Detection and Minimization of Rumor Influence in Social Network

Amit Kumar[1] Puniket Gaikwad[2] Dinesh Yadav[3] Prof. Rahul Chavan[4]
[1,2,3,4]SKN Sinhgad Institute of Technology & Science, Lonavala, Maharashtra ,India

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 rumors. Rumor block may well be a significant drawback in large-scale social networks. Malicious rumors might cause chaos in society and soought 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: Rumor Influence, Social Network

I. 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 and share every kind of knowledge with one another. on-line social network analysis has additionally attracted growing interest among researchers. 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 rumors or information. 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. 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 minimisation Problem has gained a lot of less attention, however still there are consistent efforts on planning effective ways for obstruction malicious rumors and minimizing the negative influence.

II. LITERATURE SURVEY

A. PAPER (1): 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.

B. PAPER (2): Limiting the Spread of Misinformation in Social Networks (2011)

In paper[2] 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.

C. PAPER (3): 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.

D. PAPER (4): 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 {ways|ways that|ways in that} 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.

E. PAPER (5): Blocking Links to Minimize Contamination Spread in a Social Network(2009)

We address the matter of minimizing the propagation of undesirable things, like pc viruses or malicious rumors, by block a restricted range of links in an exceedingly network, that is converse to the influence maximization downside during which the foremost potent nodes for data diffusion is searched in an exceedingly social network. This minimisation downside is a lot of basic than the matter of preventing the unfold of contamination by removing nodes in an exceedingly network.

F. PAPER (6): Least Cost Rumor Blocking in Social Networks (2013)

We address the smallest amount price Rumor block (LCRB) drawback wherever rumors originate from a community Cr within the network and a notion of protectors square measure wont to limit the dangerous influence of rumors. the matter is summarized as distinguishing a minimal set of people as initial protectors to reduce the amount of individuals infected in neighbor communities of Cr at the top of each diffusion processes. observant the community structure property, we have a tendency to listen to a sort of vertex set, referred to as bridge finish set, within which every node has a minimum of one direct in-neighbor in Cr and is approachable from rumors.

G. PAPER (7): Patterns of Temporal Variation in Online Media (2011)

We study temporal patterns related to on-line content and the way the content's quality grows and fades over time. the eye that content receives on the net varies betting on several factors and happens on terribly totally {different|completely different} time scales and at different resolutions. so as to uncover the temporal dynamics of on-line content we tend to formulate a statistic bunch downside employing a similarity metric that's invariant to scaling and shifting. we tend to develop the K-Spectral Centroids (K-SC) bunch algorithmic program that effectively finds cluster Centroids with our similarity live. By applying associate adaptive wavelet-based progressive approach to bunch, we tend to scale K-SC to massive knowledge sets

H. PAPER (8): Information Propagation Game: a Tool to Acquire Human Playing Data for Multiplayer Influence Maximization on Social Networks (2012)

In this paper, we tend to propose info Propagation Game (IPG), a framework that may collect an outsized range of seed choosing ways for analysis. Through the IPG framework, human players aren't solely having fun however additionally serving to contributory the seed choosing ways. Preliminary experiment suggests that spatial relation primarily based heuristics square measure too straightforward for seed choice in a very multiple player surroundings

I. PAPER(9):Influential Node Tracking on Dynamic Social Network: An Interchange Greedy Approach (2016)

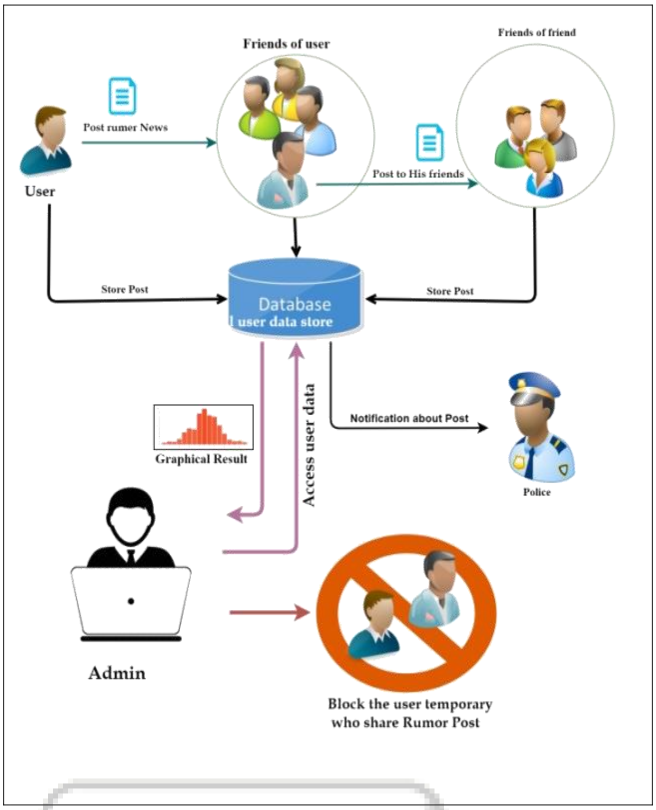
In this paper, we tend to explore a unique downside, particularly cogent Node chase downside, as AN extension of Influence Maximization downside to dynamic networks, that aims at chase a group of cogent nodes dynamically such the influence unfold is maximized at any moment. we tend to propose AN economical formula UBI to resolve the INT downside based mostly plan of the Interchange Greedy methodology. we tend to utilize the bound on node replacement gain to accelerate the method

J. PAPER (10): Robust dynamic classes revealed by measuring the response function of a social system.(2008)

In this paper, we tend to study the relief response of a social structure once endogenous and exogenous bursts of activity mistreatment the statistic of daily views for nearly five million videos on YouTube. we discover that almost all activity are often delineated accurately as a Poisson method. However, we tend to additionally realize many thousands of examples within which a burst of activity is followed by associate omnipresent power-law relaxation governing the temporal arrangement of views. we discover that these relaxation exponents cluster into 3 distinct categories and permit for the classification of collective human dynamics. this can be in line with a deadly disease model on a social network containing 2 ingredients: an influence law distribution of waiting times between cause and action and a deadly disease cascade of actions turning into the reason for future actions. This model may be a abstract extension of the fluctuation-dissipation theorem to social systems

III. 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 neighbors. 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.



IV. ALGORITHM

A. *Algorithm 1: Greedy Algorithm*

Let A_0 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 A_0
Initialization: $V_B = 0$;
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}\ υ)]
A_i: = A_{i-1}\u,
$V_B = V_B$ U {u}
end for
Output: V_B.

B. *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:

Algorithm 2 Dynamic Blocking 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
Δ_f = f (t_j |s (t_{j-1}); A_{i-1}) – f (t_j |s (t_{j-1}); A_{i-1}\υ),
u = arg max {Δ_f},
A_i: = A_{i-1}\u,
$V_B(t_j) = V_B(t_j)$ U {u}.
end for
end for
Output: $V_B(t)$.

C. *Algorithm 3: K-means Algorithm*

Let X = {$x_1,x_2,x_3,\ldots\ldots\ldots,x_n$} be the set of post and V = {$v_1,v_2,\ldots\ldots\ldots,v_c$} be the set of users.

1) Randomly select ‘c’ cluster centers.
2) Calculate the relation between each tweet and (user) cluster centers.
3) Assign the tweet to the cluster center whose relation with cluster center strong of all the cluster centers..
4) Recalculate the new cluster center using:

$$v_i = (1/c_i)\sum_{j=1}^{c_i} x_i$$

where, ‘c_i’ represents the number of data points in i^{th} cluster.

5) Recalculate the relation between post and new obtained cluster centers.
6) If no post was reassigned then stop, otherwise repeat from step 3).

V. CONCLUSION AND FUTURE SCOPE

We investigate the rumor blocking problem in social networks. We propose the dynamic rumor influence minimization with user experience model to formulate the problem. A dynamic rumor diffusion model incorporating both global rumor popularity and individual tendency is presented based on the Ising model. Then we introduce the concept of user experience utility and propose a modified version of utility function to measure the relationship between the utility and blocking time.

REFERENCES

[1] C. Budak, D. Agrawal, and A. E. Abbadi, “Limiting the spread of misinformation in social networks,” in Proc. 20th Int. Conf. World Wide Web, 2011, pp. 665–674.
[2] M. Kimura, K. Saito, and H. Motoda, “Blocking links to minimize contamination spread in a social network,” ACM Trans. Knowl.Discov. Data, vol. 3, no. 2, pp. 9:1–9:23, Apr. 2009.
[3] L. Fan, Z. Lu, W. Wu, B. Thuraisingham, H. Ma, and Y. Bi, “Least cost rumor blocking in social networks,” in Proc. IEEE ICDCS’13,Philadelphia, PA, Jul. 2013, pp. 540–549.

[4] J. Yang and J. Leskovec, "Patterns of temporal variation in online media," in Proc. ACM Int. Conf. Web Search Data Minig, 2011, pp. 177–186.
[5] R. Crane and D. Sornette, "Robust dynamic classes revealed by measuring the response function of a social system," in Proc. of the Natl. Acad. Sci. USA, vol. 105, no. 41, Apr. 2008, pp. 15 649–15 653.
[6] S. Han, F. Zhuang, Q. He, Z. Shi, and X. Ao, "Energy model for rumor propagation on social networks," Physica A: Statistical Mechanics and its Applications, vol. 394, pp. 99–109, Jan. 2014.
[7] D. Chelkak and S. Smirnov, "Universality in the 2d ising model and conformal invariance of fermionic observables," Inventiones Mathmaticae, vol. 189, pp. 515–580, Sep. 2012.
[8] W. Chen, C.Wang, and Y.Wang, "Scalable influence maximization for prevalent viral marketing in large-scale social networks," in Proc. 16th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2010, pp. 1029–1038.
[9] S. Shirazipourazad, B. Bogard, H. Vachhani, and A. Sen, "Influence propagation in adversarial setting: How to defeat competition with least amount of investment," in Proc. 21st ACM Int. Conf. Inf. Knowl. Manag., 2012, pp. 585–594.
[10] E. Serrano, C. A. Iglesias, and M. Garijo, "A novel agent-based rumor spreading model in twitter," in Proc. 24th Int. Conf. World Wide Web, 2015, pp. 811–814