SDCL: Self-Distillation Contrastive Learning for Chinese Spell Checking

Xiaotian Zhang, Hang Yan, Yu Sun, Xipeng Qiu*
Shanghai Key Laboratory of Intelligent Information Processing, Fudan University
School of Computer Science, Fudan University
{xiaotianzhang21, yusun21}@m.fudan.edu.cn, {hyan19, xpqiu}@fudan.edu.cn

Abstract

Due to the ambiguity of homophones, Chinese Spell Checking (CSC) has widespread applications. Existing systems typically utilize BERT for text encoding. However, CSC requires the model to account for both phonetic and graphemic information. To adapt BERT to the CSC task, we propose a token-level self-distillation contrastive learning method. We employ BERT to encode both the corrupted and corresponding correct sentence. Then, we use contrastive learning loss to regularize corrupted tokens’ hidden states to be closer to counterparts in the correct sentence. On three CSC datasets, we confirmed our method provides a significant improvement above baselines.

1 Introduction

Chinese Spell Checking (CSC) is a task to detect and correct spelling mistakes in Chinese sentences. It differs from Chinese Grammatical Error Diagnosis (CGED) in that CSC will not delete or insert any characters. Because CSC is usually the pre-process of downstream Natural Language Processing (NLP) tasks, CSC has been extensively studied recently (Hong et al., 2019; Cheng et al., 2020; Ji et al., 2021; Xu et al., 2021).

Since the introduction of pre-trained model BERT (Devlin et al., 2019), many works have tried to utilize the power of pre-training models to achieve good results (Hong et al., 2019; Zhang et al., 2020). BERT used the masked language modeling (MLM) task to pre-train, which forces BERT to utilize the contextual information to recover the masked token. The pre-training task makes BERT suitable to conduct predictions through semantic information. However, as pointed out in previous work (Liu et al., 2010), 83% and 48% of the CSC errors are related to phonological similarity and visual similarity, respectively. Therefore, directly using BERT to tackle this task will cause a mismatch between what BERT excels at and what this task needs. An example is depicted in Figure 1.

Previous works have tried to narrow this gap by combining confusion set into their model (Cheng et al., 2020; Hong et al., 2019). Ji et al. (2021); Zhang et al. (2021); Li et al. (2021); Liu et al. (2021); Xu et al. (2021) took one step further through adding phonetic or graphic information during the pre-training phase.

However, these methods of explicitly introducing prior information rely on additional training data or parameters, increasing the cost of training. And cross-entropy loss only changes the token embedding of the word, not the contextual embedding, as shown in Figure 2.

Instead of relying on confusion sets or further pre-training, we utilize contrastive learning (CL) to narrow the gap, by pulling together the hidden states of wrong and right character usages.

Contrastive learning gains great popularity recently for its outstanding performance in learning better image representations (Chen et al., 2020; He et al., 2020). In NLP, Gao et al. (2021a); Gunel et al. (2021) tried to use CL to get better sentence representation, the formerly used dropout to form positive samples, and the latter used samples with

| Case               | BERT Input               | BERT Output          |
|--------------------|--------------------------|----------------------|
| Masked             | 这是一个很好的 [MASK] 例。 | [MASK] → 案          |
| Graphically Similar| 这是一个很好的友 (yǒu, friend) 例。 | 友 → 案               |
| Phonetically Similar| 这是一个很好的返 (fǎn, back) 例。 | 返 → 案               |

Figure 1: Example of the CSC task. BERT cannot take advantage of the erroneous characters “友” (visually similar to “反”) or “返” (phonetically similar to “反”) to recover the expected character “反”.

*Corresponding author.

1Confusion set contains characters sound or looks like each other.
the same class as positive samples. However, these attempts are mainly focused on the sentence-level, Su et al. (2021) proposed to use the method to adapt the CL in the token-level, and it forms positive token samples by not masking out this token. To reduce training costs, We use an efficient self-distillation method to obtain the positive and negative samples(Gao et al., 2021b).

In summary, We propose a Self-Distillation Contrastive Learning (SDCL) method to alleviate the phenomenon. Without extra parameters and training data, our method use regularization loss to help BERT learn uniformly contextual embedding distribution, achieve significant performance gains on the baseline, and can even surpass specific pre-trained models achieving comparable performance to SOTA in three CSC datasets.

2 Methodology

We first introduce the formulation of the CSC task, then present the details of our proposed Self-Distillation Contrastive Learning model.

2.1 The Main Model

The CSC task can be formulated as given an input sentence $X = [x_1, ..., x_n]$ with $n$ characters, the model needs to output its corresponding correct sentence $Y = [y_1, ..., y_n]$. Usually, most tokens in $Y$ will be the same as their counterpart in $X$.

We use MacBERT (Cui et al., 2020) as a strong backbone to extract the semantic features of $X$ and then use dot products with the word embedding $W$ to output the character distribution. This process can be formulated as

$$H = \text{BERT}(X),$$

$$P(\hat{Y}|X) = \text{softmax}(W \cdot H),$$

where $\text{BERT}()$ takes the sentence $X$ as input, and outputs a contextualized dense matrix $H \in \mathbb{R}^{n \times d}$ and $d$ is the hidden state dimension; We use dot product to calculate the similarity of $W_i$ and $H_i$ rather than MLMHead() (Since there is little performance difference and we set this for implement contrastive loss), then use the result after softmax as the token distribution $P(\hat{Y}|X) \in \mathbb{R}^{n \times |V|}$, $|V|$ is the vocabulary size. After getting the token distribution, we calculate the cross-entropy loss as follows

$$L_x = -\sum_i^n \log(P(\hat{Y}_i = y_i|X))$$

2.2 Contrastive Loss

As mentioned before, most of the errors in the CSC task are caused by phonological or visual similarities, instead of semantical misuses. Therefore, it is hard for BERT to recover the right characters based on contextualized information.
| Dataset       | Method                                      | Detection Level | Correction Level |
|--------------|---------------------------------------------|-----------------|------------------|
|              |                                             | Pre  | Rec  | F1   | Pre  | Rec  | F1   |
| SIGHAN13     | FASpell (Hong et al., 2019)                 | 76.2 | 63.9 | 69.1 | 73.1 | 60.5 | 66.2 |
|              | SpellGCN (Cheng et al., 2020)              | 80.1 | 74.4 | 77.2 | 78.3 | 72.7 | 75.4 |
|              | BERT (Xu et al., 2021)                     | 79.0 | 72.8 | 75.8 | 77.7 | 71.6 | 74.6 |
|              | MLM-phonetics * (Zhang et al., 2021)       | 82.0 | 78.3 | 80.1 | 79.5 | 77.0 | 78.2 |
|              | BERT + Adversarial training ♠ (Li et al., 2021) | -    | -    | -    | -    | -    | -    |
|              | REALISE ♣ (Xu et al., 2021)                | 88.6 | 82.5 | 85.4 | 87.2 | 81.2 | 84.1 |
|              | BERT + Pre-trained for CSC ♠ (Li et al., 2021) | -    | -    | -    | -    | -    | -    |
|              | SDCL (ours)                                 | 88.9 | ↑    | 81.8 | 88.0 | ↑    | 81.0 |
|              |                                            |     |      |      |     |      |      |
|              |                                             |     |      |      |     |      |      |
| SIGHAN14     | Hybrid (Wang et al., 2018a)                | 51.9 | 66.2 | 58.2 | -    | -    | 56.1 |
|              | FASpell (Hong et al., 2019)                | 61.0 | 53.7 | 57.0 | -    | -    | 61.0 |
|              | SpellGCN (Cheng et al., 2020)              | 65.1 | 69.5 | 67.2 | 63.1 | 67.2 | 65.3 |
|              | BERT (Xu et al., 2021)                    | 64.5 | 68.6 | 66.5 | 62.4 | 66.3 | 64.3 |
|              | MLM-phonetics * (Zhang et al., 2021)       | -    | -    | -    | -    | -    | -    |
|              | BERT + Adversarial training ♠ (Li et al., 2021) | -    | -    | -    | -    | -    | -    |
|              | REALISE ♣ (Xu et al., 2021)                | 67.8 | 71.5 | 69.6 | 66.3 | 70.0 | 68.1 |
|              | BERT + Pre-trained for CSC ♠ (Li et al., 2021) | -    | -    | -    | -    | -    | -    |
|              | SDCL (ours)                                 | 69.7 | ↑    | 70.3 | 70.0 | ↑    | 67.5 |
|              |                                            |     |      |      |     |      |      |
| SIGHAN15     | Hybrid (Wang et al., 2018a)                | 56.6 | 69.4 | 62.3 | -    | -    | 57.1 |
|              | FASpell (Hong et al., 2019)                | 67.6 | 60.0 | 63.5 | 66.6 | 59.1 | 62.6 |
|              | Soft-Masked BERT (Zhang et al., 2020)      | 73.7 | 73.2 | 73.5 | 66.7 | 66.2 | 66.4 |
|              | SpellGCN (Cheng et al., 2020)              | 74.8 | 80.7 | 77.7 | 72.1 | 77.7 | 75.9 |
|              | BERT (Xu et al., 2021)                    | 74.2 | 78.0 | 76.1 | 71.6 | 75.3 | 73.4 |
|              | 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 |
|              | REALISE ♣ (Xu et al., 2021)                | 77.3 | 81.3 | 79.3 | 75.9 | 79.9 | 77.8 |
|              | BERT + Pre-trained for CSC ♠ (Li et al., 2021) | -    | -    | -    | -    | -    | -    |
|              | BERT + Adversarial training ♠ (Li et al., 2021) | 80.0 |     |     | -    | -    | -    |
|              | SDCL (ours)                                 | 81.2 | 79.1 | 80.1 | 79.3 | 77.5 | 78.3 |
|              |                                            |     |      |      |     |      |      |

Table 1: Main results of our model. The "♠" symbol means additional training data, "♣" symbol indicates extra model parameters, and "⋆" symbol means both. ↑ hints our method performs a significant test $p$-value $< 0.05$ when comparing with baseline.

We propose using an extra loss to help BERT build the connection between the erroneous characters and their corresponding right ones. We want the BERT model to output the close hidden states for the corrupted sentence and its corresponding right sentence through this loss. We propose a self-distillation method with a shared weights teacher BERT to construct positive samples for contrastive learning. Specifically, the calculation of the loss is as follows

$$
- \sum_{i=1}^{n} \mathbb{1}(\tilde{x}_i) \log \frac{\exp \left( \frac{\text{sim}(\tilde{h}_i, h_i)}{\tau} \right)}{\sum_{j=1}^{n} \exp \left( \frac{\text{sim}(\tilde{h}_i, h_j)}{\tau} \right)}
$$

where $\mathbb{1}(\tilde{x}_i) = 1$ if $x_i$ is the error token, else 0. The $\tilde{h}_i$ indicates the corresponding hidden states from teacher BERT with golden input; $\tau$ is the temperature hyper-parameter and $\text{Sim}(\tilde{h}_i, h_i)$ is the cosine similarity between these two vectors. Minimizing $L_c$ aims to make the hidden states of the corrupted tokens similar to their correct counterpart. We sample from the batch as negative samples rather than confusion set (Wu et al., 2013) to improve training speed. We also add a cross-entropy loss for the teacher BERT to repeat the inputs. We use stop gradient (sg) to decouple the gradient backpropagation to $\tilde{h}_i$ for stability during training and the final loss is as follows

$$
L_y = - \sum_{i} \log(P(Y_i = y_i|Y')),
$$

$$
L = L_x + \alpha L_y + \beta L_c,
$$

where $L_x$ is the cross-entropy loss with the outputs from the student BERT, $L_y$ is the cross-entropy loss with the outputs from the teacher BERT, and $L_c$ is the contrastive loss.
where $\alpha, \beta$ is the hyper-parameter. The general model structure is depicted in Figure 3.

3 Experiments

3.1 Data and Metrics

To show the effectiveness of our proposed method, we conduct experiments in three CSC datasets, namely SIGHAN13 (Wu et al., 2013) SIGHAN14 (Yu et al., 2014), SIGHAN15 (Tseng et al., 2015). We use the sentence-level metric for both detection and correction to evaluate (Cheng et al., 2020). Our settings are consistent with previous work (Xu et al., 2021). More details on data, metrics, and implementation can be found in the Appendix.

3.2 Main Results

The main experimental results are depicted in Table 1. Results show that adding contrastive loss consistently enhances the performance in three datasets. Moreover, our “SDCL” even surpasses various further pre-trained models.

4 Analysis

In order to show that our model can help BERT correct phonetically or visually similar errors, we design two probing tasks.

The first one is a case study to show that our model pulls together the last hidden states of different wrong character usages. The results are displayed in Figure 4. As shown, without training, BERT fails to build a connection between the correct character “庄” and other characters, and the large cosine similarity between different characters aligns well with (Ethayarajh, 2019; Gao et al., 2021a)”s observation that the pre-trained word embeddings suffers from anisotropy. The comparison between BERT and SDCL shows that contrastive loss can help BERT better capture the phonological and visual similarity between intra-class characters.

The second one is the alignment and uniformity which is used to measure the quality of representations (Wang and Isola, 2020). With the gold characters as $p_{pos}$, alignment calculates the expected distance between embeddings of paired characters in the same context.

$$\ell_{align} \triangleq \mathbb{E}_{(x,x^+) \sim p_{pos}} \| f(x) - f(x^+) \|^2 \quad (1)$$

On the other hand, uniformity measures how well the embeddings are uniformly distributed:

$$\ell_{uniform} \triangleq \log \mathbb{E}_{x,y \sim i.i.d \text{ Data}} e^{-2\|f(x) - f(y)\|^2} \quad (2)$$

where $p_{data}$ denotes the samples from confusion set. Specifically, for each sample in the test sets, we replace the source token in the wrong position with a randomly selected token from the confusion set as a negative sample. As depicted in Table 2, SDCL uniformly learn the embedding and the uniformity loss is reduced at the expense of the elevated alignment loss.

|                | BERT | SDCL (w/o CL) | SDCL |
|----------------|------|---------------|------|
| alignment      | 2.58 | 2.62          | **2.9** |
| uniformity     | -6.64 | -6.62        | **-6.88** |

Table 2: The alignment and uniformity of the model’s predictions in the test set.

5 Conclusion

In this paper, we propose Self-Distillation Contrastive Learning (SDCL) for CSC task. The proposed method uniform the contextual embedding distribution by contrastive learning with self-distillation. Experiments on three CSC datasets reveal that our method is simple and effective. It provides a new perspective to explore new state-of-the-art results in CSC task.

---

3We use the confusion set realised by (Wu et al., 2013).
References

Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey E. Hinton. 2020. A simple framework for contrastive learning of visual representations. In Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event, volume 119 of Proceedings of Machine Learning Research, pages 1597–1607. PMLR.

Xingyi Cheng, Weidi Xu, Kunlong Chen, Shaohua Jiang, Feng Wang, Taifeng Wang, Wei Chu, and Yuan Qi. 2020. Spellgcn: Incorporating phonological and visual similarities into language models for chinese spelling check. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. ACL 2020, Online, July 5-10, 2020, pages 871–881. Association for Computational Linguistics.

Yiming Cui, Wanxiang Che, Ting Liu, Bing Qin, Shi Sun. 2021a. A lightweight pretrained model for chinese spelling correction. In Proceedings of the 9th International Joint Conference on Natural Language Processing, SIGHAN@IJCNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021, pages 3544–3551. Association for Computational Linguistics.

Chong Li, Cenyuan Zhang, Xingling Zheng, and Xuanjing Huang. 2021. Exploration and exploitation: Two ways to improve chinese spelling correction models. arXiv preprint arXiv:2105.14813.

Chao-Lin Liu, Min-Hua Lai, Yi-Hsuan Chuang, and Chia-Ying Lee. 2010. Visually and phonologically similar characters in incorrect simplified chinese words. In COLING 2010, 23rd International Conference on Computational Linguistics, Posters Volume, 23-27 August 2010, Beijing, China, pages 739–747. Chinese Information Processing Society of China.

Shulin Liu, Tao Yang, Tianchi Yue, Feng Zhang, and Di Wang. 2021. Pliome: Pre-training with misspelled knowledge for chinese spelling correction. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2991–3000.

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. OpenReview.net.

Yuxuan Su, Fangyu Liu, Zaiqiao Meng, Lei Shu, Ehsan Shareghi, and Nigel Collier. 2021. Tacl: Improving BERT pre-training with token-aware contrastive learning. CoRR, abs/2111.04198.

Yuen-Hsien Tseng, Lung-Hao Lee, Li-Ping Chang, and Hsin-Hsi Chen. 2015. Introduction to SIGHAN 2015 bake-off for chinese spelling check. In Proceedings of the Eighth SIGHAN Workshop on Chinese Language Processing, SIGHAN@IJCNLP 2015, Beijing, China, July 30-31, 2015, pages 32–37. Association for Computational Linguistics.
Dingmin Wang, Yan Song, Jing Li, Jialong Han, and Haisong Zhang. 2018a. A hybrid approach to automatic corpus generation for chinese spelling check. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2517–2527.

Dingmin Wang, Yan Song, Jing Li, Jialong Han, and Haisong Zhang. 2018b. A hybrid approach to automatic corpus generation for chinese spelling check. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 2517–2527. Association for Computational Linguistics.

Tongzhou Wang and Phillip Isola. 2020. Understanding contrastive representation learning through alignment and uniformity on the hypersphere. In International Conference on Machine Learning, pages 9929–9939. PMLR.

Shih-Hung Wu, Chao-Lin Liu, and Lung-Hao Lee. 2013. Chinese spelling check evaluation at SIGHAN bake-off 2013. In Proceedings of the Seventh SIGHAN Workshop on Chinese Language Processing, SIGHAN@IJCNLP 2013, Nagoya, Japan, October 14-18, 2013, pages 35–42. Asian Federation of Natural Language Processing.

Heng-Da Xu, Zhongli Li, Qingyu Zhou, Chao Li, Zizhen Wang, Yunbo Cao, Heyan Huang, and Xian-Ling Mao. 2021. Read, listen, and see: Leveraging multimodal information helps chinese spell checking. In Findings of the Association for Computational Linguistics: ACL/IJCNLP 2021, Online Event, August 1-6, 2021, volume ACL/IJCNLP 2021 of Findings of ACL, pages 716–728. Association for Computational Linguistics.

Liang-Chih Yu, Lung-Hao Lee, Yuen-Hsien Tseng, and Hsin-Hsi Chen. 2014. Overview of SIGHAN 2014 bake-off for chinese spelling check. In Proceedings of The Third CIPS-SIGHAN Joint Conference on Chinese Language Processing, Wuhan, China, October 20-21, 2014, pages 126–132. Association for Computational Linguistics.

Ruiqing Zhang, Chao Pang, Chuanqiang Zhang, Shuohuan Wang, Zhongjun He, Yu Sun, Hua Wu, and Haifeng Wang. 2021. Correcting chinese spelling errors with phonetic pre-training. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 2250–2261.

Shaohua Zhang, Haoran Huang, Jicong Liu, and Hang Li. 2020. Spelling error correction with soft-masked bert. arXiv preprint arXiv:2005.07421.

A Data and Metrics

Following previous work (Cheng et al., 2020; Xu et al., 2021), for the evaluation of SIGHAN14 and SIGHAN15, we merge the training set of SIGHAN134, SIGHAN14, SIGHAN15 and the generated pseudo data from Wang et al. (2018b). To make sure our results are comparable with previous work, we directly use the realised processed data from Xu et al. (2021)5, more details on data processing can be found in (Xu et al., 2021). For the OCR dataset, we only train on its training set and evaluate in its testing set, and this setting is the same as (Hong et al., 2019; Ji et al., 2021).

Since the ultimate target of the CSC task is to correct all wrong usages in the sentence, we report the F1, precision and recall metrics in the sentence-level, namely, only when all characters in a sentence are correctly detected6 or corrected can deem it succeed once.

B Implementation Details

Following (Xu et al., 2021), we use the pretrained weight realised by (Cui et al., 2020). For all of our models, we use the AdamW optimizer (Loshchilov and Hutter, 2019) to optimize our model for 20 epochs, the learning rate is set to be 7e-5, and batch size is 48, $\lambda$ is set to be 0.9 and $\alpha$ is set to be 1, $\beta$ is set to be 0.05 and $\tau$ is set to be 0.9.

---

4 We add it into the training set just to make sure we use the same training data as previous work.
5 https://github.com/DaDaMrX/ReaLiSe
6 If the output prediction is not the same token as the input token, we regard our model detect this token as the token need a correction.