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Preventing Rumor Propagation In Social Network

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Abstract: ***The rapid development of online social media causes, we can share any kind of information with very fast. The information can be positive or negative. The negative news that will create many issues in our society. Negative information may be rumor or misinformation. So that it is necessary to block the propagation these type of rumors in social media. In this paper we focus on the reducing dynamic rumour influence with considering the user expertise. Here our aim is that reduce the number of users who accept these rumor. So that we using the Ising model to define rumor propagation in online social media. Also we are considering constraint of user experience utility. If the block time of each user exceeds that threshold, the utility of the network will decrease. Considering this constraint, formulate survival theory. Experiments area unit implemented supported large-scale world networks and validate the effectiveness of our methodology.***

Keywords - social network, rumour influence, rumour blocking.

I. INTRODUCTION

Within the arrival of Smartphone's, they where a rapid growth in using online social media such as Facebook,Twitter,Weibo etc. Now a days social media act as a major path or channel for sharing various kind of information. If this information positive information that will causes many good advantages to our society. If it is a negative information that will create many chaos in our society. For example some of them post the fake news related to earthquake, terrorist attack, and death of some fames personality. That will create people become confused and terrified. So that it is necessary to identify these type of rumours and it is important to block these misinformation from further its propagation.In the previous work they are using a idea "good" campaign for counteract "bad" bad information in the social media.And another work use "protectors" concept to reduce the influence of bad information .But these work have few limitations.They are not considering the the popularity of the information, and blocking time of each of the user.

Here we are considering the social media network as a directed graph G =(V,E),consisting of set of node V representing the users and set of directed edges E denoting relationship between the users. The independent cascade model help to define the rumor diffusion model.

II. PROBLEM FORMULATION

Dynamic Rumor Propagaton With Ising Model

Whenever we considering the rumor propagation,they where one of the important term is that P_{uv} .It means that the probability of u sending the rumor to v and v accepting it,that means the success probability of u activating v.The succeess of rumor propagation mainly depend up on two factors,they are global popularity and the individual tendency of the rumor topic.These factors are genneralized in Ising model. At any time stamp t_j, u is one of the activated nodes in time stamp t_{j-1}. The probability of node u sending the rumor to one of its inactive neighbors v as

$$p_u^{\text{send}}(t_j) = \frac{p_0}{\lg(10 + t_j)}, \qquad (1)$$

where p_0 is the initial sending probability at time stamp 0. On the receiving end, the probability of node *v* accepting the rumor transmitted by its parent node *u* is also given as

$$p_v^{\mathrm{acc}} = 1/\mathcal{D}_v \qquad (2)$$

where D_v is the in-degree of node v. Thus, based on the above analysis, we then give the probability of successful rumor propagation from u to v as

$$p_{\mathrm{ind}}(t_j) = p_u^{\mathrm{send}} \cdot p_v^{\mathrm{acc}} = \frac{1}{\mathcal{D}_v} \frac{p_0}{\lg(10 + t_j)}, \qquad (3)$$

It will help to defined as the individual tendency between different pair of nodes in the network. The global topic popularity of the rumor includes three phases and approximately subject to the chi square distribution, which is given by

$$p_{\mathrm{glb}}(t;k) = \frac{2^{(1-\frac{k}{2})} t^{k-1} e^{-\frac{t^2}{2}}}{\Gamma(\frac{k}{2})}, \qquad (4)$$

where $k > 0$ represents the degree of freedom, $\Gamma(\cdot)$ is the Gamma function. It explains a common social phenomenon that when a rumor spreads for a while, it may create a "rumor atmosphere" that could affect the judgements or decisions of users on online social networks. According to the Ising model , the "phase transition" of a spin involves both short-range interaction with its nearest neighbors and long-term system evolution, and is a combined result

User experience utility

The existing rumor blocking methods either blocking nodes or links in social network to prevent the further propagation. Whenever longer time a user is become blocked, that will cause user feel less satisfactory on the social media and then they are quit. So we elaborate on the user experience utility function .For simplicity, we assume that all the nodes have the same blocked time threshold T_{th}. In other words, we assume that all users have the same tolerance when being blocked. Under this assumption, we define the user experience utility function as

$$U_b = \frac{1}{N} \sum_{u=1}^{N} \frac{T_{\mathrm{th}} - T_b(u)}{T_{\mathrm{th}}}, \qquad (5)$$

where the T_{th} represents the tolerance time threshold, $T_b(u)$ is used to record the blocked time of node u in the whole propagation process.

III. PROPOSED SOLUTION

Survival Theory

In this model, we assume that the rumor has spread for some time, and it is detected at time t_0 by the system. It is also assumed that by time t_0, there have already been a total number of N_1 activated nodes, and $N_2 = {}^{N} - N_1$ nodes are remain inactive. Let V_{N1} and V_{N2} denote the set of activated and inactive nodes at time t_0 respectively. Therefore, from t_0 on, the system can be viewed as N_1 independent cascades propagating through the network, and our goal is to select K nodes and block them so that the final number of activated nodes during the observation time window T can be minimized. Let C = $(c_1,\ldots,c_{N1})$ denote the set of cascades triggered by N_1 activated nodes by time t_0. A cascade $c_i \in$ C can be represented by a*i* N-dimensional time vector $t^{c_i} = (t_1^{c_i}, \ldots, t_{N_2}^{c_i})$ where $t^c_j \in [t_0, t_0 + T] \cup \{\infty\}, j = 1,2,\ldots,N_2$ is the activated time of node j in cascade c_i. The observation time window T is decided by the user experience utility constraint mentioned in (6), and ∞ means the node is not activated until the end of the observation time ($t_0 + T$).

The survival function defined as

$$S(t) = Pr(t < T), \qquad (6)$$

where T is the occurrence time of an event of interest, t is some specified time. The survival function represents the probability that the event of interest occurs after the observation "deadline". If we use the terminology "death" to represent the occurrence of the event, we can claim that the target "survives". Then we have the cumulative distribution function $F(t)$:

$$F(t) = Pr(T \leq t) = 1 - S(t). \qquad (7)$$

Algorithm 1: Greedy Algorithm

Let A0 be the original network coefficient matrix before any nodes are blocked. The proposed Greedy algorithm tries to block the rumor as fast as possible to prevent the rumor from further propagation. The working mechanism is as following: At time t0 when we detect the rumor, we immediately select all K nodes in our budget and block them (i.e., remove all the links of it so that it cannot communicate with its neighbors).Mathematically, the Greedy algorithm aims to minimize the likelihood of inactive nodes getting activated at t1, i.e., the next time stamp after the rumor is detected. The likelihood of nodes getting activated at time t1.Then, the greedy algorithm is presented as below:

Input: Initial Edge matrix A0
Initialization: VB = 0;
for i = 1 to K do
u = arg max [f (t1|s (t0); Ai-1) - f (t1 | s (t0); Ai-1\ υ)]
Ai: = Ai-1\u,
VB = VB U {u}
end for
Output: VB.

Algorithm 2: Dynamic Blocking Algorithm

Different from the greedy blocking algorithm, which is a type of static blocking algorithm, we propose a dynamic rumor blocking algorithm aiming to incrementally block the selected nodes instead of blocking them at once. In that case, the blocking strategy is split into several rounds and each round can be regarded as a greedy algorithm. Thus, how to choose the number of rounds is also very important for the algorithm. In the following part, we will elaborate on the algorithm design and how we choose the specific parameters.

From the probabilistic perspective, we seek to formulate the likelihood of inactive nodes becoming activated in every round of rumor blocking. Accordingly, the dynamic blocking algorithm can be presented as following:

Input: Initial Edge matrix A0
Initialization: VB(t) = 0.
for j = 1 to n do
for i = 1 to kj do
Δf = f (tj |s (tj-1); Ai-1) – f (tj |s (tj-1); Ai-1\υ),
u = arg max {Δf},
Ai: = Ai-1\u,
VB(tj) = VB(tj) U {u}.

end for
end for
Output: VB(t).

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Fake account detection

We categorize user social behaviors on an online social media into two classes, extroversive behaviors and introversive behaviors. Extroversive behaviors, such as uploading photos and sending messages, result in visible imprints to one or more peer users; introversive behaviors, such as browsing other users' profiles and searching in message inbox, however, do not produce observable effects to other users. Based o n these characteristic we can detect the fake account.

SYSTEM ARCHITECTURE

The rumor propagation model taking under consideration the subsequent 3 elements: initial, the worldwide quality of the rumor over the whole social network, i.e., the final topic dynamics. Second, the attraction dynamics of the rumor to a possible spreader, i.e., the individual tendency to forward the rumor to its neighbors'. Third, the acceptance chance of the rumor recipients. In our model, galvanized by the Ising model. The major advantages of our system are Efficacy of our system is better than existing System, and system block user who shares rumor posts for particular period of time .

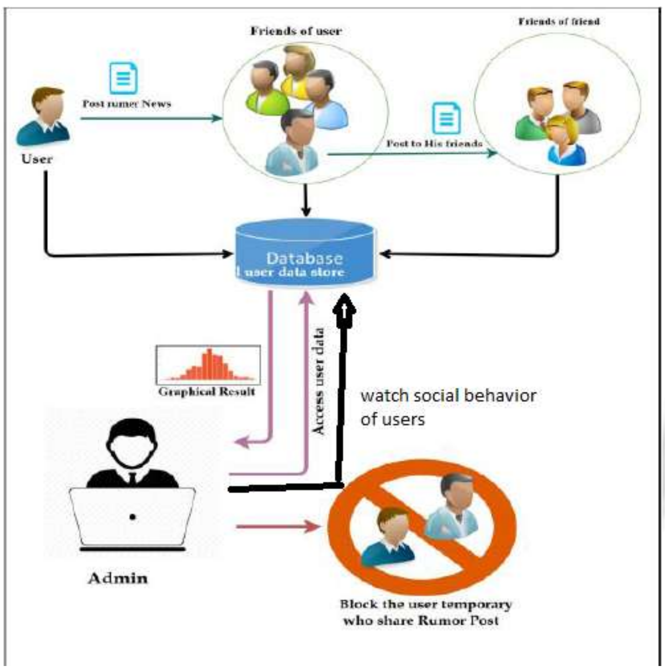

Figure 1: The system architecture of rumor blocking

SYSTEM ANALYSIS AND RESULTS

For the purpose of system analysis we use the facebook data set for analyzing the result. Whenever a news is post on the social media, it will spread very fast during its starting time.Later the speed of spreading will decreases.

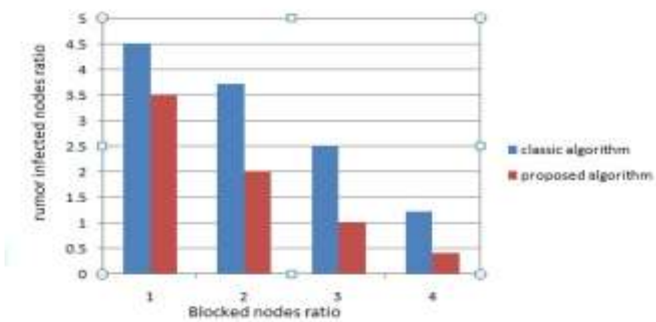

Figure 2: The rumor infection ratio under different blocking algorithm

The above chart shows rumor infection ratio, as compared to different algorithm. Here we are considering the classical algorithm and proposed algorithm. When we use the classical algorithm then the rumor infected nodes number is high, that should we can see in our graph. When we use the proposed algorithm then the number of infected node is less. Also we can see the trend that the infection ratio tends to be lower with the percentage of nodes being blocked higher. If the rumor is detected in early,then we can reduce the number of infected node.And it is easy to prevent its further propagation. For the purpose of detecting the rumor, we tend to introducing the url checking and the user opinion about the post.For the purpose of detecting the fake account we considering the individual social behavior in the online social media.Based on both extroversive and introversive behavior we can differentiate each users from others.

IV. CONCLUSION

In this paper, we investigate the rumor obstruction downside in social networks. we tend to propose the dynamic rumor influence reduction with user expertise model to formulate the matter. A dynamic rumor diffusion model incorporating each world rumor quality and individual tendency is conferred supported the Ising model. Then we introduce the thought of user expertise utility and propose a changed version of utility perform to live the connection between the utility and obstruction time. After that, we tend to use the survival theory to investigate the probability of nodes obtaining activated beneath the constraint of user expertise utility. Greedy algorithmic rule and a dynamic obstruction algorithmic rule area unit projected to unravel the optimization downside supported totally different nodes choice methods. Experiments enforced on data set in social networks show the efficaciousness of our methodology. And the social behavior profile of individuals in the social media help to differentiate from other users. That will help to detect the fake account in social media.

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