A Survey on Sentiment Classification of Movie Reviews

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***Abstract* - The explosion of social media has created unprecedented opportunities for citizens to publicly voice their opinions, but has created serious bottlenecks when it comes to making sense of these opinions. At the same time, the urgency to gain a real time understanding of citizens concerns has grown: because of the viral nature of social media (where attention is very unevenly and fastly distributed) some issues rapidly and unpredictably become important through word Of mouth.The World Wide Web has opened lots of new ways in human interactions. Users can express their opinions about various topics and discuss other user's views, Blogs, forums; online communities are all places where people can write their feelings. Classical technology in text categorization pays much attention to determining whether a text is related to a given topic, such as education, finance, entertainment, etc. However, research goes on, a subtle problem focuses on how to classify the semantic orientation of the text. Sentiment analysis is one kind of computational linguistic means sentiment analysis is the task of identifying positive and negative opinions, emotions, and evaluations.**

***Keywords* - Sentiment analysis, Movie Review Mining, Analysis**

I. INTRODUCTION

Opinions are central to almost all human activities and are key influencers of our behaviors. Our beliefs and perceptions of reality, and the choices we make, are, to a considerable degree, conditioned upon how others see and evaluate the world. For this reason, when we need to make a decision we often seek out the opinions of others. This is not only true for individuals but also true for organizations. Opinions and its related concepts such as sentiments, evaluations, attitudes, and emotions are the subjects of study of sentiment analysis and opinion mining.

Sentiment analysis, also called opinion mining, is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes. It represents a large problem space. There are also many names and slightly different tasks, e.g., sentiment analysis, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, review mining, etc. However, they are now all under the umbrella of sentiment analysis or opinion mining. While in industry, the term sentiment analysis is more commonly used, but in academia both sentiment analysis and opinion mining are frequently employed. Sentiment analysis and opinion mining mainly focuses on opinions which express or imply positive or negative sentiments.

II. DIFFERENT LEVELS OF ANALYSIS

In general, sentiment analysis has been investigated mainly at three levels:

Document level

The task at this level is to classify whether a whole opinion document expresses a positive or negative sentiment. For example, given a product review, the system determines whether the review expresses an overall positive or negative opinion about the product. This task is commonly known as document-level sentiment classification. This level of analysis assumes that each document expresses opinions on a single entity (e.g., a single product). Thus, it is not applicable to documents which evaluate or compare multiple entities.

Sentence level

The task at this level goes to the sentences and determines whether each sentence expressed a positive, negative, or neutral opinion. Neutral usually means no opinion. This level of analysis is closely related to subjectivity classification which distinguishes sentences (called objective sentences) that express factual information from sentences (called subjective sentences) that express subjective views and opinions. However, we should note that subjectivity is not equivalent to sentiment as many objective sentences can implyopinions, e.g., "We bought the car last month and the windshield wiperhas fallen off."

Entity and Aspect level

Aspect level performs finer-grained analysis. Aspect level was earlier called feature level (feature-based opinion mining and summarization) Instead of looking at language constructs (documents, paragraphs, sentences, clauses or phrases), aspect level directly looks at the opinion itself. It is based on the idea that an opinion consists of a sentiment (positive or negative) and a target (of opinion).

III. CLASSIFICATION OF EXISTING SOLUTIONS

The existing work on sentiment analysis can be classified from different points of views: technique used, view of the text, level of detail of text analysis, rating level, etc. From a technical point of view, we identified machine learning, lexicon-based, statistical and rule-based approaches.

The machine learning method uses several learning algorithms to determine the sentiment by training on a known dataset. The lexicon-based approach involves calculating sentiment polarity for a review using the semantic orientation of words or sentences in the review. The "semantic orientation" is a measure of subjectivity and opinion in text. The rule-based approach looks for opinion words in a text and then classifies it based on the number of positive and negative words. It considers different rules for classification such as dictionary polarity, negation words, booster words, idioms, emoticons, mixed opinions etc. Statistical models represent each review as a mixture of latent aspects and ratings. It is assumed that aspects and their ratings can be represented by multinomial distributions and try to cluster head terms into aspects and sentiments into ratings.

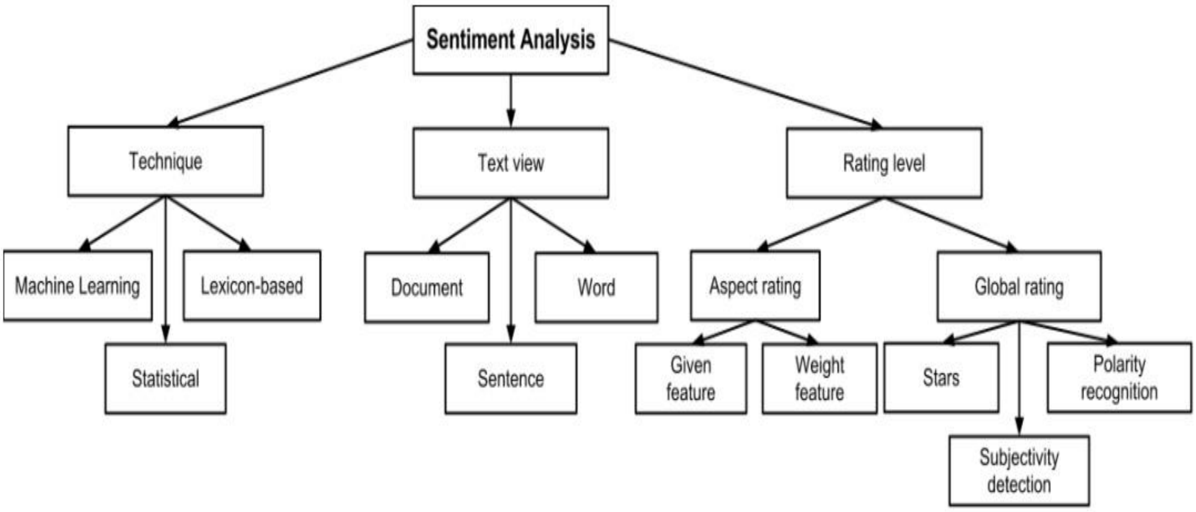

Fig. 1: Classification [6]

Another classification is oriented more on the structure of the text: document level, sentence level or word/feature level classification. Document-level classification aims to find a sentiment polarity for the whole review, whereas sentence level or word-level classification can express a sentiment polarity for each sentence of a review and even for each word. Our study shows that most of the methods tend to focus on a document-level classification.

We can also distinguish methods which measure sentiment strength for different aspects of a product and methods which attempt to rate a review on a global level. Most of the solutions focusing on global review classification consider only the polarity of the review (positive/negative) and rely on machine learning techniques. Solutions that aim a more detailed classification of reviews (e.g., three or five star ratings) use more linguistic features including intensification, negation, modality and discourse structure. Figure 1 presents a detailed classification of existing methods

IV. LITREATURE SURVEY

A. Feature-based heuristic approach

This method introduced an aspect oriented scheme that analyses the textual reviews of a movie and assign it a sentiment label on each aspect. The scores on each aspect from multiple reviews are then aggregated and a net sentiment profile of the movie is generated on all parameters. It also used a SentiWordNet based scheme with two different linguistic feature selections comprising of adjectives, adverbs and verbs and n-gram feature extraction. It had also used SentiWordNet scheme to compute the document-level sentiment for each movie reviewed and compared the results. The only restriction with this aspect-level implementation is that it is domain specific.

B. Document based SentiWordNet Approach

To make use of SentiWordNet this method first extract relevant opinionated terms and then lookup for their scores in the SentiWordNet. Authors have implemented four scoring schemes with the two feature selection variants, namely using adjectives only and using 'adverb+adjective' combine. In order to evaluate the accuracy and performance of different variants of the SentiWordNet based approaches, they computed the standard performance metrics of Accuracy, F-measure and Entropy. They computed results of four SentiWordNet based approaches for two movie reviews and two blog post datasets. They have also compared results for movie review datasets with NB and SVM based machine learning classifiers The ease of implementation of SentiWordNet allows not only allows to perform sentiment analysis, but it also makes a very reasonable case of using it as an added level of filtering for movie recommendations

C. Semantic Orientation Applied to Unsupervised Classification of Reviews

In this method Peter D. Turney presents a simple unsupervised learning algorithm for classifying reviews as recommended (thumbs up) or not recommended (thumbs down) where a review is predicted by the average semantic orientation of the phrases in the review that contain adjectives or adverbs.

The first step of the algorithm is to extract phrases containing adjectives or adverbs. First a part-of-speech tagger is applied to the review (Brill, 1994). 3 Two consecutive words are extracted from the review if their tags conform to any of the patterns in

The second step is to estimate the semantic orientation of the extracted phrases, using the PMI-IR algorithm. This algorithm uses mutual information as a measure of the strength of semantic association between two words .

The third step is to calculate the average semantic orientation of the phrases in the given review and classify the review as recommended if the average is positive and otherwise not recommended.

A review is classified as recommended if the average semantic orientation of its phrases is positive. The algorithm achieves an average accuracy of 74% when evaluated on 410 reviews from Epinions. The algorithm has three steps: (1) extract phrases containing adjectives or adverbs, (2) estimate the semantic orientation of each phrase, and (3) classify the review based on the average semantic orientation of the phrases. The core of the algorithm is the second step, which uses PMI-IR to calculate semantic orientation. The limitations of this work include the time required for queries and, for some applications, the level of accuracy that was achieved.

D. Classification based on machine learning techniques

Authors in this approach experimented with three standard algorithms: Naive Bayes classification, maximum entropy classification, and support vector machines. To implement these machine learning algorithms the following standard bag-of-features framework was used. Let {f 1 ,...,f m } be a predefined set of m features that can appear in a document; examples include the word “still” or the bigram “really stinks”. Let n i (d) be the number of times f i occurs in document d. Then, each document d is represented by the document vector d := (n 1 (d),n 2 (d),...,n m (d)).

Naive Bayes

One approach to text classification was to assign to a given document d the class c ∗ = argmax c P(c | d). We derive the Naive Bayes (NB) classifier by first observing that by Bayes’ rule,

P(c | d) =P(c)P(d | c) / P(d),

where P(d) plays no role in selecting c .

E. Method based on hybrid of three methods

This method implemented an opinion mining tool which hybrids three different methods: The first one is based on semantic patterns, which simplify the structure of the natural language syntax; the second is based on the weighted sentiment lexicon, which used as semantic feature words; and the third one is based on traditional KNN or SVM text classification method.Three algorithms, algorithm 1,algorithm 2 and algorithm 3 were tested in their experiments for each methods. Two test data sets D1 and D2 were used. First, it use the method based on the weighted sentiment lexicon (called Method 1) and method based on traditional text classification (called Method 2) to test the sentiment orientation about the 50 topics of D1. In method 2, it make use of $\chi 2$ as feature selection algorithm and KNN as classifier algorithm (k=35). For each topic, it use 2/3 of posts as training set, 1/3 of the posts as the test set. To compare the performance of the three methods, precision and recall is calculated for all topics together in D1,instead of individual one. Among them, Method 3 means the method based on semantic patterns

F. Probabilistic model for Joint Sentiment-Detection(JST)

This is extension of Latent Dirichlet Allocation (LDA) model that detects sentiment and topic simultaneously from text. This system incorporates a small amount of domain independent prior knowledge which is sentiment lexicon to further improve the sentiment classification accuracy.

The procedure for generating a word wi in document d under JST can be given as: 1) Choose a sentiment label l from the per-document sentiment distribution πd . 2) Choose a topic from the topic distribution θd,l , where θd,l is conditioned on the sampled sentiment label l. Each document is associated with S topic distributions, each of which corresponds to a sentiment label l with the same number of topics. Thus, JST model can predict the sentiment associated with the extracted topics. 3) Draw a word from the per-corpus word distribution conditioned on both topic and sentiment label.

V. CONCLUSION

Sentiment analysis has grown to be one of the most active research areas. It has thus become a necessity to collect and study opinions on the Web. Through this literature survey, the relevant works done to solve this problem could be studied. Although Many solutions have been proposed to classify sentiments of online reviews, a fully automated and highly efficient system has not been introduced till now. This is because of the unstructured nature of natural language. In this research we propose way to automatically classify movie reviews in terms of positive, negative and neutral classes using hidden markov model approach

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