ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

A Query Mechanism for Influence Maximization on Specific Users in Social Networks

Sneha Chandrakant More[1], Pramod Patil[2]

M.E Student, Department of Computer Engineering, Nutan Maharashtra Institute of Engineering and Technology, Talegaon Dabhade, Pune, Savitribai Phule Pune University, Pune India.[1]

Professor, Department of Computer Engineering, Nutan Maharashtra Institute of Engineering and Technology, Talegaon Dabhade, Pune, Savitribai Phule Pune University, Pune India.[2]

ABSTRACT: Influence maximization is introduced to maximize the profit of viral marketing in social networks. The weakness of influence maximization is that it does not distinguish specific users from others, even if some items can be only useful for the specific users. For such items, it is a better strategy to focus on maximizing the influence on the specific users. In this paper, we formulate an influence maximization problem as query processing to distinguish specific users from others. We propose an expectation model for the value of the objective function and a fast greedy-based approximation method using the expectation model. For the expectation model, we investigate a relationship of paths between users. For the greedy method, we work out an efficient incremental updating of the marginal gain to our objective function. Our experimental results show that (a) our improved greedy algorithm achieves better running time comparing with the improvement of with matching influence spread, (b) our degree discount heuristics achieve much better influence spread than classic degree and centrality-based heuristics, and when tuned for a specific influence cascade model, it achieves almost matching influence thread with the greedy algorithm, and more importantly.

KEYWORDS: labeled influence maximization; social networks; target marketing; proximity, Graph algorithms, Independent cascade model, social networks

I. INTRODUCTION

Recently, the amount of propagation of information is steadily increased in online social networks such as Facebook and Twitter. To use online social networks as a marketing platform, there is lots of research on how to use the propagation of influence for viral marketing. One of the research problems is influence maximization (IMAX), which aims to find k seed users to maximize the spread of influence among users in social networks. It is proved to be an NP-hard problem. Since they proposed a greedy algorithm for the problem, many researchers have proposed various heuristic methods.A social network the graph of relationships and interactions within a group of individuals plays a fundamental role as a medium for the spread of information, ideas, and influence among its members. An idea or innovation will appear for example, the use of cell phones among college students, the adoption of a new drug within the medical profession, or the rise of a political movement in an unstable society and it can either die out quickly or make significant inroads into the population. If we want to understand the extent to which such ideas are adopted, it can be important to understand how the dynamics of adoption are likely to unfold within the underlying social network: the extent to which people are likely to be affected by decisions of their friends and colleagues, or the extent to which "word-of-mouth" effects will take hold. Such network diffusion processes have a long history of study in the social sciences. Some of the earliest systematic investigations focused on data pertaining to the adoption of medical and agricultural innovations in both developed and developing parts of the world [8, 7, 9]; in other contexts, research has investigated diffusion processes for "word-of-mouth" and "viral marketing" effects in the success of new products [4, 7] the sudden and widespread adoption of various strategies in game theoretic settings [6, 1] and the problem of

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

cascading failures in power systems [2, 3].Viral marketing is one of the key applications of influence maximization. In viral marketing, an item that a marketer wants to promote is diffused into social networks by "word-of-mouth" communication. From the perspective of marketing, influence maximization provides how to get the maximum profit from all the users in a social network through viral marketing. However, influence maximization is not always the most effective strategy for viral marketing, because there can be some items that are useful to only specific users. These specific users can be a few people with a common interest in a given item, some or all people in a community, or some or all users in a class. There is no limit for being specific users. For example, consider a marketer that is asked to promote a cosmetic product for women through viral marketing. For the cosmetic product, the specific users are female users who are likely to use it and male users who wish to purchase it as a gift for female users. In this case, the marketer does not need to be concerned about the other users because the cosmetic product is not useful to them. Instead, it is a better strategy to focus on maximizing the number of influenced specific users, but influence maximization has the weakness that it cannot distinguish them from the other users. The only way of handling such targets with influence maximization is making a homogeneous graph with the targets and executing influence maximization on the graph. However, the result of this approach should be inaccurate, because there can be some users who are not targets but can strongly influence the targets.To overcome the weakness of influence maximization and to provide the flexibility, we formulate an influence maximization problem as query processing without predefined labels and call this IMAX query processing. In IMAX query processing, a social network is represented by a graph where a node represents an individual and an edge represents a relationship between two individuals such as the friendship.The IMAX query problem is worth receiving attention of researchers from two aspects. One is the suitability of IMAX query processing for target-aware viral marketing. As we explained, since the influence maximization problem cannot distinguish targets from the other users, it is not suitable for target-aware viral marketing. However, in the IMAX query problem, we can specify targets explicitly using a set and focus on maximizing influence on those targets. The formulation of the IMAX query problem is sufficient for modeling target-aware viral marketing in general purposes.

II. OBJECTIVE

1. To identify the limitations of existing researches related to maximizing influence on specific targets. We formulate an influence maximization problem as query processing without predefined labels to address the limitations.
2. Prove that the problem is NP-hard and that the objective function of the IMAX query problem is sub modular. Based on the sub modularity of the objective function, we present a greedy algorithm for IMAX query processing and show that it has a (1-1/e) approximation ratio.
3. Propose a new efficient expectation model for influence spread of a seed set and show that the new objective function of the expectation model is sub modular.
4. Based on the new expectation model, we propose a greedy-based approximation method to process an IMAX query with efficient incremental updating of the marginal gain of each user. We also propose an effective method to reduce the number of candidates for optimal seeds by identifying users who strongly influence targets from preprocessed data.
5. To overcome the weakness of influence maximization and to provide the flexibility, we formulate an influence maximization problem as query processing without predefined labels and call this IMAX query processing.

III. LITERATURE SURVEY

NO	Paper Name	Proposed Approach
1	F.-H. Li, C.-T. Li, and M.-K. Shan, "Labeled influence maximization in social networks for target marketing," in Proc. IEEE 3rd Int. Conf.	1. The influence maximization problem is to find a set of seed nodes which maximize the spread of influence in a social network. The seed nodes are used for the viral marketing to gain the maximum profits through the effective word-of-mouth. 2. However, in more real-world cases, marketers usually target certain products at particular groups of customers. While original influence maximization problem considers no product information and target

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

	Privacy, Security., Risk Trust, Int. Conf. Social Computer., 2011, pp. 560–563.	customers, in this paper, we focus on the target marketing. 3. We propose the labeled influence maximization problem, which aims to find a set of seed nodes which can trigger the maximum spread of influence on the target customers in a labeled social network. 4. We propose three algorithms to solve such labeled influence maximization problem. We first develop the algorithms based on the greedy methods of original influence maximization by considering the target customers. 5. Moreover, we develop a novel algorithm, Maximum Coverage, whose central idea is to offline compute the pairwise proximities of nodes in the labeled social network and online find the set of seed nodes. This allows the marketers to plan and evaluate strategies online for advertised products. 6. The experimental results on IMDB labeled social network show our methods can achieve promising performances on both effectiveness and efficiency
2	W. Lu and L. Lakshmanan, "Profit maximization over social networks," in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 479–488.	1. Influence maximization is the problem of finding a set of influential users in a social network such that the expected spread of influence under a certain propagation model is maximized. 2. Much of the previous work has neglected the important distinction between social influence and actual product adoption. However, as recognized in the management science literature, an individual who gets influenced by social acquaintances may not necessarily adopt a product (or technology), due, e.g., to monetary concerns. 3. In this work, we distinguish between influence and adoption by explicitly modeling the states of being influenced and of adopting a product. We extend the classical Linear Threshold (LT) model to incorporate prices and valuations, and factor them into users' decision-making process of adopting a product. 4. We show that the expected profit function under our proposed model maintains sub modularity under certain conditions, but no longer exhibits monotonicity, unlike the expected influence spread function. To maximize the expected profit under our extended LT model, we employ an unbudgeted greedy framework to propose three profit maximization algorithms. The results of our detailed experimental study on three real-world datasets demonstrate that of the three algorithms, PAGE, which assigns prices dynamically based on the profit potential of each candidate seed, has the best performance both in the expected profit achieved and in running time.
3	N. Barbieri, F. Bonchi, and G. Manco, "Topic-aware social influence propagation models," in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 81–90	1. We study social influence from a topic modeling perspective. We introduce novel topic-aware influence-driven propagation models that experimentally result to be more accurate in describing real-world cascades than the standard propagation models studied in the literature. 2. In particular, we first propose simple topic-aware extensions of the well-known Independent Cascade and Linear Threshold models. Next, we propose a different approach explicitly modeling authoritativeness, influence and relevance under a topic-aware perspective. 3. We devise methods to learn the parameters of the models from a dataset of past propagations. Our experimentation confirms the high accuracy of the proposed models and learning schemes
4	A. Goyal, W. Lu, and L. V. Lakshmanan, "CELF++: Optimizing	1. In this work, we introduce CELF++ that further optimizes CELF by exploiting sub modularity. Our experiments show that it improves the efficiency of CELF by 35-55%.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

	the greedy algorithm for influence maximization in social networks," in Proc. 20th Int. Conf. Companion World Wide Web, 2011, pp. 47–48.	2. Since the optimization introduced in CELF++ is orthogonal to the method used for estimating the spread, our idea can be combined with the heuristic approaches that are based on the greedy algorithm to obtain highly scalable algorithms for influence maximization
5	Y. Wang, G. Cong, G. Song, and K. Xie, "Community-based greedy algorithm for mining top-k influential nodes in mobile social networks," in Proc. 16th ACM SIGKDD Int. Conf. Knowledge. Discovery Data Mining, 2010, pp. 1039–1048	1. With the proliferation of mobile devices and wireless technologies, mobile social network systems are increasingly available. 2. A mobile social network plays an essential role as the spread of information and influence in the form of "word-of-mouth". It is a fundamental issue to find a subset of influential individuals in a mobile social network such that targeting them initially (e.g. to adopt a new product) will maximize the spread of the influence (further adoptions of the new product). 3. The problem of finding the most influential nodes is unfortunately NP-hard. It has been shown that a Greedy algorithm with provable approximation guarantees can give good approximation; However, it is computationally expensive, if not prohibitive, to run the greedy algorithm on a large mobile network.
6	W. Chen, Y. Wang, and S. Yang, "Efficient influence maximization in social networks," in Proc. 15th ACM SIGKDD Int. Conf. Knowledge. Discovery Data Mining, 2009, pp. 199–208.	1. Influence maximization is the problem of finding a small subset of nodes (seed nodes) in a social network that could maximize the spread of influence. In this paper, we study the efficient influence maximization from two complementary directions. 2. One is to improve the original greedy algorithm of and its improvement to further reduce its running time, and the second is to propose new degree discount heuristics that improves influence spread. 3. We evaluate our algorithms by experiments on two large academic collaboration graphs obtained from the online archival database arXiv.org. 4. Our experimental results show that (a) our improved greedy algorithm achieves better running time comparing with the improvement of with matching influence spread, (b) our degree discount heuristics achieve much better influence spread than classic degree and centrality-based heuristics, and when tuned for a specific influence cascade model, it achieves almost matching influence thread with the greedy algorithm, and more importantly (c) the degree discount heuristics run only in milliseconds while even the improved greedy algorithms run in hours in our experiment graphs with a few tens of thousands of nodes.

IV. EXISTING SYSTEM APPROACH

From the above literature survey we conclude that viral marketing is one of the key applications of influence maximization. In viral marketing, an item that a marketer wants to promote is diffused into social networks by "word-of-mouth" communication. From the perspective of marketing, influence maximization provides how to get the maximum profit from all the users in a social network through viral marketing. However, influence maximization is not always the most effective strategy for viral marketing, because there can be some items that are useful to only specific

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

users. These specific users can be a few people with a common interest in a given item, some or all people in a community, or some or all users in a class. There is no limit for being specific users.

V. PROPOSED SYSTEM APPROACH

We propose a new efficient expectation model for the influence spread of a seed set based on independent maximum influence paths (IMIP) among users. We also show that the new objective function of the new expectation model is sub modular. Based on the new expectation model, we present a method to efficiently process an IMAX query. The method consists of identifying local regions containing nodes that influence the target nodes of a query and approximating optimal seeds from the local regions as the result of the query. Identifying such local regions helps to reduce the processing time, when the number of targets in an IMAX query is small compared to the number of all nodes. We experimentally demonstrate that our identifying local influencing regions technique is very powerful and the proposed method is at least an order of magnitude faster than the comparison methods in most cases with high accuracy. Identifying local influencing regions makes the basic greedy algorithm about 6 times faster in the experiments.

VI. METHODOLOGY USED

In this work we propose a model in which the actors in the social networks are connected to each other for various interest/reasons. So a product/idea/event, which is to be 'spread' in the network, may be of interest to a particular set of individuals only. Here we propose a model for the Influence Maximization problem taking into account the specific area which may be of interest to one who wants to influence the network, out of the available areas. The social networks are represented as graphs where the nodes are actors and the edges represent the connections between these actors. This representation of the edge is an accumulation of multiple parameters on which the social network is based. These parameters are of diverse nature like location, interests, likes etc. The application of any method traditionally involves considering all the above mentioned parameters instead of focusing on a particular interest. So in our model we converted the traditional social graph into "interest graph", which represents a particular interest(s) of the network. By this the volume of the network and the parameters of the network are reduced subsequently bringing down the time complexity and the computational overhead of applying the method on the original graph. Once we have this graph we can move forward with the basic algorithms.

VII. ALGORITHM USED

1. Used Notations in Algorithms

$\sigma^*_T(S)$	the influence spread of seed set S under the IMIP model
$P^t(i,j)$	the tth IMIP
$\pi^h(i,j)$	the IMIPS from node i to node j
$p_v(S)$	the influence probability of node v given seed set S under the IMIP model
T_v	the influence tree of node v
$\lambda(u)$	the set of the local influencers of node u
$\theta(u)$	the set of the locally influenced targets of node u

- **Greedy Algorithm (G = (V, E), k, T)**

This algorithm provides (1-1/e) approximation.
It picks k nodes maximizing the marginal gain to the objective function at each iteration in lines 3-5.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

input: G: An input graph, k:size of a seed set, T:a set of targets
output: S : Output seed set

begin
  $S = \emptyset$;
  for $i = 1$ *to* k **do**
    $s = \arg\max_{v \in V}(\sigma_T(S \cup \{v\}) - \sigma_T(S))$;
    $S = S \cup \{s\}$;
  return S;

2. **Algorithm 2. Influ (v, i)**

This algorithm compute the influence probability of node v given seed set S under the IMIP model.We denote the immediate predecessors of a copied node i as IN (i). In lines 2-3 of Algorithm 2, if i is a leaf, then the algorithm returns 1, since a leaf corresponds to a seed. Otherwise, in lines 5-9, the algorithm computes the influence probability of i according to the IC model, and then returns it. Thus, influ (v; root (v)) returns the influence probability of v.

input v: a node in V, i: a copied node in T_v
output the influence probability of i when S is a seed set under the IMIP model

1: **begin**
2:   **if** i *is a leaf* **then**
3:     return 1;
4:   **else**
5:     $p = 1$;
6:     **for** $n \in IN(i)$ **do**
7:       $p = p(1 - p(n, i) influ(v, n))$;
8:     $p = 1 - p$;
9:     return p;

3. **Algorithm 3. findLR(G, T)**

To find candidates for optimal seeds, the proposed method finds all local influencing regions of given targets as shown in Algorithm 3.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

input: $G = (V, E)$: an input graph, T: a set of targets
output: C: a set of candidates

begin
  $M = \emptyset, C = \emptyset$;
  for $t \in T$ **do**
    for $i \in \lambda(t)$ **do**
      if *i is not in M* **then**
        $\sigma^*_T(\{i\}) = 0$;
        insert i into M;
      $\sigma^*_T(\{i\}) = \sigma^*_T(\{i\}) + p_t(\{i\})$;
      insert t into $\theta(i)$;
    insert t into C;
  for $m \in M$ **do**
    if $\sigma^*_T(\{m\}) \geq \beta$ **then**
      insert m into C;
  return C;

4. Algorithm. traverseLIT(s, t; update)

input: s: a new seed, t: a node in $\theta(s)$, *update*: a flag for updating
output: mg: the marginal gain of s with respect to the influence probability of t

begin
  $\hat{p}(t) = p(t)$
  for $s' \in leaves(s, t)$ **do**
    $\hat{p}(s') = p(s')$;
    $p(s') = 1$;
    $next(SUCC(s'), root(t), s')$;
  $mg = p(t) - \hat{p}(t)$;
  if $update = false$ **then**
    $p(v) = \hat{p}(v)$ such that $v \in T_t$ and $p(v) \neq \hat{p}(v)$;
  return mg;

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

5. Algorithm. storing (G, h, δ)

input: $G = (V, E)$: an input graph, h: the maximum number of an IMIPS, δ: a parameter in $(0, 1 - \sqrt[h]{1-\alpha})$

begin
  for $v \in V$ **do**
    compute $P^1(u, v)$ s.t. $u \in V \wedge p(P^1(u, v)) > 1 - \sqrt[h]{1-\alpha}$;
    $\lambda'(v) = \{u \mid u \in V, p(P^1(u, v)) > 1 - \sqrt[h]{1-\alpha}\}$;
    for $u \in \lambda'(v)$ **do**
      insert $P^1(u, v)$ into $\pi^h(u, v)$;
      $V' = \bigcup_{(i,j) \in P^1(u,v)} \{j\} - \{v\}$;
      $flag = false, h' = 0$;
      for $t = 2$ to h **do**
        $h' = t$;
        $F = \prod_{t'=1}^{t-1} (1 - p(P^{t'}(u, v)))$;
        $bound = min\left\{1 - \sqrt[h-(t-1)]{\frac{1-\alpha}{F}}, \delta\right\}$;
        compute $P^t(u, v)$ with $V - V'$ s.t. $p(P^t(u, v)) > bound$;
        if $P^t(u, v)$ *is empty* **then**
          if $1 - F < \alpha$ **then**
            $flag = true$;
          break;
        else if $F(1 - p(P^t(u, v))) = 0$ **then**
          break;
        insert $P^t(u, v)$ into $\pi^h(u, v)$;
        $V' = V' \cup \bigcup_{(i,j) \in P^t(u,v)} \{j\} - \{v\}$;
      if $flag \neq true$ **then**
        $p_v(\{u\}) = 0$;
        for $t = 1$ *to* h' **do**
          $p_v(\{u\}) = 1 - (1 - p_v(\{u\}))(1 - p(P^t(u, v)))$;
        insert u into $\lambda(v)$

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

6. Algorithm 6. Next(v, t, v')

input: v: a current copied node, t: the root node, v': the immediate predecessor of v

begin
  if $v = t$ **then**
    $p(v) = 1 - \frac{(1-p(v))(1-p(v')p(v',v))}{(1-\hat{p}(v')p(v',a))}$;
    return;
  $\hat{p}(v) = p(v)$;
  $p(v) = 1 - \frac{(1-p(v))(1-p(v')p(v',v))}{(1-\hat{p}(v')p(v',a))}$;
  if $p(SUCC(v)) \neq 1$ **then**
    $next(SUCC(v), t, v)$;
  return;

7. Algorithm 7. IMIP-based IMAX query (G, T, k)

input: $G = (V, E)$: an input graph, T: a set of targets, k: the size of the output seed set
output: S: a seed set

begin
  $S = \emptyset$;
  // find candidates and compute θ function
  $C = findLR(G, T)$;
  for $c \in C$ **do**
    $\Delta\sigma_T^S(c) = \sigma_T^*(\{c\})$;
  for $i = 1$ *to* k **do**
    $s = \arg\max_{c \in C-S} \Delta\sigma_T^S(c)$;
    $S = S \cup \{s\}$;
    for $c \in copied(s)$ **do**
      $p(c) = 1$;
    for $t \in \theta(s)$ **do**
      // update the influence probability of t
      $traverseLIT(s, t, true)$;
    if s *in* T **then**
      for $s' \in \lambda(s)$ **do**
        if $s' \in C$ **then**
          // reduce $\Delta\sigma_T^S(s')$ since s is a seed
          $\Delta\sigma_T^S(s') = \Delta\sigma_T^S(s') - \Delta\sigma_T^S(s', s)$;
          $\Delta\sigma_T^S(s', s) = 0$;
    for $t \in \theta^*(s)$ **do**
      if $t \in S$ *or* $t \notin T$ **then**
        continue;
      for $l \in \lambda(t)$ **do**
        $temp = \Delta\sigma_T^S(l, t)$;
        $\Delta\sigma_T^S(l, t) = traverseLIT(l, t, false)$;
        $\Delta\sigma_T^S(l) = \Delta\sigma_T^S(l) - temp + \Delta\sigma_T^S(l, t)$;

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

VIII. SYSTEM ARCHITECTURE

In this work, in order to give a new algorithm for the Influence Maximization problem, that keeps into consideration the history of actions that have been taken by the users in determining their influence over each other. Also, it uses the concept of community detection and its relationship with the field of Viral Marketing. I propose that instead of the Social Marketing & Influence model which has been used to simulate propagation of influence. In this work, in order to give a new algorithm for the Influence Maximization problem, that keeps into consideration the history of actions that have been taken by the users in determining their influence over each other. Also, it uses the concept of community detection and its relationship with the field of Viral Marketing. I propose that instead of the Social Marketing & Influence model which has been used to simulate propagation of influence. Now, to use this scanning of action log to determine probabilistic influence between any two users. Once we have these influence values we will apply topic aware influence maximization framework along with linear threshold model so that performance and influence result should get improved, with probability values that are actually significant. This approach is clearly more practical and hence more accurate than assigning random probability values to each of these edges.

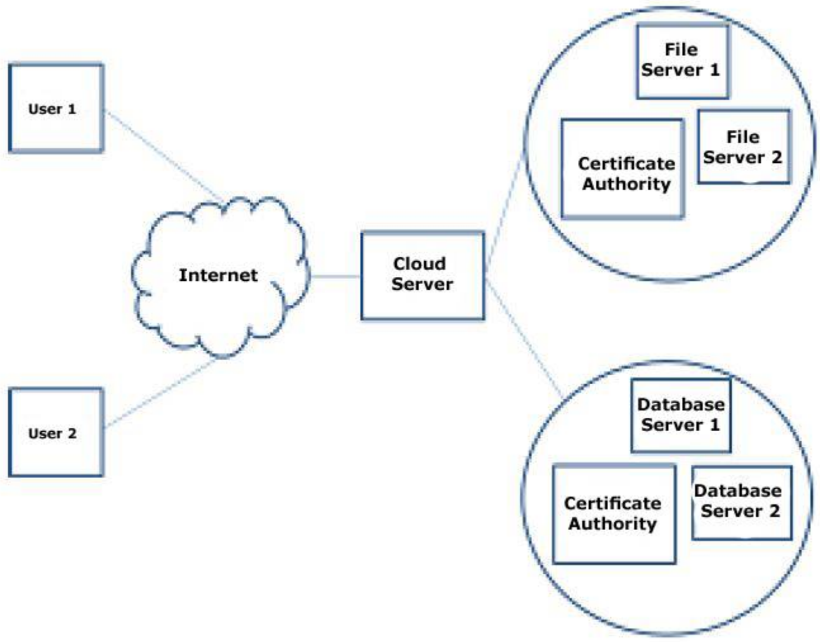
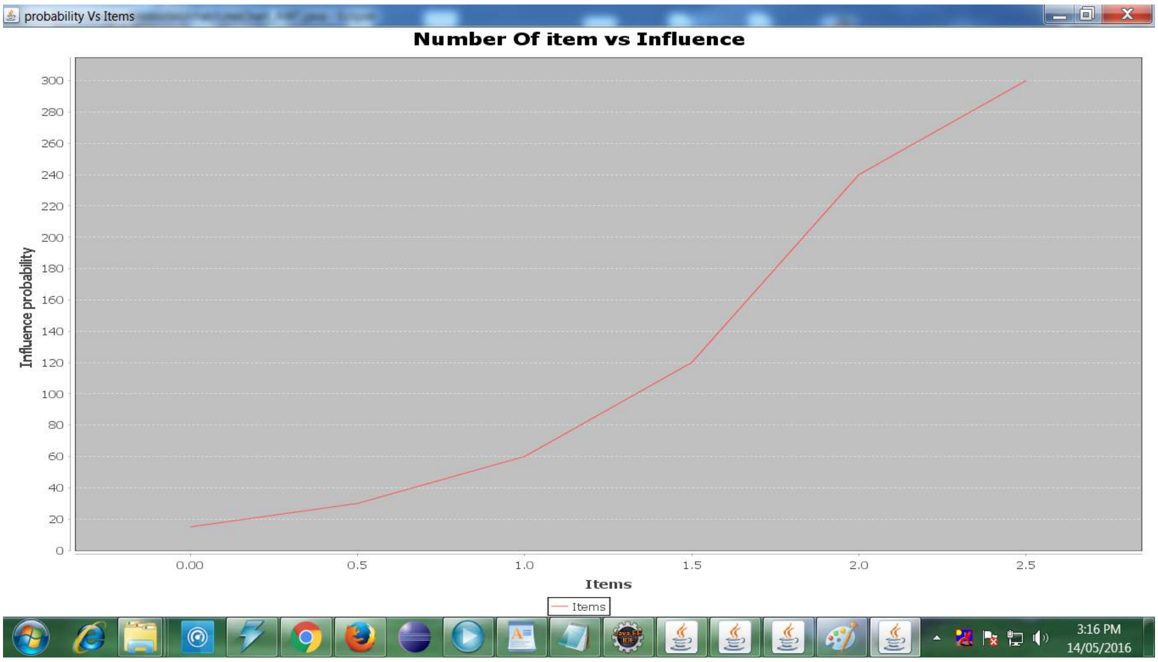


Fig 01 System Architecture

IX. EXPERIMENTAL SET UP

Data Set
We have normally based on the Graph theory mainly they are used to Tress Structured. Mainly they are called to Greedy Algorithm. All Algorithm are Based as the Interest of Person. That Data Set is making in tree format. That is containing two Algorithms for Left Side and Right Side Traversing.

Experimental Results
This experiment is to evaluate the performance of the proposed Location Based community Greedy algorithm on a Wireless Sensor Network. We have to consider following parameter.



X. CONCLUSION

In this project, we formulate IMAX query processing to maximize the influence on specific users in social networks. SinceIMAX query processing is NP-hard and calculating its objective function is #P-hard, we focus on how to approximate optimal seeds efficiently. To approximate the value of the objective function, we propose the IMIP model based on independence between paths. To process an IMAX query efficiently, extracting candidates for optimal seeds is proposed and the fast greedy-based approximation using the IMIP model.
We are going to experimentally demonstrate that our identifying local influencing regions technique is effective and the proposed method is mostly at least an order of magnitude faster than PMIA and IRIE with similar accuracy In addition, the proposed method is mostly six orders of magnitude faster than CELF++ and the identifying local influencing regions technique makes CELF++ about 3.2 times faster while achieving high accuracy.

REFERENCES

[1] W.Yu, G.Cong, G.Song, and K.Xie, “Community-based greedy algo- rithm for mining top-k influential nodes in mobile social networks,” in KDD, 2010, pp. 1039–1048
[2] F.Bass, “A new product growth model for consumer durables,” Manage- ment Science, vol. 15, pp. 215–227, 1969.
[3] V.Mahajan, E.Muller, and F.Bass, “New product diffusion models in marketing: A review and directions for research,” Journal of Marketing, vol. 54, no. 1, pp. 1–26, 1999.
[4] D. Kempe, J. Kleinberg, and E. Tardos, “Maximizing the spread of influence through a social network,” in Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining, 2003, pp. 137–146.
[5] J.Brown and P.Reinegen, “Social ties and word-of-mouth referral be- havior,” Journal of Consumer research, vol. 14, no. 3, pp. 350–362, 1987.
[6] W. Chen, Y. Wang, and S. Yang, “Efficient influence maximization in social networks,” in Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining, 2009, pp. 199– 208.
[7] J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, J. VanBriesen, and N. Glance, “Cost-effective outbreak detection in networks,” in Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining, 2007, pp. 420–429.
[8] M. Girvan and M. E. J. Newman, “Community structure in social and biological networks,” Proceedings of the National Academy of Sciences, vol. 99, no. 12, pp. 7821–7826, 2002.
[9] P. Domingos and M. Richardson, “Mining the network value of cus- tomers,” in Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining, 2001, pp. 57–66.
[10] D.Kempe, J.Kleinberg, and E.Tardos, “Influential nodes in a diffusion model for social networks,” In ternational colloquium on automata, languages and programming, no. 32, pp. 112–1138, 2005

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

[11] J.Goldenberg, B.Libai, and E.Muller, "Talk of the network: A complex systems look at the underlying process of word-of-mouth," Marketing Letters, vol. 12, no. 3, pp. 211–223, 2001.
[12] F.-H. Li, C.-T. Li, and M.-K. Shan, "Labeled influence maximization in social networks for target marketing," in Proc. IEEE 3rd Int. Conf. Privacy, Security., Risk Trust, Int. Conf. Social Computer., 2011, pp. 560–563.
[13] W. Lu and L. Lakshmanan, "Profit maximization over social networks," in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 479–488.
[14] N. Barbieri, F. Bonchi, and G. Manco, "Topic-aware social influence propagation models," in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 81–90.
[15] A. Goyal, W. Lu, and L. V. Lakshmanan, "CELF++: Optimizing the greedy algorithm for influence maximization in social networks," in Proc. 20th Int. Conf. Companion World Wide Web, 2011, pp. 47–48.
[16] Y. Wang, G. Cong, G. Song, and K. Xie, "Community-based greedy algorithm for mining top-k influential nodes in mobile social networks," in Proc. 16th ACM SIGKDD Int. Conf. Knowledge. Discovery Data Mining, 2010, pp. 1039–1048
[17] W. Chen, Y. Wang, and S. Yang, "Efficient influence maximization in social networks," in Proc. 15th ACM SIGKDD Int. Conf. Knowledge. Discovery Data Mining, 2009, pp. 199–208.