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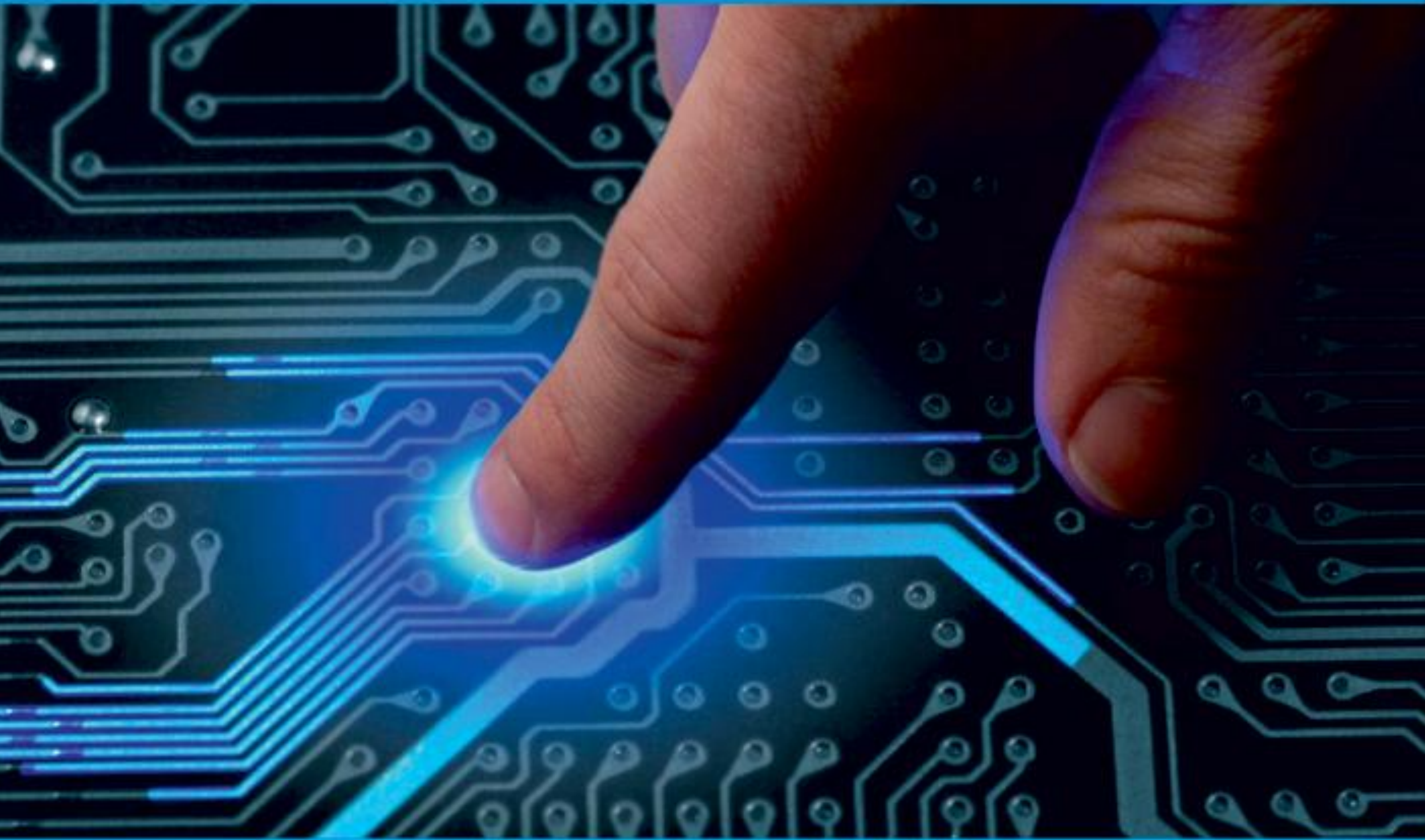

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Sentiment Analysis Techniques that Use Improved Machine Learning Algorithms

Dr.Sunil S. Khatal , Dr. Monika D.Rokade

HOD & Assistant Professor, Sharadchandra Pawar College of Engineering, Otur Dist-Pune, India

Assistant Professor, Sharadchandra Pawar College of Engineering, Otur Dist-Pune, India

ABSTRACT: Because so much data is generated on Twitter, sentiment analysis has been used in a number of studies. Many social networking sites generate enormous volumes of unstructured data streams that are challenging to manage. Such social network services generate enormous amounts of unstructured data, which makes managing it quite challenging. The objective of the study is to consistently assess the sentiment of trending tweets in the Twitter API data stream using a consensus established among a range of algorithms. We reached an agreement on the tone of trending tweets in the Twitter API data stream using a number of algorithms, including Support-Vector Machine and Naive Bayes. We employed a variety of techniques, including Support-Vector Machine and Naive Bayes.
combining the most advantageous elements of the Lexicon Method with TextBlob. We predict that by combining these methods, we will be able to get results that are more trustworthy. Textblob Storage and the Lexicon Method. We believe that by combining these methods, we will be able to provide results that are more trustworthy.

KEYWORDS: Lexicons; Machine Learning; Twitter; Data Streams; Sentiment Analysis

I. INTRODUCTION

The potential of machine learning has been impressively proven in a number of fields. Natural language processing is no exception, and it is one of the fields where machine learning has been able to show general artificial intelligence, if not entirely, then at least significantly, producing some absolutely fantastic results for extremely difficult tasks. Natural language processing (NLP) and machine learning are not particularly cutting-edge fields of research. Combining the two disciplines, however, is extremely current and assures only growth. Everyone uses a hybrid app like this on a daily basis (with a reasonably priced smart phone). Think of "keyboard word suggestion" or intelligent auto-completions; both are products of the union of natural language processing and machine learning and have subsequently grown to be essential [1].

In natural language processing, sentiment analysis plays a significant role. Its widespread applicability and the variety of business questions it is answering have propelled it to the forefront of discussion. Positive and negative emotions in text may be identified using a method called sentiment analysis. Many companies utilize it to analyze consumer opinions, monitor brand perceptions, and learn more about their clientele.

A. Categories

Sentiment analysis may determine the underlying emotions, urgency, and goals of the written words in addition to evaluating whether a text is positive, negative, or neutral in tone (interested v. not interested). In the meantime, think about these instances of typical emotional analysis:

Scaled Opinion Analysis

It is possible to interpret star ratings in reviews, such as 5/5, using this form of analysis, which is sometimes referred to as nuanced or fine-grained sentiment analysis. Sentiment analysis that detects emotions such as joy, frustration, fury, and sadness is an extension of polarity analysis. Lexicons—lists of words and the emotions they convey—or advanced machine learning algorithms are routinely used by emotion identification software [2].

Sentiment Analysis by Aspect

It is useful to note the exact qualities that readers are applauding, condemning, or ignoring when analysing the tone of a work. A classifier trained to look at just that aspect would recognise that the reviewer had a poor opinion of the camera's battery life. For instance, if a reviewer of a camera remarked, "The battery life of this camera is too short," aspect-based sentiment analysis might be useful in this situation.

Analysing across languages

While attempting multilingual sentiment analysis, complexity frequently occurs. It necessitates substantial planning and resources. Perhaps you want to keep an eye on how people feel about your brand so you can immediately spot any unhappy customers and take care of their issues. If any actions are required, you can look at quarterly variations in satisfaction. By paying more attention to your qualitative data, you may then dig into the causes of the change in sentiment [4].

Among the many advantages of sentiment analysis are:

Big Data

Nowadays, there is just too much business information for manual processing to be useful. Sentiment analysis helps businesses analyse enormous amounts of unstructured data quickly and affordably. Real-time sentiment analysis may highlight important issues, such as whether or not a social media PR catastrophe is becoming worse. Is a disgruntled customer about to leave? With sentiment analysis models, you can spot these situations right away and respond appropriately. When attempting to discern the tone of a communication, people only arrive at the same judgement around 65 percent of the time. The tagger's personal history, viewpoint, and values have a significant influence on sentiment analysis because it is such a highly subjective procedure [5].

By applying the same criteria to all of their data using a centralised sentiment analysis tool, businesses may improve accuracy and gain deeper insights from their data. There are countless applications for sentiment analysis. To further understand how sentiment analysis could be used to the benefit of your firm, have a look at some possible example texts for analysis. We'll next go on to a real-world illustration of how sentiment analysis assisted Chewy, a pet supplies firm, in interpreting its reviews more thoroughly (and effectively) [6].

B. Process of sentiment analysis

A given tool may do sentiment analysis in a different way. NLP is used, among other things, to identify word tokens (such as "delicious," "pies," etc.), grammatical categories (noun, adjective, verb, etc.), and lemmas (such as "pie" for "pies"). We perceive a phrase as a name when it contains many words, as "New York Stock Exchange." To determine a text's underlying meaning, our sentiment analysis uses morphosyntactic structure, semantic traits, and lexical knowledge. Grammatical analysis breaks down words into syntactic components, which are then assigned semantic properties [7].

Consider this example sentence: I have an overwhelming desire to visit IKEA.A willingness to go to IKEA and, presumably, make a purchase there would be a sign of a favorable attitude towards the company. We also understand that the word "desire" refers to a feeling. No negative connotation is attached to the term "so horrible," which is simply understood as an intensifying expression [8].

It allows customers to capture an in-depth knowledge of what people are saying about companies, goods, politicians, movies, and television shows by extracting all of the semantic roles in the phrase, including Agent ('I'), Action ("go"), Emotion ("Desire"), and Object ("IKEA").Comparatively, many of our rivals do not offer such in-depth analyses.They merely produce a label for each sentence or document as to whether it is good, negative, or neutral. Some additionally include a score, either in addition to or in place of a label, with the score falling anywhere from a large negative number to a large positive number (e.g., -100 to +100) [9].

Also, they seldom reveal where the favorable or bad feelings originated, making it difficult to trace back positive or negative sentiments to specific articles. Instead, they provide an overall score for all of the results [10].

Nothing here is particularly illuminating with regard to the background information necessary for appreciating the viewpoints expressed in social media posts. The importance of openness with regards to this information in validating a correct analysis cannot be overstated. Its absence casts doubt on the validity of the findings [11].If you want to go a little deeper, here's a short rundown of the many forms of sentiment analysis available today to help you narrow down your vendor choices:

C. Distinctions Between Various Sentiment Analysis Types

Sentiment analysis may be broken down into several categories.

The first method, referred to as machine learning, uses an algorithm that "learns" as it goes by examining previously gathered data. As it reinforces itself, it depends on the instruction it has received. Whatever errors it makes while learning will be hard-coded into the programme [12].

Furthermore, since these algorithms are frequently trained on questionable datasets devoid of pertinent social media data, it is not a good idea to rely on them to understand emotions. Even if it has made strides with low-level tasks, it still needs a lot of work to catch up to rule-based systems in terms of understanding the meaning of human language [13].

Rule-based systems are dependent on manually created rules andutilised to create a final score. That is as simple as it seems, and it is, but it is also quite helpful (to a degree). It does, however, have several limitations: These criteria are used to categorise the text as either positive, negative, or neutral. These collections of rules are sometimes referred to as lexicographies. Hence, the Lexicon-based Method is another name for the Rule-based Method [14].
On the other hand, the Aspect-based technique groups information into its "aspects" and then determines how individuals feel about each one. The linguistic analysis of IKEA that we discussed above accomplishes this by correlating certain emotions with specific elements of shared experience [15].

II. PROBLEM FORMULATION

The sentiment algorithm succeeds in part because it pays attention to "aspect-based" sentiment that is linguistically sophisticated. While many of our competitors and open-source sentiment algorithms can label entire phrases or pages, they are unable to give the kind of detail we do. Simplifying the definition of "sentiment" too much might result in drawing the wrong conclusions. Several user sentiment analysis tools still do so today. In the past, they worked under a number of dubious presumptions. For instance, it is very doubtful to assume that a piece of literature can be summed up as "excellent," "bad," or "neutral." If if there were just two ways to express how one feels—black or white. Nonetheless, that is not the case. Sentiment occurs on a spectrum of varied intensity, just like any human emotion. Not all forms of social media surveillance are created equal [16].

Net Sentiment, which quantifies how good or unfavourable an opinion is on a scale from -100 to 100, and Passion Intensity are added together to create Brand Passion (the strength of those emotions, from -100 to 100). This categorises whether individuals have an overall favourable opinion of a brand, conflicting opinions about it, or a negative response to it. Also, this offers brands information that they may make use of. A sentiment analysis project's success hinges on paying close attention to every last detail and understanding when and where to exert the greatest effort. Supporters of your brand may not need assistance right away. Nevertheless, if you rally your brand's most ardent supporters, they will use their own enthusiasm to persuade those who aren't yet convinced. Furthermore to finding your brand's biggest fans, it's important to track down anyone whohas anything negative to say about it. If you want to do this successfully, it's important to zero in on the source of their discontent [17].

Look closely to see if they are genuinely indifferent or if anything has actually angered them. Social media analytics may help you understand more about their goals, which can draw more clients to your business. You can find out what actually drives people's motivations by utilising the right social listening technology, which will help you create tailored messages that will connect with them. This is not to enhance the reputation of your business, but rather of theirs [18].

III. RELATED WORK

In order to analyze the tone of danmaku reviews, Li et al. (2020) build a sentiment dictionary for danmaku and introduce a novel technique based on the sentiment dictionary and Naive Bayes. The approach is quite useful for monitoring a danmaku video's overarching emotional tone and gauging how popular it will be. The temporal distribution of the seven dimensions of emotion may be derived by the methods of emotion extraction, sentiment classification, and data visualization applied to a danmaku film. The polarity of danmaku reviews may also be classified based on a weighted computation. Results from experiments demonstrate that the suggested strategy significantly improves sentiment score and polarity recognition.

In order to train their deep learning-based sentiment analysis system for product reviews, Xiao et al. (2020) crawled the reviews for digital and electrical items on Jingdong Mall with at least 100,000 ratings. The LSTM method offers a more trustworthy foundation for analyzing customer feedback than Naive Bayes or logistic regression does during training.To choose the best performer, Alatter et al. (2021) first compare the results of different Sentiment Analysis classifiers for brief texts. Then, we provide the Filtered-LDA framework, which greatly outperforms prior techniques for deducing Twitter users' emotions. Cascaded Latent Dirichlet Allocation (LDA) Models with adjustable hyperparameters are used by the framework to identify potential causes of sentiment shifts. Finally, a Topic Model with a high Coherence

Score is used to extract human-understandable Emerging Topics from the remaining tweets. At last, an innovative Twitter dashboard for sentiment reasoning is shown, which compiles the most representative tweets for each potential explanation and displays them in a single place.

In this study, Sehar et al. (2021) introduced a novel Urdu language-based multimodal dataset consisting of 1372 phrases as a first step in tackling the problem of uncovering meaningful patterns. The second is that we have introduced a unique framework for multimodal sentiment analysis (MSA) that uses a combination of auditory, visual, and textual responses to identify emotional states based on their surroundings. In addition, we have implemented fusion techniques at the decision and feature levels to enhance polarity prediction in sentiment analysis. Incorporating multimodal characteristics has been shown to increase the proposed algorithm's polarity identification accuracy from 84.32% (with unimodal features) to 95.35% in testing settings (with multimodal features).

In order to improve sentiment accuracy and predict the dynamic nature of sentiment evolution, Nazir et al. (2022) focused on problems associated it and this article provides a thorough assessment of these developments according to whether or not they have helped to bring attention to or alleviate the problem. Each study's stated Aspect Extraction and Aspect Sentiment Analysis performance is included, providing a quantitative assessment of the methodology. In order to improve sentiment categorization at the aspect level, we propose and explore future research paths by conducting a critical analysis of the offered current methods.The challenge of linguistic cross-referencing is tackled by Atkinson et al. (2022) utilizing an evolutionary computation strategy. They determined the nature of implicit co-referencing in free-form opinion texts. By comparing the results of our method to those of similar ones, we were able to perform experiments to determine how well the model could detect implicit referents in conversational communications.

The method of employing Cosine Similarity to suggest films that are like the one the user has already selected is described by Pavitha et al. (2022). Currently available recommendation algorithms perform adequately, but they do not provide sufficient justification for deciding whether or not a movie is worth seeing. This method uses machine learning to analyze the reviews of the selected film for positive and negative sentiment in order to improve the user experience. These metrics used to assess the relative performance of NB and SVM in this study. Accuracy results for SVM came in at 98.63%, while those for NB were 97.33%. Therefore, SVM is more appropriate for Sentiment Analysis than NB.

IV. MATERIAL AND METHODS

Dataset

The authors use data from guest evaluations of various hotels into their article. For each hotel, the observation data consists of a single customer review. Each review consists of a numerical rating and a star rating, as well as textual input about the reviewer's stay at the hotel. You may find the information at:

https://www.kaggle.com/jiashenliu/515k-hotel-reviews-data-in-europe

The goal for these authors is to determine if a given textual review represents a positive evaluation (the consumer is satisfied) or a negative review (the customer is not satisfied). The aggregate score of the reviews might be anything from a 2.5 and a 10 on the 10-point scale [20].

	id	Comments	Gender	Reason	Neg	Pos	Cont	Sentiment
1	1.0...	Rooms were clean.	female	leisure	0	1	0	positive
2	5.0...	Comfortable rooms, outstanding breakfast, nice service	male	business	0	3	0	positive
3	9.0...	Beautiful location	female	business	0	1	0	positive
4	13....	Friendly room service, attentive staff	female	leisure	0	1	0	positive
5	17....	Very quiet, but very expensive	male	leisure	1	1	0	mixed
6	21....	Service, quiet location, room facilities, but no parking facilities	male	leisure	1	2	0	mixed
7	25....	I enjoyed the good food, the friendly staff, the room, the cleanliness, the view, the proximity to the city center, beach, sea, the transport, the accessi...	male	business	0	3	0	positive
8	29....	Small room but cosy. Great restaurant.	male	business	1	2	0	mixed
9	33....	Price-performance ratio is right. Location is fantastic.	female	leisure	0	2	0	positive
10	37....	The rooms were newly renovated, quite spacious and clean. Prices are reasonable.	female	leisure	0	3	0	positive
11	41....	Highly recommended	male	business	0	1	0	positive
12	45....	The rooms are extremely clean and spacious.	female	business	0	2	0	positive
13	49....	We immediately felt comfortable, like at home.	male	business	0	1	0	positive
14	53....	very quiet Hhotel	male	business	0	1	0	positive
15	57....	The hotel is a dream for those seeking tranquility.	male	leisure	0	1	0	positive
16	61....	This hotel is a must in every respect : cleanliness, quality and variety of food	female	leisure	0	2	0	positive
17	65....	Service was fine.	male	business	0	1	0	positive
18	69....	Varied food at breakfast.	female	leisure	0	1	0	positive
19	73....	Price-performance ratio is great!	male	leisure	0	1	0	positive
20	77....	room ok.	male	business	0	1	0	positive

Figure 1 Dataset columns

Figure 1 depicts the columns of the dataset taken for experiment purpose. The difficult part is figuring out how to foretell this from the review's raw textual data [21].For the sake of clarity, let's classify them as follows:

- Ratings below 5 are indicative of poor evaluations.
- ratings greater than or equal to 5 are indicative of a positive review.

Handling missing values

A typical issue in many real-world datasets is the presence of blank cells. The outcomes of machine learning models can be skewed by missing values, and the models' accuracy may suffer as a result.It's necessary to determine the approach for dealing with missing data, thus it's important to analyze each column with missing values to identify the causes for the missing values [22].There are two main approaches to missing value handling:

- Getting rid of the Blanks
- Filling in the Blanks via Imputation

In most cases, you shouldn't take that tack. It is a somewhat hasty method of handling missing values.The missing value should not be removed if it is of the Missing Not At Random (MNAR) variety. The authors can get rid of a missing value if it's a Missing At Random (MAR) or Missing Completely Random (MCAR) kind [23].

The risk of losing potentially relevant information in the dataset is a major drawback of this approach.The missing values can be removed in two ways:

- Dropping a complete row is an option if there are many blanks in a row.
- It may lose everything if every row is lacking a single (column) value.

There are primarily two classes of outlier identification techniques:

- Finding outliers via analyzing data density and distance.
- Constructing a model to foretell the scattering of data points and singling out those that don't conform to a certain standard

V. PROPOSED METHODOLOGY

Researchers use machine learning and natural language processing to assess if a piece of text is positive, unfavourable, or neutral (NLP). The two main approaches to sentiment analysis are rule-based and algorithmic methods.

Analysis of Emotions Based on Rules

This is how sentiment analysis is often done, when a set of rules is created by hand. This approach makes use of NLP techniques including lexicons (lists of terms), stemming, tokenization, and parsing. Rules-based sentiment analysis works as follows: The creation of positive and negative lexicons (or "lexicons"). These words and phrases are used to communicate emotion. In lists of positive descriptions, terms like "fast," "affordable," and "user-friendly" are frequently present. The system might be adversely described as slow, costly, and complicated .

Text must be prepared before analysis can take place. The text is changed through a number of processes so that it can be read by a computer. Text is tokenized by being divided into small, manageable pieces called tokens. Tokenizing words makes it simpler to handle and analyse the data. The technique of separating a group of words into separate tokens is known as sentence tokenization. We may deconstruct statements like "the greatest customer service" into their constituent elements in this way. Words can be transformed back to their original form by utilising lemmatization. Each word's lemma is its fundamental component. Several words, including "is," "are," "am," "were," and "been," derive from the prefix "be." Also, we want to exclude information that is well known yet provides little value.

Negative aspects of rules-based sentiment analysis exist. Rule-based approaches to text analysis have limitations since they don't consider the entirety of the sentence. The complexity of human language makes subtleties like these often missed. Similar to this, rule-based systems frequently require modifications to operate at their best. Automated sentiment analysis is made possible by artificial neural networks (ANNs) and other machine learning (ML) techniques. Here, a machine learning system is trained to infer the tone from the words themselves and their placement in the sentence. The quality of the training data and the algorithm being utilised determine how effective this strategy is. To get reliable results, hybrid sentiment algorithms combine ML and rule-based techniques. While being more challenging to build, they have the ability to

We begin by extracting characteristics. Before the model can categorise the text, it must be converted into a language that a computer can comprehend. Similar to rule-based techniques, this might incorporate stopword deletion, lemmatization, and tokenization. Moreover, the language is transformed into numerical form through a process known as "vectorization." These numerical descriptions are sometimes referred to as "features". The bag of words or bag of n-grams approaches are widely employed for this purpose. They do text vectorization based on word frequency.

VI. CONCLUSION

We used a variety of classification algorithms in addition to these preprocessing techniques, including Naive Bayes, which is based on the well-known Bayes Theorem, Support Vector Machine, and two Lexicon-based algorithms. Learning more about what really works was our aim. There is no apparent victor when comparing the results of different categorization methods. When all four algorithms were run simultaneously and a majority vote was taken as the result, accuracy of 86.49% was reached. Our findings demonstrated that accuracy increased when a result was formed by combining the opinions of multiple algorithms. This is true even though there is still much room for improvement and a vast array of potential applications for combining the opinions of algorithms, combining lexical data, and combining

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