Emotion Detection from text based on Scoring Method using Fuzzy Logic

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Abstract

Within the scope of this research, we propose making use of fuzzy logic to analyze the emotional content of written text. Emotion categories do not have well-defined boundaries (e.g., pleasure, happiness, grief, shock, fright, repugnance, annoyance etc.). In order to deal with ideas that do not have clearly delineated and distinct boundaries, fuzzy logic was developed. In theory, this makes it an ideal tool for dealing with feelings and sentiments. The shift from one physiological state of emotion to another is also gradual, and it is simple to model by employing a methodology known as fuzzy logic. This paper discusses a methodology which utilizes fuzzy based scoring system for Emotion Extraction from Text. Even though there are now established standards in the industry, there is some consistency between the approaches, and the precision of the algorithms will continue to improve using the current approach.

Keywords: Emotion, Fuzzy Logic, Score Ranking, Sentiment Analysis

1. Introduction

Expression of emotional feeling between people forms an interactive web. When people talk about how they feel, it creates a web of connections between them. Emotions are a big part of how people live their lives and make decisions. Researchers are very interested in trying to figure out what's going on here. Previous research has shown that emotions can be picked up in different ways, such as through speech, facial expressions, and text. Since text is still the most common way to communicate online, we think it's important to be able to tell how people feel and express themselves in text messages [1]. There are different ways to extract emotions out of text and process them to learn more about the emotions being shown. In this paper, the detection of emotions is accomplished with the help of fuzzy logic in this particular paper. A brief Introduction of Fuzzy logic is given here forthwith.

Knowledge acquisition is the process of getting information from experts in a certain field or from training data collected in the real world. This is an important part of how knowledge engineering is used. But because human knowledge and the real world aren't very precise, it's hard to do this task with a traditional scientific model. This is because a traditional scientific model tries to represent exactly all the features of the expert system we're building and isn't very flexible. Fuzzy set theory, which Zadeh [2] came up with, should give us the tools we need to deal with how vague our knowledge is. It also lets us describe the parameters of a system with vague words instead of exact mathematical values. In real-world applications, it's easy to get numerical data from tools or the environment. Several researchers have come up with ways to use this data and different learning algorithms to let the system build its own fuzzy rules. Wang and Mendel [3] used a technique called "table lookup" to make their rules. Using neural networks [4], modular neural networks [5], or hybrid systems [6] to learn from the training examples and build the rules is a more common way to do this. Hoang and Lee [7] suggested a simpler learning system based only on fuzzy clustering and decision tables that can define membership functions and fuzzy rules without using complicated computer systems like neural networks. But the size of their decision table grows with the number of input variables, and the system gets too hard to use in the real world, where there may be a very large number of variables [8, 9]. Wu and Chen [10] have come up with another simple method for learning. Using the a-cuts of fuzzy equivalence relations and fuzzy sets, their method divides the training data into groups. The membership function for each of these groups is then found. This learning algorithm makes about half as many rules as the one by Hoang and Lee [4], but despite this, it gets slightly more accurate results than the one by Hoang and Lee.

2. Proposed Work

To create an intelligent emotion extraction engine that, using fuzzy logic, is capable of recognizing a wide range of complicated human emotions based on written content.

2.1 Methodology

The prototype of the emotion extraction engine is a generalized version that uses real-world experience and keyword tagging as its foundation. Figure 1 provides an overview of the architecture of the emotion-extraction engine. The following categories of emotions are categorized by the engine: joy, sorrow, surprise (shock), fear (fright), repugnance (disgust), and annoyance (anger).

The feelings a user perceives from their series of inputs into the emotion extraction engine are referred to as their mood. The information that is evaluated in a single sentence is entirely responsible for determining the feeling that a user is currently experiencing. It is possible for a user's mood to be inconsistent with the user's current state of emotion. For instance, a user might express a miserable mood in one sentence, despite the fact that the user just a moment ago was extolling the virtues of happy and fascinating topics. Even though the user is feeling sad, this may not be a significant emotion for them, and their overall mood may still be happy despite the fact that they are experiencing this emotion.

In order to determine the disposition of a user, it is necessary to conduct an analysis that takes into account the user's current feelings as well as the user's feelings in the past.

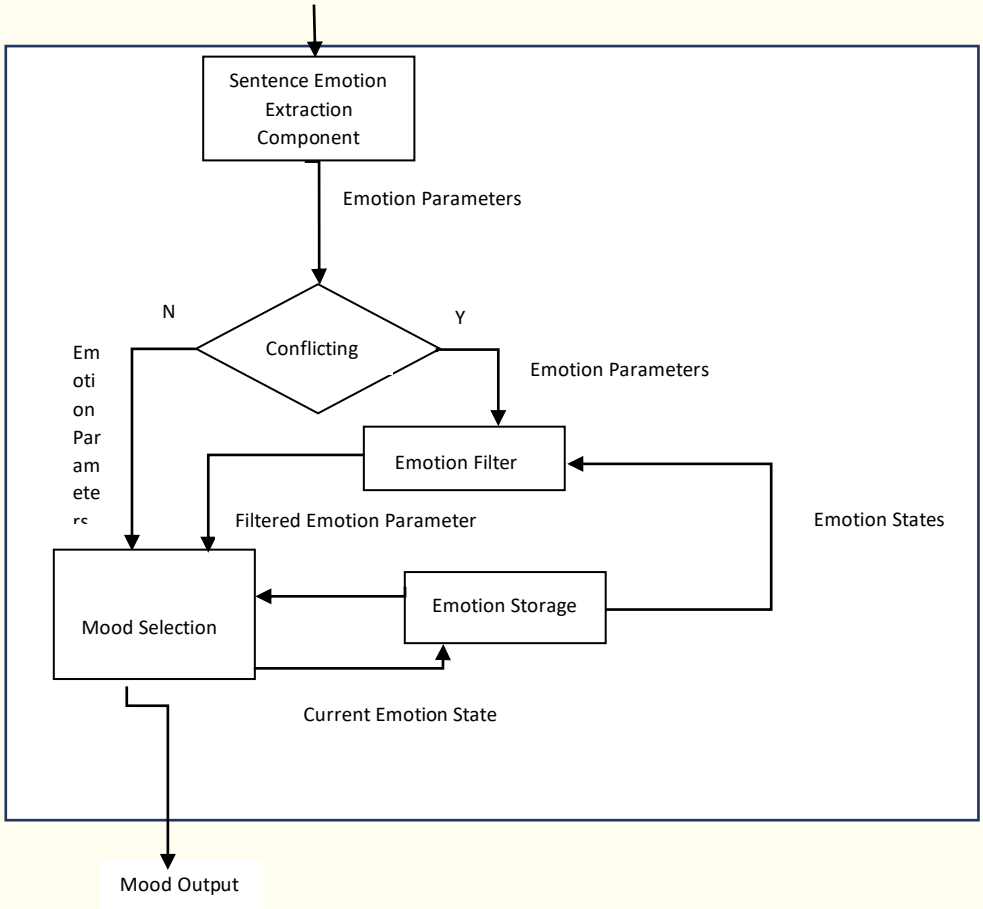

Figure.1 Mood Extraction Engine

3. Results and Discussion

3.1 Conflicting Emotion Detection

In the context of online chatting, it is not at all unusual for a user to type in a sentence that expresses more than one emotion at the same time. For instance, a user might say something along the lines of "I am glad that I was able to find employment, but I am disappointed that I must work overtime." It is not unheard of for a user to enter a sentence such as this one because it is not uncommon for people to experience a range of feelings in their day-to-day lives. When a sentence contains contrasting feelings, determining which of those feelings best represents the overall emotional state requires taking into account not only the sentence in question but also the state of mind. For instance, the happy mood in the emotion extraction engine denotes that the person's previous messages have contained an unusually high proportion of happy feelings relative to those containing other emotions. The system might interpret the user's current mood as happy rather than as both happy and sad even if the user types a sentence that contains both happy and sad feelings. The cause of this is that the individual in question was primarily

in a happy mood, and it's possible that the presence of a sad emotion did not significantly alter their mood from happy to sad.

In order to deal with contrasting feelings, a category for positive emotions and a category for negative emotions have been introduced. Joy (happiness) and astonishment (surprise) are examples of positive emotions, whereas disappointment, fear, anger, and disgust are examples of negative emotions. Conflicting emotions are only considered to exist in a sentence when both positive and negative emotions are present, and only then is the sentence treated as such. If the sentence contains contradictory feelings, then the dominant feeling is the one that gets filtered out.

3.2 Mood Selection Component

The inputs of the mood-selection component include the emotion parameters that were extracted from the sentence by the emotion extraction component, as well as the previously recorded emotions that were stored in the emotion-storage component. The determination of the current mood is the primary objective of the mood selection component.

Filtering the tense information is the first step of the mood selection component's process in order to achieve this goal so that the emotion parameters can be transformed into the emotions that are currently being experienced. For instance, the emotion parameter "happiness" "middle intensity" "present tense" is converted to the "happiness" "middle intensity" that is currently being experienced. The storage component also receives the feeling that is currently being felt. The user's previous feelings are recorded and kept in the component designated for storage. [Category of Emotion] [Intensity] is the format. The following calculations involving fuzzy data are carried out in order to transform the data on feelings into a format that is suitable for use by a fuzzy system.

3.3 Fuzzy Data Calculation

An array called "E" has been given the accumulated value of the six different types of feelings that make up "emotions." The values 0 through 5 in the array represent the cumulative intensity of the feelings of happiness, surprise, anger, disgust, sadness, and fear. These values are in ascending order. The accumulative intensity of the feelings of joy (‘happiness’), astonishment (‘surprise’), annoyance (‘anger’), repugnance (‘disgust’), sadness, and fear (‘fright’) is represented by the array elements 0 through 5. The value of each element in array E is determined by adding the current intensity of an emotion category to the average of the five highest intensities of that category. This value is then assigned to each element in the array. The accumulative intensity can then be calculated using Equation 1, as shown in the following.

$$E[x] = \sum_{i=-n}^{0} \alpha_i I_i\,(x), \qquad \text{where } x = 0,1,2,3,4,5 \tag{1}$$

Since it is presumed that users in a chatting environment will only remember the most recent conversations, the value of array E is determined by the relative intensity that has been measured over the course of the most recent n time periods. The value of Ii(x) ranges from 0 to 3, with the lowest intensity being 0 and the highest intensity being 3,

and it measures the intensity of emotion category x at discrete time i. When I is equal to zero, the values of the current emotions' intensities are stored in the Ii(x) variable.
The influence period will be set to five sentences within the framework of the emotion extraction engine because it is assumed that both positive and negative emotions will fade away at the same rate. The assumption is depicted in Figure 2, which can be found here. Figure 2 shows the value of the influence that is perceived to be exerted by emotion, and the letter t stands for the passage of time.

Figure 2. The decay of emotion over time

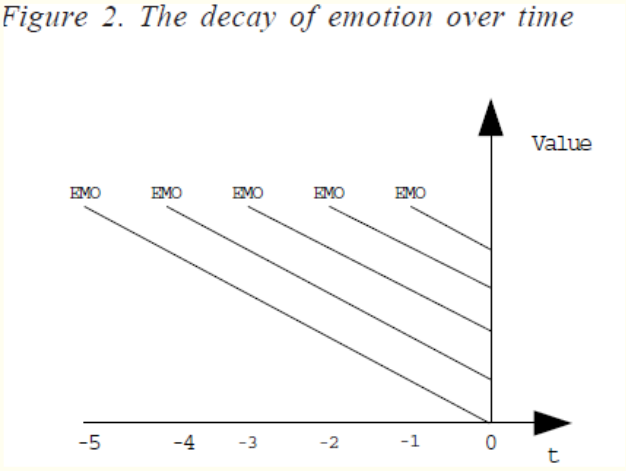

Figure 2 Emotions Decay Graph

The emotion that was experienced at a particular point in time is represented by EMO (e.g., the point in time at which a chat message is typed in (input)). It can be inferred that the user who created this Figure typed in six emotional sentences of the same intensity because the value of EMO is the same at each time point as shown in Figure 2. The current time is represented by the number zero. At time 0, however, there is no longer any noticeable effect from the EMO that occurred at time -5, indicating that the impact of the emotion input at time -5 has faded.
Among all previous EMOs, the one from time -1 has decayed the least and is therefore still very influential currently (time 0). The weight parameter in the fuzzy emotion-analysis component represents the emotion decay, and Equation 2 is used to calculate it.

$$\alpha_{i=} \alpha_{i+1} - 0.1, \quad \text{where } i = -5, -4, -3, -2$$

$$\alpha_{-1} = 0.5 ,$$

$$\alpha_{0=1} \qquad (2)$$

3.4 Fuzzy Membership Functions

In order to assist with the computation of MOOD, we make use of the fuzzy membership functions and fuzzy logic rules that are listed below. In order to lay the groundwork for

the investigation of fuzzy functions, the following definitions are given for two different fuzzy membership functions—one high and one low (Equations 3 and 4):

$$\text{Low(x)} = 1\text{-}\frac{E[x]}{\sum_{i=0}^{5} E[i]} \quad (3)$$

3.5 Fuzzy Rules

The high and low membership functions are used as a foundation for the development of fuzzy rules. The mentioned rules are:

Rule 1:

IF the emotion with the greatest intensity is "high" AND the other emotions are "low", THEN that emotion is the current mood.

Rule 2:

The current mood is the highest positive emotion and the intensity is reduced by 0.1 IF the positive emotions are "high AND the negative emotions are "low."

Rule 3:

The current mood is the highest negative emotion and the intensity is reduced by 0.1 IF the negative emotions are "high" AND the positive emotions are "low."

3.6 Mood Selection

There are no indications of the user's mood when a dialogue first begins. However, it makes sense to assume that a latest user is in impartial (neutral) mood. When the emotion extraction engine gathers more information (for example, when the user begins chatting), the fuzzy rules described earlier can be applied, and the user's current state of mind can be determined. The dominant rule can be calculated using the center of gravity (COG) as a measure. The COG point is determined by arithmetically averaging the results of the rules in this implementation (Equation 5).

$$COG = \frac{\sum_{1}^{3} rule(x)}{3} \quad (4)$$

4. Significance

The following is a list of some of the practical applications that can be derived from the proposed research work:

4.1 Financial and Business Sectors

When it comes to making decisions about online shopping, choosing events, products, and entities, customers are heavily influenced by their feelings as well as the opinions of

others. These opinions are also helpful to the banks in the process of planning and scheme development for the insurance industry.

4.2 Politics and Exit Polls

The proposed work has significant practical value for understanding what voters are thinking, which public figures support or oppose the government, and how exit polls predict election outcomes; this is so because it is common knowledge that opinions and feelings carry a great deal of weight in politics.

4.3 Email Spams

The application of the work that is being proposed has a lot of potential utility in identifying spam in email.

5. Conclusion

The future of emotion recognition looks promising. This paper discusses a methodology which utilizes fuzzy based scoring system for Emotion Extraction from Text. Even though there are now established standards in the industry, there is some consistency between the approaches, and the precision of the algorithms continues will continue to improve using the current approach.

Some of the limitations of the current work is its inability in handling the complexity of slang words and short text used in the English language despite the engine's application of several rules and algorithms. However, the emotion extraction engine can still be used within the context of Internet communication and achieve significant performance. In the near future, some of the current constraints may be eliminated as technology advances.

6. Conflict of Interest

There is no conflict of interest in this work.

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