

A multi-channel convolutional neural network for multi-label sentiment classification using Abilify oral user reviews

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Keywords: multilabel classification, sentiment classification, multi-channel convolutional neural network, abilify user reviews

Received: April 13, 2021

Nowadays, patients and caregivers have become very active in social media. They are sharing a lot of information about their medication and drugs in terms of posts or comments. Therefore, sentiment analysis plays an active role to compute those posts or comments. However, each post is associated with multilabel such as ease of use, effectiveness, and satisfaction. To solve this kind of problem, we propose a multichannel convolution neural network for multi-label sentiment classification using Abilify oral user comments. The multichannel represents the multiple versions of the standard model with different strides. Specifically, we use the pre-trained model to generate word vectors. The proposed model is evaluated with multilabel metrics. The results indicate that the proposed multichannel convolutional network model outperforms the traditional machine learning algorithms.

Povzetek:

1 Introduction

Social media has become an active part of drugs and medication users. They share the advantage or disadvantages of their medication and drugs. This information may give some insightful information about the reaction of the drug. Therefore, sentiment analysis plays a wide role to compute the opinions of drug users and caregivers. The sentiment analysis can be performed at the document level, sentence level, or aspect level [1, 2]. The document and sentence level computes the overall opinion. But, the aspect level computes opinion at a specific target or an entity. In this paper, we aim to focus on aspect level sentiment. A comment may be associated with a single label or multilabel [3]. The single label problem has only one label. However, It has two classification methods namely, binary classification or multi-class classification. The binary classification problem belongs to a binary set such as true

and false or positive and negative. The multi-class classification problem belongs to a set of more than two elements such as positive, neutral, and negative. In these problems, algorithms assign only one label to comment or instance. Multilabel classification problem belongs to a set of multiple target labels where each label maybe belongs to a binary class or multi-class.

Traditionally, the multilabel classification problems are solved using problem transformation, adapted algorithms, and ensemble learnings [3]. The problem transformation problem is further solved using the binary relevance, classifier chain, and label powerset methods [4, 5]. However, these methods use the traditional bag of words (BoW) method to represent features. These features fail to represent semantic meaning between words. Therefore, deep learning models are proposed to capture the semantic meaning between words in the input sequence. It is also proven that they outperform in many tasks such as image classifi-

cation, text classification, etc [6, 7]. In this paper, we propose a multichannel convolution neural network for multilabel sentiment classification using Abilify oral user comments. The multichannel model represents the multiple versions of the standard model with different strides. Particularly, we use the GloVe pre-trained model [8] to generate word vectors. We then evaluate the proposed multilabel metrics.

This paper is organized as follows. Section 2 briefly describes the related works. The proposed multichannel convolutional neural network for multilabel sentiment classification is presented in Section 3. In Section 4, the results and their comparison is presented. Finally, Section 5 concludes the paper.

2 Related works

In recent years, researchers widely studied clinical text and user text using natural language processing (NLP). They used both machine learning and deep learning to solve their problems. In this paper, we present the existing works on biomedical texts. Baumel et al. [9] investigated four models such as SVM, CNN, CBOW, and hierarchical attention-based recurrent neural network models for the extreme multilabel task using the MIMIC datasets. The authors indicated that the hierarchical attention-based recurrent neural network model achieves a 55.86% F1 score. Wang et al. [10] developed a rule-based algorithm to generate labels that are weakly supervised. Then, the authors used the pre-trained word embeddings to represent deep features. They employed SVM, random forest, MLPNN, and CNN algorithms. Their study indicated that the CNN model achieves the best performance score. Singh et al. [11] developed an attentive neural tree decoding model for tagging structured bio-medical texts with multilabel. This method decodes an input sequence into a tree of labels. The authors suggested that the proposed model outperforms on SOTA (state-of-the-art) approaches with biomedical abstracts. Citrome [12] reviewed the treatment of Abilify oral users with bipolar I disorder and schizophrenia. The author indicated that the tolerability of Abilify with schizophrenia appears superior to haloperidol, risperidone, and perphenazine. Rios et al. [13] demonstrated

the biomedical text classification task using CNN. They indicated that they achieved a 3% improvement over the SOTA results.

Moreover, Gargiulo et al. [14] presented a deep neural network (DNN) for extreme multilabel and multi-class text classification tasks. The authors used two models: the first one uses a word embedding with two dense layers, and the second uses the convolution, word embedding, and the dense layers. Kolesov et al. [15] performed multilabel classification on incompletely labeled biomedical texts using the SVM and RF. They used soft supervised learning and weighted k-nearest neighbor algorithms for modifying the training set. Their study indicated that both algorithms perform better. Parwez et al. [16] presented the CNN model for multilabel text classification. The authors used the domain-specific and generic based pre-trained model to predict class labels. In summary, the above authors used SVM, NB, RF, and CNN to perform multilabel classification tasks on various biomedical texts. In this paper, we propose multichannel convolutional neural network for multilabel sentiment classification using Abilify oral user comments.

3 The proposed method

In this section, we present a multichannel convolutional neural network for a multilabel sentiment classification model using Abilify oral user comments. The system architecture is shown in Fig.1. It includes data pre-processing, word embedding, multichannel CNN, merge layer, fully connected layer, and an output layer. Each of these processes is explained as follows.

3.1 Abilify oral dataset

We obtained this Abilify oral dataset from the IEEE Dataport [17, 18]. It contains 1722 user comments with their age group, gender, treatment condition, patient type, treatment duration, and labeled sentiment on satisfaction, effectiveness, and ease of use.

3.2 Pre-processing

The dataset is converted from upper case to lower case, removed punctuation lists and stop words, and retained the numbers where it describes the

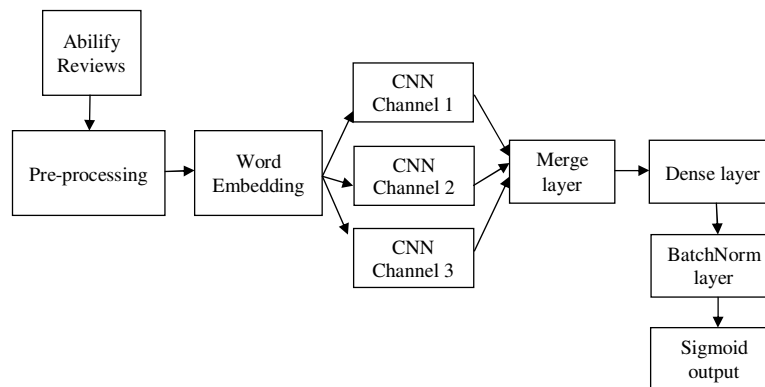


Figure 1: A multichannel convolutional neural network model

drugs in grams. Then, each instance is split into separate words using the tokenization method.

3.3 Multi-channel convolutional neural network

The multi-channel convolutional neural network represents the multiple version of the standard convolutional neural network model with different sizes of kernels. This representation allows the instance or document to process in different n-grams such as 4-gram, 6-gram, and 8-grams at the same time [19]. In particular, we define the standard convolutional neural network model with a word embedding layer, one-dimensional convolutional layer, dropout layer, max-pooling, and flatten layer. This standard version is defined with three channels for different n-grams. Each component of the channel is explained as follows.

3.3.1 Word embedding

In NLP, word embedding represents a feature learning technique where it maps the vocabulary of words or phrases into a vector space. Specifically, we use the GloVe word embedding [8] technique to generate word vectors in a fixed dimension with the semantic relationship between words.

3.3.2 Convolutional layer

Convolutional neural networks perform well in image classification and computer vision-related tasks. The convolutional layer is an important part of the convolutional neural network. It slides over an input sequence with a fixed kernel size to

generate feature maps [13, 14, 16, 19]. In this work, we use one-dimensional convolutional layers to move the kernel in one direction. This layer is mostly used to perform NLP tasks. The input and output of the 1D convolutional layer are 2D. The convoluted feature maps output the maximum, minimum, or average values using pooling layers.

3.3.3 Dropout layer

This layer is used to regularize the neural networks in terms of overfitting and underfitting. Specifically, it ignores some of the outputs in the neural network during the training process.

3.3.4 Max-pooling

The max-pooling layer is applied over each feature map to select the maximum value based on the filter size. It is smaller in size than the feature map. The output of this layer contains the most important feature values of the previous feature map [13, 14, 16, 19].

3.3.5 Flatten layer

The flatten layer converts the pooled feature map into a single column or one-dimensional array. This result is passed to a merged layer.

3.4 Merge layer

The merged or concatenate layer combines the output of each channel. These combined results passed to a fully connected or dense layer.

Data	Accuracy score	Hamming loss	F1 micro score	Accuracy per label		
				0	1	2
Validation	0.548	0.275	0.839	0.820	0.931	0.750
Testing	0.538	0.303	0.820	0.815	0.912	0.715

Table 1: Performance of the proposed multichannel CNN model.

Data	Accuracy score	Hamming loss	F1 micro score	Accuracy per label		
				0	1	2
BR_NB	55.2	0.379	71.5	60.5	68.9	57.0
BR_DT	59.6	0.343	73.9	61.9	79.7	55.3
BR_SVM	60.7	0.338	75.2	62.6	78.3	57.8
CC_NB	55.0	0.378	71.5	60.5	68.7	57.5
CC_DT	61.0	0.347	74.6	61.9	78.3	51.5
CC_SVM	60.5	0.346	75.0	62.6	77.5	55.7
LP_NB	54.1	0.385	69.4	56.6	72.0	55.7
LP_DT	60.3	0.354	74.5	60.9	77.7	55.1
LP_SVM	62.8	0.334	76.5	63.4	79.8	56.4
Proposed	53.8	0.303	82.0	81.5	91.2	71.5

Table 2: Model comparison.

3.5 Fully connected layer

A fully connected or dense layer connects the input of the flatten layer to all units of the next layer. It works the same as the feed-forward neural network.

3.6 Batch normalization layer

The batch normalization layer allows all layers of a network to learn more independently. Specifically, it standardizes or normalizes the result of previous layers. Also, this layer acts as a regularization parameter to avoid overfitting.

3.7 Sigmoid output layer

The sigmoid output function predicts the probability-based output for each label as shown in equation 1. It is successfully applied in multilabel classification problems [20].

$$f(x) = \frac{1}{1 + \exp x} \quad (1)$$

4 Results and discussion

We implemented the proposed multilabel multichannel model on Abilify oral dataset. This

dataset contains 1722 instances associated with a set of labels, namely, ease of use, satisfaction, and effectiveness. We split the dataset into training (1394), validation (155), and testing (173). The data instances are preprocessed with various tasks such as removing punctuations, stop-words, upper case to lower case, and tokenization. Then, word vectors are generated to the input sequences using the GloVe word embedding model. The proposed multichannel convolutional network model was applied to this dataset to perform the multilabel classification task. This model represents three multiple versions of the standard convolutional neural network with different kernel sizes. The standard CNN model consists of a word embedding layer, 1D-convolutional layer, dropout layer, max-pooling layer, and a flattened layer. The output of each channel is combined through a merged layer and it is passed to a dense layer, batch normalization layer, and the sigmoid output layer. Specifically, we fixed the following hyperparameters using the random approach such as input length with 150 units, 100 embedding dimension, three kernel sizes (4, 6, and 8), ReLU activation, 0.8 dropouts, pooling size 2, 10 units in the fully connected layer, 20 epochs, and Adam optimizer with a binary cross-entropy

loss function. The proposed multichannel CNN model for multilabel classification is evaluated using various multilabel metrics, namely, accuracy or exact match, hamming loss, F1-micro average score, and accuracy per label [3, 4, 18]. Table 1 shows the performance of the proposed multichannel CNN model for multilabel classification. This result is compared with the problem transformation approaches, namely, binary relevance, label powerset, and classifier chains with NB, DT, and SVM [18] as shown in Table 2. The proposed multichannel CNN model achieves better results in terms of Hamming loss (30.3%), F1 micro score (82.0%), and accuracy per label (81.5%, 91.2%, 71.5%).

5 Conclusion

In this paper, we proposed a multichannel convolution neural network for multi-label sentiment classification using Abilify oral user comments. A pre-trained model was used to generate word vectors. Then, the proposed model was evaluated with the multilabel classification metrics. The results showed that the proposed multichannel CNN model achieves the better result in terms of Hamming loss, F1 micro score, and accuracy per label than the problem transformation approaches. In future work, we study the trend of drugs and medications in different age groups using patient and caregiver reviews.

Acknowledgement

We thank Dr. S. Sridhar, Professor, Department of Information Science and Technology, Anna University, Chennai for his valuable comments and suggestions during this work.

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