# Social Emotion Classification via Reader Perspective Weighted Model

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## Abstract

With the extensive growth of social media services, many users express their feelings and opinions through news articles, blogs and tweets/microblogs. This paper is concerned with the classification of emotions evoked in a reader by varied-scale data sets. Different from previous reader perspective models which weight training documents equally, the concept of emotional entropy is proposed to estimate the weight and tackle the issue of noisy documents. The topic assignment is also used to distinguish different emotional senses of the same word. Experimental evaluations using different data sets validate the effectiveness of the proposed reader perspective weighted model for social emotion classification.

## Introduction

The development of Web 2.0 technologies has been a great boon for the generation of online data concerning user opinions. Take Sina news, a popular websites in China as an example, it has provided a new service that allows users to express their emotions after browsing articles, with each article incorporates the emotional responses shared by its readers, which they express by voting for a set of emotion labels. The aggregation of such emotional responses is known as social emotions (Bao et al. 2012).

Research into social emotion classification began with the SemEval-2007 tasks (Strapparava and Mihalcea 2007) by associating words with social emotions. However, the same word in different topics may convey different attitudes. Thus, an emotion-topic model (ETM) was proposed to explore the emotions of topics (Bao et al. 2012). The limitation of ETM is that it treats each training document equally, so the documents that evoke prominent emotions in readers are usually mixed with noisy documents which do not convey much affective meaning. Experimental results have shown that the performance of models without weighting for training documents is unstable, especially on the data set with limited training instances or features (Rao et al. 2014a). In this paper, we develop a reader perspective weighted model (RPWM) for social emotion classification over varied-scale training documents. The main contributions of this work are as follows. First, the model allows us to distinguish different emotional senses of the same word. Second, we propose the concept of *emotional entropy* to estimate the weight of different training documents. Experimental evaluations using varied-scale data sets validate the effectiveness of the proposed model for social emotion classification.

The remainder of this paper is organized as follows: We describe related work in Section 2. We present the PRWM in Section 3. Experimental evaluations are shown in Section 4. Finally, we present conclusions in Section 5.



## Related Work

Preliminary works on social emotion classification have focused mainly on exploiting the emotions of individual words. The SWAT system (Strapparava and Mihalcea 2007) employed the unigram model to annotate the emotional responses of news headlines, which scored the emotions of each word $w$ as the average of emotions for every headline that contained $w$. An emotion-term (ET) model (Bao et al. 2012) was also proposed to associate words with emotions. The limitation of such models is that the same word may evoke positive attitude in one topic but negative in another. Recently, the ETM and three reader perspective topic models, named multi-labeled supervised topic model (MSTM) and sentiment latent topic model (SLTM) (Rao et al. 2014b), and affective topic model (ATM) (Rao et al. 2014c) were developed to social emotion classification by introducing an additional topic layer between emotions and documents. However, due to the existence of noisy training documents, the performance of existing models that weight training documents equally is quite unstable (Rao et al. 2014a).

## Reader Perspective Weighted Model

In this section, we detail our reader perspective weighted model for social emotion classification. The notations of frequently-used terms is first defined. Then, we describe how to estimate the weight of documents and associate documents with words. Finally, we describe the method of predicting the social emotions of unlabeled documents.

### Notation definition

For the convenience of describing our model, we define the following notations:

| Notation | Description |
|---|---|
| $\mathbb{D}$ | Collection of training documents |
| $K$ | Number of topics |
| $E$ | Number of emotion labels |
| $W$ | Number of distinct word tokens |
| $\theta$ | Document-topic multinomial distribution |
| $\phi$ | Topic-word multinomial distribution |
| $\xi$ | Word-topic multinomial distribution |
| $\alpha$ | Dirichlet prior of $\theta$ |
| $\beta$ | Dirichlet prior of $\phi$ |
| $\gamma$ | Smoothing parameter of $\xi$ |

Table 1: Notations of frequently-used terms.

An online collection $\mathbb{D}$ consists of documents with word tokens from a vocabulary of $W$ distinct items, and a set of ratings generated by online readers over $E$ kinds of emotion labels. For example, assume that the predefined 4 emotions are joy, anger, fear, and surprise, a document $d_a$ written by an author $a$ is voted on by 4 readers over joy, 3 readers over anger, 2 readers over fear, and 1 reader over surprise. Accordingly, the emotional responses of $d_a$ can be denoted by $\{4, 3, 2, 1\}$.

The whole corpus is modeled by $K$ latent topics. The symbols $\theta$ and $\phi$ represent document-topic and topic-word multinomial distributions, respectively. $\alpha$ and $\beta$ are hyperparameters, specifying the Dirichlet priors on $\theta$ and $\phi$. The frequently-used notations are summarized in Table 1.

### Document weight estimation

Different from a typically single emotion expressed by an author, a distribution of reader attitudes can be present across the span of a document (Lin and Chen 2008). For example, two documents $d_1$ and $d_2$ may have the following number of reader ratings over four emotions: $\{0, 0, 0, 5\}$ and $\{1, 1, 1, 2\}$ ($E = 4$). Although both $d_1$ and $d_2$ have the highest ratings for the last emotion, their importance is different for that emotion. In our work, the concept of *emotional entropy* is proposed to estimate the weight of document $d_a$ in $\mathbb{D}_{e_r}$, as follows:

$$P(d_a) = \sum_{i=1}^{E}(P(e_r^i|d_a) * log_E(P(e_r^i|d_a))) + 1, \quad (1)$$

where the first item in the right side of the formula is the negative value of the emotional entropy of $d_a$, the values of which range from -1 to 0, with the lowest being readers voted for each emotion equally and the highest being all readers voted for a single emotion. The second item of 1 is used to constrain the value of $P(d_a)$ between 0 and 1. $P(e_r^i|d_a)$ is the distribution of social emotions conditioned to each document, e.g., the distributions of $d_1$ and $d_2$ mentioned above are $\{0, 0, 0, 1\}$ and $\{0.2, 0.2, 0.2, 0.4\}$, respectively.

### Associating documents with words

The aim of this part is to estimate the joint probability of document $d_a$ and word $w$. A straightforward method is based on the occurrence of words in documents; however, due to the fact of a single word may have emotional ambiguity, topic models are used as the "bridge" to associate documents with words accurately.

Many topic models such as latent Dirichlet allocation (LDA) (Blei, Ng, and Jordan 2003) have been used to extract the meaningful topics and alleviate the problem of ambiguity. We employ LDA and an approximate inference method based on Gibbs sampling (Griffiths and Steyvers 2004) in this work, as follows:

$$\theta_{d_a}^{(z)} = \frac{n_{d_a}^{(z)} + \alpha}{\Sigma_{z'}(n_{d_a}^{(z')} + \alpha)}, \phi_z^{(w)} = \frac{n_w^{(z)} + \beta}{\Sigma_{w'}(n_{w'}^{(z)} + \beta)}, \quad (2)$$

where $n_{d_a}^{(z)}$ is the number of words in document $d_a$ assigned to topic $z$, $n_w^{(z)}$ is the number of instances of word $w$ assigned to topic $z$.

The topic assignment is then exploited to estimate the multinomial distribution of word $w$ over topics, as follows:

$$\xi_w^{(z)} = \frac{n_w^{(z)} + \alpha}{\Sigma_{z'}(n_w^{(z')} + \alpha)}, \quad (3)$$

where the consistent smoothing parameter $\alpha$ in $\theta$ and $\xi$ is specified by users empirically.

Finally, the cosine-similarity is employed to calculate the joint probability of $d_a$ and $w$ as follows:

$$P(d_a, w) = \frac{\theta_{d_a} * \xi_w}{|\theta_{d_a}| * |\xi_w|}. \quad (4)$$

### Social emotion prediction

Given an unlabeled document $d_a$, the conditional probability of readers' emotion $e_r$ can be estimated by $p(e_r|d_a) \propto P(e_r) * P(d_a|e_r)$. We denote the collection of documents that evoked the reader's emotion of $e_r$ as $\mathbb{D}_{e_r}$. Then,

$$P(e_r) = \frac{|\mathbb{D}_{e_r}| + \gamma}{|\mathbb{D}| + E * \gamma}, \quad (5)$$

where $\gamma$ is a smoothing parameter used to avoid zero probability, and $E$ is the number of emotion labels.

The estimation of $P(d_a|e_r)$ is based on the conditional independence assumption that given readers' emotion of $e_r$, each word $w$ in $d_a$ is generated independently. It is consistent to social emotion classification, in which the words of $d_a$ are determined prior to the emotional responses triggered in readers. Thus, we have $P(d_a|e_r) = \prod_{w \in d_a} P(w|e_r)$. According to the Bayesian inference, $P(w|e_r)$ is proportional to the product of the probability of document $d_a$ in $\mathbb{D}_{e_r}$, and the joint probability of $d_a$ and $w$, which can be estimated by Eq. (1) and Eq. (4), respectively.

## Experiments

In this section, we detail the data sets, experiment design, and comparison with baselines.

## Data sets

To evaluate the effectiveness and adaptiveness of the proposed model, we employ the following two data sets:

(1) $SemEval$. An English data set in SemEval 2007 tasks (Strapparava and Mihalcea 2007), which contains 1250 news headlines extracted from Google news, CNN, and many others. In this data set, each headline was manually scored in a fine-grained valence scale of 0 to 100 across 6 emotion labels (i.e., "anger", "disgust", "fear", "joy", "sad" and "surprise"). After pruning 4 items with the total scores equal to 0, we use the 246 headlines in the development set for training and the 1000 in the testing set for evaluation.

(2) $SinaNews$. A Chinese corpora consists of 4570 news articles collected from the society channel of Sina (Rao et al. 2014c). The news headline, news body, and user ratings across 8 emotion labels (i.e., "touching", "empathy", "boredom", "anger", "amusement", "sadness", "surprise" and "warmness") were gathered. After preprocessing, there are 1975153 word tokens and 325434 user ratings. Each document in the data set has at least 6 word tokens and 1 user rating. Due to that adjacent news articles may have similar contexts, the 2342 documents published from January to February, 2012 were used for training, and the 2228 documents published from March to April, 2012 were used for testing.

The detailed information of the above data sets is shown in Table 2, where the number of articles for each emotion label represents the amount of documents that had the highest ratings for that emotion.

| Dataset | Emotion label | # of articles | # of ratings |
|---|---|---|---|
| SemEval | anger | 87 | 12042 |
| | disgust | 42 | 7634 |
| | fear | 194 | 20306 |
| | joy | 441 | 23613 |
| | sad | 265 | 24039 |
| | surprise | 217 | 21495 |
| SinaNews | touching | 749 | 41798 |
| | empathy | 225 | 23230 |
| | boredom | 273 | 21995 |
| | anger | 2048 | 138167 |
| | amusement | 715 | 43712 |
| | sadness | 355 | 37162 |
| | surprise | 167 | 11386 |
| | warmness | 38 | 7986 |

Table 2: Statistics of the data sets.

## Experiment design

In this part, we implemented the following baselines for comparison with our model RPWM:

(1) SWAT. The unigram model was used to annotate the emotional responses of news headlines, which scored the emotions of each word $w$ as the average of emotions for every headline that contained $w$ (Strapparava and Mihalcea 2007).

(2) Emotion-term (ET) and emotion-topic model (ETM). Methods of respectively modeling the word-emotion and topic-emotion associations (Bao et al. 2009; 2012). ET is a variant of the naïve Bayes classifier, and ETM introduces an additional emotion layer into LDA.

(3) Multi-labeled supervised topic model (MSTM) and Sentiment latent topic model (SLTM) (Rao et al. 2014b). MSTM begins by generating topics from words, and then samples emotions from each topic. SLTM, on the other hand, generates topics directly from social emotions.

(4) Affective topic model (ATM) (Rao et al. 2014c). The exponential distribution was employed to generate user ratings for each emotion label.

Table 3 presents the setting of parameters for our RPWM, where the values of hyperparameters $\alpha$ and $\beta$ on $SemEval$ (short documents) and $SinaNews$ (long documents) were determined by following (Cheng et al. 2014) and (Bao et al. 2009; 2012), respectively. The value of $\gamma$ was set to be the same as $\beta$, and the number of iterations was set to 1000. Unless otherwise specified, all parameters of the baselines of ETM, MSTM, SLTM, and ATM were set at default.

| Parameters | $SemEval$ | $SinaNews$ |
|---|---|---|
| $\alpha$ | 0.05 | 50/$K$ |
| $\beta$ | 0.01 | 0.1 |
| $\gamma$ | 0.01 | 0.1 |

Table 3: Parameters of RPWM.

The micro-averaged F1 measure was employed as the indicator of performance. The F1 measure equally weights precision and recall, and micro-averaging is one of the methods that can be used to compute a single aggregate measure when processing a collection with several two-class classifiers (Manning et al. 2008). Micro-averaging pools per-document decisions across categories, and then computes an effectiveness measure on the pooled contingency table. Due to the very imbalanced distribution of documents in certain categories for both data sets (Table 2), it is unnecessary to compute the F1 measure of each category or a macro-averaged F1 (Manning et al. 2008) that would take the average of F1 for all categories.

## Comparison with baselines

The micro-averaged F1 results of our RPWM and baselines on both data sets are listed in Table 4. Due to the limited training instances and features, the number of topics is set empirically on $SemEval$ for models employing LDA. With respect to $SinaNews$, the number of topics varies from 2 to 30 (Bao et al. 2009; 2012) as shown in Fig. 1, and the mean value is presented.

Compared to the baseline models of SWAT, ET, ETM, MSTM, SLTM, and ATM, the proposed model RPWM improves 16.14%, 17.60%, 47.95%, 75.33%, 74.90%, 12.38% on $SemEval$, and 10.84%, 30.78%, 6.09%, 12.62%, 13.37%, 13.19% on $SinaNews$, respectively. The results indicate that RPWM outperforms baselines on both data

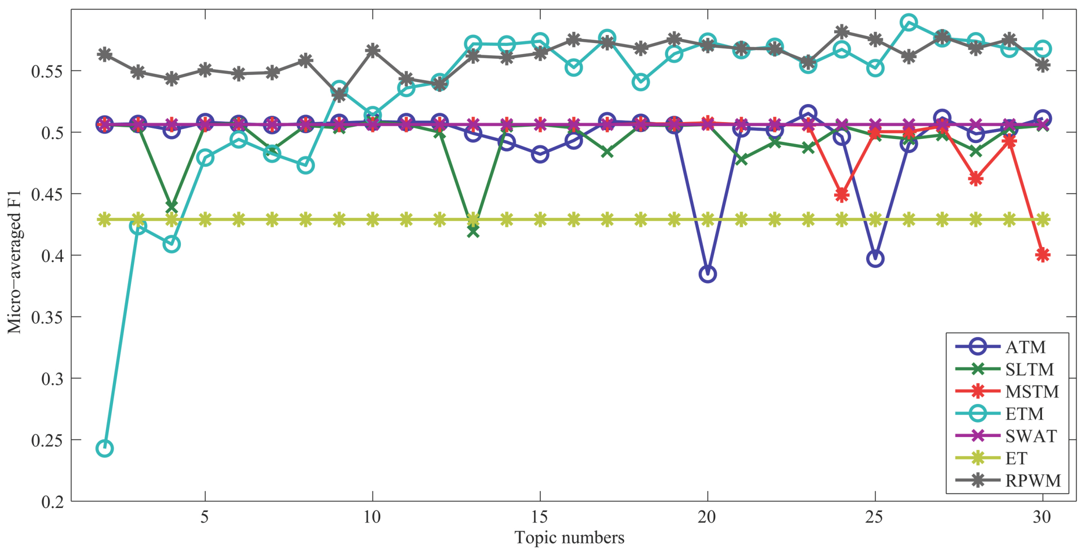


Figure 1: Performance with different topic numbers.

sets, especially for $SemEval$ that contains limited training instances or features.

## Conclusions

Social emotion classification is useful to provide users with more relevant and personalized services. In this paper, we have proposed the *emotional entropy* to alleviate the issue of noisy training documents, and used the topic assignment to distinguish different emotional senses of the same word. In future, we plan to extend our work to other areas such as stock prediction and movie recommendation.

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| Models | $Semeval$ | $SinaNews$ |
|---|---|---|
| SWAT | 31.40% | 50.63% |
| ET | 31.00% | 42.91% |
| ETM | 24.65% | 52.90% |
| MSTM | 20.80% | 49.83% |
| SLTM | 20.85% | 49.50% |
| ATM | 32.45% | 49.58% |
| **RPWM** | **36.47%** | **56.12%** |

Table 4: The micro-averaged F1 of different models.


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