Social Mood Revealed

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Abstract. Social mood, the aggregated mood of a society, emerges from complex system of individual moods and their influences on each other. The real social networks consist of millions or even billions nodes constantly interacting with each other. Can such a complex system be modeled by a graph consisting of a small number of agents with simple interactions between them? Profile of Mood States, known and well-vetted psychometric instrument, distinguishes seven mood dimensions (Tension, Happiness, Calmness, Vigor, Fatigue, Confusion and Friendliness). If we apply them to a society at large, i.e. to social mood, is it possible to measure influences of one mood dimension on another? In addition to this, is it possible to both maintain good approximations of social mood changes and be able to observe such interactions at the same time? In this work we investigate these questions and propose a framework which can approximate or even, in some circumstances, be predictive of future social mood states. The framework consists of a model of social influence and an evolutionary algorithm learning proper network topology and model parameters.

Keywords: Social Mood, Collective Emotions, Social Networks, Social Influence, Agent-Based Modeling, Complex Systems, Social Simulation, Sentiment Analysis

1 From individual to social mood

From the psychological research it is known that the emotional state, as well as the amount of information, play the main role in human decision-making [11, 9]. Traditionally, in theoretical considerations, the second factor played a more important role. For instance, *rational choice theory*, economical perspective that perceives people as *rational actors*, explains decision-making process through the paradigm of utility maximization [13]. Agents base their actions on pragmatic calculations of their best interests.

However, emotions can profoundly affect human decision-making process as well, in many cases driving an individual to make a choice that seems "irrational" in the framework of said theory. For example, behavioral finance has provided proofs stating that financial decisions are significantly affected also by emotion and mood and not only by rational utility maximization [23]. Damasio states that personally beneficial decision making requires emotion as well as reason [9]. He also proposed the *somatic marker hypothesis*, that describes a mechanism by which emotional processes can guide (or bias) behavior [5]. Pfister and Böhm have developed a classification of how emotions function in decision-making, that conceptualizes an integral role for emotions, rather than simply influencing decision making [29].

Thus, emotions affect individual choices and decisions. Does this also apply to larger groups of people, i.e. can societies experience mood states that affect their collective decision making? Prechter's *socionomic hypothesis* suggests that the social mood drives various types of social action in the areas of cultural, political and financial behaviour [30]. However, assuming that the social mood affects the society behaviour analogously to the way in which one's emotions drive his individual actions is quite unreasonable. The society is a complex system with its emergent properties. The social mood, as a state of the whole system, is something different than just a simple sum of its parts [2]. Therefore, researchers attention has been focused on finding the relations between the social mood and the behaviour of societies [23, 26, 6, 31].

The first problem with such investigations is to actually find a way to measure the social mood. Large surveys of public mood are generally expensive and difficult to undertake. That is why there were proposed some ways to assess the social mood indirectly. For example: from the results of football games [12] and from weather conditions [18]. Recently though, researchers came up with other, low-cost and very efficient, way to measure the public mood. They were able to do it through sentiment analysis of social media content such as Twitter feed, discussion forums or blogs [27, 34, 33]. Social mood measured by means of Twitter turned out to be predictive of many social phenomena including stock market [7], political elections [15, 25], box-office revenues for movies [3] etc. If social mood can be related or even predictive of so many social matters, it is important to have better ways to analyze it and to understand its behaviour.

In this paper we propose a framework that can translate huge, highly complicated social network (of individual moods and their influences on each other) to a fairly simple and an order of magnitude smaller graph of agents. It behaves in a similar manner to the real network concerning dynamics and interactions of the mood dimensions. The translated network can be then more easily analyzed.

Such a framework enhances the state of the art of social sciences, offering a tool to measure and to interpret social mood and the interactions between the mood dimensions. Its novelty is provided by its data-driven approach. Most of the social influence models employ bottom-up methodology: begin with simple rules (of agents interactions), then observe the emergent behaviour of the system [14, 32, 24, 19, 16, 10]. The goal of such investigations is to examine how the model behaves given particular assumptions. The model, however, may or may not reflect a real-life social system. We believe that we propose more holistic approach. It consists of two stages. We begin with measuring the actual social mood by the means of the real-world data. Then we tune our highly customizable model of social influence to reflect these measurements. This way we provide not only the theoretical considerations, but also a model that can indeed approximate social mood changes, that are happening in a day-to-day reality. On the other hand, it is not just a numerical approximation - the construction of the model enables one to investigate the interactions between agents, representing different mood dimensions. To the best knowledge of this paper's authors, models of mood dimension interactions have not been proposed in the scientific literature so far. The same is for data-driven models of social influence. Therefore, the proposed framework might be of a great interest for social scientists.

The paper is structured as follows. In Section 2 we describe our framework. Firstly, we explain how we assess the social mood. Then, we describe our model of social mood. The description involves a model of social influence and an evolutionary algorithm aiming to find the best network topology and model parameters. Section 3 describes the empirical experiments that were conducted. In Section 4 we discuss the results of the experiments. We draw final conclusions in Section 5.

2 Social mood translation

In a real world people affect each others individual emotional states during communication. If we sum those individual emotional states up, we will receive a global measure called social mood. The question is, if we can replace the real social network of emotional influences with its model, say with a number of nodes two times smaller? And at the same time be able to maintain similar dynamics of mood influences and good approximation of a global mood state? Then, could we create a model four times smaller? How small could that model be? It is clear that the smaller it is, the easier it would be to analyze it and to understand its dynamics.

In this paper we propose a framework, which is able to translate huge complex social network of individuals to a simple graph with fixed, small number of nodes (not more than 50 nodes). In this graph each node is an agent which is a representation of a class of individuals in the original network. Every agent apart from its mood state, has its own level of *impressionability* and *influence*. Respectively, these are the measures of how much an agent is sensitive to influence of others and how influential it is. The edge between nodes denotes their ability to affect each other. The values of parameters and the topology of the graph is determined by data-driven evolutionary algorithm which approximates the social mood time series.

The next two subsections will describe the framework in detail. First, we will describe how we measure social mood and then, how model of its dynamics is constructed.

2.1 Assessing the social mood

We measure social mood by analyzing Twitter feed in terms of 7 mood dimensions. We list them here (with explanation of what does, respectively, the low and high score of each dimension mean):

1. Tension - relaxed or anxious,

2. Happiness - happy or depressed,
3. Calmness - calm or angry,
4. Vigor - apathetic or vital,
5. Fatigue - rested or tired,
6. Confusion - sure or confused,
7. Friendliness - aloof or kind.

We use similar mood dimensions and methodology of assessing the public mood to the one used in [7] (namely Profile of Mood States). The motivation behind this is that we believe we should measure social mood in more than just one classic dimension (positive vs. negative) to obtain some number of potentially different aspects of public mood. The efficiency of this sentiment tracking tool was cross-validated against big socio-cultural events like the U.S presidential election (November 4, 2008), Thanksgiving (November 27, 2008) etc. [7, 6]. In addition to this, in [7] authors find an accuracy of 87.6% in predicting the daily up and down changes in the closing values of the Dow Jones Industrial Average index, which indicates that the classification can have good practical applications.

Data We recorded a collection of public tweets which were posted during 14 days from July 7th to July 20th, 2014. We were interested only in tweets expressing author's mood state, thus we only tracked tweets containing words: "feel" and "feeling" (20,110,489 tweets). For each post, we obtained its date and time of submission, as well as the content of the message (which is a text limited to 140 characters).

One can have an impression that the dataset is particularly small (14 days), concerning the fact that in other papers datasets can span over several months. The difference, though, is in temporal resolution of the datasets. Whereas researchers usually measure social mood in terms of days, in this work we measure it every 5 minutes. We do it to be able to observe the intraday dynamics of collective emotions and to be able to track the microchanges in social mood. We believe that such investigations may be helpful, for instance, for financial intraday traders, for trading algorithms or for people responsible for communication and public relations. If we compare the sizes of the datasets, we will obtain $14d \times 24h \times 12 = 4032$ time intervals for our dataset. In this paper experiments were conducted for time periods between 09:30 and 16:00 EST from Monday till Friday, as these are the times when New York Stock Exchange is opened. This gives us $10d \times 6.5h \times 12 = 780$ time slots. On the contrary, if we take a daily resolution into consideration and, say, we will have a dataset of 9 months, it gives us around $9m \times 31d = 279$ time intervals.

Another fact is that the volume of tweets posted nowadays is much greater than it used to be in the past. In this paper we collected 20,110,489 tweets during 14 days and in [7] authors collected 9,853,498 tweets during over 9 months.

Generating social mood time series In order to obtain a mood score of a tweet we compare each word from a tweet against each word from a lexicon of so called *emotional* words. The lexicon is derived from an existing psychometric instrument, namely the Profile of Mood States (POMS) [22]. It is known and well-vetted psychometrical instrument used to measure one's emotional state. It consists of 65 adjectives describing the mood state which are linked with different emotional dimensions. The examined person has to refer to these adjectives on a five-point scale.

To create a computational version of the test, we expand the basic lexicon of 65 adjectives from POMS with similar words, which we obtain by analysing word co-occurrences in big collections of texts. The expanded lexicon consists of 965 associated terms which are collected in the following procedure. We use Bing search engine to query for phrases "*is* [*adj*] *and*" and "*was* [*adj*] *and*", where [*adj*] denotes a particular adjective from the original lexicon which we want to find similar words to[1]. For each of the queries, we download first 200 results. For each result, we extract the word after conjunction *and*. Then we sort extracted words by most frequent occurrences. From the most frequent words we choose similar adjectives by hand. The advantage of querying search engines is that they are a relatively simple way of searching over a large collection of documents. Moreover, it also enable us to retrieve similar words which actually are in use.

Having the lexicon of *emotional* words, the social mood of Twitter feed is measured in the following way. Tokenization is performed on each tweet and then each word from a tweet is compared with each adjective from the lexicon. If there is a match, the adjective from the lexicon is mapped back to its original POMS term and via the POMS scoring table to its respective POMS dimension. Then, a counter of corresponding dimension is incremented by one.

To obtain a social mood time series we split our collection of tweets into groups of messages sent in 5 minutes long time periods. For each hour H, we distinguish time intervals: $[H{:}00, H{:}05)$, $[H{:}05, H{:}10)$, ..., $[H{:}55, H+1{:}00)$. Then for tweets from each of such time intervals, we employ our mood measuring procedure. At the end, we obtain times series:

$$M = \{M_t : t \in T\} \tag{1}$$

where t corresponds to successive time intervals and

$$M'_t = [d'_{t,1}, d'_{t,2}, ..., d'_{t,7}] \tag{2}$$

where, $d'_{t,1}, d'_{t,2}, ..., d'_{t,7} \in \mathbb{N}$ are values of respective mood dimensions: Tension, Happiness, Calmness, Vigor, Fatigue, Confusion and Friendliness.

For our social mood time series not to be dependent on the volume of tweets in a given period of time, we then normalize the values of mood dimensions in the following way. For each mood dimension $d_{t,i}$, $i \in 1, 2, ..., 7$:

$$d_{t,i} = \frac{d'_{t,i}}{\sum_{j=1}^{7} d'_{t,j}} \tag{3}$$

[1] Bing search engine distributes a dedicated API. For the details visit http://www.bing.com/dev/en-us/dev-center.

Obtaining final elements of social mood time series:

$$M_t = [d_{t,1}, d_{t,2}, ..., d_{t,7}] \tag{4}$$

All mood times series in the rest of the paper are normalized in the same manner.

2.2 Model of social mood

Real-world social mood networks consist of big number of people, each of them having their own mood state. These people can interact with their acquaintances, affecting their moods, as well as being affected by them.

Therefore, if we want to translate such a network to a smaller graph, we need to find a way to model 3 things:

1. Collective mood state of individuals - mostly, we already have it done. We model it with 7-dimensional vector like in equation (4).
2. Topology of the social network - we need to find a way to translate the connections between nodes in a big social network to analogous connections in a small graph.
3. Social influence - we need to build a model of how agents are affecting each others mood states in a small graph.

We will start with approaching the topology issue, then we will describe our model of social influence and finally we will present the evolutionary algorithm which aims to find the best topology and influence parameters. All these components will, in the end, describe our framework.

Topology of the network We use evolutionary approach to find the best network topology (as well as other parameters of the model). This choice is made, because we want the algorithm:

- to be population-based - in order to be able to compare obtained solutions at any time of the algorithm run,
- to be anytime - meaning that it can return a valid solution, even if it is interrupted before it ends,
- not to make any assumptions about the topology and the parametrs of the model.

However, evolutionary algorithm needs initial population in which topologies are somehow constructed. To model the social network in the beginning stage of the evolution, we decided to use two classes of graphs.

First class are random graphs. We believe that they are the simplest and the most natural way to initialize network topologies, concerning the fact that we take advantage of an evolutionary approach. To construct the particular graph, first we draw $p \in (0, 1)$ from the uniform distribution. Then, every possible edge occurs independently with the probability p.

Second class consists of scale-free graphs, which are graphs whose degree distribution follows the power law. The motivation behind this choice is that many real-world social networks, as well as cyberspace networks, are conjectured to be scale-free [4, 17, 8]. To generate graphs, whose node degrees follow the power law distribution, we used Barabási-Albert model [1]. The algorithm uses a preferential attachment mechanism, which means that the more connected a node is, the more likely it is to receive new links. More formally, the probability p_i that the new added node is connected to the pre-existing node i is:

$$p_i = \frac{k_i}{\Sigma_j k_j} \tag{5}$$

where k_i is the degree of node i and the sum is made over all pre-existing nodes j.

Model of social influence There exists a multitude of social influence models in the sociophysics literature. They can be classified into discrete (including binary) models and continuous models depending on the representation of opinions that are being influenced.

The typical discrete models include Ising model [14], Sznajd model [32], social impact model [24], voter model [19], etc. These descriptions of social influence, sometimes called the *toy models*, are useful for simplifying the opinion dynamics explanations (e.g. using the *temperature* notion to introduce the stochastic behaviour [14] or proposing *United we Stand, Divided we Fall* rule to implement the phenomenon of social validation [32] etc.). However in our case, the drawback of these models is their discrete nature, because our measurments of the social mood have continous characteristic.

This fact brings our attention to the continuous models, that mainly include Hegelsmann-Krause model [16], Deffuant-Weisbuch model [10] and their numerous variants and extensions [28, 20, 21, 35]. These approaches, however, also possess some limitations, as far as our work is concerned. Some of them assume bounded confidence of agents, which means that the agent adjusts its opinion only towards the opinions that are not very distinct (that lay in the ϵ-interval around the agents' opinion) [10, 21, 35]. As we want to model interactions between mood dimensions, this approach is not suited for our case (for instance a state with high value of *Happiness* may affect a state with low value of *Friendliness*). Other drawback is that some of the models assume influence dynamics, that leads to a consensus [21, 16, 28]. Consensus is not a typical feature of many social situations, neither is it a typical state of the mood dimensions dynamics. Mood dimensions do not tend to average themselves and often tend to differentiate (e.g. low value of *Happiness* and high value of *Tension*). Our model need to have a way to describe this phenomena. Another feature that it should possess is the ability to describe the fact that agents may not always be easily influenced by others.

Therefore, we propose our own model of social influence, which is similar to Hegelsmann-Krause model, but also introduces some major differences. They enable us to model the characteristics of mood dimensions dynamics, which we just mentioned. It is defined as follows:

1. $\mathcal{A} = \{1, 2, ..., n\}$ is the set of agents.
2. Each agent i, at discrete moment in time t, has its own mood state:
$$M_{i,t} = [d_{i,t,1}, d_{i,t,2}, ..., d_{i,t,D}] \tag{6}$$
where $d_{i,t,k} \in \mathbb{R}$ and D is a constant denoting the number of mood dimensions[2].
3. Each agent i, at discrete moment in time t, knows if each of its mood dimensions increased or decreased during the last time step:
$$\Delta_{i,t} = [\Delta_{i,t,1}, \Delta_{i,t,2}, ..., \Delta_{i,t,D}] \tag{7}$$
where $\Delta_{i,t,k} \in \mathbb{R}$ and $\Delta_{i,t,k} = d_{i,t,k} - d_{i,t-1,k}$, for $t > 0$. For each agent i first element of the sequence Δ_i is specified at the beginning:
$$\Delta_{i,0} = [a_{i,0,1}, a_{i,0,2}, ..., a_{i,0,D}] \tag{8}$$
where $a_{i,0,1}, a_{i,0,2}, ..., a_{i,0,D}$ are specified initial values.
4. Each agent i has its level of:
   – *influence* $\varphi_i \in [0, 1]$, which denotes how much it is affecting others,
   – *impressionability* $\delta_i \in [0, 1]$, which denotes how much it is being affected by others.
5. Agents are organized in the network $\mathcal{N} = (\mathcal{A}, E)$, where E is a set of connections or edges, which are 2-element subsets of the set $\mathcal{A}$.
6. Sequence of agent's mood states is specified as follows. For each agent i:
   – First element of the sequence is specified at the beginning:
   $$M_{i,0} = [b_{i,0,1}, b_{i,0,2}, ..., b_{i,0,D}] \tag{9}$$
   where $b_{i,0,1}, b_{i,0,2}, ..., b_{i,0,D}$ are initial values.
   – Elements of the next time steps $t > 1$ are defined using a recursive rule. For each mood dimension $d_{i,t,k}$, $k \in 1, 2, ..., D$:
   $$d_{i,t,k} = d_{i,t-1,k} + \delta_i d_{i,t-1,k} \Sigma_j sgn(\Delta_{j,t-1,k}) \varphi_j \tag{10}$$
   where the sum is made over all agents j connected to the agent i (indicated by the set E).
7. The global social mood state, at each discrete moment in time t, is defined as a sum of agents' mood states:
$$M_t = \Sigma_{i \in \mathcal{A}} M_{i,t} \tag{11}$$

Thus, in the model in every discrete time step t part δ_i of agent's i mood can be affected by its neighbours. If their particular mood dimension went up in the previous time step, the neighbours will try, taking their influence parameters φ into consideration, to increase it. In other case, analogously, they will try to decrease it.

[2] In this paper $D = 7$.

How to construct the model from Twitter data? We only described aggregated social mood $M = \{M_t : t \in T\}$ acquired from Twitter data so far. However, to be able to use it in our model of social influence, we need split data. To achieve this, the idea is to split tweets into some kind of equivalence classes associated with mood dimensions. The agents then are not representatives of individuals, but representatives of mood dimensions. The easiest way to achieve this is to employ the mood measuring procedure for each tweet, identify its dominant mood dimension (the dimension with the highest score) and then classify the tweet as Tension, Happiness, Calmness, Vigor, Fatigue, Confusion or Friendliness representative. If there is more than one dimension with the highest score, classify the tweet randomly as a representative of one of its dominant dimensions.

Using this procedure, we can obtain decomposition of tweets into seven different groups associated with mood dimensions. We can then couple each group $i \in \{1, 2, ..., 7\}$ with different agent, obtaining corresponding mood time series:

$$M_i = \{M_{i,t} : t \in T\} \tag{12}$$

Having agents as representatives of mood dimensions, we can then apply our social influence model to observe how different dimensions are influencing each other. This way, we obtain a graphical representation of influence dynamics. In this approach the influence of one mood dimension on the other is not based on the actual Twitter social graph or other kind of individuals topology. The influence is measured on the macro level, the same way that in a society optimists have an influence on pessimists or electorate of one political party has an influence on the other electorate. The influence is measured as the change in aggregated sum of micro-interactions among the individuals.

On the other hand, conducting such a simulation (running the model), we are able to calculate mood estimators $\widehat{M_{i,t}}$ - set of vectors of mood scores of every agent i, in every time step t. Those estimators can be then summed to obtain global social mood estimator $\widehat{M_t}$. It is then easy to assess how good is our estimation (and all in all - simulation) calculating the mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{|T|} \sum_{t}^{t \in T} \frac{|\widehat{M_t} - M_t|}{M_t} \tag{13}$$

We choose MAPE as a measure of performance of our simulations, because we need to compensate for two things:

1. scores of some mood dimensions are usually much greater than scores of other mood dimensions - therefore, we need percentage error to measure performance of all dimensions approximations,
2. the values of estimators may be greater or less than actual mood score - therefore, we need to measure error in absolute values.

Another thing is that, as the experiments showed, only seven agents in the model may not be a sufficient number to approximate the global social mood M

well. We may therefore want to have more than just one representative of each mood dimension. To achieve this, we introduce splitting parameter S. We then employ the same grouping procedure to tweets set as before, but after obtaining seven groups for seven different mood dimensions, we split each group into S smaller groups of the same size. In this paper $S \in \{1, 2, ..., 5\}$, therefore we conducted experiments for numbers of 7, 14, 21, ..., 35 agents in the model.

Evolutionary algorithm The main parameters that need to be adjusted in social mood model to reflect the real-world data are the network topology, Δ_0, φ and δ parameters of the agents. In our approach, we start with a random graph or scale-free graph network topology (with the same probability), random values of Δ_0 vector generated independently from [-1,1] interval and random values of φ and δ parameters generated independently from $[0, 1]$ interval. Then, we adjust these parameters using an evolutionary algorithm which is defined in the following way.

We start with population of $P = 100$ randomly generated models of social mood[3]. For each model we conduct the simulation and calculate the mean absolute percentage error (MAPE). $MAPE = [MAPE_1, MAPE_2, ..., MAPE_7]$ is also a vector, because there are 7 mood dimensions, so we calculate the mean value of this vector coordinates obtaining our final error Er.

$$Er = \frac{1}{7}\sum_{i=1}^{7} MAPE_i \tag{14}$$

We then sort our models ascending by the value of Er and build next generation of models in the following way. The m fittest models (where m is equal to 50% in our simulations) are retained in the next generation and the others are discarded. A single mutated copy is made of each remaining model so that the size of the population always remains constant. Mutations are applied to r agents from a particular model (where r is equal to 10%) and can take four forms with equal probability:

1. The agent receives new values of $influence$ φ and *impressionability* δ parameters. They are generated independently and randomly from $[0, 1]$ interval.
2. A new link in the network is added between the agent and different, randomly chosen agent.
3. An existing, randomly chosen link of the agent is removed from the network.
4. The agent receives new values of Δ_0 vector. They are generated independently and randomly from $[-1, 1]$ interval.

After G generations, we obtain the model with the least error Er which is the best fit to the data.

[3] Some parameters of the evolutionary algorithm are constrained (eg. P = 100, m = 50%, r = 10%). The values were handpicked to optimize the performance.

3 Experiments

In order to evaluate the framework, the experiments are conducted to see how well can it approximate the social mood changes and predict the future values of social mood.

3.1 Approximations of mood changes

To evaluate the quality of the framework's approximations of social mood changes, for each value of the splitting parameter S and for the number of generations $G = 300$, we test it on 60 one-hour-long time intervals. They span across 10 days in July 2014, from 7th till 11th and from 14th till 18th. The periods of time lay between 9:45 and 15:45 EST, as this is the time when New York Stock Exchange is opened (actually it is 9:30 - 16:00, but first and last quarters are the most unstable, that is why we do not want to include them). Much of the research on social mood and electronic sentiment is focused on finding financial applications, therefore we wanted to follow that trend. Each time period starts at $[H{:}45, H{:}50)$, which is the starting point, and then there are 11 time intervals that are approximated $[H{:}50, H{:}55)$, $[H{:}55, H + 1{:}00]$, ..., $[H + 1{:}40, H + 1{:}45)$. Thus, we test the approximation on $10d \times 6h \times 11 = 660$ time slots. The results can be seen in the Table 1. They were obtained against a benchmark of $G = 300$ generations in the evolutionary algorithm. These outcomes can be further improved if the computations are longer (e.g. for $S = 1$ we can achieve 2 percentage point better results if we set G to 600).

Table 1. Two tables present mean value, median and standard deviation of: approximation MAPEs (on the left-hand side) and prediction MAPEs (on the right-hand side), for each value of the splitting parameter S.

S	Mean	Median	SD
1	10.69%	9.45%	4.05
2	10.11%	8.99%	3.84
3	9.49%	8.72%	3.64
4	9.49%	8.74%	3.22
5	9.19%	8.49%	3.29

S	Mean	Median	SD
1	18.63%	17.55%	8.32
2	28.38%	22.90%	17.56
3	27.75%	21.85%	16.24
4	27.30%	25.63%	12.44
5	28.30%	23.70%	14.74

3.2 Predictions of mood changes

In order to evaluate the predictive power of the models, for each value of the splitting parameter S and for each model computed in previous subsection between 9:45 and 14:45 EST, we predict twelve following five-minutes-long time intervals. Therefore, on each of ten days, for five different starting hours, we predict twelve time intervals. Thus, in our experiment we predict $10d \times 5h \times 12 = 600$ time slots. The results can be seen in the Table 1.

4 Discussion

The comparison of social mood approximations for different values of the splitting parameter S confirms the intuitive anticipation that the larger the value is, the better are the approximations (in a matter of fact concerning all comparison indicators: mean, median and standard deviation). One could suspect this fact. In larger graphs there are more agents and more connections among them. Thus, it can be easier for the model to tune to the data. On the other hand, the person studying the graphical model would like to have as small network as possible. They are then easier to analyze and to understand. As the experiments show, the approximations of the models with smaller splitting parameters are worse by around one percentage point. In most cases, this should still be a satisfactory level of error, which one can accept for the sake of the clarity of the graphical model.

As far as the predictive power of models is concerned, the problem with social mood assessed by the means of Twitter is that this kind of system is not closed. In other words, external factors affect the social mood on Twitter, and not only users influence each other. Therefore, prediction power of a particular model is limited by the way of how the next time interval is similar to the previous one in terms of mood changes dynamics.

During our experiments the predictive power of models with the splitting parameter $S = 1$ turns out to be the best, even though they are not the best fit to the data. Most probably it is due to the overfitting of models with greater splitting parameter. In addition to this, in case of $S = 1$ there is no noise created by the interactions between the representatives of the same mood. In the Figure 1, MAPEs of ten predicted time intervals for different values of S are presented. One can notice said smaller amounts of noise for $S = 1$.

Topologies of the evolved networks are something that could be a topic of a separate investigation. From the models that we obtained during our experiments, we can state that they are different for different moments of time, concerning not only their shapes but also their parameters. These facts are not surprising and are probably due to the fact that in different moments of time people were exposed to different external factors. The question of what kind of social situation causes which kind of network topology would be an interesting issue for the future research.

From our conclusions about topologies, first notable fact is that, during the evolution, bigger networks lose their "scale-free property" (understood as a degree distribution following the power law in a graph which is not infinite). Some models' degree distributions look quite similar to the distributions following the power law, but still are disturbed. Rest of the networks turn into more random graphs.

Another fact concerning bigger networks produced by the algorithm (with $S > 2$) is that they are not really easy to read and analyze. Each mood dimension have a few representatives, but usually only some of them are connected to others. It is not clear how someone should interpret such a graph. We can say that only part of the people with particular dominant mood dimension is engaged

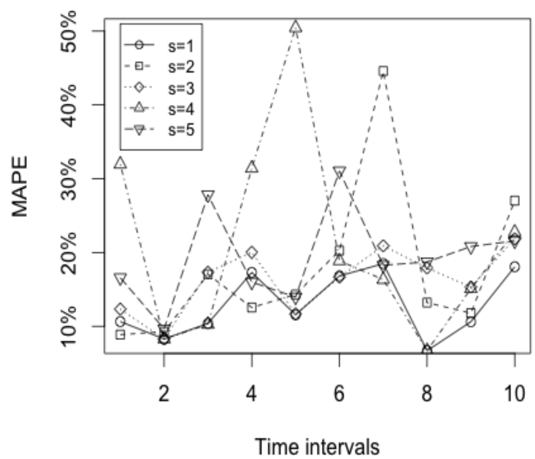

Fig. 1. Figure presents MAPEs of ten predicted time periods for different values of the splitting parameter S.

in interactions, but still conclusions are chaotic. Another issue is the interaction between representatives of the same mood dimension. The aim of the framework is to translate the complexity to something simple. It is not obvious if bigger networks can make that much of a simplification.

This brings our attention to smaller networks. Small graphs, with only one representative for each mood dimension ($S = 1$), do not possess the problems stated above. They also have bigger predictive power of social mood changes (only the approximation is a little bit worse, but as it was stated earlier - it is satisfactory). Thus, we may recommend them as a better source of information and a better tool to investigate social mood. We can see an example of such a network in Figure 2.

5 Conclusion

In this paper, we investigate whether a complex network of individual emotions influencing each other can be approximated by a small graph with similar properties. Our experiments show that small networks can indeed approximate social mood with reasonable mean absolute percentage errors ranging from 9.19% to 10.69%. These results can be further improved using longer computations. Our studies show also that if the following period of time is similar to the previous one, meaning that it is not affected by big amount of external factors, models can be even predictive of the future social mood states. The models with the

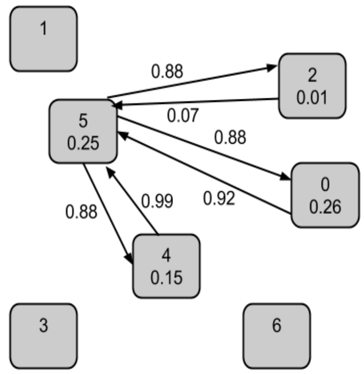

Fig. 2. Figure presents a simple graph (graphical model for case of $S = 1$) in which each node is an agent representing one of the mood dimensions: 0 - Tension, 1 - Happiness, 2 - Calmness, 3 - Vigor, 4 - Fatigue, 5 - Confusion and 6 - Friendliness. Values of *impressionability* parameters are presented inside of the nodes. *Influence* parameters are placed next to the edges.

splitting parameter $S = 1$ can predict following twelve intervals of time with mean MAPE = 18.63%.

In the literature, there are hardly any data-driven models of social mood dynamics, as well as data-driven models of social influence (there are models of these phenomena, but they are not data-driven). Thus, our attempt proposes quite complete framework of assessing and analyzing social mood based on the real-world data. One could argue, that other techniques could be used to approximate/predict social mood like Markov Models, Conditional Random Fields etc. Although, the benefit of our approach is that it creates "the map" of interactions between the mood dimensions. We are able to notice which dimension is connected to which one. We can therefore infer where the influences are and how strong they are (looking at the values of *influence* and *impressionability* parameters).

Presented framework may be useful in situations where quick information about emotion dynamics is needed. For instance, for people responsible for communication or public relations. Different situations may include, for example, financial intraday trading: algorithmic as well as conducted by human. On the other hand, when the temporal resolution of mood measurements is changed to longer periods of time, like days for instance, the framework can also be useful for long-term analysis of social mood dynamics. Such investigations might be of high interest for variety of institutions monitoring societies.

As far as future work in concerned, one can notice, that during the evolution most of the networks lose their scale-free property. Therefore, it is not clear if this is a good starting point of evolutionary algorithm. One could consider different initial topologies. Another interesting question is what types of graphs are being produced by the framework. Is it a single class or a group of them?

Apart from further work on the framework itself or studying types of networks that it produces, there are also issues more of a sociological nature. One could investigate whether different network topologies and model parameters are somehow related to the nature of real-world social events. We hypothesize that deeper studies of graphs' "shapes" and distributions of *influence/impressionability* measures can give interesting conclusions about society dynamics, as well as reflect its qualitative properties. Such correlations between social reality and topologies of small graphs could be of a great interest for social scientists.

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