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Summarizing Emotions from Text Using Plutchik's Wheel of Emotions

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***Abstract*—Text is an important and major source of communication over Internet. It is analyzed to identify interesting information and trends of communication. Within this work, we are analyzing emotions expressed by people on Internet using Plutchik's wheel of emotions. Plutchik's wheel of emotions is use as a tool to identify and summarize emotions to their primary classes. To accomplish it, we allocate a weight to each emotion depending upon the class it belongs and its distance from the center of Plutchik's wheel of emotions. These weights are then multiplied by the frequencies of emotions in text to identify their intensity level. The intensity of each emotion is summed up with the intensity of its primary emotion while summarizing it. We observed that our mechanism effectively summarize emotions from text. This paper is divided into several sections. The methodology, results and conclusions are discussed in detail in their respective sections.**

Keywords—Plutchik wheel, emotion, class, summarization, internet, blogs, communication

I. INTRODUCTION

Text analysis is the subject of major research over the recent decades. This is due to availability of online and offline data. The online text is growing at a very high pace. There is a need to develop tools and methods for solving text analysis problems. Text analysis has a lot of applications. It can be used to detect fraud in online transactions, predict the future, identify groups and people, etc.

The theme of our research is to develop methods that can be used to analyze emotions from a text efficiently and then use them for classification of the text and its summarization. Today we have various social networks, blogs, and groups where people can express and convey their emotions to others. This emotion transfer can be constructive if it is positive, and can be destructive if it is negative. There are still challenges in text analysis such as identifying a hate group online using text analysis. This is a question that still requires efforts. Emotions from a text are used to determine public opinion about a topic and to predict a future event based on it, such as election results, reaction to governmental policies, etc. The need of such system was seriously felt during the crisis of the Middle East, where governments failed to understand the people's emotions. During these events people used the online text as the major source to organize protests against the government and its policies. Similarly, American elections were linked to online groups and people who spread propaganda.

In this paper, we will use a text taken from an online blog in which people expressed their emotions about online shopping. We will analyze and summarize the emotions from text using the concept of Plutchik's wheel of emotions [1]. In 1980's Robert Plutchik divided emotions into eight main categories. Half of these emotions are positive emotions, and the other half are negative ones. They are seen as opposite to each other. We can observe this among secondary emotions, such as joy is opposite to sadness, surprise is opposite to anticipation, trust is opposite to disgust, and anger is opposite to fear. He explained each emotion in detail and divided it into subgroups, treating them as secondary and tertiary emotions in a wheel-shaped mechanism. His work describes a very interesting relationship between emotions, their intensities and polarities. He also noticed that the intensity of an emotion is high when lies in the center of the wheel and it decreases as the distance from the center increases.

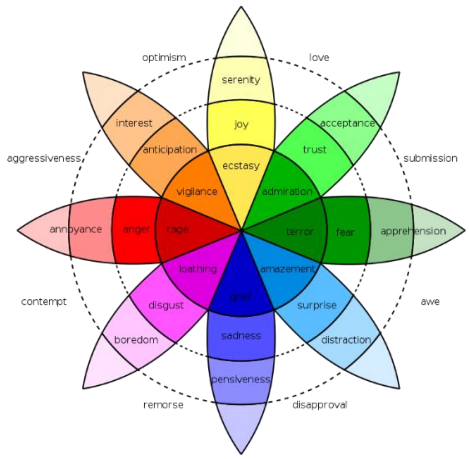

Fig. 1. Plutchik wheel of emotions

II. HISTORY OF EMOTION ANALYSIS

The analysis of emotions was began with the development of the very first general survey system in 1966. It was started by Philip Stone at University of Harvard, and it was probably the first stage of text analysis and identification of emotions from it [2]. After that, text analysis in different languages started gradually. Several scientist made remarkable contributions in text processing. Important among them was the contribution of Jayne Wiebe, Peter Turney and Vasileios Hatzivassiloglou in the early 1990s. In 1990, Jane Wiebe defined the term "subjectivity" for researching information retrieval [3]. Later, in 1997 Hatzivassiloglou revealed semantic orientation of adjectives

[4]. A few years later, in 2002, Peter Turney offered his revolutionary approach of "Thumbs up" and "Thumbs down" for positive and negative review of a text [5]. During the same year Pang proposed the mood lexicon manually for text analysis [6]. In 2009, Denecke reported an interesting study conducted in several areas to demonstrate usefulness of previous polarity estimates from SentiWordNet [7]. Recently the scientists started using different data mining tools, statistical methods, supervised, semi-supervised learning techniques and combinations to identify and analyze emotions from a text.

III. RELATED WORK

Going beyond polarity in sentiment analysis is currently not studied. However, several examples can be found where methods are used to collect more information than just polarity, such as the use of recursive auto-coder is to predict mood distributions in different dimensions [8]. The authors also promote efficient calculations using a structure they called SenticNet [9,10]. Sentimental dimensions of this structure are modeled in the hourglass model, which is a derivative of Plutchik's emotion wheel [1]. In 2012 the author gathered a large collection of tweets and experimented with self-signed hash tags of emotions [11].

It is difficult to define standards for emotion analysis from a text because emotions are usually subjective and cannot be clearly defined. The works of Parrott, Plutchik and Schroder aimed at defining standards in this area by determining the minimum set of basic emotions from which complex emotions can be constructed [12, 1, 13]. In 2012 the authors developed methods for emotion reasoning [14]. In our work we are using Plutchik's wheel of emotions to identify, analyze and summarize emotions from text.

IV. METHODOLOGY

In this work, we are purposing a new methodology that uses Plutchik's wheel of emotions for identification and analysis of emotions from a text. The work begins with the selection of a text from an online blog. In this blog people expressed their opinion about shopping online. Our system will be engaged in mining and identifying emotions from the text. Each emotion in Plutchik's wheel of emotion will be given a certain weight depending upon its intensity.

We will begin by identifying the most intense emotions from the text that are close to the center of Plutchik's wheel and then broaden up the search for its secondary and tertiary emotions along the radius of the wheel. The weight of the emotions close to the center of the wheel is 4, which is also the maximum level of intensity in Plutchik's wheel of emotions. For the emotions in second layer of Plutchik wheel of emotions, the weight is 3 and it gradually decreases by 1 from layer to layer of Plutchik's wheel of emotions as we move far from the center. We will count the total occurrences of an emotion in text C_i as in (1). Then by multiplying it with the weight of an emotionW_i, we get the intensity IE_i of each emotion in the text as in (2). The intensity of an emotion is added to the weight of primary emotion $W_{i\ primemo}$ and using this mechanism the weights of all primary emotions are updated as in (3).

$$Emotion\ Count\ C_i = \sum_{j=1}^{n} Occurence\ of\ Emotion_{ij} \quad (1)$$

$$Intensity\ of\ Emotion\ IE_i = C_i \times W_i \quad (2)$$

$$Weight\ of\ Primary\ Emotion\ W_{i\ primemo\ updated} = W_{i\ primemo} + IE_i \quad (3)$$

V. EXPERIMENT & RESULTS

We applied our methodology on the text to identify emotions using Plutchik's wheel of emotions. We observed a list of emotions from the text with different polarities. First, we searched for positive emotions, counted their frequencies and identified their weights. On multiplying the frequency of an emotion by its weight we observed the intensity of a particular emotion in the text. On summing up the intensities of all the positive emotions together we got an overall intensity of positive emotions in the text as described in table I below.

TABLE I. POSITIVE EMOTIONS IN TEXT

Emotions	Positive emotions in the text		
	Frequency	*Weight*	*Value*
Trust	15	3	45
Surprise	12	3	36
Interest	9	2	18
Amazement	5	4	20
Acceptance	4	2	8
Love	5	2	10
Awesome	7	1	7

From the above analysis, the most frequent positive emotions in the text can be observed. We can also sum up the frequencies of all positive emotions to get an overall frequency of positive emotions in text. The results of the above analysis are further elaborated using a graph plotted below in Fig. 2. Positive emotions are represented with green colour whereas the blue colour represents the emotion 'Awesome' that, according to Plutchik, is a feeling aroused because of surprise and fear that makes it a neutral emotion.

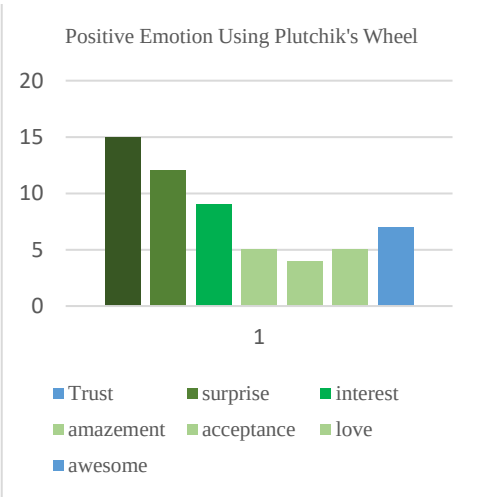

Fig. 2. Positive emotion of Plutchik's wheel identified in the text

Similarly, we observed negative emotions in the text, counted their frequencies and identified their weights. On multiplying the frequency of an emotion by its weight we observed the intensity of a particular emotion in the text. On summing up the intensities of all the negative emotions together we got an overall intensity of negative emotions in the text as described in Table II below

TABLE II. NEGATIVE EMOTIONS IN TEXT

Emotions	Negative emotions in the text		
	Frequency	*Weight*	*Values*
Sadness	6	3	18
Anger	4	3	12
Rage	4	4	16
Boredorm	2	2	4
Fear	2	3	6
Awesome	7	1	7

The result of above analysis shows the frequency of occurrence of negative emotions in the text. By summing together the frequencies of all the negative emotions from text, we can get an overall frequency of negative emotions in text. The same way we can calculate the overall weights and values of negative emotions in text. In general, it is observed that the frequency of negative emotions in text is comparatively low to positive emotions. These emotions are further explained using a graph plotted below in Fig. 3. The red colour represents negative emotions whereas blue colour represents a neutral feeling.

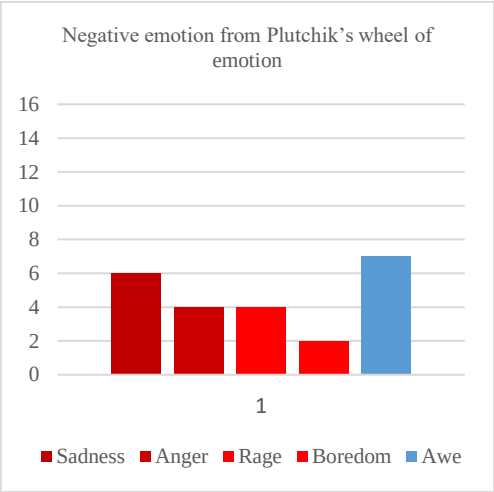

Fig. 3. Shows negative emotion and their frequencies in text

It is observable that the number of negative emotions, their frequencies and weights are less than half of the weight of positive emotions in the text. Based on the analysis of the text according to Plutchik's wheel of emotion it is observed that in the text people mostly express positive emotions about online shopping. To summarize the emotions to their primary or intensive emotion of Plutchik's wheel we add the weights of emotions to the most intense emotions of Plutchik's wheel that lies close to the center as represented in the Table 3 below. The table represents the eight primary emotions of Plutchik's wheel of emotion and their weights in the text.

TABLE III. PRIMARY EMOTIONS OF PLUTCHIK'S WHEEL OF EMOTIONS IN TEXT ALONGWITH THEIR WEIGHTS

Primary Emotion	Weight
Rage	12
Vigilance	18
Ecstasy	0
Admiration	63
Terror	13
Amazement	43
Grief	18
Loathing	4

The analysis result done for the identification of primary emotions of Plutchik's wheel of emotions from the text and their respective weights are plotted below in Fig. 4.

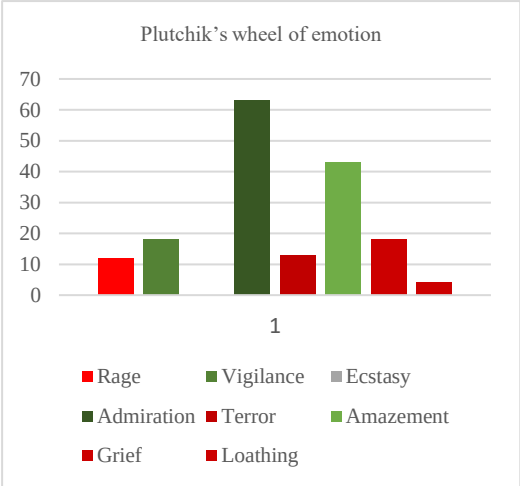

Fig. 4. Representing emotion of Plutchik's wheel along with their weights identified from text

The above analysis describes the summarized emotional contents in the text. It is observed that online shopping is an admiration and amazement for the people. From this analysis it can be concluded that in general people consider online shopping a positive mechanism and trust it. However, the feelings of rage, terror, grief and loathing can sometimes distract a customer while doing shopping online.

VI. CONCLUSION

We observed that our methodology affectively summarizes emotions in the text. Robert Plutchik's work describes the main existing emotions and is still important

while analyzing emotions in a text. It is a simple way of identifying polarity of a document and summarize its emotional contents. However, neutral emotions and feelings described in Plutchik's wheel of emotion complicate the process of summarization. In future, we will propose a mechanism to avoid complications while summarizing neutral emotions.

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