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On Sentiment Summarization of Trending Topics on Twitter

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***Abstract:** Twitter is the most popular social media and microblogging application with over a hundred million followers, providing much knowledge about everyday life. Every minute, Twitter produces many instant messages (i.e., tweets) containing utilizers' feelings, behaviors, and viewpoints. Organizations are now using the data to gauge international perception or sentiment; This necessitates the utilize of automated summary strategies, which provide a good description of trending topics. These studies analyze the meaning of trending topics on Twitter, the data sets utilized to track them, and the benefits of tracking, analyzing, and summarizing trending topics. They also assess various methodology for sentiment classification, polarity identification, and sentiment summarization techniques.*

***Keywords:** Trend, hashtag, sentiment analysis, sentiment classification, trend dataset, opinion summarization techniques, abstractive summarization, extractive summarization.*

I. INTRODUCTION

Know that many varying ages depend on the Media to collect data, exchange news, and share memes. Technological progress has had a significant impact on social life, prompting all social, educational, and governmental figures and government agencies to establish accounts on various forms of social media to disseminate their thoughts and affect their supporters. Twitter has established itself as a massive forum for sharing ideas and arguments, with millions of customers 'tweeting' each moment, generating a constant stream of real-time data. Organizations are using this data to ascertain international perception or sentiment [1].

Numerous activities, such as political issues, athletics, and entertainment, occur daily across the world. It takes much time to become aware of all these insignificant incidents, even with the assistance of numerous news websites. We collect data from Twitter tweets in order to comprehend hashtags dealing with new events. Sentiment analysis has been used in several applications such as the analysis of Android permissions [2]. Sentiment analysis can be accomplished sequential or parallel [3] using several parallel techniques such as [4], [5], and [6]. According to [7], a hashtag is a term utilized to refer to details that depict a tweet. It consists of a string followed by the symbol '#', such as #FIFA. The assistance in locating 50 million tweets per day is critical for organizing data on Twitter. Hashtags are utilized for a variety of purposes. They can be utilized to group articles according to themes, feelings (for example, #hatred or #adore), or global events (for example, sports events or scandals) that people frequently address.

The trend sign (#) is utilized just before a Tweet-related word to help categorize it and make it more visible in Twitter searching. By pressing the keys on a hashtagged expression inside a post, you can view additional Tweets, including that hashtag. Hashtags can be utilized in any part of a Tweet. Trending topics are often hashtagged extremely popular terms.

The writers of [8] clarify that a subject gets famous if it is something that the community concerns about or has a power of influence on themselves. The trend is a subject that is widely attractive and continues to increase in popularity over the period. Usually, trends are sparked by future event or situation, headline news, and reoccurring problems. It is a trove of actual information; Which necessitates effective data mining to unearth secret patterns, trends, and viewpoints. We can utilize Twitter to poll the public.

The researchers of [9] discussed the significance of Twitter data processing, which is the subject of numerous latest research items in this area of analytics. A sentiment is characterized as an individual's viewpoint, behavior, or feeling towards anything. It is a demonstration or expression of emotion or sense—for instance, a feeling of pity, pleasure, or rage. Sentiment Analysis, alternatively referred to as opinion mining, is the method of identifying and extracting thoughts from content through the utilize of natural language processing, text analysis, and computational linguistics.

Without successful data reduction or summarization processes, customers are often confronted with a vast quantity of duplicated details, making it difficult to grasp the gist of the issues and, as a result, missing utilizeful data.

The massive volume of sentimental tweets necessitates automated summarization techniques that assist utilizers in acquiring certain viewpoints, as text analysis is utilizeful and essential in various applications. We anticipate that the feedback review would provide an overview of public sentiment against a particular individual. However, individuals may express their feedbacks about different facets or subjects of an organization.

II. SENTIMENT ANALYSIS

This survey offers an overview of sentiment analysis by studying and briefly discussing the algorithms implemented for sentiment classification on Twitter. Three stages include an aspect-based or feature-based opinion summarizer: aspect identification, sentiment predicting, and overview production. The objective of the aspect recognition process is to identify the critical topics presented in thoughts. The sentiment prediction process establishes the sentimental orientation (positively or negatively) of the first phase's discovered aspects. After this, overview production is the step in which the data that will be utilized in the overview is determined [10].

Sentiment analysis is a method for assessing and quantifying people's thoughts. Concentration on polarity recognition (positive, negative, or neutral). Twitter is a microblogging platform with a plethora of simple terms advertisements and customer networking applications. For instance, politicians may be interested in determining whether or not individuals adhere to their educational approaches in the current situation. It is critical to assemble feedbacks from social media platforms and conclude that the most influential perspective is just what people like or dislike. This review paper aims to examine the idea of Twitter sentiment summarizers.

The authors of [11] suggested sentiment analysis strategies based mostly on Machine Learning (ML) methodology they employed. Various techniques applied and exploited linguistic properties to well-known machine learning algorithms, including Support vector machine, Naive Bayes, Max Entropy, Boosted Trees, and Random Forests. Text classification techniques based on machine learning can be classified loosely into supervised and unsupervised learning approaches. When it is hard to find these labelled training documents , un supervised approaches can be utilized. There are several strategies for classifying text into different categories. Specific algorithms are utilized based on the type of data. Analyzing and comprehending when to utilize which algorithm is critical for improving the quality and accuracy of results [12].

The creators of [13] addressed the primary difficulty in distinguishing sentiment analysis from conventional topic-based classification, namely that, unlike keywords, sentiment can be articulated more precisely. Sentiment demands a higher level of comprehension than standard topic-based classification; it necessitates a greater grasp of sentence meaning. The present work employs two machine learning techniques: Naive Bayes Classifier and Supporting Machines (SVM). Machine learning methods produce more refined and accurate results than earlier techniques such as human-generated baseline methods. When comparing the results of both machine learning techniques, Support vector machines outperformed the Naive Bayes Classifier, even though it wasn't a significant difference.

The creators of [14] established a method for detecting sentiment polarity in Twitter data. The extracted features included n-grams and emoticons. The experiment showed that the SVM outperformed the Naive Bayes. The Support vector machine, in partnership with unigram feature extraction, produced the best overall performance, with a precision accuracy of 81% and a recall accuracy of 74%. The dataset for this study was compiled using tweets obtained from the online system Sentiment.

The authors of [12] agreed that the Random Forest classifier, when sentiment classification is utilized, has the dominant position due to its high accuracy and efficiency, ease of comprehension, and long-term progress in outcomes. As a result, the classifier is well-suited for situations such as sentiment analysis. However, it takes a significant amount of training time and computing power, the increased efficiency achieved by decision tree aggregation more than compensates for other shortcomings. Random Forest is also extremely well received from an implementation standpoint. Numerous libraries are accessible in programming languages such as Java, Python, and R, making them extremely simple to utilize.

In [15], the authors suggested a solution for the result analysis of Twitter data by using supervision, in which their training data included tweets with emojis that served as uproarious names, introducing a framework for classifying tweet sentiment. The concept was to collect reviews systematically. The sentiment issue was approached as a binary classification problem, with tweets categorized as either positively or negatively. Training data, which included emoji in tweets, were obtained using a supervisor-based strategy. Utilize the Twitter API to do this. A variety of classification models were utilized to identify tweets, including the NB, MaxEnt, and SVM. Numerous features such as unigrams, bigrams, unigrams with bigrams, and unigrams with POS were obtained. The MaxEnt classifier, when combined with unigram and bigram functionality, achieved the best performance, with an accuracy of 83%, comparable to the NB, which produced an accuracy of 82.7%.

The Lexicon-based Strategy is predicated on using a sentiment lexicon, which is a list of previously collected sentiment terms. It is classified into two approaches: dictionary-based and corpus-based, using the statistical or semantic technique to measure sentiment polarity. The hybrid Strategy blends the two and is extremely prevalent, with sentiment lexicons actively participating in most strategies.

The authors of [16] suggested an unsupervised document-based sentiment analysis method capable of determining word docs' sentiment orientation depending on their polarity. This method classifies documents as positively or negatively and separates sentiment words from groups of files, categorizing them according to their polarity. The study demonstrates a situation of opinion mining using documents.

This scheme, which also handles negation, makes utilize of the un supervised dictionary-based technique. WordNet is a lexicon utilized to define the terminology of thought and its associated terms and antonyms. In this particular study, film reviews were gathered to serve as input for determining the polarisation of documents. Each of them was categorized as positive, negative, or neutral, and the system provided summarized outcomes displaying the total number of positive, negative, and nonpartisan documents. Thus, the computer's summary report aided choice. The sentiment polarity of a document is determined using this method based on the plurality of viewpoint vocabulary items that exist in the text.

In [17], the researchers introduced a framework for combining lexicons and dictionaries and implemented a vocabulary-based approach to classify tweets as positive, negative, or impartial. This method differentiated and graded tweet slang. The research result shows that the proposed system outperformed current frameworks, achieving an efficiency of 92% for double characterization and 87% for the multi-class category. The system is necessary to improve the effectiveness of unfavourable events and to conduct nonpartisan case reviews.

Levels of sentiment analysis [18][11] have three main levels as follows:

1) Document Level Analysis: This level establishes if this whole report conveys a positive or negative message. For example, provided a report of a Samsung phone, the system decides if the review presents an overall favourable or negative feedback of the device. The text is limited to a single topic.
2) Sentence Level Analysis: This level analyses either sentence and determines whether it expresses a negative, positive, or neutral feedback. If the sentence expresses no view, it is considered neutral.
3) On an aspect-by-aspect basis (feature-based feedback mining and summarization). The aspect level focutilizes exclusively on the viewpoint itself rather than on language constructs (documents, paragraphs, sentences, clautilizes, or phrases). SA seeks to categorize sentiment concerning the specific aspects of entities. The first step is to categorize the entities and their associated attributes. The viewpoint leaders may have disparate views on various aspects of the same individual, as in the sentence "the call quality on this phone is excellent, but the battery life is short" [19].

The extraction and choice of text features is the first step in the sentiment classification problem”feature selection”.

a) *Terms Presence And Frequency:* These are the existence and frequency estimates of single words or word n-grams. It either assigns a binary weight to terms (zero if they appear, one if they do not) or utilizes term frequency weights to show the relative value of features.
b) *Parts of Speech (POS):* identifying descriptors, which are essential factors of one's feedback.
c) *Feedback Terms and Phrases:* these are words and phrases that are often utilized to express thoughts, whether positive or negative, like or dislike. On the other hand, some phrases convey views without the utilize of feedback terms. For instance: it cost me both an arm and a leg.
d) *Negations:* the appearance of negative terms will alter one's perspective as if not good is synonymous with bad.

The authors developed a method for classifying data by considering the negation and transformation of sentences into sentiment analysis . The approaches divide sentences into reversed and normal sentences, which are represented by two distinct bag-of-words (BOW) models. Then, three general machine learning strategies are proposed for classifying these two bag-of-words: delete, transfer, and joint strategy [20].

Methodologies of feature selection can be divided into lexicon-based procedures that include human documentation and statistical techniques that are more commonly utilized. Typically, lexical-based strategies start with a limited collection of 'seed' words. They then bootstrap this set in order to expand the lexicon through synonym recognition or online resources.

The feature selection techniques treat documents as a set of words (Bag of Words (BOWs)) or as a string that preserves the document's sequence of words. BOW is more commonly utilized due to its ease of classification. The most frequently utilized feature selection procedure is to eliminate stop-words and stemming (returning the word to its stem or root, e.g., flies).

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III.DATASETS

There are numerous datasets available for sentiment summarizers on popular topics from microblogging platforms like Twitter, the first process. We can manually gather data by looking for a particular pattern “hashtags”. Second, we can utilize Twitter's API; it is incredibly simple to gather millions of tweets for training purposes. The author utilized the Twitter API to retrieve tweets that included emoticons [15]. These were utilized to categorize tweets as either positive or negative. Retweeted posts, and repetitive tweets, have been removed.

The writers of [7] utilized 140-character Twitter messages. Tweets have distinctive features due to the character limit, as utilizers frequently do not write complete sentences or utilize acronyms to condense their text material. A utilizer creates each tweet. They crawled English tweets from 23 distinct hashtags related to 2015 events and introduced the non-event hashtag ##. #love is the hashtag. They manually crawled approximately 3.3 million tweets in total. In [17], the author provided a framework for utilize with the Python package Tweepy that simplifies access to streaming API tools. This framework was utilized to extract 308,316 tweets for three items (iPhone, Nokia, and Samsung) between 10 and 11 April 2013. To facilitate further processing, all downloaded tweets were stored in a SQL Server 2012 database. Table 1 summarizes a number of datasets.

Table 1: Several datasets with the corresponding number of tweets

Retweet	47017
English tweet	151347
Manually labeled tweets	1300
iPhone	46%
Nokia	24%
Samsung	30%
Total number of tweets	308316

IV.SENTIMENT SUMMARIZATION TECHNIQUES

Applying summarization strategies on microblogging sites, like Twitter, allows the cropping of compact recaps about a specific subject debated in actual time by utilizers with significantly less time and effort, that can be advantageous for people, businesses, organizations, or organizations seeking popular feedback. As a result, it would be extremely beneficial if powerful frameworks could be built for summarising multiple parts of an interesting subject on microblogs by collecting, synthesizing, and displaying the most pertinent details.

Sentiment Summarization is distinctive from factual data summarization in that words deemed informative from a factual standpoint lack sentiment, making them utilizeless from a sentiment standpoint. We assess them using three defined summarization criteria: informativeness, linguistic clarity, and the description's utility . According to the writers, a Sentiment Summarization process takes as input a set of documents containing feedbacks regarding a particular entity of concern. It then processes all of the provided documents and generates a list of all of the input documents. This review should represent the consensus feedback expressed in all the reports and key aspects of the SA aim discussed in those reports.

There are three approaches to generating textual summaries [21] as follows.

1) The first approach, dubbed extractive-based summarization, involves extracting certain ostensibly significant portions of the specific documents contained within a set of documents and providing them as a summary of the corpus. The methods of extraction include mathematical, concept-based, topic-based, graph-based, and semantic-based approaches.
2) The second approach, referred to as abstractive summarization,for instance creating a textual summary in which the words utilized are not found in the source material, including by rephrasing the content. Three types of abstractive ATS methods exist. 1) structure-based: based on predefined structures (e.g., graphs, trees, codes, models, and ontologies); 2) semantic-based: based on knowledge objects, predicate claims, and semantic graphs); and 3) deep-learning-based approaches as neural-based or traditional, that broadly applies to any approach that is not neural-based.
3) The hybrid approach incorporates elements of both the abstractive and extractive perspectives. It is often divided into the following phases: 1) Pre-processing, 2) (explicit ATS phase): extract main sentences from the input text 3) recap development (abstractive ATS step): This is achieved by the application of abstractive materials and procedures to the first phase's derived sentences, and 4) post-processing.

Table 2: Advantages and disadvantages of the extractive [22], [23] and abstractive text summarization methods

	EXTRACTIVE	ABSTRACTIVE
Advantage	➢ Is easier and quicker than the abstractive method. ➢ higher accuracy ➢ Readers read the synopsis using the same exact terms as in the source.	➢ It produces improved summaries by using various terms that are not in the original text. ➢ Minimize the amount of text in comparison to the extractive. ➢ reduce any redundancy
Disadvantage	➢ Redundancy can be found in some synopsis sentences. ➢ Extracted sentences can be substantially higher than the standard. ➢ There are contradictions in the temporal expressions in the multi-document scenario, as extractive reports are chosen from a variety of input reports. ➢ In summary statements, there is a lack of semantics and continuity. ➢ Important info is dispersed in the sentences. Contradictory information should not be included.	➢ It is hard to produce a high-quality abstractive summary. ➢ They are highly difficult to develop becautilize they necessitate the utilize of natural language generation. ➢ Suffer from the generation of repetitive terms and an inability to interact effectively with words that are not in their vocabulary. ➢ Systems are incapable of summarizing what their representations are incapable of capturing.

Since extractive methods are restricted to the extraction of sentences or phrases, they are adaptable to a variety of domains; however, these recaps can be substantially less coherent. Although, abstractive methods result in more sophisticated summaries that often provide additional information that enhances the original content [24].

Few reports have been carried to compare the approaches of extractive and abstractive feedback summarization. According to [25], extractive methods work better than conventional summarization in general, but they are not suitable for collecting subjective knowledge because utilize they do not express the distribution of views in their pure form. Additionally, [23] states that, due to minor differences in redundant feedbacks, extractive methods are often insufficient for summarizing feedbacks. Conversely, when extractive summaries' output format is structured in aspects, recaps give critical information.

The authors of [21] defined a sentiment summarization scheme for utilized on extractive aspects. This approach incorporates a feature detector, a recently designed hybrid polarity detection system, and a novel unsupervised polarity identification and ranking algorithm [26]. They utilize an SVM (Support Vector Machine) skilled workers on a unigram bag-of-words feature set as a baseline derived from the outcomes [26].

The authors suggested a novel summarization technique based on feedback and topical feature study for producing a comprehensive summary of trending microblog topics. To be more accurate, the proposed procedure entails three stages. After pre-processing and semantically enriching each microblog entry, they extracted the issues and sentiments expressed. Then, for each subject, build a sentiment-based Word Graph and cluster it to obtain various facets of the subject. Eventually, they utilize cutting-edge summarization techniques to recap each topical aspect separately and then combine all aspect-level summaries to create a holistic overview for each issue [27].

The authors proposed a graph-based technique to generate summaries of redundant feedbacks and combine them using sentiment analysis [28]. The recaps created in this manner are abstraction-based and well-structured to convey the text's gist. They eliminated redundant sentences from the description by using the Jaccard index for similarity. The summary is then composed of the remaining topmost S (number of sentences in summary defined by the utilizer) sentences. The first dataset consists of 50 documents chosen at random from the DUC 2002. "Every year, the National Institute of Science and Technology (NIST) hosts the Document Understanding Conference (DUC)." On average, the documents contain about 500 sentences. The dataset contains approximately 500 English-language news stories, each with a gold summary. Additionally, gold summaries have been issued for the accompanying papers. They are approximately 100 words in length. In [29], the authors proposed several output formats for aspect-based feedback summarization automated summaries. The three primary output formats for feedback summaries based on aspects are structured, textual, and visual.

Structured summaries categorize their content according to their aspects and polarities (positive or negative). Thus, for certain topics, the most pertinent feedbacks or sentences are shown based on a heuristic for selection. Additionally, these summaries include the amount of positive and negative reviews and the star rating (as some e-commerce sites do).

In several cases, text summaries are created by highlighting a few reports or sentences. These evaluations or sentences must be descriptive of the pertinent information. Visual recaps summarize a utilizer's sentiment against a commodity or feature based on their polarity (positive or negative). Despite the vast number of reviews, these recaps enable people to identify what people like and hate about a product easily.

V. CONCLUSIONS

This research illustrates sentiment summarization of trending topics on microblogging such as Twitter and proposed aspect-based sentiment summarizer consisting of three phases: 1) aspect identification, 2) sentiment prediction determine the sentiment polarity we survey sentiment classification techniques. These three major approaches include the machine learning approach, lexicon-based approach, hybrid approach, and 3) summary generation.

Ther are three approaches to generating textual summaries which are extractive-based summarization, abstractive-based summarization, and hybrid approach. Additionally, we compared these three methods and display the primary output formats for input overviews categorized as organized in textual and visual ways. In this review, we discussed the meaning of trend and present the importance of the analysis of Twitter data in the domain of sentiment analysis and presented dataset methods to collect tweets.

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