Complicate then Simplify: A Novel Way to Explore Pre-trained Models for Text Classification

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Abstract

In the developing context of pre-trained models (PTMs), the performance of text classification has been continuously improved by directly employing the features generated by PTMs. However, such a way might not fully explore the knowledge in PTMs as it is constrained by the difficulty of the task. Compared to a difficult task, the learning algorithms tend to saturate early on the simple task. Moreover, the native sentence representations derived from BERT are prone to be collapsed and directly employing such representation for text classification might fail to fully capture discriminative features. In order to address these issues, in this paper we propose a novel framework for text classification which implements a two-stage training strategy. In the pre-training stage, auxiliary labels are introduced to increase the task difficulties and to fully exploit the knowledge in the pre-trained model. In the fine-tuning stage, the textual representation learned in the pre-training stage is employed and the classifier is fine-tuned to obtain better classification performance. Experiments were conducted on six text classification corpora and the results showed that the proposed framework outperformed several state-of-the-art baselines.

1 Introduction

Text classification is a fundamental task in the field of natural language processing and is widely employed in various tasks such as question answering, sentiment analysis, and information retrieval. With the continuous development of machine learning algorithms, especially the success of deep learning methods, text classification has been significantly improved, e.g. CNNs (Kim, 2014; Lai et al., 2019), RNNs (Chen et al., 2017; Zhang et al., 2020), BERTs (Cui et al., 2019, 2020; Sun et al., 2021), etc. Recently, pre-trained models have been shining in classification-based natural language processing tasks (Cui et al., 2019, 2020; Sun et al., 2021).

The advent of BERT has led to an effective enhancement of textual feature representation. A series of improved pre-trained models have been proposed, e.g. RoBERTa (Liu et al., 2019), MacBERT (Cui et al., 2020), ERNIE (Sun et al., 2020), ChineseBERT (Sun et al., 2021). For example, ERNIE learns real-world semantic knowledge by modeling words, entities and entity relationships in massive amounts of data (Sun et al., 2020). Sun et al. (2021) proposed a large-scale Chinese pre-trained model that incorporates glyph and pinyin information. The above works improve the textual representation of the pre-trained model by introducing external knowledge, without fully exploring the semantic representation in the existing pre-trained model. The recent work, prompt learning, is the technique of making better use of the knowledge from the pre-trained model by adding additional texts to the input (Liu et al., 2021). Like prompt learning, we propose to further extract more meaningful textual representations from the pre-trained model, i.e. to make the extracted textual semantic representation more discriminative for classification.

Although the current pre-trained model already obtain relatively good textual representation, it is...
still possible to further explore the information in the pre-trained representation based on our observation. As shown in Figure 1, for sentiment analysis, there are two sets of features in a sentence that indicate its positive emotional polarity, “很不错(very good)” and “下次 选择(next time choose)”. Words like “很 不错(very good)” explicitly express positive sentiment. Features like these, which are closely related to category labels, are given higher weight during training. While more implicit features like “下次(next time)” and “选择(choose)” are easily ignored as shown by the green curve in Figure 1. However, by using the two-stage framework proposed in this paper, the weights of implicit discriminative features are further highlighted without weakening the weights of the most discriminative feature as shown in the black curve in Figure 1.

Meanwhile, we notice that Yan et al. (2021) found the word representation space of BERT to be anisotropic, with high-frequency words clustered together and close to the origin, while low-frequency words were sparsely scattered. When averaging token embeddings, those high-frequency words dominate the sentence representation, inducing a bias against their actual semantics. Such phenomenon has also been observed in some previous work (Gao et al., 2019; Wang et al., 2020a; Li et al., 2020). Therefore, directly employing such representation for text classification might fail to fully capture discriminative features.

Therefore, in this paper, we consider the extracting of semantic features from a cognitive perspective by introducing auxiliary labels and constructing pre-training and fine-tuning strategies based on pre-trained models. We devise a novel approach to perform a secondary pre-training based on the pre-trained model and then fine-tuning for text classification which is similar to the process of gaining new insights through restudying old material. In the pre-training stage, the model learns a better representation of the task under consideration. In the fine-tuning stage, the classifier is fine-tuned by applying the text feature representations obtained from the pre-training stage. To fully exploit the discriminative features in the pre-trained model, in the pre-training stage, auxiliary labels are constructed to take fine-grained semantic categories into account. The introduction of auxiliary labels makes the information entropy increase. Knowledge in the pre-trained model is fully mined for a more effective discriminative semantic representation.

The main contributions are listed as follows.

- We propose a novel framework for text classification which implements a two-stage training strategy and enables “experience accumulation” and “practice what you learned” without introducing additional knowledge.

- In the pre-training stage, auxiliary labels are integrated to increase the training challenge and to exploit the knowledge in the pre-trained model fully.

- The validity of the framework is verified on seven benchmark datasets, and the proposed framework achieves better performance than several state-of-the-art baselines.

The reminder of the paper is structured as follows. Some related work is briefly reviewed in Section 2. The detailed implementation of our framework is described in Section 3. Section 4 reports the experiments and results and Section 5 shows further analysis and discussion. Finally, the paper is concluded in Section 6.

2 Related Work

The development of deep learning has led to significant improvements in text classification, and some of the more widely employed deep learning models for text classification tasks are CNNs (Wang et al., 2018; Lai et al., 2019), RNNs (Chen et al., 2017; Sachan et al., 2019; Zhang et al., 2020), and pre-trained models (Cui et al., 2019; Liu et al., 2019; Sun et al., 2021). In recent years, pre-trained models have shown excellent performance in the field of text classification. Whether CNNs, RNNs, or more recently pre-trained models, the purpose of employing deep models is to efficiently capture the textual semantic representation.

2.1 Traditional Deep Learning methods

Text representation is the basis for text classification. The first work to introduce CNNs into NLP was done by Kim (2014), and the key to the features captured by a CNN is the sliding window covered by the convolutional kernel. Johnson and Zhang (2017) proposed the Deep Pyramidal Convolutional Neural Network (DPCNN), which can effectively extract remote relational features from the text. In the process of text feature extraction employing convolutional operations, the semantic relations of sentences would be lost. Ma et al. (2015)
proposed to employ dependent syntactic trees to extract the semantic feature relations, instead of just employing adjacent word representations as feature representations. CNNs can extract local features from global information when employed for text classification, but they are unable to capture long-term dependencies, whereas RNNs can. Zhang et al. (2018) proposed a sentence-state based LSTM that incorporates the semantic relevance of words and sentences. Models such as CNNs and LSTMs capture word sense information well in locally continuous word sequences but may ignore global word co-occurrences in corpora with discontinuous and long-term semantics dependencies. Yao et al. (2019) proposed a graph-based convolutional neural network structure (GCN), which exploits global word co-occurrence information not previously considered by other models and demonstrates better robustness with less training data. RNNs suffer from gradient explosion and gradient disappearance, and cannot effectively handle long-term context-dependence. The attention mechanism can characterize the target location by linearly weighting the features of the contextual source sequence. Bahdanau et al. (2015) first applied attention mechanisms to the field of natural language processing. Yang et al. (2016) proposed a hierarchical attention mechanism model for text classification tasks, acting at the word and sentence levels respectively. With the development of deep learning, neural networks are widely employed in NLP tasks, such as the aforementioned CNNs, RNNs, GNNs and attention mechanisms, but as the available datasets are small for most supervised NLP tasks, the above models are “shallow” for NLP tasks, making it difficult to extract sufficiently rich textual representations.

2.2 Pre-trained Models

The advent of pre-trained models (PTMs) has ushered in a new era of NLP, with extensive work showing that pre-trained models on large corpora can learn generic language representations and avoid training from scratch when solving downstream NLP tasks (Liu et al., 2019; Sun et al., 2020, 2021). Since BERT, complementary pre-trained models have been designed to integrate external knowledge into PTMs for better textual representations. ERNIE combines pre-trained entity embeddings in the knowledge graph with corresponding entity mentions in text to enhance the text representation (Zhang et al., 2019). KnowBERT merges entity representations in an end-to-end manner (Peters et al., 2019). KEPLER unites knowledge embeddings with language model objects (Wang et al., 2021). K-BERT differs from the above models by introducing structured information from the knowledge graph through entity embeddings (Liu et al., 2020). It obtains an expanded tree input to the BERT by directly introducing relevant triples from the knowledge graph into the sentence. K-Adapter independently trains different adapters for different pre-trained models to introduce multiple knowledge, in order to address the forgetting problem that occurs when the above models are injected with multiple knowledge (Wang et al., 2020b). In contrast to the above approach, Qin et al. (2020) proposed the use of feature projection methods based on BERT to further improve text representation without introducing external knowledge. They consider fully mining the existing knowledge in the pre-trained model to make the feature representations involved in classification more discriminative.

3 Model

The overall framework is shown in Figure 2. The whole framework is divided into two stages: pre-training and fine-tuning. In the pre-training stage, auxiliary labels are introduced to artificially boost the training difficulty, which can better tap the knowledge from pre-trained models and obtain a more discriminative textual feature representation. In the fine-tuning stage, the textual representation pre-trained in the pre-training stage is employed and the classifier is fine-tuned to obtain better classification performance.

3.1 Problem Definition

Suppose that we have a K-class classification task, a training instance can be denoted as \((x_i, y_i)\) for \(i = 1, \ldots, N\) and \(y_i \in \{1, 2, \ldots, K\}\). Here, we introduce auxiliary labels, as shown in Figure 2. Suppose we have an encoder \(E(\cdot)\).

\[
R = E(x) \tag{1}
\]

Firstly, the model is trained employing auxiliary labels to obtain discriminative textual representation \(R\). Afterwards the classification is performed by the textual representation \(R\), and the original label \(y_i\).

Auxiliary Labels: The auxiliary labels are introduced through expanding the target labels by com-
z_i = PTEncoder(x_i)

3.2 Pre-training Pre-trained Models and Fine-tuning

The traditional text classification strategy is to obtain the textual semantic representation through the Encoder Network Encoder(·) and then employ the Classifier Classifier(·) to make predictions.

z_i = Encoder(x_i)

c_i = Classifier(z_i)

θ is the parameter of Encoder(·) and β is the parameter of Classifier(·). Their method is described as follows:

$\mathcal{L}(\theta, \beta) = - \sum_{i=1}^{N} \sum_{k=1}^{K} 1(y_i = k) \log (k \mid c_i)$

Unlike the traditional classification models described above, our approach adopts a two-stage training strategy.

Pre-training: Similarly, the input text $x_i$ needs to be represented as a textual semantic representation employing a parameters trainable encoder $PTEncoder(\cdot)$. Here, one point to focus on is that the parameters of the encoder are trainable.

$z_i = PTEncoder(x_i)$

$PTEncoder(\cdot)$, which maps $x_i$ to a discriminative representation vector shown in Equation 8.

Next, label prediction is to be performed employing $z_i$. Although the auxiliary labels are introduced, this is only done to introduce interference terms, in order for the $PTEncoder(\cdot)$ to be trained to obtain
more discriminative text features for the subsequent classification.

\[ c_1 = \text{Classifier}_1(z_i) \quad (9) \]

\( \theta_1 \) is the parameter of \( \text{PTEncoder}(\cdot) \) and \( \beta_1 \) is the parameter of \( \text{Classifier}_1(\cdot) \). Their method is described as follows:

\[ \mathcal{L}_{\text{aux}}(\theta', \beta') = -\sum_{i=1}^{N} \sum_{k=1}^{K+j} 1(y_1 = k) \log (k | c_1) \quad (10) \]

where \( j \) is the number of auxiliary labels we introduce on top of the original \( K \) targets.

In addition, there is no other effect on the classification task, as the auxiliary labels are represented in the one-hot labels as 0. Therefore, in the specific task, only the original categories are involved in the calculation of the cross-entropy loss function, and the auxiliary labels are not involved.

**Fine-tuning** : With the first stage (Pre-training), better parameters for the \( \text{PTEncoder}(\cdot) \) can be pre-trained, by which a better discriminative textual representation \( z_i \) can be obtained.

Next, the trained textual representation \( z_i \) is employed for conventional classification, i.e., no auxiliary labels are introduced and classification is performed according to the given label categories.

Here, we only perform further fine-tuning for the classifier:

\[ c_2 = \text{Classifier}_2(z_i) \quad (11) \]

\( \theta_1 \) is the parameter of \( \text{PTEncoder}(\cdot) \) and \( \beta_2 \) is the parameter of \( \text{Classifier}_2(\cdot) \). Their method is described as follows:

\[ \mathcal{L}_{\text{in}}(\theta_1, \beta_2) = -\sum_{n=1}^{N} \sum_{k=1}^{K} 1(y_1 = k) \log (k | c_2) \quad (12) \]

A summary of the two-stage training strategy described above. (1) In the pre-training stage, auxiliary labels for classification are constructed and the encoder is pre-trained employing the auxiliary labels to obtain a more discriminative feature representation \( z_i \). (2) In the fine-tuning stage, the textual representation \( z_i \) is employed for classification, where only fine-tuning is done for the classifier and the parameters of the text representation \( z_i \) are no longer updated to obtain better classification performance.

### 3.3 Textual Representation

BERT (Devlin et al., 2019) is a multilayered attention-assisted bidirectional transformer encoder model based on the original transformer model (Vaswani et al., 2017). During pre-training, BERT employed two objectives: masked language model (MLM) and next sentence prediction (NSP). The NSP is employed to predict whether two segments follow each other. The goal of NSP is to improve the performance of downstream tasks such as natural language inference (Bowman et al., 2015), which entails reasoning about the relationship between pairs of sentences. NSP is a good fit with our matching-based QA task and the matching task. Therefore, we choose the BERT as the encoding model.

The original authors of BERT proposed an upgraded version of BERT, including Whole Word Masking (WWM), which alleviates the disadvantage of masking some WordPiece tokens in pre-trained BERT. Cui et al. employed the whole word masking strategy for Chinese BERT and published a series of Chinese pre-trained models (Cui et al., 2019). The experimental performance shows that the proposed pre-trained model yields substantial improvements over BERT and ERNIE on various NLP tasks. They adapted whole-word masking in Chinese text by masking whole words instead of Chinese characters.

In view of the excellent performance achieved by BERT-wwm in Chinese tasks (Cui et al., 2019), an improved version of the BERT model proposed by Cui et al. is employed as the Encoder in our work.

### 4 Experiment

#### 4.1 Datasets

We conducted experiments on six Chinese text classification datasets, including two sentence semantic matching datasets (BQ (Chen et al., 2018) and LCQMC (Liu et al., 2018)), one text classification datasets (TNEWS (Xu et al., 2020)), one sentiment classification dataset (ChnSentiCorp1), and two Chinese question answering datasets from the NLPCC-2016 evaluation task (Duan, 2016).

**Sentence semantic matching task**: BQ is the largest Chinese question matching dataset in the banking domain. LCQMC is the largest Chinese

1https://github.com/pengming617/bert_classification/tree/master/data
semantic matching dataset available and obtained from the Baidu Knows question and answer community.

Text classification task: TNEWS selects from the news section of Today’s Headlines, with 15 news categories, including travel, education, finance, military and more. ChnSentiCorp is a Chinese sentiment classification dataset with more than 7000 hotel reviews, 5000 positive reviews and 2000 negative reviews.

Question answering task: DBQA is a document-based question answering dataset. These candidate sentences were extracted from web pages and tended to be much longer than the questions, with many irrelevant sentences. KBQA is a knowledge base based question answering dataset, and each question contained only one golden predicate.

4.2 Baselines
The following approaches are employed as the baselines, including BERT-wwm and BERT-wwm-ext (employing extended data, including Chinese Wikipedia, other encyclopedias, news, QAs and other data, with a total word count of 5.4B) (Cui et al., 2019). To evaluate the proposed approach, we additionally selected a series of pre-trained models for comparison, with RoBERTa-base, RoBERTa-large (Liu et al., 2019), MacBERT-base, MacBERT-large (Cui et al., 2020), ChineseBERT-base, and ChineseBERT-large (Sun et al., 2021).

Our approach is customized to several versions to evaluate its performance, as follows: We improve on the BERT-wwm, BERT-wwm-ext by introducing our approach to obtain RE-BERT-wwm, RE-BERT-wwm-ext. MRE-BERT fuses the textual representations of the BERT-wwm and the BERT-wwm-ext models and then introduces our approach for optimization.

4.3 Experiment Setup
The experimental setup is shown in Table 1. We found experimentally that the number of auxiliary labels is set differently for different pre-trained models and various tasks. As a hyperparameter, it needs to be adapted to the different training tasks. For LCQMC and TNEWS datasets with relatively clear classification goals and little ambiguity in the annotated data, introducing auxiliary labels did not significantly improve classification but the two-stage repetitive operation based on learning similar to human cognitive skills still improved the model’s effectiveness. In addition, the batch size is set to 64, and Adam with parameters 2e-5 is employed as the optimizer (Kingma and Ba, 2015). All experiments were performed on two Nvidia Tesla T4 GPUs.

4.4 Experiment Results
4.4.1 Matching based QA Task
As shown in Table 2, following the work of Lai et al. (Lai et al., 2019), we have implemented BERT-based Chinese KBQA and DBQA tasks based on their work. In their work, Lattice CNNs were employed as encoder, and we experimented with BERTs-base replacing Lattice CNNs as the baseline for our work.

As shown in Table 2, we have improved the experiments by employing our approach compared to the original BERT-wwm and BERT-wwm-ext. The experiments show that training through two stages is effective and our proposed approach of introducing auxiliary labels in the pre-training stage is feasible. The introduction of auxiliary labels allows for more meaningful discriminative features for classification in feature extraction.

M-BERT unites the textual semantic representations of two pre-trained models, BERT-wwm and BERT-wwm-ext. Compared to employing a single pre-trained model, BERT-wwm or BERT-wwm-ext, there is an improvement in the experimental results. The experiment also validates our previous consideration that there is variability in the textual semantic representation obtained by different pre-trained models and that an improvement can be achieved by combining multiple pre-trained models.

MRE-BERT has a significant improvement over the two BERT-base models, BERT-wwm and BERT-wwm-ext, on both DBQA and KBQA question and answers datasets. Compared to BERT-wwm, MRE-BERT has a more than 1% improvement on both datasets. There is also a substantial effect improvement in each evaluation metric compared to BERT-wwm-ext.

4.4.2 Text Classification Task
In addition, we conducted corresponding experiments on two text classification datasets, TNEWS as well as ChnSentiCorp, which have relatively few category labels.

As shown in Table 3, for the TNEWS and ChnSentiCorp datasets, which have relatively few categories, our proposed approach achieves good performance on both datasets. The experimental results for the TNEWS dataset on BERT-wwm as
| Dataset     | Scale (train/valid/test) | Model              | N\textsuperscript{a} | N\textsuperscript{t} | Epoch |
|-------------|--------------------------|--------------------|-----------------------|----------------------|-------|
| ChnSentiCorp | 9.6K/1.2K/1.2K           | RE-BERT-wwm        | 4                     | 2                    | 10    |
|             |                          | RE-BERT-wwm-ext    | 4                     | 2                    | 10    |
|             |                          | MRE-BERT           | 16                    | 2                    | 10    |
| TNEWS       | 12.1k/2.6k/2.6k          | RE-BERT-wwm        | 119                   | 119                  | 6     |
|             |                          | RE-BERT-wwm-ext    | 15                    | 15                   | 3     |
|             |                          | MRE-BERT           | 15                    | 15                   | 3     |
| DBQA        | 182k/-/-123k             | RE-BERT-wwm        | 4                     | 2                    | 2     |
|             |                          | RE-BERT-wwm-ext    | 4                     | 2                    | 2     |
|             |                          | MRE-BERT           | 128                   | 2                    | 2     |
| KBQA        | 273k/-/-156k             | RE-BERT-wwm        | 4                     | 2                    | 2     |
|             |                          | RE-BERT-wwm-ext    | 16                    | 2                    | 2     |
|             |                          | MRE-BERT           | 6                     | 2                    | 2     |
| LCQMC       | 238.7k/8.8k/12.5k        | RE-BERT-wwm        | 2                     | 2                    | 3     |
|             |                          | MRE-BERT           | 2                     | 2                    | 3     |
| BQ          | 100k/10k/10k             | MRE-BERT           | 12                    | 2                    | 5     |

Table 1: Experimental parameter settings. N\textsuperscript{a} means the whole number of auxiliary and target labels, and N\textsuperscript{t} number of target labels.

| Model | DBQA | KBQA |
|-------|------|------|
|       | P@1  | MRR  | P@1  | MRR  |
| BERT  | 90.06| 93.79| 92.88| 95.69|
| RE-BERT | 90.20| 93.80| 93.80| 96.28|
|       | 90.95| 94.38| 93.23| 95.90|
|       | 91.18| 94.57| 94.01| 96.42|
| M-BERT | 91.08| 94.36| 93.75| 96.31|
| MRE-BERT | 91.91| 95.03| 94.16| 96.56|

Table 2: Experimental results on matching based QA task. BERT represents BERT-wwm and o represents models pre-trained on extended data.

well as BERT-wwm-ext are from CLUE\textsuperscript{2} (Xu et al., 2020), and the experimental results for ChnSentiCorp are from ChineseBERT (Sun et al., 2021). The experimental results show that MRE-BERT has a better effect compared to the two base pre-trained models BERT-wwm and BERT-wwm-ext.

Table 3: Experimental on text classification task. BERT represents BERT-wwm and o represents models pre-trained on extended data.

5 Analysis and Discussion

5.1 Comparison of Different Auxiliary Labels

In order to verify the effectiveness of our approach and the effect of the auxiliary labels, we conducted some targeted experiments on the KBQA dataset.

As shown in Figure 3, we have selected a series of samples for classification after adding auxiliary labels in the pre-training stage (pre-training) for RE-BERT-wwm, BERT-wwm-ext and MRE-BERT models respectively. The w/o RE model shows the effect without our approach, from which it can be seen that models can be effectively improved by introducing auxiliary labels. With the experimental results in Figure 3, we have verified the effectiveness of our approach. The introduction of auxiliary labels helps to extract textual semantic representations efficiently, and the number of auxiliary labels needs to be set according to the needs of different models and tasks.

\textsuperscript{2}https://github.com/CLUEbenchmark/CLUE
Figure 3: Comparison of the effects of different models on KBQA dataset after the addition of auxiliary labels in the pre-training stage.

5.2 Verification Experiments

| Model         | BQ Valid | BQ Test | LCQMC Valid | LCQMC Test |
|---------------|----------|---------|-------------|------------|
| BERT base     | 86.1     | 85.2    | 89.4        | 87.0       |
| BERT$^o$      | 86.4     | **85.3**| 89.6        | 87.1       |
| RoBERTa$^o$   | 86.0     | 85.0    | 89.0        | 86.4       |
| MacBERT       | 86.0     | 85.2    | 89.5        | 87.0       |
| ChineseBERT   | 86.4     | 85.2    | 89.8        | **87.4**   |
| MRE-BERT base | 86.3     | **85.6**| 90.4        | **87.4**   |
| RoBERTa$^o$   | 86.3     | 85.8    | 90.4        | 87.0       |
| MacBERT       | 86.2     | 85.6    | 90.6        | 87.6       |
| ChineseBERT   | 86.5     | 86.0    | 90.5        | **87.8**   |
| MRE-BERT$^F$ base | 86.7 | **86.2**| 89.9        | **87.7**   |

Table 4: Validation experiments on text matching task. BERT represents BERT-wwm, $^o$ represents models pre-trained on extended data, and MRE-BERT$^F$ represents MRE-BERT with adversarial perturbation.

To further validate the effectiveness of MRE-BERT, some related experiments are conducted on two sentence semantic matching datasets and compared with current state-of-the-art pre-trained models. The experimental results show that MRE-BERT has achieved better performance compared to BERT-wwm, BERT-wwm-ext, RoBERTa-wwm-ext (Cui et al., 2019), MacBERT-base (Cui et al., 2020), and ChineseBERT-base (Sun et al., 2021).

For simple text classification tasks, we propose a novel framework for simple text classification tasks, which implements a two-stage training strategy, including pre-training based on pre-trained models and fine-tuning for classification. In the pre-training stage, auxiliary labels can be integrated to increase the training challenge and to fully exploit the knowledge in the pre-trained model. Experiments on six datasets depict that our approach outperforms the baseline BERT model for simple classification tasks. Furthermore, in the sentence semantic matching task, after adding adversarial perturbations to the embedding layer only, our basic version of the MRE-BERT model achieves promising performance, better than or equivalent to large versions of the pre-trained model, but with much fewer parameters than them. In the future, we will investigate the generalizability of our model to other classification tasks.

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