A Survey on Concept-Level Sentiment Analysis Techniques of Textual Data

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***Abstract*—Text mining is one of the branches of data mining and refers to as the computing process of finding new patterns and relations among datasets which appear not to be related. Data mining is an interdisciplinary field which uses statistics, artificial intelligence, and database systems to generate new tools for discovering patterns among datasets. Similarly, when dealing with textual data, we need to use various methods in different branches of computer science (e.g. linguistics) and statistics. This study reviews the techniques of text-based sentiment analysis pipeline including preprocessing, aspect extraction, feature selection, and classification techniques used by scholars recently. It also surveys different applications of semantic analysis in the context of social media, marketing, and product reviews.**

***Index Terms*—Sentiment analysis, deep learning, neural network, machine learning, artificial intelligence**

I. Introduction

Sentiment Analysis (SA) is one of the active research field in text mining. It identifies, extracts, quantifies, and addresses sentimental states and subjectivity of text in a computational process and systematic way. Among different applications of SA, getting insight into public opinion of various socio-political subjects via analyzing tweets and other social media textual public materials, automated analysis of historical corpus and also study of product reviews for the purpose of getting true customer feedback and customer sale prediction are crucial [1]. Due to the decreasing trend of data storage price and rapid growth of information technology, the global society stores vast amount of data every day. One of the main focuses of Natural Language processing (NLP) is to make use of Artificial Intelligence (AI) approaches to design and construct computational platforms [2]–[9]. These platforms automate the process of extracting knowledge and previously unknown interesting patterns, from both structured and unstructured text sources [10], [11]. Sentiment Analysis (SA) is the method of extracting the contextual polarity (positive, negative, or neutral) of the text. Sentiment Analysis has two major steps: Feature Selection (FS) and Sentiment Classification (SC) [1].

This paper is organized as follows. First, we review techniques of SA for textual data in section II. Then, section III discuses application of SA. Finally, we identify unsolved challenges and future works in IV, and summarize our contributions in V.

II. Techniques of Sentiment Analysis (SA) for Textual Data

SA can be modeled as a three-layer process as shown in Fig. 1:

- Sentiment Identification (preprocessing) layer in which the whole document is considered as the foundation for classifying an opinion in the document as a positive or negative sentiment.
- Feature selection layer in which the opinions and sentiments in each sentence are classified. In the case that the sentence is subjective (as opposed to objective), this layer categorizes the sentence into the bucket of sentences with positive or negative subject. Wilson et al. [12] believes that there is no fundamental difference between this layer and the upper layer as a sentence can be considered as a short document.
- Sentiment classification layer in which the sentiments are classified according to the specific aspects of entities which must be determined at the beginning of this step. Current approaches to SA are mainly based on supervised learning which is based on manual labeled samples like commercial product reviews in Google, Amazon, and other social networks product reviews in which the overall attitude of customers is explicitly specified in the review using stars, numbers, etc. Also transfer learning models [13] with machine learning models [14], [15] can improve text based applications.

We can classify the techniques of SA and affective computing [16], [17] into three major classes: statistical/learning methods, knowledge-based approaches, and a combination of the them (hybrid models).

A. Preprocessing and Aspect Extraction

In Preprocessing step, we need to clean textual data in different ways. The necessity of this step fortifies when we deal with textual data extracted from the web,

Fig. 1: Text-based Sentiment Analysis Process

or social media as such data is often noisy and has lots of web-development related data, tags like HTML, white space, or advertisement. Aspect extraction is to have the part of speech entity recognizes noun phrases and their frequency in a sentence. The reason is to eliminate and filter out those which appear rarely or less than a low-threshold. Next, we need to find non-commonly appearing aspects by using the relationships among the words exposing feelings, ideas, and aspects. In fact, the earlier phase of aspect extraction may have overseen a substantial number of aspect representations in the form of noun phrases merely for the reason of not being as frequent as the man-made lower threshold. Su [18] designed and implemented a learning method for performing clustering process with the aim of transforming and translating IACs as affective words and finding their direct, true and complete meanings which will later be used to extract emotional aspects of the text. The approach utilizes the interconnection of a directly represented aspect and a sentiment word constructing an interconnected couple in a phrase or a paragraph. Hai [19] used rule extraction techniques with the aim of translating sentiment words conveying emotions to the words directly denoting feeling-related aspects. Moreover, Zeng and Li [20] gave birth to a fantastic rule-based method which translate and transforms implicit aspects for the sake of finding explicit features using learning approaches including clustering directly represented sentiment word couples. Additionally, [21] presented a technique aspect extraction from textual data in both explicit and implicit manner. The computational platform presented in their work is based on the intuition and the interdependent organization of sentences in a passage. Also, it relies on the precision of the parsing entity extracting dependencies among the works and lexical analysis technique finding the thoughts.

B. Feature Selection

There have been many attempts by various researchers who was seeking to extract the best features that can be an ideal input for the phase of sentiment classification and automate Feature Selection (FS).

Reyes et al. proposed an algorithm based on Support Vector Machines (SVM) to perform feature selection using customer reviews of amazon [22]. Also, Yu et al. proposed another approach based on Point-wise Mutual Information (PMI) to conduct FS using stock news data [23]. In the most popular technique used by many researchers like Das and Chen [24], the process first creates lexicon dedicated to a particular domain; however some research studies like [25], [26] try to create a routine thought lexicon which can be reused in various contexts. For instance, Kim et al. [27] have done feature selection based on lexicons using a small collection of keywords and extend it using synonym relations or different web-based resources in order to get a bigger lexicon. However, these approaches have some drawbacks which can be very costly for the whole process. Whitelaw et al. have worked on the analysis of this approach and showed how costly it is, since it needs manual annotations done by humans [28]. Other works performed by Wilson et al. [12] and Kim and Hovy [27], the agreement between human judges when given a list of sentiment-bearing words is as around 60%. Moreover, some words must be deleted as they rarely appeared in the text. Deng et al. propose a term weighting scheme based on supervised learning by statistical functions which improves SA [29].

C. Classification Techniques and Supervised Learning

There exist many machine-learning solutions for SC step of SA. Van et al. used SVMs and neural networks to perform SA on relationships biography data [30]. Also, Kang et al. proposed an approach based on Naive Bayes Classifier to perform SC on restaurant review [31]. Fig. 2 classifies Semantic techniques distinctly.

1) Naive Bayes Classifier (NB): Naive Bayes classifiers is a fundamental probabilistic models which have been extensively studies in 1950s and been used for text retrieval and other types of learning processes in 1960s. It is the simplest and most frequently used techniques for classifying purposes [1]. A sophisticated and well-tuned NB classifier was introduced by Kang and Yoo to classify the sentiment of a text in a very precise way. However, it had some drawbacks as it decreases the average precision when the accuracies of the two categories are represented using mean estimation. They proved that by applying their approach on restaurant reviews, the distance between the positive negative accuracy becomes less relative to Naive Bayesian and Support Vector Machines [31].

2) Support Vector Machine (SVM): The method of SVM is an extension of the linear approaches in which we combine two or more linear classifiers know as separators to narrow down the space search gradually and then finally reach to a fine-grained accurate classification

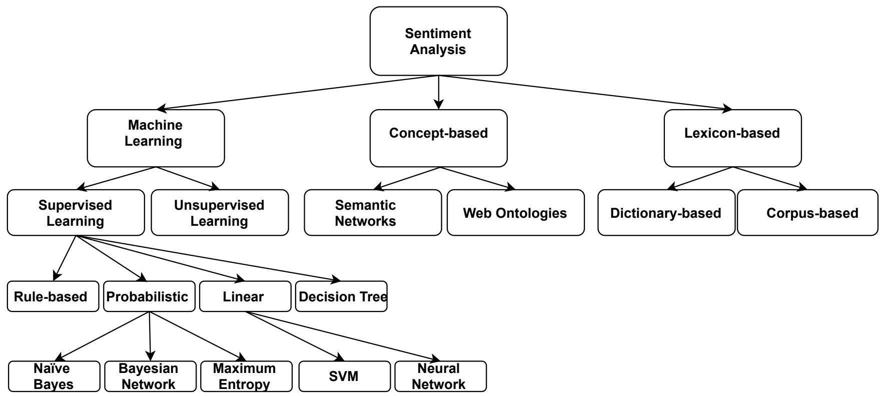

Fig. 2: Sentiment Classification Techniques

with high recall percentage. In fact, this method is used for many of the text mining tasks including SA because of its sparse nature that fits well with how textual data is [32]. Li and Li in [33] designed and implemented a platform which conducts a numeric summarization of opinions on micro-blogs frameworks. They selected and extracted the subjects and features based on the users' queries first. Then, they used the output of the earlier step as input of the classification task of thoughts and opinions using SVM. They applied their approach on twitter posts,and proved that it can recognize market intelligence (MI) which can be later used to help policy makers by designing a monitoring system to follow various opinions on different aspects of a business very fast. Sida et al. [34] proved that a hybrid method using both NB classifier for log count ratios classification and SVM can do much better in datasets compared with many other approaches. They also showed that NB classifiers in many cases are more precise than support vector machines. Finally, they demonstrate experimentally that features extracted from bigram give valuable insight into the sentiment and feelings of a corpus.

3) Bayesian Network (BN): Unlike Naive Bayesian models which work under specific circumstances, in Bayesian Networks, there is no need for the variables to be independent or for the features to be fully dependent. BNs are relations among random variables which are represented using directed acyclic graphs created to denote the probabilistic dependencies of different variables. For any pair of variables, Bayesian network creates a Conditional Probability Table (CPT) which gives detailed probability distribution of one variable if the other gives certain values. Hernandez and Rodriguez [35] used a multi-dimensional BN for conducting classification. For the sake of utilizing the relation that may exists between the three final labels, they created new auxiliary labels. In their training database, the labels of a big portion of their data were missing which makes them to use a semi-supervised learning.

4) Decision Tree Classifier: Decision tree classifier is represented by a linked data structures similar to Bayesian Networks. In this classification method, the population is divided into different parts in a hierarchical manner and based on different criteria extracted from information theory like entropy and information gain. Such division continues until the point that the classes have pure enough labels, but the classifier is not overfitting. Creating precise enough but not overfitting decision tree classifier is a challenging issue and a trade-off for which we need appropriate quantification methods of classification accuracy. Hu and Li utilized a maximum spanning tree structure for decision tree classifier which could successfully extract meaningful insight into the organization of topical terms (different aspects of individuals in an understudied domain) in the granularity-ratio of documents, paragraphs, and sentences [36].

5) Neural Networks (NN) and Deep Learning: The basic form of a neural network is identical to a linear regression. As the network becomes larger with more layers, the connections between layers create a more sophisticated classifier capable of learning more patterns. Every layer of a multilayered NN is used to linearly model a piece of a whole learning process, which is used to label and predict values of the dependent variables knowing some exogenous variables. The layered structure of the network works as follows: every layer output the materials for the use of the next layer; while consuming the output of the previous layer as input. Every layer consists of several neurons working to linearly model an integrated portion of the whole process. Since the error of different layers must give feedback to the other layers, the learning process of these classifiers are usually longer than most of other classifiers. Van et al. extracted relationship between the biography of two different humans in the form of polarity detection; i.e. they specified whether the two understudied persons have positive, neutral or negative relations. To test their approach, they used the biography of pairs who had lived in the same era and region. Their findings proved that it is possible to automate the polarity detection of relation among people's biographies. Also, if the training data is not restricted to the understudied person and contains information regarding those who have had meaningful influence on the subjects' lives, the result is more accurate. In their study, SVM and NN were the two most accurate classifiers [30]. In 2013, Socher et al. proposed a novel approach called Recursive Neural Tensor Networks (RNTN) and the Stanford Sentiment Treebank. They could improve the accuracy of polarity detection in the literature by 5.4% which is a big jump [37]. Table I presents the list of recent works, and table II lists the main sentiment data sets.

III. Applications of Sentiment Analysis

There are many areas and fields like business intelligence, health, education, market prediction, history, etc in which different researchers have tried to apply SA and some have gained interesting insight into the understudied textual data.

A. *Social Media: Tweeter and Facebook*

There are many attempts by different researchers in recent years to apply sentiment analysis and affective computing on short informal texts. Ortigosa et al. proposed a novel computational framework for analyzing the sentiment of textual data generated in Facebook [56]. Their model does polarity analysis on the Facebook posts, traces the changes in the emotions of Facebook users over time, and finally finds out how the emotions of someone's Facebook friend toward the person may change over time by analyzing the online interactions between a person and its Facebook friends. To do this, the authors of the work have created a software for first retrieving Facebook posts at-bulk and then doing SA on the behavior of Facebook users and their interaction with their friends based on the textual data generated by Facebook posts. In this study, the SA based on supervised learning had an acceptably high accuracy (83.27%). Ceron et al. [57] focused on the on-line popularity of Italian political leaders using Tweeter throughout 2011 and votes of French people communicating their ideas over Tweeter. They proved the power of Tweeter in predicting various surveys and even election results. In [58], an interesting comparison between social and traditional media has taken place. The results express that social media has a more decisive effect on the stock performance than traditional one. However, both the medias have inevitable impact on the performance of stock. This paper was the first work that has actually did advanced SA to compare televisions, radio, and other conventional media with Tweeter and other modern media outlets. In order to do feature selection, they used the frequency of keywords (n-grams) to filter out unimportant sentiment words. In [59], Paltoglou et al. generalized their approach to be implemented on any informal textual communication happening electronically either in a social media, online discussion forums or even private chats. The proposed approach is based on lexicon-based, unsupervised method which needs deep understanding of the semantical and lexical rules of the language. The goal of the model was sentiment polarity detection and subjectivity classification. The sentiment analysis performed in [60] is to detect sarcasm in social media textual data like tweets and posts of Facebook. It detects sarcasm in the tweet's body text, and finds how sarcastic a hashtag is. The precision of this work is 91% which its hashtag tokenization error is as low as 2%, and can detect polarity with a accuracy of 80%. In [61], Hutto et al. presented a dictionary for SA called VADER. This dictionary is a knowledge-based solution for conducting affective computing on social media text data. Their model reduce the classification error to as low as 4% for rule-based models assessing twitter data. Kontopoulos et al. designed and implemented a new method based on ontology-based models for analyzing the polarity words of Tweeter users [62]. In [63], Ghiassi et al. proposed a technique to analyze Tweets' sentimentally using learning methods based on bigrams obtained from the output of knowledge-based methods,and compared its performance with SVM on the same data.

B. *Marketing and Product Review*

Online shopping is a more convenient way for both customers and merchants to exchange goods than in-store shopping, it has also some drawback: online customers are not able to see the product or service in-person. As a result, product reviews are more crucial tools for customers to exchange their experiences. For this reason, the urge for identifying and extracting useful customer feedback for marketing purposes has been increased. Hu et al. in [64] proposed a novel way of analyzing how ratings and customers' feelings conveyed by the reviews can predict the sales of books over Amazon. They used a dataset containing thousands of books sold by Amazon, and found interesting results; e.g. there is no statistically meaningful relationship between ratings and sales, but there is some statistically significant connection between ratings and sentiments. Also, there exists some statistically meaningful relationship between ratings and sales. Moreover, among all reviews, the ones that come first in the list of all reviews, have more impact on sales of the product. In [65], Hu et al. introduced a novel technique for anomaly detection of product reviews in online stores like Google Play.

References	First author, Year	Method	Dataset	Measure
[38]	Li, 2020	LSTM, MKL, SVM	Stock data of Hong Kong Exchange (HKEx)	0.50 Acc
[39]	Luo, 2019	DOER	SemEval (2014, 2015, 2016)	0.83 F_1
[40]	Kraus, 2019	RF, LSTM	Movie reviews, IMDb movie reviews, food reviews (Amazon)	0.85 F_1
[41]	Wu, 2019	LSTM, Bi-LSTM	Chinese VA, Facebook, Emobank	-
[42]	Alharbi, 2019	CNN	SemEval-2016	0.87 F_1
[43]	Abid, 2019	RNN, CNN	Twitter's corpora, Stanford Twitter, Sentiment Corpus, Health Care Reform	0.91 Acc
[44]	Do, 2019	LSTM, CNN, GRU	SemEval, social network sites	-
[45]	Yang, 2019	LSTM, MemNeT	Twitter, SemEval 2014	0.80 Acc
[46]	Qian, 2018	CNN, DNN	weibo, weixin, tieba, tianya, twitter	0.80 F_1
[47]	Pham, 2018	ANN, MOEA, BP	HKD, JPY, EURO and USD	-
[48]	Preethi , 2017	RNN, NB	Restaurant, Movie (Amazon)	0.90 Acc
[49]	Gao, 2016	CNN	Movie Review, and IMDB	0.89 Acc

TABLE I: Comparison of deep-learning-based Sentiment Analysis mechanisms based on their Accuracy or F_1.

References	First author, Year	Datasets	Content	Source
[50]	Deng, 2015	MPQA	News	http://mpqa.cs.pitt.edu/corpora/mpqa_corpus/
[51]	Hu, 2004	Hu and Liu	Digital product	https://www.cs.uic.
[52]	Dong, 2016	Twitter	Tweets	https://goo.gl/5Enpu7
[53], [54]	Poniki, 2014, 2015, 2016	SemEval-14	Digital product	https://alt.qcri.org/semeval(2014/task4, 2015/task12, 2016/task5)
[55]	Maia, 2018	FiQA	Financial news	https://sites.google.com/view/fiqa/home

TABLE II: Sentiment-related data sets

Also, they evaluated the impact of fake reviews on the behavior of the clients. They used SA of textual data to gain insight into what they called “manipulated reviews” and their literature, writing style, grammatical structure, and choice of words. Their findings showed that, on average, the reviews of more than one tenth of items sold online are getting manipulated for malicious purposes. The study claimed that online customers may find out the manipulation of product ratings, but it is much harder for them to realize whether the feelings of the reviews have been manipulated. Lau et al. in [66] proposed new technique for social analytic that can be adopt to online comments of customers purchasing products from online stores. They used a hybrid of supervised and unsupervised ontology mining appropriate for fuzzy product analysis. Their assessment of the proposed method based on the experimental results has compared it with the context-free social analytic existing in the literature and showed that substantial increase of performance which can be crucial in future of online social analytic. In business analysis, Coussement and Van den Poel considered emotions expressed in client/company emails to be in a prediction model for a newspaper subscription business [67]. In [68], study by Guzman and Maalej an automated approach shows developers to filter, aggregate, and analyze consumer's reviews. They applied NLP's techniques to recognize fine-grained app features for them. The approach was evaluated with seven apps from the Apple App and Google Play to compare its results.

IV. Unsolved Challenges and Future Works

As future direction of aspect extraction, Poria et al. aimed to discover more rules for aspect extraction [21]. Another key future effort is to combine existing rules for complex aspect extraction. A further direction of extending ontology-based sentiment analysis is to integrate a fully automatic ontology-building functionality, potentially through a combination of ontology learning techniques. Nevertheless, keeping the manual and semi-automatic ontology creation approaches still remains useful, as they offer a more controlled means for building the domain vocabulary. Exploring various methods for visualizing the resulting sentiment is an additional direction for providing more thorough information to the user [62]. The SA approaches analyzing social media can be extended by obtaining much-longer term data sets and much more popular users from Twitter and various kinds of real-world data from Gallup, Billboard, etc. in order to investigate the correlation between Twitter and various kinds of real-world phenomena [69]. Furthermore, it may develop various prediction models to forecast future sentiments from Twitter, as mentioned above. This work should also develop a positive-negative influence algorithm and perform comparisons with other influence measures.

V. Summary and Conclusion

This paper studied the techniques of text-based sentiment analysis pipeline including preprocessing, aspect extraction, feature selection, and classification techniques. It compared the efficiency of different ML-based methods used by different researchers and classified them into two main categories of supervised and unsupervised methods. The supervised methods discussed in the paper includes support vector machines, Bayesian networks, decision tree classifiers, neural networks and deep learning methods. Finally, it addressed different applications of semantic analysis in the areas of social media, marketing, and product reviews.

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