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Analyzing the Complex Nature of Emotions From Written Text Using Parrott Theory of Emotions

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***Abstract*— Emotions are the main component of a person's character and personality. They are used to communicate messages and information. Emotions are represented in various ways, such as by physical actions, verbal tone, written text, etc. We are interested in identifying the emotions presented in the written text and then to analyze them. Emotions are complex in nature. An emotion exhibits its own nature and characteristics. It may represent another emotion in a written text. The complex property of emotions is similar to the characteristics of complex numbers, which are represented by their real and imaginary parts. Various algorithms are used to identify and analyze emotions in the text. These techniques usually considered each emotion as a separate element with its own characteristics. The relationship between different emotions and their influence on the overall polarity of the text has not received much attention from researchers over a period. In this work, the main idea is to analyze the complex characteristics of emotions by identifying the relationships and dependencies that exist between them. To support this idea, theories of emotions such as Plutchik's wheel of emotions and Parrott's theory of emotions are utilized. According to these theories, emotions are classified into different groups and levels depending on their intensities and dependencies. The results of the research are described in detail in the later sections of the article.**

Keywords—Parrott theory, emotion, class, summarization, internet, blogs, communication

I. INTRODUCTION

Text analysis over the past decades considered a main area of research. It is used as a mechanism for identifying and transmitting information over the Internet. The popularity of text analysis is due to the growth of the Internet. The Internet allows the persons to express their ideas, emotions, beliefs, opinions etc., more efficiently. Today, one of the important sources of accessible text is the Internet. There is a huge amount of data on the Internet, available in the form of social networks, interactive groups, blogs, etc. The text over the internet is available in different languages and is growing at a very fast pace.

People use the internet to express their opinions and emotions. A text available on the Internet is analyzed to obtain useful information from it, such as a forecast of future events, public polls, weather forecasts, people's opinions on governmental and organizational policies, etc. In general, emotions expressed in a text, paragraph, or sentence are related to each other. Some are highly dependent on each other, while others are partially dependent, with few of them simply independent [1].

In our previous works, we observed a relationship between different emotions depending on the index of their occurrence and the distance between them in the text [2-5]. In this paper, we analyze the nature of emotions and the relationship between them based on their characteristics in the written text document.

The proposed methodology helps to analyze the complex characteristics of emotions and to understand the real and imaginary parts of them. For example, let's say "**Andrey loves Lena"**. Here the only emotion explicitly presented in the sentence is love. However, it also means that he likes to spend time with her. He feels happy and shows affection towards her. Here the emotions "**happy**" and "**affection**" are imaginary emotions of the true emotions "**love**". These emotions are not presented in the text, but they do exist in the meaning. They are dependent semantically and logically on their primary emotion **love** as presented by Parrott in his work during 2001 [6].

Similarly, **Eugene is afraid of the exam**. Here the real emotion expressed in the text is "**afraid**". However, there are imaginary emotions associated with it, such as **panic, stress, horror, tension**, etc. Here we can see that an emotion expresses the existence of several nonexistent emotions in the text, or an emotion can represent many other emotions.

II. HISTORY OF EMOTION ANALYSIS

The first system that was developed to detect emotions in the text was the Inquirer system in the 1960s at the Harvard Laboratory [7]. The main goal of the system was to identify positive and negative emotions in the text. After that, there was a slight delay in the research until the beginning of the 90s, when the term "Subjectivity" was firstly introduced for research in information retrieval systems [8].

At the beginning of the 21st century, Peter Turney proposed the idea of "Thumbs up" and "Thumbs down" to present the positive and negative reviews in the text before their classification [9]. In 2002, Pang manually created a vocabulary that expressed feelings in the text [10]. In 2009, an interesting study was published on several domains to illustrate the importance of polarity indicators from the well-known SentiWordNet database [11]. It was noted that the preprocessing process of the text before analyzing emotions from it improves the results of the text analysis.

Among the various machine learning and data classification algorithms, clustering appears to be more effective for the purpose of classification of text into different clusters. The process of clustering requires a special distance function for creating the clusters of text and to automatic determine associations, similarities between different members of them [12]. Clustering has various types, such as K-means, Hierarchical, Fuzzy C-means, etc. For classification purposes, C-means and K-means are apparently more efficient and effective than others. These methods use the Euclidean distance function to divide emotions into different groups. To determine the semantic orientation of text, adjectives are seen as an important measure.

Emotional modalities and their logical formulas were used to analyze the text and its orientation. Logical models classify text emotions in different groups based on their hereditary nature [13-15]. Analysis of emotions and moods in text written in the Russian language began in the last decade. Initially, the already used templates and techniques in other languages were applied directly to the text written in Russian language. However, the difference in the writing style and syntactic features of the Russian language did not allowed existing models to analyze emotions from the text correctly and accurately [16].

In 2009, the analysis was conducted on a blog of the Russian automobile community for the analysis of emotions to determine the mood of people regarding a particular brand of car in the Russian market [17]. An experiment was conducted on a text in Romanian and Russian to find out if the spelling of their words corresponds to an equivalent phonetic word or not. The result of the experiment was used to improve the capability of the search for words in the written text [18].

Similarly, an experiment was conducted on English and Russian language reviews about the same books to observe the relationship between emotions in both languages [19]. Loukachevich and Chetviorkin proposed a mechanism for identifying Russian sentiments regarding reviews of goods and services [20]. Then Steinberger et al. built a dictionary of emotions in different languages [21]. In 2014, Poria et al. used conceptual rules in tree-structure to identify sentiments in text document [22].

Rule-based methods seemed to be a very attractive technique for creating grammar, and then for performing parsing and semantic analysis of text written in Russian language. However, the effectiveness of machine learning methods for categorizing and classifying emotions from text outclassed the rule-based mechanisms. In recent years, the syntax analysis has attracted more attention than the semantics analysis of text for analyzing emotions from it.

III. Methodology and Discussion

The purpose of this study is to identify the complex characteristics of emotions in the written text, such as the relationship between them, their dependencies, etc. For this purpose, we use the Parrott's Theory of Emotion to classify emotions into different groups.

According to him, emotions can be classified into three different levels or groups depending on their nature and intensities, such as primary, secondary, and tertiary emotions. A unique relationship exists between the emotions of one level to the emotions of another level. Primary emotions are the most intense emotions, while tertiary emotions are the least intense emotions. The relationship between emotions observed below in table 1.

TABLE 1 Parrot Theory of Emotions 2001

Primary Emotions	Secondary Emotions	Tertiary Emotions
Love	Affection	Adoration, affection, love, fondness, liking, attraction, caring, tenderness, compassion, sentimentality
	Lust	Arousal, desire, lust, passion, infatuation
	Longing	Longing
Joy	Cheerfulness	Amusement, bliss, cheerfulness, gaiety, glee, jolliness, joviality, joy, delight, enjoyment, gladness, happiness, jubilation, elation, satisfaction, ecstasy, euphoria
	Zest	Enthusiasm, zeal, zest, excitement, thrill, exhilaration
	Contentment	Contentment, pleasure
	Pride	Pride, triumph
	Optimism	Eagerness, hope, optimism
	Enthrallment	Enthrallment, rapture
	Relief	Relief
Surprise	Surprise	Amazement, surprise, astonishment
Anger	Irritation	Aggravation, irritation, agitation, annoyance, grouchiness, grumpiness
	Exasperation	Exasperation, frustration
	Rage	Anger, rage, outrage, fury, wrath, hostility, ferocity, bitterness, hate, loathing, scorn, spite, vengefulness, dislike, resentment
	Disgust	Disgust, revulsion, contempt
	Envy	Envy, jealousy
	Torment	Torment
Sadness	Suffering	Agony, suffering, hurt, anguish
	Sadness	Depression, despair, hopelessness, gloom, glumness, sadness, unhappiness, grief, sorrow, woe, misery, melancholy
	Disappointment	Dismay, disappointment, displeasure
	Shame	Guilt, shame, regret, remorse
	Neglect	Alienation, isolation, neglect, loneliness, rejection, homesickness, defeat, dejection, insecurity, embarrassment, humiliation, insult
	Sympathy	Pity, sympathy
Fear	Horror	Alarm, shock, fear, fright, horror, terror, panic, hysteria, mortification
	Nervousness	Anxiety, nervousness, tenseness, uneasiness, apprehension, worry, distress, dread

According to Parrott's theory, the emotions are classified into three groups or levels named as primary, secondary and tertiary levels. Primary emotions are independent emotions. The secondary emotions are dependent upon primary emotions whereas the tertiary emotions are dependent directly upon secondary emotions and indirectly upon primary emotions.

It means while allocating the sentiment score to each emotion, it is required to observe its relationship to other emotions and the dependencies that exist between them. The complex property of emotions is that emotion may exhibit the properties of some other emotions or it may represent other emotions in text. Based on this hypothesis, the polarity scores are allocated to emotions using the equations below.

$$polscore(A) = polscore(A) + \sum_{i=1}^{N} polscore\left(B(i)\right) \quad (1)$$

$$polscore(B) = polscore(B) + \sum_{i=1}^{N} polscore\left(C\,(i)\right) \quad (2)$$

$$\mathrm{polscore(C) = polscore(C)} \quad (3)$$

From the above equations, it can be observed that the polarity value of an emotion belonging to the main level A is the sum of its own polarity value with the polarity values of all its dependent emotions from level B and C. Similarly, polarity value of an emotion belonging to level B is the sum of its own polarity value with the polarities of all its dependent emotions in level C. whereas the emotions in level C have just their own polarity values.

In other words, the polarity score of real emotions are their own polarity, added with the polarity score of all their imaginary emotions. The results of the above equations be visualized using the figure below.

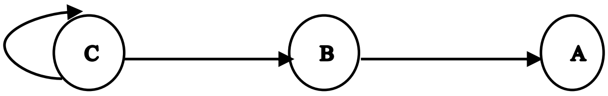


Fig. 1 Logical relationship between different emotions according to Parrott's theory of Emotions

In Fig. 1 above, state C represents tertiary emotions, presented in table 1. Emotions at this level are usually short-term and mild emotions. If they exist for a longer period, they move to a higher and extreme level of emotions in state B. Emotions in state B are secondary emotions. They have their own characteristics plus the characteristics of tertiary emotions that follow them. When secondary emotions exist at this level for a longer period, they move to the highest and most intense level of emotions called primary emotions.

Primary emotions are intense and long-lasting emotions. These are mainly irreversible emotions, and in the case to reverse them, they require a longer period. Primary emotions contain their own properties, as well as the properties of their secondary and tertiary emotions.

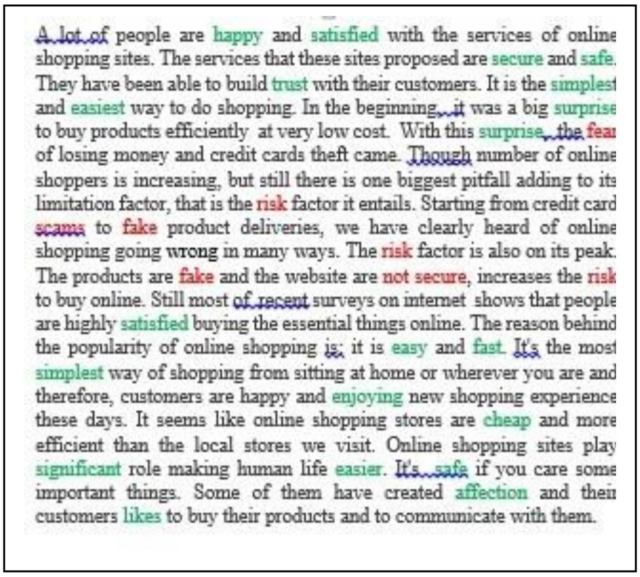
The above figure details the relationship between emotions based on the categories of emotions proposed by Parrott in his theory. We can observe that real emotions, as in the case of primary emotions, have the properties of their imaginary emotions, such as secondary (level B) and tertiary (level C) emotions.

To determine the emotions and their dependencies, each sentence from the text was analyzed separately in the experiment. When tertiary emotions explicitly exist in the text, they contain only their own estimated polarity. While secondary emotions in the text contains all the characteristics and polarity values of their tertiary emotions (imaginary emotions), as well as their own (real emotions) polarities. Similarly, primary emotions contain their own polarity values along with polarity values of their secondary and tertiary emotions (imaginary emotions).

The above methodology helps to understand the logical relationships that exist between different emotions in a text. This relationship between emotions can be used to update the polarity of each emotion in the text and to determine the overall strength of the emotion in the text.

IV. Experiment & Results

For the experiment, a text blog from the Internet was downloaded. The text contains an opinion on online shopping. Words with green color in figure 2 represents positive emotions, while words with red color represents negative emotions in the text. A part of the text from online blog is presented below in Fig. 2.



A lot of people are happy and satisfied with the services of online shopping sites. The services that these sites proposed are secure and safe. They have been able to build trust with their customers. It is the simplest and easiest way to do shopping. In the beginning, it was a big surprise to buy products efficiently at very low cost. With this surprise, the fear of losing money and credit cards theft came. Though number of online shoppers is increasing, but still there is one biggest pitfall adding to its limitation factor, that is the risk factor it entails. Starting from credit card scams to fake product deliveries, we have clearly heard of online shopping going wrong in many ways. The risk factor is also on its peak. The products are fake and the website are not secure, increases the risk to buy online. Still most of recent surveys on internet shows that people are highly satisfied buying the essential things online. The reason behind the popularity of online shopping is; it is easy and fast. It's the most simplest way of shopping from sitting at home or wherever you are and therefore, customers are happy and enjoying new shopping experience these days. It seems like online shopping stores are cheap and more efficient than the local stores we visit. Online shopping sites play significant role making human life easier. It's safe if you care some important things. Some of them have created affection and their customers likes to buy their products and to communicate with them.

Fig. 2 Blog of text from interne about online shopping

From the above text, we identified the words that express emotions in text. Those words (emotions) were then analyzed using Parrott's theory of emotions for their classification and updating of polarity scores. We applied our proposed methodology to calculate the intensities of emotions based on different levels of intensities of Parrott's theory. For making the calculations simple, a polarity score of 1 is assigned to the emotions of tertiary level, 2 to secondary emotions, and 3 to the emotions of primary level in the text. The experiment and its results are detailed below in table 2.

TABLE 2 Emotions and their Intensities in text using Parrot Theory

Emotions and their Intensities using Parrot Theory of Emotions					
Emotion	Occurrences	Polarity score	Intensity	Factor Including other intensities	Overall Intensity
Happy	1	1	1	-	1
Satisfied	2	1	2	-	2
Secure	1	1	1	-	1
Safe	2	1	2	-	2
Trust	1	1	1	-	1
Easiest	3	1	3	-	3
Surprise	2	3	6	5	30
Fear	1	3	3	9	27
Risk	3	1	3	-	3
Fake	2	1	2	-	2
Scams	1	1	1	-	1
Significant	1	1	1	-	1
Affection	1	2	2	10	20
Love	1	2	2	16	32

It was observed that the emotions have different number of occurrences with different intensities in the blog of text. Using the Parrott's theory of emotion, the intensities of the emotions in the blog of text were calculated. According to the proposed methodology, independent emotions should have a higher polarity value than their dependent emotions. This concept is the main idea of the proposed methodology. The emotions from text contain their own value of polarity along with the polarities of their dependent or imaginary emotions. The analyzed emotions from text with their intensities are plotted using the graph below.

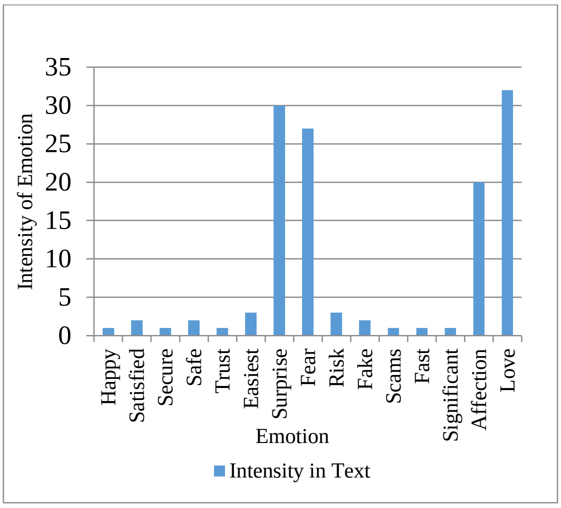


Fig. 3 Emotions and their intensities in Text

The graph above shows the primary emotions in the text contain their own characteristics, polarities along with the polarities and the characteristics of their imaginary emotions.

V. Conclusion

We observed a logical relationship between the emotions that exist in the text. Emotions that exist in the text represent several other nonexistent emotions. These nonexistent emotions are imaginary emotions of the real emotion. While identifying the intensity of an emotion, it is important to observe its logical characteristics. Emotion and its logical characteristics can affect the overall emotional polarity of text. It was observed that by considering the complex nature of emotion helps to analyze the emotional subjectivity of the text. Using this methodology, the emotions can be effectively summarized from the text.

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