International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-5, January 2020

Framework for Computing Potential Node with Higher Influence in Complex Social Network

Selva Kumar S, Kayarvizhy N

***Abstract**: The increasing data complexity in social network imposes challenges towards carrying out investigation towards analytics. Similar scenario has started evolving in social network most recently owing to the usage of ubiquitous devices which gives rise to accumulation of complex set of data that offers potential challenge to understand the potential node. Identification of potential node is an essential demand to understand the role player in social network. Therefore, this paper presents a novel analytical methodology to construct a discrete community with higher precision along with a novel progressive algorithm for identifying the potential node that offers a higher degree of influence in social network. Dynamic optimization, as well as probability theory, has been used in order to perform modeling of the proposed system. Along with an effective computational performance, the comparative analysis shows that proposed system offers better performance in contrast to existing techniques with respect to influence degree and information processing time. The inferencing of the quantified outcome status shows that the formulated approach attains ~70% performance improvement in the case of minimizing the processing time as compared to the Chen approach. The identification of potential node in four different types of networks have also significantly improved with negligible computational effort.*

Keywords: Influential Node, Social Network, Cascading Model, Directed Graph, Probability.

I. INTRODUCTION

The information pertaining to an influential degree is highly important in many business application e.g. market research, product launch, etc [1][5]. The conventional mechanism to represent the significance of a particular node in the social network is centrality metric [2][3]. According to the concept of centrality metric, the nodes are associated with a certain computed ranking value that forms the core basis of influence. However, the centrality concept has been investigated to find that it offers the flawed mechanism of constructing the centrality factor for identifying the most potential node [4]. Researcher claims that centrality metric may find the potential node with higher influence degree but they offer a minimal scale of information require exploring the best influential node [5]. However, it is one of the computationally challenging problems to identify the particular group or a set of groups with similar forms of users residing within one network group to offer the higher degree of influence. This is called as influence maximization problem in viral marketing [6]. At present, there are various studies that offer a solution to this problem using multiple techniques [7]. Majority of such problems are solved using directed graph theory that depends on vertices, edges, the weight assigned to edges mainly [8] [9]. Therefore, this paper introduces an integrated technique to offer a solution of a precise community detection and appropriate identification of potential node from the complex network. The proposed system utilizes probability theory in order to construct an analytical model with a capability to explore potential node from complex social network. Section 1.1 discusses the existing literature where different techniques of influence maximization are briefed followed by the discussion of identified research problems. Proposed the methodology to solve this problem as a solution is discussed in Section 1.2. Section 2 discusses algorithm implementations for constructing discrete community as well as a selection of appropriate potential node with higher influence in the complex social network. It is followed by the discussion of result analysis with respect to processing time and influence degree in Section 3. Finally, the conclusive remarks are provided in Section 4.

Manuscript published on January 30, 2020.
* Correspondence Author
Selva Kuamr S*, Assistant Professor, Department of Computer Science & Engineering, B.M.S College of Engineering and affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India
. Email: selva.cse@bmsce.ac.in
Kayarvizhy N, Associate Professor, Department of Computer Science & Engineering, B.M.S College of Engineering and affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India

A. Background

This section will further brief about the existing studies towards influence maximization. Our previous review paper has presented a discussion about research gap associated with the study of information propagation [10]. Various existing strategies have been evolved that has used linear thresholding mechanism for obtaining influential node in viral marketing [11]. There are also studies where structural hole identification has been utilized [12] for maximizing the influence. Other frequently used approaches are game theory [13], maximum-a-posteriori [14], diffusion-based strategy [15], usage of memetic-algorithm [16], identification of elite trajectory for cost minimization [17], greedy-based technique [18], diffusion speed-based approach [19], greedy approach with seeding strategy [20], sketch-based technique [21][22], threshold-based approach [23], etc. Similarly, various other researchers e.g. [24]-[30] have presented various techniques for addressing the problems of exploring influential node from the social network data.

The potential factors that are identified as research problems are as:

- Existing techniques mainly uses greedy-based technique which performs more recursive operation leading to computational complexity if the network and domain is massive.
- Existing studies towards influence maximization is directly formulated towards identification of influential node without emphasizing on community construction much.
- The techniques presented till date doesn't ensures any precision of identification of potential node and this results in less stabilized social network formation.
- The presence of redundant information of potential node offers an inappropriate selection of the influential node as well as result in wrong selection of community in an existing system.

Therefore, the problem statement of the proposed study can be stated as "*To design a computational model for precise selection of potential node from a discretely formed community with higher influence degree in larger and uncertain social network*."

B. Proposed System

This paper is a continuation of our prior implementation using the degree of importance [31] where we further enhance the selection of potential nodes using graph theory and probability logic. The proposed system utilizes social network data where the potential node is explored using directed weighted graph. The study also investigates the effective processing time consumption as well as on diverse test networks as well as it also computes influence degree.
. The architecture of the proposed system is as shown in Fig.1.

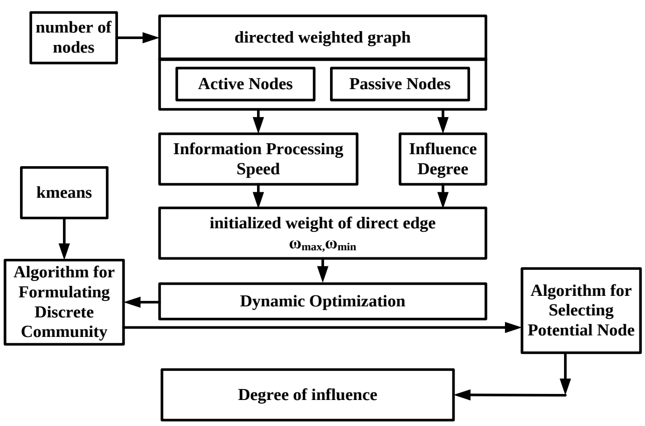

Fig. 1. Proposed Architecture

The numbers of nodes are classified into active and passive nodes depending on their capability to influence or not influence their neighbor nodes respectively. The proposed system then emphasize on maintaining better information processing speed that maintains a rate of processing the passive to active nodes at certain probability rate. The complete map of the network bears a maximum and minimum weight of direct edge that further uses dynamic optimization. The first core implementation of the proposed system is to explore the best community followed by the selection of a potential node within the community. The proposed system splits the complete community into various discrete communities where the problem is to perform mining on best X number of potential nodes. In order to overcome the problem of direct influence of adjacent communities on the outcome, the proposed system applies dynamic optimization for exploring discrete community followed by partitioning the community using K-means clustering algorithm. The next step is to use dynamic optimization for updating the influence degree and obtain information about the various local and global set of communities. This process assists in finalizing the best X number of potential nodes that will be finally subjected to mining by users. The complete system is designed using the progressive method and not iterative method that reduces the significant computational overhead in case of large networks. The next section illustrates the algorithm implementation of the proposed system.

II. ALGORITHM IMPLEMENTATION

The proposed algorithm presents a computational model for exploring the potential node while carrying out information propagation. The implementation is carried out considering two core algorithms responsible for constructing a unique community as well as for identifying the potential node in the network. This section discusses the core algorithms as follows:

A. Algorithm for Formulating Discrete Community

This algorithm takes the input of N (number of nodes), p (processing speed probability), ω (initialized weight of direct edge), Dm (distance matrix), a (probability), x (number of influential node), αin (initialized community) that upon processing leads to formulation of discrete community for a given information propagation model. The steps of the algorithm are as follows:

Algorithm for Formulating Discrete Community
Input: $N, p, \omega, D_m, a, k, \alpha_{in}$
Output: Show community
Start
1. init N→type(n), p, T_{xR}, X
2. $p_{ij} \rightarrow 2p\omega(s,d)/(\omega_{max}+\omega_{min})$
3. Eval $C_m \rightarrow D_m < T_{xR}$
4. Compute $N_{act} \rightarrow (ix(N*a/100))$
5. **For** i=1:N
6. def tag→$1+(\alpha_{in}-1)*r$
7. $A_{id} \rightarrow$ find(C_m(i)
8. **For** j=1:size(A_{id})
9. **If** β(i,j)
10. $H_i(i,j)=1$
11. **else**
12. $H_i(i,j)=0$
13. **End**
14. **End**
15. z→$\arg_{max}$(VC)
16. **For** j=1:size(A_{id})
17. **If**(VC(i)==VC(Aid(j))) && Hi(i,j))==1)
18. $n_{leaf} \leftarrow i$ & j
19. tag(c_i)→tag(c_i) A_{id}(j)
20 **End**
21. **End**
22. $C_{ent}=\arg_{max}(\omega_u/\omega_v)$
23. **If** $C_{ent}>\gamma$
24. integrate C1→C_m and update C_m & show

community→k_{means}(activeFlag), k)
25. **End**
End

The algorithm considers multiple forms of traffic-based network model *type* which is represented by the density *n* of the nodes (Line-1).

The algorithm performs the computation of the processing speed p_{ij} in order to propagate information. A new empirical form is utilized in order to compute p_{ij} (Line-2) along with the computation of a number of active nodes (Line-4) that depends on *N* and proportion of active node i.e. *a* (Line-3). The algorithm also computes the logical condition of connection map C_m only if the distance matrix i.e. D_m is found to be less than transmission range (Line-3). Hence, Line-1 to Line-4 assists in signifying the communicating node (i.e. active node) in information propagation. For all the node (Line-5), the proposed system defines a community tag on the basis of an initialized community (Line-6) followed by exploring all the adjacent nodes A_{id} (Line-7) that depends on connection map. A function *β* represents an empirical expression of β=(i*j*rand) in order to state the true condition of a potential node (Line-10) or false condition of a potential node (Line-12). A variable VC (Line-15) is formed that obtains the maximum tags of the highest possible node and the variable *z* will represent the number of communities (Line-15). For all the adjacent nodes j (Line-16), the algorithm formulates a condition when both the tags of communities are unequal (Line-17) in order to obtain the leaf node n_{leaf} (Line-18). Finally, the community tag is updated (Line-19). The maximum arguments of weights ω is checked if it is more than a defined value of γ (Line-23) in order to further integrate the smaller communities using k-means clustering algorithm (Line-24). Hence, discrete communities are obtained by implementation of this algorithm.

B. Algorithm for Selecting Potential Node

This algorithm is responsible for selecting a potential node after the discrete information of community is successfully obtained. For simpler assessment, we consider *X* number as the highest possible potential node.

The first phase of this algorithm will be to perform identification of communities followed by preliminary defining of potential nodes. The proposed algorithm uses dynamic optimization technique in order to perform a selection of community for exploring the best potential nodes *x* from the maximum initialized range *X*.

The steps of the algorithm are as follows:

Algorithm for Selecting Potential Node
Input: *X* (initialized range of influential node)
Output: identification of influential node
Start
1. **For** x=1:X
2.   p(1, x)=0 & q(1, x)=0
3. **End**
4. **For** i=1:X
5.   ix=arg_{min}(d)
6.   CC→xyt(activeFlag)
7.   xyt(ix)=0
8. **End**
9. **For** x=2:X
10.   **For** m=2:M
11.   get I→tag(m) & I(m)
12. deg_{in}→[I] & compute D= arg_{max}(ω(diff(I)))
13.   **If** p(m-1,x)≥p(M, x-1)+Δω
14.   q(m,x)=q(m-1, x)
15.   else
16.   q(m,x)=m
17.   **end**
18. potential node→CC
19. **End**
End

The algorithm extracts the potential degree *p* and signum function *q* for all the possibilities of potential node *X* (Line-2). Euclidean distance *d* between the data point of active nodes and cluster nodes followed obtaining the minimum value of *d* (Line-5). The function xyt represents a matrix with active nodes for each potential nodes (Line-9) as well as for each community (Line-10), all the member of the communities are first obtained followed by the extraction of potential nodes I (Line-11). A difference *D* in the weight is computed with respect to recently captured potential node I (Line-12). The proposed algorithm uses dynamic optimization mechanism in order to decide the community to be subjected to mining the specific x^{th} potential node. An empirical expression of degree p is formulated by arg_{max}\{*p*(m-1), *x*), *p*(M, *x*-1)+ Δω\}, which is further followed by conditional check as shown in Line-13. In either of the cases, it results in an empirical value of Signum function with respect to (m-1, x) and m respectively. In order to perform mining of x^{th} potential node, only the community who has got the highest degree of information will be preferred by the proposed algorithm. The conditional statements in Line-13 will mean that if the degree of influence of x^{th} nodes residing over the initial (m-1) set of communities are found to be lesser than that of x^{th} node present in connectivity map C_m than only x^{th} node is selected for mining or else (*m*-1) is selected. Signum function is utilized to represent the chosen community from the first *m* set of communities. The variable Δω represent the highest probability of increment of potential node considering C_m community. It is to be noted that degree of a potential node is evaluated using community C_m only and not the complete network of nodes. One of the essential observations of this algorithm is the usage of processing speed which is a direct representation of the inclination of any user to select a specific service or product identified in social network analysis. This is one of the essential characteristics in information propagation where processing of information is affected by its speed, the degree of nodes, and cardinality of preliminary communication nodes (or active nodes).

Hence, the proposed algorithm targets to exploring the ellite k number of potential nodes that have to be subjected to analytical operations in information propagation using community-based approach. The application of this algorithm can be carried out on any scale of a social network in the domain of information propagation where the algorithm can offer highly scalable identification of best potential nodes thereby reducing the computational effort to search for it and applying mining on those potential nodes. The next section highlights the output obtained by execution of these algorithms.

III. RESULT ANALYSIS

This section briefs about the results obtained from the proposed implementation. Developed using MATLAB, the results have been recorded considering 20% of the active node from different forms of network deployment types.

The dataset is constructed synthetically. (Type-1 Network: 250 nodes,
Type-2 Network: 500 nodes, Type-3 Network: 750 nodes, and Type-4 Network: 1000 nodes). A squared deployment area is considered for the study with an initialized community of X=100. The study outcome is assessed with respect to influence degree and processing time as discussed below.

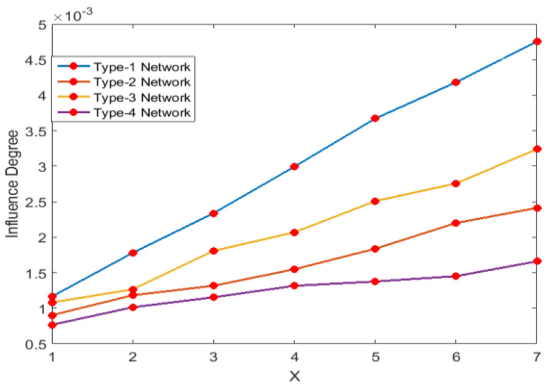

Fig. 2. Analysis for Influence Degree

Table 1 shows the quantified outcome obtained as influence degree for four different types of network models and here x ranges from 1 to 7.

Table 1: Quantified measures of Influence degree [x= 1 to 7]

Type1 N/W							
X	*1*	*2*	*3*	*4*	*5*	*6*	*7*
Influence Degree (~) (x10^-3)	*1.2*	*1.8*	*2.41*	*3.3*	*3.8*	*4.8*	*4.7*
Type2 N/W							
Influence Degree (~) (x10^-3)	*0.7*	*1.1*	*1.3*	*1.4*	*1.7*	*2.1*	*2.3*
Type3 N/W							
Influence Degree (~) (x10^-3)	*1.1*	*1.3*	*1.8*	*2.0*	*2.4*	*2.8*	*2.9*
Type4 N/W							
Influence Degree (~) (x10^-3)	*0.6*	*0.9*	*1*	*1.2*	*1.4*	*1.3*	*1.5*

The outcome shown in Fig.2 highlights that increasing of traffic load minimizes influence degree, which is a very usual agreement of the complexities associated with the identification. Type-1 network and Type-2 network are the basic representation of usual traffic condition with normal and peak load of information whereas Type-3 and Type-4 represent an abnormally higher condition of traffic. The outcome shows that Type-1 network and Type-2 network with a nearly linear trend, which is highly predictive in usual study making the user easier to understand the influence degree if the X limits are further increased. However, a closer look on Type-3 and Type-4 network doesn't show the linear behaviour of the trend. This implies that with an increase of X-limits, the likelihood of the increased value of influence degree minimizes. It should be understood that X represents a range of the potential node that is required in order to perform optimization, where optimization will mean increment in influence degree. Hence, it may be quite a common thought that increase of X limit could offer an increase in influence degree whereas the result is otherwise. The inference that can be drawn from this outcome is that proposed system doesn't require to have higher dependencies of X value to increase the better value of influence degree thereby it directly represents the optimization concept. Implying of optimization concept will mean to achieve a better outcome in presence of lesser dependencies of resources. This fact is proven in Fig.2, which shows that proposed system doesn't require to increase the number of influence degree in order to obtain better influence degree, rather it will minimize. The prime reason behind this trend is that proposed system computes the active node using the progressive method and not the iterative method; therefore the final results of influence degree are considered to be elite only for the minimal number of X. At the same time, we use probability theory in order to ensure that computation of the active node is carried out considering higher versions of updated weights of tagged community, which is formulated using k-means clustering algorithm. This has the definitive advantage on algorithm processing time too.

The study outcome of the proposed technique is being compared with the nearly similar category of work carried out by Chen et al. [32]. The authors have addressed the problem associated with the influence maximization in the social network by introducing an algorithm that was constructed using heuristics in order to speed up the process of information propagation rate over large scale network. However, it has not been shown how it behaves over different ranges of the traffic system. The comparative analysis outcome for proposed and Chen et al. [32] is exhibited in Fig.3 as follows:

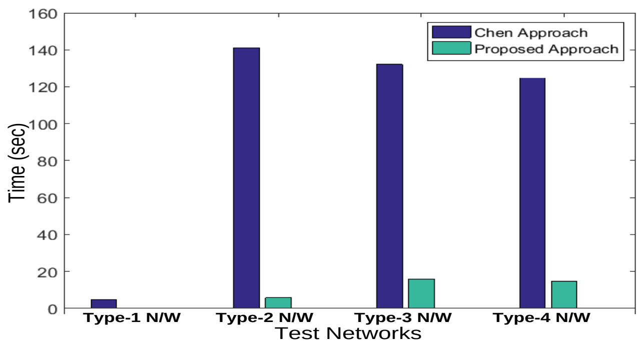

Fig. 3. Comparative Analysis of Processing Speed

The quantified outcome of time(sec) is tabulated as follows for better understanding of the test network performance in both formulated concept and Chen approach.

Retrieval Number: E5934018520/2020©BEIESP
DOI:10.35940/ijrte.E5934.018520
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Table 2: Quantified measures of time

Test Networks	*Processing Time (Sec) in proposed approach*	*Processing Time (Sec) in Chen approach*
Type-1 N/W	0.001223	3
Type-2 N/W	5	140
Type-3 N/W	18	141
Type-4 N/W	20	128

The performance parameter in Fig.3 represents processing time which is the amount of time consumed in order to make the information ready to be processed for assisting in applying mining techniques on the basis of identified communities. An interesting observation of the outcome can be seen for both proposed and existing system on different forms of the traffic system. The heuristic based-approach of Chen et al. [32] offers community detection at the cost of heuristic-based information. Although, this process doesn't have any significant problem in the smaller network (i.e. Type-1 network) but it shoots the entire problem when the density of the nodes are incremented from Type-2 network onwards. Owing to further usage of cascading model in the heuristic formulation, the processing time performance slightly improves for Chen et al. [32]; however, the performance is not that significant as compared to the proposed system. Another significant reason behind this is a disparity in the community detection algorithm where the identified active node in one community has a higher probability to affect the next set of computation for exploring the next active node for other community. This results in increased consumption of processing time. However, the proposed system acts in a very different manner. It first emphasizes on community detection unlike the work of Chen et al. [32] where precision is enhance considering the weighted factor of the direct edges as well as complete network. Moreover, it has a fixed value of X, where the algorithm always focuses on obtaining better-optimized results for higher traffic load. In order to avoid the problems like Chen et al. [32], the proposed system performs integration of different communities instead of performing an iterative operation of exploring better communities. This process results in a faster generation of data where the data are extremely less redundant and more unique assisting in much better decision making. The involved tags of the communities are also updated while exploring the process for better potential nodes. Hence, minimal processing time is a direct representation of faster information propagation on any forms of a network with uncertain traffic load. The complete algorithm execution time for the proposed system is found to be 0.244861 seconds while that of Chen et al. [32] is found to be 4.77201 seconds. Therefore, the proposed system can be said to offer better computational performance with a good balance with the identification process of a potential node in any large-scale social network with a higher degree of the complex set of information. The proposed system is more applicable as a backbone topology for performing massive data analytics on social networks.

IV. CONCLUSION

The increasing complexities of the data in the social network are becoming quite challenging to address in terms of a computational model. The prime reason behind this is lack of any referential model that can offer effective visualization of centrality-like concept. It will also mean that existing models are also somewhat inapplicable to such complex network. In such case, until and unless the influential node is not precisely found, the system cannot be subjected to any mining application. Moreover, it is computationally impossible to apply mining algorithm to all the influential nodes. There are many existing papers that have discussed the extraction of an influential node as well as addressed influential maximization problem, however, such approaches miss the dynamicity involved in the process that has resulted in an error-prone selection of the node. The proposed system addresses this problem by first splitting the complete network into smaller sub-groups in order to formulate a discrete community and further apply a novel analytical model to explore influential node. The study outcome shows that proposed system can sustain heavy traffic condition and offers significant optimization towards exploring unique influential node that can be further shortened down to apply mining operation. The analytical system for identification of potential node is significantly improved in the case of formulated system from both theoretical and numerical experimentation view-point and also the quantified measurement shows that the performance of improvement is almost 30%. On the other hand, it is also observed that the study significantly minimized the computational complexity aspect to a significant level which is ~ 60% as compared to the Chen approach [32]. The contributory aspect of this study is- the concept can be espoused into various futuristic social media applications based influential data processing and mining.

ACKNOWLEDGEMENT

We gratefully thank the Visvesvaraya Technological University, Jnana Sangama, Belagavi for financial support extended to this research work.

REFERENCES

1. X. Jin, Y. Wu and C. Jin, "Research on Stock Network Modeling and Risk Propagation Based on Complex Network Analysis," 2016 49th Hawaii International Conference on System Sciences (HICSS), Koloa, HI, 2016, pp. 1188-1194.
2. Tansel Özyer, Jon Rokne, Gerhard Wagner, Arno H.P. Reuser, The Influence of Technology on Social Network Analysis and Mining, Springer Science & Business Media, 2013
3. Guandong Xu, Yanchun Zhang, Lin Li, Web Mining and Social Networking: Techniques and Applications, Springer Science & Business Media, 2010
4. F. Grando, D. Noble and L. C. Lamb, "An Analysis of Centrality Measures for Complex and Social Networks," 2016 IEEE Global Communications Conference (GLOBECOM), Washington, DC, 2016, pp. 1-6.
5. Z. Ebadi Abouzar, L. Esmaeili and A. Hashemi Golpayegani, "Centrality measures analysis in overlapped communities: An empirical study," 2016 8th International Symposium on Telecommunications (IST), Tehran, 2016, pp. 565-570
6. X. Li, J. D. Smith, T. N. Dinh and M. T. Thai, "Why approximate when you can get the exact? Optimal targeted viral marketing at scale," IEEE INFOCOM 2017 - IEEE Conference on Computer Communications, Atlanta, GA, USA, 2017, pp. 1-9.
7. Z. Zhang, Y. Shi, J. Willson, D. Z. Du and G. Tong, "Viral marketing with positive influence," IEEE INFOCOM 2017 - IEEE Conference on Computer Communications, Atlanta, GA, USA, 2017, pp. 1-8.
8. David Easley, Jon Kleinberg, Networks, Crowds, and Markets: Reasoning About a Highly Connected World, Cambridge University Press, 2010

9. Paulo Shakarian, Abhivav Bhatnagar, Ashkan Aleali, Elham Shaabani, Ruocheng Guo, Diffusion in Social Networks, Springer, 2015
10. S. Kumar, Kayavizhy N., “A Comprehensive Insight Towards Research Direction in Information Propagation” International Journal of Advanced Computer Science and Applications(IJACSA), Volume 8 Issue 4, 2017.
11. Y. Zhu, D. Li, R. Yan, W. Wu and Y. Bi, "Maximizing the Influence and Profit in Social Networks," in IEEE Transactions on Computational Social Systems, vol. 4, no. 3, pp. 54-64, Sept. 2017.
12. J. Zhu, Y. Liu and X. Yin, "A New Structure Hole-based Algorithm For Influence Maximization in Large Online Social Networks," in IEEE Access, vol. PP, no. 99, pp. 1-1.
13. Y. Yang, Z. Lu, V. O. K. Li and K. Xu, "Noncooperative Information Diffusion in Online Social Networks Under the Independent Cascade Model," in IEEE Transactions on Computational Social Systems, vol. 4, no. 3, pp. 150-162, Sept. 2017.
14. O. Askari Sichani and M. Jalili, "Inference of Hidden Social Power Through Opinion Formation in Complex Networks," in IEEE Transactions on Network Science and Engineering, vol. 4, no. 3, pp. 154-164, July-Sept. 1 2017.
15. S. Dhamal, P. K. J. and Y. Narahari, "Information Diffusion in Social Networks in Two Phases," in IEEE Transactions on Network Science and Engineering, vol. 3, no. 4, pp. 197-210, Oct.-Dec. 1 2016.
16. M. Gong, C. Song, C. Duan, L. Ma and B. Shen, "An Efficient Memetic Algorithm for Influence Maximization in Social Networks," in IEEE Computational Intelligence Magazine, vol. 11, no. 3, pp. 22-33, Aug. 2016.
17. L. Guo, D. Zhang, G. Cong, W. Wu and K. L. Tan, "Influence Maximization in Trajectory Databases," 2017 IEEE 33rd International Conference on Data Engineering (ICDE), San Diego, CA, 2017, pp. 27-28.
18. M. Yu, W. Yang, W. Wang, G. Shen, G. Dong and L. Gong, "UGGreedy: Influence Maximization for User Group in Microblogging," in Chinese Journal of Electronics, vol. 25, no. 2, pp. 241-248, 3 2016.
19. J. Ok, Y. Jin, J. Shin and Y. Yi, "On Maximizing Diffusion Speed Over Social Networks With Strategic Users," in IEEE/ACM Transactions on Networking, vol. 24, no. 6, pp. 3798-3811, December 2016.
20. G. Tong, W. Wu, S. Tang and D. Z. Du, "Adaptive Influence Maximization in Dynamic Social Networks," in IEEE/ACM Transactions on Networking, vol. 25, no. 1, pp. 112-125, Feb. 2017.
21. X. Wang, Y. Zhang, W. Zhang, X. Lin and C. Chen, "Bring Order into the Samples: A Novel Scalable Method for Influence Maximization (Extended Abstract)," 2017 IEEE 33rd International Conference on Data Engineering (ICDE), San Diego, CA, 2017, pp. 55-56.
22. H. Zhang, D. T. Nguyen, H. Zhang and M. T. Thai, "Least Cost Influence Maximization Across Multiple Social Networks," in IEEE/ACM Transactions on Networking, vol. 24, no. 2, pp. 929-939, April 2016.
23. C. Zhou, P. Zhang, W. Zang and L. Guo, "On the Upper Bounds of Spread for Greedy Algorithms in Social Network Influence Maximization," in IEEE Transactions on Knowledge and Data Engineering, vol. 27, no. 10, pp. 2770-2783, Oct. 1 2015.
24. A. Cassidy and A. Nehorai, "Creating influential nodes in a smart building social network," 2015 IEEE International Conference on Smart Grid Communications (SmartGridComm), Miami, FL, 2015, pp. 659-664.
25. J. R. Lee and C. W. Chung, "A Query Approach for Influence Maximization on Specific Users in Social Networks," in IEEE Transactions on Knowledge and Data Engineering, vol. 27, no. 2, pp. 340-353, Feb. 1 2015.
26. L. Shi, H. Tong, J. Tang and C. Lin, "VEGAS: Visual influEnce GrAph Summarization on Citation Networks," in IEEE Transactions on Knowledge and Data Engineering, vol. 27, no. 12, pp. 3417-3431, Dec. 1 2015.
27. W. Zeng, C. Li, B. Feng, N. Yang and Q. Luo, "Discovering Most Influential Social Networks Nodes Based on Floating Influence," 2014 International Conference on Cloud Computing and Big Data, Wuhan, 2014, pp. 144-147.
28. H. Nguyen and R. Zheng, "On Budgeted Influence Maximization in Social Networks," in IEEE Journal on Selected Areas in Communications, vol. 31, no. 6, pp. 1084-1094, June 2013.
29. C. Zhou, P. Zhang, J. Guo, X. Zhu and L. Guo, "UBLF: An Upper Bound Based Approach to Discover Influential Nodes in Social Networks," 2013 IEEE 13th International Conference on Data Mining, Dallas, TX, 2013, pp. 907-916.
30. M. U. Ilyas and H. Radha, "Identifying Influential Nodes in Online Social Networks Using Principal Component Centrality," 2011 IEEE International Conference on Communications (ICC), Kyoto, 2011, pp. 1-5.
31. S.K. Shekar, K.Nagappan, B. Rajendran, “SADI: Stochastic Approach to Compute Degree of Importance in Web-Based Information Propagation” Springer-Computer Science On-Line Conference, pp.331-338, 2017
32. W. Chen, Y. Wang, S. Yang, “Efficient Influence Maximization in Social Networks”, ACM Digital Library, pp. 199-208, 2009

AUTHORS PROFILE

Selva kumar S, received the B.E. degree in Information Science & engineering and M.Tech degree in Computer Science & Engineering from VTU University, Karnataka, India in 2005 and 2008, respectively. Currently pursuing Ph.D. degree in Computer Science & Engineering from VTU University. His current research interests include Social Network Analysis, Information Propagation Analysis, web-based network analysis, Machine Learning.

Dr. Kayarvizhy, completed her Bachelors and Master of Technology in Computer Science from Pondicherry University. She holds a Ph.D. degree from Anna University, Chennai. She has over 13 years of teaching experience. Her research interests include Machine Learning, Data Science, Internet of Things and Software Metrics. She has 20 publications in various international journals and conferences. She continues to foster newer innovations through government grants like VGST in her field of interest.