Real-Time Prediction of Meme Burst

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***Abstract*—Predicting meme burst is of great relevance to develop security-related detecting and early warning capabilities. In this paper, we propose a feature-based method for real-time meme burst predictions, namely "Semantic, Network, and Time" (SNAT). By considering the potential characteristics of bursty memes, such as the semantics and spatio-temporal characteristics during their propagation, SNAT is capable of capturing meme burst at the very beginning and in real time. Experimental results prove the effectiveness of SNAT in terms of both fixed-time and real-time meme burst prediction tasks.**

Keywords—meme burst; real-time prediction; semantic analysis; spatio-temporal analysis;

I. INTRODUCTION

With the growing number of web applications and users, the Internet has become the main platform for information diffusion. Excavating and tracing information on the Internet are of great importance to understand the outside world. Meme [1], the replicator and unit of information, can be materialized as a word or phrase propagated over the Internet. Analyzing the trends of memes is an effective way of assessing dynamics of related events and topics, which is a basic requirement of security informatics applications. For example, the burst of the particular meme "Ivanka Trump" implies the potential result of the latest American presidential election. Generally, a meme diffuses via sentences or documents, through all channels over the Internet, including social media platforms (Twitter-like microblogs, blogs, forum, etc.), quote networks constructed by news websites, and other forms of interactions among webpages and users. The content of memes usually evolve rapidly, and the propagation paths of memes are embedded in unprecedented complex networks. The hardness of natural language understanding, as well as the spatio-temporal dynamics of information diffusion, further strengthen the challenge of meme trends prediction.

Existing literatures study memes from various perspectives, such as meme tracing [2], meme extracting and clustering [3]. There are also some researches working on meme burst prediction. Colbaugh and Glass [4] performed the early detection of meme prevalence by language features and network dynamical features. Their detection method was based on the fixed-time period, i.e., making prediction after a fixed time window under tracing, thus cannot predict meme burst in real-time. Weng et.al. [5] proposed a feature-based approach to address the real-time information burst predicting problem in Twitter. However, this study considered only the network-based features and partial temporal propagating features, the semantic information of meme was ignored, while the latter could be a potential indicator of meme burst [6].

In this paper, we propose a feature-based method named "Semantic, Network and Time" (SNAT) for real-time meme burst predictions. The issue under our consideration is predicting whether a meme will burst at the very beginning of its propagation. We assume that the semantic of a meme and its incipient propagating process contain useful knowledge for inferring its future popularity. By investigating semantics and spatio-temporal dynamics in meme propagations, we incorporate three sets of features, i.e., semantics-based feature, network-based feature and temporal feature. It should be noticed that the "space" we mentioned here refers to the social network space on the Internet. Each set of features is elaborated based on theoretical analysis and practical evidence. Because of the flexibility of SNAT on the tracing time, SNAT can be applied to both fixed-time and real-time meme burst predictions. We evaluate SNAT through two sets of meme burst prediction experiments: fixed-time prediction and real-time prediction. Besides, we analyze the performance of SNAT by a case study on how it works for real-time prediction. Experiments show that SNAT predicts meme burst effectively. Compared with existing works, SNAT takes full advantage of the semantics and the spatio-temporal characteristics in meme propagation, thus it is effective in predicting bursty memes at their incipient bursting stage in real-time.

For the rest of this paper, Section 2 gives a formal definition of real-time meme burst prediction and introduces the feature construction methods for our SNAT, Section 3 describes the experiments and Section 4 concludes the paper.

II. PROBLEM DEFINITION AND SOLUTION

A. Problem Definition

Assume that a meme is denoted as m, which is a particular item of the overall meme collection M. The number of times that m appears until a particular timestamp t is denoted as n_m^t. We assume that a meme is a bursty one if it appears more than a given number. Then the burst of meme m is defined as

$$y_m = \begin{cases} 1, & n_m^\infty \geq n_{th} \\ 0, & n_m^\infty < n_{th} \end{cases} , \tag{1}$$

where y_m denotes the ultimate state of the meme (burst successfully or not burst), n_{th} is the predefined threshold.

To perform meme burst prediction, i.e., to predict y_m, we construct features as the input of a binary classifier. Denote the features constructed for m as θ_m , and the output of the classifier as $h(\theta_m)$. Then the objective function of the meme burst prediction problem can be defined as

$$\Gamma(\Theta) = \frac{1}{|M|}\sum_{m\in M} l\left(h(\theta_m), y_m\right) \ , \tag{2}$$

where $l\left(h(\theta_m), y_m\right)$ denotes the loss function (e.g., log likelihood) which evaluates the difference between $h(\theta_m)$ and the ground truth y_m. Our goal is to construct the appropriate feature set Θ to minimize the objective function. Note that there is no fixed time window Δt related to θ_m , because in real-time meme burst predictions, the tracing time varies according to the dynamical characteristics of m.

B. Feature Construction in SNAT

There are three feature sets in the proposed SNAT, i.e. $\Theta=\{\theta_m | \theta_m = (\theta_m^S \oplus \theta_m^N \oplus \theta_m^T), m \in M\}$. θ_m^S is the semantics-based feature, θ_m^N is the network-based feature and θ_m^T is the temporal feature related to m. The detailed methods for feature construction are described as follows.

1) Semantics-based feature

As a meme is presented as a phrase, its future propagation can be implied in its text content potentially since some specific topics burst more frequently than others. This is our main intuition for constructing semantics-based feature θ_m^S . We primarily adopt a simple semantic feature extraction strategy, which computes the TF-IDF value of every word in the specific meme. Thus for each meme, there is a vector to present its semantical features. For all memes in M, the dimensions of the semantical vectors are the same, where each dimension corresponds to a particular word respectively.

However, there are usually a few words in one meme, thus the semantical vector of the meme is usually sparse. By leveraging the Associated Activation-Driven Enrichment method proposed in our previous work [7, 8], we activated a number of implicit words for each meme to enrich the semantical presentation. According to [7, 8], the enrichment methods are consistent with the cognitive psychological theory "Adaptive Control of Thought", and can improve the quality of semantic mining works effectively.

2) Network-based feature

It is widely accepted that the initial spreaders determine the following popularity of information to a large extent. Given a specific meme, we construct its network-based feature θ_m^N by evaluating the importance of its incipient spreaders.

Intuitively, a meme posted by some influential spreaders (users or websites) has a higher probability to be a bursty one; on the other side, bursty memes usually attract more influential spreaders. This idea of meme propagation is similar to that of the authorities and hubs analysis [9]. Based on this fact, we built a meme-spreader bi-graph for existing memes and spreaders, run the HITS algorithm [9] and get the *hub* value of each spreader. HITS algorithm evaluates and assigns an authority value and a hub value for each node in a network, where the hub value estimates the node's ability of linking to "important" nodes. In the tracing period of meme m, for the first n^* posts, we add the *hub* values of their spreaders to the network-based feature.

3) Temporal feature

Since the tracing time varies for different memes, it is necessary to define time variables before constructing temporal feature θ_m^T . Let $t_m^{n^*}$ denotes the timestamp that meme m appears the n^*-th time, then t_m^1 is the timestamp of the first appearance of meme m . If we trace the first n^* posts for a meme, the tracing process will stop at $t_m^{n^*}$, then the prediction will be triggered.

We assume that the inceptive post rate and post tendency is the crucial indicator for meme burst predictions, because the post rate reflects the popularity of a meme in the past, and the post tendency implies the future potential of meme burst. These features are described as follows.

Average post rate r_m (#post/hour) is computed through the tracing time and post numbers, which is defined as

$$r_m = \frac{n^*}{t_m^{n^*} - t_m^1} \ . \tag{3}$$

Post tendency $\boldsymbol{a_m}$ (#post/hour^2) can be defined as the acceleration of posts, i.e., the " growing rate" of the post rate. Given a meme m, we define the post tendency a_m as

$$a_m = \frac{1}{t_m^{n^*} - t_m^{n^*/2}}\left(\frac{n^*/2}{t_m^{n^*} - t_m^{n^*/2}} - \frac{n^*/2}{t_m^{n^*/2} - t_m^1}\right). \tag{4}$$

III. EXPERIMENTS

The effectiveness of SNAT is evaluated through a fixed-time predicting experiment and a real-time predicting experiment. In both experiments, the public dataset MemeTracker [2] is adopted as the dataset, and Logistic Regression is used as the classifier. MemeTracker is mainly a collection of phrases extracted from English news articles and blogs, as well as the information on when and where each meme appeared. There are 310,457 valid memes in this dataset. By setting n_{th} = 1000, we obtained 296 bursty memes and 310,161 mediocre ones.

A. Fixed-Time Prediction

In this experiment, we conducted fixed-time meme burst predictions following the literature [4], and compared the prediction accuracy with the Algorithm EW reported there. More specifically, we randomly selected 100 out of 296 bursty memes as positive cases and 100 out of 310,161 mediocre memes as negative cases, then we conducted a 10-fold cross validation and measured the average accuracy under different fixed time window Δt (12 hours, 24 hours and 48 hours). For the network-based features and the temporal features, n^* was set as the number of meme appearance within the given Δt .

TABLE I. FIXED-TIME PREDICTION RESULTS

Accuracy	Δt		
	12 hours	***24 hours***	***48 hours***
Algorithm EW	84%	92%	94%
SNAT	96%	97%	96%

Table I lists the results. It shows that 1) our proposed method SNAT achieves higher overall accuracy, compared with Algorithm EW; 2) the performance of SNAT has little relationship with Δt. The results validated the effectiveness of SNAT and its flexibility on tracing time Δt.

B. *Real-time Prediction*

In the real-time meme burst prediction scenario, we enlarged our dataset aiming to train the classifier better. More specifically, we selected all 296 bursty memes as positive cases and randomly selected 296 mediocre memes as negative cases. Compared with the fixed-time experiment above, we performed here a more difficult task because the memes whose appearance between 100 and 1000 are included. Under different values of n^*, we measured the average accuracy of SNAT prediction results through a 10-fold cross validation. To evaluate the effects of different sets of features, we also conducted predictions by using two sets each time, i.e., “S&N”, “S&T” and “N&T”. Experimental results are shown in Table II.

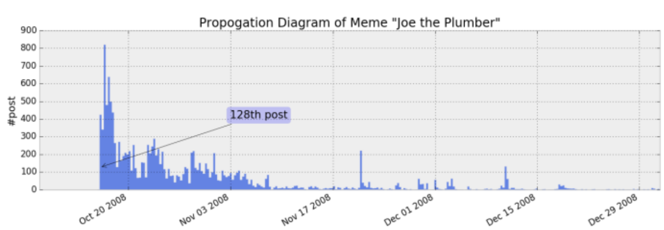
TABLE II. REAL-TIME PREDICTION RESULTS

n*		***32***	***64***	***128***
Accuracy	**SNAT**	**83.7%**	**90.5%**	**96.9%**
	S&N	81.0%	83.2%	83.5%
	S&T	70.7%	88.4%	95.4%
	N&T	79.6%	84.6%	91.2%

From Table II we can see that the performance of SNAT is sensitive to the tracing threshold n^*. With the increasing of n^*, the accuracy grows significantly, and achieves an ideal value (96.9%) when n^*=128. In most practical cases, a meme is usually in its initial phase when it has just appeared 128 times. Thus we could infer from Table II that our proposed SNAT is effective for most real-time meme burst prediction tasks. Moreover, the last three rows of Table II indict that the accuracy reduces when there are only partial features, which explains the effectiveness of the three feature sets separately.

To further explore the performance of SNAT, we conducted a case study by investigating how SNAT works on meme “Joe the Plumber”, a typical bursty meme during the 2008 American presidential election. The first record of “Joe the Plumber” in MemeTracker occurred on October 7th, 2008. After 9 days’ silence, it burst on October 16th, 2008. The statistical diagram of its propagation is shown in Figure 1. We can infer that fixed-time prediction usually fails on this meme.

Fig. 1. Propagation diagram of meme “Joe the Plumber”.



As for the semantics-based features, we found that the first few words activated by AADE are strongly related to the 2008 American election, such as “biden”, “obama”, “liberal” and “senator”. For the network-based features, there are some influential spreaders participating in the early propagation, such as Yahoo, Reuters, Washington Monthly. All of the features mentioned above contribute to the prediction tasks. Let the tracing number n^*=128, the average post rate is 0.642 and the post tendency is 123.3. Although the average post rate is ordinary, the post tendency implies the meme burst intensely.

IV. CONCLUSION

In this paper, we proposed a feature-based method SNAT for real-time meme burst prediction. The merits of SNAT include: 1) it take advantage of semantics and spatio-temporal characteristics of meme propagation synthetically, 2) it is capable of capturing the meme burst at the very beginning and in real time, and 3) it can be applied to both fixed-time and real-time meme burst prediction scenarios and achieves well performance. Experiments showed that the effectiveness of SNAT is not subject to the tracing time, which is a crucial specialty for the security related detecting and early warning.

Nevertheless, there are still some perspectives that can be explored in the future works. First, as the prediction is triggered only when given number of meme post achieves, a dynamical mechanism should be deployed. Second, considering the constant changes of network and semantic environment behind memes, more sophisticated dynamical features should be added for better performance in practical applications. Third, the effectiveness of SNAT needs to be further assessed in real-world datasets and applications.

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