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Opinion Mining and Sentiment Analysis: A Survey

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Abstract*:* Opinion Mining and Sentiment Analysis is the field of study that analyzes customer opinions, feedback, sentiments, evaluations, attitudes, and emotions from written language. It is one of the most active research areas in Natural Language Processing (NLP) and is also widely studied in data mining, Web mining, and text mining. The growing importance of sentiment analysis coincides with the growth of social media and Web 2.0 technologies such as reviews, discussion forums, blogs, micro-blogs, and social networks. For the first time in human history, we now have a huge volume of opinionated data recorded in digital form for analysis.

In this paper we do a survey of papers on Opinion Mining and Sentiment Analysis and detail the techniques used.

Key words: Opinion extraction, Opinion mining, Sentiment analysis, Subjectivity mining, Text mining

INTRODUCTION

Research in automatic Subjectivity and Sentiment Analysis (SSA), as subtasks of Affective Computing and Natural Language Processing (NLP), has flourished in the past 15 years. The growth in interest in these tasks was motivated by the birth and rapid expansion of the Social Web that made it possible for people all over the world to share, comment, consult or consume content on any given topic on their preferred channel. In this context, opinions, sentiments and emotions expressed in Social Media texts have been shown to have a high influence on the social and economic behavior worldwide. SSA systems are highly relevant to many real-world applications (e.g. marketing, eGovernance, business intelligence, social analysis) and also to many tasks in Natural Language Processing (NLP) - information extraction, question answering, textual entailment, to name just a few. The importance of this field has been proven by the high number of approaches proposed in research in the past decade, as well as by the interest that it raised from other disciplines (Economics, Sociology, Psychology) and the applications that were created using its technology.

Despite the large interest shown by the research community and the development of a set of benchmarking resources and methods to tackle sentiment analysis, SSA remains far from being a solved issue. While systems working for English on customer reviews obtain good results in sentiment classification, systems working for other languages or on Social Media texts are still struggling to surpass the baseline.

DEFINITION

Opinion Mining is the computational study of opinions, sentiments, subjectivity, evaluations, attitudes, appraisal, affects, views, emotions, etc., expressed in the form of unstructured text in Product or Services Reviews, micro blogging sites like Twitter, discussion forums, news articles, comments, feedback from emails, or any other documents.

Opinion [1] is a quintuple (e_i , a_{ij} , s_{ijkl} , h_k , t_l), where
e_i is the name of an entity
a_{ij} is an aspect of e_i
s_{ijkl} is the sentiment on aspect a_{ij} of entity e_i
h_k is the opinion holder
t_l is the time when the opinion is expressed by h_k.

RESEARCH CHALLENGES FOR SENTIMENT ANALYSIS

Sentiment analysis classifies text as positive, negative or else objective, so it can be thought as text classification task. Text classification has many classes as there are many topics but sentiment analysis has only three classes. However, there are many factors that make sentiment analysis difficult compared to traditional text classification.

1) Domain dependency: The biggest challenge faced by opinion mining and sentiment analysis is the domain dependent nature of sentiment words. One features set may give very good performance in one domain, at the same time it performs very poor in some other domain.

2) Spam: The web contains both authentic and spam contents. For effective Sentiment classification, this spam content should be eliminated before processing. This can be done by identifying duplicates, by detecting outliers and by considering reputation of reviewer [1].

3) Limitation of classification filtering: There is a limitation in classification filtering while determining most popular thought or concept. For better sentiment classification result this limitation should be reduced. The risk of filter bubble gives irrelevant opinion sets and it results false summarization of sentiment.

4) Asymmetry in availability of opinion mining software: The opinion mining software is very expensive and currently affordable only to large enterprises and government. It is beyond the common citizen's expectation. This should be available to all small and medium size businesses at affordable price, so that everyone gets benefit from it.

5) Incorporation of opinion with implicit and behavior data: For successful analysis of sentiment, the opinion words should integrate with implicit data. The implicit data determine the actual behavior of sentiment words.

6) Natural language processing overheads: The natural language overhead like ambiguity, co-reference, Implicitness, inference etc. created hindrance in sentiment analysis too.

THE PROCESS OF SENTIMENT ANALYSIS

Given a set of opinion documents D, sentiment analysis consists of the following 6 main tasks [1].

Task 1 - Entity extraction and categorization: Extract all entity expressions in D, and categorize or group synonymous entity expressions into entity categories. Each entity expression category indicates a unique entity e_i.

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Task 2 - Aspect extraction and categorization: Extract all aspect expressions of the entities, and categorize these aspect expressions into clusters. Each aspect expression cluster of entity e_i represents a unique aspect a_{ij}.
Task 3 - Opinion holder extraction and categorization: Extract opinion holders for opinions from text or structured data and categorize them.
Task 4 - Time extraction and standardization: Extract the times when opinions are given and standardize different time formats.
Task 5 -Aspect sentiment classification: Determine whether an opinion on an aspect a_{ij} is positive, negative or neutral, or assign a numeric sentiment rating to the aspect in the range of 1 to 5.
Task 6 - Opinion quintuple generation: Produce all opinion quintuples (e_i, a_{ij}, s_{ijkl}, h_k, t_l) expressed in document D based on the results of the above tasks.

DOCUMENT SENTIMENT CLASSIFICATION

This approach considers the whole document as a single entity and classifies the sentiment as positive or negative or neutral. Document-level sentiment classification assumes that the opinionated document expresses opinions on a single target and the opinions belong to a single person or product or service. It is clear that this assumption is true for customer reviews of products documents which usually focus on one product and single reviewer writes it. But in the case of forums or blogs, comparative sentences will appear. Reviewers compare one product with another that has similar characteristics and hence document level analysis is not desirable in forums and blogs.

Two type of classification techniques have been used in document-level sentiment classification, supervised method and unsupervised method.

Supervised Methods

Sentiment classification task can be formulated as a supervised learning problem with two classes, positive and negative. Product reviews mostly are used as training and testing data. Since online reviews have rating scores assigned by their reviewers, e.g., 1-5 stars, the positive and negative classes are determined using the ratings. For example, a review with 4 or 5 stars is considered a positive review, and a review with 1 to 2 stars is considered a negative review. Most research papers do not use the neutral class, which makes the classification problem considerably easier, but it is possible to use the neutral class, e.g., assigning all 3-star reviews the neutral class.

Any existing supervised learning techniques can be used to sentiment classification, such as Naïve Bayes and Support Vector Machines (SVM). In most cases, SVMs have shown marginal improvement over Naïve Bayes classifiers. When the set of training data is small, a Naïve Bayes classifier might be more appropriate since SVMs must be exposed to a large set of data in order to build a high-quality classifier. Several techniques and features are used by researchers in learning process. One of the most important tasks in sentiment classification is selecting an appropriate set of features. The most commonly used features in sentiment classification are :

1. **Terms and their frequency**: These features are individual words termed as unigram and their n-grams with associated frequency counts. These features have been shown highly effective for sentiment classification.
2. **Part of speech (POS)**: POS information is a very important indicator of sentiment expression. For example adjectives carry a great deal of information regarding a document's sentiment [1].
3. **Sentiment words and phrases:** Sentiment words and phrases are words and phrases that express positive or negative sentiments. For example, good, fantastic, amazing, excellent and brilliant are words with positive sentiment and bad, boring, slow, worst and poor are words with negative sentiment. Though almost opinion words are adjectives and adverb, nouns and verbs can also express an opinion. For example rubbish (noun), hate and like (verb) can indicate opinion in some documents.
4. **Negations:** Obviously, negation words are very important to evaluate the polarity of a sentence because they can transform the sentiment orientation in a sentence. For instance, the sentence "I don't like this camera" has negative orientation.
5. **Syntactic dependency:** Several research work in this area used word dependency based features generated from dependency tree or parsing.

One of the earliest works which used supervised method to solve sentiment classification problem is [2]. In this paper, authors used three machine learning techniques - Naïve Bayes, Maximum Entropy classification (ME), and SVM to classify sentiment of movie review documents. They test several features to find optimal feature set. Unigrams, Bigrams, Parts of Speech (POS) and position of words were used as features in these techniques. The results show that the best performance is achieved when the unigrams are used in SVM classifier.

Ye et al. [3] used sentiment classification techniques into the domain of reviews from travel blogs. They used three supervised machine learning algorithms of Naïve Bayes, SVM and the character based N-gram model for sentiment classification of the reviews on travel blogs for seven popular travel destinations in the US and Europe. They used the frequency of words to represent a document in-stead of word presence. They found SVM and N-gram approaches outperformed the Naïve Bayes approach, and that when training datasets had a large number of reviews, all three approaches reached accuracies of at least 80%.

The biggest limitation associated with supervised learning is that it is sensitive to the quantity and quality of the training data and may fail when training data are biased or insufficient. Sentiment classification at the sub-document level raises additional challenges for supervised learning based approaches because there is little information for the classifier.

Unsupervised Methods

Obviously, sentiment words and phrases are the main indicators of sentiment classification. Therefore several works have been done by using unsupervised learning methods based on such words and phrases.

Turney [4] presented a simple unsupervised learning algorithm for classifying a review as recommended or not recommended. He determined whether words are positive or negative and how strong the evaluation is by computing the words' point wise mutual information (PMI) for their co-occurrence with a positive seed word ("excellent") and a negative seed word ("poor"). He called this value the word's semantic orientation. This method scanned through a review looking for phrases that match certain part of speech patterns (adjectives and adverbs), computed the semantic orientation of those phrases, and added up the semantic orientation of all of those phrases to compute the orientation of a review. He achieved classification accuracies on reviews from various domains in the range of 84% for automobile reviews to 66% for movie reviews.

In brief, the main advantage of sentiment classification in document-level is that it provides predominant opinion on a topic, entity

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or event. The main weakness is that it does not provide details about people's interests and of course it is not easily applicable to non-reviews, such as blog and forum postings, because these posts evaluate and compare multiple entities.

SENTENCE-LEVEL SENTIMENT CLASSIFICATION

In this approach the polarity of each sentence is determined. This approach has the implicit assumption that each sentence is written by a single person and expresses a single positive or negative sentiment. A lot of early work in the region of sentence level analysis focuses on identifying subjective sentences.

This approach can be divided into two tasks. First, identify which sentence will hold the opinion. Second, classify each sentence as positive or negative. The advantage of sentence level classification lies in the subjectivity/objectivity classification.

Some challenges in this approach are many objective sentences can imply sentiments or many subjective sentences do not express positive or negative sentiments. A single sentence may contain multiple opinions and subjective and factual clauses.

McDonald et al. [5] developed a model for sentiment analysis at different levels of granularity simultaneously. They use graphical models in which a document level sentiment is linked to several paragraph level sentiments, and each paragraph level sentiment is linked to several sentence level sentiments (in addition to being linked sequentially). They apply the Viterbi algorithm to infer the sentiment of each text unit, constrained to ensure that the paragraph and document parts of the labels are always the same where they represent the same paragraph/document. They report 62.6% accuracy at classifying sentences when the orientation of the document is not given, and 82.8% accuracy at categorizing documents. When the orientation of the document is given, they report 70.2% accuracy at categorizing the sentences.

Nakagawa et al. [6], authors developed a conditional random field model structured like the dependency pars tree of the sentence they are classifying to determine the polarity of sentences, taking into account opinionated words and polarity shifters in the sentence. They report 77% to 86% accuracy at categorizing sentences, depending on which corpus they tested against.

Nasukawa et al. [7] test a sentence-level sentiment classification to find favorable or unfavorable orientation of web pages and articles. Das and Chen [8] developed a hybrid approach of different classification algorithms and compare their technique with the Naive Bayes technique.

SENTIMENT LEXICON CONSTRUCTION

Sentiment words are used in many sentiment classification tasks. These words are also identified by "opinion words" or "opinion bearing words" in literature. Sentiment words are always divided into two categories according their orientation: positive or negative sentiment words. For instance, "excellent" is a positive sentiment words and "poor" is a negative sentiment word. In addition to the single words, there are several sentiment phrases that can be used in sentiment classification tasks. Sentiment words and sentiment phrases form the sentiment lexicon.

There are three methods to construct a sentiment lexicon: manually construction, corpus-based methods and dictionary-based methods. The manual construction of sentiment lexicon is a very hard and time-consuming task and always cannot be used alone but it can be combined with other methods to improve the accuracy of these methods. Two other methods are discussed in following subsections.

Corpus-based Methods

These methods always use a seed set of sentiment words with known polarity and exploit syntactic patterns or co-occurrence patterns to identify new sentiment words and their polarity in a large corpus. The work of Hatzivassiloglou and McKeown [9] reported that it is possible to identify sentiment words (adjectives) and their polarity in sentences with a high accuracy of 82%. Following this finding, various sentiment analysis algorithms have been proposed. Turney [4] introduced one of the first algorithms for document level sentiment analysis, which achieved an average accuracy of 74% for product reviews and 66% accuracy on movie reviews.

Corpus-based methods can produce lists of positive and negative words with relatively high accuracy. Most of these methods need very large labeled training data to achieve their full capabilities. Dictionary-based approaches can overcome some of the limitations of corpus-based approaches by using existing lexicographical resources (such as WordNet) as a main source of se-mantic information about individual words and senses.

Dictionary-based methods

Dictionary-based methods to sentiment lexicon construction do not require large corpora or search engines with special capabilities. Instead, they exploit available lexicographical resources like WordNet. Accurate, domain-independent and comprehensive lists of words and their senses can be produced by these methods. The main strategy in these methods is to collect an initial seed set of sentimental words and their orientation manually, and then searching in a dictionary to find their synonyms and antonyms to expand this set. The new seed set are used iteratively to generate new sentiment words.

Esuli and Sebastiani [10] developed a technique for classifying words as positive or negative, by starting with a seed set of positive and negative words, then running WordNet synset expansion multiple times, and training a classifier on the expanded sets of positive and negative words. In its original form WordNet was not a very reliable source to build sentiment lexicons, since it introduces too much noise. Furthermore, it does not adjust the sentiment value for each sentiment word in the lexicon. It merely expands the lexicon with previously unknown sentiment words. To overcome this problem they created SentiWordNet [11] which assigns each WordNet synset a score for how positive the synset is, how negative the synset is, and how objective the synset is. This version of Senti-WordNet was released as SentiWordNet 1.0. Another common approach is bootstrapping. For example, Riloff and Wiebe [12] employed a classifier to extract subjective patterns from text which could be used to build a sentiment lexicon

In [13] authors developed a verb oriented sentiment classification approach as well as the Bag of Words approach considering adjectives, adverbs, nouns, and verbs as features. They also considered the strength of opinion terms in both approaches. They have achieved an accuracy of 65%, with a precision of 71% and recall 80%.

Then main problem of dictionary-based methods is that this methods unable to find sentiment word with domain specific orientation. A sentiment word maybe expresses positive emotion in one domain and negative emotion in another domain. For example, the word "large" has a positive orientation when it is being used for describing a computer screen and it has a negative orientation if it describes a mobile phone.

ASPECT-BASED SENTIMENT ANALYSIS

In the last 15 years the amount of textual information readily available in digital form has increased many folds. Especially, the amount of user-generated content has grown at a fast pace with Web 2.0 technologies and social media. Many costumers feel that they can make more efficient decisions based on the experiences of others that expressed in product reviews on the web [15]. Therefore,

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product reviews are very important resource to decision making for selecting a product by a costumer.

The major steps involved to produce this detailed summery of product reviews are

(1) Aspect extraction (e.g., person, product, service)

(2) Aspect sentiment orientation detection

Aspect extraction

Aspect extraction, also referred as feature extraction is one of the key tasks in aspect-based sentiment analysis. It needs the use of Natural language processing techniques in order to automatically extract the aspects or features in the opinionated documents. In recent times there has been huge interest to identify aspects and sentiments simultaneously. The method proposed in [14] is based on information extraction approach that identifies frequently occurring noun phrases. This approach is generally useful in finding aspects which are strongly associated with a single noun. But, one disadvantage of this approach is that it cannot detect the aspect terms which are of low frequency and noun phrases. Some other works include the methods to define aspect terms using a manually specified subset of the Wikipedia category [16].

More recent approaches of aspect detection are based on topic modeling that uses Latent Dirichlet Allocation (LDA) [17]. But, the standard Latent Dirichlet Allocation (LDA) is not exactly suitable for the task of aspect detection due to their inherent nature of capturing global topics in the data, rather than finding local aspects related to the predefined entity. This approach was further modified by Jo and Oh [18]. The authors first proposed Sentence –LDA (SLDA), a probabilistic generative model that assumes all words in a single sentence are generated from one aspect. They extend SLDA to Aspect and Sentiment Unification Model (ASUM), which incorporates aspect and sentiment together to model sentiments toward different aspects. ASUM discovers pairs of {aspect, sentiment} which they call *senti-aspects*. They applied SLDA and ASUM to reviews of electronic devices and restaurants. The results show that the aspects discovered by SLDA match evaluative details of the reviews, and the senti-aspects found by ASUM capture important aspects that are closely coupled with a sentiment. The results of sentiment classification show that ASUM outperforms other generative models and comes close to supervised classification methods. One important advantage of ASUM is that it does not require any sentiment labels of the reviews, which are often expensive to obtain.

Aspect sentiment orientation detection

Determining the sentiment orientation expressed on each aspect in a sentence is the second task in aspect based sentiment analysis. It must determine whether the sentiment orientation on each aspect is positive, negative or neutral. This task can be divided into the following sub tasks:

1. Extracting opinion words or phrases.
2. Identifying the polarity of each opinion words or phrases.
3. Handling opinion shifters (such as no, not, don't) and opinion intensifiers (such as very, extremely)
4. Handling but clauses.
5. Aggregating opinions (if there is more than one opinion word or phrase in a sentence).

In [14] a distance based approach was used to extract opinion words and phrases after extracting aspects. In this paper, adjacent adjective words (e.g. within the 3-words distance to the aspect) were considered as opinion words. Authors used a WordNet lexicon to calculate the polarity of each extracted opinion word. The negation words were considered in this paper but intensifiers were not extracted. For a sentence that contains a but clause which implies sentimental change for aspects in the clause, they used the effective opinion in the clause to select the orientation of the features. The opposite orientation of the sentence was used when no opinion appeared in the clause.

In [19] , Authors proposed a propagation based method to ex-tract opinion and aspect simultaneously. This method is based on the fact that there are natural relation between opinion words and aspects because opinion words are used to describe aspects. They used a bootstrapping approach. Their approach start with an initial opinion word seeds and by using several syntactic relation that linked opinion words and aspects, it try to find new aspects. Then these new aspects and available opinion words are used to identify another aspects and opinion words. The process terminates until no more new aspects or opinion words can be identified.

EVALUATION OF SENTIMENT CLASSIFICATION

Generally, the performance of sentiment classification is evaluated by using four indexes: Accuracy, Precision, Recall and F1-score. The common way for computing these indexes is based on the confusion matrix shown in Table 1.

Table 1. Confusion Matrix

	Predicted Positives	Predicted Negatives
Actual Positive instances	Number of True Positive instances(TP)	Number of False Negative instances(FN)
Actual Negative instances	Number of False Positive instances (FP)	Number of True Negative instances(TN)

These indexes can be defined by the following equations:

$$\text{Accuracy} = \frac{TP+TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Accuracy is the portion of all true predicted instances against all predicted instances. An accuracy of 100% means that the predicted instances are exactly the same as the actual instances. Precision is the portion of true positive predicted instances against all positive predicted instances. Recall is the portion of true positive predicted instances against all actual positive in-stances. F1 is a harmonic average of precision and recall.

CONCLUSION AND FUTURE WORK

Opinions are very important for anyone who is going to make a decision. It is helpful for individuals when they want to buy a product and they can decide which product to buy, by studying the summarized opinions instead of studying long reviews and making summary their selves. Opinion mining is equally important for Enterprises and helps them to know what customers think about their products. Therefore companies can take decisions about their products based on customer's feedback. Thus companies can

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modify their products features and introduce new products according to customers' opinions in a better and faster way. Thus, companies can improve the customer experience by giving them exactly what they need than what the companies wanted to sell to customers. The companies can find, attract and retain customers; they can save on production costs by utilizing the acquired insight of customer requirements.

In this paper we have introduced sentiment classification problem in different level i.e. document-level, sentence-level, word-level and aspect-level. Also, some techniques that have been used to solve these problems have been introduced. In future, more research is needed to improve the performance metrics of methods and techniques introduced in this paper

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