



An Energy Based Approach to Study Social Network Dynamics

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Abstract: The social media sites are constantly flooded with new users along with highly unstructured data from varied domains. To analyze this data without human interaction is obviously a complex task and a very hard problem. One encouraging factor is there though; this avalanche can be seen as a natural phenomenon which makes it a potential candidate to showcase Self-Organized Criticality (SOC). SOC has been the topic of interest for many researchers worldwide studying physical systems^{13,14,15,16,17}. This is the first attempt to use this phenomenon in social network analysis. In this paper we review and try to exemplify the possibilities of analyzing Social trends based on SOC dynamism. We are trying to provide a comprehensive mathematical model to showcase this.

Keyword: Self-Organized Criticality (SOC), logical model, social media, energy model, influencers.

I. INTRODUCTION

Self-Organized Criticality (SOC) has been a most sought after phenomenon in Physics to analyze dynamic system behavior. The intense interest SOC receives because it combines two fascinating concepts - self-organization and critical behavior. Third concept which makes sense these days is no less fascinating and fashionable: complexity¹⁸.

Self-organization has been used to show the ability by many non-equilibrium systems to develop structures and patterns in the absence of external control. In equilibrium thermodynamics, it is said that when temperature of the system is precisely equal to the transition temperature, something extraordinary happens. For all other temperatures, one can shake the system locally and its effect may influence only the local neighborhood. However, at the transition temperature, the local distortion will propagate throughout entire system. The effect decays only algebraically rather than exponentially. Although only "nearest neighbor" members of the system interact directly, the interaction effectively reaches across the entire system. The system becomes critical in the sense that all members of the system influence each other. The prototypical example is an earthquake.

Our focus is to analyze users' reactions based on the activities they perform at a particular time in an influence of friends. Just now India has seen a major political revolution with Social media sites playing an extremely important role in it. This paper tries to map the dynamism in the social media like twitter to SOC framework with mathematical framework suitable.

II. MATHEMATICAL AND COMPUTER MODEL

Inspired from their 1992 paper, Olami, Feder, and Christensen a model of a system representing dynamism of the Social Networks is proposed. Consider logically a graph in the figure can be an open d -dimensional cubic lattice of size $N = L^d$. To each node i we associate a dynamic variable E_i . We can think of E_i as energy of node i . As a result of some force or influence, of neighbors this value will change. To make things simple in the beginning we assume all nodes are driven at the same rate. That is, during every time step, some positive (sometimes negative) change occurs in the energy

$$E_i \rightarrow E_i + v \text{ for } i = 1, \dots, N.$$

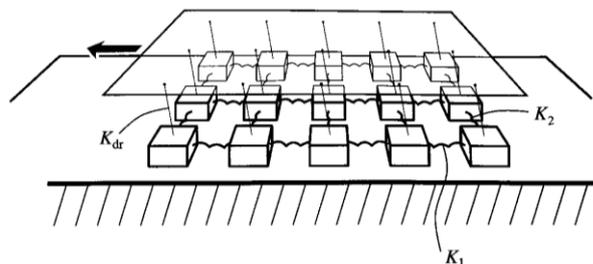


Figure 1: Earthquake model (Burridge and Knopoff 1967)

Image Source: CAMBRIDGE LECTURE NOTES IN PHYSICS 10 : Self-Organized Criticality by HENRIK JELDTOFT JENSEN

$$E_i \geq E_c \Rightarrow \begin{cases} E_i \rightarrow 0, \\ E_{nn} \rightarrow E_{nn} + \alpha E_i, \end{cases} \quad (i)$$

This notion of driving is used only as long as $E_i < E_c$ for all nodes, where E_c is some threshold. The proposed research is aimed at calculating these energies on the basis of activities performed at each node related to the issue in observation. When a node becomes unstable, $E_i \geq E_c$, the homogeneity is lost and the nodes are relaxed according to the (i) where nn denotes the neighboring nodes of the overcritical node number i . During each iteration of (i), an amount of energy is released from the system - namely, the difference between the energy that disappears at the center node E_i and the energy $\alpha.E_i$ added to each of the q_i neighbor nodes. Here q_i denotes the number of nodes in close proximity of the i^{th} node in the network: $q_i=q_c=2d$ for a bulk node in a d-dimensional cubic lattice with nearest neighbor assignment. The q for nodes which are farther from the bulk node is smaller and varies in an obvious way for surface, edge, and corner nodes of the graph. The difference between lost and added energy is accordingly given by $E_{dis}=(q_i \alpha - 1).E_i$.

The proposed work is trying to simulate SOC phenomenon to analyze web content on the social networking sites. The target is to explore the nearest neighbor influence from the earthquake computer model to analyze the dynamics of the content. Usually people post contents as a response to some political issue, or any social event etc. which shows an earthquake effect. In community or technical forums we can have similar threads related to technology which is hot or adopted by most of the organizations. The trend is dynamic and has such paradigm shift continually. We will try to target and predict such changes with establishing analogies with SOC behavior. Also politically many revolutions are seen in different countries which brings in the paradigm shift and critical decision making as currently we are witnessing in India. These changes now days are largely influenced by the social media sites. The proposed research can give an upper hand to political parties, governments to plan their strategies by analyzing the social media content.

III. THEORITICAL SUPPORT

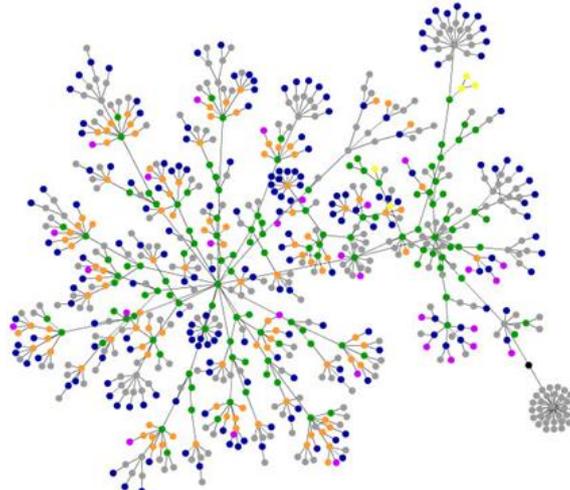


Figure 2: Social Network Graph

Image Source: <http://media02.hongkiat.com/resources-tools-for-data-visualization/html-graph.jpg>

A. Logical model to use for simulation

It is the need of computation simplicity to model the data in such a way that it depicts the overall behaviour of Social Dynamics occurring

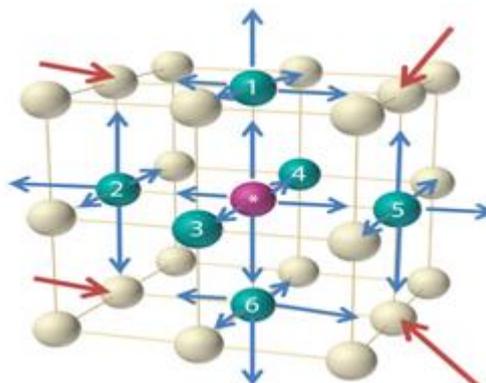


Figure 3: Logical Data Model

In Online Social Networks. The objective is to give simple simulation model to the large, complex graph above which depicts SOC behavior assuming simple scenarios. So we are proposing a logical data model which will consider all the scenarios. Here in this work we have tried to simulate this kind of system in a social network graph. One of the influential nodes in the network posts something. This becomes the initial point of disturbance which shakes its neighboring nodes and these nodes in turn forwards the same energy to their neighbors and so on.

B. Algorithm

The algorithm for the logical data models works in following way. First, choose a node as the initial seed. Second, choose top five degree nodes as the followers of the initial seed. Third, from these top five degree nodes, at random choose p numbers of nodes from the top five degree followers as the positive followers and n numbers of nodes from the top five degree followers as the negative followers. And rest of the nodes will be chosen as neutral followers. Here p is the probabilistic count of positive followers, n is the probabilistic count of negative followers and nu will be the probabilistic count of neutral followers. If the followers are chosen as positive, count will be added as a part of positive followers. Else counts will be added as a part of negative followers. Above steps will be iterated for every follower until it reaches to the end nodes.

```

Sp ← u;
Sn ← Empty;
Snu ← Empty;
Visited ← Empty;
u ← initial seed;
while all the nodes are explored do
    Select p nodes uniformly at random from neighbours of u. Add to set ptemp.
    Select p nodes uniformly at random from neighbours of u. Add to set ntemp.
    Select p nodes uniformly at random from neighbours of u. Add to set nutemp.
    while ptemp ≠ Φ do
        Select a node v from ptemp.
        if v in Visited set then
            continue;
        else if u in set Sp then
            Add a node v to Sp.
        else if u in set Sn then
            Add a node v to Sn.
        else
            Add a node v to Snu.
        end if.
    end if.
end do.
while ntemp ≠ Φ
    Select a node v from ntemp.
    if v in Visited set then
        continue;
    else if u in set Sp then
        Add a node v to Sn.
    else if u in set Sn then
        Add a node v to Sp.
    else
        Add a node v to Snu.
    end if.
end if.
end do.
Visited ← ptemp;
Visited ← ntemp;
Visited ← nutemp;
end do.

```

Figure 4: Algorithm for analysis

C. Energy model

For the logical model to be work in more effective way, we introduce the strategy to depict the behaviour of every users and propose the energy based approach.

E_E = Initial/Equilibrium Energy

E_R = Repulsive Energy

E_p = Energy of Post

E_i = Energy of User i

Step 1: Initialization

All the nodes are initialized with same energy E_i

Step 2:

$$E_E = E_{i-1} + E_i + E_{i+1} + E_{i+2} + \dots + E_{n-1}$$

$$E_R = E_E \quad \text{To be system in a stable equilibrium state}$$

Step 3:

$$E_{i-1}^1 = \sum_{i=1}^P (E_i + E_P) - \sum_{i>P}^{S-Nu} (E_i + E_P)$$

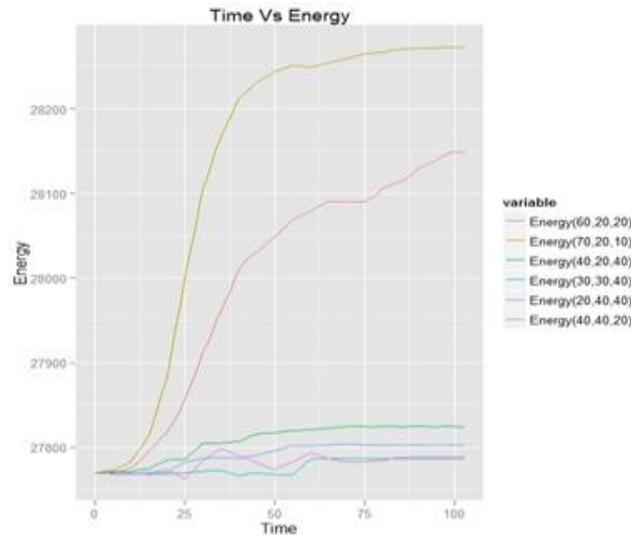
Where P is probabilistic count of positive followers to a post Nu is probabilistic count of neutral followers to a post

Step 4:

$$E_R = E_{i-1}^1 + E_i + E_{i+1} + E_{i+2} + \dots + E_{n-1}$$

IV. RESULTS AND DISCUSSION

As mentioned earlier, we have tried to organize the network in a logical structure. Then we have kept the followers' behavior variable. For example 60% will be positive, 20% negative and 20% neutral. These probabilities were varied with prior assumptions and the network was allowed to evolve.



We have observed the behavior in terms of the energy of such users against time with varying these parameters. We have got encouraging results in terms of trend observed. This definitely is showing that the pattern of response from social media users to the posts from influencers truly follows the SOC dynamics and when observed and associated with actual energies may give near accurate approximate predictions in point in time.

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