



Multimodal Sentiment Analysis - A Study on Classification Techniques for Multimodal Sentiment Analysis

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ABSTRACT: A huge amount of data is available to the web users with evolution of web technology. The available resources in web are used by the users and they also involve in giving feedbacks and thus generate additional information. It is very essential to explore, analyze and organize their opinions and feedbacks in an efficient way for better decision making. So sentiment analysis (SA) also called opinion mining (OM) is used to find the users opinion about a particular topic, product or problem in a more efficient way. The main aim of SA is to solve the problems in relation to opinions about products, movies, politics, review sites etc. In text SA, words and dependencies among opinions are the only source of information available, which will be inadequate to carry the precise opinion. But in multimodal data both audio as well as video answers are obtained from visual opinions. The tone of the speaker is determined by the vocal modulation from recorded responses whereas about sentiment nature of speaker is provided by visual data. So it is easy to fuse text based sentiment classification with audio and video features which can help the classification more accurately i.e; by combining acoustic, video and textual features which is called "multimodal sentiment analysis" that used to find the orientation of an input data. This survey paper describes about the overall idea of last update in sentiment analysis. Most recently used techniques are tackled. The main goal of this survey is to give nearly full image of SA techniques and the related fields with brief details.

KEYWORDS: Sentiment, Opinion mining, Multimodal sentiment analysis, Acoustic, Decision making.

I. INTRODUCTION

An essential component of the information period is now ready to discover the sentiment of other people. For past years, before decision making people will ask their friends or relatives about opinions. In order to know the feelings, views and feedback of the general people about a product or service most of the organization conducts opinion polls and surveys. For the past few years web documents that describes individual opinions and views are receiving greater attention. Reviews, comments, recommendations, feedbacks and ratings are usually created by people. By the evolution of WWW, users are able to tell their own opinions, views and feedback known on blogs, social sites, forums and review sites. Many firms are emerged and browse at evaluation sites to know how the public has received their product instead of conducting surveys. Information's available on the Internet are valuable data's for social psychologists, marketing people and others interested in obtaining and mining attitude and views. It is difficult to find the opinion sources, to monitoring them and to analyse it. Also it is impossible to find opinion sources online, obtain views and to express them in standard format with human intervention. So it is necessary to automate it and solution to this is sentiment analysis.

Sentiment analysis or opinion mining is a computational study that deal with natural language processing. Sentiment analysis is the study of peoples opinion, view, attitude or emotions towards an entity. The entity can represent individuals, events, problems or topics. The goal of sentiment analysis is to make computer able to recognize and express emotions. It consists of various stages such as extraction of data from various sources especially from social media websites, text classification, grouping together and then evaluating it to positive or negative or true or false values. So many researches has been done to extract the sentiments from in document, sentence or feature level sentiment analysis. In document level whole document is considered as a single object and classify the sentiment of



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whole document. In sentence level sentiment analysis first it checks whether the sentence hold any sentiment. If it contains a sentiment those sentences are classified separately and then finally aggregate it to find the exact opinion. In both sentence and document level sentiment analysis they do not focus on what people like or dislike. So for that feature level sentiment analysis is done. Here features are extracted and classified.

For past few years people express their opinion in textual format. But nowadays the scenario changes. Most of them are expressing their views in video format through face book, flipkart,etc. There come the use of multimodal sentiment analysis where different modalities such as audio, video and textual are combined together. So that performance of classification can be improved to greater extent. The objective of multimodal sentiment analysis is to develop a methodology and a system to automatically recognize sentiments expressed by people. The system will use data from several inputs which are called 'modalities' namely text, audio and video signals which can classify opinions in different domains.

The paper is organized as follows : Components of sentiment analysis is included in section 2. Workflow and feature extraction methods of sentiment analysis is included in section 3. Next chapter includes the various existing techniques ,its pros and cons. Finally the conclusion and future trend are tackled in section 5.

II. RELATED WORK

In the work 'Utterance level Multimodal Sentiment Analysis (MSA)' of Prez-Rosas, Vernica, Rada Mihalcea, and Louis-Philippe Morency [6] proposes a method for multimodal sentiment classification which can find opinions in utterance level video data streams. Here a new multimodal data set called Multimodal Opinion Utterances Dataset (MOUD) is used which consist of opinions extracted from video reviews. This work shows that multi-modal sentiment analysis can be effectively performed and also the joint use of video, audio and textual modalities can lead to error rate reductions up to 10.5% as compared to the best performing individual modality [6].

The work of Morency, Louis-Philippe, Rada Mihalcea, and Payal Doshi [17] proposes the task of tri-modal opinion mining. Data set about 47 videos was created from online social medias Youtube. The videos were obtained by considering keywords such as opinion, review, product review, camera review, business, cosmetics, hate. Each video are pre-processed so that first 30 seconds of each video is removed [17]. All the video clips are manually transcribed to extract spoken words and start time of each spoken utterances. The result of this work shows a improvement when all three sources of data are combined and these improvements are observed for both precision and recall.

Sentiment analysis in an audio visual context this work [3] focuses on automatically analyzing a speakers opinion in online videos containing movie reviews. This work uses a dataset called 'Institute for Creative Technologies Multi-Modal Movie Opinion' (ICT-MMMO) database from online social review videos. The dataset consist of 370 videos where one speaker is speaking directly at camera conveying his sentiment. Out of 370 videos 278 are classified as positive,23 as neutral and 57 as negative. Along with they use 5 sentiment labels called strongly negative, weakly negative, neutral, weakly positive and strongly positive. Features are extracted from different modalities. For acoustic feature extraction, a large set of audio low-level descriptors (LLD) and derivative of LLD combined with statistical functions. Video opinions are automatically obtained from visual inputs. Bag-of words and Bag of N grams are used for textual feature extraction. For classification SVM is used as individual classifiers. The result of multimodal fusion - ie; fusing the scores obtained from linguistic analysis with acoustic features gives an FI measure of 63.8% [3].

III. COMPONENTS OF SENTIMENT ANALYSIS

A. OPINION HOLDER (SOURCE):

Opinion holders are persons or organization who conveys the opinion or sentiment.
Eg:- "I love playing cricket".

B. OBJECT (TARGET):

Object is the item on which sentiment is expressed or conveyed. It can be a person, product, organization or a topic on which opinion is expressed.
Eg:- "I like Nano. But I don't like the steering of Nano".

C. OPINION (SENTIMENT):

A view, attitude or appraisal on an entity or object from an opinion holder.

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Eg:- "It's pity (negative) that she didn't get marry".
Following is an example for the above components in sentiment analysis:

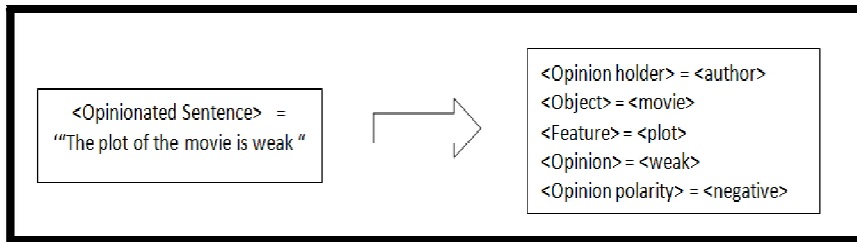


Fig.1. Example of components used in sentiment analysis

IV. ARCHITECTURE OF MULTIMODAL SENTIMENT ANALYSIS

Sentiment analysis is a method used to find and obtain opinionated information in text documents. In general, sentiment analysis tries to find the sentiment of a writer about some feature and also the total orientation of a document. The sentiment may be his or her judgment, view or evaluation. A major issue in this field is the classification of opinion, where a document is marked as a positive or negative evaluation of a target object (film, book, product etc) [20]. Figure shows the workflow of Opinion Mining of how the opinions are being extracted from people review over their comment Opinion feature extraction is a sub problem of opinion mining [20].

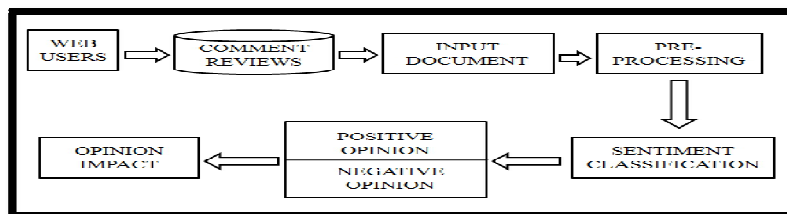


Fig. 2. Workflow of Sentiment Analysis [20]

A. PRE-PROCESSING

In this process, raw data is taken and it is pre-processed for feature extraction. This phase is further divided into number of sub phases as follows: 'Tokenization' is the process of splitting the sequence of characters into small pieces called tokens. It also removes certain characters such as punctuation marks. 'Stop word Removal' removes stop words such as 'he', 'she', 'the', 'a', 'an', etc. 'Stemming' is the process of finding the root word. 'Case Normalization' is a process of converting the entire document or sentences into lowercase / uppercase.

B. FEATURE EXTRACTION

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 (for good recommendation each feature will be weighted) feature reduction mechanisms (to optimize the classification process features are reduced)[20].

- 1) Feature Types
 - Term frequency : The presence of the term in a document carries weight age.
 - Term co-occurrence : Features which occurs together like unigram, bigram or n-gram.
 - Part of speech data: POS tagger is to separate POS tokens.
 - Opinion words : Opinion words are words which contains good or bad sentiment.
 - Negations : Negation words are not, not only, etc which changes opinion polarity in a sentence.
 - Syntactic dependency : They are represented as a parse tree and it contains word dependency based features.
- 2) Feature Selection

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- Information gain :On the basis of presence and absence of a word in a document a value is given and those which has few information gain is eliminated.
 - Odd Ratio : It is suitable for positive and negative class domain.
 - Document Frequency : It counts the number of occurrence of a term in the given number of documents in the corpus and based on the threshold computed the terms are removed [20].
- 3) Features weighting mechanism
- Term Frequency and Term Presence : Occasionally occurring words consist of greater amount of data than frequently occurring words.
 - Term frequency and inverse document frequency (TFIDF) : Each data are rated where words occurring commonly in few documents has highest rating and words occurring regularly in every document has lowest rating.
- 4) Feature Reduction
- Feature reduction reduces the feature vector size to optimize the performance of a classifier. Reduction 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 [20].

C. SENTIMENT CLASSIFICATION

An important step in sentiment analysis is classification of review text. Given a review document $D = d_1, \dots, d_n$ and a predefined categories set $C = \text{positive, negative}$, sentiment classification is to classify each d_i in D , with a label expressed in C . The approach involves classifying review text into two forms namely positive and negative. Machine learning and lexicon based approach is more popular [20].

D. OPINION IMPACT

Summarization of opinion is a major part in opinion mining process. Summary of reviews provided should be based on features or subtopics that are mentioned in reviews. After all the process are carried out final impact of the opinion is evaluated [20].

V. TECHNIQUES FOR CLASSIFICATION IN MULTIMODAL SENTIMENT ANALYSIS

Following are the algorithms for sentiment classification

A. NAIVE BAYES CLASSIFIER

This is the most widely used classification algorithm. It is based on Bayes theorem. It is proposed by Thomas Bayes (1702-1761), based on Bayes Theorem. According to this theorem, if there are two events say, e_1 and e_2 then the conditional probability of occurrence of event e_1 when e_2 has already occurred is given by mathematical formula [14]:

$$P(e_1 | e_2) = \frac{P(e_2 | e_1) \cdot P(e_1)}{P(e_2)} \quad \text{eq. (1)}$$

This classifier is implemented to calculate the probability of data to be positive or negative. So conditional probability of a sentiment is given by [16],

$$P(S|S') = \frac{P(S' | S) \cdot P(S)}{P(S')} \quad \text{eq. (2)}$$

where S is the sentiment and S' is the sentence.

The algorithm for NB is given below[12]:

Input: Message $M_e = M_{e1}, M_{e2}, M_{e3}, \dots, M_{en}$

Database: Naive Database table, N_t

Output: Positive messages $P_o = P_{o1}, P_{o2}, \dots$

Negative messages $N_e = N_{e1}, N_{e2}, \dots$

Neutral messages $N_u = N_{u1}, N_{u2}, N_{u3}, \dots$

Step 1: Messages are partitioned into words $M_i = W_{o1}, W_{o2}, \dots, i = 1, 2, \dots, n$

Step 2: If $W_{oi} \in N_t$, Return positive orientation and negative orientation

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- Step 3: Calculate total orientation of a Word = $\log(\text{positive orientation}) - \log(\text{negative orientation})$
Step 4: Repeat step 2 until end of words
Step 5: Sum the orientations of all words of a message i.e. total orientation of a message.
Step 6: Based on that orientation, message can be positive or negative or neutral.
Step 7: Repeat step 1 until Message is zero.

B. MAXIMUM ENTROPY CLASSIFIER

Max Entropy Classifier or Max-Ent is the another important classifier.[17].It is also known as loglinear, Gibbs, exponential and multinomial logic models. The idea behind Max-Ent classifiers is that we should prefer the most uniform models that satisfy any given constraint. MaxEnt models are feature based models. Then use these features to find a distribution over the different classes using logistic regression [21].ME is used for sentence boundary detection, part of speech tagging, ambiguity resolution, etc.

The algorithm for ME is given below [12]:

Input: Message $M_e = M_{e1}, M_{e2}, M_{e3}, \dots, M_{en}$

Database: Naive Database table, N_t

Output: Positive messages $P_o = P_{o1}, P_{o2}, \dots$

Negative messages $N_e = N_{e1}, N_{e2}, \dots$

Neutral messages $N_u = N_{u1}, N_{u2}, N_{u3}, \dots$

Step 1: Messages are partitioned into words $M_i = W_{o1}, W_{o2}, \dots, i = 1, 2, \dots, n$

Step 2: If $W_{oi} \in N_t$, Return positive orientation and negative orientation

Step 3: Calculate total orientation of a word = $((+\text{ve orientation}) * \log(1/+\text{ve orientation})) - ((-\text{ve orientation}) * \log(1/-\text{ve orientation}))$

Step 4: Repeat step 2 until end of words

Step 5: Sum the orientations of all words of a message i.e. total orientation of a message.

Step 6: Based on that orientation, message can be positive or negative or neutral.

Step 7: Repeat step 1 until Message is zero

C. SUPPORT VECTOR MACHINE CLASSIFIER

The aim of SVMs [19] is to find linear separators in the search space which can best disjoin the various indifferent classes. In Fig 3: x, o are the two classes and A, B, C are the three hyper planes. The best separation between the classes is provided by hyper plane A. Because of the sparse nature of input, they are best suited for SVM classification. They tend to be more correlated and can be organized into linearly separable categories. Nonlinear decision surface in the original feature space can be done by SVM [19].

SVM is primarily used for categorization. Some example of SVM usage include bioinformatics, signature/hand writing recognition, image and text classification, pattern recognition and email spam categorization. There are some extensions which makes SVM more robust and adaptable to real world problem.

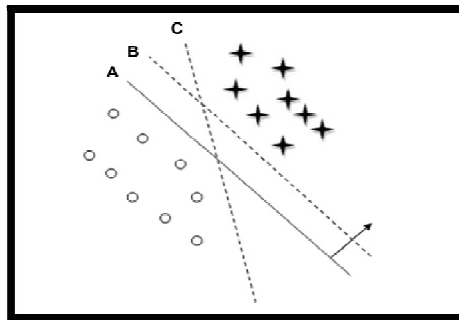


Fig. 3. Support vector machine on a classification problem [19]

D. DECISION TREE CLASSIFIER

These classifier [19] generates a tree like structure of the training data where conditions on value is used to partition the data. The presence or absence of one or more words is considered as condition or predicate. If the non

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child nodes has least numbers of records then the division of data space is done repeatedly. To correlate sets of terms, some other kinds of predicates are also existing. There are various splits such as Single Attribute split that comprises of existence or lack of certain words or phrases at a specific vertex in the tree. Documents or normally occurring words clusters and the equality of the documents to these words clusters are used by Similarity-based multi-attribute split. In order to perform split Discriminate-based multi-attribute split uses discriminates such as the Fisher discriminate. Two most decision tree classifiers are:

1. Boosted Tree (BT)

This [21] type of classifier consist of Boosting and Decision Trees. In order to reduce the assumption in supervised learning a meta mining algorithm called boosting is used. To develop weighted trees in boosting predictive algorithms are used. Then they are combined into single prediction models. By combining regression and boosting tree boosted tree works. With the help of binary split, regression trees give responses to their predictors whereas boosting is a flexible method which adds many basic prototypes to give efficient performance. When boosting algorithms are included , they will normally relate weak learners perfection. New weights are generated and data's are again rated when a weak learner is included in these type of algorithms.[21].

2. Random Forest (RF)

They [21] are entity based training method for classification that operate by constructing a multi-attitude of decision trees at training time and output the class. At inputting phase it produces multi-altitude decision trees and multiple decision trees are produced at the outputting phase. By randomly selecting trees the correlation can be reduced thereby prediction power and accuracy increases.

E. RULE BASED CLASSIFIER

Here [19], the data space is modelled with a set of rules. Condition on the feature set expressed in disjunctive normal form is represented at left hand side and the class label are represented at right hand side. The rules are on the term presence. Since this is not informative in sparse data ,term absence are rarely used. In order to generate rules there are numbers of criteria. Depending on these criteria the training phase construct all the rules. Support and confidence are the two most commonly used criteria. The absolute number of instances in the training data set which are relevant to the rule is called support. The conditional probability that the right hand side of the condition is contented if the left-hand side is contented refers to confidence[19].

F. CLUSTERING METHOD

Clustering [16] is an unsupervised learning method and has no labels on any point. Clustering technique recognizes the structure in data and group, based on how nearby they are to one another. So, clustering is process of organizing objects and instances in a class or group whose members are similar in some way and members of class or cluster is not similar to those are in the other cluster. This method is an unsupervised method, so one does not know that how many clusters or groups are existing in the data. Using this method one can organize the data set into different clusters based on the similarities and distance among data points. Fig 4 shows the clustering of data instances [16].

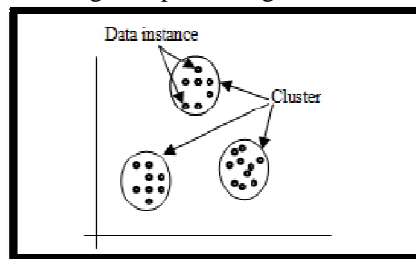


Fig. 4. Clustering [16]

G. LEXICON BASED METHOD

Lexicon techniques [7] use a dictionary to perform feature level sentiment analysis. This technique use dictionaries of words with their semantic strength and calculates a score for the polarity of document. Usually this method gives high precision but low recall. In order to express people's opinion and feelings opinion dictionary



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includes sequence of words and expressions. For example, to explore the document for which opinion want to find start with positive and negative word lexicons. Then if the text has many positive word dictionary, it is positive, otherwise it is negative. It is an unsupervised learning technique because it does not need any training or experience before to group the data.

The basic steps of the lexicon based techniques are outlined below [7]:

Step 1: Process each text by removing HTML tags, distorted characters, etc.

Step 2: Total text sentiment score is initialized to zero : $S=0$.

Step 3: Text is tokenized. Check if each token is present in a online opinion dictionary.

- (a) If token is found in dictionary,
 - i. If token is +ve, then $S = S + W$.
 - ii. If token is -ve, then $S = S - W$.

Step 4: Check the overall text subjectivity score s ,

- (a) If $S > a$ value ie; threshold, then classify the document as +ve.
- (b) If $S < threshold$, then classify the document as -ve.

Lexicon based method consist of mainly two types of techniques which is described in the following section.

1) Corpus Based Method

To solve the problem of finding opinion words with context specific orientations this approach can be used. It depends on syntactic or patterns that occur with a initial list of sentiment words to find other sentiment words in a large dictionary. "Connectives like AND, OR, BUT, EITHER-OR are the constraints used; the conjunction AND for example says that conjoined adjectives usually have the same orientation. This idea is called sentiment consistency, which is not always consistent practically. 'But' is a adversative expression which is used to indicate opinion changes". Learning is applied to a large corpus, in order to determine if two conjoined adjectives are of the same or different orientations. Form a graph with links between adjectives and to produce two sets of words: positive and negative perform clustering on the graph. A sequence learning technique called Conditional Random Fields (CRFs) method is used for extracting opinion expressions. It was used in order to discriminate sentiment polarity by multi-string pattern matching algorithm[19].

2) Dictionary Based Method

This method manually collects small set of opinion words with known orientations. Then, this set is grown for their synonyms and antonyms by searching in the well known corpora Word Net or thesaurus. The recently obtained terms will be appended to the list after that the next pass begins. If no recent words are found then the pass will stop. Inspection can be carried out by humans to eliminate errors at final stage. The major problem in this approach is the lack of ability to discover sentiment words with domain specific and condition specific orientations [19].

H. MULTI-LAYER PERCEPTRON (MLP)

It is a anticipate neural network which has one or many units with input and output layer. Data flow is from one direction to another such as from input layer to output layer. Inputs of every neuron are associated with every neuron in next layer (known as hidden layers). The hidden layer neurons are attached to other hidden layer neuron. Output layer is made up as follows: 1. Output layer is moulded with one neuron when augury is binary. 2. Output layer is moulded with N neuron when augury is non-binary. This arrangement can make a better flow of data from input layer to output layer [7].

MLP is a back propagation algorithm and it comprises of two stages [7]:

- Stage I: Forward phase ,from the input layer to output layer, the activations are propagated.
- Stage II: To update the weight and bias value errors among practical and real values and if the requested value in the output layer is generated in the backward way this stage can be used.



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VI. COMPARISON OF MACHINE LEARNING TECHNIQUES

Following table shows a comparison of various learning techniques discussed.

Table 1 : Comparison of classification techniques [21]

FEATURES	NB	ME	BT	RF	NN	SVM
Based on	Bayes theorem	Feature Based	Decision Tree	Decision Tree	Linear Classifier	Linear Classifier
Simplicity	Very Simple	Hard	Moderate	Simple	Moderate	Hard
Performance	Better	Good	Good	Excellent	Good	Good
Accuracy	Good	High	Poor	Excellent	High	High
Memory Requirement	Low	High	Low	High	High	High
Applications	Spam Detection, Doc-Classification	Diagnosis Tests	Classify Cardio-Vascular outcomes	Bio-medical	Prediction systems	Bio-informatics
Result Accuracy	Variable	Consistent	Incremental	Incremental	Consistent	Consistent
Time required for Training Classifier	Less	Moderate	High	Recurrent learning	High	High

VII. CONCLUSION AND FUTURE WORK

Sentiment Analysis is an emerging field of web data mining used to extract the knowledge from large amount of data which may be a customer comments or feedback or reviews on any product, problem, topic etc. Many techniques exist to capture the opinions in form of document level, sentence level and feature level sentiment analysis. In text based sentiment analysis, words and dependencies among them are the only available source of information. But with these information it is insufficient to convey the exact sentiment. Instead, both vocal and visual responses are there in video opinions. The tone of the speaker is determined in vocal modulations and emotional state of speaker is provided by visual data. Thus by grouping textual as well as visual data can help us to generate a better analysis model. Different classification techniques can be combined to generate better result.

The future work in this field include: visual representation, opinion mining of audio visual modalities, real-time opinion mining, efficient and better machine learning algorithms, comment and opinion recommendation algorithm, usable peer-to-peer opinion mining tools for citizens, non-bipolar assessment of opinion, automatic irony detection.

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