

Real Time Sentiment Analysis of Twitter

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ABSTRACT: Sentiment analysis is a process for categorizing and identifying opinions written by a person ,to elicit data from the text and determine their behavior. Every user gives out information about their personal and professional life to the vast world of social media to either prove something or flaunt about themselves to other individuals. Sometimes releasing of such information exceeds the limits .Hence others gain knowledge about a third person's thoughts. How a person thinks helps us in reaching a certain decision regarding their instantaneous sentiments. In this paper various applications of such sentiment analysis methods and challenges are elaborated.

KEYWORDS: Classification, machine learning, natural language processing, opinion mining, sentiment analysis, social media.

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I. INTRODUCTION

Sentiment analysis is a kind of text analysis which aims at determining the opinion and subjectivity of the reviewers. Sentiment analysis is the process of using statistics, natural language processing and text analysis to analyze the sentiment of a customer. The sentiment of the customers like what people are saying, what they mean and how they're saying it are understood by the best businesses. The sentiment of the customers can be found in tweets, comments, reviews or other places where the brand is mentioned by the people. Sentiment Analysis is the domain of understanding these emotions with software, and it's a must-understand for developers and business leaders in a modern workplace. Advances in deep learning have brought sentiment analysis into the foreground of cutting- edge algorithms as with many other fields. Today by using statistics, natural language processing, text analysis to extract and identify the sentiment of the words into positive, negative and neutral categories.

Estimation investigation is a data assignment to accomplish the sentiments of the clients. Utilizing opinion investigation researchers can examine huge quantities of archives. These sentiments can be communicated into positive, neutral and negative routes as remarks, solicitations and inquiries.

Sentiment analysis is a field of study that performs investigation of individuals assessment, disposition, estimations and emotions towards entries. Sentiment analysis is generally a classification of the text polarity in three levels namely sentence level, document level and aspect level. To decide the mentality of the creator or speaker with respect to some subject or overall polarity of an opinion is the fundamental point of sentiment analysis. The web is a huge depository for ordered and unstructured data.

The three levels namely document level, aspect level and sentence level should be possible on assumption investigation. Sentiment analysis is additionally called as opinion extraction, opinion mining, affect analysis, sentiment mining, emotion analysis, review mining, etc are the different names of sentiment analysis and they slightly perform different tasks on the basis of their names.

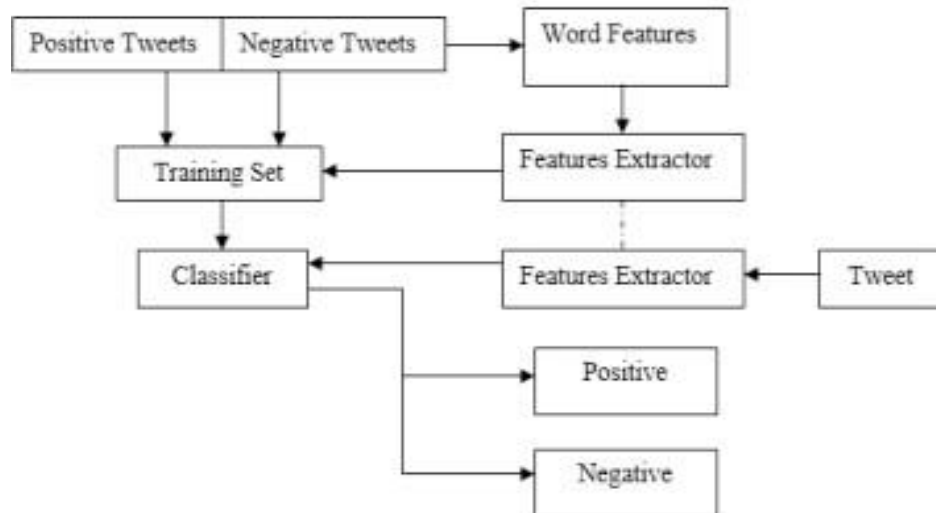


Fig-1: Sentiment Analysis Investigation

1.1. Challenges

Social media consists of everything from daily personal stories to worldwide trends. Millions of posts are updated daily but people don't have time to visualize everything that is uploaded. One of the many challenges that come forward is that there is no limit to how much a user can update their feed daily. At times the information they provide are incorrect. Spellings and grammar errors, the absence of proper sentence structure and also the use of mixed language make the received data uncertain. Not all content posted has to be of a person's interest. Social media often acts as a unidirectional way of communication as it becomes a platform to just get the word out for certain instances rather than focusing on character development.

II. TYPES OF SENTIMENT ANALYSIS

The three different levels in sentiment analysis are namely document level, sentence level and aspect level. In the document level it is identified if the review is positive or negative. In the sentence level type of sentiment analysis, it is identified whether every sentence is positive or negative. In the aspect level, entities and their features identify whether the sentiments are positive or negative.

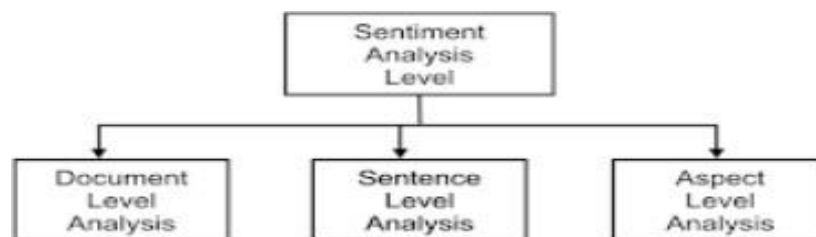


Fig-2: Types of Sentiment Analysis

2.1 Document Level Analysis

In document level, analysis task is characterize whether an entire opinion of document level communicates a positive or negative supposition. Opinions are usually subjective expressions that describes people's sentiments or feelings towards an entity or an event. Many forums or blogs allow people to express their opinion in the form of comments and reviews. When opinions are expressed in the form of reviews, instead of a simple 'Yes' or 'No' and identifying the actual emotions would need a subjective analysis of the words used in the review. In the document level of sentiment analysis, each document focuses on a single event or entity and contains an opinion from a single opinion holder. The opinion here are can be classified into two simple classes namely as positive or negative. *For example: A product review is stated as: "I bought a new phone few days ago. It's a nice phone, though it is a little big. The touch screen is really good. The voice clarity is better. I love the phone"*. Considering the words or phrases used in the review namely nice, good, better, love, the subjective opinion is said to be positive. The objective opinions are measured using the star or poll system, where indicating 4 or 5 stars indicates positive and 1 or 2 stars indicate negative.

2.2 Sentence Level Analysis

The sentence level of sentiment analysis filters out sentences which contain no opinion and determine the opinion of the entity as positive or negative. In sentence level, the fundamental undertaking goes to the sentence and makes sense of it and then every sentence is communicated as positive, negative or neutral sentiment. Neutral opinion means no opinion about any sentence. This level of investigation is immovably related to the subjectivity arrangement, which recognizes sentences called as target sentences that expresses genuine information from the sentences called as subjective sentences that expresses opinions and subjective perspectives. We ought to observe that subjectivity is not comparable to supposition and the same number of target statements can suggest feelings for example, “We purchased a new car a month ago and the windshield wiper has tumbled off.” The sentence level classification of sentiment analysis considers each sentence as a separate unit. It assumes that the sentence should contain only one opinion. Sentence level sentiment analysis has two tasks namely categorized as sentiment classification and subjectivity classification.

2.3 Aspect Level Analysis

The document level and sentence level sentiment analysis work well when they refer to a single entity. In aspect level sentiment analysis, the document level and the sentence level analyses are do not discover what exactly people liked and didn't liked. Better grained investigation is performed by aspect level sentiment analysis. Aspect level directly looks at the opinion itself. Aspect level sentiment analysis depend on the possibility that an opinion consists of a positive, negative or neutral sentiment or an objective of a sentiment. However, in many cases people talk about entities comprising of numerous aspects or attributes. The different aspects will have different opinions. It often happens in discussion forums and product reviews. *For example: “I am an Apple phone lover. I like the look of the phone. The screen of the phone is big and clear. The camera is really fantastic. But, there are few downsides too namely the battery life is not up-to the mark and access to WhatsApp is difficult.”* The valuable information about the product is hidden while categorizing the positives and negatives of this review. Hence the aspect level sentiment analysis focuses on the recognition of all sentiment expressions within a given document and the aspects to which the opinions refer.

III. TECHNIQUES

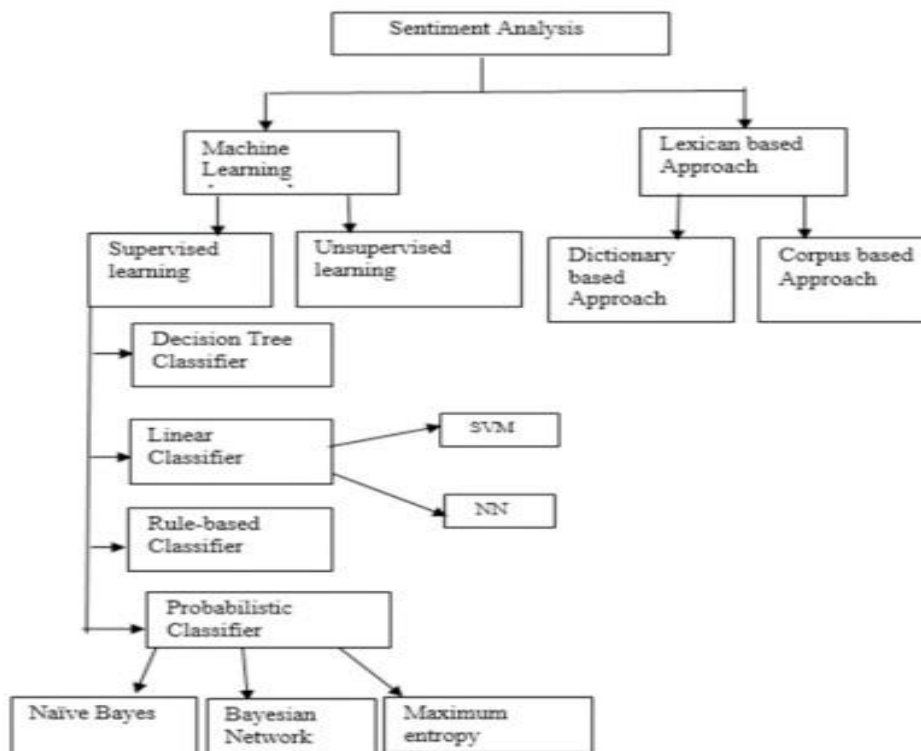


Fig-3: Sentiment Analysis Techniques

3.1. Machine Learning Techniques

Machine learning techniques are most useful techniques for the sentiment analysis for classification of text into positive, negative or neutral categories. In a machine learning based classification a training set is used by an automatic classifier to learn the different characteristics of documents, and a test set is used to validate the performance of the automatic classifier.

It is a simple, easy and effective classification algorithm. It is mostly used for document level classification. It is an approach particularly suited when the dimensionality of the inputs is high. Naive Bayes classifiers are computationally fast when taking decisions. Before learning can begin it does not require large amounts of data

3.2 Support Vector Machine

It is a supervised learning model which analyses data and patterns that can be used for classification and regression analysis. The idea behind this is to find a maximum margin hyper plane represented by vector. It finds an optimal solution. SVM is a discriminative classifier, it maps input (real-valued) feature vectors into a higher-dimensional feature space through some nonlinear mapping. SVMs are developed on the principle of structural risk minimization. SVMs can learn a larger set of patterns and able to scale better, because of classification complexity it does not depend on the dimensionality of the feature space. Whenever there is a new pattern during classification SVM have the ability to update the training patterns dynamically.

3.3 k-Nearest Neighbor

It is a classifier that relies on the category labels attached to the training documents similar to the test document. It is a type of learning where the function is only approximated locally and all computation is deferred until classification. It is a method to classify an object based on the majority class amongst its k-nearest neighbors.

3.4. Maximum Entropy

It is a technique which has proven effective in a number of natural language processing applications. It does not make any assumptions about the relationships between features, so might potentially perform better when conditional independence assumptions are not met. This method is mostly used as alternatives to Naive Bayes classifiers because it does not assume statistical independence of the random variables (features) that serve as predictors. The principle behind this is to find the best probability distribution among prior test data. The parameter values are set so as to maximize the entropy of the induced distribution subject to the constraint that the expected values of the feature/class functions with respect to the model are equal to the expected values with respect to the training data.

3.5. Association Rule Learning

It finds out the association between different variables. Variables are having different values so the changes never be constant. This type of relationship can be used while using huge database where organized collection of data is present.

IV. APPLICATIONS

4.1 Social Media Monitoring

In today's day, brands of all shapes and sizes have meaningful interactions with customers, leads, and even competition on social networks like Facebook, Twitter, and Instagram. Most marketing departments are already tuned into online mentions as far as volume— they measure more chatter as more brand awareness. By using sentiment analysis on social media, we can get incredible insights into the quality of conversation that's happening around a brand. Sentiment analysis can be used to: Analyze tweets and/or Facebook posts over a period of time to detect sentiment of a particular audience, Monitor social media mentions of your brand and automatically categorise by urgency. Automate any or all of these processes. Gain deep insights into what's happening across your social media channels. Prioritize action- Sentiment analysis lets you easily filter unread mentions by positivity and negativity, helping you prioritize issues. Track trends over time.

4.2 Brand Monitoring

Sentiment analysis can be used to: Analyze blog posts, news articles, forum discussions, and other texts on the internet over a period of time to see sentiment of a particular audience. Alert designated team members of online mentions that concern their area of work. Automate any or all of these processes. Automatically categorize the urgency of all online mentions of your brand understand a brand online presence better by getting all kinds of interesting insights and analytics. Understand how your brand reputation evolves over time. Identify potential PR crises and take immediate action. Again, prioritize what fires need to be put out immediately and what mentions can wait. Research about your competition and understand how their reputation also evolves over time.

4.3 Customer Feedback

Sentiment analysis can be used to: Analyze aggregated NPS or other survey responses. Track customer sentiment about specific aspects of the business over time. Analyze aggregated customer support interactions. Determine if a particular customer feels about your company. You can zero in on sentiment by certain interests, demographics, personas, etc. Target individuals to improve their service. By automatically running sentiment analysis on incoming surveys, you can detect customers who are ‘strongly negatively’ towards your product or service, so you can respond to them right away.

4.4 Customer Service

Sentiment analysis can be used to: Automate text classification of all incoming customer support queries. Gain deep insights into what’s happening across your customer support. Prioritize order for responding to tickets, being sure to address the most urgent needs first. Route queries to specific team members best suited to respond. Increase efficiency by assigning tickets to a particular category or team member.

4.5 Market Research

Sentiment analysis can be used to: Analyze product reviews of your brand and compare those with your competition. Compare sentiment across international markets. Analyze formal market reports or business journals for long-term, broader trends. Analyze social media posts and tweets for real-time happenings. Generate weekly, monthly, or daily reports – a sort of early warning system. Analyze reviews for unfiltered customer feedback. Tap into new sources of information. Provide information in real-time rather than in retrospect. Automated for regular(perhaps weekly) reports. Fill in gaps where public data is scarce – in emerging markets, for instance. Quantify otherwise qualitative information. Add that qualitative dimension to already gathered quantitative insights.

V. PROPOSED METHODOLOGY

Various studies are performed for sentiment analysis on textual data that primarily analyze, unorganized and unstructured data into an organized and structured manner to find the opinion polarity as positive or negative and neutral. In this paper, we proposed a methodology for a sentiment classification system to classify the sentiment polarity of the tweets. The proposed System allows us to process the Twitter data and to carry out the analysis. Figure 4 shows the basic architecture of our proposed methodology for sentiment analysis where data is extracted from twitter and then sentiment analysis is performed on that data in various phases.

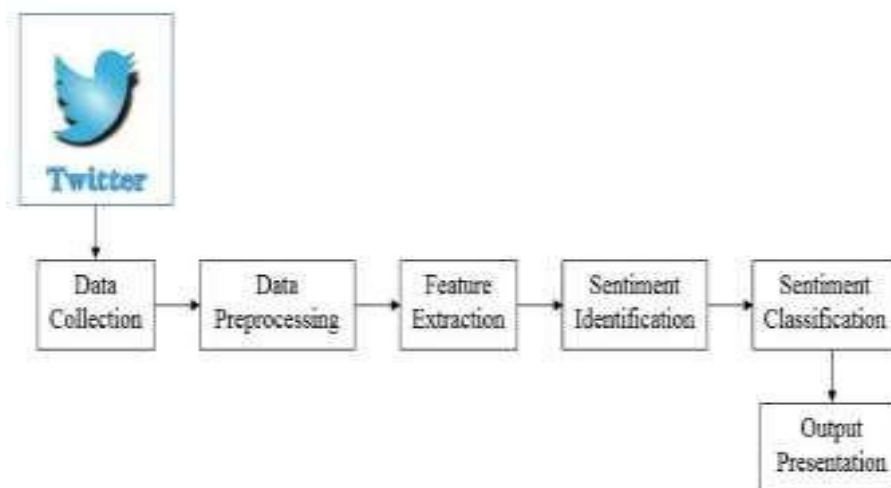


Fig - 4: Basic Architecture of Proposed Work

The proposed framework for sentiment analysis helps us to classify sentiment and their corresponding subjectivity. As figure 1 shows that Sentiment analysis process has various phases. Therefore these phases are discussed later in this section. But before that figure 5 shows the detailed architecture of our proposed framework that helps us to understand the process in a much better way.

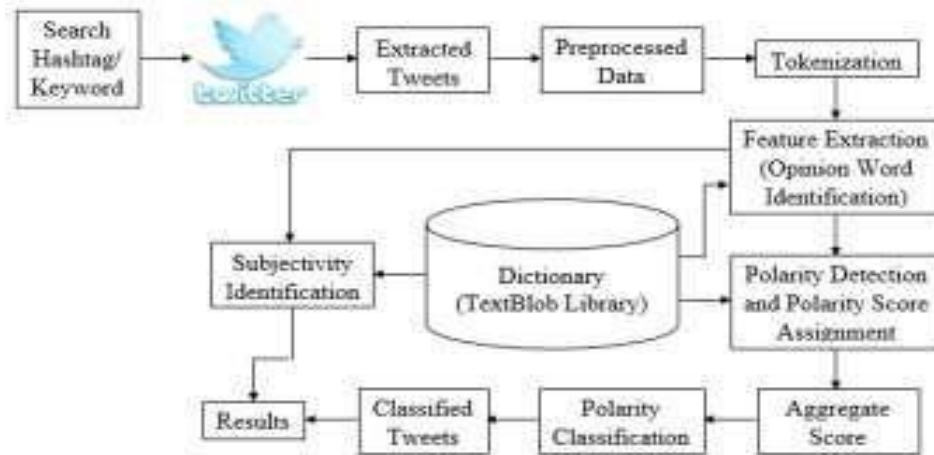


Fig - 5: Detailed Architecture for Proposed Methodology

5.1 Data Collection

We chose Twitter for our data collection as it is very popular nowadays. Tweets can be extracted from Twitter using hashtags or keywords. Hashtags or keywords are basically used to categorize tweets, making it easy to search. To extract tweets from twitter, twitter API is required. The Twitter Search API could produce a limited number of tweets at a time which is one of the constraints imposed by Twitter. The Twitter API can be accessed through the Tweepy library in python. Tweepy allows us to easily use the twitter streaming API. It manages authentication, connection, and many other services. API authentication is necessary for accessing Twitter streams. The Twitter streaming API downloads twitter messages in real time. It is useful for creating a live feed using a site stream or user stream, or for obtaining a high volume of tweets. This twitter streaming API can be used to retrieve tweets been tweeted for any hashtag or keyword. Figure 6 shows the block diagram for data collection.

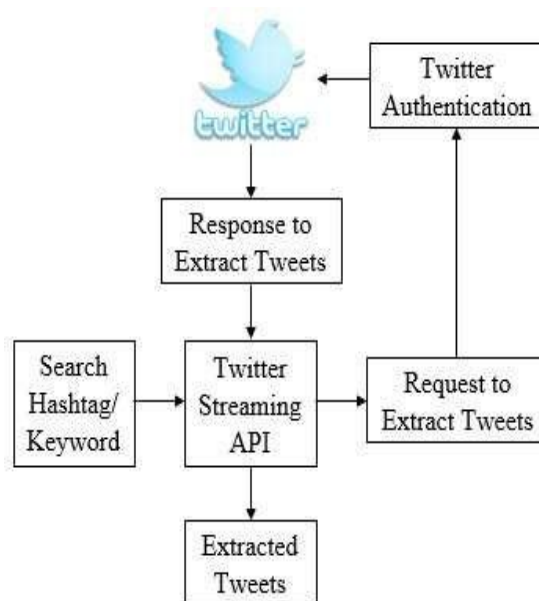


Fig - 6: Data Collection Process

5.1.1 Twitter Authentication

We need to get 4 components of data from Twitter to access the Twitter Streaming API: API key, API secret, Access token and Access token secret. These 4 components are used for Twitter authentication that can be produced by creating an application on Twitter. It requires a developer's account. If you do not already have a twitter developer's account, create the one using dev.twitter.com. Now go to <https://apps.twitter.com/> and sign in with your Twitter credentials. Click on "Create New App". Fill up the form, agree to the terms, and click "Create your Twitter application". After creating the app, go to "Keys and tokens" tab, and copy your "API key" and "API secret". Scroll down and click "Create my access token", and then copy your "Access token" and "Access token secret". In this way, we get access to consumer key, consumer secret, access token, access secret using which the API has to authenticate itself with the Twitter Authentication server. Figure-7 shows the twitter authentication process as follows:

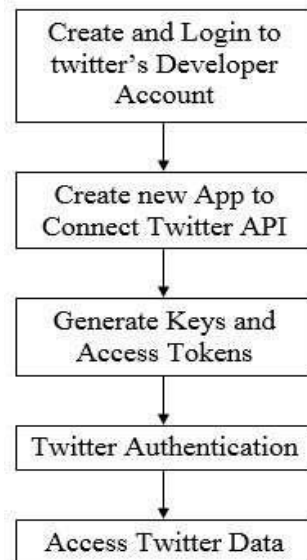


Fig - 7: Twitter Authentication

5.1.2 Accessing Twitter Data

After the authentication, we need to connect with Twitter Streaming API. Tweepy a python library enables us to connect with Twitter and download data. Once the Twitter Authentication service authenticates the API, a token is generated and made available to the API for each Twitter server transaction. Using this token, tweets are mined using hashtags or keywords. To access the data, we use the following code, and this downloaded data is stored in .csv files as or dataset.

```

auth=OAuthHandler(ckey, csecret)
auth.set_access_token(accessToken, accessSecret)
twitterStream = Stream(auth, listener())
Stream(twitterStream.filter(track=[inp]))

```

5.2 Data Preprocessing

The data which is extracted from twitter is unstructured and unorganized, expressed in various aspects by using various vocabularies, slangs, the context of writing, etc. Therefore, data preprocessing consists of data cleaning and stop word removal.

5.2.1 Data Cleaning

It includes Removal of unnecessary data such as HTML Tags, white Spaces and Special characters takes place from the Twitter dataset. This noise does not make any sense, therefore, they need to be removed. Data cleaning is achieved by importing regular expression (RE) python library. Process of cleaning data for our system is as follows:

- a. The First step is to remove the URL. URL is not considered as an essential element in the tweets and just for simplicity, URLs are removed.
- b. Twitter handlers such as '@abs' are also removed as these are not provide any weights in sentiment classification.
- c. The next step is to remove punctuation. After that, the removal of special character takes place.
- d. Non-textual contents and contents that are irrelevant for the analysis are identified and eliminated.
- e. Extra White spaces are also replaced with single white space.
- f. White spaces from the beginning and end are also removed.

5.2.2 Stop Words Removal

Stop words are the dictionary-based bag of words. These are the set of commonly used words not only in English but in any other language. Stop words focus on important word only instead of commonly used words in a language. Stop word Removal is done by eliminating the unnecessary words from the Twitter data set, So that, the resultant data set contains only the required information for the analysis. The process of stop word removal is as follows:

- a. First of all, tokenization takes place. "Tokens" are usually called as individual words and "tokenization" is

taking a text or set of text and then breaking it up into its individual words.

b. After that, all the unnecessary words are removed after tokenization such as 'a', 'an', 'the', and so on. These unnecessary words are the stop words which have no meaning.

After stop word removal, only important words that could lead to sentiment detection are left. Stop word Removal and tokenization is achieved by another python library known as NLTK.

5.2.3 Lemmatization

Lemmatization is to grouping together inflectional forms and sometimes derivationally related forms of a word to a common base form. For instance, vehicle, vehicles, vehicle's, vehicles' vehicle. Lemmatization is similar to stemming with a difference. Lemmatization generally relates to doing stuff correctly using a term vocabulary and morphological analysis, normally aimed solely at removing inflection marks and returning to the base or dictionary form of a word recognized as the lemma. Whereas Stemming generally relates to a coarse heuristic method that chops off the ends of words in the expectation of attaining this objective properly most of the time, and often involves removing derivative affixes. If faced with the token saw, stemming might return just s, whereas lemmatization would try to return either see or saw based on whether the token was used as a verb or a noun. The two may also vary in the fact that stemming most commonly collapses derivative-related words, whereas lemmatization usually collapses only distinct inflection forms of a lemma. With the assistance of the python library recognized as TextBlob, lemmatization in our proposed methodology is performed to conduct easy natural language processing tasks. TextBlob is easier, similar to many features of NLTK.

5.3 Feature Extraction

Feature extraction is an important step in opinion mining that generates a list of object, aspect, features, and opinions. The purpose of feature extraction is to extract opinion sentences which contain one or more features, aspects, and opinions. In most of the cases, aspect words are nouns and noun phrases, their opinion words are adjectives and adverbs. In this research work, features are extracted using the TextBlob library. After the preprocessing phase, only necessary words are left in tweets which are used for analysis. We extract only nouns and noun phrases from the tweets. These noun phrases are used to know the 'who' in the tweet. After the extraction of nouns and noun phrases, only words that have features or aspects such as adjective and adverb and so on are left. Therefore, in the next phase, these extracted features are classified into sentiments.

5.4 Sentiment Identification

After feature extraction, we identify the positive and negative orientation of words. These features are searched into opinion word list from the huge set of corpora in TextBlob Library to find out the sentiments. Features are searched into positive and negative word list of the dictionary. If the word is present in the positive opinion word list, then the positive Sentiment is assigned to the corresponding feature. If the word is present in the negative Word list, then the negative sentiment is assigned to the corresponding feature. If the word is not present in both the word list, then the sentiment is considered as neutral. So, the final Polarity Score for the tweet is calculated by subtracting the negative score from the positive score. The polarity score is a float ranges from [-1 to 1]. This polarity score allows us to classify the tweets according to polarity which is discussed in the next phase.

5.5 Sentiment Classification

In this phase, we classify the sentiment of the tweet by using our calculated sentiment polarity score. We classify the sentiments for two datasets. Dataset1 classify the sentiments in 3 categories as positive negative and neutral. If the polarity score is greater than 0, then the sentiment of a tweet is classified as positive. If the polarity score is less than 0 then the sentiment of a tweet is classified as Negative. And finally, the tweet is classified as Neutral, if the polarity score is equal to 0. While the dataset2 provide detailed description by classifying sentiments in 7 categories such as Strongly Positive, Positive, Weakly Positive, Strongly Negative, negative, Weakly Negative, and Neutral. If the final calculated Polarity score of the tweet is greater than 0.6 and less than or equal to 1, then the tweet is classified as strongly positive. If the polarity score is greater than 0.3 and less than or equal to 0.6 then the tweet is classified as positive. If the polarity score is greater than 0 and less than or equal to 0.3 then the tweet is classified as weakly positive. If the polarity score is equal to 0 then the tweet is classified as Neutral. If the polarity score is greater than or equal to -0.3 and less than 0 then the tweet is classified as weakly negative. If the polarity score is greater than or equal to -0.6 and less than -0.3 then the tweet is classified as Negative. If the polarity score is greater than or equal to -1 and less than -0.6 then the tweet is classified as Strongly Negative.

5.6 Subjective Identification

Subjectivity can be seen in the explanatory sentences. Subjective sentences are opinions that define the emotions of individuals towards a particular topic or subject. There are many forms of subjective expressions,

such as views, claims, wishes, convictions, doubts, and speculations. The subjective phrase is "I like gold color," although the objective phrase includes facts and has no view or opinion. For instance, an objective sentence is - "The phone's color is gold". A subjective sentence may not express any sentiment. For example, a subjective sentence is - "I want a phone to have a good battery backup", but does not express any sentiment. In our system, we get the subjectivity score for the tweets using the TextBlob library function. TextBlob Library already has a dictionary that contains subjectivity score for the words. Modifiers increase the subjectivity of a word or sentence. For example, "Very Good" is more subjective than "Good" Subjectivity is a range of values within [0.0, 1.0]. Here, 0.0 is very objective and 1.0 is very subjective.

5.7 Output

The final phase of our sentiment analysis is the visualization of the results. We use Pie charts, Trend Graphs and tables to view the results. We use a python library Matplotlib to plot Pie charts and a trend graph to plot these charts and graphs. Its numerical extension to mathematics is NumPy. And we're using Pandas for table visualization. Pandas is a software library for manipulation and analysis of data written for the Python programming language. It provides data structures and operations to manipulate numerical tables and time sequences.

We developed our system as a web application. It takes user input in the form of Hashtag or keyword and process data and visualizes results on a webpage using charts, graphs, and tables. To develop this webpage we use Dash. Dash is a productive Python framework for the development of analytical web applications. Building on top of Plotly.js, React, and Flask, Dash directly links modern UI elements such as dropdowns, sliders, and graphs to your python analytical code. Dash summarizes all the techniques and protocols needed to create an interactive web-based application. Dash is easy enough to connect your Python code to a user interface.

VI. CONCLUSION

Sentiment analysis helps in identifying people's emotional states. Attitude of the person at the time of posting certain content is also analyzed. This paper talks about elements of the different ways to deal with Sentiment Analysis in a subtle method using mostly ML and Lexicon-based approaches. This survey paper gives a detailed perspective of the distinctive applications and challenges of Sentiment Analysis.

VII. FUTURE WORK

There is still a significant amount of work to be accomplished, here we are giving a beam of light to possible future research. Currently, the proposed methodology cannot interpret sarcasm. Sarcasm is the use of irony to praise or convey contempt, sarcasm transforms the polarity of favorable or bad utterance into its reverse. It is also difficult for our proposed approach to analyze multiple languages. A multilingual sentiment analyzer is currently not feasible due to the absence of multi-lingual lexical vocabulary. We are also implementing it for stronger outcomes in our future work. The main objective of this approach in our future work is to identify empirically lexical and pragmatic factors that differentiate between sarcastic, positive and negative use of words with multilingual analysis.

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