Propagator or Influencer? A Data-driven Approach for Evaluating Emotional Effect in Online Information Diffusion

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***Abstract*—Reposting is the basic and key behavior for information diffusion in online social networks. It would be beneficial to understand the influence factors of reposting behavior and predict future reposting status, which could be practically applied in breaking news detection, marketing, social media researches and so on. Existing reposting analytics and prediction approaches mainly focus on factors related to the original information content and the social influence of the information publishers. However, online information diffuses by viral cascades instead of single-source broadcast in social network, which means some reposting behavior actually occurs in information propagators rather than the original publishers. In some social networks, users are allowed to comment when they repost, which represents their views and attitudes to the information they propagate. In this paper, we evaluate how emotional tendencies of information propagators influence future reposting. We first propose a modified sentiment analysis method and present emotional analysis on the user-generated content in online diffusion. Experiments are conducted with a real-world dataset and the results indicate the effectiveness of our fine-grained emotional features in reposting prediction.**

Keywords—Information diffusion; retweet; sentiment analysis; feature selection; online social networks

I. INTRODUCTION

Online social network (OSN) has been an important communication platform for billions of users all over the world. Various kinds of information such as news, ideas and product recommendations are published, shared and discussed in OSNs every day. Twitter[1] reported 328 million monthly active users worldwide in May 2017, while Sina Weibo[2], which is one of the most popular and representative microblogging websites in China, had more than 340 million monthly active users in the same period. Information spreads quickly and widely in these OSNs, and to understand their diffusion mechanisms will be helpful for precision marketing, viral advertising, emergency management and even anti-terrorist campaigns.

Online diffusion with diverse and complex cascades is constituted by reposting, which is a basic but essential behavior in OSNs. Researches have been carried out for understanding the influence factors of reposting. By explicitly interviewing Twitter users, Boyd et al. [1] analyzed and summarized the reasons why people repost. Suh et al. [2] presented statistical analysis and found that both social features and textual features influence the probability of reposting, and Zaman et al. [3] adopted those features into reposting prediction. Bakshy et al. [4] evaluated the influence of individual and content by measuring diffusion cascades and presented prediction by regression tree model. Petrovic et al. [5] proposed a time-sensitive approach and proved the effectiveness of time-sensitive features.

Though information spreads by cascades in OSNs, most posts do not receive any repost and most of the retweets[3] are directly reposted from the original publisher, as noted by existing studies like [18], which means that multi-generational reposting rarely happens in online information diffusions. Thus, most existing researches actually studied the diffusion mechanisms of original posts (even if original and non-original content are not specifically distinguished in some of the studied dataset) and focused on influence factors related to the original content and publishers. However, considering the massive scale of OSNs nowadays, there are still considerable amounts of retweets that do not directly repost from the original publisher but another retweet. Diffusion mechanisms for such non-original content might be quite different due to the influence of both information publisher and propagator. In addition, some social networks (Twitter and Weibo, e.g.) allow users to publish their own comment while reposting from others. The additional content, which often expresses information propagators' sentiments and opinions, should be considered separately from the original message.

In our work, we focus on the information propagators in online diffusion rather than the original publishers, and study how different fine-grained emotional status of propagators influence future reposting status. As far as we know, this is the first work that focuses on information propagators and studies fine-grained emotional influence in online diffusion.

[1] https://twitter.com/
[2] http://weibo.com/

[3] To avoid confusion, in this paper we use REPOST to represent the behavior that users transport message from others, and use RETWEET to represent the generated content by reposting behavior, including the original message and comment from the transporter if exist.

II. Related Work

We briefly discuss some research threads related to our work, which can be distinguished into studies of sentiment analysis and online information diffusion.

A. Sentiment Analysis

Existing sentiment analysis approaches can be divided into three main categories: lexicon-based approaches, supervised machine learning approaches and unsupervised machine learning approaches, according to Schouten et al. [6]. Pang et al. [7] used supervised machine learning algorithms such as Naïve Bayes and Support Vector Machine (SVM) in sentiment analysis. Hu et al. [8] proposed an unsupervised machine learning method and improved its performance by considering emoticon and product ratings. Ekman et al. [9] studied the fine-grained emotion categories and defined six basic emotional status. Mohammad et al. [10] built an emotion lexicon based on Ekman's theory. Xu et al. [11] constructed a weighted Chinese fine-grained emotion lexicon. Zhao et al. [26] proposed a hybrid method based on lexical knowledge of Weibo emoji and supervised machine learning algorithms.

B. Online Information Diffusion

For reposting prediction, Yang et al. [12] used factor graph to analyze influence factors of reposting behaviors. Kupavskii et al. [15] considered the active time of users and proposed time-sensitive factors. Zaman et al. [16] and Bao et al. [17] demonstrated the effectiveness of diffusion structural features in reposting popularity prediction. Goel et al. [18] and Yi et al. [19] presented important structural features in online diffusion. Hong et al. [20] turned the popularity prediction into classification problems and compared performances of different features. Chen et al. [21], Zhang et al. [22], Luo et al. [34] and Lee et al. [35] proposed methods using users' interactions and interests to predict whether a specific user will repost specific content, which relied on historical knowledge.

Some previous work proposed diffusion models to describe the mechanism in online diffusion, which can be categorized into graph-based and non-graph-based methods. Graph-based methods are mostly based on independent cascade model by Glodenberg et al. [23] and linear threshold model by Granovetter et al. [24]. These approaches relied on the complete network topology of user relation and calculate for each possible user pairs, which might be costly in practical application. Non-graph-based approaches are mostly based on epidemiological models and one of the most representative approaches was proposed by Leskovec et al. [25].

Emotional influence in online information diffusion has been discussed in some previous work. Jenders et al. [13], Tan et al. [14], Gruzd et al. [29], Stieglitz et al. [30], Ferrara et al. [31] and Tsugawa et al. [32] noted emotional influence in diffusion popularity and speed, in which emotional status was coarsely distinguished into positive and negative sentiment. Naveed et al. [33] presented emotion analysis with dimensional model and proved that emotional feature influences repost probability. In our work, definition of emotional status strictly follows Ekman's basic emotion theory [9], which is one of the most authoritative discrete emotion theory. Emotional influence is evaluated by various machine learning classifiers' performances, which can better deal with the hidden correlations compared to linear or generalized linear methods that widely used in previous studies (Logistic regression, e.g.).

III. Dataset and Methods

For our study to evaluate the emotional influence in online diffusion, we randomly collect tweets, retweets along with user profiles of tweet publishers and propagators from the *popular recommendation list*[4] of Weibo from December 30, 2016 to May 10, 2017. In addition, the diffusion cascade in time sequence for each original tweet is reconstructed referring to algorithm proposed by Yi et al. [19], so that we can exactly know the tweet or retweet that a retweet actually reposts from. In total, 22,270,728 retweets from 50,590 individual original tweets are observed[5], as well as a set of 9,636,074 unique user profiles which contains every user that participated in those online diffusion events.

We notice in our dataset that the average size of diffusion cascades is 440, and 51.2% of the cascades contain at least 100 nodes. Compared to the Twitter dataset constructed by Goel et al. [18], whose average cascade size is 1.3 and only 0.025% of their diffusion cascades are with at least 100 nodes, our work obviously benefits from our dataset since the rare events (retweets and multi-generational reposting) that we exclusively focus on are much more efficiently collected.

To evaluate the fine-grained emotional effect for retweets, we first define the emotional status of propagators by content and diffusion cascades. After which, we present exploratory analysis to find out the correlation between emotion and reposting status such as repost probability. Finally, the fine-grained emotional influence is evaluated by performances of reposting prediction tasks with different feature selections.

IV. Emotion Classification and Inference

In this section, the methodology we follow to define and classify each propagator's emotional status is discussed. We propose a sentiment analysis approach combining lexical knowledge with supervised machine learning algorithm, and effectively overcome the drawback of lexicon-based methods. Compared to generic algorithms, our approach can better adapt to the needs that processing text from a specific OSN. Furthermore, inferences based on emotion contagion theory are presented, which help to comprehensively depict users' emotional statuses during online diffusion.

A. Emotion Definition and Corpus

According to Ekman et al. [9], we define users' emotion into six basic categories: *happiness*, *anger*, *sadness*, *fear*, *disgust* and *surprise*. Compared to the coarse-grained approach that distinguishes emotion into positive and negative sentiment, our work would benefit from fine-grained categories, which will be demonstrated and evaluated in the experiment part.

To achieve and evaluate our emotion classification method, we construct Weibo corpus by extracting text content from Weibo dataset that mentioned in Section III. About 9.45 million comment is extracted from 22.3 million retweets, since

[4] http://d.weibo.com/

[5] A list file contains the unique id of all original tweets in our dataset could be downloaded at http://pan.baidu.com/s/1qYJMivE/.

some retweets are without any comment. We then proposed a hybrid method combining lexical knowledge and supervised machine learning algorithms, which is inspired and modified from work by Zhao et al. [26].

B. Lexicon-Based Approach

The lexicon-based step refers to the Chinese emotion lexicon presented by Xu et al. [11]. A set of emotion words for each of the six emotion categories is provided, as well as the sentiment intensity score of each emotion word.

In addition, we take emoji, which are widely used in Weibo and usually represent intense emotional tendencies, into our consideration to extend the lexicon. According to statistical analysis, we collect 98 most frequently used emoji, which cover more than 99.3% of emoji usage in our dataset. Considering the actual meaning of each emoji, we find its synonymic words in the lexicon. For each emoji, we then label the emotion category and sentiment intensity score referring to its synonymic words. Table I shows the total number of words and emoji for each emotion type in our extended lexicon.

TABLE I. ITEM AMOUNTS IN OUR EMOTION LEXICON

Emotion Type	**Hap.**	**Ang.**	**Sad.**	**Fea.**	**Dis.**	**Sur.**
Words Count	609	187	362	182	845	47
Emoji Count	41	12	11	6	21	7

For a tweet or retweet *t*, we consider items from our lexicon that could be found in *t*, and summarize the sentiment intensity score of these items by different emotion types. The emotion type with a maximum summation value is taken as the emotion category of *t*. In particular, if *t* contains no item from our lexicon, the lexicon-based approach would fail to categorize *t*.

We presented lexicon-based algorithm mentioned above to process our Weibo corpus, and observed that only 38.92% samples in the corpus could be successfully categorized. We considered the low matching ratio as the drawback of lexicon-based methods. The generic knowledge-based approaches could not ideally adapt to different domains, e.g., Weibo corpus in our work. In other words, our emotion lexicon does not sufficiently accommodate sentiment words that used by Weibo users. However, it is unrealistic to inspect every possible word in Weibo corpus and reconstruct a specialized emotion lexicon all by human annotation. Thus, a supervised machine learning method will be proposed next.

C. Supervised Machine Learning

In this subsection, lexical knowledge is combined with supervised machine learning algorithm in order to improve the performance of emotion classification. Since the Naïve Bayes algorithm has demonstrated its superiority for sentiment analysis in previous works such as [7], it is adopted as an alternative approach for the lexical method. Implementation of our Naïve Bayes algorithm follows next steps:

Dataset: About 3.68 million retweet comment has been successfully categorized using the lexicon-based method that we mentioned in the previous subsection. This part of the corpus has been appropriately categorized into six emotion types, and can be considered as labeled ground truth to train and evaluate our supervised machine learning algorithms.

Features: As a widely accepted approach to process sentiment analysis in machine learning algorithm, each comment text in our corpus is transformed into word vector, by the famous Chinese segmentation tool *jieba*[6]. Each element of the word vector is a binary value, which represents whether the corresponding word occurs in the comment text. As there are massive amounts of possible words that might occur in the corpus, only parts of words are considered as elements of the word vector, which is selected by following two groups:

1) Emotion Lexicon Features: The well-defined emotion lexicon we construct in the previous subsection includes series of words and emoji, which would be effective influence factors for emotion categorizing. This group contains 2330 features, including 2232 emotion words and 98 Weibo emoji.

2) Top N Most Informative Features: In this group, features are selected by considering their validities for emotion categorizing. Our labeled ground truth could be devided into six subdataset by emotional status, and each of them is a corpus of the corresponding emotion type. The word frequencies among different subdataset for each word are calculated, and a reasonable assumption is proposed that a word is more likely to be helpful for emotion categorizing only if the word frequencies of this word show significant difference among different subdataset. The chi-square value in chi-square test [27] is calculated to evaluate the difference of word frequencies, and words with high chi-square value are considered as informative features. The parameter N , which represents the number of words chosen in this group, would influence the performance of emotion categorizing. The appropriate value of N is explored by comparison experiments.

Task and evaluation: Our task is to successfully categorize more samples in the whole Weibo corpus, and maintain acceptable classification precision as well. For evaluation, the precision ratio of Naïve Bayes algorithms is considered, as well as the proportion of samples that could be successfully categorized by our algorithm among the whole corpus. Table II shows the performances of Naïve Bayes (NB) algorithms with different values for parameter N. The precision ratio is measured in the labeled ground truth, and we make a reasonable assumption that our machine learning algorithm maintains similar performance in the whole corpus, so that an overall evaluation can be proposed by estimating the proportion of precisely categorized samples. Figure 1 demonstrates the performances of different approaches, which convinces us to take $N = 5000$ as our final proposal. Compared to the lexicon-based method, our approach shows 48.5% improvement in categorized ratio and 37.7% improvement in precisely categorized proportion.

D. Emotion Contagion Inference

With our previous work, we achieve to categorize the emotion types for most of the retweet comment, which can represent the emotional statuses of propagators. However, according to observation in our dataset, 58% of Weibo users

[6] https://github.com/fxsjy/jieba/

repost from others without publishing any comment. To deal with those propagators, an inference method is then proposed referring to previous research by Guillory et al. [28], which demonstrated that emotion contagion did occur via text-based social networks. Boyd et al. [1] also presented that one of the reasons that people reposts was to publicly agree with someone.

Thus, a repost without any comment text is inferred to imply a same sentiment as its previous node in the information diffusion cascade. The retweets that fail to be categorized by Naïve Bayes approach will follow such inference rule as well. In particular, if both the original tweet and all retweets in the reposting chain of a propagator fail to be categorized by text-based sentiment analysis method (rarely happens according to our observations in Section V), the emotional status of this propagator is considered as *objective*.

In Section V, the emotional status of "actually categorized" and "inferred" will be distinguished as explicit and recessive ones, since they behave in quite different mechanisms during online diffusion process. Thus, in some of our following discussion, we categorize emotional status in more fine-grained level, which contains 2*7 = 14 classes (explicit, recessive; *happiness*, *anger*, *sadness*, *fear*, *disgust*, *surprise*, *objective*).

V. OBSERVATION

In this section, several exploratory analyses are presented to reveal the underlying mechanisms about the influence of propagators' fine-grained emotional statuses on information diffusion. For what we concern most about, the statistically significant evidence is observed that emotional status directly influence the information diffusion probability. In addition, the correlation between emotional status and other important factors in online diffusion such like users and time is discussed. A brief analysis on emotion contagion is also proposed.

TABLE II. PERFORMANCE OF CLASSIFICATION ALGORITHMS

Algorithm	**Precision**	**Categorized**	**Estimated Precisely Categorized**
Lexical	100%	38.9%	38.9%
NB (N=0)	73.4%	38.9%	28.6%
NB (N=1000)	92.2%	67.9%	62.6%
NB (N=2000)	89.5%	70.3%	62.9%
NB (N=5000)	87.7%	87.4%	**76.6%**
NB (N=MAX)	79.8%	92.7%	74.0%

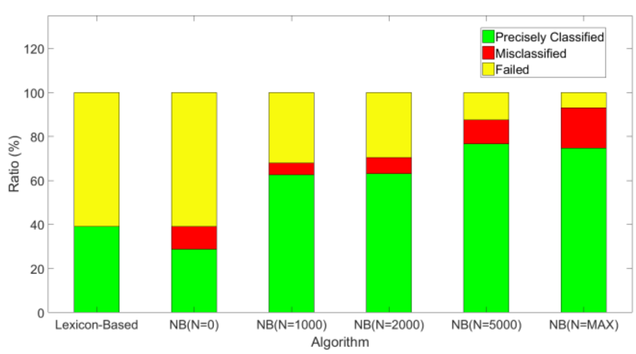


Fig. 1. Performance analysis of classification algorithms.

A. Overview

Emotional statuses of all propagators in our dataset are distinguished into fine-grained emotional categories by the approach we propose in Section IV. We notice that 38.66% of propagators express *happiness*, which take the maximum proportion. The proportion of other emotion is 29.33% for *anger*, 14.63% for *fear*, 6.98% for *disgust*, 6.75% for *surprise* and 3.54% for *sadness*. In particular, only 0.10% propagators are considered as *objective*, whose sample scale is too small that might be susceptible to outliers. Thus, the *objective* emotion is not taken into consideration in our following study.

B. Emotional Influence on Diffusion Probability

Reposting is the basic and key composition for information diffusion in OSNs. In this subsection, statistical approaches are presented and applied to figure out whether the fine-grained emotional statuses of the propagators could influence the probability for the information to be reposted again.

By reconstructing the diffusion cascades, we can find out those retweets that would be reposted again later. It is easy to understand that an information diffusion cascade is actually a tree. Thus, those retweets that would be reposted again represent the non-leaf nodes in the tree. The proportion of those reposted retweets among the subdataset of each emotional status is calculated, which might reveal the emotional influence on repost probability.

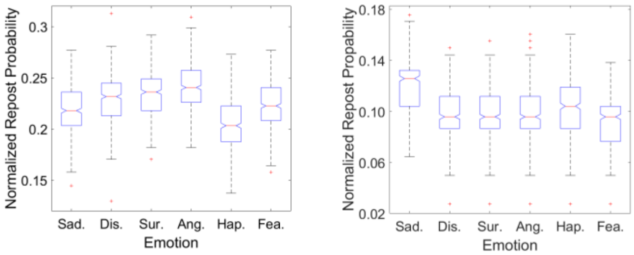
Table III shows the proportion of reposted retweets among different emotional statuses. Notice that the repost probability of explicit emotion is obviously higher than the recessive one, which proves the necessary to distinguish the emotion into these subtypes. On the other hand, *happiness* and *surprise*, which are both considered as positive sentiment by coarse-grained approaches, perform quite different in our observation.

The influence of different emotional statuses is studied then. Different emotion shows various repost probability among both explicit and recessive subtypes. An analysis of variance (ANOVA) approach is presented to evaluate whether the deviation between emotional statuses is statistically significant, whose result is shown in Figure 2.

The result indicates that fine-grained emotional influence on repost probability is statistically significant (both $p < 10^{-100}$). More specifically, retweets with *explicit-anger* performs strongest infectivity, while *happiness*, beyond our expectation, has relatively weak diffusion capacity among explicit emotion. On the other hand, a *recessive-sadness* retweet is more likely to receive another repost compared to other recessive emotion. Further analyses and demonstrations will be proposed in the following subsections.

TABLE III. REPOSTED RATIO FOR EMOTIONAL STATUSES

Emotion Type	**Hap.**	**Ang.**	**Sad.**	**Fea.**	**Dis.**	**Sur.**
Explicit	4.10%	**5.68%**	4.65%	4.81%	5.15%	5.40%
Recessive	1.56%	1.37%	**2.18%**	1.17%	1.29%	1.30%
Overall	3.00%	2.28%	**3.62%**	2.97%	3.26%	3.15%



(a) Explicit Emotion. (b) Recessive Emotion.

Fig. 2. ANOVA result for repost probability among explicit and recessive emotion. (Value of y-axis represents a normalized binomial distribution sample that resampled from our dataset, which is positively correlated with the repost probability. We take such measure to transform our Bernoulli-distributed sample so as to satisfy assumptions of ANOVA.).

C. Correlation Evaluation

As the existence of emotional influence has been illustrated, we wonder whether the influence is direct. It should not be concluded that the phenomenon observed in Section V.B is exactly caused by emotional factors directly unless the correlation between factors is evaluated. Specifically, we focus on the social features of users and time-sensitive features, which have been proven to be important influence factors for online diffusion in previous researches (Suh et al. [2] and Kupavskii et al. [15], e.g.). The correlation between emotion and factors mentioned above is analyzed then.

User Factor. The social feature of OSN users (the number of followers, e.g.) has been proven to be one of the most effective factors in online diffusion prediction by previous researches (Suh et al. [2], e.g.). In our analysis, three specific user groups are defined, and observation is taken to find out whether their emotional distributions are biased, which might cause indirect influence. We take 1% users that with the most follower numbers as popular users. About 2% of all users are verified officially by Weibo, and are grouped as verified users. In addition, 1% users with the most number of past tweets are defined as most active users. The emotional distributions among these groups and the distribution overall are shown in Figure 3. We observe that the popular users and the verified users, both of which are widely recognized to strongly influence online diffusion, follow similar emotional distribution as the overall one. Specifically, the deviation of emotion proportion for all emotion categories are less than 2% among these two groups compared to the overall distribution. We also notice that the emotional distribution among most active users seems quite different as the high proportion of *happiness* retweets. However, by Suh et al. [2], the number of past tweets rarely influence the repost probability. Thus, to a certain extent, we can consider that correlation between emotional status and user factors is not likely to cause indirect influence on diffusion probability so far as we know.

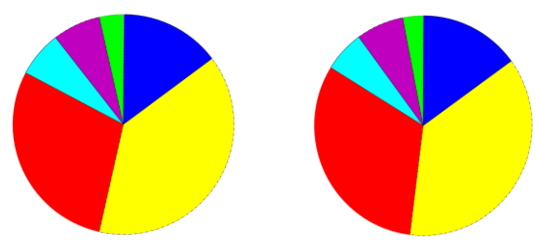
Temporal Factor. We then consider the influence of temporal factors. Specifically, we wonder whether time-varying user activity would cause indirect emotional influence. Dataset is divided into 24 subdataset by timestamp information, and each of them contains retweets that published in a specific hour. The repost probability and emotional distribution of each subdataset are calculated, by which we can learn the trend of both two values during a whole day. Figure 4.a shows that the repost probability becomes low during midnight, while from Figure 4.b we notice that emotional distribution remains nearly stable in a day. The correlation coefficient between repost probability and the proportion of each emotion is calculated in Table IV. We notice that most of the emotion statuses shows relatively low relevance with the time-varying repost probability, which means the unevenly distribution of emotion in time is unlikely to cause indirect influence on diffusion probability.

D. Emotion Contagion Analysis

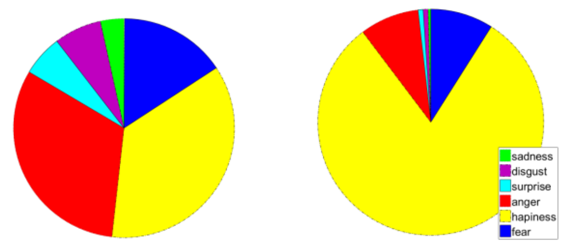
In this subsection, we briefly propose exploratory analyses about emotion contagion through online information diffusion. Figure 5.a demonstrates emotion contagion during online diffusion, as observation that the emotional status of a retweet is highly likely to be the same as which it reposts from. Note that only explicit emotion is considered here so that the result avoids being affected by our emotion inference approach. In Figure 5.b we find that a *happiness* retweet is much more likely to receive an explicit echo, which is defined as a repost that explicitly expresses the same emotion. On the other hand, Figure 5.c shows *anger* retweets receive more recessive echoes, which means reposts without any comment. We conclude from such phenomenon that people might be more likely to express some emotion such as *happiness* with their own words, and tends to present emotion like *anger* by the silent support. Figure 5.d presents the cumulative distribution function (CDF) of repost depth for each emotion, in which we notice that *surprise* retweets are relatively more contagious than other emotion and can spread through longer diffusion chains.

TABLE IV. CORRELATION COEFFICIENT BETWEEN EMOTION AND TIME

Emotion Type	Hap.	Ang.	Sad.	Fea.	Dis.	Sur.
Correlation Coefficient	-0.067	-0.117	-0.205	-0.088	0.104	0.396

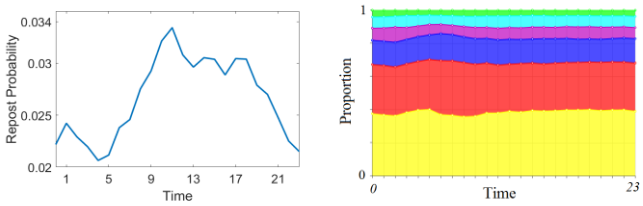


(a) Overall. (b) Popular users.



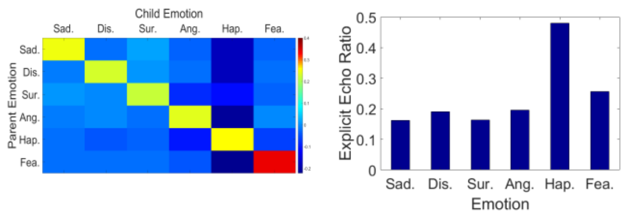
(c) Verified users. (d) Most active users.

Fig. 3. Emotional distribution overall and among specific users.

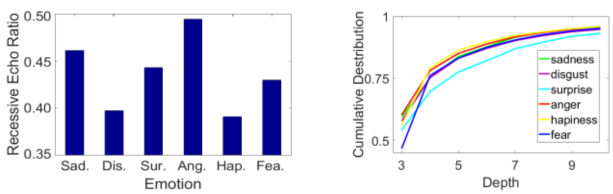


(a) Repost probability. (b) Emotional distribution.

Fig. 4. Repost probability and emotional trend in a day.



(a) Emotion transformation analysis. (b) Explicit echo ratio.



(c) Recessive echo ratio. (d) CDF of repost depth.

Fig. 5. Emotion contagion analysis.

VI. Experiments and Evaluation

In this section, the effectiveness of fine-grained emotional factors for reposting prediction is evaluated. Supervised machine learning algorithms are used to achieve our goal. Several experiments are presented to compare the performances of different algorithms with various feature selections for multiple prediction tasks.

A. Problem Statement

Our basic task of reposting prediction is to predict repost probability of a retweet. Specifically, a user *u* published a retweet *t*, whose original tweet is t_0. All retweets and the repost cascade of t_0 with timestamp, as well as all users' profiles that have reposted t_0 at the time, are known and available. We concern whether someone will repost from a given retweet *t*, which is a binary classification problem.

Some refined prediction tasks are proposed as well for better describing potential reposting status, including *popularity*, *speed* and *lifespan*. We regard the number of reposts that a retweet finally received as the *popularity* of this retweet. Repost *speed* is defined as the time interval between when the retweet was generated and when it was firstly reposted. Similarly, *lifespan* means the time interval between the published time of the retweet and when it was reposted for the last time. As it is difficult to predict the exact answers to those problems, we relax them as multi-class classification problems by well-defined division.

The emotional influence will be evaluated by comparing classification performances that with and without our fine-grained emotional features, which indicates their effectiveness. Furthermore, baseline methods with coarse-grained emotional features are performed to indicate the necessity of fine-grained emotion categories.

B. Features

Refer to existing researches on key factor analysis in information diffusion, we extract 46 different features grouped by five distinct sets. Comparative experiments with various selections and combinations of feature sets are presented.

User social features. The following features related to both the propagator and the original tweet's publisher are used: *number of followers, followees and past tweets; length of username and personal description; gender; is verified*.

Content features. Following features related to text content is used as content feature: *number of emoji, mentions, hashtags and length of text for both the original tweet and the retweet; whether the retweet contains retweet comment.*

Time-sensitive features. We consider those features in this group: *publish time (in hour and ignore date) of the retweet and original tweet; time interval since original publishing; time interval since previous retweet published*.

Statistical features. Features in this group are related to the global information of real-time diffusion cascade, including: *is the user repeatedly participate; the retweet's diffusion depth; standard deviation and median of follower numbers; proportion of gender, verified, repeatedly participating and retweet with content; average reposting time interval; structural features of cascade including scale, depth and average depth.*

Emotional features. On which we focus most in our experiments, includes *the emotional status of the propagator and the original publisher; entropy of emotional distribution; emotional composition; emotional composition weighted by users' follower numbers; proportion of emotion transformation; average path distance among nodes with same emotion*. All emotional features are defined by the fine-grained sentiment categories we proposed.

Except for features that based on user relation network and historical knowledge, which are challenging and costly to capture and maintain in practical applications, the first four feature sets mentioned above have covered the vast majority of effective features that used for reposting prediction in existing researches as far as we know. Thus, we take those feature sets as representative baselines to evaluate emotional influence during our following work.

C. Results

In this subsection, prediction performances of different classifiers are presented and evaluated, and the existence of fine-grained emotional influence has been proven.

Evaluation metrics. Reposting prediction task is a highly imbalanced classification problem since only few of the retweets receive another repost (2.7% in our dataset). As to evaluate the features' effectiveness, we are more interested in the relative performance of classifiers. Thus, we reconstruct balanced dataset by random under-sampling and measure the performances by Precision, Recall and F1-score of the positive samples. 10-fold cross validation is performed and ANOVA is used to confirm statistically significant improvement.

Algorithm selection. The prediction performances of classic supervised classifiers—viz., Logistic Regression, Decision Tree, Gradient Boosting Decision Tree (GBDT), AdaBoost and Random Forest, are compared. Three different combinations of features are used: user features only; user and content features; user, content, time-sensitive and statistical features. Performances are evaluated by F1-score and Recall, and the comparison is presented in Figure 6, which shows that GBDT performs superiorly in repost probability prediction with different feature selections. Thus, GBDT is chosen as our supervised machine learning approach in prediction tasks. We also notice that the performance of Logistic Regression is relatively poor, which might indicate that the recessive and non-linear correlation could not be fully explained by such kinds of generalized linear methods.

Comparison baselines. The user, content, time-sensitive and statistical features are widely used for reposting prediction in previous works, while some previous works ([29-32], e.g.) also took coarse-grained emotional features into consideration. Thus, we choose two feature selections as baselines:

1) *Baseline 1:* User social features, content features, time-sensitive features and statistical features.

2) *Baseline 2:* User social features, content features, time-sensitive features and statistical features, as well as emotional features that in the same form as the emotional feature set mentioned in Section VI.B, but in coarse-grained categories. Specifically, both *happiness* and *surprise* are considered the same as positive sentiment, while *anger*, *sadness*, *fear*, and *disgust* are all considered as negative sentiment.

Our approach. We propose our approach with all five feature sets that mentioned in Section VI.B. Comparing with *Baseline1*, we can evaluate the effectiveness of our emotional features. The necessity of fine-grained emotion categories can be indicated by comparing with *Baseline2*.

Performance. Table V lists the repost probability prediction performances of different methods. Notice that adding our emotional features into *Baseline1* can improve prediction performance in Precision, Recall and F1-socre. Improvements are also observed comparing with *Baseline2*. We carry out ANOVA to confirm that all improvements are statistically significant.

Refined prediction tasks. Series of experiments are presented to evaluate the effectiveness of emotional features in predicting detailed reposting status. For *popularity* prediction, we define retweets with more than 5 reposts as *popular* (7% in all reposted retweets), and retweets with more than 50 reposts as *outbreak* (1.4%). Retweets that be reposted in 10 minutes (32%) are considered as *fast* in *speed* prediction, while retweets that have not received any reposts in 3 hours (23%) are categorized as *slow*. *Long lifespan* (longer than 6 hours, 24%) and *short lifespan* (shorter than 30 minutes, 33%) are defined as well. The performance comparison is presented in Table VI, which shows the effectiveness of our fine-grained emotional features in all of the refined prediction tasks.

VII. Conclusion

In this work, the mechanism that information propagators influence online information diffusion is studied by focusing on the emotional effect in fine-grained categories, and the results are evaluated by comparison experiments of reposting prediction tasks.

To define fine-grained emotional statuses of propagators, a modified sentiment analysis approach is proposed, which improves the performance of emotion categorizing in our corpus. Exploratory analysis of user emotion reveals its correlation with diffusion status according to the statistically significant difference in reposting probability. In addition, emotional distribution indicates its independence to users' social influence and time-varying activity. Different contagious mechanisms among emotional statuses are observed as well. To predict reposting status, machine learning classifiers with different feature selections are employed in a real-world dataset. By analyzing the effectiveness of features, it is demonstrated that reposting prediction does benefit from the introduction of our fine-grained emotional features.

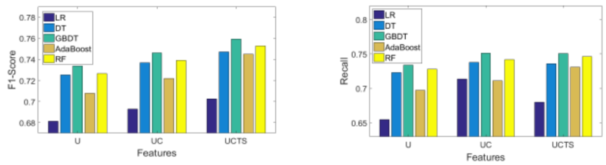
In our future work, the emotional influence would be evaluated by extended prediction experiments such as diffusion cascade structure prediction. In addition, we also aim to combine emotional features with detailed textual information (fine-grained topic, e.g.), which can evaluate various emotional effect of diverse information in online diffusion.

TABLE V. PREDICTION PERFORMANCE

Method	Precision (%)	Recall (%)	F1-score (10^{-2})
Baseline1	76.77	75.09	75.92
Baseline2	77.09	75.60	76.34
Approach	**77.69**	**75.82**	**76.74**

TABLE VI. DETAILED REPOSTING PREDICTION

Prediction Task	Class	F1-score (10^{-2})		
		Baseline1	*Baseline2*	*Approach*
Popularity	Popular	87.04	89.80	**93.79**
	Outbreak	94.97	97.09	**99.53**
Speed	Fast	63.35	64.04	**65.51**
	Slow	66.66	67.52	**68.68**
Lifespan	Long	64.40	66.02	**67.79**
	Short	58.88	60.15	**61.70**



(a) F1-score. (b) Recall.

Fig. 6. Algorithm performance comparison.

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