



A SURVEY ON OPINION MINING FRAMEWORK

Blessy Selvam¹, S.Abirami²

Department of Information Science and Technology, Anna university, Chennai, India^{1,2}

Abstract: The explosion of social media has created unprecedented opportunities for citizens to publicly voice their opinions, but when it comes to making sense of these opinions then it is a serious problem. Opinion mining is a type of natural language processing for tracking the mood of the public about a particular product. Opinion mining involves building a system to collect and examine opinions about the product made in blog posts, comments, reviews or tweets. Opinion mining can be useful in several ways in marketing, it helps to judge the success of a launch of new product, determine which versions of a product or service are popular and even identify which demographics like or dislike particular features. After the process of opinion extraction, the Sentiment analysis determines the subjectivity, polarity and polarity strength of a piece of text. The sentiment oriented words are used for providing a good recommendation to the users to make accurate decision. This paper gives a brief survey on the opinion mining framework.

Keywords: Opinion mining, sentiment analysis, sentiment lexicon, feature extraction, sentiment classification

I. INTRODUCTION

Opinion mining is used to analyze the sentiments expressed by people on the web through reviews. In recent years, large attention has been given to opinion mining because of its wide range of possible applications [1, 2]. As an example Consumers look for the opinions of the products they want to buy before buying them [3]. In general, opinion mining helps to collect information about the positive and negative aspects of a particular topic. Finally, the positive and highly scored opinions obtained about a particular product are recommended to the user. In order to promote marketing, large companies and business people are making use of opinion mining [4]. Politicians are changing their campaign policies according to the people's expectations. In figure 1, the entire framework of opinion mining is represented.

II. LITERATURE SURVEY

To mine opinions, the reviews collected can be analyzed at three levels. The first one is Document-level, which determines the overall sentiment of a given review without considering the individual aspects provided in the document and this is not suitable for certain applications. The second one is in the sentence level, which targets the sentences in the document and categorizes it as objective sentences (no opinion) and subjective sentences (with opinion). The third one is the Feature-based, which performs fine grained analysis by directly looking at the opinions rather than the document. The following phases are carried out in the opinion mining framework to mine opinions. Section 3

briefs with the data source dealt in the literature, section 4 deals with text preprocessing works, section 5 deals with feature extraction techniques, section 6 deals sentiment analysis, section 7 with sentiment classification methods, section 8 deals with tools used for opinion mining and section 9 deals with the conclusion and challenges at the end of the work.

III. DATA SOURCES

The data obtained from the below mentioned sources are used for finding opinions and providing a good recommendation for a particular application. The most commonly used sources are blogs and review sites.

3.1 Blogs

As internet usage is increasing day by day, blogging and blog pages are growing rapidly. Blog pages contain the expression of one's personal opinions. Many of these blogs contain reviews on many products, issues, etc. Blogs act as one of the sources of expressing opinion in many of the studies related to sentiment analysis [33].

3.2. Review sites

The important factor considered for making a decision by a purchaser before purchasing is to know the comments given by the previous buyer. The data given by reviewers are collected from the e-commerce websites like www.amazon.com (product reviews), www.yelp.com (restaurant reviews) [34].



3.3. Dataset's

Raw datasets are available readily and one of the most widely used review dataset for the Movie domain, namely MDS dataset, contains four different types of product reviews extracted from popular websites like Amazon.com including Books, DVDs, Electronics and Kitchen appliances[5].

3.4. Micro-blogging

In Twitter information is represented as a short text message called "tweet". The opinions about different topics are expressed in tweets and they are considered for opinion mining.

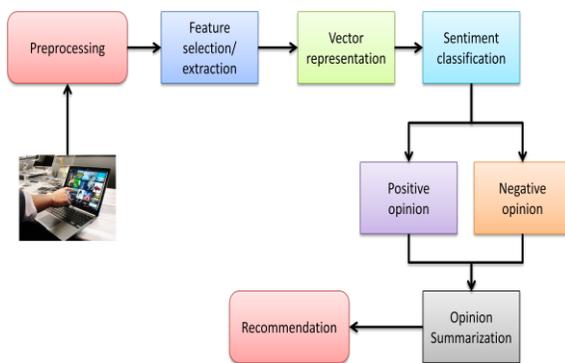


Figure 1. Opinion mining framework

IV.PREPROCESSING

The above figure.1 gives the entire frame work of opinion mining. In this phase, raw data taken and is preprocessed for feature extraction. The preprocessing phase [6] has been further divided into number of sub phases as follows: 1: Tokenization- Text document has a collection of sentences which is split up into terms or tokens by removing white spaces, commas and other symbols etc[37], 2: Stopword Removal - removes articles [35](like 'a, an, the'), 3: Stemming - decreases relevant tokens into a single type[35]. 'Eg: generalization, generally are represented as general (root word), 4: Case Normalization - English texts published contains both higher and lowercase characters and this process turns the entire document or sentences into lowercase/uppercase. After preprocessing, the sentences in the document have been represented as a feature vector.

V.FEATURE XTRACTION

The feature extraction phase deals with feature types (which identifies the type of features used for opinion mining), feature selection (used to select good features for opinion classification), feature weighting mechanism (weights each

feature for good recommendation) reduction mechanisms (features for optimizing the classification process).

5.1 Feature Types

Types of features used for opinion mining could be: 1: Term frequency (The presence of the term in a document carries weightage) [13], 2: Term co-occurrence (features which occurs together like unigram, bigram or n-gram), 3: Part of speech information (POS tagger is used to separate POS tokens). 4: Opinion words (Opinion words are words which express positive (good) or negative (bad) emotions) [13]. 5: Negations (Negation words (not, not only) shifts sentiment orientation in a sentence) [13] and 6: Syntactic dependency (It is represented as a parse tree and it contains word dependency based features) [13].

5.2 Feature selection

And finally, the target aspects obtained from various sentences are represented in vector space. Feature selection methods provide a criterion for eliminating terms from document corpus to reduce vocabulary space. Feature selection has been done in the literature in the following ways:

- 1: Information gain (based on the presence and absence of a term in a document a threshold is set and the terms with less information gain is removed) [37].
- 2: Odd Ratio (It is suitable for binary class domain where it has one positive and one negative class for classification. The algorithm is run on each class and the top- n features are taken from the sorted list).
- 3: Document Frequency (Measures the number of appearances of a term in the available number of documents in the corpus and based on the threshold computed the terms are removed) [36].
- 4: Mutual Information (The words with frequent association in the document are selected) [36].

5.3 Features weighting mechanism

Next to feature selection the feature weighting mechanism computes weight for ranking the features. The top -n feature which gets sorted will be recommended. Finally, the various feature weighting mechanisms are:

- 1: Term Presence and Term Frequency- word which occurs occasionally contains more information than frequently occurring words [14].
- 2: Term frequency and inverse document frequency (TF-IDF) - Documents are rated in [37], where highest rating is given for words that appear regularly in a few documents and lowest rating for words that appear regularly in every document.

5.4 Feature Reduction

Next to this, feature reduction reduces the feature vector size to optimize the performance of a classifier. Reduction of the number of features in the feature vector can be done in two different ways in which top n-features can be left in the vector and either low level or unwanted linguistic features



could be removed. Hence, feature reduction provides a good recommendation; the dimensionality space is reduced using the reduction approach [15].

VI. SENTIMENT ANALYSIS

The information collected from the reviews can be classified in one of the following ways to provide a good recommendation system.

6.1. Document Sentiment Classification

Supervised machine learning approaches are used for predicting the overall sentiment of the document [10]. The review document is taken as a whole and is trained with the labeled samples. Finally the document is labeled as either positive or negative as a whole. The entire process is typically composed of two steps: 1) Extracting the subjective features from the training data and converting them as feature vectors. 2) Training the classifier on the feature vectors and classifying its subjectivity.

6.2. Sentence Level Sentiment Classification

The sentence level documents are just short documents, where the documents obtained from reviews is parsed into sentences. The sentences containing opinion words are extracted and further they are classified into subjective and objective sentences. Because the subjective sentences holds opinions whereas the objective sentences will hold only factual information. The semantic orientation at sentence level is done by extracting opinion bearing terms, opinion holders and opinion-product aspect association in each sentence. Some of the techniques used are pronoun resolution and entity extraction [11].

6.3. Word or Phrase Sentiment Classification

Here, the word level consolidation of sentiments has been done. The words used are mostly adjectives or adverbs that have semantic orientation [8, 9] which classifies the given word into positive, negative and neutral classes. The model of feature-based opinion mining and summarization is proposed in [12], which extracts the sentiment words from the reviews and classifies them accordingly. The approaches used to classify sentiments at word level could be grouped into two: 1) Corpus based approaches [20] (determine the emotional affinity of words which is used to learn their probabilistic affective scores from large corpora for classifying the opinions) and 2) Dictionary based approaches (WordNet is used to extract the synonym and antonyms for a list of words iteratively, until no words are found. Finally, the words are represented as a feature vector). The word level sentiment classification provides a fine grained sentiment classification.

VII. SENTIMENT CLASSIFICATION

As a part of sentiment analysis, sentiment classification tries to classify the nature of document/sentence using machine learning and lexicon based approaches.

7.1. Machine Learning based approaches

In a machine learning based classification, documents require two sets: one is the training and the other is the test set. For training a set automatic classifiers are used that learns various characteristics of documents, and a test set is used to validate the automatic classifier's performance. A number of machine learning techniques have been adopted to classify the reviews. Machine learning techniques like Naive Bayes (NB) [17], maximum entropy (ME) [16], and support vector machines (SVM) [18] have achieved great success in text categorization.

7.1.1 Naive Bayes

The Naive Bayes algorithm is widely used algorithm for document classification [16]. Two types of feature (POS and word association) were extracted and integrated and classified using the base classifier. The feature selection methods used for fast selection and classification performance using the proposed ensemble methods [17] showed a contradiction in the performance of SVM. The focus is on written Cantonese, a written variety of Chinese. The machine learning model classifies the lexicon as a positive or negative one extracted from the review. The seed set is provided initially. The naive Bayes classifier surprisingly achieves better performance than SVM.

7.1.2. Support vector machine

The support vector machine is a statistical classification method proposed [18] for opinion mining. This paper deals with minimization of structural risk by using machine learning methods. Here, SVM sets a decision surface for separating the training data points into two classes. A decision is made based on the support vectors that are selected using the feature selection methods.

7.1.3 Bayes classifier

An ensemble technique is grouped the results of several bayes classification models to form an integrated output [16]. In this work, the two types of feature sets are designed for sentiment classification (features are integrated), namely the part-of-speech based feature sets and the word-relation based feature sets. Then, three text classification algorithms, namely naive Bayes, maximum entropy and support vector machines, have been used for each of the feature sets to predict classification scores.

7.1.4 Neural Networks

[19] Proposed an Artificial neural networks model for sentiment analysis of opinions, which divides the movie review corpus into positive or negative review. The features are extracted without sentimental word dictionary and weights are assigned. The sentiment polarity is found and opinions are classified based on the prior knowledge obtained for making decisions and finally, summarization is provided. Neural networks have also been used in the other system to classify positive or negativity [25].

7.2. Lexicon Based Approaches

Lexicon is an important indicator of sentiments called opinion words. A list of words/phrases is called sentiment



lexicon. Words in a sentence express positive or negative opinion.

7.2.1 Corpus Based Approach

Popular corpus-driven method is an early method which determines the emotional affinity of words, which is to learn their probabilistic affective scores from large corpora. [20] This research finds the happiness factor depending on the frequency of their occurrences in happy-labeled blog posts compared to their total frequency in a corpus containing mood annotated in the blog posts labeled with “happy” and “sad”. They also compare the happiness factor scores of words with the scores in the ANEW list. The ANEW list is obtained using traditional methods. [17] , In this research lexicon strength is computed using point wise mutual information for their co- occurrence with small set of positive seed words and a small set of negative seed words. Finally, the words are classified as either positive or negative.

7.2.2. Dictionary Based Approach

These approaches use lexical resources such as WordNet automatically [21] retrieve to similar words from WordNet utilizing senses of all words in the synsets that contain the emotional adjectives. Here, five of the six basic emotional categories has been described [22]. For direct affective words, weights from WordNet-Affect have been used. The affective weights are automatically acquired from a very large text corpus in an unsupervised fashion. The approach of using sentiment orientation of constituting words to determine the overall sentiment of the document does not provide good opinion, whereas sentiment often holds the composite meaning of the text, without the use of affect words. The problem of extracting the semantic orientation (SO) of a text often takes as a starting point for the problem of determining semantic orientation for individual words. The hypothesis is that, given the SO of relevant words in a text, SO for the entire text can be determined.

[23] Another researcher used a semi-automatic method to create a dictionary of words that express appraisal. Appraisal is a functional framework for describing evaluation in text: how personal feelings, judgment about other people, and appreciation of objects and art are expressed. Word similarities seem to be another way of building dictionaries, starting from words whose SO is already known. Manual and semiautomatic methods, although highly accurate, its not ideal, given that it is time-consuming and labour intensive to compile a list of all the words that can possibly express sentiment. The Semantic orientation approach to Sentiment analysis is an unsupervised learning because it does not require prior training in order to mine the data. Instead, it measures how far a word is inclined towards positive and negative.

[24] Later, another research proposed an approach which resort to other reviews discussing the same topic to mine useful contextual information and the semantic similarity

measures to judge the orientation of opinion. They attempted to tackle this problem by getting the semantic orientation of context independent opinion, then considered the context dependent opinions using linguistic rules to infer orientation of context distinct dependent opinion, The contextual information is extracted from other reviews that comment on the same product feature to judge the context indistinct-dependent opinions.

An unsupervised learning algorithm by extracting the sentiment phrases of each review by rules of part-of-speech (POS) patterns has been investigated [25]. Later, For each unknown sentiment phrase, they used it as a query term to get top-N relevant snippets from a search engine respectively. Then by using a sentiment lexicon, predictive sentiments of unknown phrases are computed based on the sentiments of nearby known sentiment words inside the snippets. They considered only opinionated sentences containing at least one detected sentiment phrase for opinion extraction. Using the POS pattern, opinion extraction has been done here.

[26] Another research, Developed a classification approach based on the k-means clustering algorithm. The technique of TF-IDF (term frequency – inverse document frequency) weighting applied over the data. A voting mechanism extracts more stable clustering result. The result is obtained based on multiple implementations of the clustering process as positive or negative groups. Finally, the term score has been used to further enhance the clustering results.

7.3. Semantic Orientation

Sentiment Classification analyzes the polarity and intensity assignments of sentiments during classification. Polarity assignment deals with analyzing the semantic orientation of a text having a positive, negative, or neutral. Whereas intensity assignment deals with analyzing, whether the positive or negative sentiments as strong, too strong, bad, very bad, etc..

7.3.1. Polarity Assignment

Sentiment polarity assignment deals with analyzing the semantic orientation of whether a text has a positive, negative, or neutral. The opinionated document is labeled with an overall positive or negative sentiment. When a news article is given as an input, analyzing and classifying it as a good or bad news is considered to be a text categorization task. Furthermore, this piece of information can be good or bad news, but not necessarily subjective (i.e., without expressing the view of the author). Summarizing reviews in order to collect information on to why the reviewers liked or disliked the product is another way of mining opinion. OpinionFinder Lexicon is created in [38]. It is an extension of the Multi-Perspective Question-Answering dataset (MPQA), that includes phrases and subjective sentences. Human annotators tagged each sentence according to the polarity classes: as positive, negative and neutral. Then, low



agreement tags are pruned. From each tweet two features related to the Opinion-Finder lexicon is extracted, OpinionFinder Positive Words (OPW) and OpinionFinder Negative Words (ONW) are the positive and negative words of the tweet that matches the Opinion-Finder lexicon.

7.3.2. Intensity Assignment

While Sentiment polarity assignment deals with analyzing the semantic orientation of a text as positive, negative, or neutral, Sentiment intensity assignment deals with analyzing, whether the positive or negative sentiments are mild or strong. Strength-oriented methods return different numerical scores which indicates the intensity of an opinion dimension expressed in a text passage. For instance, numerical scores indicate the level of positivity, negativity or another emotional dimension. Strength-oriented lexical resources provide lists of opinion words together with intensity scores regarding an opinion dimension. Here, SentiStrength Method focuses on short social web texts written in English [39]. SentiStrength considers linguistic aspects of the passage such as a negating word list and an emoticon list with polarities. From each tweet three features related to the SentiStrength method are extracted, then SentiStrength Negativity (SSN) and SentiStrength Positivity (SSP), that correspond to the strength scores for the negative and positive classes are obtained.

VIII SENTIMENT TOOLS USED FOR OPINION MINING FRAMEWORK

A variety of open-source text-analytics tools used for natural-language processing such as information extraction and classification can also be applied for opinion mining. Tools are listed below:

- 8.1. Ling Pipe – It is used for linguistic processing of text including entity extraction, clustering and classification, etc. The most mature and widely used open source NLP toolkits. This tool is considered for its speed, stability, and scalability. [28] <http://alias-i.com/lingpipe/>
- 8.2. OpenNLP - perform the most common NLP tasks, such as POS tagging, named entity extraction, chunking and co-reference resolution. [29] <http://opennlp.apache.org/>
- 8.3. Stanford Parser and Part-of-Speech (POS) Tagger - for sentence parsing and part of speech tagging from the NLP group. [30] <http://nlp.stanford.edu/software/tagger.shtml/>
- 8.4. NLTK - The natural language toolkit is a tool for teaching and researching classification, clustering and parsing. [31] <http://www.nltk.org/>
- 8.5. OpinionFinder – OpinionFinder aims to identify subjective sentences and to mark various aspects of subjectivity in these sentences, including the source (holder) of the subjectivity and words that are included in phrases expressing positive or negative sentiments. [32] <http://code.google.com/p/opinionfinder/>.

IX CONCLUSION

This paper focuses on the frame work on opinion mining and survey on some of the tasks which have been done in each phases. In our observation there are some challenges still exists in this area such as implicit feature identification, discovering opinions from comparative sentences, dealing with noisy input texts, extraction of opinion phrases and features from different corpora, extraction of multiple opinions from the same document etc. In future, these challenges could be handled in a better way for providing good recommendations to the user.

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