The characteristic feature of the complex socio-economic systems is a tight coupling of the constituent parts. Social cooperation, spontaneous emergence, formation of financial bubbles, financial flash-crashes and even mass panic actually may be a result of this coupling and also certain general gimmicks of human psychology [1, 2]. In this context we can see the individuals (or firms or other socio-economic entities) as generalized agents, which are tightly coupled with other agents via the herding interactions [3, 4]. Previous empirical research, from a point of view of the behavioral biology and sociology (see recent papers by Jens Krauze [5, 6]), has shown that one can use the tight coupling to control the collective behavior of large groups of individuals. In this contribution we approach the same problem from an agent-based modeling point of view. Namely, we study the dynamics of the agent-based herding model, original proposed in [7], in which certain agents are controlled externally.

Let consider the impact of individual agents on system at a global level. It should be evident what agents acting individually on the local scale influence their immediate neighbors, which may (or may not) spread the control further. If system is large enough then at a certain point the influence of such agents will be stopped from spreading. On the other hand if the individual acts on the global scale, then it is seen by many agents at every time. Thus in influence spreads instantly. So let us use controlled agents, with otherwise “inflexible” opinion (this concept was introduced in [8]), which interact on global scale, while other agents interact on local scale:

\[ \mu(i) \rightarrow j - \frac{1}{M_j} \Delta t. \]

(1)

while if they are interacting only on the local scale (i.e., only with their direct neighbors), the transition probabilities take the following form:

\[ \mu(i) \rightarrow j - \frac{1}{\sigma_j + \mu_j} \Delta t. \]

(2)

Here \( i \) and \( j \) are indices representing the available states, \( \Delta t \) is a small time period (small enough for one transition to be probable).

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As you can see in the figure above an extremely small number of the controlled agents is able to make a significant impact onto the stationary distribution. This brings up an interesting question how fast is the convergence towards this stationary distribution. It is pretty straightforward (use the Master equation and one-step formalism [10]) to obtain ordinary differential equation describing the macroscopic dynamics of the considered agent-based system:

\[ \dot{x} = \left(1 + h \dot{M}_j \right) x - x \left(1 + h \dot{M}_j \right) \sigma. \]

(3)

The solution of this equation is an exponential function of time:

\[ x(t) = x_0 \exp \left( \int_{0}^{t} \left(1 + h \dot{M}_j \left(1 - x_0 \right) - x_0 \left(1 + h \dot{M}_j \right) \sigma \right) dt \right). \]

(4)

Thus the convergence is exponential with the rate dependent on the individual transition rates, \( \sigma_i \) and amount of controlled agents in each state, \( M_j \). In the above \( x \) is the stationary value:

\[ \left(1 + h \dot{M}_j \right) x - x \left(1 + h \dot{M}_j \right) \sigma = 0 \quad \Rightarrow \quad -d - \frac{M_j \dot{M}_j (1 - x)}{\left(1 + h \dot{M}_j \right) \sigma} = \left(1 + h \dot{M}_j \right) x. \]

(5)

Similar dynamics are observed if the ordinary agents are also interacting on the global scale [9]. The only difference is that the system dynamics are significantly more random and the stationary PDF of the model becomes power-law instead of Gaussian.

Figure 1: A photo of experiment (on the left) which inspired the agent-based herding model (schematic representation on the right). Here we have N ants, which take food to their colony. Ants may use one of the two available paths. Interestingly enough most of the time they tend to exploit only one path. This happens due to the importance of two-agent interactions. \( \lambda \) terms, in comparison to a single-agent transitions, \( \nu \) terms.

controlling catastrophic events in the financial markets

Unlike in the society, in the financial markets any trader may make transactions with any other trader. Thus in the financial market model all of the agents should also interact on the global scale. The macroscopic dynamics of the financial markets will no longer be given by the ODE, one needs to use stochastic calculus [11, 12]. As our previous work shows the trading in financial markets has two separate time scales - a slow process representing fundamentalist-charlatan switching and a fast process representing optimism-pessimism mood fluctuations.

A slow process is a stochastic process based on modulating return, \( \gamma \), which is defined as a ratio between agents using chartist trading strategies and agents using fundamental trading strategies [11]. SDE for \( \gamma \) has the following form:

\[ d\gamma = \left[ \gamma \left(1 - \gamma \sigma^2 \right) + \left(1 + \gamma \sigma^2 \right) \right] dt + \sqrt{2 \gamma \left(1 - \gamma \sigma^2 \right)} dB_t. \]

(7)

The stationary probability density function of \( \gamma \) is a power-law, \( \gamma \to \gamma^{-1} \), thus large crashes and bubbles become probable. In order to prevent them we might use a simple rule - if absolute return \( \gamma \) is larger than \( \gamma_{\text{max}} \) we introduce \( M \) agents trading based on the fundamentals.

Let us “moderate” the time series of mood, \( \zeta \), by a similar rule as in case with \( \gamma \): if \( \zeta \leq \zeta_{\text{max}} \), we introduce \( M \) agents into the pessimist state, while if \( \zeta < \zeta_{\text{max}} \), then we introduce \( M \) agents into the optimistic state. A similar approach was proposed in [13], where agents using random trading strategy were used to calm the markets.

Conclusions

In this contribution we have approached modeling of the control of complex socio-economic systems. Namely, we have modified a well known agent-based herding model, originally introduced in [7], to include agents, whose state “inflexible” and is preserved by the control. The control over a small fixed number of the agents is able to significantly influence the behavior of the other agents, which still are based on the original rules of the model.

We find our model setup well-backed with the related experiments in the behavioral sociology and behavioral biology carried out in [5, 6]. We believe that the presented imagery of society while being simplistic still is well backed with the related experiments in the behavioral sociology and behavioral biology carried out in [5, 6]. We believe that the presented imagery of society while being simplistic still is well-backed with the related experiments in the behavioral sociology and behavioral biology carried out in [5, 6]. We believe that the presented imagery of society while being simplistic still is well-backed with the related experiments in the behavioral sociology and behavioral biology carried out in [5, 6]. We believe that the presented imagery of society while being simplistic still is well-backed with the related experiments in the behavioral sociology and behavioral biology carried out in [5, 6]. We believe that the presented imagery of society while being simplistic still is well backed with the related experiments in the behavioral sociology and behavioral biology carried out in [5, 6]. We believe that the presented imagery of society while being simplistic still is well-backed with the related experiments in the behavioral sociology and behavioral biology carried out in [5, 6].

Part of the research covered in this contribution was published in [9]. Some of the new material will be used in future research and scientific publications.

References