Text Classification Method Using Deep Learning Model Fusion and Its Application

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요 약

본 논문은 LSTM(Long-Short Term Memory) 네트워크와 CNN 딥러닝 기법을 기반으로 하는 융합 모델을 제안하고 다중 카테고리 뉴스 데이터 세트에 적용하여 좋은 결과를 얻었다. 실험에 따르면 딥 러닝 기반의 융합 모델이 텍스트 감정 분류의 정밀도와 정확도를 크게 향상시켰다. 이 방법은 모델을 최적화하고 모델의 성능을 향상시키는 중요한 방법이 될 것이다.

ABSTRACT

This paper proposes a fusion model based on Long-Short Term Memory networks (LSTM) and CNN deep learning methods, and applied to multi-category news datasets, and achieved good results. Experiments show that the fusion model based on deep learning has greatly improved the precision and accuracy of text sentiment classification. This method will become an important way to optimize the model and improve the performance of the model.

키워드
cLong-Short Term Memory, CNN deep learning methods, multi-category news datasets

Ⅰ. Introduction

In recent years, convolutional neural networks (CNNs) technology based on deep learning method [1] has made remarkable achievements in the field of computer vision, mainly applied to face recognition, image classification, natural language processing, and so on [2-5].

Ⅱ. Model Design

The CNN mentioned above can be expressed as follows.

$$IN => CONV - ReLU => POOL => FC - ReLU => OUT \quad (1)$$

Here, IN denotes an input layer, CONV denotes a convolutional layer, and ReLU (Rectified Linear Units) denotes an activation function derived

from a neural network, which can greatly shorten the learning period and improve learning efficiency. POOL represents the pooling layer, FC represents th e fully connected layer, OUT represents the output layer, and "-" means follow. The stacking of these levels constitutes the convolutional neural network s tructure in deep learning. In practical applications, t here are multiple CONV and POOL layers in the c onvolutional neural network structure, which are des igned to reduce image size and extract finer feature s. It is then classified using the fully connected lay er and finally output at the output layer. Therefore, the expression of the commonly used convolutional neural network model is as shown in (2).

$$IN => [CONV - ReLU => POOL?] * M => [FC] * N - ReLU => OUT \quad (2)$$

Ⅲ. Model Regulation

In this paper, because a very small dataset is used consisting of a training data set of 2000 images and a test data set of 800 images.

1) Data Augmentation (Fig. 1) : Data augmentation is a method that can effectively suppress overfitting. The method can generate new samples with original image data features by performing operations such as rotation, scaling, shifting, mirroring, etc. within a certain range of values of the original image, thereby achieving the purpose of increasing the number of data samples in the training set.

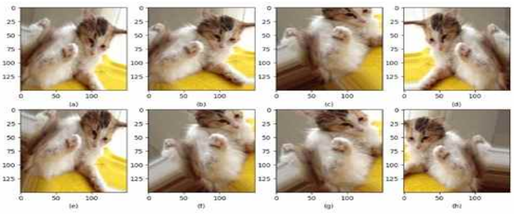

Fig. 1. Data augmentation example
: (a) original image, (b) horizontal offset, (c) vertical offset after rotation, (d) mirror image, (e) cropping, (f) vertical offset, (g) rotation, (h) mirroring and scaling.

2) Dropout (Fig. 2): Data augmentation is only an increase in the number of training samples and to some extent can suppress overfitting. However, due to the lack of diversity in the training samples after data augmentation, it is not sufficient to eliminate overfitting in the deep learning model.

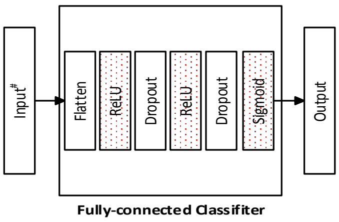

Fig. 2. Improved fully connected layer network structure diagram

Ⅳ. Experiment

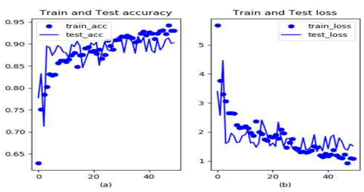

Fig. 3. Improved CNN experiment results
: (a) accuracy statistics for training and prediction, (b) loss rate statistics for training and testing.

Ⅴ. 결론

In this paper, we proposed a convergence model based on LSTM network and CNN deep learning technique. Good results were obtained when applied to a multi-category news dataset. According to the experiment, the deep learning-based fusion model greatly improved the precision and accuracy of text emotion classification.

References

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