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Emotion Correlation Mining Through Deep Learning Models On Natural Language Text

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Abstract*—Emotion analysis has been attracting experimenters' attention. Utmost former workshop within the artificial-intelligence field concentrate on feting emotion rather than booby-trapping the reason why feelings aren't or incorrectly honored. The correlation among feelings contributes to the failure of emotion recognition. during this composition, we essay to fill the gap between emotion recognition and emotion correlation mining through natural language textbook from Web news. The correlation among feelings, expressed because the confusion and elaboration of emotion, is primarily caused by mortal emotion cognitive bias. To mine emotion correlation from emotion recognition through textbook, three feathers of features and two deep neural- network models are presented. The emotion confusion law is uprooted through an orthogonal base. The emotion elaboration law is estimated from three perspectives one- step shift, limited- step shifts, and shortest path transfer. the tactic is validated using three datasets 1) the titles; 2) the bodies; and 3) the commentary of news papers, covering both objective and private textbooks in varying lengths(long and suddenly). The experimental results show that in private commentary, feelings are fluently mistaken as wrathfulness. Commentary tend to arouse emotion gyrations of love – wrathfulness and sadness – wrathfulness. In objective news, it's easy to fete textbook emotion as love and beget fear – joy rotation. These findings could give perceptivity for operations regarding affective commerce, like network public sentiment, social media communication, and mortal – computer commerce.*

***Index Terms*—Affective computing, deep neural networks, emotion correlation mining, emotion recognition, natural language processing (NLP).**

I. INTRODUCTION

EMOTION is complex, individualized, subjective and context sensitive. Emotions guide decisions, prepare the body for action, and shape ongoing behavior [1]. Philosophers tend to conclude that emotions are a subjective response to the objective world, meaning that emotions stem from the interaction between society and individuals. Individual emotions are at least in some way complex the following three aspects.

1).Constant individual value comes from many years of experience. The emotional response between individuals differs in the same context. For example, the Napoleonic War is contested with two opposing views. The proponents believe that the war attacks French feudal power and leads to historical progress, while the opponents consider the war unjustified because of its aggressive purpose.

2) Misunderstandings arise when individuals communicate. Understanding the context varies by individual background. An individual's mind deepens as they gain more knowledge of target events. The misunderstanding of the initial emotion occurs when there is a prior knowledge gap between the sender and the receiver of the information.

3) Individual emotion turmoil exists. The turmoil is influenced by external immediate negative or positive sentiment. Emotion changes along with instant conditions for the same event. It is an everyday phenomenon for most people that external conditions influence internal emotions. For example, a sweet-sounding tweet can be disruptive if your own work performance is judged negatively.

Emotions are correlated rather than independent, adding to the complexity of individual and public emotions. Emotion correlation mining can help analyze individual and public emotions at least in the following applications:

1) **Public Sentiment Analysis:** As Zhao et al. [4] pointed out that emotion variations contribute a lot to understanding the behavior of netizens and detecting abnormal events in social media.
2) **Communication in social media:** It is advantageous to generate little ambiguous messages, which are useful for the information receiver as well as for the are sensitive to both messaging and interpersonal communication. Emotion correlation mining can provide clues for the expression of the intended emotion.
3) **Human-computer interaction (HCI):** Emotions contribute to improving the HCI, for example social companion robots. Emotion is intuitive when it comes to providing cues to robots to understand and predict behavior for humanistic responses.

II. RELATED WORKS

Emotion analysis from text is one of the hot topics in modern understanding of natural language. Embedding and attentional mechanisms help a lot in emotion detection in deep learning methods. Continuous word representations, including word2vec [17], weighted word embedding [18] and the derivations [19] denoted words with dense embeddings and provided new ideas for automatic feature mining. Various types of attentional mechanisms and pre-trained models were later proposed. Wang et al. [20] proposed an embedded recursive neural network to improve emotion recognition. Barrose et al. [21] introduced personalized affective memory. In 2017, Vaswani et al. [22] proposed a new network architecture, the Transformer, based solely on attention mechanisms and completely eschewing repetitions and convolutions. With the ability

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to model bidirectional contexts, denoising autocoding-based pretraining such as BERT [23] and an autoregressive pretraining method such as XLNet [24] performed better than many other pretrained models on GLUE tasks. Some researchers solved the emotion recognition task by graph modeling , such as B. a capsule network. Popular models for understanding natural language, such as long short-term memory (LSTM),convolutional neural network (CNN),recursive autoencoder, adversarial learning and attentional mechanism [30], have been used for emotion analysis - and classification tasks applied. Electroencephalographic signals and facial expression sequences have also been used for emotion recognition with deep learning models. More complex and classification-oriented deep learning models made it more difficult to understand the correlation between emotions, even with remarkable detection accuracy.

Emotion analysis, as an important traditional branch of knowledge mining, is categorized into three levels, namely: word level, sentence level, and document level. In word level, emotion words were extracted mainly through three ways: 1) manual approach; 2) dictionary-based approach [34]; and 3) corpus-based approach. Strapparava and Valitutti developed WordNet affect through tagging a subset of synets with affective meanings in English WordNet (EWN). Staiano and Guerini presented DepecheMood, an emotion lexicon produced automatically by harvesting social media data annotated with emotion scores. Then, Badaro*et al.* provided EmoWordNet by expanding DepecheMood with the synonymy semantic relation from EWN. Emotion lexicons for different languages were developed. In SemEval 2018 Task 1: Affect in Tweets , labeled data from English, Arabic, and Spanish tweets are created for each task. Badaro*et al.* achieved the best result in the SemEval 2018 emotion classificationsubtask for the Arabic language. Features that they usedwere word embeddings from AraVec, and emotion featuresextracted from ArSEL and NRC emotion lexicon. In thesentence-level analysis, intrasentential and intersentential emotionconsistency were explored .Qiu*et al.* employeddependency grammar to describe relations for double propagationbetween features and opinions. Ganapathibhotla andLiu adopted dependency grammar for the emotion analysisof comparative sentences. The conditional random fields(CRFs) method was used as the sequence learning technique for extraction. A multitask multilabel (MTML) classificationmodel was proposed to classify sentiment and topicsconcurrently . By doing this, the closely related tasks,that is, sentiment and topic classification have been improved.Machine-learning methods were widely used in both thesentence and document levels. Naïve Bayesian,maximumentropy classification , graphical model, andpattern recognition methods were employed frequently.Zhao *et al.* explored the correlations among differentmicroblogs for social event detection. Hu and Flaxman provided multimodel sentiment analysis by combining visualanalysis and NLP to predict various emotional states of theuser in social media. Most of the previous works focused on recognizing emotions from text rather than why emotion waswrongly recognized.

III. SYSTEM MODEL

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Term Definitions:1) The terms human emotion, public emotion, and social event are commonly used in affective computing studies. While definitions of these terms may seem self-explanatory. In this article, they are defined as follows.

a) Emotion is defined in the Oxford Dictionary as a strong feeling arising from circumstances, mood, or relationships with others. Emotional reactions to significant internal and external events . This article divides human emotions into six categories as defined by Shaver et al.
b) Public emotion refers to the sum of the individuals' emotional states The emotions of audiences may differ when they pay attention to different aspects of the same event. These various emotions constitute public emotion.
c) Social Event means any type of event published online. Common themes of a social event are health, government, education, business, entertainment, unusual events, etc.

2). Emotion correlation is described as emotion confusion and evolution. Several laws are concluded.

a) Emotional confusion refers to the distance between emotions. Absolute confusion of an emotion denotes the average probability, measured over distance, that the emotion will be confused with all other emotions. The relative confusion of emotion is due to relative distance. For example, if the distance between fear and surprise is shorter than that between fear and anger, this indicates that the relative degree of confusion of surprise with respect to fear is higher than that of anger. Fear and surprise tend to be confused. Basically, there is only one absolute confusion score for a given emotion, but several relative confusion scores for that given emotion, one of the most important factors in the development of emotions. For example, another recognizes text containing love as joy, and then another internet user mistakes text containing joy for surprise. The above misjudgments contribute to the development of love joy and surprise. b) The laws mentioned in this article come from correlations between emotions. Interemotional correlation is summarized in several laws. The emotion evolution law includes a misjudgment law of emotions and a circulation law of emotions.

B. Error Analysis

1) Errors Caused by Emotion Complexity:

Complexity is made up of two parts, namely the variety of emotions and the complexity of social events. The complexity of the problem will inevitably lead to errors without considering other factors. In general, individuals' emotions are complex and influenced by individualized long-term social experiences, misunderstandings caused by prior background knowledge and external immediate mood influences. Furthermore, public emotion is composite and diverse. Social events are complex, characterized by a number of aspects. The complexity of an event correlates positively with the number of aspects. So when a reviewer pays attention to more than one aspect, his/her words can contain more than one type of emotion.

2) Errors Caused by Dataset:Text features, which represent text, are abstract basic language units. Characters (letters) form a single word, and words make up phrases, then phrases build sentences, paragraphs, and

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chapters. Character and word (explicit) are two features used frequently. In this article, implicit expression of words is employed as the third feature to reduce the sparsity caused by using words. These three kinds of features capture text information from different levels.

I)*Character:*Letter in language. The basic feature of the text, whose number is limited and thus compact in the corpus.

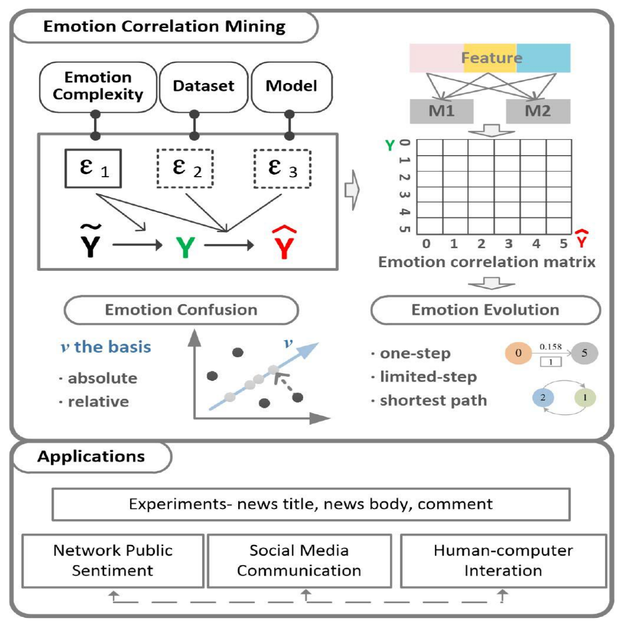
II)*Implicit Expression:*Synonym tag of words from the synonymous dictionary. If several words are synonyms, they share the same synonym tag, extracted from the HIT synonymous dictionary [HIT IR-Lab TongyiciCilin (Extended)].

III) *Explicit Expression:*Word in language. The number of features in explicit expression is not less than that in implicit expression, as synonyms share the same tag in implicit expression. In a sufficiently large corpus, there are more words than synonyms and more synonyms than characters.

3) Errors Caused by Models:Misunderstandings often occur when humans Misunderstandings often arise when people try to read the emotion from the text. Similarly, models' emotion classification results may differ given the same input text because the models' internal computational logic varies. If you look at the models as intelligent agents, models will make mistakes. To reduce the errors introduced by models, this article introduces more than one model. Due to the complementary advantages of the models, the results can be of higher authenticity and reliability. In addition, the decisions of the majority make sense even if the majority sometimes makes wrong decisions. We try to find the errors that most models make and try to infer the general error laws. Two deep learning models are set up to minimize the errors introduced by a single model.

4).Error Influence:The above three errors explain the deviation from emotion correlation. Let the errors caused by emotion complexity, datasets, and models be labeled 1, 2, and 3, respectively. Suppose _Y is the base truth of the emotion, which should be obtained from text writers and is therefore not available.

IV.System Architecture:



V.PROPOSED FRAME WORK

Emotion Classification Model:Here, two deep neural-network models, CNN-LSTM2 (M1) and CNN-LSTM2-STACK (M2), are employed for emotion recognition. In both models, the length of an input text can be either short or long. The output of the models is one of the six kinds of emotions, that is, love, joy, anger, sadness, fear, and surprise.

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The calculation process can be divided into three parts. M1 is constructed with constructed by adding an additional Part III to M1.The brief details of the three parts are described as follows.

1) ***Feature Processing:***Part I focus on feature processing that converts the original features into dense vector information. There are four operations: vector search; sliding window; convolutional calculation; and activation of rectified linear units (ReLUs).
2) ***Emotion Calculation:***. There are five operations, namely LSTM calculation, dropout operation, averaging, fully connected layer and softmax. Recurrent neural networks (RNNs) are powerful for sequence processing tasks, such as B. Text classification. A variant of RNNs, an LSTM network is able to classify and predict sequences when there are very long time delays of unknown magnitude between important moments.
3) ***Original Feature Attention:***. However, with the neural network going deep, the backward fine-tuning process in M1 becomes weak, and the vanishing gradient problem occurs. To solve this problem, a second model M2 is constructed by associating M1.

VI. EXPERIMENTAL SETUP AND RESULTS.

1).Misjudgment of Emotion*:* According to the top misconception, emotion pairs are corroborated by two or more emotion correlation matrices. For example, in the Comments, a third of the matrices are likely to misinterpret fear as anger, which has an average probability of 0.095. A third of the matrices are equally as likely to recognize fear as joy.

Overall, comments can be easily misjudged as anger, especially the texts that involve sadness and love. Conversely, anger is unlikely to be mistaken in the comments. In news body and title, the models are likely to be confused between fear and joy. The texts that cause sadness, surprise, and anger are easyto be recognized as love incorrectly.

2) Circulation of Emotion:The three conditions mentioned in Section V-B are considered for the most-likely traces in the evolution of emotion. Eight emotion shift steps are employed for the three conditions considering the validity and efficiency of computation. The most-likely traces include the phenomenon of emotion circulation under the above three conditions. Moreover, the emotion circulations that are extracted from an emotion correlation matrix $\mathbf{x}(k)$ are the same, even though the original condition differs.

3) Shortest Path of Emotion Transfer: Equation is applied for the shortest path between two emotions. The results reveal that shortest paths are one step. The shortest path can be two steps when prob1*(*sini*, sult)* is equal or near to zero.

VII. CONCLUSION

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Emotion correlation mining is important to track emotional development. The complexity of emotions and events complicates emotion recognition for both subjective and objective information. The contributions of this article are concluded as follows.

1) This article examines the correlation of emotions based on the emotion detection result of state-of-the-art deep learning models.

2) The errors caused by the data set and the models are reduced by designing three types of traits and two deep neural network models.

3) Emotion correlation is broken down by an emotion confusion law, which is undirected, and an emotion development law, which is directed.

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