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A survey on sentiment analysis

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Abstract
Sentiment analysis is one amongst the quickest growing analysis areas in engineering science, creating it difficult to keep track of all the activities within the space. We have a tendency to gift a computer-assisted literature review, wherever we have a tendency to utilize each text mining and qualitative writing. We discover that the roots of sentiment analysis square measure in the studies on belief analysis at the start of twentieth century and within the text judgment analysis performed by the linguistics community in 1990's. However, the happening of computer-based sentiment analysis only occurred with the supply of subjective texts on the net. Consequently, ninety nine of the papers are published once 2004. Sentiment analysis papers square measure scattered to multiple publication venues, and also the combined variety of papers within the top-15 venues solely represent ca. half-hour of the papers in total. We have a tendency to gift the top-20 cited papers from Google Scholar and Scopus and a taxonomy of analysis topics. In recent years, sentiment analysis has shifted from analyzing on-line product reviews to social media texts from Twitter and Facebook. Several topics on the far side product reviews like stock markets, elections, disasters, medicine, software package engineering and cyber bullying extend the utilization of sentiment analysis.

Keywords: sentiment, engineering science, Google scholar, Scopus, taxonomy

1. Introduction
Sentiment analysis is that the linguistic communication process (NLP) task managing the detection and classification of sentiments in texts. Usually, the categories considered area unit "positive", "negative" and "neutral", although in some cases finer-grained classes area unit added (e.g. "very positive" and "very negative") or only the "positive" and "negative" categories area unit taken into account. Another connected task - feeling detection - considerations the classification of text into many classes of feeling, sometimes the essential ones, as delineate by Paul oceanographer [1]. Although different in some ways that, a number of the analysis within the field has thought of these tasks along, under the umbrella of sentiment analysis. This task has received plenty of interest from the analysis community within the past years. The work done regarded the style within which sentiment are often classified from texts relating totally different genres and distinct languages, within the context of assorted applications, victimisation knowledge-based, semi-supervised and supervised ways [2]. The results of the analyses performed have shown that the different types of text need specialised ways for sentiment analysis, as, as an example, sentiments are not sent within the same manner in newspaper articles and in blogs, reviews, forums or alternative sorts of user-generated contents [3].

2. Related Work
One of the primary studies on the classification of polarity in tweets was [4]. The authors conducted a supervised classification study on tweets in English, victimization the emoticons (e.g. ":)", ":(", etc.) as markers of positive and negative tweets. (Read, 2005) used this technique to get a corpus of positive tweets, with positive emoticons ":)", and negative tweets with negative emoticons ":(". later, they use totally different supervised approaches (SVM, Na¨ıve mathematician and most Entropy) and numerous sets of options and conclude that the simple use of unigrams results in sensible results, but it will be slightly improved by the mix of unigrams and bigrams. In the same line of thinking [3]. additionally generated a corpus of tweets for sentiment analysis, by choosing positive and negative tweets supported the presence of specific emoticons. Subsequently, they compare totally different supervised approaches with n-gram options and acquire the simplest results victimization Na¨ıve mathematician with unigrams and partof-speech tags. Another approach on sentiment analysis in tweet is that of [5]. Here, the authors use a hybrid approach, combining supervised learning with the data on sentiment-bearing words, which they extract from the dekalitre sentiment wordbook [6]. Their pre-processing stage includes the removal of retweets, translation of abbreviations into original terms and deleting of links, a tokenization method, and part-of-speech tagging. They use numerous supervised learning algorithms to classify tweets into positive and negative, using n-gram options with SVM and grammar options with Partial Tree Kernels, combined with the data on the polarity of the words showing within the tweets. The authors conclude that the foremost vital options square measure those like sentiment bearing words. Finally, [5] classify sentiment expressed on previously-given "targets" in tweets. They add data on the context of the tweet to its text (e.g. the event that it's connected to). Later, they use SVM and General Inquirer and perform a multilateral classification (positive, negative, neutral).

3. Levels of Sentiment Analysis

Perhaps the most popular perspective is to categorize these studies into three levels, document level, sentence level, and entity and aspect level [7] described as follows:

- Document Level: The aim here is to work out the general sentiment of a complete document. As an example given a product review, the task is to work out whether or not it expresses positive or negative opinions concerning the merchandise. This level appearance at the document as one entity, therefore it's not extensible to multiple documents.
- Sentence Level: This level of research is incredibly near sound judgement classification and therefore the task at this level is proscribed to the sentences and their expressed opinions. Specifically, this level determines whether or not every sentence expresses a positive, negative or neutral opinion.
- Aspect Level: Instead of entirely analyzing language constructs (e.g. documents, paragraphs, sentences), this level (i.e. feature level) provides finer-grained analysis for every aspect (or feature) i.e., it directly appearance at the opinions for different aspects itself. The aspect-level is more difficult than each document and sentence levels and consists of many sub-problems. It finds totally different obtainable sentiment.

4. Approaches

Sentiment analysis approaches can be divided into machine learning, lexicon-based, statistical and rule-based approaches. The approaches of Sentiment Analysis are explained as follows [8]:-

- Machine Learning Approaches uses different algorithms to determine the sentiment by training the classifiers with the data and then by testing it on the test data.
- The Lexicon based approach calculates the sentiment polarity by calculating the semantic orientation of words or sentences.
- The rule based approach uses different rules to classify the words as positive or negative.
- Statistical models represent every review as a mix of latent aspects and ratings. It is assumed that aspects and their ratings are often diagrammatical by multinomial distributions and take a look at to cluster head terms into aspects and sentiments into ratings.

5. Conclusion

Masses of users share their feelings on social media, making it a valuable platform for chase and exploring public sentiment. Social media is one among the largest platforms where huge instant messages square measure revealed on a daily basis which makes it a perfect supply for capturing the opinions towards numerous curious topics, like product, goods or celebrities, etc. the most goal of this paper is to present associate degree overview of latest updates in sentiment analysis and classification strategies and it includes the transient discussion on the challenges of sentiment analysis that the work wants to be done. We tend to additionally found that the majority of the works done square measure based on machine learning technique instead of the lexicon based technique.

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