A Simple yet Effective Training-free Prompt-free Approach to Chinese Spelling Correction Based on Large Language Models

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Abstract

This work proposes a simple yet effective approach for leveraging large language models (LLMs) in Chinese spelling correction (CSC) task. Our approach consists of two components: a large language model and a minimal distortion model. At each decoding step, the large language model calculates the probabilities of the next token based on the preceding context. Then, the distortion model adjusts these probabilities to penalize the generation of tokens that deviate too far from the input. Different from the prior supervised fine-tuning and prompt-based approaches, our approach enables efficient CSC without requiring additional training or task-specific prompts. To address practical challenges, we propose a length reward strategy to mitigate the local optima problem during beam search decoding, and a faithfulness reward strategy to reduce over-corrections. Comprehensive experiments on five public datasets demonstrate that our approach significantly improves LLM performance, enabling them to compete with state-of-the-art domain-general CSC models.[1]

1 Introduction

Spelling errors are common in Chinese text because many Chinese characters have similar pronunciations or shapes. This similarity makes it difficult for both humans to type and for machines to recognize the characters correctly. These errors may cause misunderstandings, diminish the credibility, or degrade the performance of downstream applications (Si et al., 2023). Therefore, the research on Chinese Spelling Correction (CSC) has become urgently necessary and attracted increasing attention in recent years (Hong et al., 2019; Bao et al., 2020; Xu et al., 2021; Li et al., 2022; Wu et al., 2023; Dong et al., 2024, *inter alia*).

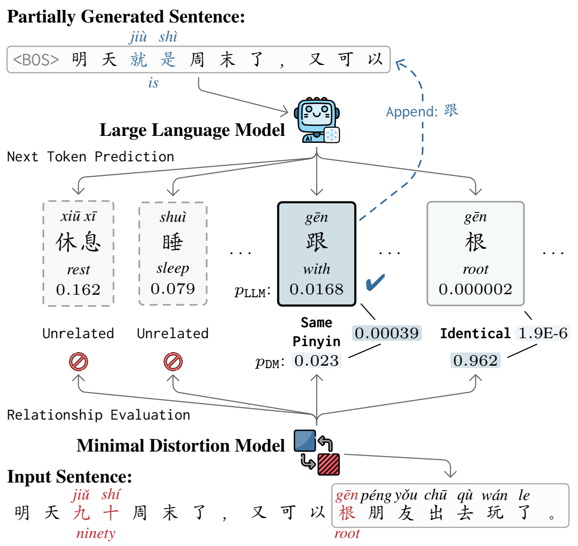


Figure 1: An illustration of our approach. The correct sentence should be "明天就是周末了，又可以跟朋友出去玩了。" (*Tomorrow is the weekend, allowing for going out to play with friends again.*).

Recently, researchers propose to leverage large language models (LLMs) to improve CSC performance. These approaches fall into two categories: *prompt-based* and *supervised fine-tuning*. The prompt-based approaches, which are widely used in the LLM era, feed CSC-related instructions and the input sentence into an LLM, and expect the LLM to output a corrected sentence. The experiment setting is called few-shot if a few CSC examples are included in the instructions, and zero-shot if no examples are provided. Li et al. (2023a) first investigate the prompt-based approach and conduct extensive experiments under different settings. Moreover, they propose different strategies for selecting proper examples. Dong et al. (2024) follow the work of Li et al. (2023a), and propose to enrich the prompt with additional information, such as pronunciation and glyph of characters. All their experiments show that the prompt-based approach leads to unsatisfactory CSC performance,

[1]Our anonymized code is available at https://anonymous.4open.science/r/simple-csc.

especially when compared to previous non-LLM based approaches.

The second class of approaches are based on supervised fine-tuning (SFT). The main difference between the prompt-based and the SFT-based approaches is the latter fine-tunes the LLM over the CSC training data. This fine-tuning is performed one mini-batch at a time, with output corrected sentences as the training objective, in a teacher-forcing manner. Li et al. (2023a) explore the SFT-based approach under various settings and using different strategies. They find that the SFT-based approach achieve better performance than the prompt-based approach. However, the performance still lags behind previous non-LLM results by large margin.

In contrast to both the prompt-based and SFT-based approaches, we propose a simple prompt-free and training-free framework to leverage LLMs for the CSC task. As shown in Figure 1, our approach consists of two components: a large language model and a distortion model. At each decoding step, the large language model generates a token based on the current context. Then a minimal distortion model determines whether the generated token is deviated too far from the input characters.

In practice, we find that the local optima problem of beam search decoding and over-correction hinder the performance of our approach. To address these issues, we propose two straightforward rewards, the length reward and faithfulness reward.

We conduct comprehensive experiments on five public datasets from various domains and genres, including more than 50,000 sentences. The results clearly show that our approach significantly improves the performance of LLMs in the CSC task. Our approach also demonstrates remarkable domain generalization capabilities, outperforming state-of-the-art domain-general CSC models trained on extensive synthetic CSC data (approximately 34 million pairs) on most datasets.

In summary, our contributions are as follows:

- We propose a simple yet effective framework to leverage LLMs for the CSC task, requiring neither additional training nor prompts.
- Two straightforward rewards, the length reward and faithfulness reward, are introduced to address the local optima problem and over-correction issue, respectively.
- Comprehensive experiments demonstrate that our approach significantly improves the performance of LLMs in the CSC task, showcasing remarkable domain generalization capabilities.

Type	Example	Proportion
`Identical`	机 (*jī*)	0.962
`Same Pinyin`	基 (*jī*)	0.023
`Similar Pinyin`	七 (*qī*)	0.008
`Similar Shape`	仉 (*zhǎng*)	0.004
`Unrelated`	能 (*néng*)	0.003

Table 1: Examples of the different distortion types of the corrected token "机" (*jī*). The distribution of the types is calculated from the development set.

2 Our Approach

Given an input sentence $\boldsymbol{x} = x_1, x_2, \cdots, x_n$, where x_i denotes a character, a CSC model outputs a sentence of the same length, denote as $\boldsymbol{y} = y_1, y_2, \cdots, y_n$. The key to the CSC task is how to model the score of the input and output sentence pair, i.e., $\texttt{score}(\boldsymbol{x}, \boldsymbol{y})$.

Under a perspective of probabilistic modeling, the joint probability can be decomposed into two parts:

$$\begin{aligned} p(\boldsymbol{x}, \boldsymbol{y}) &= p(\boldsymbol{x} \mid \boldsymbol{y})\, p(\boldsymbol{y}) \\ &= p_{\texttt{DM}}(\boldsymbol{x} \mid \boldsymbol{y})\, p_{\texttt{LLM}}(\boldsymbol{y}) \end{aligned} \tag{1}$$

The first part corresponds to a distortion model, which captures the relationships between $\boldsymbol{x}$ and $\boldsymbol{y}$. In other words, it interprets how spelling errors transform $\boldsymbol{y}$ to $\boldsymbol{x}$. Another important function of the distortion model is to make sure that $\boldsymbol{y}$ represents the same "meaning" as $\boldsymbol{x}$, i.e., faithfulness.

The second part corresponds to a large language model, which makes sure that $\boldsymbol{y}$ is fluent and correct from the language use perspective. In this work, we employ generative LLMs, including `Baichuan2`, `Qwen1.5`, and `InternLM2`.

Please note that our use of LLMs is **prompt-free**. We do not provide CSC-related instructions and examples as the prompt. More importantly, we do not give the input sentence to LLMs. We use LLMs as pure traditional language models for evaluating next-token probabilities.

2.1 A Minimal Distortion Model

Our distortion model adopts character-level factorization:

$$\log p_{\texttt{DM}}(\boldsymbol{x} \mid \boldsymbol{y}) = \sum_i \log p_{\texttt{DM}}(x_i \mid y_i) \tag{2}$$

To further simplify the model, we do not compute distortion probabilities for specific character pairs, i.e., (c_1, c_2). Instead, we first classify

(c_1, c_2) into one of five distortion types, denoted as $\texttt{type}(c_1, c_2)$. Then we use the probability of the type as the distortion probability of the character pair:

$$p_{\texttt{DM}}(c_1 \mid c_2) = p(\texttt{type}(c_1, c_2)) \quad (3)$$

Table 1 illustrates the distortion types. The proportions are obtained from small subsets of popular CSC training data, described later in §3.1. We directly employ the proportions as the distortion probabilities.

Please note that we claim our approach as **training-free**, since the LLMs are used in an off-the-shelf manner and the distortion model only relies on several frequency values, which can be easily counted from a small dataset.

Given (c_1, c_2), we implement a simple rule-based tool to decide the distortion type. Among the five types, "Similar Pinyin" and "Similar Shape" are more complex to handle. We give details in Appendix A, and release the tool, along with other code in this work.

2.2 Next-token Probabilities from LLM

Typically, the output vocabulary of a LLM contains both single- and multi-character tokens. In other words, given a sentence $\boldsymbol{y} = y_1 ... y_n$, there exists many ways to segment it into a sequence of tokens. We use $\boldsymbol{t} = t_1 ... t_m$ to denote a specific token-level segmentation of $\boldsymbol{y}$, i.e., a path for the LLM to generate the character sequence, where $t_j = c_1 \dots c_k$ and $k \geqslant 1$. Then, the log probability of $\boldsymbol{y}$ can be decomposed as:

$$\log p_{\texttt{LLM}}(\boldsymbol{y}) = \sum_j \log p_{\texttt{LLM}}(t_j \mid \boldsymbol{t}_{<j}) \quad (4)$$

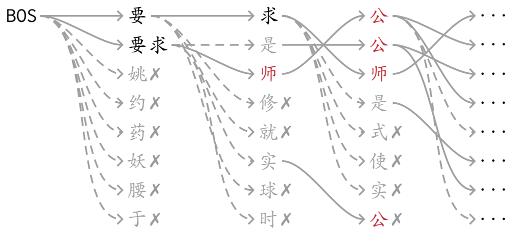
After combining the distortion model, the probability of a partial output sentence is:

$$\begin{aligned} \log p(\boldsymbol{x}, \boldsymbol{t}_{\leqslant j}) = & \log p(\boldsymbol{x}, \boldsymbol{t}_{<j}) \\ & + \log p_{\texttt{LLM}}(t_j \mid \boldsymbol{t}_{<j}) \\ & + \sum_{r=1}^{k} \log p_{\texttt{DM}}(c_r \mid x_{l+r}) \end{aligned} \quad (5)$$

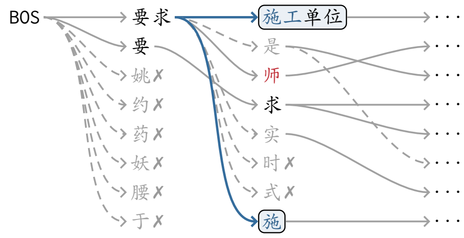
where $k = \ell(t_j)$ and $l = \ell(\boldsymbol{t}_{<j})$ are the lengths of t_j and $\boldsymbol{t}_{<j}$, respectively.

2.3 Beam Search Decoding

During inference, the basic operation at step j is to select a token t_j and append it to the current partial sequence $\boldsymbol{t}_{<j}$. We follow the standard practice, and adopt beam search decoding, that only retains



(a) w/o Length Reward



(b) w/ Length Reward

Figure 2: A real example of the decoding process for the input sentence "要求师公单位对..." (*Requesting the master unit to* ...). Here, "施工" (*shīgōng*, *construction*) is misspelled as "师公" (*shīgōng*). Without the length reward, the correct character "施" is fail to be select into the beam.

the top-K candidates at each decoding step for computational efficiency. We adopt a beam size of 8 throughout the paper.

In particular, one technical detail is closely related with our length reward strategy and thus worthy of further discussion. As discussed above, most LLMs generate sentences at token-level and one token may contain either a single character or multiple characters. This implies that the beam search procedure is aligned according to token numbers rather than character positions. In other words, at any given inference step, candidates in the beam may varies greatly in the number of characters generated so far. For instance, one candidate contains 5 characters, whereas another candidate contains 8 characters.

2.4 Length Reward

Our preliminary experiments show that the vanilla approach, as described in Equation 5, produces unsatisfactory results. Detailed analysis shows that the paths explored in the beam search space are dominated by single-character tokens, as shown in Figure 2a. As we all know, multi-character tokens are created by merging characters that frequently occur together, capturing the most common patterns in the language. LLMs are trained for and, in turn, very good at generating multi-character tokens. Therefore, it is counter-intuitive to deprive

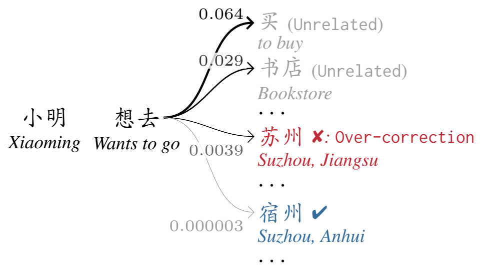


Figure 3: A real example of the probabilities for the next token, given the partial sequence "小明想去" from the sentence "小明想去宿州" (*Xiaoming wants to go to Suzhou, Anhui*).

such capability from LLMs.

To handle the issue, we design a simple length reward so that the model favors and keeps multi-char tokens during beam search:

$$\begin{aligned}\texttt{score}(\boldsymbol{x}, \boldsymbol{t}_{\leqslant j}) = \texttt{score}(\boldsymbol{x}, \boldsymbol{t}_{<j}) \\ + \log p_{\texttt{LLM}}(t_j \mid \boldsymbol{t}_{<j}) \\ + \sum_{r=1}^{k} \log p_{\texttt{DM}}(c_r \mid x_{l+r}) \\ + \alpha \times (\ell(t_i) - 1)\end{aligned} \tag{6}$$

where α is a hyperparameter for balance the weight of the length reward, considering that the other two components use log probabilities, whereas the length reward uses numbers directly. Please note that we use $\texttt{score}(\cdot)$ instead of $p(\cdot)$, since the values are no longer probabilities.

As shown in Figure 2b, thanks to the length reward, the correct token "施工单位" (*construction unit*) is now ranked within the top-K candidates.

2.5 Faithfulness Reward

Under our prompt-free use, the LLM component is unaware of the input sentence, and only focuses on the fluency and correctness of the output sentence from the language use perspective.

We observe that our approach, even with the length reward, tends to over-correct the input sentence, i.e., changing its original meaning. Figure 3 gives an example. Given the partial output sentence, i.e., "小明想去" (*Xiaoming wants to go to*), the LLM component gives a probability of 0.0039 to "苏州" (*sūzhōu*), which is a very famous city in Jiangsu Province. In contrast, it gives a much lower probability of 3×10^{-6} to the original input token, i.e., "宿州" (*sùzhōu*), which is a less famous city in Anhui Province. The distortion model fails to remedy such great gap. As the result, our approach adopts the "correction". However, under such circumstances, it is better to reserve the original tokens.

To mitigate this issue, we introduce a faithfulness reward:

$$\begin{aligned}&\texttt{score}(\boldsymbol{x}, \boldsymbol{t}_{\leqslant j}) = \texttt{score}(\boldsymbol{x}, \boldsymbol{t}_{<j}) \\ &+ \log p_{\texttt{LLM}}(t_j \mid \boldsymbol{t}_{<j}) \\ &+ (1 + H_{\texttt{LLM}(\cdot)}) \times \left(\begin{array}{c} \sum_{r=1}^{k} \log p_{\texttt{DM}}(c_r \mid x_{l+r}) \\ + \\ \alpha \times (\ell(t_i) - 1) \end{array} \right)\end{aligned} \tag{7}$$

where $H_{\texttt{LLM}(\cdot)}$ denote the entropy of next-token probabilities.[2] If the entropy is high, meaning that the LLM is uncertain about the next token, the distortion model, along with the length reward, will play a more important role in deciding the next token. From Table 1, we can see that the "Identical" type has a much higher probability than others. That is, the distortion model always favors the original input tokens.

3 Experimental Setup

3.1 Datasets.

Real-world test sets We perform experiments across five distinct CSC datasets: **Sighans** (Wu et al., 2013; Yu et al., 2014; Tseng et al., 2015), **CSCD-IME** (Hu et al., 2022), **MCSCSet** (Jiang et al., 2022), **ECSpell** (Lv et al., 2023), and **Lemon** (Wu et al., 2023), covering a broad spectrum of domains and genres. The details and statistics of these datasets can be found in Appendix B. For Sighans, we utilize the revised versions released by Yang et al. (2023b), which have been manually verified and corrected for errors of the original datasets, and name them as **rSighan** for clarity.

Pseudo development set Since there is no publicly available, manually labeled, domain-general development set for CSC, we have chosen to split a small portion of the existing synthetic training data for hyperparameter tuning, naming it **Pseudo-Dev**. Specifically, we use 1,000 sentences each from the synthetic training data of Hu et al. (2022) and Wang et al. (2018) as our development set.

Selected datasets for analyses Given the absence of a domain-general development set for CSC and the potential limitations of the **Pseudo-Dev** set in representing real-world data, we conduct

[2] Since LLMs have different output vocabularies $\mathcal{V}$, we divide the entropy by $\log|\mathcal{V}|$, which can be understood as the maximum entropy, and the value will fall into $[0, 1]$.

System		rSighans S-F↑	rSighans C-F↑	rSighans FPR↓	CSCD-IME S-F↑	CSCD-IME C-F↑	CSCD-IME FPR↓	MCSCSet S-F↑	MCSCSet C-F↑	MCSCSet FPR↓	ECSpell S-F↑	ECSpell C-F↑	ECSpell FPR↓	Lemon S-F↑	Lemon C-F↑	Lemon FPR↓
`Domain-Specific SOTAs` (*Trained on in-domain gold-standard data of each dataset*)																
`ReaLiSe`†		69.3	80.7	10.1	*41.4*	*44.2*	*27.6*	*17.8*	*27.6*	*12.0*	*34.9*	*45.4*	*13.7*	*28.2*	*31.6*	*19.1*
Hu et al. (2022)		–	–	–	74.4	76.6	–	–	–	–	–	–	–	–	–	–
Jiang et al. (2022)		–	–	–	–	–	–	80.9	–	–	–	–	–	–	–	–
Liu et al. (2023)		–	–	–	–	–	–	–	–	–	85.7	–	5.4	–	–	–
`Domain-General SOTAs` (*Trained on about 34M synthetic CSC data*)																
`Finetuned BERT`		47.5	**57.5**	16.9	**52.0**	**53.9**	**25.7**	35.3	48.5	7.5	57.1	64.9	**6.4**	48.0	49.3	13.1
`Softmasked BERT`		**47.7**	57.4	15.1	51.0	53.4	28.5	35.3	48.5	8.1	57.6	66.2	7.6	47.2	48.8	13.1
`ReLM`		47.3	56.9	**9.6**	49.5	51.6	29.3	**37.8**	**50.2**	**6.8**	**59.3**	**68.4**	8.6	**50.2**	**51.3**	**11.8**
`LLMs` (*without CSC-specific training*)																
`Baichuan2` (`13B`)	`ZSP`	19.0	18.4	49.1	22.6	14.5	35.3	13.6	8.0	77.5	34.5	22.3	30.3	17.5	9.8	40.9
	`FSP`	31.8	38.5	21.4	35.7	32.7	10.5	42.6	47.1	4.4	56.8	53.1	5.8	35.1	25.2	9.5
	`OUR`	**59.1**	**70.9**	**10.4**	**63.2**	**66.2**	**16.5**	**66.0**	**76.9**	**1.7**	**84.5**	**89.8**	**4.9**	**53.2**	**56.2**	**9.1**
`Qwen1.5` (`14B`)	`ZSP`	29.0	31.4	41.1	34.3	31.3	24.5	40.2	45.4	3.8	50.9	49.0	14.4	31.8	26.8	16.1
	`FSP`	32.2	35.1	45.7	44.4	40.7	20.0	39.0	43.0	20.6	57.4	58.0	13.5	36.9	30.3	19.8
	`OUR`	**54.4**	**68.0**	**17.2**	**52.6**	**57.7**	**25.8**	**61.1**	**72.6**	**3.1**	**81.6**	**88.2**	**6.5**	**45.9**	**49.9**	**14.3**
`InternLM2` (`20B`)	`ZSP`	31.0	30.4	57.3	34.9	29.2	40.6	19.0	12.5	80.5	45.2	37.5	31.6	32.8	26.5	27.8
	`FSP`	24.0	28.3	50.0	30.3	26.2	23.4	28.3	29.5	36.2	46.5	44.6	26.3	28.4	19.4	28.6
	`OUR`	**57.1**	**70.0**	**12.6**	**60.7**	**64.1**	**19.7**	**63.2**	**72.9**	**2.6**	**82.4**	**88.8**	**5.1**	**49.8**	**53.7**	**10.7**

Table 2: Main Results. †: We reran the released code of `ReaLiSe` (Xu et al., 2021), along with their released models, to obtain the results. `ReaLiSe`, was trained on the in-domain, gold-standard data of the Sighans dataset and represents a SOTA model for it. The numbers in *gray* represent the out-of-domain results for `ReaLiSe`.

in-depth analyses on three distinct datasets to cover a broad spectrum of language use. These include errors made by Chinese learners (**rSighan** *15*), colloquial and diverse text from novels (**Lemon** *Nov*), and formal and standard text from official documents (**ECSpell** *Odw*).

3.2 Evaluation Metrics.

We follow the convention to use the **sentence-level correction** F_1 (**S-F**) score as the main evaluation metric. Besides, we also report **character-level correction** F_1 (**C-F**) and **sentence-level false positive rate** (**FPR**) to provide a more comprehensive view of the model performance.

3.3 Baselines

We compare our approach against prompt-based method under two settings: zero-shot prompting (**ZSP**) and few-shot prompting (**FSP**). For few-shot settings, we use the `BM25` and `Rouge` similarity metrics to select 10 most similar in-context examples for each input sentence, as proposed by Li et al. (2023a), from the **Pseudo-Dev**. During inference, we adopt the greedy decoding strategy.[3] The prompt details can be found in Appendix C.3.

We do not compare against supervised fine-tuning methods in this study for two reasons. First, our approach is training-free, making direct comparisons with supervised fine-tuning methods unfair. Second, supervised fine-tuning methods are computationally expensive and time-consuming, particularly for large-scale LLMs.

To provide a more comprehensive comparison, we also present results from state-of-the-art domain-general CSC models trained on 34 million pairs of synthetic CSC data for reference. These include **Finetuned BERT** (Devlin et al., 2019), **Softmasked BERT** (Zhang et al., 2020), and **ReLM** according to (Liu et al., 2023).[4]

Additionally, for datasets that include in-domain manually annotated data, we report results from models specifically trained on it, serving as another reference point.

3.4 Hyperparameters

We conduct experiments on three open-source LLMs: the `Baichuan2` (Yang et al., 2023a), `Qwen1.5` (Bai et al., 2023) and `InternLM2` (Cai et al., 2024). We use the "Base" version of each LLM family. The distortion probabilities for each

[3]We observe that the improvement of beam search is marginal and sometimes even detrimental.

[4]The results of these models were obtained by running the released code along with the corresponding checkpoints provided at `https://github.com/gingasan/lemon.git`.

Input	商务部前头，11月底完成
Reference	商务部牵头，11月底完成
ReLM	商务部牵头，11月底完成
BC2 13B ZSP	商务部前面，11月底完成
BC2 13B FSP	商务部日前，11月底完成
BC2 13B OUR	商务部牵头，11月底完成
Input	虎珀酸索莉那新片主要功能是什么
Reference	琥珀酸索利那新片主要功能是什么
ReLM	琥珀酸索莉那新片主要功能是什么
BC2 13B ZSP	琥珀酸索利那新片主要功能是什么
BC2 13B FSP	虎珀酸索莉那新片主要功能是什么
BC2 13B OUR	琥珀酸索利那新片主要功能是什么

Table 3: Qualitative examples of our approach and the baselines. Corrections marked in "Blue" are correct or suggested by the reference, while those in "Red" are incorrect.

		S-F↑	S-P↑	S-R↑	C-F↑	C-P↑	C-R↑	FPR↓
rSighan *15*								
ReLM		55.5	61.1	50.8	61.0	78.5	49.9	9.5
GPT3.5	ZSP	41.2	41.0	41.4	44.6	40.0	50.5	25.9
GPT4	ZSP	43.5	38.1	50.8	47.1	37.9	**62.2**	47.5
BC2 13B	OUR	59.6	66.5	54.0	67.3	78.3	59.0	**8.3**
Q1.5 14B	OUR	57.6	62.5	53.4	66.0	74.1	59.4	10.2
IL2 20B	OUR	**60.5**	**67.2**	**55.0**	**67.8**	**78.7**	59.6	**8.3**
Lemon *Nov (1000)*								
ReLM		36.4	46.7	29.8	36.0	49.2	28.3	14.3
GPT3.5	ZSP	19.4	20.8	18.1	19.6	17.4	22.5	30.4
GPT4	ZSP	30.6	28.4	33.1	31.9	25.2	**43.4**	33.5
BC2 13B	OUR	**45.3**	**53.7**	**39.1**	**49.1**	**57.0**	43.2	**13.1**
Q1.5 14B	OUR	38.2	41.7	35.3	43.7	44.5	43.0	21.8
IL2 20B	OUR	42.8	49.9	37.5	46.4	52.8	41.4	15.3
ECSpell *Odw*								
ReLM		66.5	67.5	65.6	73.0	86.4	63.1	7.1
GPT3.5	ZSP	57.1	61.4	53.4	59.1	60.3	57.9	5.0
GPT4	ZSP	73.1	73.0	73.3	75.6	73.8	77.5	5.0
BC2 13B	OUR	**92.0**	**94.4**	**89.7**	**93.8**	95.6	**92.1**	**0.4**
Q1.5 14B	OUR	87.4	88.6	86.3	91.6	91.8	91.3	2.9
IL2 20B	OUR	91.1	92.9	89.3	**93.8**	**95.9**	91.8	**0.4**

Table 4: The comparison to GPT family on the rSighan 15, Lemon Nov, and ECSpell Odw datasets. The version of GPT3.5 is 'gpt-3.5-turbo-0125', GPT4 is 'gpt-4-0613'. BC2 is short for Baichuan2, Q1.5 for Qwen1.5, and IL2 for InternLM2.

type of distortion model were derived from the statistics of the Pseudo-Dev dataset. During inference, we adopt beam search with a beam size of 8. We tuned α, on the Pseudo-Dev, exploring a range from 0.0 to 5.0 in increments of 0.5. Eventually, α was set to 2.5 for all experiments.

4 Main Results

4.1 Results on CSC Datasets

The main results of our approach and the baselines on the CSC datasets are shown in Table 2.

Results show that, after applying our approach, all three LLM families outperforms their zero-shot and few-shot prompting baseline on all five datasets by a large margin. Our approach not only achieves a higher sentence- and character-level correction F_1 score, but also reduces the false positive rate.

Compared to the recent state-of-the-art domain-general CSC models, which are trained on 34M synthetic CSC data, our approach also achieves competitive or even superior performance on most datasets, especially on the MCSCSet and ECSpell datasets. The results indicate that our approach has a better generalization across different domains and genres than the current domain-general SOTAs.

However, our approach still largely lags behind the domain-specific SOTAs trained on the gold-standard labeled data (from 1.2 to 21.8 on S-F score) of each dataset. Take the Baichuan2 model as an example. The smallest gap (1.2) is on the ECSpell dataset, which may be because the text in that dataset is more formal and standard, while the largest gap (19.8) happens on the MCSCSet dataset, on which the text contains many medical terms and abbreviations, requiring profound domain knowledge. The gap between our approach and the domain-specific SOTAs indicates that, though our approach has shown a good generalization ability, there is still a large room to be perfected.

4.2 Qualitative Examples

We provide two qualitative examples to illustrate the performance of our approach in Table 3.

In the first case ("*Led by the Ministry of Commerce, to be completed by the end of November*"), the word "牵头" (*qiāntóu, led by*) is misspelled as "前头" (*qiántóu, front*) in the input sentence. Both the ZSP and FSP baselines mistakenly put their attention on the character "前" (*front*) and incorrectly correct "前头" to "日前" (*a few days ago*) and "前面" (*front*), respectively. Such corrections are not only implausible but also linguistically awkward. In contrast, the domain-general model ReLM and our approach successfully correct the misspelling.

In the second case ("*What are the main functions of Solifenacin Succinate Tablets*"), the name of the drug "琥珀酸索利那新片" (*Solifenacin Succinate Tablets*) is misspelled. To correct the misspelling,

	rSighan *15*		Lemon *Nov*		ECSpell *Odw*	
	Dev	True	Dev	True	Dev	True
Distortion Model: $\log p_{\texttt{DM}}$						
Idt.	-0.04	-0.03	-0.04	-0.02	-0.04	-0.02
Sa.P.	-3.75	-4.00	-3.75	-4.66	-3.75	-4.17
Si.P.	-4.85	-5.02	-4.85	-5.45	-4.85	-5.87
Si.S.	-5.40	-8.63	-5.40	-8.04	-5.40	-6.66
S-F↑	59.8	**+0.9**	43.2	0.0	89.7	-0.8
C-F↑	68.2	**+1.4**	47.7	**+0.2**	93.0	-0.3
FPR↓	8.1	0.0	13.6	+0.3	1.3	0.0

Table 5: The impact of distortion model on the performance of Baichuan2 7B. "True" denotes that the distortion model is derived from the **true** distortion distribution of each dataset. " Dev" represents the distortion model from the Pseudo-Dev.

the knowledge of the medical domain is required. In this case, the ReLM model fails to correct the misspelling, while the zero-shot prompting baseline and our approach successfully correct it. It is worth noting that the few-shot prompting baseline also fails to correct the misspelling, which indicates that the inclusion of inappropriate examples may lead to worse performance.

5 Discussion

5.1 Comparison to GPT family

In the domain of LLMs, the GPT family stands out as a top-tier leader. This subsection presents a comparison between GPTs and our approach.

Since we have to pay to use the GPT family, conducting a comprehensive evaluation becomes very expensive. As a result, we have limited our comparison to a small-scale study, focusing on the three datasets mentioned in Section 3.1.[5]

Compared to both GPT3.5 and GPT4, our approach achieves higher sentence- and character-level corrections F_1 scores across all datasets, along with a significantly reduced rate of false positives. However, our approach may exhibit a lower recall rate for character-level corrections compared to GPT4, indicating that our approach might miss some errors that GPT4 can successfully correct.

5.2 Effectiveness of the Estimated Distortion Model

The distortion model is a key component in our approach. In this work, we utilize a minimal distortion model and directly estimate the distortion probabilities from the statistics of the Pseudo-Dev dataset. Obviously, this estimation will be different from the true probabilities.

[5] The original Lemon-Nov dataset includes 6,000 sentences, which is excessively large for our scope. Therefore, we selected the first 1,000 sentences for this comparison.

	S-F↑	S-P↑	S-R↑	**C-F**↑	C-P↑	C-R↑	**FPR**↓
rSighan *15*							
Vanilla	18.0	15.9	20.6	20.7	14.3	37.6	52.9
w/ LR	+39.4	+43.4	+35.0	+43.7	+53.3	+23.9	-38.4
w/ FR	+3.8	+6.2	+0.8	+5.4	+8.3	-6.6	-19.3
w/ Both	+41.9	+50.1	+34.1	+47.4	+63.5	+23.0	-44.8
Lemon *Nov*							
Vanilla	19.4	18.0	20.9	23.6	17.1	38.3	38.5
w/ LR	+17.1	+19.5	+14.6	+19.0	+21.9	+8.6	-13.7
w/ FR	+9.0	+13.5	+4.7	+8.5	+13.5	-4.5	-18.8
w/ Both	+23.9	+34.2	+16.0	+24.1	+38.4	+3.6	-25.0
ECSpell *Odw*							
Vanilla	65.3	65.3	65.3	70.4	65.4	76.2	10.1
w/ LR	+25.4	+26.9	+24.0	+22.5	+28.5	+15.6	-9.7
w/ FR	+4.7	+11.2	-0.8	+7.5	+19.7	-4.5	-6.7
w/ Both	+24.4	+26.4	+22.5	+22.6	+29.9	+14.6	-8.8

Table 6: Ablation results of Baichuan2 7B. "LR" and "FR" represent "length reward" and "faithfulness reward" respectively. "Both" means using both length reward and faithfulness reward.

To verify the effectiveness of the estimated distortion model, we conduct experiments comparing the estimated distortion model with the true distortion model. The results are presented in Table 5. The upper part of the table shows the difference between the estimated distortion model and the true distortion model. We can see that the estimated one is quite close to the true one, except for the Similar Shape distortion type. The lower part shows that the difference between the performance them is marginal, indicating that the estimated distortion model is sufficient for our approach to achieve a good performance, and has good generalization ability across different datasets.

5.3 Impact of the Length Reward

In this work, we propose a length reward strategy to alleviate the local optima problem during the beam search decoding. The "w/ LR" column in Table 6 shows the performance change when including the length reward to the vanilla decoding process. Results clearly show that the length reward significantly improves the performance on all three datasets, yielding an average improvement of +27.3 in terms of the sentence-level correction F_1 score and +28.4 in the character-level correction F_1 score. This improvement can be attributed to increases in both precision and recall, indicating that the length reward is crucial to our approach.

5.4 Impact of the Faithfulness Reward

The faithfulness reward component is designed to mitigate the over-correction problem. As shown in Table 6, the vanilla decoding process typically has a much higher character-level recall than precision. The faithfulness reward, as shown in the "`w/ FR`" column, can effectively improve the precision, though it may slightly reduce the recall. Overall, the faithfulness reward balances the trade-off between precision and recall, leading to a higher correction F_1 score.

5.5 Impact of Combining Both Rewards

The "`w/ Both`" column in Table 6 shows the performance change when including both the length and faithfulness rewards. In datasets with less formal text, more colloquial expressions, and more diverse name entities, like the rSighan-15 and Lemon-Nov datasets, the combination of the two rewards can achieve a better performance than using them separately. However, on the ECSpell-Odw dataset, which is composed of formal text and standardized collocations, the effectiveness of combining the two rewards is less significant.

6 Related Works

6.1 Chinese Spelling Check

Previous research on the CSC task can be divided into three eras, accompanied with paradigm shift.

The Early Unsupervised Era Early CSC approaches mainly utilized unsupervised pipeline systems (Yeh et al., 2013; Yu et al., 2014; Yu and Li, 2014; Huang et al., 2014; Xie et al., 2015). These systems typicaly consist of three main components: an error detection module to identify potential errors in the input sentence, a confusion set to generate candidate corrections for each detected error, resulting in numerous candidates, and a statistical n-gram language model to rank these candidates and select the most probable correction.

The Supervised Learning Era By 2018, the advent of techniques for automatically generating pseudo-labeled data had begun to address the challenge of data scarcity in CSC (Wang et al., 2018), marking a shift in the paradigm of CSC research towards a supervised learning era dominated by deep neural networks. This era saw researchers exploring various avenues to enhance CSC performance. Some focused on finding better model architectures (Zhang et al., 2020; Zhu et al., 2022), while others delved into more effective training strategies (Liu et al., 2022; Wu et al., 2023; Liu et al., 2023). Additionally, there was an effort to enrich models with information beyond text, such as phonetic or visual features (Cheng et al., 2020; Xu et al., 2021; Li et al., 2022; Liang et al., 2023).

The LLM Era Our work represents an initial foray into what could be considered the third era of CSC research: the LLM era. This phase explores the potential of LLMs in addressing the CSC task. As mentioned in the introduction, related studies in this era fall into two categories: *prompt-based* and *supervised fine-tuning*. In contrast to these methods, our approach requires neither additional training nor prompts.

6.2 Decoding Methods of LLMs

Intervening in the decoding process is a common approach to improve LLMs' task-specific performance. There are two popular approaches in this category: **Contrastive decoding** and **Constrained decoding**. Contrastive decoding (Li et al., 2023b) refines the output probabilities by comparing the output probabilities of expert and amateur models, being successful used in reasoning improvement (O'Brien and Lewis, 2023) and hallucination mitigation (Shi et al., 2023). Constrained decoding, on the other hand, uses constraints to guide the decoding process, making the output more aligned with the task-specific requirements (Wang et al., 2023; Geng et al., 2023).

Our work is closely related to the constrained decoding approaches, where a distortion model is used to influence the LLM decoding process.

7 Conclusion

In this work, we propose a simple, training-free, and prompt-free approach to leverage LLMs for the CSC task. Two components, a large language model and a minimal distortion model, co-operate to correct spelling errors. We alleviate the local optima problem and over-correction issue, with two simple strategies, length reward and faithfulness reward, respectively. Our comprehensive experiments have shown that our approach significantly improves LLM performance. Through our approach, LLMs demonstrate remarkable domain generalization capabilities, surpassing SOTA domain-general CSC models, that are trained on extensive synthetic CSC data, on most datasets.

Limitations

The scope of this study is limited to the task of Chinese spelling correction, which is a subset of text error correction. Our approach is not equipped to directly address complex text errors that involve grammar, semantics, or pragmatics. To tackle these errors, one could design an appropriate distortion model, though it might necessitate the adoption of more intricate rules or the implementation of a model based on neural networks. In our future work, we aim to explore ways that would allow our approach to handle these complex errors.

Moreover, our approach can be applied to any task that involves converting a given input into a natural language sentence. It utilizes a model to measure the transformational relationship between the input and the output of a large language model, ensuring that the outputs meet the specific requirements of the task. It would be interesting to investigate the effectiveness of our approach to other tasks, such as text summarization and machine translation, through the development of task-specific transformation models.

References

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. 2023. Qwen technical report. *ArXiv preprint*, abs/2309.16609.

Zuyi Bao, Chen Li, and Rui Wang. 2020. Chunk-based Chinese spelling check with global optimization. In *Proceedings of EMNLP*, pages 2031–2040, Online.

Zheng Cai, Maosong Cao, Haojiong Chen, Kai Chen, Keyu Chen, Xin Chen, Xun Chen, Zehui Chen, Zhi Chen, Pei Chu, Xiaoyi Dong, Haodong Duan, Qi Fan, Zhaoye Fei, Yang Gao, Jiaye Ge, Chenya Gu, Yuzhe Gu, Tao Gui, Aijia Guo, Qipeng Guo, Conghui He, Yingfan Hu, Ting Huang, Tao Jiang, Penglong Jiao, Zhenjiang Jin, Zhikai Lei, Jiaxing Li, Jingwen Li, Linyang Li, Shuaibin Li, Wei Li, Yining Li, Hongwei Liu, Jiangning Liu, Jiawei Hong, Kaiwen Liu, Kuikun Liu, Xiaoran Liu, Chengqi Lv, Haijun Lv, Kai Lv, Li Ma, Runyuan Ma, Zerun Ma, Wenchang Ning, Linke Ouyang, Jiantao Qiu, Yuan Qu, Fukai Shang, Yunfan Shao, Demin Song, Zifan Song, Zhihao Sui, Peng Sun, Yu Sun, Huanze Tang, Bin Wang, Guoteng Wang, Jiaqi Wang, Jiayu Wang, Rui Wang, Yudong Wang, Ziyi Wang, Xingjian Wei, Qizhen Weng, Fan Wu, Yingtong Xiong, Chao Xu, Ruiliang Xu, Hang Yan, Yirong Yan, Xiaogui Yang, Haochen Ye, Huaiyuan Ying, Jia Yu, Jing Yu, Yuhang Zang, Chuyu Zhang, Li Zhang, Pan Zhang, Peng Zhang, Ruijie Zhang, Shuo Zhang, Songyang Zhang, Wenjian Zhang, Wenwei Zhang, Xingcheng Zhang, Xinyue Zhang, Hui Zhao, Qian Zhao, Xiaomeng Zhao, Fengzhe Zhou, Zaida Zhou, Jingming Zhuo, Yicheng Zou, Xipeng Qiu, Yu Qiao, and Dahua Lin. 2024. Internlm2 technical report. *ArXiv preprint*, abs/2403.17297.

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 ACL*, pages 871–881, Online.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL-HLT*, pages 4171–4186, Minneapolis, Minnesota.

Ming Dong, Yujing Chen, Miao Zhang, Hao Sun, and Tingting He. 2024. Rich semantic knowledge enhanced large language models for few-shot Chinese spell checking. *ArXiv preprint*, abs/2403.08492.

Saibo Geng, Martin Josifoski, Maxime Peyrard, and Robert West. 2023. Grammar-constrained decoding for structured NLP tasks without finetuning. In *Proceedings of EMNLP*, pages 10932–10952, Singapore.

Yuzhong Hong, Xianguo Yu, Neng He, Nan Liu, and Junhui Liu. 2019. FASPell: A fast, adaptable, simple, powerful Chinese spell checker based on DAE-decoder paradigm. In *Proceedings of W-NUT*, pages 160–169, Hong Kong, China.

Yong Hu, Fandong Meng, and Jie Zhou. 2022. CSCD-IME: correcting spelling errors generated by pinyin IME. *ArXiv preprint*, abs/2211.08788.

Qiang Huang, Peijie Huang, Xinrui Zhang, Weijian Xie, Kaiduo Hong, Bingzhou Chen, and Lei Huang. 2014. Chinese spelling check system based on tri-gram model. In *Proceedings of CIPS-SIGHAN*, pages 173–178, Wuhan, China.

Wangjie Jiang, Zhihao Ye, Zijing Ou, Ruihui Zhao, Jianguang Zheng, Yi Liu, Bang Liu, Siheng Li, Yujiu Yang, and Yefeng Zheng. 2022. Mcscset: A specialist-annotated dataset for medical-domain Chinese spelling correction. In *Proceedings of CIKM*, pages 4084–4088.

Jiahao Li, Quan Wang, Zhendong Mao, Junbo Guo, Yanyan Yang, and Yongdong Zhang. 2022. Improving Chinese spelling check by character pronunciation prediction: The effects of adaptivity and granularity. In *Proceedings of EMNLP*, pages 4275–4286, Abu Dhabi, United Arab Emirates.

Xiang Lisa Li, Ari Holtzman, Daniel Fried, Percy Liang, Jason Eisner, Tatsunori Hashimoto, Luke Zettlemoyer, and Mike Lewis. 2023b. Contrastive decoding: Open-ended text generation as optimization. In *Proceedings of ACL*, pages 12286–12312, Toronto, Canada.

Yinghui Li, Haojing Huang, Shirong Ma, Yong Jiang, Yangning Li, Feng Zhou, Hai-Tao Zheng, and Qingyu Zhou. 2023a. On the (in)effectiveness of large language models for Chinese text correction. *ArXiv preprint*, abs/2307.09007.

Zihong Liang, Xiaojun Quan, and Qifan Wang. 2023. Disentangled phonetic representation for Chinese spelling correction. In *Proceedings of ACL*, pages 13509–13521, Toronto, Canada.

Linfeng Liu, Hongqiu Wu, and Hai Zhao. 2023. Chinese spelling correction as rephrasing language model. *ArXiv preprint*, abs/2308.08796.

Shulin Liu, Shengkang Song, Tianchi Yue, Tao Yang, Huihui Cai, TingHao Yu, and Shengli Sun. 2022. CRASpell: A contextual typo robust approach to improve Chinese spelling correction. In *Findings of ACL*, pages 3008–3018, Dublin, Ireland.

Qi Lv, Ziqiang Cao, Lei Geng, Chunhui Ai, Xu Yan, and Guohong Fu. 2023. General and domain-adaptive Chinese spelling check with error-consistent pretraining. *TALLIP*, 22(5).

Sean O'Brien and Mike Lewis. 2023. Contrastive decoding improves reasoning in large language models. *ArXiv preprint*, abs/2309.09117.

Weijia Shi, Xiaochuang Han, Mike Lewis, Yulia Tsvetkov, Luke Zettlemoyer, and Scott Wen-tau Yih. 2023. Trusting your evidence: Hallucinate less with context-aware decoding. *ArXiv preprint*, abs/2305.14739.

Chenglei Si, Zhengyan Zhang, Yingfa Chen, Xiaozhi Wang, Zhiyuan Liu, and Maosong Sun. 2023. READIN: A Chinese multi-task benchmark with realistic and diverse input noises. In *Proceedings of ACL*, pages 8272–8285, Toronto, Canada.

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 SIGHAN*, pages 32–37, Beijing, China.

Bailin Wang, Zi Wang, Xuezhi Wang, Yuan Cao, Rif A. Saurous, and Yoon Kim. 2023. Grammar prompting for domain-specific language generation with large language models. *ArXiv preprint*, abs/2305.19234.

Dingmin Wang, Yan Song, Jing Li, Jialong Han, and Haisong Zhang. 2018. A hybrid approach to automatic corpus generation for Chinese spelling check. In *Proceedings of EMNLP*, pages 2517–2527, Brussels, Belgium.

Hongqiu Wu, Shaohua Zhang, Yuchen Zhang, and Hai Zhao. 2023. Rethinking masked language modeling for Chinese spelling correction. In *Proceedings of ACL*, pages 10743–10756, Toronto, Canada.

Shih-Hung Wu, Chao-Lin Liu, and Lung-Hao Lee. 2013. Chinese spelling check evaluation at SIGHAN bake-off 2013. In *Proceedings of SIGHAN*, pages 35–42, Nagoya, Japan.

Weijian Xie, Peijie Huang, Xinrui Zhang, Kaiduo Hong, Qiang Huang, Bingzhou Chen, and Lei Huang. 2015. Chinese spelling check system based on n-gram model. In *Proceedings of SIGHAN*, pages 128–136, Beijing, China.

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 *Proceedings of ACL-IJCNLP*, pages 716–728, Online.

Aiyuan Yang, Bin Xiao, Bingning Wang, Borong Zhang, Ce Bian, Chao Yin, Chenxu Lv, Da Pan, Dian Wang, Dong Yan, Fan Yang, Fei Deng, Feng Wang, Feng Liu, Guangwei Ai, Guosheng Dong, Haizhou Zhao, Hang Xu, Haoze Sun, Hongda Zhang, Hui Liu, Jiaming Ji, Jian Xie, Juntao Dai, Kun Fang, Lei Su, Liang Song, Lifeng Liu, Liyun Ru, Luyao Ma, Mang Wang, Mickel Liu, MingAn Lin, Nuolan Nie, Peidong Guo, Ruiyang Sun, Tao Zhang, Tianpeng Li, Tianyu Li, Wei Cheng, Weipeng Chen, Xiangrong Zeng, Xiaochuan Wang, Xiaoxi Chen, Xin Men, Xin Yu, Xuehai Pan, Yanjun Shen, Yiding Wang, Yiyu Li, Youxin Jiang, Yuchen Gao, Yupeng Zhang, Zenan Zhou, and Zhiying Wu. 2023a. Baichuan 2: Open large-scale language models. *ArXiv preprint*, abs/2309.10305.

Liner Yang, Xin Liu, Tianxin Liao, Zhenghao Liu, Mengyan Wang, Xuezhi Fang, and Erhong Yang. 2023b. Is Chinese spelling check ready? understanding the correction behavior in real-world scenarios. *AI Open*, 4:183–192.

Jui-Feng Yeh, Sheng-Feng Li, Mei-Rong Wu, Wen-Yi Chen, and Mao-Chuan Su. 2013. Chinese word spelling correction based on n-gram ranked inverted index list. In *Proceedings of SIGHAN*, pages 43–48, Nagoya, Japan.

Junjie Yu and Zhenghua Li. 2014. Chinese spelling error detection and correction based on language model, pronunciation, and shape. In *Proceedings of CIPS-SIGHAN*, pages 220–223, Wuhan, China.

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 CIPS-SIGHAN*, pages 126–132, Wuhan, China.

Shaohua Zhang, Haoran Huang, Jicong Liu, and Hang Li. 2020. Spelling error correction with soft-masked BERT. In *Proceedings of ACL*, pages 882–890, Online.

Chenxi Zhu, Ziqiang Ying, Boyu Zhang, and Feng Mao. 2022. MDCSpell: A multi-task detector-corrector framework for Chinese spelling correction. In *Findings of ACL*, pages 1244–1253, Dublin, Ireland.

A Implement of Distortion Model

A.1 Standard of Transformation Types

Identical Transformations An identical distortion occurs when the input character is the same as the correct character.

Same Pinyin Characters that share the same pronunciation, disregarding tone, undergo a "`Same Pinyin`" distortion. Due to the existence of heteronyms in Chinese, such as "和", which can be pronounced in multiple ways including "*hé*", "*hè*", "*huó*", "*huò*", and "*hú*", we classify two characters as undergoing a same pinyin distortion if they share at least one pronunciation. The `pypinyin`[6] library is utilized to determine character pronunciations, with the `ktghz2013` and `large_pinyin` from `pypinyin-dict`.[7] providing a more accurate pronunciation for these determinations.

Similar Pinyin We categorize distortions as "`Similar Pinyin`" when two characters have pronunciation that is recognized as similar by predefined rules, which are based on Yang et al. (2023b). For instance, '*qī*' and "*jī*" are considered similar due to the common mispronunciation of the consonant "*q*" as "*j*". A list of consonants and vowels considered similar can be found in Tables 7 and 8, respectively.

Similar Shape The similarity in the shape of characters is evaluated by combining their four-corner code with their radical and component information. For example, the characters "机" and "仉" have the four-corner codes "47910" and "27210", respectively. Given that the last digit primarily serves to distinguish characters with identical preceding digits and that "机" and "仉" share two of these digits, their four-corner code similarity is calculated as $2 \times \frac{1}{4} = 0.5$. Considering their radical and component ("木, 几" for "机" and "人, 几" for "仉"), which share the component "几" but differ in radicals, their similarity is $1 \times \frac{1}{2} = 0.5$. Thus, the overall similarity is averaged to 0.5. With a similarity threshold set at 0.45, these characters are considered to undergo a similar shape distortion. Furthermore, character pairs where one is a radical or component of the other, such as "机" and "几", are also classified under similar shape distortions.

All non-Chinese characters are only allowed to be transformed into themselves.

[6] https://github.com/mozillazg/python-pinyin
[7] https://github.com/mozillazg/pypinyin-dict

Corrected → Input										
j	→	○	*q*	*x*	*z*	☒	☒	☒	☒	☒
q	→	*j*	○	*x*	☒	*c*	☒	☒	☒	☒
x	→	*j*	*q*	○	☒	☒	*s*	☒	☒	☒
z	→	*j*	☒	☒	○	*c*	*s*	*zh*	☒	☒
c	→	☒	*q*	☒	*z*	○	*s*	☒	*ch*	☒
s	→	☒	☒	■	*z*	*c*	○	☒	☒	*sh*
zh	→	☒	☒	☒	*z*	☒	☒	○	*ch*	*sh*
ch	→	☒	☒	☒	☒	*c*	☒	*zh*	○	*sh*
sh	→	☒	☒	☒	☒	☒	*s*	*zh*	*ch*	○
r	→	○	*l*	☒	☒	☒	☒	☒	☒	
l	→	*r*	○	*n*	*d*	*t*	☒	☒	☒	
n	→	☒	*l*	○	*d*	*t*	☒	☒	☒	
d	→	☒	*l*	*n*	○	*t*	*b*	☒	☒	
t	→	☒	*l*	*n*	*d*	○	☒	*p*	☒	
b	→	☒	☒	☒	*d*	☒	○	*p*	*m*	
p	→	☒	☒	☒	☒	*t*	*b*	○	■	
m	→	☒	☒	☒	☒	☒	*b*	*p*	○	
g	→	○	*k*	*h*	☒					
k	→	*g*	○	*h*	☒					
h	→	*g*	*k*	○	*f*					
f	→	☒	☒	*h*	○					

Table 7: Consonants with similar pronunciation.

Corrected → Input							
an	→	○	*ang*	*uan*	*uang*	*ian*	☒
ang	→	*an*	○	*uan*	*uang*	☒	*iang*
uan	→	*an*	*ang*	○	*uang*	*ian*	☒
uang	→	*an*	*ang*	*uan*	○	☒	*iang*
ian	→	*an*	☒	*uan*	☒	○	*iang*
iang	→	☒	*ang*	☒	*uang*	*ian*	○
en	→	○	*eng*	*un*	☒		
eng	→	*en*	○	☒	☒		
un	→	*en*	☒	○	*ong*		
ong	→	☒	☒	*un*	○		
in	→	○	*ing*				
ing	→	*in*	○				
o	→	○	*uo*				
uo	→	*o*	○				
ü	→	○	*u*				
u	→	*ü*	○				

Table 8: Vowels with similar pronunciation.

A.2 Type Priority

In scenarios where a character can be classified under multiple distortion types, for example, "机" (*jī*) and "玑" (*jī*), which can be classified as both having

Datasets	rSighans			Cscd	Mcsc	ECSpell		
Subsets	Y13	Y14	Y15	Test	Test	Law	Med	Odw
#Sentence	1,000	1,062	1,100	5,000	19,650	500	500	500
Error Ratio	97.70	56.69	56.18	46.06	50.00	51.00	45.20	52.40
Average Length	74.33	50.01	30.64	57.63	10.91	29.74	49.60	40.51
Average Err./Sent.	1.48	0.88	0.78	0.51	0.93	0.78	0.71	0.81
Distortion Type Proportion (%)								
Identical	98.01	98.25	97.45	99.12	91.47	97.38	98.56	98.01
Same Pinyin	1.62	1.30	1.83	0.74	6.60	1.82	1.15	1.55
Similar Pinyin	0.28	0.40	0.66	0.13	1.05	0.51	0.19	0.28
Similar Shape	0.05	0.01	0.03	0.00	0.39	0.25	0.08	0.13
Unrelated	0.04	0.04	0.02	0.00	0.45	0.04	0.01	0.02
Recall Upper Bound	97.24	97.18	98.71	99.70	90.82	97.65	98.67	98.47

Datasets	Lemon							Pseudo-Dev
Subsets	Car	Cot	Enc	Gam	Med	New	Nov	–
#Sentence	3,410	1,026	3,434	400	2,090	5,892	6,000	2,000
Error Ratio	51.09	46.20	50.99	38.75	50.38	50.00	50.23	93.55
Average Length	43.44	40.12	39.83	32.99	39.28	25.16	36.24	36.94
Average Err./Sent.	0.56	0.47	0.52	0.41	0.49	0.55	0.57	1.42
Distortion Type Proportion (%)								
Identical	98.64	98.78	98.63	98.73	98.64	97.80	98.43	96.15
Same Pinyin	0.90	0.75	0.93	0.89	0.94	1.50	0.95	2.34
Similar Pinyin	0.31	0.25	0.28	0.26	0.27	0.51	0.43	0.78
Similar Shape	0.02	0.07	0.06	0.01	0.02	0.05	0.02	0.40
Unrelated	0.12	0.14	0.09	0.11	0.12	0.13	0.16	0.31
Recall Upper Bound	91.38	89.34	94.28	90.54	92.82	93.98	89.08	88.03

Table 9: The statistics of the datasets used in the experiments. **Recall Upper Bound** represents the sentence-level upper bound of the recall under the distortion model that we use in this work.

the same pinyin and a similar shape, we prioritize the distortion type according to the following order: 1) Identical; 2) Same Pinyin; 3) Similar Pinyin; 4) Similar Shape; 5) Unrelated.

A.3 Using an Inverted Index for Efficient Distortion Model Calculation

During each decoding step, the distortion model calculates the probability of transforming the input sequence $x_{a:b}$ into a candidate token t_i:

$$g(x, t_i) = \sum_{r=1}^{k} \log p_{\mathtt{DM}}(c_r \mid x_{l+r}), \tag{8}$$

where the function $g(x, t_i)$ must be computed for each candidate token t_i in the vocabulary $\mathcal{V}$, resulting in a huge computational cost.

To address this challenge, we propose the use of an inverted index to reduce the calculation process, by only considering relevant tokens, and ignoring irrelevant tokens. For a token, we can preconstruct indexed entries to represent it, such as <0,ji,SamePinyin>, <1,kou,SimilarPinyin>, and <0,仉,SimilarShape> for "机构" (*jī gòu*). Upon receiving an input sequence, the index enables rapid retrieval of relevant tokens, thereby limiting probability calculations exclusively to these tokens. As the subset of relevant tokens is substantially smaller than the complete token set, employing an inverted index considerably reduces the computational burden.

A.4 Small Tricks for Distortion Model

We adopt three small tricks to enhance our distortion model. First, for character pairs commonly misused in everyday writing, such as "的", "地", and "得", we categorize these as "Identical" distortions, allowing the model to correct these errors with lower difficulty.

Second, we found that, although the previously described rules adequately cover most similar relationships between characters, a few exceptions, approximately 0.01% of total character pairs, still

System and User Prompts for baselines

System Prompt:
你是一个优秀的中文拼写纠错模型，中文拼写纠错模型即更正用户输入句子中的拼写错误。

User Prompt:
你需要识别并纠正用户输入的句子中可能的错别字并输出正确的句子，纠正时必须保证改动前后句子必须等长，在纠正错别字的同时尽可能减少对原句子的改动(不添加额外标点符号，不添加额外的字，不删除多余的字)。只输出没有错别字的句子，不要添加任何其他解释或说明。如果句子没有错别字，就直接输出和输入相同的句子。

Figure 4: Prompt templates used in our FSP and ZSP baselines.

persist. To identify these outliers, we leveraged tools from previous studies (Wu et al., 2023; Hu et al., 2022) by incorporating their structure confusion sets and spelling similarity matrices. We classify character pairs found within the structure confusion set or those with a spelling similarity matrix distance of less than 1 as "Other Similar" distortions.

Finally, we have chosen not to entirely exclude unrelated distortions. Instead, we allow each token to possess up to one unrelated character distortion, to which we assign a very low probability.

Employing these tricks has led to marginal yet consistent improvements in our approach's performance.

B Details of Real-world Test Sets

This section details the test sets used in our study, providing insights into their composition and relevance to real-world Chinese text.

- **Sighan series**: This series of datasets is one of the most widely used benchmark datasets for Chinese spelling correction (Wu et al., 2013; Yu et al., 2014; Tseng et al., 2015). However, it faces criticism for two main reasons: firstly, it consists of essays written by Chinese learners, which may not accurately represent typical Chinese texts. Secondly, its limited diversity could hinder the evaluation of models' generalization capabilities. Despite these concerns, we include it in our evaluation to allow for comparison with prior studies. However, we utilize the revised version by Yang et al. (2023b), which has manually verified and corrected the errors in the original dataset.
- **CSCD-IME**: A real-world Chinese social media corpus collected and annotated by Hu et al. (2022). It can better represent the variety of texts found in real-world settings and includes a broad spectrum of errors.
- **MCSCSet**: A large-scale corpus from the medical domain, collected and annotated by Jiang et al. (2022). It features numerous errors specific to medical terminology, making it an excellent resource for evaluating models' generalization capabilities in this area.
- **ECSpell**: A small-scale, multi-domain corpus annotated by Lv et al. (2023). It encompasses three domains: legal documents, medical treatments, and official document writing.
- **Lemon**: The most recent and largest multi-domain corpus to date, collected and annotated by Wu et al. (2023). It spans seven domains: law, medicine, encyclopedia, gaming, automotive, contracts, news, and novels.

The detailed statistics of these datasets are shown in Table 9.

C Details of Experiments

C.1 Evaluation Details

Following the convention of Lemon dataset, we ignore all sentences that the length of the input sentence is not equal to that of the output sentence. During evaluation, we convert all full-width punctuation to half-width and remove all whitespaces from the input and output sentences to guarantee a fair comparison.

C.2 Levenshtein Alignment for Character-Level Evaluation

Traditional point-wise evaluation methods fall short when models add or delete characters, as they can inaccurately mark all subsequent characters as incorrect due to a single addition or deletion. To overcome this, we implement Levenshtein algorithm to align the model output with the target sentence. This approach allows us to calculate character-level

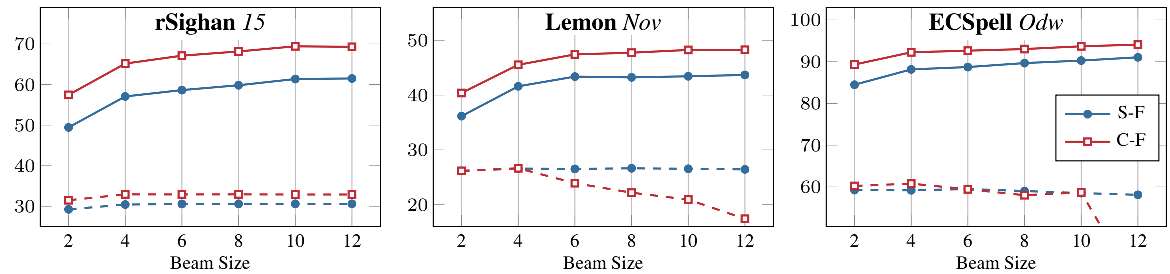


Figure 5: The scores of `Baichuan2 7B` with different beam sizes. The solid lines represent the results of our approach, and the dashed lines represent the results of the few-shot baseline. We can observe that larger beam sizes may lead to worse C-F scores in few-shot settings.

metrics based on the aligned results, providing a more reasonable evaluation of character-level performance.

C.3 Prompt Examples

In this work, we use the prompt-based method to activate the CSC ability of the baseline LLMs. The task-specific instructions are adopted from Li et al. (2023a). The prompt used for the baselines are shown in Table 4. We disable the sampling mechanism and set the temperature to 0.0 to ensure deterministic decoding.

C.4 Pre- & Post-processing for Baselines

In this study, we employ several pre- and post-processing techniques to mitigate the errors introduced by the limitations of baseline systems. This ensures a fair comparison between our approach and the baselines.

BERT-based baselines Most current CSC models utilize BERT. However, BERT presents challenges that can degrade performance during evaluation: 1) *Full-width Punctuation:* BERT's tokenization process may normalize full-width punctuation to half-width, leading to numerous unnecessary punctuation replacements. To counter this, we prevent the model from modifying the original punctuation; 2) *Special Tokens:* BERT-based models may predict a special '[UNK]' token in some cases, resulting in the removal of the original character. In these instances, we retain the original character when a special token is predicted; 3) *Input Length Limitation:* BERT-based models show limited generalization beyond their maximum training length. We truncate inputs to a maximum length of 128 characters and concatenate the remaining characters to the output.

LLM baselines The outputs of LLMs sometimes fail to align with evaluation, primarily due to their inadequate instruction-following capability. To address this, we apply specific rules for post-processing: 1) *Redundant Phrases:* We remove redundant phrases such as "修改后的句子是：" (*The corrected sentence is:*), identified through common patterns input in the model output; 2) *Redundant Punctuation:* Many sentences in the dataset lack terminal periods, yet some models inappropriately add them. To prevent incorrect evaluations due to this discrepancy, we remove any added terminal period if the original sentence did not have one.

D More Analyses

D.1 Influence of Beam Size

During searching the most likely correction sequence, the beam search algorithm is used to avoid the exponential growth of the search space and the local minimum caused by greedy search. Knowing the impact of the beam size on the performance helps researchers to choose a proper beam size to balance the trade-off between the performance and the computational cost. The results are shown in Figure 5. Though the larger beam size consistently leads to better performance, the improvement becomes marginal when the beam size is larger than 6.

E Detailed Results

Due to the space limitation, we only present the average results of each dataset in the main text. The detailed results of each dataset are shown in Table 10, Table 11, and Table 12.

Datasets		rSighans			ECSpell			Lemon						
Subsets		Y13	Y14	Y15	Law	Med	Odw	Car	Cot	Enc	Gam	Med	New	Nov
Domain-Specific SOTAs (*Trained on in-domain gold-standard data of each dataset*)														
ReaLiSe		70.1	64.0	73.9	*38.9*	*23.1*	*42.8*	*32.5*	*40.1*	*29.1*	*12.6*	*31.8*	*31.2*	*20.2*
Liu et al. (2023)		–	–	–	91.2	82.4	83.6	–	–	–	–	–	–	–
Domain-General SOTAs (*Trained on about 34M synthetic CSC data*)														
Finetuned BERT		50.6	40.4	51.6	58.5	47.8	65.1	52.0	63.1	45.3	32.8	50.7	56.1	35.8
Softmasked BERT		**51.6**	40.2	51.3	58.5	48.5	65.9	52.3	63.8	44.1	28.3	48.9	55.6	**37.7**
ReLM		45.8	**40.6**	**55.5**	**60.4**	**50.9**	**66.5**	**53.3**	**66.7**	**47.7**	**33.7**	**53.8**	**58.8**	37.1
LLMs (*without CSC-specific training*)														
Baichuan2 (13B)	ZSP	26.4	12.0	18.5	37.6	23.0	43.0	15.3	14.9	24.0	12.7	21.6	19.8	14.1
	FSP	41.1	23.1	31.3	60.2	50.4	60.0	32.2	45.3	38.9	24.6	39.0	39.7	26.4
	OUR	**63.6**	**54.1**	**59.6**	**82.6**	**78.9**	**92.0**	**52.7**	**62.9**	**51.9**	**37.1**	**60.1**	**63.9**	**43.5**
Qwen1.5 (14B)	ZSP	41.6	17.4	28.1	53.3	38.9	60.7	28.5	42.0	33.8	20.5	35.3	37.3	25.3
	FSP	45.3	22.1	29.2	60.8	44.1	67.2	34.2	49.1	42.5	23.7	41.2	38.3	29.6
	OUR	**56.9**	**48.6**	**57.6**	**84.1**	**73.2**	**87.4**	**46.0**	**57.2**	**44.6**	**28.3**	**52.9**	**55.8**	**36.4**
InternLM2 (20B)	ZSP	42.3	20.9	29.7	47.7	31.9	55.9	29.8	42.6	34.3	21.2	40.0	34.7	27.2
	FSP	34.0	16.4	21.6	48.2	34.0	57.1	24.9	37.6	31.1	16.1	35.8	31.8	21.8
	OUR	**57.8**	**53.1**	**60.5**	**83.9**	**72.3**	**91.1**	**49.7**	**59.0**	**48.2**	**31.8**	**55.9**	**63.3**	**40.5**

Table 10: The detailed **sentence** level correction F_1 score.

Datasets		rSighans			ECSpell			Lemon						
Subsets		Y13	Y14	Y15	Law	Med	Odw	Car	Cot	Enc	Gam	Med	New	Nov
Domain-Specific SOTAs (*Trained on in-domain gold-standard data of each dataset*)														
ReaLiSe		85.0	76.3	80.9	*48.7*	*34.4*	*53.0*	*37.4*	*42.7*	*32.9*	*16.3*	*33.8*	*35.1*	*23.2*
Domain-General SOTAs (*Trained on about 34M synthetic CSC data*)														
Finetuned BERT		64.3	51.0	57.2	66.3	59.0	69.5	53.0	64.1	46.0	35.6	52.3	57.5	36.3
Softmasked BERT		**65.6**	49.3	57.3	67.2	61.3	70.0	53.6	63.3	45.4	31.6	51.0	57.9	**38.5**
ReLM		58.6	**51.1**	**61.0**	**68.3**	**63.9**	**73.0**	**54.4**	**66.1**	**48.2**	**37.5**	**55.1**	**60.5**	37.1
LLMs (*without CSC-specific training*)														
Baichuan2 (13B)	ZSP	29.6	11.2	14.5	20.5	16.6	29.8	7.8	7.4	12.5	4.1	11.9	14.2	10.6
	FSP	51.8	29.7	34.0	54.9	52.5	51.8	14.0	35.3	23.0	9.5	29.5	39.0	26.2
	OUR	**79.1**	**66.3**	**67.3**	**88.8**	**86.7**	**93.8**	**57.5**	**64.0**	**56.5**	**39.6**	**61.7**	**66.2**	**47.9**
Qwen1.5 (14B)	ZSP	48.8	18.9	26.5	53.5	35.4	58.1	27.1	26.8	32.0	12.7	32.1	35.1	21.5
	FSP	51.3	23.3	30.6	61.5	45.9	66.6	20.0	38.3	34.0	18.5	37.6	34.7	28.9
	OUR	**75.2**	**62.8**	**66.0**	**88.6**	**84.5**	**91.6**	**52.4**	**56.3**	**49.6**	**34.3**	**54.6**	**59.5**	**42.6**
InternLM2 (20B)	ZSP	46.0	18.1	27.3	40.5	22.8	49.3	24.7	31.9	29.7	12.3	31.0	29.2	26.6
	FSP	42.4	19.4	23.2	46.5	34.7	52.6	11.1	25.2	15.1	7.8	28.2	28.6	20.1
	OUR	**76.8**	**65.5**	**67.8**	**88.9**	**83.6**	**93.8**	**54.6**	**62.0**	**53.1**	**36.7**	**57.9**	**65.9**	**45.3**

Table 11: The detailed **character** level correction F_1 score.

Datasets		rSighans			ECSpell			Lemon						
Subsets		Y13	Y14	Y15	Law	Med	Odw	Car	Cot	Enc	Gam	Med	New	Nov
Domain-Specific SOTAs (*Trained on in-domain gold-standard data of each dataset*)														
ReaLiSe		13.0	9.6	7.7	*10.6*	*18.6*	*11.8*	*20.9*	*13.4*	*20.8*	*22.5*	*16.5*	*16.7*	*22.6*
Liu et al. (2023)		–	–	–	7.4	6.5	2.2	–	–	–	–	–	–	–
Domain-General SOTAs (*Trained on about 34M synthetic CSC data*)														
Finetuned BERT		21.7	16.5	12.5	**4.9**	11.3	**2.9**	12.3	8.3	13.9	22.5	8.3	9.4	17.3
Softmasked BERT		13.0	17.6	14.5	6.1	11.7	5.0	12.4	7.1	14.8	**20.4**	9.6	10.6	**16.6**
ReLM		**4.4**	**15.0**	**9.5**	7.8	**11.0**	7.1	**12.1**	**5.6**	**12.6**	20.8	**5.7**	**8.4**	17.5
LLMs (*without CSC-specific training*)														
Baichuan2 (13B)	ZSP	34.8	58.3	54.4	26.9	43.1	21.0	40.6	54.2	35.9	41.6	35.4	41.1	37.6
	FSP	21.7	19.4	23.2	7.8	**9.1**	**0.4**	8.3	7.4	10.2	20.0	4.6	8.3	**7.7**
	OUR	**8.7**	**14.1**	**8.3**	**4.5**	<u>9.9</u>	**0.4**	**5.9**	**6.9**	**8.9**	**19.2**	**3.9**	**5.7**	<u>13.0</u>
Qwen1.5 (14B)	ZSP	34.8	54.4	34.2	5.7	35.4	**2.1**	18.5	15.8	**13.5**	**18.4**	11.8	14.0	**20.7**
	FSP	30.4	52.8	53.9	9.8	27.0	3.8	17.9	21.6	20.5	26.9	15.0	18.9	18.1
	OUR	**21.7**	**19.6**	**10.2**	**4.9**	**11.7**	<u>2.9</u>	**11.2**	**7.8**	<u>14.8</u>	<u>29.4</u>	**5.4**	**10.1**	<u>21.2</u>
InternLM2 (20B)	ZSP	65.2	58.0	48.8	26.5	50.7	17.7	28.8	23.7	30.0	30.6	23.0	34.0	24.2
	FSP	39.1	56.5	54.4	23.7	37.2	18.1	27.0	29.0	29.8	38.4	22.5	25.2	28.3
	OUR	**13.0**	**16.5**	**8.3**	**2.5**	**12.4**	**0.4**	**8.5**	**6.9**	**12.2**	**22.5**	**3.7**	**6.1**	**15.1**

Table 12: The detailed sentence level false positive rate.