Which is better? A Modularized Evaluation for Topic Popularity Prediction

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Abstract. Topic popularity prediction in social networks has drawn much attention recently. Various elegant models have been proposed for this issue. However, different datasets and evaluation metrics they use lead to low comparability. So far there is no unified scheme to evaluate them, making it difficult to select and compare models. We conduct a comprehensible survey, propose an evaluation scheme and apply it to existing methods. Our scheme consists of four modules: classification; qualitative evaluation on several metrics; quantitative experiment on real world data; final ranking with risk matrix and *MinDis* to reflect performances under different scenarios. Furthermore, we analyze the efficiency and contribution of features used in feature oriented methods. The results show that feature oriented methods are more suitable for scenarios requiring high accuracy, while relation based methods have better consistency. Our work helps researchers compare and choose methods appropriately, and provides insights for further improvements.

Keywords: Topic Popularity Prediction; Social Network; Twitter; Features; Survey; Evaluation

1 Introduction

Social network has become an indispensable part of our life, where users have access to posting and reading messages to and from the public. Everyday, in social networks, there are millions of messages posted about a wide range of topics. However, after a period of information dissemination, only a few prevailing topics will burst. Prediction of popularity of topics has meaningful impacts on many services and applications, such as marketing, advertisement, search engine queries and recommendation system [1,2]. News media utilizes online social networks to maximize their news visibility [3]. Hence, predicting the popularity of topics in social network is significant for both academia and industry.

Formally, we define the topic's popularity as the number of messages related to it [6] and the popularity fluctuates with time. The objective of topic popularity prediction problem is to detect topics and predict their popularities in the near future utilizing the obtainable information.

Various topic popularity prediction methods proposed by previous works have different properties such as accuracy and complexity, which leads to different

suitability and feasibility under diverse scenarios. They all claim that they have great performance in the experiments. However, tested on different datasets and evaluation metrics, those methods have little comparability between each other, which makes it difficult to choose an appropriate one under specific scenarios. The objective of this paper is to perform a fair and strict evaluation of each topic popularity prediction method with a uniform evaluation scheme.

We have collected the literatures about topic popularity prediction in social network published recently as completely as possible. After the survey, we, as the third party, develop a four-module evaluation scheme in order to make a convictive comparison to the topic popularity prediction methods comprehensively. We classify all the methods into two categories: *feature oriented methods* and *relation based methods* in the first module. In the second module, we carry out a qualitative evaluation representing the temporal, spatial, and platform universality. We also list some properties such as core algorithms and data preprocessing procedures, which fix their position among various problem situations. We further perform the scheme's third module: a quantitative experiment utilizing a dataset grabbed from Twitter. We test the methods based on the whole dataset without any optimization and give the accuracy evaluation which is objective and valuable to refer. In the fourth module, we rank the methods by $MinDis$ metric based on risk matrix [4]. With various demands under different scenarios, we can use $MinDis$ to evaluate models and choose an appropriate method.

Moreover, in feature oriented methods, features are the linchpin to ensure the accuracy. However, extracting features costs a lot, which requires to use efficient features to improve the accuracy and reduce the complexity at the same time. Therefore, we also give an evaluation of features' contribution.

The contributions of our work are listed as follows:

- We conduct a comprehensive survey on topic popularity prediction in social network, which is shown in the qualitative evaluation section;
- We propose a four-module evaluation scheme to fairly compare and rank existing or prospective methods under different scenarios;
- We give an evaluation of features' contribution on this problem.

The paper is organized as follows. We first give some definitions in Section 2. In Section 3, we introduce our evaluation scheme. In Section 4, we classify the topic popularity prediction methods and give a qualitative evaluation of them. Section 5 shows the quantitative comparison results of the methods. Section 6 talks about the final ranking module. Section 7 deals with the efficiency of the features using in machine learning models. In Section 8 we give summaries and conclusions.

2 Technical Preliminaries

Definitions: The **social network** is defined as a graph, $SN = (U, E, M)$. U is the set of the users (nodes) and E is the set of the edges in the graph defined as (u_q, u_p), which is weighted by times that u_p interacts (mention or reply)

with u_q. M is the set of messages posted by U. A **topic** h can be described as (U^h, E^h, M^h), where U^h have posted messages about h , M^h, and E^h are all the interactions at h. We divide the time T into a series $T_1, T_2, ..., T_t$. The **time series** of h is $TS^h = TS_1^h, TS_2^h, ..., TS_t^h$. TS_t^h is (U_t^h, E_t^h, M_t^h) which means a part of (U^h, E^h, M^h) where M_t^h is the messages in M^h posted in T_t and U_t^h only contains the users who post messages in M_t^h. Formally, the **popularity** P of h in time period T_t, P_t^h, is defined as $|M_t^h|$ [6].

Problem Statement: Given a social network SN, the problem of topics popularity prediction is to predict P of the topics in T_{t+1} using the information, or features in (U, E, M) before T_t. In our evaluation, we specify the purpose of the prediction to be predicting whether a topic will be popular.

3   The Evaluation Scheme

In this section, we elaborate our Topic Popularity Prediction Evaluation Scheme, which can be divided into 4 modules: *Classification, Qualitative Evaluation, Quantitative Experiment*, and *Final Ranking*. The scheme is shown in Figure 1.
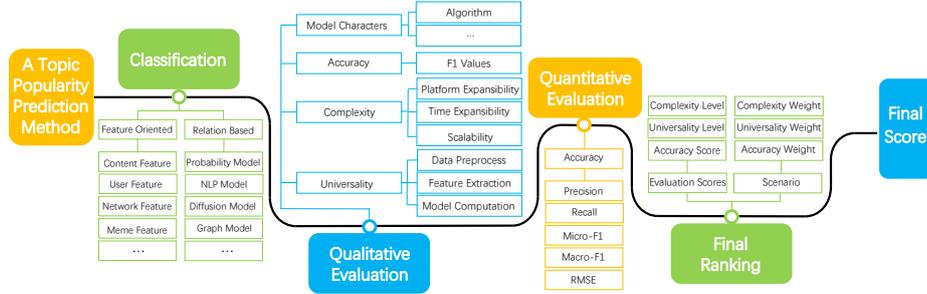

Fig. 1. The Evaluation Scheme

3.1   Classification and Qualitative Evaluation Overview

According to our investigation, we classify the methods briefly into two categories: *Feature oriented methods* and *Relation based methods*. *Feature oriented methods* use raw features and universal classification or regression models to predict. *Relation based methods* aim at building a specific model by finding the mathematics relationship between the features and the popularity.

Qualitative evaluation is performed to learn about the characteristics of each method. Three main metrics: accuracy[1] (a), complexity (c), and universality (u), as well as other properties such as denoising processes and algorithm categories, are evaluated.

We divide the three metrics into 3 levels and we provide a criteria table (Table 1) for them. These three metrics describe the synthetic performance of a method and we can use this criteria for all methods.

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[1] Accuracy is measured by F1 score.

Table 1. Criteria on Qualitative Evaluation

Level	Accuracy	Complexity[2]	Universality
HIGH	$(60\%, 1)$	If the complexity of preprocessing and extracting more than 20% of the features is $O(n^2)$ or the main model's complexity is over $O(n^2)$.	Easy to transplant to other platforms (social network) and can deal with huge data stream in any time period
MEDIUM	$(30\%, 60\%)$	Few parts of the methods have a complexity over $O(n^2)$ but they are not in a absolute dominant role.	Have some limits to transplant to other platforms or can deal with common cases of data
LOW	$(0, 30\%)$	If most preprocessing procedures, feature extracting, and the main model can be done within $O(n)$.	Only be used in some specific situations or constricted to data scale

3.2   Quantitative Experiment Overview

Qualitative evaluation gives out accuracy level of the methods. In this module we evaluate precision more elaborately, excavate deep level information and achieve more precise and fairer evaluation.

Based on the unified big dataset from Twitter, we perform the experiments on topic popularity prediction methods, which makes the result comparable and gets rid of possible "cherry-picking" problems.

3.3   Final Ranking Overview

With the results of previous steps, we gain insights from risk management and employ risk matrix [4] to generate the weights due to the nature that a model's final score should be considered by the category of probability against the category of importance. Then we rank models by presenting a novel metric, dubbed as **MinDis**.

We use w_{a1}, w_{a2}, w_{rm}, w_c, and w_u to represent the importance weights of *Macro-F1*, *Micro-F1*, *RMSE*, complexity, and universality.

MinDis is a metric proposed to describe how far a method is away from the ideal method according to the Euclidean Distance for a specific application scenario. It is formulated as:

$$MinDis = \sqrt{Dis_{F1_{mac}} + Dis_{F1_{mic}} + Dis_{rm} + Dis_c + Dis_u} \qquad (1)$$

In the equation $Dis_{metrics}$ represents $w_{metrics}(E(metrics) - metrics)^2$. This shows the Euclidean Distance of a metrics between the evaluated method and the perfect one in theory. $MinDis$ can be used to rank all the methods under a specific scenario to select the most appropriate method.

4   Classification and Qualitative Evaluation

We first classify the methods and give a qualitative evaluation of them, which is aimed at comprehensively analyzing the method characteristics and giving an introduction of their merits and drawbacks.

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[2] n is the number of tweets or users, and we only consider the number of traversal times in the complexity.

4.1   Feature Oriented Methods

In general, the topic popularity prediction problem for these methods can be divided into several parts: data preprocessing, denoising, feature extracting, and machine learning. For features are the key factors, in order to find efficient features, we briefly divide all the features further into six categories [6] (shown in Table 2).

In Table 2 we list all the metrics used to investigate the feature oriented methods in our evaluation scheme. Some methods treat hashtags as topics and utilize directly obtained features to train a classifier [5,6], while other methods pre-process the features to detect the topics and then train the machine learning algorithms [20]. The metrics in the evaluation scheme are described below:

Accuracy, Complexity, and Universality: Refer to Table 1.

F. Categories: Features impact the accuracy and efficiency directly. In Table 2, we list the categories of features a method adopts and the size of the feature space (**Number of Features**). Due to the limited space, we use **1 - 6** to denote six kinds of features: **Content**, **User**, **Network**, **Meme**, **Hashtag**, and **TimeSeries** respectively. We further evaluate feature effectiveness in Section 7.

Denoise: Denoising is an influential procedure to promote the performance of prediction. Some methods generate an equal internal time series (TS) to obtain information in early time intervals. Some use *critical drop* point to extract potential burst keywords. Others detect emerging topics (DET), and predict whether they will burst.

Table 2. Qualitative Evaluation of Feature Oriented Methods

Method	Paper	Publish	Accuracy	Complexity	Universality	F. Categories						Number of Features	Algorithm	Denoise
						1	2	3	4	5	6			
F-I	[5]	AS-IS&T	Medium	Medium	High	*	*	*	*	*		18	Classification	TS
F-II	[6]	SIGIR	Low	High	High	*	*	*	*	*	*	26	Classification	TS
F-III	[18]	ITAIC	High	High	Medium		*	*				6	Unsupervised Learning	CD
F-IV	[19]	ARCS	-	High	Medium	*			*	*		3	Clustering	-
F-V	[20]	SIGIR	High	High	Medium	*			*			6	Co-training & semi-supervised	DET
F-VI	[21]	ICWSM	High	High	Medium	*		*		*	*	Many	Classification	-
F-VII	[1]	IJCAI	-	High	Low	*	*					-	DTCN	-
F-VIII	[28]	IC-BNMT	High	Low	High	*	*	*	*			8	SVM	-

4.2   Relation Based Methods

Different from feature oriented methods, relation based methods regard the social network as heterogeneous distributions.

Geographical records of social networks work as sensors to find regions' interests. Thus, [15] proposed a geographical method, Latent Geographical Topic

Analysis (LGTA), which combines contents and locations. A much more popular type of methods is hashtag-based[7]. Performances of these methods are more stable than others due to the empirical studies of burst hashtags patterns. Many other models are proposed based on Natural Language Processing (NLP), probability theory, graph theory, and so on. Clustering is another interesting approach. [27] clustered users into groups and predicted the group-level popularity which improves the accuracy.

The evaluation results are listed in Table 3. The chosen metrics in the evaluation platform can be described as follows:

Accuracy, **Complexity**, and **Universality** are the same as above.

Recognition Time: This metric depicts how long a method can predict, such as R-IV can predict a topic two days prior to its burst on the civil unrest datasets.

Data Preprocessing: Some methods preprocess data before prediction, thus have high dependences on how well data are preprocessed.

Field: We summarize the field of knowledge the methods base on. Geographical methods are accessible in most platforms and languages, with a relative low accuracy. Methods based on graph theory and NLP can detect hot topics much earlier than others. However, they have a heavy dependence on preprocessing procedure.

Table 3. Qualitative Evaluation of Relation Based Methods

Method	Paper	Published in	Model	Accuracy	Complexity	Recognition Time	Universality	Data Preprocessing	Field
R-I	[7]	CIKM	IMA	Medium	Low	-	High		Probability (hashtag)
R-II	[9]	AAAI	PreWHether	High	Low	Medium	Medium		Probability
R-III	[8]	Sci. W. J.	Prerecognition Model	Medium	Medium	High	High	*	NLP
R-IV	[13]	SIGKDD	NPHGS	High	High	High	Medium	*	Graph Theory
R-V	[15]	IW3C2	LGTA	Low	Low	Low	High		Geographical
R-VI	[16]	WWW	Temporal and Spatial Model	Medium	Medium	Medium	Medium		Geographical
R-VII	[17]	CIKM	Hybrid Model	High	Medium	Low	High	*	Probability
R-VIII	[22]	Neurocomputing	Diffusion Model	Medium	Medium	Medium	High		Graph Theory
R-IX	[25]	NIPS	Latent Source Model	High	Low	Low	High		Probability
R-X	[26]	TWEB	SPIKEM	High	Medium	-	High		Probabilistic
R-XI	[27]	WWW	GPOP	High	Medium	High	High	*	Tensor decomposition
R-XII	[23]	JIIS	EdgeMRF	-	Medium	-	High		MRF

5   Quantitative Experiment

We perform a quantitative experiment based on a real world dataset to guarantee the fairness. We choose five methods to evaluate: F-I, F-II, R-I, R-II and R-III,

for they are all proposed recently, contain relatively complete feature spaces, and have great universality.

5.1 Introduction of the Experiments

Our dataset is grabbed from Twitter containing about 2 million tweets from August 1, 2015 to January 31, 2016. After filtering, all the data we used are tweets post in English because different languages may need different tokenization methods. Table 4 shows the detailed statistics about the dataset. In our evaluation, the time period is set to be 1 day.

Table 4. Detailed Information about the Dataset

Statistic	Value	Statistic	Value
Number of Tweets	2.5 M	Number of Followers	4.5 M
Number of Users	1.5 M	Number of Tweets with Hashtag	35K
Number of Retweet	0.7 M	Fraction of Tweets with Hashtag	1.4%

We conduct 10-fold cross validation on all the data to train the methods using machine learning models. All the features are extracted without any unfair optimization. We choose 5 metrics: *Precision*, *Recall*, *Macro-F1*, *Micro-F1*, and *RMSE* to measure their performance. *F1* is an metric that synthesizes precision and recall. *Macro-F1* is impacted mainly by the prediction accuracy of rare classes (popular topics). *Micro-F1* is similar to *Macro-F1*, but it is impacted mainly by the prediction accuracy of common classes (non-popular topics). We employ *RMSE* to uncover integral constancy of the methods

5.2 Results of the Quantitative Experiment

We choose the data in 7 days to fairly compare both two kinds of methods. Feature oriented methods are further experimented with the half-year data, dubbed as (Origin). In Table 5, we list the accuracy of each method and we compare them in Figure 2.

Comparison between Feature Oriented Methods and Relation Based Methods: From Figure 2, we can find that feature oriented methods perform better than relation based methods in precision, recall, and Macro-F1. This meets expectations, for feature oriented methods take more factors into account and the process of training with big data can give a more exact relationship between the factors and popularity. While *RMSE* and *Micro-F1* scores shows that feature oriented methods have a lower performance in prediction of non-popular topics, which may be because the model is over-fitting.

Comparison within Feature Oriented Methods: From Figure 2, we can see that when predicting for only 7 days, F-I with a smaller feature space has a better performance. It gives an expression to the importance of feature choice and the process to get rid of noise. For denoising, in F-I, only information in
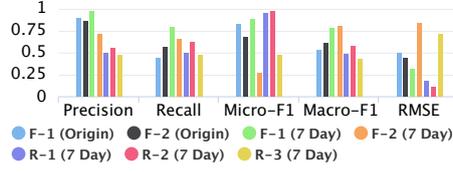
Fig. 2. Five Index Scores of Each Method

Table 5. Five Index Scores of Each Method

Method	Precision	Recall	Macro-F1	Micro-F1	RMSE
F-I (Origin)	0.9064	0.4421	0.5367	0.8381	0.4983
F-II (Origin)	0.8671	0.5798	0.6194	0.6915	0.4554
F-I (7 Day)	**0.9789**	**0.8000**	0.7889	0.8947	0.3244
F-II (7 Day)	0.7619	0.6667	**0.8148**	0.2857	0.8452
R-I (7 Day)	0.5070	0.5005	0.4942	0.9668	0.1822
R-II (7 Day)	0.5627	0.6290	0.5839	**0.9879**	**0.1100**
R-III (7 Day)	0.4856	0.4907	0.4358	0.4800	0.7211

time interval t is used to denoise. While in F-II, time interval $t-4, t-3, ..., t-1$ are also used. It is possible that F-I does a better job in denoising in this short period prediction because the information used for denoising in F-I is closer to the predicted time period and can reflect the features more accurately.

F-I (7 Day) has a higher accuracy than F-I (Origin). However, F-II (7 Day) is worse than F-II (Origin). This shows F-I is more suitable in short period prediction than F-II, while F-II is more suitable in predicting rare class in both situations for its Macro-F1 value is higher. In long period prediction, both of them have great accuracies.

Comparison within Relation Based Methods: From Figure 2 we find that R-II consistently achieves better performance than the other two relation based methods. The three latent features: *Sum, Average Rate of Change,* and *Standard Deviation* help the model to detect hot topic patterns in a universal way.

However, R-I uses three features detected from experiential studies. Setting a class of miscellaneous does not always perform well because their patterns are not constant and will have different performances in different datasets. In our experiments, R-I is too sensitive to find enough hot topics. More effective features should be implemented to better classify patterns of events.

R-III is a language-related solution. Its performance displayed in Figure 2 is quite different from the other two, especially on Micro-F1 and RMSE. Micro-F1 proves that NLP methods are apt to predict with a large scale of data, or "rich" data. For its experiments are based on microblogging data, we find it defective to process Twitter data and this method highly depends on pretreatment of posts, and users should manually reprocess the clustering results. A high RMSE reveals its precariousness.

6   Final Ranking

With the evaluation results above, we rank the methods by *MinDis* metric to fit different demands. We implement the ranking steps under 4 classical scenarios respectively.

I: This scenario is under a balance requirement, where the importances of every metric are the same.

II: This scenario is under a complexity oriented requirement which is widely used in real time prediction. Low complexity and high universality are required to deal with large flow data stream from different platform.

III: Accuracy is heavily weighted and Macro-F1 has the biggest weight, which shows that the precise prediction of rare classes is important under this scenario. This situation conforms to recommendation systems' requirement.

IV: We highly consider consistency with the goal of choosing a method with consistent performance.

Table 6. Risk Matrix of Scenario III

	Negligible	Marginal	Critical	Catastrophic
Certain				
Likely		c		
Possible		u	$F1_{mic},$ $rmse$	$F1_{mac},$
Unlikely				
Rare				

Table 7. Weights under Each Scenario

Scenarios	w_c	w_u	w_{a1}	w_{a2}	w_{rm}
I	0.200	0.200	0.200	0.200	0.200
II	0.286	0.285	0.143	0.143	0.143
III	0.182	0.091	0.363	0.182	0.182
IV	0.125	0.125	0.125	0.125	0.5

We adopt risk matrix to determine the weight of metrics under different scenarios. The columns show different levels of severity if the metrics are too bad while the rows show how possible and frequent each good metric can be achieved in all methods. Each level has an interval of 20%. According to our survey, 50% methods have low accuracy, thus, the likelihood of Micro-F1 and Macro-F1 is Possible. Similarly, the likelihood of high complexity, low universality and high RMSE are likely, possible and possible respectively. Table 6 shows the risk matrix of scenario **III**. The weights of metrics under it can thus be specified as in Table 7. We do the same for scenario **II**, **III** and **IV**. Users can make up their own scenarios.

We use the weights and previous evaluation results to calculate *MinDis*. The values of low, medium, and high level are 0.4, 0.5 and 0.6 because they can keep the relatively balance relationship among the metrics and guarantee that there is no one metric overwhelming in the final results. The results are listed in Table 8. F-I (7 Day) outperforms others under three scenarios while R-II (7 Day) stands out under scenario IV showing a better consistency. .

Table 8. Final Ranking of All the Methods in Each Scenario

Scenarios	F-I (Origin)	F-II (Origin)	F-I (7 Day)	F-II (7 Day)	R-I (7 Day)	R-II (7 Day)	R-III (7 Day)
I	0.3160	0.2991	**0.1848**	0.5018	0.2471	0.2170	0.4730
II	0.2697	0.2528	**0.1608**	0.4241	0.2221	0.2019	0.4016
III	0.3603	0.3282	**0.1979**	0.4849	0.3194	0.2709	0.5112
IV	0.3943	0.3656	0.2466	0.6521	0.2031	**0.1842**	0.5786

7 Evaluation of Effectiveness of the Features

In this section, we analyze the features widely used in this problem, and evaluate their efficiency based on numerical experiments in order to choose appropriate

features. LibSVM is used as the machine learning model. We train the model using the whole dataset, and then 7-day data. 10-fold cross validation is used to separate training and testing data.

Altogether we take 34 features into account. The features are classified into six categories [6]. We list all the features in Table 9 with some qualitative analyses: *Complexity* which means the complexity to extract the feature, *Temporal* representing whether this feature varies with time, and *Graphic* telling us whether this feature describes graph (U_t^h, E_t^h).

The features are described as follows:

Table 9. Features Used in Feature Oriented Methods

No.	Name	Description	Complexity	Temporal	Graphic
F_{c1}	NumEmo	The total number of emoticons included in T_t^h	Medium	*	
F_{c2}	NumSpeSig	The total number of special signals like "!!!!" or "Goooood!" included in T_t^h	Medium	*	
F_{c3}	SentiOHash	The value of positive and negative points calculated by SentiStrength model	Medium		
F_{c4}	Topics	20-Dimension topic distribution vector derived from T_t^h using LDA model	High		
F_{u1}	ActOUser	Average activities of U_t^h gained by PageRank [24]	Medium	*	*
F_{u2}	MaxOF	The max number of followers of users in U_t^h	Medium	*	*
F_{u3}	AvOF	Average number of followers of users in U_t^h	Medium	*	*
F_{h1}	Length	The length of the hashtag	Low		
F_{h2}	multiFreq	Fraction of tweets having more than one hashtags	Medium	*	
F_{h3}	Clarity	Kullback Leibler divergence of word distribution between T_t^h and tweets collection T	High		
F_{h4}	ExtClar	The extension of F_{h3}	Quite High		
F_{h5}	NumInHash	Whether a number is contained in the hashtag	Low		
F_{h6}	NumOWord	The number of words in a hashtag	Low		
F_{n1}	Degree	The average degree of nodes in G_t^h	High	*	*
F_{n2}	Density	The density of G_t^h	High	*	*
F_{n3}	Order	The order of G_t^h	High	*	*
F_{n4}	EntrODD	The entropy of degree distribution of G_t^h	High	*	*
F_{n5}	NumOBUser	The number of border users of G_t^h	Quite High	*	*
F_{n6}	ExpVec	Exposure vector of border users	Quite High	*	*
F_{n7}	CompFrac	Ratio between number of connected components and number of nodes in G_t^h	High	*	*
F_{n8}	Weight	The average weight of edges in G_t^h	High	*	*
F_{n9}	TriFrac	Fraction of users forming triangles in G_t^h	High	*	*
F_{m1}	NumOUser	The number of users in the U_t^h	Medium	*	
F_{m2}	FracOUser	The fraction of users who have posted tweets with hashtag h in the G_t	High	*	
$F_{m3,4}$	NumO@, FracO@	The Number and feaction of tweets in which the author has @ someone else in the T_t^h	Medium	*	
$F_{m5,6}$	NumORT, FracORT	The Number and fraction of retweets in the T_t^h	Medium	*	
F_{m7}	NumOT	The number of tweet in the T_t^h	Medium	*	
F_{m8}	FracOURL	The fraction of tweet having URL in it in the T_t^h	Medium	*	
F_{t1}	Mn	The mean value of the time series	High	*	
F_{t2}	MnD	The standard deviation value of the time series	High	*	
F_{t3}	Sd	The mean value of the absolute first-order derivative of time series	High	*	
F_{t4}	SdD	The standard deviation value of the absolute first-order derivative of time series	High	*	

Content Features F_c**:** They reflect the meaning and sentiment of posts. Previous studies show that negative topics are more likely to be popular [11]. Therefore, the features describing sentiment (F_{c1}, F_{c2}, F_{c3}) are taken into account.

User Features F_u**:** Because a tweet posted by a more active user is more likely to be popular, F_{u1} is listed in. F_{u2} and F_{u3} are extracted to reflect the number of followers who affect the dissemination of tweets.

Hashtag Features F_h**:** Hashtag Features show the number of words (F_{h6}), clarity (F_{h3}), and some other information. For instance, "livemusic" and "Epl" are two hashtags. "livemusic" has two words and a clearer meaning.

Network Features F_n**:** The graph (U_t^h, E_t^h) is described by network features. Border users represent those who is not in U_t^h but follows the users in U_t^h. F_{n6} is a 15 dimension vector and dimension D_i denotes that the number of border users following i users in U_t^h is D_i. A three nodes cycle in the graph is a triangle and let the set of triangles be Δ_t^h. F_{m2} is $|\Delta_t^h| \, / \, (|U_t^h|(|U_t^h| - 1)(|U_t^h| - 2) \, / \, 3)$. Let C_t^h stands for the set of disconnected parts of the graph. F_{n7} is defined as $|C_t^h| \, / \, |U_t^h|$.

Meme Features F_m**:** Meme Features are mainly about "numbers" and "fractions" in tweets such as the number and fraction of tweets with "@".

Time Series Features F_t**:** Time series can be described by the polynomial fitting curve and the absolute first-order derivative of the fitting curve. Their mean value and standard deviation value are chosen as features.

Some of these methods are multidimensional such as Topics (F_{c4}) whose dimension is 20, so the whole feature space has 68 dimensions. We remove each feature from the feature space [14], use the new feature space to train the classifier respectively, and rank all the removed features by its relative contribution (RC), which is:

$$RC = -1000(A_i - A_s)$$

A_i is the average value of *Macro-F1* and *Micro-F1* when F_i is removed from the feature space and A_s is the standard average value with the whole feature space.

We first evaluate with the whole **half-year training data**. The fifteen most efficient features (Rank1-Rank15) and the fifteen least efficient features (Rank54-Rank68) are listed in Table 10. We observe that, **first**, meme features are more efficient, F_{m1} and F_{m7} can reflect the present incidence of the topics. A tweet with URL contains more abundant contents that people are more interested in, so F_{m8} is also an efficient feature. **Second**, border users can decide how widely the topic will be disseminated, so F_{n5} is the most efficient feature. **Third**, there are 5 dimensions of Topic Vector among the Top 15, which reflects an actual phenomenon that some specific topics have a relatively high possibility to be popular. **Fourth**, there is no Time Series Feature in Top 15. **Fifth**, F_{n6} does not perform as efficient as expected. It is likely that the low dimensions of the vector are too undistinguished to help classify the popularity. While the high dimensions of the vector need a relatively complete dataset to work efficiently. **Sixth**, except for the F_{c4}, most of the efficient features are temporal and graphic. However, the complexities of them are commonly high. In the evaluation with only **7-day** training data, the results are similar. We also find that time series features are more suitable in short period training to describe the latest trends.
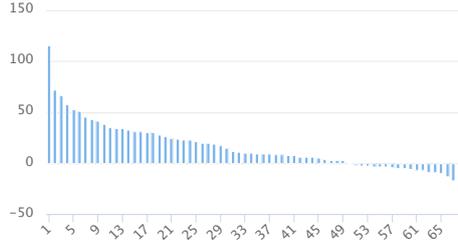
Fig. 3. The Relative Contribution of the Feature

Table 10. The 15 Most Efficient Features and the 15 Least Ones

Rank	Feature	Rank	Feature
1	F_{n5}: Number of Border User	54	F_{h2}: Co-occurrence Frequency
2	F_{m1}: Number of User	55	F_{m6}: Fraction of Retweet
3	F_{m8}: Fraction of URL	56	F_{n6}: D-3 of Exposure vector
4	F_{m7}: Number of Tweet	57	F_{t2}: mnD
5	F_{h3}: Clarity	58	F_{c4}: D-4 of Topic Vector
6	F_{m2}: Fraction of User	59	F_{c4}: D-6 of Topic Vector
7	F_{c4}: D-15 of Topic Vector	60	F_{c1}: Count of Emoticons
8	F_{c4}: D-17 of Topic Vector	61	F_{h4}: Extension Clarity
9	F_{m4}: Fraction of @	62	F_{n6}: D-4 of Exposure vector
10	F_{u1}: Activity of User	63	F_{n2}: Graph Density
11	F_{n7}: Component Fraction	64	F_{n6}: D-10 of Exposure vector
12	F_{c4}: D-5 of Topic Vector	65	F_{c4}: D-17 of Topic Vector
13	F_{c4}: D-12 of Topic Vector	66	F_{u3}: Average of Followers
14	F_{c4}: D-16 of Topic Vector	67	F_{n8}: Edge Weight
15	F_{u2}: Max of Followers	68	F_{c3}: Sentiment of Hashtag

8   Conclusion

This work proposes a rigorous evaluation scheme for forecasting the rise of certain topics in social media and surveys the existing methods based on it. Prior methods' experiments are based on different datasets, which results in low comparability among them and there is no prior research performing the evaluation. In our scheme, we first classify the methods into two categories: *Feature Oriented Methods* and *Relation Based Methods*. We then perform qualitative evaluation and quantitative experiment based on a real-world dataset. We give out the final ranking values to greatly reflect their comprehensive performance under given scenarios. The evaluation results show that *Feature Oriented Methods* are more suitable for accuracy dominant scenarios and *Relation Based Methods* have better consistency. It also provides several detailed findings. First, denoising essentially suits models to different scenarios. Second, the number of features and data samples have no special relation to the prediction performance. Therefore, choosing efficient features is important. Third, *Feature Oriented Methods* have a higher accuracy but they suffer from heavy overhead such as feature extracting. In addition, we evaluate the efficiency of 34 features used in *Feature Oriented Methods*. The results show that features about graph and temporal information are more efficient. In all, our work reveals different characteristics of the methods, provide guidelines on selecting appropriate methods under different scenarios, and help select efficient features for applications.

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