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A Study on Various Classification Techniques for Sentiment Analysis on Social Networks

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Abstract - *Sentiment analysis, which is additionally called as opinion mining, involves in building a system to gather and examine opinions regarding the merchandise created in journal posts, comments, reviews or tweets. Sentiment Analysis is the study of automatic identification of online user's preference and classification of these preferences into its positive, negative or neutral orientation. A major problem occurs when we try to determine the sentiment or the class of these data i.e. whether the data is good or bad. Analyzing the sentiment of a text, document or an article is a challenging task in the world. Several methods were implemented for sentiment analysis throughout the years, but still more improvement and perfection is needed. Here in this paper various sentiment analysis techniques are reviewed.*

Key Words: Opinion Mining, Classification Techniques, Sentiment Analysis, Sentiment Classification, Summarization.

1. INTRODUCTION

E-commerce and the rapid growth of the social media, individuals and organizations are progressively using the content on these media for decision making purpose [1], [2]. Hence there is a need for effective and accurate automated approach which predicts the opinions presented in the reviews. Opinion mining systems classify opinion data available on web into their respective opinion polarity of positive, negative or neutral. In the current web era, opinion mining is one of the widely studied topics under Web Mining and Natural Language Processing. Opinion mining is analyzed at the document level, sentence level and aspect level. This survey aims to give a closer look on these enhancements and to summarize and categorize some articles presented in this field according to the various Sentiment Analysis (SA) and Sentiment Classification (SC) techniques.

The sentiment classification techniques, as shown in Figure 1 are discussed with more details illustrating related articles and originating references as well.

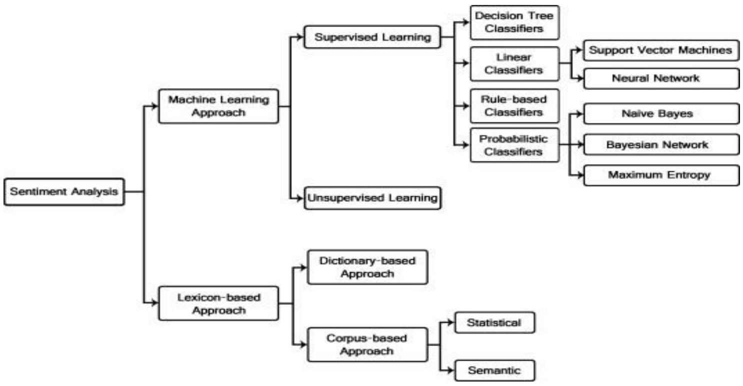

Figure 1 - Sentiment classification techniques.

2. RELATED WORKS

Opinion mining is a popular research topic because of its wide range of application as well as various challenging research problems involved. It is studied under various fields including Data Mining, Information Retrieval, Web Mining and Natural Language Processing. We now present some of the related work carried out. Mining Hu and Bing Liu [3] aim to summarize all the client reviews of a product. This report task is totally different from ancient text report as a result of the others area unit solely curious about the precise options of the merchandise that customers have opinions on and conjointly whether or not the opinions area unit positive or negative. The others don't summarize the reviews by choosing or revising a set of the initial sentences from the reviews to capture their small print as within the classic text report. During this paper, the others solely specialize in mining opinion/product options that the review the others have commented on. variety of techniques area unit given to mine such options. They proposed a technique where summarization of the reviews was performed in 3 steps as 1) Mining of product aspects reviewed by customers. 2) Opinion sentence identification in each review and determining whether particular sentences is positive or negative, each opinion sentence should contain features extracted in step 1, which is extract based on step 1. 3) Summarizing the results. They used online Word Net dictionary to predict semantic orientations and orientation of opinion sentences, which gave a good accuracy in predicting sentence orientation, the average accuracy of the five products is 84%. For this research work, authors worked with customer opinions on different products like cellular phone, DVD player, digital cameras and mp3 player. These opinions were collected from Amazon.com and Cnet.com.

Long Jiang et al [4] specialize in target-dependent Twitter sentiment classification; particularly, given a question, the others classify the emotions of the other sets as positive, negative or neutral in keeping with whether or not they contain positive, negative or neutral sentiments this question. Here the question is the target of the emotions. The state-of the-art approaches for finding this downside continually adopt the target-independent strategy, which may assign tangential sentiments to the given target. Moreover, the progressive approaches solely take the other set to be classified into thought once classifying the sentiment; they ignore its context (i.e., connected the other sets). The others, as a result of the other sets area unit typically short and a lot of ambiguous, typically it's not enough to think about solely this the other set for sentiment classification.

Rui Xia et al [5] we have a tendency to propose a model referred to as twin sentiment analysis (DSA), to handle this downside for sentiment classification. we have a tendency to initial propose a completely unique information growth technique by making a sentiment-reversed review for every coaching and take a look at review. On this basis, we have a tendency to propose a twin coaching algorithmic rule to create use of original and reversed coaching reviews in pairs for learning a sentiment classifier, and a twin prediction algorithmic rule to classify the take a look at reviews by considering 2 sides of 1 review. we have a tendency to conjointly extend the DSA framework from polarity (positive-negative) classification to 3-class (positive negative-neutral) classification, by taking the neutral reviews into thought.

Jithe and Eduard [6] propose a semi-supervised bootstrapping algorithmic rule for analyzing China's foreign relations from the People's Daily. Our approach addresses sentiment target clump, subjective lexicons extraction and sentiment prediction in a much unified framework. Totally different from existing algorithms within the literature, time data is taken into account in our algorithmic rule through a hierarchical theorem model to guide the bootstrapping approach.

Ryan McDonald et al [7] investigate a structured model for together classifying the sentiment of text at variable levels of roughness. Abstract thought within the model relies on commonplace sequence classification techniques victimization strained Viterbi to make sure consistent solutions. The first advantage of such a model is that it permits classification selections from one level within the text to influence selections at another.

Duyu Tang et. al, [8] propose to make large-scale sentiment lexicon from Twitter with an illustration learning approach. we have a tendency to solid sentiment lexicon learning as a phrase-level sentiment classification task. The challenges area unit developing effective feature illustration of phrases and getting coaching information with minor manual annotations for building the sentiment classifier. Specifically, we have a tendency to develop an obsessive neural design and integrate the sentiment data of text (e.g. sentences or tweets) into its hybrid loss operate for learning sentiment-specific phrase embedding (SSPE). The neural network is trained from large tweets collected with positive and negative emotions, with none manual annotation.

Alec Go et al [9] introduce a completely unique approach for mechanically classifying the sentiment of Twitter messages. These messages area unit classified as either positive or negative with relation to a question term. This is often helpful for customers United Nations agency need to analysis the sentiment of product before purchase, or firms that need to watch the general public sentiment of their brands. There's no previous analysis on classifying sentiment of messages on micro blogging services like Twitter.

Xiaowen et al [10] propose a holistic lexicon-based approach to finding the matter by exploiting external evidences and linguistic conventions of tongue expressions. This approach permits the system to handle opinion words that area unit context dependent, that cause major difficulties for existing algorithms. It conjointly deals with several special words, phrases and language constructs that have impacts on opinions supported their linguistic patterns. It conjointly has a good operate for aggregating multiple conflicting opinion words in a very sentence. A system, referred to as Opinion Observer, supported the projected technique has been enforced.

Preslav Nakov et al [11] have projected SemEval-2013 Task 2: Sentiment Analysis in Twitter, including 2 subtasks: A, AN expression-level subtask, and B, a message level subtask. The others used crowdsourcing on Amazon Mechanical Turk to label an outsized Twitter coaching dataset at the side of further take a look at sets of Twitter and SMS messages for each subtasks. All datasets utilized in the analysis area unit free to the analysis community.

Andrew et al [12] gift a model that uses a combination of unattended and supervised techniques to be told word vectors capturing linguistics term–document data also has made sentiment content. The projected model will leverage each continuous and multi-dimensional sentiment data also as non-sentiment annotations. We instantiate the model to utilize the document-level sentiment polarity annotations gift in several on-line documents (e.g. star ratings). We have a tendency to value the model victimization little, widely used sentiment and judgment corpora and realize it out-performs many antecedently introduced strategies for sentiment classification.

Maite et al [13] gift a lexicon-based approach to extracting sentiment from text. The linguistics Orientation calculator (SO-CAL) uses dictionaries of words annotated with their linguistics orientation (polarity and strength), and incorporates intensification and negation. SO-CAL is applied to the polarity classification task, the method of assignment a positive or negative label to a text that captures the texts.

In 2011, Magdalini Eirinaki, Shamita Pisal and Jaspinder Singh [14], introduced an opinion search engine system which consist of two novel opinion mining algorithms, one for identifying and extracting the features that are most important and characteristic of each review, and other that takes as input these features, assigns ranks to them and decides the final classification of the review as positive, neutral, or negative. For identifying and extracting the features the High Adjective Count (HAC) algorithm extracts nouns for which lots of opinions are available. The noun is scored based on the adjective associated with it, which can be used to rank and filter the nouns. For ranking purpose The Max Opinion score algorithm assigns ranks to the extracted features by making use of the opinion scores allotted by HAC algorithm. The aspect based opinion summary demonstrated here, assist users in focusing on various aspects of the product a customer is interested in, offering small summary of the search. Their experimental results showed that their algorithm succeeds to classify more than 87% of the reviews correctly in the worst case and has close to 97% accuracy in the best case. For this research work, authors worked on the product review datasets provided by Prof Bing Liu, which are DVD Player (small) Data Set (90 reviews), DVD Player (large) Data Set (300 reviews) and Vacuum Data Set (40 reviews).

In 2014, Edison Marrese-Taylor, Juan D. Velasquez and Felipe Bravo-Marquez [15], presented an extension of an existing Bing Liu's [2], aspect-based mining approach in order to apply it to the tourism domain, particularly to opinions available on the web in the manner of tourism products reviews. They developed new and more complex NLP-based rules for subjective and sentiment classification. The process consisted of three distinct steps which are 1) Aspect identification, for aspect extraction from the review. 2) Sentiment prediction, to determine sentiment orientation on each aspect. 3) Summary generation, to present processed results in a simple manner. Their experimental results showed that their extension is able to perform better than that of Liu's model for tourism domain. Their experimental results showed that their extension is able to perform better than that of Liu's model, with an average accuracy of 95%. For this research work, authors collected reviews about hotels and restaurants from Lake District in TripAdvisor, which consisted of 1435 reviews of 100 restaurant and hotel.

In 2013, Hasiang Hui Lek and Danny C.C. Poo [16] presented an approach to perform aspect-based sentiment classification for Twitter, which made use of a POS tagger, a sentiment lexicon and a few gazetteer list to produce results of the form [aspect, sentiment words, polarity]. They used a layered classification approach which uses the aspect-based classifier as the first layer classification and the tweet-level classifier as the second layer classification. The process consists of three main steps: 1) Aspect sentiment extraction, to determine list of possible aspect candidates along with their associated sentiments and polarity. 2) Aspect ranking and selection, aspect candidates are ranked and set of most important aspects are selected. 3) Aspect classification, aspects are obtained along with their polarity for each tweet. For tweet level sentiment classification, they experimented with Maximum Entropy and Naïve Bayes classifiers. Aspect based opinion classifier is then added to existing tweet-level opinion classifier using three methods like 1) Layered classification, for precise classification of the sentiments associated with the target aspect. 2) Sentiment words as features, for using sentiment words associated with aspect as feature for tweet level opinion classification [17]. 3) Polarities as features, for using opinion orientation of aspect as a feature [17]. Their experimental results showed that their classification is more effective than a classifier trained using target-dependent features, with an accuracy of 84.2%. For this research work, authors used four datasets: Stanford Twitter Sentiment (STS) consisting of 800,000 positive an 800,000 negative tweets, Sander Twitter Corpus (STC) consisting of 511 positive and 561 negative tweets, Telecommunication Company Dataset 1 & 2 (TCD1/TCD2) consisting of tweets from two different telecommunication companies in Singapore.

In 2010, Hongning Wang, Yue Lu, Chengxiang Zhai [18], covered a problem in text mining called Latent Aspect Rating Analysis (LARA) for analyses of opinions expressed in online reviews at aspect level. A set of opinion sentences holding overall ratings and a list of aspects are given as input to LARA, which then identifies each individual reviewer's hidden ratings on specific aspects and the comparative stress a reviewer has placed on different aspects. To solve the problem of LARA, this paper introduced a new Latent Rating Regression (LRR) model. Where aspect rating is used to indicate the degree of satisfaction presented in the review towards the aspect and aspect weights are used to indicate the degree of emphasis placed by reviewer of the review on aspect. Their experimental results showed that their demonstrated LRR model can solve LARA problem in an effective manner, revealing differences in aspect ratings even when the overall ratings are the same as well as differences in user's rating behavior on various aspects. For this research work, authors collected 235,793 hotel reviews from a website Trip Advisor in a period of one month.

In 2011, Jianxing, Zhazj, Wang and Chuats [19], developed an aspect ranking algorithm which identifies significant aspects by taking into account aspect frequency as well as impact of customer's opinion given to individual aspects on the overall rating of opinions. They recognized significant aspects by applying shallow dependency parser. For deciding opinion orientation on multiple aspects they used a SVM based sentiment classifier and for ranking significant aspect they used a Multivariate Gaussian Distribution approach. Their experimental study demonstrated the effectiveness of their approach in identifying vital aspects from the opinions. They used the results obtained from the aspect ranking and applied it to classify document-level opinions for improving the performance of classification results. For this research work, authors used a dataset containing customer's reviews in 4 different domains on 11 products, which were crawled from various web sites like gsmzrena.com, viewpoints.com, cnet.com and reevoo.com.

More over a lot of work and researches are applied for sentiment analysis or opinion mining. There is a huge open research field to work for the same. Many machine learning techniques were implemented in a document to analyze its sentiment [20], [21], [22], and [23]. Using movie reviews referred as data, they found that the supervised machine learning techniques performs better than the human-produced baselines [24], [25]. Works concluded by examining factors make the sentiment classification problem more challenging. Another piece of work was done where an inference was build based on standard sequence classification techniques to ensure consistent solutions [26]. The primary advantage of such a model is that it allows classification decisions from one level in the text to influence decisions at another. [27] Describes another way to sentiment analysis, in which support vector machines (SVMs) was used to bring sources of information, including some favorable measures for phrases and adjectives and knowledge of the topic of a text together. A lot of work and experiments were done to classify the sentiment class using naive bayes classifier [28], [29], [30]. [31] introduced an EM-like approach that combines Expectation Maximization (EM) algorithm with Naive Bayes classifier. Sentiment analysis of tweets is now a growing research area where multiple works are going on to determine the type of tweets [32], [33], [34]. This also shows how to collect a twitter corpus automatically for sentiment analysis and opinion mining. Researchers have also worked for collecting data from online sites like any movie review site or any online shopping site. These researches show us that a good sentiment analyzer, which can easily determine an emotion, feelings, etc., is very necessary nowadays. These articles are categorized according to their contributions in the various SA techniques.

3. SUMMARY GENERATION

The last step in the process of aspect based opinion mining is summary generation which varies from different application and approaches. It basically summarizes the overall process by representing reviews along with the aspects commented in the review and its corresponding opinion associated with each aspects. In some of the approach summary also present the score in terms of stars associated with different aspects in addition to its opinion orientation.

4. PROBLEMS AND DIRECTIONS

The major challenge in opinion mining lies in the fact that reviewer refer differently to different kinds of the products when writing reviews on the web. Hence domain plays a vital role in case of opinion mining. The other challenge in opinion mining is the problem of Natural Language Processing (NLP). It takes into the consideration various unsolved problems in NLP like word sense disambiguation, co-reference resolution and negation handling. With the help of Part-of-Speech Tagging (POS), Aspect Extraction, Opinion Word Extraction and Analysis on multiple aspects we can use a machine learning based sentiment classifier along with an efficient ranking scheme.

5. CONCLUSION

In this paper, provides the review of sentiment analysis problem, which is currently, a well-known research domain for handling large amount of unstructured data available on web. Sentiment detection encompasses a large choice of applications in information systems, additionally as classifying reviews, summarizing review and different real time applications. There unit of measurement on the face of it to be many different applications that is not mentioned. It's found that sentiment classifiers unit of measurement severely captivated with domains or topics. From the upper than work it's evident that neither classification model consistently outperforms the alternative, differing kinds of choices have distinct distributions. it's jointly found that differing kinds of choices and classification algorithms unit of measurement combined in a cheap suggests that thus on beat their individual drawbacks and have the good thing about each other's deserves, and eventually enhance the sentiment classification performance. Hence in future to improve the accuracy of classification results various approaches need to be combined to overcome drawback of individual approaches and gain from each other's benefits.

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