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ENHANCED OBJECTIVE SENTIMENTAL ANALYSIS USING NLP TECHNIQUES

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Abstract

Sentiment Analysis is the analysis of the opinions of people and emotional input to an organization that can be goods, services, individuals or events. Classification of sentiments seeks to identify general opinion of social media users about business items or activities of everyday life. With the introduction of social networks, forums and blogs, this feedback became a significant factor in the decision of the customers to buy or choose any product today; a large versatile computing system provides us with a very complicated way to evaluate these feedbacks by performing various data-intensive natural language processing (NLP) and machine-learning tasks. One of these tasks is text categorization, a very efficient method to determine the feeling of customers. Whether the feeling is positive, negative or neutral, the categorization tells. The purpose of our research is to improve text classification techniques to enhance the overall result of sentiment analysis. Despite the widespread use and popularity of certain techniques, it is not clear which technique is best to recognize polarity. This study intends to fill this gap by comparing five famous sentiment classification methods such as Naïve Bayes, Maximum Entropy, Neural Networks, Bayesian Network, and Support vector machine. The analysis based results will show which approach performs better.

1. Introduction

Social media today occupies an enormous chunk of everybody's. They are gradually becoming the communication platform for each means. Social Media is actually affecting the user's point of view or individual thoughts. It is now an essential component of digital marketing. In business and public policy wide range of applications uses sentiment analysis. Sentimental analysis is now being used from certain product marketing to unsociable behavior identification. With technological advancements and the increasing prevalence of day-to-day social media platforms, the gap between businesses and customers is slowly decreasing. Sentiment is primarily about perceptions; beliefs, emotional responses and viewpoints. The opinion or feelings of a person are mostly subjective, meaning that an individual's opinion or mood from a piece of text is analyzed accurately.

Analysis of sentiment is the study of the views of people and emotional feedbacks regarding an entity which might be merchandise, services, people or events. The opinions are most presumably be expressed as reviews or comments (Islam *et al*, 2018). Text has two main types in the world: facts and viewpoints. Square facts evaluate impartial expressions of entities, occurrences and their characteristics. Opinions are typically personal terms representing the thoughts, perceptions or feelings of individuals towards persons, events as well as their characteristics (Malik *et al*, 2016).

With Analysis of Sentiment for the intent of reading a text analysis, They tend to be in area unit primarily wanting to induce Associate in Nursing understanding of the perspective of an author with relevance a subject in a Text piece and its polarity; either positive, neutral or negative. Analysis of Sentiments alludes to the application of the language system and the techniques of text analysis to identify and obtain objective data out of a subjective piece of matter. Provided the limitations in its impartial Analysis, it is needed to Continue to reduce the gap by presenting perspectives from the analysis of all techniques and steps involved in this process When information keeps growing, so needs to be sorted out. There are about 8.23 tweets every second on Twitter, almost 510 comments are posted every minute, 294,000 statuses are revised, and Walmart, a multinational dept-store discount chain, manages more than 1 million consumer transactions (Behdenna *et al*, 2018) per hour, 136,000 photographs are shared on face book Analysis of sentiment can be studied at three stages Document level, Sentence level, aspect level. Document level sentiment analysis supposes that each paper expresses views on a singular entity. Analysis of sentence level associates the task at this stage to figure out if a viewpoint has been reflected by each sentence. Assessment of the aspect level conducts a finer evaluation and requires the language process to be used (Mohamed *et al*, 2018).

All in all, sentiment analysis can be very useful in tracking social networks, as it can enable us to obtain an overall view of the broader public viewpoint behind certain topics. Study of sentiment is the mathematical analysis of relational meanings: the statistical processing in text of emotional expression. There are many benefits to derive from information systems that can obtain information about people& assessment, viewpoint, feeling about a product, individual, event, organization, or specific issue (e.g. security reasons) (Fang *et al*, 2015). Machine learning techniques are often based on supervised approaches to classification, where sensitivity detection is presented as binary (i.e. positive or negative) (Malik *et al*, 2016). The function of machine learning is to find the input text class label based on dataset and computational model (Shivhare *et al*, 2012).

The limited research readily accessible shows that machine learning methodologies (Naïve Bayes,Maximum Entropy and SVM) are more appropriate for Twitter than the LIWC method based on lexicons (Tausczik *et al*, 2010). Similarly, techniques of classification (SVM and Multinomial Naive Bayes) are often more appropriate for Twitter than SentiWordNet (Bermingham *et al*, 2010). It is difficult to say, though, either one classification technique is healthier than all lexical ways across completely different situations nor if it are able to do identical level of coverage as some lexical methods (Gonçalves *et al*, 2013). For classification purpose we choose some popular and widely used supervised machine learning algorithms. The algorithms are Multinomial, Bernoulli NaïvemBayes, Linear Support Vector Machine, Maximum Entropy, Neural Network and Bayesian Network (Islam *et al*, 2018).

The rest of the paper is arranged according to the following classification. The related works are first presented in Section 2 which provides background information on the related research areas involved in the identification of opinions. Then explain the approaches to classification of the representative opinion, with the matrix for comparison in section 3. The entire paper dissects in Section 4 after that conclude with future scope in Section 5.

2. Background

The first to introduce the idea of social network was Anthropologist John Barnes. In 1954, the consequences of over two years of study in the city of Bremnes (today Bomlo) in Norway were explain on the pattern of classes and groups of social (Barnes *et al*, 1954). The sociological and analytical clarification gave by James Mitchel is to describing a social network (Mitchell *et al*, 1969). A social network was defined by Wasserman and Faust as a finite set of actors and the relations defined on them (Wasserman *et al*, 1994).

According to the supporters of this research, the public relation culture modifies their content to a large extent. This dissertation (developed at Harvard since the 1970s) lays the foundation for the social networks analysis (SNA). SNA's aim is to model different properties of social structures, beginning with the graphs of mathematical theory and the use of algebra (Carrington *et al*, 2005).

Twitter is one of the most famous social networks. The company declared in a tweet at the end of 2012: There are now over 200 million active monthly @twitter users. Analysis of this large amount of data is therefore an interesting challenge for researchers, but it is also essential for those who work at different levels in the recent information society. Twitter has been the focus of researcher attention since 2009 (Go *et al*, 2014). The authors describe a recent important application in (Allisio *et al*, 2013) to understand how public sentiment is shaped, how it can be fetched and how it polarizes candidates and issues. One of the major drawbacks is how to collect a corpus for Sentiment Analysis and Opinion Mining goals (Hassan *et al*, 2013; Cambria *et al*, 2013) automatically. All of these issues pose major challenges.

2.1 Related Work

Opinion Mining and Sentiment Analysis involves removing sentiment terms from reviews of users as well as automated identification and sentiment analysis. Opinion Mining and Attitude Analysis includes removing words of sentiment from online reviews as well as automated analysis of recognition and feelings.

Concentrating on handling the issue of polarity changes, they suggested a model called dual sentiment analysis (DSA) in paper (Santanu *et al*, 2016) to characterize the reviews by considering two sides of a critique. The sentiments of reviews from 5 totally different e-shopping sites, collected from on-line supply are analyzed in (Xia *et al*, 2015).

The main source of big data is social media. The data on social media is noisy and unorganized. The vector machine was applied to evaluate Twitter's TV program performance (Alshari *et al*, 2016). Monitoring of emotion has many web uses. One of them is the analysis of the picture review. Online reviews contain sentences that are both subjective and objective. Objective information does not contain feelings or opinions, so in such cases only subjective information is helpful (Bhoir et al, 2015).The classifier Naïve bayes is used to derive qualitative sentences. The classifier Naïve Thomas Bayes provides a lot of the right outcome than SentiWordNet.

Tsytsarau and Palpanas (Tsytsarau *et al*, 2012) additionally conducted a detail survey covering the main topics of SA. Another more related area of research is that of determining the genre of texts; subjective genres, such as “editorial” is often one of the possible categories (Stamatatos *et al*, 2000). Other works explicitly attempt to find features indicating that subjective language is being used (Hatzivassiloglou *et al*, 2000). Most of the work based on classifying the semantic orientation of individual words or phrases using a pre-selected set of seed words or linguistic heuristics (Hatzivassiloglou *et al*, 1997; Turney *et al*, 2002).

In his work on text classification with supervised machine learning, however, T Joachim advised that Support Vector Machine is one of Naïve Bayes or Decision Tree's most active classifiers (Joachims *et al*, 1998). Other researchers and Naïve Bayes have also accepted the superiority of Support Vector Machine over Decision Tree (Dumais, 1998).

After a comprehensive review of the literature, we agreed to do a comprehensive analysis for text classification on some commonly used as well as less studied supervised machine learning algorithms to support the performance of these algorithms in terms of predictive accuracy and specific analytical metrics. Dasondi *et al*., 2016 used the algorithms using a sentence-level dataset obtained from Twitter.

Poria *et al*, 2017 applied the multi-algorithm and usedkSupport Vector Classifiers (SVM), Multilayer Perceptron (MLP) and Extreme Learning Machine (ELM) at the function and decision level to conduct supervised English-language sentiment analysis. The algorithms have been applied to a database of YouTube. The outcome was 64.20 percent of the highest accuracy. Xing *et al*., 2015 proposed a work on amazon customer reviews to categorize negative phrases. Data processing for the data collected between February and April 2014 is carried out at the rate of sentence and review.

Bhatt *et al*, 2015 used iPhone 5 reviews derived from Amazon's website and proposed akrule-based retrieval of product feature sentiment analysis. POS technique is implemented at each and every sentence level as well as the outcome area unit displayed in charts. Kamal *et al*, 2013 used supervised and rule based techniques to evaluate online product reviews. Bhumika *et al*, 2017 contrast the machine learning models and relate the comparison of efficiencies of these models for Twitter data.

Xia *et al*, 2015, recommend a study on amazon reviews for items to recognize negative Sentences. IPhone 5 was used by Bhatt *et al*, 2015 feedback from the website of Amazon and suggested a policy based product interface for analysis of sentiment retrieval. POS methodology is applied at all sentence levels as well as the unit area of results shown in the graphs. Kamal *et al*, 2013 used monitored and regulatory techniques to examine online reviews views of goods. POS technique is applied at each and every point of sentence as well as the unit area of results shown in the graphs. Kamal *et al*, 2013 used controlled, rule-based strategies to undermine the viewpoints of online product review sites.

Table 1: Comparison of classification techniques

Algorithm	Type	Study	Features	Merits	Demerits	Dataset	Accuracy
Neural network	Supervised	Chaturvedi *et al*, 2018 Mijwel *et al*,2018 Shahiri et al, 2015 Vinodhini *et al*, 2016	• It implemented mathematical model neurally. • Large number of processing elements. • Mapping capabilities.	• Information store on whole network • Tolerate the corruption • Able to work with insufficient knowledge • High performance speed	• Hardware dependence • Unexplained Problem of network • Unknown duration	Twitter tweets Internal Assessments CGPA	91.4% 81% 75%
Bayesian Network	Supervised	Vidisha *et al*, 2016 Vohra *et al*, 2013	• It is conditionally independence. • Flexible	• It offers a graphical representation of the freedom in a dataset.	• Implementation of it is un workable. • It may allow t	Not Applicable	

		Ang *et al*, 2016	quantitative choice of next test. ● Easy to modify and maintain. attri	● Even with very sma ll sample sizes, the Bayesian networks can show good pred iction accuracy. ● BNs may also be us ed in combination with other Bayesian methods of analysi s.	he expert tea m working on it to have tim e and test. ● In the sense o f BNs there ar e no abstract minimum lim its for the am ount of data.		
Support vector machine	Super vised	Hassan *et al*, 2017 Chaturvedi et al, 2018 Munir *et al*, 2018 Hassan *et al*, 2017 Mohamed *et al*, 2018	● Used for classification and recognition problems ● Obtains the best solution of small data size ● The surface is optimally defined	● High precision performance ● Good work even if the dataset is not linear ● Complex nonlinear data points are easily managed ● .The problem of fitting is not the same as other approaches. ● Enhanced precision relative to other classifier.	● Lack of data visibility. ● the big size of data ● High complexity and wide classification memory demand in many cases ● The high computational cost ● Compared to other methods, it requires more time to train.	Social media Tweeter IMDB dataset Amazon dataset Social media	91% 92.3% 88.63% 92.18% 91%
Naïve Bayes	Super vised	Go *et al*, 2009 Hassan *et al*, 2017 Behera *et al*, 2015 Sharma *et al*, 2012 Schumaker *et a*l, 2012 Padmaja *et al*, 2013 Padmaja *et al*, 2013	● Simple probabilistic classifier ● Use for classification and regression challenges. ● Strong independent assumption ● Performs well on numeric and textual data	● Handles real and discrete data. ● Optimal time performance, quite good results ● Computationally efficient ● Cost effective ● Fast learning process Suitable for small data	● Perform poor on co related features. ● Precision decreases if data is small. ● Require large number of records to obtain good results ● Assume independence of features.	Tweeter reviews Tweeter dataset, 20news group tweeter reviews IMDB dataset Amazon	81.3 83 84.2 83.16% 90.42%
Maximum entropy	Super vised	Go *et al*, 2009 Hassan *et al*, 2017 Kamal *et al*, 1999	● Converts labeled feature sets to vectors using encoding ● Calculate weights of features ● Feature-based models ● Estimate probability		● A lot of computations ● Computation complexity ● Less accurate nb ● Efficiency is low	Tweeter reviews Tweeter dataset, 20ne group WEBK B:	80.5 80 8.08

Padmaja *et al*, 2013 Padmaja *et al*, 2013	distribution ● Generative approach, uses the environmental data	Industry Sector:	18.90

A. Neural network

Neural network is another popular technique used in educational data mining. It has the advantage of having the ability to detect all potential interactions between variables of predictors Even in the complex nonlinear relationship between dependent and independent variables, neural networks could do a complete detection without any doubt. Neural network technique is therefore chosen as one of the best method of prediction. Eight (8) papers were published using the framework of Neural Network through the meta-analysis review. The papers present a model of the Artificial Neural Network to predict the performance of students. Neural Network's attributes are data on admission, students' attitudes towards self-regulated learning and academic performance. In addition to the Decision Tree process, the rest are the same papers where researchers used both techniques (Shahiri *et al*, 2015).The twitter dataset is a manually annotated selection of 498tweets as positive, negative, or neutral. In metric, the high accuracy of a simple neural network (NN) is 91.4% (Chaturvedi *et al*, 2018).

B. Bayesian Network

A Bayesian Network (BN) is a graphical model for a set of variables (features) related to probability. The most well-known example of statistical learning algorithms is the Bayesian networks (Vidisha *et al*, 2016). Compared to decision trees or neural networks, the most interesting feature of BNs is most certainly the possibility of taking into account prior information on a given problem, in terms of structural relationships among its features (Islam *et al*, 2018). The classifier Naïve Bayes is the freedom of the apps. Naïve Bayes ' conclusion is to assume that each of the components is wholly dependent (Vohra *et al*, 2013). This prompts the Bayesian Network to display which is a directed acyclic diagram and whose nodes correspond to random variables, and the edges represent conditional dependencies. Bayesian Network viewed the variables and their relationship as a whole. In this way a total joint distribution of probability over each of the elements is solved for a model.

Bayesian network uses a direct graph to represent random attributes and conditional dependency, and nodes represent random variables. Bayesian Network makes computational processes faster and speedier and more reliable for large databases Bayesian networks are based on the principle of Bayes, so that they can argue against the direction of causation. The BN's computational complexity in text mining is extremely expensive; therefore, BN is used very little of the time. Bayesian Network was used to find a real problem.

C. Support vector machine

The definition of SVM is provided by Vapnik et al., which is focused on statistical learning theory (Vapnik *et al*, 1998; Vapnik *et al*, 1998). Initially, SVMs were designed for binary classification, but could be extended efficiently for multiclass problems (Chistianini *et al*, 2000). The support vector machine classifier generates a high-dimensional hyper plane or several hyper planes that are useful for classification, regression and other efficient tasks. Because of this, SVM has many attractive features that make it popular and promise empirical performance. SVM constructs a hyper plane to isolate the data points in the original input space. Using the association law, optimal function is extracted in the first stage and in the second phase the PSO is used to discover best kernel parameters for SVM to increase the classifier model's accuracy.

D. Naïve Bayes Classifier

The Naïve Bayes algorithm is a deterministic classifier with a strong and naïve presumption of independence based on the Bayes theorem. (Go *et al*, 2009; Padmaja *et al*,2013) This assumption does not greatly affect the consistency of the text, but makes classification algorithms very easy to apply to the problem. If the classifier experiences a word that was not seen in the training set, the likelihood of both classes would be null and nothing to compare. Laplacian smoothing can solve this problem. In this method, Bernoulli Naïve Bayes is also used to treat replication (Schumaker *et al*, 2012). Nave Bayes is a model of machine learning that can be used for challenges of classification and regression (Hassan *et al*, 2017). Binary Naive Bayes and Multinomial Naive Bayes are different types of Naive Bayes algorithm (Behera *et al*, 2015). It is supposed to be one of the most basic text classification techniques with different applications in email spam detection, personal email sorting, and classification of documents, language detection and feeling detection Experiments show that this algorithm works well with numerical and textual data. Although other techniques such as boosted trees, random forests, Max Entropy, supporting vector machines, etc. often outperform it. Naïve Bayes classifier is quite efficient because it is less computational and requires a small amount of training data. Naïve Bayes vectorization performance is very poor in text categorization when features are co-related (Patra *et al*, 2013). It is popularly used not only for text classification, but also for any other classification problems, as it is quick and simple to learn (Vohra *et al*, 2013). Naïve Bayes classifier defines the likelihood of a document belonging to a specific class. The strengths of the Bayes classifier are: simplicity of implementation, quick learning process, and good results. (Padmaja *et al*, 2013). The main theoretical disadvantage of NB methods is that it tends to assume conditional independence among the language characteristics (Behera *et al*, 2015).

E. *Maximum Entropy Classifier*

Maximum Entropy is also recognized as a classifier of conditional exponential or logistic regression. Encoding the maximum entropy classifier converts labeled feature sets into vectors. This encoded vector is then used to measure weights for each element, which can then be combined to decide the most likely tag feature (Hassan *et al*, 2017).

Max Entropy models are models based on features. In a two-class scenario, finding a distribution over the classes is the same as using logistic regression. Maximum Entropy makes no assumptions as to its characteristics, unlike Naive Bayes (Go *et al*, 2009). This means we can add to Maximum Entropy features such as bigrams and phrases without worrying about overlapping features. The model is shown in the following:

$$P_{ME}(c|d,\lambda) = \frac{\exp[\Sigma_i \lambda_i f_i(c,d)]}{\Sigma_{c'} \exp[\Sigma_i \lambda_i f_i(c,d)]}$$

C is the class in this formula, d is the tweet, and π is a vector of weight. The weight vectors determine the meaning of a classification feature .A higher weight means a strong marker for the class. The weight vector is determined by mathematical optimization of the lambdas so that the conditional probability is maximized.

Theoretically, Maximum Entropy is better than Naive Bayes because it better manages the overlap of features. Naive Bayes, however, can still perform well on a variety of Naïve Bayes issues in practice. Nonetheless, it is more difficult to implement the total entropy algorithm and the learning process is slower (Padmaja *et al*, 2013).

3. Discussion

Analysis of sentiment is the study of the views of people and emotional feedbacks regarding an entity which might be merchandise, services, people or events. Most certainly, the viewpoints are expressed as feedback or comments. Determining a writer's attitude towards some subject or the overall feeling in a text is the basic goal of performing an examination of feelings. Report level, sentence level and phrase level can be used to forecast sentiment. Throughout business and public policy, a wide range of technologies utilizes sentiment analysis. Through specific product messaging to antisocial behavior identification, emotional analysis is now being used. The widely available sentiment analysis approach is machine-learning. Machine learning models are often based on supervised approaches to classification, where sensitivity detection is represented as binary (i.e. positive or negative).

To train classifiers, this approach requires labeled data while one of the advantages of learning-based approaches is their ability to adapt and construct trained models for specific purposes and contexts, their drawback is the scarcity of labeled data and therefore the method's poor applicability to new data. This is because for certain projects, marking data may be costly or even prohibitive. Depending on the context they were created, the lexical methods vary. This paper surveys text classification, text classification mechanism of different term weighing methods, and comparisons between different algorithms for classification.

In this paper, five techniques of text classification are described for sentimental analysis. The brief discussion of machine learning approaches is also performed such as naïve bayes, neural networks, support vector machine, Bayesian networks, maximum entropy, these techniques are critically analyzed and identify its features, merits and demerits. The study is based on pertinent papers and analyzed each algorithm's performance differently on various types of data sets. Provided this, each technique's advantages and disadvantages are furnished and highlighted demerits are addressed to improve the gray areas of these techniques.

4. Conclusion

The application of sentiment analysis to mine the vast amount of data has become a major research issue today. Recent business organizations and researchers are working to find the best system for evaluating emotions. Although some of the algorithms were used in the analysis of sentiment, they give good results, but no algorithm can solve all the challenges. Most researchers have recorded high accuracy of Support Vector Machines (SVM) compared to other algorithms, but it also has limitations. Nevertheless, it is found that the classification of feelings depends on the context. Different types of classification algorithms should be combined to resolve their individual limitations and benefit from the merits of each other, and improve the efficiency of classification of feelings. These applications are very much needed in the industry. Each business wants to know how customers and their rivals feel about their products and services. Analysis of sentiment for new applications can be built. Sentiment analysis techniques and algorithms have made good progress, but many challenges remain unresolved in this area. Further work to address these problems can be conducted in the future.

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