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A Comprehensive Survey on Aspect Based Sentiment Analysis

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Abstract— Sentiment analysis is a growing field in natural language processing to analyze and determine the polarity of given text or data in sentence level or document level. Sentiment analysis is widely used in social media, as it became an excellent source for people and individual to analysis also known as feature based sentiment analysis is a fine grained analysis where the aim is to identify different aspects expressed in document or sentence level. This approach allows the user to extract the most important aspects from the opinion expressed. This paper presents a brief survey of aspect-based sentiment analysis and its various approaches, metrics used for evaluation and latest research challenges.

Keywords— sentiment analysis, NLP, polarity, aspect, opinion mining

I. INTRODUCTION

Sentiment analysis (or) opinion mining is next big thing in research area, it allows us to mine data from social media and analyze whether they denote positive opinion or negative opinion. The data may be either product reviews, customer suggestions or even articles. This feedback helps individual to buy a product and also the organization developing the product.

Sentiment analysis is not an easy task due to the highly unstructured environment of natural language and the complexity of a machine to interpret the meaning of a sentence. But the reviews and value of the opinion from the reviews is greater than ever day by day. For solving this problem a method must be made to understand and interpret the human emotions and feelings.

Opinion mining can be done at three different levels, which are Document Level, Sentence Level and Aspect or Feature Level .In document level, the overall opinion about the document is finding out and classifies them as positive or negative. In sentence level, each sentence in the document is analysed for finding the fine grained opinions about different topics in a document. Finally, classify the opinion expressed in a sentence as positive, negative, or neutral. The reviews from a product or restaurant give an overall opinion whether positive and negative. It needs more fine- grained analysis of reviews to mine these mixed opinions, aspect level perform this task. Hence aspect based opinion mining is preferred in the work.

The factors that should be considered for a good aspect-based opinion mining algorithm in order to extract the right information which are: implicit aspect, multi-aspect in a sentence, question based sentences, domain and language adaptability, which affect the accuracy and effectiveness of an aspect based opinion mining algorithm. Let's discuss about the above mentioned factors one by one. Firstly, implicit aspects are those features which are implied in a sentence for example: "The restaurant was expensive" here implicit aspect is price [12]. Secondly, multi-aspects are those features which are mentioned in a single sentence, however, where one aspect is positive and other aspect is negative for example: "The food is very good, but the atmosphere is not good" [6]. Thirdly, question based sentences are self explanatory for example: "is the picture quality of this X camera is good?"[5]. Therefore, the customer is concerned about knowing the "picture quality" aspect. The fourth is explicit features which are the inverse of implicit features. Explicit features are directly mentioned in a sentence for example: "their services is excellent", here 'service' is explicit feature [6]. Finally, domain and language adaptation is that the aspect-based opinion mining algorithm can be flexible to multiple domains and languages.

The rest of the paper is organized as follows. Section 2 provides the approaches used for Aspect Based Sentiment Analysis. Section 3 provides the details of Aspect Based sentiment Analysis Tasks, Section 4 provides the details about evaluation measures and section 5 provides conclusion and future scope of the ABSA.

II. APPROACHES IN ASPECT BASED SENTIMENT ANALYSIS

A. Frequency –based Approach

In most of the reviews only a limited set of words is used often, these words are single nouns and compound nouns which are known to be aspects. The words that occur frequently are termed as frequent words or aspects. This approach was the most common method for aspect detection. The most familiar method using frequency based approach is [1].It considers single and compound nouns for aspect extraction. The author in [2] followed an unsupervised information extraction system namely OPINE to extract important product features from reviews and later a classification technique is applied. A most important shortcoming of the frequency based approach is the majority of the noun and noun phrases having a high frequency are mistakenly seen as aspects. To overcome this issue, in [3] Red Opal introduced a system, for a phrase to be considered as aspect, a word or bigram has to appear more often higher than the given baseline frequency .This method suggested that users prefer bigram features over unigram features .The baseline statistics method is used in [4], where it used to filter the list of high frequency noun phrases. Additionally in [5] have used part -of-speech (POS) pattern filter such that every aspect needs to be followed by adjective to identify frequent nouns and noun phrases from the reviews.

B. Syntax-Based Approach

As an alternative of focusing on frequencies to discover aspects, syntax-based methods and find aspects by way of the syntactical associations they are in. An extremely easy relation is the adjectival modifier relation between a sentiment word and an aspect, as in 'fantastic food', where 'fantastic' is an adjective modifying the aspect 'food'. A strong point of syntax-based methods is that low frequency aspects can be originated. Yet, to get good coverage, many syntactical relations need to be described.

To alleviate the low recall crisis, a generalization step for syntactic patterns using a tree kernel function is projected in this paper [6]. Given a labelled data set, the syntactic patterns of all the annotated aspects are extracted. Then, for the unseen facts, syntax trees of all sentences are obtained. As an alternative of straight trying to discover an accurate match between the aspect pattern and the syntax tree, both are split into several different substructures. Then the comparison between the pattern and a sentence can be calculated as the numeral of matching substructures. The common convolution tree kernel is used to figure similarity scores for each pair of substructures, with a threshold determining whether a pair is a match or not.

In [7], [9] and [8], aspect detection and sentiment lexicon expansion are seen as interrelated problems for which a double propagation algorithm is projected, featuring parallel sentiment word expansion and aspect detection. With every extra known sentiment word, additional aspects can be originated, and with extra known aspect words, extra sentiment words can be found, etc. The algorithm continues this method until no more extra sentiment words or targets can be initiated. To find sentiment words based on known aspect words, and the other way around, a set of rules based on grammatical relations from the employed dependency parser, is raised. A big advantage of this method is that it only needs a small seed set to work properly compared to the large corpus most trained classifiers require.

C. Supervised Machine Learning Approach

There are only quite a few supervised machine learning methods for aspect detection that are entirely machine learning methods. Since the power of supervised approaches lies in the features that are used, feature construction regularly consists of other methods (e.g., frequency-based methods) in order to generate more significant features that simplify better than plain bag of- words or part-of-speech features.

Aspect detection is cast as a labeling problem in [10], which is solved by linear chain Conditional Random Field (CRF), familiar in natural language processing, for processing a entire sequence of words. This context of a word is automatically considered when assigning it a label. Multiple features are used for determining the best label for a word, which also includes the actual word, its part-of-speech tag, and also the other factors like, whether a direct dependency relation exists between this word and a sentiment expression, whether this word is in the noun phrase that is close by to a sentiment expression, and whether this word is in a sentence that actually has a sentiment expression. The ground-truth from a subset of the used data sets [11] [12] [13] is used to train the model.

D. Unsupervised machine learning

Unsupervised machine learning approach towards aspect based sentiment classification can resolve the problem of domain dependency and reduce the need for labeled training data. However, a large amount of data is usually needed to successfully train these type of data. The most common approach used is LDA, which is a topic model proposed in [14].LDA is similar to probabilistic latent semantic analysis which uses a dirichlet pior for topic distribution instead of a uniform topic distribution [15]. The disadvantage of LDA is that the generated topics are unlabeled, that shows no direct correspondence between topics and specific aspects or entities. Since LDA was designed to operate on the document level, implementing it for the much finer-grained aspect-level sentiment analysis is complicated. The first LDA-based approach for aspect-level is discussed in [16]. To overcome this problem an extension to LDA is proposed known as Multi-grain LDA which has two model level namely global and local. This model approach [17] increases the accuracy of the local topics that should represent the sought aspects. In [18] a similar notion is described where a distinction is made between global and local topics. In [19] LDA is combined with a Hidden Markov Model (HMM) to distinguish between aspect-words and background words. In [20] another way of another way of adding syntactic dependencies is shown, where the topic model employs two vocabularies to pick words from. In [21] so-called cold start problem is proposed which incorporates product categories and the reviewers into the model. This distribution over the aspects with reviewer comments or with rating gives a more accurate prediction for products with little or no data. In [22], a supervised joint aspect and sentiment model is proposed to determine the reviews on aspect level. It simultaneously models both aspect and sentiment words to improve the quality of found aspect topics.

E. Hybrid Approach

This approach is a combination of two methods that are used known as hybrid method which has two types: serial hybridization, where the output of one phase forms the input of next phase, and parallel hybridization, where two or more methods are used to find complementary sets of aspects. In [23] serial hybridization is used, where Pointwise Mutual Information [24] is used to find possible aspects, which then imported into a naïve bayes classifier to output a set of explicit aspects.

serial hybridization also used in [25], where the Dice similarity measure [26] is used to cluster noun phrases that are about the same aspect, and [27] which targets pros and cons to find aspects using frequent nouns and noun phrases, feeding those into an SVM classifier to make the final decision whether it is an aspect or not. The parallel hybridization can be found in [28], where a MaxEnt classifier is used to find the frequent aspects, for which there is ample data, and a rule-based method that uses frequency information and syntactic patterns to find the less frequent ones. In this way, available data is used to drive aspect detection, with a rule-based method that acts as back-up for cases where there is not enough data available.

III. ASPECT BASED SENTIMENT ANALYSIS TASKS

The most important objective of Aspect Based Sentiment Analysis is to identify the aspects of the given target entities and sentiment expressed for each aspect. The objectives of Aspect Based Sentiment Analysis can be done through the following tasks. The first task is the extraction of aspect terms and grouping aspect terms into aspect categories. The second task is about identification of polarity of the aspect terms and polarity of the aspect categories of each sentence. The above tasks are divided into four sub tasks namely: Aspect Term Extraction (ATE), Aspect Term Polarity (ATP), Aspect Category Detection (ACD) and Aspect Category Polarity (ACP).

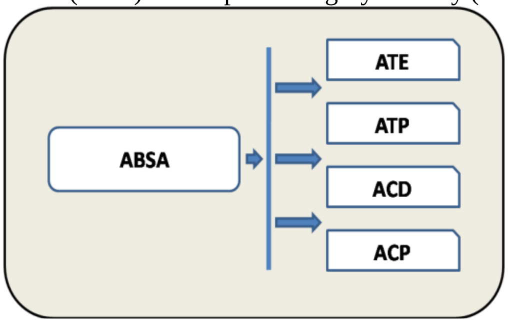

Fig.1. Aspect based sentiment analysis task

A. Aspect Term Extraction

The work of first sub-task Aspect Term Extraction (ATE) is also known as information extraction task is to identify all the aspect terms given in each review sentence. There can be multiple aspects, in a sentence and every aspect need to be extracted. The aspect in the aspect terms of the sentence can be expressed by a noun, verb, adverb and adjective. It is well known that 60% - 70% of aspect terms are explicit nouns. The aspect terms can also consist of multiword entities such as “screen size”. These multiword entities and their aspects are considered to be much critical than single word aspects. The researchers have used various processes for extracting aspect terms, like Word N-grams, Bigrams, Word cluster, Casting, POS tagging, Parse dependencies, Relations and Punctuation marks. The various Methods used for extracting aspect terms , such as Conditional Random Fields (CRF), Support Vector Machines (SVM), Random trees and Random Forest.

The researchers have proposed various methods for Aspect Extraction Task. They are FREQ baseline, H&L method, H&L+W2V method and FREQ+W2V method. All these methods come under unsupervised learning and can be used across domains with minimum changes. The FREQ baseline is considered to be the most efficient method because it returns the most distinct nouns and noun phrases from the reviews in each dataset by decreasing the sentence frequency. Researchers have also used LDA (Latent Dirichlet Allocation) based methods for Aspect extraction.

The method of Hu and Liu (2004) extracts all the different nouns and noun phrases from the reviews of each dataset and consider them as candidate distinct aspect terms. In a co-occurrence based method [30] for category discovery a dictionary based sentiment classification algorithm is used through which aspects can be identified by annotation process. On the other hand, by using the training set to count how frequently each word appears within an aspect, a simple probability should be computed , which specifies the chance that this word is an aspect word or not. The above probability is also used for filtering a set of noun phrases, such that the noun phrases remaining will have at least one word. The aspect probability for the noun phrases holding the value greater than or equal to 0.05 and the noun phrases with the probability below 0.05 are removed. This process will remove some of the determiner words from the initial noun phrase, as those are excluded.

A modelled Aspect extraction [31] as sequential labelling task and extract features is used for CRF training. In addition to the common features used in Named Entity Recognition (NER) systems, it also uses the available external resources for building different name lists and word clusters. A supervised machine learning algorithm [31] is used to extract the aspect term. An aspect can be expressed by a noun, adjective, verb or Input Text adverb. But the recent research in (Liu, 2007) shows that 70% of the aspect terms are explicit nouns and the aspect terms can contain of multiword entities. In [33] Aspect term can be extracted using casting as a sequence tagging task, in which each token in a candidate sentence is denoted as either Beginning, Inside or Outside (BIO). Conditional Random Fields [35] (CRF) is used for extracting aspect terms and BIO model for representing aspect terms. The conditional random fields (CRF) and a liner chain CRF are used for determining the conditional probability. The authors employ a graph co-ranking approach

[34], to model aspect terms and opinion words as graph nodes, and then they generate three different sub-graphs defining their bond between the nodes. To obtain a list of dependable aspect term, the candidates rank the nodes using a combined random walk on the given three sub graphs.

B. Aspect Term Polarity

The second sub-task is aspect term polarity is that, within a sentence for a given set of aspect terms, the task is to determine the polarity of each aspect term: positive, negative, neutral or conflict (i.e., both positive and negative). Here in the identification of Aspect term polarity different features like Word N-grams, Polarity of neighboring adjectives, Neighboring POS tags and Parse dependencies and relations have been widely used by researchers. The sentiment of aspect in [30] is computed by using sentiment value of each n-gram and distance between the n-gram and the aspect. In [31] Aspect lexicon based on additional information such as POS for polarity identification was developed by the author. In [32] a new class called conflict has been introduced along with they developed a method called RFC (Random Forest Classification. They have used many futures in this classification like local context, POS, chunk, prefix and suffix. In [33] aspect term polarity, they have extracted it by using various features like word N-grams, polarity of neighboring adjectives, neighboring POS tags and parse dependencies and relations.

In [34] the author reusing the generated Word2Vec model, developed a polarity lexicon for the corresponding domain with the perception that a polarity word in a domain should be more "similar" to a set of "very positive" words than to a set of "very negative" words, and vice versa. This is engaged the in-domain generated Word2Vec models since the polarity of words may differ between domains and wanted to detain the polarity for each particular domain. In [35] the words that affect the sentiment of the aspect term are assumed to be close in most of cases and thus used a context window of 10 words in both directions around the target aspect term.

C. Aspect Category Detection

The third sub-task is Aspect Category Detection, in which the task is to identify the majority of categories that are discussed in each sentence. Aspect categories are usually difficult to find than the aspect terms as defined in Aspect Term Extraction, and at times they do not even occur as terms in the sentence. Aspect category detection [35] is based on a set of binary Maximum Entropy classifiers. The final decision is merely calculated from decisions of various individual classifiers.

Aspect category classification [29] is based on a set of available binary classifiers, one classifier for each category found in the training set. To create a training example each sentence in the training set, the extracted features from all words in the sentence is taken. The co-occurrence based algorithm [30] is used for category detection. The algorithm is a co-occurrence matrix that captures the frequency of the co-occurrences between words in the sentence and the annotated aspect category, gives mapping from words to aspect categories.

Aspect category detection [33] is considered as multi label classification problem. In a given instance, it should predict all labels that instance fit into. In [36] Aspect category detection the authors have used supervised classification approach and each task is done by identifying every entity E and attribute A pair E#A towards which an opinion is expressed.

D. Aspect Category Polarity

The final sub-task is Aspect Category Polarity is which it takes the information from the previous task (Aspect Category Detection) to determine the polarity of each aspect category discussed in review sentence. The sentiment of aspect category [30] is computed by calculating the distance between n-gram and the corresponding aspect. The aspect category polarity has been detected using just unigram and bigram features in [33].

In aspect category polarity detection [35], the whole sentence is taken into account, and maximum entropy classifier is used to distinguish one category with other. In [36] for sentiment polarity classification, authors have extracted Bag of Words and Wordnet Synset features from both train and test data and implemented them on variety of classifiers (like Stochastic Gradient Descent, SVM, Adaboost) multiple times and stored the confidence scores obtained from decision functions of each of these classifiers.

IV. EVALUATION METRICS

Most of the research work uses accuracy, precision, recall, and F1 to measure quantitative performance. There are multiple measures are in use to evaluate sentiment analysis, they are Ranking Loss, Mean Absolute Error, and Mean Squared Error.

The performance of the various approaches for the subtasks of Aspect Based Sentiment Analysis has can be evaluated through precision (P), recall (R) or F-score (F) depending on the subtask, which are defines as

$$P = \frac{\mathrm{TP}}{\mathrm{TP+FP}}\ ,\ R = \frac{\mathrm{TP}}{\mathrm{TP+FN}}\ \text{ and }\ F = \frac{\mathrm{2.P.R}}{\mathrm{P+R}}$$

Where TP (True Positive), TN (True Negative), FP (False Positive) and FN (False Negative) are the cases correctly classified or incorrectly classified, and F-score is the some average of precision and recall metrics.

V. CONCLUSION

Sentiment analysis is still in growing phase using different NLP techniques. This paper surveys about aspect based sentiment analysis and its various approaches has been briefly discussed above. Aspect based sentiment analysis deals with each and every aspects or entities given in the sentence and it's been achieved through the four main subtasks mentioned above. It clearly shows Sentiment analysis is the key to future events and predicting future outcomes of public opinions.

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