

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

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**ABSTRACT:** Impact expansion is acquainted with augment the benefit of viral promoting in informal communities. The shortcoming of impact augmentation is that it doesn't recognize particular clients from others, regardless of the possibility that a few things can be helpful for the particular clients. For such things, it is a superior technique to concentrate on augmenting the impact on the particular clients. In this paper, we plan an impact boost issue as inquiry handling to recognize particular clients from others. We propose a desire model for the estimation of the target capacity and a quick ravenous based guess strategy utilizing the desire model. For the desire model, we examine a relationship of ways between clients. For the ravenous strategy, we work out a productive incremental overhauling of the peripheral addition to our goal capacity. Our trial results demonstrate that (an) our enhanced avaricious calculation accomplishes better running time contrasting and the change of with coordinating impact spread, (b) our degree markdown heuristics accomplish much preferable impact spread over great degree and centrality-based heuristics, and when tuned for a particular impact course display, it accomplishes practically coordinating impact string with the covetous calculation, and all the more vitally.

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

## I. INTRODUCTION

As of late, the measure of engendering of data is relentlessly expanded in online informal communities, for example, Facebook and Twitter. To utilize online informal communities as a promoting stage, there is heaps of examination on the best way to utilize the spread of impact for viral showcasing. One of the examination issues is impact expansion (IMAX), which means to discover  $k$  seed clients to augment the spread of impact among clients in interpersonal organizations. It is ended up being a NP-difficult issue. Since they proposed an avaricious calculation for the issue, numerous scientists have proposed different heuristic strategies. An interpersonal organization the chart of connections and communications inside a gathering of people assumes a crucial part as a medium for the spread of data, thoughts, and impact among its individuals. A thought or advancement will show up for instance, the utilization of phones among understudies, the selection of another medication inside the therapeutic calling, or the ascent of a political development in a flimsy society and it can either cease to exist rapidly or make huge advances into the populace. In the event that we need to comprehend the degree to which such thoughts are received, it can be imperative to see how the progression of reception are prone to unfurl inside the hidden informal organization: the degree to which individuals are liable to be influenced by choices of their companions and partners, or the degree to which "verbal" impacts will grab hold. Such system dispersion forms have a long history of study in the sociologies. A portion of the soonest methodical examinations concentrated on information relating to the reception of medicinal and agrarian advancements in both created and creating parts of the world [8, 7, 9]; in different connections, research has explored dispersion forms for

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"verbal" and "viral showcasing" impacts in the achievement of new items [4, 7] the sudden and across the board selection of different techniques in diversion theoretic settings [6, 1] and the issue of falling disappointments in force frameworks [2, 3]. Viral promoting is one of the key utilizations of impact boost. In viral advertising, a thing that an advertiser needs to advance is diffused into informal organizations "by overhearing people's conversations" correspondence. From the point of view of showcasing, impact boost gives how to get the greatest benefit from every one of the clients in an informal community through viral promoting. Notwithstanding, impact expansion is not generally the best technique for viral promoting, on the grounds that there can be a few things that are helpful to just particular clients. These particular clients can be a couple people with a typical enthusiasm for a given thing, a few or all individuals in a group, or a few or all clients in a class. There is no restriction for being particular clients. For instance, consider an advertiser that is approached to advance a corrective item for ladies through viral promoting. For the corrective item, the particular clients are female clients who are liable to utilize it and male clients who wish to buy it as a present for female clients. For this situation, the advertiser does not should be worried about alternate clients in light of the fact that the restorative item is not helpful to them. Rather, it is a superior procedure to concentrate on expanding the quantity of impacted particular clients, however impact expansion has the shortcoming that it can't recognize them from alternate clients. The main method for taking care of such focuses with impact expansion is making a homogeneous chart with the objectives and executing impact boost on the diagram. Notwithstanding, the consequence of this methodology ought to be mistaken, in light of the fact that there can be a few clients who are not targets but rather can emphatically impact the objectives. To conquer the shortcoming of impact augmentation and to give the adaptability, we define an impact amplification issue as inquiry handling without predefined names and call this IMAX question preparing. In IMAX question handling, an interpersonal organization is spoken to by a diagram where a hub speaks to an individual and an edge speaks to a relationship between two people, for example, the kinship. The IMAX inquiry issue merits getting consideration of scientists from two perspectives. One is the reasonableness of IMAX question preparing for target-mindful viral advertising. As we clarified, subsequent to the impact augmentation issue can't recognize focuses from alternate clients, it is not reasonable for target-mindful viral promoting. Notwithstanding, in the IMAX question issue, we can indicate targets expressly utilizing a set and concentrate on boosting impact on those objectives. The plan of the IMAX question issue is adequate for displaying target-mindful viral promoting when all is said in done 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.

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### 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. Privacy, Security, Risk Trust, Int. Conf. Social Computer., 2011, pp. 560–563.	<ol style="list-style-type: none"> <li>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.</li> <li>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 customers, in this paper, we focus on the target marketing.</li> <li>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.</li> <li>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.</li> <li>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.</li> <li>6. The experimental results on IMDB labeled social network show our methods can achieve promising performances on both effectiveness and efficiency</li> </ol>
2	W. Lu and L. Lakshmanan, "Profit maximization over social networks," in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 479–488.	<ol style="list-style-type: none"> <li>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.</li> <li>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.</li> <li>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.</li> <li>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.</li> </ol>
3	N. Barbieri, F. Bonchi, and G. Manco,	<ol style="list-style-type: none"> <li>1. We study social influence from a topic modeling perspective. We introduce novel topic-aware influence-driven propagation models that</li> </ol>

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	<p>“Topic-aware social influence propagation models,” in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 81–90</p>	<p>experimentally result to be more accurate in describing real-world cascades than the standard propagation models studied in the literature.</p> <ol style="list-style-type: none"> <li>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.</li> <li>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</li> </ol>
4	<p>A. Goyal, W. Lu, and L. V. Lakshmanan, “CELFF++: Optimizing the greedy algorithm for influence maximization in social networks,” in Proc. 20th Int. Conf. Companion World Wide Web, 2011, pp. 47–48.</p>	<ol style="list-style-type: none"> <li>1. In this work, we introduce CELFF++ that further optimizes CELF by exploiting sub modularity. Our experiments show that it improves the efficiency of CELF by 35-55%.</li> <li>2. Since the optimization introduced in CELFF++ 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</li> </ol>
5	<p>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</p>	<ol style="list-style-type: none"> <li>1. With the proliferation of mobile devices and wireless technologies, mobile social network systems are increasingly available.</li> <li>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).</li> <li>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.</li> </ol>
6	<p>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.</p>	<ol style="list-style-type: none"> <li>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.</li> <li>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.</li> <li>3. We evaluate our algorithms by experiments on two large academic collaboration graphs obtained from the online archival database arXiv.org.</li> <li>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,</li> </ol>

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		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.
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## 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 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.

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## 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 $t$ th 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.

input:  $G$ : An input graph,  $k$ :size of a seed set,  $T$ :a set of targets

output:  $S$  : Output seed set

```

1: begin
2:    $S = \emptyset$ ;
3:   for  $i = 1$  to  $k$  do
4:      $s = \arg \max_{v \in V} (\sigma_T(S \cup \{v\}) - \sigma_T(S))$ ;
5:      $S = S \cup \{s\}$ ;
6:   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,  $influ(v; \text{root}(v))$  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  $p$ ;

```

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### 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.

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

```

1: begin
2:    $M = \emptyset, C = \emptyset$ ;
3:   for  $t \in T$  do
4:     for  $i \in \lambda(t)$  do
5:       if  $i$  is not in  $M$  then
6:          $\sigma_T^*(\{i\}) = 0$ ;
7:         insert  $i$  into  $M$ ;
8:          $\sigma_T^*(\{i\}) = \sigma_T^*(\{i\}) + p_t(\{i\})$ ;
9:         insert  $t$  into  $\theta(i)$ ;
10:    insert  $t$  into  $C$ ;
11:    for  $m \in M$  do
12:      if  $\sigma_T^*(\{m\}) \geq \beta$  then
13:        insert  $m$  into  $C$ ;
14:    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  $t$

```

1: begin
2:    $\hat{p}(t) = p(t)$ 
3:   for  $s' \in leaves(s, t)$  do
4:      $\hat{p}(s') = p(s')$ ;
5:      $p(s') = 1$ ;
6:      $next(SUCC(s'), root(t), s')$ ;
7:    $mg = p(t) - \hat{p}(t)$ ;
8:   if  $update = false$  then
9:      $p(v) = \hat{p}(v)$  such that  $v \in T_t$  and  $p(v) \neq \hat{p}(v)$ ;
10:  return  $mg$ ;

```

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### 5. Algorithm. storing $(G, h, \delta)$

**input:**  $G = (V, E)$ : an input graph,  $h$ : the maximum number of an IMIPS,  $\delta$ : a parameter

in  $(0, 1 - \sqrt[h]{1 - \alpha})$

```

1: begin
2:   for  $v \in V$  do
3:     compute  $P^1(u, v)$  s.t.
        $u \in V \wedge p(P^1(u, v)) > 1 - \sqrt[h]{1 - \alpha}$ ;
4:      $\lambda'(v) = \{u | u \in V, p(P^1(u, v)) > 1 - \sqrt[h]{1 - \alpha}\}$ ;
5:     for  $u \in \lambda'(v)$  do
6:       insert  $P^1(u, v)$  into  $\pi^h(u, v)$ ;
7:        $V' = \bigcup_{(i,j) \in P^1(u,v)} \{j\} - \{v\}$ ;
8:       flag = false,  $h' = 0$ ;
9:       for  $t = 2$  to  $h$  do
10:         $h' = t$ ;
11:         $F = \prod_{t=1}^{t-1} (1 - p(P^t(u, v)))$ ;
12:        bound =  $\min\{1 - \sqrt[h-t]{\frac{1-\alpha}{F}}, \delta\}$ ;
13:        compute  $P^t(u, v)$  with  $V - V'$  s.t.
           $p(P^t(u, v)) > \text{bound}$ ;
14:        if  $P^t(u, v)$  is empty then
15:          if  $1 - F < \alpha$  then
16:            flag = true;
17:            break;
18:          else if  $F(1 - p(P^t(u, v))) = 0$  then
19:            break;
20:          insert  $P^t(u, v)$  into  $\pi^h(u, v)$ ;
21:           $V' = V' \cup \bigcup_{(i,j) \in P^t(u,v)} \{j\} - \{v\}$ ;
22:        if flag  $\neq$  true then
23:           $p_u(\{u\}) = 0$ ;
24:          for  $t = 1$  to  $h'$  do
25:             $p_u(\{u\}) =$ 
               $1 - (1 - p_u(\{u\}))(1 - p(P^t(u, v)))$ ;
26:          insert  $u$  into  $\lambda(v)$ 

```



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

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

```

1: begin
2:   if  $v = t$  then
3:      $p(v) = 1 - \frac{(1-p(v))(1-p(v')p(v',v))}{(1-\hat{p}(v')p(v',a))}$ ;
4:     return;
5:      $\hat{p}(v) = p(v)$ ;
6:      $p(v) = 1 - \frac{(1-p(v))(1-p(v')p(v',v))}{(1-\hat{p}(v')p(v',a))}$ ;
7:     if  $p(SUCC(v)) \neq 1$  then
8:        $next(SUCC(v), t, v)$ ;
9:   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

```

1: begin
2:    $S = \emptyset$ ;
3:   // find candidates and compute  $\theta$  function
4:    $C = findLR(G, T)$ ;
5:   for  $c \in C$  do
6:      $\Delta\sigma_T^S(c) = \sigma_T^*(\{c\})$ ;
7:   for  $i = 1$  to  $k$  do
8:      $s = \arg \max_{c \in C-S} \Delta\sigma_T^S(c)$ ;
9:      $S = S \cup \{s\}$ ;
10:    for  $c \in copied(s)$  do
11:       $p(c) = 1$ ;
12:      for  $t \in \theta(s)$  do
13:        // update the influence probability of  $t$ 
14:         $traverseLIT(s, t, true)$ ;
15:      if  $s$  in  $T$  then
16:        for  $s' \in \lambda(s)$  do
17:          if  $s' \in C$  then
18:            // reduce  $\Delta\sigma_T^S(s')$  since  $s$  is a seed
19:             $\Delta\sigma_T^S(s') = \Delta\sigma_T^S(s') - \Delta\sigma_T^S(s', s)$ ;
20:             $\Delta\sigma_T^S(s', s) = 0$ ;
21:          for  $t \in \theta^*(s)$  do
22:            if  $t \in S$  or  $t \notin T$  then
23:              continue;
24:            for  $l \in \lambda(t)$  do
25:               $temp = \Delta\sigma_T^S(l, t)$ ;
26:               $\Delta\sigma_T^S(l, t) = traverseLIT(l, t, false)$ ;
27:               $\Delta\sigma_T^S(l) = \Delta\sigma_T^S(l) - temp + \Delta\sigma_T^S(l, t)$ ;
```

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## 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.

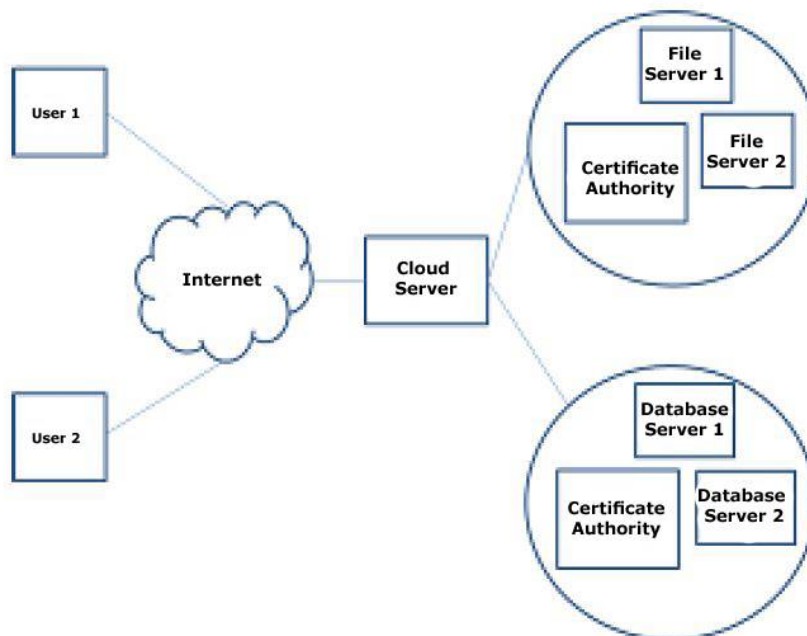


Fig 01 System Architecture

## 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.

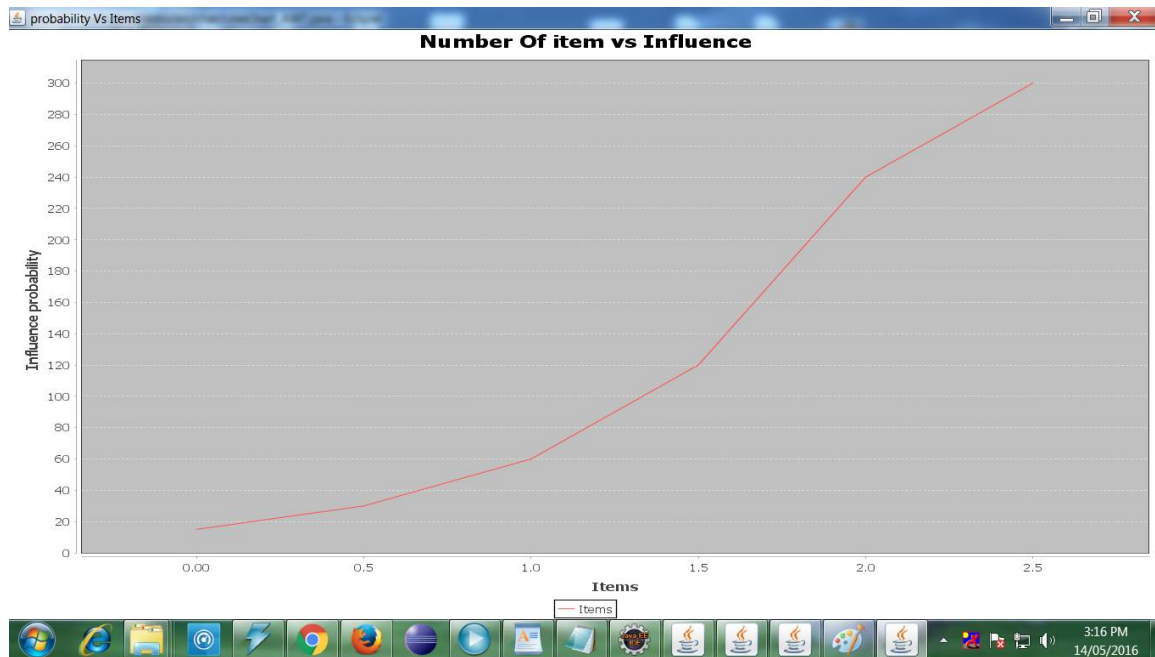
### Experimental Results

This experiment is to evaluate the performance of the proposed Location Based community Greedy algorithm on a Mobile Social Network. We have to consider following parameter.

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## X. CONCLUSION

In this project, we formulate IMAX query processing to maximize the influence on specific users in social networks. Since IMAX 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.

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