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# Universal affective model for Readers' emotion classification over short texts

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ABSTRACT

As the rapid development of Web 2.0 communities, social media service providers offer users a convenient way to share and create their own contents such as online comments, blogs, microblogs/tweets, etc. Understanding the latent emotions of such short texts from social media via the computational model is an important issue as such a model will help us to identify the social events and make better decisions (e.g., investment in stocking market). However, it is always very challenge to detect emotions from above user-generated contents due to the sparsity problem (e.g., a tweet is a short message). In this article, we propose an universal affective model (UAM) to classify readers' emotions over unlabeled short texts. Different from conventional text classification model, the UAM structurally consists of topic-level and term-level sub-models, and detects social emotions from the perspective of readers in social media. Through the evaluation on real-world data sets, the experimental results validate the effectiveness of the proposed model in terms of the effectiveness and accuracy.



## 1. Introduction

With the rapid development of social media service providers, there is an increasing affective data such as the review comments and/or the vote counts of emotions on news articles, which reflect the emotion tendency and perspective from users (Bosco, Patti, & Bolioli, 2013). As one of the most important medium in the modern world, the Web can effectively not only convey users' positive or negative sentiments but also express more detailed emotions such as happiness, fearfulness, or surprise (Shaikh, Prendinger, & Ishizuka, 2008). The emotional voting service provided by many online news sites and social media communities enables users to express their emotions after reading news articles (Bao et al., 2009). Social emotion mining techniques have drawn greater attention of researchers in the machine learning and natural language processing (Cambria & White, 2014), for that they can be employed in various applications including sentiment retrieval (Ku, Liang, & Chen, 2006) and opinion summarization (Eguchi & Lavrenko, 2006). Early studies of social emotion classification primarily focused on identifying the emotional tendency of each individual word, because it was believed that the words in the natural language played a crucial role in expressing various emotions (Kazemzadeh, Lee, & Narayanan, 2013). The SWAT system (Katz, Singleton, & Wicentowski, 2007) adopted a word-emotion mapping dictionary to judge social emotions of unseen news headlines, which this dictionary was exploited by a supervised method. The emotion-term model (ETM) (Bao et al., 2009; 2011) modeled the associations between emotions and words from the authors perspective. These mentioned term-level models performed well in sentiment polarity classification of labeled short texts (Rao et al., 2016), because words in short texts were more easily and accurately mapped to sentiment polarity than diverse emotion labels.

However, those models, which assumed that a word is a unique key feature for sentiment analysis, are difficult to address the problem of sentiment ambiguity over multi-label texts (Quan & Ren, 2010). The sentiment ambiguity refers that the same word may express different emotions in various contexts. To address this problem, it was suggested to explore emotion distribution under specific topics by the emotion-topic model (ETM) (Bao et al., 2009). Those topics represented the objects, real-world events, or abstract entities which indicated the contexts of the sentiment (Stoyanov & Cardie, 2008). The ETM, which learned from the machinery of latent variable topic models like the Latent Dirichlet Allocation (LDA)

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model (Blei, Ng, & Jordan, 2003), can distinguish different meanings of a single word. The ETM is developed for sentiment analysis from authors' perspective rather than readers'. The readers' perspective is more natural to understand the emotions of readers after they read the news article, while authors' perspective reflects the emotions of authors when they write the article (Lin & Chen, 2008). The affective topic model for social emotion detection (ATM) (Rao, Li, Wenyin, Wu, & Quan, 2014c) was proposed for detecting reader emotions towards certain topics by introducing an emotional intermediate layer. One limitation of the ATM is difficult to detect emotions from short texts, which are frequently occurred in social documents like tweets.

In light of these considerations, we propose the universal affective model (UAM) to detect social emotions over short texts from readers' perspective. The main contributions of this research are listed as follows.

- To enhance the semantic relationships between biterms, we combine biterms with keywords which are extracted by a new paradigm named Average Term Frequency Inverse Document Frequency (ATF-IDF).
- To differentiate various semantic meanings of the same word in short texts, our proposed the UAM based on the biterm topic model (BTM) (Cheng, Yan, Lan, & Guo, 2014) by adopting an intermediate layer which bridges emotion labels and topics.
- A word-level emotional lexicon is established for background words in the corpus by using SWAT.
- Through conducting experiments on 3 different data sets including a sensibly small and unbalanced news headlines with 6 emotions, a large social network short documents annotated over 2 emotions, and a larger online news articles annotated over 8 emotions, the effectiveness of the proposed model is verified.

The remaining sections of this paper are organized as follows. In Section 2, the related research studies are reviewed. In Section 3, the proposed UAM for readers' emotion classification are elaborated. Experiments are introduced in Section 4. The conclusion and future research directions are discussed in Section 5.

## 2. Related work

### 2.1. Sentiment analysis

The sentiment analysis aimed to identify and extract the attitude of a document (i.e., reaction of an online news reader to either a topic or the content of the document (Gangemi, Presutti, & Reforgiato Recupero, 2014)). In some earlier studies, the mission of sentiment analysis was to estimate whether the text is positive or negative by analyzing the entire text and the rating scores in reviews (Cambria, Schuller, Liu, & Wang, 2013a). A classification algorithm (Das & Chen, 2001) was exploited by Das and Chen to capture the latent opinions of markets from stock message boards. These latent opinions were further used as the steering of decision-making in the financial market. Turney (2002) attempted to classify the sentiment orientations of user reviews by using a unsupervised learning method. Pang, Lee, and Vaithyanathan (2002) classified movie reviews as positive or negative with an algorithm which is the combination of maximum entropy, naive Bayes, and support vector machine (SVM)(Adankon & Cheriet, 2009). However, some words may express different sentiments in specific domain applications (e.g., bull shows positive in the financial market) (Bollegala, Weir, & Carroll, 2011), these studies encountered a problem that a classifier trained by data in one domain may achieve poor performance in another one (Pan, Ni, Sun, Yang, & Chen, 2010). To solve this problem, several algorithms for domain-independent sentiment classification have been proposed (Bollegala et al., 2011). Another solution to capture different sentiments of the same word is conducted by introducing a topic layer. For instance, Rao proposed a contextual sentiment topic model for adaptive classification (Rao, 2016). Poddar et al. proposed a model to determine opinions by modeling aspects, topics, and sentiments jointly (Poddar, Hsu, & Lee, 2017).

Considering the remarkable performance in computer vision, deep neural network models have been recently employed for sentiment analysis over documents. In a preliminary study, Kim (2014) employed a convolutional neural network (Collobert, Weston, Karlen, Kavukcuoglu, & Kuksa, 2011) to generate both task-specific and static vectors for sentence classification. Due to the limited contextual information in short messages, Santos and Gattit proposed a deep neural network architecture which jointly uses representation at the character-level, word-level and sentence-level to perform sentiment analysis (Santos & Gattit, 2014). To exploit the information provided by sentiment lexicons, Shin et al. integrated lexicon embeddings and an attention mechanism into convolutional neural networks for sentiment analysis (Shin, Lee, & Choi, 2016).

The above algorithms and models have been applied in sentiment classification at levels of pages or paragraphs primarily. Some limitations have been identified if more fine-grained levels (e.g., sentences or clauses) have been used (Cambria, Schuller, Liu, Wang, & Havasi, 2013b). Sentiment analysis becomes more challenge as the opinion holders are anonymous and noisy data is often mixed with useful information (Moreo, Romero, Castro, & Zurita, 2012). For example, many fake comments, offensive comments or comments for advertisement are always appeared in different e-commerce sites and social media communities. Therefore, there has been another stream of research studies about opinion spam filtration (Jindal & Liu, 2008; Moreo et al., 2012) and noisy label aggregation in social media (Zhan et al., 2017). Some survey studies of sentiment analysis discuss the future research directions in this area (Cambria et al., 2013a; Cambria et al., 2013b).

### 2.2. Social emotion detection

Social emotion detection, which aimed to identify readers' emotions evoked by news headlines, has attracted increasingly attentions in the research communities since the emergence of the SemEval-2007 Tasks (Katz et al., 2007). This research was based on the hypothesis that all words including neutral ones can effectively express the positive or negative emotions of the author, and then evoke corresponding pleasant or painful reactions from readers (Shaikh et al., 2008).

The SWAT system (Katz et al., 2007) detected social emotion of unlabeled news headlines through a word-emotion lexicon. In this lexicon, each word is associated to multiple emotion, such as fear, anger, joy, surprise, etc., with each label has an emotion score respectively. However, the limited information in news headlines makes it difficult to detect emotions correctly and consistently (Katz et al., 2007; Quan & Ren, 2010). It was considered to make use of all words in the body of a news item in the emotion term (ET) model (Bao et al., 2009; 2011) and word-emotion (WE) method (Rao, Lei, Liu, Li, & Chen, 2014a). ET was designed to establish relationships between words and emotions based on the naive Bayes classifier. The WE method used maximum likelihood estimation to generated a word-level emotional lexicon, and then utilized this lexicon to detect emotion based on all terms in the news content. However, these word-level methods are unable to distinguish the different semantics of the same words under various contexts due to the issue of ambiguity (i.e., the same word may convey positive emotions in one context but negative emotions in another one) (Bollegala et al., 2011; He, Lin, & Alani, 2011; Quan & Ren, 2010). To deal with this, a semantically rich hybrid