

# Driving Chinese Spelling Correction from a Fine-Grained Perspective

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## Abstract

This paper explores the task: Chinese spelling correction (CSC), from a fine-grained perspective by recognizing that existing evaluations lack nuanced typology for the spelling errors. This deficiency can create a misleading impression of model performance, incurring an “invisible” bottleneck hindering the advancement of CSC research. In this paper, we first categorize spelling errors into six types and conduct a *fine-grained evaluation* across a wide variety of models, including BERT-based models and LLMs. Thus, we are able to pinpoint the underlying weaknesses of existing state-of-the-art models - utilizing contextual clues and handling co-existence of multiple typos, associated to *contextual errors* and *multi-typo errors*. However, these errors occur infrequently in conventional training corpus. Therefore, we introduce new error generation methods to augment their occurrence, which can be leveraged to enhance the training of CSC models. We hope this work could provide fresh insight for future CSC research.

## 1 Introduction

This paper studies the evaluation principle for Chinese spelling correction (CSC), a fundamental task in natural language processing to rectify all potential spelling errors in a Chinese sentence. Evaluation plays a critical role in CSC research, where the researchers are allowed to understand the way models behave and guide for further solutions. Due to the profoundness of Chinese language, there are diverse misspelling variations in real human corpora. However, existing benchmarks (Tseng et al., 2015; Lv et al., 2023; Wu et al., 2023b) are constrained to producing an overall score for all kinds of spelling errors, providing a coarse reflection of models’ performances. This deficiency incurs an “invisible”

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Figure 1: Samples of different types of spelling errors.

barrier that bottlenecks the progress of CSC research. In this paper, we propose a fine-grained evaluation principle, named **FiBench-CSC**, in the hope of navigating the follow-up research.

We categorize the spelling errors in a Chinese sentence to six distinct types. Figure 1 offers an illustration of five of them. We first categorize the errors by the way they are misspelled. **Phonological error** and **morphological error** are the two most common error types, stemming from pinyin and stroke similarities inherent in Chinese characters (Liu et al., 2010). The former is caused by users’ keyboard input or audio speech recognition, while the latter is caused by handwriting. These two types of errors are rich in the confusion sets, which are used to generate synthetic errors on top of monolingual sentences. We group the remaining errors not conforming to any of these two types to **non-similarity error**.

Second, we categorize the errors by the number of them within a single sentence, i.e. **single error** and **multi-typo error**. The latter refers to cases where there is more than one typo in one sentence. Co-existence of multiple typos may largely distort the context and create intricacy for correction. For example in Figure 1, there are two typos

at the same time, where “饮食” is misspelled to “饮事” and “消化” is misspelled to “消话”. The correction of the latter typo necessitates the correct understanding of the former phrase “饮食规律”, which is disturbed by the typo “饮事”.

Third, we introduce **contextual error**. This type of errors locally manifests as a correct phrase within the sentence. However, their correction strongly relies on utilizing contextual clues. For example in Figure 1, “语言” (lingual) is misspelled to “预演” (preview), both of which are legitimate Chinese words. Only if referring to the subsequent context of “多语言服务” (multilingual services), can one figure out the final answer. The edit pairs of contextual errors vary case by case and may not be found in the confusion sets. Given that many CSC models are constructed based on confusion sets, correction of contextual errors can be a challenging task, requiring much more than memorizing edit pairs from the training corpus.

In FiBench, we reorganize the target dataset into six subsets, each associated with one specific error type, thus allowing for an ever fine-grained insight into models’ strengths and shortcomings. Our paper unfolds as below. In §2, we conduct a comprehensive FiBench evaluation choosing a broad range of CSC models. While state-of-the-art counterparts show adeptness in using phonological and morphological clues, we pinpoint contextual and multi-typo errors that they notably struggle with. However, the contextual errors are sparse in conventional confusion sets. In §3, we introduce new methods for error generation to synthesize the contextual and multi-typo errors given arbitrary sentences with the assistance of LLMs. In §4, we harness the new synthetic sentences to refine the training of CSC models, and witness a blazer to state-of-the-art performance by boosting the target efficacy in specific errors.

## 2 FiBench

In this section, we scrutinize existing benchmarks from a fine-grained perspective. The findings in this section serve as the foundation for the subsequent methods and experiments in the paper.

### 2.1 Categorization Principle

#### Phonological & Morphological & Non-similarity

We obtain the phonological errors and morphological errors by checking if the edit pair in the sentences exists in the associated confusion set, while

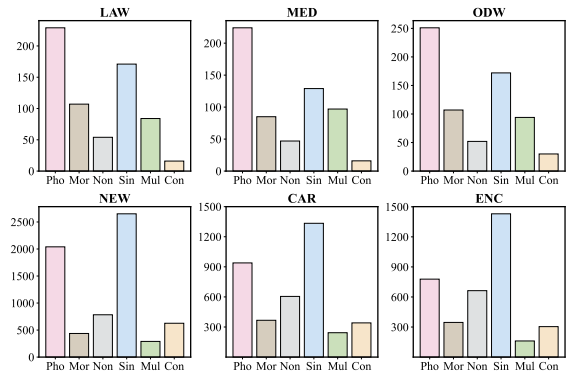


Figure 2: Statistics of error types in six chosen domains.

categorizing the rest into non-similarity errors. The confusion sets employed in our study are released by Liu et al. (2022).

**Contextual** To obtain the contextual errors, we check if the edit pair in the sentence can form a legitimate word within the locality by referring a fixed vocabulary. The logic behind is that if the error cannot form a correct phrase, it can be easily detected without referring to the context.

**Single & Multi** We obtain the single and multi-typo errors simply by counting the number of typos in the sentence.

### 2.2 Datasets

We conduct experiments on two public datasets, ECSpell (Lv et al., 2023) and LEMON (Wu et al., 2023b). **ECSpell** is a small-scale CSC benchmark with three specific domains: LAW (law) with 1,960 training and 500 test samples, MED (medical treatment) with 3,000 training and 500 test samples, and ODW (official document writing) with 1,728 training and 500 test samples. **LEMON** is an open-domain CSC benchmark with a diverse set of real-life spelling errors across multiple domains. In our experiments, we choose three domains as representative: NEW (news title) with 5,887 test samples, CAR (car) with 3,245 test samples, and ENC (encyclopedia) with 3,274 test samples.

Figure 2 eventually demonstrates the statistics of six error types in ECSpell and LEMON. From our categorization principle, there will be overlap of samples among each error subset.

### 2.3 Models and Methods

We span a broad range of CSC methods including BERT-based models and LLMs.

**BERT** The pre-trained BERT (Devlin et al., 2019) is the fundamental architecture to perform

the CSC task in the way of sequence tagging.

**Soft-Masked BERT** Zhang et al. (2020) apply a GRU network as the additional detector and mask the detected errors in the sentence softly to encourage the correction.

**MDCSpell** Zhu et al. (2022) design a paralleled detector-corrector network to enhance the correction. The new detector network is initialized by another BERT encoder.

**CRASpell** Liu et al. (2022) augment the original sentence by introducing an additional typo in the context and optimizing a smoothness loss (Jiang et al., 2020; Wu et al., 2023a) on it.

**Masked-Fine-Tuning** Above counterparts model CSC by sequence tagging. We apply the masked-fine-tuning technique (MFT) to boost the tagging process (Wu et al., 2023b), which is designed to enhance the language modeling aspect of CSC learning.

**ReLM** Rephrasing Language Model (ReLM) (Liu et al., 2024) is a non-autoregressive language model, which regards CSC as sentence rephrasing on top of entire semantics.

**LLM** Similar to ReLM, CSC is a sentence rephrasing task for large language models (LLMs), where they rephrase the sentence in an autoregressive manner. However, we find that generative models suffer from the over-paraphrase issue. To address this, we use the prompt Detect whether there are any misspelled words in the sentence. If there are any, please correct them. The important trick here is that the model won't do anything on the input sentence if there are no errors detected, which we find useful for reducing the above issue. We adopt Baichuan2-7b (Yang et al., 2023) in our experiments. We find that applying masked-fine-tuning technique can boost the performance of Baichuan2-7b. We also instruct GPT4 (OpenAI, 2023) and Qwen2-72b (Bai et al., 2023; ?) to perform this task through in-context learning with 5 shots. For each sentence, the in-context samples are uniformly chosen from sentences into the same error type in the training set. The prompt we use is Please correct the spelling errors in the given sentence, ensuring that the modified sentence is the same length as the original one. If there are no errors in the sentence, please copy it exactly as it is. We post-process the output of the LLMs to obtain the corrected sentence.

**Tagging vs. Rephrasing** In the following paper, we will use the term *tagging models* and *rephrasing*

*models*. It is worth noting that current CSC models can be categorized into tagging and rephrasing, by their training objectives. The former corresponds to BERT, Soft-Masked BERT, MDCSpell, CRASpell, while the latter corresponds to ReLM and a series of autoregressive models.

## 2.4 Training Setup

For all the experiments of BERT-based models, we adopt the pre-trained models open-sourced by Wu et al. (2023b). Each model is trained on 34 million synthetic pair-wise sentences from wiki2019zh and news2016zh. On ECSpell, we further fine-tune each model separately on the three domains for 5,000 steps with the batch size selected from {32, 128} and learning rate from {2e-5, 5e-5}. Especially for fine-tuning Baichuan2, we set the learning rate to 3e-4 and use LoRA (Hu et al., 2022a) with  $r = 8$  and  $\alpha = 32$  to improve efficiency. On LEMON, We evaluate each pre-trained model in zero-shot learning on each LEMON domain.

## 2.5 Evaluation Result

Table 1 reports the performances of a line of CSC models on ECSpell and LEMON.

**Models show nice adeptness in addressing phonological and morphological errors.** From results on ECSpell, We find that current state-of-the-art models perform perfectly (f1 more than 0.95) on phonological and morphological errors after domain-specific finetuning. We can also see that these two types of errors are less challenging for models under zero-shot learning, compared to the other types. It indicates that the similarity clues like pronunciations and shapes are rich in the training corpus for CSC models to fit the error model (Wu et al., 2023b).

**A performance disparity emerges when models moving from addressing a single typo to multiple typos.** For multi-typo errors, we find distinct trends between fine-tuned models and zero-shot models. Among the fine-tuned models, performances of all BERT-based models drops slightly when moving from addressing a single typo to multiple typos. This indicates that domain-specific fine-tuning can help train a better language modeling, making multi-typo errors less challenging. However, **under zero-shot learning, the performance of all models on multi-typo errors deteriorates substantially**, including ReLM, which is considered more powerful in language modeling. This indicates a potential issue in conventional training pro-

		Phono.	Morpho.	Non-s.	Single	Multi	Contextual	Overall
EC-LAW	BERT <sub>MFT</sub>	99.1	99.0	97.1	98.2	93.4	94.9	94.0
	Soft-Masked <sub>MFT</sub>	99.7	99.0	<b>99.9</b>	<b>99.4</b>	<b>97.0</b>	97.0	96.0
	MDCSpell <sub>MFT</sub>	99.1	99.9	<b>99.9</b>	99.1	<b>97.0</b>	94.9	<b>97.1</b>
	CRASpell <sub>MFT</sub>	99.3	99.0	99.0	98.5	95.2	97.0	95.6
	ReLM	<b>99.9</b>	<b>99.5</b>	96.2	98.8	96.4	<b>98.0</b>	95.6
	Baichuan2	93.6	92.3	94.3	92.4	85.7	80.8	92.8
	Qwen2-72b (5-shot)	85.7	85.9	74.0	84.7	62.6	59.1	72.7
	GPT4 (5-shot)	77.7	82.6	80.5	80.2	56.1	56.2	76.6
EC-MED	BERT <sub>MFT</sub>	<b>99.7</b>	<b>99.4</b>	<b>98.6</b>	97.6	77.8	<b>78.1</b>	86.5
	Soft-Masked <sub>MFT</sub>	98.8	97.0	94.3	95.2	87.9	<b>86.1</b>	87.4
	MDCSpell <sub>MFT</sub>	98.6	99.4	93.3	96.4	87.0	<b>84.3</b>	88.7
	CRASpell <sub>MFT</sub>	98.2	98.2	96.7	96.4	<b>92.6</b>	<b>83.0</b>	89.6
	ReLM	98.4	97.3	97.6	<b>98.3</b>	90.3	<b>74.9</b>	<b>89.9</b>
	Baichuan2	90.8	91.6	86.6	86.6	77.7	80.0	79.8
	Qwen2-72b (5-shot)	73.2	78.5	80.4	77.8	63.9	58.4	59.7
	GPT4 (5-shot)	74.5	80.4	74.9	77.1	62.1	59.9	66.4
EC-ODW	BERT <sub>MFT</sub>	<b>97.1</b>	96.2	87.7	90.8	83.4	83.4	87.3
	Soft-Masked <sub>MFT</sub>	96.3	<b>97.1</b>	85.7	90.7	89.7	86.1	88.4
	MDCSpell <sub>MFT</sub>	96.7	96.2	<b>90.7</b>	<b>92.4</b>	89.2	87.0	90.4
	CRASpell <sub>MFT</sub>	96.9	96.2	86.5	90.4	<b>92.3</b>	<b>90.3</b>	89.5
	ReLM	<b>97.1</b>	<b>97.1</b>	88.6	<b>92.4</b>	91.3	89.4	<b>91.6</b>
	Baichuan2	89.8	94.3	<b>92.1</b>	85.6	87.2	88.8	87.5
	Qwen2-72b (5-shot)	94.9	93.3	80.3	87.7	81.9	80.6	81.8
	GPT4 (5-shot)	87.1	83.9	75.5	76.6	71.6	61.8	73.3
LE-NEW	BERT <sub>MFT</sub> <sup>†</sup>	71.3	72.0	<b>45.0</b>	63.9	<b>11.3</b>	49.3	56.0
	Soft-Masked <sub>MFT</sub> <sup>†</sup>	71.8	72.1	<b>42.8</b>	64.0	<b>10.8</b>	50.4	55.6
	MDCSpell <sub>MFT</sub> <sup>†</sup>	<b>74.9</b>	73.2	<b>37.7</b>	65.6	<b>11.0</b>	53.0	57.3
	CRASpell <sub>MFT</sub> <sup>†</sup>	72.9	73.8	<b>38.9</b>	64.4	<b>5.6</b>	50.7	55.4
	ReLM <sup>†</sup>	<b>74.9</b>	<b>75.8</b>	44.0	<b>67.0</b>	<b>10.2</b>	52.2	58.8
	Qwen2-72b (5-shot)	64.4	69.2	<b>48.3</b>	60.0	<b>42.7</b>	55.3	57.4
	GPT4 (5-shot)	69.1	70.5	50.5	64.7	41.8	<b>67.7</b>	<b>63.4</b>
LE-ENC	BERT <sub>MFT</sub> <sup>†</sup>	62.4	62.1	<b>35.5</b>	53.9	<b>5.7</b>	42.1	45.2
	Soft-Masked <sub>MFT</sub> <sup>†</sup>	59.3	62.1	<b>33.9</b>	52.8	<b>5.6</b>	39.4	44.1
	MDCSpell <sub>MFT</sub> <sup>†</sup>	<b>63.8</b>	66.7	<b>33.7</b>	54.7	<b>7.3</b>	41.4	46.1
	CRASpell <sub>MFT</sub> <sup>†</sup>	62.8	68.1	<b>39.2</b>	56.8	<b>4.9</b>	43.3	47.6
	ReLM <sup>†</sup>	63.1	63.4	41.4	56.5	<b>3.3</b>	39.8	47.6
	Qwen2-72b (5-shot)	55.8	67.0	46.8	54.5	<b>36.7</b>	47.1	48.3
	GPT4 (5-shot)	61.1	<b>75.1</b>	<b>56.6</b>	<b>66.1</b>	35.4	<b>61.0</b>	<b>60.6</b>
LE-CAR	BERT <sub>MFT</sub> <sup>†</sup>	74.1	65.9	<b>45.3</b>	64.5	<b>4.2</b>	47.5	51.9
	Soft-Masked <sub>MFT</sub> <sup>†</sup>	73.6	67.4	<b>47.1</b>	64.5	<b>7.6</b>	46.8	52.2
	MDCSpell <sub>MFT</sub> <sup>†</sup>	74.8	70.3	<b>38.3</b>	64.0	<b>8.1</b>	43.4	51.9
	CRASpell <sub>MFT</sub> <sup>†</sup>	74.6	<b>71.8</b>	<b>42.7</b>	64.7	<b>5.9</b>	45.5	51.9
	ReLM <sup>†</sup>	<b>76.8</b>	66.3	45.0	<b>65.7</b>	<b>9.7</b>	44.7	53.5
	Qwen2-72b (5-shot)	55.7	61.7	40.2	49.5	30.4	44.6	45.5
	GPT4 (5-shot)	65.0	61.3	<b>52.0</b>	61.7	<b>33.2</b>	<b>50.1</b>	<b>56.5</b>

Table 1: Fine-grained performances on ECSpell (EC-x) and LEMON (LE-x). We report the F1 score for each error type and the overall F1 score on all sentences. “Non-s.” refers to the non-similarity errors. † refers to the zero-shot performance of the corresponding models. The subscription MFT indicates that the model is trained using masked-fine-tuning.

cess that researchers might overlook constructing samples that contain multi-typo errors, resulting in models’ inability during testing.

**Contextual errors pose a consistent challenge in every scenario.** For finetuned models, **contextual errors remain challenging, particularly in the domain of medical treatment (MED). On average, the F1 performance on contextual errors drops by**

**7.1 points compared to the overall F1 score across five BERT-based methods.** However, for zero-shot models, all of them struggle with contextual errors. **Correspondingly, their performance on non-similarity errors also encounters a big decline.** The poor performance in handling non-similarity errors and contextual errors from LEMON highlights the importance of domain-specific knowledge and fea-

tures for spelling correction. This indicates that open-domain CSC is the greatest challenge currently faced by the community.

**LLMs show potential in open-domain CSC, but there is room for improvement in handling phonological errors.** We find that the few-shot performances of Qwen-72b and GPT-4 on ECSpell are weaker than those of fine-tuned BERT-based models. However, on LEMON, an open-domain benchmark, their performances surpass those of the BERT-based models, particularly in handling multi-typo and contextual errors. This is mainly due to their strong reasoning ability and the extensive knowledge acquired during pre-training. Nonetheless, their performance on phonological typos is weaker than that of BERT-based models, which are trained on 34 million synthesized examples using a confusion set. **This fine-grained comparison suggests directions for further open-domain CSC research.** For LLMs, incorporating phonological similarity could enhance their performance in CSC. Additionally, equipping BERT-based models with more knowledge is crucial, and data augmentation using LLMs can be a potential solution.

Based on Fibench, we have the following conclusions. Firstly, the performance of CSC models fine-tuned on domain-specific data is quite high. However, open domain CSC, which is more representative of real-world applications, remains challenging and warrants further study. Secondly, **existing CSC models exhibit deficiencies in addressing two specific types of errors, bottlenecking their overall performance in practical applications.** However, sentences that comprise contextual and multi-typo errors are rare in typical training sets. Therefore, there emerges a very need for methods to generate them artificially, which forms the follow-up section.

### 3 Error Generation

In this section, we discuss the error generation method to automatically generate contextual errors with the assistance of the powerful lexical processing capability of LLMs, as well as the synthesis method to generate multi-typo errors.

#### 3.1 Contextual Error

We design a three-step pipeline. Given a sentence, we first tokenize it into words using the segmentation tool and randomly select one of them as the target word. We prompt GPT4 to substitute the

**Substitution:**  
You are a native Chinese speaker to modify the given sentence following the requirements below.

1. Change the word in "<>" to a new word using the same number of characters.
2. The new word in "<>" is correct within the local context.
3. The new word in "<>" should induce a wrong or strange meaning of the new sentence.
4. Do not change the other words outside of "<>".

**Input:**  
比赛至今他从未出现, 可见他是一个<鸽子>。  
**Response 1:**  
比赛至今他从未出现, 可见他是一个<毒瘤>。  
**Response 2:**  
比赛至今他从未出现, 可见他是一个<歌者>。

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**Verification:**  
You are a skilled Chinese writer. People admire you. I will give a pair of sentences, please help me decide the following situations:

1. two sentences are in the same meaning, and they are both grammatically and contextually correct.
2. two sentences are in different meanings, but they are both grammatically and contextually correct.
3. two sentences are supposed to be in the same meaning, but either is not grammatically and contextually correct.

**Input 1:**  
比赛至今他从未出现, 可见他是一个<鸽子>。  
比赛至今他从未出现, 可见他是一个<毒瘤>。  
**Response 1:**  
2  
**Input 2:**  
比赛至今他从未出现, 可见他是一个<鸽子>。  
比赛至今他从未出现, 可见他是一个<歌者>。  
**Response 2:**  
3

Figure 3: Prompts we use to generate contextual errors.

target word for a new word. The prompt for substitution is shown in Figure 3. In this prompt, we instruct GPT4 to follow two primary principles: 1. the new word is still a legitimate Chinese word; 2. the new word will introduce an unnatural semantics to the entire sentence.

The first step is a tough task even for GPT4. It is likely to solely paraphrase the given sentence or introduce another word, potentially retaining correctness while altering the original meaning. If either of two situations occurs, we will acquire an invalid sentence pair. To address this, we design the second step to verify the validity of the output sentence from the first step. As detailed in Figure 3, we further prompt GPT4 to identify the relationship between the output sentence in the first step and the original one. Only if both sentences convey the same meaning and one contains grammatical and contextual error, do we keep this sentence pair.

LLMs like GPT4 lean to make somewhat unstable responses. To ensure reliability, we eventually employ a ruled-based filter to verify if the new word can form a legitimate expression by checking its existence in a word vocabulary.

From Table 2, we can find that the generated

	Pin	Mor	Non-sim.	Sin.	Multi.	Context.
LAW	46	4	141	74	58	132
MED	52	16	138	52	76	128
ODW	65	15	156	79	78	157

Table 2: Statistics of the generated contextual errors.

contextual errors contain more non-similarity and multi-typo examples, which are also more challenging for CSC models. This demonstrates that our error generation method can produce additional training examples specifically designed to address the weaknesses of current CSC models.

### 3.2 Multi-typo Error

We construct a distribution to synthesize multiple typos in one sentence. Each typo can be any of a contextual error, phonological error, or morphological error. The last two errors are sampled from the associated confusion sets, while the contextual errors are generated using the prior method. Given an arbitrary sentence, we introduce  $N$  typos in it.  $N$  follows the  $p$ -Binomial distribution  $\sim \text{Binomial}(n, p)$ , where  $n$  is the number of characters in the sentence. When  $N$  is determined, specifically, we uniformly sample  $N$  positions in the sentence and replace each of them with: 1. a phonologically similar character 60% of the time; 2. a morphologically similar character 30% of the time; 3. a character/word making a contextual error 10% of the time. This is due to the empirical fact that contextual errors occur at a lower frequency in real-world sentences.

## 4 Data Augmentation

In this section, we refine the existing datasets using the error generation methods introduced in § 3. Based on the augmented data, we introduce several effective training strategies to facilitate stronger CSC models.

### 4.1 Strategy

We have observed that models fine-tuned on EC-Spell exhibit a greater susceptibility to contextual errors. Therefore, we randomly sample a proportion of the target sentences in the training set and generate new contextual errors on them. Given that contextual errors occur less frequently in natural language, excessive introduction of them may compromise the model’s overall performance. Hence, we **complement the training data with 100 new**

	LAW		MED		ODW	
	Con	All	Con	All	Con	All
ReLM	98.0	95.6	74.9	89.9	89.4	91.6
ReLM <sup>♣domain</sup>	<b>100.0</b>	<b>96.4</b>	<b>87.7</b>	<b>90.7</b>	<b>95.9</b>	<b>92.1</b>
ReLM <sup>♣wiki</sup>	97.1	95.0	78.2	90.0	91.9	90.5
BERT	94.9	94.0	78.1	86.5	83.4	87.3
BERT <sup>♣domain</sup>	<b>95.9</b>	<b>95.5</b>	<b>89.2</b>	<b>89.5</b>	<b>85.7</b>	<b>90.1</b>
BERT <sup>♣wiki</sup>	93.0	94.9	86.1	88.9	77.7	88.3
	NEW		ENC		CAR	
	Mul	All	Mul	All	Mul	All
ReLM	10.2	<b>58.8</b>	3.3	47.6	9.7	53.5
ReLM <sup>♣CT</sup>	<b>18.7</b>	58.6	12.9	<b>48.3</b>	<b>22.0</b>	<b>54.3</b>
ReLM <sup>♣FS</sup>	15.7	56.6	<b>14.1</b>	46.2	15.4	52.1

Table 3: Results after data augmentation. “CT” refers to continue-training and “FS” refers to few-shot.

**samples with contextual errors** for each domain ( $\sim 5\%$  of original training samples). Additionally, in § 3, we have conjectured that adaption to contextual errors strongly depends on domain-specific signals. We prepare another 100 samples with contextual errors for comparison, where the target sentences are sourced from Chinese wikipedia.

For open-domain CSC, models are pre-trained on a large scale of pair-wise sentences without being fine-tuned on specific training sets. We thus employ two strategies, **continue-training** and **few-shot learning**. Instead of undergoing a new round of complete pre-training, we choose to continually train the model on refined sentences. Specifically, we refine the synthetic pair-wise sentences from wiki2019zh (each already with one typo) by imposing random additional typos to them, and train the prior model for another one epoch. Since the sentence initially contains a typo, we set  $p$  for the Binomial distribution to a lower value 0.001. Another more efficient approach is to construct a few samples with highly concentrated errors to allow the model to quickly adapt to the multi-typo error type. We set  $p$  to 0.1 and generate 100 samples with multi-typo errors. However, our experience suggests that this rapid method can trade off the performance on the rest error types.

### 4.2 Result

In this section, we conduct experiments on masked-fine-tuned BERT and ReLM, which are tagging and rephrasing models respectively. The upper part of Table 3 showcases the effectiveness of incorporating new contextual errors. Significant performance improvement can be observed in the domains of

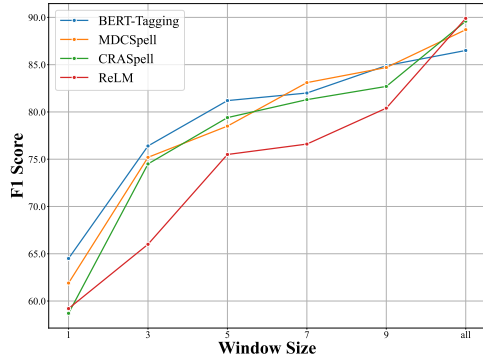


Figure 4: The variation of F1 score with the local context size. We choose EC-Med as the representative domain

MED and ODW. For instance, on MED, the performance on contextual errors of ReLM increases from 74.9 to 87.7, which further results in the improvement of the overall performance. On the other hand, we find that constructing contextual errors using the general corpus doesn’t yield significant benefit, which is consistent with our prior hypothesis in § 3.

From the lower part of Table 3, we find that continue-training enhances certain aspects of the model in a more stable manner. For multi-typo errors, the resultant ReLM gains a significant boost from 10.2 to 18.7 on NEW, 3.3 to 12.9 on ENC, and 9.7 to 22.0 on CAR respectively. On the other hand, the improvement brought by few-shot learning is also notable. However, we find that it rapidly deteriorates the overall performance. In our experiments, each model has been fine-tuned for only 3 epochs on few-shot samples. This is due to the fact that few-shot samples may significantly distort the natural data distribution.

## 5 Further Analysis

### 5.1 Analysis of Contextual Errors

As discussed in Section 2, contextual errors present significant challenges for CSC models. To analyze the impact of context on model predictions, we truncate the local phrases surrounding the typo and examine how varying the truncation window size affects CSC models’ performance. Specifically, we symmetrically truncate the source sentence by retaining only the  $2n - 1$  neighboring words around the erroneous characters, then calculate the F1 score for these truncated samples.

From Figure 4, we find unsurprisingly that performance of all the models improve with the growth

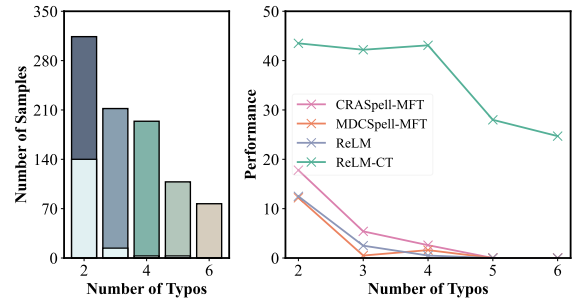


Figure 5: Left: Statistics of the number of typos in each example. Right: Variation of performances (F1) with the increasing number of typos. We choose LE-ENC as the representative domain.

of context size. Meanwhile, ReLM, which significantly outperforms the baseline model BERT-Tagging, performs worse than BERT-Tagging when the context size is below 9. This indicates that ReLM, with its rephrasing training objective, is more dependent on the entire sentence for making corrections rather than relying on the local words.

### 5.2 Analysis of Multi-typo Errors

For multi-typo errors, CSC models can be vulnerable to contextual noise while making the correction (Zhu et al., 2022; Liu et al., 2022). **Furthermore, we look deeper into the impact of the number of typos co-existed in the sentence** by grouping the multi-typo errors by their numbers. Considering that multi-typo errors with more than two typos are sparse in the test sets of ECSpell, we supplement them with additional samples generated using the method described in § 3 to investigate the influence of the number of typos in a single sentence.

The results are depicted in Figure 5. Intuitively, all models experience a decline in performance when the number of typos rises. Among tagging models, CRASpell outperforms other counterparts, suggesting that optimizing the smoothness loss during training effectively allows the model to adapt to multi-typo errors. We also find that continue-training with more multi-typo errors can significantly improve the performance on multi-typo errors. The F1 score of ReLM keeps above 0.4 with less than 4 typos in one sentence, which demonstrates the effectiveness of our data augmentation method.

### 5.3 Case Study

We further offer a closer look on concrete cases. The case study comprises two parts. We first demonstrate the newly generated sample (TRG)

Case 1: synthetic contextual error
雷击债券余额不超过公司净资产的百分之十。[SRC] 累计债券余额不超过公司净资产的百分之十。[TRG]
Case 2: synthetic multi-typo error
知识单权利人在许诺合同中进行价格歧视。[SRC] 知识产权权利人在许可合同中进行价格歧视。[TRG]
Bad Case 1: exploiting contextual clues
首先要简单的修剪美貌四周的碎毛。[SRC] 首先要简单的修剪眉毛四周的碎毛。[TRG] 首先要简单的修剪美貌四周的碎毛。[Original] 首先要简单的修剪眉毛四周的碎毛。[Augmented]
Bad Case 2: addressing multi-typo error
契而不舌的艰苦追求,使我们国内领先。[SRC] 锲而不舍的艰苦追求,使我们国内领先。[TRG] 契而不舌的艰苦追求,使我们国内领先。[Original] 锲而不舍的艰苦追求,使我们国内领先。[Augmented]

Table 4: Case study.

given SRC by our methods. In case 1 (*The cumulative bond balance shall not exceed ten percent of the company’s net assets*), we synthesize the contextual error “雷击” (lightning) → “累计” (accumulative). The correction of this error necessitates the model not only to seek clues from the context but also consider phonological similarity. Case 2 (*Intellectual property rights holders engage in price discrimination in licensing contracts*) contains two typos, where the correction of the second error “许可” (license contract) → “许诺” (promise contract) is strongly dependent on the correction of the first one “知识单权” → “知识产权” (intellectual property rights).

In the second part, we demonstrate the two cases where the model could successfully address them after undergoing data augmentation. In bad case 1 (*First, trim the stray hairs around the eyebrows*), the original ReLM fails to detect the contextual error “眉毛” → “美貌”. After fine-tuning on augmented contextual errors, the augmented ReLM can successfully address it. In bad case 2 (*Persistent and strenuous efforts have made us a leader in the domestic market*), the augmented ReLM successfully detects the two typos.

## 6 Related Work

**Enhancing CSC with External Signals** To enhance the model performance, a large body of recent CSC research focuses on introducing external signals, e.g. phonological and morphological similarity (Wang et al., 2019; Liu et al., 2021; Huang

et al., 2021; Sun et al., 2023; Liang et al., 2023), negative samples (Li et al., 2022b), retrieval (Song et al., 2023), auxiliary objectives (Liu et al., 2021; Li et al., 2022a); another line of work focuses on disentangling the detection and correction module (Zhang et al., 2020; Zhu et al., 2022; Huang et al., 2023). In contrast to these efforts, this work centers on the foundation principles for CSC.

## Foundation Study for CSC and Benchmark

Foundation study plays an essential role in the research. Wu et al. (2023b) explore the two underlying sub-models behind a general CSC model, the error model and the language model. Liu et al. (2024) discuss the primary training objective for the CSC task. Jiang et al. (2024) furthers align the CSC learning with language modeling. All these studies let us better understand the basic mechanism of CSC models. This paper focuses on the evaluation principle and offers an ever fine-grained perspective. Benchmarking is equally important. Recently, many efforts offer new benchmark standards, e.g. IME (Hu et al., 2022b) for phonological errors, ECSpell for multi-domain (Lv et al., 2023), MCSC for medical-specialist errors (Jiang et al., 2022), LEMON for open-domain CSC (Wu et al., 2023b). A similar effort is Hu et al. (2022b), which synthesizes a large number of errors by approximating the real error distribution. Yet, diverging from their paths, this paper focuses on the refinement of existing benchmarks with synthetic data. It potentially skews the real error distribution as we pitch that it is those lower-frequency errors that pose the bottleneck of CSC models.

## 7 Conclusion

This paper identifies and categorizes spelling errors in Chinese into various types. We conduct a fine-grained evaluation across a broad spectrum of CSC models in both finetuning and open-domain benchmarks. The nuanced assessment offers a clear view of each model’s strengths and weaknesses, especially for LLMs, which is crucial for their practical application and future enhancement. Additionally, we introduce automatic error generation methods specifically designed for contextual errors and multi-typo errors where current models show notable vulnerability. We demonstrate that continue-training on these augmented examples can enhance the corresponding aspect of CSC models. We also study the impact of context and number of typos to CSC models.



## 8 Limitations

Our evaluation covers the most representative CSC methods in recent years while does not encompass all possible ones. Future work can further improve the landscape of FiBench. Besides, the experimental results demonstrate the potential of LLMs in open-domain benchmark and in certain aspects, such as tackling multi-typo errors and processing contextual signals. However, our paper primarily focuses on BERT-based models, without deeper exploration of LLMs. In the other hand, our study uncovers several valuable future directions. Open-domain CSC emerges as a notable challenge with sparse exploration. Firstly, we long for effective methods for handling **negative transfer between error types and domains**. Secondly, we aim to study how to complement the strengths of BERT-based models in phonetic similarity, generation stability, and efficiency with the powerful semantic and knowledge capabilities of large language models (LLMs), achieving a synergy of their respective advantages. Lastly, we long for **greater diversity in the training corpus** to enhance the base models. In this paper, we only consider the models trained from the source of wikipedia.

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