Enhancing Pre-trained Language Model with Lexical Simplification

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Abstract

For both human readers and pre-trained language models (PrLMs), lexical diversity may lead to confusion and inaccuracy when understanding the underlying semantic meanings of given sentences. By substituting complex words with simple alternatives, lexical simplification (LS) is a recognized method to reduce such lexical diversity, and therefore to improve the understandability of sentences. In this paper, we leverage LS and propose a novel approach which can effectively improve the performance of PrLMs in text classification. A rule-based simplification process is applied to a given sentence. PrLMs are encouraged to predict the real label of the given sentence with auxiliary inputs from the simplified version. Using strong PrLMs (BERT and ELECTRA) as baselines, our approach can still further improve the performance in various text classification tasks.

1 Introduction

Pre-trained language models (PrLMs) such as BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), and ELECTRA (Clark et al., 2020) have led to strong performance gains in downstream natural language understanding (NLU) tasks, including text classification. However, (Li et al., 2020; Jin et al., 2019) demonstrate that it only takes a few simple synonym replacements to mislead the prediction of PrLMs on various text classification tasks. Such result indicates that lexical diversity can pose a negative impact on the accuracy of semantic meaning understanding for PrLMs.

In order to reduce lexical diversity, previous works have proposed some approaches for lexical simplification (LS) (Gooding and Kochmar, 2019; Qiang et al., 2020). By substituting complex words with their simpler alternatives in original sentences, LS can generate a simplified sentence version, which is much easier to understand for human readers. Inspired by these studies, we leverage LS as a paraphrasing tool to enhance the prediction accuracy of PrLMs in text classification tasks.

A well-designed LS rule customized to neural network (e.g. PrLM) is crucial for our overall approach. However, existing LS methods are not suitable for PrLMs. Current methods (Gooding and Kochmar, 2019; Qiang et al., 2020) are mainly for human readers to simplify reading process, but not for neural network to improve prediction accuracy. Furthermore, current LS methods are very time-consuming. This is because they apply large pre-trained neural networks to detect and replace the complex words in a recursive way (Qiang et al., 2020). Therefore, we design a lexical simplification method based on lemmatization and rare word replacement (abbreviated as LRLS), which is more effective and serves better to our purpose, to generate simplified version of given sentence.

In order to better accommodate the LRLS lexical simplification method with PrLMs and improve the overall performance, an auxiliary framework is designed and executed. The simplified sentence generated by LRLS serves as an auxiliary input in both training and inference phase of PrLMs. In this way, PrLMs are able to make the right decision based on both the original sentence and the simplified perspective. Thus, the challenge posed by lexical diversity in text classification can be significantly reduced.

A series experiments are conducted on various text classification tasks. Empirical results show that our approach can notably improve the performance PrLMs. Meanwhile, ablation studies prove the effectiveness of our LRLS method. Furthermore, we also compare our LRLS method with other paraphrasing method used in data augmentation, such as randomly replacement of several words by synonyms (Wu et al., 2019; Wei and Zou,
Table 1: performances (%) across five text classification tasks for models with and without LS.

| Model       | SST-2 | MR   | CR   | SUBJ | AG   | Avg  |
|-------------|-------|------|------|------|------|------|
| BERT\textit{BASE} | 92.4  | 86.1 | 90.0 | 97.3 | 94.2 | 92.0 |
| +LS         | 93.5(+1.1) | 88.1(+2.0) | 90.8(+0.8) | 98.0(+0.7) | 95.0(+0.8) | 93.1(+1.1) |
| ELECTRA\textit{LARGE} | 96.7  | 90.0 | 94.3 | 97.4 | 94.6 | 94.6 |
| +LS         | 97.5(+0.8) | 91.4(+1.4) | 94.5(+0.2) | 98.1(+0.7) | 95.3(+0.7) | 95.3(+0.7) |

2 Method

2.1 LRLS Lexical Simplification Process

A well-adapted LS process is the essential to our approach. Previous works (Li et al., 2020; Jin et al., 2019) show that the prediction of PrLMs would be easily misled by replacing only a few words with their synonyms in the given sentences. By carefully observing the adversarial examples, we find that changing the tense of verbs, changing the singular and plural form of nouns, and replacing words by its less frequent synonyms compose the majority of the adversarial examples. The observation is also confirmed by (Mozes et al., 2020).

Inspired by such observation, our LRLS method is developed with two major steps: (1) lemmatization by transforming verbs and nouns into corresponding lemmas, and (2) replacing rare words with theirs more common synonyms. Firstly, we employ Natural Language Toolkit (NLTK) to detect the verbs and nouns in the given sentences, and transform every verb to its infinitive form and every noun to its singular form. Secondly, according to a word frequency list\footnote{https://github.com/hermitdave/FrequencyWords}, we label every word whose frequency is less than a frequency threshold $n_f$ as a rare word in the given sentence. We then use a word embedding from (Mrkšić et al., 2016), which is specially curated for locating synonyms, to find the top $n_s$ synonyms of identified rare words with the highest cosine similarity. Each rare word is replaced by its synonym with the highest frequency. A part-of-speech (POS) check is also applied to ensure that all the synonymous candidates hold the same POS as the original words.

2.2 Simplified Sentence As Auxiliary Input

Following (Devlin et al., 2018), the original sentence and its simplified version are combined together in to a single sentence. In our approach, the original and simplified sentences are differentiated in two ways. First, a special separation token ([SEP]) is inserted between the two sentences. Second, a learned segmentation embedding is added to every token which indicates whether it belongs to the original sentence or the simplified sentence. In both training and inference phases, we feed PrLMs the original-simplified sequence as inputs. The rest of implementations remain the same as the original PrLMs.

3 Experimental Setup

3.1 Benchmark Datasets

We conduct our experiments on five benchmark text classification tasks: (1) SST-2: Stanford Sentiment Treebank (Socher et al., 2013), (2) CR: customer reviews (Hu and Liu, 2004; Liu et al., 2015), (3) SUBJ: subjectivity/objectivity dataset (Pang and Lee, 2004), (4) MR: Movie reviews (Pang and Lee, 2005), and (5) AG: AG’s News, classification task with regard to four news topics: World, Sports, Business, and Science.

3.2 Baseline Models

We use (1) BERT-base (Devlin et al., 2018) with 12 layers, 768 hidden units, 12 heads and 110M parameters, and (2) ELECTRA-large (Clark et al., 2020) with 24 layers, 1024 hidden units, 16 heads and 340M parameters as our baseline PrLMs.

4 Experiments

In this section, comprehensive experiments and analysis are conducted. For all the experiments, we average results from three different random seeds.

4.1 Our Approach Make Gains

As shown in Table 1, we run both BERT-base (Devlin et al., 2018) and ELECTRA-large (Clark et al., 2020), with and without LS, across all five datasets. The average gain is 1.1 for BERT-base and 0.7 for ELECTRA-large. As ELECTRA-large is a very strong baseline, the result prove the effectiveness...
of our approach. As shown in Figure 1, we select several examples from MR and SST-2 to further illustrate how PrLMs can benefit from the auxiliary inputs of simplified sentences.

### 4.2 Impact of Lexical Simplification Process

Since our LRLS method is composed of two steps: transformation of verbs and nouns into their lemmas, and replacement of rare words. To investigate the impact of different LS methods, we firstly apply the two steps separately and compare with our LRLS method. We also include BERT-LS (Qiang et al., 2020), which leverages masking language model of BERT to generate synonym candidates of rare words, for further comparison.

As shown in Table 2, the lemma transformation and rare words replacement are both effective, but we can further improve the performance by combining these two methods together. The performance of our method also exceeds that of BERT-LS. Moreover, our method is more than a hundred faster than BERT-LS, since our method is entirely rule-based, while BERT-LS uses a large pre-trained neural network to detect and replace the complex words recursively.

### 4.3 Words Replacement Hyperparameters

The process of the rare word replacement is controlled by two hyperparameters: \( n_f \) and \( n_s \). \( n_f \) is the frequency threshold under which the word will be labelled as rare word and replaced. The larger the \( n_f \), the more words will be replaced. \( n_s \) is the number of synonym candidates. The larger the \( n_s \), the larger possibility that the rare words will be replaced by more common but less similar candidates. In order to investigate the effect of these two hyper-parameters, we change these two hyperparameters separately and conduct experiments on MR and SST-2 to see the impact on the performance.

As shown in Figure 2, the best performance gain is obtained with middle-sized \( n_f \) and \( n_s \), which is consistent with our expectation. Because if \( n_f \) and \( n_s \) is too small the simplified sentence will be almost the same as the original version, on the contrary if \( n_f \) and \( n_s \) is too large, it may change the underlying meaning of the sentence.

### 4.4 Alternative Frameworks

We use simplified sentences as auxiliary inputs to improve the prediction accuracy of PrLMs. However, there are other frameworks to incorporate lexical simplification with PrLMs.

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**Figure 1:** Examples that show how auxiliary inputs from simplified sentences help the PrLMs to make the right prediction. In the result column, **Baseline** demonstrates the original prediction made by BERT, and **LRLS-Aux** shows the prediction generated with the auxiliary inputs from simplified sentences.

**Figure 2:** Average performance gain over MR and SST-2. \( n_s \) is the number of synonym candidates and \( n_f \) is the threshold of the frequency under which the word will be replaced.

| Method   | MR     | SST-2  |
|----------|--------|--------|
| BERT Base | 86.4   | 92.4   |
| Lemma    | 87.6   | 93.1   |
| RR       | 87.7   | 92.9   |
| BERT LS  | 87.9   | 93.1   |
| LRLS     | 88.1   | 93.5   |

Table 2: Performances (%) using different LS methods. **Lemma** represents the transformation of verbs and nouns into their lemmas, **RR** represents the replacement of rare words.
One alternative framework is to feed PrLM only the simplified sentences in both training and inference phases. In this case, prediction is made solely based on simplified versions.

Another framework is to leverage LS as a data augmentation technique. To illustrate, let \( D = \{ x_i, y_i \}_{i=1...N} \) denote the training dataset. For a given sample \( \{ x_i, y_i \} \) in the training dataset, we generate an augmented sample by simplifying the sentence \( x_i \) to \( x'_i \) and preserving the label \( y_i \). In this way, we generate an augmented dataset \( D' = \{ x'_i, y_i \}_{i=1...N} \). PrLMs can thus learn from both the training set \( D \) and the augmented set \( D' \).

Experiments are conducted to compare our framework with the two alternative frameworks mentioned above on BERT-base.

| Method       | MR  | SST-2 |
|--------------|-----|-------|
| BERT\text{\em Base} | 86.4 | 92.4 |
| LRLS only    | 86.5 | 92.1 |
| LRLS Aug     | 87.9 | 92.6 |
| LRLS Aux     | 88.1 | 93.5 |

Table 3: Performances (%) using different frameworks to leverage simplified sentences. \textbf{LRLS only} represents predictions made solely based on simplified sentences, \textbf{LRLS Aug} represents the use of simplified sentences for training data augmentation, \textbf{LRLS Aux} represents using simplified sentences as auxiliary inputs.

As show in Table 3, framework using simplified sentences as the only input (\textbf{LRLS only}) would slightly harm the performance of PrLM. This is because a part of semantic meanings carried by original sentences may be lost during the simplification process. Experiments also show that leveraging lexical simplification for data augmentation (\textbf{LRLS Aug}) is also beneficial for the overall performance. However, this framework would double the training time and the performance is still worse than our framework (\textbf{LRLS Aux}).

### 4.5 Alternative Paraphrasing Methods

While we leverage LRLS method to paraphrase the original sentence and generate auxiliary inputs for PrLMs, we wonder if other commonly used paraphrasing techniques are effective.

These paraphrasing methods include (1) random replacement of several words by their synonyms (Wu et al., 2019; Wei and Zou, 2019), (2) translating an existing example \( x \) in language A into another language B, and then translating it back into A to obtain a paraphrased example \( x' \) (back-translation) (Xie et al., 2019; Edunov et al., 2018), and (3) randomly delete several words in the sentence (cutoff) (Shen et al., 2020).

The upper mentioned paraphrasing methods are applied on original sentences respectively to generate auxiliary inputs, and then incorporated into PrLMs. Performance on MR and SST-2 from different paraphrasing methods are compared.

As show in Table 4, cutoff would slightly harm the overall performance. This is because it simply randomly deletes several words in the original sentence to generate a paraphrased version, which tends to twist the original semantic meaning and adds noise for predictions. Although back-translation and random replacement can slightly boost the performance of PrLMs, our LRLS method remains the most effective.

| Method                              | MR  | SST-2 |
|-------------------------------------|-----|-------|
| BERT\text{\em Base}                | 86.4 | 92.4 |
| +back-translation                   | 87.0 | 92.8 |
| +cutoff                             | 86.3 | 91.6 |
| +random replacement                 | 87.3 | 92.5 |
| +LRLS                               | 88.0 | 93.5 |

Table 4: Performances (%) using different paraphrasing techniques to generate auxiliary inputs.

## 5 Conclusion

This paper proposes a novel approach that leverages lexical simplification and to reduce lexical diversity and enhance the performance of PrLMs on text classification. Experiments on various text classification tasks demonstrate that our approach consistently improves strong baselines.

Within the framework, we incorporate a specially designed lexical simplification process based on lemmatization and rare word replacement (LRLS) for better performance. Our comprehensive analysis also show that compared with other paraphrasing techniques used in previous works, LRLS is a more effective paraphrasing method to offer auxiliary information for prediction.

Furthermore, an effective framework (LRLS Aux) leveraging LRLS as auxiliary information is designed. Unlike data augmentation which only leverages paraphrased information in training phase, LRLS Aux incorporates the information in both training and inference phase and achieves better performance gains. Such framework may shed the light for more future studies.
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