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The Identification of the Emotionality of Metaphorical Expressions Based on a Manually Annotated Chinese Corpus

DONGYU ZHANG[1,2], **HONGFEI LIN**[2], **PUQI ZHENG**[2], **LIANG YANG**[2], **AND SHAOWU ZHANG**[2]
[1]School of Software, Dalian University of Technology, Dalian 116620, China
[2]School of Computer Science and Technology, Dalian University of Technology, Dalian 116024, China

Corresponding author: Hongfei Lin (hflin@dlut.edu.cn)

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ABSTRACT Metaphorical expressions are frequently used to convey emotions in human communication. However, there is limited research on the detection of emotionality in metaphorical expressions, although a number of studies have focused on sentiment analysis and metaphor detection separately. We, therefore, attempt to identify emotions in Chinese metaphorical texts. We first construct a manual corpus with an annotation scheme, which contains annotations of metaphor, and emotional categories. We then use the corpus as a train-and-test set to identify the emotions in metaphorical expressions automatically with three methods. The first method is based on a field dictionary and field conflict. The second method is based on a support vector machine. The third method is based on deep learning, and it applies the long short-term memory model to identify the emotion of metaphor. The experimental results show that the third method performs better in identifying metaphor tasks, while the first method works better for emotion classification. In this paper, we compared the strength of heuristic, stochastic, and deep learning approaches, which contributes to a challenging natural language processing issue: the detection of emotionality in metaphor.

INDEX TERMS Emotionality of metaphor, understanding of semantics, deep learning, field conflict.

I. INTRODUCTION

In times of a resurgence in artificial intelligence, intelligent robots help us to understand its bright future, as they are the epitome of artificial intelligence. To provide robots with human intelligence, we have to consider not only intelligence quotient (IQ), but also emotional quotient (EQ). That is, emotion cannot be ignored by any deep study of robots with high human intelligence. Metaphor is widely used in human language [1], and it plays an important role in expressing emotion [2]. For example, in the instance "she was boiling," the angry, emotional self is conceptualized as "water," and so it is expressed metaphorically in terms of "boiling." Humans often use metaphorical expressions such as "he lost his temper," rather than direct emotional expressions such as "he is angry" to convey their emotions. Thus, to have a better understanding of human emotion, it is necessary to identify and understand metaphor.

Metaphor has a deep and extensive research tradition in linguistics, where it has been discussed from every angle, including cognitive linguistics, psycholinguistics, and language teaching. In recent years, the interaction between metaphor and emotion has attracted attention from scholars in many disciplines such as psychology [3], [4], linguistics [5], [6], and neuroscience [7]–[9]. However, computing emotion in metaphor is likely to be at an early stage [10], although there are relatively numerous studies on automatic metaphor detection and sentiment analysis separately. The study of emotions in metaphor not only helps machines to identify metaphorical expressions, but also excavates specific emotional tendencies and develops the analysis of emotion based on text [11]; thus, it deserves more study.

To this end, we have constructed a verified valid metaphor corpus with annotation of a range of emotions, and we propose three methods to identify the emotions in metaphorical expressions based on the corpus. The first method is based on a field dictionary and field conflict. We computed the similarity of the fields of tenor and vehicle, judging metaphors by this value, and identified the ground of metaphor and emotion classification. The second method, SVM, considers the identification of metaphor as a binary classification problem related to the literal meaning or metaphorical meaning of words, using word vectors to determine field, and it then classifies them with SVM. The third method is based on deep learning, and it applies the LSTM model to identify the emotions in metaphors. The experimental results show that the third method performs best in identifying metaphor tasks, while the first method works best for emotion classification. Our comparison on the strength of three approaches contributes to a challenging NLP issue: the detection of emotionality in metaphor.

II. RELATED WORKS

A. RESOURCES

There are many datasets that cover sentiment analysis and metaphor detection separately. However, few datasets involve emotion in metaphors. Given this, below we summarize these annotated datasets with emotions and metaphors respectively.

1) METAPHOR RESOURCES

The Master Metaphor List [12] is a database with annotations of 203 metaphor mappings and corresponding instances. The mappings are organized by ontology, they include metaphor instances from published literature, online forums, and students' compositions, and they have been edited manually. However, the analysis in the MML is based on the intuition of experts, with no lexicon to prove its significance. Metalude is an online, interactive corpus of English metaphors that contains over 9,000 entries. Like MML, Metalude [13] is a corpus containing annotated metaphorical expressions with target and source domains. Its data mainly comes from English dictionaries. The most obvious feature of Metalude is that it collects stationary/lexicalized metaphor, which is different from MML. Metalude has rigid rules for identifying "lexicalized metaphor." As a sub corpus of BNC Baby, the VU Amsterdam Metaphor Corpus is the biggest manually annotated linguistic metaphor corpus available [14]. It includes over 200,000 words, with four genres: newspapers, academic texts, novels and sessions. The Pragglejaz Group designed MIPVU (Metaphor Identification Procedure VU), which divides and identifies literal and metaphorical meanings based on rigorous rules of definition of vocabulary and dictionaries.

2) EMOTION RESOURCES

There are several studies on sentiment annotation for sentiment analysis that aimed at automatically detecting polarity (positive, negative, or neutral) in text. These studies involve developing classifiers for writers' attitudes towards a variety of domains and texts such as tweets, online reviews, and documents [15]–[17]. In addition, some research focuses on annotation, with a range of emotions such as anger, sadness, etc. For example, some work conducted annotation of datasets for Ekman's six emotions (joy, sadness, anger, fear, disgust, and surprise) [18]–[19]; other work focused on Plutchik's eight emotions (joy, sadness, anger, fear, disgust, surprise, trust, and anticipation) [20]–[21]. Most of these datasets have been used as training and test sets, and these emotion classification approaches have been used to develop machine learning algorithms to classify emotions in text, despite some rule-based approaches. In particular, some work involves construction of emotion resources in Chinese [22]–[25].

B. METAPHOR DETECTION

Mason [26] presented a computing system known as CorMet, which aims to analyze verbal metaphor via a comparison of the ratio of relevant words of focused word in a field with that in general dictionary to get feature verbs of specific field. The author then applied the priority learning algorithm and obtained preferential semantics; they showed them with vectors and clustered these verbs with K-means to obtain metaphorical characteristic of this field.

Shutova and Sun [27] presented a bottom-up method. They clustered some metaphorical sentence seeds at the beginning and added phrases that contain verbs or nouns that appear in seeds of the corresponding class. This clustering method considers verbs as source domain and nouns as target domain in verb-object construction. After clustering, they obtained more verb-noun combinations and could identify analogous metaphorical usage.

Shulder and Hovy [28] applied the tree accounting method to identify metaphor. This method also uses abstract classification in WordNet, although WordNet could be replaced by another relevant resource here.

Gandy *et al.* [29] identified metaphor based on a corpus, using elicitation and clustering with WordNet, while reducing the dependence on background knowledge and making it easier to extend to language with little semantic knowledge.

Emerging neural approaches of metaphor detection focus on word embeddings and automatically learn features from the data, and they have shown their state-of-the-art performance [30]–[33]. These models present low-dimension vectors of words by converting words from unlabeled data, and thus they are independent of manually crafted data for training.

Some scholars work on metaphor detection in Chinese [34]–[35]. For example, Jia *et al.* [36] studied nominal metaphor to identify whether the meaning of nouns is literal or not (metaphorical usage) by computing similarity between nouns or using machine learning methods; Hongfei *et al.* [37] first used dependency parsing to extract tenor and vehicle, and then confirmed category and computed word semantic similarity, classifying them with Support Vector Machine to identify metaphorical sentences.

Some works for detection of metaphor in a language are noted below:

Su *et al.* [38] presented a method to explain noun metaphor based on semantic association. According to the source domain's nature, they obtained possible meanings and combined context, computing correlation degrees between the target domain and the source domain from different angles. They then chose the best meaning with the strongest degree as metaphorical explanation.

Fass [39] proposed and built a Met* system to explain metaphorical language. When explaining metaphorical or metonymic sentences, the system searches for metaphorical or metonymic usage and common ancestor vectors to explain meaning. The Met* model depends on various elements, such as completeness of preference rules, structure body, and normalization of sentences, etc.

Veale [40] proposed a metaphor explanation model called Talking Points. It extracts the characteristics of the source domain and the target domain from WordNet, applying analogy to achieve explanation. This model considers hypernyms with higher abstract degrees when extracting characteristics, building the relationship between the source and target of the sentence to explain metaphor.

C. EMOTION DETECTION

Previous work on NLP has proposed several approaches to emotion detection, which focus on a text classification task, aiming at separating texts that conveys positive and negative sentiments(see [41] for a review). Approaches include supervised [42]–[45] and unsupervised machine learning [46]–[47]. Recent approaches to emotion detection involve word representations embedded on word vectors [48]. There is also work exploring emotion detection in Chinese [49]–[51].

However, compared with research on the detection of metaphor and emotion, there are fewer studies of the identification and explanation of emotion in metaphor, although emerging approaches for sentiment analysis of figurative texts have been proposed in the area of NLP [52]–[55]. We thus propose methods to identify emotions in metaphor, comparing common methods of identification and explanation of metaphor, as well as considering the characteristics of the emotion in metaphor. Identification of emotion in metaphor can be divided into two parts: metaphor identification and emotion identification.

III. CONSTRUCTION OF THE CORPUS

A. TERMS AND DATA COLLECTION

According to the theory of the construction of corpus and sentiment computing in linguistics, we define sentiment, classification of sentiment, metaphor, tenor, vehicle and other relevant concepts and features. We deal with these concepts from the angle of convenient and formalized emotional metaphor expressions, based on literature research, experts' opinions, and instances, and we finally determine the boundary lines of relevant concepts for the corpus in Chinese and English.

We use "sentiment" as an example. Psychologists have lots of definitions and descriptions of sentiment (see [56]–[57]), and they discuss the relationships and differences in emotion, affect, mood, and feeling. The literature [58] has elaborate partition: "emotion" is triggered by irritation, a short and strong psychological reaction; "mood" is an experience and a feeling of emotion; the scope of "affect" is extensive, including "emotion" and "mood," with sustainability and sociality; "feeling" emphasizes the process of sentimental experience and feeling. For this paper, we define "sentiment" as all subjective reactions and experiences of people to objective things, and we do not distinguish these concepts to make it easy for computers to understand, express, and analyze, from the angle of sentiment computing.

According to the concept definition, the aim of construction, and the application requirements, the process of collection follows one principle: it contains abundant emotional information. Because of the goal of sentiment computing, we choose to collect texts with rich emotions. We focus on resources with rich emotions, such as novels, theatre, network reviews, etc.

B. ANNOTATION FRAME

Corpus annotation is processing the original resource and choosing annotating codes and forms to help to save the text and to make it machine readable. The text encoding initiative (TEI) is the most famous coding standard for international information all over the world. Multinational scholars formulate TEI, and it is easy to describe, annotate, and analyze text. Considering the characteristics of emotional metaphor, special requirements such as elegant simplicity and brachylogy, and the advantages of TEI, we apply the annotating system that combines TEI and custom standards to improve the accuracy, consistency, and speed of annotation. We focus on the sentence level. We annotated tenor, vehicle, ground and source/target domain as well as emotion categories, intensity, and valence (positive, negative, neutral).

C. QUALITY MONITORING SYSTEM

The building work of the emotional metaphor corpus is complex and huge; thus, we have seven staff to finish the annotation. Although we have already discussed and analyzed the standards and principles of annotation, there are still differences in metaphor understanding because of subjective factors. The seven staff members are divided into three groups with two members each and one group with one, using a cross validation method.

The statistical analysis showed that 89% of annotating tasks were completed by the first group, 8% were transferred to next group, and 3% were determined by final group.

Having a standardized operating method is very important for accuracy and consistency of inputting and annotation. We wrote detailed instructions for annotation with an explanation of every entry, diffculty, and common problem, including plenty of examples. The sentiment corpus of Dalian University of Technology and the emotional words therein support our work.

D. ANNOTATION RELIABILITY

Metaphor annotations are very subjective; therefore, it is necessary to verify the reliability of annotators. Three independent annotators annotated the same 500 sentences in the corpus to assess inter-annotator agreement. We use the κ statistic to measure inter-annotator agreements [59] for emotion annotation. κ is calculated as below:

$$\kappa = \frac{P(A) - P(E)}{1 - P(E)} \tag{1}$$

The agreement on the identification of tenor, vehicle and ground was $\kappa = 0.57$; the agreement on the identification of emotion categories was $\kappa = 0.71$, which shows the annotators were reliable.

IV. ALGORITHM OF IDENTIFICATION OF METAPHOR

The essence of metaphor is the matching of two entities that belong to different fields with obvious differences, but with some parts in common at the same time. Metaphor achieves cognition by mapping familiar concepts onto the unknown. In this process, we perceive the field of familiar things or concepts as the source domain and the corresponding unknown as the target domain. Both source and target domain belong to the field concept.

The definition of a metaphorical expression is {tenor∈ source domain, vehicle∈target domain, ground, emotion∈ emotion of word}, and the identification of metaphor is based on the mapping between sentences and the metaphorical expression.

The rationale for the identification and explanation of metaphor is firstly to discover "the difference", i.e., semantic conflict, deciding whether the usage of the word is literal or not. This is done mainly by building a field dictionary, which allocates a word to different fields and assigns the word different level values according to the word's literal meaning. If two words belong to different fields, we compute the degree of conflict of field to identify metaphor. Then we find the similarity of two entities – the ground.

A. IDEDTIFICATION OF METAPHOR BASE ON FIELD CONFLICT

1) SEMANTIC FIELD

Since the mapping of source and target appears in different fields, there is usually conflict, as the main characteristic of metaphor. Tenor and vehicle are essential parts of metaphor. We identified them after syntactic analysis, divided them into their fields, and identified metaphor by computing the value of conflict between the fields of tenor and vehicle.

Because a field partition rule with a tree structure is necessary when computing field conflict, it is important to design a reasonable field rule. In this paper, field is the semantic domain to which the word (tenor or vehicle in metaphor) belongs. One word may have several meanings or parts of speech. In this case, we divided their fields according to context. In this paper, we mainly referred to Roget's International Thesaurus [60] and Synonymy Thesaurus [61] when designing the field rule. We formulated field codes with a tree structure to reflect the hyponymy of entities by analyzing collected metaphorical sentences and a network corpus (see Figure 1).

Field Classification:
1. Root
1.1 Human
1.1.1 Natural Quality
1.1.1.1 Sex
1.1.1.1.1 Male
1.1.1.1.2 Female
1.1.1.2 Body
1.1.1.2.1 Upper limb
1.1.1.2.2 The legs
1.1.1.2.3 Head
1.1.1.2.4 Trunk
1.1.1.3 Place of origin
1.1.1.3.1 Birthplace
1.1.1.4 Occupation
1.1.1.4.1 Government agency
1.1.1.4.2 Professional and technical personnel
1.1.1.4.3 Business
1.1.1.4.4 Producer
1.1.1.4.5 Soldier
1.1.1.5 Appearance
1.1.1.5.1 Mouth
1.1.1.5.2 Nose
1.1.1.5.3 Ear
1.1.1.5.4 Eye
1.1.1.5.5 Eyebrow
1.1.1.5.6 Face
1.1.1.6 Organ
1.1.1.6.1 Heart
1.1.1.6.2 Liver
1.1.1.6.3 Lung
1.1.1.6.4 Spleen
1.1.1.6.5 Kidney
1.1.1.6.6 Stomach
1.1.1.6.7 Gallbladder
1.1.1.7 Characteristics
1.1.1.7.1 Rational type
1.1.1.7.2 Emotional type
1.1.1.7.3 Will type
1.1.1.8 Relationship
1.1.1.8.1 Marriage relationship
1.1.1.8.2 Generational relations
1.1.1.8.3 Relationship

FIGURE 1. Field Classification Example.

2) FIELD CONFLICT

We first extracted tenor and vehicle of sentences and found that there are plenty of expressions that have a human as tenor and sometimes they are demonstrative pronouns, named or missing. Thus, when identifying metaphor for these cases where missing tenor or tenor is a named entity, we consider that the default is human and validate its rationality after experiment.

In the process of extracting tenor and vehicle, we used dependency parsing as an auxiliary tool and combined existing annotation in the Metaphor Corpus [62]. We preserved all possible vehicle words to avoid missing vehicles, giving them different weights when computing conflict based on their position and analyzed them according to a threshold value. The field information will be annotated automatically after extracting process.

First, we annotated these words directly if they were existing nodes in the field dictionary; second, we referred to the artificially annotated field of tenor and vehicle in the metaphor corpus and assigned the field code; third, we searched the most similar word by word vector and assigned the same field code for these words that have not occurred in field rules and the metaphor corpus.

Since the field rule is a tree structure, the case that tenor and vehicle appear in the same way from root to leaf refers to a literal expression. For example, with "The tiger is a fierce animal", we extract tenor – "tiger" and vehicle – "animal" from the sentence. "Tiger" is a leaf node of "animal" in the field rule (there may be many layers between them, but the tenor node appears in the path from root to vehicle node). The relation in this example is defined as "hyponymy" in Hownet [63], and this paper follows this relation. Thus, this example is determined as literal usage.

There are many kinds of hyponymy in Chinese expressions and Table 1 presents some common ones that are

TABLE 1. Hyponymy patterns in Chinese.

<table>
<tr><th>Pattern Label</th><th>Hyponymy Patterns in Chinese</th></tr>
<tr><td>Ptn1</td><td><NP2>[,]<例如|如|比如|譬如|像|包括|有|特别是|尤其是><NP1></td></tr>
<tr><td>Ptn2</td><td><NP1><等等|等|和其他|以及其他|及其他><NP2></td></tr>
<tr><td>Ptn3</td><td><NP1><是|为><最|较><的><NP2></td></tr>
<tr><td>Ptn4</td><td><NP1><是|为><NP2><之一|的一（量词/q）></td></tr>
<tr><td>Ptn5</td><td><NP1><是|为><数词(/m)><量词(/q)><NP2></td></tr>
</table>

used with identification of emotion. NP1 denotes hyponym and NP2 denotes hypernym. The main usage of Ptn1 and Ptn2 appears in the process of identification of tenor and vehicle, and Ptn3, Ptn4 and Ptn5 are used in computing field conflict. They are all key objects.

Since extracted tenor and vehicle are entities, we focused on the noun which matches the syntax model in the process of extracting. In consideration of multiple vehicles in a sentence, we computed conflict value with tenor respectively and weighted average. After analyzing the syntactic structure, we noticed that the core word usually exists in the tail of the sentence. Therefore, we increased its weight and applied experience value from multiple experiments as the weight value. The conflict value is computed as follows:

$$Cnf(s1, s2) = 1 - \frac{\alpha * \min(dpt(s1), dpt(s2))}{Dis(s1, s2) + \alpha * \min(dpt(s1), dpt(s2))} \tag{2}$$

In this formula, Dis (s1, s2) denotes the distance between two entities in the field rule tree; dpt(s) denotes the depth of entity in the tree; min(dpt(s1),dpt(s2)) is the smaller value of depth of two entities; α is depth parameter and we used the experience value of 0.8 after experiment. The threshold was set as 0.48, according to experience. The collocation will be determined to be metaphorical if the conflict value is over 0.48, and literal when the value is less than 0.48. This method can effectively distinguish hyponymy and sentences whose tenor and vehicle belong to same concept.

3) EXPLANATION OF THE EMOTION OF METAPHOR

The identification of grounds in the emotion of metaphor is based on the identification of metaphor. According to the syntactic relation model, we ascertained the possible position of the ground, and extracted possible vehicles and screened them. If there was not a ground word, we analyzed emotion on the basis of vehicle with other tools such as *Constructing the affective lexicon ontology* [64] and *Constructing the affective commonsense knowledge-base* [65], and classified emotions (positive/negative/neutral) in metaphorical sentence. On the other hand, if there were multiple possible grounds, we needed to analyze consistency for all grounds and compute similarity by combining existing emotional words in a train set and determining the final emotion of the metaphorical sentence.

TABLE 2. Common ground word patterns in Chinese.

<table>
<tr><th>Pattern Label</th><th>Common Ground Word Patterns</th></tr>
<tr><td>Ptn1</td><td><N1><是(is)|像(as)|好像(like)|如同(as)|仿佛(as)|似(as...as)|好似(as)|若><N2><一样|一般|似的></td></tr>
<tr><td>Ptn2</td><td><N1><是|就是|像|如同||仿佛|似|好似|若><N2></td></tr>
<tr><td>Ptn3</td><td><的><N2></td></tr>
</table>

Input: 那个律师像一个老狐狸。“The lawyer is like a sly fox.”
Output: （<律师：本体>，<狐狸：喻体>，<喻底：狡猾>，<情感：负向/憎恶>）
(<tenor:lawyer>,<vehicle:fox>,<ground:sly>,<emotion:negative/hate>)

B. IDENTIFICATION OF THE EMOTION OF METAPHOR BASED ON SUPPORT VECTORS

We utilized the Sougou Network Corpus to train word vectors, which contains 130 million original web pages, over 5TB, ensuring the universality of word vectors. The training model applies the Skip-gram model. After adjusting parameters and training, it extracts vectors of words that are related to the metaphor corpus, and every vector is 200-dimension. It projects words to a high dimensional vector space and expresses inner semantic relations between words. Experiments have proven its practical significance in finding most similar words.

After training word vectors, it combines them into sentence vectors. This paper combines word vectors directly, sums them to obtain sentence vectors in sentence space, and uses sentence vectors as input of SVM. The process of training applies ten times cross validation to ensure the objectivity of results. We used the LIBSVM tool package, which supports multiple classifications to help classify emotion.

C. IDENTIFICATION OF EMOTION BASED ON THE DEEP LEARNING LSTM MODEL

The difference between this approach and SVM is that the latter uses an external corpus to train word vectors as input for the model. LSTM instead creates word vectors by itself. It inputs a corresponding hash code of a word into a sentence. The dimension of word vector space was set to 8000 and low-frequency words or new words in test corpus was set to default code, which ensures a stationary dimension of the model and increases the robustness of the model for unknowns.

The algorithm needed mapping in the beginning, and then an input layer, embedded layer, LSTM layer, and prediction layer were added successively. We can also add a discarding layer in the LSTM layer to discard some instances randomly. The parameter can be adjusted so that we avoid over-fitting in this model by discarding samples randomly. The prediction layer can predict multiple classifications and solve the binary classification problem of metaphor, as well as the multiple classification problem of emotion. The LSTM layer is the core of this model. It computes the influence of previous input and the weight of influence in different times in order to make the model have memory.

V. ANALYSIS OF EXPERIMENTAL RESULTS

This section shows the best experimental results of the three methods relating to the identification of the emotion of metaphor after multiple experiments. They all apply ten times cross validation and use averages as a final result.

The experiment data was chosen from our corpus, containing 1296 metaphorical sentences. We extracted the same number of non-metaphorical sentences from the same place to train identification of metaphor. This ensures the balance of the corpus and the reliability of experimental results.

Accuracy, Recall and f-value:

$$\text{Accuracy} = \frac{\text{The number of correct sentences in this class}}{\text{The number of sentences in this class}} \times 100\% \tag{3}$$

$$\text{Recall} = \frac{\text{The number of correct sentences of this class}}{\text{The number of sentences of this class in test set}} \times 100\% \tag{4}$$

$$\text{f-value} = \frac{2 * \text{Accuracy} * \text{Recall}}{\text{Accuracy} + \text{Recall}} \times 100\% \tag{5}$$

The results of identification of metaphor are shown in Table 3, while the emotion classification results are shown in Table 4 as follows.

TABLE 3. Experimental results of metaphor identification.

Method	Accuracy (%)	Recall (%)	F-value (%)
Field conflict	76.5	79.4	77.9
SVM	68.3	66.3	67.3
LSTM	69.1	70.0	69.5

TABLE 4. Experimental results of metaphor emotion identification.

Method	Accuracy (%)	Recall (%)	F-value (%)
Based on similarity	69.8	78.7	74.0
Based on field conflict	80.0	79.5	79.7
Based on SVM	85.0	84.1	84.6
Based on LSTM	84.1	86.1	85.2

We compared our method to the experiment's selected algorithm [37] for the identification of metaphor, which achieves identification of metaphor without emotion. It is similar to the field conflict method, and identifies metaphor with SVM based on semantic similarity and category partition. The experimental result indicates that our method based on a field dictionary and conflict is better than the method based on word similarity, which shows that it will be more efficient if both the parameters "field" and "conflict threshold" are considered together.

With reference to identifying metaphor, the machine learning method performs better, while the deep learning method is close to traditional machine learning method; both have little higher Recall and F-value. The quota of these two methods is higher than that of the method based on field conflict. The reason for this is that there are more links in the field conflict method and the understanding of a sentence from semantic analysis is easily affected by the corpus process of extracting tenor and vehicle and automatic field annotation, etc. The Accuracy and Recall will suffer from the fact that metaphorical usage is various and obscure in natural language, and we cannot judge train sets and test sets only based on field conflict.

With reference to identifying emotion, the field conflict method reflects its superiority. Since this method is based on conceptual metaphor theory, preserves semantic and basic structure of metaphor, and determines emotion combined with the corpus, emotional word, and common emotion collocation, it has better performance and is more intelligent than the machine learning method. After the analysis, we found that inaccurate emotion classification is related to unbalanced emotion in the train set and small sample data.

VI. CONCLUSION

On the basis of the constructed emotion metaphor corpus, this paper used three methods to realize the recognition of the emotion of metaphor. The first one is based on domain long distance. The second one is the emotion metaphor recognition algorithm based on word vectors and a support vector machine. The third one is based on the deep learning LSTM model. The paper combines the methods of metaphor recognition with semantic understanding, domain attribution, and deep learning. After large-scale corpus experimentation and adjustment, LSTM has a better effect in metaphor recognition, and the method of domain conflict is more effective in emotion recognition. This paper not only presents the methods that help machines to identify metaphor expressions as well as excavating specific emotional clarification, but also contributes a high-quality resource that is scarce and valuable for the detection of the emotionality in metaphorical texts. In addition, our study involves Chinese, in addition to English, which will help research on emotion analysis in other languages, particularly Sino-Tibetan languages. We also suggest that it may be possible for the corpus to contribute to further investigating mechanisms underlying emotion in metaphor from the perspective of different cultures in future work.

There are some limitations in this work. For example, the recognition of metaphorical sentences lacks the appropriate handling of the absence of metaphor and certain openness. Moreover, this work is based on the emotion metaphor corpus, and the accuracy and completeness of the corpus have an important influence on the recognition of the emotion of metaphor. In future work, we will improve and expand the metaphor corpus, and hope to consider more kinds of metaphor usage to improve the openness and accuracy of metaphor recognition.

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DONGYU ZHANG received the M.A. degree in applied linguistics from Leicester University, U.K., in 2006. She is currently pursuing the Ph.D. degree in computer application technology with the Dalian University of Technology, Dalian, China.

From 2006 to 2012, she was a Lecturer with the School of Software, Dalian University of Technology, Dalian, China.

Since 2013, she has been an Associate Professor with the School of Software, Dalian University of Technology, Dalian, China. Her research interests include natural language processing, sentiment analysis, and social computing.

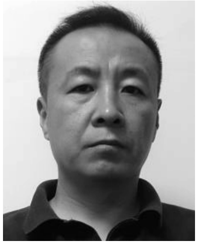
HONGFEI LIN received the B.S. degree in mathematics from Northeastern Normal University, Changchun, China, the M.S. degree in computer application from Dalian University, Dalian, China, and the Ph.D. degree in computer software and theory from Northeastern University, Shenyang, China, in 2000.

From 2000 to 2005, he was an Associate Professor with the School of Electronic and Information Engineering, Dalian University of Technology, Dalian, China. Since 2005, he has been a Professor with the School of Computer Science and Technology, Dalian University of Technology, Dalian. He founded the Laboratory of Information Retrieval (DUTIR) in 2001. His publications run to over 150 papers, and he holds seven patents. He serves as an editor for several journals. His research interests include natural language processing, text mining, sentiment analysis, social computing, information retrieval, and bioinformatics.

Dr. Lin is a member of the Association for Computational Linguistics, the China Association of Artificial Intelligence, the China Computer Federation, and the Chinese Information Processing Society. He was a member of the IEEE International Conference on Bioinformatics & Biomedicine Program Committee from 2009 to 2017.

PUQI ZHENG was born in 1989. In 2014, she received the B.S degree in computer science and technology and the M.S in computer technology in 2016. She is an engineer in the experimental center of computer basic teaching of the Dalian University of Technology. Her research interests include sentiment analysis and metaphor analysis.

LIANG YANG was born in1986. He received the B.S. degree in software engineering in 2009, the M.S degree in computer application in 2012, and the Ph.D. degree in computer application in 2016. He is currently working as a Lecturer with the School of Computer Science and Technology, Dalian University of Technology. He presided over the National Natural Science Foundation Project (NSFC), received the third prize from the National Youth Artificial Intelligence Innovation and Entrepreneurship Conference in 2016 and published over 30 papers. His research interests include emotion calculation, emotion analysis, and social computing.



SHAOWU ZHANG was born in 1967. He received the B.S. degree in computer science and technology in 1989, the M.S. degree in computer application in 1992, and the Ph.D. degree in operation science and control theory in 2012. His research interests include emotion calculation, public opinion analysis, and social media treatment. He presided over the national natural science foundation project and the Liaoning Natural Science Foundation Project. He has published over 40 papers.