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Sentiment classification with the BERT procedure based on deep learning

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ABSTRACT

The need for Sentiment classification is a critical step in determining how people feel about a product, service, or issue. To solve the sentiment categorization problem, many natural language processing models have been developed. The majority of them, however, have concentrated on binary sentiment categorization. In this study, we tackle the fine-grained sentiment categorization task using BERT, a powerful deep learning model. Experiments show that without complicated architecture, our model outperforms other popular models in this job. In the process, we also demonstrate the utility of transfer learning in natural language processing.

Keywords: *Sentiment Classification, Natural Language Processing, Deep Learning*

1. INTRODUCTION

The Sentiment classification is a type of text classification in which a piece of text is assigned to one of several predetermined sentiment categories. It's a challenge of supervised machine learning. Positive and negative sentiment are the two available classes in binary sentiment categorization. There are five classes in fine-grained sentiment classification (very negative, negative, neutral, positive, and very positive).

The input to the sentiment classification model, like any other machine learning model, must be a fixed-size vector of numbers. As a result, we must convert a text—a sequence of words encoded in ASCII or Unicode—into a fixedsized vector that contains the text's relevant information. For this purpose, many statistical and deep learning NLP models have been proposed. There has been a recent surge in the development of NLP and other deep learning architectures.

While transfer learning (pretraining and finetuning) has become the industry standard in computer vision, NLP has yet to completely embrace the concept. The transfer learning revolution in NLP has begun with neural language models like as word vectors [1], paragraph vectors [2], and GloVe [3]. BERT (Bidirectional Encoder Representations from Transformers) [4], a deep bidirectional language model based on the Transformer architecture [5], was recently published by Google researchers, and it enhanced the state-of-the-art in several popular NLP tasks.

2. RELATED WORK

Sentiment classification is one of the most prominent NLP problems, and as a result, there has been a lot of research and advancement in accurately handling this task. The majority of the algorithms have concentrated on binary sentiment classification, owing to the availability of huge public datasets such as the IMDb movie review dataset [6]. Only a few significant deep learning NLP methods used to sentiment categorization are discussed in this section.

The embedding process converts a text into a fixed-size vector, which is the first stage in sentiment classification. Researchers first faced the difficulty of learning word embeddings since the amount of terms in the lexicon after tokenization and stemming is restricted. Mikolov et al. [1] proposed the first promising language model. They used enormous amounts of unlabeled text to train continuous semantic representations of words that could be fine-tuned for downstream tasks. To learn semantic word embeddings effectively, Pennington et al. [3] employed a co-occurrence matrix and exclusively trained on nonzero entries. For a lower vocabulary size and faster training, Bojanowski et al. [7] split words into character n-grams.

Next, a variable number of word vectors are combined into a single fixed-size document vector. Taking the total or the average is a simple method, but it loses the ordering information of words and hence produces poor results. By exploiting the innate tree structure of natural language phrases, Tai et al. [8] employed recursive neural networks to generate vector representations of sentences. For enhanced interaction between child nodes in recursive networks, Socher et al. [9] presented a tensor-based compositionality function. The Stanford Sentiment Treebank (SST) dataset was also introduced for fine-grained sentiment classification. Tai et al. [10] used several types of long short-term memory (LSTM) networks to classify sentiment, while Kim [11] used convolutional neural networks (CNN).

All of the methods described above are context-free, in the sense that they generate a single word embedding for each word in the lexicon. "Bank" is represented similarly in "bank deposit" and "river bank," for example. Contextual embeddings have been the subject of recent language model research. From a left-to-right and right-to-left LSTM-based language model, Peters et al. [12] retrieved context-sensitive characteristics. To train deep bidirectional representations from unlabeled texts, Devlin et al. [4] presented BERT (Bidirectional Encoder Representations from Transformers), an attention-based Transformer architecture [5]. Because it is not reliant on sequential or recurrent connections, their design not only achieves state-of-the-art outcomes on many NLP tasks, but also allows for a significant degree of parallelism.

3. METHODOLOGY

Sentiment classification takes a natural language text as input and returns a sentiment score of 0, 1, 2, 3, or 4 as a result. From the input sentence to the output score, system comprises three stages. To create a sentiment classifier, we employ a pre-trained BERT model.

A. BERT

BERT (Bidirectional Encoder Representations from Transformers) is an embedding layer that uses both left and right context conditioning in all layers to train deep bidirectional representations from unlabeled texts. It is pretrained using the following objectives from a large unsupervised text corpus:

• Masked word prediction: In this task, 15% of the words in the input sequence are masked out, then the complete sequence is given to a deep bidirectional Transfomer [5] encoder, which then trains the model to predict the masked words.

• Next sentence prediction: BERT takes two sentences A and B as inputs and learns to categorise whether B genuinely follows A or is just a random sentence.

B. PROPOSED METHOD

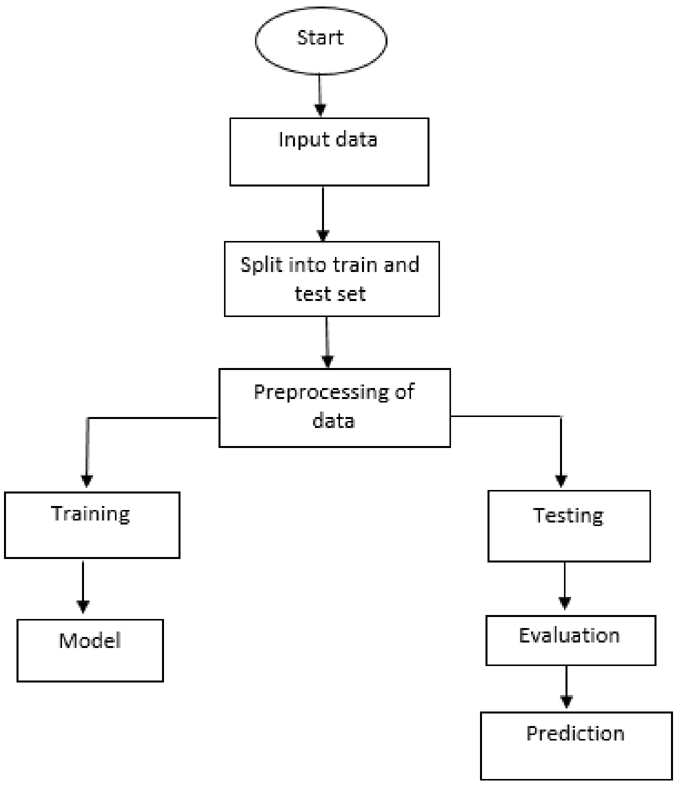


Fig 1: Block diagram model for proposed method

- **Input Format**

BERT requires a specific format for its input token sequence. Every sequence should start with a [CLS] token (classification token), and each sentence should end with a [SEP] token (separation token).

- **Pre-Processing**

Text preprocessing is a technique for cleaning up text data before feeding it to a machine-learning model. Text data comprises a wide range of noise, including emotions, punctuation, and text capitalised differently. Because machines cannot understand language, they want numbers, this is merely the beginning of the issues we will confront. As a result, we must devise a method for converting text to numbers that is both quick and efficient.

Pre-processing in the typical or conventional manner is a time-consuming and user-centric process. Under the hood of normal pre-processing processes, the following stages are carried out:

1. Lower casing the corpus
2. Removing the punctuation
3. Removing the stopwords

4. LITERATURE SURVEY

The usefulness of current lexical resources and linguistic factors for performing SA on Twitter messages and similar microblogging posts was highlighted by Kouloumpis et al. [16].

In comparison to part-of-speech traits and those pertaining to an established sentiment lexicon, the researchers believe that microblogging is more relevant and appropriate. Microblogging elements are unlikely to improve training data, according to the authors.

Another study [17] integrating rule-based classification and supervised learning procedures indicated that hybrid classification was more relevant and yielded promising results. Since the turn of the century, SA has risen to prominence as one of the most explored subjects in natural language processing (NLP) [18,19].

To streamline SA approaches, researchers have been continually evaluating sentences of various sorts. Mudinas et al. proposed a concept level SA system (psenti), which has been found to be more effective than a lexicon-based approach [20]. According to the findings of their study, the hybrid strategy is far more efficient and yields more accurate results.

Tripathy et al. developed four machine learning techniques for sentiment classification in their study [31]. Nave Bayes, Maximum Entropy, Stochastic Gradient Descent, and Support Vector Machine were the methods used. Their research showed that progressive classification can help reach accuracy. IMDB, a popular movie review website, was used to perform their investigation. Utilizing a mix of TF-IDF and count vectorizer techniques, the authors were able to obtain consistent high accuracy using an n-gram approach. To address the issue of words and punctuation marks that, while humanly understandable, lack a formal definition in the English lexicon, the authors created a new list of such words to aid with SA. In their research work, Mitchel et al. modelled sentiment detection. Their research focused on demonstrating the applicability of sentiment recognition as a problem involving sequence tagging [21].

Later research [22] looked at word embedding and automated feature combination using neural networks, which built on their findings. Arun et al. then conducted a SA on tweets about the Indian economy's demonetization.

Their method of investigation [23] consisted of extracting data from Twitter and converting it to text. This text was supposed to be the input dataset. Following the removal of stop words, SA was done in order to determine the polarity of the words and, as a result, the real tweets could be classified as positive or negative.

For SA, a new strategy was proposed to deal with demonetization, its consequences, and the public outcry it sparked. In the study, bigrams, data cleansing, polarity, sentiment scores, and graphical approaches were all applied. Researchers [12] looked analysed a collection of tweets in Spanish to conduct a comparative investigation of several algorithms for SA and topic detection.

Tweets, according to the authors, are difficult to judge because of the absence of context and the unusual shortness of the material involved. The authors of another e-commerce and online product review study [24] noted that public opinion and the opinions of buyers of products sold on online retail platforms will have far-reaching implications in terms of profitability and economic feasibility.

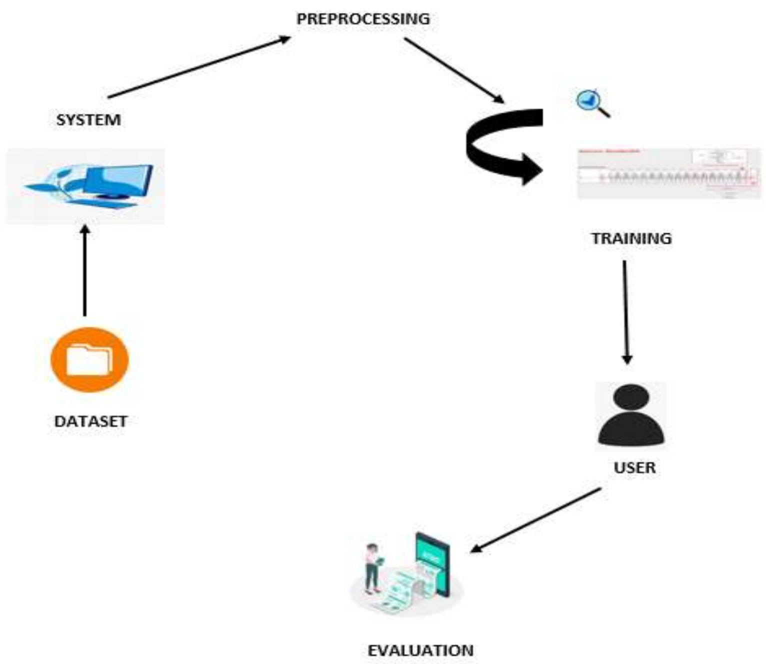
As a result, businesses and entrepreneurs invest in opinion mining and SA to develop strategies for staying ahead of the competition. The authors use the FRBAS R package to implement fuzzy rulebased systems (FRBS) with Mamdani and Takagi Sugeno Kang (TSK) models. The authors next compare these models to alternative categorization strategies, grading them on precision, recall, f-measure, and overall performance.

The authors [24] discovered a substantial dearth of resources to carry out SA in Arabic while investigating the feasibility and efficacy of SA in the context of Arabic tweets. The authors used Jordanian Arabic tweets in their study and used a variety of supervised machine learning algorithms to look at them. According to their findings, SVM classifiers with TF-IDF and bigrams outperformed Nave Bayesian classifiers. The authors gathered over a thousand Arabic tweets written in Jordanian dialect for their experiment.

The two machine learning methods, SVM and NB, were then applied to a set of ngrams with varied weighting schemes and stemming strategies.

When the authors [25] introduced a semisupervised recursive auto-encoding strategy for forecasting sentiment distributions without the need of sentiment lexica or rules involving polarity shifting, it received a lot of attention. The authors suggested the recursive neural tensor network (RNTN) in their study [27] to analyse and distinguish phrases and sentences of various lengths.
An alternate technique of sentiment categorization was presented in another research [28] for analysing sentences of various lengths and terms. While hyper parameter tweaking for word vectors has been the research of choice [29], the authors [30] have chosen deep recursive neural network (DRNN) for sentiment classification assignments. Surprisingly, the authors [32] believe that larger datasets including crowd sourcing and semi-supervised learning have significantly higher promise for improving classification outcomes.

5. ARCHITECTURE



6. CONCLUSION

Sentiment Analysis is now widely regarded as being crucial from a socioeconomic aspect. Understanding sentiment analysis and the approaches that can help achieve accuracy in a range of input forms is crucial for businesses, institutions, and individuals to survive and prosper. The applications and limitations of sentiment categorization in single and cross domains are discussed in this survey article. Subjectivity analysis, negation management, and polarity categorization must all be completed before sentiment analysis can begin.

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