Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 6, No. 4, October 2002 (© 2002)

Self-Organization and Resource Exchange in EVS Modeling

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Two versions of a model, named Resource, were developed within the Ensembles with Variable Structure (EVS) approach. The EVS-approach represents interacting groups (populations) with a flexible structure of connections and a diversity of elements (agents), where agents possess an abstract set of characteristics, and seek to form connections with other agents according to the degree of compatibility between these characteristics. The model presented here studied a role of parameters related to a flow of resource through the agents of a population. Individual sociability appeared to be a key parameter in the self-organization of the population. The percentage of an individual resource that an agent is allowed to spend was also an important resource-related parameter. Some other phenomena are reported as well.

KEY WORDS: EVS modeling; resource; clustering; self-organization.

INTRODUCTION

Self-organization in nature can be represented as a process of grouping of many elements into a system, i.e. big clusters of interconnected and interacting elements. There are qualitative and quantitative factors of such a clusterization. Our modeling of Ensembles with Variable Structures (EVS) is devoted to the study of the role of factors, such as size, diversity and sociability of a population, on the clustering behavior and group dynamics

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in a population of agents (Trofimova, Mitin, Potapov, & Malinetzky, 1997; Trofimova, 2000a, Trofimova, 2000b). The EVS-approach represents populations of interacting agents with a flexible structure of connections and a diversity of them, where agents possess an abstract set of characteristics, and seek to form connections with other agents according to the degree of compatibility between these characteristics. EVS models also use the *sociability* parameter, which is the maximum number of connections that an agent can establish or hold.

Our models are based on a spin glass algorithm, extended to a higher diversity of agents and to the use of resource related characteristics. In the majority of EVS models each agent receives some resource and spends some resource at each time step. We consider the concept of resource broadly: it could refer to energy, matter, chemical elements, time, information, money, service, emotional exchange, and so on. EVS uses this concept in order to simulate a principle of openness of natural systems and the dissipation of energy or other resources.

Thus, briefly the main properties of EVS models are: (a) There is similarity with cellular automata, as the characteristics of each element are discrete numbers, and evolution occurs in discrete time. (b) There is nonlocality of connections between agents. (c) Population has a *diversity* of elements, defined via some parameters or vectors. (d) Agents randomly check other agents in the matter of *compatibility*. (e) The number of connections to be checked/established is limited by the parameter of *sociability*. (f) The structure of connections between elements is very dynamic and stochastic. (g) "Mutual agreement" principle: connections between agents appear only when both agents "agree" to establish it, and if one agent wants to terminate it, the connection breaks. (h) Each agent receives and spends some resource at each time step, allowing the simulation of *resource flow* through the agent and through the system.

Each connection carries with it a relative valuation on the part of the agent forming it, and the agents attempt to optimize their valuations over time. We considered the situation in which the distribution of connections is uniform throughout the population: every element can potentially establish contact with every other agent with equal probability, and hold this contact if it is profitable. All of these properties together distinguish the EVS approach from such multi-agents models like random graphs (Palmer, 1985), percolation models (Grimmett, 1989), cellular automata (Burks, 1970), random boolean networks (the best review is Arbib, 1995) self-organized criticality (Bak, Tang, & Wiesenfeld, 1987) or the Kauffman model (Kauffman, 1993).

Analysis of clustering and affiliation behavior has been carried out for the Compatibility model (Trofimova & Potapov, 1998; Trofimova, Potapov, &

Sulis, 1998). In this model, individual agents attempted to minimize the costs associated with the establishment of cooperative (but very dynamic) links with neighboring agents. A phase transition was observed as a function of sociability with the critical point $\mathbf{S_c} = \mathbf{P^{0,6}}$, where $\mathbf{P}$ is the population size. Below $\mathbf{S_c}$, the population organized into a large number of small, connected clusters. Above $\mathbf{S_c}$, the population organized mostly into a single large cluster. A critical role of sociability appeared in other phenomena and other models of EVS.

Continuous phase transitions have been extensively studied and two well known models, percolation models (Grimmett, 1989), and random graph models (Palmer, 1985) bear a striking similarity to the Compatibility model. In all of these models, connections are established between a collection of vertices. The difference between the models lies mostly in the fact that in percolation and random graph models, the connections, once established, are fixed, as are the vertices. Thus the percolation and random graph models simulate equilibrium conditions. In contrast, connections in the Compatibility model are highly dynamic with large fluctuations occurring for all values of the sociability. There is also some similarity between effects of Compatibility model and self-organized criticality (Bak et al., 1987), as well as Kauffman's model (Kauffman, 1993). A difference between our model and former models is that they considered a population of identical elements or a very low diversity of elements. In addition to that, EVS models deal with the flow and exchange of resources between elements during their connections, while other models do not.

Thus sociability, (the limit on the number of connections that an agent can hold or check) appeared to be a key parameter governing some quantitative features of self-organization of a system, and our interest was to study the impact of two different kinds of sociability applied in a resource-exchange model: 1) when sociability of each agent is ordered as individual characteristics, and 2) when there is an overall limit of allowed connections for a system.

The Compatibility model demonstrated that after the phase transition a majority of agents affiliate in large clusters, but there is always a very small number of agents which do not belong to this majority, and constitute their own small clusters (Fig. 1). As all agents in the Compatibility model had fixed individual vectors in a vector space of characteristics, one might think that this diversity of agents prevented them from affiliation into the clusters of the "majority." In our opinion diversity is not the only factor that leads to the existence of "odd" small clusters, as connections in the Compatibility model were highly dynamic and had large fluctuations, so each given agent actually did affiliate in large clusters in some moments and happened to affiliate in small clusters in other moments of time. To clear this matter we decided

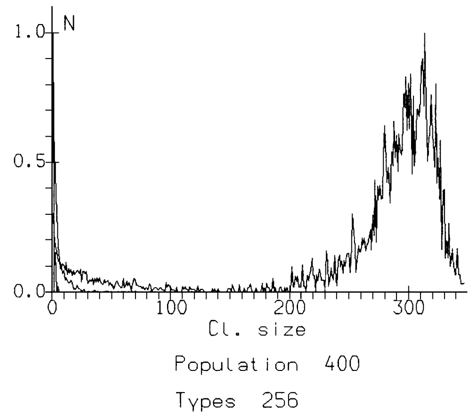

Fig. 1. Cluster distribution functions for population 400 and sociability above $\mathbf{S_c}$. The *x*-axis represents size of clusters, the *y*-axis represents number of such clusters normalized against the mode.

to use the "Adaptation" version of our "Resource" model and to allow an agent to change its configuration (individual characteristics) in order to be similar with agents to which it is connected.

The third goal of our study was associated with the proposition that individual differences on the limit on the input and output of resource during the resource exchange between agents might play a role in the self-organization of a system. Our first Functional Differentiation model (FD-1) showed a phenomenon, which is intuitively well-known: under the condition of variable structure of connections and exchange of a resource an amount of resource received from the other agents is approximately the same for various agents, but the strategy of spending a resource plays the biggest role in functional differentiation (Trofimova, 1999). The majority of elements of a natural population is usually exposed to incoming resources and possibilities more or less equally, and the differences between these elements lies mainly in operating with these resources and possibilities. If agents usually receive a resource with the same probability, but spend it with various strategies and distribution, it is important to know what "spending" parameter to use in modeling.

Thus the goals of the "Resource" model were: (a) to study the impact of two different kind of sociability, applied in a resource-exchange model; (b) to study the impact of an adaptation algorithm, when an agent can change its characteristics; (c) to study a role of various resource "spending" parameters and self-organizational dynamics of the models.

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"Resource" Models

In the two versions of the "Resource" model presented here (Resource-1, named previously "Adaptation" and Resource-2) the agents were also given a set of differences a priori, expressed as a vector of traits. The differences of this model from other EVS models are:

1. Individual differences of agents were not abstract traits, but three characteristics of output resource. (a) fixed necessary expenses per step (life expenses), which an agent cannot avoid; (b) maximum number of expenses per step (including the cost to have a connection); (c) maximal allowed percentage of expenses derived from the residual of an agent.
2. Agents could change their characteristics in order to get more profit, based on similarities with other agents (adaptive algorithm), so it could become closer to the "average individuality."

Each agent attempted to minimize its costs depending upon the degree of similarity in type between itself and those agents with whom it had forged links. The initial distribution of values by traits was random as was the formation of links.

Population sizes were 100, 200, 300, 400. All runs took 5000 steps (for smaller populations). In order to achieve the indicated properties, a Monte-Carlo method was used to search for connections and for the spin glass simulation.

Transition rules from state to state included the establishment of connections between agents with maximal compatibility (Euclidean distance in a space of parameters, normalized in such a way that the maximum possible distance equals 1). An agent received an award depending upon the similarity of connections. Thus at each step an element had its current amount of resource X_i and:

1. Incoming resource: (a) some randomly distributed resource between the values of -5 and $+15$, integer numbers (b_i); (b) an award for similarity with an agent in an established connection as a coefficient $(2 \cdot (1 - r_{ij}))$: the more close in configuration the agents are, the larger is this coefficient.
2. Outgoing resource: (a) individually determined, fixed necessary expenses per step (life expenses), which an agent can not avoid (n_i); (b) individually determined maximum of expenses per step (including the cost to have a connection), having values between 10 and 40 (Z_i); (c) individually determined maximal allowed percentage of expenses derived from the residual of an agent, ranging in value

between 5% and 95%, in 5% increments (P_i); (d) expenses, associated with the mismatch between connected agents $D_i = \min(P_i * (X_i(t) - n_i), Z_i)$.

Evolution was ordered by following formula:

$$X_i(t+1) = X_i(t) - n_i - D_i + b_i + \sum_{j \in J_i} 2 * (1 - r_{ij}) * D_j / k_j,$$

where k_i – amount of connections of *i-th* agent; J_i – a set of current connections of *i-th* agent, where k_i – is a power of set J_i.

The goal of every agent was to maximize the last term in this equation, i.e. the flow of resource through itself, using (a) the structure of connections, and (b) a change of internal values along three spending parameters n_i, Z_i, P_i. A search for connections followed a probabilistic Monte-Carlo algorithm. The initial distribution of values by traits was random as was the formation of links. All values of the parameters were relative: maximal possible values were normalized by 100.

Thus, the system was allowed to evolve to a stationary state, as every agent could change its configuration in order to be similar with the other agents.

The Resource-2 model extends the Resource-1 (“Adaptation”) model, as it also examines the situation in which the agent receives a resource depending on its similarity to those with whom connections are established. It also compared the “similarity” criterion of optimization with the other, more “economical” criterion, when an agent does not receive special profit for a similarity, and should just store as much resource as possible. Thus this model examined two different strategies of agents to choose the connections at each step (criterion of optimization): (a) to give preference to connections with agents located closer in the space of the “spending” characteristics (similarity strategy, like before); or (b) to give preference to connections that provide greater quantities of a resource then other possibilities (profit strategy; such strategies are popular in the economical models).

In addition the Resource-2 model considered two type of limitation on the number of connections: (a) Individual sociability of each agent, which is the maximum number of connections that an agent can establish with other agents (as in the Compatibility model). (b) Overall limit of allowed connections, i.e. the maximal number of connections in the system. In this case we do not order the personal sociability of agents as before (so agents could establish as many contacts as they want), but the total number of connections in the system is limited and cannot be changed (like in neural network models).

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RESULTS AND DISCUSSION

Limits of Similarity

The Resource-1 (Adaptation) model allowed agents to change their "individuality" towards similarity with other contacting agents: agents received more resource for this similarity, paying only a little charge for the self modification. The system was allowed to evolve to stationarity, as every agent could change its behavior. Figure 2 shows a simple graphical example of the evolution of such a system, which is similar to the same situation in Fig. 1. The difference here is that for behavior that was closer to the others, an agent received additional resource, and this, to our mind should lead to complete conformity for all populations.

It was conjectured that the system should evolve towards a fixed point attractor, i.e. homogeneity of the population, in which all agents have minimized their costs to the same degree. Surprisingly, it appeared that *small regions or cluster of cells would persist* in which these attributes would continue to fluctuate in a chaotic or possibly periodic manner. In other words, the system was frustrated, indicating symmetry breaking. Thus, even for such a simple model, individual differences persist in the face of similarity

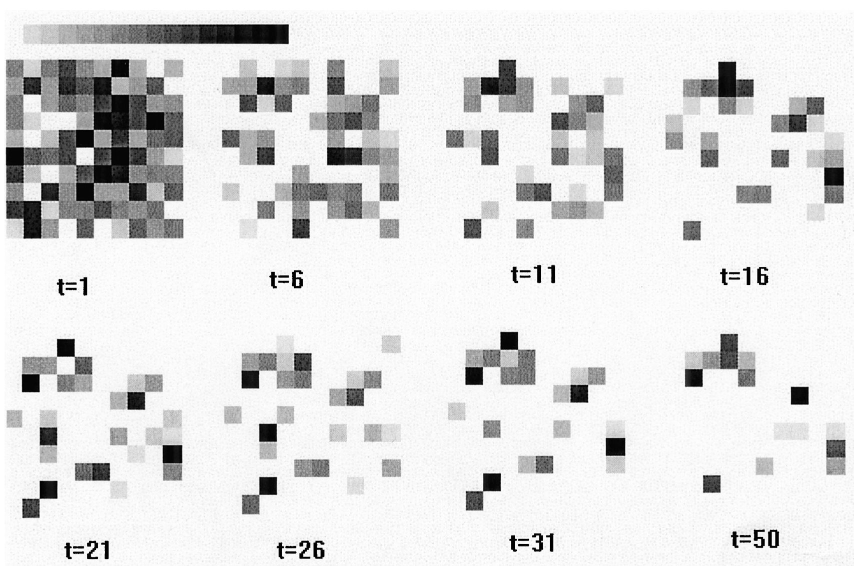

Fig. 2. An example of evolution of a population of 100 agents. A gray-color scale above shows the degree of "similarity" of agents in existing connections. The lighter the color the more similar an agent is to its "partners."

among the majority of the population, even with a profitable "adaptation" algorithm.

This raises a deep question as to whether individual differences are a dynamical necessity. The presence of "outsiders" is probably important in the self-organization of a system into a large cluster of diverse and interacting elements. "Personality," or individual particularities of these outsiders does not matter, as the content of clusters fluctuates, and from time to time each agent of a population appears to be outside of the majority. The existence of small clusters outside of an interconnected majority is probably necessary for the dynamics of a system, giving to this dynamic the freedom to change the structure of connections and still hold majority of elements connected.

This phenomenon might find an analogy in group psychology and sociometrics: in any group, at any moment, we could find the person who has the lowest rank in a group according to some criteria, but this person will not receive this lowest rank during the next measurement. Also we could always find moments when an opinion or behavior of a certain member of a group, even if he was the most popular before, moves him temporarily to an "outsider" position. A diversity of "configurations" of interacting agents gives to a system the necessary flexibility of structure and organization, so, it seems that no system wants to loose this diversity.

Comparison of two Types of Sociability

A study of two types of sociability, individual sociability and a global limit of connections in a system, demonstrated that individual sociability is still a key parameter in the appearance of big clusters. The histograms in Fig. 3c show the cluster sizes in a population (a number of agents having 0, 1, . . . , 10, and more than 10 connections). In both cases, when the maximum number of allowed connections had limits individually for each agent, agents managed to create big clusters, unifying the majority of them.

The other type of sociability—the overall number of connections can be interpreted as reflecting the technological possibilities of cooperation and communication in a system. For analogy we can imagine a set of service stations that can effectively serve an average number of clients per day, but, if by some reason all clients decide to come in one day, they should stay in line, waiting and competing for service. The other example of a overall limit can be the situation of a high price on connections or interactions, so that only a certain number of agents can afford it in one step of time, as the resources for paying this price are limited in a system. Our results showed that if the total number of connections over a system is limited but sufficient to integrate the system, it nevertheless does not integrate, even maximizing individual profit to form connections.

It seems that the emergence of a system does not like the competition between the agents for the connections in every interaction. The speed of adaptation of elements to each other (their unification) is slower in the case in which there is a limit on the total number of connections. A population with such a limitation tends to lose its total resource and does not form groups of connected elements. With such limits agents cannot come to consensus and affiliate with other agents effectively.

Figure 3 shows also the average distance between agents as time progresses (3a) and the average resource of an agent as time progresses (3b). The profit-orientation algorithm helped an agent to save its resources, while similarity with other agents did not, even when it was effected through an

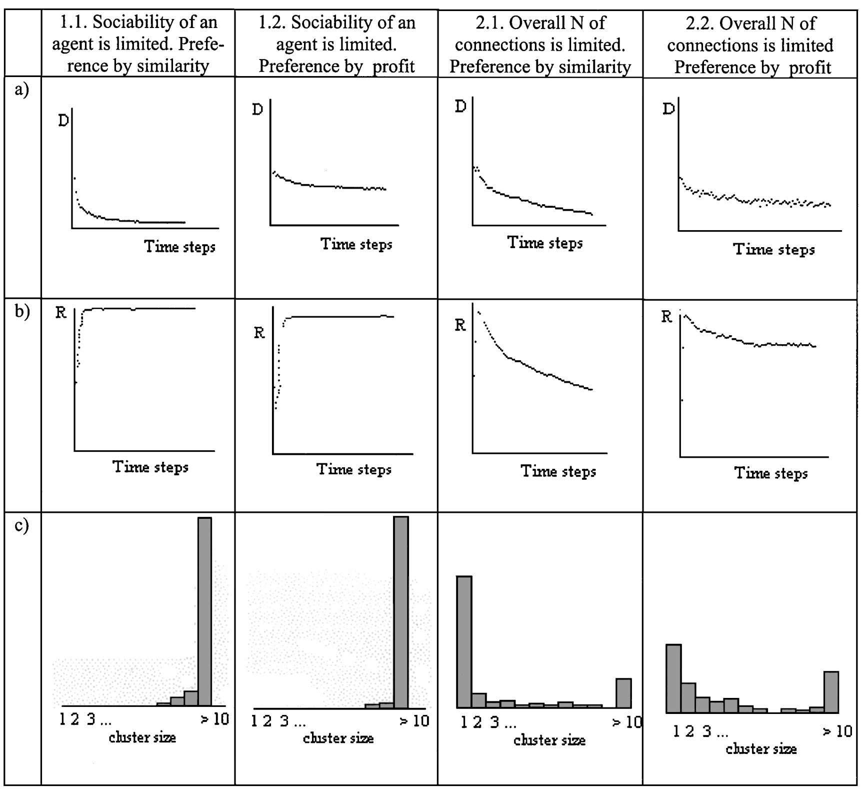

Fig. 3. Effects of Resource model: (a) average distance between agents with evolution, (b) average resource of an agent with evolution, (c) cluster sizes.

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award for a similarity. However the profit-orientation was not much help in the integration of agents into a big cluster, when the overall number of connections was limited. The last picture in Fig. 3c shows a diversity of small clusters, which finds analogy in American economics during the 19th century. In the condition of low technology of communications and interactions even a "free market" does not lead to an integrated system, however such a system emerges as soon as technology or social conditions give a freedom of interaction to agents, even without a profit-oriented strategy. No wonder that such an integrated system appeared in totalitarian regimes without a free market economy. One can expect totalitarian tendencies in multi-national economics as well.

Expense Parameters

We analyzed the process of self-organization in some modeled systems through an examination of the structure of connections, taking a space of three spending characteristics. This space is a unit cube, and each agent is represented as a point in this cube (3-dimensional space of characteristics). Each connection between two agents could be presented as a line between two corresponding points. Figure 4 shows a plane of parameters Z and P of a cube having a structure of connections for cases of both type of sociability. One can see how individual sociability creates a more integrated and rich structure of connections than an overall limit of connections on a system.

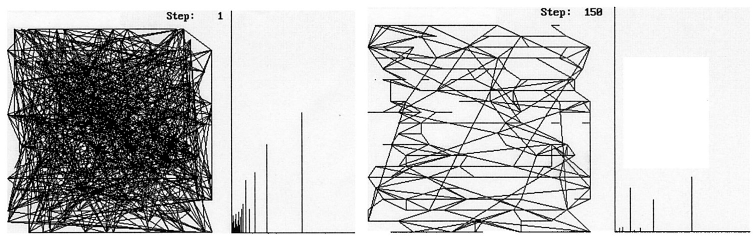
In the case of limits on the overall number of connections in a system one of three "spending" parameter plays the major role in the self-organization of the population. This parameter is the maximal allowed percentage taken from existing resources, which an agent could then distribute through its connections.

The dominance of this "relative" parameter over direct "expense" parameters might again remind us about the ensemble nature of the scales that we use in measurement and the interconnectedness of the properties of multi-agent systems, especially based on exchange of a resource.

CONCLUSIONS

We found that several parameters of the systems under study played a significant role in their dynamics and self-organization:

1. *Individual Sociability*: determines the self-organization of a system into a big cluster(s) of interconnected agents.



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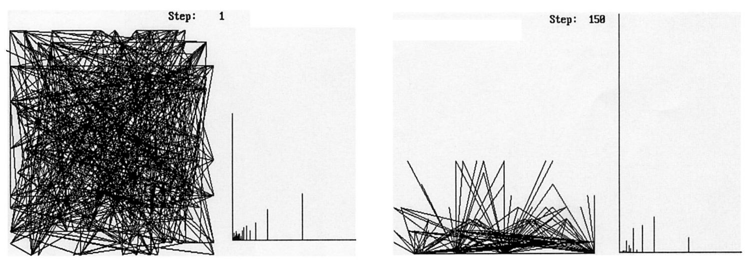

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Fig. 4. Evolution of structure of connections between agents presented for two cases: individual differences in sociability (A) and overall limit of connections in a population (B). The figure shows the coordinates of agents (vertices of graphs), connected by lines in the plane of parameters Z and P.

2. *Profit-orientation*: saves resources of an agent, but does not help in self-organization of a system.
3. *Maximal allowed percentage taken from existing resources*, which an agent could distribute by connections: in the case of limits on the overall number of connections in a system it plays the major role in the self-organization of the population.
4. In a system with flexible connections between elements, individual differences persist in the face of similarity among the majority of the population, even with a profitable "adaptation" algorithm.

ACKNOWLEDGMENT

The authors are very grateful to Dr. William Sulis for the final editing of this paper.

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