Twitter Sentiment Analysis for Customer Reviews: Extracting Insights from Social Media

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***Abstract* — In social media applications, consumer sentiment analysis has been more popular recently, especially in fields like healthcare, criminal justice, finance, travel, and academia. Knowing how customers view products is essential to learning about different goals and evaluations. However, manual processing is becoming more difficult due to the growing amount, subjectivity, and variety of social network data. In real-world applications, machine learning approaches have been used to address this difficulty.**

With an emphasis on the hospitality and tourism industry, this article investigates the usefulness, breadth, and applicability of machine learning algorithms for consumer sentiment analysis in online reviews. The objective of our systematic literature evaluation is to identify research gaps and suggest future possibilities for this topic by comparing, analysing, and understanding the numerous attempts and orientations made.

There are two key ways that our work adds to the body of existing material. First, we look into how machine learning methods might be used to online reviews in the hospitality and tourism industry to analyse customer sentiment. Second, in order to answer particular research issues in this field, we suggest a methodical procedure for locating and gathering observational data as well as findings from relevant, high-calibre studies.

***Keywords*—Sentiment analysis, machine learning, online reviews, recommendation prediction, detection of fake reviews, hospitality, and tourism.**

I. INTRODUCTION

Social media has become a vital part of our everyday lives in the current digital era, and businesses are using it more and more to engage with their clientele. User-generated content has proliferated since social media's inception, making it difficult for companies to stay on top of the discussions surrounding their brands. Opinion mining, or sentiment analysis, is a method for removing and examining subjective information from textual data, including posts on social media. It can assist companies in comprehending the feelings, viewpoints, and attitudes that their clients have about their name, goods, or services.

Measuring customer satisfaction is crucial for businesses to enhance their goods and services because it plays a major role in their success. Conventional techniques for evaluating consumer happiness, such focus groups and surveys, can be costly and time-consuming. Sentiment analysis of social media posts provides an economical and effective means of gauging customer happiness. Through social media discussion monitoring, businesses may pinpoint areas for improvement, immediately resolve consumer grievances, and cultivate a favourable brand image.

This study aims to investigate how sentiment analysis affects social media in order to gauge consumer happiness. How well does sentiment analysis measure customer happiness on social media? is the study question. This essay examines the literature on sentiment analysis, its uses in social media, the value of customer happiness, as well as sentiment analysis's drawbacks and difficulties. A case study of a company that has effectively used sentiment analysis to gauge consumer happiness on social media is also be included in the paper.

The overall goal of this research article is to shed light on the advantages and difficulties of utilizing sentiment analysis to gauge social media user happiness. Businesses may make wise judgments, enhance their goods and services, and establish a positive brand image by knowing the feelings and viewpoints of their customers.

II. LITERATURE SURVEY

Sentiment analysis, sometimes referred to as opinion mining, is a branch of research that examines people's beliefs, attitudes, and feelings on particular objects, people, or services. Sentiment analysis has grown in significance in gauging client happiness as social media has grown.

Prior studies have demonstrated the potential of sentiment analysis in gleaning insightful information from social media data. For example, a study conducted in 2014 by Medhat et al. included a thorough summary of the most recent advancements in sentiment analysis, including a range of methods and uses. The writers talked about current trends in sentiment analysis and related fields and categorized the relevant publications based on their contributions to the field.

Nandwani and Verma (2015) covered the methods and difficulties of sentiment analysis in another paper. The writers outlined every step of the process for finishing sentiment analysis assignments and assessed the benefits and drawbacks of various strategies. They also looked at sentiment analysis's difficulties and suggested future paths.
This study analyses the literature on sentiment analysis and its application to customer satisfaction evaluation in order to provide answers to these research topics. The purpose of the literature review is to emphasize the research topics that this study attempts to address, identify gaps in the literature, and summarize the body of existing research.

In sentiment analysis research, survey methods are frequently employed to gather information from social media sites. Surveys are a useful tool for learning about consumer attitudes and opinions about particular companies. Survey methods do have certain drawbacks, though. For example, because some users may not opt to engage in surveys, the thoughts and attitudes expressed on social media may not be fully represented in the data collected via surveys. Furthermore, respondents may not give truthful or accurate answers in surveys due to response bias.

This research employs a mixed-methods approach to overcome these limitations, fusing survey techniques with other data collection strategies like content analysis and social media data mining. This strategy offers a more thorough comprehension of customer satisfaction and sentiment analysis applications in assessing it.

In conclusion, sentiment analysis is a useful method for evaluating client happiness in the social media era. There are still certain gaps in the literature, despite the fact that earlier studies have offered insightful information about sentiment analysis and its application in evaluating customer happiness. By responding to the research issues mentioned above and utilizing a mixed-methods approach, this study seeks to close these gaps by offering a more thorough knowledge of customer satisfaction and the application of sentiment analysis in evaluating it.

Benefits of the aforementioned survey methods:

The article gives a thorough introduction to sentiment analysis and how it's used in social media to gauge user happiness. It draws attention to the value of customer happiness in business as well as the shortcomings of conventional methods of measuring it. The literature review poses the research topics that this study attempts to address and points out gaps in the current body of knowledge. The article also covers the benefits of survey methods, such as their potential for representative sampling and their capacity to deliver organized data. It does, however, also recognize the drawbacks of survey methods, including response bias and the possibility of false self-reporting. All things considered, the information offers a strong basis for comprehending the status of sentiment analysis research today and its possible uses for assessing customer satisfaction.

Limitations and drawbacks of the surveyed procedures mentioned above:

Sentiment analysis is a method for figuring out the emotional tenor of text data, and it's frequently used in social media to gauge user satisfaction. It can identify distinct emotions, urgency, and goals in addition to polarity. Sentiment analysis comes in different flavors: aspect-based, multilingual, and emotion detection. Benefits include real-time problem identification, effective processing of massive volumes of data, and customization of goods and services to meet the demands of clients. Nevertheless, drawbacks include the possibility of linguistic ambiguity, algorithmic bias, and the requirement for modification to satisfy particular business requirements. Sentiment analysis offers a more thorough and fast evaluation of consumer satisfaction than traditional survey methods, but it also has trouble catching subtle differences.

III. PROPOSED WORK

Gathering and evaluating consumer thoughts, sentiments, and attitudes toward a company or its products from a variety of sources, including social media, online reviews, surveys, and direct feedback, is one of the components of a proposed system for evaluating the impact of sentiment analysis on social media to gauge customer satisfaction. Text analytics, machine learning techniques, and natural language processing (NLP) are used to extract meaningful patterns and trends from massive datasets, identify sentiment, and comprehend and interpret human language. Tweet sentiment analysis has been done using a variety of methods. We have employed the feature vector approach in our research.
The complete suggested system architecture is depicted in the accompanying Figure.

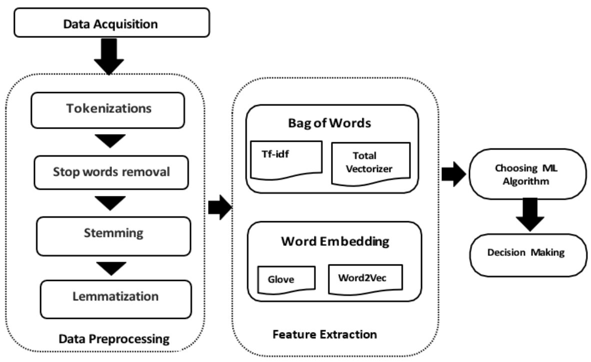

Figure 1: CSA process diagram

The suggested system is in different stages of development. Movie reviews posted on Twitter are used to construct a data set. As is well known, misspellings and slang are common in tweets. Thus, we conduct sentiment analysis on tweets at the sentence level. There are three stages to this. Pre-processing is completed in step one. Next, pertinent features are used to generate a feature vector. Ultimately, tweets are categorized into good, negative, and neutral classes using various classifiers.

A) Input Data:

As noted by Feldman (2013), a corpus of documents in various formats, such as the following, can be the input of a SA system.

• PDF: a file format that includes all of the information about the document (text, fonts, and graphics);
• TXT: a plain text format. In this sense, neither the operating system nor the program can affect how the document is presented;
• HTML: a markup language that is often used by web browsers and web applications to compose and interpret text and other content;
• XML, or extensible markup language, is a text format that is hierarchical. Tags that enable annotation of the document in a syntactically discernible manner from the text contain the text;

• JSON: a data format frequently used for asynchronous browser-server communication;
• Microsoft Word: available in both doc and docx formats;
• Comma-separated values: a file format frequently used for tabular storage in plain text format.

B) Data Pre-processing:

During text analysis, many words have no effect on the sentiment orientation of the text. Since each word in the text is viewed as one dimension, words like 'what', 'how', and 'when', for instance, do not contribute to the polarity of the text and can be eliminated to lower the problem's dimensionality. Moreover, messages are in raw form and typically contain a lot of noise as well as incomplete or inconsistent data portions, especially when they originate from online social networks. As a result, the process of cleaning and preparing the text for classification — known as data preprocessing becomes essential. Preprocessing in SA is comparable to text mining's conventional preprocessing. Typical text mining preprocessing procedures consist of:
• Stemming, which breaks down words into their common root, or stem;
• Lemmatization, a stemming-related technique that groups together a word's various inflected forms, such as walk, walking, walked, so they can be analysed as a single item;
• Tokenization, which divides a text stream into smaller elements called tokens (tokens are typically composed of words);
• Negation handling; this involves eliminating terms such as determiners like the, a, an, and another, coordinating conjunctions like for, an, nor, but, or, yet, so, and prepositions like in, under, toward, and before.
Preprocessing necessitates additional steps if input data originates from social networks (SNs). These steps include online text cleaning (such as eliminating URLs, HTML tags, or the Retweets tag [RT]), enlarging acronyms or abbreviations, managing or eliminating emoticons, and substituting or eliminating repeated characters like the "o" and the "p" and "y" in the words "coooooool" or "happyyyyyyyyyyyyyy" (Brody & Diakopoulos, 2011; Desai & Mehta, 2016; Go, Bhayani, & Huang, 2009; Haddi, Liu, & Shi, 2013).

C) Feature extraction:

The goal of this work is to extract features, like sentiment or opinion-expressing words, that best characterize the text's primary attributes.

<u>Models for text representation:</u>

The text must first be represented using the bag-of-words model (BOW) or vector space model (VSM), which are appropriate for mining methods.
Since every word is viewed as a feature by the BOW model, feature space has multiple dimensions equal to the number of distinct words (Feldman & Sanger, 2007).

Take into account the following sentences, for instance:
1. "Your iPhone may be old, but it's still in good condition."
2. "Why people want the iPhone 7 is beyond me."
3. "I'd like an iPhone 7,"

The BOW model first generates a list of every unique word that appears in each of the three phrases, eliminating any repetitions; this list is provided in Table 1 as list W. With three vectors of occurrences, S.1, S.2, and S.3, respectively, we may record the term occurrences of all the distinct terms in the three prior sentences from this list, as Table 1 illustrates.
This model is frequently employed due to its ease of use in the categorization process, however, it has the drawback of erasing the text's syntactic information. The statements, "Awww your iPhone is old, but it is not so bad," and "Awww your iphone7 is bad, but it is not so old," should be taken into consideration. In the BOW model, they are represented by the same vector of occurrences, despite the fact that it is obvious that they have different syntax, meanings, and opinions.
The vector space model reduces the document to a string while maintaining the word order (Žzka, 2015).
The most common characteristics of SA are outlined and described in the paragraph that follows.
N-grams are a collection of n contiguous items—in this case, words—that are taken out of the BOW model. Every feature has an associated set of n words, where each word has a value of true while the feature is present and false otherwise. Bi-grams, in which n = 2, or a collection of bigrams and unigrams are frequently used N-grams (Go et al., 2009; Spencer & Uchyigit, 2012). As an illustration, the following unigrams, bigrams, trigrams, and 4-grams are found in "The most general features in SA":

- Unigrams: the broadest characteristics in sentiment analysis.
- Bigrams: the most common, all-encompassing, sentiment-related features in SA.
- The most general features, most general features in, sentimental features in, and features in SA are represented by trigrams.
- The most general features, sentimental features in, and features in SA are represented by fourgrams.

Annotating a term in a text (or corpus) to denote a specific speech segment is known as part-of-speech tagging. The phrase "I want Iphone7," for instance, is marked as follows: I (pronoun P), want (verb VB), and Iphone7 (noun PP).
Negations: Since words like "not" and "never" are frequently found in lists of stop words, they are excluded from text analysis. However, this approach ignores the possibility that negation can flip the sentiment polarity. Researchers from SA have attempted to incorporate negations into the feature vector because polarity classification heavily relies on them. Beginning with negated words, authors in work (Das & Chen, 2007) add a new feature by attaching NOT- to the terms.

D) Features selection techniques:

These techniques can be understood as combining a measure that selects pertinent features with an individual search process to identify new feature subsets. Lexicon-based approaches and the most popular statistical methods are examples of features selection techniques (Medhat et al., 2014). Lexicon-based methods often start by adding only terms that express strong sentiment to the feature set. Next, by using internet resources or synonym detection, this set is expanded. SentiWordNet, a well-known lexicon that is an extension of WordNet (http://wordnet.princeton.edu/), is one example.
Statistical techniques fall into four categories and are entirely automatic:

- Frequency-based selection: Removing words that don't frequently occur in the corpus is a standard technique to reduce the dimension of a text. The percentage of a document where a characteristic appears is called its frequency. Phrase frequency typically highlights documents that also happen to employ a frequent phrase when it is present, which is why tf-idf—or "term frequency-inverse document frequency"—was developed as a new statistical measure. Let's say we want to add a word to the corpus. The increase in its tf-idf is inversely proportional to the frequency of that word and directly relates to how many times it appears in the document. As a result, when a phrase occurs frequently in a document and its rate is high, the document's tf-idf weight is high. However, because words that appear only once in a particular corpus are high-precision markers of subjectivity, frequency-based selection may eliminate words that are helpful for categorization (Mejova & Srinivasan, 2011; Wiebe, Wilson, Bruce, Bell, & Martin, 2004).

- Point-wise mutual information: Mutual information in probability considers the interdependence of two variables. A method for evaluating the significance of feature subsets with regard to the prediction problem is the Mutual Information criteria. Suppose x represents a word (in this example, words represent features) and y represents a class (i.e., y is a target variable for classification; in this context, y can be the polarity of a sentence).The degree of co-occurrence between the class y and terms x is taken into consideration while defining "pointwise mutual information" (PMI). Specifically, PMI is described as:

  where p(x|y) denotes the conditioned probability of x given y and p (x, y) denotes the likelihood of x and y occurring together. According to Bouma (2009), the difference between the expected and actual probabilities of a specific co-occurrence of events, p (x, y), is measured by the PMI.

  The word "x" and the class "y" are positively correlated if the PMI score is greater than 0. If they are perfectly correlated, that is, p(x|y) = 1, then an upper bound is determined; in fact, PMI (x, y) = −log p(x), which is positive since log(x) is negative for $x \in (0, 1)$. Conversely, if there is a negative correlation between x and y, the PMI score is be less than 0. Specifically, if p(x|y) = 0, then PMI $\rightarrow -\infty$.

  It should be mentioned that by defining, for instance (Turney, 2002), PMI can be utilized to ascertain the unknown polarity of a word wi that is positively linked with another word wj with known polarity.

  Polarity(wi) is equal to PMI (wi{excellent}) – PMI (wi, {poor}).

Mutual selection based on point-wise mutual information has a flaw in that scores are not comparable when terms have significantly different frequencies since the marginal probability of each term affects the score.

- Knowledge acquisition. It illustrates how information is obtained for class prediction of an arbitrary text document based on the presence or absence of a feature.
- Ratio of gain. Smaller sets of features are gradually chosen in an iterative manner. The iterations end when a certain number of features are left. Information gain is enhanced by gain ratio.

E) A machine learning-based approach

As previously mentioned, supervised and unsupervised techniques can be used to categorize machine learning techniques. A supervised learning-based system seeks to develop a model that can approximate the intended outcomes for all of the supplied unlabelled instances and can generate the results supplied during the training phase. Classification and regression algorithms are the two types of supervised learning algorithms (Batrinca & Treleaven, 2015).

Decision tree classifiers, rule-based classifiers, probabilistic classifiers (Naive Bayes, Bayesian network, maximum entropy), and linear classifiers (SVMs, neural networks) are a few examples of classification techniques. Deep learning (DL) techniques have recently been tested to enhance sentiment categorization for SA tasks. The papers (Tang, Qin, & Liu, 2015) and (Zhang, Wang, & Liu, 2018) provide a thorough and in-depth summary of DL approaches used for sentiment detection.

One of the earliest works to employ machine learning classification methods to ascertain sentiment at the document-level as opposed to the topic-level was that of Pang, Lee, and Vaithyanathan (2002). Using a dataset of movie reviews, the authors trained and evaluated three machine learning algorithms: Naive Bayes, maximum entropy classification, and support vector machines. The results indicate that while the relative performances of the three methods are not very different, the SVM typically outperforms the others, and unigrams outperform all other features taken into consideration. As previously mentioned, this study also notes that topic-level sentiment classification outperforms document-level sentiment classification in terms of accuracy.

Boiy and Moens (2009) provide another example of sentiment classification of a product review using supervised algorithms. The author specifically sought to identify topic-level positive, negative, and neutral polarity in web pages including blogs, forums, and product reviews written in English, Dutch, and French. SVM, maximum entropy, multimodal Naive Bayes classifiers, and even other features were taken into consideration in this study. However, in this instance, the models were aggregating following a cascaded architecture made up of three layers. An 83% accuracy was obtained for English texts using Unigrams with linguistic parameters unique to each language and a maximum entropy classifier; for Dutch and French texts, the accuracy was 70 and 60%, respectively, outperforming SVM and multinomial Naive Bayes.

The authors of Sharma and Kaur (2015) provide a method for predicting personality from Twitter that is based on a logistic regression classifier.

Regression techniques are typically applied in cases when the target attribute is ordinal or continuous rather than nominal. For score polarity detection tasks (Drake, Ringger, & Ventura, 2008) or to calculate confidence scores (Ertugrul, Onal, & Acarturk, 2017; Onal, Ertugrul, & Cakici, 2014), regression applications are thus found in SA.

Labelled data is necessary for supervised algorithms to construct a classification model. These data are hard to get by for messages sent over the Internet, though. The application of unsupervised or semi-supervised techniques has been suggested by several researchers. A semi supervised tweet SA method is developed by da Silva, Coletta, Hruschka, and Hruschka (2016), and it is based on the C3E algorithm (consensus between classification and clustering ensembles).

Unsupervised learning is a machine learning approach in which the computer system is first given certain unlabelled inputs, which are then categorized and arranged according to the recognition of standard features. In contrast to supervised learning, the classes need to be automatically learned because they are not known beforehand. Unsupervised learning algorithms fall into two categories: association and clustering.

The goal of clustering is to divide the data into meaningful classes or groups (clusters) where each member has a set of recurring traits. The groups are unknown a priori, unlike in the classification, and as the method relies on unsupervised learning, the user does not supply any samples of previously categorized data. Techniques for cluster analysis can be separated into partitional and hierarchical clustering. While partitional clustering separates the data into nonoverlapping sections, hierarchical clustering seeks to produce a hierarchical decomposition of a dataset. For SA, the latter is more suitable and beneficial. One common approach for clustering is K-means. The authors of Li and Liu (2012, 2014) demonstrate the efficacy of the clustering-based method in SA.

Association learning is a type of rule-based machine learning technique where links and dependencies between particular data properties are examined. Rule-based techniques have been used primarily in SA's product extraction process to enhance the review polarity categorization, as demonstrated by Yang and Shih (2012).

IV. SENTIMENTAL ANALYSIS TOOLS

Numerous SA tools have been developed and put forth. Among those sponsored by commercial initiatives and university research, we selected 24 primary instruments for comparative study. These assessments were carried out throughout the years 2015–2017. All of the tools that were taken into consideration, with the exception of the Opinion Finder tool, were offered as software as services. As a result, all that was needed to test the functionality that the tool enabled was a system registration when necessary. It should be mentioned that the tests were run using trial versions in the case of non-free tools and full versions of those that were.

In order to distinguish the class of generic tools (GT) from the SNs tools class and to identify the accessible tools from the unavailable tools, a preliminary test was conducted. Subsequent to this initial segmentation, diverse experimental batteries were conducted based on the distinct tool typologies under analysis. The tests were carried out step-by-step for the generic tool class. The first test battery involved the analysis of brief texts with strong positive or negative polarities, as well as factual words like "You hate me," "The movie was beautiful," and "Yesterday I went shopping." A multilingual system would translate and analyze the same sentence in multiple languages. The best classification results are obtained for all the tools when the input texts are in English.

Texts with greater articulation were loaded into a second test battery. It was decided that comparing the outcomes of this second test battery would be inappropriate due to the variety of the GT class's functionality and licenses.

In reference to the test battery for the SN tool group, searches were conducted using user or hashtag names. These searches included public profiles such as those of Donald Trump and Hillary Clinton, the 2016 US presidential candidates, or news events such as the use of the hashtags #PrayForBelgium on Twitter in reference to the attacks in Belgium in 2016 or #euro2016 in reference to the UEFA European soccer championships.

It is important to note that Cogito and Alchemy API may interface with data from Social Networks in addition to having generic tool features. The two tools were part of the SN tools group to demonstrate the potential for analyzing data retrieved from social networks, although all three of the above-described test batteries were run on these two.

Every test was conducted to assess the primary features of every tool, such as the availability of the application program interface (API), the type of input required, the license to use, and the presentation of the results.

V. EVALUATION CRITERIA

For the purpose of evaluating SA tools, four primary criteria or analytical aspects have been determined. These are arranged as follows:

a) Technology: this covers the product's accessibility, supported operating systems, if the tool is offered as software as a service, and whether the utility features a command-line interface or an intuitive user interface.
b) Interoperability, which covers the availability of APIs and the programming languages in which they can be used;
c) Visualization: if data is presented visually, consider how user-friendly and rich the visualization is, as well as whether the system displays several kinds of graphs;
d) Analysis: this covers the kind of data that must be entered, the data that is retrieved as an output, the degree of analysis, and the kind of analysis that is done. The languages that the various tools offer for analysis (e.g., English, French, Spanish, Italian, etc.) is another crucial feature that should be noted.

Specifically, the following were assessed in relation to the tool's analysis type evaluation: the SA tasks it completed, the depth of analysis it reached, the languages it supported, the scalability of the model, and so on.

Each tool, as would be expected, includes a polarity detection task. This task can be described as positive/negative, positive/negative, or neutral, and it can also be used with or without a numerical score within a predefined range or graphical interpretation.

The studied tools in the Appendix are separated into two subsections: a collection of tools that perform SA of data that is not directly obtained from social networks is included in the second subsection, while some tools in the first one offer a link or working on data extracted from social networks. The tools are discussed for each of the previous assessment criteria in alphabetical order within each subsection.

A) Technology aspects:

The features of 24 SA tools' technologies are compiled in Tables 3 and 4. The tool's name, URL, and any related references are contained in the first column labeled "Tools" in both tables. The type of license that is offered is shown in the "License" column: "demo," "free tool," "pay," or registration. It also specifies whether or not the tool was operational (✒) at the time the table was compiled. The user-friendliness of a tool is reflected in the "user-friendliness" column. According to Tables 3 and 4, most tools offer a demo version or a license-free version that is more limited than the full version but nevertheless customizable and chargeable. Furthermore, as previously said, practically all of the tools are designed to resemble web services; they are easy to use and appropriate for intuitive operation, which for the most part doesn't even require programming knowledge.

TABLE 2 Summarization of the variables considered for each dimension

Dimension	Considered variables
Technology	Software availability, O.S., SaaS, User-friendliness, availability, license
Interoperability	API availability, presence of library for the most used program languages
Visualization	Polarity with colors, function plots, graph representations, pie charts, bar charts, tag clouds and geo-references' availability
Analysis	Input data and output data type, data extraction's availability, analysis level and analysis type, text's language and time slot analysis' availability

TABLE 3 Comparison of social networks tools with respect to the technology's features

Social networks tools			
Tool	License	Availability	User-friendliness
25Trends	Free	—	√
AlchemyAPI	Registration for demo/pay for full version	—	√
BuzzTalk	Free	√	√
Cogito	Demo version/pay for full version	√	√
Happy Grumpy	Free	√	√
OpinionCrawl	Free	√	√
Sentiment140	Log in with Twitter account	√	√
Social Mention	Free	√	√
TweetMood	Free	√	√
Uclassify	Demo/pay for full version	√	√

TABLE 4 Comparison of generic tools with respect to the technology's features

Generic tools			
Tool	License	Availability	User-friendliness
Lymbix	Registration for demo/pay for full version	—	√
Meaningcloud	Demo/free license version/pay for full version	√	√
Miopia	Free	√	√
Opendover	Demo/pay for full version	√	√
Opinion Finder	Free	√	—
Repustate	Registration for demo version/pay for full version	√	√
Semantria	Some test free/30 days free trial/pay for full version request for demo version	√	√
Sentigem	Free/registration request for API	√	√
SentimentAnalyzer	Free	—	√
Texsie	Free	√	√
Textmap	Free	√	—
Text-processing	Free-demo	—	—
TheySay	Free	√	√
Vivekn	Free	—	√

Abbreviation: API, application program interface.

B) Aspects of analysis

Regarding the analytical features, seven variables have been identified, as shown in Table 2. For each set of tools, the seven factors were broken down into two tables to help the reader understand how the tools were compared. Specifically, Tables 5 and 6 display the variables that are strongly linked to the different analysis jobs that the tool completes, and Tables 7 and 8 reveal the variables that are most directly related to data management.

Tables 5 and 6 specifically summarize the "analysis level," which is whether the tool performs the analysis tasks (e.g., polarity detection or emotion recognition) at sentence-level ("SL" in Tables 5 and 6) or document-level ("DL"), and if it recognizes polarity even in single words (in the table it is referred to as word level or "WL"); if the tool only performs sentiment analysis (SA) from social network data, or specifically from Twitter, they are referred to as "Social Network's Sentiment Analyzer" or "Twitter Sentiment Analyzer" ("SNs SA" and "TSA" respectively), and in this case an overall polarity for the extracted posts is indi-categorized, in which posts or tweets are considered altogether; TSA tools also produce a document level polarity, where each document consists of a single tweet, in addition to the overall polarity. When it comes to commercial instruments for which the methodology is unknown, a word level polarity is a definite sign of a lexicon-based approach. The SA tasks that the tool provides are indicated by the "analysis type" variable. As anticipated, every tool includes a polarity detection task (represented by PD), which can be expressed as either positive or negative values (represented as P/D) or as positive or negative/neutral values (represented as P/N/Ne), and it can be used with or without a numerical score within a predefined range or graphical interpretation.

The supported languages are listed in the "Language" column along with, if needed, some remarks regarding the function that each language performs. It should be noted that only the features associated with the tested versions have been mentioned in situations where a full version was not tested and more information was not available in the tool's documentation. Last but not least, Table 5 also includes the variable "time slot analysis," which, when accessible, provides details regarding the quantity of posts that the tool extracted and examined or the analysis's time window.

TABLE 5 Comparison of social networks tools with respect to analysis feature

Social networks tools				
Tool	Analysis level	Analysis type	Language	Time slot analysis
25Trends	TSA	PD (P/N/Ne)	Arabic, English, partially Spanish	No info
AlchemyAPI	DL/WL	PD (P/N/Ne/Mixed), SFE	English, French, Italian, German, Portuguese, Russian and Spanish	No info
BuzzTalk	SNs SA	PD (P/N/Ne) and ER	Posts are translated into English From 67 different languages. Analysis is done in English	Last 28 days
Cogito	WL/SL/SNs SA	PD (P/N), ER (80 emotions), SFE, Fact Detection.	For demo and API versions only English is supported	Last 20 tweets
Happy Grumpy	TSA	PD (P/N/Ne), and ER (Happy/Grumpy score)	Thai Russian Indonesian Turkish Korean Hindi German Arabic French Japanese Portuguese Chinese Italian Spanish	Last 15 days
OpinionCrawl	DL	PD (P/N/Ne) and topic detection	English, French, German, Spanish, better results with English	Three views (days weeks, months) are available
Sentiment140	TSA	Topic PD (P/N) and tweet PD (P/N/Ne)	English, Spanish	Last 50 tweets
Social Mention	SNs SA	PD (P/N/Ne) and Sentiment Measure (Strength, Sentiment, Passion, Reach)	Italian, English, Spanish, French, German	Six views are available: anytime, last hour, last 12 hr, last day, last week, last moth
TweetMood	TSA	PD (P/N/Ne) with percentage on the total Number of tweets, Popularity score, Comparative analysis among three terms, Tweets labeled examples	English	The data shown is until March 2013
Uclassify	DL	PD (P/N) with percentage, ER (Happy/Upset) with percentage; SFE	English	No information about

Abbreviations: AL, aspect level; API, application program interface; DL, document level; ER, emotion (or sentiment) recognition; PD, polarity detection; SD, subjectivity detection; SFE, semantic feature extraction; SL, sentence level; SNs SA, social networks' sentiment analyzer; TSA, Twitter sentiment analyzer; WL, word level.

TABLE 6 Comparison of generic tools with respect to analysis features

Generic Tools			
Tool	Analysis level	Analysis type	Language
Lymbix	DL	PD (P/N/Ne)with score, Dominant ER, Intensity level mood with score	Good results for English texts, with other language good only language detection
Meaningcloud	DL/WL	PD (P/N/Ne), SD, SFE, Irony detection	Spanish, English, French, Portuguese and Italian
Miopia	WL/SL	PD(P/N/Ne)	Italian, English, Spanish, French, German, Indonesian, Portuguese
Opendover	DL/WL	PD (P/N) and Attitude detection	English
Opinion Finder	DL	PD (StrongN/WeakN/Ne/WeakP/StrongP) and SD	English
Repustate	DL	PD (P/N), ER, SFE	Arabic, Chinese, English, German, French, Italian, Russian and Spanish
Semantria	DL/WL/AL	PD (P/N/Ne) and Intention Extraction	Arabic, Danish, Dutch, English, French, German, Hebrew, Indonesian, Italian, Japanese, Korean, Malay, Mandarin, Norwegian, Polish, Portuguese, Russian, Spanish, Singlish, Swedish, Turkish
Sentigem	DL/SL	PD (P/N/Ne)	English
SentimentAnalyzer	DL	PD (P/N/Ne)	English, German, French
Texsie	DL/SL/WL	PD in range [-10 a 10], (Very N/N/Ne/P/Very P)	English
Textmap	WL	PD (P/N) and SD	English
Text-processing	DL	PD (P/N) both in range [0,1] and SD	English Dutch French
TheySay	DL/SL/WL	PD (P/N/Ne) with percentage and confidence level up to 1 ER, SFE	English
Vivekn	DL	PD(P/N/Ne)	English

Abbreviations: AL, aspect level; DL, document level; ER, emotion (or sentiment) recognition; PD, polarity detection; SD, subjectivity detection; SFE, semantic feature extraction; SL, sentence level; WL, word level.

Tables 7 and 8 are first compared the "data entering," which indicates the type of input required by the tool, then the "data output," reporting known information about the output of the analysis and finally, the column "data export," provides information about the possibility of exporting analysis results.

TABLE 7 Comparison of generic tools with respect to analysis features more related to data management

Social networks tools			
Tool	Data entering	Data output	Data export
25Trends	Text loading	Web page	No data export
AlchemyAPI	URL/text/text file loading	Web page	In json visualization format it is possible to copy the file json
BuzzTalk	Text/keyword loading	Web page	No data export for Demo version
Cogito	Text/URL loading	Web page	No data export, available UTF-8, JSON or XML format
Happy Grumpy	Twitter account, hashtag loading	Web page	csv file
OpinionCrawl	Keyword loading	Web page	No data export
Sentiment140	keyword, account, or hashtag loading	Web page	No data export
Social Mention	Text/keyword loading	Web page	csv file
TweetMood	Text loading	Web page	No data export
Uclassify	Text/URL loading	Web page	No data export

TABLE 8 Comparison of generic tools with respect to analysis features more related to data management

Generic tools			
Tool	Data entering	Data output	Data export
Lymbix	Text loading	Web page	Response body
MeaningCloud	Text loading	Web page	json, excel
Miopia	Text loading	Web page	No information about
Opendover	Text loading	Web page	rdf
Opinion Finder	File txt loading	txt file	txt
Repustate	Text loading on a file xls available in the site	Web page	Excel file
Semantria	Text, file xls, blog's URL loading	Web page	json, excel
Sentigem	Text loading	Web page	Using API Json response format
Texsie	Text/keyword loading	Web page	No information about
Textmap	Keywords loading	Web page	No information about
Text-processing	Text loading (up to 50,000 characters)	Web page	No information about
TheySay	Text loading	Web page	No information about
Vivekn	Text loading	Web page	No data export

Abbreviation: API, application program interface.

As seen again in Tables 5 and 6, three significant variables that are part of the analytical dimension are:

• the quantity of languages that are supported (Tables 5 and 6 show this data).

• the level of detail in the polarity detection task; • the level of detail in the emotion detection task when the tool completes it;

The subsequent figures showcase all the tools categorized under SNs tools and GT with respect to:

• the division between P/N Polarity Detection and P/N/Ne Polarity Detection (Figure 3); • the number of supported languages (Figure 2);

It's important to highlight that HappyGrumpy is the richest SN tool in terms of supported languages, while Semantria is the richest language generic tool with the greatest number of supported languages. Furthermore, only one language is supported by 9 (of 13) general tools and 5 (of 10) SNs tools.

Eighteen out of the twenty-four instruments offer three-class polarity identification, as shown in Figures 3. It should be noted, nonetheless, that the studies revealed that the tools—aside from Opinion Finder—cannot tell the difference between objective material and writing with a neutral polarity.

Out of the 24 tools under consideration, only 7 (Happy Grumpy, Uclassify, Social Mention, Alchemy API, Lymbix, TheySay, and Cogito) offer an emotion recognition task. In terms of the quantity of recognized emotions, Cogito is the most comprehensive tool. Appendix A contains a thorough explanation of the emotion recognition granularity for every instrument under consideration.

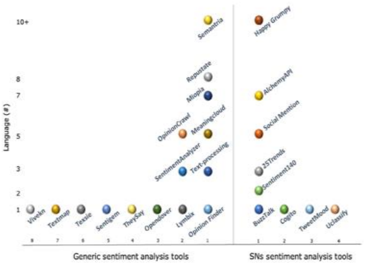

FIGURE 2 Comparison of generic tools and social networks tools w.r.t. the number of supported text languages for the analysis

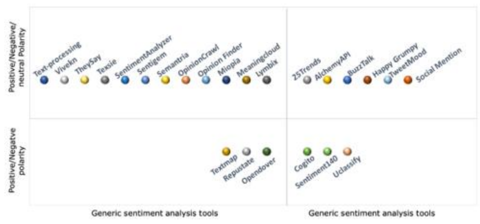

FIGURE 3 Comparison of generic tools and social networks tools w.r.t. the granularity of polarity recognition task

C) Aspects of interoperability

The availability of clients and APIs for the most widely used programming languages is taken into consideration while determining compatibility. The information gathered is shown in Tables 9 and 10.

TABLE 9 Comparison of social networks tools with respect to interoperability

Social network tools	
Tool	API language
25Trends	POST or GET methods can be used
AlchemyAPI	HTTP calls, PYTHON, PHP, RUBY, NODE.JS. Client java available
BuzzTalk	—
Cogito	REST API HTTPS based
Happy Grumpy	Not available
OpinionCrawl	The APIs are provided as a Service. The API supports SOAP and REST protocols (HTTP GET or POST)
Sentiment140	The API are provided as a service (REST calls with HTTP protocol)
Social Mention	REST calls with response in JSON, PHP, and XML formats
TweetMood	Not available
Uclassify	REST calls with HTTP protocol, or JSON, or XML. Libraries for Java, PHP, Ruby, Python

Abbreviation: API, application program interface.

TABLE 10 Comparison of tools on interoperability

Generic tools	
Tool	API language
Lymbix	Since Lymbix is designed for integration with third party applications
Meaningcloud	Ruby, PHP, .NET, JavaScript, Java and Python, C, C#, Node.js, Shell
Miopia	The APIs are provided as a service. A client is available in Python
Opendover	The API is made available by a web service accessible using SOAP or RESTful protocols witch results are made available as JSON and XML format
Opinion Finder	Not available
Repustate	RESTful API. Client are released in: PHYTHON, RUBY, GO, JAVA, C#, PHP
Semantria	The APIs are provided as a service. Client availability for: Java, javascript, .NET, PHP, Python, Ruby, e node.js
Sentigem	HTTP and HTTPS calls
SentimentAnalyzer	Not available
Texsie	The APIs are provided as a service
Textmap	API provided as a service
Text-processing	API provided as a service. REST calls with HTTP protocol. Available client for java, ruby, python, php, and objective-c
TheySay	REST calls with HTTP protocol. Client for Java, Scala, Python, Ruby, Node.js, R and PHP
Vivekn	REST calls with HTTP protocol, JSON response

Abbreviation: API, application program interface.

D) Features of the user interface

Regarding the user interface dimension, consideration has been given to the visual presentation of the knowledge collected from the text for each tool. In this situation, having a clear first picture of the analysis and, in certain situations, being able to recognize some of the unexpected elements that the system has deemed relevant for the study are made feasible by well-presented data. Figure 4 and Tables 11 and 12 illustrate the usage of colors for each instrument.

If some plotting functions, bar charts, pie charts, and tag clouds are used to depict the features taken into consideration in the analysis, then it draws attention to the polarity in the text. Specifically, it was discovered that several SN tools used a word cloud to display analysis results among the previously described visual representations. Basically, an info-graphic technique called a tag cloud shows the user a weighted representation of the words (or tags) in a piece of Web text. The similarity, frequency, and relevance of a word in the text in relation to the other terms is indicated by its color, font size, and position in a tag cloud. A word cloud is used in the context of SA to display the entities or elements that have been taken out of the text. In a generic word cloud, word polarity can be represented by color, while frequency is shown by font size. An important point to note is that the map, which is unique to Cogito given the tools and versions examined in this study, geo-references the data derived from the analysis.

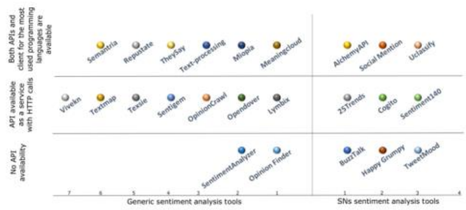

FIGURE 4 Comparison of generic tools and social networks tools w.r.t. application program interfaces availability

TABLE 11 Comparison of social networks tools with respect to interface

Social networks tools							
Tool	Polarity color	Function plot	Graph Repr.	Pie chart	Bar chart	Tag cloud	Georef.
25trends	√	—	—	√	√	√	—
AlchemyAPI	√	—	—	—	—	—	—
BuzzTalk	—	√	—	—	—	√	—
Cogito	—	—	—	—	—	—	√
Happy Grumpy	—	√	—	√	—	—	—
OpinionCrawl	√	—	—	√	—	√	—
Sentiment140	√	—	—	√	√	—	—
SocialMention	—	—	—	—	√	—	—
TweetMood	√	√	√	√	√	—	—
Uclassify	—	—	—	—	√	—	—

VI. LITERATUE SURVEYS COMPARISON

One of the fields of study that is expanding the fastest is SA. It can be challenging to keep track of all the suggested ways and all the research initiatives due to the high volume of published SA articles each year. For this reason, a number of surveys and literature reviews have been published recently to give an overview of various SA research subjects. An overview of these surveys is intended to highlight the ways in which they differ from the current work in this section.

33 sentiment analysis reviews were taken into consideration, and they were categorized using the following four macro categories: tool's classification (TC) review, domain-oriented (DO) sentiment analysis review, specific task or specific technology oriented (STO) sentiment analysis review, and general sentiment analysis review (GSA). The 33 works are summarized in Table 13.

Within the larger GSA category, the majority of the surveys under consideration seek to provide a general overview of the key duties, important difficulties, and SA approaches. The generic sentiment analysis over-view (GSA-O) review, which compares some existing works generally grouped by tasks or approaches, and the generic sentiment analysis comparative (GSA-C) review, which delves deeper into the algorithms, approaches, or tasks, were further separated from the GSA class. The GSA-O review aims to provide a critical picture of the SA framework.

TABLE 12 Comparison of generic tools with respect to interface

Generic tools							
Tool	Polarity color	Function plot	Graph Repr.	Pie chart	Bar chart	Tag cloud	Georef.
Lymbix	—	—	—	—	—	—	—
MeaningCloud	√	—	—	—	—	—	—
Miopia	√	—	√	—	—	—	—
Opendover	√	—	—	—	—	—	—
OpinionFinder	—	—	—	—	—	—	—
Repustate	—	—	—	—	—	—	—
Semantria	√	—	—	—	—	—	—
Sentigem	√	—	—	—	—	—	—
SentimentAnalyzer	√	√	—	—	—	—	—
Texsie	—	—	—	—	—	—	—
Textmap	—	√	√	—	—	—	—
Text-processing	√	—	—	—	—	—	—
TheySay	√	—	—	—	—	—	—
Vivekn	–	—	—	—	—	—	—

TABLE 13 Comparison of main sentiment analysis surveys published between 2008 and 2018

Survey reference	Social media data analysis	Classification	Main focus
2008			
Pang, Lee, et al. (2008)	—	GSA-S	Basic tasks and approaches of SA
2012			
Korayem, Crandall, and Abdul-Mageed (2012)	—	DO	SA techniques for Arabic language
Li and Liu (2012)	—	GSA-S	
2013			
Cambria, Schuller, Xia, and Havasi (2013)	✓	STO	An introduction to multimodal SA
Feldman (2013)	✓	GSA-O	SA techniques applications and challenges
Routray, Swain, and Mishra (2013)	✓	GSA-O	present SA tools without giving detailed informations
2014			
Abbasi, Hassan, and Dhar (2014)	✓	TC	Tool's benchmarking
Medhat et al. (2014)	—	GSA-S	SA main task/approaches classification
2015			
Batrinca and Treleaven (2015)	✓	DO	Social media analytics and SA represents a particular case study
Patel, Prabhu, and Bhowmick (2015)	—	GSA-O	SA tasks, approaches, algorithm overview
Ravi and Ravi (2015)	✓	GSA-S	Comparative review of Tasks, approaches and applications
Serrano-Guerrero et al. (2015)	—	TC+GSA	Free access Web services SA tools comparison
Thakkar and Patel (2015)	✓	DO	SA basic approaches for Twitter domain
2016			
Balazs and Velásquez (2016)	✓	STO	Information data fusion techniques
Chopra and Bhatia (2016)	—	GSA-O	Basic SA approaches
Devika, Sunitha, and Ganesh (2016)		GSA-O	Comparative review of Basic SA approaches
Giachanou and Crestani (2016)	✓	DO	Main approaches for SA in Twitter
Hussein (2016)	—	GSA-S	SA challenges
Mntyl, Graziotin, and Kuutila (2016)	—	GSA-S	Use bibliometric tools to carry a SA literature review
Pradhan, Vala, and Balani (2016)	—	GSA-O	Basic SA approaches
Sharef, Zin, and Nadali (2016)	✓	DO-STO	SA techniques in a Big Data framework
2017			
Abirami and Gayathri (2017)		GSA-S	Basic SA approaches
Chaudhari and Chandankhede (2017)	—	STO	Sarcasm Detection Task
Lo, Cambria, Chiong, and Cornforth (2017)	✓	GSA-S	SA challenges
Rajamohana, Umamaheswari, Dharani, and Vedackshya (2017)	—	STO	Opinion Spam detection
Save and Shekokar (2017)	—	STO	Domain adaption SA techniques
Soleymani et al. (2017)	✓	STO	Multimodal SA
Yadollahi, Shahraki, and Zaiane (2017)	—	STO	Emotion mining
2018			
Chaturvedi, Cambria, Welsch, and Herrera (2018)		STO	Subjectivity detection

Abbreviations: DO, domain-oriented; GSA, general sentiment analysis; SA, sentiment analysis; STO, specific technology oriented; TC, tool's classification.

Mntyl et al. (2016) conducted a quantitative research of SA articles using typical bibliometric study tools in conjunction with text mining and clustering techniques. The authors of this review demonstrated that there were over 7,000 SA publications, nearly all of which were released after 2004. These findings attest to the fact that SA is a popular subject in many different disciplines of study and represents one of those where research is expanding at a quicker rate. Once more, Mntyl et al. (2016) demonstrates that four of the top 20 publications cited on Google Scholar and Scopus are reviews of previous research. Pang and Lee's (2008) survey were found to be the most referenced article on both Google Scholar and Scopus.

The survey conducted by Medhat et al. (2014) reports the primary advancements in SA applications and algorithms based on a review of 54 articles that were published between 2010 and 2013. The authors categorize applications of GSA into five classes: sentiment classification, feature selection, emotion detection, constructing resources (such as dictionaries or annotated lexica corpora), and transfer learning (also known as domain adaptation). A classification of the 54 studies based on the central SA addressed the problem is given, and each of the primary approaches are examined.

A comprehensive literature review encompassing over 160 papers is presented by Ravi and Ravi (2015). The review comprises seven main dimensions, five of which delineate distinct SA tasks, and additional subcategories that are dedicated to distinguishing further reviewed articles based on subtasks, approaches, techniques, or applications.

Over the past few years, using deep learning techniques to perform SA has become a standard procedure. A survey of over 100 works pertaining to deep learning applications in SA was proposed by Zhang et al. (2018). Beginning with an introduction of neural networks, the basic designs of deep learning were introduced. Specifically, autoencoder, convolutional, long short-term memory, recurrent (with and without attention mechanisms), and recursive neural networks are highlighted. Subsequently, a thorough literature review of deep learning techniques applied to sentiment analysis is conducted. This review includes an overview of multiple papers that have been chosen as the most representative works related to various sentiment analysis tasks, such as sentiment analysis with word embedding, multimodal and multilingual SA, document, sentence, and aspect level classification, aspect extraction and categorization, opinion expression and extraction, opinion holder extraction, and SA with word embedding.

Few publications discuss and examine the web services tools that are currently available for SA. Just four out of the 33 reviews papers that were taken into consideration mentioned at least one SA tool. The most frequently cited review, specifically, is (Feldman, 2013). The essay makes two contributions: first, it presents a generic architecture of a SA system; second, it outlines research difficulties related to SA, including sentiment lexicon acquisition and comparative SA as well as SA at the document, phrase, and aspect levels. The associated methodology and open challenges for each review paper are mentioned below. Furthermore, a sample SA tool is provided for every SA domain that is highly pertinent.

The Routray et al. (2013) study addresses GSA applications, primarily in relation to opinion spam detection, market research, and product reviews. It also gives a succinct overview of ten SA tools, some computational approaches, and assessment measures.

Abbasi et al. (2014) conducted a benchmarking analysis on Twitter data using 20 different tools that perform SA. Using Amazon Mechanical Turk's crowdsourcing service, the tool performances were assessed and contrasted across five topics: retail consumer goods, technology, security, pharmaceuticals, and telecommunications. In order to examine the relationship between topic and performance, the accuracy attained on the datasets of the five domains was reported for each instrument under consideration. In addition, a hierarchical taxonomy of the most often erroneous tweets was produced, along with an error analysis.

To the best of our knowledge, Serrano-Guerrero et al.'s (2015) paper is the most current systematic review that makes use of SA tools. In this research, 15 free SA tools that are accessible as online services are compared, and their SA classification abilities on three distinct datasets are examined. The following comparative review discusses nine out of the fifteen tools that were taken into consideration in the cited work, although it focuses on the analytic capabilities of particular tools differently. Furthermore, the major goal of our work is to identify the key distinctions between SA techniques used in the general domain and those employed specifically in the monitoring of social networks and social media. It has been suggested that the current work is an expansion of the previous two research described. To be more precise, the work takes into account several elements of the functions of the upgraded tools. For instance, as far as we are aware, no research has compared the tools in relation to any other emotion classification task than polarity detection.

VII. CONCLUSION

Because of its many uses, sentiment analysis is a significant field in natural language processing (NLP). The first attempts at sentiment analysis used conventional machine learning methods, preprocessing the text to eliminate stop words, normalize it, and express it using features based on frequency, like bag of words or TF-IDF. After being cleaned, the text was sent into machine learning algorithms for categorization, like SVM and naive Bayes. However, as NLP has advanced, academics' attention has turned to deep learning methods. Text is initially encoded into pretrained word embeddings like GloVe, word2vec, or fastText in deep learning.

Deep learning models like CNN, LSTM, GRU, and others use these embeddings to extract patterns from the text. In order to enhance performance, several sentiment analysis systems also employ an ensemble method, merging predictions from various deep learning or machine learning models. The Internet Movie Database (IMDb), Twitter US Airline Sentiment, Sentiment140, and SemEval-2017 Task 4 datasets are a few often used sentiment analysis datasets.

More trustworthy language models are required as, in spite of sentiment analysis's advancements, caustic and badly organized texts can still fool current techniques. Furthermore, future research should concentrate on fine-grained sentiment analysis that incorporates classes with different emotional intensities, such as strongly positive, strongly positive, neutral, negative, and strongly negative. The majority of current sentiment analysis works categorize sentiments into coarse categories, such as positive, negative, and neutral. Another interesting field that could be applied to strategic decision making is sentiment quantification, which computes the polarity distribution of an issue.

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