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Agent-based modelling of excitation propagation in social media groups

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This paper investigates excitation information propagation in artificial societies. We use a cellular automaton approach, in which it is assumed that social media is composed of tens of thousands of community agents, where useful (innovative) information can be transmitted to the closest neighbouring agents. The model's originality consists of the exploitation of artificial neuron-based agent schema with a nonlinear activation function to determine the reaction delay, the refractory (agent recovery) period and algorithms that define mutual cooperation among several excitable groups that comprise the agent population. In the grouped model, each agent group can send its excitation signal to the leaders of the groups. The novel media model allows a methodical analysis of the propagation of several competing innovation signals. The simulations are very fast and can be useful for understanding and controlling excitation propagation in social media, planning, and social and economic research.

Keywords: agent-based modelling; dissemination of innovation; excitation waves; grouped populations; cellular automaton; neural networks

1. Introduction

An exponential increase in the amount of information exchanged between individuals or economic or social units makes it necessary to understand the ways and regularities of detailed information-transmission processes in complex social media. Analyses of questions, such as how people, organisations and social media in general react to innovation or new information, play a leading role here. This sort of knowledge allows the actions of individuals and social groups to be predicted and partially controlled.

Social life is increasingly characterised by interdependencies among actors (individuals, companies or institutions), which give rise to self-organisation phenomena, feedback loops and unpredictable and sometimes counterintuitive interaction patterns (Helbing, 2013). Agent-based models can simulate and help to understand macro-level phenomena from the bottom up. The rule-based approach to agent-based modelling is simple, flexible and intuitive. Agent-based modelling promises to be a major tool for providing a better understanding of the complexities that fundamentally challenge the way social phenomena are approached. Cognitive architectures may serve as a good basis for building mind- and brain-inspired, psychologically realistic cognitive agents for various applications that require or prefer human-like behaviour and performance (Suna & Helieb, 2013). Examples of this type of information-transmission research

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include adopting new technology (Rogers, 2003) and the diffusion of innovations in social networks (Acemoglu, Ozdaglar, & Yildiz, 2012; Keller-Schmidt & Klemm, 2012; Valente, 1996; Young, 2006). To our knowledge, the major area of virtual wave-based social simulations and applications is related to emerging research in social-networking, agent-oriented and multi-agent systems. As a matter of fact, wave- or field-based modelling is usually applied in studies inspired by nature. Such analysis is necessary in the search for a better understanding of very complex, large and highly dynamic physical, biological and social networks. Unfortunately, these studies use the wave-like coordination approach as a technical solution without a deeper exploration of the basic nature of such an approach.

For instance, in social-networking research, because of its large scale and complexity, attempts are frequently being made to simulate social networks using wave-propagation analysis (Plikynas, 2007, 2010). Some of the applications deal with message-broadcasting and rumour-spreading problems (Wang, Tao, Xie, & Yi, 2012) and simulations of rapidly changing social and financial phenomena (Raudys, 2013; Raudys & Raudys, 2012). In mainstream research papers, individuals and social units are represented by agents that are affected by their social and physical surroundings and produce cognition-based behaviour patterns (Perc, Gmez-Gardenes, Szolnoki, Flora, & Moreno, 2013; Wijermans, Jorna, Jager, van Vliet, & Adang, 2013). Comprehension of social behaviour is sought by relating intra- and inter-individual levels of behaviour generation to emerging behaviour patterns at the individual or group level. In social-networking research, interactions are mostly realised through connections between pairs of nearby agents.

As an example of the necessity for wave-propagation research in social spheres, we look at the analysis of some time series of high-dimensional financial data used in automated trading systems (ATS) (Raudys, 2013; Raudys & Raudys, 2012). In Figure 1 we depict two time series of profit/loss financial time series. In ATS we use hundreds or even thousands of investments for decision-making. To develop and train such a complex trading system, we need the same or higher number of training vectors (Raudys, 2013).

Economic and financial markets are changing very rapidly nowadays. Two years' (less than 500 trading days') history becomes lengthy. For this reason, in the development and testing of diverse versions of trading schemas, we include artificial data generated by means of the wave-propagation model. Figure 1 illustrates an example of two synthetic time series. The data

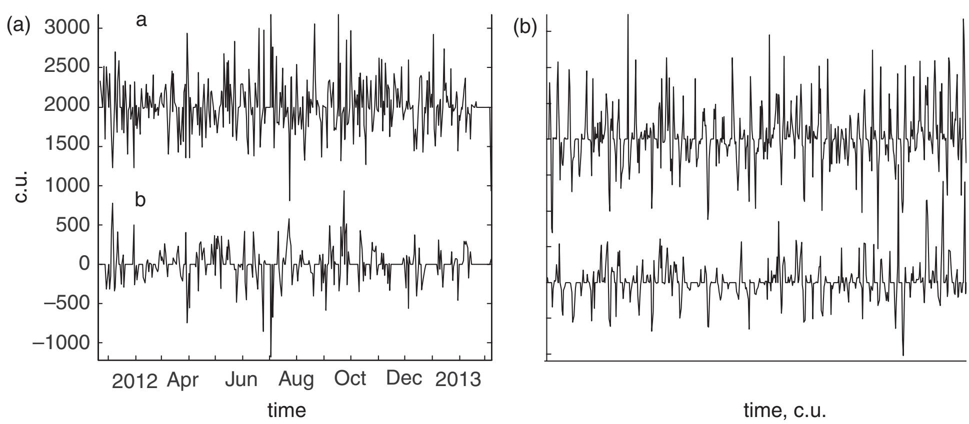

Figure 1. Fluctuations of profits generated by algorithmic trading systems during 15 months period (on the left) and fluctuations of profits simulated by means of an excitable media model (on the right).

generation was based on the hypothesis that the economic and financial world is composed of a large number of mutually communicating social actors that exchange innovative information in a similar way to how we have described this in the social media model. We modelled ATS as sets of neighbouring nodes in an excitable media network. Sums of excitations of groups of social agents modelled the profits and losses of the investment. We also introduced an investment risk, where the ATS refuse to make investments if the risk is too high. A change in the parameters of the data-generating rule allows diverse economic activities to be investigated. Moreover, we can generate a large number of principally diverse wave-propagation patterns. Therefore, the developer of decision-making algorithms can have long time series sufficient for reliable robustness evaluations of algorithms. Our analysis shows that synthetic data are useful for modelling chaotic economic behaviours observed in real life and developing automatic decision-making algorithms that can withstand unexpected changes in the real world.

In this paper, we try to use an almost universal methodology: the stimulation signal propagation in an excitable media. It takes the bottom-up approach, which is used successfully in many research disciplines, such as particle physics, micro and cell biology, chemistry, medicine, meteorology and astrophysics (Ben-Jackob & Cohen, 2000; Martin & Granel, 2006; Moe, Rheinbolt, & Abildskov, 1964; Spach, 1997). We propose that these kinds of models can also be used in the analysis of information–propagation processes in social media, and can lead to a deeper conceptual understanding of the fundamental nature of information dissemination in societies of virtual agents. The objective of this paper is to demonstrate this statement.

Theoretical and subsequent simulation analyses in this area belong to methods based on systems of nonlinear differential equations. This approach investigates phenomena in continuous space and time. Many researchers claim that real objects and processes have a discrete nature. Therefore, cellular automaton (CA) research has been adopted in many research fields (Bandini, Federici, & Vizzari, 2007; Chua, Hasler, Moschyt, & Neirynck, 1995; Mehta & Gregor, 2010). In CA-based models, the excitation signals are transferred to neighbouring knots (agents and cells). CA-based models are much simpler, easier to understand and faster to simulate using computers. Computer simulations were first performed by Moe et al. (1964), who laid out a virtual neural network (NN) on a rectangular grid, used 0 or 1 outputs for each cell (node of the network) and measured time in discrete periods. A plethora of subsequent researchers developed the CA approach further. In these models, the number of excited states is greater than 1, and more than one neighbour must be active in order to induce a resting cell to an excited state (see the short review in Raudys [2004]).

The propagation of information, new technologies and cultural matters are nonlinear phenomena, such as wave propagation and chaos origination. The differential equations and cellular automata methodologies both allow us to model a number of signal propagation patterns that have been observed experimentally in physical, chemical and social media, e.g. regular uniform wave propagation outwards from a point of starting excitation, the generation of spiral waves after their initiation, waves surrounding a non-conductive obstacle, disorganised activity and broken wave propagation in one or several directions. These phenomena have been actively investigated in numerous disciplines, including chemistry, biology, meteorology, ecology, medicine, engineering, physics and astrophysics. Some researchers believe that these models are universally inspired by nature because they exhibit oscillating cells, cooperative self-organisation and collective behaviour (Ben-Jackob & Cohen, 2000; Chua et al., 1995; Mehta & Gregor, 2010; Steele, Tinsley, & Showalter, 2008). Some of the authors started using similar models in a much wider sphere of research disciplines, including ecology, epidemiology and, possibly, the economic and social sciences (Berestycki, Rodriguez, & Ryzhik, 2013; Litvak-Hinenzon & Stone, 2007; Yde, Jensen, & Trusina, 2011).

In classical media models, the similarity between the agents is measured geometrically as a distance in two-dimensional (2D) or three-dimensional (3D) space. In research into economic and social phenomena, similarities are typically characterised by the larger number of characteristics of a dissimilar nature. Therefore, in this paper, for practical applications we assume that the distance or similarity between agents can be defined freely (see the next section). Measures of similarity may be applied to define match and connectivity between agents (nodes of excitable economic or social media). Like in the grid-based models, each node sums the input signals transmitted from neighbouring nodes. In the new model, however, the magnitudes of the output signals and their release times depend on the sum of the accumulated inputs.

This paper is organised as follows. For a simpler explanation of the virtual agent population model and for visualisation purposes, we describe and extend a 2D cellular, grid-based, social media model and its modifications in Section 2. Diverse excitation-signal propagation patterns are demonstrated. In Section 3 we introduce a group-based agent model in which the agent population is split into groups. Inside a single group, the excitation signals are transmitted only to neighbouring nodes. Limited interaction of groups, as well as propagation of diverse informational signals, is allowed. In Section 4 we consider the propagation of two competing excitations in the grouped agent population. Section 5 summarises the simulation results and discusses the potential for further studies.

2. The basic model

2.1 Hexagonal 2D CA model

To understand the main properties of the model of signal propagation in excitable economics or social media, we will first describe its simplified versions: 2D rectangular and hexagonal models of an excitable medium. The basic model consists of nodes (cells and agents) spaced on regular grids (see Figure 2). It is assumed that an excitable medium is composed of tens of thousands of community agents, where useful (innovative) information can be transmitted to the closest neighbouring agents (see the arrows in Figure 2).

Each element of the grid is represented by a single-layer perceptron, which has a number of inputs (say p), that uses weights (connection strengths between the nodes) $w_1, w_2, \ldots, w_p$ and x_i (denotes signals received via inputs) to calculate a weighted sum $\arg = \sum_{i=1}^{p} w_i x_i$, and produces an output, $o = f(\arg)$ by using sigmoid nonlinearity, $f(\arg) = 1/(1 + \exp(-\arg))$ habitually

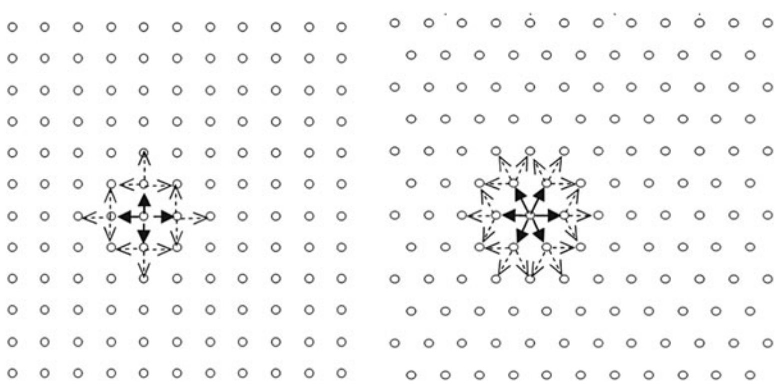

Figure 2. Rectangular and hexagonal grid-based models and directions of the transmitted signals. Excitation originates from a randomly chosen point in the regular spaced grid.

used in artificial NNs (Haykin, 1998; Raudys, 2001). We adopted this function for feasible needs:

$$f_s(\text{arg}) = \frac{\gamma}{1 + \exp(-\eta \cdot \text{arg} - \theta)} \quad \text{if arg} \le \Delta^*; \quad f_s(\text{arg}) = 0 \text{ otherwise,} \tag{1}$$

where $\Delta^* \le 0$ is an *a priori* defined sensitivity threshold. In simulations, we used $\gamma = 1.333$, $\eta = 5$, $\Delta^* = 0.4$ and $\theta = -1.333$. The constants were selected to have the weights w_i, and outputs o, between 0 and 1.

After obtaining excitation signals from neighbours, the agent calculates the weighted sum and after some delay fires out transformed sum of input signals, $f_s(\sum_i w_i x_i)$, accumulated during two previous time periods. In our cellular automata model, the signal transfer time, t_{transf}, is discrete, $1, 2, \ldots, m$. This time depends on the strength of the accumulated output signal, o. For that reason, the output signal interval (0, 1) is split into m equal intervals, corresponding to time periods, $1, 2, \ldots, m$ (see Figure 3).

In our social media model, we have a negative feedback loop: *the larger the excitation signal, arg, the later the jth agent will fire out its output signal*. To define t_{transf}, we followed observations from CA and differential equation-based excitable media models (see Spach [1997]): the longer the delay in transferring the excitation, the greater the node-to-node strength of the signal. The minimal transmission time can be equal to 1, i.e. the cell does not transmit a signal if $f(\text{arg}) < 1/m$. The minimal transmission time is also affected by sensitivity threshold, Δ^*. The proportionality of the signal-transmission delay to the strength of the signal makes the CA-based model more similar to differential equation-based models. This is a very important new feature of the model. Both the discrete time and the negative feedback introduce stochastic (chaotic) components. Comparative experiments showed that the utilisation of fixed or variable time delays essentially changes the characteristics of the model. To speed up computer calculations, a look-up table was used to find $o = f(\text{arg})$. The use of the look-up table introduces additional stochastic components into the model. Accumulated signals are transferred only to non-excited neighbouring agents.

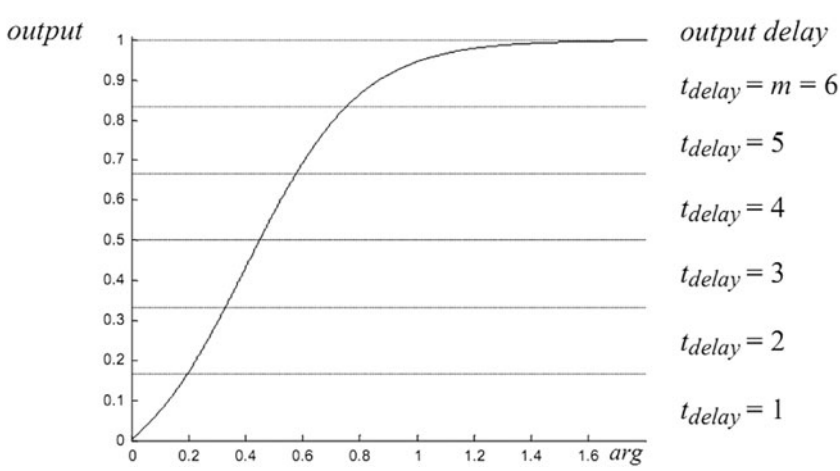

Figure 3. Dependence of the output, $o = f_s(\sum_i w_i x_i)$, the signal transmission delay, t_{delay}, on the input, the weighted sum, arg.

An important parameter traditionally used in signal propagation models is *the refractory period*, t_{refr}, the number of elementary time periods; after excitation, the node cannot be excited again. In our model, the refractory period is determined by the saturation, sat_j, of the jth agent after its excitation and the strength of potential new excitation, o_{new}. Just after excitation, $\mathrm{sat}_j = o$. The saturation exponentially decreases with time, t:

$$\mathrm{sat}_j(t) = o \times \exp(-\alpha_{\mathrm{refr}}(t - t_{\mathrm{excitation}})). \tag{2}$$

When saturation falls below a threshold,

$$\Delta^* - \beta \times (o_{\mathrm{new}} - \Delta^*), \tag{3}$$

the refractory period terminates, and the jth agent can be excited by a new excitation signal, o_{new}, if $o_{\mathrm{new}} \geq \Delta^*$. In the above equations, $\alpha_{\mathrm{refr}} = 1/(refr \times m)$, and β is a small positive constant. The parameter *refr* is the *a priori* determined time constant, *the refractory time parameter*. This parameter can be common to all agents or individuals. Equation (3) shows that powerful excitations of neighbouring agents, o_{new}, can shorten the refractory period by a small amount. For simplicity, in experiments reported in this paper, $\beta = 0$.

The size and the shape of the media are also important characteristics. In this paper, for 2D illustrations we used a hexagonal shape, where we have N_y nodes along each edge (Figure 4). The border nodes may transfer their outputs only to adjacent cells. If the excitation spreads from the centre of the media towards the edges, after reaching the edge the excited cells can find unexcited cells to transmit a signal to. In such a case, the propagation of the signals closest to the media edges fades.

We emphasise again that the single-layer perceptron is a model of information processing and transmission inspired by nature (Haykin, 1998). It has a number of universal properties (Raudys, 2003). The introduction of nonlinearity into the excitable media model perceptibly influences the wave-propagation patterns. A very important peculiarity of excitable social media is not the physical signal, but that the information is transmitted from one media element to others. The following lists the parameters that can be used to specify concrete social media

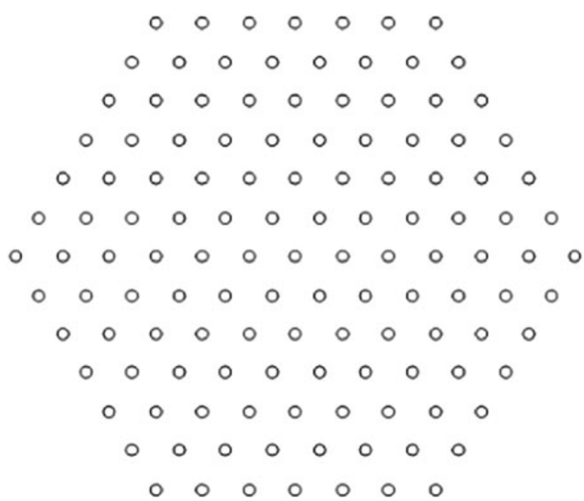

Figure 4. Hexagonal shape of a 2D excitable media with $N_y = 7$ nodes in each side.

models:

- N_y is the number of nodes on each edge of the hexagonal media in 2D space;
- p is the number of neighbours, and the shape of the grid;
- $w_1, w_2, \ldots, w_p$ is the connection's weights;
- the concrete parameters of the transfer function, $o = f(\arg)$;
- Δ^* is the sensitivity threshold;
- $\arg_{\text{start}}$ is the starting excitation, and the position of the cell (or cells) in the grid that transmit the starting excitation;
- m is the maximal time-delay periods in the signal-transmission process;
- t_{refr} is the rule and its parameters that determine the refractory period;
- t_{transf} is the rule used to determine the excitation time (Figure 3) and
- the rules used to determine the similarity and neighbourhood of the media nodes.

The parameters and required rules can be the same for all nodes in the social media; however, they can also be fixed for each node (agent) individually. In principle, the parameters can be learned during the simulation of media evolution in changing environments (for a similar example, see Raudys [2008]). Finding an appropriate set of parameters is a subject for future research. In a strictly hexagonal 2D media model, we can select either 6 or 18 neighbours. In a number of simulation studies, we investigated non-homogeneous media. For that reason, we shifted the nodes randomly to left–right and up–down directions. We were then able to specify the neighbourhood according to new distances. In principle it is possible to define the nearest neighbours arbitrarily. Such attributes of excitable media are more natural and more desirable for the analysis of economic and social systems.

2.2 Interpretation of the model's parameters

In this section we provide more details of how to use and interpret the model's parameters in the applied social media analysis tasks. In the analysis, we need to bear in mind that the *interpretation of the model's parameters depends on the particular social problem to be solved*. In different tasks, interpretations can differ in essence.

In general, parameter N_y describes the size of the agents' population in the social-media simulation. In a virtual experimental setting, agents are spatially distributed in either hexagonal or rectangular grids. In a social analysis, the agents can be spatially distributed in spaces of higher dimensionality.

Depending on the type of grid, parameter p determines the size of the neighbourhood, i.e. the number of closest neighbours surrounding an agent. The agent sends an excitation signal (new information) to those neighbours only. In general, the neighbourhood can be determined in terms of common business activity, shared interests, religion, family relations, family relationships, organisational infrastructure and scheme of social network.

Parameters $w_1, w_2, \ldots, w_p$ denote agents' weights of input connection with their neighbouring agents; in other words, the strength of the social relationships between neighbouring agents. Strong connection weights cause regular signal propagation. Weak weights are associated with chaotic behaviour.

The parameter for transferring the excitation signal to neighbouring agents $o = f(\arg)$ is determined in Equation (1). Mathematically, it describes the nonlinear output transmitted from a particular agent to its closest neighbours. It cannot be smaller than 0 or larger than 1. Depending on the application in question, this function can be changed in order to reflect specific needs of the wave-propagation set-up process. However, in this paper the output function we have presented was selected by trial and error after numerous attempts to obtain different wave-propagation patterns.

Parameter Δ^* denotes the sensitivity threshold. It is related to the minimum value of input excitation that can excite a neighbouring social agent. The agent does not get excited if the sum of input signals is smaller than $\Delta^* - a \times (o_{\text{new}} - \Delta^*)$; see Equation (3). It must be remembered that humans live in a noisy environment and strive to filter and adapt important information only. In the prospective research, we foresee introducing a dependence of the sensitivity threshold on the type of research task. Determining a suitable threshold value could enhance an agent-specific reaction to dissimilar types of information, which is so common in social domains.

Parameter $\arg_{\text{start}}$ is the magnitude of the signal (innovation, etc.) which begins excitation (triggering) in the simulated social media. It is related to the position of the starting cell (or cells) in the grid. If the magnitude of the triggering signal is too small or too powerful, in some cases this causes the signal to either vanish or overwhelm the population. In fact, the origin of the source of excitation is task dependent and requires thorough further investigation. We infer that the triggering signal is produced by an innovator whose individual parameters allow useful information to be accumulated and tested outside of the noisy environment. This line of research, though, requires yet another layer of sophistication in our model.

Parameter m characterises the model complexity (smoothness of nonlinear transfer function). It denotes a maximum elementary time-delay period, t_{transf}, in the signal-transmission process ($t_{\text{transf}} = 1, 2, \ldots, m$; see Figure 2). If m is too large, more computer time is required; if it is too small, the CA-based social media model is too simplified. We have established its value by trial and error after several attempts to obtain consistent wave-propagation patterns.

The parameters of activation function (1) define the rule used to calculate the excitation delay, t_{transf}. After receiving the excitation signal, the social agent needs time to distinguish between useful and erroneous information. A number of elementary time periods, t_{refr}, characterise a refractory (rest) period after the agent fires out the excitation information to its neighbours. The refractory period plays a key role in all excitatory systems, including social systems. After becoming excited, the agents become involved in the process of mastering the new information, performing necessary changes in their own activity (behaviour, manufacturing, etc.). This is why some modern societies have better means to participate in the high-speed information economy than others. Determination and the use of excitation states are essential in social and business analyses, such as advertising media scheduling (Baron & Sissors, 2010), epidemic dynamics (Martin & Granel, 2006) and diffusion of innovations (Alkemade & Castaldi, 2005). In each specific application domain, we need to find an explanation of formal parameters of the universal model by a constituent set of observable variables.

2.3 Excitation signal propagation patterns in 2D space

In economic and social systems analysis, 3D, 4D or higher dimensional models are preferable. If the space has more dimensions, this enhances the visualisation of the wave propagation. 2D illustrations show interesting patterns of excitation-wave propagation.

In simulation studies we performed hundreds of experiments using hexagonal grids. We found that some of the parameters affect wave propagation only in a very narrow interval of their variation. Outside this interval, the wave propagation ceases. In some cases, adequate selection of other parameter values can restore the wave-propagation process. To introduce non-homogeneity, in some simulations the coordinates of the model's nodes were affected by a small noise. In our experiments the triggering of the social media ($\arg_{\text{start}} = 0.7$) was carried out on the node at the very centre of the media model. If excitation is sufficiently powerful, a strong signal with some delay (see Figure 2) is transferred to $p = 6$ neighbouring nodes. Then, each of the p already excited nodes transfers their output signals to a further one, two or even three non-excited nodes (see Figure 2, right). In Figure 5(a), (c) and (d), we show four wave-propagation patterns. In the media on the far left and right (a),(d), the nodes were placed strictly hexagonally, while in the two central media (b),(c) the nodes were placed in a non-uniform way. To make the distribution of the nodes non-uniform and ensure bursting, a noise was added to the coordinates of the nodes. The other parameters of the four media models were as follows: $N = [184\ 146\ 124\ 104]$; weights $= [0.7\ \ 0.8\ \ 0.7\ \ 0.73]$; refractory period refr $= [29\ \ 5\ \ 4\ \ 2.5]$; excitation threshold $= [0.5\ \ 0.6\ \ 0.45\ \ 0.55]$ and noise level $= [0.0\ \ 0.5\ \ 0.5\ \ 0.0]$. More examples of excitation-wave patterns can be seen in Figure 5.

If the weights and initial excitation are small and the excitation threshold is too high (or very small), the wave propagation may cease. In intermediate situations, gaps (non-excited nodes) appear in a circle of excited nodes. If the refractory period is long, the gap is quickly filled by excitations from neighbouring nodes. If the refractory period is short, after the excitation the nodes can be excited again without a lengthy delay. In such cases, the number of non-excited nodes increases quickly and the wave can start to propagate backwards. Such a situation is observed in the propagation patterns depicted in Figure 5(b)–(d).

If the values of the weights are close to 1, almost all the incoming signals can be transferred on. We then have a regular hexagonal-formed signal propagation, even in situations where the refractory period is short. This situation is depicted in Figure 5(a) and (d). Freshly (for the two most recent time periods) excited nodes are shown in black, and cells in the refractory period are shown in grey. In the edge of this media, $N_y = 37$, refractory period $t_{\mathrm{refr}} = 4$ and weight $w = 0.8$.

In Figure 5(a) we have a strictly hexagonal model with a comparatively long refractory period. The wave-propagation pattern is almost circular (see the wave after $t = 160$ time steps). Later, the wave reaches the hexagonal edges of the media. After 300 steps in six corners, we see only a few exited nodes. We can also observe a small number of grey nodes close to the end of the refractory period. After two time periods, all the excited nodes disappear. Only the nodes in the refractory period remain. After a couple more time periods, they disappear as well. In short, a novel social media investigations approach allowed us to obtain diverse wave-propagation patterns observed in real-world experiments (Litvak-Hinenzon & Stone, 2007; Reber, 1996).

3. Social media model composed of several agent groups

The analysis of cell behaviours in biology and social organisations of human beings and enterprises shows their clustered structure and even their synchronised behaviours. The same is

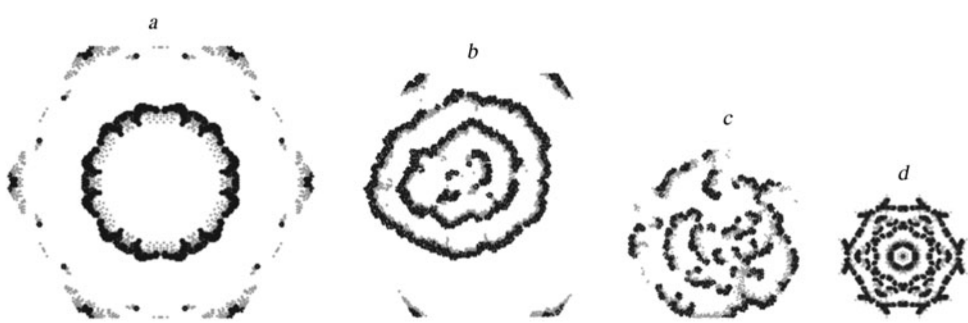

Figure 5. Diverse wave propagation patterns after (a) 160 and 300 wave propagation steps; (b)–(d) 215 wave propagation steps in four social media examples differing in size and other model parameters.

confirmed by theory and by simulations of wave-propagation processes (see Section 2.3, also Chua et al., 1995) and other approaches (Keller-Schmidt & Klemm, 2012). It is believed that group interests are driving forces of evolution in biology and human society (Frank, 2003). In general, many aspects of nature, biology and even society have become part of the techniques and algorithms used in computer science, or have been used to enhance or hybridise techniques through the inclusion of advanced evolution, cooperation or biology (see the review by Cruz, Gonzlez, & Pelta, 2011).

With this knowledge in mind, we developed *a structured schema of agent society*. The agents (the nodes in the model) are split into groups with diverse characteristics (parameters of the social media model). It is assumed that the groups in the single population are partners and share the innovative information they get from outside. Inside a single group, the wave excitation and propagation are performed as described in Section 2. If a large number of nodes in the single media (group) exceed *a certain level*, the group leader transmits excitation (innovation) signals to leaders of other groups of the agent populations (the central nodes in the groups). To determine this level, we selected a fraction $T_{\text{excitation}} = 0.02$ of the recently excited nodes in a central area of the media as a criterion to transmit excitation information to other partner groups. The central area was characterised by a fraction of the total number of agents found excited in that area. In simulations, we used $N_{\text{closest}} = 0.8$. In Figure 6 we present the wave-distribution patterns after $t = 361$ and $t = 516$ wave-propagation steps. In this experiment we have one group (c) in which the signal does not fade, and three groups in which the signals vanished after reaching the media edges. Because the model parameters of the groups are different, the disappearance of the excitation in diverse groups occurs at different moments in time. For that reason, diversity of the groups is an almost essential condition for the survival of the excitation waves in the agent population.

Mathematical notation aside, the motivation behind the group approach is very simple. To simulate complex social agent-based systems, explicit information encoded in the properties of individual agents is not sufficient, as social agents are not actually so individual. Social agents are open systems influenced by the external (i.e. not only local, but also regional and global)

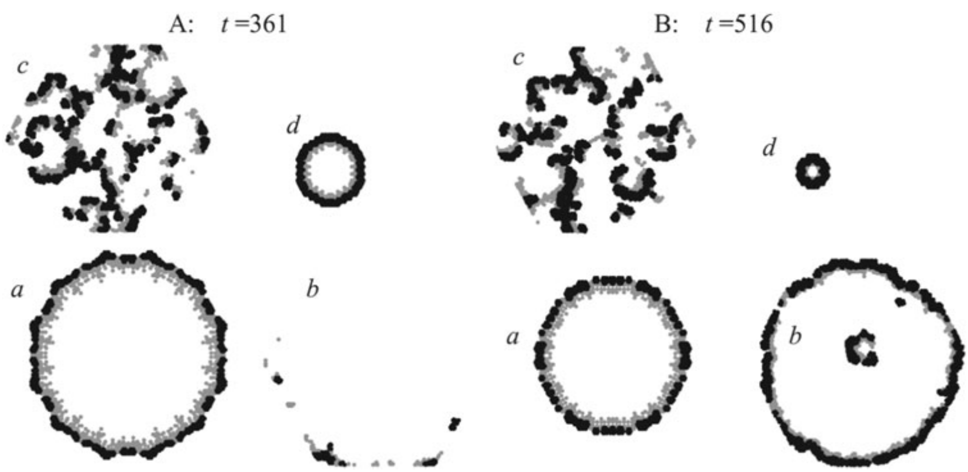

Figure 6. Wave patterns in four (NG = 4) agent groups after (A) 361 wave propagation steps and (B) 516 wave propagation steps. Parameters: sizes N_y = [128 120 108 74]; weights = [0.7 0.8 0.7 0.8]; refractory period = [20 16 4 4]; excitation threshold = [0.5 0.6 0.45 0.5]; noise level = [0.0 0.6 0.5 0.0].

environment at large (Bandini et al., 2007). The new social media model provides new perspectives on observing the phase-dependent field-like reality of social-media excitations (DePaoli & Vizzari, 2002; Plikynas, 2010; Reber, 1996). These findings lead us to the idea that contextual (implicit) information via the mechanism of dissipating excitation waves is distributed in fields, and that those fields, although expressing some global information, are locally (mostly unconsciously) perceived by the agents. Based on the earlier considerations, we foresee the further expansion of the present information-transmission model. We need to introduce the global variables and states of the whole system. In such a simulation, a global implicit as well as local explicit level of contextual information could be captured and effectively exploited (Bandini et al., 2007).

4. Propagation of two competing signals in populations of agents

Of course, bi-modal simulation is a mere simplification of social multi-modal reality. Nevertheless, such reductionism helps us to observe the basic features of excitation–propagation dynamics. In fact, two competing excitation modes (originating from two different excitation centres) are often perceived in social media; for instance, two competing major parties, presidential candidates, opposing opinions, genders or states of faith. This happens naturally, even in complex heterogeneous agents' environments where extreme competition (or cooperation) boils down to just two dominating states of social excitation. Hence, bi-modal modelling of such states of social excitation reveals from bottom to top the agents' parameters, which foster observed social behavioural patterns.

4.1 Two colliding waves and their breakdown

Up until now, we have considered the propagation of innovation (excitation) signals in unexcited social media. In reality, everybody – human beings, the economy and social organisations – is already excited by previous innovations. In fact, the competitive dissemination of innovations takes place; that is, one innovation is replaced by another. In order to meet such a multi-excitatory reality, we have to enrich a single excitation model with multi-excitatory properties, where several competing signals can be modelled.

First, let us consider a single excitable media model where two signals begin propagating from different nodes. In the 2D example in Figure 7(a) (after $t = 100$ propagation time steps), we see two propagating excitation (innovation) waves. Both excitation signals are propagating in strictly hexagonal media. A relatively short refractory period usually causes chaotic but periodic patterns for both propagating signals. After the waves collide (Figure 7(b), after $t = 170$

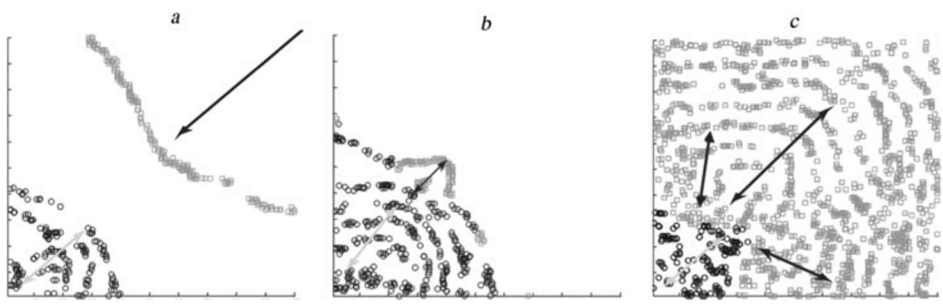

Figure 7. Annihilations of two colliding waves and their breakdown.

propagation time steps), almost all the nodes near the collision area are in their refractory period. Due to a short refractory period, the excited nodes of both signals are able to find some nodes whose refractory period has just ended. In Figure 7(b), we can see that the signal represented by black squares is dominant and the signal represented in grey has almost died; however, after 100 time periods, the grey signal recovers and begins to dominate almost all areas of the media space. The character of the wave propagation remains the same during the subsequent 10,000 time steps (Figure 6(c)).

By changing the parameters of the social media, we can observe an enormous variety of wave-propagating patterns, with one signal outperforming another and the other dying, and slow or rapid movement of boundaries between two differently excited areas. An analysis of a large number of simulations with a variety of model parameters can lead us towards a better understanding of wave-colliding mechanisms.

4.2 Propagation of two signals in the grouped population

Like Keller-Schmidt and Klemm (2012), the authors of this paper assumed at first that innovations were rare. In Sections 2 and 3 we considered the propagation of innovation signals in empty, non-excited social media. In previous grouped-agent population models, the innovation excitation from outside arose just after the end of the refractory period in the central area of the nodes. Nowadays, scientific, technological, political and economic innovation appear fairly frequently. In reality, we do not have an unexcited economy or social media. They are all full of activity due to previous fruitful ideas.

In order to analyse the propagation of two (EXS = 2) or more excitation signals that appear at different moments in time, we expanded the grouped structure of the agent population. In the analysis of two, the old and new, innovations, we considered a population composed of NG = 4 agent groups. Each group controls two excitable social media: one for the propagation of each single innovation signal. In total, we had to examine the wave-propagation patterns in 2NG = 8 groups of media. To bring the model closer to problems we face in reality, we introduced the mutual influence of two groups of parameters allocated to each solitary agent group. We supposed that the propagation of alternative signals (first four groups of media) would influence the media parameters of the remaining four groups: the excitation threshold refractory period and the magnitudes of the weights. In such a way, one excitation signal disturbed the propagation of another signal. We investigated a variety of scenarios and found innovative information propagation patterns, e.g. (i) both signals propagate in the population of the groups and (ii) new signal wins or loses, etc.

A variety of possibilities require a separate large-scale study. A twofold analysis of information propagations in the grouped excitable social media model, however, shows that the wave-propagation approach can be useful for understanding the distribution of a variety of innovations and controlling their dissemination processes.

5. Concluding remarks

In this paper we have presented a new information-propagation approach developed to simulate excitations in large social media. Our model provides a bottom-up method of simulating and investigating information–diffusion properties in social media based on the characteristics of the simulated simple agents. Before concluding, we interpret the social context and reality a little more broadly. Hence, meaningful information can be understood as an economic resource or intangible commodity in modern societies, where a large share of gross national product is produced by the information-related service sectors. Therefore, depending on the properties of the social networks, some societies perform better than others in the new information economy.

Following the line of these investigations, we should observe that the majority of agents act as information-processing, storing and transmitting nodes. Models like those presented in this paper help to reduce investigation problems to the most fundamental constituent parts. In this way, bottom-up and wave-like excitation–propagation research assists us to identify the most basic properties of social agents, which produce observed phenomena such as information broadcasting, destruction, competition between several sources of excitation and excitation of transfers to other social domains. The main results of our analysis are as follows.

(1) To make the wave propagation approach useful in excitable social media, we expanded CA- and artificial NNs-based schemas (Raudys, 2004) and suggested a novel schema in which the node excitation and recovery times depend on the strength of the signal accumulated during two time periods for a single node. Our results indicate that the nonlinearity of the activation function plays an especially important role.
(2) This paper provides insights into, and an overview of, the interpretation of basic parameters; for example in the applied case of advertising media scheduling, we have shown a concrete way to exploit the excitation saturation decay function.
(3) Broadening the homogeneous media model to make it heterogeneous revealed population-clustering dynamics and conditions of cooperation between different groups. We showed that a clustered and diverse nature of the population is vital for the overall performance of a society.
(4) We investigated a large number of wave-propagating patterns in differently structured multi-group populations of agents and found propagation patterns frequently observed in the case of the diffusion of innovations, the spread of behaviour in online social network experiments, the diffusion of messages in social groups, etc. To view these and other simulation results, visit our online virtual lab (V-lab) at http://vlab.vva.lt/; MEPSM1 model, login: Guest; password: guest555.
(5) We suggested a structure and model for population groups in order to analyse the dissemination of two or more competing innovation signals. This provides new possibilities to understand what kinds of social media characteristics influence the dominance of one or another of the signals.

Our analysis supports the conclusion concerning the bursting branching process of evolution observed in databases and theoretically explained in Keller-Schmidt and Klemm (2012). In summary, this paper presents a mechanism to explore and set parameters for uniform, chaotic, spiral and rhythmic oscillations as well as bursting excitation–propagation patterns that originate from essentially similar basic properties; namely, agents' propensity to adopt a new behaviour depending on the proportion of a neighbouring reference group that has already adopted it.

Based on the observed oscillation dynamics in the grouped population simulations, we infer our models in accordance with chaos theory, where rhythmic oscillations are typical indicators of (i) coherence between the constituent parts (i.e. agents) and (ii) self-organisation on the whole-system scale (Osipov, Kurths, & Zhou, 2007). There are also such implications for self-organised social systems, as coherence between agents is mainly established through the constant recalibration (i.e. propagation of excitation waves) of agents' states. This is why waves of excitation occur rhythmically in self-organised social systems. Hence, simulations of oscillations (waves of excitation) in social systems from the bottom-up (i.e. agents' perspectives) could yield new knowledge and surprising results concerning conditions for the occurrence of coherent social order. It therefore appears to be essential to direct our prospective research efforts towards the simulation of oscillations in social systems.

Analysis of the synthetic data generated by modelling wave propagation can help to distinguish the most important factors that affect the social phenomena under investigation. For instance, in the absence of reliable empirical data, wave-propagation modelling becomes a useful instrument to determine the attributes necessary for carrying out, for example, effective sociological surveys, political campaigns and news distribution. We also intend to bring into play 2D and 3D visualisations of excitation–propagation patterns in the analysis of time series of high-dimensional financial data used in automated trading (Raudys, 2013; Raudys & Raudys, 2012).

The agent groups and wave-propagation-based model can be expanded in a number of ways. Various agent-proximity measures can be applied, and simultaneous propagation of several dissimilar information waves can be considered. We can introduce the global variables and states of the whole system to transmit excitations to distant neighbours. We can adjust the size, refractory period and importance of the agents. The agent groups can be joined into sub-populations. We will then obtain multi-level, hierarchical structures of agent populations. An important task, which has not yet been touched upon, is an automated evaluation of the model's parameters. The simulation of media evolution during long sequences of innovation becomes a useful tool here (Raudys, 2008). In the prospective research, however, we plan to simulate and examine concrete social phenomena and seek for task-dependant interpretations of the parameters (or sets of them) for single models.

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