Social Emotion Classification via Reader Perspective Weighted Model

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Abstract

With the development of Web 2.0, many users express their opinions online. This paper is concerned with the classification of social emotions on varied-scale data sets. Different from traditional 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 social emotion classification model.

Introduction

Many news websites have 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, in which the concept of *emotional entropy* is proposed 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.

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 present the details of our reader perspective weighted model for social emotion classification. Given a document d_a written by an author 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 training documents as $\mathbb{D}$, the collection of documents that evoked the reader's emotion of e_r as $\mathbb{D}_{e_r}$. Then,

$$P(e_r) = \frac{|\mathbb{D}_{e_r}| + \gamma}{|\mathbb{D}| + E * \gamma}, \tag{1}$$

where γ 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.

The probability of d_a in $\mathbb{D}_{e_r}$ measures the weight of each document under the same emotional category. 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:

$$P(d_a) = \sum_{i=1}^{E} (P(e_r^i|d_a) * log_E(P(e_r^i|d_a))) + 1, \quad (2)$$

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.

The joint probability of document d_a and word w can be estimated by the occurrence of words in documents simply. However, due to words may have emotional ambiguity, the topic assignment is used as a "bridge" to associate documents with words accurately. We denote the multinomial distribution of document d_a over topics as θ_{d_a}, and the multinomial distribution of word w over topics as ξ_w. Then, the cosine-similarity is employed to calculate the joint probability of d_a and w as follows:

$$P(d_a, w) = \frac{\theta_{d_a} * \xi_w}{|\theta_{d_a}| * |\xi_w|}. \quad (3)$$

The above multinomial distributions (i.e., θ_{d_a} and ξ_w) can be estimated by Gibbs sampling, as follows:

$$\theta_{d_a}^{(z)} = \frac{n_{d_a}^{(z)} + \alpha}{\Sigma_{z'}(n_{d_a}^{(z')} + \alpha)}, \xi_w^{(z)} = \frac{n_w^{(z)} + \alpha}{\Sigma_{z'}(n_w^{(z')} + \alpha)}, \quad (4)$$

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, and the consistent smoothing parameter α is specified by users empirically.

Experiments

In this section, we detail the data sets, experimental design and results. To evaluate the effectiveness and adaptiveness on the proposed model, two data sets were employed: $SemEval$ (Strapparava and Mihalcea 2007) and $SinaNews$ (Rao et al. 2014c). The first data set contained 1250 real-world news headlines, and each headline was manually scored across 6 emotions. After pruning 4 items with the total scores equal to 0, we used the 246 headlines in the development set for training and the rest for testing. The second data set consisted of 4570 documents from Sina news, and reader ratings over 8 emotions. Due to that adjacent documents 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.

We implemented the following models for comparison: SWAT (Strapparava and Mihalcea 2007), ET and ETM (Bao et al. 2012), MSTM and SLTM (Rao et al. 2014b), and ATM (Rao et al. 2014c). All parameters were set empirically. Table 1 present the micro-averaged F1 measure of different models, from which we can observe that RPWM outperformed baselines on both data sets, especially for $SemEval$ that contains limited training instances or features.

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 1: The micro-averaged F1 of different models.

Conclusion

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. For future work, we plan to improve the *emotional entropy* by developing a generalized index of document importance.

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