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SENTIMENT ANALYSIS BASED ON FINE GRAINED FEATURE REPRESENTATION OF DOMAIN SENTIMENT DICTIONARY

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Abstract

The era of information technology has grown tremendously over the decade. In the existing opinion mining technology, the response time and the accuracy are not up to the expectation. The sentiment analysis is not accurate in the traditional systems. The method failed to divide the opinion holder, tendency and the opinion object from the opinion given by the holder/user and it results to the failure in obtaining the overall report of the positive and negative feedbacks of the object. The proposed fine grained opinion mining can perform better in analyzing the holder, tendency, and expression from the statement. This accuracy of the proposed system is consistent in the case of large datasets such as reading the reviews of the customers and filters the positive and negative opinion in an accurate manner. The proposed system uses the external sentiment directory for comparing the opinion given by the user and predefined emotional data stored in the directory.

Keywords:

Opinion Mining, Sentiment Analysis, Emotional Mining, Conditional Random Field, Machine Learning

1. INTRODUCTION

The main goal of fine-grained opinion mining is to obtain emotional elements (such as opinion holders, opinion objects, opinion expressions, etc.) from opinion texts (such as user comment texts, etc.) and judge the emotional tendency expressed in the text based on these information For example, in the opinion text "I think the quality is good", the opinion holder "I" uses the opinion expression "good" to express the "positive" emotional tendency for the opinion object "quality". The results of fine-grained opinion mining can usually be applied to opinion summarization and opinion retrieval. The emotional elements obtained by fine-grained opinion mining depend on the specific task requirements and specific fields. Taking e-commerce review texts as an example, most of the viewpoint holders are first-person, and the viewpoint objects and viewpoint expressions are continuous sequence fragments appearing in the text. Therefore, for this kind of text, usually only the object of opinion and expression of opinion are obtained, and it is regarded as a sequence labeling problem. However, there is not necessarily a one-to-one relationship between viewpoint expression and viewpoint object in the same sentence, and the emotional tendency in the same sentence is not necessarily single. For example, "the product is affordable but not durable", and the viewpoint object "product" corresponds to multiple viewpoint expressions and multiple emotional tendencies. If the sequence labeling model is used purely, it is difficult to accurately judge the emotional orientation.

In order to solve the above problems, we adopt the task framework shown in Fig.1. For the opinion text, we first use the sequence labeling model to identify the sequence of emotional elements, and then use the matching algorithm to integrate it into a structured combination of emotional elements. In the sequence labeling part, the sequence label adopts the I0B2 label system in which TGT represents the object of opinion, XpR represents the expression of opinion, and the additional labels p, M, and N are used for XpR to represent the expression of positive, neutral, and negative opinions, respectively. Aiming at the results of sequence labeling, we use triplets <viewpoint object, point of view expression, sentimental tendency> to generate emotional element combinations. Among them, the emotional tendency part uses values 1, 0, and 1 to represent positive, neutral, and negative tendencies, respectively.

At present, the more commonly used sequence labeling models are conditional random field (CRF) and bidirectional long-short-term memory conditional random field (BiLSTM CRF) [5]. Among them, CRF is a traditional machine learning method, and BiLSTM CRF is a combination of deep learning and traditional machine learning methods. Therefore, how to use external sentiment dictionary resources to improve the performance of fine-grained opinion mining is a topic worthy of research.

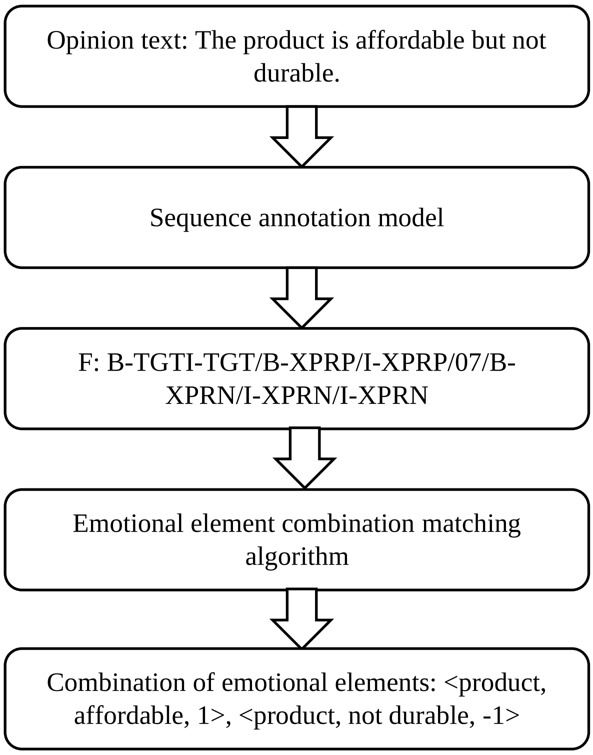

Fig.1. Fine-Grained Opinion Mining Task Framework Adopted

Aiming at the deficiencies of existing methods, we propose a method based on domain sentiment lexicon feature representation on the basis of fine-grained opinion mining using sequence labeling models: firstly, a new e-commerce domain sentiment lexicon is constructed based on the labeled data, Then, on the real data of e-commerce review texts, we design the feature-based domain sentiment lexicon for two commonly used sequence annotation models, CRF and BiLSTM CRF, respectively. Experimental results show that this method based on feature representation of domain sentiment lexicon achieves good results on both models and outperforms other sentiment lexicons.

The rest of the paper is structured as follows: Section 1 introduces the related work; Section 2 introduces the sentiment lexicon resources; Section 3 and 4 details our proposed method; Section 5 presents the experiments and results analysis; Section 6 presents the conclusions.

2. LITERATURE SURVEY

In this section, we first introduce the international research status of relevant methods and technologies for opinion mining from the aspects of topic identification, holder identification, statement selection and sentiment analysis, and then introduce several mature opinion mining methods and technologies. Opinion Mining Application System. Finally, it introduces the research status of domestic opinion mining methods and technologies, mainly discussing the methods and technologies of opinion mining.

A social network opinion leader refers to a person who publishes an opinion in a social network and is recognized by most people and has a certain influence on the participants in the social network. Opinion leaders were first proposed by Lazarsfeld [1], and they are defined as “some people who are very active in the interpersonal network and have certain representativeness and high prestige”. Opinion leaders tend to take the initiative to share their views, and their views will also have a certain degree of influence on others. Opinion leaders are usually the hub of the interpersonal communication network [2], they spread their subjective opinions to others, thereby influencing others' views on events, and gradually become the guides of public opinion. Internet opinion leaders are different from opinion leaders in traditional life. They are no longer limited by time and space. Users can browse opinion leaders’ speeches anytime and anywhere. Therefore, the emergence of opinion leaders can deepen the connection between ordinary users and public opinion events.

The existence of opinion leaders on social networks can not only promote the dissemination of public opinion on the Internet, but also affect the trend of public opinion [3], especially in the environment of major emergencies, the anxiety, curiosity, and anxiety of netizens will make the event more concerned. The temperature rises rapidly in a short period of time, and users are eager to understand the progress of emergencies and spread relevant information about the incident. In such an environment where the popularity of events continues to rise, the role of opinion leaders in guiding public opinion is often doubled compared to usual. In the process of continuous development of events and continuous dissemination and evolution of public opinion, opinion leaders use specific methods to participate in the dissemination of public opinion within a given range and play a role that cannot be underestimated in the evolution of public opinion.

Opinion leaders can spread correct information in social networks through their own influence. Information, dispel rumors and popularize disaster prevention knowledge, and guide netizens to view public opinion events from an objective and correct perspective.

2.1 OPINION LEADER NODE INFLUENCE

Influence was originally considered to be a phenomenon in which individuals interact with others to change their own thoughts, attitudes, or behaviors [4]. The influence of network public opinion nodes is the standard to measure the contribution of information nodes in the process of network public opinion information dissemination [5]. Node influence is the product of the average distance carried by information and appeal. In the dissemination of social network public opinion events, the user's position in the network structure and its own attributes determine the user's influence in the dissemination of public opinion [6] the influence of user nodes is not only related to the number of adjacent nodes, but also influenced by the number of adjacent nodes. Influence of neighboring node influence. After a user publishes content in a social network, other users will interact with the publisher, forwarding, commenting, and liking the content. Therefore, the node influence of the content publisher on the social media platform will also be affected by other users who interact with him.

Especially in social networks, opinion leaders are special nodes in the social network, and their position and node influence in the social network are more important than ordinary user nodes [7]. As an important node for information communication and public opinion dissemination among users, opinion leaders can further expand the scale of information dissemination and increase the speed of information dissemination by relying on their strong voice and good Internet user base, relying on their own node influence advantages, to achieve certain influence the development of public opinion on events.

Regarding the mining of opinion leaders in social networks, researchers focus on graph structure, user content, user behavior records and other aspects, and comprehensively use social network theory and various machine learning methods. The research objects cover not only the traditional BBS network, blog network, but also microblog networks such as Weibo and Twitter. Recently, professional platforms with user interaction, such as online stock platforms and online learning platforms, have also become research hotspots due to their social network attributes.

Existing studies on opinion leader mining have different focuses. References [8-10] based on the social network structure, use node in-degree, between the centrality, proximity centrality and other characteristics to measure the influence of nodes, but the accuracy is not high, and it cannot reflect the influence of nodes well. Literature [11-13] discovers opinion leaders in the community by constructing a social network and based on user behavior and interest fields. Literature [14-19] starts from the content published by users, analyzes text semantic information, mines potential emotions of users, and then finds opinion leaders in the community. In the microblog social network, it is of great significance to study new node feature models and design opinion leader mining algorithms by comprehensively considering network topology, topic semantics and text emotion factors.

3. SENTIMENT DICTIONARY RESOURCES

The Sentiment dictionary resources are described as follows.

3.1 CONSTRUCTION OF SENTIMENT DICTIONARY IN E-COMMERCE FIELD

This paper focuses on fine-grained opinion mining for opinion texts in the e-commerce field. According to the method proposed in this paper, a domain sentiment dictionary for the e-commerce domain is needed. For the opinion text in the field of e-commerce, its special features mainly include the following points:

- Most of the texts are short, formal or casual.
- Perspective holders are mostly first-person.
- Usually for e-commerce products or product-related attributes, the delivery service.
- Opinion evaluation can be performed on opinion objects such as service or after-sales service.
- Contains opinion object entries and opinions unique to the e-commerce field.

3.2 EXPRESSION TERMS

These characteristics determine the composition and distribution of emotional elements in opinion texts in the field of e-commerce. For opinion texts in the field of e-commerce, we mainly build corresponding emotional dictionaries for the correspondence between opinion expressions and emotional tendencies. Opinion expression can only reflect a single emotional tendency, for example, “delicious” only reflects a positive tendency; it can also reflect multiple emotional tendencies, for example, “high” reflects a negative tendency in “high price” and reflects a positive tendency in “cost-effective” tendency. Therefore, we define opinion expressions into the following four categories according to the different emotional tendencies reflected:

- Positive opinion expression
- Expression of neutral opinion
- Expression of negative opinion
- Multipolar expression of opinion

Among them, the first three categories of expression of opinion only reflect a single situation. Sensitive tendencies, the fourth category reflects a variety of emotional tendencies.

In addition to the above opinion expression entries, when constructing the sentiment dictionary. Entries that are closely related to the expression of opinions have also been added.

3.3 NEGATIVE WORDS

The function of negative words is to reverse the emotional tendency of opinion expression, and its addition can also retrieve the emotional information of opinion expressions with negative prefixes that do not appear in the sentiment dictionary. The addition of negative words indirectly expands the emotional information of the emotional dictionary.

The key point of constructing the emotional dictionary in the field of e-commerce is to obtain the corresponding relationship between the expression of opinions and emotional tendencies in the e-commerce review texts. Due to the limited resources in the field, this paper directly extracts the combination of emotional elements in the training data used in the experiment to construct an emotional dictionary in the e-commerce field.

Table.1. Examples of sentiment dictionary entries in the field of e-commerce

Positive opinion expression	Value for money, affordable, comfortable
Expression of neutral opinion	A fly in the ointment, average, passable
Expression of negative opinion	Can't afford to hurt, poor review, expensive
Multipolar expression of opinion	Watery, big, tall
Negative Words	No how no so

First, the corresponding relationship between viewpoint expression and emotional tendency is extracted from the combination of emotional elements and summarized to obtain emotional entries in the candidate field. For candidate results, we performed manual inspection and corrected some errors. Finally, the corrected opinion expression vocabulary is used as a sentiment dictionary in the field of e-commerce. Table.1 gives examples of entries of each category in the sentiment dictionary in the field of e-commerce.

3.4 COMPARISON WITH OTHER SENTIMENT DICTIONARIES

We selected two emotional dictionaries, namely HowNet emotional dictionary and Dalian University of Technology emotional dictionary and compared them with the emotional dictionary in the field of e-commerce constructed in this paper.

For the convenience of comparison, we unify the entries of the two sentiment dictionaries with the sentiment dictionary in the field of e-commerce. For the HowNet Sentiment Dictionary, since it only divides opinion expressions into positive and negative tendencies, we equate them into positive opinion expressions and negative opinion expressions and leave the other three categories blank. For the Dalian University of Technology Sentiment Dictionary, it divides the expression of opinions into four categories: positive, neutral, negative, and both positive and negative. Therefore, we correspond to the four categories in the definition and leave the negative word category empty.

We compare the three emotional dictionaries from the two aspects of the statistical information of the entries based on the sentiment dictionary and the specific terms in the entries. Table.2 gives the opinion expression categories and related statistical information of the three sentiment dictionaries.

Table.2. Opinion expression categories and related statistical information of the three sentiment dictionaries

Emotional Dictionary	Field	HowNet	Dalian University of Technology
Front	844	4566	11229
Neutral	82	NA	5375

The Negative	2084	4370	10784
Multipolar	99	NA	78
Negative Words	29	NA	Na

Entry statistics are only one aspect of measuring a sentiment lexicon. The Table.3 shows the common entries and e-commerce fields of the three sentiment dictionaries comparison results for unique entries in the sentiment dictionary.

Table.3. Comparison of Similarities and Differences of Sentiment Dictionary Entries

	Category	Number of entries	Example
Shared entries	Front	164	Well-deserved reputation, crisp, stylish
	Neutral	9	Make do with, barely, ordinary
	The Negative	110	Messy, inferior, cumbersome
	Multipolar	0	NA
	Negative Words	0	NA
E-commerce field Sentiment dictionary Unique entry	Front	660	Great value for money, great value, five stars
	Neutral	73	Just make do with it, general, medium review
	The Negative	1974	No credit, off-brand, fragile
	Multipolar	99	Watery, big, tall
	Negative Words	29	No how no so

The sentiment dictionary in the field of e-commerce has many unique entries highly related to the e-commerce field. Words highly related to the e-commerce field in two general dictionaries. The number of items is small.

Table.4. Sentiment Dictionary Labels for Different Sentiment Dictionaries

Emotional dictionary	Field	HowNet	Dalian University of Technology
Front	DoUP	HowUp	DuUP
Neutral	DoUM	NA	DuUM
The Negative	DoUN	HowUN	DuUN
Multipolar	DoP	NA	DuP
Negative Words	DoN	NA	NA

4. METHOD BASED ON DOMAIN SENTIMENT LEXICON FEATURE REPRESENTATION

The subdivision 4.1 describes the data representation of domain sentiment directory.

4.1 DATA REPRESENTATION BASED ON DOMAIN SENTIMENT DICTIONARY

The fine-grained opinion mining method we propose takes e-commerce review texts as the research object. For e-commerce review texts, we use the e-commerce domain sentiment lexicon constructed in Section 3 to generate data representations.

For the generation of data representation, we adopt the following method: first, use the domain sentiment dictionary to perform maximum positive matching on the raw text of e-commerce reviews to obtain the position of the specific opinion expression in the raw text, and then use the I0B2 tagging system to generate sentiment dictionary tags. will eventually.

The obtained sentiment dictionary tags are combined with the raw text to form a data representation based on the sentiment dictionary. An example of data representation based on domain sentiment dictionary is shown in Table.5. In the example in Table.5, the opinion expressions “affordable” and “not durable” both appear in the domain sentiment lexicon. Among them, Do Up represents the positive opinion expression label of the domain sentiment dictionary, and DoN represents the negative word label.

Table.5. Example of data representation based on domain sentiment dictionary

Produce	Mouth	Reality	Benefit
O	O	B DoUP	I DoUP
But	Do Not	Resistance	Use
O	B DoN	B DoUP	I DoUP

4.2 CRF MODEL BASED ON DOMAIN SENTIMENT DICTIONARY

CRF is a discriminative model, and linear chain conditional random fields (Linear chain CRF) are usually used in sequence labeling tasks. According to the definition of the model, the task of sequence labeling can be transformed into the following form. Given an input sequence in the form: $x = 1, 2... n$, the task goal is to predict a label sequence with the same length as the input sequence: $y = y_1, y_2,...,y_n$, each position in the label sequence corresponds to the input sequence. Then, the conditional probability $P(y|x)$ is calculated by Eq.(1).

$$P(y\mid x)=\frac{1}{Z(x)}\exp\left(\sum_{i,k}\lambda_k f_k\left(y_{i-1},y_i,x\right)\right)+\left(\sum_{i,k}\mu_k f_k\left(y_i,x\right)\right) \quad (1)$$

Among them, Z (work) is the normalization factor, f_k and g_k are transfer characteristic function and state characteristic function, their output values are Boolean values. For f_k, when y_i1, y_i, work meet the specific value of the transfer characteristic function, the output is 1, otherwise it is 0. G_k is similar. A_k and μ_k are the weights of the corresponding feature functions respectively. During the training process, each set of examples consisting of the input sequence and the label sequence trains each variable in the model by maximizing the log-likelihood probability of Eq.(1). When testing, given a set of input sequence instances x_r in the test data, select the output sequence y that satisfies Eq.(2) as the best predicted label sequence.

$$y^* = \arg\max P\left(y' \mid x'\right) \tag{2}$$

For the design of the feature template of the CRF model, we use the feature template shown in Table.6

Table.6. Feature templates used by CRF model

F1	char[n], n three {3, 2, 1, 0, 1, 2, 3}
F2	char[n]%char[n ten 1], n three {2, 1, 0, 1}
F3	char[n 1]%char[n ten 1], n three {0}
F4	dict[n], n three {3, 2, 1, 0, 1, 2, 3}
F5	dict[n]%dict[n ten 1], n three { 2, 1, 0, 1}
F6	dict[n 1]% dict[n ten 1], n three {0}

Table.7. Examples of Features Generated by CRF model

F1	Product; Product; Real; Benefit; But; Not; Resistance
F2	Product% real; real% benefit; benefit% but; but% Not
F3	real% but
F4	0;0;B DoUp;I DoUp;0;B DoN;B DoUp
F5	0%B DoUp; B DoUp%I DoUp; I DoUp%0; 0%B DoN
F6	B DoUp%0

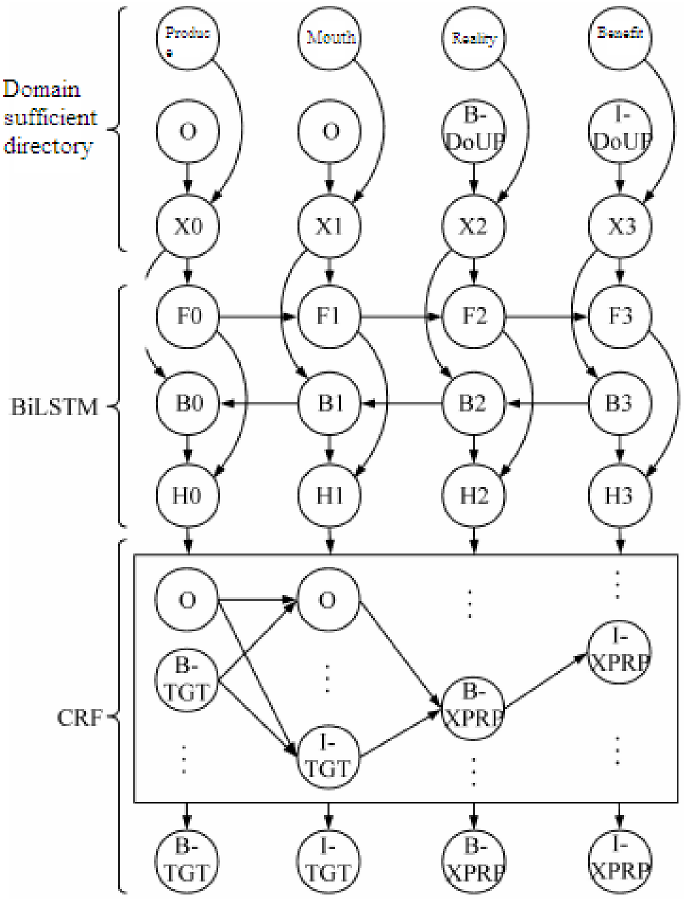

Fig.2. BiLSTM CRF framework

Among them, N represents the offset from the current position (0 represents the current position), char represents the character, and dict represents the value of the emotion dictionary label, and the specific value is consistent with Section 3.1. The features generated by templates F4, F5, and F6 are used as sentiment dictionary features. Taking the character "Hui" in the current position in Table.5 as an example, the features generated according to Table.6 are shown in Table.7 shown. In 3.3 BiLSTM-CRF model based on domain sentiment dictionary Fig.2 is the BiLSTM CRF framework used in this experiment.

The first layer is the data presentation layer. Its effect is to give us the input of word sequence and sentiment lexicon label sequence is mapped to the vector level Input representation. In this experiment, there are two kinds of input representations, one is the word representation, and the other is the sentiment dictionary representation, which are respectively obtained through the index relationship established in advance. Then, the word representation and the sentiment dictionary representation are concatenated to obtain the final input representation.

The second layer is the BiLSTM layer. Its function is to convert the input representation obtained by the first layer into the hidden layer representation output. Long short-term memory network (LSTM) is a special recurrent neural network (RNN) model, and its main structure is shown in Eq.(3).

$$\begin{gathered} I_t=\sigma(X_t \cdot W_{xi}+H_{t-1} \cdot W_{hi}+b_i) \\ F_t=\sigma(X_t \cdot W_{xf}+H_{t-1} \cdot W_{hf}+b_f) \\ O_t=\sigma(X_t \cdot W_{xo}+H_{t-1} \cdot W_{ho}+b_o) \\ C_t = \tanh(X_t \cdot W_{xc}+H_{t-1} \cdot W_{hc}+b_c) \\ C_t = F_t \odot C_{t-1}+I_t \odot C_t \\ H_t=O_t \odot \tanh(C_t) \end{gathered} \tag{3}$$

Among them, X_t represents the input representation at time t, and σ represents sigmoid function, $\odot$ is element dot product operation, It, F_t, o_t are respectively t. The result of input gate, forget gate and output gate at time, CH represent the candidate cell state, cell state and hidden layer state at time t, w and b represent the corresponding weight and bias respectively. Finally, we represent the hidden layer state as the output of the LSTM model.

TM for an input time series is usually from left to right Perform calculations to obtain the hidden layer representation, which is recorded as F for better to characterize the relationship of the context, BiLSTM will calculate the hidden layer representation F from left to right for the input time sequence t, and then concatenated to get the final hidden layer representation $H_t = F_t, B_t$.

The third layer is the CRF layer. Assuming that the number of labels marked by the sequence is k, for the input sequence x=1, 2,…n, after the calculation of the first three layers, a score matrix P with a dimension of $\eta \times k$ can be obtained. An element $P_{i,j}$ represents the score of the i^{th} input state labeled as the j^{th} label. For a set of predicted label sequences $y = y_1, y_2,…,y_n$, define its score as shown in Eq.(4).

$$Score\left(x, y\right) = \sum_{i=0}^{n} A_{y_i, y_{i+1}} + \sum_{i=0}^{n} P_{i, y_i} \tag{4}$$

Among them, A is the transfer score matrix, and $A_{i,j}$ represents transfer from label i.

Move to the score for label j. y_0 and y_n are the start and end tags in the tag sequence respectively and need to be added to the original tag set. Therefore, A is a square matrix of order k+2. Thus, we get the conditional probability $P(y|x)$ based on all possible label sets Y_x as shown in Eq.(5).

$$P(y \mid x) = \frac{e^{Score(x,y)}}{\sum_{\tilde{y} \in Y_x} e^{Score(x,y)}} \tag{5}$$

During training, maximize the pair of correct label sequences as in Eq.(5). Number Likelihood Probability. When testing, select the result y that satisfies Eq.(6) as the best predicted label sequence.

$$y^* = \arg_{\tilde{y} \in Y_x} \max Score(x, y) \tag{6}$$

4.3 EMOTIONAL ELEMENT COMBINATION MATCHING ALGORITHM

Use the above sequence labeling model to label the experimental data. The object of view, expression of view and emotional tendency contained in it can be obtained, and the combination and matching of emotional elements can be carried out. Different from the case where neither the head entity nor the tail entity is empty in the relation extraction task, the opinion object in <opinion object, opinion expression, sentiment tendency> can be empty. Such problems make matching difficult. Therefore, this experiment uses the algorithm shown in Table.8 for matching.

Algorithm 1: Combination Matching Algorithm of Emotional Elements

Input 1: Set of all sequence labels L={*B TGT*, *I TGT*, *B XpR*.,*I XpR*., 0}

Input 2: Sequence labeling result A= {<*work*$_1$, y_1>, <*work*$_2$, y_2>,...<*Work*$_n$, y_n>}, where in y_i L, 1 "i" η

Input 3: Short sentence punctuation mark set P

Input 4: Emotional propensity function

$$p(x) = \begin{cases} 1 & x = XPRP \\ 0 & x = XPRM \\ -1 & x = XPRN \end{cases}$$

Output: The set T= {<T_1, X_1, P_1> ,…< of T, of X, of P>}, where of is the total number of combinations of emotional elements

1: for<work i, y_i> in A do

2: if x is in P the n y_i← B-PUNCT

3: end for

4: Perform chunk operation on the I0B2 tag of A to obtain the combination result in the tag block B={<c_o, L_o>}, L_j three {*TGT*, *XpR*., *PUNCT*}, 1<j<o

5: According to the *PUNCT* label, carry out short sentence segmentation operation on B, and reconstruct the two-tuple of each short sentence into a set, and obtain C = {S_1, S_2, ... S_p }, p is the number of short sentence punctuation, S_k = {<u_1 , v_1 > , <u_2, v_2 >, ... <u_L, v_s>, <u_s *ten* 1, *PUNCT*>}, s is the total number of emotional elements in each short sentence

6: for S_k in C do

7: for <u_m,v_m> in S_k do

8: if v_m = XPR then

9: if v_{m-1} = TGT then will <u_{m-1},u_m,$p(v_m)$> Join in T

10: else if v_{m+1}=TGT then will <u_{m+1},u_m,$p(v_m)$> Join in T

11: else<*NULL*,u_m,$p(v_m)$> join in T

12: end if

13: end if

14: end for

15: end for

For this algorithm, we give a concrete example as shown in Fig.3. For the sequence annotation results of the sentence "very bad, the quality is not good", we first use the comma in the middle as a delimiter to separate it into two Short sentences. For the emotional elements of the short sentence "very bad" "<*bad*, *XpRN*>", locked to get the opinion expression "bad", but its neighbors

"<*NULL*, *bad*, 1>". For the sentiment element "<*quality*, *TGT*>, <*bad*, *XpRN*>" of the short sentence "bad quality", lock to get the opinion expression "bad", and its left nearest neighbor match gets view Point object "Quality", so return the result of combination of emotion elements "<Quality volume, not good, 1>".

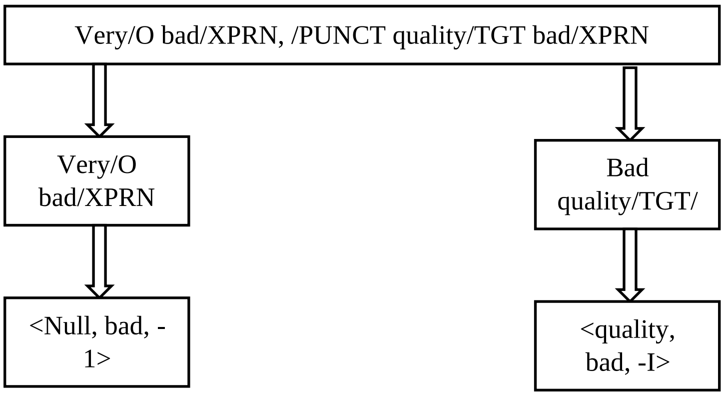

Fig.3. Example of Combination Matching of Emotional Elements

5. EXPERIMENTAL RESULTS

This section first introduces the experimental data, followed by the sentiment dictionary data, then introduce the experimental setup, and then introduce the evaluation method of the experiment, and finally the experimental results, method comparison and case analysis.

5.1 EXPERIMENTAL DATA

The data of this experiment comes from the corpus of the rematch stage of the BDCI2017 TASk12 competition, which belongs to the type of e-commerce comment text, and a total of 20,000 e-commerce comment texts are labeled examples. The labeling methods of the original corpus are shown in Table.8.

Table.8. An Example of the Original Corpus Annotation Method

Original Text	Emotional Element Combination
Bad contact, average effect	<Contact; Bad; 1 ;>, <Effect; Fair; 0 ;>

We perform initial preprocessing on the raw data. Firstly, we Shuffle the order of the original corpus, and preliminarily convert the corpus to the ratio of 8.1.1 split into training set the preprocessing results are converted into sequence annotation data. An example of conversion is shown in Fig.4 shown.

Segment the original text in each instance with short sentence punctuation marks as the boundary to obtain several short sentences and match each emotional element combination with these short sentences. If there is a matching result, it will be marked on the short sentence according to the position of each element in the emotional element combination. Finally, the experimental data conforming to the sequence labeling rules were obtained.

Considering that the sentence lengths of the 20,000 labeled examples are uneven, in the actual training process, we divide the original examples in the training set, verification set, and test set into short sentences. The Table.9 gives their related statistics:

Table.9. Statistics Related to Experimental Data

	Training set	Validation set	Test set
Original instance count	16000	2000	2000
Number of phrase instances	67155	8591	8562
average sentence length	814	812	824
Number of combinations of emotional elements	33215	4084	4236

5.2 SENTIMENT DICTIONARY DATA

To carry out the experiment *L* comparison, we also use HowNet Sentiment Dictionary and Dalian University of Technology Sentiment Dictionary. Since the method proposed in Section 3 can extended to any sentiment lexicon, so in the specific experiment we use three emotional dictionaries to add emotional dictionary labels to the experimental data obtained in Section 4.1. Different sentiment lexicons will generate different sentiment lexicon marks sign. The Table.10 shows the sentiments of different sentiment dictionaries for the same instance Dictionary label results.

Table.10. Examples of Tags Generated by Different Sentiment Dictionaries

	Gender	Price	L	Do not	Can
Domain Sentiment Dictionary	O	O	O	B DoN	B DoP
HowNet Sentiment Dictionary	O	O	O	O	B HowUP
Dalian University of Technology Sentiment Dictionary	O	O	O	O	O

5.3 EXPERIMENTAL SETUP

In this experiment, we use two sequence labeling models: CRF and BiLSTM CRF. For CRF, we use the feature template designed in Section 3.2, and the number of iterations is set until the convergence condition is met. For BiLSTM CRF, we follow the parameters shown in Table.12 conduct experiment.

Table.12. BiLSTM-CRF Parameter Settings

Parameter	Value
Word indicates dimension	64
Sentiment Lexicon Represents Dimensionality	32
Hidden layer dimension	100
Optimizer	RMSprop
learning rate	0.001
Batch size	64
Epoch	100
Drop out	0.5

For the selection of BiLSTM CRF experimental results, we measure the F1 value of the verification set after each epoch training and store the model every time they obtained F1 value reaches the maximum value. After all the training is over, we get the model with the best F1 value on the verification set. Use this model to test the test set to get the final experimental results.

5.4 EVALUATION METHOD

In this experiment, we evaluated the sequence labeling results and the combination matching results of emotional elements. For the results of these two stages, the accuracy rate (precision), recall rate (Reca11) and F1 value are used for evaluation. They are the same in formula structure, but different in specific meaning. The calculation methods of P (precision rate), R (recall rate) and F (F1 value) are given as shown in Eq.(7) ~ Eq.(9):

$$P=|A\cap G|/|A| \tag{7}$$

$$R=|A\cap G|/|G| \tag{8}$$

$$F=2PR/(P+R) \tag{9}$$

For the evaluation of sequence annotation results, A represents the total number of emotional element sequences (opinion objects and viewpoint expressions) in the prediction set, G represents the total number of emotional element sequences in the standard set, and IA gate GI represents the total number of emotional element sequences that completely match the prediction set and the standard set. For the evaluation of the matching results of emotional element combinations, A represents the total number of emotional element combination results in the prediction set, and G represents the emotional element combination in the standard set. The total number of results, IA gate GI represents the exact match between the prediction set and the standard set the total number of sentiment element combination results.

6. EXPERIMENTAL RESULTS

In this experiment, we conducted a total of two groups. Each set of experiments has 4 different sets of fine-grained opinion mining models. The two sets of experiments are based on CRF and BiLSTM CRF respectively, and the four sets of models are BASE LINE, ten H0WNET, ten DUTIR, ten D0MAIN. That Among them, BASELINE only uses word features to represent training, ten H0WNET adds feature representations of HowNet emotional dictionary based on word feature representation, ten DUTIR joins Dalian University of Technology emotional dictionary feature representation, ten D0MAIN joins e-commerce domain emotional dictionary feature representation. Table.13 presents all the results. From the experimental results, it can be seen that:

Table.13. Experimental Results

Test group	Model	Evaluation of Sequence Annotation Results		
		P	**R**	**F1**
CRF	BASELINE	82.33	75.15	78.58
	+HOWNET	82.72	75.80	79.11 (+0.53)
	+DUTIR	82.46	75.52	78.84 (+0.26)
	+DOMAIN	82.37	77.10	79.65 (+1.07)
BiLSTM-CRF	BASELINE	79.16	79.00	79.08
	+HOWNET	80.03	79.00	79.51 (+0.43)
	+DUTIR	79.39	79.36	79.39 (+0.31)
	+DOMAIN	81.01	79.90	80.45 (+1.37)
Test group	**Model**	**Evaluating the result of combination matching of emotional elements**		
		P	**R**	**F1**
CRF	BASELINE	72.63	64.84	68.51
	+HOWNET	72.92	65.60	69.06 (+0.55)
	+DUTIR	72.62	65.33	68.78 (+0.27)
	+DOMAIN	72.16	66.87	69.55 (+1.04)
BiLSTM-CRF	BASELINE	70.37	67.58	68.95
	+HOWNET	70.86	67.41	69.09 (+0.14)
	+DUTIR	70.52	67.70	69.08 (+0.13)
	+DOMAIN	73.14	69.27	71.15 (+2.20)

Compared with the BASELINE of the same experimental group, the F1 value of each model after adding the feature representation of the emotional dictionary has been improved, indicating the effectiveness of the emotional dictionary.

Whether it is in the experimental group CRF or in the experimental group BiL STM CRF, the model based on the feature representation of the domain sentiment dictionary ten D0MAIN is better than the other two models adding other emotional dictionary feature representations, indicating that the domain sentiment dictionary can. To better improve the performance of fine-grained opinion mining tasks in the domain.

The overall performance of BiLSTM CRF is better than that of CRF, showing that Deep learning models are more suitable for this task.

6.1 COMPARISON WITH OTHER WORK

We compared the experimental results obtained by this method with other methods, and the comparison results are shown in Table.14. Among them, Lazarsfeld et.al Based on the literature [14J, using Semi MarkovCRF as the sequence annotation model; Weissmana et.al Based on the literature [7J, using RNN as the sequence annotation model. Since the experimental data used in this paper lacks pre-trained distributed representation and language features, the actual measured performance is slightly lower than the method proposed by the original author. 0ur corresponds to the model BiLSTM CRF + D0MAIN with the best performance in Table.13. It can be seen from the comparison that our model achieves the best results.

Table.14. Comparison with Other Methods

Model	Evaluation of Sequence Annotation Results			Evaluating the result of combination matching of emotional elements		
	P	**R**	**F1**	**P**	**R**	**F1**
Lazarsfeld et.al	82.97	74.11	78.29	73.00	63.83	66.11
Weissmana et.al	74.23	76.54	75.37	69.08	63.44	66.69
Ours	81.01	79.90	80.45	73.14	69.27	71.15

6.2 EXAMPLE ANALYSIS

After analyzing the sequence annotation prediction results obtained by each model on the test set, we found that: the biggest effect of adding the feature representation of the sentiment dictionary to the sequence tagging model is to improve the prediction effect of the original benchmark system (BASE LINE) for low-frequency opinion expressions.

Compared with other sentiment dictionaries, domain sentiment dictionaries have higher coverage. It is illustrated with two examples given in Table.15. Since the two sets of experiments achieved consistent prediction results, they were combined.

Table.15. Example Analysis

Example	Reliable in quality	
Standard answer	Winning in [Quality/TGT] [Reliable/XPRP]	
Model	**Forecast result**	**Does it appear in the sentiment dictionary**
BASELINE	Reliable in quality	N/A
+HOWNET	Winning in [Quality/TGT] [Reliable/XPRP]	Yes
+DUTIR	Winning in [Quality/TGT] [Reliable/XPRP]	Yes
+DOMAIN	Winning in [Quality/TGT] [Reliable/XPRP]	Yes
Example	**Logistics to 5 stars**	
Standard answer	[Logistics/TGT] give [5 stars/XPRP]	
Model	**Forecast result**	**Does it appear in the sentiment dictionary**

BASELINE	Logistics to 5 stars	N/A
+HOWNET	Logistics to 5 stars	No
+DUTIR	Logistics to 5 stars	No
+DOMAIN	[Logistics/TGT] give [5 stars/XPRP]	No

In the first instance, the opinion expression "reliable" only appeared 6 times in the training data, which is a low-frequency opinion expression, so it is difficult for the BASELINE model of the two experimental groups to identify it. And "reliable" appears in the Sentiment Dictionary of HowNet, Sentiment Dictionary of Dalian University of Technology, and Sentiment Dictionary of E-Commerce, so each model added to the feature representation of the Sentiment Dictionary recognizes it.

In the second example, the opinion expression "5 stars" is the rating tendency of products in the e-commerce field, which has certain field characteristics. Since this entry only appears in the emotional dictionary in the field of e-commerce, only 10 domain models recognized it.

7. CONCLUSION

This paper proposes a fine-grained opinion mining method based on feature representation of domain sentiment lexicon. We first construct a new sentiment dictionary in the field of e-commerce, and then construct a feature representation on the e-commerce review text based on the dictionary and add it to the input part of the sequence labeling model. This method makes full use of the emotional dictionary resources without complex feature design and time-consuming preprocessing operations and enriches the feature representation of the input part of the sequence labeling model. The experimental results show that the method based on the sentiment lexicon in the e-commerce field has achieved good results on the two sequence annotation models of CRF and BiLSTM CRF and surpasses other sentiment lexicons.

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