A Study of Sentiment Analysis Methods, Tools and Challenges.

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Abstract

Sentiment Analysis is the process of computationally identifying and categorizing opinions expressed in a piece of text especially in order to determine the writers' attitude towards a particular topic, product etc, is positive, negative or neutral. Evolution of new generation technologies and fair access to the internet in countries like India, public opinions over social media, expression of sentiment on products and services are fast and furious in present days. These opinions have great value for companies to materialize profits and understand the market for their future strategic decisions. Presently sentimental analysis has wide scope in understanding customer experience, market research and consumer insights. Other applications include social media analytics, emotion and customer predictions.

Keywords: Sentiment Analysis, classification, Feature selection, emotion detection, transfer learning, prediction, machine learning, building resources.

Introduction :

Sentiment Analysis is typically used to analyze people's sentiments, opinions, appraisals, attitudes, evaluations and emotions towards such entities as organizations, products, services, individuals, topics, issues, events and their attributes, as presented online via text, video and other means of communication. These communications can fall into three broad categories, namely positive, neutral and negative. These categories involve many names and slightly different tasks, such as opinion mining, opinion extraction, sentiment mining, subjectivity analysis, customer complaint, effect analysis, emotion analysis, review mining and review analysis. Many techniques for SA have been introduced. These techniques can be categorized into the following: Application-oriented, which ranges from stock price predictions to public voice analysis, crowd surveillance and SA-based customer care; fundamental approaches, including word-level sentiment disambiguation, sentence-level SA, aspect-level SA, concept-level SA, multilingual SA and linguistic features analysis; and social intelligence, which exploits the public's online content generation to analyze such inputs as pandemic spreading, emotion and responses towards local events.

2. General Approaches of Sentiment Analysis

Sentiment Polarity Detection SA, also known as opinion mining, is the extraction of positive or negative opinions from (unstructured) text. Sentiment classification has several important characteristics, including various tasks, features, and techniques. Three important sentiment polarity tasks are a) Identifying whether text is objective / subjective or whether subjective text has a positive/negative orientation. b) Determining the level of the classification (document/sentence level).Polarity classification of sentiment is classified into document-level, sentence-level and phrase level classification. Document-level classification classifies the document as positive, negative, or neutral. Sentence-level classification considers and classifies only a sentence determining whether a sentence is subjective or objective. To capture multiple sentiments that might exist within a single sentence, phrase-level classification is performed.

2.1 Sentiment Analysis Features: Four types of explicit features have been used, namely syntactic, semantic, link-based and stylistic features. Most common set of features for SA, Syntactic attributes contain word n-grams tags and punctuation. Moreover, these attributes contain phrase patterns, which make use of POS tag n-gram patterns. They illustrated that phrase patterns like 'n+aj' (noun followed by a positive adjective) usually denote positive sentiment orientation, whereas 'n+dj' (noun followed by a negative adjective) often expresses a negative sentiment. In 2004, Wiebe applied collections, where certain parts of fixed n-grams were exchanged with general word tags. Whitelaw et al. (2005) applied a set of modifier features (e.g., very, mostly and not). The presence of these features transformed appraisal attributes for lexicon items. Link/citation analysis is applied in link-based features to detect sentiment from the web and documents. Efron et al. (2004) demonstrated that opinion web pages are linked to one another. Link-based features have been used in limited studies. Thus, the effectiveness of such features for SA remains unclear. Stylistic features contain structural and lexical attributes, which are used in many previous stylometric/authorship works.

2.2 Implicit Features: Studies on implicit features in SA have focused on semantic and linguistic rules to identify the embedded message, which is not typically expressed using predefined keywords. Instead, the meaning is delivered using similar conceptual-based expressions. Semantic features try to identify polarity or provide intensity-related scores to words and phrases. In Semantic Orientation (SO) method mutual information was calculated to compute the SO score of each word/phrase automatically. Manual or semi-automatically produced sentiment lexicons commonly use a primary set of automatically generated terms that are manually filtered and coded with polarity and intensity information. User-defined tags are used to indicate whether certain phrases have positive or negative sentiment. Semi-automatic lexicon generation tools were used by to construct a set of strong subjectivity, weak subjectivity and objective nouns. They also used other features, such as bag-of-words, to classify English documents as either subjective or objective.

2.3 Appraisal group: Term lists are initially created using WordNet and are then filtered manually for constructing the lexicon. In Appraisal Theory, each expression is manually classified into several appraisal classes, such as attitude, the polarity of phrases, orientation and graduation. Manually generated lexicons have also been used for affect analysis. Affect lexicons are used with fuzzy semantic typing to analyze movie reviews and news articles. Hate and violence in extremist web forums were analyzed using manually constructed affect lexicons

2.5 Semantic attributes: These contain contextual features that represent the semantic orientation of surrounding text. Semantic attributes have been useful for sentence-level sentiment classification.

2.6 WordNet: It is a large electronic lexical database for English and it continues to be developed and maintained. WordNet consists of synsets from major syntactic categories, such as nouns, verbs, adjectives and adverbs. The current version of WordNet (3.0) contains over 117,000 synsets, comprising over 81,000 noun synsets, 3,600 verb synsets, 19,000 adjective synsets and 3,600 adverb synsets (Poli et al., 2010). WordNet has been used for synonym collection, whereas SentiWordNet has been used to identify the semantic orientation of each sentence or extracted feature.

2.7 SentiWordNet: It is a lexical resource for opinion mining. It is a lexicon base that is similar to WordNet, but it is extended with the lexical information about the sentiment of each synset contained in WordNet. Three different polarities, namely positivity, negativity and objectivity, are assigned to each synset in WordNet. The two most common versions of SentiWordNet used in many studies are SentiWordNet 1.0 and SentiWordNet 3.0. Apart from being used in monolingual studies, SentiWordNet can also be used in multilingual SA

2.7 SenticNet: This is built by using semantic computing. It is the latest semantic resource specifically developed for concept-level SA. It exploits both Artificial Intelligence (AI) and semantic web technique to recognize, interpret and process natural language opinions better over the web. SenticNet is a knowledge base that can be applied in the development of many fields, such as big social data analysis, human-computer interaction, electronic health etc.

2.8 Linguistic Rules: Most of the rule-based linguistics approaches are applied to clause-level or concept-level sentiment classification. The algorithm adopts a pure linguistic approach and considers the grammatical dependency structure of the clause by using SA rules. Linguistic rules are useful for dealing with the semantic orientation of context-dependent words and they are very helpful for extracting implicit features. These features are those that are not clearly mentioned but are rather implied in a sentence. All existing works on implicit aspect extraction were based on the use of Implicit Aspect Clue (IAC) and rule-based method to extract implicit aspects. They mapped the implicit aspect to the corresponding explicit aspect.

3. Sentiment Classification Techniques

3.1 Sentiment Classification through Machine Learning: The Machine Learning (ML) approach applies the ML algorithm and uses linguistic features with the aim of optimizing the performance of the system using example data. Typically, two sets of documents are required in an ML-based classification. These documents are the training and testing sets. A training set is used by the classifier to learn the document characteristics, whereas a testing set is used to validate classifier performance. The text classification methods using the ML approach can be divided into supervised and unsupervised learning methods. The supervised methods use a large number of labelled training documents.

The unsupervised methods are used when these labelled training documents are difficult to find. The supervised methods achieve reasonable effectiveness but are usually domain specific and language dependent and they require labelled data, which is often labor intensive. Meanwhile, the unsupervised methods have high demand because publicly available data are often unlabelled and thus require robust solutions. Therefore, semi-supervised learning has been introduced and has attracted considerable attention in sentiment classification. In unsupervised learning, it uses a large amount of unlabelled data along with labeled data to build better learning models.

The most popular ML techniques that have achieved great success in text classification are Support Vector Machine, Naive Bayes and Maximum Entropy. The other well-known ML methods in natural language processing are K-Nearest neighbor, ID3, C5, centroid classifier, winnow classifier and the N-gram model.

3.1 Decision Tree Classifier

In Decision Tree classifier, the interior nodes were marked with features and edges that are leaving the node were named as a trial on the data set weight. Leaves in the tree are good, by categorization. This categories whole document by starting at the root of the tree and moving successfully down through its branches till a leaf node is reached. Learning in decision tree adopts a decision tree classifier as an anticipated model in which it maps information of an item to conclusions of that item's expected value. In a decision tree, the large amount of input can figure out by using authoritative computing assets in the finite time. The main advantages of decision tree classifier are, it is easy to understand and to interpret. This classifier requires small data preparation. But these concepts can create complicated trees that do not generalized easily.

3.2 Linear Classifier

In linear classifier, for classifying input vectors to classes they use linear decision margins. There are many types of linear classifiers. Support vector machine is one of them. This classifier provides a good , scatter between various classes.

3.2.1 Neural Network

Neural network includes numerous neurons in which this neuron is its elemental unit. Multilayer neural network was used with non-linear margins. The results of the neuron in the previous layer will be given as input for the next layer. In this type of classifier training of data set is more complicated, because the faults must be back-propagated for various layers.

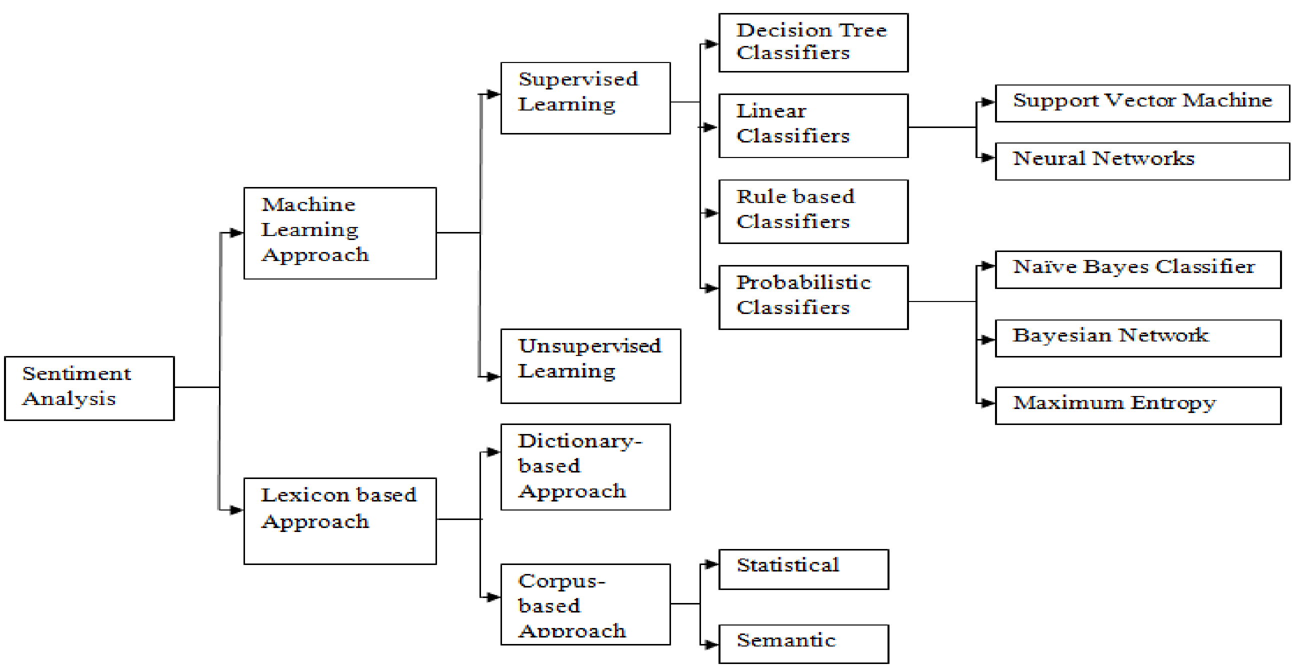

Fig 2: Sentiment Analysis Techniques

3.2.2 Support Vector Machine

Support Vector Machine (SVM) is known as the best classifier that provides the most accurate results in speech classification problems. They achieved by creating a hyper plane with maximal Euclidean distance for the nearest trained examples. Support Vector Machine hyper plane is completely resolved by a comparatively minute subset of the trained data sets which are treated as support vectors. The remaining training data sets have no access to the qualified classifier. So scattered text classification, the classifier SVMs have been applied successfully and also used in different sequence processing application. SVMs are used in hypertext and text classification since they do not require labeled training dataset.

3.3 Rule-Based Classifier

As the name indicates in rule-based classifiers, data set is designed along with a group of rules. In rules left-hand side indicates the condition of aspect set and right hand indicates the class label.

3.4 Probabilistic Classifier

These classifiers use various forms of categorization. This variety of forms takes each and every class as part of that mixture. All various elements are the productive model in which it gives the probability of inspecting a distinct word for that element. These classifiers are also known as generative classifiers. Some of the probabilistic classifiers are Naïve Bayes, Bayesian Network and Maximum Entropy.

3.4.1 Naïve Bayes Classifier

A Naive Bayesian classifier is one of the familiar supervised learning techniques which are frequently used for classification purpose. Their classifier is named as naïve since it considers the contingency that is actually linked are not depending on the further. Calculation of whole document feasibility would be the substance in an aggregation of all the feasibility report of a single word in the file. These Naïve Bayesian classifiers were frequently applied in sentiment categorization since they are having lower computing power when comparing to the other approach but independence assumptions will provide inaccurate results.

3.4.2 Bayesian Network

The main disadvantage of Naïve Bayes classifier is its independent assumption of aspects in data sets. This assumption is the reason for the start of using Bayesian Network. This Bayesian network is directed non-cyclic graph where nodes correspond to variables and those edges are correspond to conditional independence. In text classification, Bayesian Network is not usually used since it is expensive in computation.

3.4.3 Maximum Entropy

Maximum Entropy classifier is parameterized by a weight set that is used to associate with the joint-future, accomplished by a trained data set by encoding it. This Maximum Entropy classifier appears with the group of classifiers such as log-linear and exponential classifier, as its job is done by deriving some data sets against the input binding them directly and the result will be treated as its exponent.

3.5 K- Nearest Neighbour Classifier

K-Nearest Neighbour is an unsupervised learning algorithm for text classification. In this algorithm, the entity is classified with various trained data set along with their nearest distance against each entity. The advantage of this algorithm is its simplicity in text categorization. It also works well with multi-class text classification. The main drawback of KNN is it needs a large amount of time for categorizing entities where a huge data set is inclined.

3.6 Strength/Sentiment Scoring: Sentiment strength is calculated by manipulating the frequency of matched lexicons according to polarity. Extended studies in this challenge include prior polarity, dependency rules, negation identification and summarization. These approaches, however, are still far from being able to infer the cognitive and affective information associated with natural language, given that they mainly rely on knowledge bases that are still too limited to process text efficiently at the sentence level. Moreover, such text analysis granularity might still be insufficient, given that a single sentence may contain different opinions about different facets of the same product or service. To this end, concept-level SA aims to go beyond a mere word-level analysis of text to provide novel approaches to opinion mining and SA that enable more efficient passage from unstructured textual information to structured machine-processable data in any domain.

4. Sentiment Analysis Tools

Shortlist of 8 practical tools to track user sentiment:

1. Meltwater: Assess the tone of the commentary as a proxy for brand reputation and uncover new insights that help you understand your target audience.

2. Google Alerts: A simple and very useful way to monitor your search queries. Its used to track “content marketing” and get regular email updates on the latest relevant Google results. This is a good starting point for tracking influencers, trends and competitors.
3. People Browser: Find all the mentions of your brand, industry and competitors and analyze sentiment. This tool allows you to compare the volume of mentions before, during and after your marketing campaigns.
4. Google Analytics: A powerful tool for discovering which channels influenced your subscribers and buyers. Create custom reports, annotations to keep uninterrupted records of your marketing and web design actions, as well as advanced segments to breakdown visitor data and gain valuable insights on their online experiences.
5. HootSuite: A great tool that allows you to manage and measure your social networks
6. Tweetstats: This is a fun, free tool that allows you to graph your Twitter stats.
7. Facebook Insights: If you have more than 30 Likes on your Facebook Page you can start measuring its performance with Insights. See total page Likes, a number of fans, daily active users, new Likes/Unlikes, Like sources, demographics, page views and unique page views, tab views, external referrers, media consumption and more!
8. Social Mention: The social media equivalent to Google Alerts, this is a useful tool that allows you to track mentions for identified keywords in a video, blogs, microblogs, events, bookmarks, comments, news, Q&A, hash tags and even audio media. It also indicates if mentions are positive, negative, or neutral.

5. Future opportunities and challenges

SA has focused on the techniques, applications and web services but none of the available studies have focused on the SA approaches' adaptability for big data.

Data generated for analysis is continuous and ever-changing, hence, there is increasing the possibility of new linguistic features being created, such as new acronyms, emoticons, idioms and terminologies, which require an update of the SA model.

Research Problem, Aim and Objectives

- Large amount of opinion data may be challenging to review.
- Opinions, Feelings and Views about products, sites, and movies, political polarity is often tricky based on the nature of the author factors viz., expertise of the author in the subject, presentation skills and knowledge of the subject.
- Most approaches have the bottle necks like
    - Sometimes words are not enough to express our emotions.

- People may actually use sarcasm in expression.
- Some words in languages may have no or exact translation in English language.
- To reduce the variables to be predicted for summarizing the opinion.
- To improve the accuracy of prediction.

Opinions mining results of various works are still not satisfactory. The unavailability of good dictionaries is the reason for dictionary-based approach. There is a need to improve the process by handling indirect mention (pronouns), CLAUSES, co references, negation and irony (sarcasm).

Techniques sentimental analysis is suitable for what kind of application needs to be explored.

Proportion of opinion account for prediction needs attention. To explore the possibility of some empirical relations based on previous works for prediction.

Trust worthiness of the authors and their opinions on certain topic or products can be found and verify if its compromised by some companies or political parties.

Sentimental analysis in regional languages like Telugu as scope for research as the need is inevitable with people have access to Telugu keyboard aids in writing blogs, reviews on local products and also this results in understanding the local market from bigger domain of people.

Sentiment Analysis techniques are commonly based on textual sources. In fact, many other multimedia sources should also be processed, some of which are important sources for examples exhibiting expressions of mocking, sabotaging and sarcasm, which is sensitive content for companies' reputations and for competitiveness planning. Therefore, multi-modal Sentiment Analysis techniques are probably going to be in high demand in the near future.

Trustworthiness of the data in Sentiment Analysis analysis is a challenge. Some Sentiment Analysis techniques have focused on detecting deceptive reviews and cyber bullying messages Determining trustworthiness of the data demands more norms and logical reasoning which should be considered using many factors and not limited to only the current message being processed but also other messages being posted by the same message sender, for his profile to be considered. Sentiment Analysis techniques should also be updated to be able to reason and determine the levels of uncertainty, validity, messiness and trustworthiness of the data.

The area to be explored is unsupervised learning and verify if its capable of delivering similar accuracy as supervised learning techniques in the determination of subjectivity in Sentiment. Author Sentiments expressed in natural languages by using concepts of emotions that originate in psychology needs efforts for accuracy of analysis. And also if we can get closer to the heart of the matter by using this foundation and looking into the cognitive model of emotions or is doing so not worth. The challenge is to know if model is flexible enough to accommodate recognition and understanding of metaphors. And see if this can be achieved by unsupervised machine learning approaches.

7. Conclusion

The future of sentiment analysis vests not only in improving the accuracy and speed of various algorithms discussed but also in the area of whether we can correlate sentiment with behaviour. To associate sentiment with behaviour needs to be explored in the area of predictive analytics and Lexi analytics. The new demand would not be to say if its overall positive or negative but users want which part of the discussion or feedback is positive and negative. And also sentences of comparison in forums don’t result in any polarity which needs semantic analysis. So there will be a trend towards greater use of NLP techniques such as syntactic parsing, co reference resolution, etc, in addition to machine learning methods.

Supervised learning is not always possible so there is need of unsupervised learning for sentiment analysis. In unsupervised learning sentiment analysis on the sentences is achieved by classifying the review based on the average semantic orientation of the phrases which is time consuming and level of accuracy is not sufficient for some application. Difficulty of accuracy might be addressed by using semantic orientation combined with other features in a supervised classification algorithm.

Future research could be dedicated for the challenges.

8. Major Approaches of research

1. Conceptual
2. Theoretical

3. Empirical and Normative

Types of Research

1. Basic Research.
2. Applied Research.
3. Problem oriented research.
4. Problem solving.
5. Quantitative Research.
6. Qualitative Research.

Mixed mode of research needs to be followed for this problem.

9.Research Plan

Assessing and identification of problems and scope in sentimental Analysis	2016-17
Literature review and understanding the related work in the area	2017-18
Possible solutions to problem of research and comparative analysis	2018-19
Publication of results in premier journals and review through experts	2019-20

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