

Anasis on Vitality Ranking In Social Networking Services : A Dynamic Network Perspective

J. Swapna Priya¹, Koppolu Venkatesh²

koppolu.venkatesh6994@gmail.com

ABSTRACT

Several users keep interacting with one another on a daily basis. One fascinating and necessary downside within the social networking services is to rank users supported their vitality in a very social networking services are current at several on-line communities like twitter.com and weibo.com. Associate in nursing correct ranking list of user vitality may benefit several parties in social network services like the ads suppliers and web site operators. Though it's terribly promising to get a vitality-based ranking list of users, there square measure several technical challengers because of the big scale and dynamics interactions among users on social networks. Samples of social network embrace however don't seem to be restricted to social networks in micro blog sitesand academic collaboration networks.

Keywords : Distributed Systems, Checking Data, Social Networks, User Activity and Security.

I.INTRODUCTION

Social networking is major role in this generation. It is very important to develop the web technology. Social networking frequently used at many online platforms. Social networking is make easy to building of social relations among users, share interest, activities, background working and physical connections. Some services are users to connect with each other. In this generation Facebook and Twitter is the most famous social networking sites in all over the world. People instantly using this social networking sites. There are different types of social media available in this social networks. A user can getting updates about connected friends postings, comment the postings and retweet the postings. Within the time period millions of users posting such as images, audio, videos and commenting at these social media sites.

One of the important and interesting problem in this social media networking is how to rank to users on their growing with historical data. Accurate ranking of users will provides many applications in social networking sites. Social media advertisements provides better strategy to follow their ads ranked vitality of users. While it is very promising for many parties vitality ranking of users. There are many technical problems to taken in this social networking. First, we could not only study about the user interactions with others. Also need to other user interactions collectively. If one user can interact with too many user interactions with in the time period. We may conclude different vitality of the users when most of his friends. Second, Scale of social networking is increases, it becomes more challenging user vitality ranking. Because of large number of nodes to be increases of an individual node. Third different many online sites evolve over time, the vitality of users also get change over time.

Thus the efficient methods needed to obtain the vitality of users at different times.

LITERATURE OF SURVEY

Authoritative Sources in a Hyperlinked Environment

[24]: The network structure of a hyperlinked environment can be a rich source of information about the content of the environment, provided we have effective means for understanding it. We develop a set of algorithmic tools for extracting information from the link structures of such environments, and report on experiments that demonstrate their effectiveness in a variety of contexts on the World Wide Web. The central issue we address within our framework is the distillation of broad search topics, through the discovery of —authoritative information sources on such topics. We propose and test an algorithmic formulation of the notion of authority, based on the relationship between a set of relevant authoritative pages and the set of —hub pages that join them together in the link structure. Our formulation has connections to the eigenvectors of certain matrices associated with the link graph; these connections in turn motivate additional heuristics for link-based analysis. While our techniques are not specific to the www, we find the problems of search and structural analysis particularly compelling in the context of this domain. The www is a hypertext corpus of enormous complexity, and it continues to expand at a phenomenal rate. Moreover, it can be viewed as an intricate form of populist hypermedia, in which millions of on-line participants, with diverse and often conflicting goals, are continuously creating hyperlinked content. Thus, while individuals can impose order at an extremely local level, its global organization is utterly unplanned—high-level structure can emerge only through a posteriori analysis. Our work originates in the problem of searching on the www, which we could define roughly as the process of discovering pages that are relevant to a given query. The quality of a search method necessarily requires human evaluation, due to the subjectivity inherent in notions such as

relevance. We begin from the observation that improving the quality of search methods on the www is, at the present time, a rich and interesting problem that is in many ways orthogonal to concerns of algorithmic efficiency and storage. In particular, consider that current search engines typically index a sizable portion of the www and respond on the order of seconds. Although there would be considerable utility in a search tool with a longer response time, provided that the results were of significantly greater value to a user, it has typically been very hard to say what such a search tool should be computing with this extra time. Clearly, we are lacking objective functions that are both concretely defined and correspond to human notions of quality. Ideally, we would like to focus on a collection S of pages with the following properties.

- a. S is relatively small.
- b. S is rich in relevant pages.
- c. S contains *most (or many) of the strongest authorities*.

Fast PageRank approximation by adaptive sampling

[5]: PageRank is typically computed from the power of transition matrix in a Markov Chain model. It is therefore computationally expensive, and efficient approximation methods to accelerate the computation are necessary, especially when it comes to large graphs. In this paper, we propose two sampling algorithms for PageRank efficient approximation: Direct sampling and Adaptive sampling. Both methods sample the transition matrix and use the sample in Page Rank computation. Direct sampling method samples the transition matrix once and uses the sample directly in PageRank computation, whereas adaptive sampling method samples the transition matrix multiple times with an adaptive sample rate which is adjusted iteratively as the computing procedure proceeds. This adaptive sample rate is designed for a good trade-off between accuracy and efficiency for PageRank approximation. We provide detailed theoretical analysis on the error bounds of both

methods. We also compare them with several state-of-the-art PageRank approximation methods, including power extrapolation and inner-outer power iteration algorithm. Experimental results on several real-world datasets show that our methods can achieve significantly higher efficiency while attaining comparable accuracy than state-of-the-art methods. Surveys on PageRank computation can be found in Berkhin and Langville and Meyer. Existing methods are space- and time-consuming when applied to very large graphs. It is therefore imperative to seek efficient methods to accelerate the computation. As a highly efficient and a widely used technique, sampling can make the computation tractable for large-scale data which otherwise could not be processed by ordinary means. Since PageRank is computed from large length of random walks, we can estimate it iteratively after each random walk step by sampling. In this paper, we discuss the use of the non-uniform sampling method for low-rank matrix approximation during PageRank computation in large graphs. The remainder of this paper is organized as follows. It introduces the related work and proposes direct sampling and adaptive sampling for PageRank approximation. It gives the theoretical error analysis of two sampling methods and derives an adaptive sampling rate choosing scheme. Reports the experimental results. Concludes this paper. Random Matrices.

Our methods are based on the fact that if B is a matrix whose entries are independent random variables, then with high probability the spectrum of B will be close to the spectrum of $E[B]$. In particular, the matrix $B - E[B]$ with high probability will have small 2-norm. To understand why this is so, observe that each row of $N = B - E[B]$ is a vector of zero-mean, independent random variables, so that the inner product of any two rows is tightly concentrated around its expectation, that is, 0. In other words, the rows of N are effectively orthogonal making it impossible for a single vector to have nontrivial inner product with many of them simultaneously. Theorem 3.1 formalizes this notion by combining a

very recent improvement by Vu [2005] of the main result in Füredi and Komlós [1981] to bound $\text{Median}(_N_2)$, with a concentration result for $_N_2$ by Alon et al. [2002], based on Talagrand's inequality.

Graph-based Ranking Algorithms for Sentence Extraction, Applied to Text Summarization [21]: This paper presents an innovative unsupervised method for automatic sentence extraction using graph based ranking algorithms. We evaluate the method in the context of a text summarization task, and show that the results obtained compare favorably with previously published results on established benchmarks.

Graph-based ranking algorithms, such as Kleinberg's HITS algorithm (Kleinberg, 1999) or Google's PageRank (Brin and Page, 1998), have been traditionally and successfully used in citation analysis, social networks, and the analysis of the link-structure of the World Wide Web. In short, a graph-based ranking algorithm is a way of deciding on the importance of a vertex within a graph, by taking into account global information recursively computed from the entire graph, rather than relying only on local vertex-specific information.

A similar line of thinking can be applied to lexical or semantic graphs extracted from natural language documents, resulting in a graph-based ranking model called Text Rank (Mihalcea and Tarau, 2004), which can be used for a variety of natural language processing applications where knowledge drawn from an entire text is used in making local ranking/selection decisions. Such text-oriented ranking methods can be applied to tasks ranging from automated extraction of key phrases, to extractive summarization and word sense disambiguation (Mihalcea et al., 2004).

In this paper, we investigate a range of graph based ranking algorithms, and evaluate their application to automatic unsupervised sentence extraction in the

context of a text summarization task. We show that the results obtained with this new unsupervised method are competitive with previously developed state-of-the-art systems.

Graph-based ranking algorithms are essentially a way of deciding the importance of a vertex within a graph, based on information drawn from the graph structure. In this section, we present three graph-based ranking algorithms – previously found to be successful on a range of ranking problems. We also show how these algorithms can be adapted to undirected or weighted graphs,

Context based user ranking in forums for expert finding using Word Net dictionary and social network analysis [9]: Currently, online forums have become one of the most popular collaborative tools on the Internet where people are free to express their opinions. Forums supply facilities for knowledge management in which, their members can share their knowledge with each other. In this regard, the main problem regarding to the knowledge sharing on forums is the extensive amount of data on them without any mechanism to determine their validity. So, for knowledge seekers, knowing the expertise level of each member in a specific context is important in order to find valid answers. In this research, a novel algorithm is proposed to determine people's expertise level based on the context. Ask Me forum is chosen for the evaluation process of the proposed method and its data has been processed in several stages. First of all, a special crawling program is developed to gather data from Ask Me forum. Then, raw data is extracted, transformed, and loaded into a designed database using SQL server integration services. Expertise sharing through Internet applications is considered as the next step of knowledge management for organizations by many scholars. Since available knowledge resources and expertise are limited in organizations, the demands for seeking knowledge from external sources such as Internet are increasing. Nowadays, employees often seek knowledge from

Internet applications for problem solving, especially in industries where finding the best solution is challenging [1, 2]. Some of these applications like forums play an important role in knowledge sharing among their members.

Node Centrality in Weighted Networks: Generalizing Degree and Shortest Paths [16]: Social network scholars are increasingly interested in trying to capture more complex relational states between nodes. One of these avenues of research has focused on the issue of tie strength, and a number of studies from a wide range of fields have begun to explore this issue. 2004; Brandes, 2001; Doreian et al., 2005; reeman et al., 1991; Granovetter, 1973; Newman, 2001; Opsahl and Panzarasa, 2009; Yang and Knoke, 2001). Whether the nodes represent individuals, organizations, or even countries, and the ties refer to communication, cooperation, friendship, or trade, ties can be differentiated in most settings. These differences can be analyzed by defining a weighted network, in which ties are not just either present or absent, but have some form of weight attached to them. In a social network, the weight of a tie is generally a function of duration, emotional intensity, intimacy, and exchange of services (Granovetter, 1973). For non-social networks, the weight often quantifies the capacity or capability of the tie (e.g., the number of seats among airports; Colizza et al., 2007; Opsahl et al., 2008) or the number of synapses and gap junctions in a neural network (Watts and Strogatz, 1998). Nevertheless, most social network measures are solely defined for binary situations and, thus, unable to deal with weighted networks directly (Freeman, 2004; Wasserman and Faust, 1994).

SFP-Rank: significant frequent pattern analysis for effective ranking [6]: Ranking documents in terms of their relevance to a given query is fundamental to many real-life applications such as information retrieval and recommendation systems. Extensive study in these application domains has given rise to the development of many efficient ranking models. While most existing research focuses on developing

learning to rank (LTR) models, the quality of the training features, which plays an important role in ranking performance, has not been fully studied. Thus, we propose a new approach that discovers effective features for the LTR problem. In this paper, we present a theoretical analysis on which frequent patterns are potentially effective for improving the performance of LTR and then propose an efficient method that selects frequent patterns for LTR. First, we define a new criterion, namely feature significance (or simply significance). Specifically, we use each feature's value to rank the training instances and define the ranking effectiveness in terms of a performance measure as the significance of the feature. We show that the significance of an infrequent pattern is limited by using formal connection between pattern support and its significance. Then, we propose a methodology that sets the support value when performing frequent pattern mining. Finally, since frequent patterns are not equally effective for LTR, we further provide a coverage-based significant pattern generation algorithm to discover effective patterns and propose a new ranking approach called Significant Frequent Pattern based Ranking (SFP-Rank), in which the ranking model is built upon the original features as well as the significant frequent patterns. Our

experiments confirm that, by incorporating significant frequent patterns to train the ranking model, the performance of the ranking model can be substantially improved.

Fast montecarlo algorithms for matrices i: approximating matrix multiplication: Motivated by applications in which the data may be formulated as a matrix, we consider algorithms for several common linear algebra problems. These algorithms make more efficient use of computational resources, such as the computation time, random access memory (RAM), and the number of passes over the data, than do previously known algorithms for these problems. In this paper, we devise two algorithms for the matrix multiplication problem. Suppose A and B (which are $m \times n$ and $n \times p$, respectively) are the two

input matrices. In our main algorithm, we perform c independent trials, where in each trial we randomly sample an element of $\{1, 2, \dots, n\}$ with an appropriate probability

distribution P on $\{1, 2, \dots, n\}$. We form an $m \times c$ matrix C consisting of the sampled columns of A , each scaled appropriately, and we form a $c \times n$ matrix R using the corresponding rows of B , again scaled appropriately. The choice of P and the column and row scaling are crucial features of the algorithm. When these are chosen judiciously, we show that CR is a good approximation to AB .

This algorithm can be implemented without storing the matrices A and B in RAM, provided it can make two passes over the matrices stored in external memory and use $O(c(m+n+p))$ additional RAM to construct C and R . We then present a second matrix multiplication algorithm which is similar in spirit to our main algorithm. In addition, we present a model (the pass-efficient model) in which the efficiency of these and other approximate matrix algorithms may be studied and which we argue is well suited to many applications involving massive data sets. In this model, the scarce computational resources are the number of passes over the data and the additional space and time required by the algorithm. The input matrices may be presented in any order of the entries (and not just row or column order), as is the case in many applications where, e.g., the data has been written in by multiple agents. In addition, the input matrices may be presented in a sparse representation, where only the nonzero entries are written.

We are interested in developing and analyzing fast Monte Carlo algorithms for performing useful computations on large matrices. Examples of such computations include matrix multiplication, the computation of the singular value decomposition of a matrix, and the computation of compressed approximate decompositions of a matrix. In this paper, we present a computational model for computing on massive data sets (the pass-efficient model) in which our algorithms.

RELATED WORK

Related work can be grouped into two categories. The first category is most relevant that includes the work on measuring and ranking user in social network system. The second category is about the work on measuring user in network system.

First, the user ranking algorithm in social network system has drawn a lot of attention in the research literature. The best known node ranking algorithms are PageRank and HITS. Sergey Brin and Lawrence Page [2] proposed the PageRank to rank websites on the Internet. PageRank is a link analysis algorithm which is based on the directed graph (webgraph). The rank value indicates the importance of a particular node that represents the likelihood that users randomly clicking will arrive at any particular node. And, in [11], the authors presented two sampling algorithms for PageRank: efficient approximation: Direct sampling and Adaptive sampling. Both methods sample the transition matrix and use the sample in PageRank computation. The hyper-link-induced topic search (HITS) was developed by Jon Kleinberg [9]. This algorithm is a link analysis algorithm which ranks the webpages. The authors presented a set of algorithmic tools for rating and ranking the webpages from the directed graph of Internet environments. Furthermore, this work proposed a formulation of the notion of authority. PageRank/HITS is to find important websites that are linked to more different important websites and they do not consider the difference of nodes' contribution to links at all, but in this paper we want to find those nodes that relatively contribute more to the interactions linked to them. However, Meeyoung Cha et al. [5] proposed a method to measure the user influence in Twitter using the directed links information, and present the comparison of three static measures of influence. However, they

investigate the dynamics of user influence across topics and time which give a guide to the following research. Meanwhile, Yuanfeng Song and Wilfred Ng et al. [16] proposed a theoretical analysis on which frequent patterns are potentially effective for improving the performance of LTR and then propose an efficient method that selects frequent patterns for LTR. Also, Weng et al. [18] developed a Twitterer rank algorithm based on PageRank to measure the influence of Twitterers. With a focus on both the topical similarity and the link structure into account, they proposed to measure the influence of users in Twitter with a topic-sensitive which means the influence of users vary in different topics. Besides, the user ranking based on the influence of user, in [8], [13], the expertise is considered as the ranking factor, both of them propose to measure the expertise level for user with the iteration information. There are other ranking factors for user ranking like [19] that rank the user with the authority score. In those user ranking algorithms, the PageRank idea is widely used in [18], [8] which pay more attention to the link analysis than content analysis. The algorithms based on link analysis were used for measuring the ranking factor that carried out as a research project which ranks the transferred emails. In [4], [12], their work found that the ranking algorithms using link analysis have better results than the content methods. Nonetheless, the user rank is still under-explored with the influence and expertise score. Instead, in this paper, we focus on the ranking of user active level in social networks rather than focusing on measuring the influence or other factors.

Second, the work on measuring user is a basic step of the proposed ranking task. To the best of our knowledge, the work about measuring users in social network concept was firstly proposed in [6] that they proposed to model the user's network value which defined as "the expected profit from sales to other users she may influence to buy" by the model of a Markov random field. To different types of network, the

measuring factor is not limited by the value of user, in [5], the work expands the value to influence which

can better reflect the characteristics of user in social network system. Romero et al. [15] have developed the influence of user based on the information forwarding activity of user, the influence model is based on the concept of passivity and used the similar method to HITS to quantify the influence of users. In addition, in [1], the author computing the influence on Twitter by tracking the diffusion of URL from one user to another with three assignments. Furthermore, them predicting the individual user or URL influence by the regression tree model.

PROPOSAL SYSTEM

PREDICTING THE USER VITALITY

In this section, we introduce and address the problem of predicting the user vitality based on the model and inference of user vitality in a social network.

The successful prediction of user vitality could benefit many applications in most social networking sites such as Facebook and Twitter. Particularly, as the number of users in most social networking sites is very large, it is very important to know in advance who will be or will not be very active in the future. First, the site operators may design early and useful strategy to encourage inactive users to interact with others and content. This could help them maintain the global user vitality of a social networking site. Second, the site operators may also decide better ads display strategy by using the future user vitality. For instance, they may deliver and display interesting ads to active users rather than inactive users as the former group has better chance to propagate the ads to others or click the ads directly. This could help them not only save cost for ads display, but also target potential users in a more accurate way, which will consequently help them improve their ads revenue. Particularly, in this paper, we will show the prediction of vitality for those users who are ranked on the top because these users often have high influence in the social networks and

could bring more benefit to social networking sites if predicting their vitality successfully.

Other than predicting the vitality of individual user, we also address the prediction of vitality for a group of users in this paper. As we know, there are many groups formed in social networking sites. Users in each group often behavior very similarly. For instance, they often chat, tweet and re-tweet with each other. While it may be very challenging to predict the vitality of each single user, it may be easier to predict the aggregate vitality of a group of users. Plus, the successful prediction for a group of users could be beneficial for many parties on social networking sites as well.

4.1 Basic Forecasting Model

There are some existing models that could be used for predicting the dynamic vitality score, such as Markov model [17] and exponential smoothing forecast [3]. Based on the characteristic of the data from social networking system, we choose the triple exponential smoothing [3] to predict the dynamic vitality score of each user in this paper. Furthermore, we also propose a way to obtain the vitality score of a group users with the triple exponential smoothing. The exponential smoothing model is a classical method for prediction with time series data. As we know, the simple form of exponential smoothing could be presented as in Equation 1.

$$S_t = x_t + (1 - \alpha) S_{t-1} \text{ -----(1)}$$

However, the simple exponential smoothing does not work well when there is a temporal trend in the data. To this end, we decide to adopt the triple exponential smoothing to predict the dynamic vitality score. Triple exponential smoothing takes into account seasonal changes that are often the tendency of timeseries data. The seasonal changes are essentially repeating behaviors that occur every a few time periods. Coincidentally, we also often observe such seasonal trend in the user activity data collected from online social networking sites. That is why we adopt the triple exponential smoothing model in this paper. The formula of triple exponential smoothing could be presented as follows.

$$\begin{cases} S_t = \alpha \frac{y_t}{I_{t-L}} + (1 - \alpha)(S_{t-1} + b_{t-1}) \\ b_t = \gamma(S_t - S_{t-1}) + (1 - \gamma)b_{t-1} \\ I_t = \beta \frac{y_t}{S_t} + (1 - \beta)I_{t-1} \\ F_{t+m} = (S_t + mb_t)I_{t-L+m} \end{cases} \quad (2)$$

In Equation 2, y is the observation number of interactions and t denotes the index of each period. $(0 < \alpha < 1)$ is the data smoothing factor, $(0 < \gamma < 1)$ is the trend smoothing factor, and $(0 < \beta < 1)$ is the seasonal change smoothing factor. The general formula for the initial trend estimation b_0 is:

$$b_0 = \frac{1}{L} \left(\frac{x_{L+1} - x_1}{L} + \frac{x_{L+2} - x_2}{L} + \dots + \frac{x_{L+L} - x_L}{L} \right) \quad (3)$$

Based on Equation 3, we will be able to get the predicted vitality score. According to the characteristic of social network data, we proposed an improved triple exponential smoothing model to predict the vitality ranking score of each user.

The Improved Model For Predicting the Ranking Score

As we know, in the triple exponential smoothing model, there are two important parameters which affect the prediction result: the smoothing factor and the initial smoothed value. For the initial smoothed value, we use the average of the vitality scores of users in the last time periods as the initial smoothed value. For the smoothing factor, it is difficult to get the ideal value. Furthermore, in the social network systems each individual node has independent smoothing factor because each node indicates an individual user who has unique behavior in the system. If we want to predict the vitality score of each node, we have to find the smoothing factor for each node. In this paper, we use the weight-based method to adjust the factor based on previous information. For example, to predict the vitality score of the user j in time period $i + 1$, the initial smoothed value is generated by the sequence.

$$IM_j^i = \left| \frac{t\alpha_j^i - t\alpha_j^{i-1}}{t\alpha_j^i} \right| \quad (4)$$

Furthermore, the smoothing factor is generated within time period i and we will use the vitality score of time period $i - 1$ to predict that in

time period i . Then we will use the simulated annealing method to adjust the smoothing factor. When the simulated annealing method ends, we get an appropriate result of the smoothing factor that will be used for predicting the vitality score of period $i + 1$. As we know, when the value of smoothing factor is close to one, we have less smoothing effect and give greater weight to recent changes. On the other hand, when the vitality score of a user is high and the user has a great change in recent time period, we assume this trend will continue in next time period. The input is the computed users' vitality score in the first N periods. The initial smoothed value of each node is calculated by the average vitality score of first 3 periods. Then, we use Equation 4 to generate the smoothing factor of each node. When we get these two parameters, we can predict the users' vitality score of time period $N + 1$ with Equation 2. We can even further rank users based on the predicted vitality score in time period $N + 1$.

CONCLUSION

In this paper, we presented a study on user vitality ranking and prediction in social networking services such as microblog application. To analyze the user vitality ranking data in Hadoop ecosystem. Hadoop ecosystem is Hive, Pig, Map Reduce, if you want analysis to find some deep analysis the dynamic interactions among users on social networks. In future the Spark 100 times faster than Hadoop, it is easily analyzed faster.

REFERENCES

1. H. Li, Y. Ge, and H. Zhu, Point-of-interest recommendations: Learning potential check-ins from friends, in Proc. ACM SIGKDD Int. Conf. Knowledge Discovery Data Mining, 2016.
2. H. Li, R. Hong, D. Lian, Z. Wu, M. Wang, and Y. Ge, A relaxed ranking-based factor model for recommender system from implicit feedback, In IJCAI, pp. 1683–1689, 2016.

3. L Wu, Y. Ge, Q. Liu, E. Chen, B. Long, and Z. Huang, Modeling users' preferences and social links in social networking services: a joint-evolving perspective,? in Proc. 13th AAAI Conf. Artif. Intell.,2016, pp. 279–286.
4. H Li, R. Hong, S. Zhu, and Y. Ge, Point-of-interest recommender systems: A separate-space perspective,? in Proc.IEEE Int. Conf. Data Mining, 2015, pp. 231–240.
5. W Liu, G. Li, and J. Cheng, Fast PageRank approximation by adaptive sampling,? Knowledge. Inf. Syst., vol. 42, no. 1, pp. 127–146, 2015.
6. Y Song, W. Ng, K. Wai-Ting Leung, and Q. Fang, SFP-Rank: Significant frequent pattern analysis for effective ranking,? Knowledge. Inf. Syst., vol. 43, no. 3, pp. 529–553, 2015.
7. Y Yang, R. N. Lichtenwalter, and N. V. Chawla, Evaluating link prediction methods,? Knowl. Inf. Syst., vol. 45, no. 3, pp. 751–782, 2015.
8. S Kumar, F. Morstatter, and H. Liu, Twitter Data Analytics. Berlin, Germany: Springer, 2014.
9. A Omidvar, M. Garakani, and H. R. Safarpour, Context based user ranking in forums for expert finding using WordNet dictionary and social network analysis,? Inf. Technol. Manage., vol. 15, no. 1, pp. 51–63, 2014
10. K. Zhao, J. Yen, G. Greer, B. Qiu, P. Mitra, and K. Portier, Finding influential users of online health communities: A new metric based on sentiment influence,? J. Amer. Med. Informat. Assoc., vol. 21, no. e2, pp. e212–e218, 2014.based on sentiment influence,? J. Amer. Med. Informat.Assoc.,
11. S. Brin and L. Page, Reprint of: The anatomy of a large-scale hyper textual Web search engine,? Computer.Network, vol. 56, no. 18, pp. 3825–3833, 2012.
12. E. Bakshy, J. M. Hofman, W. A. Mason, and D. J. Watts, Everyone's an influencer: Quantifying influence on Twitter,? in Proc. 4th ACM Int. Conf. Web Search Data Mining, 2011, pp. 65–74.
13. P. E. Brown and J. Feng, Measuring user influence on twitter using modified k-shell decomposition,? 2011
14. D.M. Romero, W. Galuba, S. Asur, and B. A. Huberman, Influence and passivity in social media,? in Machin Learning and Knowledge Discovery in Databases. Berlin, Germany: Springer, 2011, pp. 18–33.
15. M Cha, H. Haddadi, F. Benevenuto, and P.K. Gummadi, Measuring user influence in Twitter: The million follower fallacy,? in Proc. IntAAAI Conf. Weblogs Social, 2010, vol. 10, pp. 10–17.
16. T. Opsahl, F. Agneessens, and J. Skvoretz, Node centrality in weighted networks: Generalizing degree and shortest paths,? Social Network., vol. 32, no. 3, pp. 245–251, 2010.
17. J. Weng, E.-P.Lim, J. Jiang, and Q. He, Twitter Rank: Finding topic-sensitive influential twitter,? in Proc. 3rd ACM Int. Conf. Web Search Data Mining, 2010, pp. 261–270.
18. Y. Yamaguchi, T. Takahashi, T. Amagasa, and H. Kitagawa, TURank: Twitter user ranking based on user-tweet graph analysis,? in Proc. 11th Int. Conf. Web Inf. Syst. Eng., 2010, pp. 240–253.vol. 21, no. e2, pp. e212–e218, 2014.
19. J. Jiao, J. Yan, H. Zhao, and W. Fan, Expert Rank: An expert user ranking algorithm in online communities,? in Proc. Int. Conf. New Trends Inf. Service Sci., 2009, pp. 674–679.
20. R. G. Brown, Smoothing, Forecasting and Prediction of Discrete Time Series. North Chelmsford, MA, USA: Courier Corporation, 2004.
21. R. Mihalcea, Graph-based ranking algorithms for sentence extraction, applied to text summarization,? in Proc. ACL Interactive Poster Demonstration Sessions, 2004, Art. no. 20.
22. C. S. Campbell, P. P. Maglio, A. Cozzi, and B. Dom, Expertise identification using email communications,? in Proc. 12th Int. Conf. Inf. Knowledge. Manage, 2003, pp. 528–531.
23. P. Domingos and M. Richardson, Mining the network value of customers,? in Proc. 7th ACM SIGKDD Int. Conf. Knowledge. Discovery Data Mining, 2001, pp. 57–66.
24. J. M. Kleinberg, Authoritative sources in a hyperlinked environment,? J. ACM, vol. 46, no. 5, pp. 604–632, 1999.
25. S. Wasserman and P. Pattison, Logit models and logistic regressions for social ne