Ranking Online Memes in Emergency Events Based on Transfer Entropy

Saike He¹, Xiaolong Zheng¹, Xiuguo Bao^{2*}, Hongyuan Ma², Daniel Zeng^{1,3}, Bo Xu⁴, Guanhua Tian⁴, Hongwei Hao⁴

¹State Key Laboratory of Management and Control for Complex Systems, Institute of Automation,

Chinese Academy of Sciences, Beijing 100190, China

² CNCERT/CC, Beijing, China

³Department of Management Information Systems, University of Arizona, Tucson, AZ 85721, USA

⁴ Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China

{saike.he, xiaolong.zheng, dajun.zeng, boxu, guanhua.tian, hongwei.hao}@ia.ac.cn, bxg@isc.org.cn,

mahongyuan@foxmail.com

* The corresponding author

Abstract—The rapid proliferation of online social networks has greatly boosted the dissemination and evolution of online memes, which can be free text, trending catchphrase, or micro media. However, this information abundance is exceeding the capability of the public to consume it, especially in unusual situations such as emergency management, intelligence acquisition, and crime analysis. Thus, there calls for a reliable approach to rank meme appropriately according to its influence, which will let the public focus on the most important memes without sinking into the information flood. However, studying meme in any detail on a large scale proves to be challenging. Previous bottom-up approaches are often highly complex, while the more recent top-down network analysis approaches lack detailed modeling for meme dynamics. In this paper, we first present a formal definition for meme ranking task, and then introduce a scheme for meme ranking in the context of online social networks (OSN). To the best of our knowledge, this is the first time that memes have been ranked in a model-free manner. Empirical results on two emergency events indicate that our scheme outperforms several benchmark approaches. This scheme is also robust by insensitive to sample rate. In light of the scheme's fine-grain modeling on meme dynamics, we also reveal two key factors affecting meme influence.

Keywords-meme ranking; transfer entropy; peer influence

I. INTRODUCTION

Recent years, the great proliferation of online social networks (OSN) has made them the hub and conduct of information contagion. During this process, there is a kind of niche content, varying in form, while keeping majorly consistent. That is the theme, the topic, or the motif, which we generally call '*meme*'. Meme is a concept first coined by Dawkin [1], which refers to a cultural gene passed from person to person. In OSN, it can be free text, trending catchphrase, or micro media such as photo, video, audio clip, or animated gif. Nowadays, there are thousands of memes diffusing and evolving on newly emerging social platforms, where they go in and out of popularity at a rapid pace, sometimes even faster than we can recognize [2]. However, such information abundance is exceeding the capability of the public to consume it, especially in unusual situations

such as emergency management [3], intelligence acquisition [4], and crime analysis [5]. Thus, it calls for a reliable approach to rank meme appropriately. This will allow the public to focus their limited attention on the most important memes, avoiding sinking into the information flood. However, studying meme in any detail on a large scale proves to be unusually difficult. Previous bottom-up approaches try to model meme diffusion process with various propagation models [6-8]. This line of study often makes various assumptions about the exact diffusion process, which clearly do not hold in real-world situations. On the other hand, the more recent top-down network analysis approaches are commonly statistical based [9, 10], thus lacking detailed modeling for meme dynamics.

In this paper, we formally define meme ranking as a task that prioritizes meme which involves high audience engagements and port extraordinary influence [11] on the public. This formulation is consistent with the concept of memetic in videos [12]. Accordingly, we propose a scheme to rank memes in the context of online social networks. As far as we know, this is the first time that memes have been ranked in a model-free manner. Unlike previous work, our ranking scheme is based on *transfer entropy* [13, 14], which is able to capture complex nonlinear dynamic process without explicit modeling on exact underlying interactions. Empirical results on two emergency events indicate that our scheme outperforms several benchmark approaches in meme ranking task. This scheme is also robust and insensitive to different sample rates. Due to the scheme's fine-grain modeling on meme dynamics, we also reveal two key factors that affect meme influence. Our findings may provide practical implications for those who want to understand meme with respect to its influence among the public.

The rest of the paper is structured as follows. Section 2 presents the technical details for our methodology of meme ranking. In Section 3, we report the results of our evaluation study. Section 4 concludes this paper with a summary and a discussion for future research.

II. METHODOLOGY

A. Modeling

According to our formulation for meme ranking task, we intend to rank memes according to their influence exerted over users along their diffusion traces. However, quantifying meme influence on each individual proves to be difficult, since it requires answering the essential counterfactual question: what is the outcome if the meme is not exposed to a user. As a solution, we measure the influence indirectly by examining the mutual effect within user peers that spread the same meme. This effect can be readily quantified by peer influence.

Thus, we calculate the influence of each meme by summarizing the influence of all the users involved in spreading it. Considering the varying volume of uses in different memes, we average the total value as:

$$Influ_{m} = \frac{1}{\# U_{n}} \sum_{u \in U_{m}} Influence(u)$$
(1)

where $Influ_m$ quantifies the popularity of meme *m*, U_m represents the collection of users engaged in spreading it, and Influence(u) is the influence of user *u*.

Then we can rank meme based on this influence score. This outlines our general strategy for meme ranking task. In what follows, we will detail the calculation of influence based on transfer entropy for each user pair.

B. Definition for transfer entropy

For a pair of users x and y, we record their behaviors in two Markov processes $X=x_t$ and $Y=y_t$. Then, the transfer entropy from user x to y is given by:

$$TE\left(\mathbf{X} \rightarrow \mathbf{Y}\right) = H\left(y_{t+1} \left| \mathbf{y}_{\mathbf{t}}^{\mathbf{n}} \right) - H\left(y_{t+1} \left| \mathbf{y}_{\mathbf{t}}^{\mathbf{n}}, \mathbf{x}_{\mathbf{t}}^{\mathbf{n}} \right)\right)$$
(2)

where $\mathbf{x}_{\mathbf{t}}^{\mathbf{m}} = (X_t, \dots, X_{t-m+1})$, $\mathbf{y}_{\mathbf{t}}^{\mathbf{n}} = (Y_t, \dots, Y_{t-n+1})$, and *m* and *n* are the orders (memory) of the Markov process

m and *n* are the orders (memory) of the Markov process X and Y respectively¹; H(*) calculates entropy over a given distribution.

Transfer entropy given by (2) quantifies the amount of information that can be used to predict the behaviors of user y, which is a reflection of influence wiled by user x. Then the influence of user x Influence (X) is calculated by

summarizing all the influence he wielded on other users:

$$Influence(X) = \sum_{Y \in Follower(X)} TE(X \to Y)$$
(3)

where *Follower(X)* is the set of followers belong to user x.

III. EXPERIMENTS AND RESULTS

This section first describes the datasets used and illustrates our experimental design. Then, experimental results are reported and analyzed.

A. Datasets

We apply our meme ranking scheme on two datasets collected from Sina Weibo², a Twitter-like microblogging system in China. Each dataset corresponds to one emergency event recently occurred in 2014.

1) MH370: This event repsonds to the flight accident that Malaysia Airlines lost contact with one of its flights on Mar. 7, 2014. This flight crashed in the southern Indian Ocean after losing contact for more than 20 days.

2) Kunning knife rampage: This event refers to a mass knife attack at Kunning railway station that leaded to 33 people dead and at least 140 wounded. This rampage is severely blamed by the public in China.

These two emergency events attract worldwide attention, and are fiercely discussed in the 'Hot Topic' section of Sina Weibo. Within each topic, there are thousands of meme threads (mutations of one original phrase) diffusing among the users, each constitutes a complete meme trace.

In this study, we crawled down the top 10 most popular meme threads for each topic, which already manifest enough information for meme tracing and ranking. Statistical information of the two datasets (hereafter, MH370 and Kunming) are shown in Table 1.

TABLE I. STATISTICAL INFORMATION OF DATASETS

Items	MH370	Kuming
Nr. of messages	285,712	113752
Nr. of users	267,131	107363
Messages per user	1.07	1.10

Note: MH370 and Kunming datasets are collected respectively on Mar. 25th, 2014 and Mar. 2nd, 2014.

B. Experimental Design

Overall, we are interested in three issues related to meme ranking:

- (1) How does the proposed approach performances in meme ranking task?
- (2) Is the approach robust enough?
- (3) What are the Key factors that determine meme influence?

To obtain reliable answers for these questions, we randomly select user behaviors with corresponding timestamps from the whole dataset. This manipulation can alleviate the affection caused by selection bias, and guarantee that the sampled data used are representative enough for the whole volume [14].

In the following experiments, we execute 10 independent runs for each approach, and the results are averaged over all the runs. If not explicitly pointing out, we adopt a sample rate of 5% for each meme.

¹ For the sake of simplicity, we take m=n=3.

² <u>http://www.weibo.com</u>

C. Performance of meme ranking

This subsection presents our experimental results of meme ranking. Apart from our proposed approach, we also introduce three benchmark approaches for comparison, which are representative for the mainstream techniques. Finally, we present our evaluation framework.

1) Benchmark 1: Followers-centered approach

This approach is based on the followers of an individual user u. It utilizes the number of followers of u to measure his influence. The basic idea is that influentials tend to wield influence over a wide scale of users, and follower number can be considered as a rational criterion of quantifying such influence. For each meme m, its overall influence score *Inf FolloNr_m* can be defined as:

$$Inf_FolloNr_{m} = \frac{1}{\# U_{m}} \sum_{u \in U_{m}} \# Follower(u)$$
(4)

where U_m represents the collection of users engaged in the diffusion process of meme *m*, *Follower(u)* is the collection of all followers of user *u*, and operator #(X) means the volume size of set *X*.

2) Benchmark 2: PageRank

PageRank is an alternative approach in influence identification which considers both link number and their qualities. Thus, we assume it to outperform follower number-based approach. As a complete collection for the underlying network structure is almost impossible, we design to utilize the dynamic repost network, and execute PageRank algorithm on it. Then, the influence of meme m is given by:

$$Inf_PageRank_{m} = \frac{1}{\# U_{m}} \sum_{u \in U_{m}} PageRank(u)$$
(5)

where PageRank(u) is the corresponding PageRank value of user u.

3) Benchmark 3: Dynamic information based approach

This approach employs dynamic information as the measurement. According to Romero et al. [15], the level of user activity should be taken into account for an accurate quantification of influence. Here, we desgin to use the repost behavior of each user as influence measurement. The overall influence score for meme m is formulated as:

$$Inf_RepostNr_{m} = \frac{1}{\# U_{m}} \sum_{u \in U_{m}} \# Repost(u)$$
(6)

where Repost(u) is the set of all the repost behaviors of user u.

4) Evaluation Metric

One of the primary goals in this section is to clarify whether we can rank meme appropriately only based on partial data collected. As such, we use the ranking results of hot topics given by Sina Weibo as the gold standard for evaluation. For evaluation, we utilized a modified version of Edit Distance to generate a normalized similarity score, as formulated in (7).

$$Sim(src, tar) = 1 - \frac{edit_dist(src, tar)}{max_length(src, tar)}$$
(7)

where '*str*' and '*tar*' represent two objects to be measured, *edit_dist()* is a function calculating edit distance, *max_length()* denotes the maximum length of the two objects.

Now, the similarity score has a unified value interval of [0,1], and high values indicates high similarity.

 TABLE II.
 Performance comparison for meme ranking task

Dateset	Follower_ Num	PageRank (E-6)	Repost_ Num	ТЕ
MH370	0.10	0.20	0.20	0.40
Kunming	0.10	0.30	0.30	0.40

Note: Follower_Num', 'PageRank' and 'Repost_Num' indicates comparison experiment group of benchmark 1, benchmark 2, and benchmark 3, respectively; 'TE' indicates experiment group of our proposed approach using transfer entropy.

5) Initial Results

We tested our proposed approach together with three benchmarks for meme ranking task. Experimental results are listed in Table II.

We notice three key aspects from the results. First, PageRank outperforms follower number-based approach. This may suggest that approaches based on static network structure are insufficient in meme ranking task, while PageRank can benefit ranking by considering influence propagation along the network of user relationships. Second, we find that dynamic information is effective in meme rank, and performs consistently better than follower number-based approach. This result support previous findings that dynamic is more reliable in influence identification. Third, our proposed scheme outperforms all the benchmark approaches in both datasets. This may be attributed to its advantage in modeling complex nonlinear relationships among users with few assumptions.

D. Robustness with regard to sample rate

Since we have conducted randomization on the original dataset, one question associated with this manipulation may arise: does the sample rate influence the final ranking result? In this part, we will try to answer this question. In our design, we conduct randomization on dataset with different sample rates (Table III).

TABLE III. MEME RANKING RESULTS WITH DIFFERENT SAMPLE RATES

Dateset	SR=1 %	SR=5%	SR=10%	SR=15%	SR=20%		
MH370	0.20	0.40	0.40	0.30	0.20		
Kunmin g	0.30	0.40	0.40	0.50	0.20		
Note: 'SR' represents 'sampling rate'.							

From Table III, we notice that the ranking results are insensitive to sampling rates. For MH370 dataset, the performance is 0.30 in average with standard deviation of 0.10; while for Kunming dataset, the average performance is

0.36 with standard deviation of 0.11. This verifies the robustness of our approach which is insensitive to different sample rates.

E. Key factors that affect meme influence

One key trait of transfer entropy is the ability of capturing fine-grain notions of social dynamics. This allows us not only to quantify meme influence as a whole, but also scrutinize the detailed social dynamics among users engaged in its diffusion process.

Primarily, we check how the distribution of user influences meme popularity. To this end, we record the portion of uses whose influence exceeds a threshold θ of the total influence of each meme. According to our empirical study, memes with high level of influence are prone to rely on a large portion of user to spread it. The Pearson's Correlation Coefficient between them is 0.62 (p<0.05) for MH370 and 0.66 (p<0.05) for Kunming dataset. This indicates that the influence of meme is achieved by a wide scale of users on its diffusion trace, and just a small amount of high influential users cannot guarantee its wide spread.

Also, we notice that there is a portion of users wielding non influence according to transfer entropy (zero influence users). Empirical study suggests that influential memes tend to contain less zero influence users. The Pearson's Correlation Coefficient is -0.65 (p<0.05) for MH370 and -0.53 (p<0.1) for Kunming dataset. This negative correlation can be explained partly by the concept of re-diffusion intention [16] in word-of-mouth market. Under its theory framework, we articulate that if a meme is really influential, then the re-diffusion intention of users is high, thus other users are more likely to be influenced by this meme exposed to them. So, the possibility that users release no influence by spreading meme is low.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we have given a formal definition for meme ranking task, and tried to solve it based on a model free approach. Experimental results suggested that our approach based on transfer entropy outperforms three benchmark approaches, which represent the mainstream techniques. Our scheme is also effective and insensitive to sample rates in randomized trials. Based on micro level analysis, we observe two intriguing findings: (1) The influence of meme is achieved by a wide scale of users on its diffusion trace; (2) Popular memes tend to contain less zero influence users.

In our future work, we intend to explore whether other information also benefits meme ranking task, i.e. user inertia, content, and so on. Since each meme is considered independently in this paper, we hope to design a unified modeling framework for multi-meme diffusion, and examine whether it will present better ranking results.

ACKNOWLEDGMENT

We would thank for each member of SMILES group in Institute of Automation, Chinese Academy of Sciences. Especially, we would thank for Kainan Cui, Zhu Zhang, and Chuan Luo for useful discussions. We also appreciate the data sharing from Tao Wang and proof checking by Fangyuan Wang. This work was supported in part by the following grants: The National Natural Science Foundation of China under Grant No. 71025001, 71103180, 91124001, 61175040, 71272236, and 61172106; The Beijing Natural Science Foundation under Grant No. 4132072, by the Ministry of Health under Grant No. 2012ZX10004801, by the Early Career Development Award of SKLMCCS, and by the Grant No. 2013A127.

References

- [1] R. Dawkin, *The selfish gene*, New York City: Oxford University Press, 1976.
- [2] L. Weng, A. Flammini, A. Vespignani, and F. Menczer, "Competition among memes in a world with limited attention," *Scientific reports*, vol. 2, 2012.
- [3] M. Latonero, and I. Shklovski, "Emergency management, Twitter, and social media evangelism," *International Journal of Information Systems for Crisis Response and Management (IJISCRAM)*, vol. 3, no. 4, pp. 1-16, 2011.
- [4] H. Chen, Intelligence and security informatics for international security: Information sharing and data mining: Springer, 2006.
- [5] L. Liu, J. Eck, and I. Global, Artificial Crime Analysis Systems: using computer simulations and geographic information systems: Information Science Reference Hershey, 2008.
- [6] N. T. Bailey, *The mathematical theory of infectious diseases and its applications*: Charles Griffin & Company Ltd, 5a Crendon Street, High Wycombe, Bucks HP13 6LE., 1975.
- [7] R. M. Anderson, R. M. May, and B. Anderson, *Infectious diseases of humans: dynamics and control*: Wiley Online Library, 1992.
- [8] R. W. Thommes, and M. Coates, "Epidemiological Modelling of Peer-to-Peer Viruses and Pollution," INFOCOM 206, pp. 1-12.
- [9] D. Ienco, F. Bonchi, and C. Castillo, "The memeranking problem: Maximizing microblogging virality," in Data Mining Workshops (ICDMW), 2010 IEEE International Conference on, 2010, pp. 328-335.
- [10] F. Bonchi, C. Castillo, and D. Ienco, "Meme ranking to maximize posts virality in microblogging platforms," *Journal of Intelligent Information Systems*, vol. 40, no. 2, pp. 211-239, 2013/04/01, 2013.
- [11] X. Zheng, Y. Zhong, D. Zeng, and F.-Y. Wang, "Social influence and spread dynamics in social networks," *Frontiers of Computer Science*, vol. 6, no. 5, pp. 611-620, 2012.
- [12] L. Shifman, and M. Thelwall, "Assessing global diffusion with Web memetics: The spread and evolution of a popular joke," *Journal of the American society for information science and technology*, vol. 60, no. 12, pp. 2567-2576, 2009.
- [13] R. Vicente, M. Wibral, M. Lindner, and G. Pipa, "Transfer entropy—a model-free measure of effective connectivity for the neurosciences," *Journal of computational neuroscience*, vol. 30, no. 1, pp. 45-67, 2011.
- [14] S. He, X. Zheng, D. Zeng, K. Cui, Z. Zhang, and C. Luo, "Identifying Peer Influence in Online Social Networks Using Transfer Entropy," *Intelligence and Security Informatics*, pp. 47-61: Springer, 2013.
- [15] D. Romero, W. Galuba, S. Asur, and B. Huberman, "Influence and passivity in social media," *Machine Learning and Knowledge Discovery in Databases*, pp. 18-33, 2011.
- [16] C. M. Z. Jingjing, "An Experimental Research on the Determinants of Re-diffusion Intention of Online Word-of-mouth [J]," *Journal of Zhejiang University (Humanities and Social Sciences)*, vol. 5, pp. 016, 2008.