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Towards Sentiment Analysis and Opinion Mining From Multimodal Data

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Abstract*: The ease accessibility of internet and web application paves way for people to express their opinion and emotion to the society. Social networks captures the view of people on products, politics, movie etc., the review given by customers decide the success and leverage the popularity of the product in the market. The challenges rely on the technology, which are employed to trace information accurately from the available data. Sentiment analysis on textual data is widely used to assess the customer satisfaction. Sentiment can also be perceived from the mixture of text, audio, facial expression, visual display etc. This survey defines multimodal sentiment analysis and review recent methods which adopts mixture of inputs for multimodal sentiment analysis. This survey outlines the different approaches followed to extract feature from multimodal data.

Index Terms: Cloud computing, Data security, User behavior, Decoy technology, Fingerprint authentication, Face recognition.

I. INTRODUCTION

According to Darwin, [1] emotions increases the chance of survival by being appropriate reactions to emergency events in the environment. Emotions are evolved naturally from the people on their day-to-day life tasks. Emotions have unique characteristics with each other. Ekman [2] has differentiated the difference in emotions using nine characteristics. This uniqueness makes us to find out the opinion of a person. Emotion require a trigger and it last for few minutes, where as feelings are results of emotion.

The terms sentiment, opinion and affection convey similar meaning in Sentiment Analysis. There are different definitions for emotion. Munezero [21] clearly depicted the differences between emotion, sentiment and opinion. Emotion depends on external trigger and stays for few minutes, but sentiment last for days and months. Opinion is an individual perception on information.

II. SENTIMENT ANALYSIS

Sentiment analysis identifies the opinion of the reviewer on a subject. Nasukawa [3] has focused on improving the accuracy of the sentiment analysis by understanding the relationship between subject and sentiment. He has adopted syntactic parser and semantic lexicon to achieve accuracy in determining sentiments in web pages. Lillian [4] proposes subjectivity extraction from the document by eliminating objective content, which facilitate the polarity classification. Cut-based approach is used to classify the polarity. In sentiment Analysis there are three use cases; they are Sentiment holder, polarity and Topic. This has been represented in the fig 1.

III. SENTIMENT ANALYSIS METHODS

Kerstin [5] focus on multilingual framework for determining polarity in the document. The multilingual sentence is translated into english and the words are mapped to its sentiment classes using SentiWordNet. Bhadane [6] broadly classifies the NLP text classification into Lexical method and Machine learning method. Term weighting scheme [7] in sentiment analysis is a supervised algorithm, which is based on two factors Importance of term in a document (ITD) and importance of a term for expressing sentiments (ITS). Term weighting scheme calculates the ITD using the term frequency.

Theresa [8] determines the neutral and polar terms in the statement and identifies the contextual polarity in the document by removing the ambiguity in the polar expressions. Basant Agarwal [9] statement extracted from the corpus is given as queries to concept net to extract their semantics. Minimum redundancy and maximum relevance methods are adopted to extract important terms and the Machine learning model is built to identify the positive and negative words in the document. Pak [10] proposed a method to automatically collect the sentiment corpus for opinion mining and does linguistic analysis on the corpus. Based on the linguistic analysis the sentiment classifier is built to determine the positive and negative sentiment for the given corpus.

IV. SUPERVISED APPROACH:

Data from social media are to be converted into a labeled data to apply any supervised learning algorithms. Supervised approach builds a model that classifies the polarity of the given document. Chikersal [11] follows a rule based approach, where the tweet is labeled and each tweet is converted to feature vector based on word N-grams, POS tags, then Support Vector Machine classifier is deployed to categorize the positive, negative and neutral sentiments. Supervised approach require class label in the corpora. Defining label manually for

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the corpora is a tedious task, hence supervised algorithms are inefficient.

V. Unsupervised approach

The increase in usage of social media generates huge amount of data. This makes positive sign for the companies to analyze the opinion of the people on their product. The social media data are huge and unlabelled. Labeling the sentiment for those data are a tedious job, so unsupervised approach is preferred for various applications. Hu [12] defines an unsupervised approach to derive sentiment for emotional signals. Emoticons are also popularly used for expressing sentiment. Traditional Lexicon based methods fail to capture sentiment and no general structure is followed to classify emoticons. Hu categorize the emotional signals into emotion indication and correlation. An Unsupervised learning framework is built to capture the sentiments in the document. Milagros [13] proposes a text classification method based on dependency parsing. The unsupervised method constructs lexicon based on the polarity expansion method to leverage the accuracy of the model.

VI. Text based Sentiment Analysis

Lexicon based method is a traditional way of capturing Sentiment from a document. Visual SA is a new approach in MSA. Social media user's share their opinions in any of the three formats, but current research focuses on the following context of multimodal data,

1. human-machine interaction and human-human interaction
2. Spoken reviews and video blogs
3. Analyzing image and its tags

The representation of the word is a complex task in all NLP systems. The common method to represent a word is symbols, but this does not capture the relation of the Lexicons. Vector models are built to define the relation between the words based on the similarities in the words. To group words based on their similarity algorithms such as bag-of-words, term frequency are used. Kontopoulos [14] has proposed ontology based method, where the process is divided into two phases namely ontology creation and sentiment analysis. In the first phase an automatic sentiment scores are assigned to each tweet post based on its feature of the subject. The second phase does the sentiment analysis on the tweet post. Maas [15] defined a probabilistic model which understands the word representations. Using this unsupervised model the similarities in the word are being identified and the sentiments are derived later using predictor function. There are more surveys on text, audio or visual SA, but we focus on MSA. This provides an idea for researchers in affective domain and computer vision communities.

VII. Multimodal Sentiment Analysis

Multimodal SA is an emerging SA technique, more research works has to be carried out to see its complete potential. Multimodal sentiment analysis is a fusion of text, audio and video sentiments.

There are number of research works which has explored the sentiments from text data. The multimodal data includes textual, speech and visual information people posts their reviews in text, speech or visual form. All these three forms are fused together to make multimodal SA.

Table 1: Overview of Multimodal Data

Mode of Data	Example	Features
Text	customer opinion	Lexicon based dictionaries, POS, tf, idf with a supervised learning approach
Audio	spoken reviews	vocal signals, eg: prosody, pitch, volume
Image	visual image	computer vision, to capture sentiments through CNN
Multimodal	vlogs	fusion of text, paralinguistic features, emoticons and visual expression

Banziger [17] does MERT (Multimodal Emotion Recognition Test) on videotaped emotion portrayals by professional actors. An interface has been created to present 30 test stimuli to participants. There were two sessions to recognize the characteristics of the participants, behavioral and non-verbal sensitivity is recorded. The facial and vocal data extracted from the participants are given fed into MERT system to recognize the emotions.

Wagner [18] fuses different modes of data using feature-level and decision-level fusion. In feature-level all the features from different modes of data are grouped into a single feature set. The disadvantage of feature-level fusion is missing of single attribute value in a data set will make results non-meaningful. Decision-level fusion method breaks the feature set into smaller subgroups which develops a small classification models. These small classifier outputs are grouped to form one single ensemble decision model.

Liandong [19] uses MFCC, MFB and PCM methods for audio feature extraction and HOG, LPQ, MSDF methods for video feature extraction. In the fusion network SVM classifier is used to group the fetures extracted and to make decision. The feature extracted are linearly separable, hence I 103 SVM classifiers are used for fusion classification.

Poria [20] has created a image frames from videos and features are extracted from every frames. For feature extraction Luxand FSDK software was used. The average of the feature values extracted from each image frame is computed to draw the feature vector for the facial expressions. The facial feature vector is fed into ELM classifier to compute sentiment analysis.

VIII. Conclusion

In this survey we presented the traditional methods for performing Sentiment analysis

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and the best practices in feature extraction. Since the sentiment can be captured from different modes of data, best methods for fusing those different modes of data are also mentioned. The review shows that Multimodal Sentiment Analysis outperforms unimodal Sentiment Analysis.

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