Detection and Minimization Influence of Rumor in Social Network

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Abstract - *With the fast development of big scale on-line social networks, on-line data sharing is becoming omnipresent daily. Numerous info is propagating through on-line social networks similarly as every the positive and negative. Throughout this paper, we tend to tend to focus on the negative data problems just like the on-line rumours. Rumor block may well be a significant drawback in large-scale social networks. Malicious rumours might cause chaos in society and sought to be blocked as soon as potential once being detected. during this paper, we tend to propose a model of dynamic rumor influence reduction with user expertise (DRIMUX).Our goal is to cut back the influence of the rumor (i.e., the number of users that have accepted and sent the rumor) by block an exact set of nodes. A dynamic Ising propagation model considering every the worldwide quality and individual attraction of the rumor is given supported realistic state of affairs. To boot, altogether completely different from existing problems with influence reduction, we tend to tend to require into thought the constraint of user experience utility. Specifically, each node is assigned a tolerance time threshold. If the block time of each user exceeds that threshold, the utility of the network will decrease. Underneath this constraint, we tend to tend to then formulate draw back as a network abstract thought drawback with survival theory, and propose solutions supported most probability principle. Experiments area unit implemented supported large-scale world networks and validate the effectiveness of our methodology.*

Key Words: Social network, Rumor Influence Minimization, rumor blocking strategies, survival theory.

1. INTRODUCTION

With the speedy development and rising quality of large-scale social networks like Twitter, Facebook etc., many in numerable individuals area unit ready to become friends[10] and share every kind of knowledge with one another. On-line social network analysis has additionally attracted growing interest among researchers.[11],[12] On one hand, these on-line social platforms offer nice convenience to the diffusion of positive info like new ideas, innovations, and hot topics. On the opposite hand, however, they will become a channel for the spreading of malicious rumours or information [1], [15], and [16]. As an example, some individuals could post on social networks a rumor concerning associate degree approaching earthquake, which can cause chaos among the group and thus could hinder the conventional public order. During this case, it's necessary to discover the rumor Source and delete connected messages, which can be enough to stop the rumor from any spreading. However, in bound extreme circumstances like terrorist on-line attack, it might be necessary to disable or block connected Social Network (SN) accounts to avoid serious negative influences. For instance, in 2016, the families of 3 out of the forty 9 victims from the metropolis cabaret shooting incident filed a causa against Twitter, Facebook and Google for providing “material support” to the coercion organization of the Islamic State of Republic of Iraq and Asian nation (ISIS)[17].These companies then took measures to dam connected accounts, delete relevant posts and fan pages on their social network platforms to stop the ISIS from spreading malicious info. to boot, Facebook etv. even have issued relevant security policies and standards to assert the authority to dam accounts of users once they square measure against rules or in danger [18]. without doubt, malicious rumors ought to be stopped as presently as potential once detected in order that their negative influence will be reduced. Most of the previous works studied the matter of increasing the influence of positive info through social networks. quick approximation ways were additionally planned to influence maximization drawback. In distinction, the negative influence attention, however still there are consistent efforts on minimization Problem has gained a lot of less planning effective ways for obstruction malicious rumours and minimizing the negative influence.

2. LITERATURE SURVE

PAPER(1): DRIMUX: Dynamic Rumor Influence Minimization with User Experience in Social Networks(2016)

In this paper, we have a tendency to specialize in the negative info issues like the web rumors. Rumor obstruction could be a significant issue in large-scale social networks. Malicious rumors may cause chaos in society and therefore got to be blocked as shortly as attainable once being detected. during this paper, we have a tendency to propose a model of dynamic rumor influence reduction with user expertise (DRIMUX). Our goal is to attenuate the influence of the rumor (i.e., the amount of users that have accepted and sent the rumor) by obstruction a precise set of nodes

PAPER (2): Maximizing Acceptance Probability for Active Friending in Online Social Networks (2013)

In this paper, we have a tendency to advocate a recommendation support for active friending, wherever a user actively specifies a friending target. To the most effective of our data, a recommendation designed to supply steerage for a user to consistently approach his friending target has not been explored for existing on-line social networking services. to maximise the likelihood that the friending target would settle for a call for participation from the user, we have a tendency to formulate a replacement optimisation downside, namely, Acceptance likelihood Maximization (APM), and develop a polynomial time rule, known as Selective invite with Tree and In-Node Aggregation (SITINA), to seek out the best resolution. we have a tendency to implement a full of life friending service with SITINA on Facebook to validate our plan. Our user study and experimental results reveal that SITINA outperforms manual choice and therefore the baseline approach in resolution quality with efficiency.

PAPER (3): Limiting the Spread of Misinformation in Social Networks (2011)

In paper developed four malicious applications, and evaluated Andromaly ability to detect new malware based on samples of known malware. They evaluated several combinations of anomaly detection algorithms, feature selection method and the number of top features in order to find the combination that yields the best performance in detecting new malware on Android. Empirical results suggest that the proposed framework is effective in detecting malware on mobile devices in general and on Android in particular.

PAPER(4): Efficient Influence Maximization in Social Networks (2009)

In this paper, we have a tendency to study the economical influence maximization from 2 complementary directions. One is to enhance the first greedy formula and its improvement to more scale back its period of time, and also the second is to propose new degree discount heuristics that improves influence unfold. we have a tendency to measure Our algorithms by experiments on 2 giant educational collaboration graphs obtained from the net deposit information arXiv.org.

PAPER (5): A Fast Approximation for Influence Maximization in Large Social Networks (2014)

This paper deals with a completely unique analysis work a couple of new economical approximation algorithmic program for influence maximization, that was introduced to maximise the good thing about infectious agent promoting. For potency, we tend to devise 2 of exploiting the 2-hop influence unfold which is that the influence unfold on nodes inside 2-hops removed from nodes in a very seed set. Firstly, we tend to propose a brand new greedy methodology for the influence maximization drawback exploitation the 2-hop influence unfold. Secondly, to hurry up the new greedy methodology, we tend to devise a good manner of removing uncalled-for nodes for influence maximization Based on optimum seed's native influence heuristics.

3. EXISTING SYSTEM

Most of the previous works studied the matter of maximizing the influence of positive data through social networks..In distinction, the negative influence diminution drawback has gained a lot of less attention, however still there are consistent efforts on coming up with effective ways for block malicious rumors and minimizing the negative influence. Kimura et al. Studied the matter of minimizing the propagation of malicious rumors by block a restricted range of links in a very social network. They provided 2 completely different definitions of contamination degree and planned corresponding optimisation algorithms. Fan et al. investigated the smallest amount price rumor block drawback in social networks. They introduced the conception of "protectors" and check out to pick a borderline range of them to limit the dangerous influence of rumors by triggering a protection cascade against the rumor cascade. However, there square measure some limitations in those works.

Algorithm:1 Greedy 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. Correspondingly, the likelihood
function is given by

$$f(t_1|s(t_0)) = \prod_{v \in V_{N_2}} \sum_{u:t_u \leq t_0} \alpha_{uv} p_{uv}(t_1) \times \prod_{\varrho:t_\varrho \leq t_0} e^{-\alpha_{\varrho v} \int_{t_\varrho}^{t_1} p_{\varrho v}(\tau) d\tau}.$$

Correspondingly, the objective function is

$$\min_{\mathbf{A}} \quad f(t_1|s(t_0))$$
$$\text{s. t.} \quad \alpha_{uv} \in \{0, 1\}.$$

Then, the greedy algorithm is presented as below:

Input: Initial Edge matrix A_0
Initialization: VB = 0;
for i = 1 to K do
$u = \arg\max [f(t_1|s(t_0); A_{i-1}) - f(t_1 | s(t_0); A_{i-1} \backslash \upsilon)]$
$A_i := A_{i-1} \backslash u$,
VB = VB U {u}
end for
Output: VB.
Mathematical Model of Existing System

System S as a whole can be defined with the following main components.

S= {I, O, P, s, e, U, Uf, Ad};

S=System
s=Initial State
e=Final State
U= user
Uf=Set of user friends
Ad=admin

Input {I} = {Input1, Input2}
Where,
Input1=Text
Input2=Images

Procedures {P}= {Up,Sp,Ubloack,Rdetect}
Where,
Up=upload post.
Sp=Share Post.
Ubloack= Block user who sent or shared rumor text and images.
Rdetect=Detect rumor text and images.

Output {O} = {Output1, Output2}
Where,
Output1=detecting rumor texts & images
Output2=block user who sent or shared rumor text and images

s= {initially system will be in a state where user are not enrolled, Only admin of system.}

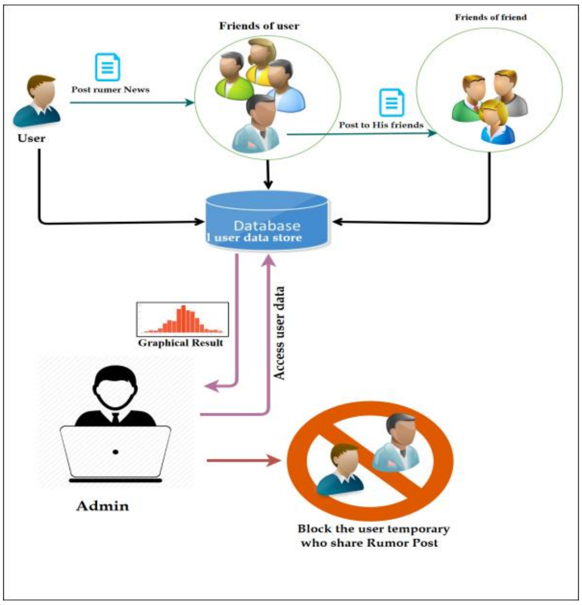
e= {users are enrolled and successfully post or share text or images & admin detect and rumor text and images and also block user who sent or shared rumor text and images }

Result of Existing System:

Existing system Detect rumor post and text and block user who sent rumor test or image for long time so they may quit social network. And not delete rumor post.

4. PROPOSE SYSTEM

We propose a 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 neighbours. Third, the acceptance chance of the rumor recipients. In our model, galvanized by the Ising model, we have a tendency to mix all 3 factors along to propose a cooperative rumor propagation chance. In our rumor interference ways, we have a tendency to think about the influence of interference time to user expertise in universe social networks. therefore we have a tendency to propose a interference time constraint into the standard rumor influence diminution objective perform. in this case, our technique optimizes the rumor interference strategy while not sacrificing the web user expertise.



we have a tendency to use survival theory to investigate the chance of nodes turning into activated or infected by the rumor before a time threshold that is set by the user expertise constraint. Then we have a tendency to propose each greedy and dynamic interference algorithms mistreatment the most chance principle.

Advantages of Proposed System

1) Efficacy of our system is better than existing System.
2) Our system block user who shares rumor posts for particular period of time

Result of Proposed System:

Proposed system Detect rumor post and text and block user who sent rumor test or image for short period of time so they not quit social network. And delete rumor post to avoid chaos among the crowd.

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.

Input: Initial Edge matrix A_0
Initialization: $V_B(t) = 0$.
for j = 1 to n do
for i = 1 to k_j do
$\Delta_f = f(t_j \mid s(t_{j-1}); A_{i-1}) - f(t_j \mid s(t_{j-1}); A_{i-1} \backslash \upsilon)$,
u = arg max $\{\Delta_f\}$,
$A_i := A_{i-1} \backslash u$,
$V_B(t_j) = V_B(t_j) \cup \{u\}$.
end for
end for
Output: $V_B(t)$.

Algorithm:3 K-means Algorithm

k-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriori. The main idea is to define k centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as barycenter of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new center. A loop has been generated. As a result of this loop we may notice that the k centers change their location step by step until no more changes are done or in other words centers do not move any more.

1. Initialize **cluster centroids** $\mu_1, \mu_2, \ldots, \mu_k \in \mathbb{R}^n$ randomly.
2. Repeat until convergence: {

   For every i, set
   $$c^{(i)} := \arg\min_j \|x^{(i)} - \mu_j\|^2.$$
   For each j, set
   $$\mu_j := \frac{\sum_{i=1}^m 1\{c^{(i)} = j\} x^{(i)}}{\sum_{i=1}^m 1\{c^{(i)} = j\}}.$$
   }

Mathematical Model of Existing System

System S as a whole can be defined with the following main components.

S= {I, O, P, s, e, U, U_f, Ad};

S=System
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Input {I} = {Input1, Input2}
Where,
Input1=Text
Input2=Images

Procedures {P}= {U_p,S_p,U_{bloack},Rd_{etect}, R_{delete}}
Where,
U_p=upload post.
S_p=Share Post.
U_{bloack}= Block user who sent or shared rumor text and images.
R_{detect}=Detect rumor text and images.
R_{delete}= Delete rumor text and images

Output {O} = {Output1, Output2, Output3}

Where,
Output1=detecting rumor texts & images
Output2=delete rumor texts & images
Output3=block user who sent or shared rumor text and images

s= {initially system will be in a state where user are not enrolled, Only admin of system.}

e= {users are enrolled and successfully post or share text or images & admin detect and delete rumor text and images and also block user who sent or shared rumor text and images }

5. CONCLUSION

In this paper, we tend to 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 tend to 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 planet social networks show the efficaciousness of our methodology.

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