SURVEY PAPER ON INFLUENTIAL NODE DISCOVERY ON DYNAMIC SOCIAL NETWORK

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Abstract: As both informal community structure and quality of influence between people develop always, it requires to follow the influential hubs under a dynamic setting. To address this issue, we investigate the Influential Node Tracking (INT) issue as an expansion to the customary Influence Maximization issue (IM) under powerful informal organizations. While Influence Maximization issue goes for distinguishing a lot of k hubs to amplify the joint influence under one static system, INT issue centres around following a lot of influential hubs that continues augmenting the influence as the system develops. Using the smoothness of the advancement of the system structure, we propose an efficient calculation, Upper Bound Interchange Greedy (UBI) and a variation, UBI+. Rather than building the seed set from the beginning, begin from the influential seed set we find already and execute hub substitution to improve the influence inclusion. Besides, by utilizing a quick refresh strategy by figuring the peripheral increase of hubs, our calculation can scale to dynamic informal organizations with a huge number of hubs. Observational investigations on three genuine substantial scale dynamic informal organizations demonstrate that our UBI and its variations, UBI+ accomplishes better execution as far as both influence inclusion and running time.

Index Terms- Influential node tracking, substantial scale, influential maximization issue.

1 INTRODUCTION

The procedures and elements by which data and practices spread through interpersonal organizations have long interested scientists within many areas. Understanding such forms can possibly reveal insight into the human social structure, and to affect the techniques used to promote behaviours or products.

Influence expansion is the issue of choosing a little arrangement of seed hubs in an informal organization, to such an extent that their general influence on different hubs in the system, defined as per specific models of dissemination, is expanded. Promoting effort is generally not a one-time bargain, rather ventures do a continuing effort to expert bit their items by seeding influential hubs consistently. Regularly, a promoting effort may keep going for a considerable length of time or years, where the organization occasionally distributes spending plans to the chose influential clients to use the intensity of the informal impact. Under this circumstance, it is normal and essential to understand that social or data systems are dependably elements, and their topology advances continually after some time. For instance, joins show up and vanish when clients pursue/unfollow others in Twitter or companion/unfriend others in Facebook. In addition, the quality of influence also keeps changing, as you are more influenced by your companions who you contact every now and again, while the influence from a companion as a rule fades away as time slips by on the off chance that you don't contact with one another.

Therefore, a lot of hubs influential at one time may prompt poor influence inclusion after the advancement of 1 organization, which recommends that utilizing one static set as seeds crosswise over time could prompt inadmissible execution. Notably, focusing at various hubs at various time winds up fundamental for the achievement of viral advertising. We proceed to illustrate the idea of considering the dynamic perspective in influence amplification utilizing a precedent in Figure 1. In this precedent, clients are associated by edges at various time, every one of which demonstrates a client may influence over another client. Numbers over each edge give the comparing influencing probabilities. For instance, there is an edge somewhere in the range of v1 and v3 at t = 0 and the edge is erased at t = 1. Also, client v1 will influence v2 with a likelihood of 0.7 at t = 0, and the influencing likelihood is 0.2 at t = 1. This implies client v1 would no longer influence v3 at t = 1 and v2 can't be actuated by v1 by likelihood 0.7 at t = 1. Assume we are asked to find a solitary seed client to augment the normal number of influenced clients. Without any dynamic constraint, that is all the snapshots are amassed into one weighted static chart, client v1 will be returned as the outcome. Instinctively, it is relied upon to influence Diary OF L ATEX CLASS FILES, VOL. XX, NO. X, SEPTEMBER 201X 2 the maximal number of clients among all clients. Notwithstanding, if we aim to find a single seed user that influences the maximal number of clients at various time, client v2 will turn into the new outcome at time t = 1. Instinctively, this is on the ground

2 RELATED WORK

The proposed arrangement does not scale to large networks as it requires a large number of Monte-Carlo recreations for influence estimation. Following the fundamental work numerous analysts have been chipping away at structure efficient calculations for Influence Maximization issue, prompting countless strategies. The proposed strategies can be primarily sorted into two kinds. The first type of calculations goes for improving the efficiency of the hill climbing voracious calculation while safeguarding the $1 - 1/e$ estimation. For instance, Leskovec et al. structure the CELF technique to quicken the avaricious calculation by using the sub seclusion of the target capacity to do languid assessment. All the more as of late, Zhou et al. have accomplished further quickening by joining upper bound on the influence work. In view of the possibility that $p_{u,v}^{G(s)} \leq = p_{u,v}^{G}$, in this work, we use a similar thought in our UBI calculation with an improved upper destined for hub substitution gain. In addition, we separate the equation that is utilized to compute the hub substitution increase to two pieces of minor increase and afterward our real undertaking progresses toward becoming to give an upper bound and a lower bound of the negligible increase. With the figuring of the upper and the lower bound on the terms, we accomplish a lot more tightly bound than simply improving the strategy. In addition, we plan an efficient strategy to refresh the upper bound as system structure changes.

In any case, all the past strategies expect to find the influential hubs under one static system. To the extent we are concerned, the only paper on Influence Maximization under dynamic systems is by Aggarwal et al.. In any case, their work is only possibly identified with this paper in that they focus on finding a seed set at time t, that maximizes the influence at some $t+\Delta$ given the elements of the development of system amid the interim $[t, t + \Delta]$. We center around optimizing of influential hubs. Additionally, our calculation can be connected when the adjustments in system structure have just been found by their examining technique.

3 PRELIMINARIES AND PROBLEM STATEMENT

In this section, we first introduce the diffusion model, namely the Independent Cascade Model and the Influence Maximization for static network. We then formally state our Influential Node Tracking problem as a generalization of the Influence Maximization problem to dynamic social networks. Table 1 lists the symbol notations used in this paper.

3.1 Diffusion Model and the Influence Maximization Problem

In this work, we study the social influence under the widely adopted Independent Cascade (IC) model. Under the IC model, the social network is modeled as a directed network $G = (V,E)$, where V corresponds to the individuals while E represents the sets of social links between the individuals.

The IC model describes a simple and intuitive diffusion process. Starting from a seed set S, which begins active (having adopted the behaviour), the diffusion process unfolds in discrete time steps as follows. When a node u becomes active in step t, it attempts to activate all currently inactive neighbours in step t+1. For each neighbour v, it succeeds with the known probability $p_{u,v}$. If it succeeds, v becomes active; otherwise, v remains inactive. Once u has made all these attempts, it does not get to make further activation attempts at later times.

Given the seed set S, we define the influence coverage of S as the expected number of activated nodes when the diffusion process ends, denoted by the influence function $\sigma(S)$. The *Influence Maximization* (IM) problem under the IC model aims at finding a seed set $S \subseteq V$ of size at most k to maximize the influence function $\sigma(S)$.
Formally, the IM problem is defined as the following optimization problem:

$$S* = \underset{|s| \le k}{argmax}\,\sigma(s)$$

Though it has been shown by Kempeetal.in [3] the matched IM problem under IC model is NP-hard, the following good properties of the IC model allow for approximate algorithm to discover the influential nodes: the influence functionσ(S) under the IC model is monotone and submodular [3]. 1 The above properties lead to a simple greedy algorithm (Algorithm 1) proposed by Nemhauser et al. for maximizing monotone submodular functions. The algorithm repeatedly chooses the node with the maximum marginal gain and adds it to the current seed set until the budget k is reached. Proved by [23], this algorithm approximates the optimal solution with a factor of the (1 − 1/e) for the Influence Maximization problem.

Algorithm :1 Greedy (G = (V,E), k) 1: initialize S = ∅
2: **for** i = 1 to k **do**
3: v∗ = argmaxv ∈ V−S {σ(S +{v})−σ(S)}
4: S = S + {v∗}
5: **end for**
6: **Output** S

3.2 Influential Node Tracking Problem

The traditional Influence Maximization problem aims at finding influential nodes for only one static social network. However, real-world social networks are seldom static. Both the structure and also the influence strength associated with the edges change constantly. As a result, the seed set that maximizes the influence coverage should be constantly updated according to the evolution of the network structure and the influence strength. In this work, we model the dynamic social network as a series of snapshot graphs,G_1…..G_T.We assume that the nodes remain the same while the edges in each snapshot graph change across different time intervals. Each snapshot graph is modelled as a directed network, G^t= (V,E^t) which includes edges appearing during the periods under consideration. Moreover, a set of propagation probabilities Ptu,v is associated with each snapshot graph Gt. Our goal is to track a series of seed sets, denoted as S^t,t = 1,...,T, that maximizes the influence function $\sigma^t(\,)$at each of the snapshot Gt. More formally, we define the above task as the Influential Node Tracking problem. 1. Recall that a set function f is monotone if f(S +x) ≥ f(S) for any element x; and f is submodular if it has diminishing
T.
returns: f(S + x)−f(S) ≥ f(T + x)−f(T) for any element x whenever S ⊆
Influential Nodes Tracking (INT). Let G = $\{G^t\}_1^T$be a dynamic social network. The influential nodes tracking problemistodiscoveraseriesofseedsetsS^1,..,S^T whose size is at most k, such that , S^T = argmaxS ∈ V,|S|≤k$\sigma^t(S)$ for all snapshot graphs G^t,t = 1,...,T.

4 PROPOSED METHODS

For real dynamic social network ,it is unlikely to have abrupt and uncommon changes in diagram structure in a brief timeframe. Subsequently, the closeness in structure of charts from two continuous previews could prompt comparative seed sets that amplify the influence under each diagram. In view of the above thought, we propose UBI calculation for the INT issue, in which we find the seed set that boosts the influence under G^{t+1}dependent on the seed set St we have effectively found for diagram. Rather than developing the seed set for chart G^{t+1} from the beginning, begin with $s^t$and ceaselessly refresh by supplanting the hubs in $s^t$to improve the influence inclusion. Our calculation first utilizes an underlying set and a few rounds of trade heuristic to amplify the influence, as referenced in the paper. So the exchange heuristic clearly chips away at a depiction diagram. At the point when reached out to the dynamic chart, our calculation just needs to exchange for a couple of more adjusts after each time window wand can achieve a fasted update. More detailed depictions about how our technique takes a shot at the preview diagrams and dynamic systems will be displayed in the following two subsections.

4.1 Interchange Heuristic

We use the Interchange Heuristic proposed in[a sour strategy to supplant the hubs in St. Beginning from a subjective set.Interhange Heuristic means to find a subset S0 ⊆ V that differs from S by one node and hashes am cardinality. It has been appeared by Nemhauser et al. in that applying Interchange Heuristic to monotone submodular work until no further improvement is conceivable prompts an answer with guess ensure 1/2. Be that as it may, it stays to determine how we ought to pick set S0 in the Interchange Heuristic. In this work,
we pick S0 so as to augment the increase accomplished by means of the substitution for any fixed versus ∈ S. Let
δv,vs(S) be the supplanting gain by changing from versus ∈ S to v ∈ V − S. Let v ∗ = argmaxv δv,vs(S), we pick
S0 = S −vs + v∗.

This methodology needs to assess the increase by supplanting versus with any hub in v ∈ V − S, which calls for
|V − S| times of impact estimation. The estimation by running MonteCarlo reproductions is excessively expensive notwithstanding for system with moderate size. Roused by the UBLF enhancement proposed, we utilize the upper bound on supplanting increase to decrease countless estimations.Accept that we have officially
V − S. Give the upper bound on the substitution a chance to pick up be determined the upper bound on supplanting gain δu,vs(S) for any hub $\bar{\delta}_{(u,v_s)}$ ∈ (S), at that point if for hub u with the end goal that be $\bar{\delta}_{(u,v_s)}$(S), ≤$\delta_{v,v_s}(S)$, the costly calculation of trading gain for hub u ends up superfluous as its increase is destined to be less or meet than that for hub v. The calculation of $\bar{\delta}_{(u,v_s)}$(S), will be introduced in next segment.

We utilize the subroutine in Algorithm 2 to do the Interchange Heuristic for any fixed versus
$v_s \in S$. In the event that the biggest supplanting gain $\delta_{v,v_s}(S)$, is not exactly a given limit with γ ≥ 0, we stop to discover another versus for exchange (line 5-7). This lessens the calculations for the instance of irrelevant upgrades and quickens the procedure of exchange.

Algorithm 2 Interchange (G=(V,E),S,v_s, $\bar{\delta}_{(u,v_s)}$(S))

1:Set $\delta_{v,v_s} \leftarrow \delta_{v,v_s}(S)$, v$\in V - S$

2:Set $cur_v \leftarrow false, v \in V - S$

3:while true do

4:v*=argmaxv$\in V - s\{\delta_y, vs\}$

5:if $\delta_{v*,vs} \leq y\sigma(S)$

6:break
7: end if

9: $S \leftarrow S - v_s + v$
10: break
11:else
12: $\delta_{v^*,vs} \leftarrow \sigma(S - v_s + v^*) - \sigma(S)$
13: $cur_{v^*} \leftarrow$ **true**
14:end if
15: end while
16: Output S

With the exchange methodology characterized above, we present our Upper Bound Interchange Greedy, in short UBI as Algorithm 3.

Algorithm 3 UBI($G = (V,E),S$)
1: Compute $\bar{\delta}_{v,vs}(S)$ for $v \in V - S, v_s \in S$
2: **for** i = 1 to $|S|$ **do**
3: v_s^* = argmax$vs \in S\{\bar{\delta}_{\cdot,vs}(S)\}$
4: $S \leftarrow$Interchange($G, S, v_s^*, \bar{\delta}_{\cdot,v_s}(S)$)
5: Update $\bar{\delta}_{v,vs}(S)$ fo r any $v \in V - S, v_s \in S$ according to the interchange result
6: **end for**
7: **Output** S

It ought to be seen that as opposed to doing hub substitution until no further improvement is conceivable, we apply at most |S| rounds of substitution in our usage. While giving up the hypothetical assurance, we altogether improve the productivity of our strategy, as it might take an exponential number of substitutions until no improvement exists. As we will delineate in the exact examinations, the proposed technique accomplishes practically identical outcomes as the slope climbing eager calculation where the 1−1/e estimation is ensured.

4.2 Upper Bound of Node Replacement Gain

In this segment, we delineate the main strange part in our UBI calculation, in particular the calculation of the upper bound of the substitution gain $\bar{\delta}$u,vs(S). Zhou et al. first utilize the upper bound on impact capacity to quicken the voracious calculation in persuasive seeds choice [13]. Following their philosophy, we propose a more tightly upper bound on the substitution gain by barring the impact along ways, which incorporate approaching edges to the seed set.

Fundamentally, our undertaking is to figure an upper bound on δv,vs(S) for any v $\in$ V − S so as to quicken the Trade Heuristic subroutine. We have

$\delta_{v,vs}(S) = \sigma(S - v_s + v) - \sigma(S)$

$= \rho_v(S - v_s) - \rho_{vs}(S - v_s)$ (1)

where ρS(T) = σ(S + T) − σ(T) is the marginal gain by adding set S to the existing node set T. The major task is to provide an upper bound on the first term ρv(S−vs) and a lower bound on the second term ρvs(S −vs). In the next two sections we will provide the upper bound and the lower bound of the marginal gain.

4.2.1 Upper Bound of Marginal gain

In this section, we illustrate the computation of the upper bound on the marginal gain ρS(T). Let APv,i(S) be the probability that node v is activated exactly at step i under the seed set S. The essential step to achieve a tighter bound is to use probability, APv,i(S|T) instead of APv,i(S) used in [13]. Informally, APv,i(S|T) stands for the probability that node v is activated exactly at step i without the help from nodes in set T. Let G(T) be the graph where the set of node T is "excluded" from G in terms of the diffusion process, namely the propagation probability pG(T) u,v associated with G(T) is defined as follows:

At that point, APv,i(S|T) can be formally defined as the probability that hub v is enacted precisely at step I under the modified diagram G(T). It ought to be seen that APv,i(S|T) = APv,i(S|S + T) as hubs in S are as of now initiated toward the starting, accordingly evacuating the approaching edges to hubs in set S does not make a difference. We need the following lemma to describe the properties of APv,i(S|T) so as to infer our destined for substitution gain.

Lemma 1. For any v ∈ V , S,T ⊆ V ,S ∩ T = ∅ and i = 0,1,...,|V −S|, we have:APv,i(S + T)−APv,i(T) ≤ APv,i(S|T) = APv,i(S|S + T)

Lemma 2. For any v ∈ V, and S,T ⊆ V , S∩T = ∅ we have ρS(T) ≤ I(S)T |V−S| X i=0 (PG(S+T))i ·1 where T is for vector/matrix transpose and T is for the seed set.

Lemma 3. For v ∈ V , and S,T ⊆ V , we have the following inequation: σ(S + T)−σ(T) ≥ σ(S|C(T)) (2) where C(T) = {v|v ∈ V,d(T,v) < ∞} is the set of nodes connected from the nodes in T and σ(S|C(T)) is the influence activated by the seed set S without propagating along any node in C(T).

Lemma 4. For v ∈ V , and S,T ⊊ V, the lower bound of the marginal gain ρS(T) is: ρS(T) ≥ I(S)(E + P(S + C(T)))·1 (3) where P(S+C(T)) represents for the probability matrix for G(S + C(T)) and E for the identity matrix.

4.3 Fast Update of the Replacement Upper Bound

We have told already the best way to figure a more tightly bound on the swap gain for one static system with a fixed seed set S. In any case, as system changes always, we have to refresh the upper bound by the adjustments in spread likelihood. In addition, as we incorporate new hub into the seed set S, we additionally need to refresh the upper bound as the proliferation likelihood lattice PG(S+T) likewise changes. Let ΔP be diverse in engendering likelihood between the two diagrams G **and** G0 related with spread likelihood networks P and P0, in particular ΔP = P−P0. The refresh of the bound comes down to the refreshing of segment vector UG. Utilizing the second request estimation of network reversal, we can refresh UG around as pursues:

Our UBI algorithm only updates the upper bound and the UBI+ algorithm updates both the upper bound and the lower bound.LetΔ = {(u,v)|ΔPu,v 6= 0},and the updating algorithm for UBI and UBI+ is shown in Algorithm 4 and 5.

As in UBI algorithm, we do not particularly calculate the lower bounds owe just simply run Monte-Carlo simulations or use other heuristics to estimate Lj.

5 EXPERIMENTS

In this area, we direct broad trials on three genuine powerful extensive scale systems to assess the execution of our calculation for the INT issue.

5.1 Experiment Settings First, we run our trials on three genuine unique systems, Mobile, HepPh and HepTh to think about UBI and UBI+'s execution on various scales. Aftereffects of these analyses is appeared in Section 5.2.1 and 5.2.2. In Section 5.2.3, we run UBI and UBI+ on a benchmark for viral advertising to demonstrate our strategies' execution on viral promoting. Datasets. The first one, Mobile system utilized in [5] is separated from cell phone call records in a city amid July 2007. Every hub speaks to a cell phone client and each telephone call between two clients makes an edge. The HepPh and HepTh gave in 2003 KDD glass are two reference systems removed from the diverse areas of e-print arXiv2. In this system, every hub compares to a paper instead of a author. We create an edge between node u and v, if paper v refers to paper u. HepPh, HepTh and Mobile datasets are altogether coordinated systems. The basic statistics of the three networks are summarized in Table 2. We utilize the accompanying strategy to build the preview charts from the above datasets. At time stamp t, we produce the depiction Gt = (V,Et),V = SV t containing every one of the edges happening in the time window [t · Δt,t · Δt + ω] where ω is the extent of the perception window and Δt is the separation between two back to back previews. Fundamentally, ω controls the quantity of edges in every depiction chart, while Δt chooses the comparability between two back to back preview diagram. Along these lines by utilizing diverse parameters ω and Δt, we can create a group of depiction diagrams with various properties for our following tests. The quantity of edges in every depiction diagram produced from the systems is appeared in Figure 2.

Spread likelihood. We allot the engendering likelihood on each edge by the accompanying two broadly received models. • Uniform Activation (UA): UA show doles out likelihood consistently. We set all the spread probabilities to 0.05 in our examinations. • Degree Weighted Activation (DWA): DWA appoints likelihood of each edge (u,v) as Pu,v = 1/din(v) where din(v) is the in-level of hub v. Algorithms under comparison. We compare UBIalgorithm with the accompanying cutting edge calculations.

IMM: IMM algorithm, which is a near-linear time greedy algorithm introduced in [20]. We run IMM algorithm for = 0.01 as provided in the source code. • IRIE:IRIE is the most advanced heuristic method under IC model. We run IRIE algorithm independently for each snapshot graph with parameters α = 0.7 and θ = 1/320 as reported in [17]. • Degree: As a baseline comparison, simply select the nodes with the highest degrees. • UBI:OurUBIalgorithmusingSP1M[4]forinfluence estimation with γ = 0.01. The initial seed set S0 is generated by Greedy. In UBI algorithm, we only calculate the upper bound of marginal gain when calculating the upper bound of node replacement gain. • UBI+: Our UBI algorithm which calculates both the upper bound and the lower bound of the marginal gain when calculating the upper bound of node replacement gain. We do not include other baseline methods for INT problem since it has already been shown that Greedy always has the best influence coverage while IRIE has slightly worse performance but runs significantly faster than other methods in time [17]. We use the average of 20000 rounds of MonteCarlo simulations as estimation of the actual influence in order to evaluate the seed sets discovered by the algorithms. Moreover, all the experiments are carried out on a server with 32 cores (2.13G Hz) and 64G memory.

5.2Experiment Results

5.2.1Experiment Results of UBI

Influence coverage and running time on real dynamic networks. We first present our main result on comparing our UBI algorithm to other baseline methods on three real world dynamic networks. For Mobile network, we set the window size to one hour while the time difference is set to two minutes. For both HepPh and HepTh network, we set the window size to three years and the time difference to one month. Moreover, we choose the seed size k as 30. The results on influence coverage of the selected seed sets for each snapshot graph are shown in Figure 3 and Figure 4. As Greedy is too slow to finish within a reasonable time, we do not include Greedy on Mobile datase

5.2.2Experiment Results of UBI+ Influence coverage on dynamic networks. We present our result on comparing our improved UBI algorithm, UBI+ to UBI on three real-world dynamic networks. For Mobile network, we set the window size to one hour while the time difference is set to two minutes. For both HepPh and HepTh network, we set the window size to three years and the time difference to one month. Moreover, we choose the seed size k as 30. We calculate the average influence spread over all snapshot graphs for all three networks and present the results in Table 9 and Table 10. For the above results, we can easily find that our UBI+ algorithm achieves a better influence spread than UBI. Notice that UBI+ merely reaches about 2% and 1% better on the Hepph and Hepth dataset, this is because that UBI already performances very close to the influence spread upper bound(which is also the Greedy algorithm's result), so UBI+ only reaches an influence much closer to the theoretically influence bound. However, UBI+ get a 10% improvement in Mobile dataset and this shows that our new algorithm significantly improves the result in large datasets. Similar to the experiment results of UBI, the average influential users coverage of UBI+ is are 154, 119, 143 for Mobile, Hepph and Hepth dataset.

Running time on dynamic networks. As it can be seen from Table 11 and Table 12, though being a little slower becausethat an additional bound need to be computed, UBI+ performs as well as UBI in running time. Notice that UBI+ achieves significant improvement in influence coverage in large datasets as the previous experiment shows, so a slight increase in the consumption of time is acceptable. So, in conclusion, UBI+ performs better than UBI in solving INT problem in large datasets. In small datasets, because that UBI already performs well so that UBI+'s improvement is not obvious.

5.2.3Experiment Results of UBI and UBI+ on viral marketing Benchmark for viral marketing We use the benchmark proposed by Amit Goyal, etc. in [24] to measure our methods' performance. We generate a dataset by applying their benchmark algorithm to the Flixster dataset. The working principle of the benchmark is that the propagation probabilities between users in a social network can be learned from users' actions, such like making comments on movies, traveling to scenic spots, etc.We generate snapshot graphs from the flicker dataset generated by the benchmark mentioned in the previous section. From Table 13, it can be seen that UBI and UBI+, similar to the results on HepPh, HepTh and mobile, achieves close influence spread to Greedy and IMM.This also

supports our previous experiment results that UBI and UBI+ performs well in real dynamic networks. These experiments prove that our proposal works better on viral marketing.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we investigate a novel issue, specifically Influential Node Tracking issue, as an expansion of Influence Maximization issue to dynamic systems, which goes for following a lot of influential hubs progressively with the end goal that the influence spread is expanded at any minute. We propose an efficient calculation UBI to take care of the INT issue put together idea of the Inter change Greedy method. We utilize the upper bound with respect to hub substitution addition to quicken the procedure. Moreover, an efficient method for updating the upper bound is proposed to handle the evolution of the network structure. Broad tests on three genuine informal communities demonstrate that our technique outflanks cutting edge baselines regarding both influence inclusion and running time. At that point we propose UBI+ calculation that improves the calculation of the upper bound and accomplishes better influence spread. As an immediate future work, we might want to sum up our UBI calculation to follow influential hubs under the other broadly received dissemination show, Linear Threshold demonstrate under powerful systems. Also, it will intrigue in the event that we can consolidate our work with [21]. That is to follow a series of influential nodes where the diffusion process is also done under a dynamic system rather than the static depiction chart.

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