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Tweet Sentiment Polarity Detection Based on Semantic Similarity

Sanaa Hammad Dhahi and Jumana Waleed

Department of Computer Science – College of Science – University of Diyala, Iraq

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ORCID: https://orcid.org/0000-0001-6125-3501

Email: sanaahammad@uodiyala.edu.iq

Abstract

Nowadays, social networks such as Twitter or Facebook become a robust means of learning about the users' opinions and share their emotions towards specific subjects in a form of comments, to analysis these emotions sentiment analysis process is applied, which is used to discover the opinions of people on social media sites. It focuses on detection the polarity (positive, negative, or neutral). In recent years, it has been demonstrated that deep learning models are promising solution to the challenges of natural language processing (NLP). This study is devoted to apply semantic similarity approach for sentiment classification in addition to use lexical approach and Bag-of-Words model to perform a comparison among them. For examining the performance, precision, recall, accuracy, and F1 scores measurements with two datasets (STS-Test & SS-Tweet) for testing and sentiment140 for training have been used. The experimental results show the accuracy of the proposed approach about 81.0%.

Keywords: Sentiment Analysis (SA), Doc2Vec, Semantic Similarity, deep learning.

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تحديد قطبية المشاعر في تويتر بناءً على التشابه الدلالي

سناء حماد ضاحي وجمانة وليد

قسم علوم الحاسوب – كلية العلوم – جامعة ديالى، العراق

الخلاصة

في الوقت الحاضر، أصبحت الشبكات الاجتماعية مثل Twitter أو Facebook وسيلة قوية للتعرف على آراء المستخدمين ومشاركة عواطفهم تجاه مواضيع محددة في شكل تعليقات، لتحليل هذه المشاعر يتم تطبيق عملية تحليل المشاعر، والتي تستخدم لاكتشاف آراء الناس على مواقع التواصل الاجتماعي وتركز على الكشف عن القطبية (إيجابية، سلبية، أو محايدة) في السنوات الأخيرة، تم إثبات أن نماذج التعلم العميق هي حل واعد لتحديات معالجة اللغة الطبيعية. يدرس هذا البحث القدرة على تطبيق منهج التشابه الدلالي لمهمة تصنيف المشاعر بالإضافة إلى استخدام المنهج المعجمي ونموذج حقيبة الكلمات لإجراء مقارنة بينهما. لفحص الأداء، تم استخدام قياسات الدقة والتذكر والدقة ونتائج F1 مع مجموعتي بيانات (STS-Test و SS-Tweet) للاختبار وsentiment140 للتدريب. أظهرت النتائج التجريبية إن دقة المنهج المقترح هي 81.0%.

الكلمات المفتاحية: تحليل المشاعر، Doc2Vec ، التشابه الدلالي، التعلم العميق.

Introduction

In recent years, sentiment analysis plays an increasingly important role in natural language processing. Governments, corporations and agents benefit from huge online resources of opinions such as reviewing sites and personal blogs where this information analyzed and opinions are explored. The fundamental goal of emotion categorization is to explore texts online (reviews, blogs, comments, etc.) if they contain positive or negative emotions [1]. Sentiment analysis deals with revealing thoughts, emotions, and opinions. It is commonly used to understand natural language processing. The primary goal is to define people's thoughts on a specific topic or to determine the full polarity of a text (document) [2]. This means that the sentiment analysis is used to extract and retrieve information from raw, unstructured data and then present it as a judgment or evaluation and consider any type of sentiment [3]. The researchers classify the topic of SA into three levels as document, sentence, and aspect levels. Document- level aims to determine whether an entire document carry positive, negative, or neutral opinion, sentence level- aim to determine the polarity of each sentence separately, assuming that each sentence has only one opinion about one entity and aspect level is performing more realistic analysis than document and sentence levels based on the supposition that opinion consists of feelings and aim [2]. Further, the emotions that are expressed about those entities are determined. For example, "Even though the service is not good, I still love the food"; Here, "service" and "food" are the entities on which an opinion is expressed. If the aspect-based SA approach is used the model identifies the entities and then determines the opinions regarding these entities. This method is also referred to as feature-level opinion mining as well [4].

Sentiment analysis is used primarily in different fields such as:

a**)** In the marketing field: The corporations used SA to improve marketing strategies and better understanding to customer opinions about the products. Also, it's possibly identify the responding to the campaigns or product launches, the opinion about the brand and the reasons why customers are reluctant to purchase products [5].

b) In the field of politics: It is utilized to review the political opinions and discover the consistency and inconsistency of the political statements and actions. Also it used for the prediction of the election results [5].

c) Sentiment analysis also is used to track and analyze social phenomena, for the spotting of potentially dangerous circumstances and identifying the overall attitude of the blogosphere [5].

d) Healthcare: There are many medical blogs on the internet. These blogs deal with medical information and health-care topics like types of diseases, treatments, and medications. As a result of the health-related experiences and medical histories these blogs provide for both patients and practitioners, sentiment analysis tools must be expanded to use it in the medical fields [6].

e) Decision making: One of the important fields which SA can be used is decision making systems. In the field of financial investment, many news, blogs, articles and tweets on every

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public company which SA can use them as a huge resource to explore the articles discussing companies and overall the sentiments that are related to them as a single score which may be utilized by an automated trading system. An example of this type of system is Stock Sonar [7].
f) The government agencies can discover general people's opinions and concerns by watching social media, where the people can express their opinions about government policies, expose corruption and other violations of government officials. Moreover, it considers as a fast and popular way to report any bad attitude in society [8].

Literature Review

Many researchers have been done to deal with sentiment analysis, to deal with the problem associated with NLP some of them use semantic similarity concepts in SA which can improve the results of the tweets classification, and others employ different techniques to classification positive and negative opinion from the text. Here is a review of a number of these works.
Hassan Saif, Yulan He and Harith Alani [9]:They proposed a method in which semantic concepts are extracted from named entity tagger tools and using this feature as an additional feature into a training dataset for SA. The main idea of this method is that the specific entities and concepts are played an important role in sentiment which tends to have a more robust correlation with positive or negative sentiments, even if those entities never appeared in the training set then knowing these correlations helps to decide the sentiment of semantically relevant entities. The experimental results show that an average increase of F harmonic accuracy score of identifying both negative and positive sentiment of around 6.5% and 4.8% over the baselines of unigram and part of speech features respectively.Geetika Gautam and Divakar yadav [10]: They present a semantic WordNet synonym analysis approach of SA in twitter dataset. This method depend on examining semantic synonym similarity between training datasets and words in the testing, when it is found this similarity, it will replace the words in the testing dataset with their synonyms in the training dataset. The experimental results show that the naïve byes technique which gives us a better result 88.2 than the maximum entropy 83.8 and support vector machine is being subjected to unigram model which gives 85.5

a better result than using it alone. Further the accuracy is again improved when the semantic analysis WordNet is followed up by the above procedure taking it to 89.9% from 88.2%.

Brett Duncan and Yanqing Zhang [11]: They used a feed forward neural network to categorize feelings that was experimented with for sentiment analysis of tweets. The training set of tweets are collected using the Twitter API using positive and negative keywords. The testing set of tweets are collected using the same positive and negative keywords. The accuracy average (the number of properly categorized tweets divided by the number of improperly categorized tweets) was 74.15%.

Metin Bilgin and Izzet Fatih Senturk [12]: They perform SA on English and Turkish Twitter messages using Doc2Vec Two different versions of the Doc2Vec algorithm (DM) and (DBOW) are used Doc2Vec algorithm was run on Positive, Negative and Neutral tagged data using the Semi-Supervised learning method. The accuracy of DM and DBOW on the Turkish dataset is 0.44 and 0.46 respectively, while their accuracy on the English dataset is 0.62 and 0.63 respectively.

Jun Qian, Zhendong and Chongyang Shi [13]: They propose a method modeling text based on deep learning approach, which can automatically extract text feature. As for word vector representation, we incorporate linguistic knowledge into word representation, and use three different word representations in our model. The performance of the sentiment analysis system shows that our method is an efficient way analyzing user's sentiment on weather events.

Sahar Sohangir, Dingding Wang, Anna Pomeranets and Taghi M. Khoshgoftaar [14]: They seek for determining whether deep learning models can be adapted to improve sentiment analysis performance for StockTwits. They apply some of neural network (NN)models such as long-term memory, doc2vec, and convolutional neural networks. The results show that a deep learning model can be used effectively to analyze financial sentiment and that the convolutional neural network is the best model for predicting authors' emotions in the StockTwits dataset. The performance of the convolutional neural network on the StockTwits dataset is 0.9897 compare to Deep Learning models CNN in financial sentiment analysis((10,000 steps) is 0.9093.

Anton Barhan, Andrey Shakhomirov and Saint-Peterburg [15]: They proposed up a model which can extract from Twitter data the sentiment polarity of tweets. The features extracted were words containing emotional symbols and n-gram. The results show that the Support Vector Machine (SVM) performance is better than the Naïve Bayes (NB). SVM in combination with unigram feature extraction is the best performing method, which obtaining a precision of 81% and a recall of 74%.

Ahmed Sulaiman, M Alharbi and Elise Doncker de [16]: They used a traditional machine learning (SVM and NB) and deep learning-based models (LSTM, CNN, and MLP). The performance of these models on the HCR dataset is lower compared to their performance on the SemEval dataset. The accuracy of SVM and NB on the SemEval dataset is 84.93% and 86.19%, respectively, while their accuracy on the HCR dataset is 77.78% and 77.21%, respectively. On the SemEval dataset, LSTM and CNN attain 88.69% and 87.35% in accuracy, respectively. Conversely, they produce a low accuracy score, 76.14%, on the HCR dataset.

Nhan Cach Dang, María N. Moreno-García and Fernando De la Prieta [17]: They performed a comparative study of the performance of the three most popular deep learning models (DNN, CNN, and RNN) on eight datasets with two text processing techniques (TFIDF and word embedding), these algorithms were applied to predict the sentiment polarity of the text and classify it according to that polarity. The experimental result shows that the accuracy of Sentiment140 dataset with TF-IDF feature and DNN, CNN and RNN model are (0.764, 0.766 and 0.569), with word embedding feature are (0.788,0.800 and 0.828) respectively Tweets Airlines with TF-IDF feature are (0.859,0.854 and 0.828) with word embedding feature are (0.897,0.903 and 0.904) Tweets SemEval with TF-IDF feature (0.836, 0.813 and 0.548) with word embedding feature are (0.836,0.843 and 0.851). IMDB movie reviews (1) with TF-IDF feature are (0.852.0.823 and 0.563) with embedding feature are (0.845,0.860 and 0.870) IMDB movie reviews (2) with TF-IDF feature are (0.855,0.806 and 0.587) with embedding feature are (0.802,0.826 and 0.866). Cornel movie reviews with TF-IDF feature are (0.704, 0.678 and

0.507) with embedding feature are (0.702,0.213 and 0.766). Book reviews with TF-IDF feature are (0.758,0.727 and 0.516) with embedding feature are (0.745, 0.766 and 0.733) Music reviews with TF-IDF feature are (0.768,0.692 and 0.517) with embedding feature are (0.708,0.744 and 0.731).

Sentiment Analysis Methods

1. Bag of Words (BOW) Model

In this model, the text is converted into a bag of words as each entry matchs to the number of occurrences of a specific term in the sentence. The attribute matrix is constructed with dimensions' m * n where m is the number of sentences and n is the number of unique words in the group [18]. Therefore, a group of tweets can be represented as shown in Table 1, in which there are n tweets and m terms [2] Each tweet is represented as tweet $_i$ = (a_{i1}, a_{i2}, …, a_{im}), where aij is the frequency of term t_j in the tweet$_i$ This value can be calculated in various ways [19].

	T_1	T_2	…	T_M
tweet$_1$	a_{11}	a_{12}	…	a_{1m}
tweet$_1$	a_{21}	a_{22}	…	a_{2m}
…	…	…	…	…
tweet $_n$	a_{n1}	a_{n2}	…	a_{nm}

Table 1: Representation of tweets.

2. Lexical Method

Lexical method approach usually uses a dictionary or glossary of pre tagged words. Every word in the text is compared to the dictionary. If there is a word in the dictionary, a polar value is added to the text's "polarity score". For example, if a match is found with the word "excellent", which is indicated in the dictionary as positive, the total polarity score of the blog will be increased. If the total polarity of the text is positive, then this text is described as positive, otherwise it is negative [20].

3. Document to Vector (Doc2Vec) Model

In some references Doc2Vec is referred to as Paragraph2Vec. which is a modified version of the Word2Vec method that building a vector by carrying words in a spatial manner [21,22,23]. The only modification made according to the Word2Vec algorithm is addition of a document ID, as shown in figures 1 and 2.

$$\frac{1}{T}\sum_{i=k}^{T=-k}\log p\left(w_i \,\middle|\, w_{t-k}, \ldots, w_{i+k}\right) \quad (1)$$

Eq. 1 gives the sequence of w1, w2,, wT training words.

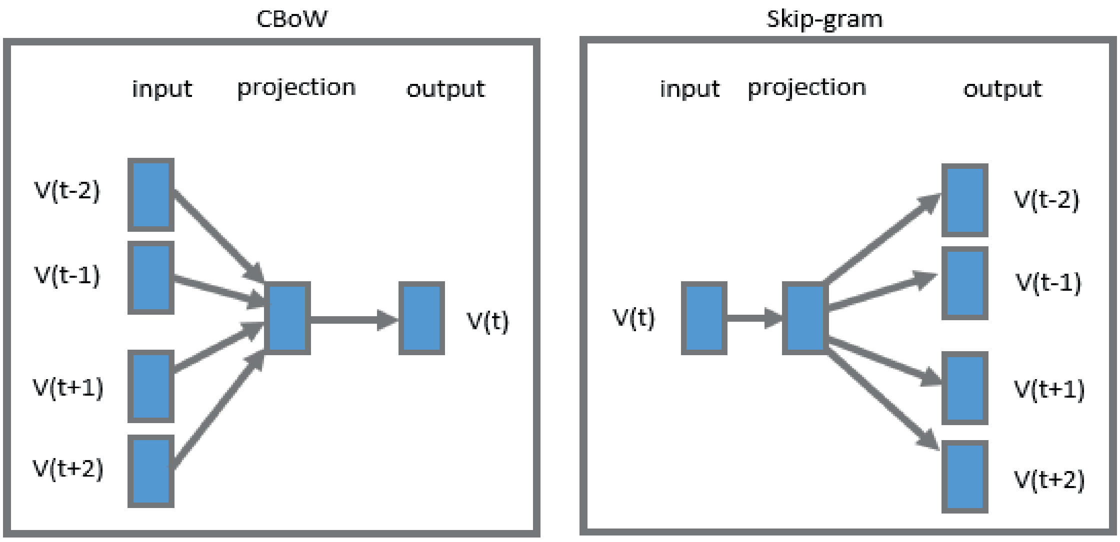

Figure 1: Word2Vec (CBOW and Skip-gram)

There are two different methods in the Word2Vec algorithm: Continuous bag of words (CBoW) and Skip-Gram (SG). These methods have been configured for Doc2Vec and have been translated into two methods: Distributed Memory (DM) and Distributed bag of words (DBoW).

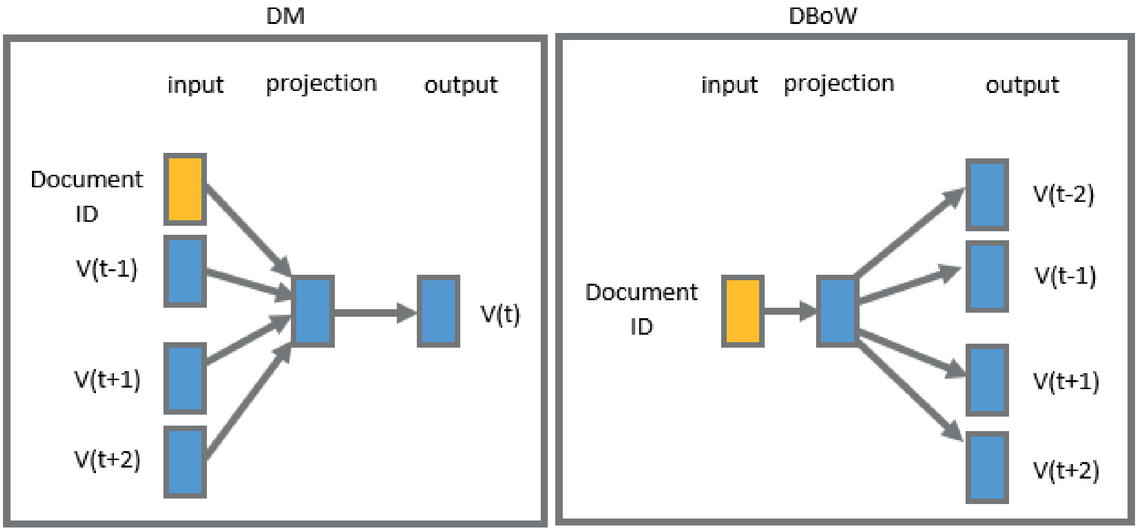

Figure 2: Doc2Vec (DM and DBoW)

The proposed methodology

1. Preparing Label

Preparing label shows a particular tweet class. The labeling process is a crucial part of data preprocessing in this approach, although it is considered simple. The training set of the proposed model is based on tweets texts with pre-identified two targets (Positive/Negative). In this process, each tweet with a positive target mapping to a label = 1 and with a negative target to a label = -1. This mapping is an essential part of computing the semantic similarity feature that used through algorithms.

2. Pre-Processing

Although tweets are limited to 140 characters, it has a frequency of slang, misspellings, emoticons, and special symbol much higher than in reviews. Therefore, Pre-processing used to ensure the validity of the texts of the tweets to improve performance relevant to sentiment classification. This phase involves several steps which are as follows:

1) Tweet's words simplifications aspect:

• Lowercasing the tweet text.

• Substituting multiple spaces with a single space.

• Slang and acronyms are handling by substituting or expanded to their original words based on external resources (Internet Slang Dict). In general, the user tends to used slang words to save keystrokes and tweet-length. Each slang or acronym token refers to an explanation. For example, "121" is "one to one", "lol" is "online love".

• Simplifying negative mentions. It is a process of replacing acronyms of negation to standards tokens such as "can't", "won't" into "cannot", "will not".

• Reverting words with repeated characters, which are commonly used in tweets, e.g. "looooooove" into English words with the fewest characters. This process returns the original word "love" based on wordnet.

2) Tweet's noise removing aspect:

• Remove digits and numerals. Based on the assumption that all the content the user writes in the Tweet has a purpose. In general, numbers are used to support user opinion and can classify as objective content. In general, numbers are removed from tweets with detection sentiment tasks.

• Remove stop words. Although, stop words have a role in completing the meaning of a sentence but they lead to low performance of classifiers. Based on a specific list of words, the tokens are removed from tweet text. This method assumes that these words can be indicators that reflect a certain type of user’s feelings towards a specific topic.

• Remove punctuation marks and special characters. The assumption with the stop words, it also extends to punctuation marks and special characters. Where excluded the exclamation mark "!" and question mark "؟" and @ at the start of words and URLs from removing.

3) Tweet's content handling aspect:

• Tagging / Tokenization was performed using the Stanford1 NLP Part-Of-Speech Tagger, it a tool can tag the parts of speech in a tweet. (https://nlp.stanford.edu/software/tagger.shtml).

• Lemmatize and stemming both are used for reducing variants word (lemma, stem) forms, except stem may generate a word that doesn’t exist in the dictionary, unlike lemma which can be found a word in the dictionary. Therefore, stemming may not be useful in the NLP application. This method adopts Lemmatize instead of the stemming algorithm. Because it used SentiWordNet from NLTK library as a knowledge base to found the sentiments score or polarity of tweet's words. And the SentiWordNet relies on WordNet (English dictionary). As a result, SentiWordNet may not recognize too many stems or forms of words that result from the stemming.

• Negation handling represents an essential step, and it also a challenge to approaches for specifying sentiment polarity that adopt a supervised ML. The negation can reflect the polarity of tweets as in ("Um...Bobby Jindal (& Scott Walker) don't love America or its Constitution--particularly the 14th Amend"). Thus, it can constitute a weakness in the classifier's performance. Algorithm 1 illustrates the handling of negation.

Algorithm 1: Anti - Negation algorithm

```
Input: Tweet, WordNet, negation list
Output: updated tweet
Parameter: wi = individual words,n= length of tweet
Begin:
Word_tokenize [] = w1, w2, …..wn
For each word wi in tweet do
if wi in negation_list then
retrieve next Adj word wi+1
end
if wi== ' not ' then
retrieve next word wi+1
retrieve synonym = syn (wi+1)
generate antonym = ant (wi+1)
replace ' not ' = ant (wi+1)
remove wi+1
end
End
```

A technique is used to process negation in texts as sub-tasks with SA. This technique deals with the negation words in two aspects. First, it adopts a method of handling negation based on antonyms of adjectives. Second, the negation words consider as features. Briefly, when appears any word of a tweet that belongs to the negation list. Searches for the first adjective that appears after negation word direct. If found, replace the word (adjective) by antonyms based on WordNet and remove the negation word. And if there is no adjective after the negation word, then it is counted (increase negation counter) to use as one of the features.

3. Semantic similarity computation

In this paper, the suggested approach works on determining the impact of semantic similarity to represent the texts of the tweets for sentiment analysis. It is a value of the average of two highest semantic similarity scores of tweets under processing with rest corpus tweets multiply by these labels values (1, -1). This proposed approach exploits the Doc2Vec cosine similarity score to determine the maximum semantic similarity score, then multiply by the label value (1, -1) of the tweet has max similarity from corpus tweets. To encompass subjective sentiment information with semantic similarity into the suggested model, using the equations described below:

$$\mathbf{Semsim} = (\max[_i^n \mathrm{Sim}(\mathrm{tweet}\ T_i)]) \times T_i.\mathrm{Label} \quad (2)$$

$$\mathbf{Semantic\ similarity\ feature} = \frac{\sum_{j=1}^{2} \mathrm{Semsim}_j}{2}$$

$$= \frac{\left(\sum_1^2 (\max[_i^n Sim(tweet.T_i)]) \times T_i.Label\right)}{2} \quad (3)$$

Eq.2 finds (Semsim) the max value of similarity (sim) of the tweet under process and the rest corpus tweets (Ti), then multiply by the corresponding label value of tweets has high similar score every time. While Eq. 3 finds the final value of the semantic similarity feature, it computes the average of the two highest values. This methodology takes into account the possibility of similar the tweet's content to more one tweets have different sentiment polarity (positive and negative), due to the negation words and different styles of writing among users. Therefore, the system proposes a type of normalization through Eq.3.

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Experimental result

Two datasets are used in the evaluation of this paper. Table 2 shows the dataset's statistics. The Stanford Twitter sentiment corpus presented by [24], a corpus contains two different sets. Sentiment140 is a training set, it contains 1,600,000 tweets extracted from Twitter and automatically labeled in positive and negative sentiments based on the emoticons expressing. And test set (STS-Test), it is an unbalanced label contains 498 tweets distributed in 139 neutrals, 177 negatives, and 182 positive tweets. STS-Test is manually annotated. In this proposed approach, a subset from Sentiment140 include 20000 tweets with a balanced label are used, and 139 tweets with neutrals label are ignored. The rest are used in the evaluation process.

Sentiment Strength Twitter Dataset (SS-Tweet) introduced by [25]. SS-Tweet is a tweet dataset manually labeled; it includes 4,242 tweets. Each item in SS-Tweet consists of tweet's text and the values of sentiment strengths of positive and negative. i.e., number between 1 (not positive) and 5 (extremely positive), while the -1 (not negative) and -5 (extremely negative). This technique doing a preparing label to tweets of the dataset with positive and negative labels rather than sentiment strengths. To allow using this dataset for sentiment polarity classification. Only removing all tweets with equal values of positive and negative sentiment strengths. The final dataset consists of 1333 positive and 945 negative tweets.

Table 2: Types of the dataset using in the proposed approach

DATASET	NUMBER OF TWEETS	LABEL OF TWEETS	
		Positive	Negative
Sentiment140	20.000	10.000	10.000
STS-Test	498	182	177
SS-Tweet	4,242	1333	945

Evaluation

The fundamental evaluation in this paper is sought whether the polarity of tweets detected by the proposed methodology corresponds with the ones that were manually annotated. The detection accuracy that used here, adopts the confusion matrix for summarizing the results. The detection performance determines by computing the number of correct and incorrect classification for the positive and negative polarity of each tweet. In order to compare the performance, this work has used three different techniques. In addition to the proposed technique which adopts semantic similarity, it uses lexical approach and Bag-of-Words model in a sentiment classification task. For examining the performance used the precision, recall, accuracy, and F1 scores measurements.

Discussion

The paper's strategy for evaluation is to performed polarity detection tests on complete tweets of two datasets (STS-Test & SS-Tweet). While the third datasets (Sentiment140) is used in the word embedding approach, where the Doc2vec classifier is trained to find similar meaning between words. This work applied the Naive Bayes classifier as machine learning algorithms within the BOW model. Table 3. and Table 4. show the performance results of the tweets polarity detection experiments for the STS-Test dataset and the SS- Tweet dataset respectively, for each of the three techniques. While Table 5 displays the confusion matrix, that summarizes the predictions that correct and incorrect for both the positive and negative polarity of tweets for the proposed approach.

Table 3: Performance results of the tweets polarity detection for STS-Test dataset.

TECHNIQUE	LABEL	PRECISION	RECALL	F1	ACCURACY
Proposed Approach (used Semantic Similarity)	N	0.79	0.82	0.81	**0.81**
	P	0.82	0.78	0.8	
BOW	N	0.85	0.70	0.77	0.78
	P	0.72	0.86	0.79	
Lexical Approach	N	0.63	0.72	0.68	0.66
	P	0.69	0.59	0.64	

Table 4: Performance results of the tweets polarity detection for SS-Tweet dataset.

TECHNIQUE	LABEL	PRECISION	RECALL	F1	ACCURACY
Proposed Approach (used Semantic Similarity)	N	0.63	0.78	0.69	**0.72**
	P	0.81	0.67	0.73	
BOW	N	0.55	0.79	0.65	0.64
	P	0.77	0.53	0.63	
Lexical Approach	N	0.53	0.69	0.60	0.62
	P	0.72	0.57	0.64	

Table 5: Confusion matrix of the tweet's polarity detection result for the STS-Test & SS-Tweet datasets.

DATASET	LABEL	N	P
STS-Test	N	149	31
	P	93	143
SS-Tweet	N	734	211
	P	438	895

The work's objective from these experiments to help in understanding the impact and evaluate the semantic similarity, specifically deep learning adopted by this paper compared to conventional techniques used to detect sentiment polarity automatically with twitter texts.

As seen in Tables 3 and 4 The proposed paper's method used a technique to finds the semantic similarity value based on the doc2vec model with manually labeled values of tweets for sentiment polarity detection with independent domains. The paper's method shows the highest results compared to other conventional methods.

Although, the lexical approach is simple where no require any type of learning. But it needs powerful resources of linguistic (e.g., vocabulary, synonyms, emotional and slang dictionary). That can be explained the degradation in results.

On the other side, the BOW considers is a simple model and effective computation representation for raw texts. It facing many issues such as the high dimensions and a sparse matrix, vocabulary size when new words come. The BOW also shares lexical techniques the deteriorate in address the synonyms and open domain (which is what the paper would like to avoid it through semantic similarity). In general, the semantic similarity contributes to improving the sentiment polarity detection through it overcomes some problems with previous traditional techniques such as synonyms.

Conclusions

This paper proposed an approach that uses the semantic similarity values based on embedding representation and manually labeled values of tweets for sentiment polarity detection. Experimental results present that the approach gives better performance than some traditional techniques. From the obtained results, it can be noticed that the effect of semantic similarity distance is improved the detection performance. It's able to better detect sentiments polarity from a dictionary and BOW techniques.

The main disadvantage that may be indicated in the proposed approach the vocabulary size, which may explain the disparity between the accuracy of the results (82,72) for different datasets (STS-Test & SS-Tweet) respectively.

This weakness can be treated as future work, by combining the proposed approach with a lexical approach, through using external resources it represents a vocabulary of a language such as WordNet for the English language. When a new word comes out and is not found in the corpus, will be searched in external resources (WordNet) for the close word to it in the corpus. Then, compute semantic similarity.

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