Multiagent context–dependent model of opinion dynamics in a virtual society

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Abstract. To describe the diversity of opinions and dynamics of their changes in a society, there exist different approaches — from macroscopic laws of political processes to individual–based cognition and perception models. In this paper, we propose mesoscopic individual–based model of opinion dynamics which tackles the role of context by considering influence of different sources of information during life cycle of agents. The model combines several sub–models such as model of generation and broadcasting of messages by mass media, model of daily activity, contact model based on multiplex network and model of information processing. To show the applicability of the approach, we present two scenarios illustrating the effect of the conflicting strategies of informational influence on a population and polarization of opinions about topical subject.

Keywords: Context–Dependent Modeling, Multiagent Modeling, Opinion Dynamics, Virtual Society.

1 Introduction

Modeling of evolving human opinions can be used for a deep understanding and influence on the processes of dissemination of information about publicly significant events and topics. Models of the opinions dynamics imitate the dissemination of information about political companies [1] and entertaining content [2], the interaction of agents in social networks [3] and training online communities [4].

Wide variety of models that are used to study opinion dynamics can be divided into three different levels: (i) macromodels, reflecting the longitudinal dynamics of public sentiment at the level of the entire population and its strata, (ii) mesomodels, capturing interactions between individuals via network–based or multiagent approach, and (iii) micromodels, describing decision–making process of an individual. However, at the moment there is a lack of models, linking the different levels (i.e. society, communities and individuals) in frames of a holistic system. In this study, we address the problem of modeling the opinion dynamics from a perspective of emergence, dissemination and influence of information processes in a virtual society. Here and further by virtual

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society we mean a simplified digital image of a society aimed to represent its main entities and interactions between them.

We consider aggregated opinion dynamics at the population level as the result of informational influence at the micro–level. Linking of micro– and macro–levels takes place in a mesoscopic context–dependent model (Bruce Edmonds in his recent study [5] underlines that accounting context in social sciences is a way to integrate qualitative and quantitative models, and to understand emergent social processes while combining formal and data–driven approaches). In frames of this study, a time–aware context binds together agents, information channels and information messages, thereby determining conditions of information spread. Another important implication of using contexts is an opportunity to account for different types of behavior and reactions in different situations. Examples of contexts in a virtual society are social network (or even particular page in it) and household.

Proposed mesoscopic model presents several mechanisms of tackling the contexts: (i) individual model of context switching sets daily schedule of online and offline contexts, (ii) link between two agents (an edge of a complex network) may be activated only if they are in the same context, (iii) agents have context–dependent memory and patterns of behavior including rules of choice of information channels within the context. Simulation of peer–to–peer interaction together with influence of one–to–many information channels (e.g. mass media or opinion leaders) allows to explore the aggregated dynamics of a virtual society for predefined types and preferences of agents and scenarios of population–level informational influence.

The rest of the paper is organized as follows. Section 2 presents a brief overview of related works. Section 3 describes main entities of the proposed model, their evolution laws and the relationships between them. Section 4 provides the results and interpretation of two simulated illustrative scenarios ("Information war" and "Opinion on the hot topic"). Finally, Section 5 discusses the borders of applicability of proposed model and further research directions.

2 Related works

Agent–based approaches for modeling of opinion dynamics can be classified according to several distinctive features: way of presenting opinion and modeling process (discrete, continuous), rules for changing opinions (homogeneous or heterogeneous parameters of agents, the influence of agents' views on each other, various constraints on interactions, etc.), way of representing a network and interaction of agents, type of information to be disseminated.

Discrete opinion models allow to investigate areas where one of the possible solutions must be taken, for instance, a binary view (yes or no) or a range of values, like in [6, 7]. However, such models do not allow investigating processes related to negotiation problems or fuzzy attitudes. This drawback can be eliminated using continuous models. Lorenz [8] points out that domain of continuous opinion dynamics models covers decision of multiple types of task consensus, information spread, influence etc. In addition, the variables giving the opinion can be changed continuously (see, e.g. [9]). In this

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paper, Martins investigates continuous opinion models based on the interaction of simplified agents. Author compares the results of the application of Bayesian updating rules to estimating certainty about the value of a continuous variable (representing their opinion for a given topic) to confidence interval–based approaches.

One of the prime questions that is being answered in the field of opinion dynamic is how actors (or agents, which is a common term for modeling research) change their opinion through interactions. Classical opinion models operate with static rules which are universal for all the agents. To take into consideration different types of behavior, there have been carried out attempts of introducing heterogeneous rules of opinion change. For instance, the work of Salzarulo [10] seeks to improve the model known as social judgement, previously introduced by Jager and Amblard [11], which assigns constant rejection/agreement rates for interaction of agents. Salzarulo's model of meta–contrast incorporates the self–categorization theory to provide the formalization of the embeddedness of the opinion update rules in the context of interaction. In addition, there are studies devoted to the fact that agents can interact with each other if they have close opinion about problem under consideration (for example, in work of Lorenz [8]). In the paper [12], authors suggest an approach to the formation of communities where the agents are grouped together with a similar opinion and can sever ties with agents if their opinion is very different.

Characteristics of the network that binds agents together socially (when the network describes the structure of sustained relations between agents) or communicatively (through recurring or single–time acts of information exchange) are extensively studied in the works dedicated to opinion modeling. For instance, in [13] authors suggest that there is a randomness threshold that leads to convergence to central opinion which is in line with Salzarulo [10] who additionally assumes that non–random small–world networks can produce extreme opinions. Further, Grabowski and Kosiński [14] highlight the role of critical phenomena in opinion dynamics. Two major factors contributing to these are the influence of mass media and the global context of interaction. Other studies connect the evolution of the opinions with the evolution of the networks representing relations between agents. For instance, in [15] authors conclude that at different scales, given the dynamic nature of social relationships, the strategies for active opinion propagation undertaken by a group shall be diverse as to gain support yet maintain integrity.

What distinguishes our work from the majority of research articles on opinion dynamics is that though it operates with networks and mechanisms of their construction, it as well looks into the diversity of the types of users and the features of how information can be obtained by users using the context change.

3 Model description

3.1 Model entities

Proposed model of information spreading in a society describes the change in the attitude of agents to entities (other agents, opinion leaders), information channels (media),

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and information sources. We assume that each agent is characterized with a set of constant social values which determines the attitude to other entities. In other words, each agent has a position (represented as vector) in a space of social values, and the distance is this space between two entities influences their opinion about each other. An agent shares the position with members of his or her social group. A position on an agent is assumed to be fixed, but an agent can change his vision of social values of other entities according to a received information messages (IMs). This results in changing the distance between entities.

Formally, an agent as a member of a social group is represented by a tuple *A = (V, Y, M, G, C (G))* where *V* is a vector encoding the position in the space of social values (each element of *V* ranges from –1 to 1), *Y* is a set of vectors with current positions of other entities, *M* is the set of IMs stored in memory, *G* is the social group to which the agent belongs, *C(G)* is a schedule of context switching that depends on the agent's social group.

Agents receive information messages during peer–to–peer interaction or passive perception in 'one–to–all' (e.g. media broadcasting) cases. The information messages (IM) are transmitted using information channels and are represented by the tuple *IM = (s, r, q, x, y, b, c)* where *s* is a source, *r* is a receiver, *q* is a topic (it denotes a unique event to be discussed and serves as a unique id for a group of messages), *x* denotes who expresses the relation (the message generator), *y* – to whom the relation is expressed (the subject), $b \in [-1,1]$ – evaluation of the subject, $c \in [0,1]$ – credibility of IM. A subject and a topic also have their positions in a space of social values. Received information messages change agents' opinion. Evolution of opinion for an agent on the subject is then simulated by a long–term model of information processing. This model calculates the result of informational influence taking into consideration memory of an agent (e.g. history of interaction with an information source, current positions of other entities in a place of social values).

The model of society imitates the process of information exchange in a population on a range of topics. The model is based on a simplification that the person (the agent in the model) receives information messages from two sources: the media (mass media) and other people. We also assume that there is special type of agents called opinion leaders whose aim is to disseminate their opinion within a population. The opinion leaders may use broadcasting facilities of mass media and may prefer different contexts and schedules of working with audience. Agents constituting the audience of mass media also have own preferences of information sources and context switching. Thus, a model of society includes two sub–models: (i) the model of interaction of opinion leaders with media (and thus with the audience of media), and (ii) the model of context switching which regulates interaction of agents with media and peer–to–peer interactions of agents. Here a context binds together sources and receivers of information messages in a timely manner.

3.2 The "Opinion Leader–Media" model

The "Opinion leader (OL)–Media" model determines conditions of generation and transfer of information messages from the OL to agents through the media. Each OL in

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the model has a schedule that characterizes the frequency and the type of messages transmitted to each media in model. The media is an entity that receives, transforms, stores and transmits information messages to an agent. At each iteration, OL can broadcast a message to one of the media. Then the message is filtered and stored in the media memory (interaction is based on [17]). After that, the agent in a suitable context ("Media context" and "Online media context", depending on the type of media) receives all IM stored in the media memory. The memory of each media is updated every few days.

An example of the interaction scheme of an agent with OL is shown in **Fig. 1**. The scheme uses the following notation: *IM* – information message; *L(IM)* – leader's information message; *F_np* – newspaper filter; *F_tv* – TV filter; *F_on* – online media filter.

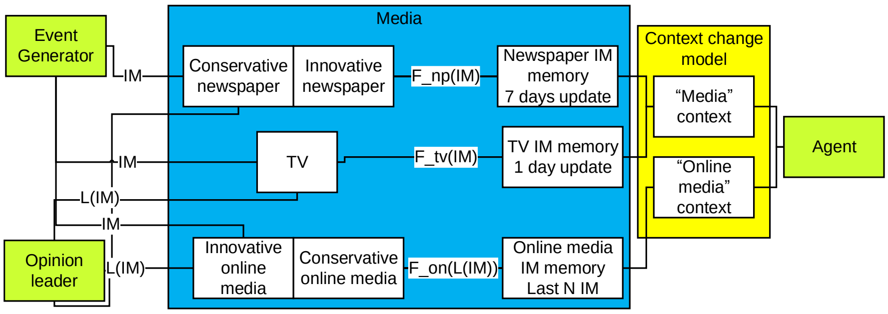

Fig. 1. Media–agent interaction scheme

After getting into the media, the information message is transformed in accordance with the filtering model (if a source of information is considered as unreliable, a media may replace the attitude with its own position), which based on [9]:

$$F\big(IM(T)\big) = \mathrm{d}\frac{IM(T)+P(T)}{2} + (1-\mathrm{d})P(T), \tag{1}$$

where *F(IM (T))* is an opinion after filtering, *IM(T)* is an opinion encoded in initial information message, *P* is an opinion of the media about topic *T*, *d* is the degree of confidence in the source. In the tuple, only one parameter changes after filtering – an opinion on the topic. If the value of the expression is greater than 1 (modulus), it is considered equal to +/– 1.

3.3 The "Agent–Agent" model

Circulation of information messages between agents is regulated by: (i) the model of context switching (a context determines occupation of an agent at a given time, for example, sleep or work), and (ii) the contact network of agents, which determines the interaction of agents within the same context (for example, agents can send messages to each other if there is a working contact between them, and they are simultaneously in the context of "communication with colleagues").

As mentioned above, each agent has a G – social group, and C(G) denotes a schedule of contexts that depend on a social group. A context is an element from the set of all

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contexts available for a modeling scenario, meaning the current occupation of an agent. Within the scenarios presented in the work, contexts that include "communication" are significant (agents in them can exchange messages within the "Agent–Agent" model), as well as the "media" context (receiving messages in the "Opinion Leader–Media model"). The schedule of context switching *C(G)* is a set of triples (time of beginning, time of end, type of context). The schedule must cover the entire simulation time.

For an exchange of messages between two agents, three conditions must be met. First, the agent should be in a context suitable for exchanging messages with other agents. Secondly, the agent must be connected by a special type of edge in the contact network graph with another agent in the same context. And third, there should be messages for exchange in the memory of agent.

A contact network is created at the beginning of the simulation, and is an undirected graph without self–loops. The edges of the graph are divided into 3 categories: friends, family, colleagues / classmates (thus, in fact this network is a multiplex).

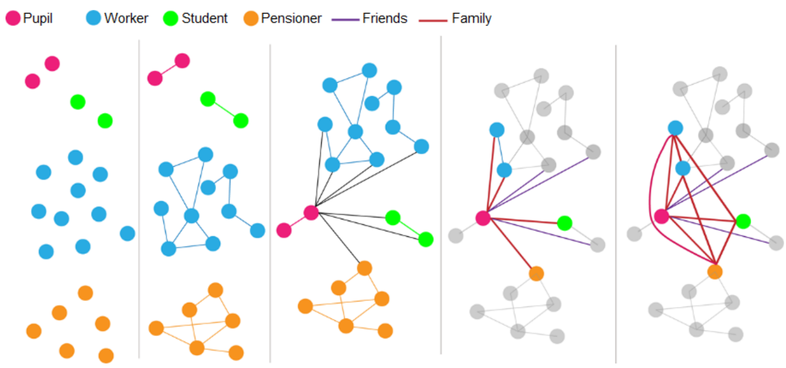

Fig. 2. Stages of generation of the contact network

The procedure of generating a contact network consists of four steps. The first stage is the assignment of the age category and social group to each agent. Then, edges are randomly generated within the members of social groups, as well as the types of these edges. The third stage of network generation is the creation of "family" edges. For each of the members of a fixed social group, edges are created with members of the other social groups. The types of edges are assigned randomly. Then, "family ties" can occur between the "family" edges agents associated with the agents of different social groups. The last stage is the creation of friendly relations between the representatives of other social groups. **Fig. 2** shows all the steps described.

When the agent is in a fitting context (one of the communication contexts, for example, "communication with family"), and there are agents suitable for sending messages, a pair of agents for communication are randomly chosen. After this, we randomly select the agent–sender, which transmits to the other agent a random message from a fixed number of the last.

The agent's opinion about other entities of the model (agents, and opinion leaders) is formed based on distance in the space of social values (SV). Values are the moral

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foundations that people rely on to form an attitude towards other entities. The mechanism for changing attitudes to other entities is described in detail in the section "The long–term behavior model". The vector of social values is a vector of the dimension of the number of social values, with values from the interval [–1;1]. Each value corresponds to the ratio of the agent to the SV from –1 (sharply negative) to 1 (sharply positive).

3.4 The long–term behavior model

This model runs to recalculate the values of fields of long–term memory of agent after each context change. Using a set of IMs obtained within the context, the long–term behavior model updates the values of the relation to other entities ($\varphi_k(t)$ – the relation to the *k*–th entity), opinion about the relation of other entities to social values ($\gamma_k(t)$ – the relation of k–th entity to one of possible social values).

The updated opinion on the newsbreaks is calculated by the following formulas:

$$O_\chi(t+1) = O_\chi(t) + \alpha \frac{\sum_{k=1}^{K_\chi} b_{\chi k} c_{\chi k} v_k(\varphi/2+1)}{K_\chi} \tag{2}$$

$$|O_\chi(t+1)| \leq \frac{\sum_k |v_k|}{M} \tag{3}$$

Then the values for representing social values of other entities must be recalculated:

$$\gamma_k(t+1) = \gamma_k(t) + \alpha\left(\frac{\sum b}{K} - \gamma_k(t)\right)\frac{\sum c}{K} \tag{4}$$

as well as the agent's relation to other entities:

$$\varphi_k = 1 - \frac{d(v,\gamma_k)}{\sqrt{M}}, \tag{5}$$

where *K* is the number of messages, *b* and *c* are the values of the evaluation and credibility in the messages, *M* is the number of social values, α is the rigidity coefficient, and $d(v,\gamma_k)$ is the Euclidean distance between the vectors.

3.5 Simulation cycle

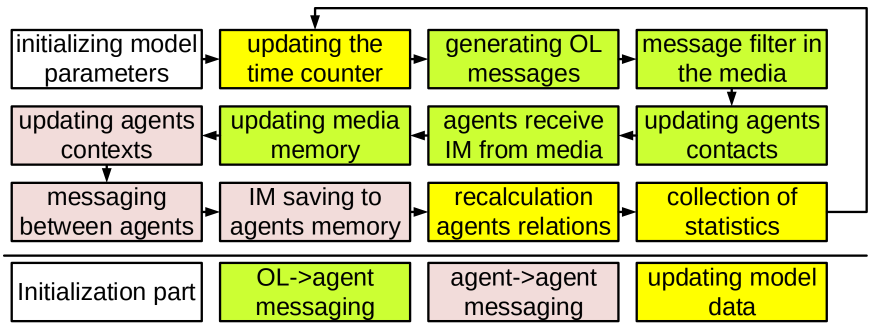

Fig. 3. Scheme of simulation cycle

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Fig.3 shows the scheme of simulation cycle. At the beginning of the simulation, basic parameters and components are initialized, such as the contact network, the context change model, the agents' relation to entities and social values. In addition, the identity of each agent is initialized to one of the social groups. Belonging to the social group is used in the initialization of the degree of radicalism of the agent. Then, a simulation run is started, consisting in the sequential execution of an iterative procedure, which includes the following steps: generating messages and storing them in the media memory; updating the current context of each agent; receiving messages from media memory by agents in suitable contexts; sharing of messages between agents; recalculation of the attitude of agents to the entities of the model; collection of statistics of the model.

4 Experimental study

Proposed model is complex in a sense that it describes different types of entities (each one with built–in sub–models of external activity and opinion dynamics) and relationships between them (via contexts and networks). To use this framework, one needs to specify the input parameters of models, and the rules of evolution of parameters for a given input. The experimental study presented further was aimed to validate the proposed way of combining the models by considering simple scenarios of informational influence. These scenarios were constructed in a way allowing interpretable and predictable results of a given strategy of influence on the population. Thus, it becomes possible to compare the results from our model with predicted output. By doing so, we show that proposed mesoscopic model may reproduce the results on a macro level by aggregating the results of a micro–level. The program was implemented using Python programming language. The computation time for the scenario "Information war" (for three months,1000 agents) is 170 seconds.

4.1 Initial parameters

Table 1. Basic schedule of context switching for different social groups (an example).

<table>
<tr><th></th><th>Pupils</th><th>Students</th><th>Workers</th><th>Pensioners</th></tr>
<tr><td>8:00–9:00</td><td colspan="3">Internet Media</td><td>Communication with family</td></tr>
<tr><td>9:00–12:00</td><td colspan="2">Study</td><td>Work</td><td>Rest</td></tr>
<tr><td>12:00–13:00</td><td colspan="3">Communication with one–grader /classmates / colleagues</td><td>Communication with friends</td></tr>
<tr><td>13:00–14:00</td><td colspan="3">Study</td><td>Rest</td></tr>
<tr><td>14:00–15:00</td><td colspan="3">Way home</td><td>Personal business</td></tr>
<tr><td>15:00–16:00</td><td colspan="3">Communication with friends</td><td>Communication with friends</td></tr>
<tr><td>16:00–18:00</td><td colspan="4">Hobby</td></tr>
<tr><td>18:00–19:00</td><td colspan="4">Communication with family</td></tr>
<tr><td>19:00–21:00</td><td colspan="4">Media</td></tr>
<tr><td>21:00–8:00</td><td colspan="4">Sleep</td></tr>
</table>

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We use the assumption that the agent has an identical schedule every day. Also, we assume that members of one social group have one schedule.

Table 1 shows the schedules of contexts for members of different social groups. Within the scenarios presented in the work, there are four social groups: pupils, students, workers and pensioners. **Table 2** presents data on the statistics of the number of connections between agents of different age (and social groups) based on data from [18]. Casual edges are generated according to **Table 2**.

Table 2. Average number of edges between agents, depending on the social group.

	Share of total agents	Pupil	Student	Worker	Pensioner
Pupil (15–18)	10%	6.39	2.02	3.62	0.49
Student (19–24)	10%	1.67	4.40	5.2	0.57
Worker (25–59)	50%	0.7	0.97	6.72	1.88
Pensioner (60+)	30%	0.37	0.61	3.47	3.09

Table 3. Edges type for social groups.

	Friend edge	Colleagues and etc edge	Family edge
Pupil–pupil	0.2	0.8	0
Student–student	0.2	0.8	0
Worker–worker	0.2	0.7	0.1
Pensioner–pensioner	1	0	0
Other types	0.2	0.7	0.1

The types of edges are assigned in accordance with **Table 3**, that indicates the probabilities of assigning a specific type of edge to the rib, depending on the social groups of agents. The number of recent messages from which the message is selected for transmission in these scenarios is five.

Social values initialization

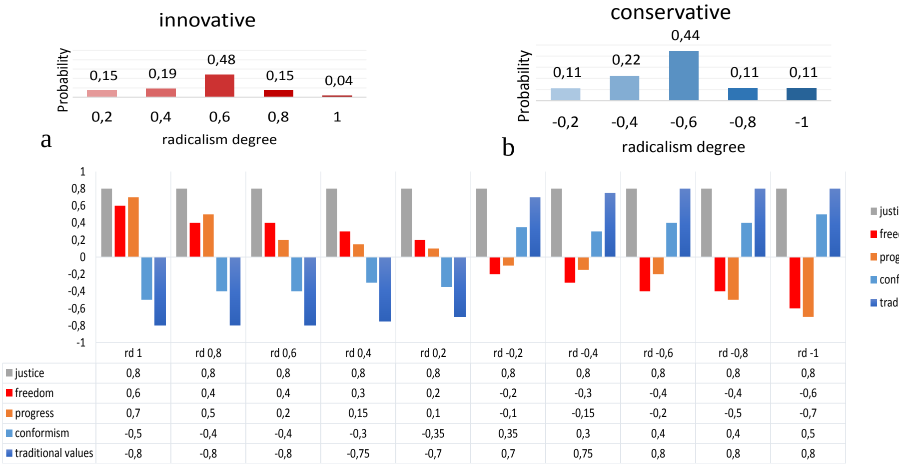

Fig. 4. Data for the initialization of social values

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Social values (within the framework of the scenarios presented in the work) are: justice, freedom, conformism, progress, traditional values. We use values based on work [19].

The vector of social values of the agent is initialized at the beginning of modeling and does not change in its process. The initialization algorithm consists of three steps. The first step is to randomly assign to the agent the direction of the views: "innovator" or "conservator". Then, depending on the direction of the views, the agent is given a degree of radicalism (according to **Fig. 4a** and **Fig. 4b**). The vector of social values is calculated in accordance with **Fig. 4 (bottom)**, depending on the degree of radicalism.

4.2 Scenario “Information war”

We developed the scenario "Information war" with the aim to investigate the dynamics of opinions about opinion leaders with different social values (in this case, conservative and innovative). We simulate the translation of leaders' attitudes toward social values (stage one), the conservative leader's broadcast of disinformation about the innovative leader (stage two), and the "exposure" of the conservative leader (stage three). In the scenario, we simulate the broadcasting by the two opinion leaders ("Conservator" and "Innovator") of their attitude to social values and change of opinions about these leaders in society.

The model simulates the work of five media: "Innovative Newspaper"," Conservative Newspaper", "Innovative Internet Media", "Conservative Internet Media", “TV”. To identify the intensity of the appearance of opinion leaders in these media, we collected the data on the speeches of Russian politicians in five Russian media.[1]

The scenario consists of 3 stages (each with 30 model days). At the first stage, each of the opinion leaders broadcasts through the media their attitude to random SV. At the second stage, with an intensity of once every 1.5 hours, the casual media receives reports of the leader–innovator's negative attitude to the values "freedom" and "progress."

In the third stage, with an intensity of once every 1.5 hours, messages are sent to the random media that refute the reports of the second stage. With the same intensity, reports are received about the negative attitude of the leader–conservative to the SC "justice". The script was launched for 1000 agents and 90 days of modeling time. In this scenario, a simplification is used, which is that the trust of all agents to both opinion leaders is equal to 1.

Fig. 5 shows the graphs of the change in attitude towards the conservative (**Fig. 5a**) and innovative (**Fig. 5b**) opinion leaders. As can be seen from **Fig. 5a**, at the first stage the attitude of innovator agents to the Leader–Innovator improves, and to the Leader–Conservative worsens, as reports about their social values are received. The attitude of conservative agents during the first stage varies in the opposite way.

At the second stage, the attitude towards the Leader–Conservative does not change (in the absence of messages). The relationship to the Leader–Innovator changes in the opposite (in comparison with the first stage) because the messages themselves contain the opposite meaning. In the third stage, the ratio of all agents to the Conservative Agent

[1] kremlin.ru; www.spb.kp.ru; navalny.com; tvrain.ru; www.1tv.ru;

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is significantly deteriorating, due to the good opinion of each agent to the social value of "justice."

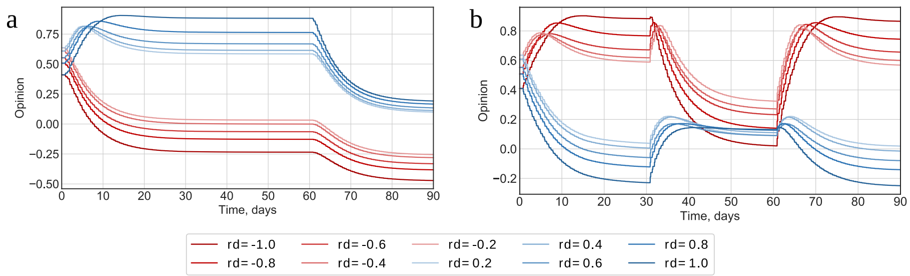

Fig. 5. Opinion about two OL depending on the degree of radicality: (a) – conservative, (b) – innovative; “rd” in legend – radicalism degree

4.3 Scenario “Opinion on the hot topic”

This experiment was aimed to study change of opinions about the topics and the people involved in spreading the information. The purpose of this scenario is to show the process of opinion’s polarization in society regarding to hot topics.

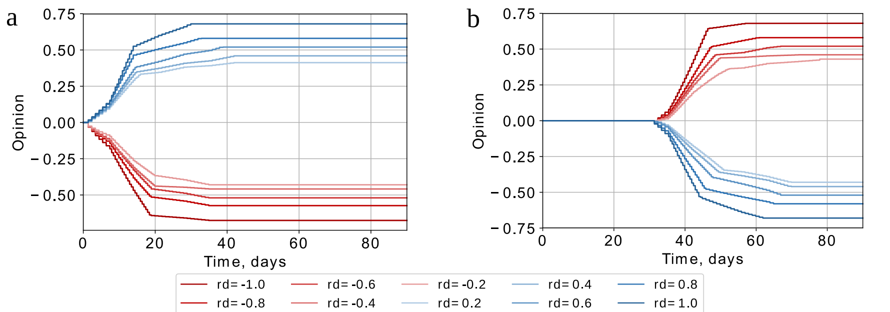

Fig. 6. Opinion about two topics depending on the degree of radicality: (a) – conservative, (b) – innovative; “rd” in legend – radicalism degree

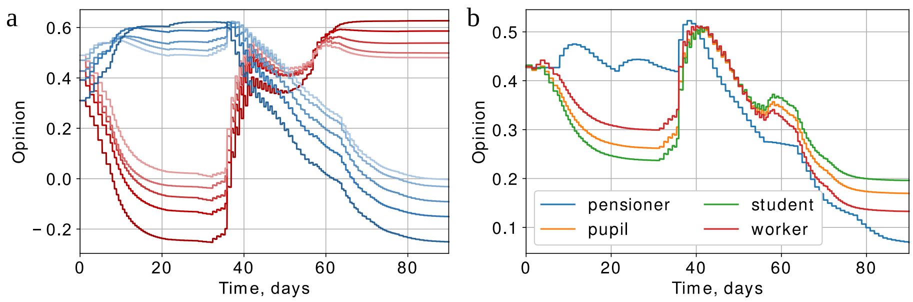

Fig. 7. Opinion about the source of information, depending on: (a) the degree of radicalism, (b) – the social group

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This scenario has all the same assumptions about entities and social values as in the previous scenario. Model describes the behavior of 1000 agents and the source of information (e.g. government) that creates the messages related to social values about two topics: conservative and innovative. For conservative topic IMs contain negative attitude towards freedom/progress and positive towards traditional values/conformism. In contrast, for innovative topic IMs contain positive attitude towards freedom/progress and negative towards traditional values/conformism. Messages are broadcasted through the media. We assume that conservatives are more likely to trust conservative media and agents with similar SVs (same for innovators). Therefore, innovators read innovative media, conservatives are conservative (newspaper and Internet–media).

The scenario was simulated within 90 days. The first 30 days of the entity broadcast through the media conservative topics, the following days – innovative. Thus, after 30 days, the messages regarding to first topics are gradually replaced by messages dedicated to the second one.

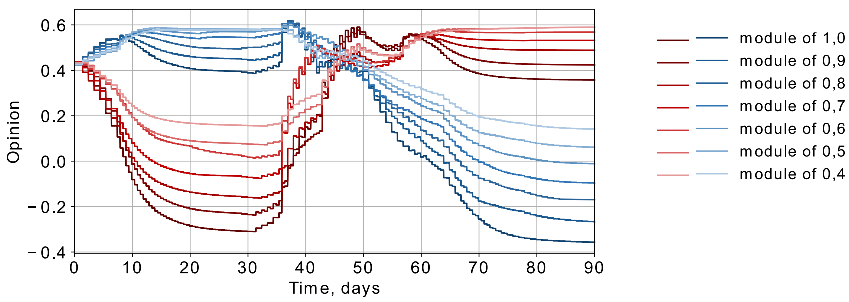

Fig. 8. Influence of the radicality of the assessment in information messages

Fig.6 shows the peculiarity of the influence on the formation time of opinions in different groups. On all the charts of color denotes radicalism degree from innovative (red color) to the conservative (blue color). The messages generated by the source of information effect on opinion about it of agents from different social groups and with degrees of radicalism (**Fig.7**). After the appearance of messages in the media dedicated to second topic, fluctuations are observed in attitude towards the leader. This is due to the fact that the media contain messages with different attitudes of the source towards the same social values. Thus, agents can change their attitude both towards improvement and deterioration. In the initial assumptions, social groups have different distributions of degrees of radicalism, so a change in their attitude toward the source has a different character (**Fig.7b**).

This scenario allowed us to investigate the process of polarization of opinions in society regarding a hot topic. Agents interact more often and tend to trust ideologically "close" media (conservatives read conservative media, innovators read innovative), so there is a polarization effect and a change in the attitude to the leader when he discusses different topics.

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5 Conclusion and future works

In this paper, we propose a multiagent context–dependent model of the dynamics of opinions based on distance in the space of social values. The model includes message exchange between agents based on varying contexts and a multiplex contact network, as well as a model for transmitting the information via the media. In addition, a long–term information processing model is proposed that regulates the effect of the received message on the agent's opinion. Experimental study demonstrates expressive abilities of a model in two scenarios: "Information war" and "Opinion on the hot topics" illustrating the effect of the conflicting strategies of informational influence on a population and polarization of opinions about topical subject. For these synthetic scenarios, parameters of a model were identified partially based on the evidence from a published literature, partially from the observed data. The results of experiments show that the model reproduces the expected dynamics of opinions (which is implicitly prompted by a logic of considered scenarios).

This study is mostly aimed at demonstrating a way of combining models of different scales to reproduce aggregated opinion dynamics from the actions of individuals. In our opinion, increase in the complexity of this solution compared to simpler basic models is an essential step towards more realistic, data–driven models of public attitudes. Although this complexity brings additional challenges of proper identification of parameters and model calibration, the advantage of this approach is a possibility to describe processes of informational influence in a real society (in contrast to abstract, idealized network models of opinion dynamics) while respecting the peculiarities of circulation of information flows (in contrast to macro models). To be used for real–world scenarios, the model has to be supplemented with a calibration tool which allows to choose the optimal implementation of sub–models (e.g. model of opinion update) and to tune sub–models according to an observable data (from social networks and traditional mass–media to the sociological surveys).

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References

1. Gatti, M., Cavalin, P., Neto, S.B., Pinhanez, C., dos Santos, C., Gribel, D., Appel, A.P.: Large–scale multi–agent–based modeling and simulation of microblogging–based online social network. In: International Workshop on Multi–Agent Systems and Agent–Based Simulation. pp. 17–33 (2013)
2. Ryczko, K., Domurad, A., Buhagiar, N., Tamblyn, I.: Hashkat: large–scale simulations of online social networks. Soc. Netw. Anal. Min. 7, 4 (2017)
3. Peng, W., Shuang, Y., Jingjing, Z., Qingning, G.: Agent–Based Modeling and Simulation of Evolution of Netizen Crowd Behavior in Unexpected Events Public Opinion. Data Anal. Knowl. Discov. 31, 65–72 (2015)
4. Zhang, Y., Tanniru, M.: An agent–based approach to study virtual learning communities. In: System Sciences, 2005. HICSS'05. Proceedings of the 38th

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Annual Hawaii International Conference on. p. 11c—11c (2005)
5. Edmonds, B.: The Room Around the Elephant: Tackling Context–Dependency in the Social Sciences. In: Non–Equilibrium Social Science and Policy. pp. 195–208. Springer (2017)
6. Hu, H.–B., Wang, X.–F.: Discrete opinion dynamics on networks based on social influence. J. Phys. A Math. Theor. 42, 225005 (2009). doi:10.1088/1751–8113/42/22/225005
7. Yildiz, E., Acemoglu, D., Ozdaglar, A., Saberi, A., Scaglione, A.: Discrete Opinion Dynamics with Stubborn Agents*.
8. Lorenz, J.: Continuous opinion dynamics under bounded confidence: A survey. Int. J. Mod. Phys. C. 18, 1819–1838 (2007)
9. Martins, A.C.R.: Bayesian updating rules in continuous opinion dynamics models. J. Stat. Mech. Theory Exp. 2009, P02017 (2009)
10. Salzarulo, L.: A continuous opinion dynamics model based on the principle of meta–contrast. J. Artif. Soc. Soc. Simul. 9, (2006)
11. Jager, W., Amblard, F.: Uniformity, bipolarization and pluriformity captured as generic stylized behavior with an agent–based simulation model of attitude change. Comput. Math. Organ. Theory. 10, 295–303 (2005)
12. Yu, Y., Xiao, G., Li, G., Tay, W.P., Teoh, H.F.: Opinion diversity and community formation in adaptive networks. Chaos An Interdiscip. J. Nonlinear Sci. 27, 103115 (2017)
13. Amblard, F., Deffuant, G.: The role of network topology on extremism propagation with the relative agreement opinion dynamics. Phys. A Stat. Mech. its Appl. 343, 725–738 (2004)
14. Grabowski, A., Kosiński, R.A.: Ising–based model of opinion formation in a complex network of interpersonal interactions. Phys. A Stat. Mech. its Appl. 361, 651–664 (2006)
15. Benczik, I.J., Benczik, S.Z., Schmittmann, B., Zia, R.K.P.: Opinion dynamics on an adaptive random network. Phys. Rev. E. 79, 46104 (2009)
16. Leifeld, P.: Polarization of coalitions in an agent–based model of political discourse. Comput. Soc. Networks. 1, 7 (2014)
17. Sobkowicz, P.: Opinion dynamics model based on cognitive biases. arXiv Prepr. arXiv1703.01501. (2017)
18. Mossong, J., Hens, N., Jit, M., Beutels, P., Auranen, K., Mikolajczyk, R., Massari, M., Salmaso, S., Tomba, G.S., Wallinga, J., others: Social contacts and mixing patterns relevant to the spread of infectious diseases. PLoS Med. 5, e74 (2008)
19. Graham, J., Haidt, J., Nosek, B.A.: Liberals and conservatives rely on different sets of moral foundations. J. Pers. Soc. Psychol. 96, 1029 (2009)

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