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Identifying Influential Users in Facebook - A Sentiment Based Approach

S. Raamakirtinan* and L. M. Jenila Livingston

School of Computing Science and Engineering, VIT University, Chennai Campus, Vandalur-Kelambakkam Road, Chennai - 600127, Tamil Nadu, India; raamakirtinan.s2013@vit.ac.in, jenila.lm@vit.ac.in

Abstract

Objective: Identifying influential users in online communities is important in the era of social networking. For example it is extremely helpful to promote product/campaign or immunize rumors among its members. **Method:** In this paper we propose a hybrid approach where influential rank of a user is calculated using a Sentiment Weighted Page Ranking Algorithm (SWPR). The core logic behind this methodology is, any interaction between two nodes is taken into consideration and its associated sentiment is calculated. Then it considers degree centralities for general rank calculation and the sentiment associated of a user is fed as its 'weight'. **Findings:** After experimenting our proposed methodology with 532 nodes and tracing the data, it's inferred that infection spread by top 10 users ranked by SWPR is higher and faster than page rank influential users. The newly proposed ranking methodology exceed spreading rate when compared with other traditional network metrics and other ranking methods. Further interpreting the data, we also see that infection rate varies based on context of the data. Mostly it was sentiment driven and for few cases it was context driven with mild effect of underlying sentiment. The experimental results show that, considering users associated sentiment as weight, gives much more accuracy than traditional ranking methods. **Improvement:** Our proposed algorithm performs better by identifying influential users more accurately than other methods. As the accuracy improved, the campaign and product promotions reached faster to desired members.

Keywords: Influential Analysis, Information Diffusion, Sentiment Analysis, Social Media, User influence

1. Introduction

In the area of social network analysis, influential analysis has become the predominate area of interest among researchers[1]. Organizations of all sizes from small firms to large multi-national corporations are now using social media for improving their businesses[2]. A social networking site like Facebook is just a reflection of social structure and its ties[3]. Being a popular site, it has become a right platform for marketing too. Earlier marketing in social media was done by searching for an expertise in that field or finding the most important social media pages and marketing though them[4-6]. But now a days companies are interested to market only to potential buyers and also to people who will potentially influence (spread their product) to a larger audience, through word of mouth[6]. But the underlying challenge here is, to find right set of users in social network who can effectively spread the information. To find appropriate list of people for marketing, each user in social network is weighed based on a score named influential score and top 'n' users whose influential score is high is targeted for marketing.

There were many methods proposed by various researches to identify the influential users and rank them. Most of the work done in influential user analysis where using link analysis method. Link analysis is the method of tracing the connections between the objects to develop models based on the patterns in the relationships by applying graph theory techniques[7]. We will have brief look at their works.

Kempe et al. showed that optimal solution for finding most influential nodes is NP-hard, but a natural greedy algorithm can approximate the optimal solution[8]. In the same year Campbell who was working on Expertise

** Author for correspondence*

Identification in Email network, compared two algorithms: context based approach and graph based ranking algorithm (HITS). After comparing rankings provided by both algorithm using precision and recall measures, it was found that the graph based algorithm performs better than context based algorithm[5]. In later years, it was observed that different topics propagate differently in networks[9]. To address this topic-level social influence, Topical Affinity Propagation (TAP) was proposed[10]. This TAP model is capable to take results of any topic modeling and the network structure to perform topic-level influence propagation. Whereas Kitsak et al. demonstrated that efficient spreaders are located within the core of the network and can be identified using k-shell decomposition analysis[11]. In later point of time, Eirinaki et al. proposed a ranking mechanism called Profile Rank, which basically considers popularity parameters of a profile like, number of friends, testimonials, number of profile views etc[12]. Later Spread Rank algorithm using CTMC-ICM model was proposed. This uses Continuous-Time Markov Chain (CTMC) into the Independent Cascade Model (ICM), through which influential node set was extracted effectively than distance-based centrality metrics[13]. But this method was not scalable for huge data sets.

Page and Brin founders of Google, proposed a ranking algorithm to rank and sort pages on web, which was a huge success[14-15]. Here in this paper we extend this algorithm to find influential user in social networks by using a hybrid technique to improve accuracy of influential score.

2. Proposed Methodology

As we discussed in previous section, most of the methods handled to identify influential spreaders were mainly based on social network structure. And few were trying to narrow down influential user using based on user's content in the network. Here, we hypothesis that considering users network structure as well as its content for analysis will help to find influential users more accurately. This is achieved by adding appropriate sentimental scores as its weight to the centrality measures. We chose Facebook as platform for our research as it is rated as the top platform among its peers like Twitter, YouTube etc[16]. As shown in Figure 1, the proposed architecture has the following components.

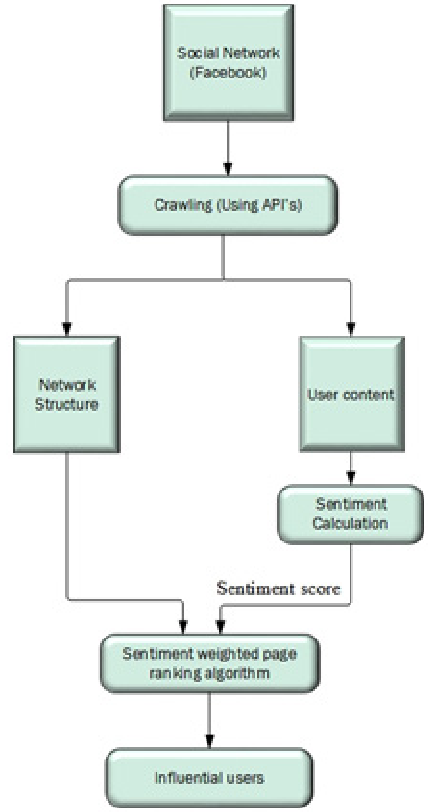

Figure 1. Complete architecture of proposed methodology.

2.1 Crawling:

To find influential user, the foremost step is to get data from online social networks. Now in this work we consider our social network as Facebook. These days Facebook has started giving API keys to crawl publicly available data and own data private data. This can be achieved by using Graph API. Here in this context, we restrict our network extraction to a set of friendship network alone for purpose of experimentation.

2.2 Network Structure

Figure 2. Crawled network structure.

The crawled data itself basically forms network structure (G). For the ease of explanation we can formulate that G= (V, E). Here, vertices (V) are the nodes of the network and edges (E) represent the relationship between two nodes. In real world scenario vertices represent users and edges represent relationship (friendship) between the users as shown in Figure 2.

Here all the dots represent vertices/user (V) and the lines between them are the relationship/edges (E). Also it can be observed that, it has three major clusters. Each node in this cluster will have different influencing score based on their position and sentiment associated to it. We will see this detail in experiential section of this paper.

2.3 User Content

Apart from crawling user's network, their own posted data like status update, shared post and replies to any of the post posted are also crawled for sentiment calculation. Figure 3 shows a user's post and its responses. To elaborate, all the contents (data) of users who were present in network structure, has to be crawled. In this case we user 'Facepager' tool to crawl the user content.

Figure 3. Sample user content with varying sentiment (users are anonymized for privacy reason).

2.4 Sentiment Calculation

Machine learning based classification provides an accurate prediction and also improves the performance of the results[17]. Hence we use Microsoft Azure ML to calculate sentimental score[18]. And sentiment analysis can be implemented by using both supervised approach and unsupervised approach[19]. Here we employ supervised approach as we have already have data set in repository. Sentiment is calculated as per the flow shown in Figure 4.

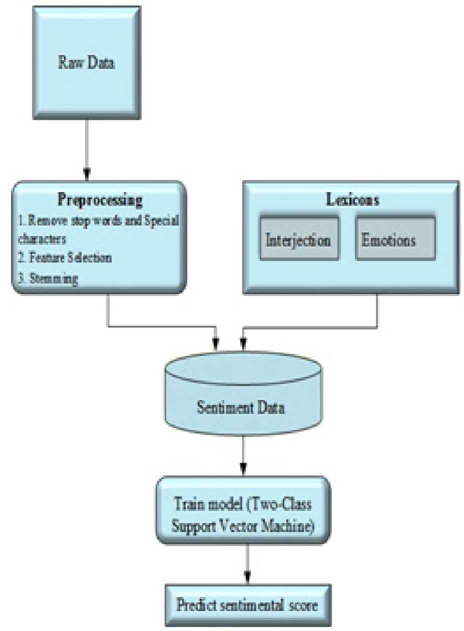

Figure 4. Sentimental score calculation.

2.4.1 Pre-processing

In this step unimportant things like stop words, special characters and digits are removed. Further the data is stemmed. i.e., reducing inflected (or sometimes derived) words to their word stem, base or root form. Parallel to stemming "Feature selection" is also done. Feature selection is the process of selecting a subset of relevant, useful features for use in building an analytical model. It helps to narrow down the field of data to most valuable field.

2.4.2 Lexicons

In social network we will be frequently encountering 'interjection words' (Ex: Aah!, aww, hmm, phew etc.,) and also 'emotions s' (Ex: ☺,☹,:-P,:-0 etc..,). These interjections & emotions cannot be identified by the system by default. Hence these words and its associated sentiment will be passed to repository where mapping between words and its lexicons will be mapped.

2.4.3 Sentiment Data Repository

It is place where the data is placed after all pre-processing is done and the data is staged for sentimental score calculation.

2.4.4 Training the System

To make the system calculate sentimental score of a post, initially it must learn from few sample data. Here we use supervised learning techniques where the sample data maps to positive/negative/neutral sentiment associated. In this process, data is evaluated by the machine learning algorithm, which analyzes the distribution and type of the data, looking for rules and patterns that can be used later prediction. Here we use Two-Class Support Vector Machine algorithm to train and score the data. Data is split into two sets 80% training set and 20% test set and model is trained.

2.4.5 Sentiment Score

After training the model, it is tested with rest of 20% data and its accuracy of sentiment score is measured. And if accuracy is below threshold level, it's re-trained with fresh set of data and tested again until it meets the threshold level of accuracy. Here we set 85% as threshold level. After the system has become accurate enough, real data set is applied and its sentiment score is obtained. At this stage we have sentimental score of each user in the system.

2.5 Ranking Algorithm

This is the core part of the model where influential user is calculated. As we discussed in section 2, there were several algorithms have been developed to find most influential user. Here we propose sentiment weighted page ranking algorithm (SWPR) where user's sentimental score is the key metric.

2.5.1 Sentiment Weighted Page Ranking Algorithm

In this model, similar to page rank, we propose a ranking where sentiment is added as its weight. Here are the basics for SWPR algorithm, i.e., all users are considered as nodes and links between users are treated as edges. In this calculation, we consider our graph as bi-directional graph rather than an undirected one. Because although a link exist between two users in social network, only in few cases there are people (Ex: celebrities) where they are massively followed and in turn, they do not follow their fans. Most cases friendship/link exists bi-directionally and we consider them primarily.

The basic ideology of this SWPR algorithm is that, there are many cases where a person with high link count (or) influential score which is solely calculated based on network structure alone doesn't correspond to our common sense notion of importance. The reason is all though the relationship (links) may have created long ago with a varying sentiment (most likely with a positive sentiment) and will continue to exist till now. But at present it's most likely that sentiment between those two users might have changed to either negative or highly positive. It's known that a person will get influenced only if he/she has positive sentiment towards that person. And as sentiments vary based on time period, influential score too vary (as its dependent on sentiment). Hence, here algorithm works with the logic where influential score is co-related to sentimental score.

A simple example is that, supposing if user X is having negative sentiment towards user Y or Z, then X will not promote/spread the message of Y or Z. In other case if X was having neutral sentiment towards Y or Z and if their relationship moves towards a strong bonding over period of time, then X will definitely be influenced by Y or Z and will strongly recommend the messages from Y and Z. This relationship strength is detected based on interaction between X, Y and Z. And this interaction score is measured here as sentimental score.

So to summarize, the algorithm considers all back links of users into account and prorogates rakings through links. To simplify a user will be ranked as most influential user if sum of ranks of its backlinks influential rank is high. Then here too we can say that a user may not keep on following all the feeds a particular user or particular users friend list and get influenced. That is after following few back links, a person may randomly jump to other users any follow them. This probability is also assumed to be 0.85 (similar to original page ranks damping factor value). By considering all the above factors we can model influential score of a user as

$$IF(U) = \frac{1-d}{N} + d\sum_{U_i \to U} \frac{IF(U_i)}{L(U)} * SW_{(Ui)}$$

Where,
U = User
IF(U) = Influential score of user
L(U)= Number of followed
$U_i \to U$ = backlinks of all followers
d = damping factor (0.85)
N = total number of users considered for ranking

In this algorithm the value for 'SW' variable is calculated as below

$$SW = \frac{S_{S(U_i)} - \min(S_S)}{\max(S_S) - \min(S_S)}$$

where $S_{s(U_i)}$ is given as

$$S_{S(U_i,U)} = \frac{Sentiment\ of\ U_i\ on\ U}{\sum Sentimental\ score\ in\ system}$$

Here is the pseudo code of algorithms used

SWPR Algorithm

Input: Graph file (G) of users with their inter-connections and array of its associated weights S (u)

Output: An N element array which represents SWPR for each users

Step 1. Initialization d → 0.85; N←Number of users in G

Step 2. For all u in G do

Step 3. IntSPR(u) ← 1/n /*Initialize rank*/

Step 4. If u has valid sentiment score then

Step 5. IntSPR(u)←IntSPR(u)*S(u) /*Add sentiment weight*/

Step 6. End for

Step 7. While SWPR not converging do

Step 8. d_u←0

Step 9. For each u in G with no outlinks do /*In case of celebrities*/

Step 10. $d_u \leftarrow d_u + d * \left(\frac{IntSPR(u)}{N}\right)$

Step 11. End for

Step 12. For each u in G

Step 13. NewSPR(u)←$d_u + \left(\frac{1-d}{N}\right)$ /*for random jumps*/

Step 14. For all u in G with inlinks do

Step 15. NewSPR(u) ←NewSPR(u)+ $d^* \frac{IntSPR(iu)}{Outlinks(iu)}$

Step 16. End for

Step 17. End for

Step 18. IntSPR←NewSPR /*update new rank on every irritation*/

Step 19. End while

Sentiment Weight Calculation

Input : Node ID and its associated raw data

Output: Sentimental score for each node id

Step 1. Read raw data from repository

Step 2. Train and test the system with 80:20 using known 'sentiment to data' mapping

Step 3. S_i←0

Step 4. For all Ni in Repository

Step 5. use "2 class support vector model" to rate sentimental score /*Sentimental score cal*/

Step 6. S_i←S_i+S_{Score} /* S_{Score} is output of support vector model*/

Step 7. If Ni has sub-comments

Step 8. Go to step 5

Step 9. N_i←N_{i++}

Step 10. End for

Step 11. For all Ni whose sentimental score is not NULL /*Sentimental score normalization*/

Step 12. $S_i \leftarrow \frac{S_i}{\sum Sentimental\ Scores}$

Step 13. $SW_i \leftarrow \left(\frac{S_i - \min(S_{Score})}{\max(S_{Score}) - \min(S_{Score})}\right)$

Step 14. Return N_i, SW_i /*Return node_id and its sentimental weight*/

Step 15. End for

As we said in the start of this paper, we use the calculated sentiment score $S_{(U1,U)}$ as a weight to influential score calculation IF (U) to find precise influential user. And it is to be noted that this parameter is evenly distributed based on number of people, the particular user is following. Figure 5 is simple demonstration flow of sentimental score among various users.

For example, if a user (node) is found to have sentimental score of 100 in sentimental score calculation phase, then if the user is following 2 users, then the sentimental score is divided into two and each user is weighted with a sentimental score of 50. That is sentimental score is equally split based on number of people the current user is following. The same scenario is represented in Figure 5.

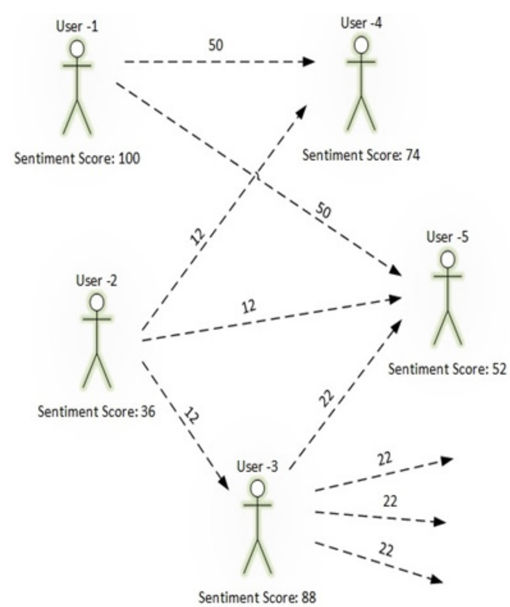

Figure 5. Illustration of Sentiment score distribution.

3. Experiments and Results

It's inferred that, some users play more active role in distributing content than others[20]. Thereby to evaluate spreading influence of this proposed method we compare the information diffusion rate with other ranking methods. In this as specified in the architecture, initially Facebook network data is crawled using API's. Table 1 portrays network properties taken for this experiment.

Table 1. Network attributes taken for this experiment

Facebook friends network	
No of nodes	532
No of edges	16851
Avg Degree	63.35
Graph Density	0.119
Avg Clustering Coefficient:	0.57

And now crawled network structure is kept aside temporarily and data (wall posts, likes and comments) associated to nodes are crawled. After this crawling is over, we will be having raw data (natural language) associated for each nodes in the network. Now that before performing sentiment analysis, as specified in Figure 4, cleaning and cleansing (pre-processing) is done. Here Table 2 lists the quick representation of sample data before pre-processing.

Table 2. Raw data retrieved - Example

Node_ID 253 Post:	**At rallies in UP &Uttarakhand, Narendra Modi said that time for negative politics is over. Cong must change anti-poor mindset #politics**
Node_ID 154 response:	I wish modiji for bihar election to get clear majority, Jay hind!!!
Node_ID 98 response:	Yeppy…..Well said namoji,BJP will win Bihar also
Node_ID 45 response:	Errr….When BJP was in opposition it did not allow to pass GST bill vital fir the nation's economy. Now its preaching congress

Supposing if we consider Node_Id: 253, data is processed as part of preprocessing step stop word and special characters like.., '!!!',&' etc., are removed. Word stemming is carried out in next step (Ex: 'rallies' to 'rally', 'preaching' to 'preach'). In further steps interjections are converted to respective sentiments. And the data is stored in repository for sentiment analysis. Finally this pre-processed data from repository is processed using Microsoft's Azure ML's 'Two class support vector model'. Before processing actual data this model is pre-trained using 80:20 ratio of training and test set. Once the model is trained and tested enough, actual data from repository is feed and its associated sentiment is obtained.

It is to be noted that each positive sentiment associated data is marked with +2, neutral sentiment with +1 (based on hypothesis that, the effort to write a non-negative post on the topic, the user is positively contributing to the spread of news about the subject) and negative sentiment with 0. The same is denoted by $w_+ = +2$, $w_0 = +1$ and $w_- = -2$. Below stated Table 3 showcases data after sentiment and topic categorization for the post mentioned in Table 2.

Table 3. After sentiment and topic categorization of table2 data

Node_ID 253 Post Category	**: Political**
Node_ID 154 response's sentiment score	: +2
Node_ID 98 response's sentiment score	: +2
Node_ID 45 response's sentiment score	: -2

Apart from sentiment calculation, post categorization is also done using bag of words model (BoW), which will help to identify "which user is influential in which topic". And Figure 6 show cases, how edge weight mapping is done. For example in this Node_ID: 235, edge weight (sentiment value) with varying polarity is obtained based on its interaction with various other nodes. This same procedure applied for the next node and is iterated for all users data continuously until, complete sentiment classification is done.

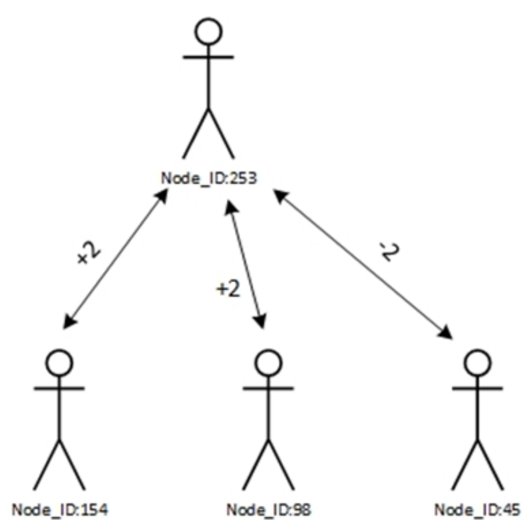

Figure 6. Edge weight mapping.

Once all edges sentiment is calculated, there will be edges with varying sentimental weights ranging from negative to positive values. To achieve standardization, unity-based normalization is carried out as per the formula

$$\textit{Sentiment Weight} = \frac{S_S - \min(S_S)}{\max(S_S) - \min(S_S)}$$

Where, S_S is the sentiment score which was previously calculated. Once this is applied we get edge weight values ranging from 0 to 1. Below Table 4 lists sample edges with its sentiment weight and unity-based normalization applied .

Table 4. Sample edges with its sentiment weight applied

Edge Id	Source Node	Target Node	Sentiment Weight
1478	Aasif Hameed	Ayyappan Chandran	0.4
1525	Aasif Hameed	DileepUdayakumar	0.2
1510	Aasif Hameed	GunasekaranRan-gasamy	0.01
1505	Aasif Hameed	SunilrajSudhakar	0.55
1501	Aasif Hameed	Vijay Bose	0.3
6442	AathiSeshan	Swathe Siva	0.8
2283	AathitiyanSomu	DileepUdayakumar	0.2
2295	AathitiyanSomu	Hara Ganesh	0.9
2238	AathitiyanSomu	SaravananThangavelu	0.68
2267	AathitiyanSomu	SunilrajSudhakar	0.55
895	Abishek Raju	Venkat Ram	0.7
8832	AnandBalakrish-nan	DileepUdayakumar	0.2
8788	AnandBalakrish-nan	Raja Vignesh	0.6
8804	AnandBalakrish-nan	SunilrajSudhakar	0.55
8786	AnandBalakrish-nan	Vijay Bose	0.3
8806	AnandBalakrish-nan	Vishnu Jayavel	0.5
15506	Anand Shan-mugam	Swathe Siva	0.8

At this stage, we have got all necessary data to compute the influential user based on proposed ranking methodology. So on applying the proposed ranking IF (U) algorithm we get users ranked based on sentimental weight obtained. This Table 5 listed below contains top 10 users who are ranked by various ranking methods including SWPR algorithm .

Table 5. Top 10 influential ranked users, by various methods

Node Id	Node Label	SWPR	PR	BCR	CCR
317	Suresh Raaj	1	1	1	1
500	Vidhya Ranganathan	2	3	6	3
512	VimalVijayan	3			
383	SakthiVel	4	6	3	9
419	Senthil Kumar	5	10	4	
257	Naveen Kumar	6	9	2	8
206	LoganathanSub-ramani	7			
20	Anandamurugan-Selvaraj	8			
376	Sadeesh Tirunelveli	9			
355	Ramnath Sam	10			
85	Dileep Udayakumar		2	5	2
90	Dinesh Prabhu		4	8	4
472	Sunilraj Sudhakar		5	7	5
180	Kathirvel Sengodan		7	10	6
399	SaravananThan-gavelu		8	9	7
508	Vijay Bose				10

Legends
- SWPR - Sentiment Weighted Page Rank
- PR - Page Rank
- BCR - Betweenness Centrality rank
- CCR - Closeness Centrality Rank

2.6 Comparison with Various Ranking Methods

With the above list of top ten influential users, a simple Susceptible-Infected (SI) model based evaluation was done. That is, top 10 ranked influential users in each method were asked to promote two types of content (a). A electronic gadget based post and (b). Political post. Then its spending influence (infection rate) is analyzed.

Upon tracing the data, it's inferred that infection spread by top 10 users ranked by SWPR is higher and faster than page rank influential users. The newly proposed ranking methodology exceeded spreading rate when compared with other traditional network metrics like betweenness centrality and closeness centrality too, this can be seen in Figure 7 and Figure 8. Further interpreting the data, we also see that infection rate varies based on context of the data. This difference can be noted by comparing Figure 7 and Figure 8. Here both the graphs are plotted under same set of top 10 ranked users, but the infection time varies.

In Figure 7 we see that, after initializing the process, spreading rate chosen based on other ranking methods lags a bit in start of the process but SWPR takes a great lead at start and continues the trend .

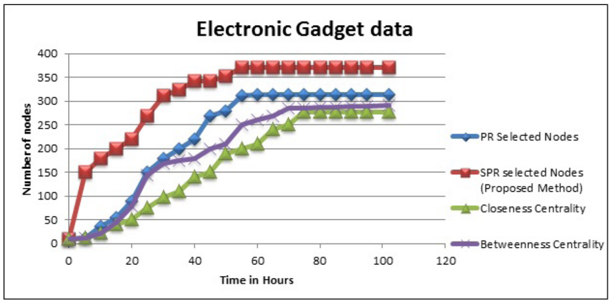

Figure 7. Comparison between various ranking methods for electronic gadget data post.

Also we note that in political data (Figure 8), SWPR initial spreading rate is slightly lower than electronic gadget data, but latter picks up the similar trend as that of electronic gadget data.

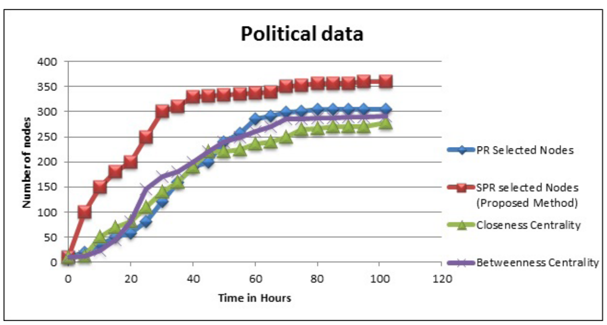

Figure 8. Comparison between various ranking methods for political data post.

These above graphs gives us an impression that, same user behaves differently based upon the context of the post. That is, a user doesn't get infected for few contexts and gets infected faster for few of the post. This purely depends upon user's personality. This personality can be partly categorized based on the sentiment data obtained in initial phase of this test. If we get more sentimental data relating to a particular context (in this case political data), we will be able to infer that particular user is more interested in 'political' topics and political data can be promoted to that user instead of other context related data. The same applies for all other context post too.

4. Conclusion and Future Works

From the above formulation, experimentation and results we infer that, the rate of diffusion increases as more of one's friends adopt the message. And to identify influential users accurately network structure and user positions isn't alone enough. Considering and processing users content (wall posts & it's sentiment) along with network structure gives much more understanding about user to the system. This made the algorithm to narrow down the influential users more precisely when compared to other methods.

In future work we would like to examine that if this method can still be improved further by taking into account of frequency of user's status updates, user's activeness and profile information along with this data set. Another interesting dimension for exploration is that, integrating the above ranked users along with sentiment repository by building a customized recommendation system using 'multiple intelligence theory', as this might be greatly suited for efficient marketing.

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