certain time to choose a contribution and, at the end of each round, all received information about others contributions. If the objective of 120 MU is not fulfilled at the end of the game then there is no action against the collective risk they faced (fight against climate change or protect a public space). In all experiments individuals lose their earnings with a 90% probability.

2.1.2 Sociodemographics review of each dataset

If we look specifically at each experiment first we have the one done at Festival de Joc del DAU in December 2015 were 324 participants (41.36% women, 58.64% men) played 54 games. In terms of age the the mean value and standard deviation is 32.31

$\pm$13.17 years and most of the people had vocational school background (48.15%). In one half of the 54 games (162 subjects) the participants had the same initial endowment of 40 MU, while in the other half the initial endowment was distributed unequally in such a way that participants could receive an initial endowment from 20 to 60 MU. Along the analysis we are going to refer to the equal initial endowment situation as an homogeneous game while the unequal case is called heterogeneous game. The possible actions for participants when they select the quantity given to the common fond was 0,1, 2, 3 and 4.

The second one was done in the street with some cabins to isolate participants and followed the same experimental procedure as in DAU. In terms of the treatment categories all this games were heterogeneous (unequal initial distribution of the endowment). 108 individuals (39.02% women, 60.98% men) participated in this experiment playing 18 games. In terms of age and education the mean and standard deviation for the age was 29.19 $\pm$14.51 years and the most selected educational background was vocational school (37.96%). In this case the possible selections that players could do was 0,2,4 which were the most used in DAU experiment.

The third experiment was done at Viladecans (VIL from now on) were participated 180 subjects (23.89% women, 76.11% men) which played 30 games. In this case we did not have the exact but a range of age. Most of the participants had an age between 14-19 years old (30.56%) followed by the range 45-54 years (22.22%). In terms of studies the most selected option was vocational school (28.89%). As in the street case the possible actions that individuals could select to contribute to the common fund was 0, 2 and 4.

2.2 Two treatment games: Homogeneous vs Heterogeneous

To work in comparable terms with the literature we mentioned in Chapter 1 we organized the data based on the endowment heterogeneity. There are two treatment groups, the heterogeneous games (unequal initial distribution of the endowment) and the homogeneous (equal initial endowment distribution). The idea of both treatments is to control the exogenous effects of the participants in the study. This will be the basic way we am going to work and present data.

The second important argument to such split is the volume of data used. There are 270 individuals in the heterogeneous treatment and 342 in the homogeneous which is better for the cluster and classification analysis.

Now lets see in more detail the methodological construction for each part of the study.

2.3 Methodological Structure

2.3.1 Firsts steps

To do the analysis we managed both Python and R, being Python the most used. R was very useful in all the work related with clustering and also to identify distributions of our results.

Before started we needed to clean the data for all subjects that: 1) were test games which had to be eliminated, 2) individuals that did not decided all the actions because he or she left the experiment in the half, and 3) some players that registered themselves but finally didnt started the game. For all these cases we basically erased their profiles from all datasets.

TABLE 2.1: Normalized contributions per round according selection

Initial Endowment	0	2	4
20	0	1.00	2.00
30	0	0.67	1.33
40	0	0.50	1.00
50	0	0.40	0.80
60	0	0.33	0.67

Once data was cleaned then we had to normalize the data. Actually what we do is not a traditional normalization (were values are transformed to a 0 to 1 scale). It was done dividing all contributions by the initial endowment that each participant had and then multiplying per 10 to have the normalized value per round. We did not standardize the data because it did not follow the basic conditions: first, data with different types or different order, and second, a variable variance along the game.

As we can see in Table 2.1 normalized contributions goes from 0 to 2 (2 is the weight associated to an individual with an initial endowment of 20 contributing 4 in a certain round). This way of normalizing was also used in Vicens et al., 2017.

2.3.2 Exploratory Analysis

Once data was clean and normalized we started with the data overview by looking at basic variables as the average contribution per round (with their standard error), the accumulated average contribution per game with their standard deviations and standard errors, that is the classical statistical analysis for GT. These results are comparable with the ones obtained by the traditional literature in this research line.

We also explore the total contribution ratio (total contribuion over the initial endowment, TCR from now on) which is equivalent to the sum of the normalized contributions. We used histograms as the mean to identify the distribution, and Pdf and Cdf have been the curves we used to analyse such distributions. Using R library "fitdistrplus" we could find the best distribution of the contribution ratio for each treatment group. In both cases the best fit is a normal distribution so we used the T-test to determine the independence or not between both treatments.

To complement this information we plotted, as in Vicens et al., 2017 the average contribution per round with the TCR per initial endowment with the standard error as errorbar. Both plots gives important information about which group (in the heterogeneous treatment) is assuming the costs in the fight against climate change.

The next subsection of this initial analysis goes deeper in the evolution analysis of the games. In this case we followed the method established in Ledyard, 1995, Vicens et al., 2017 or Waichman et al., 2018, studying what happens in the first round and at the end of the game. Seems that results are coherent for all experiments.

The exploratory analysis is closed with a composition analysis of the games based on the categories defined in Manfed Milinski et al., 2008, that is, free-rider, fair, and altruistic players. In this case we adopt these three categories to classify, in an ad hoc way, participants of the experiment. These categories are defined according to their TCR. As the TCR has a range from 0 to 1 we divided the space in three regions (0-33%, 33-66%, 66-100%). Having assigned each individual to a category we are going to analyse the results in terms of which compositions, from all posibles, are actually emerging in these games.

We also used PCA to reduce the dimension of our initial dataset from 10 to 2 to be able to visualize all players in a plane. As it is explained in Hastie, Tibsharani, and Friedman, 2009, Principal Components are a sequence of projections of the data, mutually uncorrelated and ordered in variance. Principal Components themselves, a priori, are not able to explain much of the contributions patterns in our problem (see the complete information about PCA at Appendix D). However, it was useful to easily identify that were differences in the distribution of individuals according their treatment group.

2.3.3 Unsupervised Learning: Cluster Analysis

The basic strategy followed in this second analysis is, first, the application of unsupervised cluster methods using as input data the normalized contribution table for each treatment or game. The analysis of these clusters gives a first classification of our players to then do an integral analysis of the characteristic of these clusters. The variables used for this characterization are the initial endowment, the TCR and the evolution of the average contribution of these groups.

To identify groups we tried different unsupervised clustering algorithms as K-Means, Hierarchical clustering, Agglomerative clustering and DBSCAN ("density based spatial clustering of applications with noise"). From all these algorithms it was K-Means the one that clustered better the data we had. In Appendix C there are the assignment of each individual according the method plotted in the first two principal components plane and the analysis of the results.

So, following the definition given by Bishop, 2006, K-Means algorithm consists in the partition of a data set $x_1, \ldots, x_N$ in K different groups. Data contains information of N observations of a random D-dimensional Euclidean variable x. The basic intuition of the functioning of K-Means is that inter-group distances are smaller than the distances with other groups. The formalization of this idea can be represented as:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} ||x_n - \mu_k||^2$$

This function is usually is called a distortion measure. First it creates a vector μ_k, with $k = 1, \ldots, K$, that represents the prototype of each cluster (can be understood as the center of the cluster). Then the algorithm looks assigns a cluster to each individual based on the minimization of the square of the distance between each point to the closest prototype. $r_{nk} \in 0, 1$ is a binary indicator variable and assigns 1 if the individual n is assigned at cluster k or 0 otherwise.

The objective is to minimize J and to do so the algorithm uses a two steps method to find the optimal $\{r_{nk}\}$ and $\{\mu_k\}$. First the algorithm assigns a value for μ_k and then minimizes J with respect r_{nk}, the second step is to fix r_{nk} and minimize J with respect to μ_k. This method is called the Expectation-Maximization (EM) algorithm and keeps running until certain minima is fulfilled. In practice, the K-Means algorithm is very fast (although the dimensions of our data are not very high), but it falls in local minima, thats why we restart it several times.

Once K-Means was selected as the method to cluster our data we tried to look for the optimal number of clusters following the nexts criteria.

TABLE 2.2: The optimal number of clusters for each criteria

Dataset	NBclust	GAP	Cal & Hara	Krz & Lai	Hartigan	Silhouette
Heterogeneous	3	2 (-0.68)	2 (58.87)	6 (11.86)	3 (19.62)	2 (0.22)
Homogeneous	3	2 (-1.63)	2 (54.55)	4 (7.16)	3 (15.51)	2 (0.13)
Het DAU	3	2 (-0.51)	2 (38.17)	3 (14.71)	3 (8.40)	2 (0.23)
STREET	3	2 (-0.94)	2 (22.34)	8 (4.85)	3 (7.41)	3 (0.18)
Hom DAU	4	2 (-1.47)	2 (30.32)	4 (16.46)	4 (11.04)	2 (0.15)
VIL	3	2 (-1.75)	2 (28.02)	10 (3.90)	3 (14.71)	2 (0.12)

Clustering methods and optimal K

To first evaluate the possible optimal number of clusters we used the NbClust library from R. This package uses 30 different indices and recommend to the user the best scheme given a distance (euclidean, manhattan,...), the minimum and maximum number of clusters, and a method (K-Means in this case).

After the first evaluation of the results NbClust recommends to use 3 clusters for heterogeneous games (heterogeneous DAU and STREET) while there wes a discrepancy for the homogeneous games (K = 4 for homogeneous DAU and K = 3 for VIL). The second optimal result for both datasets is K = 2 with a very close value between them. If instead of the four datasets we use the data at treatment level (homogeneous vs heterogeneous games) the result is K = 3 for heterogeneous and also for homogeneous games.

The results for the Gap Statistic (Tibshirani, Walther, and Hastie, 2001) gives two clusters for all datasets. In the article the authors use simulated well separated data and compare the gap statistic performance with Calinski and Harabasz (1974), Krzanowski and Lai (1985), Hartigan (1975) and Silhouette (1990) criteria. We are going to took these same indices to identify the optimal number of clusters. The results are presented in Table 2.2.

The value inside the parentheses corresponds to a value index that is used to assign a certain number of clusters. Each index has their own rule. For Calinski and Harabasz, Krzanowski and Lai and Silhouette the number of clusters is selected according the maximum value of those indices. For the Gap Statistic the condition is the smallest number of clusters such that the critical value is high or equal 0. For Hartigan the rule is the maximum difference between hierarchy levels of the index.

Other methods we reviewed were, for example, Gaussian Mixed Models which was not finally used in this study but can be another alternative for identifying the optimum number of groups of our population. This method needs that the input variable of the model could be generated from a gaussian distributions. As we will see in Chapter 3 the TCR distribution for both treatments fits this condition so it is left for future tests to check his performance. Another interesting method that was finally not used, is the stability method. An interesting overview of this method can be followed at Luxburg, 2010.

At the end of this process we finally opted for focusing on the possibility that K = 3 for heterogeneous games and K = 2 for the homogeneous ones. If we only take into account the quantity of indices recommending one optimum or another we would keep the global NbClust result (K = 3 in both cases) but, we thought that PCA analysis gave insights that the distribution of contributions is homogeneous which could imply that the number of clusters could be lower than 3, being K = 2 or even K = 1.

Identification of groups

Once we have identified the optimal number of clusters we are going to analyse particular variables to identify and characterize the clusters we have found. To do so we used two basic approaches. First, we do basic statistical analysis of each cluster, that is, we analyse the amount of individuals, the distribution in the initial endowment, the TCR of each clusters and finally the evolution in the average contribution. To do such analysis we are going to use the classic statistics tecniques used in the exploratory analysis. We will show that the variables selected are good enough to find significant common patterns between members of each cluster.

Second, we are going to evaluate the differences in the clustering classification before and after the objective is fulfilled. This will be a measure of how robust the clusters are (if they mantain their mean patterns) and will allow us to discuss the implication of the ending rounds in terms of change of patterns.

2.4 Supervised Algorithms: Can we classify individuals by their gender correctly?

Supervised algorithms are a bunch of tools that can be useful for the prediction capacity in a CRD. It would have been interesting to analyse the prediction capacity of success of a game if we had a sample with both targets well represented. However, as we had information about the gender of each participand we used it as a target variable to check if we can predict the gender of a person based only on the contributions they do. To do so we applied supervised learning and tested for different classifiers to see which one gives better results. The classifiers we selected are: Logistic Regression, Naive Bayes, Support Vector Machine, K Nearest Neighbors, Decision Trees and Linear Discriminant Analysis. A 5-fold cross validation method has been used for each of the models. We will see in the Chapter 4 how well this methods works and which possibilities opens for future research. The resulting accuracy of each model will be complemented with an analysis of the basic classification parameters (precision, recall and f1-score) and the confusion matrix (Müller and Guido, 2016).

Chapter 3

Exploratory Analysis

3.1 Data Exploration

Before start with the analysis of the clustering results lets do a quick exploration of the different datasets. This review will be useful not only to understand the data but also to do a first comparison with the other literature related with the CRD.

The most valuable information gathered from the experiment are the contributions done by participants along ten rounds. The variables studied in this chapter are the ones most studied for the other papers in this field. First we will see the average contribution, the accumulated contributions per game, and the TCR. Next, we want to answer the question who contributes more? analysing the different contributions according the initial endowment. It follows the analysis of the dynamics of the game, a topic that has not been deepened a lot but analysed in Waichman et al., 2018. Finally it is presented the "composition analysis" of the games and we will see which type of individuals is more frequent in each treatment.

3.1.1 Average Contribution

The evolution of the average contribution per group of 6 individuals gives the most general overview of the tendencies that could emerge for the different treatments. We can observe in Figure 3.1 a decreasing tendency of the mean and a standard error (SE) contribution from a maximum of 2.62 $\pm$0.08 MU at round two since a minimum of 1.24 $\pm$0.13 MU at round ten for heterogeneous games, and from 2.77 $\pm$0.07 MU to 0.99 $\pm$0.11 MU for homogeneous games. The dotted line represents the fair contribution to take as a reference. The total average contribution is 2.16 $\pm$0.05 MU for heterogeneous and 2.17 $\pm$0.03 MU for homogeneous games.

As a general behavior, participants are more altruistic along firsts rounds since the objective was shortly to be fulfilled. Close to round 8 (which is the mean ending round for most of the datasets) the ending round effects impose and the average contribution falls between 30 to 50%.

This result can also check the universality behavior of this tendency in all experiments. However, this robust decreasing tendency does not reproduce previous results. For example at Manfed Milinski et al., 2008 and Manfred Milinski, Röhl, and Marotzke, 2011 average contributions were below the fair one since last rounds were treatment groups with a high loss rate (probability of losing all earnings in case of not succeed in the game) increased their contributions to fulfill the objective. Increasing the strategies at the end and not at the beginning was found as the most stable solution in a collective-risk game according the simulations of Abou Chakra and Traulsen, 2012.

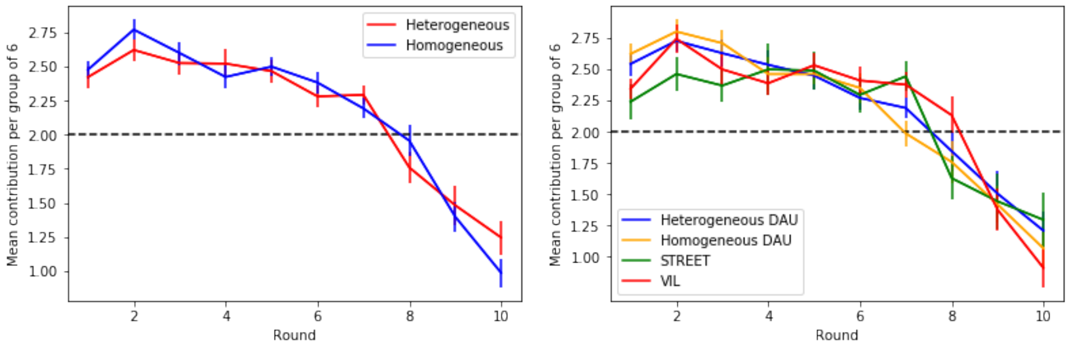


FIGURE 3.1: The normalized average contribution per group of 6 with the standard error. Dotted line represents the fair average contribution.(Left) Treatment level. (Right) Dataset level.

3.1.2 Accumulated contribution

In Figure 3.2 we can see the accumulated average contribution per game of each treatment group. In aggregated terms the accumulated contribution falls above the fair level in all rounds which is a direct consequence of the altruist behavior in the first half of the game.

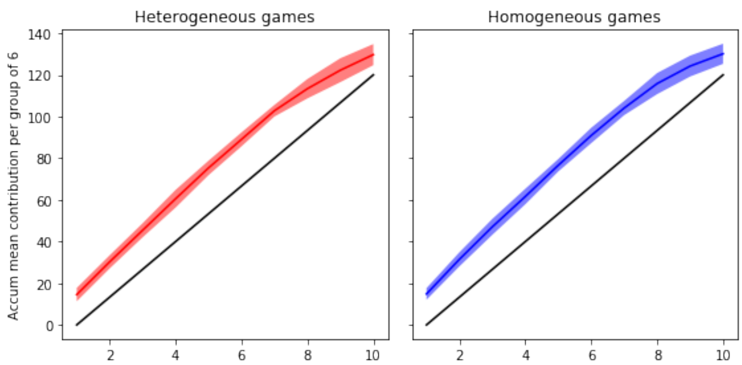


FIGURE 3.2: Average accumulated contribution for each treatment, the straight line shows the fair accumulated contribution and the shadow represents the standard deviation. (Left) Heterogeneous games. (Right) Homogeneous games.

The shadow of each line represents the standard deviation at each round. This results seems to have two basic characteristics, first, that the tendency of the accumulated average contribution changes before the objective is fulfilled. This change must be related with the ending game effects and indicates the more strategic behaviour at few rounds of getting the objective. The second is the standard deviation at each round, we can appreciate that along the game the sd increases from the first round since the round 4, that is, the middle of the game. In the mean of the game participants show more disparity than the beginning or end of the game.

Also we can observe that the maximum standard deviation correspond to the rounds 8 to 10. At this point of the game the objective is usually accomplished and most of the participants use a free-riding strategy. However, there are also people that keep contributing in an altruistic way because they dont care about the personal benefit or because they are fully committed with the climate change. We will see in Chapter 4 the differences in the clustering assignment caused by these lasts rounds.

3.1.3 Total contribution ratio

Looking at the pdf of the TCR (total contribution ratio) we can see that for homogeneous games the histogram is closer to the gaussian than the heterogeneous, although this was the best result (A). For heterogeneous games the values are more disperse with a significant density of users contributing more than 85% of their initial endowment.

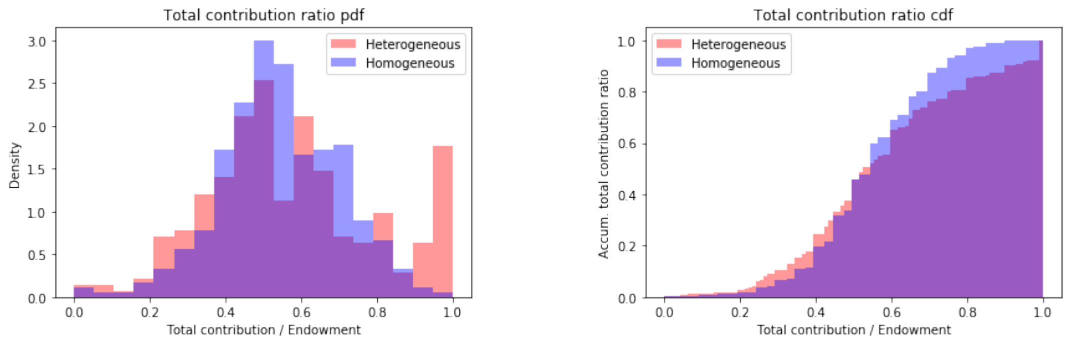


FIGURE 3.3: (Left) PDF and (Right) CDF of the TCR distribution according the treatment group.

The cumulative version shows in a better way the tendency in both treatment games. The curve for homogeneous games is sharper round 0.5 indicating that most of the users contributed close to 50% of their endowment. Heterogeneous games has a much flatter curve which means that the TCR has heavier tails.

As we have mentioned in Chapter 2, if we fit both distributions (proportional endowment contributed for each treatment) the best approximation is a gaussian with a mean value close to 0.5 ($\mu \pm \sigma^2 = 0.57 \pm 0.22$ for heterogeneous games, and 0.54 ± 0.15 for homogeneous (A)). Heterogeneous games have a higher average TCR and a higher standard deviation for this distribution. This means that the the homogeneous treatment has a less disperse distribution with a value closer to the 0.50 that would be the proportional equilibrium contribution defined as a resolution concept by Waichman et al., 2018.

3.1.4 Who Contributes? rich, poor or middle class

We want to focus on heterogeneous games and see in more detail who did the contributions, the rich players (50-60 MU) or the poor ones (20-30 MU). What we observe in Figure 3.4 is that in absolute terms those that had higher initial endowment also contributes more (normalized average contribution and standard error of 1.48 $\pm$0.08 MU for an initial endowment of 20 MU and 2.70 $\pm$0.09 MU for those with 60 MU) to the common fund. However, in terms of the average proportion of endowment contributed what we see is the opposite tendency. The users with an initial endowment of 20 MU contributes a 74% of their budget while the richests ones a 45%.

It must be taken into account that the richest players cannot contribute all their initial endowment so we see a decrease in the standard deviation. This fact is represented in Figure 3.4 with black points which represent the maximum TCR.

We can decompose the results in Figure 3.4 at dataset level to see in a qualitative way that the behavior across treatments are coherent in all datasets (Figure 3.5). In the heterogeneous games the TCR decreases while the initial endowment is higher. For homogeneous games still is more interesting as the frame in both experiments

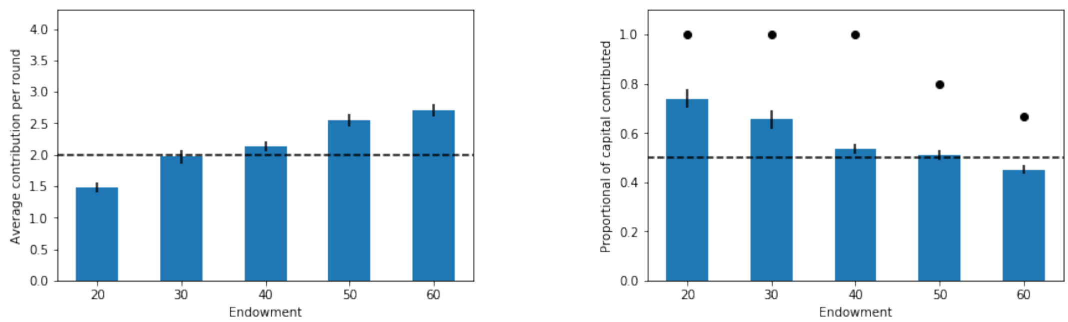


FIGURE 3.4: (Left) Average endowment contributed with standard error. (Right)Average proportional endowment contributed with the standard error. Dots lines represent the fair average selection.

were different (climate change for Homogeneous DAU and local conflict for Viladecans). In general terms the behavior is similar with a mean TCR close to the 50%.

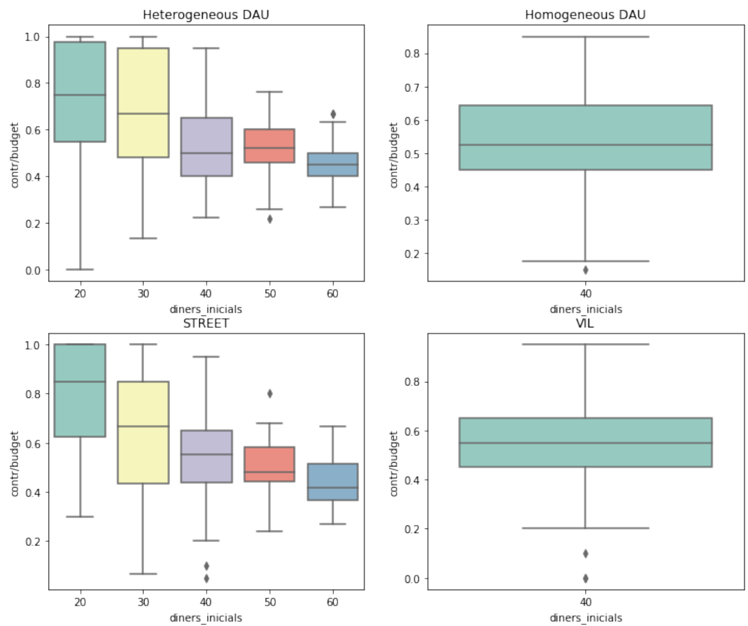


FIGURE 3.5: Boxplot with the average proportion of endowment contributed for each initial endowment per each dataset.

3.1.5 Evolution of contribution selections

Looking at the number of times that each selection is done along the ten rounds we can see common patterns in both treatments. In Figure 3.6 we can check that in all games the most repeated option in the first round is the selection of 2 MU. After this first round we can see that an important amount of players changed their selection of 2 MU to contribute 4 MU. It is also remarkable the increase of 0 selections at the end of the game. This is due to the fact that the objective is already fulfilled and a rational behavior is shown in the majority of users.

We can also see evolution patterns of data by looking at the first five and the last five rounds separately. In Appendix B we can see the amount of times a certain selection is chosen in the first half of the game and in the second half. The tendency in all datasets is that there are a few free-riding contributions (0 or 1) in the first half

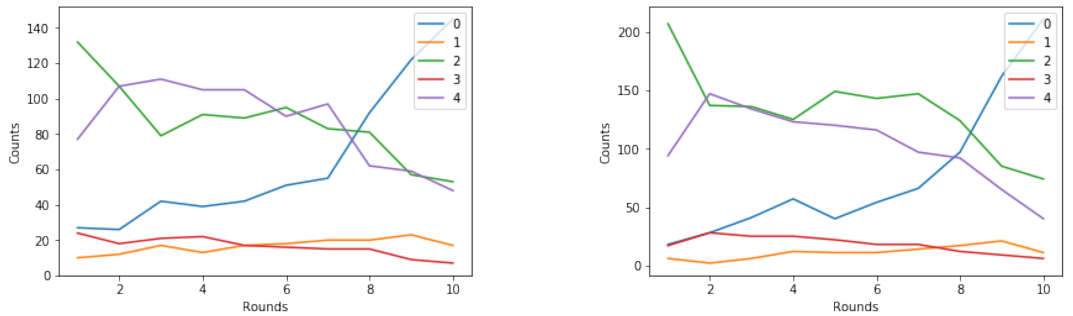


FIGURE 3.6: Line plot with the total amount of each possible selection at each round. (Left) Heterogeneous games. (Right) Homogeneous games.

of the game and then increases as a consequence of the ending game effect. At same time the number of fair and altruistic contributions decline in the second part of the game and are more abundant at the beginning. If we do the same analysis but taking out the out of the objective rounds we can see

3.1.6 Categories: free-rider, fair & altruist

At this point we have identified the TCR as an important variable to grasp the general behavior of the participants in each treatment group. It is true that this variable does not take into account the evolution of the contribution or how individuals answer to other individuals contributions but they are informative enough to assign a category to each player according if he/she is a free-rider, fair player, or altruistic.

As it is explained in Chapter 2 we use the three categories defined in Manfed Milinski et al., 2008 to explain this general behavior. To assign each category to each individual we splitted the rank 0-1 in three ranges (from 0-33%, from 33-66% and from 66-100%) and if the contribution ratio falls in one of these ranges we assigned the corresponding category.

This particular division in three categories can be considered ad hoc but we though it makes sense for two elements: first, allows to classify individuals in a general way which can be completed and better specified in the posterior analysis. And, second, the ranges threshold can be justified. For example, it is known that people does not follow in general strong free-rider attitudes so the low margin (0 - 33%) captures this set of possible free riding behaviors. The second threshold at 66% gives the possibility to consider a player with an initial endowment of 60 an altruist player. As their maximum TCR contribution is 2/3 the range 66 - 100% allows to include players with all initial endowments.

This exploratory analysis is done at dataset level (separating homogeneous from heterogeneous games in the DAU case). Lets start with the heterogeneous cases:

For the STREET dataset in 10 out of 18 games we have at least one free rider in the game. The most repeated composition is a game with no free riders, at least one altruist and the rest fair players. There are 7/18 games with this characteristics. We have 11 different compositions and a ratio of composition per game of 61.1%. In this experiment 34 participants are classified as altruist, the ratio of altruist is 34/108 = 31.5%.

In the Heterogeneous DAU dataset in 15 out of 27 games there is at most one free rider. The most repeated composition has no free riders, at least one altruist and the rest are fair players (10/27). The ratio compositions/games is 8/27 = 29.63%. And altruists represents the 30.2%.

Now the results obtained for the homogeneous games. For the VIL experiment in 12 out of 30 games we found one free rider as much. The most repeated composition has 5 high fair and one altruist (9/30). If we add these games with only fair people the amount rises to 14/30. In this case the ratio compositions/games is 33%. Another relevant parameter is the number of altruists players in VIL experiment. There are only 39 altruist with a ratio of 37/180 = 21.6%, a little bit lower than in the heterogeneous case.

Finally, for the Homogeneous DAU dataset, we have 10 out of 27 games with one free rider as much. The most repeated composition has no free riders, one altruist and the rest are fair players (11/27). The composition ratio is the same as in the heterogeneous dau case (29.63%). The altruist ratio is a 37/162 = 22.8%.

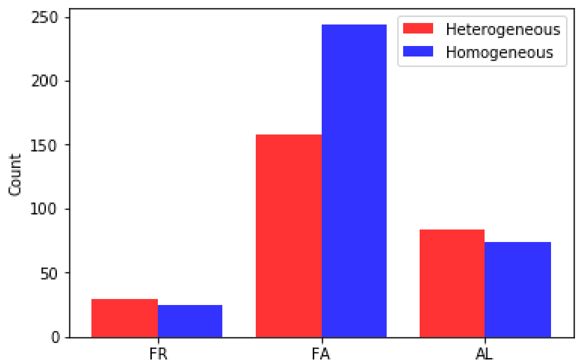


FIGURE 3.7: This bar plot represents the number of users of each category (free-rider, fair, altruist) according the treatment

After this analysis we can see first that in heterogeneous games there are more free riders and also more altruist individuals than in the homogeneous case. Having the same success rate in both cases the heterogeneous distribution of initial endowment made that participants played more extreme strategies in proportional terms. Homogeneous games shows the opposite tendency, mostly fair players in the majority of games. The composition ratio seems to not capture particular elements of each treatment. The chi-square test confirms that both treatments has a different distribution of the categories we defined ($\chi^2 = 32.45$, p-value < 0.01).

Chapter 4

Results

4.1 Game theoretical results

4.1.1 General behavior in the games

In contrast with Manfed Milinski et al., 2008 and the rest of experiments of the CRD the success rate in our games is 100%. All games reach the objective irrespective of the initial endowment. This implies that most of the basic results, as the average or the accumulated contribution, have different values comparing to the collective risk literature that has been mentioned.

What we observe in our data is that individuals contributes above the fair contribution in the firsts rounds and then starts decreasing when the objective is reach. This pattern is the opposite to the one found at Manfred Milinski, Röhl, and Marotzke, 2011 that contributions were below the fair one along all treatments and all rounds. These differences are discussed in Chapter 5 in more depth but they must come from the context. In lab-in-field experiments the data obtained comes directly from the people in their own context and conditions are necessarily more real.

4.1.2 What happens when we have inequality?

First of all, we tested the difference or not in the average contribution between both treatment groups. The results of the t-test indicates that there is not statistical significance between both treatments (p-value > 0.1). Instead, if we look at the TCR for both treatments we found a p-value for the t-test of 0.06 so it is statistically significant at 90% but not at 95%.

Although the results of the average contribution distribution have no differences (the total amount of contributions per treatment are similar), the TCR distribution has some nuances to take into account. There is a disproportionate amount of participants which contributes closed to 100% of their endowment in the heterogeneous treatment while there were very few in the homogeneous case. This situation has important consequences in the discussin about which context favors the collective success in front a dilemma. When there is inequality we should add the knowledge of other fields as economic or psychology to do our reasoning complete.

In economic terms letting an unequal distribution of resources suppose that some of the participants lose their ability to earn, so consume and invest. Actually, we can check the evolution of the Gini coefficient for the homogeneous and heterogeneous games. When this coefficient is equal 1 we are in a situation of perfect inequality, while for a value of 0 it is called perfect equality. The results are plot in Figure 4.1. What we observe is that in most of the rounds the heterogeneous group had a higher value of this index until the last round were homogeneous games exceeds the heterogeneous one. The Gini index increases in most of the rounds with an increase specially sharp since round 7 for heterogeneous games and round 8 for homogeneous ones. The total increase of Gini coefficient is 0.347 for heterogeneous while 0.478 for homogeneous.

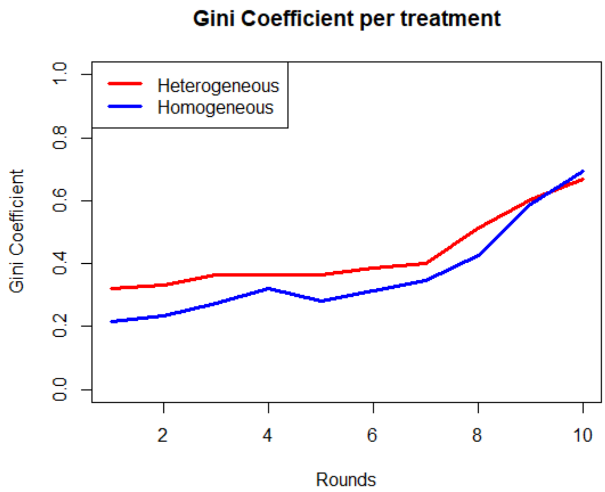


FIGURE 4.1: Evolution of the Gini coefficient for both treatments.

4.1.3 First-round results

To analyse the evolution in the CRD some of the papers has focused their attention to the different stages of the game. The results obtained related with the first round behavior are coherent with the ones found by Manfed Milinski et al., 2008, Waichman et al., 2018 and Ledyard, 1995. Our results show that the most selected contribution (independently of their initial endowment) is 2 MU (in 48.9% of cases for the heterogeneous treatment and 60.5% for homogeneous games). It seems that the first round is used by the participants as a training round, were they try to identify others behavior and establish their own strategy.

Manfed Milinski et al., 2008 put this result as: *"Surprisingly, almost all groups provided 2 per person in the first round, an all fair-sharer situation."*. And Waichman et al., 2018 found that the first round contribution its very similar between the symmetric group (homogeneous treatment) and the loss heterogeneity group with a 50% of the members contributing 2. As we can see, the results in terms of the first round action are the same in all experiments.

4.1.4 Ending Round Effects

In Waichman et al., 2018 tried to predict the final outcome of a game given the initial selection of each participant. The results they found were that higher the contributions at the beginning, more probability of success the game had. This result is not directly comparable with our data but what we see is that higher initial contributions implies that groups reach the objectives faster.

If we look in more detail the games that meet the final objective earlier (round 6 or 7) comparing with the ones that needs the last round we found:

- STREET case: average contribution (ending games at round 7) of 2.5 MU while for these ending games at round 10 is 1.99 MU.

- HOM DAU case: average contribution (ending games at round 7) of 2.50 MU while for games that meat the goal in the final round is 2.08 MU.

We can observe that the average contribution is higher in the games which fills the objective earlier (at round 7) while is lower in those that fill the objective in the last round.

4.1.5 Particular Strategies: Free-Rider, Fair, Altruist & Conditional Cooperation

We have seen in the general composition analysis that TCR differ between homogeneous and heterogeneous games.

It is hard to detect pure strategies in the games as for example it is the free rider case. In our data we can only detect three pure free riders (no contribution along 10 rounds), one in the heterogeneous DAU dataset and two in the VIL experiment. These three individuals represent the 0.50% of our total database. We can do the same exploration for pure altruists. If we look at the number of participants that selected 4 in all rounds represented only the 0.66%. for all experiments. This results show that pure strategies are rare which is something that past literature already found. For example, for the free rider case, in Ledyard, 1995 already appears different categorizations for this strategy defining pure free rider (contribute 0 in all rounds) and weak free rider (contributes 0 in most of the rounds).

Conditional cooperation is another classic strategy discussed in Keser and Winden, 2000 and in Fischbacher, Gächter, and Fehr, 2001. This strategy emulates the classic strategy in GT tip-for-tat or win-stay lose-shift. Consists in contributing more if others also contribute more and vice versa. According to the results obtained in final questions 4 and 5 for DAU and STREET datasets participants did not follow a conditional cooperation behavior. However, if we define a new dummy variable which captures this behavior evaluating if a players follows a conditional cooperation strategy at each round (1 if your contribution at round t is higher than your contribution at t - 1 and your contribution at t - 1 was lower than the average contribution of the group, 0 otherwise), we can confirm that this pattern is followed in 50% of the individuals along 50% of the rounds (see the results in Appendix E). This result is coherent with the results found in the references mentioned above where this strategy was followed by 50% of the individuals.

4.1.6 Composition of groups

We have seen in Chapter 3 there is a different distribution of free-riders, fair, and altruistic players according to the treatments. In the heterogeneous games the number of free-riders and more altruistic individuals is larger than in the homogeneous case. This finding complement the results of the average contribution and the TCR, and allows to defend that exists a polarization in the game strategies caused by the unequal distribution of resources. In an egalitarian system the cost of contributing is shared proportionally between individuals in a natural way.

4.2 Clustering analysis and characterization of groups

What we want is to evaluate the advantages of using ML techniques to study data related with PGG or CRD and identify which techniques are better to work with. The analysis of the clustering results will allow to discuss the scope of ML in these games and answer to the questions we have presented at the beginning in Chapter 1.

In this section, we are going to show the differences between both treatment groups (homogeneous and heterogeneous games) by means of the cluster analysis. Once we have identified these groups we are going to proceed to do the first characterization of the members who compose them. To do so we analyse three things: 1) statistical information about the contributions they do, 2) initial endowment, TCR pdf and cdf and the evolution of the average contribution of each cluster, 3) the differences of these clusters in different temporal regions (before the objective is fulfilled, and with all the information).

We must take into account that since now the unique way to identify clear patterns have been assuming general categories obtained from theory or using a conventionalism from other experiments (Waichman et al., 2018). In the exploratory analysis we have used this approach to consider individuals as free riders, or which one is fair or altruist. This approach has the drawback to be unable to consider little deviations from the pure and perfect strategies or categories. From now on this schema is only useful to characterize previous groups found by K-Means. Lets see which results we found.

4.2.1 Clustering results - Statistical information

Cluster analysis has been the most important methodology to identify homogeneous players in all different datasets (Appendix C). To do the cluster analysis with the maximum number of individuals we summed up the four datasets according their treatment group (or homogeneous game or heterogeneous). We will see later how these groups are distributed on the PC plane (or can be checked at Appendix D).

As we have mentioned in Chapter 2 one drawback of K-Means is the need to specify the optimum number of clusters as an input variable of the model. As we have explained in the methodological section we finally chose K = 3 and K = 2 as the optimal number of clusters for the heterogeneous and homogeneous games respectively.

Now if we look at the basic statistical information in terms of population and average contribution per cluster we have, for the heterogeneous games:

- Cluster 1: 51 participants (18.89%) with an average contribution of 2.24 $\pm$0.56 MU (0.79 $\pm$0.17 MU).
- Cluster 2: 152 participants (56.30%) with an average contribution of 1.90 $\pm$0.75 MU (0.42 $\pm$0.12 MU).
- Cluster 3: 67 participants (24.81%) with an average contribution of 2.70 $\pm$0.80 MU (0.75 $\pm$0.14 MU).

It is important to remark the disproportionate amount of individuals in cluster 2 compared to the rest (56.3% of all population). This cluster could be representative of the mean behavior of participants in the heterogeneous games. For the homogeneous case we have finally decided to explore the results for K = 2. What we found is:

- Cluster 1: 186 participants (54.39%) with an average contribution of 1.76 $\pm$0.43 MU (0.44 $\pm$0.11 MU).

- Cluster 2: 156 participants (45.61%) with an average contribution of 2.66 ±0.40 MU (0.66 ±0.10 MU)

For homogeneous games we found two compensated clusters (55-45%) but the big one (cluster 1) has an average contribution under the fair one while the smaller (cluster 2) has an average contribution above the fair.

4.2.2 Characterization of groups

To go deeper in the definition of our clusters lets see the results for the initial endowment of the members of each group, the proportion of capital contributed distribution through the Pdf and Cdf and the evolution of the average contribution of each cluster.

Initial endowment per cluster

To represent the initial endowment of each cluster we used a percentage stacked plot. In Figure 4.2 we can see the proportion of individuals of each cluster according their initial endowment.

FIGURE 4.2: Percentage barplot with the percentage of population from each cluster and initial endowment.

The result shows that cluster 1 is composed mostly with people with low initial endowment and, as we have seen, with an average contribution above the fair one (2.24MU). For clusters 2 and 3 we can appreciate that both had members with all initial endowments. However, cluster 2 has most of the rich inividuals and cluster 3 show a bigger proportion of poor inidividuals.

For homogeneous games we can see the differences in the proportion of population that contains each cluster according the game (Homogeneous DAU and VIL). As we can see in Figure 4.3 there are no differences in the proportion of population of each cluster according the dataset what suppose good news in terms of the experimental procedure because it means that was consistent in both experiments.

Total contribution ratio Pdf and Cdf for each cluster

We repeated the computation of the TCR distribution for each of the clusters at each treatment. The results for the heterogeneous games are plot in Figure 4.4.

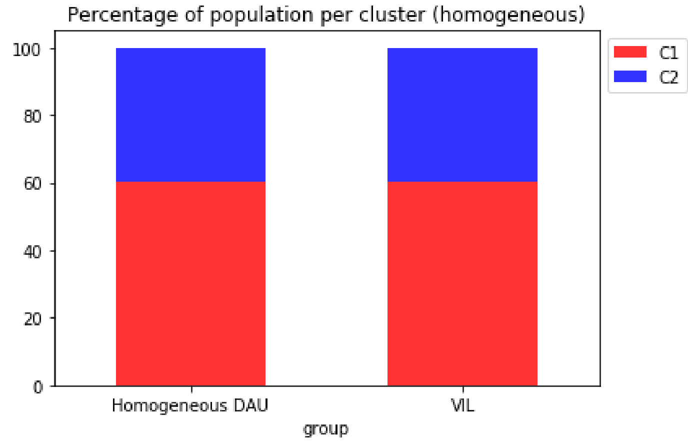


FIGURE 4.3: Proportional population assigned to each cluster for homogeneous DAU and VIL datasets.

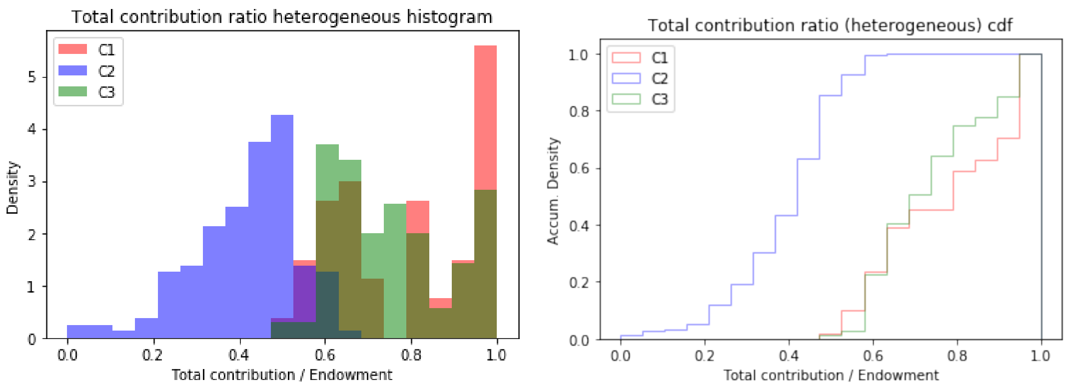


FIGURE 4.4: (Left) PDF and (Right) CDF of the TCR distribution per cluster. Heterogeneous games.

We can see that cluster 2 is composed by individuals with the lowest TCR while cluster 1 contains most of the altruistic players. Cluster 3 seems to be the fair group with a TCR between cluster 1 and 2. The mean and standard error for all clusters are the following: cluster 1) $\mu_{prop} = 0.788 \pm 0.024$, cluster 2)$\mu_{prop} = 0.418 \pm 0.010$, and cluster 3) $\mu_{prop} = 0.751 \pm 0.017$.

For homogeneous games we have the plot of the Pdf and Cdf in Figure 4.5. We can see that both distributions have a close pattern in terms of the accumulated distribution. Actually there is not statistical independence between both distributions according the t-test (p-value > 0.1). The mean and standard error for each cluster is: cluster 1) $\mu_{prop} = 0.545 \pm 0.030$ and cluster 2) $\mu_{prop} = 0.582 \pm 0.031$.

The TCR for homogeneous games does not give strong enough patterns to consider a particularly informative variable. However, for the heterogeneous games still we can identify separated regions for each clusters. According T-test the unique non independent clusters are cluster 1 with respect cluster 3 as the p-value = 0.18. We did the same analysis for the average contribution but results were less significative so we discarded them.

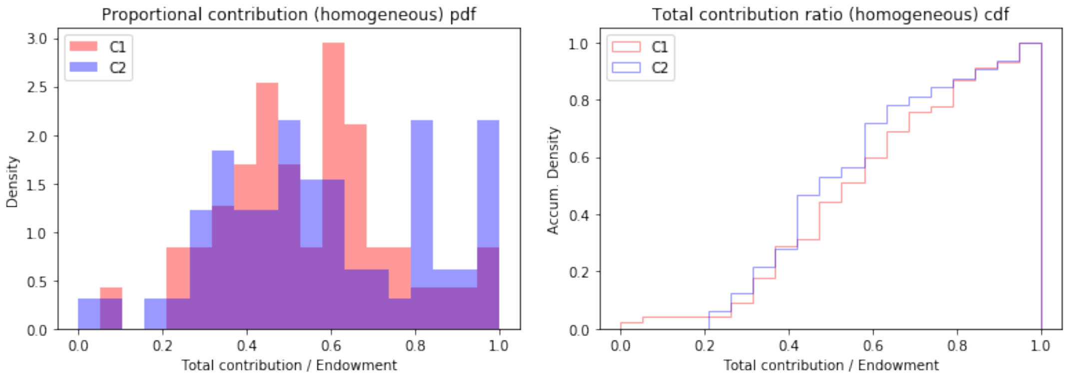


FIGURE 4.5: (Left) PDF and (Right) CDF of the TCR distribution per cluster. Homogeneous games.

Evolution of clusters

If we look at the evolution in the average contribution we gain new information about which type of players represents each cluster. In Figure 4.6 we plot the average contribution of each cluster at each round with the standard error.

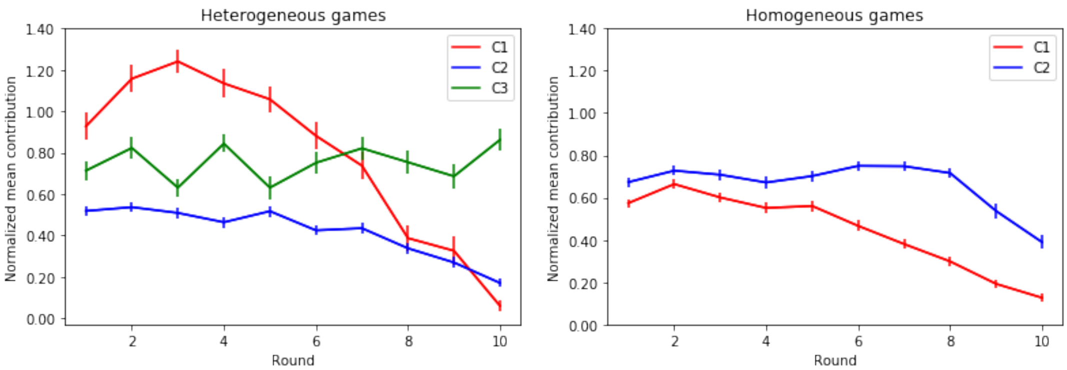


FIGURE 4.6: Evolution of the normalized average contribution with the SE.

In heterogeneous games each cluster follows a particular dynamics in terms of contributions. Cluster 1 represented a cluster for people with relatively low initial endowment that contributed almost everything they have. We can see in Figure 4.6 how they start contributing large amounts to the common fund since they mostly ends his/her budget. Between cluster 2 and cluster 3 there were differences in terms of the initial endowment (cluster 2 had more rich individuals while cluster 3 proportionally more poor participants) and the TCR (cluster 3 contributes on average a larger part of their endowment). In terms of the evolution of the average normalized contributions we can also see differences between both clusters. While cluster 2 average contribution tends to decrease members of cluster 3 mantains their contributions since the end of the game. Moreover, cluster 3 had a normalized average contribution above cluster 2 at all rounds, with a maximum difference of 0.69 MU at round 10 and a mínimum of 0.11 MU at round 5.

4.2.3 Ending Round Effects on clustering

How would change our classification groups if we eliminate the ending rounds of the game?. We can repeat the analysis by looking only at these rounds were the objective was still not fulfilled. Those are fundamental to decide the success of the game. In Figure 4.7 we can see which individuals were assigned in another cluster once those rounds were eliminated. This gives an idea about two different overviews of the game, before and after the objective is fulfilled.

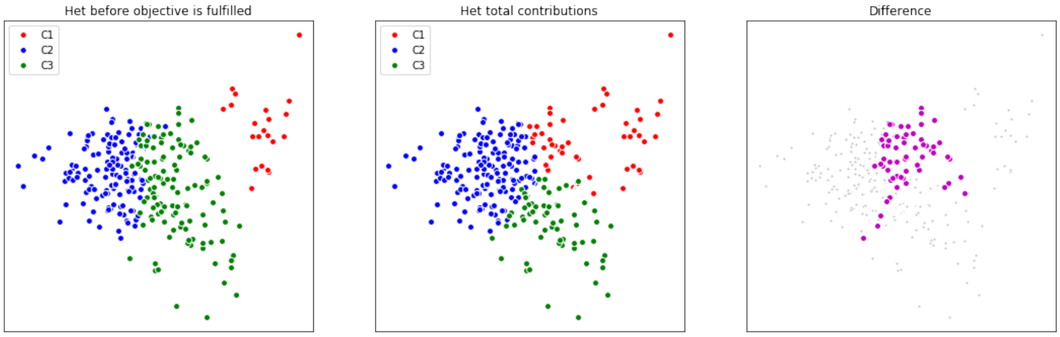


FIGURE 4.7: Individuals in the PC plane colored according their clusters before and after the objective is fulfilled (heterogeneous)

In this new situation 60 individuals of clusters 1 and 2 are classified in cluster 3 (22.2% of population). The proportion of individuals at each cluster is 8.15%, 47.41% and 44.44% respectively. Cluster 3 can be considered the "fair" and compensates cluster 2 that was the cluster with more free riders. The new average contribution and standard error are 2.24 $\pm$0.10 MU (0.95 $\pm$0.02 MU), 1.77 $\pm$0.06 (0.39 $\pm$0.01 MU), 2.56 $\pm$0.07 MU (0.69 $\pm$0.01 MU).

In Figure 4.8 we can see that before the objective was fulfilled cluster 1 had only members with an initial endowment of 20 or 30 MU. This means that there are individuals with an initial endowment of 40 and 50 MU that keeps contributing after the objective is fulfilled showing a "hyper-altruistic" behavior deciding to lose money before keep for themselves. Although these changes in the assignation of some individuals, we can check that general patterns persist if we compare with Figure 4.2.

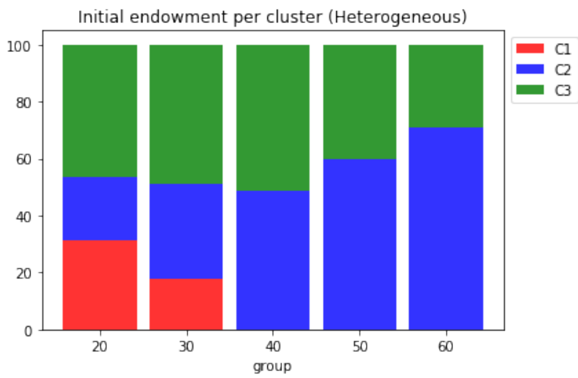


FIGURE 4.8: Percentage stacked bar plot of members of each cluster according their initial endowment.

In Figures 4.9 and 4.10 we represented the TCR for each cluster before and after we have substracted the final rounds. Cluster 1 has a average TCR of 0.94 $\pm$0.08 MU, 0.39 $\pm$0.12 MU for cluster 2 and 0.69 $\pm$0.14 MU for cluster 3. What we observe is that before the objective is fulfilled there is an important group (cluster 3) which loses importance in terms of population once the objective is fulfilled. Cluster 3 has a statistically different distribution in their TCR distribution (t-test: p-value = 0.004) before and after the objective is fulfilled. In this cluster we have a significantly amount of individuals (44%) which sustains a high average contribution, giving around 70% of their initial endowment. The evolution in the average contribution is stable around 2.56 MU.

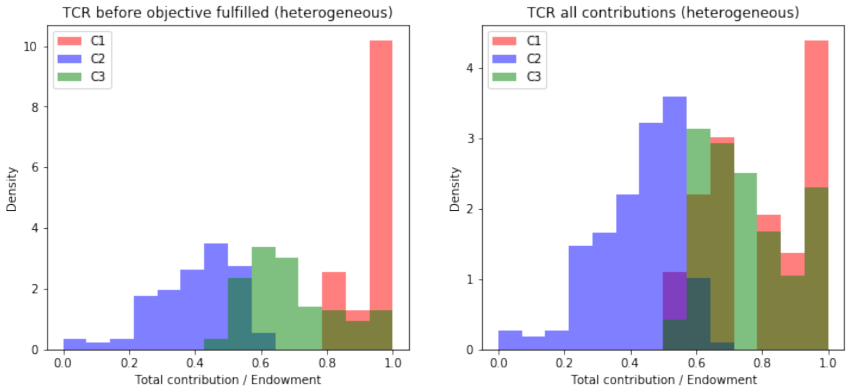


FIGURE 4.9: Histograms with the TCR for each cluster (Left) before and (Right) after the objtective is fulfilled.

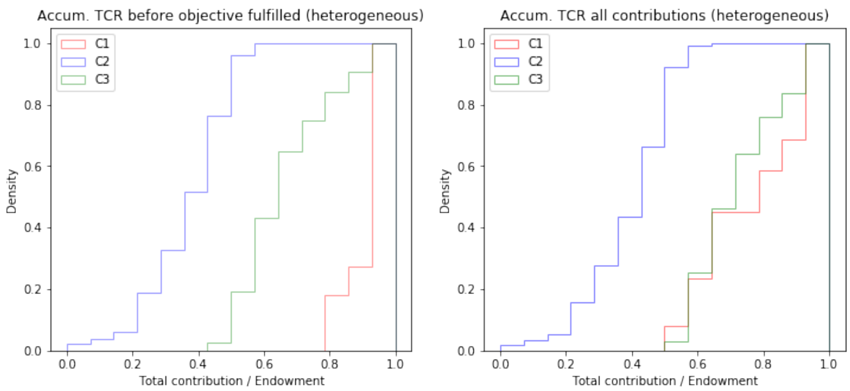


FIGURE 4.10: Cdf of the total contribution ratio for each cluster (Left) before and (Right) after the objtective is fulfilled.

What we conclude from a qualitative point of view is that on average the TCR shows clear patterns before the objective is fulfilled for heterogeneous games. We can see in Figure **??** that the Cdf's are clearly separated and the T-test between all three distribution had a p-value < 0.01. According to this result we can think that these rounds played after the objective is fulfilled can be considered as noise.

For the homogeneous case individuals classified in cluster 2 before the objective was fulfilled, went to cluster 1 once the experiment is over. Before the objective is fulfilled cluster 1 represents the 53.5% of population while cluster 2 the 46.5%, so the number of members at each cluster does not change. The percentage of individuals classified in different clusters is 15.5%.

In this case what we see is that both groups exchange the average TCR between them. In terms of the Pdf and Cdf there are not significant differences, which is the reason why we have not added them. In both treatments the evolution of clusters has the same patterns as the total contributions case.

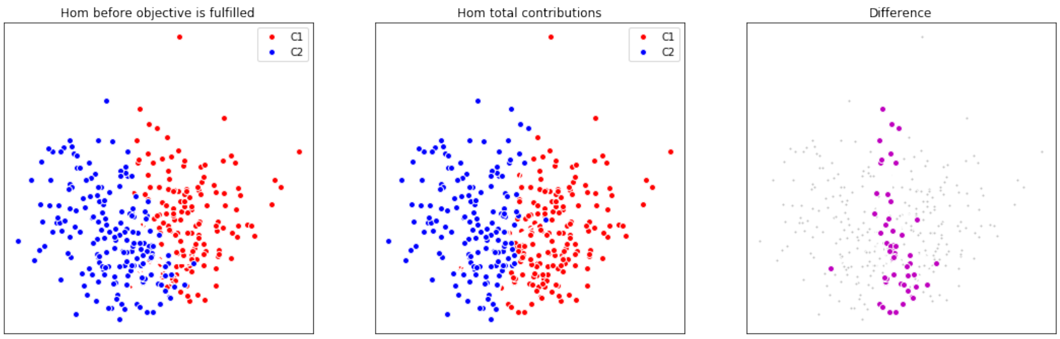


FIGURE 4.11: Individuals in the PC plane colored according their clusters before before and after the objective is fulfilled (homogeneous).

This section allows to confirm several aspects of the clustering analysis on CDR data. First we can confirm that clusters are robust in terms of maintaining their general characteristics before and after the objective is fulfilled (average contribution and proportional endowment contributed). Although, we can appreciate in a clearer way the patterns with only the information before the objective is fulfilled. This implies that these ending rounds after the objective is fulfilled could be considered as noise for the identification of the patterns and might be discarded in future analysis.

Second, the exchange of individuals before and after the objective is fulfilled give relevant information about the patterns followed by players once the game is over. We have seen for the heterogeneous case that the game starts with two equilibrated clusters representing the 40% of the population each of them (cluster 2 and 3, the "free-rider" and "fair"). But, once we take into account the ending rounds some of the individuals classified as "fair" end up in the free rider or the "altruist" cluster (cluster 1).

4.3 Classification analysis according to gender

Gender difference in GT has been an object of study for different papers (Gneezy, Leonard, and John A. List, 2009, J. Alberto Molina et al., 2013 & José Alberto Molina et al., 2018). Still there is not a definitive conclusion about which particular patterns characterize both genders. The results of this section want to try new tools to study this phenomena. Do a classification based on the contributions of each jubject can be a new measure. The good or bad performance of the classifiers we are going to test can be indicative of a possible existence or not of patterns according gender.

Supervised algorithms allow us to test the prediction capacity of a model to classify individuals according a certain target. In this case we evaluated the following models: Logistic Regression (LogReg), Naive Bayes (GNB), Support Vector Machine (SVM), K Nearest Neighbors (KNN), Decision Trees (DecTree) and Linear Discriminant Analysis (LDA) with the aim to see which one fits best our data, using the gender (male = 0, female = 1) as target and the normalized average contribution table as the input. The accuracy score results are presented in Table 4.1.

We can appreciate that the maximum accuracy score obtained for heterogeneous games is 0.579 and 0.681 for homogeneous. Both are low values taking into account that a random algorithm would give a final score classification of 0.5.

TABLE 4.1: Results for classifications algorithms

Dataset	LogReg	DecTree	KNN	LDA	GNB	SVM
Heterogeneous	0.519	0.510	0.551	0.510	0.528	0.579
Homogeneous	0.678	0.572	0.608	0.670	0.652	0.681

TABLE 4.2: Results for classifications report

Dataset	Best Classifier	av. Precision	av. Recall	f1-score
Heterogeneous	SVM	0.33	0.57	0.42
Homogeneous	SVM	0.48	0.70	0.57

However, we complement these results with the analysis of the confusion matrix and the relevant classification report parameters. We summerized precision, recall and f1-score of the best classifiers in Table 4.2.

Precision wants to limit the "false positives" while recall detects the "true positives" trying to reduce the "false negatives". In this case a false positive would be a man classified as a women and a false negative a women classified as a man.

The results show very low values with a maximum f1-score of 0.57. Homogeneous results are better but still not good enough to considerer that we can read any pattern. The principal drawback in this computation is the amount of data used as input. We need to increase the samples which could can be done artificially and a posible line for future research.

We must cross the results of the classification report with the confusion matrices obtained for the classifier with a higher test score and per treatment. The confusion matrices are:

$$\text{Heterogeneous} \qquad\qquad \text{Homogeneous}$$
$$\begin{array}{c} \\ class_m \\ class_f \end{array}\begin{array}{c} \begin{array}{cc} pred_m & pred_f \end{array} \\ \begin{pmatrix} 31 & 0 \\ 23 & 0 \end{pmatrix} \end{array} \qquad \begin{array}{c} \\ class_m \\ class_f \end{array}\begin{array}{c} \begin{array}{cc} pred_m & pred_f \end{array} \\ \begin{pmatrix} 48 & 0 \\ 21 & 0 \end{pmatrix} \end{array}$$

As we can observe in the confusion matrices something should be wrong with SVM. This classifier always predicted that individuals are males which is incorrect. If we look for the best results in terms of the classification report and confusion matrix for the rest of classifiers we found: 1) for heterogeneous games Logistic Regression and Linear Discriminant Analysis had the best results in terms of the confusion matrix (more individuals are predicted as true positive or true negative) and f1-score (0.57) than SVM.

$$\text{LogReg (heterogeneous)}$$
$$\begin{array}{c} \\ class_m \\ class_f \end{array}\begin{array}{c} \begin{array}{cc} pred_m & pred_f \end{array} \\ \begin{pmatrix} 27 & 4 \\ 17 & 6 \end{pmatrix} \end{array}$$

2) For homogeneous games K-Nearest Neighbors presented the best result in terms of both the confusion matrix (more individuals are predicted as true positive or true negative) and the f1-score (0.580).

$$\text{K-NN (homogeneous)}$$
$$\begin{array}{c c} & \begin{array}{cc} pred_m & pred_f \end{array} \\ \begin{array}{c} class_m \\ class_f \end{array} & \begin{pmatrix} 38 & 10 \\ 17 & 4 \end{pmatrix} \end{array}$$

As we can see supervised learning algorithms results are not very robust in classifying correctly men and women based on their contributions. We must be very cautious about these results because samples have not been of the optimum dimension. However, if this result becomes true would imply that gender patterns are not obvious so we must conclude that the level of cooperation or implication of each gender is not determinant whilde predicting actions in collective dilemmas. It would be interesting for future research the creation of new dummy variables that could become more crucial target variables for our games.

Chapter 5

Discussion

One of the important objectives of this study has been the evaluation of which particular methods from ML are useful for the analysis of CRD, and which scope these techniques have to show new patterns that we did not found with the traditional classical statistics analysis. After this work we are convinced that the tools given by ML are useful although the limitations we have found in terms of the dimension of our dataset. At the moment not many academics focused on the use of ML to study CRD, we expect with this master thesis to give more arguments to do so.

Before start with the advantages we have found using ML lets remember that these techniques need a huge amount of data to allow the algorithms learn in a proper way the information they are reading. Although we have worked with a large sample taking into account this kind of experimentation, the dimension of our data needs to be larger to improve in the precision and consistency of our prediction capacity.

Apart from that, we have shown that the use of unsupervised learning techniques allows the identification of groups of people with common patterns, without being based on predefined categories or pure strategies, as it is in the traditional game theoretical approach. Common patterns in the initial endowment, the percentage of endowment contributed and the evolution of such contributions has become a good proxy to characterize the results found by the clustering algorithm. We have also shown that the differences in the clustering assignation before and after the objective is fulfilled give useful insights to discuss the ending round effects and the consistency of clusters in CRD games.

For the game theoretical discussion we must start pointing one of the most remarkable facts of our data that contrast with the rest of the literature as it is that all games had succeed in reaching the threshold objective. It is surprising taking into account that the experimental design was reproduced from Manfed Milinski et al., 2008. In that case, they obtained a success rate of 50% in the treatment group with the loss probability of 90% (as in our experiments) in the rest of treatments (with a lower loss probability) almost all games failed in reaching the threshold value. Our success rate repercutes in the rest of variables (average contribution, accumulated,...) observing different patterns than in other experiments. In general we have people that contributes above the mean or fair contribution in most of the cases which could indicate a predisposition of people from south Europe to cooperate more (hypothesis pointed in Vicens et al., 2017 in the climate change framework).

In terms of treatment results we conclude that there are not significant differences neither in the success rate, nor in the TCR between both. However, we have found differences in the composition of games in both treatments having the heterogeneous games a more polarized composition with proportionally more free riders and altruist players than the homogeneous games. We have also detected an unbalanced distribution of the costs in the heterogeneous case were those individuals with larger initial endowment contributed proportionally less than the poorest ones. In terms of climate action, for example, this result should be taken into account to ensure a fair distributions between individuals of the cost of fighting against climate change and try to avoid the increase of free rider behaviors.

We cannot conclude as in Waichman et al., 2018 and Burton-Chellew, May, and West, 2013 which treatment (homogeneous or heterogeneous initial endowment) does it better in terms of cooperation because our success rate is 100% for both treatments. However we can confirm that collaborate in an unequal situation with your relatives redistributes in an unfair way the costs of that collaboration. Therefore, all new policies addressing to such collective actions such as climate change mitigations need to consider beforehand several socio-economic aspects. This is what literature frames within the concept of environmental justice.

Appendix A

Fit of distributions

For the proportional contribution we need to see which is the best distribution that fits these particular variable. Using the fitdistrplus library in R we have that for heterogeneous games the two possible best distributions are a beta or a normal one. After testing both distributions the normal one shows better results in terms of the AIC parameter and the Q-QPlot (results in the R archive publicgoods.r).

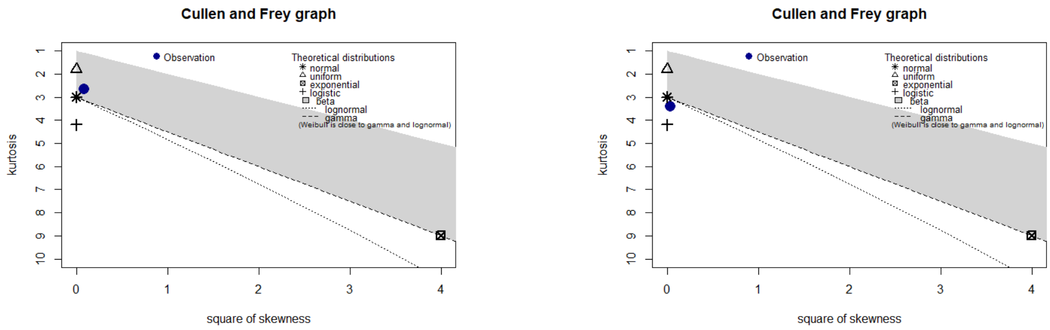


FIGURE A.1: Cullen & Frey chart to determine the best fit for a certain distribution.

For homogeneous games the best fit is very closed to the normal one. I compared the results with the gamma distribution and again the AIC and Q-Q Plot supports the normal distribution as the best one. The results obtained for the mean (μ) and standard deviation (σ) of such distributions are: μ= 0.571 $\pm$0.013 and σ= 0.219 $\pm$0.009 for heterogeneous games and μ= 0.542 $\pm$0.008 and σ= 0.153 $\pm$0.006 for homogeneous games.

Appendix B

Evolution related results

Ending rounds of the game

We understand the ending round as the one where the objective is fulfilled. As we see the ending round its an important variable that gives idea about the efficiency of players filling the objective and ensuring their own savings. The mean ending round value (±the standard error of the mean) is 8.81 ±0.23 for heterogeneous DAU, 9.0 ±0.24 for STREET, 8.85 ±0.19 for homogeneous DAU and 8.73 ±0.17 for VIL. We can see in figure B.1 the distribution of endings for each dataset.

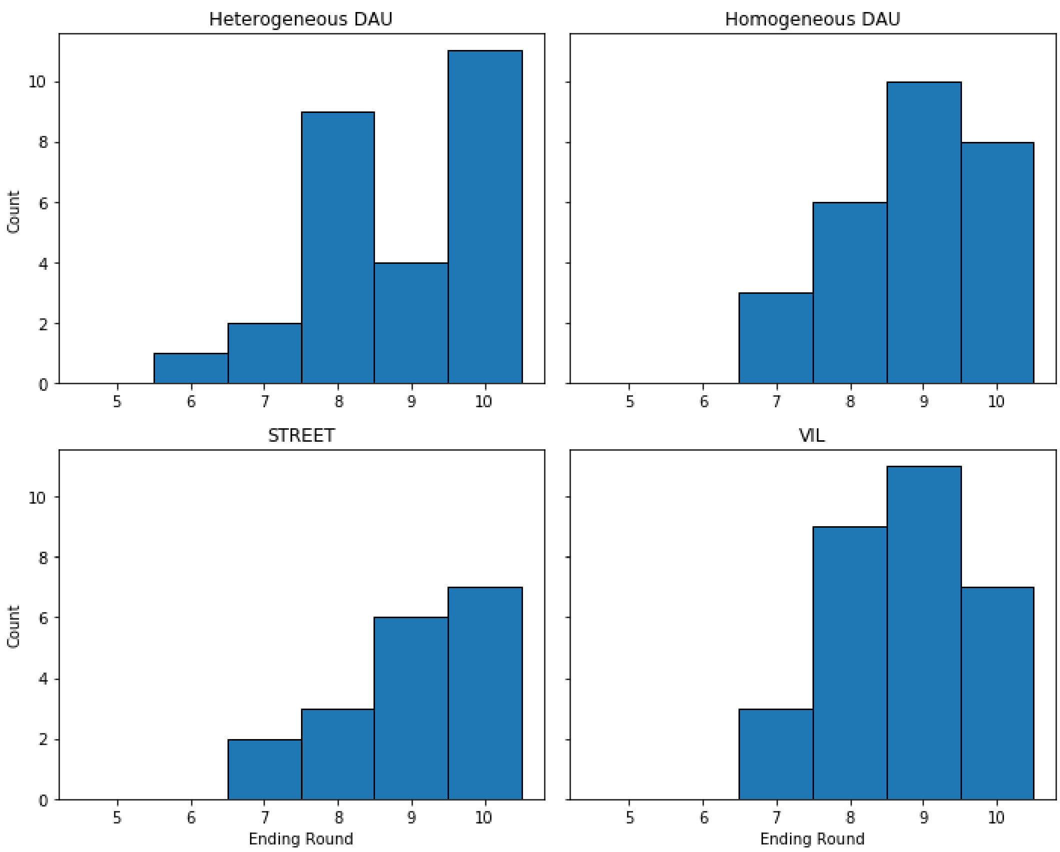


FIGURE B.1: Histograms at dataset level with information about the number of times a certain game has finished at certain round.

Differences between the two half of the game

Comparing both halfs of the contribution table to identify possible patterns was already tested for Vicens et al., 2017. In figure B.2 we can check the differences between both periods.

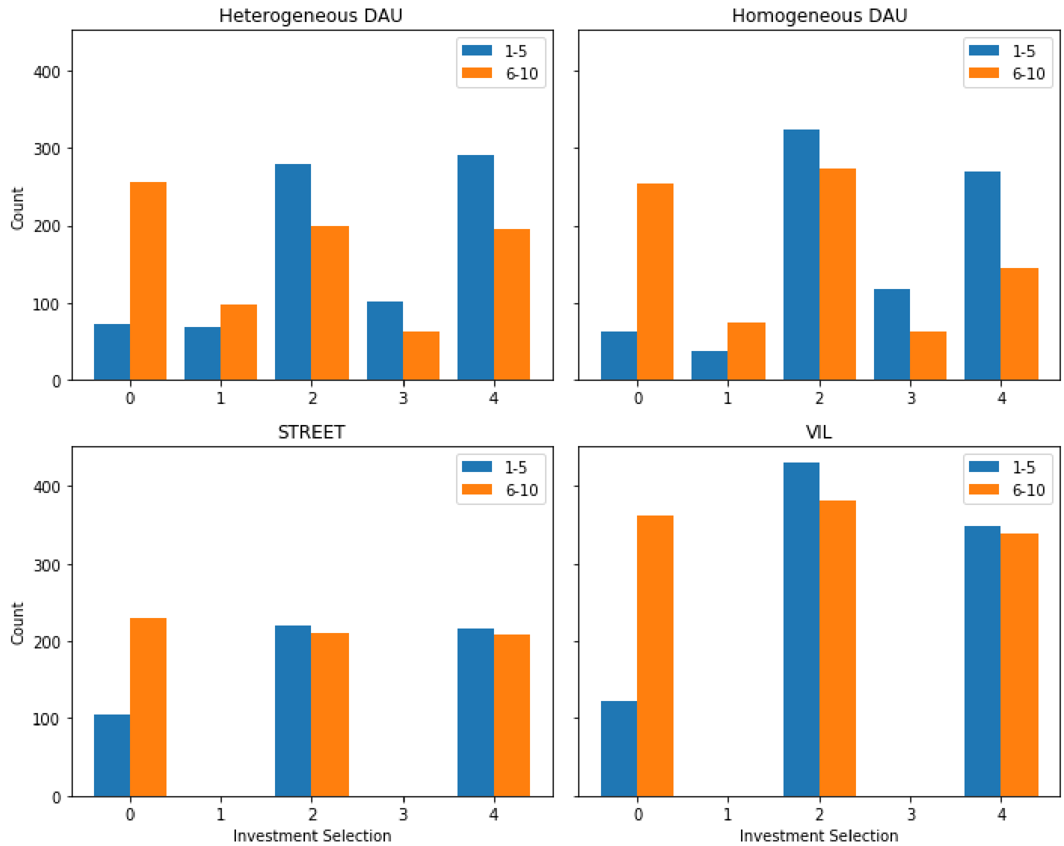


FIGURE B.2: Barplot with the accumulated selections of each contribution in the first half and the second half of the CRD

Appendix C

Cluster results

Besides K-Means we have tried other unsupervised clustering algorithms to identify simillar groups. Specifically we computed Hierarchical clustering, Agglomerative clustering and DBSCAN (following Müller and Guido, 2016). In Figure C.2 we have the results obtained for each of the cluster algorithms. Comparing with K-Means all these algorithms had more difficulties on the identification of groups. We can see that borders are much more diffuse. For Hierarchical clustering the dendogram analysis indicated that the optimum K could not be K = 2. For this reason we plotted the results having cut the three to obtain K = 3. The black points for DBSCAN plots are those that the algorithm cannot classify. This method does not need to add the optimal as input so we tried to identify the minimum number of samples to find the K we chose after the clustering indices analysis. The results have been $min_sample =$ 5 for heterogeneous and 4 for homogeneous clusters although the number of clusters found is larger than the optimum case (K = 4 in both cases).

We also tried another clustering method which was called "maximum a-posteriori Dirichlet process mixtures" (MAP-DP) proposed by Raykov et al., 2016. This algorithm is more flexible than K-Means because it relaxes the input of the optimal number of clusters, and suits for our data. In our case the results with this method gives extra clusters (K = 7 for heterogeneous games and K = 4 for homogeneous) and not well distributed as can be seen in Figure C.1.

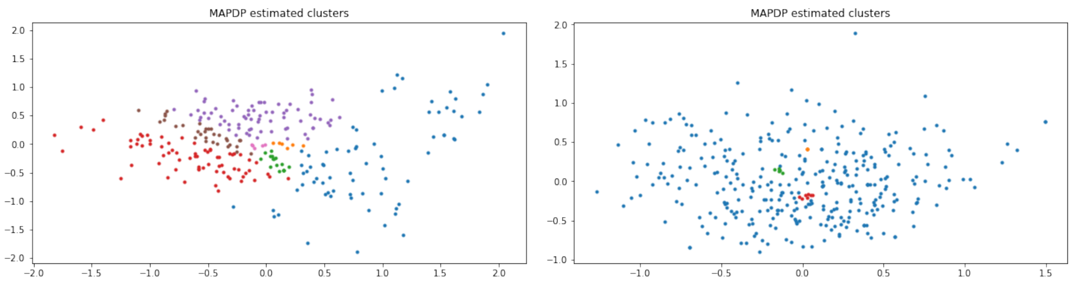


FIGURE C.1: Clustering results for the MAP-DP algorithm

(A) Heterogeneous

(B) Homogeneous

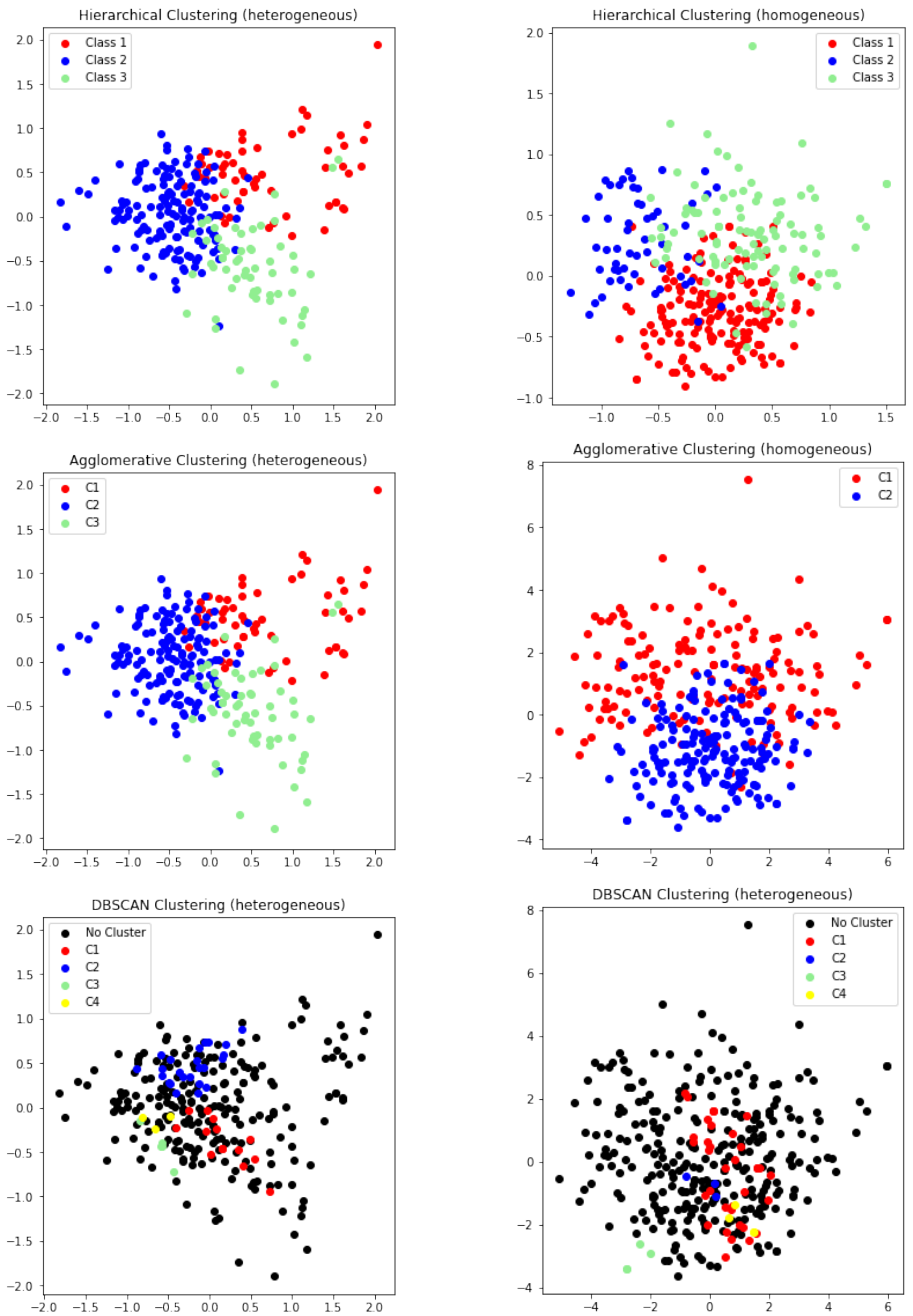


FIGURE C.2: Clustering results on the PC plane. Each line is devoted to hierarchical clustering results, agglomerative clustering and DBSCAN respectively

Appendix D

PCA results

Principal Component Analysis allows to show in two dimensions the position in a plane of all users according their contributions. After normalizing the data I fit the pca of sklearn and then I plot the first two principal components. The variation of data captured by the first two principal components are 44.3% for the heterogeneous case and 38.4% for homogeneous game. Although they are very low values, which mean that there are a lot of information left compared to the original data, the principal components allows to represent the information in a plane and at least we see the different distributions among treatments on it. Let's see in figure D.1 the accumulated variance of the principal components for each treatment:

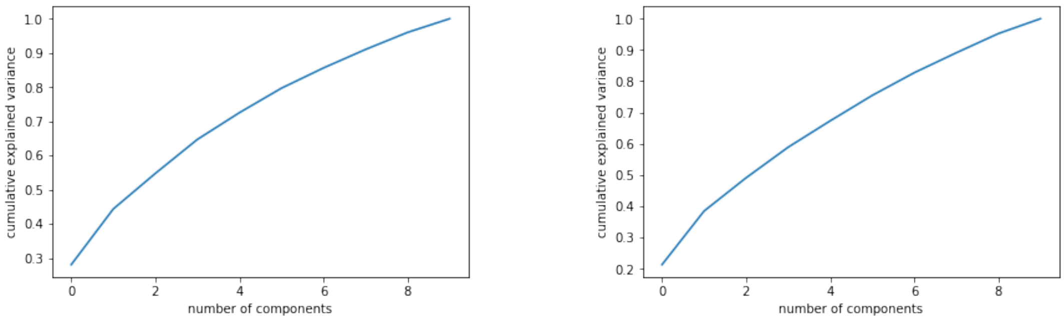


FIGURE D.1: Accumulated variance of each principal component (left for the heterogeneous case and right for the homogeneous.

Although the little drawback related with the little explanation capacity of the first two PCA the result in figure D.2 shows that the distribution of the players in this plane differs between heterogeneous and homogeneous games. For homogeneous games users are printed closely around the (0,0) point and distributed in a quite homogeneous way. This situation does not give much information about particular groups or clusters that could have. Instead, for the heterogeneous case, individuals are spread in a different way on the plane. There is an important nucleus at (0,0) (similar as in the homogeneous case) but then a significant amount of individuals are distributed in particular zones farther from the center.

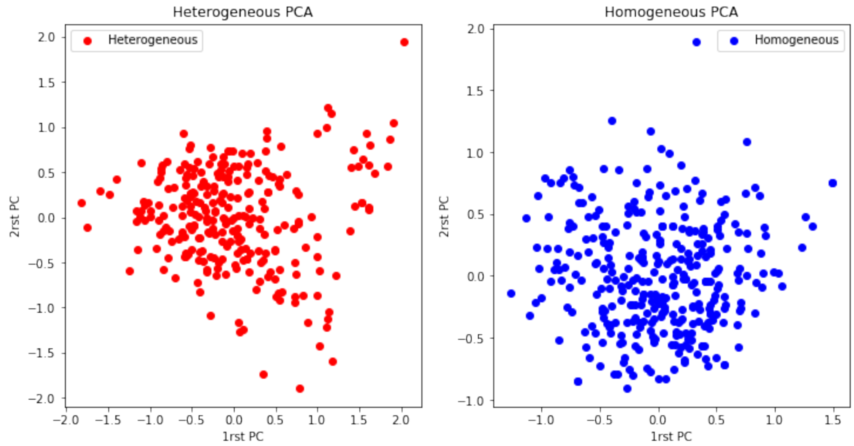


FIGURE D.2: Scatter plot of the two first principal components for both treatments (the left for heterogeneous games and the right for homogeneous ones

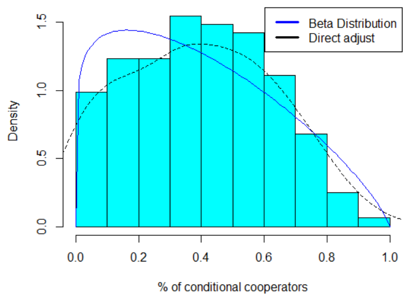
The difference observed seems to indicate that there can be more different clusters in the heterogeneous case than the homogeneous one. This is going to be confirmed in the cluster analysis part were we use PCA to visualize the distribution of these clusters.

Appendix E

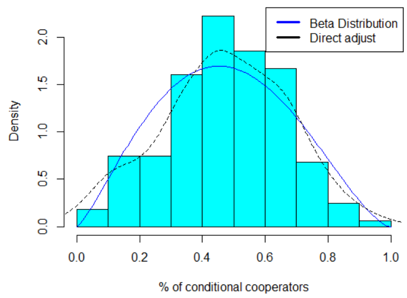
Conditional Cooperation

Conditional cooperation is a classic strategy in game theoretical games. We build a new binary variable that was 1 if the individual acted as a contidional cooperator at round t and 0 otherwise. The results obtained for the distribution of individuals are in Figure E.1. The fit curve is computed based on the results by the functions defined at the "fitdistrplus" library of R. The best one for all datasets was a beta distribution.

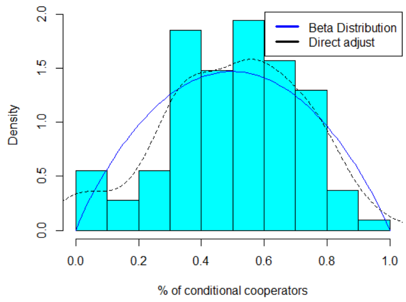
(A) Heterogeneous DAU



(B) Homogeneous DAU



(C) STREET



(D) VIL

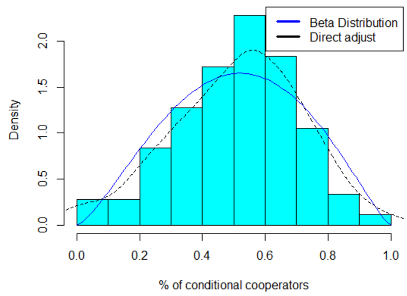


FIGURE E.1: Distribution of conditional cooperators in each dataset. X-axis represent the proportion of times individuals follows such rule.

The parameter values of each distribution are: (α,β) = (1.155, 1.789) for heterogeneous DAU, (1.931, 1.939) for STREET, (2.336, 2.614684) for homogeneous DAU and (2.430, 2.313) for VIL.

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