An Overview of Feature Based Opinion Mining

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Abstract— **Opinion mining is becoming a popular area in today's world but before the invention of web 2.0 people were only able to view the information but now they are also able to publish the information on Web in the form of comments and reviews. The user generated content forced organization to pay attention towards analyzing this content for better visualization of public's opinion. Opinion mining or Sentiment analysis is an autonomous text analysis and summarization system for reviews available on Web. Opinion mining aims for distinguishing the emotions and expressions expressed within the reviews, classifying them into positive or negative and summarizing into the form that is quickly understood by users. Feature based opinion mining performs fine-grain analysis by recognizing individual features of an object upon which user has expressed his/her opinion. This paper gives an idea of various methods proposed in the area of feature based opinion mining and also discusses the limitations of existing work and future direction in feature based opinion mining.**

Keywords*— *Opinion mining, Feature extraction, Sentiment classification, Sentiment analysis, Opinion summarization

I. INTRODUCTION

Since the advancement of the technologies, many people use internet to express their feedback or opinion, as reviews, comments or question answers on forums, blogs and social websites, which increases the amount of user generated content on the internet. This user generated content can be very useful for both a user and an organization. For instance, tourists can check reviews and experiences published by other travelers on specific hotel on different tourism web sites before booking the hotel. For hotel organization, the reviews available on the web could be used to make surveys, focus groups in market research.

However, due to the large number of opinions or feedbacks published on web it is very difficult for users to analyze all web opinions. All reviews are in the form of plain text which is written in any natural language, therefore to get valuable information from those reviews we need help from other domains like Natural Language Processing (NLP) and Data Mining. To analyze and summarize the opinions that are expressed on web manually is a difficult task. Therefore, we require an automated sentiment analysis system which will provide us the feedback or opinion accurately.

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Opinion mining or sentiment analysis involves an area of NLP, computational linguistics and text mining, and refers to a set of techniques that deals with data about opinions and tries to gain valuable information from them. Opinion mining has its applications in almost each and every promising area, from customer products, services, financial services, and healthcare to political elections and all social events.

Motivation

Customer's review contains very useful information which could be used for analysis purpose by the researchers. It is common behavior to consider other customer reviews about the product before purchasing it, even before the foundation of internet. In today's world people face the problem of handling huge amount of data or information, for eg. If we want to check opinion or reviews about an hotel we go through the internet and check review about that hotel but due to lot of reviews available it creates confusion in the mind of user which enhances the decision making process. Normally people try to purchase the best product form the market in cheapest price which satisfy their need.

From the e-commerce point of view, receiving customers' opinions can significantly improve its policies for the sake of increasing the income. Generally, each products contains thousands of opinions, therefore it is a difficult task for a customer to analyze all of them. Also, it could be a very tedious task to find opinions about some specific features about a product which is generally a need of a routine customer. Feature based opinion mining system examines opinions at feature level and produce comprehensive summary of opinions which help customers in the decision making.

The rest of the paper is structured as follows. In section II, we discuss basics of opinion mining and tasks of feature based opinion mining. Section III presents the outline of the related work, evaluation parameters. Section IV lists issues in feature based opinion mining. Finally, section V concludes the paper.

II. OPINION MINING

Opinions are very important among all human activities as they highlight the behavior of the people. People always tend to know other peoples' opinions, whenever they need to make some decision. Nowadays, businesses and organizations always look for getting their customers' reviews about their goods and services. Each and every user wants to know the opinion of various other customers on a product before buying it, while in political election, public opinion about a specific political leader is important before making a voting decision.

An opinion is the personal view of an individual; it represents the individual's ideas, judgments, beliefs, assessments and evaluations about a specific topic, item or subject. One's opinion about a subject can either be positive or negative, which is referred as the semantic orientation or polarity or sentiment.

An opinion has three main elements, i.e.

- The opinion source: author of the review
- Target of the Opinion: object or its feature
- Opinion polarity: positive or negative

All of these elements are vital for opinion identification. “Opinion mining is the problem of recognizing the expressed opinion on a particular subject and determining the polarity of opinion”. It provides broad view of the sentiments expressed via text, and to classify and summarize the opinions, it enables further processing of the data.

A. Level of Opinion Mining

In general, opinion mining has been explored mainly at three stages by researchers:

1) Document level: At document level opinion mining, whole opinion or review is classified into positive or negative. For example, consider a movie review; based on the opinion words present in the review we classify the movie reviews as positive or negative. The main issue of this level is that a whole review is expressed on a single subject. Thus, it is not applicable to reviews in which single review expresses opinion on multiple subjects.

2) Sentence level: At this level task of opinion mining is to classify opinion at sentence level. It categorizes every sentence into a positive, negative, or neutral opinion. Sentence which contains no opinion or unrelated words are considered as neutral opinion. The sentence level opinion mining systems may contain subjectivity classification as the pre-processing step. Subjectivity classification is the task of classifying sentences into the objective or subjective sentences. Objective sentences are the sentences that represent factual information and subjective sentences are the sentences that represent subjective opinions.

3) Feature or Aspect level: The document level as well as the sentence level analysis does not describe the exact liking of the people. Feature level opinion mining performs fine-grained analysis. It is also referred to as feature based or aspect based opinion mining [2]. Feature level analysis directly looks at the opinion itself instead of looking at language constructs like clauses, sentences or paragraphs. It is based on the fact that user may express his/her opinion on specific feature or aspect of an entity rather than entity itself. Feature or aspect of an entity upon which opinion is expressed is referred as target of an opinion.

An opinion whose target is not identified is of restricted use. Opinion targets are of much importance because single sentence may contain multiple targets from which each target has different opinion. For example, consider the sentence “Even though the music of the movie is not good, I like the story of the movie” obviously has a positive attitude but the sentence is not completely positive. The sentence is

positive about the story, but due to its music quality it is negative. In various applications, opinion targets are represented by entities and/or their different aspects. Thus, the aim of this level is to identify polarities of entities and/or their aspects. Feature based opinion mining system provides a structured summary of opinions about entities and their aspects, and hence converts the unstructured data to structured data which can be further used for all kinds of qualitative and quantitative analysis.

B. Opinion Mining Tasks

Generally, Feature-based Opinion Mining studies consist of three tasks: Aspect identification, Sentiment classification and Summary generation.

1) *Aspect Identification:* The main goal of this task is to identify and extract relevant topics from the text which will be further used for summarization. In [3], Hu and Liu present a technique based in statistics and NLP. In their proposed system, syntax tree parsing and part-of-speech (POS) tagging are used to detect nouns and noun phrases (NP). Then, the most frequent nouns and NPs are identified by using frequent item set mining. Then using distinct linguistic rules, the discovered sets of nouns and NPs are filtered. The aspects of the entity that are made up of more than one word, usually represent real objects together and they also remove redundant aspects too. They also extract non-frequent features using an approach by finding nouns or NPs that appear near to opinion words with high frequency. This approach does not extract adjectives or any other kind of non-object aspects.
2) *Sentiment Classification:* The next task is sentiment classification which determines the semantic orientation of each aspect. Ding et al. [4] proposed system uses a lexicon and rule-based approach. Their method depends on opinion words, a list of positive and negative words contained in sentiment word dictionary. It is used to determine the semantic orientation of the words in the review. Distinct linguistic rules are put forward to consider other special words that change the orientation. These rules handles negative words ‘‘no’’ or ‘‘not’’ and also some general negation patterns. Though these rules may appear simple, but it is important to handle them with caution, as all rules or word will generate the different meaning each time they appear in the text. Ding et al. [4] developed the rules that use an aggregation score function to evaluate the semantic orientation of each feature in a sentence that contains multiple opinion words.

3) *Summary Generation:* The last task is summary generation, to represent processed results in a proper form which can be easily understood by users. Bing Liu [2], [5], defines a kind of summary which is called as

aspect-based opinion summary in which there are various bar charts showing number of positive and negative reviews about each and every aspect of a single entity. Liu et al [6] states that a set of selected products can be compared and described using the bar charts, which shows the set of all aspects of the chosen products in the chart. In this chart, each bar above or below the x-axis can be represented in two scales: (1) the percentage of positive or negative opinions on reviews and (2) the actual number of positive -or negative opinions normalized with the most number of opinions on any feature of any product.

III. LITERATURE SURVEY

The research in the field of opinion mining has been increased since advancement in the field of NLP. K. Khan et al. [7] review the various advancement in opinion mining research. According to T sytsarau et al. [8] opinion mining methods can be classified in four approaches: Machine Learning, Dictionary, Statistical, and Semantic.

A. Machine Learning Approach

The machine learning method consists following stages. First, a training dataset is acquired, that could be either annotated or not with sentiment labels. Second, each review is presented as a vector of features. Third, a classifier is trained to differentiate among sentiment labels by analyzing the relevant features. Finally, the trained classifier is used to identify sentiments for new reviews.

Zhai et al. 2011 [9] applied the machine learning method for opinion mining on Chinese language. Ngram feature extraction algorithm was used to extract the features from the labeled documents. The extracted features were used to represent document in vector form on which the training and classification steps were based. For the sentiment classification task Support Vector Machine (SVM) classifier was used. Spam reviews and comparative reviews are not considered in opinion mining task.

The performance of machine learning algorithms is very much dependent on the quantity and quality of training data, which is less compared to the extent of unlabeled data. The performance of this approach also depends on data selection or feature selection method and the choice of algorithm to some extent.

B. Dictionary Approach

The Dictionary Approach uses a pre-built dictionary which defines semantic orientation of words, such as the SentiWordNet, which is the standard dictionary today. Existing opinion mining approaches use these dictionaries mainly for identifying semantic orientation of opinion words. Semantic orientation of a single sentence or review is generally calculated by averaging the semantic orientation

values of individual words. For instance, most of the dictionary base methods aggregate the semantic orientation values for a sentence or whole review, and estimate the resultant polarity using simple rule-based algorithms.

Zhu et al. 2011 [10] uses Chinese sentiment lexicon Hownet for sentiment classification of restaurant reviews in Chinese language. It applies bootstrapping method for identification of features. A sentiment value of a review is computed by summing the sentiment values of all opinion words occurring in the review. The resultant semantic orientation value of a review shows its corresponding polarity, that is, greater than 0 for positive, equal to 0 for neutral and less than 0 for negative.

C. Statistical Approach

The Statistical Approach aims to obtain polarity values via the co-occurrence of adjectives in a corpus. Here, corpus-Specific dictionary is created to achieve adaptability. To solve the problem of unavailability of some words, this approach uses a very large corpus. It is also possible to use the complete set of indexed documents on the Web as the corpus for the dictionary construction Peter, Turney[11].

The existing statistical methods are based on the fact that similar opinion words mostly appear together in a corpus. Similarly, if two words usually appear together in the same context then they are possibly having the same semantic orientation. Thus the semantic orientation of a new word is determined by calculating the relative frequency of co-occurrence with other word, which invariantly preserves its polarity. To achieve this, Peter, Turney [11], [12] proposed to use the point-wise mutual information (PMI) criterion for statistical dependence, replacing probability values with the frequencies of term occurrence F(x) and co-occurrence F(x near y):

$$PMI(x, y) = log_2 = \frac{F(x\ near\ y)}{F(x)F(y)} \quad (1)$$

Semantic orientation for any word x is calculated as the difference between PMI values computed against positive words (words), e.g. “good”, and negative words (nWords), e.g. “bad” [11]:

$$PMI\text{-}IR(x) = \sum_{pePWords} PMI(x, n) - \sum_{nenWords} PMI(x, n) \quad (2)$$

Turney et al. considers the statistics of the web search engine of AltaVista to find out the co-occurrence frequencies (F).

D. Semantic Approach

The Semantic Approach depends on various principles for calculating the similarity between words and thus provides sentiment values directly. The basic principle of this approach is that semantically related words should obtain similar

sentiment values [8].

WordNet is a dictionary that is used to determine sentiment polarities and defines different types of semantic relationships among words. WordNet can be used to determine the senses of words because some words can have multiple interpretations. The possibility to disambiguate senses of words using WordNet can serve as a way to include the context of these words into the opinion analysis task. Like statistical methods, two sets of seed words with positive and negative sentiments are used as a starting point for bootstrapping the construction of a dictionary.

Hu and Liu [2], [3], [6] used WordNet to acquire a list of sentiment words by iteratively expanding the initial set with synonyms and antonyms. However, this method has some shortcomings. This method does not deal with context dependent opinion words.

Ding, Liu and Yu [4] proposed a holistic lexicon based approach to handle the context dependent opinion words. This method applied special linguistic rules. This approach uses external information and indications in other sentences and other reviews, instead of looking at the current sentence alone. This method is improvement of the method used in [2].

M. Eirinaki et al. 2011 [13] presents a feature-based opinion mining technique which used HAC(High Adjective Count) to identify the features from opinion and proposed Max Opinion Score algorithm for sentiment classification. To identify the polarity of reviews, features extracted from title also considered separately.

The researchers of the opinion mining field have shown less concern to the domain of opinions. The accuracy of sentiment analysis methods highly depends on the domain of interest [14]. The majority of the work [2]-[4], [6], and [13] had been carried on Product domain.

M. Taylor at al. [15]-[16] has applied feature-based opinion mining techniques on hotels and restaurants reviews. Association rule mining was applied as feature extraction method. For sentiment classification holistic lexicon based approach [4] was used. However the algorithms were only able to extract 35% of the explicit features.

E. Rule based method

Rule-based methods handle the previously listed challenges better as it is possible to build dedicated rules for anaphora resolution, processing negations and intensifiers, target identification [18], source identification, and meta-phor disambiguation [19]. However, in order to attain acceptable success rates it is necessary to restrict the domain of application as much as possible. Thus, their main disadvantage is the difficulty of building generic extraction patterns and lexicons to extract all sentiment-related expressions contained in the data and to assign them a relevant label in varying contexts. Some authors have proposed

different solutions, such as expanding the affective lexicon with new entries based on semantic similarity [20] or linear programming [21].

Supervised machine learning methods make it possible to generate more interoperable models, but they require the availability of labeled data for training. The quality of the models learned strongly depends on the reliability of sentiment annotation, which is affected by raters' subjectivity as existing annotation guides are rare. Besides, this type of methods allows building models that are sometimes difficult to interpret and control, which is why hybrid (statistical and rule-based methods) are sometimes used [22] [23]. Also some authors propose methods that provide more control, e.g., [24] uses conditional random fields (CRF) tackling opinion source identification as a sequential tagging task, whereas [25] identifies the target of the opinion with CRF. In [27] a Bayesian network is also used to model pragmatic dependencies to improve agreement analysis in meetings.

The tendency is now to handle the drawbacks of each type of method using hybrid methods, which bring both the generalizable nature of machine-learning approaches and the in-depth modeling offered by semantic rules. For instance, [18] uses probabilistic models for disambiguation, and tools like Auto Slog provide supervised pattern trainers that have been used for opinion source identification [24], while [26] proposes merging unsupervised machine learning algorithms with supervised ones.

Different contexts and domains of application may intro-duce other specific challenges. It is thus important to keep in mind that the performance of such systems is strongly dependent on:

The type of data to be analyzed: the style and the language register of the writer/speaker, the quality of the syntactic structure of the data (tweets and oral transcription versus newspaper). For example, sentiment detection in social networks or transcriptions of speech must be able to cope with ill-formed linguistic structures [28] and other phenomena such as orthographic mistakes, emotions and other symbols [29].

The classes of sentiment that are considered: classification according to ten classes is indeed more difficult than for two classes. Performance also depends on the choice of classes being studied, e.g., discriminating between appreciation and judgment is generally more difficult than between positive and negative.

The quality of the ground-truth annotations: evaluating performance consists of analyzing differences between ground truth annotations and system decisions. In the field of sentiment, we cannot speak about actual human error, since the situation is more complex (subjectivity of the annotations, and imbalanced proportion of emotional and neutral contents [30]).

F. Comparative Evaluation

In this section we give an overview of different feature extraction and sentiment classification methods applied in feature based opinion mining as discussed earlier. Table I presents comparison of different feature extraction methods based on the parameter precision and recall. Table II presents comparison of different sentiment classification methods.

TABLE I. COMPARISON OF VARIOUS FEATURE EXTRACTION METHODS

Paper	**Domain**	**Language**	**Feature Extraction**		
			Method	***Precision***	***Recall***
Turney 2002 [11]	Automobile Movie	English	Pattern based extraction	-	-
Hu and liu 2006 [5]	Product	English	Association rule mining	72	80
M.Taylor 2013 [15]	Hotels	English	Association rule mining	38	33
Eirinaki 2012 [13]	Product	English	High Adjective Count algorithm	-	-
J. Zhu 2011 [10]	Hotels	Chinese	Multi-aspect bootstrapping	69	56
Ding, Liu, 2008 [4]	Product	English	Association rule mining	72	80

TABLE II. COMPARISON OF VARIOUS SENTIMENT CLASSIFICATION METHODS

Paper	Sentiment Classification			
	Method	***Accuracy***	***Precision***	***Recall***
Turney 2002 [11]	PMI-IR method	74	-	-
Hu and liu 2006 [5]	Rule based algorithm with WordNet	84	-	-
M.Taylor 2013 [15]	Holistic linguistic Method	-	90	93
Eirinaki 2012 [13]	Max opinion score algorithm using manual dictionary	87	-	-
Z.Zai 2011[9]	SVM	83	-	-
J. Zhu 2011 [10]	Dictionary based	75	-	-
Ding, Liu, 2008 [4]	Holistic linguistic Method	-	92	91

IV. CHALLENGES AND ISSUES

Despite numerous research efforts, feature based opinion mining studies and application still have limitations and margins for improvement.

- Limitations of natural language processing, such as context dependency, semantic relatedness and word sense ambiguity, have created feature based opinion mining challenging.

- Feature based opinion mining systems that uses machine learning approach are domain dependent which require manual labeling of data, a difficult task to accomplish.
- Opinion spamming has become an issue due to fake opinions in reviews and forum discussions given by the users which may affect the decision of genuine users.
- Domain dependency is another issue, because the target features specific to domain may have different meanings or interpretations when applied to different domain.
- As reviews are crawled from web, they are from different locale so it may consist of different human languages. Multilingual effect also makes opinion mining difficult.

V. CONCLUSION

The paper discusses various methods of sentiment analysis and tasks of feature based opinion mining. We have stated some of the approaches of feature based opinion mining and compared various feature extraction and sentiment classification techniques. Majority of work done in opinion mining is at document level and sentence level. Most of them have paid little attention to opinion spam and domain dependency. Feature based opinion mining is still an open area of research due to the fact that we can improve the accuracy of feature based opinion mining system by adding spam opinion detection, comparative review detection and multilingual Review handling mechanisms. For spam opinion detection any machine learning methods can be applied and to evaluate opinion of foreign language machine translation techniques can be used.

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