An overview of Sentiment Analysis with Domain Specific Lexicon

***Abstract*—Sentiment analysis is a relatively new field of study at the intersection of computer science and linguistics that aims to find an opinion expressed in a text. It has received a swell of interest in both academia and industry. There are two major approaches for sentiment analysis task. Machine learning-based approach and lexicon-based approach. The machine learning approach is based on training corpora annotated with polarity information. The lexicon-based approach is based on using sentiment lexicon and it provides better accuracy. However, it produces a sub-optimal performance when general purpose sentiment-lexicon is leverage. We present an overview of sentiment analysis with domain-specific lexicon with focus on approaches that automatically construct domain-specific lexicon for optimal accuracy. Finally, studies show that domain-specific lexicon provides better performance than using a general-purpose lexicon.**

***Index Terms*—sentiment analysis, opinion mining, lexicon-based, domain-specific, machine learning**

I. Introduction

The emergence of Web 2.0 and exponential growth of social media has changed how people use an Internet from read-only participation to read-write participation. Participants now actively contribute their opinion rather than reading the Web content passively [1]. There are approximately 4.2 billion Internet users out of 7.6 billion world population and 3.03 billion are active in social media such as Twitter, Facebook and Instagram. On average, an internet user has 7.6 social media accounts [2]. This digital revolution and paradigm shift allows users to express an opinion and sentiment on several areas such as government, commerce, tourism, politics, education, health and many entities [2]. For example, on average, 6,000 tweets per-second are made on Twitter and 91.8 million blog posts are published every month on Wordpress only [2]. These raise the need to find insight and knowledge buried through such a medium.

Traditionally, people, businesses and government use traditional approaches to find feedback or opinion on a particular subject. For example, if people want to buy a new mobile device, they consult their friends, relatives or acquaintance who had bought a similar product or service for opinion and recommendation which will either be positive or negative. Thereafter, they use the feedback received to determine the worthiness of the product to prevent disappointment. But, such single or few opinions may not statistically make an informed. But, such single or few opinions may not statistically make an informed decision. In the same way, businesses conduct survey and opinion poll to find out about the users' opinion and feedback on their product with a view to improving customer services and marketing strategy. In International politics, the government sent spies to another country to monitor the country activities. Also, they use a survey to find people reaction and acceptance towards new and existing policies. However, with the rapid increase of a vast amount of user-generated rich-opinionated resources, the classical tools such as survey and Natural Language Processing techniques for analysing and understanding users opinion are sub-optimal [3] [4]. To this end, better and automated way of mining opinion and summarization from such resources is needed [5].

Sentiment analysis is a study that aims to find sentiment, opinion, emotion, attitude computationally from people's written text [6]. It is a relatively new research area and depending on the domain, it is often referred to with a different nomenclature such as: *opinion mining, opinion analysis, opinion extraction, sentiment mining, sentiment extraction, subjectivity analysis, emotion analysis, review mining* and many more terms are evolving. Two most widely use names that appear and use synonymously in the academic literature that refers to the general umbrella of the field are sentiment analysis and opinion mining. In contrast, only the term sentiment analysis is widely used in industry [7]. Sentiment analysis has been successfully applied in many domain and applications such as recommender systems, user reviews and politics [8].Businesses also use sentiment analysis to find consumer opinion on product and services to improve their business and service delivery [9].

There are two basic approaches for sentiment analysis. Lexicon-based approach and Machine Learning-based approach.The machine learning approach is based on training corpora annotated with polarity information. The Lexicon-based approach is based on using polarity of lexicons and it provides better accuracy [10]. Recently, a hybrid approach has been that exploit the strength of two or more techniques to offer better performance [11].

The lexicon-based approach is mostly performed with general-purpose sentiment lexicon because they have the advantage of wider coverage. However, the main problem with using general-purpose lexicon is that sentiment lexicon is domain-dependent. General purpose sentiment lexicon do not offer expected accuracy across different specific-domain. Recently, there is a swell of interest in the area of domain-specific lexicon-based sentiment analysis and provides better better accuracy [12].

This paper aims to provides an overview of the sentiment analysis with a focus on domain specific-Lexicon. To this end, we discussed the state-of-the-art automatic domain-specific lexicon generating approach.

The paper first gives an overview of sentiment analysis in section II. Section III discusses approaches of sentiment analysis. The domain-specific lexicon-based approach is presented in section IV and section V conclude the paper.

II. Overview of Sentiment Analysis

Much of the early research on textual information processing focused on mining and retrieval of factual information, such as information retrieval, text classification or text clustering. Research in sentiment analysis started relatively in the year 2001 [13] [8] and the phrase *"opinion mining"* was first use in 2003 [14]. In [15], they reported that 99% of all the research on sentiment analysis have been published after the year 2004, thereafter, a considerable number of researches on sentiment analysis has been done in the area, but little has been explored on the area of sentiment analysis with domain-specific.

Pang and Lee [8] identify three factors which trigger interest in sentiment analysis research. First, the rise of machine learning methods in natural language processing and information retrieval; Second the availability of datasets for machine learning algorithms to be trained on, due to the blossoming of the Worldwide Web and, specifically, the development of review aggregation websites; Thirdly, the realization of the fascinating intellectual challenges and commercial and intelligence applications that the area offers. There are many research lines in sentiment analysis, Fig. 1 highlights most prominent areas of research in the area of sentiment analysis.

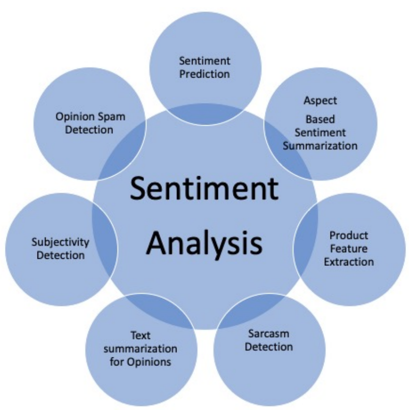

Fig. 1. Areas of research in sentiment analysis

A. Levels of Sentiment Analysis

According to [6], based on the levels of granularity, the sentiment analysis has been mainly investigated at three different levels: document level, sentence level and aspect level. In contrast, Kumar & Sebastian [17] reported four different levels, with the addition of word level as depicted in Fig 1.

Word Level: Sentiment analysis at word level involves finding adjective part-of-speech as a source of sentiment indicator. in the same way, part-of-speech such as a noun, verb and adverb sometimes indicates subjectivity and opinion [16].

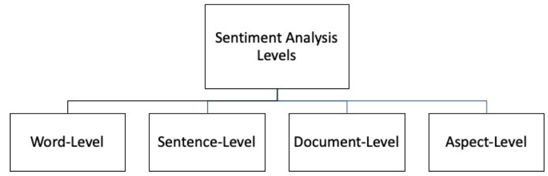

Fig. 2. Four Levels of sentiment analysis

Sentence level: Sentiment analysis at sentence level deals with an opinion expressed in each sentence within a document.It finds the polarity of each sentence as either positive, negative or neutral (no opinion). Subjectivity classification is closely related to this concept; it deals with categorising sentences as either subjective sentences or objective sentences. However, subjectivity is different from sentiment because some objective statement may imply opinions e.g. "I bought a new computer yesterday and the battery does not last long" [6].

Document Level: This is sometimes called a document-level sentiment classification. In document level, the whole contents of the document are summarized to a single opinion. Here, it is assumed that each document contains an opinion on a single entity, thus sentiment analysis at this level is not practicable for a document that contains an opinion on multiple entities [6].

Aspect level: This level of analysis is more difficult than sentence level and document level analysis. It is also called feature level or feature-based opinion mining and summarization [17]. This level identified that any opinion without targets is meaningless and then consider that each opinion contains a target and sentiment. Therefore, the aim of the aspect or entity level is to find sentiments on entities and/or their aspect. For example, the sentence The iPhones call quality is good, but its battery life is short it evaluates two aspects, call quality and battery life, of iPhone (entity). The sentiment on iPhones call quality is positive, but the sentiment on its battery life is negative. The call quality and battery life of iPhone are the opinion targets [6].

B. Sentiment Lexicon

Sentiment lexicon (lexical resource) is a dictionary of a lexical item with corresponding semantic orientation and it plays a significant role in sentiment analysis task. The lexical item conveys a single meaning and can be words (e.g. good and bad), word senses, phrases (I am over the moon, it arrived) and idiomatic expression. The semantic orientation can be in several forms such as words (positive, negative or neutral) and phrases (strongly positive, mildly positive and strongly negative). A specific range of values is also used to indicate a ranking of the sentiment strength. For example, using 1 to 5 ranking with 1 has least ranking strength and 5 has the highest ranking strength. In this scenario, 3 being the middle is considered neutral. The lexicons are created either manually or automatically [18].

1) Manual Generation of Sentiment Lexicon: In this approach, sentiment lexicons are created manually. It consists of using an existing dictionary or corpus and manually select a lexical item that have sentiment orientation. Thereafter, the lexical items are annotated manually with pre-defined sentiment strength, for example, 5-points sentiment strength (-2 to +2). This process has the advantage because humans rather than machine annotate each lexical item , it is accurate, but not perfect. Hence, sentiment analysis with this lexicon achieve better performance. However, this method has a drawback. It is time-consuming and daunting due to the inherent nature of manual activity involve. Therefore, they are limited to small coverage [18].

2) Automatic Generation of Sentiment Lexicon: In this approach, sentiment lexicon is generated from several approaches. Some approaches use a seed word from which other sentiment words are generated. Bootstrap approach is also use and ranks words based on a similarity measures [19]

C. Examples of Lexicon

Some of the widely adopted lexicons are briefly discussed in this section.

1) WordNet: This is an online English General lexical resource database. It contains adjectives, nouns and verbs group into synonyms set through semantic relation [20]

2) SentiWordNet: SentiWordNet is a lexical resource with a high level of coverage developed by SentinwoEsuli and Sebastiani [21]. Positive, negative and neutral are three sentiment orientation used for each synset. It was developed from the WordNet. In SentiWordNet, words may contain different meaning and therefore different polarity. For example, ”cold” may mean having a low temperature as in cold beer or without human warmth or emotion as in cold person. SentiWord uses glosses for each word entry to distinguish one from another [21].

3) WordNet-Affect: WordNet-Affect lexicon was created originally from WordNet synsets [22]. It consists of ”Affective Knowledge” which describes moods, feelings and attitude. WordNet-Affect is one of the widely use lexicons because it is not limited to single-word concepts.

4) SenticNet: The SenticNet is publicly available lexical resource for concept-level sentiment analysis. The lexicon includes both semantic and affective lexical unit. It provides over 30,000 multi-word expressions to enable fine-grain analysis of natural language opinion. It uses sentiment orientation between -1 and 1(-1 being extremely negative and +1 extremely positive) [23].

5) General Inquirer: This is a General Lexical system developed at Harvard for content analysis research in the behavioural sciences. The system uses two dictionaries: psycho-sociological dictionary and an anthropological dictionary used for studying themes in the folktales of many traditions and culture. The two dictionaries contain category of words. During sentence analysis, General Inquirer look-up these dictionaries and find in which category, the word belongs if it exists [24].

6) Bing Lius Opinion Lexicon: This is a freely available sentiment lexicon developed by Bin Liu. It consists of English opinion lexicon being developed continuously. The lexicon contains a list of positive and negative words close to 6800 [25].

III. Approaches to Sentiment Analysis

There are two basic approaches to use in sentiment analysis. Machine learning-based and Lexicon-based approach as shown in Fig. 3. The former is based on training corpora annotated with polarity information and the latter is based on using polarity of lexicons and it provides better accuracy . Until recently, a hybrid approach has been explored in [3] [11].

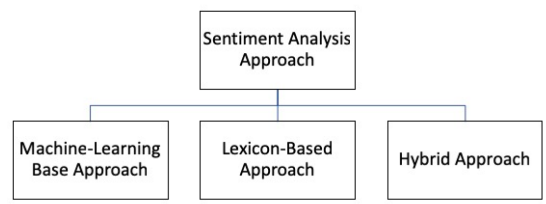

Fig. 3. Three approaches two sentiment analysis

A. Machine Learning Methods for Sentiment Analysis

Considerable research in sentiment analysis uses machine learning approach to perform sentiment classification. We briefly expound both the two approaches of supervised and unsupervised machine learning methods.

1) Supervised sentiment classification : Text classification has long been an existing research field and the task of sentiment classification is similar to the text classification. Text classification classifies text base on topics such as politics, religion and sports while sentiment classification classifies text to categories (classes) such as excellent, good neutral, bad and very bad. Some studies use numeric sentiment polarity values [7].

Similar to text classification method, supervised sentiment classification method uses a learning algorithm trained with sentiment-labelled data to classify an unseen document. The typical process of sentiment classification is shown in Fig. 4. First, standard text pre-processing, feature engineering and vector-space representation are applied to the training and test documents drawn from a problem domain. After that, a machine learning algorithm is employed to learn prediction model during a training phase. The model is then used in the testing phase to do classification (or regression) of unseen documents. One of the most important steps in the sentiment classification process outline is feature engineering. Feature engineering uses existing knowledge from the problem domain and thereafter create features that make machine learning more effective. feature engineering process involves three phases of activates: feature discovery, feature selection and feature weighting.

Previous research on sentiment analysis focus on using the standard machine learning algorithm Such as Naive Bayes,

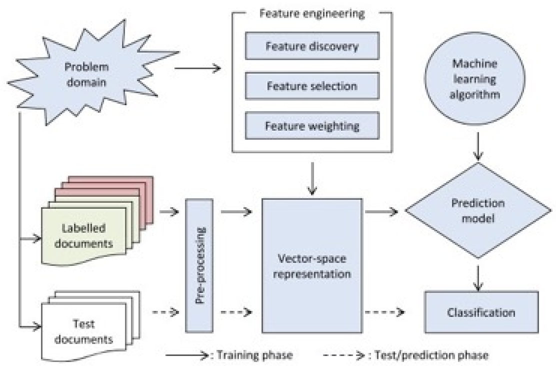

Fig. 4. Supervised sentiment classification method

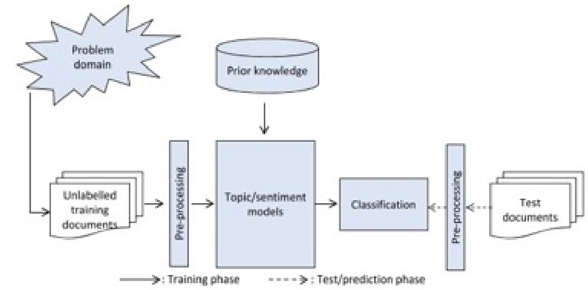

Fig. 5. Unsupervised sentiment classification method

Maximum Entropy and Support Vector Machine. One of the pioneer study that experiments the three techniques performance one sentiment analysis task [13] reported that standard machine learning techniques perform better than human-produced baselines. However, the three machine learning methods performed poorly on sentiment classification compare to traditional topic-based categorization. The sub-optimal performance indicates that sentiment classification task is more difficult than topic classification. This is because the topic can be easily identifying by keyword alone while sentiment can be expressed in a subtler manner. For instance, How could anyone sit through this movie? contains no single word that is obviously negative. Hence fine-grain analysis is required with sentiment classification.

Recently, dedicated methods for sentiment classification has been developed to improve accuracy. One of the techniques developed use score function [14]. The approach starts by training a classifier using a corpus of self-tagged reviews drawn from websites. Thereafter, the same corpus is then employed to improve their classifier before applying it to sentences obtain from web searches. Authors experimental result accuracy conducted with same data outperforms the traditional machine learning algorithms approaches

2) Unsupervised sentiment classification : The unsupervised sentiment classification process is shown in Fig. 5. At the training phase, unlabeled documents are pre-processed and a probabilistic topic modelling methods are employed to detect both topic and sentiment. Prior knowledge in the form of seed sentiment-bearing terms is required to guide the process. Thereafter, the sentiment class of a text document can be determined based on the topic used to compose the document. Standard topic modelling approaches assume a three-layered hierarchical framework, where topics are associated with documents, and words are associated with topics. For sentiment detection, this framework is extended with an additional sentiment layer in between documents and topics or with sentiment classes as an additional topic model [26].

One of the pioneering unsupervised learning methods was proposed by Turney [13]. It is a simple unsupervised learning algorithm that classifies reviews base on the average semantic orientation of the phrases that contain adjectives and verbs. It classifies review as recommended if positive and not recommended if negative. The machine learning-based approach accuracy for sentiment is not up to the mark compared to the lexicon-based approach.

B. Lexicon-based approach (Linguistic Approach)

The lexicon-based sentiment analysis approach is sometimes referred to as corpus-based lexicon approach if it uses lexicons that are generated from corpus or dictionary-based approach if the lexicon is generated from a dictionary. Its workflow is shown in Fig. **??**. The first step is the creation of sentiment lexicon or adoption of an existing one (which is mostly the case by many researchers). The next step is to pre-process the document to be classified and each word in the document is assigned the corresponding prior polarity from the sentiment lexicon. Finally, the prior polarities are adjusted to reflect contextual polarities (contextual analysis) and sum-up to find the sentiment orientation of the document. The sentiment orientation of the document is classified as either positive if the sum is positive or negative if the sum is negative and neutral if the final sum is 0. Variation of this exist and the difference is mainly based on what value is assigned to sentiment words in sentiment lexicon, how negation is handled etc. with the rapid increase of automatic generation of the domain-specific lexicon, the lexicon-based approach is now leverage to provide better accuracy [27].

IV. Hybrid Approach

Until recently, a hybrid approach for sentiment analysis has been explored by researchers. They combine the strength of sentiment analysis approach for optimal accuracy. In their work [28], they leverage the strength of rule-based classification and supervised learning . The combined approach achieved higher accuracy when experiments on movie reviews, product reviews and Myspace comments. In [3], they perform Twitter sentiment analysis with a combination of lexicon-based approach and trained classifier. They claimed their result performs better than state-of-the-art baseline.

V. Domain Specific Lexicon-based Approach

This approach appeared in literature with a different name such as; *Domain-dependent, Context-dependent, Domain-Specific, Domain-Oriented, Domain-based and Target specific*.

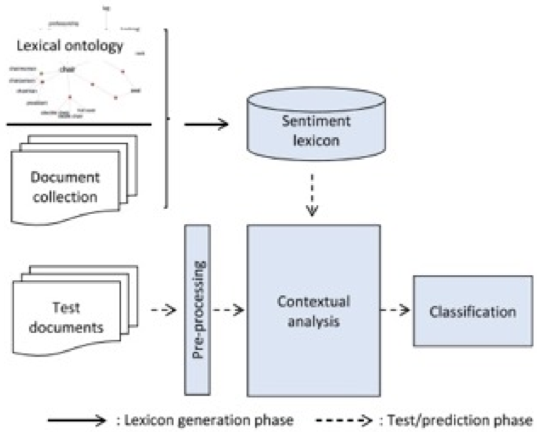

Fig. 6. Lexicon-based method for sentiment analysis

The performance of Lexicon-based approach over machine learning approach depends on the type of sentiment-lexicon is used. The lexicons are categories into two sub-classes based on their coverage [10].

A. General Purpose Lexicon

These are lexicons develop and use in sentiment analysis without any relation between the domain in question and the lexicon; they are nonspecific and can be used to find an opinion across domains such as a movie, social media, health and government. However, with the advantage of wide coverage, the lexicon losses accuracy in sentiment analysis because sentiment words are often domain-dependent [28]. This is the inherent challenge associated with general purpose sentiment lexicon: a single word, in one domain, may contain positive polarity and at the same time contain negative polarity in another domain. Hence, the choice of word orientation is define by the context in which the word is used. For example, the word suck appears to have both negative and positive orientation in the following sentence: *"the camera we bought sucks,"* this is a negative statement, but it can be used as a positive statement as in *"The vacuum cleaner we bought really sucks"*.

To exacerbate the situation, sentiment lexicons sometimes have different sentiment orientation in the same domain. This makes the task of sentiment analysis even more harder. For example, in camera domain, the word "long" have a different orientation in the following sentences. *"The battery life is long and It takes a long time to focus"*. The first sentence indicates positive opinion while the latter indicates negative opinion [24]. Consequently, several researchers now used to use the domain-specific lexicon for better accuracy.

B. Domain-Specific Lexicon

Alternative to general-purpose lexicon, domain-specific lexicon are developed. They are generated from general purpose lexicon or a new one is generated from scratch. The lexicon-based sentiment analysis approach performance reaches an optimal expectation when domain-specific lexicon is leverage. On the other hand, it gives sub-optimal when general purpose lexicon is leverage. However, manual generation of the domain-specific lexicon for each domain is a laborious and mind-numbing task. To this effect, automatic methods for domain-specific has been explored [12], [31], [32] .

In [12], domain-specific lexicon from movie review corpora is automatically created and experimental results performance shows improvement over the manually created sentiment lexicons. Their method involves two steps, They first generate corpus-based lexicon, each sentiment-bearing word is labelled with both positive or negative and polarity weight. Secondly, the lexicon is used in sentiment classification which shows improvement. The advantage of their approach is being domain agnostic and therefore very useful in creating domain-specific lexicons in many domains.

In the same way [29] proposed an approach for generating domain-specific lexicon through double propagation. Firstly, the technique uses a seed word to extract sentiment-bearing words and features. The extracted lexical items are then used iteratively to find new sentiment word and features until sentiment-bearing words are exhausted. They also proposed a method that assign polarity level to the sentiment words identified during sentiment extraction. Both proposed approaches provide satisfactory performance.

The study [11] devised a novel approach that exploits the idea of context coherency to automatically build a domain-focused lexicon for sentiment analysis. The context coherency is a phenomenon in which explain that same polarity seems to always appear adjacent within context. The reported accuracy of this approach is 94% and proved to be effective and can be easily adopted in a different domain

A recent study [30] introduced a new domain-specific generation method from unlabelled review data. This approach is divided into two part, the first task is labelling the training reviews with polar values (negative and positive) and lexical unit with the higher ranking score are selected and used as training data. The second task uses the selected training data to obtain new domain-focused sentiment lexicon. The approach offered better performance when compared with other domain-specific lexicon base approach that uses SentMI and SenProf lexicon

VI. Conclusion

We discussed an overview of sentiment analysis in this paper. It is a sub-field of natural language processing that find an opinion on human written text. It has been employ in different areas such as business and government. At a basic level, there are two approaches to perform sentiment analysis.Machine learning-based approach and lexicon-based approach. Until recently, a hybrid approach has been explored that combine the strengths of two or more methods. The lexicon-based approach performance has been shown to outperform machine-learning approach mainly when the domain specific lexicon-based approach are employed. But, creating the domain-specific lexicon is a tedious and boring task. Therefore, novel approaches for automatic construction of domain-specific lexicon methods has been explored from recent literature.

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