Multi-Agent Based Models of Social Contagion and Emergent Collective Behavior

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Abstract— **A deeper understanding of emergence of global patterns in social systems such as diffusion of ideas, emergence of norms & conventions, higher organizations, collective wisdom and evolution of culture; through simple and predictable local interactions of individuals, has been a long quest for sociologists. Agent-based modeling is the latest approach which has virtually replaced the use of traditional techniques of equation based models & micro simulations for social systems analysis. This new paradigm, in addition to being applied to model & analyze various social systems, is also finding widespread application in diverse domains such as economics, business organizations and computational systems. The findings of agent-based models of social systems not only help obtaining a better understanding of the investigated phenomenon but also provide valuable inputs for design of agent-based computational formulations for solving different problems in varied domains. In this paper, we have tried to characterize the use of multi-agent based modeling approach of social contagion and emergent collective behavior along with our experimental work on neighbourhood aggregation model. The paper concludes with a short discussion of the relevant implications for multi-agent systems design.**

Keywords- Agent-based modeling, Social Contagion, Collective Behavior, Emergence, Multi-agent systems.

I. Introduction

Understanding behavioral patterns as complex as that of human beings, is a difficult task. While Psychologists aim to understand individual behavior, Sociologists make the entire society as their unit of analysis. They focus on understanding social behaviors, i.e., behaviors of groups & their interactions. Sociologists have historically adopted two approaches towards this end: macro-simulation and micro-simulation [1]. Macro-simulation adopts a top-down approach in modeling the social phenomenon. It resorts to equation based modeling, where the entire system statistics is represented as a set of differential equations. Micro-simulation also takes a system-level forecasting view, but it allows modeling changes in individual units. Both these approaches have proved useful for forecasting global macro-scale behaviors. However, when one is interested in dynamics of emergence of the global system behavior, both these approaches fail miserably. A reductionist approach often fails to explain the dynamics of emergent behavior, therefore a detailed analysis of emergence requires keeping the actors at the focus and observing the interactions among them. Agent-based models provide an easy-to-use and analytically appropriate technique towards this end.

Agent-based modeling is a bottom-up approach, where a system is modeled as a set of agents [2], [3], [4]. Each agent is capable of producing some behaviors. Usually the behavioral rules programmed in the agents are kept limited to those believed to be affecting or affected by the phenomenon being studied. The agents are allowed to interact with the environment and also with other agents. Interactions could be localized to neighbourhood or to other distant agents, depending on the topology modeled. Building an agent-based model for a social phenomenon requires: (a) identifying agents; (b) determining agent behavioral rules; (c) identifying agent relationships and interactions; (d) deciding an appropriate agent computing platform; and (e) implementing the model and observing the results [5]. Agent-based models employing a large number of agents are often termed as Multi-agent based models. Multi-agent based models have been applied to study a variety of social phenomenon involving multiple actors. This approach has many attractive features that make it more suitable for exploring collective behaviors.

Simple and predictable local interactions of individuals sometimes produce amazing collective behaviors. Economic markets, leaderless groups, nations, World Wide Web are all examples of emergent collective behavior. Creating agent-based computational models of social units (e.g. families, firms or nations) helps in analyzing the dynamics of emergence of collective behaviors and building useful theories. Social contagion, one of the most studied phenomena, refers to spread of ideas, influence, conventions, religion and culture etc. The focus in agent-based modeling of social contagion, however, is not only limited to spread of information but also focuses on the global behaviors that may result out of it. In this paper, we aim to characterize the multi-agent based modeling approach to collective behaviors (Section 2); describe our experimental work on neighbourhood aggregation model (Section 3 & 4) followed by a short discussion of the relevant issues.

II. Multi-Agent Based Modeling Approach to Emergent Collective Behaviors

Collective behaviors are those behaviors attributed to individuals working in a group. Groups are known to produce collective behaviors, some of which cannot be understood by reductionist analysis to the individual level. These behaviors are generally termed as emergent behaviors. Emergence is referred with the notion of "*the whole is more than the parts*". One of the earliest & classical definitions of emergence is attributed to Broad [6]. 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 behavior in social systems is thus usually referred to those behaviors which cannot be attributed to any individual actor, but is a global outcome of interaction of individuals working together [7], [8], [9]. Though emergent behaviors come from the individual agents, it is the interactions that make it difficult to analyze them. An emergent behavior, therefore, cannot be predicted through analysis at any level simpler than that of the system as a whole [10]. The concept of emergence is now widely used in complex systems and distributed artificial intelligence literature [11], [12]. The complex feedback loop of interactions resulting into non-linear system dynamics is what makes the analysis of emergent collective behavior difficult and calls for methods like Agent-based modeling [13].

The multi-agent based modeling approach of collective behaviors is now considered the most suitable technique to answer the generativist's question 'How could the decentralized local interactions of heterogeneous autonomous agents generate the given regularity?'[14]. It provides a number of opportunities for modeling large scale collective systems including online social networks and the World Wide Web (Web). Large amount of data available on the Web through blogs, newsgroups, and social networking sites can be used to study idea contagion and group formation on the Web, with important implications about these phenomena in natural settings. Multi-agent based modeling can also be used to make predictions about public response and success or failure of a proposed policy, by programming agent test-beds and then exploring the potential consequences of public policies, that may have complex non-linear dynamics, in a the simulated setting [15]. For example questions like 'what would be the impact on society if uniform civil code is introduced?' or 'what would be the impact on demography if parents are allowed to choose the sex of their child?' can be explored using agent based models. One of the key research questions that agent-based models attempt to explore is to find the mechanisms, by which individuals within groups learn to cooperate, compete, form coalitions, form organizational structures, create new ideas, and coordinate complex activities.

Most of the work on agent-based computational modeling of collective behavior revolves around three key themes: (a) social contagion; (b) patterns and organizations; and (c) cooperation [16]. Social contagion is the spread of an entity or influence between individuals in a population via interactions between agents. Rumors, fads and fashions are few examples of social contagion. Models of social contagion target deeper understanding of the effect of the information contagion on the macroscopic behavior. Work on patterns & organizations centers around identifying and analyzing emergence of global behavioral patterns and organizational structures from limited local interactions of individuals. Thomas Schelling's segregation model [17], although not implemented as computational agents, is one of the first works of this class. There has been good amount of subsequent research on human settlement patterns [18], human trails [19], traffic jams [20], group formation and cultural differentiation [21]. The last but one of the most complex themes is cooperation. Work on cooperation deals with evolution of cooperation in groups where agents often perform limited and selfish behaviors. Evolution of cooperation, setting up of global norms & conventions, and evolution of trust are the key research areas of this theme. Axelrod's evolution of cooperation [22] is one of the most promising and representative work of this type.

III. MODELING SOCIAL INFLUENCE AND NEIGHBOURHOOD AGGREGATION

We have devised a model of social influence to analyze the effect of neighbourhood on an individual's behavior and to understand the collective behaviors of groups of individuals. The model is based on works on social influence by Axelrod [23] & Lustic [24] and a voting model [25]. Axelrod in his culture model assumed that every individual has a set of features with varying traits corresponding to each trait, i.e., if an individual's feature list has five features, then each feature can have distinct values (represented by different numbers). He suggested that agents who are similar in at least one feature interact and become more similar as a result. This further increases their chances of interactions. The basic idea is that agents are influenced by their neighbours and also influence them. The conception of features can be viewed as the behavior potential of agents. An agent thus, interacts with other agents in its neighbourhood and may change their behavior potential. In this process agent may itself agree to change some of its behaviors by allowing its feature values to be changed. Interactions determined by similarity are likely to produce homogenizing tendency. The simulation results of Axelrod's culture model have shown that though there is a strong tendency towards convergence, some stable regions of dissimilarity persists in the model. Rousseau & Veen [26] have proposed a similar but more complex model of political identities.

We have modified the model setup with a view that an agent's behavior potential is influenced by not only the agents in its neighbourhood who are similar to it, but by all the agents in its neighbourhood. An agent is taken to a slightly extreme situation where its own future behavior is determined by the present behaviors of its neighbouring agents. The agent is likely to change its behavior potential towards the trait value favored by majority of its neighbouring agents. The behavior contagion thus favors behavior occurring in majority. This extension has a more computer science coloration as it resembles the often encountered resource sharing and load balancing scenario in multi-agent systems. In our basic setting, we used only simple neighbourhood aggregation to influence the behavior potential of an agent. An individual tries to adopt the trait values for each of its features based on the majority trait for that feature in its neighbourhood. The newly acquired behavior then influences the other agent in the neighbourhood in the next time step. Simulation results show that a parameter as simple as neighbourhood behavior aggregation can produce interesting, stable & behaviorally similar groups. Moreover the model is very sensitive to the initial distribution of agent feature set. The basic setup was then extended by introducing a noise (possibly to model factor of innovation, creativity or effect of external sources such as mass media) in the behavior potential (feature set) of a small number of agents. This is done by randomly changing trait values of few features of some of the agents with a new trait value, after the initial stability is obtained in the population. The behaviorally modified agents now de-stabilize the behavior groups and force them to a new aggregation of changed scenario. The noise is continued at regular intervals. Simulation results produce amazing patterns. Sometimes stable groups are able to survive the noise, sometimes the noise results in changing group dimensions with interesting stable circular strip like patterns or bigger groups eating out smaller groups. The results are quite different from that obtained in simple voting model. The following section details the simulation setup and the results.

IV. EXPERIMENTAL SETUP & RESULTS

We have implemented the model using Net Logo [27] platform Version 4.04. Net Logo is a language highly suitable for modeling emergent phenomenon and has easy to use features for programming & report generation. We devised a 20 X 20 torus (a grid with wrapped edges) where each location or coordinate in the grid (called a Patch) represents an agent of our model. Each agent has a number of features (varying from 2 to 8), and each feature can take different trait values (ranging from 4 to 12). Numeric values are used for simplicity of the model. The size of the neighborhood, termed as range of interaction, for each agent varies from an eight neighborhood to a sixteen neighborhood. An agent is given a group id based on its concatenated feature set. Agents who have the same group id, i.e. same set of trait values for every feature, are supposed to belong to the same group. A simple count of distinct group ids gives us the different types of agents present at any instance on the grid.

For a proper visual representation of the groups of agents, we have utilized the group ids to associate colors to different agents. Thus the agents having same feature set, at any point of time on the grid, are represented by same color. Net Logo represents colors as numbers in the range 0 to 139. If we use a number outside the 0 to 139 range, it will repeatedly add or subtract 140 from the number until it is in the 0 to 139 range. This limitation of only 140 colors for groups implies that only 140 distinct groups may be visible at any given time on the grid. Since our model has a total of 400 agents with randomly generated feature set in the beginning we created a color id parameter to define the color of an agent. This color id is generated by calculating the modulus of group id of an agent by 140. Since Net Logo has only a fixed set of hues denoted by numbers 5, 15 … 135 and the rest of the numbers are a darker or brighter shade of these hues, it is sometimes hard to detect subtle difference in shades on the screen resulting into different agents looking similar.

The model is setup with an initial assignment of random trait values to different features of the agents. Every agent automatically gets a group id and color id based on the feature values as explained in the previous paragraph. As the simulation proceeds the agents are allowed to interact resulting into a behavior contagion. In the simple setup, at every iteration, an agent surveys the agents in its neighbourhood and determines its own trait values for each of the features. The trait value of a feature of the called agent is compared with the trait values for the same feature in all the agents in its neighborhood. The trait value which occurs in majority in the neighborhood is taken as the favored or ‘majority’ trait value of that feature in this neighborhood. In the next tick of the model the trait value of this feature in the called agent is then swapped with the majority trait value for that feature determined in the previous tick. This procedure is repeated for every feature and for all agents and their neighborhood. As the model proceeds the grid starts becoming stable and homogeneity starts arising. This becomes apparent from the colors seen in the agent grid and decreasing value of the number of groups. Each similar colored group on the grid has agents which share the same set of features; hence the number of regions formed at any point of time in the model is a clear indication of the spread of homogeneity. We run the model with different combinations of number of features (ranging from 2 to 8), number of trait values per feature (ranging from 4 to 12) and range of aggregation (varying from 4 to 12). A screenshot of the agent grid for two different runs with varying parameter values is shown in Figure 1.

A factor of noise (creative or externally induced behaviors) in the behavior potential, as explained in the previous section, was then introduced in the model after the initial stability. This noise was to disrupt the stable groups of similar behavior agents. The noise was implemented by randomly choosing a few agents across the grid and then changing the trait values of two of their features by new random trait values. The noise disrupted the groups and an overall reduction in the number of groups formed is seen. The disruptive noise, modeled as an agent’s capability to occasionally produce new and creative behaviors, rather than always blindly following the majority, produces a homogenizing tendency, resulting in interesting patterns. Sometimes wrapped around strips of identical agents are formed which are largely able to sustain the disruptive noise and in some cases the bigger groups tend to increase their membership substantially. Figure 2 shows a screenshot of the agent grid of a run at two time steps with disruptive noise. Figure 3 shows a plot of number of groups vs. time aggregated over a number of runs. The results are different from that of the simple voting model. The experimental setting can be extended further by making some of the agents mobile and more influential.

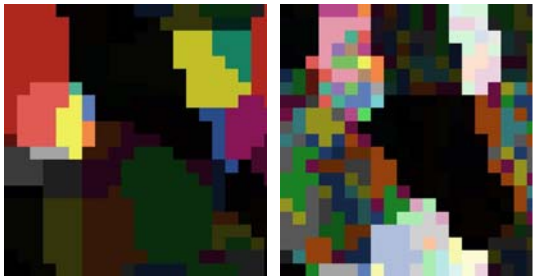

Figure 1. A snapshot of the two runs of the simple neighbourhood aggregation model. On the left is the agent repertoire with range of interaction=3, number of features=4, number of traits per feature=8; Figure on the right has these parameter values as 2,8 and 12 respectively.

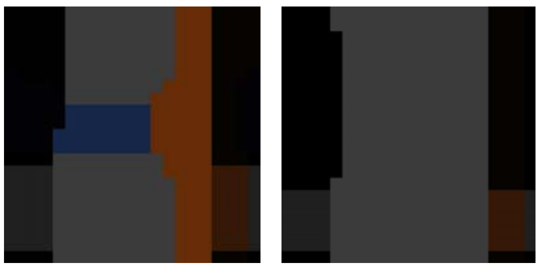

Figure 2. A Snapshot of the run with innovative trait introduced at regular intervals with range of interaction=3, number of features=4 and number of traits per feature=8. Figures on the left and right are after 2000 and 6000 ticks respectively.

V. CONCLUSION

We have characterized the agent-based modeling approach with special reference to modeling emergent collective behaviors. The experimental model of behavior aggregation based social contagion designed by us gives interesting and new results as compared to earlier such models. When an agent decides it own future behavior in favour of the majority behavior in its neighbourhood, the population soon converges to a stable state, after which no change occurs. And the stable state reached is sensitive to the initial distribution of feature values of the agents. However, when a noise is introduced after the initial stability is reached; the agent population shows varied reactions. In some cases, the stable regions starts reorganizing themselves and eventually circular strip like patterns are seen which then by and large remain stable. In few cases an almost complete homogeneity is observed. This is different from the results obtained in voting model in two respects: (a) In voting model irrespective of the initial distribution of agents, almost equal sized favouring group is observed for both votes; and (b) introducing a disruptive noise in voting model does affect the stability but only to a small extent. Making agents capable of producing relatively complex behaviors have changed the situation. Our simple model of a collective of agents going through a behavioral contagion based on the neighbourhood majority produces interesting results which can also have important implications for not only group formation and collective behaviors in social systems but also multi-agent systems employing a society of artificial agents.

Closed societies like that of tribes and islands in absence of a creative behavior potential seems to set up different cliques which is very sensitive to initial population distribution. When agent behaviors become more diverse either due to creatively generated behaviors or external influence, groups are still formed, but continuous innovation disrupts the stability in favour of bigger and majority groups. There could be another way to perceive it. Bigger groups tend to be more tolerant to external noise, and in situations of disasters modeled as disruptive noise, they may embrace other smaller groups in their strong shielding identity. It also has interesting resemblance with behavior of crowds where the majority induced mob mentality of crowds is often extremely difficult to manage. The model is also somewhat similar to the algorithmic formulation used by evolutionary algorithmic techniques of problem solving, like genetic algorithms [28] and memetic algorithms [29]. Both of these techniques use the convergent populations toward the global solutions possibly by introducing noise in terms of mutation to prevent premature convergence. The model has broad implications for multi-agent systems design [30] as well. The effect of social influence (particularly of interacting agents seen as neighbouring agents in the model) should be carefully observed and analyzed in any algorithmic formulation for self-organizing or distributed control applications. Whenever the designed system is required to work for applications having strong interrelationship among agents, where the control is highly distributed, or the system shows emergent and self-organization phenomenon; the formulation should be properly analyzed along the dimensions of behavioral complexity of the agents and the effect of any noise encountered by the system. The model could be further extended by incorporating parameters like trust in interactions; weighted interrelated behavior potentials and mobility of the agents.

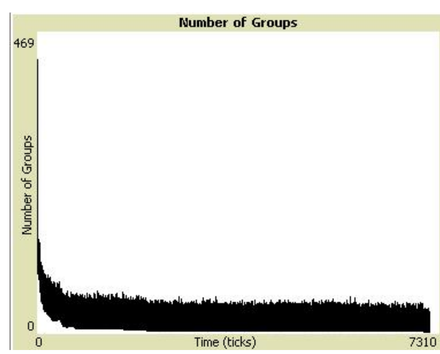

Figure 3. The plot shows the number of distinct groups vs. time of the model on 20 X 20 grid, aggregated over 20 runs.

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