Sentiment Analysis: State of the Art

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***Abstract*— We presented the state of art of sentiment analysis which contained about the purpose of sentiment analysis, levels of sentiment analysis and processes that could be used to measure polarity and classify labels. Moreover, brief details about some resources of sentiment analysis are included.**

***Keywords*— sentiment, analysis, natural language processing, nlp, sentiwordnet,**

I. Introduction

Sentiment can be defined as a tendency to experience certain emotions in relation to a particular object or person [1, 2]. Sentiment is expressed usually in writing, such as products review, websites, blogs, forums, etc. Sometimes, opinions are hidden within long sentences, making them difficult to reads and extract.

There is a technique called, 'sentiment analysis' that relates to natural language processing, text mining and linguistics [3]. The main goal of sentiment analysis is to identify the polarity of natural language text [4], which is not limited to positive and negative [5]. Sentiment analysis can be referred to as opinion mining as both study people's opinions, appraisals and emotions towards entities, events and their attributes [6].

The following section contains examples of some languages to which sentiment analysis has been applied.

[7]developed a lexicon resource in German called, GermanPolarityClues. It was created using a combination of a semi-automatic translation method and a manual assessment and extension of individual polarity-based term features. The results demonstrated that GermanPolarityClues attained performance of 87.6% F1-measure. F1-measure is an average precision and recall used frequently to measure the overall performance of the method. More details of this can be found in [8].

[9] have used sentiment analysis to develop Thai resources for classifying hotel reviews by creating their own domain-independent lexicons. [10] extended the previous work of [9] by using features and polar words based on syntactic pattern analysis. From this, they constructed a Thai lexicon by increasing the data to approximately 12,000 reviews, covering 620 hotels. Their tasks achieved between 85% and 87% F1-measure.

[11] used both Chinese and English lexicons to improve sentiment analysis in Chinese. [12] analyzed Chinese opinion by using the structure of Chinese words. They tested 4 tasks: word extraction; word polarity detection; sentence extraction; and sentence polarity detection. The results showed that they obtained the highest score for sentence extraction at 80% F1-measure and the lowest score at 54% F1-measure for sentence polarity detection.

[13] analyzed French movie reviews using the lexicon-based method, SentiWordNet, part-of-speech and stopwords. They translate from French to English using SentiWordNet for polarity extraction. From their experiments, they achieved over 85% accuracy.

[14] developed a system to analyze product reviews for Vietnamese at sentence level. There is no public corpus available for Vietnamese sentiment analysis; therefore, they have to use GATE to create their own rule-based system. GATE is an open source software for use in text processing, more details of which can be found in [15]. Data was collected from an online product-advertising page featuring two categories - laptops and desktops – and 3,971 sentences. An annotation tool called Callisto [16] has been used to amend their corpus. They used GATE JAPE Grammar [17] to specify their rules, which can be divided into four types: dictionary lookup words correction; sentiment word recognition; sentential sentiment classification; and features evaluation. Their results showed that they achieved around 63% F1-measure at sentence level.

[18] analyzed financial text by selecting their own sentiment words in Arabic and creating a rule for classifying the stem word when using it in combination with various affixes.

II. Purposes of sentiment analysis

The purpose of sentiment analysis is to identify opinions or attitude in terms of polarity. It can be used in various fields, such as business, politics and psychology. Therefore, the brief details of some sentiment analysis applications are presented in this section.

A. Business

Sentiment analysis has been used in many business tasks, such as advertising, marketing, production, etc. In terms of advertising, the internet is the best medium through which to promote businesses as it will reach various groups of customers. Sentiment analysis could be used to help ensure that the website's contents fit with the commercial content so that it is not detrimental to the reputation and popularity of the company and/or brand [19].

Marketing and production are the main keys for the company and brand that can use sentiment analysis for predicting pricing and demand of the products. For example, [20] analyzed sentiment in weblogs towards movies, both before and after their release, and tested that sentiment is associated with the number of references in the weblogs, which is fewer that of the box office. The results showed that sentiment can be used to predict ticket sales for a movie, along with other factors such as genre and season.

Moreover, sentiment analysis can be used to analyze product reviews from customers. For example, [21] used sentiment analysis to classify customers' reviews of hotels by using a star rating to categorize the reviews as bad, neutral and good. This task showed that reviews could be classified correctly, probably with 90% accuracy, by using sentiment analysis.

B. Politics

Various political organizations use sentiment analysis to analyze public opinion in relation to policies, legislation, politics, government agencies, etc. For political postings on microblogs, Twitter has been analyzed by various researchers. For example, [22] use more than 100,000 tweets posted in the weeks leading up to the German federal election to predict electronically the outcome. They compare the results with the actual electoral votes. The results showed that the mean absolute error (MAE) of the prediction is only 1.65%. Therefore, it could be said that tweets are sufficiently reliable to predict the outcomes of electronic results. More details of MAE can be found in [23].

C. Psychology

The researches in psychology are also concerned with emotion, which plays an important role in dreams [24-26]. Normally, the emotions in dreams are assessed and analysed by the dreamers themselves. In 2006, sentiment analysis was used to classify structures of dreams' contents, whether they are positive or negative [27]. They used humans to annotate the contents of dream according to four levels. Next, they compared the results with machine learning, which yielded an accuracy rate of 50%, with 0.577 of the mean squared error (MSE). More details of MSE can be found in [28].

III. Levels of sentiment analysis

Sentiment analysis can be performed at various levels: word, phrase, sentence and document. The brief details of each can be found in the following section.

A. Document-level sentiment analysis

Document-level analysis determines the sentiment of the whole document; for example, news, reviews, forums and blogs. Various machine learning algorithms approach for document level. [29] used unsupervised learning to classify more than 400 reviews. Three steps were used to process the documents. First, they extracted the adjectives and adverbs by using a method of part-of-speech tagger, adopted from [30]. Second, Pointwise Mutual Information and Information Retrieval algorithm (PMI-IR) was used to evaluate the sentiment orientation of extracted phrases. Finally, the average semantic orientation of phrases was calculated and customer reviews were classified as 'recommended' or 'not recommended' by achieving 74.39% accuracy. More details of PMI-IR can be found in [31]. [32] used semi-supervised leaning to determine the orientation of subjective terms. [33] used three machine learning algorithms based on supervised learning to classify reviews, whether they are positive or negative.

B. Sentence-level sentiment analysis

There are two tasks at the sentence level. First, the sentences will be classified as subjective or objective. Second, polarity of subjective sentences will be classified. [34] developed techniques based on supervised learning to classify sentence level. In their task, the polarity of each subjective sentence was identified by adopting the method from [29]; however, it used seed words from [35] and a statistic algorithm called, 'log-likelihood ratio' to calculate polarity scores. [36] used minimum cuts in a sentences graph to classify subjective sentences. [37] classify each sentence in the review by using machine learning to analyze the polarity of phrases and merge them by incorporating the effects of conjunctions to make a decision on the overall polarity of a sentence.

C. Phrase-level sentiment analysis

This sub-section involves the classification of the polarity of phrases, such as noun phrase, verb phrase, prepositional phrase, etc. [38] used machine learning and a variety of features to classify content polarity at phrase level. First, they analyzed each phrase, whether they were neutral or polar. Next, polar phrases were used and their contextual polarity classified as as positive, negative, neutral or both positive and negative using polarity shifters. [39] adopted statistical mechanics called, 'Potts model' to extract the semantic orientations of noun and adjective phrases. [40] used lexical scores from the Dictionary of Affect in Language (DAL) and syntactic n-grams to predict the polarity of phrases within the sentences.

D. Word-level sentient analysis

Most tasks use word level to classify at the sentence and document level. Word level is concerned with analysing the polarity of words. There are two methods that can be used to classify sentiment at word level: lexicon-based and corpus-based [41-43].

- Lexicon-based methods

Measuring the polarity derived from text based on sentiment analysis is involved in these methods [42]. Lexicon-based methods can be referred to as dictionary-based methods. Sentiment lexicons are words that have a polarity score [44]. For example, 'good' positive score is 0.75, negative score is 0 and neutral score is 0.25 [45]. [46] assigned a polarity score to a list of words to classify opinion based on the given topic and a set of related text. [47] explore the calculation of positive or negative in financial news messages. [48] assigned polarity scores to the documents to calculate and classify their labels based on a graph-ranking algorithm. [49] studied the benefit of sense-level polarity information for the task of sentiment classification.

- Corpus-based methods

These methods concerned train sentiment classification by using corpora of documents that are labelled with polarity [42]. The polarity of sentiment did not have to be 'positive' and 'negative'. Moreover, there can be more than two labels of polarity [50]. [51] classify the corpus of blog posts from the LiveJournal using labels of 'happy' and 'sad'. [52] classified tweets using sentiment analysis, according to whether or not they are related to a company. [53] investigated predicting sentiment at different levels of granularity for a text using a global structured model. [54] investigate using sentiment analysis to classify paraphrases into various categories. [21] used three labels to classify customers reviews: 'bad', 'neutral' and 'good'. [55] used sentiment classification to analyse emotions in suicide notes.

IV. Polarity measurement and label classification

This section presents some processes that can be used to measure polarity scores and classify polarity labels.

A. *Polarity scores from resources*

There are some lexicon resources that consist of polarity scores, such SentiWordNet and SentiStrength. More details of these can be found in section 5. Some researchers adapted those scores for use in their works. For example, [49] summed up the values of synsets for each tag on SentiWordNet and assigned labels to them: -1, 0 and +1. Other tags that do not appear in SentiWordNet will assign label '0'. The tags in SentiWordNet are noun, adjective, adverb and verb; for example, the word 'short' has 11 adjective, three noun, seven adverb and two verb senses. According to this, the term 'short' in the adjective tag will be '-1', as the sum of positive scores (0.5) is lower than that of negative scores (3.5) over all 11 adjectives. This is the same for the adverb and verb tags. Meanwhile, the term 'short' in the noun tag has the label '0' because positive and negative scores are zero over three noun senses in SentiWordNet.

B. *Human classification*

By using humans to classify the contents, the researchers will find more than two annotators to score the words using ranging. Ranging can vary, depending on the agreement between the researchers and annotators. After that, the statistical measure of the agreement of annotators will be used. [47] used humans to annotate polarity in financial news. They used three annotators to annotate a set of 30 texts ranging from 1 (very negative) to 7 (very positive). Then, Krippendorf's alpha was used to measure the agreement of annotators. More details of this method can be found in [56].

C. *Reviews rating*

Reviews rating is used in various organizations, such as hotels, cinemas and restaurants; whereby customers can review their products or/and services. Some researchers used the rating scales to annotate the score of the contents. [21] used sentiment analysis to classify customers' reviews of hotels. They assigned weight to the star rating used to annotate the reviews; for example, 1 star, 2 star, 3 star, 4 star and 5 star are weighted as -2, -1, 0, +1 and +2, respectively. Then, the reviews with values of -2, 0 and +2 are assigned labels as bad, neutral and good, respectively for use in the comparison.

D. *Emoticons*

The icons that can be used to express emotion are called 'Emoticons' [57, 58]. These are normally used in social networks, such as Facebook and Twitter. For example, [59] divided tweets in to three groups by using emoticons for classification. If tweets contain positive emoticons, they will be classified as positive and vice versa. Other tweets that did not have positive/negative emoticons will be classified as neutral. However, tweets that contain both positive and negative emoticons are ignored in their study. Their task focused on analyzing the contents of social media by using n-gram graphs, and the results showed that n-grams yielded high accuracy when tested with C4.5 but low accuracy with Naïve Bayes Multinomial (NBM). Both C4.5 and NBM are used for text classification, more details of which can be found in [60].

E. *Feature-based analysis*

Feature-based analysis is focused on target entities and components of the opinions. The targets could be service, product, organization, topic, etc. Components can be referred to as attributes and features. [61] studied customer reviews by focusing on the product features. First, they identified a product's features from the customer's reviews. Next, they identified reviews of each feature, whether they are positive or negative. Finally, they summarized the overall reviews of each feature and used them in their experiment.

V. Resources of sentiment analysis

There are some sentiment analysis resources that can be used to classify contents, such as SentiWordNet, SentiStrength, etc.

A. *SentiWordNet*

SentiWordNet [45] is a freely-–available and widely used electronic resource. For example, [62] used SentiWordNet to determine the polarity of text within a multilingual framework. [63] used SentiWordNet to calculate positive and negative scores to determine sentiment orientation. [64] used SentiWordNet as a linguistic lexical resource for sentiment summarization of feedback in academic essay writing. In 2010, the latest version of SentiWordNet was presented to the public [65].

SentiWordNet is the result of the automatic annotation of all the synsets of WordNet [66, 67], according to the notions of positive, negative and neutrality, to which each synset allocates three numerical scores Pos(s), Neg(s) and Obj(s). Each of the three scores ranges from 0.0 to 1.0 and their sum is 1.0 for each synset. This means that there is the possibility of having non-zero scores for all three.

The methods used to generating SentiWordNet were adapted from the methods of PN-polarity and SO-polarity [68]. PN-polarity is used to determine whether the opinion is positive or negative, while SO-polarity determines whether the opinion is subject or objective. The methods relies on the quantitative analysis of annotates associated with synsets and on the use of the resulting quantity term representations for semi-supervised synset classification [69]. Semi-supervised classification is a machine-learning technique for use with both labelled and unlabelled data. More details of semi-supervised classification can be found in [70].

B. *SentiStrength*

SentiStrength [71] is also available to use free of charge and has been used by some researchers. For example, [72] use SentiStrength to classify sentiment expressed in microblogs. [73] investigated online hotspot forums, using SentiStrength to calculate sentiment scores of the existing text in each forum.

SentiStrength is the sentiment analysis methodology used to judge whether a sentence has a positive or negative sentiment. The methodology was developed using nearly 4,000 comments on MySpace by [74]. They used three annotators and Krippendorf's alpha to measure their agreement. The data has been separated into two groups: trail data and testing data. Trail data was used to identify algorithms for judgment and suitable scales. Algorithms were identified, ranging from 1 to 5. They were used alongside testing data for final judgment and these will be SentiStrength's lexicon.

VI. Conclusion

In this paper, the basic terms of sentiment analysis have been described. The goal of sentiment analysis is to determine the polarity of words, phrases, sentences and documents. Sentiment analysis is used in various fields, such as business, politics and psychology. Levels of sentiment analysis and the processes used to generate polarity and labels have been analyzed. SentiWordNet and SentiStrength have been identified as the resources of sentiment analysis. For future work, we plan to investigate machine leaning and other techniques that could be used to classify the data (for example, FrameNet).

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