Agent Based Models of Social Systems and Collective Intelligence

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Abstract: **Agent-based modeling and simulation techniques have now become a suitable and popularly used approach to build useful models of social systems, which not only helps to get better understanding of various social phenomena but also enriches the agent-based computing paradigm in return. Agent-based models allow simulating social units such as individuals, households, organizations or nations and their direct or indirect interactions. These models demonstrate how global order and collective intelligence can emerge from relatively simple local interactions and can explain the dynamics of the emergent behaviour. The Agent-based modeling approach has provided the bridging link between psychological & sociological analysis of individual and social behaviours respectively, which was otherwise missing. This generative, proof-by-construction approach has also complemented the individual-centered research in cognitive science by showing that individual alone is not the crucial unit of cognition but is affected by environment and society besides affecting them as well. In this paper, we have given an analytical account of Agent-based modeling of emergent collective social behaviours, on these lines, along with relevant theoretical & experimental outcomes and their implications for multi-agent systems.**

Keywords- Agent Based Computing, Collective Intelligence, Computational Sociology, Emergence, Multi-Agent Systems.

I. INTRODUCTION

In Agent-based modeling (ABM) a system is modeled as a set of autonomous agents, who can perceive the environment and act on the basis of some behavioural rules. The agents represent the actors in the system; environment represents the surroundings including neighbouring agents; and the behaviour rules model the interaction of the agent with other agents as well as with the environment. ABM can be used to model a number of phenomena in varied domains like Markets & Economy, Organizations, World Wide Web and Social Systems etc. Availability of fast and cheap computing power, coupled with other advances in computational sciences has paved the way for use of ABM as a favoured modeling and simulation technique. Since last few years ABM has become the frontrunner tool of the Sociologists and Psychologists who try to model social behaviours, particularly the behaviour of groups. A large number of researches are now being carried out using this generative approach to model and analyze social phenomenon, such as spread of rumors, diffusion of ideas, emergence of cooperation, emergence of conventions & social norms, evolution and dynamics of spread of religions and cultures etc.

Collective Intelligence is defined as intelligence of groups comprising of many individual actors. Human (even insect and animal) groups working together are known to produce collective behaviours which seem intelligent. Individual actors participating in generation of collective behaviour often do not understand or even perceive the final global behaviour. They can see and interact only in their local neighbourhoods. These simple and local interactions are known to produce emergent global behaviours, such as ant colonies, bird flocks, human settlements, organizations and markets. The foraging behaviour of ants [1], flocking behaviour of birds [2], complex patterns of human settlements [3], forms of organizational behaviour and working of markets [4] are all examples of Collective Intelligence in action. Understanding how (and possibly why) these complex and intelligent collective behaviours emerge from limited local interactions; have been a primary research question for sociologists since decades. ABM seems to provide the right methodology and tool towards this end. The application of ABM approach in this endeavor on one hand helps in getting a better understanding of the system under study and at the same time ABM application to social systems provides new principles and mechanisms for the broad area of agent-based computing.

The development of social simulation over the past half century can be grouped into three broad periods: macrosimulation, microsimulation and agent-based models [5]. Sociologists, particularly computational sociologists, first tried macrosimulations to model problems in supply-chain management, inventory control in a warehouse, urban traffic, spread of epidemics, migration and demographic patterns. Macrosimulations consist of a set of differential equations that take a holistic view of the system. However, taking the complete system as the unit of analysis had inherent limitations. Microsimulations focused on the use of individuals as the unit of analysis but continued with macro-level forecasting used in macrosimulations. Though microsimulations modeled changes to each element of the population but they did not permit individuals to directly

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interact or to adapt. The main focus remained forecasting macro effects of public policies that alter individual behaviours. ABM, the third methodology, takes a pure bottom-up approach and keeps the individual at the centre. It allows modeling individual actors in the population and their interactions with each other as well as with the environment. This makes it a highly suitable technique for analysis of emergent group behaviours resulting only from local interactions of individuals. Besides, there are many other advantages of this approach. This paper tries to characterize the key components of ABM approach (Section 2), present a relevant account of use of ABM to model and analyze emergent collective behaviours (Section 3) and report our experimental work on the paradigm of social influence (Section 4). The paper concludes with a discussion of experimental outcomes and their implications for the broad area of agent-based computing.

II. AGENT BASED MODELING APPROACH

From a practical modeling point of view, an Agent can be defined as an identifiable discrete individual with a set of characteristics and rules governing its behaviours and decision making capability [6]. Agents are situated in the environment and are autonomous. An Agent can be simple reactive entity or capable of goal directed behaviour. Agents usually contain a base-level set of rules for behaviour as well as a higher-level set of “rules to change the rules” [7]. ABM is a bottom-up approach which starts with identification of constituent agents of a system and their particular behaviours. The system is then modeled as a collection of such autonomous agents which can interact with the environment as well as with each other. Agent based modeling of social systems often makes the following four assumptions: (a) Agents are autonomous; (b) Agents are interdependent; (c) Agents follow simple rules; and (d) Agents are adaptive and backward looking [8].

A. *Motivation for ABM*

Traditional modeling approaches to social systems relied on equation-based models that operate with a macro perspective. They operate on population attributes & their distributions and lack the focus on individual’s role. Equation-based models, though useful for macro-scale behaviour predictions, fail to model social systems (or processes) that lack central coordination, systems that are very complex in terms of their interdependencies and systems which produce novel emergent behaviours in absence of a clear understanding of the collective phenomenon. Axtell [9] takes this argument a level further and suggests that there are three distinct uses of Agent-based computational models of social systems: (a) when numerical realizations can be proposed and solved: agent models can be used as social simulations; (b) when a mathematical model can be formulated but can only be partially solved: agent based models can be useful tool of analysis; and (c) when mathematical models are either apparently intractable or provably insoluble: agent based modeling is perhaps the only technique available for systematic analysis. Availability of fast & cheap computing power along with rich easy-to-use software environments also favours the use of ABM in Social Sciences.

B. *When to use ABM*

Although technically simple, ABM is conceptually deep. ABM’s inherent programming simplicity may result into its improper use. Modeling a complex social process requires high conceptual clarity and analytical ability. A key issue, therefore, is to decide when to use ABM for modeling social systems. An indicative list of situations when it is better to think and model in terms of agents is: (a) when there is a natural representation of actors as agents; (b) when the interactions between the agents are complex, non-linear, discontinuous, or discrete; (c) when agents exhibit complex adaptive behaviours; (d) when the population or topology of interactions is heterogeneous; and (e) when agents have spatial component to their behaviours & interactions. ABMs in social sciences involve human agents, whose behaviours are often complex, irrational and subjective; therefore, one needs to think carefully about the social phenomenon at hand before going for ABM. Further, the model needs to be built at the right level of description, with only the right amount of details. Unnecessarily adding complexity to a model can make it useless.

C. *Benefits of ABM*

Understanding social systems not only requires understanding the individuals that comprise the system but also how individuals interact with each other resulting in global behavioural patterns, which can be sufficiently novel. ABM is well suited for this social science objective. ABM helps researchers in investigating how large-scale macro effects arise from the micro-processes of interactions among many agents. Axelrod and Tesfatsion [10] call ABM the third way of doing science besides induction and deduction. They state that specific goals pursued by researchers take four forms: empirical, normative, heuristic, and methodological. ABM applied to social sciences take a methodical approach that could permit two important developments: (a) rigorous testing, refinement, and extension of existing theories that are difficult to evaluate using mathematical & statistical techniques; and (b) a deeper understanding of fundamental causal mechanisms in multi-agent systems. Bonabeau [11] goes a step further in proposing that ABM is a mindset and not merely a technology. He summarizes benefits of ABM over other modeling techniques in three statements: (a) ABM provides a natural description of a system; (b) ABM captures emergent phenomena; and (c) ABM is flexible.

D. *Steps involved in ABM*

Designing an Agent-based model of a social system require first identifying the purpose of the model, i.e., the potential question to be answered. The typical steps to be followed afterward can be summarized as following: (a) identifying the agents and their behaviour rules; (b) identifying agent relationships and their interaction patterns; (c) selecting an ABM platform; (d) obtaining the required relevant data; (e) validating the agent behaviour model; (f) running the model and recording the outputs; (g) analyzing the outputs with a viewpoint of linking micro-scale behaviours of the agents to macro-scale behaviour of the system; and (h) validating the model outcomes and hence the model.

E. ABM Computational Resources

Many rich and easy to program software platforms and toolkits for ABM are now readily available. Some of the popular modeling tools (particularly for social sciences) are: Net Logo (http://ccl.northwestern.edu/netlogo/), Repast (http://repast.sourceforge.net/),Swarm (http://www.swarm.org), and MASON (http://cs.gmu.edu/~eclab/projects/mason/). Net Logo is a multi-agent programming language and modeling environment designed in Logo programming language. It is highly suitable for modeling and exploring emergent phenomena. Repast is basically an agent-based social network modeling toolkit but has rich libraries to study dynamics of social processes as well. Swarm is a multi-agent simulation package to simulate the social and biological interactions of agents and their emergent collective behaviour. Swarm has two versions, namely Objective-C and Java versions. MASON is one of the latest Java platforms in this group. In addition to these platforms, there are many other toolkits & APIs available for modeling and visualizing social systems.

F. Validating ABM

ABM, now an established scientific research practice, needs to incorporate a proper methodology of validation in order to verify the robustness of its findings and to truly act as a bridge between disciplines. Since simulation results of ABM are very sensitive to how agents are modeled, validation of computational model & simulation results is a critical issue in ABM [12]. Several approaches for validation of agent-based computational models have been proposed. Carley & Gasser [13] categorizes the validation approaches into three broad categories: (a) *theoretical verification*, which determines whether the model is an adequate conceptualization of the real world with the help of situation experts; (b) *external validation*, which determine whether the results from the model matches the results from the real world; and (c) *cross-model validation*, which compares the results of the model with other models. All these approaches are essentially aimed at validating the model at the macro level. Gilbert [14], on the other hand, emphasized that in order to completely validate a model it should be validated not only at macro-level but also at micro-level. Before going for a macro-level validation it is necessary to confirm that micro-level behaviours of agents are adequate representation of the actors in the system. *Econometric validation* and *companion modeling techniques* have been advocated to be suitable for empirical verification of social system models [15]. There are, however, still some methodological problems arising in empirical validation of agent-based models [16], and validation continues to be one of the central epistemological problems of computer simulation and modeling methods including ABM [17].

III. ABM & EMERGENT COLLECTIVE BEHAVIOUR

Agent-based modeling of social systems focus particularly on how simple and predictable local interactions generate highly complex emergent global patterns such as diffusion of ideas, emergence of social order & norms, cultures and collective action. The emergent global patterns and system-level structures are sometimes entirely of new type, that are not apparent from the behaviours of individual actors. The bottom-up (generative) approach adopted by ABM helps in a detailed analysis of *how* and *why* of the emergent system-level behaviours.

A. Characterizing Emergent Behaviour

The concept of emergence has been first discussed in Philosophy and is now widely used in complex systems and distributed artificial intelligence literature [18], [19], [20]. However, it still lacks a universal definition. Emergence is generally referred to in the notion of "*the whole is more than the parts*". One of the earliest & classical definitions of emergence is attributed to Broad [21]. His definition of emergence asserts that there are certain wholes, composed of constituents (say) A, B and C, in some relation R to each other; that have certain characteristic properties which cannot be deduced from the most complete knowledge of properties of A, B and C in isolation or in other wholes which are not of the form R (A, B, C). Emergent behaviour in social and multi-agent systems is usually that behaviour which cannot be attributed to any individual agent, but is a global outcome of agent coordination [22], [23], [24]. An emergent behaviour, therefore, cannot be predicted through analysis at any level simpler than that of the system as a whole [25]. Though emergent behaviours come from the individual agents, it is the set of interactions that make it difficult to analyze them. Individuals interact to produce different global behaviours, which affect other individuals and their behaviours; this in turn affects the original individuals (*immergence*) [26]. This complex feedback loop makes the analysis of emergent behaviour difficult and calls for methods like ABM [27].

B. Early Agent-based Models of Emergent Behaviours

John Conway's proposal of cellular automata based "Game of Life" [28] and Craig Reynolds's "Boid Simulation" [2] can be regarded as one of the earliest and simplest Agent-based models of emergent collective behaviour. Conway proposed a two-dimensional grid of cells where each cell can be *On* or *Off* based on three simple rules: (a) a cell will be *On* in the next generation if exactly three of its eight neighbouring cells are currently *On*; (b) the cell will retain its current state if exactly two of its neighbours are *On*; and (c) the cell will be *Off* otherwise. Two important things to note here is that the interaction rules are very simple and use only local information. Conway distributed the *On* and *Off* cells randomly on the grid and allowed the system to run. After several iterations distinctive novel patterns emerge which can sustain for indefinite periods.

The Boid simulation of Reynolds, models the interactions of agents (birds) with simple behavioural rules: (a) *Cohesion*: each agent steers toward the average position of nearby flock mates; (b) *Separation*: each agent steers to avoid crowding local flock mates; and (c) *Alignment*: each agent steers toward the average heading of local flock mates. The model is run by initially placing the agents at random locations and then allowing the behavioural rules to operate iteratively. Surprisingly, even with three simple rules applying only locally, leaderless flocks emerge. A snapshot of a typical run of a Net Logo implementation of Boids simulation is shown in Figure 1.

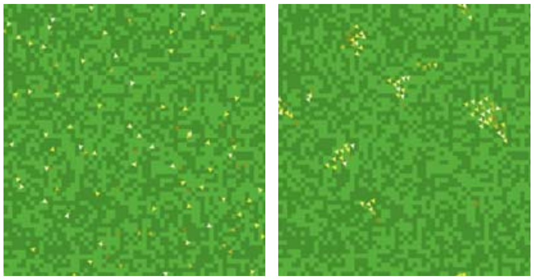

Figure 1. A Snapshot of the Net Logo implementation of the Boid model on a 30 X 30 grid, with 100 agents. Pattern on the left is the initial random placement, whereas pattern on the right is the boid arrangement after 1200 ticks.

C. ABM applied to Complex Collective Behaviours

ABM is currently being applied to model a variety of complex social phenomenon where simple local interactions generate emergent system-level behaviours. Some representative & relevant work can be found in [29], [30] & [31]. Macy & Willer [8] group most of the work on Agent-based modeling of collective behaviours in two categories: (a) *models of emergent structure* which includes works on cultural differentiation, homophilous clustering, idea diffusion, convergent behaviours and norms; and (b) *models of emergent social order* which include viability of trust, cooperation and collective action in absence of global control. Goldstone & Janssen [32] also identify three similar themes for Agent-based computational models of collective behaviour namely: (a) p*atterns and organizations* which include settlement patterns & segregation, human group behaviours and traffic patterns; (b) *social contagion* which include spread of ideas, fashions, cultures & religions; and (c) *cooperation* which include evolution of cooperation, trust & reputations and social norms & conventions. Our focus in this paper is particularly on models of cultural convergence & differentiation in presence of social influence.

D. Modeling Social Influence & Cultural Convergence

Social influence assumes that individuals (or agents) often imitate good behaviours through their interactions with other individuals. Its dynamics depends on familiarity of the interacting individuals, density of the neighbourhood, and popularity and spatial proximity of the other individuals. Interesting models of social influence have been proposed by Carley [33], Axelrod [34] and Axtell [35], Coleman [36], Nowak et al [37] etc. Axelrod, in his social influence model of dissemination of culture [34], focused on factors of local influence (tendency for people who interact to become more similar) and homophily (tendency to interact more frequently with similar agents). The more agents interact, the more similar they become; and the more similar they become, the more likely they are to interact. Axelrod expected convergence and homogeneity as the outcome but simulation shown that despite the strong converging pressure, stable regions of diversity persisted.

Axelrod basic model included sites arrayed on a grid. These sites are the basic actors of the model. Each site can interact only with its immediate neigbours (typically 4 or 8). Agents who are similar to each other interact with each other and become more similar. Axelrod's model captures culture as a group of features with multiple trait values per feature. However, the emphasis is not on the content of a specific culture but on the way in which culture is likely to emerge and spread. The simulations with varying parameters regarding grid size, number of features and number of traits per feature resulted in polarization, despite the only mechanism for change being convergence towards a neighbour. We have extended Axelrod's social influence model along two different dimensions: (a) introduction of a global bias towards a particular set of trait values for features; and (b) making some sites more influential (thereby making them highly contagious and less prone to changes).

In the first extension we incorporated the effect of a global bias, in favour of a particular culture, by introducing a tendency to favour a global trait value for a particular feature. This global bias can be viewed either as a strong effect of mass-media or a high global selective pressure (may be the result of a global norm or convention). When an agent interacts with another similar agent in its neighbourhood, it tries to find a dissimilar feature in the target agent and offers its own feature value for that feature to the target agent. However, unlike normal social influence model the target agent may accept or may defer acceptance of the offered value by the source agent, based on the condition that whether the offered value is a globally favoured value or not. If it's a globally favoured one the target sets its corresponding feature to the offered value; otherwise rather than accepting the offered value, it increments the number of offers for this trait value for this feature, in its feature-offer list. When a change threshold is reached the offers for normal values (which are not the favoured ones) are accepted. This is to model the fact that an idea/ trait may find favour with an individual irrespective of it being a globally favoured trait, if it is possessed by a majority of agents in the neighbourhood of the agent concerned. We run the model many times with varying parameters. The results are reported in Section 4.

Second extension involved making some agents highly influential, such that they will always affect agents in their neighbourhood and will not be affected by a normal agent. However, when an influential agent interacts with another influential agent and there similarity level is greater than a threshold value; they will become more similar by making one of their dissimilar features same. If two influential agents with similarity less than the threshold interact; they will become more dissimilar by changing one of their similar features. This is to model the fact that when two influential individuals, who are quite similar, interact with each other they tend to agree on more aspects rather than disagreement. However, if the two interacting influential agents are substantially dissimilar they may tend to differ more by artificially increasing the differences. We wanted to see the effect of presence of few influential agents in the system on the behaviour of other agents and the global macro-level behaviour of the system. We expected that stable cultural regions should develop around the influential agents. However, the results, reported in the following section, are slightly different.

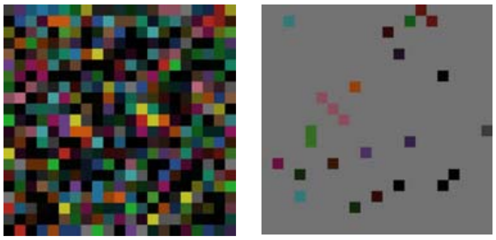

Figure 2. A Snapshot of the first extended model on a 20 X 20 agent grid. Figure on the left is the initial agent repertoire, whereas figure on the right is the agent repertoire after 100000 ticks.

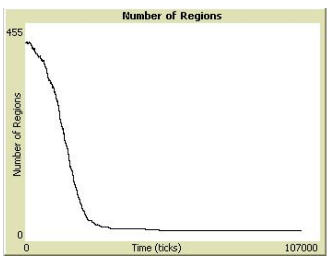

Figure 3. The plot shows the number of distinct regions vs. time on a run of 20 X 20 grid, aggregated over 20 runs.

IV. EXPERIMENTAL RESULTS

We have implemented the extended models using Net Logo platform [38]. In the first setting we created a 20 X 20 wrap-around agent grid, with each agent characterized by a set of features (say 5), where each feature can have different numerical values (say 1 to 5). An agent can interact with another agent in its neighbourhood (typically Moore neighbourhood). An agent randomly selects another agent in its neighbourhood to interact. Interaction between these two agents is conditional upon there being at least one similar feature between them. In the simple model, when the agent finds a target agent for interaction, it tends to adopt the trait value of the target agent, corresponding to one of the dissimilar features. This makes the interacting agents more similar. In case of the two agents being completely dissimilar, no interaction takes place. This process is run iteratively. We modified this setup by making certain trait values for different features being globally favoured (say 12345 may be a highly favoured feature set). When an agent now interacts with a target agent it tends to adopt a trait value, corresponding to a dissimilar feature, from the target if it is a globally favoured trait value. Otherwise it simply increments its offer-set for this trait value. When the not globally favoured offers for a feature increases a threshold it is adopted by the agent. We made a number of runs of this model to observe the effect of a global bias towards a particular feature set. A typical screenshot of the agent grid for the run is shown in Figure 2. The grey color patches contain the globally favoured feature values. Figure 3 plots the number of stable regions vs. number of ticks, averaged over 20 runs. The social influence dynamics tends to make the agents more similar with the passage of time. However, few stable regions (of dissimilarity) still persist. This is due to the fact that once agents become dissimilar enough no further interaction takes place, as the similarity is the precondition for interactions.

Figure 4. A Snapshot of the second extended model on a 20 X 20 agent grid with ‘I’ labels denoting influential individuals. The figure shows group formation around the influential agents after 400000 ticks.

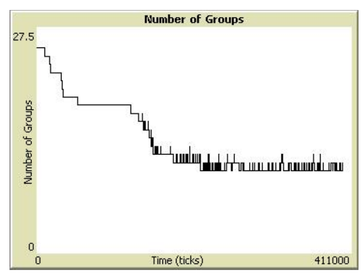

Figure 5. The plot shows number of distinct groups (on vertical axis) vs. number of tics (on horizontal axis), averaged over 20 runs on a 20 X 20 wrap around agent grid.

In the second experiment, we made some of the agents special, by associating a high influence score with them and placed them at random locations on the grid. Usually the number of influential agents is kept very low (typically 1 to 2% of the total number of agents). The influential agents always affect the agents in their neighbourhood who interact with them and are generally not affected by other agents (non-influential). Moreover, the influential agents tend to have access to a greater neighbourhood. When an influential agent interacts with another influential agent, it may adopt one of the trait values of the target subject to their being substantially similar. In case they are only marginally similar they may become more dissimilar by changing one of their similar feature values. We expected that the agent population will converge and stable regions of similarity may be formed around influential agents. We made a number of runs of the model with varying parameters of number of features (ranging from 2 to 5) and the number of traits per feature (varying from 5 to 10). A typical screenshot of a run is shown in figure 4. A plot of number of groups vs. number of ticks averaged over 20 runs is shown in Figure 5. The results are somewhat different from that expected. Though influential agents tend to show their influence over their neighbourhood, but oscillations are noticed along the group boundary. The agents on the edges of the group tend to keep changing group memberships thereby preventing complete stability. The following section analyzes the results and their implications for agent-based computing paradigm, in general, and multi-agent systems, in particular.

V. CONCLUSIONS

ABM is now one of the favoured modeling techniques, not only in physical & computational sciences but also in social sciences. More amazingly, it is playing a double ended role, by providing appropriate modeling and analysis tool for understanding social systems & processes, and thereby generating new principles and mechanisms for designing multi-agent systems. Emergence of desired collective behaviour in multi-agent systems calls for appropriate principles to be followed while designing multi-agent systems. This inverse problem of characterizing the mechanisms producing desired emergent behaviours can be solved by applying ABM approach to modeling emergence in natural systems. A number of research works are being done to analyze the dynamics of emergence of macro-level behaviours in agent collectives, particularly those regarded as collective intelligent behaviours, are being pursued at different places.

The social influence theory and the experiments done in this paper elaborates upon a number of issues concerned with multi-agent systems design, namely the homogeneity and heterogeneity of agents, the way in which one agent can have influence over other agents in its neighbourhood, issue of emergent macro-level convergence patterns obtained only through local interactions and the effect of presence of global bias (such as norms or conventions) & leader agents (such as central or core agents) on agent behaviours. The model suggests that strong social influence of agents over their neighbourhood can have a homogenizing & converging tendency even in relatively heterogeneous agent populations. Presence of an external norm can also help in attaining desired macro-level behaviour. Moreover, central (leader) agents need not always favour convergence of opinions among agents in a multi-agent system. Different leaders tend to influence the agents in a different forceful way and can lead to non-convergent behaviours of agents in their influence. The designer of a multi-agent system aiming for desired collective intelligence at macro-level, thus needs to carefully look into the role of factors like social influence, global bias and leader agents.

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