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Advancements and Challenges in Sentiment Analysis: A Comprehensive Review of Frameworks and Future Trends

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Abstract: *Sentiment Analysis (SA), also known as Opinion Mining (OM), is the field of study that deals with the computational treatment of opinions, sentiments, and subjectivity expressed in text. It has gained significant traction in recent years due to the ever-increasing volume of user-generated content available online. SA techniques are employed in a wide range of applications, including social media monitoring, product reviews analysis, and customer feedback evaluation. Machine learning algorithms play a crucial role in SA, providing effective methods for extracting and classifying sentiment from text data. In this Survey we tried to present the broad impression of current and precedent study on sentiment analysis and present admirable research queries and methods for future research.*

Keywords: *Sentiment Analysis, Opinion Mining, Machine Learning, Text Classification, Social Media Monitoring, Product Reviews Analysis, Customer Feedback Evaluation.*

1. Introduction

Today reviews or comments play an impact on customer procuring through e-commerce websites. This sharing gives attitude, emotion, or reaction about customer. The comments may be about goods, or services or any related things. To make decision on the availability of opinion rich and huge volume of information (Example comments in Amazon, Flipkart, Twitter, Facebook etc.,). We need an intelligent system for learning opinions. This analysis is known as Sentiment Analysis or Opinion Mining. It will help the individuals, Organizations, and Government to know what the attitude of public about their particular product or service is [1]. Opinion mining is a task which combines Natural Language Processing (NLP) and machine learning techniques to analyze text as positive, negative or neutral. For example," I had an Intel XOLO Q1100 for about 2 years. It works brilliantly, durable and reliable. Its display is beautiful and the phone is fast and perfect size to fit into my pocket", is a positive opinion. Opinions may be Direct and Indirect. The expression of sentiment on some objects is referred as Direct Opinions. For instance," Sony Xperia S is excellent phone with excellent Camera Quality and Gaming", is a positive opinion for Sony mobile phone. Indirect op inions are comparing two or more objects with similarities and differences. For example, "Intel XOLO Q1100 is far better than iPhone. I look at the customization, ease of use, menus, and speed everything". In the above example, the author compares the features of mobile phones.

Subjectivity Detection is a technique to determine opinion as subjective or objective expression from a piece of text. For instance, (1) Digital Camera is a good device for taking photographs. (2) The quality of picture on this camera is good. Both the sentences contain sentiment bearing words good, despite first sentence is an objective or factual sentence (i.e., does not convey any sentiment) whereas second one depicts opinion about that camera, is a subjective sentence. Sentiment Classification is to organize the subjective sentence as positive, negative or neutral from the document, also known as polarity classification. Sentiment Summarization gives sentiment summary at aspect level.

The applications of Opinion Mining are: Brand Sentiment analysis helps to understand the tastes, preferences and customer patterns by mining unstructured data from blogs and social media. Competitor analysis is also important for organizations to compare with their peers and able to know their strength and weakness of their products. In marketing intelligence, business organizations collect feedback from customers through email or social media and analyze which aspects of the product or service they are having difficulty. This type of analysis is known as complaint analysis which detects new problems faced by the customers. In Audio and Video processing, opinion mining procedures are used as an input feature for text to speech synthesis, and online video analysis. In Financial industry, opinion mining is used to predict stock market and to analyze it. Government will take decision based on opinion polls collected from social web sites to know their strength and weakness.

Major challenges are addressed in various research works [2]: Entity Identification is an important task in opinion mining. A sentence may contain multiple entities, the opinion mining system needs to identify on which entity the opinion is expressed. Opinion Holder Detection is a task of detecting opinion topics and opinion holder. Opinion Classification determines whether the opinion of the sentence is positive, negative or neutral. Opinion spam Detection is one of the major task used to identify the bogus opinions in reviews and forums. Sarcasm identification is a common technique that a sentence may contain implicit opinion without the presence of any opinion bearing words, identifying such sentence is a major issue in opinion mining. The objective of this work gives methodologies and recent developments of Sentiment Analysis that can be applied in day to day activities.

Rest of the paper is organized as follow: in section 2 we explained sentiment analysis framework, its classes and levels of classification. Section 3 gives overview of various challenges of sentiment analysis. Section 4 presents previous work done by various researchers in the field of sentiment analysis. Section 5 shows problem statement of the SA. In section 6 we gives some future research direction and lastly we conclude our work in section 7 followed by references we used.

2. Sentiment Analysis

The area of study that interprets people's opinions, against any particular topic, about any event etc. in text mining it is known as opinion mining or sentiment analysis. It produces a vast problem zone. There are also various names and having different tasks, e.g., sentiment analysis, opinion extraction, opinion mining, sentiment mining, affect analysis, subjectivity analysis, review mining, etc. [24]

2.1 Sentiment Analysis Framework

This section discusses the basic Sentiment analysis framework which can be used to judge the emotions from website. This framework consists of three main steps. The first step being data collection, followed by preprocessing of the data collected. The last step is the classification which categorizes the data processed into either positive or negative. Fig. 1 gives the basic overview of sentiment analysis framework.

A. Data Collection

Sentiment Analysis can be done on any data. The data can either be collected from any data set or can be extracted from any website. Data set is available online with thousands of reviews along with the label of positive and negative. On the other hand, extracting data from web is a lengthy task but one can perform sentiment analysis on the data of their own choice.

B. Pre-Processing

Data extracted from the web contains several syntactic features that may not be useful and therefore data cleaning and filtering needs to be done. In order to remove the unprocessed data, this step needs to be performed. It is imperative to preprocess all the data to carry out further functionalities. The various pre-processing steps involved are given as below:

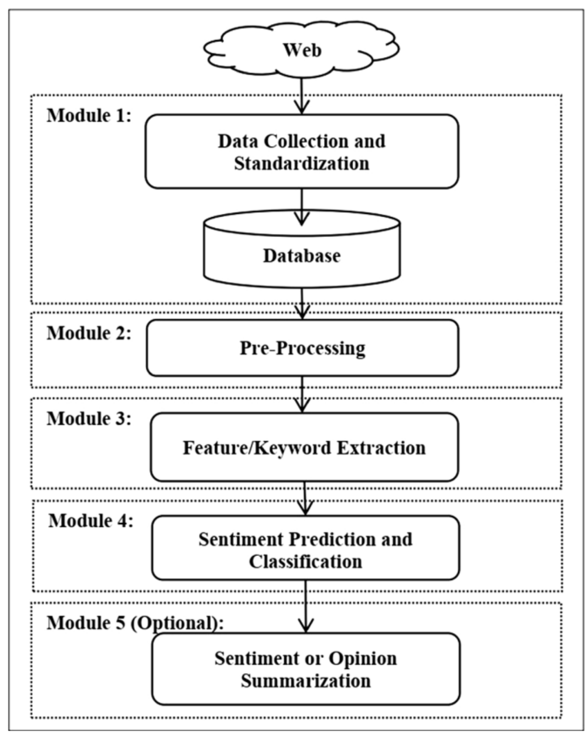

Fig. I: Sentiment Analysis Framework

1) Removing URLs

URLs are of no use while performing sentiment analysis and can sometimes lead to false analysis. For example "I have logged in to www.happy.comasI·mbored... This sentence is negative but because of there is one positive word in the uri, it becomes neutral thus leading to a wrong prediction. To avoid the chances of false prediction, URLs must be removed.

2) Filtering

Repeated letters in words like "thankuuuuu" are often used to show the depth of expression. However, these words are absent in the dictionary hence the extra letters in the word needs to be eliminated. This is done on the basis of a rule that a letter cannot repeat itself more than three times and if there is such letter that will be eliminated.

3) Questions

Words like "what", "which", "how" etc., does not contribute to polarity and thus such words must be removed in order to reduce the complexity.

4) Removing special characters

In order to remove discrepancies during the Sentiment Analysis process, special characters like '[] {} 0/' should be removed. For example "it's good:" If these characters are not eliminated before performing sentiment analysis, they will get combined with the words and those words will not be recognized. To avoid the situation, removal of such characters is important.

5) Removing Stop words and emoticons

Stop words are words that should be excluded in order to proceed with the SA process. Stop words don't carry as much meaning, such as determiners and prepositions (in, to, from, etc.) and thus needs to be filtered. Most of the times, while writing a review, people tend to use emoticons in order to express their feelings better. Although, these emoticons help in better understanding of the emotions but while performing Sentiment analysis, this can mislead and predict wrong.

6) Lemmatization or stemming

Lemmatization and stemming aims to reduce inflectional and related forms of a word to a common base forms. Stemming achieves its goal correctly most of the time by removing the ends of the words. Whereas, lemmatization does the same process properly with the use of a vocabulary and morphological analysis of words.

7) Tokenization

Tokenization refers to splitting the sentence into its desired constituent parts. It is an important step in all NLP tasks.

2.2 Classes of Sentiment Analysis

Sentiments can be classified into three classes' .i.e. positive, negative and neutral sentiments.

a) **Positive Sentiments**: These are the good words about the target in consideration. If the positive sentiments are increased, it is referred to be good. In case of product reviews, if the positive reviews about the product are more, it is bought by many customers.
b) **Negative Sentiments**: These are the bad words about the target in consideration. If the negative sentiments are increased, it is discarded from the preference list. In case of product reviews, if the negative reviews about the product are more, no one intend to buy it.
c) **Neutral Sentiments**: These are neither good nor bad words about the target. Hence it is neither preferred nor neglected.

2.3 Levels of Sentiment classification

There are three different levels of sentiment classification. i.e. word level, phrase level and document level sentiment classification.

a) **Word Level Classification**: this classification is done on the basis of the words which indicate the sentiment about the target event. The word may be noun, adjective or adverb. This type of classification gives accurate classified sentiments.
b) **Phrase Level Classification**: This type falls in good as well as bad category. The phrase denoting the opinion is found out from the sentence and the classification is done. But it sometimes gives inaccurate results if a negation word is added in front of the phrase. The phrase refers to combination of two or more words which are closely related to each other.
c) **Document Level Classification**: In this level of classification, single document is considered about the opinionated text. A single review about the single topic from this document is considered. But sometimes it is not beneficial in case of blogs and forums as customers may compare one product with the other which has similar characteristics. Again the document may consist of the irrelevant sentences which don't resemble to opinion about the event.

3 Challenges in Sentiment Analysis

Sentiment analysis can be thought as content categorization task since it classifies text as positive, negative or objective. However, sentiment analysis is challenging as compared with conventional content characterization, although it has only three classes because of the following factors [3].

3.1 Sarcasm and Conditional Sentences

If a user is using a positive sentence about a product but his/her intentions are negative. In other words, we can say that the meaning is just opposite. These kinds of sentences

fall in the category of sarcasm. It is very difficult for a system to identify the sarcastic sentence. Different users use sarcasm in a different manner. How this different intention can be understood by the system? It is a challenging task. For example, ‘This movie is good enough to waste money’ is a sarcastic sentence [3].
To understand the conditional sentences is also a typical task for a system. For example, ‘The movie will be perfect if the story is interesting’. Several attempts have been made to detect sarcasm. Twitter has been a crucial source of training such models. Using ‘hashtags’, Twitter posts as a gold standard, for example, ‘#sarcasm’. Another major resource is product reviews from www.Amazon.com.
Lexical features are used to classify the sarcastic and non-sarcastic tweets based on the dictionary-based tags. A final classification was performed by SVM and logistic regression technique [4]. Machine learning approach with grammatical features was used to detect sarcasm in Dutch tweets which were hashtagged. A balanced winnow was implemented, and the result was favorable [5]. A rule-based approach with hashtag-based sentiment was also used for Twitter dataset. In this, they not only consider the range of sarcastic modifier to observe meaning of tweets but also sentiment’s polarity [6]. Again, a rule-based approach is applied with lexical, implicit incongruity, explicit incongruity and pragmatic features for Twitter data and discussion forum [7].

3.2 Spam Detection

There are so many users who try to post the negative reviews to pamper other’s reputation. In today’s scenario, it is challenging task to identify the spam among the many reviews. So, it is essential to develop such a system which can identify spam and can remove it [3]. Three approaches, i.e. genre identification text, psychogrammatical deception detection and text categorization, were used for finding misleading opinion. A tool called LIWC—Linguistic Enquiry and Word Count—is used by second approach called Psycholinguistics Deception detection [8]. A hierarchical framework was used for spam detection using singleton review [9]. They find a correlation between volume of single review and rating because as the review increases, the rating decreases or increases dramatically. Different classifications of machine learning algorithms, i.e. support vector machine, decision tree, LogitBoost, Bagging, KNN and AdaBoost, were implemented on two real and large public datasets. By using these approaches, the best overall results were achieved by the bagging of decision tree in this scenario in which they did not combine features. Adaptive Boosting (AdaBoost) attained the highest performance with the combination of features Survey of Challenges in Sentiment Analysis vectors. The evaluated techniques showed the best result for balanced classes [10].
A shallow dependency parser technique is used to compute sentiment score. A relationship between spam reviews and sentiment score was given by them. Spam review detection was combined with sentiment analysis. Furthermore, by using the discriminative rules, the spam reviews can be also identified from the abnormal time window. The case study and the experiment showed the efficacy of these methods [11]. In contrast to earlier work, they noticed deceptive reviews do not express the emotions as strongly as the genuine reviews do. They used rule-based method for deceptive spam dataset. They used deep grammatical features to build a better deceptive spam detection model. The final result of this approach gave an improvement in performance by 1.1% [12].

3.3 Anaphora Resolution

During the sentiment analysis, pronouns are ignored by most of the researchers. It is difficult for a system to identify what a pronoun or noun refers to in the sentence. In many situations, pronouns also play an important role to know about the users’ perception. For example, ‘The movie is awesome. It contains many good actions as well as emotions’. In this example the word ‘it’ refers to movie. We cannot refer ‘good’ to ‘movie’ without knowing the reference of ‘it’ [3]. The problem of source co-reference resolution was proposed by [13]. However, they used partially supervised clustering rather than using simply supervised learning algorithms. Supervised machine learning approach with two semantic features was used to improve the co-reference resolution accuracy [14].

3.4 Negation Handling

Negation handling in sentiment analysis plays an important role in altering the polarity of the associated adjective and hence the polarity of the text. Negation words include not, neither, nor, etc., for example, ‘The movie is good’ should be classified as positive. ‘The movie is not good’ should be classified as negative. This type of sentences can be handled by reversing the polarity of the adjective occurring after a negative word. But this solution fails to entertain the cases like ‘No wonder the movie is good’ and ‘Not only the story was interesting, the songs were also entertaining’. Negation has not been tackled completely with the use of mathematical models and language processing techniques.
In French context of sentiment analysis [15], they differentiated different types of negative operators, negative quantifiers and lexical negations by using grammatical

features. Tree kernel based scope detection which uses the parse information which is syntactically structured. Added to this, a way of selecting attributes which are compatible for different PoS, as features have an efficiency which is imbalanced for 232 S. Singhal et al. classifying scope, which is affected by PoS was explored by them [16]. An automatic system was developed to detect negation and speculation cues by using machine learning approach. It is the first system which is trained and tested on the SFU Review corpus annotated with speculative and negative information. The results reported—92.37% in F1 and 89.64% for negation—are encouraging. In scope detection task, the results—F1, 84.07% in negation, 78.88% in speculation, G-mean, 90.42% for negation and 87.14% for speculation, and PCRS, 71.43% in speculation and 80.26% in negation, are very promising [17].

3.5 Word Sense Disambiguation

Word sense disambiguation is identifying which sense of a word is used in a sentence as the single word has multiple meanings. It is controlled by the sense of the word in that context, for example, 'Small'. If we relate small with television, it sounds negative sense. But if talk about a mobile phone, it can be positive. It depends on the user, what he likes or not. So it is difficult to determine this for a system.

Some researchers including [18–20] initiate by creating lexicon dictionaries where words are associated with the prior polarity out of context. The contextual polarity of a word present in a phrase may differ from the word's prior polarity because a word may appear in different senses. Additionally, it is difficult to define the prior polarity for several words such as long, short, think, deeply, entirely, small, feel, practically, etc. because they do not carry specific polarity by themselves. Grammatical features were used to determine the polarity of polar clause [21]. These grammatical features include modifications features, structure features, and sentence features. Instead of disambiguating the word sense, the effect of enhancers, negation and modifiers is determined using the word context. Speech pattern matching method was used to resolve disambiguation of words at the sentence level [22]. In order to determine the polarity of the sentence, parts of speech pattern are extracted and compared with WordNet glossaries in order to identify the appropriate sense in SentiWordNet. However, results achieved through parts of speech pattern matching are not satisfactory because a word used in the same parts of speech pattern may not have the same sense. In order to identify the disambiguate sense of the word, four tasks were proposed [23].

a) Exact boundaries of the text are determined where opinion about a feature is articulated.
b) Context of word is identified in a sentence using an appropriate method.
c) Context matching mechanism is provided in order to obtain the polarity of the corresponding context from the lexicon.
d) Lexicon dictionary is built which not only contains the senses of words in a particular domain but also supports a context matching mechanism.

The results show that these methods considerably improve the overall performance of feature level sentiment analysis.

4. Related Work

There are various text mining approaches used to mine the data.

Prabhsimran Singh, et.al. [25] They have examined this government policy the demonetization from the ordinary person's viewpoint with the use of the approach of sentiment analysis and using Twitters data, Tweets are collected using certain hashtag (#demonetization). Analysis based on geo-location (State wise tweets are collected). The sentiment analysis API used from meaning cloud and classified the states into six categories, they are happy, sad, very sad, very happy, neutral, and no data.

Xing Fang, et. al. [26] they have solved the issue of sentiment polarity categorization, and it is one of the basic problems of sentiment analysis. Online product reviews data is used in this study, collected from Amazon.com. In this paper Investigation for both sentence-level categorization and review-level categorization are achieved. Scikit-learn software is used for this study. Scikit-learn is an open source machine learning software package in Python. Naïve Bayesian, Random Forest, and SVM: These classification techniques selected for categorization.

Geetika Gautam, et.al. [27] they contribute to the sentiment analysis for customers' review classification. Already labeled twitters data is used in this task. They have used three supervised techniques in this paper: naïve-Bayes, Max-entropy and SVM followed by the semantic analysis which was used along with all three methods to calculate the similarity. They have used Python and NLTK to train and classify the: naïve-Bayes, Max-entropy and SVM. Naïve-Byes approach gives a better result than the Max-entropy and SVM with unigram model gives a better result than using SVM alone. Then the correctness is then increased when the Word- Net of semantic analysis is applied after the above procedure.

Neethu M S, et. al. [28] in this paper, they analyze the twitter data related to Electronic products using Machine Learning approach. They existent a new Feature-Vector for

classification of the tweets and extricate peoples' opinion about Electronic products. Thus Feature-Vector is created from 8 relevant features. The 8 features used are special keyword, presence of negation, pos tag, and number of positive keywords, emoticon, and number of negative keywords, number of negative hash tags and number of positive hash tags. Naïve-Bayes and SVM classifiers are implemented using built in functions of Matlab. Max-Entropy classifier is implemented using Maximum-Entropy software. All the used classifiers have almost equal performance.
Akshay Amolik, et. al. [29] in this paper they proposed a more correct model of sentiment analysis of twitter data about reviews of coming Hollywood and Bollywood movies. With the help of classifiers and Feature-Vector such as SVM and Naïve-Bayes we are accurately classifying these tweets. For sentiment of each tweet Naïve-Bayes has better precision than to SVM, but slightly lower accuracy and recall. SVM has better accuracy than Naïve Bayes. The Feature-Vector gives more good sentiment analysis than of selected classifier. The accuracy of classification will increase with the increase of training data.

5. Problem Statement & Challenges

The exponential growth of user-generated content across digital platforms, including social media, online reviews, and customer feedback, has created an urgent need for effective methods to extract and analyze sentiment from text data. Sentiment Analysis (SA), also known as Opinion Mining (OM), addresses this challenge by leveraging computational techniques to identify and classify the opinions, sentiments, and subjectivity expressed in text. However, the complexities of human language, such as sarcasm, irony, and multilingualism, pose significant challenges to achieving accurate and reliable SA.

Key Challenges:

- Handling Sarcasm and Irony: Sarcasm and irony are often used in text to convey subtle meanings that can be difficult for machines to interpret correctly. This can lead to inaccurate sentiment classification, especially when dealing with informal language and social media conversations.
- Multilingual Sentiment Analysis: The ability to analyze sentiment in multiple languages is essential for understanding global trends and opinions. However, developing effective multilingual SA models is challenging due to cultural nuances, language variations, and the lack of labeled data in many languages.
- Domain Adaptation: SA models trained on generic data may not perform well when applied to specific domains, such as finance, healthcare, or legal documents. Domain adaptation techniques are needed to improve the performance of SA models in different contexts.
- Real-time Sentiment Analysis: The ability to analyze sentiment in real-time is crucial for applications such as social media monitoring and customer service. However, developing efficient real-time SA models is challenging due to the computational complexity of machine learning algorithms.
- Explaining SA Predictions: Machine learning models often produce "black box" predictions, making it difficult to understand the reasoning behind their decisions. Explaining SA predictions is crucial for building trust in SA models and ensuring their fairness and reliability.

6. Future Research Direction

Future research directions for Sentiment Analysis based on a comprehensive survey of machine learning algorithms and applications:

- *Addressing Sarcasm and Irony:* Researchers should focus on developing models that can better understand the nuances of sarcasm and irony, incorporating contextual information, and exploring semi-supervised and unsupervised learning approaches.
- *Multilingual Sentiment Analysis:* Collecting and curating multilingual sentiment datasets, developing cross-lingual representation learning techniques, and investigating the use of multilingual neural language models are crucial steps forward.
- *Domain Adaptation:* Transfer learning techniques, domain-specific features and representations, and meta-learning algorithms hold promise for adapting SA models to specific domains.
- *Real-time Sentiment Analysis*: Efficient machine learning algorithms, edge computing, and lightweight neural networks are essential for real-time sentiment analysis.
- *Explaining SA Predictions:* Interpretable machine learning models, attention mechanisms, and contrastive learning can help explain the reasoning behind SA predictions.

7. Conclusion

As the information is growing gradually, because of which receiving all statics is about to impractical but probable steps could be taken to acquire most of the valuable information from it. This could be accomplished via sentiment analysis which gives the emotions, intelligence of the sentence or the different movie reviews or product reviews. There are a range of regions in sentiment analysis domain which are still untouched and lot of enhancement in existing methods could be done with accurate comprehension. Likewise because of the huge textual data, it is unfeasible to interpret all the information to pull out constructive information for a human being. In this paper, survey has been done of previous work related to text and reviews sentiment analysis, so that new research area can be explored by looking into the merits and demerits of the current techniques and strategies.

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