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MINIMIZATION OF INFLUENTIAL NODE TRACKING IN DYNAMIC SOCIAL NETWORKS

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Abstract- A mobile social network plays an important role as the spread of information and influence in the form of "word-of-mouth". It is basic thing to find small set of influential people in a mobile social network such that targeting them initially. It will increase the spread of the influence .The problem of finding the most influential nodes in network is NP-hard. It has been shown that a Greedy algorithm with provable approximation guarantees can give good approximation. Community based Greedy algorithm is used for mining top-K influential nodes. It has two components: dividing the mobile social network into several communities by taking into account information diffusion and selecting communities to find influential nodes by a dynamic programming. Location Based community Greedy algorithm is used to find the influence node based on Location and consider the influence propagation within Particular area. Experiments result on real large-scale mobile social networks show that the proposed location based greedy algorithm has higher efficiency than previous community greedy algorithm.

Keywords: Mobile social network, Influence maximization, community greedy algorithm, Location based community greedy algorithm

I. INTRODUCTION

With the speedy development and rising quality of large - scale social networks like Twitter, Facebook etc., many in numerable individual's area unit ready to become friends and share every kind of knowledge with one another. On - line social network analysis h as 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 minimization 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.

Mobile social network plays an important role in social Network. It's a main issue to search out a set of influential people in a mobile social network. It will maximize the influence. An organization would really like to promote a replacement product, hoping it'll be adopted by an outsized fraction of the network. The corporate plans to at first target small variety of "Influential" people of the network by giving them free samples of the product. The corporate hopes that first selected users can advocate the product to their friends; their friends can influence their friends'. Friends and then on, therefore several people can ultimately adopt the new product through the powerful spoken impact. Similar things may apply to the promotion of concepts and opinions, like political candidates attempt to find early supporters for his or her political proposals and agendas and rewriting the influence of them to induce a lot of supporters, government authorities or firms associate degree to win public support by finding and convincing an initial set of early adopters to their concepts. The most cogent nodes are referred to as NP-hard.

Due to the NP-hardness of SIM, we focus on processing it approximately with theoretical bounds. Leveraging the monotonicity and sub-modularity of influence functions, a naıve greedy algorithm [27] can provide a $(1 - 1/e)$ approximate solution for SIM. However, the greedy algorithm requires $O(k \cdot |U|)$ ($|U|$ is the number of users in the network) influence function evaluations for each update. Empirically, it takes around 10 seconds to select 100 seeds from a network with 500, 000 users, which hardly matches the rates of real-world social streams. Another closely related technique to SIM is Streaming Sub-modular Optimization (SSO) [3,18]. Existing SSO approaches [3, 18] can provide solutions with theoretical guarantees for maximizing sub-modular functions with cardinality constraints over append-only streams. However, to the best of our knowledge, none of the proposed SSO algorithms can support the sliding window model.

The rest of the paper is organized as follows: Section II describes the related work; Section III presents the proposed work; Section IV presents the experimental analysis of the proposed study and finally concludes in Section V.

II. RELATED WORK

This section presents the prior works of the dynamic sensor networks. The author in [6] studied 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 maximize the likelihood that the friending target would settle for a call for participation from the user, we have a tendency to formulate a replacement optimization 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.

The author in [7] 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 suggested that the proposed framework is effective in detecting malware on mobile devices in general and on Android in particular. The author in [8] 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.

The author in [9] discussed completely unique analysis work a couple of new economical approximation algorithmic program for influence maximization that was introduced to maximize 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 draw back 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.

The author in [10] studied on 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 minimization downside is a lot of basic than the matter of preventing the unfold of contamination by removing nodes in an exceedingly network. In [11], 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 t he 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.

The author in [12] suggested 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. In [13], explored 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.

III. PROPOSED WORK

This section presents the working model of our proposed model. The main objectives of the study are:

- To propose an efficient algorithm, Upper Bound Interchange Greedy (UBI), to tackle Influence Maximization problem under dynamic social network, which we term as Influential Node Tracking (INT) problem.
- To track a set of influential nodes which maximize the influence under the social network at anytime.
- To start from the seed set maximizing the influence under previous social network. Then we change the nodes in the existing set one by one in order to increase the influence under the current social network.

The proposed model composes of four phases, namely,

A) User

A user is a person who uses a computer or network service. Users generally use a system or a software product without the technical expertise required to fully understand it. Power users use advanced features of programs, though they are not necessarily capable of computer programming and system administration.

B) Admin

Administrator has the responsibility of ensuring that the administrative activities within an organization run efficiently, by providing structure to other employees throughout the organization. These activities can range from being responsible for the management of human resources, budgets and records, to undertaking the role of supervising other customer. These responsibilities can vary depending on the customer and level of education.

C) Influence maximization

The traditional Influence Maximization problem aims at finding influential nodes for only one static social network. However, real-world social networks are seldom static. Both the structure and also the influence strength associated with the edges change constantly. As a result, the seed set that maximizes the influence coverage should be constantly updated according to the evolution of the network structure and the influence strength.

D) Greedy Approach

Greedy Approach is designed to achieve optimum solution for a given problem. In greedy approach, decisions are made from the given solution domain. As being greedy, the closest solution that seems to provide an optimum solution is chosen. Greedy approach tries to find a localized optimum solution, which may eventually lead to globally optimized solutions. However, generally greedy algorithms do not provide globally optimized solutions.

The following are the merits achieved:

- Our algorithm achieves comparable results as hill-climbing greedy algorithm approximation is guaranteed. The algorithm has the time complexity of O (k n), and the space complexity of O(n), where n is the number of nodes and k is the size of the seed set.
- To improves the computation of node replacement upper bound.
- To evaluate the performance on large-scale real social network.

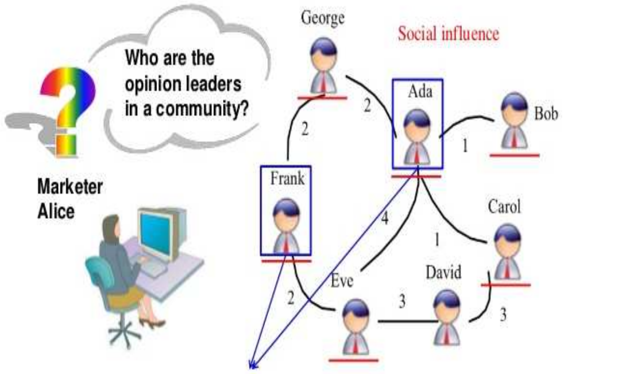

Fig.3.1. System Architecture

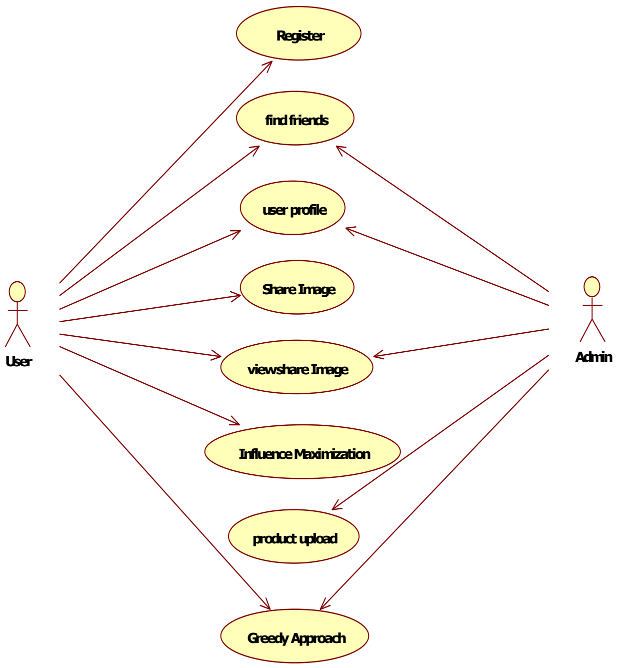

Fig.3.2 Proposed workflow

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the experimental analysis of proposed study in JAVA framework.

Fig. 4.1 Start page of the influence node systems

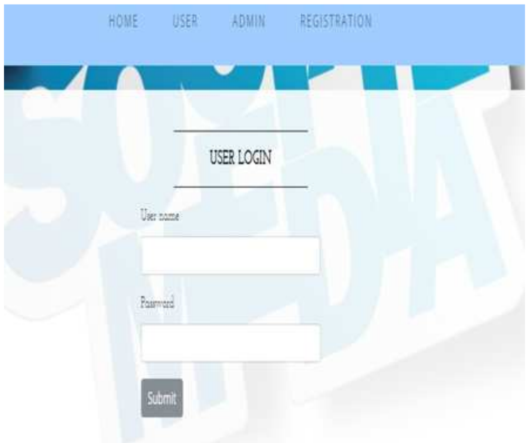

Fig.4.2 User's login

Fig.4.3 Working of interchange greedy approach

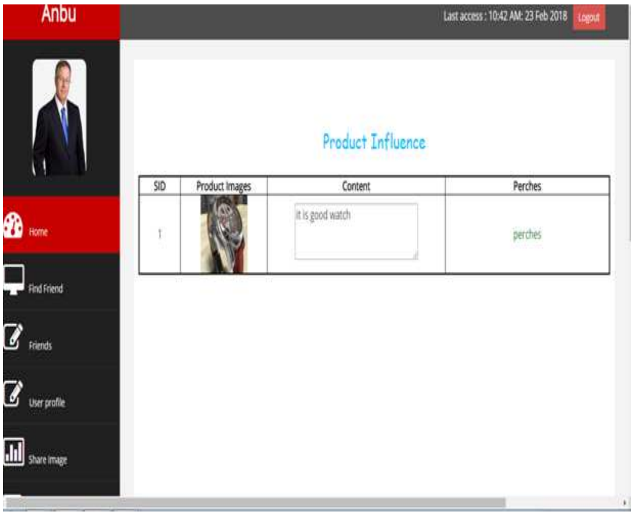

Fig. 4.4 Viewing the products influence of the systems from user's login.

V. CONCLUSION

Influence maximization (IM), which selects a set of k users (called seeds) to maximize the influence spread over a social network, is a fundamental problem in a wide range of applications such as viral marketing and network monitoring. Existing IM solutions fail to consider the highly dynamic nature of social influence, which results in either poor seed qualities or long processing time when the network evolves. To address this problem, we define a novel IM query named Stream Influence Maximization (SIM) on social streams. Community based Greedy algorithm is used for mining top-K influential nodes. It has two components: dividing the mobile social network into several communities by taking into account information diffusion and selecting communities to find influential nodes by a dynamic programming. Location Based community Greedy algorithm is used to find the influence node based on Location and consider the influence propagation within Particular area. Experimental results have shown the effectiveness of the proposed model.

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