International Journal of Future Generation Communication and Networking
Vol. 13, No. 4, (2020), pp. 3585–3601

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

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***Abstract***

*Maximization of impact is applied to optimize the value of social network viral marketing. The fragility of power Maximization is that, even though certain products may only be beneficial for certain uses, it would not distinguish individual users from others. For it is a smarter approach to concentrate on optimizing the effect on the particular consumers of such products. We formulate an impact in this article, Question of maximization we explore a partnership of paths for the expectation model, Users-between. We are carrying out an optimal cumulative modification of the marginal benefit to our objective equation for the greedy process. We Conduct tests using real-life datasets to test the proposed approach and equate the findings with those of current approaches. Which are tailored to the problem? The approach proposed is from our experimental data, at least an order of magnitude quicker than the one introduced. In certain instances, current techniques though maintaining high precision.*

***Index terms: -*** *Graph algorithms, maximization of control, autonomous cascade model, and social networks*

## 1 INTRODUCTION

To make use of social networks online as a There is plenty of study into how to utilize the marketing platform, Influence transmission with viral marketing. One of the Ones Study challenges are the maximization of impacts (IMAX), which since they suggested a Many researchers have a greedy algorithm for the dilemma, Proposed different methods of heuristics. One of the main effect applications of viral marketing is Maximizing. A component that a marketer uses in viral marketing wants to facilitate the propagation of social networks through "communication benefit on a social network from all members By way of viral marketing. Influence maximization, however, It's not necessarily the most successful viral marketing technique, and there could be some things that are beneficial to particular items only Oh. Users. A few persons with a particular user may be these specific users.

Popular interest in a specific object, any or all persons in a specific item Group, including any or more of a class's users. There are no threshold unique users for becoming. Find a marketer, for example, the marketing of in this situation, there is no reason for the marketer to be worried regarding nice the cosmetic product is not beneficial, the other users towards them. Instead it is a smarter approach to work on optimizing the amount of individual users affected, however the effect the drawback of maximization is that it does not differentiate those of the other consumers. The only way to manage those issues Targets with maximization of control generates a homogeneous Chart with the goals and maximization of impact implementation on a map. The outcome of this strategy, however, It can be unreliable, since certain users might be there who this are not goals, although the targets may be highly affected.

Centered on concentrating on particular goals. Maximization of influence [2]. In [2], each user is labeled with until handling requests, multiple predefined names; a question contains certain logos that specify a



ISSN: 2233-7857 IJFGCN

marketer's objectives Wants to impact. It is not flexible, however to pre-define every user's labels before processing the message, because a query No formulation may be produced for goals that do not share any current name. We should include a new logo in this situation, like a new mark. Certain goals. Additionally, if we use a pre-processed framework to measure outcomes, when implementing a framework, we can easily change the structure. Nevertheless the expense of upgrading the current mark is expected to be elevated. Big. There is another analysis that can be extended to Influencing a particular part of a social network. Lu and, uh, Lu and Lakshmanan [3] implies a difference in maximization of influence which distinguishes being affected and adopting an object for the maximization of benefit. If a consumer is impaired by their problem, for an object, then with some likelihood, the consumer adopts it. Thus by setting the chance for a consumer who is not their dilemma should tackle a goal of adopting an object to 0 maximizing the effect on individual goals. Nevertheless, it is important to search all users a hundred times while we have one hundred things aligned with multiple goal sets. Apparently, it is impractical to track all users while we they've got several such things. If there are these two questions, there is no Novel issue that maximizes the effect of processes on Clear priorities and the versatility to manage different tasks
Products without supplementary charges.

To resolve the deficiency of maximization of influence We devise an impact and to have versatility, Issue maximization as database processing without predefined query processing Labels and name this IMAX sorting of requests. IMAX in Processing of questions, a social network is defined by a Graph where a person and an edge are defined by a node a friendship between two persons, such as that's fellowship. Each edge up; v has a chance that u Influences v. The distribution, with certain probabilities on sides, the independent cascade is modeled on results. Model for (IC). User U has a one-time ability to use the IC model an uninfluenced neighbor v is affected at time t · 1 while u is impacted at the moment t. If u cans not impact v, there is no second Chance to manipulate u v. Nonetheless, v may be affected when there is an edge from w to v by another person, w And W is motivated. Additionally, if u is impaired at time t, U will not be impaired again for a period of time t. Beneath the IC An IMAX query model consists of the seed set size k and the goal size k T node collection, and k seed users are asked to optimize the amount Users that are impacted by the users listed in the questionnaire.

We presume that the number of targets is even higher. Oh. Than k. The amount of users impacted can be calculated by the estimated number of users who are impacted. The question of the IMAX query is worth getting attention from Two-dimensional scholars. One is the appropriateness of the IMAX Processing of questions for target-aware viral marketing. As we, as we Explained, because the issue of optimizing influence cannot it is not appropriate for separating targets from other apps. Viral target-aware advertisement. In the IMAX query, however, Issue, we can specifically define goals using a set and a set Focus on optimizing their effect on those priorities. The wording for simulation, the IMAX question issue is appropriate for viral target-aware ads for general purposes. Next, the other one is usefulness. There are in the modern universe, many users who choose to advertise many products for different reasons Purposes by accessing social networks online. From an IMAX question Processing may be a breakthrough to successfully market an object. Among such users, the number of possible users is the number of potential users. IMAX processing requests can be very broad. This suggests that performance For IMAX query processing; this is a rather important issue.

IMAX query handling though is NP-hard, like the effect issue of maximization. And there is sub modularity throughout the issue of maximization of influence is retained in IMAX Query processing, various approaches used to influence For IMAX query handling, maximization will also be used. However the handling of the IMAX question is inefficient. In we know goal nodes, as opposed to maximization of influence; we want to affect that when an IMAX question is given. It this implies an appropriate approach for an IMAX question should be used. Rapidly classify the nodes that significantly impact the goals Query for data preprocessed. Because of current policies Do not use the effect



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maximization issue or use the We need to pay attention to the essence of query handling, Question processing to establish a modern, powerful system for processing queries Processing Query IMAX. We suggest a new productive expectation in this article, Model for the distribution of control of a seed set centered on independent Paths of highest impact (IMIP) among users. We the current goal function of the new expectation also reveals that he framework is sub modular. Centered on the latest forecast ode, we present a method of processing an IMAX effectively Request. Ask. The strategy consists of defining local areas that include Nodes that impact a query's target nodes and Approximating optimal seeds as the optimal seeds from the nearby regions the query's result. It is beneficial to recognize those local areas the processing time is decreased where the amount of goals in the process compared to the amount of both of them, an IMAX question is tiny Uh, nodes. We use a greedy one to estimate optimum seeds Process focused on a marginal gain against the new target to work. Furthermore, we present a technique to gradually update each user's marginal benefit to accelerate the Process Selfish. Contributions of theirs. This paper produces the following

Contributors: We understand the limits of current science. Connected to optimizing the effect on particular goals. As a maximization question, we devise an impact maximization issue as Processing of queries without predefined labels to answer the limits. We are showing that the problem is NP-hard such that the objective feature of the function is The IMAX question issue is a sub modular issue. On the basis of Objective feature sub modularity, we present A selfish IMAX query analysis algorithm and It indicates that it has an approximation ratio of ð1 ?? 1 = e. We suggest a modern powerful model of expectation for Spreading the impact of a seed package. We are showing that the expectation model's current goal function is Sub modulated. Centered upon the modern model of anticipation, we suggest a system of greedy-based approximation Effective incremental analysis of an IMAX question Updating of each user's incremental benefit. We they also suggest an efficient approach for minimizing the by defining the number of candidates for optimum seeds Users that greatly impact goals from Preprocessed knowledge.

Experimentally, we prove that our identity is the technique of local affecting regions is very powerful. At least an order of magnitude and the suggested approach are faster than the methods of comparison in much of the Cases of elevated specificity. Determining environmental sources Regions make the fundamental greedy algorithm of in the trials, 6 times quicker. The remainder of this article is structured as follows. Under Section 2, similar studies are reviewed. The IMAX question we are formulating Under the IC model in Section 3, and showing the NPhardness problem, And the sub modularity of its role as a goal. In Section 4.1, after the accurate calculation of power distribution it is so costly that we are designing a modern paradigm of standards for the distribution of power. Then we build an appropriate algorithm, Centered on the expectation model for IMAX query processing Within Section 4.2. We show the quality and efficacy of via numerous studies, the suggested approach Within Section 5. We draw assumptions and define the prospects of In Section 6, functions.

## 2 RELATED WORKS

The production of IMAX queries originates from optimizing the effect. The first analysis of Domingo's and Richardson [4] impacts maximization as an algorithmic question focused on a Markov Area at random. Maximization of influence is formulated by Kemp et al. under the fundamental models of diffusion [1]. Since power, since influence NP-hard is maximization, Kemp et al. suggest a Greedy methodology and shows that its accuracy is greater than those from other naive tactics. Leskovec et al. are improving the With the Cost-Effective Lazy Forward, Selfish process Selection of (CELF) [5]. Goyal et al. boost the selfish CELF System by the manipulation of sub modularity [6]. [7] Wang et al. Propose a selfish, community-oriented approach based on the detection of in groups, power spreads. [8], [9] Chen et al. Emphasis on decreasing the expense of the impact measure Disseminated. They suggest a randomly based greedy strategy Graphs and a degree-based method generated in which the Nodes of the maximum productive degree are selected as influential about seeds. Prefixes except full impact are also proposed.



ISSN: 2233-7857 IJFGCN

Heuristics of PMIA (arborescence) where seed nodes Influence of the other nodes on the maximum effect the route to each node from the seed node [9]. In the heuristics for PMIA, if the full direction of impact from seed node s to s another seed node s0 in their greedy-based node v contains node v the algorithm determines the next limit, so their algorithm Route of control from s to v which does not include s0. Nonetheless because computing it in query processing time is The PMIA heuristics are costly and unreliable for IMAX. Processing Question. Like the heuristics of the PMIA, the proposed This approach also uses some optimum impact in this paper Paths, however the heuristics of the PMIA are more powerful than Centered on preserving several alternate paths on a pre-processed novel Architecture. Jiang et al. [10] current virtual simulations Annealing-based tactics used to avoid incarceration The Greedy Approach problem. [11] Jung et al. using a framework to suggest a new approach for effect rating Linear equations, and present a way to use their equations rating approach for optimizing impacts. Those current ones For IMAX query analysis, the methods are not valid, since they should not be used explicitly and are not successful at doing so.

An IMAX question is processed. There are several versions of the maximization of influence Things such as IMAX query handling. One is competitive, one is Maximization of influence that recognizes several Competitive social network technologies [12], [13], [14]. [14] A new variation was proposed by Bharathi et al. [12] Maximization of control to model the situation when several within a social network, technologies compete. Carnes et al. [13] reflect on another situation concerning a new product. It is launched into a market in which a rival sector is competing Items are now being sold. [14] Iran and Ortiz Introducing a modern method to optimizing influence Centered on the principle of non-cooperative games and formulating a latest graphical game class that models the actions of graphical games in social networks, each person. Maximization of effect is another interesting problem. Diffusion networks in constant time [15], [16]. Gomez—Gomez Maximization of influence formulation by Rodriguez and Scholkopf[15] Diffusion and on the completely continuous time model of diffusion Propose an approach to overcome it by taking advantage of temporal Dynamics in networks of diffusion. Du et al. [16] improvement of the in terms of scalability, work by Gomez-Rodriguez and Scholkopf Inference and Neighborhood by graphical model Estimation of scale. One noteworthy feature of Du ET a work.'s is that they sing actual historical details i.e., activity logs of users) to analyse the [16] process. There is an earlier thesis that exploits actual historical history. Data for optimizing influence [17]. In [17], Goal A strategy for optimizing power dependent on maximization is suggested by et al. Upon actual historical knowledge and test it with reference to the Real knowledge distribution. We also conduct in this job Experiments focused on the real propagation of knowledge, such as [17], but in another way. Any study has developed fresh variants focused on recent research. Several potential viral marketing restrictions. Sin ginger [18] formulates a variety of maximization of influence representing maximization of influence the expense of getting a budget for seeds in viral marketing Boundary. One dilemma was formulated by Goal et al. [19] in order to find the minimum seed size collection meets a threshold for the degree of Dissemination and the other issue of minimizing time when attaining the threshold. As we have mentioned in the section 1, current research is in position and can establish goals for Maximizing influences. Li et al. [2] concentrate on optimizing Influence on goals whose mark is part of a question. In [2], since Li et al. believe that the possibility of a customer is another has uniformly dispersed factors, their algorithm in the tests, they are not compared. Propose Lu et al. Another variance described in the maximization of influence Part 1 of Section [3]. Nonetheless, they consider just the Linear A model of the threshold (LT) that is distinct from the IC About model. The algorithm proposed in [3] is therefore not compared with that proposed in [3]. Either one. There is no difference, to the best of our experience, of Maximization of effects that can accommodate IMAX queries without any alteration, sorting. In the sense of approaching a component of a social network, IMAX question analysis is linked to subject level analysis. Analysis of social power [20], [21], [22]. The primary assignments How to create a new one successfully are one of these tests. Model of propagation effect and social influence estimation between users focused on historical data at topic stage. The Description The [22] approach may be focused on topic-level impact. To identify top-k influencers on clear priorities, updated, but it



ISSN: 2233-7857 IJFGCN

Topic-level historical data is needed. The two assignments are focused on Historical evidence at the subject level is outside the reach of this article.

## 3 PROBLEM DEFINITIONS

In this essay, a social network is defined as a led network Graph G 1⁄4 vie, where V is a list of nodes representing Users and E are a set of directed edges that reflect interactions Users-between. For any up edge; v to 2 E, up; v to have a Weight, referred to as put; v ??, which is the possibility that u V specifically affects v. A null set is denoted as; Diffusion model Effect. We agree the power is Propagated according to the IC model from seed nodes. Let's leave things to S ?? V is a collection of seeds so that s is affected for every s 2 S originally at 0.0. Period Let St. V is a list of nodes, each of which is affected by a node in St1 at time t. Let go of knout' be a set of out-of-the-box neighbors. Node U 2 St, therefore has One-time ability to independently effect an uninfluenced citizen Neighbor v 2 knout with put; v at the moment t ɛ́ 1. If v is if v Influenced by t·1 at the time we put v into StŞ1. From the original this diffusion system runs iteratively at time 0 with S0 1⁄4 S Up to St0 1⁄4; where t0 x 0.0. Provided a range of T ?? V goals, the Effect of seed set S distribution on goals in T, which is Denoted as sty as, is determined by the amount of predicted nodes, which are impacted by one of the S nodes. When T 1⁄4 V, sty as becomes the target feature of Maximizing influences. Computing vs. as ??, as shown in [9] #P-is rough. Computing for any T ?? V, such as T 61⁄4; ST as ?? is even #P-hard, since vs. as ?? 1⁄4 sty as ?? ٿ vs. at as ??. To The estimated simulations of sty as ??, Monte-Carlo is included in the Experimentation. Following the simulations, sty as is estimated the total number of users impacted by simulations IC model and viral marketing for target-aware. Provided a certain level of three kinds of users may occur in the target aware object to be marketed, marketing viral. First of all there are target customers who are Have a stake in the object. Second, non-targets occur, Users who can be inspired to bring the product to Mates of theirs. There are, finally, non-target consumers who are they are resistant to being impacted by the thing; since they do they don't want to introduce it to their mates. It is clear to see that the first case can be treated by the IC model. And the situation of the second. The IC model does not however, accommodate the third event, since certain immune systems can not differentiate Nodes from other people. Nonetheless, we can quickly alter to endorse the third case by introducing one requirement, the IC model it. To it. The changed IC model notes that once consumer u has Opportunity to harm an uninfluenced neighbor v, who is Not resistant, at time t Ş 1 when u is affected at time t. Fortunately, it is, This transition impacts the planned change just slightly Process, since immune nodes can be treated like Except that they do not impact other nodes and nodes, seed nodes Spreading of power is not counted. It's because the seed is Nodes will not be affected by another node, such as Nodes of Resistant. Thus, we adhere to the original for convenience. IC model to clarify the methodology suggested in the remainder of the Oh. Document. Alternatively, we would describe how to minimally alter the Section 4.2 of the suggested system for treating immune nodes. Propagation likelihood. For each pair, such as I j 2 V ?? V that there is at least one direction between I and j, let the effect be affected the chance of affecting j is from I to j. This is the same as the one as the chance of impacting j while I is the only one Uh, crop. Note the up; v ?? 2 E, put; v ?? is the likelihood for any tip. U affects v through the edge up; v ??. We name this, uh, this the immediate effect from u to v. put; v ?? does not require any Indirect consequence on another route from u to v. Since a path from u to v.

The route comprises of several edges, the indirect effect of a path it is possible to view the direction as a set of direct influences of on the path's margins. For each direction P in G, the impact on the direction P, denoted pap, is determined as,

$$p(P) = \prod_{(u,v)\in P} p(u, v).$$

It is above the handling of IMAX requests and maximization of influence he exact impact on each edge should be calculated. We oppose clear factors are given. The 3.1 description (Influence Maximization



ISSN: 2233-7857 IJFGCN

query). Underneath the IC model, given the G 1⁄4 vie guided graph, an IMAX query K-seed set S calls for maximization of sty as ?? by S ?? V and S Where a range of goals is T. The IMAX question issue is NP-hard and its target the function, sty, and is sub modular. Theorem 1. Theorem1. Provided a G 1⁄4 vie guided graph, IMAX query the procedure is NP-hard.

TABLE 1
Frequently Used Notations in This Paper

| | |
|---|---|
| $\sigma_T^*(S)$ | 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 $u$ |

2. Theorem. Provided a G 1⁄4 vie guided graph and a set of targets T, sty: from 2V! R, where 2V is V's power collection, is Sub modulated. Proof. See Section 2.2 of the Additional Content, Accessible Uh. Online. To one can clearly see that sty grows monotonically. The selfish, because sty is sub modular and monotonic, the method defined in Algorithm 1 offers a ð1 x 1= e-approximation. It selects k nodes that optimize at each iteration, the marginal benefit for the objective function 3-5 in row.

**Algorithm 1.** Greedy Algorithm $(G = (V, E), k, T)$

**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** $S$;

Since sty is sub modular, current methods for manipulating For IMAX query processing, maximization may be added.hey are not however, built to use the essence of handling requests. With IMAX Processing Effectively querying with high precision, we need a fresh pre-processed A system that needs a fair amount of space centered on A concrete and effective paradigm of expectation for impact Disseminated.

## 4 ALGORITHMS

### 4.1 Independent Maximum Influence Paths-Based Expectation Model

Table 1 in Section 4 lists commonly encountered notations. Since the distribution of impact of a seed set is determined by #Hard, The Monte-Carlo simulations are commonly used in current research. Approximating the distribution of power. The simulations are already very pricey, though, so we need a new one. Model of assumption for approximating the distribution of influence. The challenge in estimating the distribution of power lies in That a node will impact another node across separate nodes the roads and paths are intertwined intricately. Therefore, the the modern paradigm of standards begins by simplifying the pathways With a major wealth, named liberty, Between trails. For any two routes that the destination shares If they do not disclose any, and can share the source, Except for the destination and the root node, the two directions To be autonomous is specified. A significant finding is presented in the sovereignty of roads. Suppose two, suppose two Paths P, Q are autonomous and they do not share the routes
Source of. If a seed is the source of P, the other nodes in P will the seed may be affected, but nodes cannot be affected in Q Oh, by the crop. This discovery contributes to (2).



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Let the likelihood of an effect of a node v 2 V be the probability of A node of a specified seed set S affects the v and it is labeled as pHs; v. For each node v 2 V, if all routes Starting from a seed and getting v as the destination is The impact separately of each other through the IC model, The likelihood of v is reckoned with be,

$$p(S,v) = 1 - \prod_{P \in \pi(S,v)} (1 - p(P)), \qquad (2)$$

The set of the seeds and PHS is where S; v ?? is the set of all the seeds. Paths from S to v plants.
Next to successfully simplify diverse paths between nodes, we concentrate on finding a direction that reflects the between two nodes, impact. For each pair if; j to 2 V to V, The set of all paths from I to j is denoted as phi; j-. Let's, uh, let us defining the maximum direction of impact P1ði; j from I to j as j P1ði; j' 1⁄4 rag maxP2pði; j'pðP'. From the greatest impact Route, we derive a more general description that represents the Using freedom, power between two nodes between routes, which is the highest independent effect of Set route Set path (IMIPS). For every direction P, and the path set p, if path P is distinct from any of the paths in set p, we can Identify this as P
p.Definition 4.1 (The Highest Impact Direction Independent Determined). The individual limit for each pair if; j al 2 V al V, Effect direction set with the integer parameter h from I to j, Referred to as phi; j', is,

$$\pi^h(i,j) = \begin{cases} \emptyset & \text{for } h = 0 \\ \bigcup_{t=1}^{h} \{P^t(i,j)\} & \text{for } h \geq 1, \end{cases} \qquad (3)$$

*where* $P^t(i,j) = argmax_{P \in \{P | P \in \pi(i,j) \wedge P \perp\!\!\!\perp \pi^{t-1}(i,j)\}} p(P)$. *We call* $P^t(i,j)$ *the tth independent maximum influence path from i to j.*

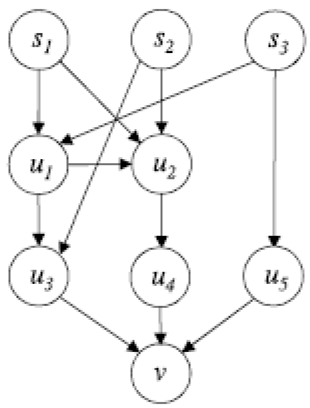
IMIPS phi; j ?? is determined as follows, given the two nodes I and j. P1ði; j ?? is mainly determined by running the Dijkstra's hat algorithm. Then for 2 t h, Patti; j ?? is measured iteratively After excluding nodes, the Dijkstra algorithm IMIPs from G have already been measured on t ?? 1, excluding I and j. In we may create IMIPS from one node to another in this way. A modern paradigm for aspirations. Approximating the effect efficiently distributed, we suggest a new model, which is the Independent expectation-based maximum influence route The Model (IMIP model). The model of IMIP says that a node affects another node in their IMIPS, from one of the routes. The IMIP model's intuition is as follows. Find the case of a node being a fresh seed in the greedy that algorithm. When the new seed is on the seed, as we stated, Maximum direction of control from node v to a particular node u, The alternate limit is located in the PMIA heuristics in[9] The direction of impact from v to u, as the seed blocks v on the Maximum trajectory of impact. It is reasonably pricey, though to calculate it within the processing period of the email. In the Model IMIP, and if the new seed is on one of the v-to-u IMIPs, we can Use freedom to accurately predict the impact of v to u the other IMIPs, among others and (2). It's the intuition that is Of the Model IMIP. Analyzing mistakes. As only a constant is protected by the IMIP model, the amount of different pathways from one node to another, there must have been an IMIP model flaw. Nonetheless, we the argument that the IMIP model error is generally limited in terms of Social Online Networks. Two findings are focused on this assertion. Next, data is commonly used in online social networks. Inside a very limited number of hops, diffused from a seed [23] and [24] and [25]. The portion of sampled rewets, for instance, More than 95.8 percent of the overall sampled is within two hops. [25] Rewets. It implies that the lengths of effective authority are many routes are one hop or two hops. Second, one jump, one hop, and two-hop routes, sharing the same destination, by extension, they are still independent of each other. Centered and based on these results, as the IMIP model is such that it encompasses Solid paths of power, making sense of the argument. Additionally, we check the argument experimentally in the supplementary content, open on-line. When a node s 2 V is the only one, under the IMIP model, the seed is quickly affected from s to a non-seed node v 2 V Calculated as 1 x Q P2phðs; v ?? ð1 and pap ?? by (2). Furthermore, Calculating whether several seeds in a seed set S are present, The



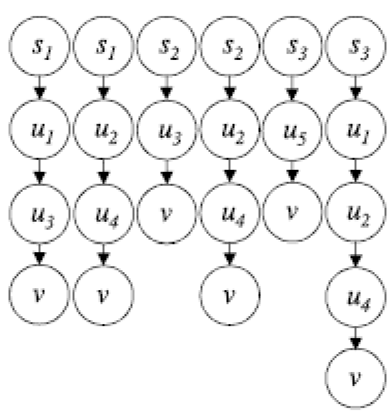
ISSN: 2233-7857 IJFGCN

likelihood of impact of a non-seed node v is not negligible, Since there is no certainty that all IMIPs begin with The multiple seeds are separate from each other. Tree of Power. Let us implement an easy way of coping with the problem of seed multiples. As a node is impacted, from the seeds to the node below just via the IMIPs We consider the IMIP model a system consisting of the IMIPs to measure the node's likelihood of impact as Comes. Follows. Let us take into account a seed collection of S ?? V and a non-seed set Node v 2 V. At best, there are josh IMIPs in S PHs s2S; v. To measure the likelihood of impact of the v seed set S given by v we use a directed tree under the IMIP model, in which the root is a node called v. The impact tree of v, we name it,

Denote it as TV, and construct it as follows. Initially, TV just had the root, one node v. For each P IMIP in S S2S pHs; s2S pHs; v, first In a series beginning with a common part of P and TV, we see From v in the path of P in reverse. We copy nodes, then, and the margins (with weights) of the remaining portion of P to the remaining portion of P Place of the popular component before the first node in TV. For instance, Fig. An instance of IMIPs and an effect 1 indicates uh, tree. The initial graph is shown in Fig. 1a as well as the IMIPs from Seeds (s1, s2, s3) corresponding to node v is displayed in Fig. 1b. 1b. Find the from left to right, we look at each IMIP in Fig. 1b to the Create the tree of control v. Then the last IMIP is for egg, < s3; u1; u2; u4; v >. Additionally, Fig. 1c indicates the condition




(a) A part of graph $G$




(b) The IMIPs from $s_1$, $s_2$, and $s_3$ to $v$



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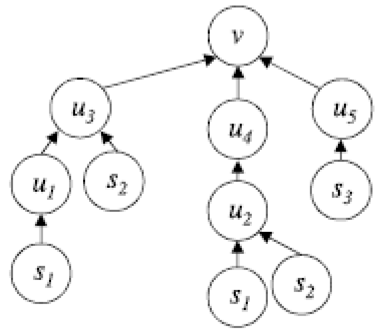
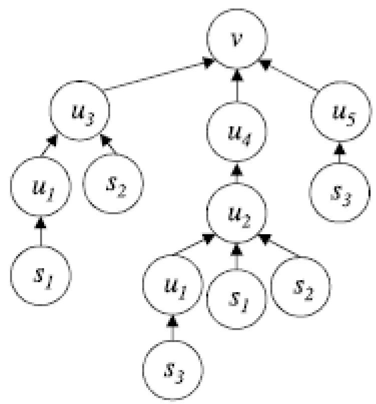


(c) Before processing the last IMIP to build the influence tree of $v$



(d) The influence tree of $v$

Fig. 1. An example of IMIPs and an influence tree.

We are looking at the last IMIP to build the effect Tree of v. We find the popular component for processing the last IMIP in Telex. < u2; u4; v > we would then copy u1; s3; ðs3; u1; and ðu1; u2e to the location of the common element before u2. After the impact tree of v, which processes the last IMIP, is constructed as that's mentioned in Fig. 1d.—1d. Computation of the likelihood of effects. Now we are willing to compute, The possibility of impact of node v provided to seed set S under Model IMIP. Let paves denote the likelihood of impact, Under the IMIP model, the seed set S of v is given. Bear in mind the Node v is influenced only by the seed IMIPs. Under the IMIP scheme, to v Furthermore, both IMIPs from the TV contain seeds to v. The likelihood of impact, thus, Under the IMIP model, v in G is the same as the effect Probability of the TV root where all leaves in TV are plants. Notice that a tree of control is made up of copied nodes and the nodes the likelihood of effect of a copied node u varies from that of a copied node u the likelihood of control of the initial node of u in G, with the exception of Root, root. Then we can compute the effect recursively, the chance of node v in G by naming influence; root, where Root ?? is the root of TV (there is just one v in v in case of v) the tree of influence of v, and root al 1⁄4 v), as defined in 2 algorithm. We are talking to the immediate ancestors of a Node I has been copied as Indi. In Algorithm 2, lines 2-3, if I am a Leaf, so the algorithm returns 1, since a leaf matches through a seed. Otherwise, the algorithm computes on lines 5-9 According to the IC model, and the effect likelihood of I and it is retrieved. Therefore, impact; root' returns the power Likelihood of v.



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**Algorithm 2.** $influ(v, i)$

```
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
begin
    if i is a leaf then
        return 1;
    else
        p = 1;
        for n ∈ IN(i) do
            p = p(1 − p(n, i)influ(v, n));
        p = 1 − p;
        return p;
```

The case of two copies nodes may be troubling. Here are distinct possibilities of control in an influence graph, which correlates to the same node in G. Only in Fig. 1, they are, they are 1, n TV, two nodes correspond to u1, but those nodes correspond to u1, you will have varying chances on TV. This situation, in reality, is The IMIP model is still consistent. Assume the two are the nodes in TV share the same likelihood of effect. This indicates the effect on the route from s1 to u1 is considered to be the effect on the direction from s3 to u2 is computed. This case, however, clearly violates the model of IMIP, because the direction < s1; u1; u2; u4; v > is taken into account, and if it is not an IMIP, it influences the chance of v. That is, that is, why are we keeping various probabilities of effects on TV for In G, a server? Via sub modularity. Provided a goal range of T, based on Algorithm 2, We describe the effect of seed set spread, as well as a seed set S, Under the IMIP scheme, S as sat as' 1⁄44 P For v2T paves. We're showing the s-T function: 2V! R would be sub modular. Lemma 1-Lemma 1 (Incremental Update Lemma). Being provided a node, V 2 V, a seed s 2 S, and a direction P 2 PHS; v, take into account the P is being introduced into Telex. For some edge, then, if; j ?? in TV, If phi ?? rises, pðj ??, which corresponds to an edge on P, Improves as,

$$p(j) = 1 - \frac{(1-\hat{p}(j))(1-p(i,j)p(i))}{(1-p(i,j)\hat{p}(i))}, \qquad (4)$$

Where for node a 2 TV, pea is a new likelihood of impact in TV, ^pea ?? is the likelihood of an old impact on TV, and Phi; j'^pði' 61⁄4 1. Proof. See Section 2.3, available in the supplementary content, Uh. Online. To 3. Theorem. Provided a G 1⁄4 vie guided graph and a set of targets T, the s-T function: 2V! R would be sub modular. Proof. See Section 2.4, included in the supplementary content, Uh. Online. To Under the IMIP, from the power spread feature s-T we will suggest an appropriate greedy-based process model, to estimate IMAX loading of questions. Since, in reality, Algorithm 2 induces costs that are always costly, we work on effectively In Segment 4.2.2, measuring the marginal benefit to sit.

## 5 EXPERIMENTS

We carry out several studies with many similarities. True Data Sets and Processes. In these tests, we concentrate on checking the utility of the system suggested on the basis of the paradigm of IMIP and gradual upgrading. On an Intel(R) i7-990X 3.46 GHz Processor device, we ran the tests. 48 GB of RAM.

### 5.1 Experimental Environment

Methods of reference. In the studies, we use the following 6 methods of comparison.

- The suggested approach in this paper is IMIP.
- CELF++ is an enhanced, greedy algorithm that exploits in [6], sub modularity.
- CELF++LR is the CELF++ form for recognizing Regions and cultural influences.



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- PMIA is a greedy algorithm that is based on the limit Paths of control between nodes [9]. Inside PMIA, to prune out maximal effect, the parameter u is used Paths that have little control. We have scheduled u 1⁄4 1 x Fife Ph 1 x a, Since 1 x Fife 1 for the same reason as u, a ph is used as in the article here. One of the new algorithms for optimizing influence is IRIE [11]. [...] We've set a 1/4 0:7 for IRIE, which is a 1/4 0:7 the element of damping, because it's not the same as ours. As
- IRIE also exploits the full power of PMIA and IMIP. The journey from a seed to a node that has the same node the u-parameter. For IRIE, the same value of u is used in
- PMIA for the same description. Using the CD model in [19], CD is the greedy solution. A probabilistic model based on the users' model is the CD model. Logs for historic operation. We just use this technique for the experiment linked to the real distribution of power. Model of Direct control. For clear effect modeling, which is we use the likelihood that a consumer affects a neighbor as a function of two styles. The model Bernoulli (BN) says that for any edge up; v 2 E, it is deemed to be a Bernoulli trial Influences v. Then, as the approximation of full chance, Clear effect on up; it can be calculated that v ?? is nu! Yeah, v=nu, Where nu, where nu! V is the sum of behavior distributed from u to v, Nu and nu is the amount of u-conducted acts. The Kemp The weighted cascade (WC) model is introduced in [1] by et al. The WC model notes that the neighbors' direct impacts Node v is equivalent to 1=din where din is the index of node v to v From v. Data Sets. We use eight actual data sets for studies. Wiki-Vote, Opinions, Slashdot, Poke, and Amazon Goals are written by Jure Leskovec.1 online. The Fluster

The data collection is included in [19], and Moshe publishes it online. The Dig data set was implemented in Jamali.2 [26]. Wiki-Voting It is focused on elections to facilitate administration and when user U votes on user v, there is an edge from u to v. Opinions It's a who-trust-whom media network online and Slashdot It is a new platform linked to technologies where there are Inter-user friendships. Amazon is a network that co-purchases where the edge from u to v is while u and v are Co-purchased on a daily basis. Goals are a social, location-based culture Network service in which customers can post their positions from mates. Dig is a forum for internet news and Fluster is a social networking platform. Website where a person can post feedback and ratings of movies with boyfriends. Poke is the most famous media social network online. Slovakia's network infrastructure. Besides marriages,

TABLE 2
Statistics of Our Data Sets

| Data set | Wiki-Vote | Epinions | Slashdot | Amazon | Pokec |
|---|---|---|---|---|---|
| Node | 7K | 76K | 77K | 262K | 1.6M |
| Edge | 104K | 509K | 906K | 1.2M | 30.6K |
| Degree | 14.6 | 6.7 | 11.7 | 4.7 | 18.8 |

| Data set | Gowalla | Digg | Flixster |
|---|---|---|---|
| Node | 197K | 279K | 0.8M |
| Edge | 1.9M | 1.7M | 11.8M |
| Degree | 9.7 | 6.2 | 15 |
| Action | 6.4M | 3M | 8.2M |

Info. Profile data is used in the Poke data collection. We are going to use the data for the profile to specify actual goals. The example in Table 2 is the Statistics of the 8 sets of results. Degree denotes degree in Table 2, the typical node and action degree denotes the number Logs in operation. A log is made up of a consumer, an object, and the time when the object is affected by a customer. Dig, Goals, and Fluster includes all activity logs and graph info. They are the Used for studies on the true distribution of power and the Model BN. Remember that if there are many logs of operation for a We use only the earliest one a pair of nodes and an object, since it is not necessary to impact an already influenced node for the same item again. Furthermore, under the model of WC, among the three results, only the result from Fluster is seen. Sets, because of the small space. The Goals Result and Dig demonstrates a close theme to that of Fluster. To we use Wiki-Vote to equate CELF+++LR with CELF++. Which is a comparatively limited collection of results? In order to evaluate the scalability of the We use Fluster and Poke for the number of nodes. Query generating. We produce a for the experiments Syntactic query, with the following three criteria. First of all, we Select nodes at random as part of the overall goals to be created. Let p1 denote a



ISSN: 2233-7857 IJFGCN

International Journal of Future Generation Communication and Networking
Vol. 13, No. 4, (2020), pp. 3585–3601

parameter for the percentage of the randomly chosen goals. First for the remainder of the segment, we will as a goal, pick a node uniformly at random and do Starting from the node, breadth-first quest along in-bound with corners. We look for each visited node in the breadth-first search, with likelihood p2, select it as a goal. We want a particular one, Node with probability p3, and we submit when we want it, Standardized randomness, to perform the same thing. Which is something we echo upon fulfillment of the remaining portion of the overall goals? It is possible to model this process of producing syntactic queries for the three parameters, separate distributions of goals. To govern how many goals are associated, p1 and p3 are used, and p2 is used to regulate how many objectives occur in a related sub graph. If, for example, p1 1⁄4 1 or p3 1⁄4 1, both goals are chosen arbitrarily. When the p1 and p1 values are set, and the importance of p2 is high, goals are likely to be high, p3 is low and linked. We set p1 1⁄4 0:25 in the experiments, p2 1⁄4 0:5, 5, p2 1⁄4 0:5, 0:02 and p3 1⁄4. This suggests that 25% of goals are standardized. Distributed and some related constitute the others Sub graphing. Targets should be in the modern world uniformly distributed or linked sub graphs constitute Centered on software. We are of the view that our climate in the real world, that includes those aspects. Notice that we were playing Experimentation of other p1, p2, and p3 environments, and their findings have the same effects as those of the in the next segment, other settings.

TABLE 3
The Sensitivity Tests of the Parameters

| $\alpha(\times 0.001)$ | 5 | 16.25 | 27.5 | 38.75 | 50 |
|---|---|---|---|---|---|
| IS | 1211.77 | 1202.65 | 1197.94 | 1195.98 | 1193.02 |
| R(s) | 0.1278 | 0.03385 | 0.0213 | 0.016 | 0.01375 |
| $\beta$ | 0 | 1 | 1.5 | 2.0 | 2.5 |
| IS | 1211.75 | 1211.77 | 1211.75 | 1211.6 | 1211.68 |
| R(s) | 0.1646 | 0.1278 | 0.1139 | 0.105 | 0.09915 |
| $h$ | 1 | 2 | 3 | 4 | 5 |
| IS | 1210.47 | 1211.91 | 1211.7 | 1211.68 | 1211.77 |
| R(s) | 0.107 | 0.12245 | 0.12635 | 0.1278 | 0.1278 |
| $\delta(\times 0.0001)$ | 5 | 30 | 55 | 80 | 105 |
| IS | 1211.77 | 1211.12 | 1210.6 | 1208.32 | 1206.44 |
| R(s) | 0.1278 | 0.1107 | 0.099 | 0.06465 | 0.046 |

One might think about how much this generation of inquiries is the methodology mirrors the modern world. Therefore, we even obtain actual extracts, Queries from Poke’s profile details and studies the questions.

### 5.2 Experimental Results

About criteria. The sensitivity tests are performed for a, b, h and d, Under the WC model, which are parameters for IMIP, using Opinions. Pinions. Provided a 1⁄4 0:005, b 1⁄4 1:0, h 1⁄4 5, and d 1⁄4 0:0005, we are Vary to get a result for each parameter. The outcomes of sensitivity Tests are seen in Table 3 and the effect are denoted As IS and R respectively, distributed and operating time. In the outcome of the sensitivity test for a as a grows bigger, the effect spread and the running time becomes less and smaller. More brief, respectively. The reasoning is that we do not understand any impact below the IMIP model's standard. This induces more mistakes for a bigger one when measuring the impact spread the running time to making it shorter. Next, let us look at the sensitivity test outcome for b. As a consequence, even though b is larger, the distribution of power is the running time remains almost constant and is becoming shorter. This, this, the approach for defining local factors suggests that In Algorithm 3, regions do not miss a tone of powerful Nodes on goals (i.e. real positives). Moreover a bigger one the b value determines the number of outcome candidates for the algorithm. 3 lower and the running time are influenced by it. Through various approaches, we also test the suggested process. IMIPs with full numbers. The impact while h 1⁄4 1, the spread is slightly thin, but the effect is low when h > 1, Spreads are large and equal to one another. Likewise, the When h grows bigger, running time becomes longer. And if the effects stretched when h 1⁄4 2 is large enough, we set h 1⁄4 5 for in the majority of the experiments, stability. The



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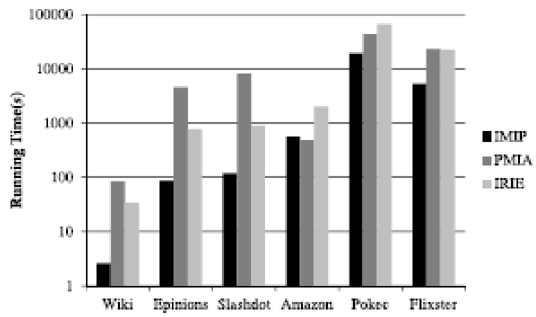
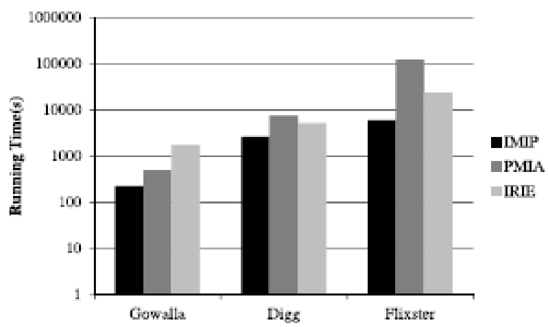
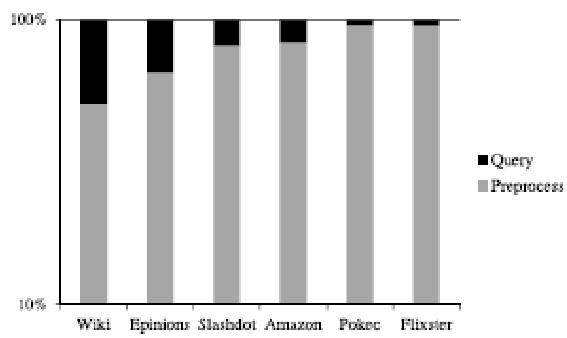
last parameter of the approach suggested is d, which is d. It is used to stop IMIPs from computing whose effect is too small. As a consequence, when we set d to a greater amount, the value is set to d. The distribution of effects becomes greater and running becomes stronger. Time's becoming shorter. We set a d to a smaller enough Price greater than 1 x Fife For the remaining studies, ph 1 a, because the distribution of power is constant when d < 1 Fife 1 x a ph. Our parameter settings for the remainder of the experiments in the supplementary content, accessible online, they are seen.




(a) Running time (with preprocessing time, WC)




(b) Running time (with preprocessing time, BN)




(c) Ratio between preprocessing time and query time, IMIP, WC



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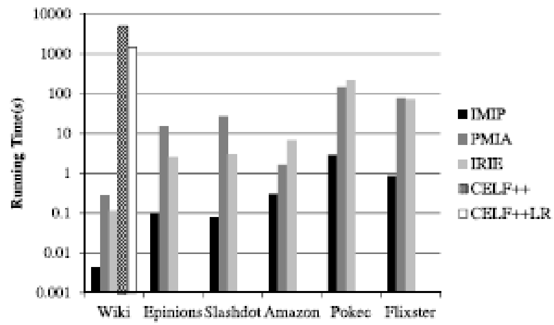
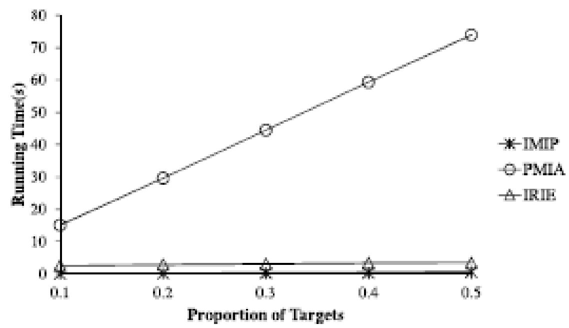
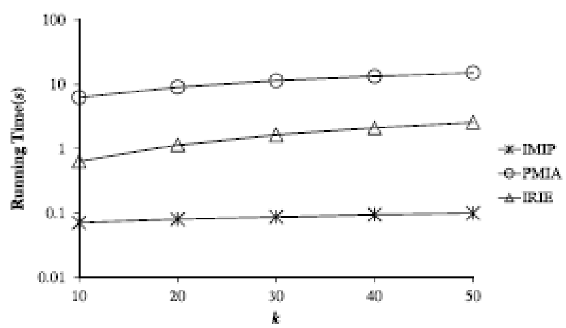



(d) Running time per query (without preprocessing time)




(e) Running time vs. the size of targets (Epinions, WC, $k = 50$)




(f) Running time vs. $k$ (Epinions, WC)

Fig. 2. Running time analysis (k ¼ 50).

We calculate the value of each parameter experimentally. Taking performance and efficacy into account. Round running time. Comparison of running time and working time Spread of influence, assessment of CELF++ and CELF++LR Under the WC model, only for Wiki-Vote, since they are Too slow, in other conditions, to run. To compare IMIP and its rivals with regard to We generate 300 queries for productivity, each of which this involves 10% of users and runs each method for processing these questions. Preprocessing is completed one time before Queries arrive and there is no need for preprocessing for each Processing Question. Oh. Figs. 2a and 2b illustrate the conclusions of from this experiment, and the preprocessing is used in them Oh, period. IMIP clearly outperforms its rivals in the findings. In most instances. The running time of IMIP on Amazon Due to preprocessing, it is longer than that of PMIA, IMIP's Moment. Fig. Fig. 2c illustrates the ratio of preprocessing to In IMIP, period and query processing time, and Fig. 2d Displays the run time per question (excluding preprocessing) it's time). Even if IMIP at Amazon is slower than PMIA, When we consider time together for preprocessing



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in Fig. Fig. 2a, the running time per IMIP question is much longer. In Fig., shorter than that of PMIA. 2d.—2d. As shown in Fig. 2c, 2c, Preprocessing is the bulk of the operating time of IMIP Oh, period. Therefore the output difference between IMIP and any of the in terms of operating time per question, the competitors

It's much broader. Up to two orders of magnitude are IMIP Faster than PMIA and IRIE, and there are six orders, faster than CELF++ in magnitude. CELF++LR is 3.2-fold Quicker than CELF++.The impact of the goal scale. IMIP, PMIA and IRIE checked, Under the WC paradigm of varying sizes of goals. This, this, the scalability of the number of objectives is linked to the experiment. This experiment's outcome is seen in Fig. 2f. 2f. Inside the Consequently, when half of the IMIP is already quicker than PMIA and IRIE, Targets apply to all apps. The PMIA slope is steeper than that of the one of IMIP and IRIE. Because IRIE analyses all users through iteration, to change the rating of power irrespective of amount for goals, the IRIE runtime is not influenced by the amount of priorities as well as the PMIA. The gentle slope of the IMIP illustrates that the amount of goals less impacted by IMIP is PMIA and IRIE as well. Propagation of power. We determine the similarity with each data collection; Methods distributed with 50 syntactic in terms of impact Queries, each containing 10% of users, as well as four questions from actual profile data extracted. The consequence of the syntactic question evaluation is demonstrated. With Figs. From 3a and 3b. In this scenario, with several data sets, IMIP reaches spreads of control equal to PMIA spreads IRIE, and. Based on Poke's profile info, we specify several Lists of priorities that will overlap with and compare the proposed Procedure for the collections. For this, we use the WC model for The Experiment. This experiment has four sets of targets: Men, kids, grown-ups and non-grown-ups. As illustrated IMIP is much quicker than PMIA and IRIE in Table 4.

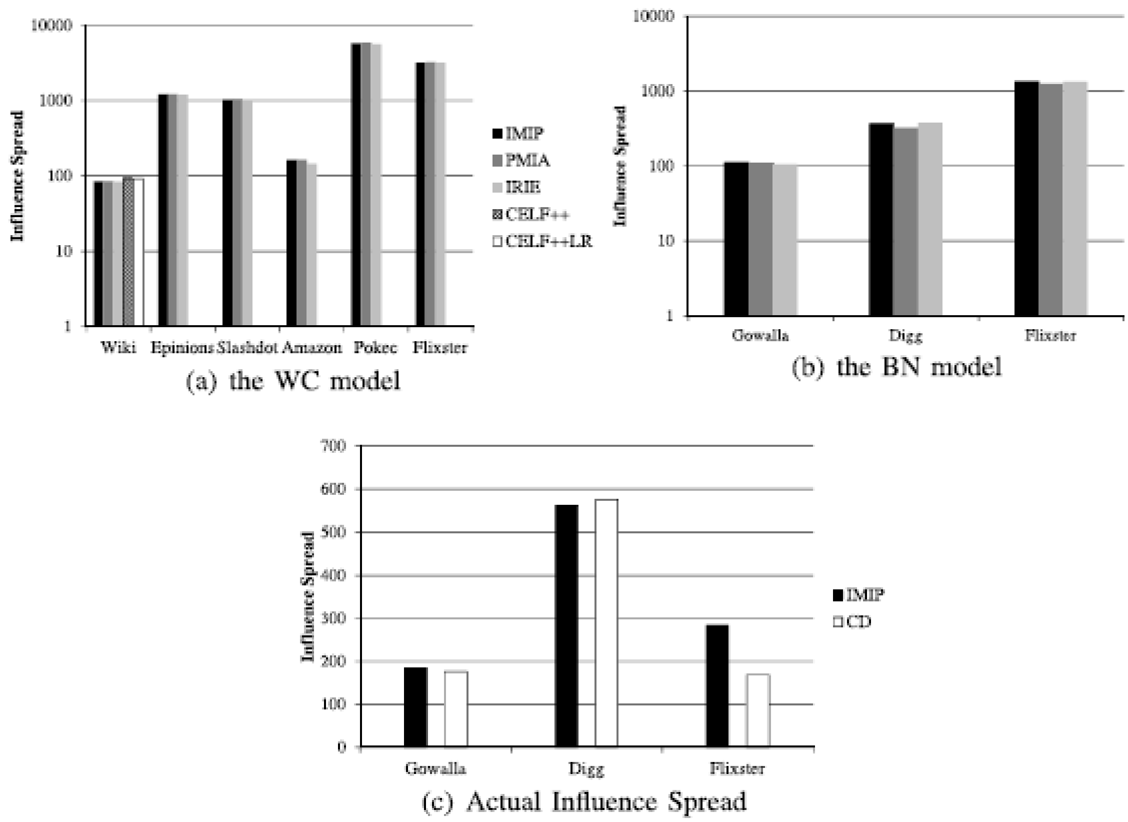


Fig. 3. Influence spread analysis (k ¼ 50).



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TABLE 4
Influence Spread and Running Time with Real Targets in Pokec, WC, $k = 50$

| IS | Men | Women | Adults | Non-adults |
|---|---|---|---|---|
| IMIP | 19678.1 | 22539.6 | 25411.9 | 17620.5 |
| PMIA | 20267.1 | 22931.7 | 25511.3 | 17782.9 |
| IRIE | 19580.9 | 22168.7 | 25418.3 | 17321.7 |
| R(s) | Men | Women | Adults | Non-adults |
| IMIP | 8.652 | 9.55 | 10.152 | 7.805 |
| PMIA | 473.69 | 539.636 | 613.081 | 466.488 |
| IRIE | 279.692 | 283.359 | 285.372 | 272.611 |

The sets of goals scatter when attaining comparable impact. Since a consumer is either male or female, or adult or adult, Non-adult, at least the men's set or the women's set have As goals, 50 percent of subscribers, and the same is true for the A list of adults or a collection of non-adults. Consequently, this experiment It also illustrates the scalability of the suggested approach with In spite of the number of actual goals and the number of real targets, With whole nodes. Achieved the real distribution of power. In order to prove that the suggested methodology seeks a collection of seeds that can render wide In fact, we compare the proposed impact distribution, System utilizing the CD model with the greedy method in [19]. The we also established that the direct effect on an edge has the same value on the edge of direct credit as is found in Model for CD. Furthermore, to catch the real impact, Goal et al. take the seed set by a system, distributed accomplished by a method, Calculated and analyzed by the process with the effect Their proposed CD model projected distribution. Reason for the CD model has the lowest distribution estimation defect. In contrast to the other rivals in [19]. Nonetheless, there the assessment of other rivals may be unjust, since the product of the Greedy Process seed set using the CD model of necessity; it has more control than its rivals. Accordingly, in this analysis, we take another approach to test the true the distribution of power achieved by a system is as follows. Provided a set of nodes a we want to test, let us evaluate we think about an impacted node that can be reached from In A, every affected node with a path consisting of affected nodes in an item's activity logs. We refer to it as an in truth, the node of A was influenced and denoted the number of Days that a node u is an A node that is actually affected in the test sequence, as nab; u'. And, we take all of that into consideration, Nodes are objectives and measure a seed set A with a system in the train collection that we want to test. In addition, we calculate the A nodes that are currently impacted. In the test range, for each object. We predict, ultimately, the as the cardinality of the set, the real impact distribution of A Of all the nodes u of A genuinely impacted (and distinct) Thus, nab; u ?? is higher than the threshold. That threshold helps them manipulate the degree of trust for what an experiment. We defined the threshold in this experiment, 50 to Dig's, 30 to Fluster, and 2 to Oglala's, according to the sparseness of each collection of results. The train collection is made of the overall activity logs, 60 percent. The product of IMIP and CD comparison with respect to the exact extension of power is seen in Fig. 3c. 3c. the distinctions for the data sets, the actual affected spreads achieved by IMIP and CD are not important. Nonetheless, in [19], the seeds that the greedy algorithm uses to set the IC Model findings, with reference to very low performance Under the CD paradigm, the effect has expanded. Goal et al. as. The EM algorithm, examined, often decides a to be powerful the uninfluential node. Which is why we make use of the direct credit [19] for instead setting direct factors Of the Method EM? Based on this exam, we describe IMIP considers a collection of seeds that can have a major effect. Spread with an effective probability model in fact for outright factors. Overall, IMIP, the approach introduced, is even more effective relative to PMIA and IRIE thus producing comparable results Yeah, precision. Furthermore, we understand that the planned the system will produce a real distribution of power close to that of the one with the CD.

## 6 CONCLUSIONS



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We devise IMAX question processing in this paper to optimize the effect of social networks on individual people. After the treatment of IMAX questions is NP-hard and the measurement of its #P-hard target function, we concentrate on how to estimate efficiently optimal plants. Approximating the importance of We propose the IMIP model centered on the objective function, Separation of routes. Production of an IMAX question It is suggested to extract candidates for ideal seeds effectively. And using the swift greedy-based approximation Model IMIP. Experimentally, we show that our local identity The technique of manipulating regions is effective and the proposed Mainly, the approach is at least an order of magnitude quicker than PMIA and IRIE with similar precision In comparison, the proposed PMIA and IRIE with similar precision The procedure is largely six orders of magnitude faster than CELF++ and the local affecting regions methodology concept Allows CELF++ quicker by around 3.2 times thus achieving Good precision. For IMAX query handling in the future, we would suggest more varied target distributions, such as consumers in On the basis of the same group or the same university Static users' accounts. First we'll add the IMAX question to Processing to the linear form of the threshold and checking whether the concepts are also relevant in this article.

## REFERENCES

[1] D. Kemp, J. Kleinberg, and E. Taros, “Maximizing the spread of influence through a social network,” in Proc. 9th ACM SIGKDD Int. Conf. Know. Discovery Data Mining, 2003, pp. 137–146.
[2] 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, Secure., Risk Trust, Int. Conf. Social Compute., 2011, pp. 560–563.
[3] W. Lu and L. Lakshmanan, “Profit maximization over social networks,” in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 479–488.
[4] P. Domingo’s and M. Richardson, “Mining the network value of customers,” in Proc. 7th ACM SIGKDD Int. Conf. Know. Discovery Data Mining, 2001, pp. 57–66.
[5] J. Leskovec, A. Krause, C. Guest in, C. Fallouts, J. VanBriesen, and N. Glance, “Cost-effective outbreak detection in networks,” in Proc. 13th ACM SIGKDD Int. Conf. Know. Discovery Data Mining, 2007, pp. 420–429.
[6] A. Goal, 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. [7] Y. Wang, G. Cong, G. Song, and K. Xian, “Community-based greedy algorithm for mining top-k influential nodes in mobile social networks,” in Proc. 16th ACM SIGKDD Int. Conf. Know. Discovery Data Mining, 2010, pp. 1039–1048.
[8] W. Chen, Y. Wang, and S. Yang, “Efficient influence maximization in social networks,” in Proc. 15th ACM SIGKDD Int. Conf. Know. Discovery Data Mining, 2009, pp. 199–208.
[9] 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. Know. Discovery Data Mining, 2010, pp. 1029–1038.
[10] Q. Jiang, G. Song, C. Ago, Y. Wang, W. Si, and K. Xian, “Simulated annealing based influence maximization in social networks,” in Proc. 25th AAAI Conf. Art if. Intel. 2011, pp. 127–132.
[11] K. Jung, W. Hoe, and W. Chen, “Ire: Scalable and robust influence maximization in social networks,” in Proc. IEEE 12th Int. Conf. Data Mining, 2012, pp. 918–923.
[12] S. Bharathi, D. Kemp, and M. Sale, “Competitive influence maximization in social networks,” in Proc. 3rd Int. Conf. Internet Netw. Econ., 2007, pp. 306–311.
[13] T. Carnes, C. Nagarajan, S. M. Wild, and A. van Sullen, “Maximizing influence in a competitive social network: A follower’s perspective,” in Proc. Int. Conf. Electron. Commerce, 2007, pp. 351–360.
[14] M. Iran and L. Ortiz, “A game-theoretic approach to influence in networks,” in Proc. 25th AAAI Conf. Art if. Intel. 2011, pp. 688– 694.
[15] M. G. Rodriguez and B. Scholkopf, “Influence maximization in continuous time diffusion networks,” in Proc. Int. Conf. Mach. Learn., 2012, pp. 313–320.



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