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Extracting Emotional Reactions Expressed by Emojis in Social Media

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ABSTRACT: There exists some tools to extract emotional reactions from text by using sentimental analysis which are error prone and time consuming. The accuracy of extracting emotional reactions will be lower for many applications by using sentimental analysis, because it requires a harder time of understanding the context of text, language. To overcome the above mentioned difficulties extracting emotional reactions from emojis can be developed very effectively as emojis are language, text independent indicators of emotions. Our work proposes a system to extract the emotional reactions from emojis by using its unicode value and its sentiment score combined with image processing. The proposed system is used in classifying the universal emotions: Happiness, Sadness, Anger and Fear by extracting the emojis which are used to express the emotions. This system mainly focuses on consumers' reaction towards a new product, where negative results can help companies improve product before making them general. Here first we separate the emojis from the text in a tweet using methods of regular expression module. Each and every emoji is associated with a unique Unicode which is used to identify the type of reaction of corresponding emoji.

KEYWORDS : Emojis, Social media platforms, Image Processing, Unicode, Emotions, Sentimental Analysis, Emotional Reactions

I. INTRODUCTION

Emotions form a very important and basic aspect of our lives. Whatever we do, whatever we say, somehow does reflect our emotions, though may not be directly. To understand the very fundamental behaviour of a human, we need to analyze these emotions through some emotional data, also called the affect data. Analyzing this data over the Internet means we are spanning across the whole content. The emotion analysis provides a way for opinion mining. The unicode value and its sentimental score is used in classifying the universal emotions: Happiness, Sadness, Anger and Fear. With consumers posting their emotions on Snapchat, Facebook, Twitter and Instagram as well as on websites and in videos plenty of emotional data available. Emotions recognition technology typically categorizes emotions. Emotions analysis is used to gauge consumer reaction to new product in text groups; negative results can help companies improve product before they make them general available. Hence this system proposes extracting emotions from emojis using the unicode value and its sentimental score based solutions combined with image processing.

II. RELATED WORK

Reactions to Events/Posts in Social Media

There are various domains that specifically investigate reactions to events as expressed in social media are diverse (e.g., computer sciences, social sciences, geography, linguistics, and natural sciences), which implies that the purposes of these analyses will also vary widely. In all of the studies that we analyzed, a message or post published on a social media platform related to a given event is considered to be a reaction. The most commonly examined social media platform is the microblogging service Twitter, but Facebook and the Chinese microblogging service Sina Weibo are examples of other platforms studied. Typically, references to a given event are made through particular keywords or hyperlinks contained in a message and by using a temporal window to limit data collection to the issue attention cycle around the event [1], i.e., the period in which public attention to an event rises and drops off.

For the study purpose of related work includes investigating the diffusion of reactions [2,3,4,5]; analyzing the way that an event is perceived, i.e., the attitudes and concerns triggered by a social media post [6,7,8,9]; identifying trusted or credible information sources [10]; type of post detection from reactions including monitoring [10,11]; the assessment of the effectiveness of advertising campaigns [12]; sales prediction [13]; or interrelationships with the news media [14,15,16].

Emojis in Social Media

Emojis are language independent. In 2013 and 2014, more than ten billion emojis were used on Twitter [7]. There are various applications to track the amount of emojis usage in Twitter Application and one of the web application is (<http://emojitracker.com/>) webtracker which is used to track emoji use on twitter in real time. According to [5], tweets containing emojis are more emotional. These researchers created a sentiment lexicon

(http://kt.ijs.si/data/Emoji_sentiment_ranking/) for the 751 most frequently used emojis, and the majority of them are positive. [6] developed a method for creating emotional vectors of emojis by automatically using the collocation relationship between emotional words and emojis derived from weblogs.

Various research projects elaborate extracting emotions from Twitter messages by including hashtags, emojis, emoticons, internet slang, etc without considering space. Likewise, numerous space-related approaches analyze social media data by applying emotion detection or sentiment analysis.

Utilizing Emojis for Emotional Analysis

Emojis are much more diverse in emotional expression than emoticons because as pictorial symbols, they allow a more creative scope and possibilities of expression than a combination of ASCII characters. A disadvantage of emojis is that the sentimental and semantic interpretation of emotion and thus their usage might differ between individual users and usage context. However, variations in interpretation (regarding sentiment and semantics) can also be caused by different viewing platforms (e.g., Android, iOS) as emojis render differently

Misspelled or misused words can create problems for text analysis to extract the emotional reaction. Autocorrect and grammar correction applications can handle common mistakes, but don't always understand the writer's intention.

With spoken language, mispronunciations, different accents, stutters, etc., can be difficult for a machine to understand.

Since emojis are less error prone give high accuracy for emotional analysis we preferred to use emojis rather than text and natural language processing tools. The usage of emojis has developed rapidly in present world. Humans started expressing their feeling in form of emojis

III. PROPOSED WORK

This project proposes system to extract the emotional reactions from emoji's by using the unicode value and it's sentimental score combined with image processing. The proposed used in classifying the universal emotions : Happiness, Sadness, Anger and Fear by extracting the emoji's which are used to express the emotions. This project mainly focuses on consumers reaction towards a new product, where negative results can help companies improve product before making them general. Here first we separate the emoji's from the text in a tweet using methods of regular expression module. Each

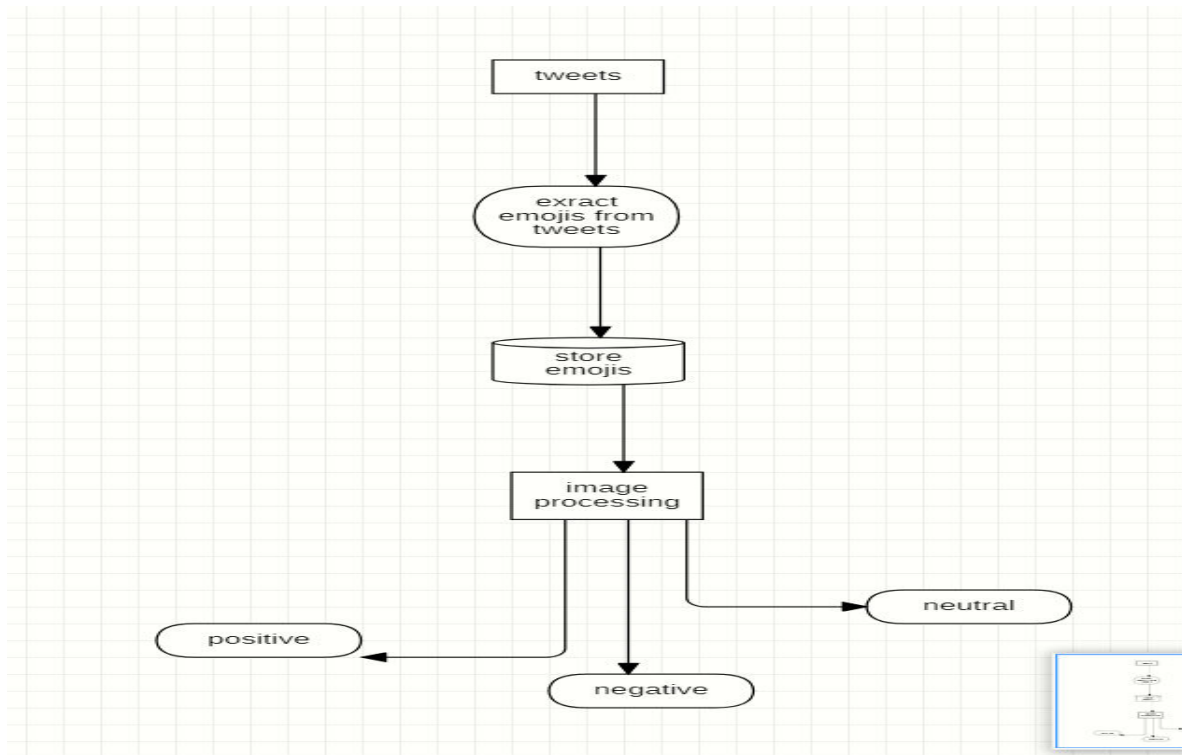
and every emoji is associated with a unique –Unicode which is used to identify the type of reaction of corresponding emoji.

Our work aims at utilizing emojis to analyze reactions regarding emotions. Sentiment analysis using the corresponding sentimental score of emoji and affect analysis are applied. Sentiment analysis measures the overall polarity of emotions and sentiments, usually in the sense of positive, negative, and neutral. In contrast, affect analysis considers emotional content and thus a significantly larger number of potential emotions, such as joy, sadness, hate, excitement, fear, etc.

Extracting tweets is the main aim of the project. In this project, the first steps is to separate emoji's form text and store in a Database. Analyzing the emotions of an emoji which are stored in a database by using the sentiment score and unicode value of corresponding emoji and image processing Fig. Architecture Diagram for the Proposed system

Separating the emojis form text/tweets:

The libraries required to extract tweets from social media platforms like twitter and facebook are i) emoji ii) open c v iii) regex



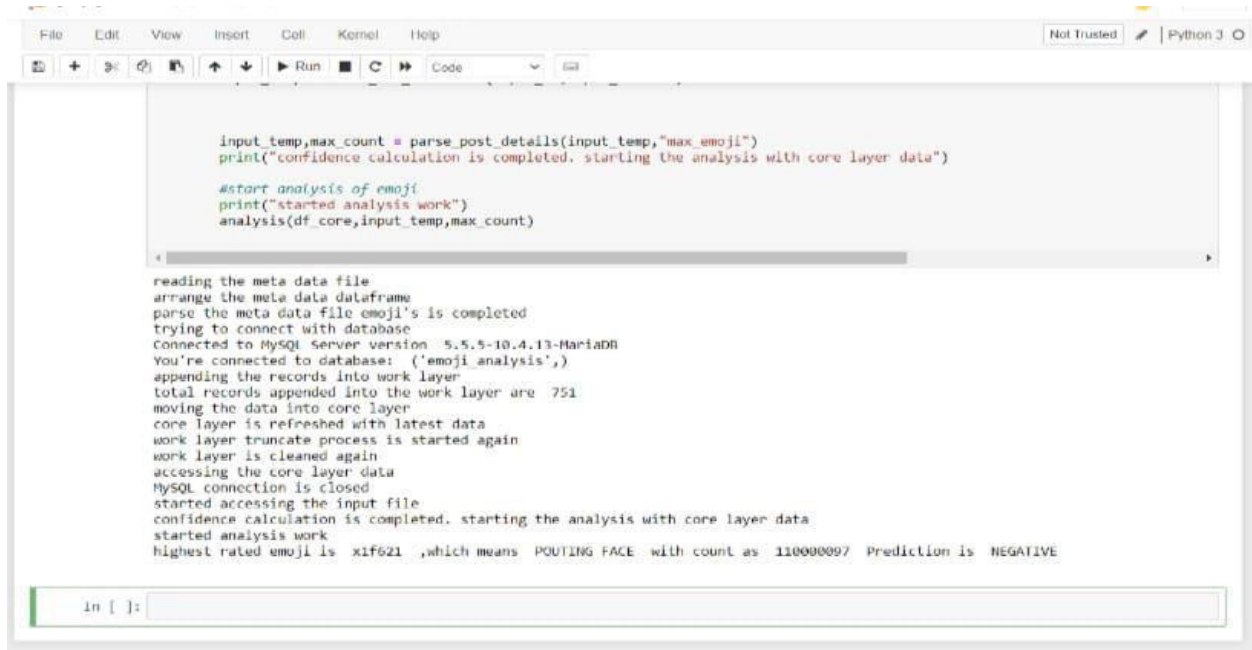
- i) emoji: There are multiple ways to print the emoji's in python. Every emoji has a Unicode associated with it. Emoji's also have a CLDR short name, which can also be used. Emojis are language independent and error prone.
- ii) OpenCV: OpenCV mainly focuses on image processing and analysis including features like object detection. OpenCV (Open Source Computer Vision Library) is an open source computer vision and AI programming library. OpenCV was worked to give a typical framework to PC vision applications and to speed up the utilization of machine insight in the business items.
- iii) Regex: A regular expression specifies a set of strings that matches it and extract the text or group of letters from the input file. As text is separated from the input file the emojis are used for the further processed for emotional analysis.

Consider a text file named as emoji_df, to a Python regular expression to extract all emoji. And yes, a CSV file that can be imported as a DataFrame for general use. The dataset also provides additional functionality for emoji for the advertools online marketing package:

- As a DataFrame emoji_df
- As a search option to search for emoji advertools.emoji_search
- One of the extract_ functions that extract emoji from a text list and sperates the emojis .

Emotional Analysis

To obtain a sentiment score for an individual emoji, we first consider unicode of emojis and then calculate it's sentimental score with respect to the value Zero. If the sentiment score is greater than zero corresponding emojis is analysed as positive, if sentiment score is less than zero it is analysed as negative, if it is zero then analysed as neutral. Then, system categorizes all the processed emojis based on their sentimental score which we calculated using unique Unicode values. As the part of final step, the highest rated category of emoji is predicted based on no of no emojis in each category and finally a post in social media is analysed. When most of the processed data consists of emojis with negative emotional reactions like sad, anger, pouting face the output is analysed as a negative emotional reaction towards a particular post.



```

input_temp,max_count = parse_post_details(input_temp,"max_emoji")
print("confidence calculation is completed. starting the analysis with core layer data")

#start analysis of emoji
print("started analysis work")
analysis(df_core,input_temp,max_count)

reading the meta data file
arrange the meta data dataframe
parse the meta data file emoji's is completed
trying to connect with database
Connected to MySQL Server version 5.5.5-10.4.13-MariaDB
You're connected to database: ('emoji_analysis',)
appending the records into the work layer
total records appended into the work layer are 751
moving the data into core layer
core layer is refreshed with latest data
work layer truncate process is started again
work layer is cleaned again
accessing the core layer data
MySQL connection is closed
started accessing the input file
confidence calculation is completed. starting the analysis with core layer data
started analysis work
highest rated emoji is x1f621 ,which means POUING FACE with count as 11009097 Prediction is NEGATIVE

```

IV. CONCLUSION AND FUTURE ENHANCEMENT

The proposed system that utilize emojis are less time-consuming than empirical surveys, less complex than sentiment/affect analysis based on NLP, and therefore less prone to typical language processing errors, such as errors caused by negations. Hence, the utilization of the proposed approach for affect analysis to another model case with a higher emoticon proclivity may give more agent results.. Utilizing the co-event of hashtags and specific emoticons for deciding the positive or negative schematization of a subject is a type of notion investigation since it considers the extremity of a web-based media post and not a bigger number of expected feelings, like delight, pity, disdain, and so forth, as influence examination does. Along with the emojis the usage of hashtags increases the accuracy to extract the emotional reactions.

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