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HEMOS: A novel deep learning-based fine-grained humor detecting method for sentiment analysis of social media

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A B S T R A C T

In this paper we introduce **HEMOS** (**H**umor-**EMO**ji-**S**lang-based) system for fine-grained sentiment classification for the Chinese language using deep learning approach. We investigate the importance of recognizing the influence of humor, pictograms and slang on the task of affective processing of the social media. In the first step, we collected 576 frequent Internet slang expressions as a slang lexicon; then, we converted 109 Weibo emojis into textual features creating a Chinese emoji lexicon. In the next step, by performing two polarity annotations with new "optimistic humorous type" and "pessimistic humorous type" added to standard "positive" and "negative" sentiment categories, we applied both lexicons to attention-based bi-directional long short-term memory recurrent neural network (AttBiLSTM) and tested its performance on undersized labeled data. Our experimental results show that the proposed method can significantly improve the state-of-the-art methods in predicting sentiment polarity on Weibo, the largest Chinese social network.

1. Introduction

With the tremendous popularity of web 2.0 applications, people are free to express opinions on social networks such as Twitter, Facebook or Weibo[1] (the biggest Chinese social media network that was launched in 2009). These new communication channels generate massive amounts of data daily, which become an insightful information source for various research purposes, often using Natural Language Processing (Kavanaugh et al., 2012). One of its popular and essential tasks is sentiment analysis, which mainly focuses on automatic sentiment predicting from online user-generated content but also draws interest from other fields as psychology, cognitive linguistics, or political science. Sentiment analysis can be useful in election result forecasting, stock prediction, opinion mining, business analytics, and other data-driven tasks (Li, Rzepka, & Araki, 2018a). Sentiment analysis has been widely used in real-world applications that analyze the online user-generated data, such as opinion mining, product reviews analysis, and business-related activity analysis (Zhao et al., 2018). Sentiment analysis in English has achieved noteworthy success in the recent two decades. On the other hand, classifying sentiment in other languages, for example Chinese, remains at an early stage (Wang et al., 2013). The current sentiment analysis mainly focuses on text-based user-generated content. However, various new forms of semiotic information on social networks such as emoji, images, and memes, allow users to express themselves more creatively. Emojis and slangs have

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[1] https://www.weibo.com

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become a noticeable part of online informal expression on social networks.

Humor is one of the personal aspects which defines us as human beings and social entities. It is a very complex, as well as ubiquitous concept, which we could simply define by the presence of amusing effects, such as laughter or well-being sensations, a set of phenomena which play a relevant role in our lives (Reyes, Rosso, & Buscaldi, 2012). Before we had spoken or written language, humans used laughter to express our enjoyment or accession in certain situations (Mathews, 2016). In today's society, people tend to write funny jokes, play word games, use emojis or memes to comment on current affairs by “white sarcasm”,[2] and relieve life stress by self mocking, often in very creative ways.

Emojis are ideograms and smileys used in electronic messages and web pages. Originating from Japanese mobile phones in 1997, this kind of pictograms became increasingly popular worldwide in the 2010s after being added to several mobile operating systems. In 2015, Oxford Dictionaries named the “Face with Tears of Joy” emoji 😂 the “Word of the Year”. In our opinion ignoring emojis in sentiment research is unjustifiable because they convey a piece of significant emotional information and play an important role in expressing emotions and opinions in social media (Guibon, Ochs, & Bellot, 2016; Li, Rzepka, Ptaszynski, & Araki, 2019b; Novak, Smailović, Sluban, & Mozetič, 2015).

Internet slang is similarly ubiquitous on the Internet. The emergence of new social contexts like micro-blogs, discussion groups, community-driven question-and-answer websites, and social networks has enabled slang and non-standard expressions to abound on the Web. Despite this, slang has been traditionally viewed as a form of non-standard language and a form of language that is not the focus of linguistic analysis. In consequence, it has mostly been neglected (Kulkarni & Wang, 2017).

Furthermore, We also noticed that the conventional sentiment analysis generally considers only three dimensions (positive, negative, and neutral) for text classification, while the usage of some pictograms in sentiment analysis is hard to be simply classified as either positive or negative. Especially, many emojis and slangs seem to be used purely for laughter, self-mockery, or jocosity, which communicates an implied irony that is intensively used in Chinese conversation on social networks (Li et al., 2019b). Thus, we believe that humor, as one of the most common expressions in natural language, can also be regarded as a useful dimension for sentiment analysis with an emoji dataset.

In this paper, to fill the gap described above, we focus on humorous posts using Internet slang and emojis on Weibo to establish:

1) whether both slang and emojis improve sentiment analysis by recognizing humorous entries which are challenging to polarize;

2) whether adding new “optimistic humorous type” and “pessimistic humorous type” categories improve the result of sentiment polarity prediction.

To perform experiments, we collected 576 frequent Chinese Internet slang expressions as a slang lexicon. Then we converted 109 Weibo emojis into textual features creating a Chinese emoji lexicon.

We utilized both lexicons with a deep learning approach, attention-based bi-directional long short-term memory recurrent neural network for sentiment analysis of social media, and classified posts into four categories “positive,” “negative,” “optimistic humorous type” and “pessimistic humorous type.” Our experimental results show that the proposed method can significantly improve the performance for predicting sentiment polarity on Weibo.

Our main contributions are as follows:

- We collected 576 frequent Chinese Internet slang expressions as a Chinese slang lexicon.
- We converted the 109 Weibo emojis into textual features creating Chinese emoji lexicon.
- We empirically confirmed inherent humor characteristic to Chinese culture visible on Weibo and divided Weibo posts into four categories: positive, negative, optimistic humorous, and pessimistic humorous.
- We applied the slang lexicon and emoji lexicon to an attention-based bi-directional long short-term memory recurrent neural network (AttBiLSTM) and proposed HEMOS (see Section 6), a fine-grained humor detecting method for sentiment analysis of social media.

2. Related research

Traditionally, sentiment analysis is a binary approach that classifies the text emotions into positive, negative and neutral. Peng, Cambria, and Hussain (2017) have conducted a comprehensive literature review on Chinese sentiment analysis. According to their findings, the methodologies for Chinese sentiment analysis can be generally categorized with supervised machine learning approach and unsupervised knowledge-based approaches. For this study, we mainly focus on supervised machine learning approaches.

There are generally three separate stages for machine learning-based sentiment analysis tasks, which are text segmentation, feature extraction, and sentiment classification. Text segmentation divides a text into meaningful tokens. Feature extraction retrieves both sentiment features and raw segmented words features and represents them in a bag of words (BoW). Finally, the dataset is fed into a machine learning model for assigning the sentiment score to the given text. The commonly used algorithms are Naïve Bayes, maximum entropy, SVM, neural networks and others (Dhande & Patnaik, 2014; Khan, Baharudin, Lee, & Khan, 2010; Vinodhini & Chandrasekaran, 2012).

One representative example of such studies is an empirical work performed by Tan and Zhang, who categorized sentiment in Chinese documents (Tan & Zhang, 2008). Four features, namely mutual information, information gain, chi-square, and document frequency, were tested separately on five different algorithms, including centroid classifier, k-Nearest Neighbor, Winnow classifier,

[2] Similar to “white lie”, we define this special kind of sarcasm with good intentions as “white sarcasm”.

Naïve Bayes (NB) and Support Vector Machine (SVM). Among these algorithms, the information gain and SVM features were found to yield the best performance under topic-dependent classifiers. Chen et al. proposed a novel sentiment classification method that incorporated the existing Chinese sentiment lexicon and convolutional neural network (Chen, Xu, Gui, & Lu, 2015). Their results showed that the proposed approach outperforms the convolutional neural network (CNN) model with only word embedding features (Kim, 2014).

These Chinese sentiment classification approaches, although they have achieved satisfying outcomes, only consider a pure text-based dataset from a polarity-base perspective. In addition to the classical binary label classification problem (positive, negative, or neutral), Liu and Chen proposed a multi-label sentiment analysis prototype for micro-blogs (Liu & Chen, 2015). They also compared the performance of eleven state-of-the-art classification methods (BR, CC, CLR, HOMER, RAkEL, ECC, MLkNN, RF-PCT, BRkNN, BRkNN-a and BRkNN-b) on two microblog datasets. Although Liu and colleagues consider multi-label classification, none of the papers consider humorous as a dimension for sentiment classification.

Recently, for sentiment analysis in the English language, more researchers have realized the value of emoji and slang dataset. Wu et al. constructed an English slang dictionary (named SlangSD) for sentiment analysis tasks and proved its ease of use (Wu, Morstatter, & Liu, 2016). In the research of Soliman, Elmasry, Hedar, and Doss (2014), the authors constructed a Slang Sentimental Words and Idioms Lexicon (SSWIL) of opinion words. They also proposed a Gaussian kernel SVM classifier for Arabic slang language to classify Arabic news comments on Facebook[3]. The proposed classifier achieved precision of 88.63% and recall of 78%. Manuel and others presented an approach for finding the sentiment score of newly found slang sentiment words in blogs, reviews and forum texts on Internet (Manuel, Indukuri, & Krishna, 2010). A simple mechanism for calculating sentiment score of documents using slang words with the help of Delta Term Frequency and Weighted Inverse Document Frequency technique is also presented in their paper.

Chen et al. proposed a novel scheme for Twitter sentiment analysis with extra attention to emojis (Chen, Yuan, You, & Luo, 2018). They first learned bi-polarity emoji embeddings under positive and negative sentimental tweets individually, then trained a sentiment classifier by attending on these bi-polarity emoji embeddings with an attention-based Long Short-Term Memory network (LSTM). Their experiments have shown that the bipolarity embedding was effective for extracting sentiment-aware embeddings of emojis. When it comes to Chinese social media Weibo, Zhao et al. built a system called MoodLens (Zhao, Dong, Wu, & Xu, 2012), which is the first system for sentiment analysis of Chinese posts in Weibo. In MoodLens, 95 emojis are mapped into four categories of sentiments (angry, disgusting, joyful, and sad), which serve as class labels of the entries. They collected over 3.5 million labeled posts as the corpus and trained a fast Naïve Bayes classifier, with an empirical precision of 64.3%. However, the precision in their method was still relatively low, and emotion of many emojis has been changed dramatically. More specific analysis of Weibo emojis is discussed in Section 5.

In 2017, Felbo, Mislove, Søgaard, Rahwan, and Lehmann (2017) proposed a powerful system utilizing emojis in their Twitter sentiment analysis model called DeepMoji. During this study, 1246 million tweets containing one of 64 common emojis were trained by a Bi-directional Long Short-Term Memory (Bi-LSTM) model to interpret the sentiment within the online tweets. DeepMoji also works well for sarcasm detection task with a verified accuracy rate of 82.4%. Their system even outperforms human detectors who managed to acquire a 76.1% accuracy rate. Although sarcasm and irony tend to convey negative sentiments in general, since these two factors may reverse the overall sentiment score of given text, we found that in Chinese social media (Weibo in our example), in addition to the represented positive and negative sentiments, users tend to express an implicit humor that escapes the traditional bi-polarity.

More recently, in our previous research (Li, Rzepka, Ptaszynski, & Araki, 2018b), we analyzed the usage of the emojis with a facial expression used on Weibo. We applied the emojis polarity in an Long Short-Term Memory recurrent neural network (LSTM) and classified Weibo posts into three categories: positive, negative, and humorous. In Li, Rzepka, Ptaszynski, and Araki (2019a), we proposed a attention-based GRU network model using emoji polarity to improve sentiment analysis on smaller annotated data sets. Our experimental results showed that the proposed method can significantly improve the performance of sentiment polarity prediction. Both of these studies assign a hyper-parameter to the probability of the deep learning model's softmax output, and apply the labelled emojis from the work of Li et al. (2018a) as emoji polarity. Then we assign a hyper-parameter to the emoji polarities to calculate the final probability output of sentiment classification. However, we found that many Weibo entries carry humorous aspects like self-mockery and contain some optimistic or pessimistic emotional load. It is quite easy to make a wrong prediction by simply classifying them into a "humorous" category without polarizing it. Therefore, to tackle this problem, we propose a fine-grained humorous classification method to improve the results of bi-polarity sentiment analysis.

3. Humor in Chinese culture

Humor is a tendency of experiences to provoke laughter and provide amusement, and it also can be defined as a reliable elicitor of exhilaration (Ruch, 1993). However, many theories exist about what humor is and what social function it serves. In the long course of history, regions with different cultural backgrounds have had different interpretations of humor. In ancient Greece, Plato first suggested a view in the "Philebus" that the nature of humor is an ignorance in the weak, who are thus unable to retaliate when mocked. Later, in his famous "Poetics", Aristotle proposed that an ugliness that does not disgust is fundamental aspect of humor (Jones, 2005). In ancient Sanskrit drama titled "Natya Shastra", Bharata Muni defined humor as one of the nine emotional reactions, which can be invoked in the audience by the simulations of emotions that the actors perform (Sharma, 2011). Humor expressions

[3] https://www.facebook.com/

Fig. 1. Example of Weibo post with Internet slang and emojis. The entry says "After jogging, I'm starving. Someone sent me a picture of skewers. I'm too tired for romance".

were first documented around 2500 BC in China when the first Chinese poetry and literary books appeared (Yue, 2010). In ancient China, humor was considered traditionally as subversive or unseemly in the Confucian culture, which ritual and propriety. It was usually perceived as irony and sarcasm. On the other hand, Taoism placed a high value on humor. Both core ideas and expressions of Taoism reflect the wisdom of humor (Yue, 2014). At present, Chinese people tend to express implicit humor on social media, and some posts can be seen as pessimistic irony, while other entries can be considered as a pure joke or optimistic self-deprecation. More specific analysis of these phenomena is discussed in the next paragraph. Nowadays, humor became a ubiquitous human phenomenon that occurs in all types of social interaction (Vieweg, Hughes, Starbird, & Palen, 2010). It is also a form of communication (often creative) that bridges the gap between various languages, cultures, ages, and demographics (Furnham, 1984). Most of us laugh at something funny many times during a typical day (Martin, 2006). Laughter releases endorphins, relaxes the body, and helps to relieve stress. Although it is a form of play, humor serves several cognitive, emotional, and social functions (Martin & Ford, 2018). However, humor is an emotion that is difficult to define. Linguists, psychologists, and anthropologists have taken humor to be an all-encompassing category, covering any event that amuses, or is felt to be amusing (Attardo, 2010). Different people will not necessarily find the same things equally funny. Many things which strike one group as funny may bore another group, and some jokes are private or individual, often restricted in their funniness to just one or very few individuals. As Raskin (2012) states, "This universality of humor is further reinforced by the fact that surprisingly many jokes or situations will strike surprisingly many, if not all people, as funny. Therefore, we are dealing with a universal human sentiment, humor. Responding to humor is a part of human behavior, ability, or competence, other parts of which comprise such important social and psychological manifestations of human as language, morality, logic, faith, etc." Therefore, we hypothesize that the recognition of humorous emotion is of great significance for sentiment analysis.

One interesting thing we found from analyzing Weibo is that people tend to express implicit humor that escapes the traditional bi-polarity of positive and negative. Moreover, emojis seem to play an essential role in enhancing such effect. Fig. 1 shows an example of a Weibo microblog that includes emojis and Internet slang. In the second line of the post, 累觉不爱 (*lei jue bu ai*[4]) is an abbreviation of 很累，感觉自己不会再爱了 (*hen lei, gan jue zi ji bu hui zai ai le* which means "too tired for romance"). As illustrated in Fig. 1, the forms of such expressions are often shortened to a "phrase" that consists of four Chinese characters. These expressions are similar to the usage in English, such as "lol" (laugh out loud) "idk" (I don't know), "ASAP" (as soon as possible), but for Chinese expression, it carries more creative, complex and ambiguous meaning.

In general, this particular form of expression can be seen from Chinese *chengyu*, which is a four-character phrase whose meaning was inherited from the older generations containing moral concepts, pearls of wisdoms or previous experiences. Nowadays, *chengyu* still plays a vital role in Chinese conversations and education. However, the young generation tends to adopt this form and give it new meanings that carry a sense of implicit humor, self-mocking or amusement inside the digital context. Typically, Internet slang

[4] In this paper we use italic to indicate romanization of Chinese language (*pinyin*).

Table 1
Examples of our Chinese Internet slang lexicon.

Type	Examples (origin)	English translation
Numbers	233 (哈哈哈)	"laughter"
Latin alphabet abbreviations	TMD (他妈的)	"Damn"
Chinese contractions	人艰不拆 (人生已经如此的艰难有些事情就不要拆穿)	"Life is so hard that some lies are better not exposed."
Neologisms	屌丝	"Loser"
Phrases with altered or extended meanings	壕 (土豪)	"Vulgar tycoon"
Puns and wordplay	河蟹 (和谐)	"Harmony"
Slang derived from foreign language	欧尼酱 (お兄ちゃん)	"Brother"

expressions are humorous, satirical, or ironic, which is also a crucial aspect of what makes them appealing and widely accepted. Such informal articulations are popular and extensively used in Chinese social media platforms and more examples can be found: *lei jue bu ai, ren jian bu chai* (life is so hard that some lies are better not exposed), *xi da pu ben* (news so exhilarating that everyone is celebrating and spreading it around the world).

Emojis are generally used to enhance or emphasize the sentiment of certain content. However, another interesting phenomenon we observed is that the meaning of certain emojis may change with time. For instance,  was initially designed for expressing a "bye-bye" gesture. However, it seems that more people gradually started to use this emoji for a funny way to express an artificial smile of refuse or self-mockery, and this usage is currently becoming trendy inc Chinese social media. In the research of Li et al. (2018b), the authors confirm this effect, underlining that this emoji tends to carry more humor rather than negative polarity. For example, in the following post: "After jogging, I'm starving. Someone sent me a picture of skewers. I'm too tired for romance  ". In this context, the post is trying to express a humorous nuance of a pessimistic attitude. In such situations, emojis and slang seem to play a pragmatic role in denoting humor rather than merely exhibiting positive or negative moods.

4. Lexicon of Chinese online slang

Slang, as a trendy form of informal language expression are widely used on social media for posting or commenting (Jones & Schieffelin, 2009). It appears in people's everyday life, which has changed the way how people communicate with each other's from a great extent. However, due to the unstructured nature and tricky meaning under different contexts, it causes great difficulties for machine to extract the sentiment polarity directly.

Because Internet slang is not easy to process automatically, it can cause significant difficulty in the polarity recognition task. For improving the performance of Chinese social media sentiment analysis, we created a Chinese Internet slang lexicon (examples shown in Table 1).

576 Chinese slang phrases that are frequently used on the Internet were identified and stored in our Chinese Internet slang lexicon. They originate from various sources, including the Internet New Words Ranking List, Baidu Baike,[5] Wikipedia[6] and social media systems such as Baidu Tieba[7] and Weibo[8] (the time span of the processed data is between 2010 and 2019).

After analysis, we divided the entries into seven following categories:

- Numbers: such as 233 ("laughter/lol": Chinese use 233 to express "can't stop laughing" because 233 is an emotional sign in a Chinese BBS site[9] and the sign is the character number 233 in the list of all the emojis); 213 ("a person who is very stupid"); 520/521 ("I love you").
- Latin alphabet abbreviations: Chinese users commonly use a QWERTY keyboard with pinyin enabled. Upper case letters are quick to type, and no transformation to ideograms follows. (lower case letters are automatically converted into Chinese characters). Latin alphabet abbreviations (rather than Chinese characters) are also sometimes used to evade censorship. Such as SB ("dumb cunt"); YY ("fantasizing/sexual thoughts"); TT ("condom").
- Chinese contractions: e.g. *ren jian bu chai* ("life is so hard that some lies are better not exposed": This comes from the lyrics of a song entitled "*Shuo Huang*" ("Lies"), by Taiwanese singer Yoga Lin. This slang reflects that some people, especially young people

[5] https://baike.baidu.com
[6] https://en.wikipedia.org
[7] https://tieba.baidu.com
[8] https://www.weibo.com
[9] https://www.mop.com

in China, are disappointed by reality); *lei jue bu ai* ("too tired for romance": this slang phrase is a literal abbreviation of the Chinese phrase "too tired to fall in love anymore". It originated from an article on the Douban[10] website, a Chinese social networking service website allowing registered users to record information and create content related to movies, books, music, recent events and activities in Chinese cities. The article was posted by a 13-year-old boy who grumbled about his single status and expressed his weariness and frustration towards romantic love. The article went viral on the Chinese Internet, and the phrase started to be subsequently used as a sarcastic way to convey depression when encountering misfortunes or setbacks in life); *gao da shang* ("high-end, impressive, and high-class": a popular meme used to describe objects, people, behavior, or ideas that became popular in late 2013).

- Neologisms: *diao si* ("loser": The word *diao si* is used to describe young males who were born into a low-income family and are unable to improve their financial status. People usually use this phrase in an ironic and self-deprecating way); *ye shi zui le* ("nothing to say": it is a way to gently express your frustration with someone or something that is entirely unreasonable and unacceptable); *dan shen gou* ("single dog": a term which single people in China use to poke fun at themselves for being single).
- Phrases with altered or extended meanings: *hao* or *tu hao* ("vulgar tycoon": This word refers to irritating online game players who buy large amounts of game weapons to be gloried by others. Starting from late 2013, the meaning has changed and now is widely used to describe nouveau-riche people in China who are wealthy but less cultured.); *bei tai* ("spare tire": A girlfriend or boyfriend kept as a "backup", "plan B", just in case of breaking up with the current partner).
- Puns and wordplay: 河蟹 ("river crab": pun on 和谐, another Chinese characters pronounced *he xie*, meaning "harmony").
- Slang derived from foreign language: 工口 (The word *gong kou* comes from the Japanese katakana *ero*, which translated from English "erotic" into the abbreviation of the katakana エロチック, meaning "sensual").

5. Lexicon of Chinese social media emojis

Facial expressions are a powerful tool in social communication (Batty & Taylor, 2003). Basic facial expressions of emotion are universal, (Ekman & Friesen, 1971) reported that six (anger, happiness, fear, surprise, disgust and sadness) are readily recognized in different cultures. Although there are many unknown factors in continually changing moods of human beings, expressing feelings is one of the most basic functions of our communication, also by using emojis which have become a global phenomenon. However, due to different cultural backgrounds and different contexts, misunderstandings commonly occur when communicating with emojis (Rzepka, Okumura, & Ptaszynski, 2017). Moreover, according to our previous observations, the meaning of certain emojis might change over time, and it is often difficult to interpret them as positive or negative. It seems that some emojis are used just for fun, self-mockery, or jocosity, which expresses an implicit humor characteristic in Chinese culture. For instance,  originated from the Japanese Shiba meme in 2013,[11] and has now become one of the most widely used emoji on Weibo. Weibo also developed a cat  version of  emoji. It is a clue for users to indicate that they know the real thought behind the words. The  is also known as "doge saves life", which is a humorous/informal way to express disagreement and avoid being attacked at the same time. Some users include this emoji in their messages just for being cute/funny without specific meaning.  is a reference to the phrase *chi gua qun zhong*, which refers to onlookers who are watching a situation just for fun. By using  in a post or comment, users are usually mocking themselves by showing they have no interest in the given topic and do not want to join the discussion.  is a bar of soap and its existence is probably inspired by an iconic joke about bending over for a bar of soap in a men's shower room. In most situations at Weibo, the passed message is "be careful of the situation," but sometimes it seems not to carry the original meaning and to make the content entertaining. Another example of changing the original meaning is , which, instead of being just a cheerful smile, started to carry a more passive than a positive attitude. By using this emoji in Chinese social networks, users could be expressing sarcasm, a passive-aggressive attitude, or even contempt.  can sometimes reverse the sentiment of the sentence.

The examples given above show that pictograms seem to play an important role not only in expressing emotions but also in conveying humorous content. There is also a high possibility that this phenomenon can cause significant difficulty in sentiment detecting task. Therefore, we decided to build a lexicon of emojis before adding them to our system to facilitate classifying emotions in Weibo.

Because Weibo emojis have no corresponding Unicode[12] assigned, they are formatted to Chinese letters within square brackets when scrapped. For example,  is transformed into [微笑] ("smile"). This conversion provided us with the possibility of building a Chinese emoji lexicon based on these tags. Consequently, 109 Weibo emojis (see Fig. 2) were selected and converted into textual features for building the lexicon. More examples are shown in Table 2.

6. Proposed method

Inspired by the works on Internet slang and emojis mentioned above, we utilized both lexicons with attention-based bi-directional long short-term memory recurrent neural network for sentiment analysis of Chinese social media to build our HEMOS system. In the real-life (offline) dialogue between human beings, besides tone changes, we usually express emotions with body language. In social networks, this nonverbal type of communication can partially be mimicked by using emojis (Aldunate & González-Ibáñez, 2017).

[10] https://www.douban.com
[11] https://en.wikipedia.org/wiki/Doge_(meme)
[12] https://unicode.org/emoji/charts-13.0/full-emoji-list.html

Fig. 2. 109 Weibo emojis which can be transformed into Chinese character tags.

Hence, as a working hypothesis, we assume that all microblogs with emojis convey non-neutral emotions. First, we add the Chinese slang lexicon and Chinese emoji lexicon to a segmentation tool for matching new words and pictograms. Then we use the updated tool to segment the sentences of a large data set. Second, we apply the segmentation output into the word embedding tool for acquiring word vectors. Next, we apply the word embedding model, which considers Internet slang and emojis, to train an attention-based bi-directional long short-term memory recurrent neural network model (AttBiLSTM) with training data to learn an output representation. In the last step, we input testing data into the AttBiLSTM model, and we use a softmax classifier to obtain the predicted results and output their probability.

To solve the problems of humor detection encountered in the previous research (Li et al., 2018b), we applied AttBiLSTM model to achieve a fine-grained classification method for classifying Weibo divided into four categories: positive, negative, optimistic humorous and pessimistic humorous. The "optimistic humorous" category includes jokes, self-mockery and jocosity and etc., while the "pessimistic humorous" category contains sarcasm and irony. We believe that the proposed fine-grained classification method can more effectively detect humorous expressions and improve the results of "positive/negative" bi-polarity sentiment classification.

In our experiments, we focus on the humorous posts using Internet slang and emojis on Weibo in order to verify:

1) if both slang and emojis lexicons improve sentiment analysis results by recognizing humorous entries which are difficult to polarize;

2) if adding new "optimistic humorous type" and "pessimistic humorous type" categories improve the result of bi-polarity sentiment prediction.

6.1. Attention-based bi-directional long short-term memory recurrent neural network

The architecture of attention-based bi-directional long short-term memory recurrent neural network model (AttBiLSTM) is shown in Fig. 3; our proposed model mainly consists of word encoder, attention layer and softmax layer. The details are presented below.

6.1.1. Word encoder

Considering that the entries of Weibo are sentences of less than 140 words, in contrast to related work of Yang et al. (2016), in our research we focus on sentence-level social media sentiment classification. Assuming that a sentence contains n words $(w_1, w_2, \ldots, w_n)$, w_k denotes the kth word in a sentence and n presents the length of a sentence, every word is embedded into a d-dimensional vector which is called word embedding (Bengio, Ducharme, Vincent, & Jauvin, 2003). Then, an embedding matrix $M^{n \times d}$ is generated by word embedding layer, where n is the length of the sentence and d is the embedding size. Finally, the matrix is applied as input for the bidirectional LSTM networks.

Bidirectional LSTM networks are well-suited to classifying, processing, and making predictions based on time series data because there can be lags of unknown duration between important events in a time series. Bidirectional networks outperform unidirectional ones, and Long Short Term Memory (LSTM) is much faster, and also more accurate than both standard Recurrent Neural Networks (RNNs) or time-windowed Multilayer Perceptrons (MLPs) (Graves & Schmidhuber, 2005).

An LSTM network computes a mapping from an input sequence $x = (x_1, \ldots, x_T)$ to an output sequence $y = (y_1, \ldots, y_T)$ by calculating the network unit activations using the following equations iteratively from $t = 1$ to T. The equations of the LSTM cell are as follows (Hochreiter & Schmidhuber, 1997):

Table 2
Examples of Chinese emoji lexicon.

Emoji	Textual feature	Emotion/implication
	[微笑]	"smile"
	[可爱]	"lovely"
	[太开心]	"too happy"
	[鼓掌]	"applause"
	[嘻嘻]	"hee hee"
	[吃瓜]	"watermelon-eating"
	[挤眼]	"wink"
	[馋嘴]	"greedy"
	[黑线]	"speechless/awkward"
	[汗]	"sweat"
	[挖鼻]	"nosepick"
	[哼]	"snort"
	[怒]	"anger"
	[委屈]	"upset/fell wronged"
	[可怜]	"pathetic"
	[失望]	"disappointment"
	[悲伤]	"sad"
	[泪]	"weep"
	[害羞]	"shy"
	[污]	"filthy"
	[爱你]	"love face"
	[亲亲]	"kissy face"
	[色]	"leer"
	[舔屏]	"lick screen"
	[憧憬]	"longing"
	[二哈]	"dog leash"
	[摊手]	"smugshrug"

$$X = \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} \tag{1}$$

$$f_t = \sigma(W_f \cdot X + b_f) \tag{2}$$

$$i_t = \sigma(W_i \cdot X + b_i) \tag{3}$$

$$o_t = \sigma(W_o \cdot X + b_o) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c \cdot X + b_c) \tag{5}$$

$$h_t = o_t \odot \tanh(c_t) \tag{6}$$

where the W terms denote weight matrices, W_i, W_f, W_o are diagonal weight matrices for peephole connections, the b terms denote bias vectors (b_i is the input gate bias vector), σ is the logistic sigmoid function, and i, f, o and c are respectively the input gate, forget gate, output gate and cell activation vectors, $\odot$ is the element-wise product of the vectors, the cell input and cell output activation functions, generally (as well as in our research) *tanh*. x_t denotes the word embedding of the input of LSTM cell and h_t is the vector of the hidden state. The specific schematic is illustrated in Fig. 4.

The bidirectional LSTM networks contain two independent LSTMs, which acquire annotations of words by merging information from two directions of a sentence (Graves & Schmidhuber, 2005). Specifically, at the time step t, the forward LSTM calculates the hidden state fh_t based on the previous hidden fh_{t-1} state and the input vector x_t, while the backward LSTM calculates the hidden state

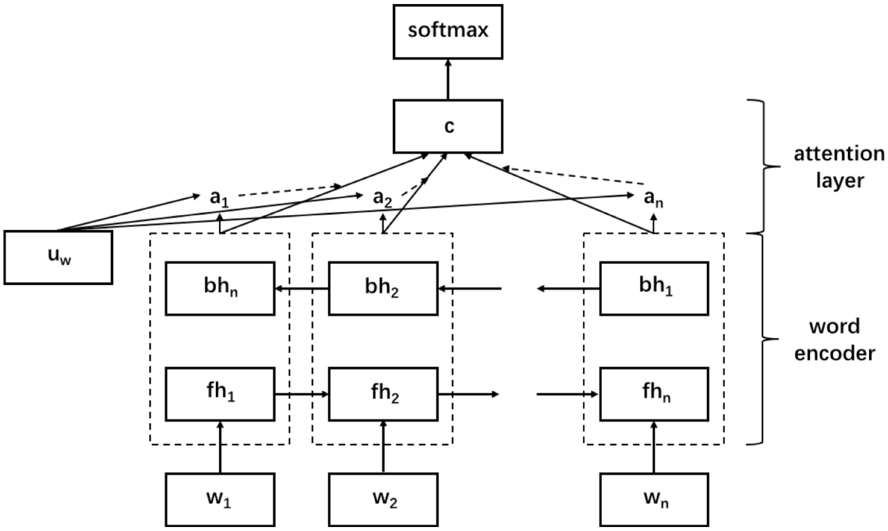

Fig. 3. The architecture of AttBiLSTM model.

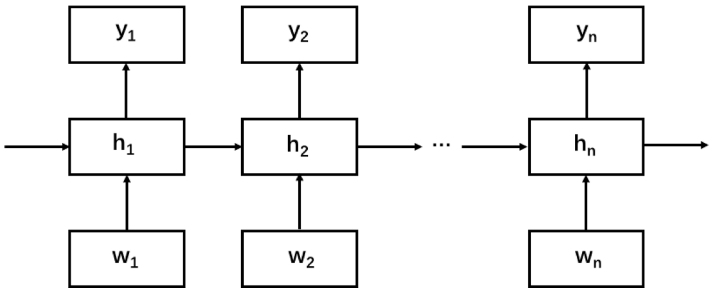

Fig. 4. The architecture of LSTM model.

bh_t based on the opposite hidden state bh_{t-1} and the input vector x_t. Finally, the vectors of two directions are concatenated as the final hidden state. The two LSTM neural network parameters in bidirectional LSTM networks are independent of each other, and they share the same word embeddings of the sentence. The final output h_t of the bidirectional LSTM model at time step t is defined as following:

$$h_t = [fh_t, bh_t] \tag{7}$$

6.1.2. Attention layer

Our proposed model projects a raw Weibo post into a vector representation, on which we build a classifier to perform sentiment classification. In this subsection, we introduce how we build the sentence-level vector progressively from word vectors by using the attention structure. Not all words contribute equally to the representation of the Weibo entry meaning. Hence, we introduce attention mechanism to extract words which are important to the meaning of the post and show how we calculate the total of the representation of those informative words to form a sentence vector.

As we mentioned above, the bidirectional LSTM networks produce a hidden h_t state at each time step. We first feed the word annotation h_t through a one-layer MLP to learn a hidden representation u_t. Then we measure the importance of the word as the similarity of u_t with a word-level context vector u_w and get a normalized importance weight α_t through a softmax function. Secondly, we compute the sentence vector c as a weighted sum of the word annotations based on the weights. The context vector u_w can be perceived as a high-level representation of a fixed query of "the informative word" over the words like those used in memory networks (Sukhbaatar, Weston, Fergus et al., 2015). The equations are described as follows:

$$u_t = \tanh(W_w h_t + b_w) \tag{8}$$

$$\alpha_t = \frac{exp(u_t^{\mathrm{T}} u_w)}{\sum_t exp(u_t^{\mathrm{T}} u_w)} \tag{9}$$

$$c = \sum_t \alpha_t h_t \tag{10}$$

6.1.3. Softmax layer

The word context vector u_w is randomly initialized and jointly learned during the training process. The outputs of softmax layer $\hat{y}$ are the probabilities of each category. The softmax function is defined as (Bridle, 1990; Merity, Xiong, Bradbury, & Socher, 2016):

$$\hat{y} = softmax(W_c c + b_c) \tag{11}$$

where W_c is the weight and b_c is bias, both of them calculated during the model training process.

7. Experiments

7.1. Preprocessing

Initializing word vectors with those obtained from an unsupervised neural language model is a popular method to improve performance in the absence of a large supervised training set. For our experiment, we crawled a large dataset of 7.6 million posts from Weibo API from May 2015 to July 2017 for calculating word embeddings. Firstly, we filtered images and videos and treated them as noise. Secondly, we added the Chinese Internet slang lexicon and Chinese emoji lexicon into the dictionary of Jieba,[13] a python package for Chinese text segmentation. Followed by the text segmentation with Jieba, the output of tokens is fitted into the word2vec model (Mikolov, Chen, Corrado, & Dean, 2013) for training. The output of the vectors has a dimensionality of 300, and then they were trained through the continuous skip-gram model.

In the next step, we collected 4000 Weibo posts containing ambiguous (🙂, 🐶, 😂, 🤷, 😏, 🤭, 😤, 🙄) emojis, ensuring each entry has only one emoji of given type (cases with more emojis of the same type were allowed). To use these posts as our training data, we asked three Chinese native speakers (each of them being a Weibo user for more than eight years) to annotate posts using four category labels: "positive," "negative," "optimistic humorous," and "pessimistic humorous." After one annotator labeled polarities of all posts, two other native speakers confirmed the correctness of his annotations. Whenever there was a disagreement, all evaluators decided the final polarity through discussion. We verbally confirmed with all annotators that they understood the meaning of "optimistic humorous" and "pessimistic humorous" categories.

We trained the AttBiLSTM model with 10 epochs to discover that the performance achieved the highest value when the dropout rate was 0.25, and the batch size was 64. The validity of the model was examined by 10-fold cross-validation.

7.2. Performance test

Using the trained word2vec model, we passed word vectors of training data into the AttBiLSTM model to train the proposed model. We collected and annotated 180 Weibo entries with the eight emojis mentioned above as a testing set, deleting images and videos. Then we used the proposed method to calculate the probability of each category and confirmed the precision, recall, and $F1$-score.

We compared the results of (a) two-categories sentiment classification by the AttBiLSTM method only; (b) two-categories sentiment classification by the AttBiLSTM considering Internet slang and emojis lexicons; (c) four-categories sentiment classification by AttBiLSTM method only, with our proposed method (d) four-categories sentiment classification by AttBiLSTM considering Internet slang and emojis lexicons. In two-categories sentiment classification, "optimistic humorous" and "pessimistic humorous" labels were treated as "positive" and "negative".

Results of two categories sentiment classification are shown in Tables 3 and 4, respectively. Tables 5 and 6 show the results of four-categories sentiment classification methods. The results proved that:

1) both slang and emojis lexicons can improve sentiment analysis results by recognizing humorous entries which are challenging to polarize;

2) adding new "optimistic humorous" and "pessimistic humorous" categories can improve the result of bi-polarity sentiment prediction;

3) our proposed methods can obtain the best performance for humor detecting and traditional bi-polarity sentiment analysis.

Limited to small annotated data, the precision of the "negative" and "pessimistic humorous" was relatively low, but by adding "optimistic humorous" and "pessimistic humorous" categories and considering Internet slang and emojis, the $F1$-score of each category outperformed previous method. Our proposed four-categories sentiment analysis approach has improved the performance showing that low-cost, small-scale data labeling can outperform widely used state-of-the-art when emoji and slang information is added to the learning process.

8. Considerations

In our proposed approach, we paid more attention to emojis and Internet slang in humorous microblogs. We investigated how adding these features influence the previously proposed methods for recognizing humorous posts which are problematic when it comes to semantic analysis. Fig. 5 presents an example of a microblog that was correctly classified by our proposed method as "optimistic humorous" while the baseline recognized it incorrectly as a negative one.

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

Table 3
Results of two categories sentiment classification by AttBiLSTM method only.

Categories	Evaluation	Results
Positive	Precision	69.07%
	Recall	82.76%
	*F*1-score	74.71%
Negative	Precision	78.05%
	Recall	50.00%
	*F*1-score	60.95%

Table 4
Results of two categories sentiment classification by AttBiLSTM considering Internet slang and emojis lexicons.

Categories	Evaluation	Results
Positive	Precision	82.35%
	Recall	84.48%
	*F*1-score	83.40%
Negative	Precision	73.77%
	Recall	70.31%
	*F*1-score	71.99%

Table 5
Results of four categories sentiment classification by AttBiLSTM method only.

Categories	Evaluation	Results
Positive	Precision	71.15%
	Recall	70.00%
	*F*1-score	70.57%
Negative	Precision	68.89%
	Recall	67.39%
	*F*1-score	68.13%
Optimistic humorous	Precision	72.72%
	Recall	60.61%
	*F*1-score	66.18%
Pessimistic humorous	Precision	39.29%
	Recall	61.11%
	*F*1-score	47.83%

Table 6
Results of our proposed method.

Categories	Evaluation	Results
Positive	Precision	89.79%
	Recall	88.00%
	*F*1-score	88.89%*
Negative	Precision	78.57%
	Recall	71.74%
	*F*1-score	74.99%*
Optimistic humorous	Precision	79.71%
	Recall	83.33%
	*F*1-score	81.48%*
Pessimistic humorous	Precision	65.00%
	Recall	72.22%
	*F*1-score	68.42%*

*$p < 0.05$.

This post and similar entries were usually posted as a comment a GIF or video showing a referee who displays her or his skills in basketball by performing a slam dunk. This entry seems to express an implied humorous nuance of an exaggerated surprise when the poster saw how good the referee was. Because this expression is accompanied by 🤷 emoji, it improves the performance of classification and predicts the implicit humorous meaning.

As a solution of problems of humor detection encountered in previous research (Li et al., 2018b), the fine-grained sentiment classification method we proposed can detect the emotions of Weibo posts more clearly. In Fig. 6, we show an example of a microblog

Post: 裁判：我当初就是因为没有对手，才选择做裁判的
Pinyin: *Cai pan: Wo dang chu jiu shi yin wei mei you dui shou, cai xuan ze zuo cai pan de*
Segmentation: 裁判/：/我/当初/就是/因为/没有/对手/，/才/选择/做/裁判/的/[摊手]
Translation: Referee: Because there was no opponent who could beat me, I chose to become a referee

Fig. 5. Example of correct classification of humorous post.

Post: 吃饱了就有力气减肥了
Pinyin: *Chi bao le jiu you li qi jian fei le*
Segmentation: 吃饱了/就/有/力气/减肥/了/[阴险]/[阴险]
Translation: When your stomach is full, you get the strength to reduce weight

Fig. 6. Another example of correct classification of humorous post.

which was correctly classified by our proposed method as "optimistic humorous," while the baseline recognized it as a positive one. As the evaluators agreed, it seems that this user wrote a joke just for fun, and our proposed method correctly recognized this kind of emotion.

Error analysis showed that the results of detecting negative emotions and "pessimistic humorous" emotions in our proposed method were still relatively low, which is closely related to the difficulty in recognizing sarcasm and irony. We plan to train more deep learning models and increase the amount of data to improve the results of pessimistic humorous detecting in the future.

Furthermore, some posts were wrongly predicted due to new slang missing from both the parser's dictionary and our slang lexcion which brought clearly negative impact on the results. In the research of Ptaszynski et al. (2016), the authors pointed that a typical cause of gradual decrease of performance of systems dealing with Internet language has been the fact, that Internet slang has been constantly changing. This point is also reflected in our research; in Fig. 7 we show an example of a post misclassified as "pessimistic

Post: 名人英文金句翻译与当下流行语神对应, 励志心灵鸡汤秒变毒鸡汤
Pinyin: *Ming ren ying wen jin ju fan yi yu dang xia liu xing yu shen dui ying, li zhi xin ling ji tang miao bian du ji tang*
Segmentation: 名人/英文/金句/翻译/与/当下/流行语/神/对应/, /励志/心灵鸡汤/秒/变毒/鸡汤/[doge]
Translation: Translation of English familiar quotations corresponds to the current Internet slang, chicken soup becomes poisonous chicken soup in seconds

Fig. 7. An example of an "optimistic humorous" post misclassified as "pessimistic humorous".

humorous" category, but annotated as "optimistic humorous" by annotators. Slang expressions as *miao bian* ("changing in seconds") and *du ji tang* ("poisonous chicken soup") were parsed incorrectly, and one shifted character caused mis-recognition by the segmentation tool. *Du ji tang* is a slang word transformed from *ji tang* which means "anti-motivational quotes" (for example: "Some are born great, some achieve greatness, and some wind up like you" or "I'm not lazy, I am just highly motivated to do nothing"). As the abbreviation of "Chicken Soup for the Soul" book series, *ji tang* is used to express the meaning of "motivational quotes" in recent years. Abundant new words similar to *du ji tang* are emerging on social media every year. Adding new phrases to slang lexicon is costly, and it is not enough to keep up with the speed of Internet slang evolution. To deal this phenomenon, a character level contextualized word embedding method (for example, pre-trained Chinese word embedding model by BERT) could be considered in the next stage of this research.

9. Conclusions and future work

In this paper, we proposed HEMOS (Humor-EMOji-Slang) system for fine-grained sentiment classification. We collected 576 frequent Chinese Internet slang expressions and created a slang lexicon; then, we converted the 109 Weibo emojis into textual features creating a Chinese emoji lexicon. Furthermore, with new "optimistic humorous type" and "pessimistic humorous type" added, we created the basis for a new, four-level sentiment classification of Weibo posts. We applied both lexicons to our novel deep learning approach, namely attention-based bi-directional long short-term memory recurrent neural network (AttBiLSTM) for more fine-grained sentiment analysis of Chinese social media. Our experimental results show that the HEMOS system can significantly improve the performance for predicting sentiment polarity on Weibo.

In order to achieve an even more effective Chinese sentiment analysis method, we are going to increase the amount of labeled data to solve the problem of visibly lower results for "pessimistic humorous" and "negative" categories in the proposed fine-grained classification.

In this study, we exclude images and videos. However, in further research, it would be interesting to add images to the data source. We assume this may enhance the text sentiment analysis since stickers and memes also carry emotions. To utilize such additional information, an image processing phase must be added during the preprocessing stage.

Moreover, during the data labeling phrase, we found that, compared with regular users, there is a high occurrence of posts with specific emojis that are used by spammers (users that spread malicious links or commercial content). Dealing with this problem could be an interesting research topic, and our methods could be useful for differentiating regular users from spammers.

Our ultimate goal is to investigate how much the newly introduced emotion-related features are beneficial for sentiment analysis by feeding them to a deep learning model, which should allow us to construct a high-quality sentiment recognizer for a wider spectrum of sentiment in the Chinese language.

CRediT authorship contribution statement

Da Li: Conceptualization, Formal analysis, Writing - original draft. **Rafal Rzepka:** Supervision, Writing - review & editing. **Michal Ptaszynski:** Writing - review & editing. **Kenji Araki:** Writing - review & editing.

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