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Research on Sentiment Classification Method Base on Multi-objective Evaluation Subject

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Abstract. In public opinion events, netizens often comment on multiple subjects involved in public opinion events from multiple perspectives. However, in traditional research methods, due to the lack of fine-grained classification of these evaluation subjects, the sentiment classification of netizens' evaluation in public opinion events is not precise and accurate. This paper proposes an emotion classification method based on multi-objective evaluation subjects. Firstly, the method combines dependency parsing to identify the emotional words and different evaluation subjects in the comment text; Secondly, use the semantic relationship and emotional rules between the comment text to segment and associate the various emotional tendencies of different evaluation subjects in the sentence; Finally, long-short term memory neural networks are used to classify the emotions of different evaluation subjects in the same event. Using four types of review text as a data set, the experimental results of books show that compared with the traditional LSTM model method, the precision rate, recall rate and F1 value of the MO-LSTM sentiment classification method are improved by 6.6%, 7.9% and 5.5% respectively. This method can accurately identify the emotional tendency and help find the root causes of negative emotional tendencies of public opinion in the event analysis.

Keywords: text sentiment classification, evaluation subject, dependency parsing, LSTM

1 Introduction

With the development of the Internet and the rise of Web2.0, due to its openness, virtuality, anonymity and other characteristics, how to capture and analyze the emotional trend of the public through the complex public opinion information has become a very important research topic [1-3]. Sentiment analysis or opinion mining is a computational study of people's views, emotions, emotions, evaluations and attitudes towards products, services, organizations, individuals, problems, events, topics and their attributes [4-5]. In the event comment, netizens will express their emotions from different angles, so there will be multiple objective evaluation subjects in the comment text. Therefore, due to the lack of fine-grained in the emotion classification, it is not accurate to distinguish the emotional tendency of the event. This paper classifies the different emotional tendencies of different evaluation subjects under the same event, so as to improve the accuracy of emotional judgment of the event itself.

Sentiment classification is a goal related problem [6]. In public opinion events, the target can be the object or domain described by the text, or the specific evaluation subject in the text. When different objectives are targeted, the traditional emotion classification methods are usually ineffective. Therefore, the goal-oriented fine-grained sentiment classification research is more practical. At present, there are some difficulties in the study of sentiment classification of multi-objective evaluation subjects: the accuracy of the evaluation subject identification in the text, the Segmentation of sentences containing multiple evaluation subjects, and the determination of the final emotion expression of the text with multiple complex emotional tendencies. To solve the above problems, the main technical contributions of this paper are summarized as follows:

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(1) This paper proposes a sentiment classification method based on multi-objective evaluation subjects. First of all, it combines dependency syntactic analysis with emotional semantic feature rules to determine different evaluation subjects. and the sentences containing multiple subjects and multiple emotional tendencies are segmented.

(2) Aiming at the emotional loss caused by subject segmentation in multi-objective evaluation, we propose three emotional rules. Then, syntactic analysis, semantic analysis and affective analysis are used to determine the final emotion of different evaluators, and various emotion sets under different evaluation subjects are obtained.

(3) Finally, a multi-target subject emotion classification model based on LSTM is established. The model not only trains the text to generate new text feature vectors, but also calculates the weight information of the hidden layer state sequence under different evaluation subjects, which can well improve the fine-grained emotion classification performance of the traditional LSTM network.

(4) This article uses the Chinese data set (including 4 types of comment text data sets) published on the Internet as the experimental object. The experimental results show that the method has better classification effect than the ordinary deep network model, and it is more accurate to distinguish the emotional tendency of different evaluators in the event.

The rest of the paper is structured as follows: Section 2 briefly discusses related works and analyzed the advantages and disadvantages of existing writings. Section 3 proposes a method of emotion classification based on multi-objective evaluation subjects, and introduces the definition of evaluation subject recognition, emotional association rules and multi-objective evaluation subject emotional classification models. Section 4 take 4 types of comment text data sets published on the internet as the experimental objects, and discusses our experimental results. Section 5 gives conclusions and looks forward to future work.

2 Related Work

The method proposed in this article essentially involves natural language processing technology and specific target analysis technology, so the following two kinds of sentiment classification methods focusing on statistical machine learning and specific target analysis will introduce related work.

At present, short text sentiment classification mainly adopts statistical natural language processing and emotional semantic characteristics [7]. The most commonly used English vocabulary semantic web is WordNet [8], created by Princeton University Through the semantic network of nouns, verbs, adverbs and adjectives, choose words with obvious emotional tendency as seed words to distinguish different emotional categories. Taboada added emotional polarity and intensity labeling analysis based on the emotional dictionary, and considered the influence of degree adverbs and negative words on sentiment analysis [9]. The earliest method of text sentiment classification is the supervised learning method proposed by Pang in 2002. Machine learning is used to analyze the positive and negative sentiment tendency of video review data at the text level [10]. Socher R On the basis of RNN text classification model, LSTM text sentiment classification model is further proposed, LSTM solves the long-term dependence problem that RNN cannot solve through gate mechanism [11]. Chen proposed a long-distance sentiment analysis model based on multiple attention mechanisms, Through weighted memory machine, more complex features can be extracted, and the expression ability of the model can be enhanced, and the emotion classification can be more accurate [12].

Traditional machine learning methods have achieved good results in general sentiment analysis tasks, but they need to rely on complex artificial rules and feature engineering. In the same comment text, there are often multiple different target words and multiple emotional polarity, and different targets in the same sentence are often predicted to have the same emotional polarity [13]. Target specific sentiment analysis is to identify the emotional polarity of a specific target in a text by learning the information of the text context, It is a deeper emotional analysis and a fine-grained text classification task [14]. Different from general affective analysis, target specific affective analysis aims to analyze the emotional polarity of different evaluation subjects in a text. It not only depends on the context information of the text, but also considers the emotional information of multiple objects in the text. Wang spliced the target content with the corresponding intermediate state of the sequence in the long and short-term memory network, and calculated the attention-weighted output, which effectively solved the emotional polarity problem of the context for different targets [15]. Zhang proposed a target sentiment analysis model based on recurrent neural network and dependency tree, which uses sentence component structure and sentence dependency tree to obtain the representation of specific aspects, which effectively improves the accuracy of sentiment analysis for specific targets [16]. Liang combined various attention mechanisms with convolutional neural network at the same time, and integrated word vector, part of speech and position information to improve the effect of target sentiment analysis [17]. Lappas T uses an adaptive neural network model to learn the relationship between a specific target and the word and the syntactic structure of the sentence, and expands the emotional information in the sentence through the connection between the word and the target word, thereby effectively determining the emotion orientation of the specific target in the sentence [18].

To sum up, in the text sentiment analysis method based on machine learning, the type of classifier has little influence on the final classification result. Which is mainly the selection of text features, the advantages and disadvantages of features have a greater impact on the final classification effect. Therefore, this paper proposes a sentence segmentation method based on semantic, existential syntax and emotional rules, the complex text with multiple evaluation subjects is divided into multiple single subject sentiment sentences, and the input sentences are divided into different target regions according to the position of different evaluation subjects. The calculation time of LSTM network is reduced by reducing the length of input text. Finally, the multi-objective emotion classification of multi-objective subjects is completed by MO-LSTM classifier, and the classification effect is checked to evaluate the accuracy of the method.

3 Multi-objective Evaluation Subject Recognition and Emotion Association Classification Method

The emotion classification based on multi-objective evaluation subjects is mainly to distinguish the emotions of different evaluation subjects in the same public opinion event, and to correlate the emotions expressed by different evaluation subjects, so as to effectively discover the essential reasons in the event public opinion analysis, and to judge the emotional tendency of public opinion events more accurately. The process is shown in Fig. 1: First, the review text data set is preprocessed, and the evaluation subjects (A, B, C...) and emotion-oriented words (Neg, Pos, Neu) in the text are evaluated using dependency syntax analysis and semantic features. Perform recognition and extraction, and divide the text containing multiple evaluation subjects into multiple single evaluation subject sentences; the text containing multiple evaluation subjects and multiple emotional expressions are segmented and correlated according to emotion rules; The text containing a single evaluation subject and multiple emotional expressions uses semantic analysis to identify the final emotion expressed. After word2vec training, the segmented single evaluation subject sentences are expressed in terms of the vectorial features. The long-short term memory neural network is used to identify the emotions of multiple targets, and the emotional tendencies expressed by the same evaluation subject are correlated. Finally, the emotion classification of different evaluation subjects in the same event is completed.

3.1 Identifying Multi-objective Evaluation Subject Word Based on Dependency Parsing

Dependency parsing is to analyze the sentence structure by analyzing the dependency relationship among the components in a sentence, and identify and locate the “subject, predicate, object, definite condition and complement” in the sentence. In this paper, we use the subject predicate, verb object, the attribute-head phrase, adverbial-verb phrase, verb complement, Object Preposition in dependency syntax to identify the evaluation subject words and emotional words in the comment text, as shown in Fig. 2. According to the syntactic rules, the logical structure of sentences is analyzed to complete the identification of evaluation subjects and emotional words, and the multi-objective evaluation subjects are segmented. Semantic analysis is to calculate the semantic relevance between the context and the target, and identify negative words, degree words, adverbial words, progressive words and coordinate words in the comment text with multiple semantic relations, including turning, parallel, progressive and so on. According to the semantic relations, we can judge the emotion finally expressed.

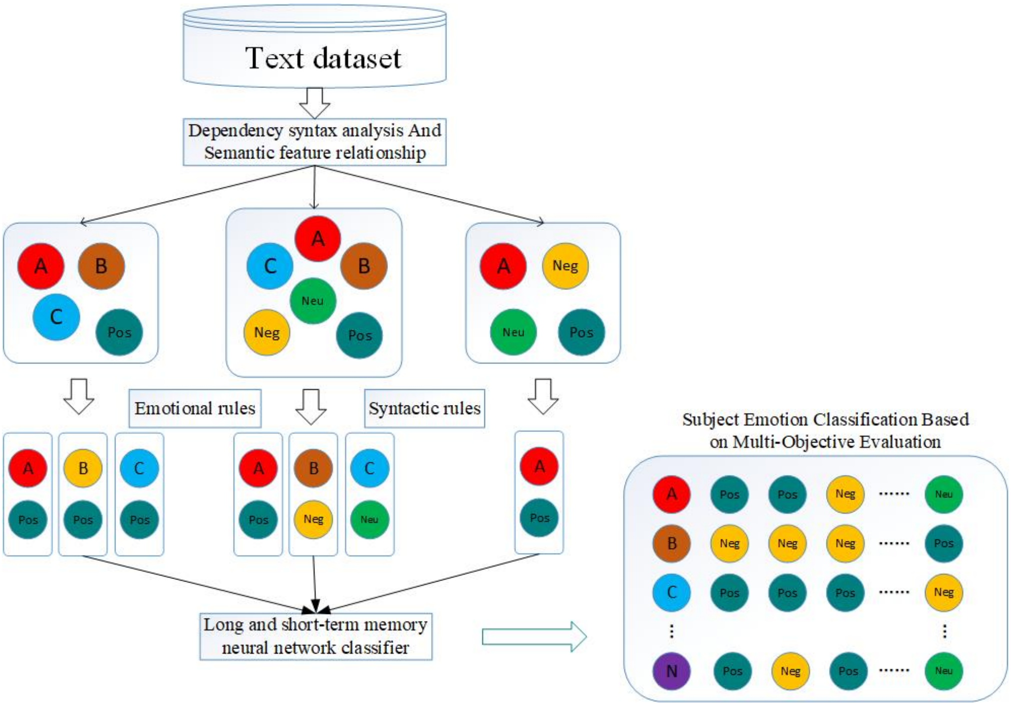

Fig. 1. Flow chart of a multi-objective sentiment classification model

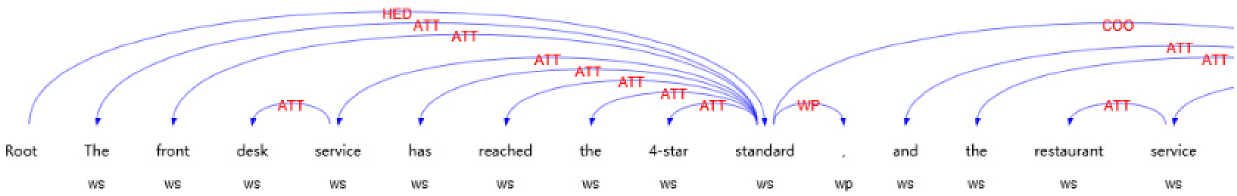

Fig. 2. Dependency syntax analysis example

There are 15 types of dependency parsing relation combinations, and six of them are selected to identify and extract the emotional subject word pairs in the comment text. As shown in Table 1, Subject predicate relationship (SBV): the subject is generally a noun, and the predicate is an adjective or verb, which is also an emotional expression word; Verb object relationship (VOB): the general noun of the object is also the subject word in the emotional elements, and the emotional word is generally a verb, noun or adjective; The prepositive object relationship (FOB): the subject word of the emotional element is generally a noun, and the subject word takes the subject word as the prepositive object, and the emotional word is generally a verb; The attribute-head phrase(ATT): the subject is generally a noun and the subject word of the emotional element, and the emotional word acts as a modifier; Adverbial-verb phrase (ADV):Adverbs are used to modify emotional words, the commonly used adverbs are whether they are definite or degree adverbs; Verb complement relationship (CMP): the subject words are mostly verbs, and emotional words are adjectives or nouns, which are mainly used to modify or supplement the subject words.

Table 1. Using dependency syntax analysis to identify emotional subject word pairs

Rule	Part of speech pairs	Dependency relationship	Example
1	N + adj/v	SBV	High price performance ratio
2	N + v/n/adj	VOB	No Bluetooth function.
3	N + v	FOB	He reads all books.
4	N + v/n/adj	ATT	Low resolution of screen
5	N/v/adj	ADV	Cannot install
6	V + adj/n	CMP	General heat dissipation

In the comment text, emotional words reflect the emotional tendency of the reviewers and affect the final classification results. Because of the complexity and diversity of the comment text, there are multiple target evaluation subjects in the text, for example, the hotel reviews will involve rooms, facilities, services, attitudes, foreground, location and other evaluation subjects. Books, stories, authors, quality, paper, layout, text, language, etc., are identified in the book category; some of the evaluation subjects identified after processing are shown in Table 2.

Table 2. Some evaluation subjects in various data sets

Data set	Evaluation subject
Hotel	Room, decoration, bathroom, toiletries, bathtub, air conditioning, environment, area, facilities, bed, pillow, hygiene, corridor, carpet, price, transportation, location, location, sound insulation, noise, restaurant, breakfast, taste, reception, service, Phone, parking lot, booking ...
Book	Author, story, content, quality, text, language, picture, writing, piracy, opinion, reason, plot, character, friend recommendation, bookstore, order, quality, printing, smell, book cover, quality, packaging, customer service, Delivery, service ...
Electronics	Mobile phone, screen, function, system, keyboard, battery, cooling, drive, camera, mouse, performance, battery life, appearance, memory, sound, hard drive, camera, pixel, Bluetooth, call, signal, configuration, price, speed, design, Cost-effective, quality, brand, service ...
Milk	Mengniu, Yili, brand, milk, yogurt, milk powder, enterprise, product, packaging, taste, nutrition, supermarket, shelf life, production date, quality, breakfast, advertising, domestic production, event, price, publicity, customer service ...

3.2 Emotion Rules Based on Multi-objective Evaluation

In order to avoid the emotional loss between the evaluation objects in the sentence segmentation process, the annotated text containing multiple target evaluation objects and multiple emotional words is segmented through syntactic analysis and emotional rules to obtain the emotional sentence of a single evaluation subject. In this paper, 3956 comments with neutral emotion expression are analyzed, and the different evaluation subject markers contained in the special sentences such as parallel, progressive and turning are segmented. Then, according to the semantic features and sentiment analysis, the segmented subject is associated with the emotion expressed, and the following emotion rules are summarized.

Rule 1. If there are multiple evaluation subjects with single emotion in the text sentence, the multiple subjects share the same emotion, and the text is divided into multiple sentences with single subject and single emotion. For example, the food and drug administration, the food safety administration, the State Administration of radio, film and television, and relevant government departments are really a group of useless wine bags. Here, the drug administration, food safety bureau and other subjects share one emotion.

Rule 2. If there are multiple evaluation subjects and different kinds of emotions in the text, they should be divided according to the expression order and semantic relationship of the emotional subjects in the text. For example, the fake vaccine is hateful and must be strictly investigated and punished, the state system is also constantly improving. In fact, China’s legal system is very sound and strict, but the national quality needs to be improved, according to the emotion expressed, the sentences are divided into three single subject sentences.

Rule 3. If there is no subject in the first half of the text sentence and the subject appears in the second half of the sentence and the sentence is segmented, then the evaluator defaults to the event itself. If the emotion in the latter part of the sentence is similar to the emotion in the preceding paragraph, the former paragraph may share the same subject with the latter paragraph; if the latter part is opposite to the former, the sentence should be divided into two evaluation subjects and emotions. It was terrible, Gao and her accomplices must be brought to justice and sentenced to death. The first half of this sentence belongs to the no subject sentence, so the subject is the vaccine incident by default, and the subject of the second half sentence is related to his emotion, the emotional expression of the former and the latter segment is aimed at the main body of the hospital.

3.3 Multi-objective Text Representation Based on Word2vec Word Vector

Use The word2vec model was developed by CBOW [19] (continuous bag of words) and Skip-gram [20], both of which are based on Huffman trees. The initialization value of the intermediate vector stored in the non-leaf node in the tree is zero vector, while the word vector of the word corresponding to the leaf node is randomly initialized. The training input of CBOW model is the word vector corresponding to the context related word of a feature word, and the output is the word vector of the specific word [21]. The network structures of CBOW and Skip-gram models are input layer, mapping layer and output layer. Skip-gram is the word vector of a specific word, while the output is the context word vector corresponding to a specific word. The input layer is the word vector of n-1 words around the word W(t). From the input layer to the mapping layer, the words are added in vector form, and the Huffman tree is constructed from the mapping layer to the output layer. Starting from the root node, the mapping layer values are logistic classified along the Huffman tree, and the intermediate vectors and word vectors are constantly modified to obtain the word vector W(t) corresponding to the word W(t). Skip-gram, like the CBOW model, only reverses the causality of CBOW, as shown in Fig. 3.

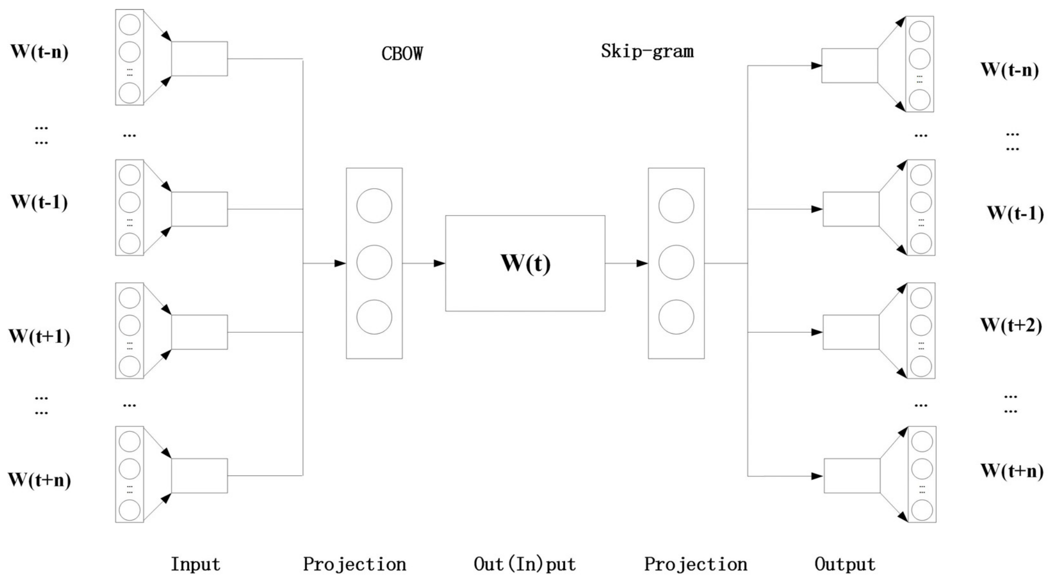

Fig. 3. Schematic diagram of the working principle of Word2vec

Word2vec uses neural network language model NNLM (Neural network language model) and N-gram language model to express each word as a real vector [22]. Using word vector to represent text as input to LSTM network model, word vector solves the problem of vector space model and one-hot, and maps high-dimensional sparse feature vectors into low dimensional dense word vectors, effectively avoiding the occurrence of dimensional disasters. It can directly calculate the semantic correlation between words. The Word2vec model is used to train the already labeled good texts in the dataset, so that the expression of emotional words in the text is generated to the quantitative expression, and the vectorization of sentences is achieved through the linear superposition of the emotional word vectors.

3.4 Multi-objective Emotion Classifier Based on Long and Short Term Memory Neural Network

This article takes the different emotional subjects in the comment text as the object, divides the sentence into segments, and divides the sentence with them. The logical features of different emotional subjects in text can be retained, and the emotional information of different subjects in text can be distinguished, such as text $S = \{w_1, w_2, \cdots t_i \cdots t_j \cdots w_n\}$. There are t_i and t_j In this paper, the length of two subject words is h independent statement of $r_1 = \{w_m, \cdots t_i \cdots w_{h+m-1}\}$ and $r_n = \{w_n \cdots t_j \cdots w_{h+n-1}\}$. As shown in Fig. 4, this is a comment text about hotels. In one sentence, there are five different evaluation subjects: room, air, air conditioning, service, breakfast, and three kinds of emotional expression. However, in the traditional experiment, the sentiment of this sentence is neutral, it is obviously not very accurate. This comment is based on the positive emotional expression of the room environment and restaurant service, while it is negative for the quality of the air conditioning and breakfast in the room. In order to make the final sentiment classification more accurate, five evaluation subjects in the text are identified and their expressed emotions are correlated, and the text is divided into three paragraphs for discrimination and classification.

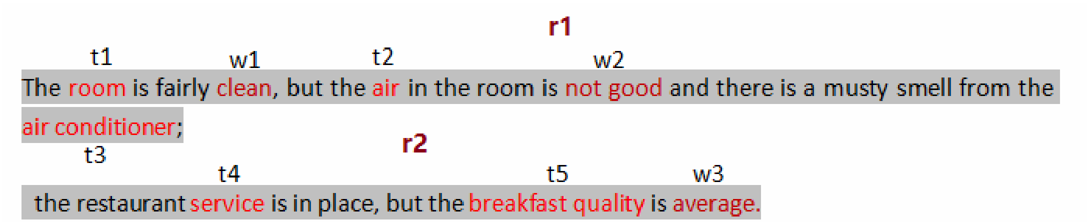

Fig. 4. Hotel text dataset review text

In order to make the network focus on the information of specific emotional subjects in sentences, the extracted feature vector and the word vector of a single emotional subject are input in the form of attention vector, as shown in Fig. 5 local LSTM network structure. The input of LSTM is composed of the word vector in the text, the output of the previous hidden layer and the emotional word vector of the emotional subject $e = \{w_h \times h_i + w_{r1} \times r_1 + \cdots + w_{rn} \times r_n\}$. of which $w_h \in R^l$ Is hidden layer output h_i Weight matrix of R^l In order to hide the dimension of output in the layer, the parameters of weight matrix can be adjusted to mine the emotional information of different features in sentences in the process of LSTM training, so as to make the classification result more accurate.

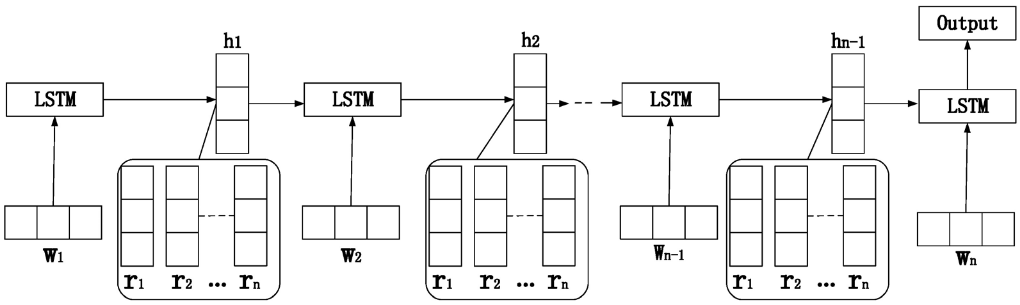

Fig. 5. Evaluation subject segmentation LSTM network structure

4 Data Results and Analysis

4.1 Experimental Data

In this paper, teacher Song-Bo Tan is selected to conduct experiments on four kinds of data sets with marked emotion categories published on the Internet. By comparing with the existing models which have achieved better results, the effectiveness of emotion classification based on multi-objective evaluation subjects in emotion analysis tasks is verified. In this experiment, user comments are obtained by using skip gram training of word2vec, each word vector is set to 100 dimensions. Chinese data are processed by using the Jieba toolkit. All target words are segmented and word vectors are trained. The emotional polarity of the data samples is divided into three categories: positive, negative and neutral. The data set is divided into test set and training set in the ratio of 2:8. The statistics of classification of experimental data sets in this paper is shown in Table 3, in which Train is the training set and Test is the test set, Subject is the amount of text and the number of subjects after dividing the wrong text according to the evaluation subject.

Table 3. Statistics of experimental data set classification

Data	Positive sentence	Neutral sentence	Negative sentence
Hotel-Train	1371	1173	1443
Hotel-Test	274	234	288
Hotel-Subject	338(142)	372 (191)	353(127)
Book-Train	1270	1099	1481
Book-Test	154	218	296
Book-Subject	226(96)	346(143)	323(113)
Digital -Train	2806	804	2740
Digital -Test	560	160	548
Digital-Subject	714(217)	281(152)	682(176)
Milk-Train	951	880	1136
Milk -Test	190	176	226
Milk-Subject	243(98)	279(138)	274(112)

4.2 Experimental Setup

The experiment uses the server running environment as Win64 bits and Python3.7 versions; segmenting Chinese data sets by using the word segmentation tool; using the Word2vec tool in the vector training phase, using the Keras deep learning framework to complete the LSTM model development, and using the deep learning framework tensorflow1.14 as the running backend; the model parameter training model selects CBOW, and the dimension of the word vector is set to 100 dimensions. The context window size is 7; the experimental specific parameter settings are shown in Table 4.

Table 4. Experimental parameter settings

Parameter name	Parameter value
vocab-dim	100
window-size	7
n-epoch	4
batch-size	32
dropout	0.5

4.3 Experimental Evaluation Index

The evaluation indicators used in this article are mainly precision rate P, recall rate R and F1 value, the classification index is shown in Table 5, TP and FP represent the number of texts consistent with the actual classification results, while FN and TN represent the number of texts inconsistent with the actual classification results.

Table 5. Classification results representation

Attribution category	Fall into this category	Not in this category
Actually belongs to this category	TP	FN
Actually not in this category	FP	TN

Where the precision rate P is the accuracy rate of classification:

$$P = \frac{tp}{tp + fp} \times 100\% . \quad \textbf{(1)}$$

The recall rate R is the integrity of the classification:

$$R = \frac{tp}{tp + fn} \times 100\% . \quad \textbf{(2)}$$

The formula of comprehensive value F1 is as follows:

$$F1 = \frac{2(P \times R)}{P + R} \times 100\% . \quad \textbf{(3)}$$

LSTM is a time loop neural network model, which can retain the word order relationship of input features, and can solve the problem of sentence length dependency to a certain extent, but cannot optimize the model for specific goals. The MO-LSTM model proposed in this paper combines the segmentation of multi-objective evaluation subjects with the LSTM network. The comparative experimental results of the two models are shown in Table 6.

Table 6. Comparison of experimental results

Index	Hotel		Electronics		Milk		Book	
Positive	LSTM	MO-LSTM	LSTM	MO-LSTM	LSTM	MO-LSTM	LSTM	MO-LSTM
P	0.836	0.883	0.848	0.879	0.837	0.873	0.846	0.875
R	0.812	0.851	0.917	0.898	0.821	0.880	0.779	0.858
F	0.846	0.873	0.881	0.888	0.828	0.876	0.811	0.866
Negative	LSTM	MO-LSTM	LSTM	MO-LSTM	LSTM	MO-LSTM	LSTM	MO-LSTM
P	0.846	0.892	0.910	0.896	0.825	0.879	0.795	0.861
R	0.801	0.838	0.835	0.876	0.840	0.871	0.858	0.877
F	0.828	0.876	0.870	0.885	0.832	0.874	0.825	0.868

From the experimental results in Table 6, it can be seen that the classification result of the model based on multi-objective evaluation subject is better than that of the general depth model. After the target segmentation of different subjects in the text, the model can be optimized for specific target domain information in the training process.

Compared with the LSTM model in the book dataset with better classification results, the precision, recall and F1 value are increased by 6.6%, 7.9% and 5.5% respectively. To verify the classification performance of the multi-objective sentiment classification (MO-LSTM) model proposed in this article, the accuracy comparison experiments were conducted with traditional machine learning SVM, CNN model and LSTM deep learning model. The accuracy refers to how many judgments are correct in all judgments, that is, the positive judgment is positive, and the negative judgment is negative. That is, the proportion of all the correct predictions, the calculation formula is as follows:

$$ACC = \frac{tp + tn}{tp + tn + fp + fn} \times 100\% . \quad \textbf{(4)}$$

Among them, 20% of the preprocessed text data sets are randomly selected for the experiment, and the ratio of training set to test set is cross verified according to the method of 8:2. After the experiment, the comparison of the accuracy of sentiment classification of four types of text is shown in Fig. 6 and Fig. 7.

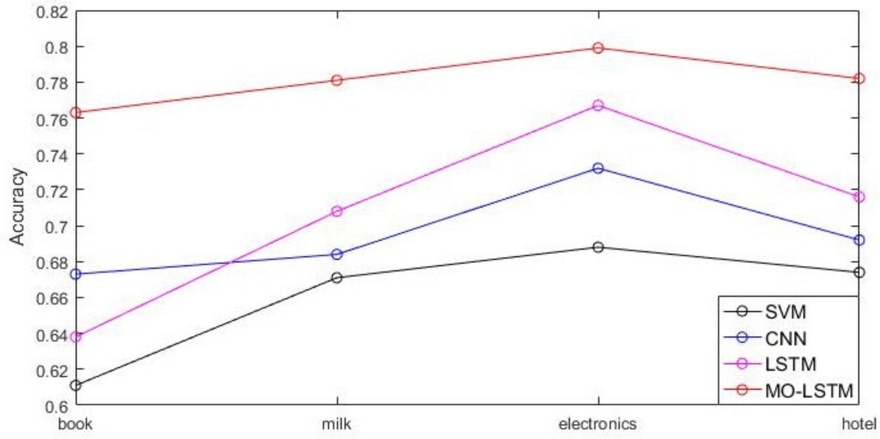

Fig. 6. Comparison chart of accuracy rate of positive affective tendency

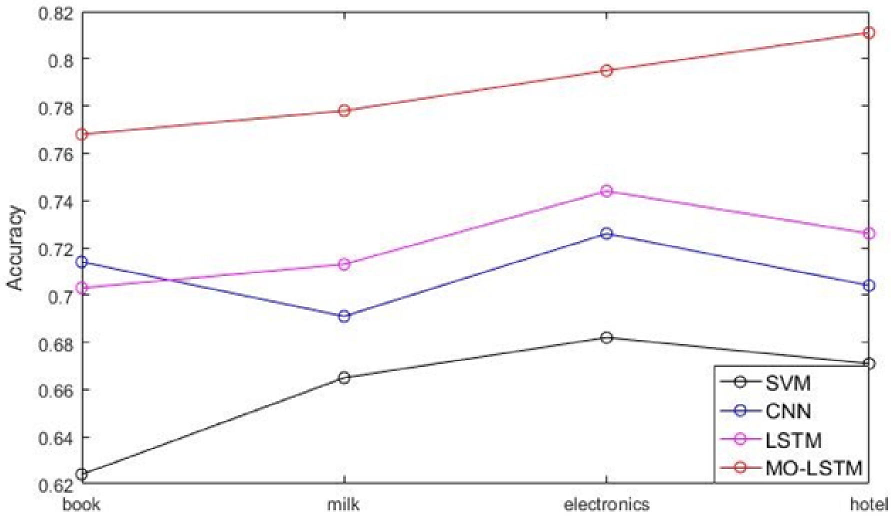

Fig. 7. Comparison chart of accuracy rate of negative affective tendency

The results show that SVM has better performance than the traditional methods in depth classification. But the classification results are strongly dependent on the selection of artificial features. The fusion model in this paper is 14.8% more accurate than the SVM classification results; The convolution neural network model based on CNN uses the features obtained after word segmentation as the input of the network model, but it can't optimize the model for specific objectives, and the classification result of MO-LSTM is higher than 9%; The accuracy of the multi-object classification model MO-LSTM proposed in this paper is 6.5% higher than that of the single LSTM model. MO-LSTM combines the target vector with the input features by segmenting the multi-objective subjects, then calculates the weight information of the hidden layer state sequence, and then outputs the weighted synthesis. It can improve the fine-grained sentiment classification performance of the traditional LSTM network, and the length of the text sentence input is shortened according to the multi-objective evaluation subject classification, which greatly reduces the time of classifier discrimination. In conclusion, the emotion classification method based on multi-objective evaluation subject proposed in this paper can help to improve the effect of short text sentiment classification, and verify the feasibility of the method in this paper.

4.4 Analysis and Discussion

According to the experimental results on four different types of review text data sets, the accuracy of the proposed multi-objective evaluation subject combined with LSTM model in emotion analysis task is verified. It can effectively identify different subject targets in the text and correlate their emotional polarity, compared with the traditional emotion classification model, it has better emotion classification effect. Among them, the improvement effect is more obvious in the book review text data set, and the Precision, recall rate and F1 value of the traditional emotion classification model are improved by 6.6%, 7.9% and 5.5% respectively. We also find that the judgment results are affected by the positive words in the evaluation subject words. For example: new packaging, new decoration, such a large front desk, expensive motherboard, etc. Therefore, in the emotional classification, we should separate the evaluation subject from the emotional expression sentence, and separate the emotional expression sentence after determining the evaluation subject.

5 Conclusion

In this paper, we propose a sentiment classification method based on multi-objective evaluator. This method can segment the multi-objective subject sentences in text by using the relationship between semantic relations and syntactic features, and combining with dependency parsing. Based on long-term and short-term memory neural networks, a multi-objective emotion classification model (MO-LSTM) is established. Through training and testing four different types of annotated text data sets, the accuracy of the deep network model based on the traditional LSTM architecture increased by 7.4% (POS) and 6.7% (NEG) on average. The experimental results prove the effectiveness of the method. Moreover, the time cost of the proposed model is short. However, based on the fact that certain emotional subjects may lose words that have an important impact on a specific target when the region is unreasonably divided, we will analyze and improve the problem of emotional loss caused by segmentation in non-target subject sentences and multi-object sentences to study the emotional rules in different situations in more detail.

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References

[1] J.-J. Wu, Research on Chinese Text Sentiment Classification Based on Deep Learning and Its Application in Public Opinion Analysis, [dissertation] Xiangtan University 2017.

[2] H.-W. Wang, L. Xie, Y. Pei, Literature Review of Sentiment Classification on Web Text, Journal of the China Society for entific and Technical Information, 2010.

[3] P. Zhang, Research on Sentiment Classification Methods of Web Review Texts, [dissertation] Chongqing University 2015.

[4] B. Liu, Sentiment Analysis and Opinion Mining Synthesis Lectures on Human Language, Technologies Morgan & Claypool 5(1)(2012) 1-167.

[5] Y. Wang, M. Huang, X. Zhu, Attention-based LSTM for aspect-level sentiment classification, in: Proc. 2016 Conference on Empirical Methods in Natural Language Processing, 2016.

[6] Y. Deng, H. Lei, X.-Y. Li, A multi-hop attention deep model for aspect-level sentiment classification, Journal of University of Electronic Science and Technology of China, 2019.

[7] X.-B. Tang, J. Zhu, F.-H. Yang, Research on sentiment classification of online reviews based on sentiment ontology and KNN algorithm. Information studies: Theory & Application 39(6)(2016) 110-114.

[8] L. Gatti, M. Guerini, Assessing sentiment strength in words prior polarities, in: Proc. International Conference on Computational Linguistics, 2012.

[9] M. Taboada, J. Brooke, M. Tofiloski, Lexicon-based methods for sentiment analysis, Computational Linguistics 37(2)(2011) 267-307.

[10] B. Pang, L. Lee, S. Vaithyanathan, Thumbs up? sentiment classification using machine learning techniques, in: Proc. Empirical Methods in Natural Language Processing, 2002.

[11] K.-S. Tai, R. Socher, C.-D. Manning, Improved semantic representations from tree-structured long short-term memory networks, Computer and Language 5(1)(2015) 36.

[12] P. Chen, Z. Sun, L. Bing, Recurrent attention network on memory for aspect sentiment analysis, in: Proc. 2017 Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, 2017.

[13] S.-Y. Chen, C. Peng, L.-S. Cai, A deep network model for specific target sentiment analysis, Computer Engineering 45(3)(2019) 292-298.

[14] M. Hu, B. Liu, Mining and summarizing customer reviews, in: Proc. Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, Washington, USA, August 22-25, 2004 ACM, 2004.

[15] Y. Wang, M. Huang, X. Zhu, Attention-based LSTM for aspect-level sentiment classification, in: Proc. 2016 Conference on Empirical Methods in Natural Language Processing, 2016.

[16] S.-Y. Chen, S.-L. Zhang, Y.-H. Han, Research on multi-scale data mining method, Journal of Software 27(12)(2016) 3030-3050.

[17] B. Liang, Q. Liu, J. Xu, Aspect-based sentiment analysis based on multi-attention CNN, Journal of computer research and development (2017).

[18] T. Lappas, Fake reviews: the malicious perspective, in: Proc. 2012 International Conference on Application of Natural Language to Information Systems, 2012.

[19] M. Tang, L. Zhu, X.-C. Zhou, A document vector representation based on Word2Vec, Computer Science (6)(2016) 214-217.

[20] C. Zhao, F.-X. Zhu, S.-C. Liu, Link prediction method based on Skip-Gram model, Computer Applications and Software 34(10)(2017) 241-247.

[21] Q. Zhou, Question similarity computation based on deep learning and topic model, [dissertation] Beijing Institute of Technology 2016.

[22] T. Mikolov, K. Chen, G.-S. Corrado, Efficient estimation of word representations in vector space, in: Proc. 2013 International conference on learning representations, 2013.