Modelling Global Pattern Formations for Collaborative Learning Environments

Corrado Grappiolo, Yun-Gyung Cheong, Rilla Khaled, Georgios N. Yannakakis
Centre for Computer Games Research
IT University of Copenhagen
Rued Langgaards Vej 7 Copenhagen, Denmark
Email: {cogr, yugc, rikh, yannakakis}@itu.dk

***Abstract*—We present our research towards the design of a computational framework capable of modelling the formation and evolution of global patterns (i.e. group structures) in a population of social individuals. The framework is intended to be used in collaborative environments, e.g. social serious games and computer simulations of artificial societies. The theoretical basis of our research, together with current state of the art and future work, are briefly introduced.**

I. Introduction

The interactions among a population of social individuals (agents) — due to factors such as the agents' attitude, personality, cultural biases and stereotypes, and history of past interactions [1] — yield complex dynamics which lead to the formation of global patterns, intended as the behaviour of the system as a whole [2]. Global patterns, such as group identities and norms, influence the behaviour of the individuals in an indirect, implicit manner [2], with the potential threat of generating and aggravating social conflicts, such as social discriminations and other forms of inequalities. The ability to monitor the formation of global patterns, model their structures and their influence on the society is important, as it will not only provide an instrument for understanding the causes of social conflicts, but will also contribute to the evaluation of the effectiveness of intervention methods. A way to effectively detect global pattern formations is through modelling the local-to-global transition (e.g. from agent interactions to group structures). However, doing so is not a trivial task due to the recurrent influence of the global structure in the society-system[1].

The main questions this research intends to answer to are: (1) is it possible to create a computational model capable to represent the local-to-global transition? (2) is it possible to *predict* the formation and evolution of global patterns, and infer characteristics of their internal structures? (3) what constitutes the indirect mechanism and how does it influence the agents? (4) is it possible to intervene at the global level (e.g. by means of regulations) in order to affect the behaviour of the local level? As our research is informed by the Complex Adaptive Systems (CAS) literature [1], [2], our intention is to leverage the concepts, theories and findings of social and behavioural sciences in identifying the emergent properties of complex systems [3]. Our research is structured into four areas of investigation: (1) exploration of existing theories on global pattern formation; these are usually qualitative and focus on aspects of interaction which are abstract and complex (i.e. collaboration and fairness); (2) formalisation of the theories through computational measures and learning algorithms, and contextualisation of them in realistic social scenarios, such as social dilemmas; (3) implementation of the social scenarios in computer simulations of artificial societies [4], [5]; which will facilitate preliminary validation of our models; (4) extension of application of our models and social scenarios to human-based collaborative (virtual) environments, such as multiplayer games, which will enable final evaluation of the effectiveness of our models.

As such, global pattern modelling represents a new tool for the creation of educational environments (serious games) that convey concepts like conflict, collaboration, and fairness. Further afield than educational environments, global pattern modelling may contribute to research fields such as behavioural and social sciences, evolutionary dynamics, collective behaviour, as well as macroeconomics and political sciences.

[1]Sometimes it is referred to as *emergence of complexity* [1]

II. State of Our Research

We are currently conducting experiments based on artificial societies to establish optimal learning algorithms and metrics for detecting consolidated group identities (i.e. the ability of an individual to identify himself or herself with his or her group [6]) in the population. The agents interact with each other by means of the social ultimatum bargain game [7]. Several initial configurations representing different group identities (which imply social preferences [8]) have been defined and are being maintained, that is, the agents will not adapt their behaviours in response to behavioural dynamics. We are now going to briefly describe the society's interaction protocol and the structure of the Group Modelling framework (GM) which would allow us to detect group identities.

A. The Social Ultimatum Bargain Game in Use

The interaction protocol is hereby briefly introduced. (1) a population $\mathcal{P}$ of n agents are first divided into m partitions P; (2) for each partition, an agent a_i is randomly selected to become the provider agent of the social ultimatum bargain game, all the other agents of the partition become receiver agents; (3) the provider agent bargains with each receiver agent over an equal endowment e. For each bargain, a_i proposes an offer $0 \leq o_{i,j} \leq e$ to receiver agent a_j; according to the social relationship between the agents — which are consequence of the agents' group identities — the offers will variate in generosity [8]; (4) a_j can either accept the offer or refuse it; (5) the final outcome for a_j is either 0 or $o_{i,j}$; the final outcome for a_i is the sum of all the $(e - o_{i,j})$ accepted bargains.

B. Measuring Levels of Cooperation

To detect the existence of sub-groups in the population, and to assign a group identity to the individuals, we analyse the different levels of cooperation amongst the agents through their interactions [6]. Our hypothesis is that by observing the level of cooperation [10] of a provider agent with respect to the whole partition P_k, we can understand which receiver agents he *prefers* to bargain with. This would imply that he is more altruistic and collaborative [10] with some of the agents in the partition, hence is more likely to share the same group identity.

For the current state of our research we are considering both deterministic and stochastic metrics of provider agent's favourability which return a value indicating whether the agents under consideration belong to the same group or not (*in/out-group* values [6]). We will refer to the metrics as *interaction classifiers*, denoted with $\mathcal{I}$.

C. Learning Collaboration

To learn cooperation values among the individuals which encompass the history of past interactions [1] we are currently considering the following *Constant-α Monte Carlo* update rule for non-stationary environments [9]:

$$\mathcal{C}_{i,j}(t) = \mathcal{C}_{i,j}(t-1) + \alpha \left[\mathcal{I}_t - \mathcal{C}_{i,j}(t)\right] \quad (1)$$

$\mathcal{C}_{i,j}(t)$ is the cooperation value between the provider agent a_i and the receiver agent a_j up to the t-th interaction, $\mathcal{I}_t$ is the level-of-cooperation-value computed by the interaction classifier introduced in Section II-B, and α is a constant step-size parameter. Finally, collaboration values are obtained by considering reciprocal altruism [1], [10] through the following equation:

$$\mathcal{C}^{\triangle}_{i,j}(t) = \frac{1}{2}\left(\mathcal{C}_{i,j} + \mathcal{C}_{j,i}\right) \quad (2)$$

D. Detecting Group Identities

The collaboration values $\mathcal{C}^{\triangle}_{i,j}$ are then used as a dissimilarity matrix by a clustering algorithm. The number of group identities and the corresponding agents are then determined. We are currently investigating the use of the complete-link clustering algorithm with elbow rule as validity method.

III. Future Work

Our future work will follow four concurrent paths. First, we will seek for the best methods and parameters in order to make our framework robust with respect to the size of the society (n), locality (m) and partial observability of the interactions (m). On that basis, ongoing research on the definition of a group-based metric of fairness is being conducted. As fairness of offer distribution is an abstract, subjective, and ambiguous term we designed several ad-hoc metrics of fairness based on key and generic elements of fair offers, such as the amount of the offer and the need of the receivers. We then tested those against human notions of fairness, by running a crowdsourcing experiment in which participants were asked to compare levels of fairness of dissimilar offer distribution scenarios in a resource management game environment [11]. Preliminary results suggest that some of our fairness metrics are consistent with human notions of fairness and are both accurate and robust across different game scenarios and levels of fairness distribution complexity. Second, we will enrich the level of complexity of the artificial agents, e.g. by representing affect and enabling adaptation; we will also augment the possibilities of social interactions by introducing other social dilemmas, such as the tragedy of the commons [6]. Third, we will investigate methods for modelling the internal group structures, such as leaderships and norms [12], and the between-group dynamics (e.g. evolution). We will also investigate methods to intervene at global level (e.g. by modifying the interaction protocols) in order to affect, in a feedback loop, the behaviour of the society, in order to achieve envisaged goals, such as the maximisation of collaboration or the reduction of social inequalities. Finally, we will consider game-based environment, and will increase its level of abstraction by concealing money-related notions and instead representing social conflict scenarios [10].

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