Contextual Similarity is More Valuable than Character Similarity: Curriculum Learning for Chinese Spell Checking

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Abstract

Chinese Spell Checking (CSC) task aims to detect and correct Chinese spelling errors. In recent years, related researches focus on introducing the character similarity from confusion set to enhance the CSC models, ignoring the context of characters that contain richer information. To make better use of contextual similarity, we propose a simple yet effective curriculum learning framework for the CSC task. With the help of our designed model-agnostic framework, existing CSC models will be trained from easy to difficult as humans learn Chinese characters and achieve further performance improvements. Extensive experiments and detailed analyses on widely used SIGHAN datasets show that our method outperforms previous state-of-the-art methods.

1 Introduction

Chinese Spell Checking (CSC) aims to detect and correct spelling errors contained in Chinese text (Li et al., 2022). CSC is receiving more and more attention because it benefits many applications, such as essay scoring (Dong and Zhang, 2016), OCR (Afli et al., 2016), and ASR (Wang et al., 2018). As a fundamental NLP task, CSC is challenging because the Chinese spelling errors are mainly caused by confusing characters, i.e., phonologically/visually similar characters (Liu et al., 2021). As shown in Table 1, “

| Error Type        | Phonetically Similar (83%) |
|-------------------|----------------------------|
| Input             | 带(dài, bring)帽子.        |
| Correct           | 戴(dài, wear)帽子.        |
| Translation       | He wears a hat.           |

Table 1: Examples of Chinese spelling errors. The wrong/correct characters are in red/blue.

set to introduce phonological/visual similarities into the models to improve the CSC performance. However, these existing methods simply focus on the character similarity provided by the confusion set, but ignore the context of the characters. In fact, in a sentence with a spelling error, the context of the error position provide more useful information that facilitates the CSC process. For example, in in Table 1, if model pays attention to “帽子(hat)” in the context, it will easily associate the wrong character “带(dài, bring)” with the correct character “戴(dài, wear”). Therefore, we believe that the contextual similarity of the characters is more important for the CSC task than the character similarity.

In this paper, we aim to enhance CSC models by introducing contextual similarity of Chinese characters. Considering that the CSC task itself is inseparable from human learning, we hope that the model can learn like a human learns to correct spelling errors. We all know that for a student who is just beginning to learn Chinese characters, the teacher always teaches him or her from easy to difficult. Therefore, inspired by the process of humans learning Chinese characters, we also want to guide the model to learn from easy to hard. And this motivation just coincides with curriculum learning.

The core idea of curriculum learning is to train models from the easy samples to the hard ones (Soviany et al., 2021a). And the key to curriculum learning is to design a mechanism to measure the
difficulty of samples. Benefiting from this mechanism, we naturally use the contextual similarity of characters as the metric for measuring the sample’s difficulty, so as to organize the scattered training samples into ordered samples for model training. More specifically, we train the model in the order from samples with low contextual similarity to samples with high contextual similarity. Hence, the model achieves better performance than only using the traditional character similarity of confusion set. Moreover, our curriculum learning framework is model-agnostic so that it brings stable improvements for most existing CSC models.

The contributions of our work are summarized as: (1) We empirically verify that contextual similarity is more valuable than character similarity in the CSC task, which is instructive for future works. (2) We propose a simple yet effective curriculum learning framework that enhances the CSC models to explicitly focus on the contextual similarity between Chinese characters. (3) We achieve new state-of-the-art performance on SIGHAN benchmarks and conduct extensive analyses to demonstrate the effectiveness of our proposed method.

2 Methodology

2.1 Motivation

The core of our work is how to make the CSC models explicitly pay more attention to the context of Chinese characters. Therefore, we propose to use contextual similarity as the metric to measure the difficulty of samples in curriculum learning.

Based on detailed observation, we get the following two obvious facts: (1) A sample is more difficult if it has more wrong characters. (2) A sample is more difficult if the wrong character it contains is more similar to the corresponding correct character. According to these two facts, we design a specific difficulty evaluation strategy and propose the curriculum learning framework for the CSC task. More specifically, as shown in Figure 1, our curriculum learning framework is divided into two parts: Difficulty Evaluation and Curriculum Arrangement, which will be described in Sections 2.2 and 2.3 respectively.

2.2 Difficulty Evaluation

In the difficulty evaluation module, we aim to assign a difficulty score to each training sample in the whole training set $S$. For each sample, we employ an encoder $E(\cdot)$ (e.g., BERT or other CSC models), to transform the characters in the wrong sequence $s_i$ and correct sequence $t_i$ to the corresponding contextual representations $E(s_i)$ and $E(t_i)$.

After obtaining the contextual representations of the wrong/correct sentence, we use the representation corresponding to the wrong position to calculate the cosine similarity, and then the similarities corresponding to all positions with an error are summed up as the difficulty score of the sample:

$$d_i = \sum_{j \in W_i} \frac{E(s_i)_j \cdot E(t_i)_j}{\|E(s_i)_j\| \cdot \|E(t_i)_j\|},$$

where $d_i$ is the difficulty score of $i$-th sample, $W_i$ are the positions with error. To verify the effective-
Table 2: The performance of our CL method and all baseline methods. "↑" indicates that our CL method is able to enhance the corresponding baseline. We underline the previous state-of-the-art performance for convenience. The results on SIGHAN13/14 are shown in Appendix A.4.

| Dataset   | Method                          | Detection Level | Correction Level |
|-----------|---------------------------------|-----------------|-----------------|
|           |                                 | Pre  | Rec  | F1   | Pre  | Rec  | F1   |
| SIGHAN15  | SpellGCN (Cheng et al., 2020)   | 74.8 | 80.7 | 77.7 | 72.1 | 77.7 | 75.9 |
|           | PLOME (Liu et al., 2021)        | 77.4 | 81.5 | 79.4 | 75.3 | 79.3 | 77.2 |
|           | MLM-phonetics (Zhang et al., 2021) | 77.5 | 83.1 | 80.2 | 74.9 | 80.2 | 77.5 |
|           | Soft-Masked BERT (Zhang et al., 2021) | 67.6 | 78.7 | 72.7 | 63.4 | 73.9 | 68.2 |
|           | CL (Soft-Masked BERT)           | 70.1↑| 81.4↑| 75.3↑| 65.8↑| 75.7↑| 70.4↑|
|           | BERT (Xu et al., 2021)          | 74.2 | 78.0 | 76.1 | 71.6 | 75.3 | 73.4 |
|           | CL (BERT)                       | 77.6↑| 81.2↑| 79.4↑| 75.6↑| 80.2↑| 77.8↑|
|           | REALISE (Xu et al., 2021)       | 77.3 | 81.3 | 79.3 | 75.9 | 79.9 | 77.8 |
|           | CL (REALISE)                    | 78.0↑| 82.7↑| 80.3↑| 76.8↑| 80.7↑| 77.8↑|

2.3 Curriculum Arrangement

In this section, we describe an Annealing method to arrange all the training samples $S$ into an ordered curriculum based on the difficulty scores that are introduced in Section 2.2.

Firstly, we sort all training samples in ascending order of their difficulty scores and split them into $k$ subsets $\{S_1, S_2, ..., S_k\}$. Note that these subsets are non-overlapping for preventing over-fitting and improving the generalization performance.

Then we arrange a learning curriculum which contains $k + 1$ training stages. At the $i$-th stage ($i \leq k$), we further split each of the $k$ subsets $\{S_1, S_2, ..., S_k\}$ into $k$ parts by order of difficulty. For each subset $S_j$, we obtain $\{S_{j,1}, S_{j,2}, ..., S_{j,k}\}$ and use the $i$-th part $S_{j,i}$ for this $i$-th stage, thus the final training set $C_i = \{S_{1,i}, S_{2,i}, ..., S_{k,i}\}$ is employed for the $i$-th stage. It is worth mentioning that the training set $C_i$ will be shuffled for maintaining local stochastics within $i$-th stage.

For the former $k$ stages, the model is trained on the $C_i$ for one epoch one after another to lead the model learning from easy to difficult. At the last stage (i.e., the $k + 1$-th stage), the model is trained on the whole training set $S$ for fitting the original distribution of training data.

3 Experiments

3.1 Datasets

**Train data** Following previous works (Zhang et al., 2020; Xu et al., 2021), we use the same training data which contains SIGHAN 2013 (Wu et al., 2013), SIGHAN 2014 (Yu et al., 2014), SIGHAN 2015 (Tseng et al., 2015) and a generated pseudo training dataset (Wang et al., 2018).

**Test data** To ensure fairness, models’ performance is evaluated in the same test data as these baseline methods in sentence detection and correction level, from the test datasets of SIGHAN 13/14/15. The other datasets details and experimental setup are shown in Appendix A.2 and A.3.

3.2 Baseline Methods

We select advanced strong models which are based on the traditional confusion set as baselines: SpellGCN (Cheng et al., 2020) applies GCNs to learn the character similarity from confusion set. PLOME (Liu et al., 2021) designs pre-training strategy based on the confusion set. MLM-phonetics (Zhang et al., 2021) introduces phonetic similarity into masked language models from confusion set. In addition, we select three popular CSC models to be combined with our proposed curriculum learning (CL) method: BERT (Devlin et al., 2019) directly fine-tunes the $BERT_{BASE}$ model on the CSC training data. Soft-Masked BERT (Zhang et al., 2020) utilizes the confusion set to generate sufficient training data. REALISE (Xu et al., 2021) extracts and mixes semantic, phonetic, and graphic information.

3.3 Experimental Results

Table 2 shows the results of our CL method compared to various baselines. We can see that, by reordering the easy-to-difficult training samples, our CL method yields consistent gain with a large margin against all baselines.

Particularly, unlike most models which introduce character similarity through confusion set, our CL
Method | Correction F1 | ∆
--- | --- | ---
REALISE | 77.8% | −
Only Difficulty Evaluation | 78.4% | +0.6%
Only Curriculum Arrangement | 78.2% | +0.4%
Using Character Similarity | 78.3% | +0.5%
CL (REALISE) | 78.7% | +0.9%

Table 3: Results of ablation studies. "∆" indicates the absolute F1 improvements on correction level.

The method achieves better performance by explicitly focusing on the contextual similarity. Additionally, the significant improvements over the three models (i.e., Soft-Masked BERT, BERT, and REALISE) verify the model-agnostic characteristic and effectiveness of our proposed framework.

### 3.4 Ablation Study

To explore the contribution of each component in our curriculum learning framework, we conduct ablation studies with the following settings: 1) only using difficulty evaluation to sort training samples for the training process of REALISE, 2) only using curriculum arrangement to randomly arrange training stages for the training process of REALISE, and the training samples of each stage are randomly selected. 3) Besides, to verify the advantage of contextual similarity, we also use the confusion set-based character similarity as the difficulty metric in our CL framework.

From Table 3, we observe that both difficulty evaluation and curriculum arrangement bring improvements for REALISE, which indicates the rationality of these two modules we design. Particularly, the main motivation of our work is to measure the difficulty of samples by contextual similarity. The greater improvements that only using difficulty evaluation brings to REALISE than only using curriculum arrangement and using character similarity reflects the correctness of our motivation that contextual similarity is more valuable than character similarity in the CSC task.

### 3.5 Parameter Study

The key parameter in our proposed framework is the number of subsets \( k \), so it is essential to study its effects. Figure 2 illustrates the performance change of CL (REALISE), we find that when the value of \( k \) reaches a certain value, the performance of the model does not improve anymore. In fact, this phenomenon is consistent with the process of human learning. Imagine that when the courses are divided too trivially (that is, when the value of \( k \) is too large), it is difficult for humans to learn effective knowledge from too many courses. Therefore, it is critical to choose the best \( k \), although there are stable improvements based on REALISE at all values of \( k \).

### 3.6 Statistics Study

In our method, the training dataset is divided into \( k \) subsets with different levels of difficulty. Therefore, we further explore the features of easy/difficult samples. Figure 3 shows the statistical distinctions of training samples in the different subsets. Among ten different levels of difficulty, we find that samples in the easier subsets are shorter than these samples in more difficult subsets. In addition, the more difficult samples are, the more error characters we can find in sentences. This result verifies our observed fact that is mentioned in Section 2.1.

### 4 Conclusion

In this paper, we aim to exploit the contextual similarity of characters to obtain better CSC performance than character similarity contained in traditional confusion set. Additionally, we propose a simple yet effective curriculum learning framework for the CSC task. With the help of such a model-
agnostic framework, most existing CSC models significantly perform better.
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A Appendix

A.1 Related Work

Chinese Spell Checking In the field of CSC, many works focus on constructing and employing confusion set to guide the models to correct the erroneous characters. Hybrid (Wang et al., 2018) utilizes OCR and ASR-based methods to automatically generate pseudo training sentences and construct high quality confusion set. Pointer Networks (Wang et al., 2019a) incorporates a copy mechanism into a Seq2Seq model and infuses the network with off-the-shelf confusion set (Wang et al., 2018) for acquiring corrected characters. SpellGCN (Cheng et al., 2020) employs graph convolutional network and pre-defined confusion set (Wu et al., 2013) to generate candidate characters for the CSC task. PLOME (Liu et al., 2021) and MLM-phonetics (Zhang et al., 2021) optimize the masking mechanism of masked language models via confusion set and achieves previous state-of-the-art performance. Besides, REALISE (Xu et al., 2021) and PHMOSpell (Huang et al., 2021) design BERT-based fusion network to capture multi-modal information, including phonetic and graphic knowledge in Chinese characters.

To the best of our knowledge, existing CSC works improve model performance by introducing character similarity provided by confusion set, but has not made the model focus on contextual similarity of Chinese characters. As a matter of fact, the context of the spelling error position is able to provide vital information for CSC task. In this paper, it is the first time that contextual similarity is applied successfully into the CSC task.

Curriculum Learning The idea of curriculum learning is to train deep learning-based models from easy samples to difficult samples, which is firstly proposed in (Bengio et al., 2009). And it has been widely used in various tasks of Computer Vision (Ionescu et al., 2016; Jiang et al., 2018; Soviany et al., 2021b). With the great success in the field of CV, curriculum learning has attracted an increasing number of researchers to apply this strategy to all kinds of NLP tasks, which include Machine Translation (Wang et al., 2019b), Question answering (Liu et al., 2018), Reading Comprehension (Liang et al., 2019).

A.2 Dataset Statistics

Originally, the characters of SIGHAN datasets are in Traditional Chinese. Similar to the previous works, we transfer the data into simplified Chinese characters using the OpenCC tool\(^2\). The statistics of our used datasets are presented in Table 4.

| Training Data | #Sent | Avg. Length | #Errors |
|---------------|-------|-------------|---------|
| SIGHAN13      | 700   | 41.8        | 343     |
| SIGHAN14      | 3,437 | 49.6        | 5,122   |
| SIGHAN15      | 2,338 | 31.3        | 3,037   |
| Wang271K      | 271,329 | 42.6    | 381,962 |
| **Total**     | 277,804 | 42.6      | 390,464 |

| Test Data  | #Sent | Avg. Length | #Errors |
|------------|-------|-------------|---------|
| SIGHAN13   | 1,000 | 74.3        | 1,224   |
| SIGHAN14   | 1,062 | 50.0        | 771     |
| SIGHAN15   | 1,100 | 30.6        | 703     |

Table 4: Statistics of datasets.

A.3 Experimental Setup

To certify the effectiveness of our approach, we add the CL module into these baselines and implemented them based on Huggingface’s Pytorch implementation of Transformer library (Wolf et al., 2020). During the training phase, we follow the REALISE (Xu et al., 2021) and Soft-Masked-Bert (Zhang et al., 2020) to set our hyper-parameters. For REALISE, the learning-rate is set to \(5 \times 10^{-5}\), the batch size is set to 32. In addition, warming up and linear decay are utilized during the model training with the AdamW optimizer. As for Soft-Masked-Bert, we maintain a learning rate \(2 \times 10^{-5}\) and fine-tune the parameters with Adam. During the testing phase, we evaluate the effect of a method in both detection and correction utilizing sentence-level accuracy, precision, recall, and F1 score. The order of training examples is the only difference between these baselines and our CL approach. Empirically, we choose \(K = 10\) as the number of subsets in our method for CSC task.

A.4 SIGHAN13/14 Results

Due to the limitation of the pages, we put the experimental results on SIGHAN3/14 in Table 5.

A.5 Case Study

Table 6 shows the comparisons between the low and high similarity spelling errors. In the first example, “怒(nü)” is the erroneous character. “女(nü)” is the corrected character. The two characters

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\(^2\)https://github.com/BYVoid/OpenCC
| Dataset | Method | Detection Level | Correction Level |
|---------|--------|-----------------|------------------|
|         |        | Pre  | Rec  | F1   | Pre  | Rec  | F1   |
| SIGHAN13| SpellGCN (Cheng et al., 2020) | 80.1 | 74.4 | 77.2 | 78.3 | 77.7 | 78.2 |
|         | DCN (Wang et al., 2021) | 86.8 | 79.6 | 83.0 | 84.7 | 77.7 | 81.0 |
|         | MLM-phonetics (Zhang et al., 2021) | 82.0 | 78.3 | 80.1 | 79.5 | 77.0 | 78.2 |
|         | Soft-Masked BERT (Zhang et al., 2021) | 81.1 | 75.7 | 78.3 | 75.1 | 70.1 | 72.5 |
|         | CL (Soft-Masked BERT) | 83.7↑| 77.5↑| 80.5↑| 77.9↑| 73.5↑| 75.6↑|
|         | BERT (Xu et al., 2021) | 85.0 | 77.0 | 80.8 | 83.0 | 75.2 | 78.9 |
|         | CL (BERT) | 87.2↑| 79.6↑| 83.2↑| 85.7↑| 78.8↑| 82.1↑|
|         | REALISE (Xu et al., 2021) | 88.6 | 82.5 | 85.4 | 87.2 | 81.2 | 84.1 |
|         | CL (REALISE) | 89.2↑| 83.3↑| 86.1↑| 88.1↑| 82.4↑| 85.1↑|
| SIGHAN14| SpellGCN (Cheng et al., 2020) | 65.1 | 69.5 | 67.2 | 63.1 | 67.2 | 65.3 |
|         | DCN (Wang et al., 2021) | 67.4 | 70.4 | 68.9 | 65.8 | 68.7 | 67.2 |
|         | MLM-phonetics (Zhang et al., 2021) | 66.2 | 73.8 | 69.8 | 64.2 | 73.8 | 68.7 |
|         | Soft-Masked BERT (Zhang et al., 2021) | 65.2 | 70.4 | 67.7 | 63.7 | 68.7 | 66.1 |
|         | CL (Soft-Masked BERT) | 66.4↑| 71.5↑| 68.9↑| 64.8↑| 69.9↑| 67.3↑|
|         | BERT (Xu et al., 2021) | 64.5 | 68.6 | 66.5 | 62.4 | 66.3 | 64.3 |
|         | CL (BERT) | 66.1↑| 70.4↑| 68.2↑| 63.3↑| 68.0↑| 65.6↑|
|         | REALISE (Xu et al., 2021) | 67.8 | 71.5 | 69.6 | 66.3 | 70.0 | 68.1 |
|         | CL (REALISE) | 68.9↑| 72.0↑| 70.4↑| 67.5↑| 70.6↑| 69.0↑|

Table 5: The performance of our CL method and all baseline methods. “↑” indicates that our CL method is able to enhance the corresponding baseline. To compare with previous models conveniently, we underline the previous state-of-the-art performance on SIGHAN13/14 datasets.

| Input: 前总统老布什的孙(nü)很可爱。 | The anger of former President Bush Sr. is very cute. |
| Correct: 前总统老布什的孙女(nǚ)很可爱。 | The granddaughter of former President Bush Sr. is very cute. |
| Difficulty: 0.541 |

| Input: 他们将联袂(zhù)演这部作品。 | They will live in this work together. |
| Correct: 他们将联袂主(zhˇu)演这部作品。 | They will star in this work together. |
| Difficulty: 0.927 |

Table 6: Examples of spelling errors with low and high difficulty score. We mark the input wrong/correct characters in red/blue.

are only slightly acoustically similar. Therefore, the low difficulty score evaluated by our CL-REALISE of this example is reasonable. In the second example, the erroneous character “住(zhù)” is extremely similar to the corrected character “主(zhˇu)” in both shape and pronunciation level. The difficulty score of the latter example is also significantly higher than the first example. This suggests that the model has learned how to distinguish between highly similar and slightly similar Chinese spelling errors.