Analysis of User Vitality Prediction, Ranking and Providing Ads in Social Networking Services Based on Users Profile

Mr. Nilesh Gholap[1], Mr. P. B. Vikhe[2], Mr. M. R. Bendre[3]

[1] Student, Department of Computer Engineering, PREC, Maharashtra
[2] Assistant Professor, Department of Computer Engineering, PREC, Maharashtra
[3] Assistant Professor, Department of Computer Engineering, PREC, Maharashtra

ABSTRACT

Social networking services have been predominant at numerous online networks, for example, Twitter.com and Weibo.com, where a huge number of users continue cooperating with one another consistently. One interesting and important issue in the long range social networking services is to in a convenient manner. A precise ranking list of user vitality could benefit many parties in social network services such as the ads providers and site administrators. Despite the fact that it is exceptionally encouraging to acquire a vitality-based ranking list of users, there are numerous specialized difficulties because of the huge scale and dynamics of social networking data. In the system, there is a unique point of view to accomplish this objective, which is quantifying user vitality by analyzing the dynamic interactions among users on social networks and their profiles. The facility to build the social relations or social networks among users for instance, activities, share interest and physical connections is carried out by social networking services. Through such service, users could stay connected with each other and be informed of friends behaviors such as posting at a platform, and consequently be influenced by each other. Hence the system is a novel strategy to learn the latent profiles of social users rank them and recommend ads. To evaluate the performance of proposed algorithms collected two dynamic social network data sets.

Keyword: - *Multimedia Social Networks, Intention Prediction, Behavior Pattern.*

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1. INTRODUCTION

With the development of web technology, social networking service has been prevalent at many online platforms. Through such service, users could stay connected with each other and be informed of friends behaviors such as posting at a platform, and consequently be influenced by each other. For instance, in today’s Twitter and Weibo (one of the most popular social networking sites in China), a user can get the instant updates about his connected friends postings and could further re-tweet or comment the postings. Within a time period, millions of users may take different actions such as posting and re-tweeting at these social networking sites. One interesting and important problem is how to rank users based on their vitality with historical data. An accurate vitality ranking of users will provide great insight for many applications in most online social networking sites. For instance, online ads providers may make better strategy for delivering their ads via considering the ranked vitality of users; site operators may design better practices for online campaigns (e.g., online survey) via leveraging the ranking list.

While it is very promising for many parties to provide a vitality ranking of users, there are many technical challenges to tackle this problem. First, to decide the vitality of a user, could not only examine his own interaction with others, but also need to look into the interactions of other users collectively. For instance, suppose one user has had many interactions with most of his friends in a time period, may conclude different vitality of this user when most of his friends also have had many interactions in the same time period versus when most of his friends do not have had many interactions. Second, as the scale of social networks increases, it becomes more challenging to rank the vitality of users because a large number of nodes (users) may influence the vitality of an individual node (user). Third, as the social networks in many online sites evolve over time, the vitality of users may also change over time.

2. LITERATURE SURVEY

2.1 Measuring User Reputation on Twitter Using Page Rank Algorithm:

This study presented a novel ranking framework that arranges the social user communications and activity based on the user's active performance to be calculated. Intuitively, the social user communications are observed. Relied on this, the active score is predicted for each social user. To consider the social communications in the method of interchange based on the re-tweet communication between Twitter users.

Specially, here it referred to the mutual acceptance of each other's tweets between two users in the model of a re-tweet. Second, the regression evaluation is done for the scored active. By performing so, Authors accomplished accurate results on the current events. Experimental evaluation is approved on the real-time application, Twitter which shares the varied events instantly that further to showed the efficiency of the presented Page Rank algorithm.

2.2 Measuring User Influence in Twitter:

An in-depth comparison of various measures of influence such as retweets, in degree and mentions can be generated using large amount of data collected from twitter. Based on these measures, authors investigate the dynamics of user influence across topics and time. They make several interesting observations. Users who have high in degree are optional to influential in terms of spawning mentions or retweets. Second, most influential users can hold significant influence over a multiple topics. Third, influence is not gained spontaneously or accidentally, but through concerted effort such as limiting tweets to a single topic.

2.3 Everyone's an Influencer: Quantifying Influence on Twitter:

In this paper authors investigate the attributes and relative influence of 1.6 M Twitter users by tracking 74 million diffusion events that took place on the Twitter follower graph over a two month interval in 2009. Unsurprisingly, authors find that the largest cascades tend to be generated by users who have been influential in the past and who have a large number of followers. URLs which are rated more interestingly or elicited with positive feelings are likely to spread.

2.4 Twitter rank: Finding topic sensitive influential Twitters:

Twitter consist of micro blowing services which employs a social networking model called following. In following each user can select who he/she wants to receive tweets without initial permission. It is observed that 72.4% of the users in Twitter follow more than 80% of their followers, and 80.5% of the users have 80% of users they are following follow them back.

3. SYSTEM OVERVIEW

Many interactions often keep going on within online social networks over time. Examples of interaction include but are not limited to the re-tweeting, mention, and sending message.

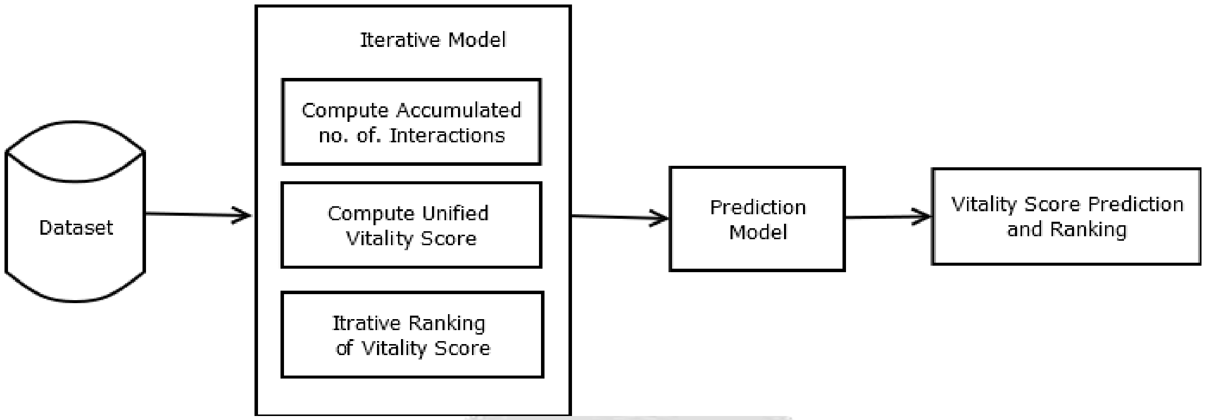

Figure 1 System Architecture

The goal is to rank user vitality based on all interactions in a time period. Another goal is to rank all users from high vitality to low vitality for a time period based on all previously observed interactions. Such a vitality-based ranking list of users may provide a good guidance for the social networking service providers to understand the dynamics of systems. They may directly find the relatively most active users and make better operation and business decisions upon the findings.

CONCLUSION

A system on user vitality ranking and prediction in social networking services such as Ads Providers. First it introduces a user vitality ranking problem, which is based on dynamic interactions between users on social networks. To solve this problem, two algorithms are applied to rank users based on vitality. While the first algorithm works based on the two user vitality measurements, the second algorithm further takes into account the mutual influence among users while computing the vitality measurements. Then it presents a user vitality prediction, ranking and providing Ads based on user's profile. The accurate results of both user vitality ranking and prediction could benefit many parties in different social networking services, e.g., a user vitality ranking list could help ads providers to better display their ads to active users and reach more audiences.

REFERENCES

[1] N. Abirami1, K. Manohari, "Measuring User Reputation on Twitter Using Page Rank Algorithm", International Journal of Engineering Science Invention (IJESI), 2018.
[2] Meeyoung Cha, Hamed Haddadi, Fabrcio Benevenuto and Krishna P. Gummadi, "Measuring User Influence in Twitter: The Million Follower Fallacy", Association for the Advancement of Artificial Intelligence, 2010.
[3] Eytan Bakshy, Jake M. Hofman, Winter A. Mason and Duncan J. Watts, "Everyones an Influencer: Quantifying Influence on Twitter", 2011.
[4] Jianshu WENG, Ee Peng LIM, Jing JIANG and Lawrence Page, "Twitterrank: Finding topic-sensitive influential Twitterers", Proceedings of the Third ACM International Conference onWeb Search & Data Mining, 2010.
[5] Sergey Brin and Lawrence Page, "The anatomy of a large-scale hypertextual Web search engine", Computer Networks and ISDN Systems, 1998.
[6] Jian Jiao, Jun Yan, Haibei Zhao, and Weiguo Fan, "Expertrank: An expert user ranking algorithm in online communities", In New Trends in Information and Service Science, 2009.
[7] Rada Mihalcea, "Graph-based ranking algorithms for sentence extraction, applied to text summarization", In Proceedings of the ACL, 2004.
[8] Tore Opsahl, Filip Agneessens, and John Skvoretz, "Node centrality in weighted networks: Generalizing degree and shortest paths", Social networks, 32(3):245251, 2010.
[9] Daniel M Romero, Wojciech Galuba, Sitaram Asur, and Bernardo A Huberman, "Influence and passivity in social media", In Machine learning and knowledge discovery in databases, pages 1833. Springer, 2011.
[10] Yuto Yamaguchi, Tsubasa Takahashi, Toshiyuki Amagasa, and Hiroyuki Kitagawa, "Turank: Twitter user ranking based on user-tweet graph analysis", In Web Information Systems Engineering WISE 2010.