Chinese Spelling Corrector Is Just Language Learner

Anonymous ACL submission

Abstract

This paper emphasizes the Chinese spelling correction of self-supervised learning, which means there are no annotated errors within the training data. This setting is a pivotal issue that has received broad attention in the community. Our intuition is that humans are naturally good correctors with exposure to monolingual sentences, which contrasts with current unsupervised methods that strongly rely on the usage of confusion sets to produce parallel sentences. In this paper, we demonstrate that learning a spelling correction model is identical to learning a language model from monolingual data alone, with decoding it in a greater search space. We propose *Denoising Decoding Correction (D^2C)*, which selectively imposes noise upon the source sentence to solve out the underlying correct characters. Our method largely inspires the ability of language models to perform correction, including both BERT-based models and large language models (LLMs). We show that the self-supervised learning manner generally outstrips the confusion set in specific domains because it bypasses the need to introduce error characters to the training data which can impair the patterns in the target domains. We evaluate our methods on multi-domain datasets Syn-LEMON and ECSpell.

1 Introduction

Chinese spelling correction (CSC) stands as a fundamental task in natural language processing, supporting many downstream applications, e.g. web search (Martins and Silva, 2004; Gao et al., 2010), named entity recognition (Yang et al., 2023b), optical character recognition (Afli et al., 2016; Gupta et al., 2021). Recent studies (Wu et al., 2023a; Liu et al., 2024) show that simply using the supervised signals within parallel sentences to fine-tune pre-trained language models (PLMs) achieves notable results across a series of benchmarks.

However, the great cost of annotation is blamed for the low accessibility of parallel sentences.

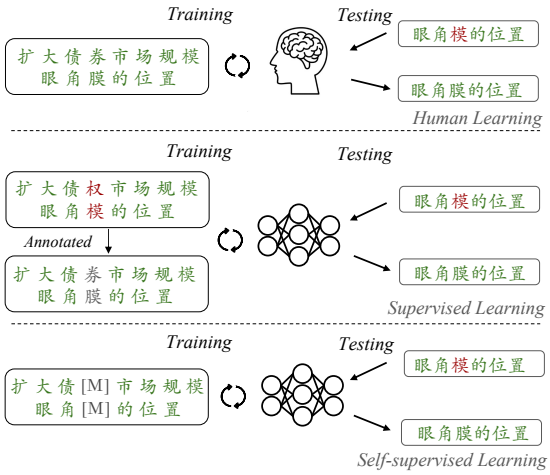

Figure 1: Comparison of human learning, supervised learning, and proposed self-supervised learning process for spelling correction. [M] refers to the mask token.

Therefore, these models remain mediocre in handling massive domains in real applications. This paper thus emphasizes the value of self-supervised learning, where only monolingual data is used to adapt models to specific target domains, which still achieved marginal progress in recent years.

Previous unsupervised methods (Zhao and Wang, 2020; Liu et al., 2021; Li, 2022) focus on synthesizing pseudo parallel sentences, while the supervised signals do not derive from the real distribution but from the confusion set (an empirically constructed word set of common misspelled cases). By replacing certain characters in the original sentences with those in the confusion set, parallel sentences are obtained for fine-tuning the models. However, the gap between the confusion set and the real error patterns in the target domain can induce a high false positive rate (Wu et al., 2023a). This paper raises a bold idea: *Can machine spelling correction learn from monolingual data alone?*

Intriguingly, humans naturally learn to rectify mistakes in a sentence with minimal exposure to parallel data. We give an illustration in Figure 1,

which shows that humans only learn to use the correct sentences (monolingual data) in daily life. When encountering a sentence with an error character "模" (*mold*), they can correct it to "膜" (*cornea*) with ease based on their knowledge. In contrast, the machine spelling correction models cannot do this if it isn't exposed to annotated edit pairs like "模" → "膜" in the training process.

In this paper, we demonstrate that a machine spelling corrector can also be learned from solely monolingual data as illustrated at the bottom of Figure 1. The key is to have the model learn semantics rather than character-to-character editing. In light of this, we find that rephrasing models (Liu et al., 2024), where the source sentence will first be encoded into the semantic space, and then rephrased to the correct sentence, demonstrate this ability. We call this manner self-supervised spelling correction. However, the resultant models still exhibit a low recall tendency.

To this end, we propose a novel decoding algorithm *Denoising Decoding Correction (D^2C)*, which selectively imposes noise upon the source sentence to solve out the underlying correct characters. We apply D^2C to two architectures: bidirectional models (represented by ReLM (Liu et al., 2024), the state-of-the-art model in Chinese spelling correction) and auto-regressive models (represented by a series of LLMs (OpenAI, 2023; Touvron et al., 2023; Yang et al., 2023a)). D^2C achieves a significant performance boost over raw language models, trained with monolingual data.

To evaluate our method's performance across different domains, we propose a LEMON (Wu et al., 2023a) training set synthesized by GPT3.5, which only contains monolingual sentences. This dataset permits the fine-tuning and evaluation of self-supervised models in different domains.

We summarize the contributions of this paper.

• We demonstrate that spelling correction can be intrinsically transferred by language modeling on monolingual data.

• With the proposed novel decoding algorithm, we build an effective self-supervised learning manner, allowing the spelling correction models to adapt to target domains at a minimal expense.

• We build synthetic monolingual training data from LEMON to benchmark the unsupervised domain adaption in the community.

2 Related Work

Correcting spelling errors poses a challenging yet crucial task in natural language processing. Early endeavors primarily relied on unsupervised techniques, assessing sentence perplexity as a key metric (Yeh et al., 2013; Yu and Li, 2014; Xie et al., 2015). Recent methods model spelling correction as a sequence tagging problem that maps each character in a given sentence to its accurate counterpart (Wang et al., 2018, 2019). On top of pre-trained language models (PLMs), some BERT-based models with the sequence tagging training objective are proposed. Zhang et al. (2020) identify the potential error characters by a detection network and then leverage the soft masking strategy to enhance the eventual correction decision. Zhu et al. (2022a) use a multi-task network to minimize the misleading impact of the misspelled characters (Cheng et al., 2020). There is also a line of work that incorporates phonological and morphological knowledge through data augmentation and enhances the BERT-based encoder to assist mapping the error to the correct one (Guo et al., 2021; Li et al., 2021; Liu et al., 2021; Cheng et al., 2020; Huang et al., 2021; Zhang et al., 2021). Recent studies (Wu et al., 2023a; Liu et al., 2024) focus on the rephrasing training objective, which achieves notable results.

While in the unsupervised spelling correction domain, previous works focus on generating pseudo annotated data or detecting error characters with confusion dataset (Zhao and Wang, 2020; Liu et al., 2021; Li, 2022). We are the first to raise a notable self-supervised method with pure monolingual Chinese spelling correction data in the community. Our method inherits the ability of PLMs and presents a transferability from language modeling to spelling correction.

3 From Language Modeling to Spelling Correction

This section serves as the preliminary of our work. The basic effort is to learn spelling correction from monolingual data. We call it self-supervised spelling correction. We first discuss the transferability between language modeling and spelling correction. Second, we point out that rephrasing is the primary training objective for self-supervised spelling correction.

We discuss the transferability from two angles: (1) The coherence of training objectives between rephrasing spelling correction and language mod-

eling. (2) The knowledge in spelling correction is included in the pre-training process.

3.1 Language Modeling

First, we introduce the training objectives of language modeling.

Given an input sentence $Y = \{y_1, y_2, \cdots, y_n\}$ of n characters, (auto-regressive) language modeling seeks to solve the character $\mathbf{y}_i$ based on its left context, namely $P(y_i|y_1, y_2, \cdots, y_{i-1})$. A spelling correction model can be learned by two dominant objectives, sequence tagging and rephrasing.

3.2 Spelling Correction

Second, we introduce the training objectives of spelling correction.

Spelling correction aims to rectify the underlying misspelled characters in the source sentence. Denote the source sentence as $X = \{x_1, x_2, \cdots, x_n\}$ and the target sentence as $Y = \{y_1, y_2, \cdots, y_n\}$ and suppose x_i is one of the typos in X, the model learns to correct x_i to y_i based on the entire source sentence, namely $P(y_i|x_1, x_2, \cdots, x_n)$.

Tagging The above modeling process can also be viewed as sequence tagging from X to Y. While this has been widely adopted in previous work, a recent study (Liu et al., 2024) shows that tagging-based spelling correction models will lean towards point-to-point editing, thus ignoring the specific context. The final training objective degenerates into $P(y_i|x_i)$.

Rephrasing In comparison, rephrasing (Liu et al., 2024) is shown to be a more effective training objective for spelling correction. It specifically seeks to rewrite the entire sentence after it, namely $P(y_i|x_1, x_2, \cdots, x_n, y_1, y_2, \cdots, y_{i-1})$. To ensure that the rephrasing process is based on semantics instead of copying, a ratio of noise (e.g. masking with an unused token) is introduced to the source sentence, written as $P(y_i|\tilde{x}_1, \tilde{x}_2, \cdots, \tilde{x}_n, y_1, y_2, \cdots, y_{i-1})$.

3.3 Self-supervised Spelling Correction

The unsupervised learning setting is naturally akin to language modeling, where the model is trained on monolingual data. Comparing the above two training objectives with language modeling, we find that rephrasing and language modeling are formally the same. In rephrasing, the input sentence is the concatenation of the source and target. This implies that the spelling correction model can better utilize the knowledge in a pre-trained language model and be transferred from it more easily.

3.4 Knowledge in Vanilla PLMs

The second tiny experiment is to probe the pre-trained knowledge in pre-trained language models. We hypothesize that, after large-scale pre-training, the language model already contains the literal knowledge needed for spelling correction. What we do is to mask the error characters in the source sentence and have the vanilla model (non-fine-tuned one) predict that. From Table 1, we see that the vanilla model can already recall the correct characters in its top-k candidates without any fine-tuning on spelling correction. For example, in about 90% of the cases, the model's top 10 predictions have covered the correct answer.

	LAW	MED	ODW
Top-20	93.8	88.8	93.8
Top-10	90.8	86.0	90.6
Top-5	86.9	82.0	88.7
Top-1	69.5	66.3	76.8

Table 1: Accuracy of the top-k predictions of MLM from the vanilla BERT model.

It indicates that the pre-trained language models have already possessed the needed knowledge for spelling correction in the form of mask infilling.

3.5 Tagging Model vs. Rephrasing Model

In this section, we evaluate the tagging model and rephrasing model on self-supervised spelling correction and present empirical results in Table 2, which reveals that the rephrasing model hugely surpasses the performances of the tagging models in self-supervised spelling correction.

Monolingual Data It shows that the tagging model trained on monolingual data is powerless. We conjecture that the model only learns point-to-point copying since the source is always the same as its target, thus losing the ability to make modifications to the source sentence. In contrast, the rephrasing model can learn well even with monolingual data. It paves the wave for us that pre-trained language models can learn spelling correction from solely monolingual data.

Shuffling of Characters We conduct a second tiny experiment to compare that the rephrasing (Liu

	Method	LAW	MED	ODW
Mono.	Tagging	0.5	0.6	0.5
	Tagging-MFT	10.1	5.3	10.5
	Rephrasing	**71.3**	**68.6**	**71.9**
Shuf.	Tagging	29.5	15.3	16.7
	Tagging-MFT	**34.0**	**17.3**	**18.9**
	Rephrasing	27.6	12.3	13.3

Table 2: Comparison (F1) of tagging and rephrasing on monolingual (self-supervised) / shuffled characters. The details of the models and dataset are in Sec. 6. Mono. means monolingual and Shuf. means shuffled.

et al., 2024) and tagging training objective for self-supervised spelling correction. Specifically, we shuffle the characters in the source and target sentences in correspondence to spoil their semantics. We use these highly noisy samples to fine-tune the rephrasing and tagging models. From Table 2 (Shuf.), we find that the tagging model outperforms the rephrasing model on samples that do not convey semantic information. It inversely verifies that the tagging model learns more of point-to-point editing at the expense of semantics. As aforementioned, it is the semantics that are the key to learn spelling correction from monolingual data. In this paper, therefore, we pick rephrasing as the primary training objective for self-supervised spelling correction.

4 Synthetic LEMON Train Set

LEMON (Wu et al., 2023b) is a multi-domain benchmark that allows us to evaluate the multi-domain generalization of CSC models. However, for each domain, it only has a test set without a train set. We release a synthetic LEMON train set, which GPT3.5 generates. This synthetic train set allows us to evaluate self-supervised models' performance across multiple domains.

The synthetic data is generated in two steps: (1) Extract the words in each domain. (2) Randomly select words and request GPT3.5 to generate monolingual sentences mimicking the style of specific domains. See our prompts in the appendix10.

The train set's information is in the table 3.

GAM	ENC	COT	MEC	CAR	NOV	NEW
2389	2489	1707	2222	2381	3669	4273

Table 3: Number of sentences in each training set.

5 Method

In this section, we propose an enhanced decoding method to unleash the potential of pre-trained language models further. We also propose a method that uses a confusion dataset to upgrade the recall score as another option.

5.1 Two Rephrasing Architectures

Our method focuses on rephrasing-based spelling correction, which can be achieved in two architectures, non-auto-regressive rephrasing, and auto-regressive rephrasing.

Auto-regressive models Auto-regressive model is the primary choice to generate the rephrasing following the input sentence, represented by GPT-like models (Brown et al., 2020) and large language models (LLMs).

To improve the quality of rephrasing, it is an easy yet effective way to mask a ratio of characters in the source sentence with an unused token. In this paper, we denote the masked source sentence as $\tilde{Y} = \{\tilde{y}_1, \tilde{y}_2, \cdots, \tilde{y}_n\}$.

ReLM Rephrasing Language Model (ReLM) (Liu et al., 2024) is the current state-of-the-art spelling correction model based on BERT (Devlin et al., 2019). It rephrases the source sentence by infilling the mask slots. Specifically, the model is fed with the concatenation of the source sentence and a sequence of mask tokens. Due to the bidirectional nature of BERT, the rephrasing process can be written as $P(y_i|\tilde{y}_1, \tilde{y}_2, \cdots, \tilde{y}_n, m_1, m_2, \cdots, m_n)$, where m_i refers to the mask token. As opposed to auto-regressive models, ReLM predicts all characters at once.

5.2 Denoising Decoding Correction

In self-supervised spelling correction, where the source sentence equals the target sentence, the resultant model trained with rephrasing still suffers from a low recall when testing on real sentences because there is no mask token. Therefore, we can introduce mask tokens to test sentences. A more severe situation happens when there are multiple errors in one sentence. The cascade effect of errors makes it even harder to correct the error characters. To this end, we propose a novel decoding algorithm, where we actively introduce noise to the source sentence and encourage the model to recall more candidates. Since the mask operation in the inference stage is consistent with that in the

training stage of rephrasing, the model's correction capability can be boosted. We call this method *Denoising Decoding Correction (D^2C)*.

Concretely, we first mask the characters in the source sentence from the left side during each iteration if the character's confidence is lower than β (0.995). The character in such a position is regarded as a potential error. To determine which character to update, we send this sentence to the model and figure out whether the original character appears in its **top-k** candidates. If it does, we remain the original character, else we record the new character and its confidence if this confidence is bigger than a **threshold** ϵ. After each iteration, we choose the character with the biggest confidence recorded before and update the original sentence with it. We do iterations continually until there is nothing to update after an iteration. Note that once a character is updated, the confidence of the other characters will change correspondingly. As the error number decreases, the challenges associated with multi-typo spelling correction will also diminish. So this iterative decoding is robust to multiple errors.

We notice that picking a character with the biggest confidence in each iteration costs a large decoding overhead. Given that there is always a small number of errors in a sentence, we rank the characters in the sentence by their confidence from the lowest to highest, mask the top α of them respectively, and send the sentence to the model. Figure out whether the original character appears in its top-k candidates. If it does, we remain the original character (same as original D^2C strategy), else we update it with a new character that has the highest confidence if this confidence is bigger than a threshold ϵ.

Pseudo code The overall procedure of D^2C is described in Algorithm 1.

Algorithm 1: *D^2C*

Input: Source sentence Y; threshold ϵ, top-k.
Output: predict result Z

Sort the characters in Y on their confidences ascendingly and record the indices I;
for $i \in I$ **do**
  Mask y_i;
  Get top-k predictions $\{y_i^1, y_i^2, \cdots, y_i^k\}$;
  Get confidences $\{p_i^1, p_i^2, \cdots, p_i^k\}$;
  if $y_i \notin \{y_i^1, \cdots, y_i^k\}$ ***and*** $p_i^1 > \epsilon$ **then**
    Replace y_i with y_i^1;
    Decode the new Y and update it;
  else
    Keep y_i unchanged;
  end
end
$Z = Y$;

5.3 Fine-tune with Confusion Set

Considering the low recall rate, we can also change some tokens with a confusion set instead of mask tokens during the fine-tuning process. The confusion set is built based on the pronunciations and fonts in Chinese. We can use a confusion set to produce a parallel dataset as a train set. For a monolingual sentence, we randomly choose one character and replace it with a character in the confusion set.

Concretely, our method to use the confusion set is as follows: we initially train our self-supervised model using entirely monolingual data and then use a rate of the monolingual data to continually fine-tune the model with the confusion set.

6 Experiments

In this section, we report the empirical results of a series of spelling correction benchmarks.

We concentrate on two benchmarks:

• *ECSpell* (Lv et al., 2023): a small-scale multi-domain Chinese spelling correction dataset of Law (LAW), medical treatment (MED), and official document writing (ODW), which is particular in that there are a large number of errors in the test set that do not appear in the training set;

• *Syn-LEMON* (Lv et al., 2023): it is generated from LEMON (Wu et al., 2023b) which spans 7 different domains with a total of 19,130 synthetic train samples.

We consider the following methods:

• *BERT* (Devlin et al., 2019): the fine-tuned tagging model based on BERT;

• *MDCSpell* (Zhu et al., 2022b): the strongest tagging model with a multi-task network of error detection and correction;

• *Masked-FT (MFT)* (Wu et al., 2023a): a simple yet effective fine-tuning technique on tagging models to uniformly mask the non-error characters in the source sentence;

• *ReLM* (Liu et al., 2024): the newly released state-of-the-art models on spelling correc-

	Method	EC-LAW (%)				EC-MED (%)				EC-ODW (%)			
		F1	P	R	FPR	F1	P	R	FPR	F1	P	R	FPR
Supervised	BERT	38.6	42.1	35.7	12.2	24.2	27.1	21.9	10.5	24.9	29.9	21.3	13.9
	BERT-MFT	74.6	73.2	76.1	14.3	61.7	62.4	60.9	10.5	60.8	59.7	62.0	18.9
	MDCSpell-MFT	81.5	77.2	86.3	15.9	65.1	62.3	68.1	16.8	64.1	61.3	67.2	21.4
	Baichuan2	86.0	85.1	87.1	4.5	73.2	72.6	79.3	5.5	82.6	86.1	79.3	4.0
	ReLM	**95.8**	**93.6**	**98.0**	5.7	**89.9**	**86.6**	**93.5**	7.4	**92.2**	**93.3**	**91.1**	2.5
Self-supervised	BERT	0.5	0.7	0.4	9.0	0.6	0.9	0.4	8.0	0.5	0.8	0.4	12.4
	BERT-MFT	10.1	14.1	7.8	9.4	5.3	7.7	4.0	9.1	10.5	15.1	8.0	12.8
	MDCSpell-MFT	36.2	45.3	30.2	9.4	20.9	28.7	16.4	8.8	25.9	33.7	21.7	13.7
	Baichuan2	23.5	25.5	21.6	26.5	17.4	25.2	13.3	13.5	24.4	27.2	22.2	20.9
	Baichuan2-UD	26.9	30.8	23.9	20.4	18.3	27.4	13.7	11.7	28.0	32.7	24.4	14.5
	Baichuan2-D^2C	27.6	30.6	25.1	22.4	20.2	26.2	16.4	12.4	30.5	33.8	27.8	17.5
	ReLM	71.3	78.1	75.7	0.4	68.6	70.8	66.5	7.02	71.9	79.7	65.5	0.8
	ReLM-UD	89.5	**89.2**	89.9	4.7	**79.3**	**74.1**	85.4	18.5	84.6	**88.5**	81.0	2.3
	ReLM-Conf.(10%)	83.8	79.1	89.0	15.6	70.8	67.5	74.4	14.7	75.5	71.5	79.8	18.5
	ReLM-Conf.(100%)	84.1	77.7	91.8	19.7	69.7	57.6	88.4	41.1	73.4	68.5	79.1	19.3
	ReLM-D^2C	**90.2**	87.7	**92.9**	8.6	75.7	66.8	**87.4**	25.5	**85.9**	85.7	**86.1**	7.3

Table 4: Results on ECSpell, where F1, P, R, FPR refers to the F1 score, precision, recall, and false positive rate. Conf. (10%) means continually fine-tuning the self-supervised model with 10% confusion data. Conf. (100%) means continually fine-tuning the self-supervised model with 100% confusion data.

tion, which rephrases the sentence in a non-autoregressive manner;

• *Baichuan2-7b* (Yang et al., 2023a): one of the strongest Chinese LLMs following the autoregressive architecture;

• *User Dictionary (UD)* (Lv et al., 2023): an enhanced decoding method that leverages an expertise dictionary (law, medical treatment, and official document writing) to bias the beam search.

6.1 Training Settings

For BERT-based models, we set the batch size to 128 and the learning rate to 5e-5, swept from grid search. For Baichuan2, we set the batch size to 32 and the learn rate to 3e-4, and use LoRA (Hu et al., 2022) to reduce the training budget. For supervised spelling correction, the masking ratio is chosen from {0.2, 0.3}, while for self-supervised spelling correction, it is set to 0.5.

When fine-tuning with the confusion set, we set the batch size to 64 and the learning rate to 5e-5.

6.2 Results on ECSpell

Table 4 summarizes the performances of different training methods on ECSpell and we also report the supervised performances for reference. For self-supervised spelling correction, we first find that ReLM outperforms MDCSpell-MFT by 35.1, 47.7, and 46.0 absolute points of F1 respectively on LAW, MED, and ODW, suggesting the great promise of rephrasing models.

When empowered with D^{2}C, it further significantly produces the increase of 18.9, 7.1, and 14.0 absolute points. The biggest increase is in the recall rate, which is consistent with the design of D^{2}C. Furthermore, we find that D^{2}C is competitive against using a user dictionary (UD), or even more powerful. It suggests that some of the domain knowledge in the user dictionary has already been stored in the pre-trained language models, and D^{2}C plays a key role in unlocking the great power of pre-training.

When empowered with the confusion set, the increase is weaker. The confusion set method increases the FPR score, which even meets 41.1 on MED. A higher confusion rate is related to a higher FPR score.

6.3 Results on Syn-LEMON

Table 5 summarizes the results of self-supervised methods on Syn-LEMON. It indicates that except GAM(game) and NOV(novel), using the confusion set outperformed D^{2}C's F1 score. These variances reveal that different domains always have distinct data properties, and these properties play a role in varying performance outcomes between employing the confusion set and D^{2}C.

7 Discussion

7.1 D^{2}C v.s using Confusion Set

We compare D^{2}C and the data augmentation method using the confusion set, a widely used technique in previous work. In Table 4 we find that

Method	GAM	ENC	COT	MEC	CAR	NOV	NEW
Previous SotA (Wu et al., 2023a)	33.8	48.6	67.2	54.3	53.1	38.6	58.7
ReLM	63.7	51.5	69.3	57.6	55.3	43.9	58.6
ReLM-D^{2}C	**65.5**	53.7	69.6	58.4	58.6	**50.0**	63
ReLM-Conf.(100%)	46.5	**58.6**	**75.5**	**65.8**	**63.3**	49.7	**70.0**
ReLM-Conf.(10%)	52.2	51.7	71.1	55.1	55.0	40.4	59.2

Table 5: Results on LEMON. Conf. (100%) means 100% data is trained as a confusion set and Conf. (10%) means we use 90% data as self-supervised training data and 10% data as continued fine-tuning confusion data.

D^{2}C outperforms using the confusion set on two of the chosen datasets. Table 5 indicates that D^{2}C surpasses using confusion set on GAM and NOV.

First, the results indicate that both D^{2}C and using the confusion set can increase the recall rate. The common phenomenon is caused by different reasons. The confusion set introduces the character-to-character correction during the training process that is similar to test examples. While D^{2}C introduces mask tokens to the test examples, which is inherited from the fine-tuning process. However, using the confusion set has a disadvantage compared with D^{2}C. The non-matching segments in the confusion set can cause gaps in the real error patterns in the testing time. Therefore, using the confusion set always has lower P scores and higher FPR scores. D^{2}C is a more suitable choice when it comes to domains that contain professional knowledge.

Second, compared to D^{2}C, using the confusion set is relatively straightforward and efficient. Employing the confusion set presents an alternative approach in various application scenarios, offering efficiency but potentially posing a risk to performance.

	Models	F1(%) LAW	MED	ODW
Supervised	MDCSpell (I)	71.8	51.3	54.9
	MDCSpell (E)	7.5	4.0	0.8
	MDCSpell-MFT (I)	94.3	78.4	81.7
	MDCSpell-MFT (E)	76.0	60.7	57.8
Self-supervised	MDCSpell-MFT (I)	52.6	32.9	32.1
	MDCSpell-MFT (E)	48.0	26.0	33.7
	ReLM (I)	93.2	73.5	82.2
	ReLM (E)	92.5	74.7	73.1
	ReLM-D^2C (I)	98.2	79.2	88.3
	ReLM-D^2C (E)	97.0	81.5	82.7

Table 6: Performances on seen (I) and unseen (E) errors, measured by F1 scores.

7.2 Seen and Unseen Errors

To take a closer look at the correction ability, we divide the test set into two subsets, exclusive (E) and inclusive (I) sets, which refer to the test errors that occur or do not occur in the training set.

From table 6, it is discernible that supervised models fit the internal error set well but the performances drop sharply on the external error set. While models trained with monolingual data have a high degree of similarity between the performance on the external error set and the internal error set. Besides, D^{2}C boosts the performance on the external and internal sets simultaneously.

Surprisingly, MDCSpell-MFT performs even better on self-supervised learning than supervised on the exclusive set. It suggests that the tagging objective degenerates the learned representation in the pre-trained language model, incurring a drop in generalizability.

7.3 Effect of Mask Rate

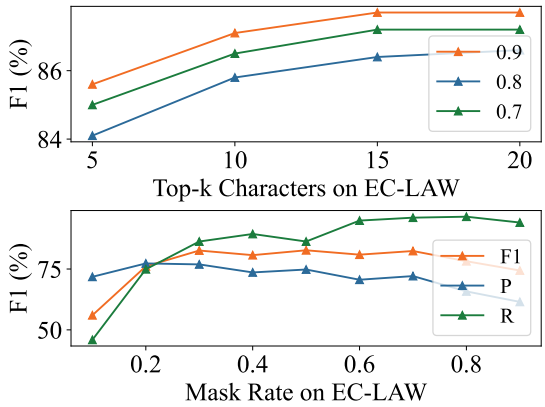

Figure 2: Self-supervised performances with different mask rates on Law of Ecspell.

We also investigate the impact of mask rate. From Figure 2 it is apparent that the F1 scores on ECSpell's Law keep improving when the mask rate grows from 0% to about 30%, and then drop

slightly. To dig further, an increase in the mask rate uplifts recall (R) scores more apparently than precision (P) scores while P scores either lean to unchanged or even decline. Because the monolingual fine-tuning process introduces noise solely through mask tokens, the models are more inclined to preserve the source sentences without modification, which means lower R scores. During the evaluation stage, error characters serve as noise for the model, therefore a higher mask rate boosts models' performances on R scores.

7.4 Effect of Hyperparameters

We access the effect of hyperparameters in D^{2}C. As a representative, we depict the curves on ReLM in Figure 2.

Threshold Figure 2 shows that different datasets are suitable with different thresholds (ϵ). For example, D^{2}C with higher ϵ (0.9) gains better performances on LAW, MED, and ODW domains. It reveals that ϵ should be set based on different datasets.

Top-k There is a common phenomenon in Figure 2 that a higher top-k character uplifts the F1 score under different thresholds ϵ.

7.5 Efficiency

We compare the decoding efficiency of D^{2}C and normal decoding in Table 7. We can observe that compared with decoding each sentence directly, D^{2}C requires about twice the time on ReLM and three times the time on Baichuan.

	Dataset	Normal (s)	D^{2}C (s)
ReLM	EC-MED	0.024	0.048
	EC-LAW	0.022	0.038
	EC-ODW	0.022	0.044
Baichuan	EC-MED	1.0	3.2
	EC-LAW	0.6	1.6
	EC-ODW	0.7	2.2

Table 7: Comparison between D^{2}C and normal decoding on ReLM and Baichuan, by second per sample.

8 Case Study

We further showcase some cases to illustrate how D^{2}C improves the decoding process.

Multi-typo In this case, (How does calcification (钙化) of the meniscus (半月板) occur), error characters are (钙→ 改) and (半→ 伴) , which are very similar in pronunciation but meaningless as words in the sentence. We noticed in the experiment that ReLM without D^{2}C failed to correct this sentence with two error characters while successful with a single error character if one of the two errors has been corrected before. Therefore, with D^{2}C we introduce noise into the source sentence to correct "伴" and "改" step by step.

SRC	伴月板改化的病因有哪些
TRG	半月板钙化的病因有哪些
ReLM	伴月板改化的病因有哪些
ReLM-D^{2}C	半月板钙化的病因有哪些

Table 8: Multi-typo case can be better corrected by D^{2}C. Blue characters are right and red are wrong.

Not recall Considering sentences in spelling correction sometimes have short lengths, models receive limited semantics information and tend to under-correct error characters just like the case in Table 9. This case (How to calculate children's weight (体重)) has the error pattern of (体→ 休), which are similar in terms of their visual appearance. In the presence of semantics limitations, D^{2}C directs models to reword specified positions to incorporate more suitable characters and effectively mitigate the issue of under-correction.

SRC	小孩休重怎么计算
TRG	小孩体重怎么计算
ReLM	小孩休重怎么计算
ReLM-D^{2}C	小孩体重怎么计算

Table 9: D^{2}C improves the recall rate.

9 Conclusion

This paper studies self-supervised spelling correction based on the rephrasing-based models. We demonstrate that machine spelling correction does not necessitate parallel data, and can be learned from monolingual data alone. We propose a novel decoding algorithm named *D^{2}C* to effectively enhance the recall ability of the self-supervised model. We also compare the D^{2}C method with using the confusion set method. Results on Chinese spelling correction showcase the significant improvement brought by our method. We hope this paper can bring new insight and vigor to future research on self-supervised spelling correction.

Limitations

Our work focuses on Chinese. Other languages such as Korean have not been studied in this work. D^2C costs a decline in the speed of single sentence processing.

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10 Prompts

10.1 Extract Words

Sentences are extracted from the original LEMON dataset.

```
1. Please extract the words in the given sentences
2. Your answer should be in Chinese and JSON format
{sentences}
Your answer format:
"words":
["word1", "word2",...],
["word1", "word2",...]
...
]}
```

10.2 Generate Data

We propose the GAM domain's prompt as an example.

```
1. You are a professional game writer. Try to use your professional knowledge and think step by step.
2. Please make your answers diverse in formats, words, and expressions.
3. Generate 5 smooth sentences Using the given word sets
4. Your answer should be abundant and include details, but not too long
5. Try to generate realistic and fluent sentences like a human writer
6. Your answer should be in Chinese in JSON format
7. Your generated sentence should follow the style of my given example sentences
This is my given word sets:
"words":
["word1", "word2",...],
["word1", "word2",...]
...
]}
This is my given example sentences:
{sentences}
Your answer:
[sentence1,sentence2,...]
```