Style Change Detection Based On Bert And Conv1d

Notebook for PAN at CLEF 2022

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Abstract
For the style change detection task of the 2022 PAN competition, the goal of the task is to identify the text positions of author switches in a given multi-author document. There are three subtasks in it. Task 1 is to cut the text into two authors' texts at the paragraph level; task 2 is to find the location of all writing style changes for texts written by two or more authors; task 3 is for texts written by two or more authors to find the locations of all writing style changes, where style changes now occur not only between paragraphs but also at the sentence level. This paper proposes a method based on the Bert pre-training model and one-dimensional convolution to process the task. This method regards judging the number of authors and the location of text changes as a binary classification task based on the similarity of two texts. For the prediction of the three tasks accomplished by the proposed method, the f1 scores of task 1, task 2, and task 3 in the test set are 0.74, 0.41, and 0.63, respectively.

Keywords
Style Change Detection,Bert,One-dimensional convolution, Pre-training Model

1. Introduction

The task of style change detection plays a very important role in the current detection of whether an article involves plagiarism. By comparing the similarity of different text paragraphs, people can quickly check which paragraphs and sentences of the article involve plagiarism, and whether the article involves plagiarism,and the number of authors to identify which passages were written by which author. The tasks of the PAN 2022 Evaluation Laboratory are divided into three sub-tasks. Among them, task 1 is to ask us to find the paragraphs where the style changes among different paragraphs of an article and divide them. Task 2 is a text written by two or more authors, find the location of all writing style variations, and assign that paragraph to the corresponding author number. Task 3 is that the change of writing style may also occur between sentences in the paragraph, and it is necessary to mark the position where the writing style changes between sentences. All three subtasks are extremely challenging tasks.

After analyzing the three tasks, it is important to find the similarities between the given texts to complete the task. Therefore, the model of Bert and one-dimensional convolution can be used to solve the problem in this experiment. Task 1 is similar to task 3. Task 1 is to identify between paragraphs, while task 3 is to identify between sentences. This experiment can extend task 1 to task 3, divide sentences from paragraphs and put them into the model for training,to identify the writing style changes between sentences. And the models for task 1 and task 2 can be used together. This paper use

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the Bert pre-training model and one-dimensional convolutional neural network to extract feature information between texts, and build this model to complete three tasks.

2. Background

This year's PAN2022 style change detection task is divided into three sub-tasks:

1.Style Change Basic: for a text written by two authors that contains a single style change only, find the position of this change (i.e., cut the text into the two authors' texts on the paragraph level)

2.Style Change Advanced: for a text written by two or more authors, find all positions of writing style change (i.e., assign all paragraphs of the text uniquely to some author out of the number of authors assumed for the multi-author document)

3.Style Change Real-World: for a text written by two or more authors, find all positions of writing style change, where style changes now not only occur between paragraphs, but at the sentence level.

Among the three tasks, task 1 and task 2 correspond to task 2 and task 3 of last year's PAN2021 style change detection task, respectively, and this year's task 3 becomes judging whether there is a change in writing style between sentences. All documentation is provided in English and may contain any number of style changes caused by up to five different authors. The specific tasks are shown in Figure 1.

There are three different datasets based on three different subtasks, and each dataset has three parts:

1.Training set contains 70% of the whole dataset and includes ground truth data. Use this set to develop and train models.

2.Validation set contains 15% of the whole dataset and includes ground truth data. Use this set to evaluate and optimize models.

3.Test set contains 15% of the whole dataset, no ground truth data is given. This set is used for evaluation.

The training set and validation set can be used to train and evaluate the model, and then input the test set into the model to generate the final result of the experiment. Finally,the generated results are submitted to the TIRA platform to calculate the F1 score for evaluating the output of the model.

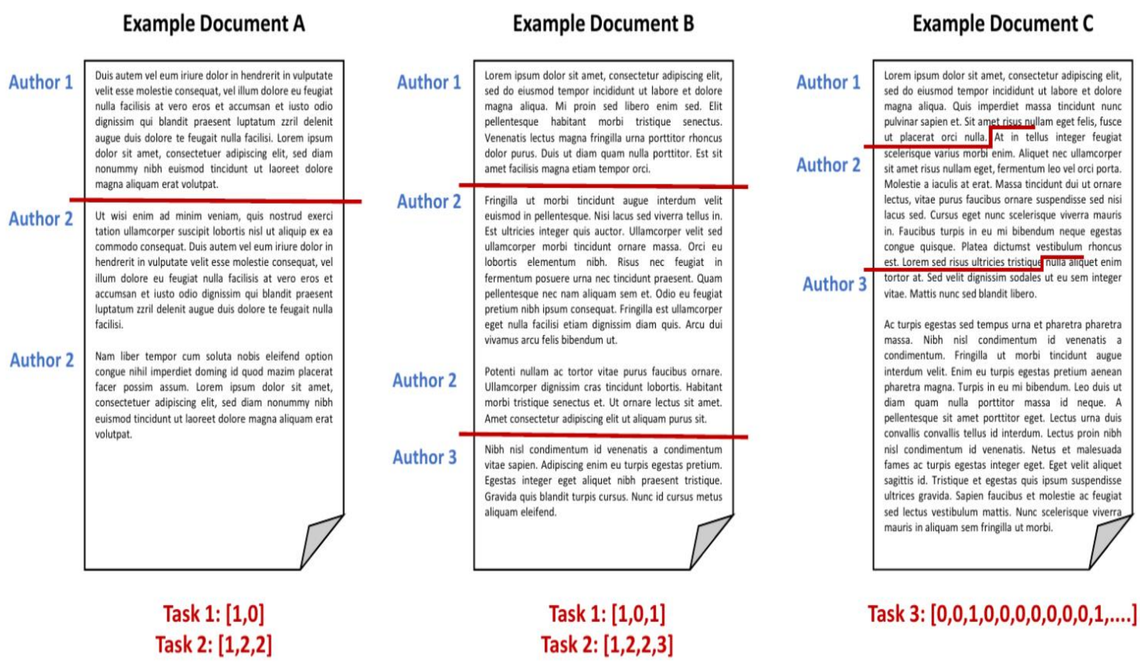

Figure 1: Possible scenarios and the expected output for the tasks[9]

3. Method

After analyzing the task, task 1 and task 3 can be regarded as a binary classification task by referring to [7] [8].The input data for task 1 is paragraphs, and the input for task 3 is divided into sentences. When the similarity between the two input paragraphs or sentences is low, the model will output 1, proving that they were written by two or more authors, and 0 otherwise. Task 2 is also based on this method to calculate the author's number.

3.1. Bert

Bert[2] is a new language model proposed by Google in October 2018. The full name is Bidirectional Encoder Representations from Transformers (Bert). Unlike some recent language models such as ELMo, BERT pre-trains deep bidirectional representations by jointly conditioning the left and right contexts at all layers, and also enhances the understanding of long-range semantics by assembling long sentences as input. Bert can be fine-tuned to be widely used in various tasks. It only needs to add a output layer and does not need to adjust the model structure for the task. It has achieved state-of-the-art performance in some tasks such as text classification and semantic understanding.

3.2. One-dimensional convolution

One-dimensional convolution(Conv1D) can well obtain the feature representation of sentences. The words in a sentence are composed of n-dimensional word vectors. If the length of the sentence is m, the size of the input matrix is m*n. Conv1D performs a convolution operation on the input. For text data, the filter no longer moves laterally, but only moves down the column dimension along the direction of the word. Apply the filter to obtain the convolutional vector, perform the maximum pooling operation on each vector, and finally obtain the feature representation vector of the sentence, and then input the obtained feature representation into the classifier for classification, and determine the difference between two sentences or paragraphs.The process is shown in Figure 2.

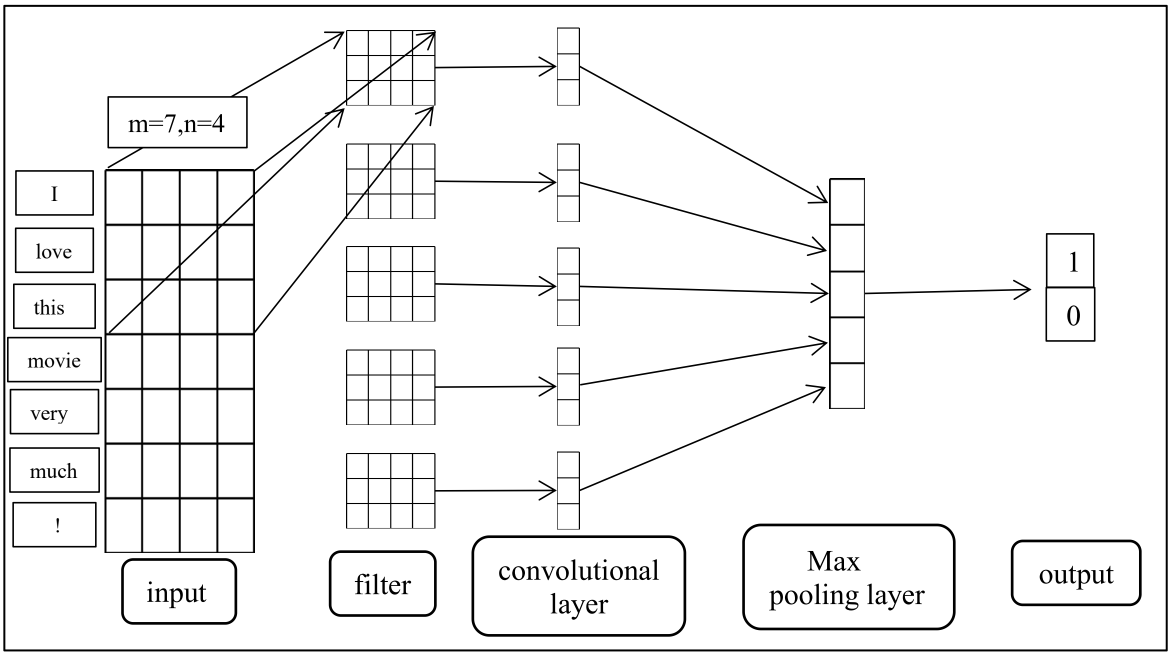

Figure 2:Process of Conv1D

3.3. Bert model add Conv1D model

The model structure used in the paper is the pre-trained Bert model and Conv1D,The overall model structure is shown in Figure 3. First, for the input sentences or paragraphs, this experiment will preprocess the data and process them into a token form suitable for processing by the model. Then input the processed data into the Bert model, where most of the data processing refers to the data processing method in the Bert source code. In the pre-trained Bert model, Bert will fine-tune according to the input data to adjust its parameters. After the fine-tuning of the Bert model is completed, the output of Bert will be input into Conv1d. In Conv1d, the input will be convolved along the word direction to extract features, and then the output of Conv1d will be input into the Max pooling layer to extract the important vocabulary features. Finally, the model is connected to a classifier, the output of the Max pooling layer will be input into a classifier, the classifier will judge the similarity between them and output 1 or 0, 1 is written by multiple authors, 0 is not, Use this to complete tasks 1 and 3. Task 2 compares any input paragraph with other paragraphs, and counts the similarity between them, so as to calculate the number of different authors.

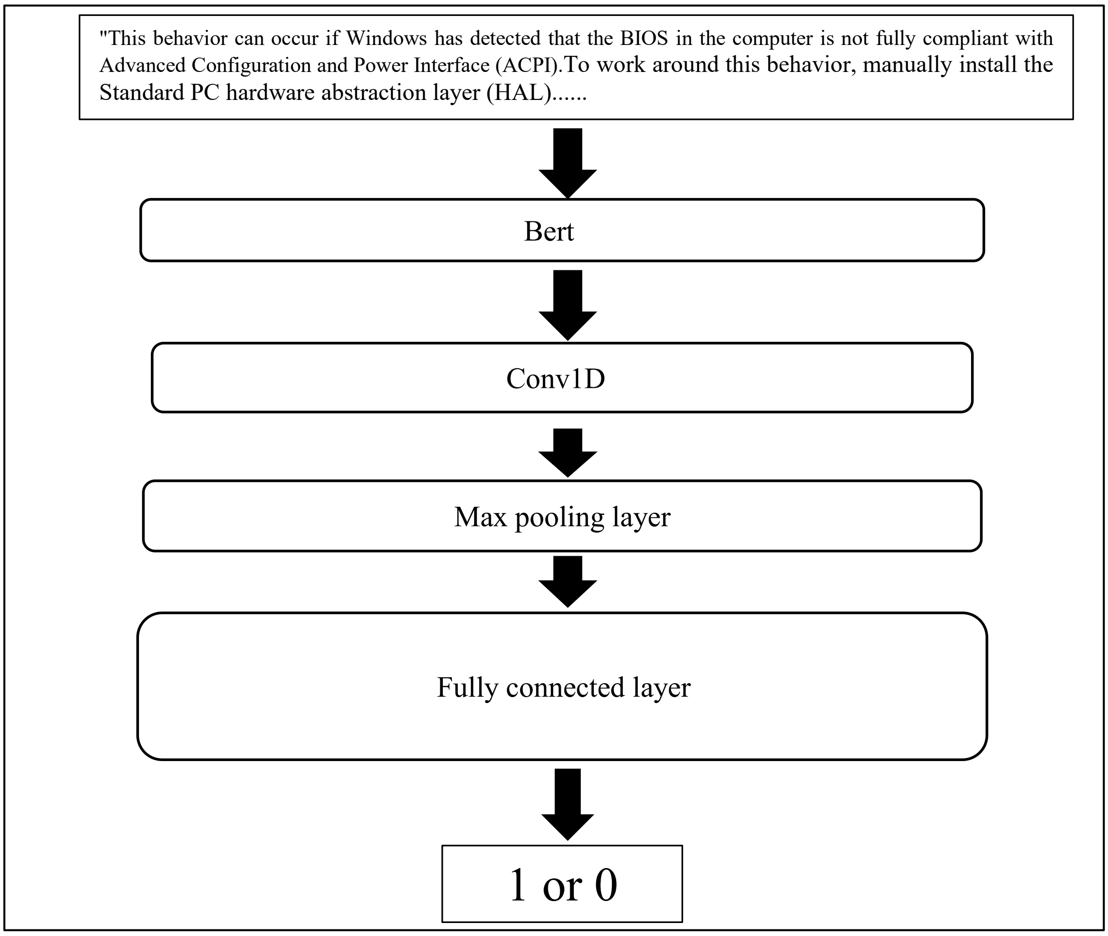

Figure 3:The overall structure of the model

4. Experimental Setting

The experiment is carried out on the server in the laboratory, the graphics card is RTX2080 with 8GB of video memory. The scale of the Bert pre-training model used this time is 12-layers, 768-hidden, and 12-heads. The maximum length of the input sentence is set to 256, and the batch size is set to 4, which can save resources and running time when training the model.

This experiment fine-tune the model using the given training and validation sets for each task to accomplish three tasks. For each task, the training sets are input into the model for training to obtain the weights of the models, and use the validation set to verify the effectiveness of their training on each model. In this way, the best model weights for each task are obtained and saved.

Finally, the test sets are inputted into the trained model, generate the output results of each task, and submit the generated results to the TIRA evaluation platform for the evaluation and calculation of the F1 score.

5. Result

It can be seen that the F1 scores of task 1 and task 3 are not very different on the validation set and test set, but the score of task 2 is not high. The reason may be that there is an error in predicting the similarity of paragraphs, and the error is further propagated when calculating the author number, so there is still a large improvement in task 2.

Table 1
F1 score and accuracy of the trained model on the validation set

	Task1	Task2	Task3
Accuracy	0.8379	0.7643	0.6525
F1 score	0.7417	0.4423	0.6468

Table 2
Test set F1 score of the trained model

	Task1	Task2	Task3
F1 score	0.7471	0.4170	0.6314

6. Conclusion

This paper proposes a method of using Bert and one-dimensional convolution model to process the style change detection task. The model learns and predicts the similarity of the given text to complete task1 , task2 and task3 in this PAN competition. The final test set F1 scores of each task are 0.7471, 0.4170, and 0.6314, respectively. There is room for improvement in this experiment, and the cumulative propagation of errors in task 2 leads to less than ideal results for task 2. In this model, the basic version of Bert model is used. In the future, a larger-scale pre-trained Bert model or a better Roberta model can be used to better learn the given text information.

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