ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 4, Issue 9, September 2017

Detection and Analysis of Influence by Renowned Leaders in Online Social Networks

[1] Sr.SujathaYeruva
[1] Department of CSc
[1] St.Francis College For Women, Hyd -16

Abstract - **Social networks (SNs) are part and parcel of human life: inhabitants progress, influence and are influenced by their acquaintances. The quantity of knowledge accessible on SNs is gigantic with the advent of World Wide Web, allowing the qualitative exploration of information. Social network analysis (SNA) has been gaining thought from divergent areas like social science, economics, psychology, biology. The swift rise of the net SN sites and their publically procurable knowledge attaining API's has crystallized the prosperity of SNA analysis. Tracing potent users and their influence is one among the trendiest topics of SNA. Contemporary exploration of associations among the members of a SN reveals that through direct contacts individuals influence indirect ones. Substantive data concerning the prestigious users and also the ability to predict them could also be leveraged for many applications. This analysis work employs Pareto Front function to mark the outstanding leaders that is followed by an empirical analysis of the results of their dependable influence.**

Keywords:--- **Influence measure, Pareto front function , Renowned Leaders, Social Networks**

INTRODUCTION

Social Networks(SNs) have been part of human beings right from their existence, as they are born to live in a planet of relations. The hottest explosion of web applications and mobile devices has made online social network(OSN) more accessible than ever before [1]. SNs are formed whenever and wherever individuals interrelate with others. These associations can portray any sort of authorship, friendship, relationship, etc. [2]. Information floods in a network where persons influence each other [3]. People connect with each other beyond geographical and timeline obstructions, shrinking the limitations of physical boundaries in creating new ties [4]. In the last few years the number of users of OSNs gained considerable popularity and grown at an extraordinary rate [5]. One common type of social analysis is the identification of communities of users with related interests, and in such groups the identification of the most "influential" users. A simple notion of influence is that the range of connections, and potent users act as hubs inside their community [1]. SNA has received increasing interest in many different areas in recent years, including role detection [6], community detection [7], etc.

A SN is a directed graph of relationships and interactions within a group of personnel. It plays an indispensable role as a way for the spread of information, ideas, and influence among its contacts [8]. Users are indicated by nodes in the graph and thus the directed arcs between the nodes indicate relations. Edges that are drawn from a node indicate an out-degree of a node. Similarly, the edges that terminate at a node sort the in-degree of the node. In short, the out-degree of a node could be a measure of the influence or expansiveness a node exerts on the other nodes. Similarly the in-degree of a node is an estimate of the extent to it the node is influenced i.e. receptivity or popularity by the rest of the nodes.

SNA area is gaining increasing importance in influencing client behavior, political, religious belief and opinion. Nevertheless transmittance of influence across the network makes for fascinating study [9]. A study of SNs like Facebook, Twitter and YouTube reveals that variety of users can exert colossal influence on an outsize section in areas of endorsing, religious and social values and in disseminating data. The core of the issue is to discover people who exert most influence on a multitude, so that these individuals could be targeted for promoting social awareness [10]. There is a necessity not solely to urge the leaders in each community, moreover classify their levels of leadership, since each leader inevitably influences and directs the thinking and activity inside the community directly or indirectly through his followers. This could be true of the religious, political and notably the business culture at present. Sighting of the copious levels of leadership in each profession could also be adapted to promote individuals from one area to consecutive one or in selecting right people for additional business training contract. Religious and political leaders also can be chosen to impact crucial role for an advancement of dynamic social changes. Once the seeding of a positive thought is completed, with the foremost influencing leaders it's fascinating to analyze and see as what number of their followers needs to be compelled to succeed in the utmost certain inhabitants.

The significance of determining and discriminating the leadership in each given community motivated to look out for a reliable technique of discovering the degree of headship. In the preceding work [11], the primary study to delegate influence in every level with Pareto front function in SNs had been thought of. In this paper undeviating influence on immediate generation has been taken up for study.

Efficient engineering usually necessitates the determination of numerous concurrent conflicting objectives. One of the foremost powerful tools for deciding such objectives in a computational setting is multiobjective optimization [12]. Out of the many strategies to resolve multiobjective optimization issues, Pareto solutions are considered to produce the most effective solution. [13 – 16]. The multiobjective problem considered in this research involves the following two objectives to trace influential nodes (i)As nodes with high out-degree reach out to many other nodes to influence, it is desirable that high ratio of out-degree to in-degree nodes with low in-degree nodes are considered, (ii)while many nodes reach to the high in-degree nodes to influence it is desirable that high in-degree nodes with low ratio of out-degree to in-degree nodes are considered. Leadership is attained in a network by applying the Pareto front function. It produces the consistent Pareto front of a set of points [17]. The expression Pareto front is named after Vilfredo Pareto, who used the concept in his studies of economic efficiency and income distribution [18]. In words, this description explains that Pareto optimal if there be no possible vector of verdict variables x ϵ F which would diminish some condition without causing a simultaneous increase in at least one former condition. This concept almost always gives not one resolution, but instead a set of results called the Pareto optimal set. The vectors equivalent to the solutions incorporated in the Pareto optimal set are called non-dominated. The method of the objective functions whose non-subjugated vectors in Pareto optimal group is called the Pareto front [19]. This study employs the Pareto front function to identify the leaders and their followers in subsequent level. The experimental outcome show that the number of leaders and their influence on immediate generation can gradually decrease. The structure of the paper is as follows: in section 2 related work is presented, in section 3 dataset used and experiments conducted in this analysis work is explored, and in section 4 suggested algorithm and results are discussed, last of all conclusions are drawn in section 5.

II. LITERATURE SURVEY

Masses of people have a propensity to register and partake in OSNs like Facebook, Flickr, LinkedIn, Twitter and MySpace. Facebook alone got 802 million daily active users on average by March 2014 [20]. Revitalization of interest in OSN created numerous researchers to review and contribute for the further analysis. Techweb [21] affirmed that the nearly half of all net users attract amenities in Social networking. Becker, J. A. H., & Stamp, G. H. [22], made a study that primeval face-to-face communication has engorged subsequently to diverse regions of computer-mediated communication. OSNs burgeoned enormous popularity since they were innovated a decade ago. Tian Zhu, et al. reflected the influence intensification problem of discovering a trivial subset of nodes in a SN that could exhaust the possibilities the spread of influence [23].

Malaika B, Farhod P. K [24], have wanted that it absolutely was affordable to work out their competence to have a significant impact on acquisition objectives to “signal”, “benevolence” and “integrity”, consecutively. If e-merchants want to make use of a corporate blog with facial photograph, it's suggested to merge it with the merging of a social networking web site like Facebook so as to flavor up opinions of “benevolence”. Noni Keys, Dana C. OSNs offer a novel platform for product elevation and announcement. Influence intensification problem raised in viral marketing has established a lot of considerations in recent times. Huiyuan Zhang, Thang N. Dinh, and My T. Thai stated that taking advantage of the total number of influenced users is not the primary concern; rather, permitting further activated users clamp positive beliefs is of prime importance [25]. Huiju Park, Hira Cho [26] confirmed the positive relationship among obligation to a SN on-line community and data in search of activities at the neighborhood. This association was anticipated to be qualified by individuals’ sensitivity to cluster conformity. Thomsen and Timothy F. Smith [27] state that Leadership is essential among organizations in facilitating links between the two and in external policy support. It conjointly helps develop data and inspiration for improvement.

Flavio et al used customary models of data spreading to argue that through empirical observation discovered among peers patterns of correlation emerge naturally from a varied kind of subtleties, being primarily independent of the type of facts as how it extents, and even on the category of underlying network that interlocks persons. In addition they demonstrated that the influence of every person will be more widespread when the network is sparser and clustered [28]. The findings of Linyuan lu, Yi-Cheng Zhang, Chi ho Yeung, Tao zhou [29] indicate that on-line communities will intensify the influence of some vary of significant users for the advantage of all completely different users. They used the leadership topology and recognized very important users to develop an adaptable and parameter-free algorithm, the Leader Rank, to measure user influence. Ulrike Pfeil, Panayiotis Zaphiris, Stephanie Wilson [30], offered an analysis of a web support community for older people. They conferred that definite series of messages amid the on-line community are associated to the extent of activity thus providing prized insight in to the role of message series in supporting on-line support communities for older individuals. Bruce Hoppe, Claire Reinelt [31], offer a structure for visualizing numerous forms of leadership networks and uses case examples to sight outcomes typically associated with each kind of network. Statistical frameworks that validate the benefits of forming multiple relations together for every substantive and prognostic functions were developed by Asim Ansari, Oded Koenigsberg, and Florian Stahl [32]. They collectively affirmed that the utilization of knowledge in one relationship that may be accustomed predicts property in another. Keith S. Coulter, Anne Roggeveen [33], specify that closeness to the supply of a persuasive communication have less of an impact in on-line social networks compared to ancient WOM on message acceptance. Shweta Garg, Sanjeev Kumar analyzed the information diffusion behavior of social network by studying the behavior of an infection flow in a social network where it is formed by Erdos Renyi method. This analysis show that if information is required to spread in social networks like Facebook, then it is needed to post on a network of friends with an average degree between 1.0 to 3.5 and the size of network does not matter much more in the speed of information spreading [34].

Amit Goyal, Francesco Bonchi, Laks V. S. Lakshmanan [35], present an innovative frequent pattern mining methodology to figure out leaders and tribes in social networks. Reihaneh Rabbany Khorasgani, Jiyang subgenus Chen, Osmar R. Zaïane [36] conferred an algorithmic program that starts by finding talented leaders in an extreme such networks then iteratively accumulates followers to their close leaders to form communities that later uncovers latest leaders in every cluster and amass followers all over again until convergence. The binary concept technique projected by D. M. Akbar Hussain [37], offers a clear image to seek out the role of a pace setter or follower that's robust to come back to a choice with standard centrality measures. Lars Backstrom, Dan Huttenlocher, Jon Kleinberg, Xiangyang LAN [38] performed a study on the event of informal dependent groups within a massive organization who offers insight into the organization’s overall decision-making behavior.

Sun and Tang pioneered a investigate survey of social influence analysis models and algorithms for measuring social influence. They discussed influence maximization and its application in viral marketing [39]. On the other hand, analytical models have in addition been studied for social networks for an extended time. For instance, work [40] aimed to hunt out the foremost authoritative nodes and build probabilistic models for infective agent promoting, and work [41] tried to hunt out the foremost authoritative nodes in several of the foremost wide studied models in SNA. In [42], authors performed theoretical analysis on information cascades supported random graphs whereas in [43] authors analyzed topological cascade patterns throughout an enormous product recommendation network empirically.

III. DATASET USED AND EXPERIMENTS CONDUCTED

MATLAB R2009a was used to perform the experiments. Within the estimated methodology the social network is represented using a directed graph data structure [44] with nodes representing users and thus the directed arcs between the nodes representing interactions. The edges that terminate at a node is the in-degree of the node. Likewise, the edges that emanate from a node represent the out-degree of the node. Therefore an out-degree of a node is taken into consideration as an amount of influence that the individual node has on totally different nodes, whereas an in-degree of a node is assumed as an amount of influence that a selected node gets by the opposite nodes.

YouTube is one of the predominant social networking site which supports video sharing. Anyone with the Internet access can upload a video which can be viewed instantly by any amount of spectators. It is one of the best video platforms which created lot of impact shaping the large events of the world. YouTube serves as a predominant social network on its own, linking registered users through subscriptions that alert subscribers of social and content updates of the subscribed-to users [45]. General public was encouraged to submit their queries

ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 4, Issue 9, September 2017

using YouTube during CNN/YouTube presidential debates [46]. In response to this people obtained arousing replies from the candidates who framed the election in new ways as visual images are more powerful than any other form of expressions. Seven out of sixteen 2008 presidential candidates publicized their campaign using YouTube [47] which altered the political scenario. Formerly it was used to motivate young voters gradually it affected other demographics and had become more important than direct mail [48]. To investigate social networks and their influence, a sample of data collected through crawls of the user graphs of the YouTube by Alan Mislove; et al [49] is taken. The data set has been anonymized in order to safeguard the privacy of the users. The dataset consists of an edge list, that is, the list of all user-to-user directed links that are enclosed within the crawls. Each line holds two user identifiers separated by a tab, denoting that a link exists from the first to the second. YouTube social media's registered users can subscribe content updates of other prominent registered users. Users who are subscribed-to form an in-degree and users whose content had been subscribed form an out-degree. In this manner from the sample data, the out-degree and in-degree of each node is calculated and therefore the node that encompasses a minimum of one out-degree is taken into account for empirical study. 5,69,913 distinctive nodes match this criterion and are thought-about for added investigations. Among the initial spherical it had been discovered that the in-degree of few nodes was zero. The nodes with in-degree zero are people who will influence others however don't seem to be influenced by others. They're the absolute leaders inside the community. The nodes with in-degree as zero and their followers are eliminated from the sample data thus discriminate and confirm future level of their followers.

The degree of reachability of a node determines the amount of influence a node will have on others. Nodes with high magnitude relation of out-degree to in-degree reach out extravagantly and are extraordinarily potent. Further the nodes that have high in-degree might influence several completely different nodes as they'll propagate the influence that they received from different nodes. To trace the leaders Pareto front function is applied. Pareto front function produces the coherent Pareto front of a set of points. Thus, with the assistance of the Pareto front function set S leaders are picked up as S= {(x, y) | x<xi ∀ xi and y<yi ∀ yi for i=1 to n} where x is the rank of the in-degree (ID) and y is the ratio of the ranks of out-degree (OD) to in-degree with i ranging from node 1 to node n. This is been depicted in Fig.1 where Pareto set of leaders are highlighted in green. Therefore the primary level of non-absolute leaders and their followers are discovered and removed to reckon future level of leaders in conjunction with their followers in three different cases as discussed above. The strategy is perennial until there aren't any important sorts of followers left among the overall population.

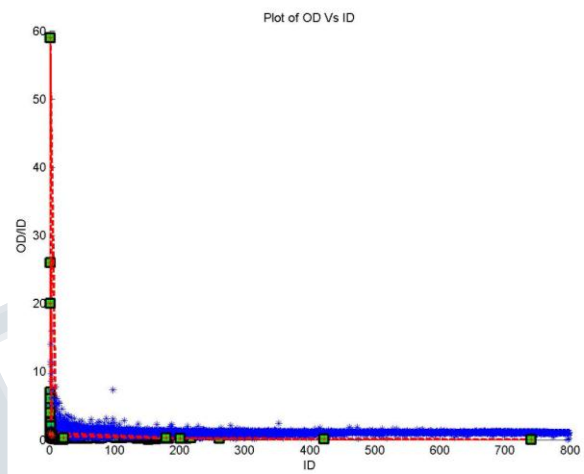

Fig.1.Leaders depicted from Pareto front

IV. PROPOSED ALGORITHM AND RESULTS

From the static set of users influential leaders were computed using Pareto Front function. Followed by it their followers were considered after eliminating the predecessors at each level. Two cases of analysis of tracing the leaders were considered. In the following sections these cases are described in where Tables 1 and 2 are the outcome of the analysis of the two cases.

A. Case 1:

In the first case leaders along with their followers were detected and eliminated from the original set of nodes. From the remaining set of nodes the same course of action is considered. It's procedure is as follows:

Step 1: Calculate the out-degree, in-degree of all nodes. Categorize the nodes with in-degree zero. They are the born leaders.

Step 2: Calculate the ratio of out-degree to in-degree and the ranks of in-degree and ranks of the ratio of out-degree to in-degree.

Step 3: Apply Pareto front function to find leaders from the ranks that were calculated in step 2.

Step 4: Find the followers of the leaders found in step 3

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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Vol 4, Issue 9, September 2017

Step 5: Remove the leaders and followers that were found in steps 3 and 4
Step 6: Repeat Steps from 2 to 5 till there are no significant number of leaders and followers left in the total population.

Levels	Leaders	Followers	% of Accumulated Leaders	% of Accumulated Followers
1	14	71918	0.002	12.62
2	18	26988	0.006	17.35
3	20	18852	0.009	20.66
4	29	18875	0.014	23.97
5	23	12480	0.018	26.16
6	26	12221	0.023	28.31
7	31	10532	0.028	30.16
8	32	11592	0.034	32.19
9	32	9309	0.039	33.82
10	36	9034	0.046	35.41
11	38	9327	0.052	37.05
12	36	7423	0.059	38.35
13	46	9902	0.067	40.09
14	44	8048	0.075	41.50
15	46	7715	0.083	42.85
16	54	9372	0.092	44.50
17	51	8672	0.101	46.02
18	50	7251	0.110	47.29
19	51	6262	0.119	48.39
20	50	6417	0.128	49.51
21	50	5826	0.136	50.54
22	46	4946	0.144	51.40
23	52	5859	0.154	52.43
24	49	5467	0.162	53.39
25	55	5969	0.172	54.44
26	53	5305	0.181	55.37
27	53	5242	0.190	56.29
28	53	5049	0.200	57.18
29	48	4287	0.208	57.93
30	57	5098	0.218	58.82
31	62	5180	0.229	59.73
32	60	4709	0.240	60.56
33	57	4251	0.250	61.30

Table 1. Leaders and their subsequent Followers

Table 1 depicts the outline of the experiment in case 1. Significant leaders were figured out using Pareto Front function. Subsequently their followers up to 33 generations were considered after eliminating their predecessors at each level till there were no more significant nodes left in the original set.

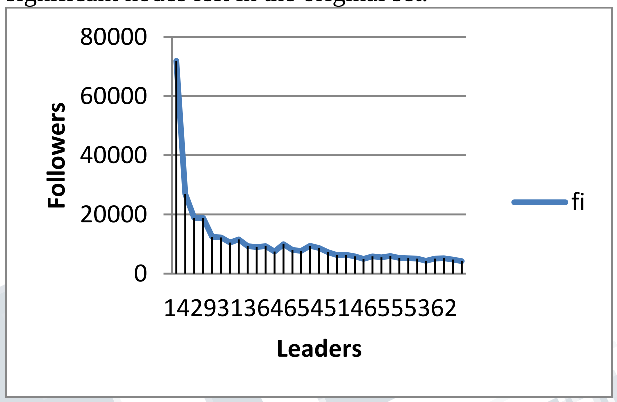

Fig 2. Followers influenced by their leaders at each level

The influence of leader nodes monotonically decreases down the levels. This is depicted in Fig. 2. After the initial level of influence there is a very negligible growth in influence within the consecutive generations. Fig. 3 depicts the cumulative percentage of the leaders along with their followers.

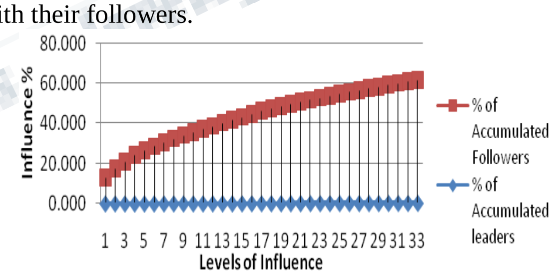

Fig.3. Cumulative Percentage of Influence between Leaders and Followers

B. Case 2

In the second case, leaders, followers and the consecutive followers of followers till the discovery of significant number of followers were detected and eliminated. It's procedure is as follows:

Step 1 to 4: Same as in case 1
Step 5: Remove the leaders that were found in steps 3
Step 6: Find out the followers of the followers found in step 4
Step 7: Remove the followers that were traced in step 6

Step 8: Repeat Steps 6 to 7 till there are no significant number of followers left in the total population.

Node Type	Number of influential nodes	Accumulated percentage of influential nodes
Leaders	14	0.001
Followers1	71889	6.316
Followers2	386518	40.265
Followers3	473433	81.849
Followers4	143949	94.493
Followers5	38403	97.866
Followers6	10499	98.788
Followers7	2751	99.030
Followers8	815	99.102
Followers9	199	99.119
Followers10	57	99.124

Table 2. Leaders and their subsequent Followers

Table 2 depicts the outline of the experiment in case 2. With Pareto Front function significant leaders were figured out and subsequently their followers up to 10 generations were considered after eliminating their predecessors at each level.

The influence of leader nodes and their followers gradually declines. After the initial level of influence there is a very negligible growth in influence within the consecutive generations. This is depicted in Fig. 4.

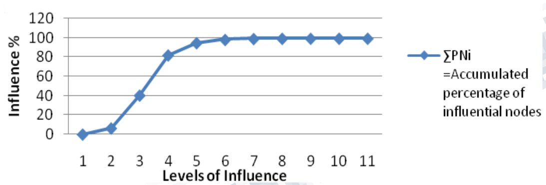

Fig.4.Accumulated percentage of influential nodes

C. Comparison among the cases

In case 2 it takes 2 generations to cover the population of 40.265% where as in case 1 it takes 13 generations to cover 40.152% of the population.

Case	No. of levels	% of Influence
1	13	40.152
2	2	40.265
2	10	99.124
1	33	61.30

Table 3.Comparison of Influence between Case 1 And 2

In case 2 by 10 generations it can cover 99.124% of the population whereas in case 1 even after 33 generations only 61.30% of population is covered. Therefore case 2 is best when comparing among case 1 and case 2. This comparison is drawn from tables 1 and 2 is depicted in table 3.

CONCLUSION

With the exploitation of data sets publicly availed and procured online for the research community an analysis of the users of OSNs is carried on. Experiments of the study determine that at the highest level there are very few central users who make high impact on colossal amount of inhabitants which is the strength of this study. Each consequential level of followers has diminishing range followers influenced by them. In order to have an enormous amount of impact on the society, it is enough to consider few important users who in turn can influence their followers. Results of this work can be employed to determine eminent leaders of a SN who play a most important role in influencing massive amount of people. The detection of such promising leader groups help in several areas like, in commerce promoting prominent persons who could enhance major growth of a business community; skilled leaders of assorted faculties in spreading the information; religious, political and social leaders in haulage of fundamental social improvements. Work was aimed solely using a static data on users who produce an influence on their immediate followers and their successive followers. This effort can be further progressed on real-time and dynamic data with multiple platforms subjected to a specific domain and study how the percentage of influence of various users would reach.

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