Sensing Users Emotional Intelligence in Social Networks

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Abstract. In this age of constant digital communication and social interaction, people are paying a lot of attention to how users' emotional intelligence affects their interactions and well-being on social networks. This research investigates the application of information systems and telecommunications technologies in the detection and analysis of users' emotional intelligence within the realm of social networks. The concept of emotional intelligence, which involves the capacity to notice, comprehend, regulate, and use emotions in a proficient manner, has significant importance in influencing encounters and relationships in the online domain. This article explores potential models of emotional intelligence based on sentiment analysis of social network data. Self-awareness, self-regulation, intrinsic motivation, and interpersonal connections are based on four principles. These four-dimensional models aggregate four numerical indicators to quantify emotional quotient. This study uses Twitter, a popular social network, to predict emotional intelligence in individuals or groups. This finding assesses users' emotional intelligence using four variables and shows their positive, negative, and neutral sentiments. The program we are developing is based on uploading Twitter datasets and forecasting emotional intelligence using algorithms and tools based on tweets, retweets, and followers, among other scenarios. The four dimensions allow us to feel emotions. Twitter datasets are in text files with JSON data.

1. Introduction

The advent of the digital era has brought about a significant transformation in the manner in which individuals establish connections, exchange information, and engage in communication on a global scale through the use of social networks. These platforms facilitate a digital environment where individuals may freely articulate their opinions, emotions, and experiences, resulting in an unparalleled magnitude of online engagements.

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The idea of emotional intelligence (EI) has become more important in this dynamic environment for comprehending and negotiating the complexity of human communication. Emotional intelligence refers to the ability to recognize, understand, regulate, and use emotions, both within oneself and in others, hence impacting the overall quality of interpersonal interactions and relationships.

Prior attributions research focused on collecting demographic information about consumers. Several studies also drew conclusions about users' personalities based on their connections to others. Despite efforts to apply AI for things like privacy analysis and aberrant behavior identification or privacy protection and system security, our work here focuses on the privacy disclosure based on language published by users in social networks. Moreover, there is no relevant study on social network-based EI prediction.

In 1920, Thorndike introduced the idea of "Social Intelligence," and in the following year, Alexander introduced the in 1938 with the idea of Non-intellectual Factors. Gardner first presented the idea of multiple intelligences in 1987 [1]. The core principles and theories of EI may be traced back to this period. Salovey and Mayer, two American psychologists, rethought EI and formally established the systematic theory in 1990. Bar-On added his own term to the mix as well. In 1985, Bar-On released his Emotional Quotient Inventory, in which he first established the notion of the emotional quotient. According to the Bar-On model, there are many interconnected competencies, practices, and attitudes that make up these EI factorial components [2].

The proposed social network-based emotional intelligence prediction models to measure emotional regulation skills.

The psycho-emotional intelligence idea states that these types of models include self-control, self-awareness, self-motivation, and interpersonal skills [3].

As far as we are aware, this is the first attempt at estimating a user's emotional intelligence using data collected from social media platforms.

Based on the themes discussed by users with low and high scores, we categorize people according to their emotional intelligence [4].

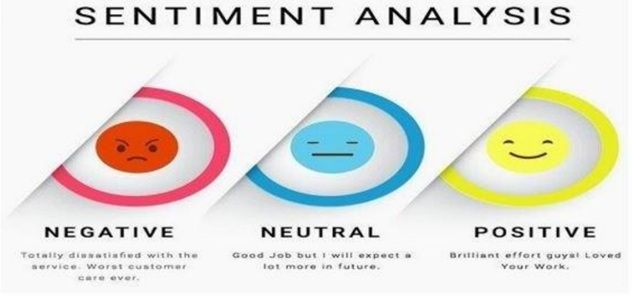

Fig.1: Sentimental Analysis [5]

1) Self-Awareness can be calculated by finding all sentiment positive words intensities and if this value is high then it will be detected as awareness.
2) Self-Regulation can be calculated by dividing number of positive sentiment words with negative sentiment words and if resultant value greater than 0.5 then user is in swing mood.
3) Self-Motivation can be calculated by multiplying Self-Regulation value with 25 and if resultant value 0.5 then user will be in depress state
4) Social relationship: Here we will find users number of followers, retweet and it will divide by total mood swings and if resultant value > 0.2 then it will consider as influential in social network else user is not having impact/influence on social media.

So, by using above four dimensions we can sense emotions from user’s social networking post. To implement this paper, we are using Twitter Dataset and this dataset is in JSON format. The goal is to learn about emotional intelligence prediction models that can reveal something about a user's emotional intelligence only by looking at their social media posts and comments. Emotional intelligence, as defined by the Bar-On model, can be broken down into any number of sub-skills [6]. We use Twitter data to make predictions about a user's emotional quotient. Based on the amount of comments, the number of retweets, and the time of publication, we apply a set of principles derived from theories of emotional intelligence to the language that we post. As a result, the psycho-EI theory necessitates that the models be founded on four pillars: intrinsic motivation, internal control, external awareness, and interpersonal connections.
Emotional intelligence may be broken down into these four categories, each representing a different facet of the trait [7].
Understanding one's own emotional state, as well as appraising and expressing those feelings, and being aware of the subtle distinctions between them, is a hallmark of self-awareness. Users' self-worth is being quantified by evaluating the sentiments expressed in their tweets and retweets.
The ability to effectively manage and control one's own emotions and impulses is indicative of self-regulation. The quantification of a user's emotional instability or disorder is determined by observing a low variation and high mean of sentiment values pertaining to emotional fluctuations. The aforementioned value is obtained through the analysis of the rate of fluctuation in popular sentiment.
Self-motivation assesses the extent to which a user or users maintain an upbeat mental attitude and how quickly they bounce back from negative experiences like despair and disillusionment. The length of time it takes to get from feeling down to feeling stable emotionally is another indicator.
Analyzing relationships, feelings, and the potential for harmony in social interactions are all quantified by "social-relationships" scores. As a result, they are able to keep up their positive social interactions. Number of followers, comments, and retweets might be indicative of network structure. We also think that fluctuations in temperament and the general level of emotional expression are results of interpersonal interactions.

2. Related work

The user's mood may be deduced from the types and intensities of the sentiment words used in the text. We quantify the worth of introspection by examining the sentiments expressed in users' tweets. We put our models to the test on Twitter, one of the most popular social media platforms, and use it to forecast the emotions of over a hundred thousand users or a single user [8].
The precision of our predictions serves as evidence for the dependability of our models. In order to get a deeper understanding of the underlying principles governing users' emotional expression in social networks, we categorize users based on their emotional intelligence and conduct a comparative analysis of the dimensions between users with low and high scores [9]. The ability to control disruptive emotions and impulses is part of self-regulation. Emotional intelligence means taking control of one's feelings. A user's emotional instability or disorder can be quantified by a high mean of sentiment values, a low variance, and frequent emotional fluctuation.
The extent to which attitudes shift provides us with a measure of self-worth [10].
The level of self-motivation indicates how quickly an individual bounces back from negative experiences. Users' ability to motivate themselves can be gauged by how quickly they bounce

back from depression and establish a condition of emotional stability. Interpersonal harmony and the capacity to infect others' feelings are quantified by one's social connections [11]. The ability to sustain positive social interactions is facilitated by high EI. Social connections may be inferred from metrics like the number of replies and retweets. We take into account the frequency and magnitude of mood changes as elements that shape interpersonal connections [12]. In [13-16] the authors have been explored various machine learning techniques on visual communications and also employed machine learning techniques in their research for getting effective image feature extraction.

To figure out the emotional score, divide the number of positive words by the number of negative words plus one. Since there is no change in numbers, the sentiment value will always be more than 0. Also, the Zero Division Error could be avoided by adding 1 to the denominator.
The majority of prior research on the prediction of individuals' emotional intelligence (EI) relies on the use of questionnaires, which have the ability to elicit dishonest or unconscientious responses. Consequently, this may result in prediction outcomes that are possibly erroneous.

3. Proposed technology

Awareness of one's own and other people's feelings is self-awareness. There are several classes of emotion words, and five levels of intensity within each class. The frequency with which feelings are conveyed can be gauged by counting the number of times sentiment terms appear in the entire text. A user's state of mind can be inferred from the distribution of sentiment words across several labels. The capacity to distinguish nuanced emotions is shown in the frequency with which sentiment words of varying intensities appear within the same category. Also, the user's present feeling affects whether or not the emotion can be communicated vert correctly. As a result, a text's emotional intelligence may be gauged by calculating its sentiment value. Here is how we define self-awareness:

$$A = \frac{1}{K}\sum_{i=0}^{k}\left(\frac{w_s}{w_n} + \frac{w_i}{w_c} + \frac{w_p}{w_s}\right)\mathrm{E}_\iota \quad (1)$$

- Where, wn is the number of words
- The variable "ws" represents the number of emotion words.
- The variable "wc" represents the total count of emotion word categories.
- The variable "wi" represents the count of distinct levels of sentiment intensities in the set of sentiment words.
- The variables "i" and "k" represent the number of time frames.
- The average sentiment value in the time frames is denoted as Ei.

The capacity to control one's own emotions is reflected in one's level of self-regulation. The low standard deviation and high mean of emotional responses are both indicators of a high value of self-control. If the user's variance values in a given time frame are greater than 0.1, then the users emotional state has varied during that period. We also use entropy as a measure of the variability in a user's feelings. Let's pretend that m is the user's total amount of happy feelings and. Entropy is defined by the formula

$$R = \frac{1}{k}\sum_{i=0}^{k} \frac{E_j + 1}{(\sigma_i \, X \, entropy \, X \log t) + 1} \tag{2}$$

- Where, t is the typical distance across which the variation of opinion values has been measured
- The maximum acceptable value is 0.1, and the emotion value is more than 0.5.
- The location at which the mood fluctuation becomes evident. The sentiment expressed in tweets or retweets by users serves as a reflection of their emotional state, and we take into account the fluctuations in individuals' moods over a 28-day period. That is to say, we employ intervals of 28 days for people whose mood swings occur over longer periods of time than that.

It is possible to quantify a person's level of self-motivation by tracking the length of time it takes them to move from a sad or disappointed to an emotional, or stable, state, as well as the percentage of time they spend in each of these states. It is possible to classify a time period as a sad stage if the average sentiment value of users within a certain time window is less than 0.5. It is determined by averaging the number of trials when the time window was greater than or equal to 0.5. The self-motivation also depends on the user's emotional state. Hence, the following is a definition of intrinsic motivation:

$$S = \left(arctan \frac{1}{k}\sum_{i=1}^{k} log\left(\frac{N_{ci} \, X \, N_{ti}}{N_{di}}\right) X \, E_i \right) X \, 2 \div \pi \tag{3}$$

- The variable Ndi denotes the quantity of mood swings.
- The NCI (Normalised Comment Index) is a metric that quantifies the relationship between the number of comments and the number of followers.
- The Nti metric is a quantitative measure that considers the ratio between the number of retweets and the number of followers during a specific time window denoted as 'i'.

To get the ultimate convergence of values, the post-calculation values are subjected to a procedure where the photographs in the training collection are assigned to either the retinal region or artefacts based on the inverse tangent function. The ratings are standardised on a scale ranging from 0 to 1.

$$S = \left(arctan \frac{1}{k}\sum_{i=1}^{k} \frac{W_p \, X \, E_i \, X \, 25}{W_s \, X \log t_i} \right) X \, 2 \div \pi \tag{4}$$

4. Experimental results

Using information retrieved from the internet archieve database, we calculate a user's EI. The data sets are annotated by hand to determine the quality of the information and to facilitate testing. The tweet IDs, totalling 23,706, have been anonymised to ensure privacy. These tweet IDs have been classed based on their relevancy, and the information contained within them has been categorised into six distinct categories: infrastructure damage, service disruption, personal experience, weather updates, weather predictions, and storm warnings. In addition, the data is annotated to indicate the existence of toponyms, encompassing both instances with and without toponyms. Furthermore, the data is categorised based on location, distinguishing between local, distant, and generic toponyms. Lastly, the data is classified according to granularity, which pertains to the level of specificity of the toponyms, including

hyper local, municipal, and regional designations. The thorough categorization of datasets enables researchers to analyse crisis-related information behaviours and volunteered location information behaviours during a hyper local crisis occurrence. This enables the evaluation and enhancement of automated geolocation, filtering, and event detection methodologies, which may be employed to assist both people and crisis responders.
We downloaded the data in the form of JSON format the file contains all users list. We wrote some python code to create a new text file and store single json user data.
The Emotions will be calculated by analyzing the four dimensions and the graphs will be displayed in the form as shown in the below figure.
Tweet Analysis the following data will be displayed an ever user given in the text field. It shows the USERNAME, Tweet Text, Retweet Count, Following, Followers, Repetition, Hashtag, Num Replies, Favourite Count, Created Date, URL’s, Tweet Words Length. These are the parameters considered for analysis.
The below figure 2 defines the levels of different emotions like positive, negative, neutral. Thee y-axis define the number.

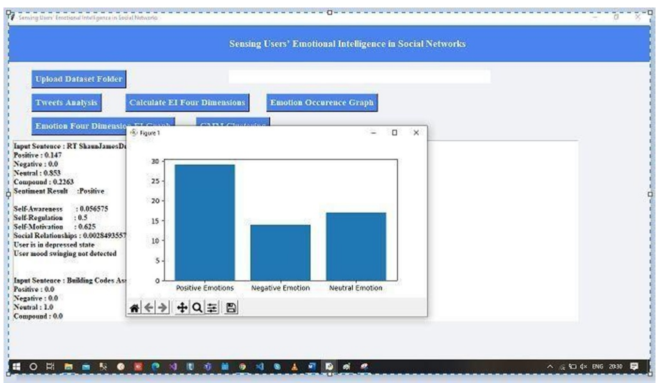

Fig.2: Emotion Levels

The Fudan NLP Group gathered data from Weibo, which we use to figure out how intelligent a person is. The data set has more than two million people and 1.5 billion tweets. The naive Bayesian method uses Weibo data as the training data set. For the trial, I chose 100,000 Twitter users who have more than 500 tweets and more than ten friends and followers. There are 105,176,341 microblogs.

The microblog is very short (only 140 words), and it has a lot of noise information like @, tags, URLs, and other things that aren't important for analyzing mood in a single microblog. So, we clean up the noise and separate the words.

The sentiment score may be determined by assessing the ratio between the count of positive words and the count of negative words, plus one. Given the absence of any variation in data, it may be inferred that the emotion value will consistently exceed zero. Additionally, the inclusion of a value of 1 in the denominator would prevent the occurrence of a Zero Division Error.

5. Conclusion

In this piece, we develop prediction models for assessing users' EI via the examination of social network posts and interactions. The models are articulated along four dimensions: one's own awareness, control, motivation, and connections with others. We put our models to the test on Twitter, one of the most popular social media platforms. Using four numbers and their total, we predict the emotional intelligence of over 100,000 Twitter users in our research. A normal distribution of users' EQ was discovered during the experiments. The findings also show that women have stronger emotional intelligence than men. In addition, we categorize users from the standpoint of emotional intelligence to further show the intrinsic rule of users' emotional expression in social networks by comparing the themes discussed by users with low scores and high scores.

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