# On the (In)Effectiveness of Large Language Models for Chinese Text Correction

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#### **Abstract**

Recently, the development and progress of Large Language Models (LLMs) have amazed the entire Artificial Intelligence community. As an outstanding representative of LLMs and the foundation model that set off this wave of research on LLMs, ChatGPT has attracted more and more researchers to study its capabilities and performance on various downstream Natural Language Processing (NLP) tasks. While marveling at ChatGPT's incredible performance on kinds of tasks, we notice that ChatGPT also has excellent multilingual processing capabilities, such as Chinese. To explore the Chinese processing ability of ChatGPT, we focus on Chinese Text Correction, a fundamental and challenging Chinese NLP task. Specifically, we evaluate ChatGPT on the Chinese Grammatical Error Correction (CGEC) and Chinese Spelling Check (CSC) tasks, which are two main Chinese Text Correction scenarios. From extensive analyses and comparisons with previous state-of-the-art finetuned models, we empirically find that the Chat-GPT currently has both amazing performance and unsatisfactory behavior for Chinese Text Correction. We believe our findings will promote the landing and application of LLMs in the Chinese NLP community.

#### 1 Introduction

Large Language Models (LLMs) have achieved remarkable progress in the last few years and are gradually becoming the fundamental infrastructure in the field of Natural Language Processing (NLP) and even Artificial Intelligence (AI) (Zhao et al., 2023). In particular, ChatGPT <sup>1</sup>, the superstar in the LLMs family has recently gained unprecedented attention. Benefiting from its emergent abilities (Wei

et al., 2022a) and the advantages of the chain-ofthought (Wei et al., 2022b), ChatGPT seems to be sweeping various downstream tasks of NLP with a unified conversational paradigm. In the past few months, ChatGPT has been extensively evaluated on all kinds of NLP tasks and has shown performance beyond expectations, such as Natural Language Understanding (He and Garner, 2023), Information Extraction (Wei et al., 2023), and Text Summarization (Yang et al., 2023). In addition to ChatGPT's general ability for various tasks, Chat-GPT's excellent multilingual adaptability is also impressive. As one of the most spoken languages in the world, Chinese has always been a challenging and research-worthy language in the NLP community because of its unique language nature and characteristics (Liu et al., 2010). Therefore, this paper conducts a comprehensive evaluation of Chat-GPT's capability on a fundamental and challenging Chinese NLP task: Chinese Text Correction (Zhao et al., 2022).

Chinese Text Correction aims to detect and correct various errors contained in the input Chinese text (Zhao et al., 2022). According to the types of errors, Chinese Text Correction is generally divided into two categories of tasks: Chinese Grammatical Error Correction (CGEC) (Wang et al., 2020b; Ye et al., 2022) and Chinese Spelling Check (CSC) (Wu et al., 2013a; Li et al., 2022b; Zhang et al., 2023). The CGEC task focuses on the grammatical errors that Chinese-as-a-Second-Language (CSL) learners tend to make during their language learning process and Chinese native speakers accidentally make in their daily life. Due to the difference in language proficiency, the focus of the CGEC task for CSL learners and the CGEC task for Chinese native speakers is also different. Because the CSL learners do not have a high level of mastery of Chinese, the grammatical errors they often make mainly involve the addition, deletion, replacement, and reordering of characters, while the grammati-

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<sup>1</sup>https://chat.openai.com

cal errors made by the Chinese native speakers are often more subtle and difficult, which has higher requirements and challenges for the model to understand the Chinese grammatical rules. As for the CSC task, it is for automatically checking the spelling errors in Chinese text. Because of the characteristics of Chinese characters, Chinese spelling errors are mainly caused by phonetically or visually similar characters. Therefore, CSC is challenging because it requires not only complex semantic knowledge but also phonetics/vision information to assist the models to find the correct characters. It can be seen from the above that Chinese Text Correction is a practical and complex Chinese application scenario, and studying the Chinese text correction ability of ChatGPT can well reflect its Chinese processing ability.

In this paper, we conduct a comprehensive study to evaluate the Chinese error correction ability of ChatGPT. First, according to the characteristics of CGEC and CSC, we carefully design task-specific prompts to guide ChatGPT to behave like a corrector. Then, we explore some widely used in-context learning prompting strategies to further inspire the correction ability of ChatGPT. We conduct extensive experiments on CSL and native CGEC benchmarks, as well as CSC datasets from multiple domains. It is worth noting that the charm of text correction is that it is an extremely subjective task, that is, there may be multiple reference sentences for an erroneous sentence, so the automatic evaluation of benchmarks and objective metrics may not truly reflect the performance of the model, hence, we also conduct a deep manual evaluation to observe ChatGPT's more realistic correction ability.

Through comparisons with previous state-of-theart fine-tuned models and detailed analyses, we obtain the following findings and insights:

- Although there is a significant difference between the automatic and human evaluation results, Chinese Text Correction is still very challenging for LLMs. And the performance of LLMs still has a large gap with the previous fine-tuned small models. There are various reasons for this gap, and we conduct detailed analyses in the experimental section.
- For the Chinese Text Correction field, LLMs also have some bright spots. We find that LLMs have better domain adaptability and data tolerance ability than traditional models.

Well-designed prompts and in-context learning strategies can effectively improve the Chinese text correction ability of LLMs. Therefore, for Chinese Text Correction, when designing input prompts and in-context example selection strategies, the characteristics and settings of the task must be considered.

#### 2 Methodology

#### 2.1 Task-specific Prompts

To guide ChatGPT to behave like a CGEC model or a CSC model, we manually design task-specific prompts as shown in Figure 1. In fact, ChatGPT's general-purpose power makes it have a certain text polishing ability, but we found that if there are no task-specific restrictions on the input prompts, ChatGPT is very easy to play freely when doing text polishing or error correction, thus violating some basic settings and principles of the Chinese Text Correction task. Therefore, considering that most Chinese Text Correction datasets and evaluation metrics focus on the minimum change principle (Nagata and Sakaguchi, 2016), that is, the model is required to make as few edit operations as possible to the input sentence, we ask Chat-GPT to minimize the changes to the original input sentence in the prompt. In addition, for the CSC sub-task, since its task setting is that the input and output sentences are of equal length, we require ChatGPT to ensure that the length of the corrected sentence is equal to the length of the sentence before correction, so as to avoid adding or deleting punctuation marks or Chinese characters. As for the CGEC sub-task, because many grammatical errors involve making changes to the sentence structure, such as structural confusion and improper word order, to avoid some meaningless and unnecessary edits made by ChatGPT, we also ask it to avoid unnecessary edits to the sentence structure or word expression.

It is worth mentioning that the task-specific constraints we add in prompts do not imply that Chat-GPT cannot perform text correction without these constraints. Rather, if ChatGPT is to generate sentences without these constraints, it could have more creative freedom, which could create a gap between the grammatically correct sentences it generates and the existing Chinese Text Correction datasets and evaluation metrics. This gap may result in lower performance in error correction when evalu-

识别并纠正下列句子中可能含有的拼写错误并输出正确的句子。要求必须保证纠正后的句子与纠正前的句子长度相等,纠正错误的同时尽可能减少对原句子的改动,避免对句子结构进行不必要的更改或添加。只输出没有错别字的句子,不要添加任何其他解释或说明。如果原句子是正确的句子,则直接输出原句子。输入: ...

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分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。输入: ..."

识别并纠正下列句子中可能含有的语法错误并输出正确的句子。要求在纠正错误的同时尽可能减少对原句子的改动,避免对句子结构进行不必要的更改或添加。只输出没有语法错误的句子,不要添加任何其他解释或说明。如果原句子是正确的句子,则直接输出原句子。输入: ...

system\_prompt = "你是一个优秀的中文语法纠错模型,中文语法纠错模型即更正用户输入句子中的语法错误。"
user\_prompt = "你需要识别并纠正用户输入的句子中可能含有的语法错误并输出正确的句子,纠正时尽可能减少对原句子的改动,提供准确、简洁和清晰的纠正结果,避免对句子结构或词汇表达进行不必要的更改或添加。只输出没有语法错误的句子,不要添加任何其他的解释或说明。如果句子没有语法错误,就直接输出和输入相同的句子。输入: ...."

Figure 1: Task-specific prompts of the CSC (中文拼写纠错) and CGEC (中文语法纠错) tasks. In our study, we try different ChatGPT base models, such as text-davinci-003 and gpt-3.5-turbo. We mark the key information related to the task characteristics in the prompt in red.

ated. Therefore, in order to objectively and realistically evaluate ChatGPT's error correction performance on existing traditional datasets, we carefully designed the prompts in Figure 1.

#### 2.2 In-context Learning Strategies

Many works (Xie et al., 2022; Bansal et al., 2023; Dai et al., 2023) have shown that ChatGPT possesses extraordinary in-context learning ability (Dong et al., 2023), i.e., by giving ChatGPT a small number of task examples to enhance its performance on specific tasks. To comprehensively study the in-context learning ability of ChatGPT in Chinese Text Correction scenarios, we design the following three sample selection strategies:

- 1. **Select random erroneous samples**: Randomly select several sentences with text errors and their corresponding correct sentences from the dataset.
- Select correct and erroneous samples: Both samples without text errors and samples with text errors are selected. The purpose of this design is to let ChatGPT learn to correct mistakes while not forgetting to modify the correct input sentences.
- Select hard erroneous samples: From the dataset, select the confusing samples where the wrong sentence is similar to the correct

sentence, that is, these samples are challenging and difficult for the model to correct errors. Specifically, we employ the BM25 algorithm to retrieve N samples (N=100 in our work) from specified training datasets that are similar to the input sentence, including source and target sentences. Then these samples are ranked based on the ROUGE-L similarity between the source sentence and the input sentence. We select the top-K samples with the highest ROUGE-L scores and integrate them into the prompt. We hope that by introducing such hard samples, ChatGPT can be stimulated to handle complex text errors.

#### 3 Experiments

In this section, we present our experimental setup and findings on two CTC tasks, namely CSC and CGEC. OpenAI provides a range of LLMs, which are accessible through the APIs<sup>2</sup>. For our research, we specifically choose two advanced models from the GPT-3.5 series: text-davinci-003 and gpt-3.5-turbo, as the focus of our investigation. The text-davinci-003 is a variant of GPT-3 that has been trained using Reinforcement Learning from Human Feedback (RLHF). On the other hand, gpt-3.5-turbo serves as the underlying model for ChatGPT, incorporating a larger dataset and also

<sup>2</sup>https://platform.openai.com/docs/
api-reference/introduction

trained on GPT-3 with RLHF.

CSC Test Data	#Sent	Avg. Length	#Errors
SIGHAN15	1,100	30.6	703
LAW	500	29.7	390
MED	500	49.6	356
ODW	500	40.5	404
MCSCSet <sup>†</sup>	1,000	10.9	919
CGEC Test Data	#Sent	Avg. Length	#Errors
NLPCC	2,000	29.7	1,981
MuCGEC	1,137	44.0	1,082
NaCGEC (Dev.)	500	56.2	482

Table 1: Statistics of the datasets that we use in experiments. We report the number of sentences (#Sent), the average sentence length (Avg. Length), and the number of spelling errors (#Errors). † means we randomly sample 1,000 items from the raw 19,650 test set.

#### 3.1 Experimental Settings

**Datasets** For the CSC task, select three widely used datasets for evaluation. SIGHAN15 (Tseng et al., 2015), which is written in hands by Chinese-as-a-Second Language (CSL) learners. A domain-specific dataset (Lv et al., 2023), which includes three domains. LAW data is collected from question stems and options of the multiple-choice questions in the judicial examination. MED data is collected from QA pairs from online medical treatment consultations. **ODW** is official document writing data comprising of news, policies, and national conditions officially reported by the state. A medical-domain dataset MCSCSet (Jiang et al., 2022), which is collected from extensive real-world medical queries from Tecent Yidian. For the CGEC task, we use three widely used datasets for evaluation. NLPCC (Zhao et al., 2018) is the GEC task in the NLPCC 2018 shared tasks. MuCGEC (Zhang et al., 2022a) is a multi-reference multi-source evaluation dataset collected from CSL learner sources. NaCGEC (Ma et al., 2022) is a dataset that the grammatical errors made by native Chinese speakers in real-world scenarios, such as examinations and news sites. The statistics of the used datasets are shown in Table 1.

**Evaluation Metric** For the CSC task, we adopt the precision, recall, and F1 scores on sentence-level as the evaluation metrics following the previous work (Xu et al., 2021). Sentence-level metrics are stricter than character-level metrics since a sentence is considered to be correct if and only if all errors in the sentence are successfully de-

tected and corrected. The main results are reported on the detection and correction sub-tasks. For the CGEC task, we employ a character-based spanlevel ChERRANT scorer (Zhang et al., 2022a) for evaluation, which computes Precision, Recall, and  $F_{0.5}$  between the gold edit set and the system edit set.

Compared Methods To evaluate the performance of LLMs, we select some advanced and strong CSC and CGEC models as our baselines: BERT (Devlin et al., 2019) encodes the input sentence first. Then, a classifier (e.g., linear layer) is used to pick the correction character from the vocabulary for each character. SoftMasked-**BERT** (Zhang et al., 2020) is consist of Detection Network and Correction Network. MedBERT-Corrector (Jiang et al., 2022) is a CSC model that takes advantage of the domain knowledge in medicine. REALISE (Xu et al., 2021) is a multimodal CSC model which leverages semantic, phonetic, and graphic knowledge. Two-Ways (Li et al., 2021) utilizes the weak spots of the model to generate pseudo-training data. LEAD (Li et al., 2022a) learns heterogeneous knowledge from the dictionary, especially the knowledge of definition. BART-Large-Chinese (Shao et al., 2021) is a Chinese BART model employed as a sequence-to-sequence (Seq2Seq) grammatical error correction baseline. BART (Lewis et al., 2020) is a Transformer-based Seq2Seq pre-trained model (Dong et al., 2022), which utilizes denoising auto-encoder (DAE) as the pre-training task. **GECToR-Chinese** (Zhang et al., 2022b) is a Chinese variant of GECToR using StructBERT (Wang et al., 2020a) as its semantic encoder. GEC-ToR (Omelianchuk et al., 2020) is an iterative sequence-to-edit (Seq2Edit) GEC approach.

#### 3.2 Human Evaluation

After assessing the performance of LLMs using automated metrics, it is crucial to complement these objective measures with human evaluation. While automated metrics play an important role in model evaluation, they still have a lot of inherent limitations. It is not acceptable for sentence lengths to be modified when calculating automation metrics in the CSC task. Different from nonautoregressive architecture, the decoder-only LM architecture makes the length of the sentence hard to control. For example, if the input sentence is "今天是重要的天", the LLMs output will probably

Dataset	Model	I	Detectio	n	Co	orrection	n n
		P	R	F	P	R	$\mathbf{F}$
SIGHAN15	REALISE (Xu et al., 2021) Two-Ways (Li et al., 2021) LEAD (Li et al., 2022a)	88.6	82.5 - 83.4	85.4 80.0 85.8	87.2 - 87.2	81.2 - 82.4	84.1 78.2 84.7
(Tseng et al., 2015)	text-davinci-003 gpt-3.5-turbo	21.2	36.8 30.1	26.9 21.9	15.4	26.6 25.1	19.5 18.2
LAW	Soft-Masked BERT (Zhang et al., 2020) BERT (Devlin et al., 2019) ECSpell (Lv et al., 2023)	55.2 79.0 78.2	49.3 68.6 67.8	52.1 73.4 72.6	39.8 71.4 72.2	35.6 62.0 62.6	37.6 66.3 67.1
(Lv et al., 2023)	text-davinci-003 gpt-3.5-turbo	27.8 42.0	42.0 43.5	33.4 42.8	23.6	35.7 34.9	28.4 34.3
MED	Soft-Masked BERT (Zhang et al., 2020) BERT (Devlin et al., 2019) ECSpell (Lv et al., 2023)	44.4 76.0 75.8	45.1 67.2 65.8	44.7 71.3 70.4	26.8 66.4 67.6	29.2 57.6 58.6	28.0 61.7 62.8
(Lv et al., 2023)	text-davinci-003 gpt-3.5-turbo	14.8 30.5	27.4 42.0	19.2 35.4	11.2 23.5	20.8 32.3	14.6 27.2
ODW	Soft-Masked BERT (Zhang et al., 2020) BERT (Devlin et al., 2019) ECSpell (Lv et al., 2023)	53.4 82.6 82.4	49.0 65.8 70.1	51.1 73.2 75.8	37.5 75.9 76.9	35.1 62.1 62.1	36.3 68.3 70.0
(Lv et al., 2023)	text-davinci-003 gpt-3.5-turbo	38.0 63.8	50.8 54.6	43.5 58.8	30.9 52.2	41.2 44.7	35.3 48.1
MCSCSet (F. 2022)	BERT (Devlin et al., 2019) MedBERT-Corrector (Jiang et al., 2022) Soft-Masked BERT (Zhang et al., 2020)	87.1 87.0 87.0	86.1 86.3 86.3	86.6 86.6 86.7	80.9 81.0 81.2	80.1 80.5 80.5	80.5 80.6 80.9
(Jiang et al., 2022)	text-davinci-003 gpt-3.5-turbo	23.9 36.0	36.4 36.2	28.8 36.1	12.5 25.0	19.0 25.1	15.0 25.0

Table 2: The automatically evaluated performance of ChatGPT and all baselines in CSC.

change the sentence to "今天是重要的日子". The output sentence will be determined as wrong by automated metrics, while we think it is correct based on the commonsense. Therefore, human evaluation is necessary because it can eliminate this kind of bias caused by automated metrics.

Specifically, for the CSC task, we employ three dimensions to judge each output sentence: correctness, consistency, and necessity. Correctness means the output sentence is fluent and without typos. Consistency means the output sentence can not change the meaning of the input sentence. Necessity means the edits are necessary. For the CGEC task, we employ two dimensions to judge each output sentence: correctness and consistency. Correctness refers to the output sentence without grammatical errors. Consistency indicates that the meaning of the output sentence aligns with the meaning of the references.

#### 3.3 Main Results

Table 2 and Table 3 show the automatic evaluation results of LLMs and baseline models on various datasets. We observe that:

- For CGEC and CSC, despite our careful constraints on the output of ChatGPT, it still falls far short of the performance of fine-tuned small models on all datasets and all automatic evaluation metrics. This phenomenon shows to a certain extent that for the currently very popular LLMs represented by ChatGPT, the Chinese Text Correction scene is still very challenging and hard.
- 2. For the CGEC task, we see that the model performs particularly poorly on NaCGEC, which indicates that the dataset for native Chinese speakers is more challenging than those for foreign language learners, so CGEC for native Chinese speakers will be a research direction worth studying in the future.
- 3. For different variants of ChatGPT, we find that in the Chinese Text Correction scenario, text-davinci-003 has stronger processing capabilities than gpt-3.5-turbo for daily and general texts (e.g., the SIGHAN15 dataset and CGEC datasets), while for special or datascarce text domains (e.g., the LAW and MED

MODEL		NLPCO	2	N	<b>IuCGE</b>	C	N:	NaCGEC P R F			
MODEL	P	R	F	P	R	F	P	R	F		
Seq2Seq-Baseline (BART-Large-Chinese) Seq2Edit-Baseline (GECToR-Chinese)	1	26.1 24.7	34.1 37.2			36.1 34.2		7.6 15.3	14.6 14.9		
text-davinci-003 gpt-3.5-turbo	19.6 14.4	23.1 27.2	20.2 15.9	29.3 20.4	26.0 32.4	28.6 22.0		10.7 11.7	7.2 6.3		

Table 3: The automatically evaluated performance of ChatGPT and all baselines in CGEC.

MODEL		GO	OD	BAD				
MODEL	Strict	Middle1	Middle2	Soft	Strict	Middle1	Middle2	Soft
REALISE	89.9	92.2	90.8	93.4	8.2	8.2	9.4	9.7
text-davinci-003 (0 shot)	49.5	72.0	57.1	82.8	30.5	31.4	39.3	40.2
text-davinci-003 (2 shot)	56.4	73.5	61.9	80.8	27.2	27.8	34.4	35.0
gpt-3.5-turbo (0 shot)	54.1	78.7	60.1	87.5	32.9	34.7	43.8	45.6
gpt-3.5-turbo (2 shot)	68.9	78.9	73.3	84.7	28.7	30.2	34.7	36.3

Table 4: Human evaluation on the SIGHAN15 dataset. We report the proportion of samples in each category to the total samples in the dataset. Considering the quality of the dataset affects the results a lot, we split the dataset into two parts using the correctness of the source sentence and ground-truth sentence. **GOOD** means that ground-truth sentences are fluent and without grammatical errors. **BAD** indicates that the ground-truth sentence contains grammatical errors. To evaluate the quality of the output sentences, we employ three dimensions: correctness, consistency, and necessity. **Strict** denotes that the output sentence is without typos, maintains consistency with the source sentence in terms of meaning, and the edits are necessary. **Middle1** means the output sentence is without typos and maintains consistency with the source sentence, but necessity is not considered. On the other hand, **Middle2** indicates that the output sentence is without typos and the edits are necessary, but consistency is not considered. **Soft** means the output sentence is without typos.

datasets), gpt-3.5-turbo performed better than text-davinci-003. According to the facts that OpenAI has disclosed to the community, gpt-3.5-turbo has made special optimizations for chat applications compared to text-davinci-003. We guess that this optimization gives ChatGPT a stronger domain adaptation capability.

MODEL	Correctness	Consistency	Crt & Csit
Seq2Edit-Baseline	40.3	85.7	35.3
text-davinci-003 (0 shot)	41.1	74.8	36.1
text-davinci-003 (2 shot)	38.7	77.3	33.6
gpt-3.5-turbo (0 shot)	66.4	57.1	33.6
gpt-3.5-turbo (2 shot)	62.2	63.0	38.7

Table 5: Human evaluation on the MuCGEC dataset. We report the proportion of samples in each category to the total samples in the dataset. **Crt & Csit** implies the attainment of both these qualities simultaneously.

#### 3.4 Human Evaluation Results

Table 4 and Table 5 present our human evaluation results for CSC and CGEC, respectively. Compared with the results of the automatic evaluation, we know that the human evaluation results show that the error correction ability of ChatGPT is not

so far from that of traditional fine-tuned models. This shows that the traditional automatic evaluation metrics widely used in Chinese Text Correction tasks cannot truly and objectively reflect the correction ability of LLMs, and the design and development of new evaluation metrics for LLMs is an important and valuable future direction.

We also have different observations on the two sub-tasks according to human evaluation results. For the CSC task, the gap between the performance of LLMs on the GOOD samples and the BAD samples is not as significant as that of the small fine-tuned model, which indicates that LLMs are more fault-tolerant to input data, while traditional fine-tuned small models are more sensitive to the quality of input data. Additionally, for good samples, the models perform better when the necessity is not considered than when the consistency is not considered, while for the bad samples, the models perform better when the consistency is not considered than when the necessity is not considered. For good samples, the model performs better when the necessity is not considered than when the continuity is not considered, while for the bad samples, the model performs better when the continuity is not considered than when the necessity is not consid-

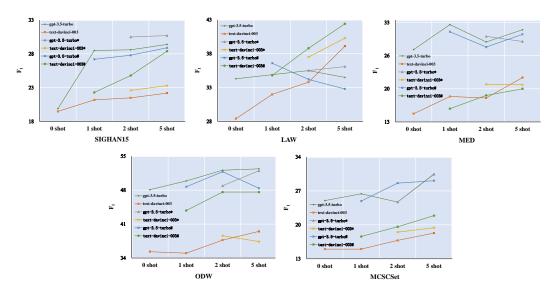


Figure 2: The experiments of in-context learning strategies on the CSC task. We select the correction  $F_1$  score to plot the chart. The \* means with Select correct and erroneous samples in-context learning strategy. The # means with Select hard erroneous samples in-context learning strategy.

ered. This phenomenon shows that when the sentence quality is good, the challenge of the CSC task is how to reduce unnecessary editing, and when the sentence quality is poor, the challenge of the CSC task is how to keep the meaning of the source sentence as much as possible. For the CGEC task, we see that LLMs sometimes perform better than the traditional fine-tuned small model, according to the results of human evaluation. However, the performance of LLMs on the Consistency metric is steadily worse than that of the small model. This also proves our view that when LLMs like Chat-GPT perform text error correction, it always tends to play freely, so that sometimes it will change the meaning of the source sentence. Therefore, to make LLMs well adapted to the CGEC task, it is necessary to study how to make LLMs perform more controllable content generation.

#### 3.5 Analyses and Discussions

#### 3.5.1 Reasons for the Errors of LLMs

We analyze the results of LLMs and conclude some main reasons that cause the wrong output of LLMs:

- The typos in the sentence change the semantics of the sentence badly. It is even difficult for humans to correct this kind of typos. For example, "遭(超)级市场". The typo in the sentence makes it hard to fix.
- Lacking fine-grained knowledge such as some specific location names appearing in the dataset. For example, "市大" and "师大". It

- can not be corrected without specific training data or fine-grained knowledge.
- We do not know the training data of ChatGPT, so data distribution will influence ChatGPT's expression habits. It will correct the uncommon but correct expression to satisfy its habits. For example, "交往多少朋友" will be corrected as "交谈多少朋友", which is called overcorrection.
- Lack of multimodal information. In the Chinese Spelling Check task, morphological and phonological information about characters is crucial. We find that ChatGPT knows the pinyin of Chinese characters, but it can not understand how to pronounce it, so it is hard for ChatGPT to correct phonological errors. For example, ChatGPT prefers to correct "参加误会" as "参加宴会" instead of "参加舞会".
- ChatGPT tends to generate fluent output, but often alters the original meaning of input sentence incorrectly. For instance, "孩子的兴趣无一没有跟父母的兴趣相干(All of the child's interests are related to the parents)" is corrected as "孩子的兴趣没有一个与父母的兴趣相关(None of the child's interests are related to the parents)", instead of "孩子的兴趣无一不是跟父母的兴趣相干".
- In certain cases, ChatGPT encounters challenges in striking a balance between the pre-

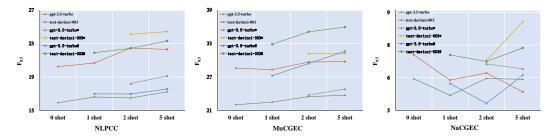


Figure 3: The experiments of in-context learning strategies on the CGEC task. We select the  $F_{0.5}$  score to plot the chart. The \* means with **Select correct and erroneous samples** in-context learning strategy. The # means with **Select hard erroneous samples** in-context learning strategy.

cision and the imperative of minimizing modifications in text error correction, thereby resulting in under-correction (or incomplete correction). For example, "我从个个的经验来谈这个题目" should be corrected to "我从个人的角度来谈这个题目(I will discuss this topic from my perspective)" or "我根据个人的经验来谈这个题目(I will discuss this topic based on my experience)", but ChatGPT erroneously revise it to "我从个人的经验来谈这个题目".

## 3.5.2 Effect of Different In-context Learning Strategies

Figure 2 and Figure 3 show the automatic evaluation results of LLMs with different in-context learning strategies. Note that the specific values of the model performance are shown in Appendix A. In most cases of Figure 2 and Figure 3, the model performance is the best when selecting hard erroneous samples, followed by when selecting correct and erroneous samples, and the performance improvement when selecting random erroneous samples is the weakest. Such experimental results reflect the effectiveness of our in-context learning strategies designed for the Chinese Text Correction scenario. Particularly, our experiments show that adding a certain proportion of correct samples to the example samples of the in-context learning of LLMs can bring more performance improvements. We believe that this will provide some guiding significance for the application of LLMs to the Chinese Text Correction scenario in the future.

#### 3.5.3 Effect of Sample Difficulty

To further study the Chinese error correction ability of LLMs, we observed the performance of the large model for samples of different difficulties. Specifically, for the CSC task, we measure the difficulty of a sample according to the length of the source

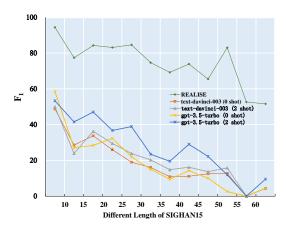


Figure 4: The experiments of how the sentence length impacts the model performance on the CSC task. We select the correction  $F_1$  score to plot the chart.

MODEL	1 -	r = 1		' = 2	N_T	_
	D-F	C-F	D-F	C-F	D-F	C-F
REALISE	91.0	90.1	66.3	62.8	42.9	39.3
text-davinci-003 (0 shot)	41.2	32.4	30.2	11.2	10.7	3.6
text-davinci-003 (2 shot)	47.5	35.5	27.1	12.4	10.7	3.6
gpt-3.5-turbo (0 shot)	37.8	31.1	26.8	19.0	7.1	3.6
gpt-3.5-turbo (2 shot)	47.5	40.9	37.2	31.4	25.0	10.7

Table 6: The automatically evaluated performance of LLMs and baseline on SIGHAN15. We divide the dataset into three categories based on the number of typos in a sentence. **N\_T** stands for the number of typos in a sentence.

sentence and how many typos (i.e., error Chinese characters) it contains. It is worth noting that for the CGEC task, measuring the difficulty of a sample is an overly subjective process (Ye et al., 2023), so we do not involve the CGEC task in this part of the experiment.

Table 6 shows the performance of the model for samples containing different numbers of typos, and Figure 4 shows how the model performance varies with the length of the input sentence. We see that the performance of all models decreases when the input sentences become more difficult,

MODEL	P	_E	M	_E	M_E	&P_E	ОТН	ERS
MODEL	D-F	C-F	D-F	C-F	D-F	C-F	D-F	C-F
REALISE	82.0	80.5	93.3	93.3	87.5	86.8	92.3	87.2
text-davinci-003 (0 shot)	30.5	22.0	41.4	34.5	51.8	38.0	48.8	29.3
text-davinci-003 (2 shot)	36.3	25.2	69.0	34.5	51.2	39.7	48.8	29.3
gpt-3.5-turbo (0 shot)	30.4	23.9	55.2	41.4	42.6	35.5	24.4	19.5
gpt-3.5-turbo (2 shot)	41.9	35.6	61.5	38.5	46.9	40.1	55.0	50.0

Table 7: The automatically evaluated performance of LLMs and baseline on SIGHAN15. We divide the dataset into four categories based on the types of typos found in the sentences. The **P\_E** means the typo is a phonological error, while **M\_E** means the typo is a morphological error. The **M\_E&P\_E** represents sentences with a typo that is both a phonological error and a morphological error. **OTHERS** indicates that it does not fall into any of the above error categories.

i.e., contain more typos or are longer in length. But interestingly, the performance degradation of LLMs is significantly larger than that of the traditional fine-tuned model. We think that maybe LLMs cannot handle multiple errors in a sentence well when dealing with the CSC task, which requires the model to have strong reasoning ability. At the same time, we find that the performance degradation of LLMs with in-context learning is slower than that of LLMs without in-context learning, which suggests that an effective in-context learning strategy can improve the ability of LLMs to handle complex CSC samples to a certain extent.

MODEL	text-	davinci-(	003 (2 shot)	gpt-3.	5-turbo (2	2 shot)
	P	R	F	P	R	F
Structural Confusion	8.8	9.2	8.9	11.6	21.6	12.8
Improper Word Order	2.2	1.9	2.1	5.9	6.7	6.1
Missing Component	7.0	7.5	7.1	4.3	8.8	4.8
Improper Collocation	7.3	7.4	7.3	2.6	3.2	2.7
Improper Logicality	8.8	7.7	8.6	7.1	10.7	7.6
Redundant Component	9.9	8.6	9.6	5.8	9.9	6.4

Table 8: The automatically evaluated performance of LLMs on different types of grammatical errors on the NaCGEC dataset.

### 3.5.4 Fine-grained Performance Analysis

To deeply explore the real performance of LLMs for the CSC and CGEC tasks, We report in detail the performance of LLMs when handling fine-grained error types in Table 7 and Table 8. Judging from the fine-grained performance of CSC in Table 7, LLMs handle morphological errors better than phonological errors. This experimental result can be explained from the perspective of linguistics. Because Chinese characters are pictographic characters, the meaning of most Chinese characters is closely related to their shape and stroke structure, but the connection with their pinyin pronunciation is relatively weak. Therefore, while LLMs such

as ChatGPT can capture the meaning of Chinese characters, they also capture the structural characteristics of Chinese characters in a sense, which leads to their better performance in processing morphological errors. Of course, this explanation is just a reasonable guess based on the experimental results. After all, ChatGPT is still a black box, and its interpretability research in the Chinese text correction field is also a very interesting direction in the future. As for the CGEC results in Table 8, we can see that text-davinci-003 has the worst performance for the type of "Improper Word Order", and gpt-3.5-turbo has the worst performance for the type of "Improper Collocation". This reflects how improving the generalization performance of LLMs among various fine-grained grammatical errors will be very challenging.

#### 3.6 Case Study

We conduct error case studies for LLMs, as presented in Table 9 and Table 10.

- Missing Detection (CSC), refers to instances where the LLMs fail to identify an error in the given sentence.
- Wrong Direction (CSC), pertains to situations where the model corrects the wrong section of the input, resulting in a grammatically correct sentence but altering the intended meaning of the original input.
- Inconsistent Context (CSC), describes cases where the model overlooks the contextual information when making corrections.
- **Incorrect Expression (CSC)**, denotes scenarios where the output sentence still contains typographical or grammatical errors.

Missing Detection	Input: 情给李小姐打电话。 Translation: Feeling call Miss Li. Output: 情给李小姐打电话。 Translation: Feeling call Miss Li. Correct:请给李小姐打电话。 Translation: Please call Miss Li.
Wrong Direction	Input: 他收到山上的时候,非常高兴。 Translation: When he received up the mountain, he was very happy Output: 他收到信件的时候,非常高兴。 Translation: When he received the mail, he was very happy. Correct: 他走到山上的时候,非常高兴。 Translation: When he walked up the mountain, he was very happy.
Inconsistent Context	Input: 他们的吵翻很不错,再说他们做的咖哩鸡也好吃! Translation: Their quarrel is pretty good, and their chicken curry is delicious too! Output: 他们的巧舌如簧很不错,再说他们做的咖哩鸡也好吃! Translation: Their glib is pretty good, and their chicken curry is delicious too! Correct:他们的炒饭很不错,再说他们做的咖哩鸡也好吃! Translation: Their fried rice is pretty good, and their chicken curry delicious too!
Incorrect Expression	Input: 这次署假小花去台北旅行顺便去看她的男朋友。 Translation: This sign holiday, Xiaohua went to Taipei to visit her boyfriend by the way.  Output: 这次教假小花去台北旅行顺便去看她的男朋友。 Translation: This uncle holiday, Xiaohua went to Taipei to visit her boyfriend by the way.  Correct: 这次暑假小花去台北旅行顺便去看她的男朋友。 Translation: This summer holiday, Xiaohua went to Taipei to visit her boyfriend by the way.

Table 9: Cases from the SIGHAN15 test set. The "Output" is from gpt-3.5-turbo 2 shot. We categorized the types of model errors into the following categories: **Missing Detection, Wrong Direction, Inconsistent Context**, and **Incorrect Expression**. We mark the wrong/correct characters.

- Improper Collocation (CGEC), refers to instances where the model produces output that includes incorrect or unnatural combinations of words or phrases, resulting in poor collocation.
- Over Correction (CGEC), occurs when the model excessively modifies the input sentence, resulting in an overcorrection that may introduce errors or change the intended meaning.
- Missing Component (CGEC), refers to situations where the model fails to add necessary components or elements to the sentence, leading to an incomplete or ambiguous output.
- Improper Logicality (CGEC), refers to instances where the model fails to correctly understand the logical relationship or common sense knowledge in a sentence, resulting in modified sentences that still contain logical errors.
- Under Correction (CGEC), denotes cases where the model inadequately corrects the input, leaving behind errors or failing to address the grammatical or typographical issues present.

#### 4 Related Work

Chinese Text Correction is a Chinese application closely related to daily life. Due to the complex characteristics of the Chinese language, Chinese Text Correction is a fundamental yet challenging task (Zhao et al., 2022). According to different types of errors, Chinese Text Correction is mainly divided into two categories, namely CGEC and CSC, and CGEC is further divided into CSL CGEC and native CGEC based on different target user groups. For the CSL CGEC task, with the Lang8 (Zhao et al., 2018) and HSK (Zhang, 2009) corpora as resources, the NLPCC2018 (Zhao et al., 2018) and CGED (Rao et al., 2018, 2020) are widely used evaluation benchmarks. Besides, considering the subjectivity of the grammatical error correction task and the diversity of correction methods, multi-reference CGEC evaluation datasets such as YACLC (Wang et al., 2021) and MuCGEC (Zhang et al., 2022a) are also constructed from the Lang8 corpus. However, the above-mentioned datasets are all derived from the grammatical errors made by foreign Chinese learners in their process of learning Chinese. There is a large gap between the language usage habits of foreigners and Chinese native speakers. This gap will cause the models trained or evaluated on these datasets to be unable to adapt well to a wider range of Chinese application scenarios. Therefore, researchers recently begin to pay attention to the CGEC task focusing on Chinese native speakers. The latest native CGEC datasets include FCGEC (Xu et al., 2022) and NaCGEC (Ma et al., 2022). Compared with the relatively simple CSL CGEC task, the types of Chinese grammatical errors that the native CGEC task focuses on are more complex, such as structural confusion, improper logicality, missing component, redundant component, improper collection, and improper word order. The CSC task mainly focuses on Chinese spelling errors caused by confusion of pronunciation and strokes. For quite a long time in the past, the SIGHAN datasets (Wu et al., 2013b; Yu et al., 2014; Tseng et al., 2015) are the only evaluation benchmark for the CSC task and are widely used by researchers. Recently, considering the singleness of the SIGHAN datasets, some new CSC datasets have been proposed to evaluate the performance of the CSC model in different domains (Lv et al., 2023; Jiang et al., 2022).

In the field of Grammatical Error Correction, in

Improper Collocation	Input: 我们改变了我们的地球,所以我们要保护这个地球的自然。 Translation: We changed our earth, so we need to protect the earth's natural. Output: 我们改变了地球,所以我们要保护地球的自然。 Translation: We changed the earth, so we need to protect the earth's natural. Correct:我们改变了我们的地球,所以我们要保护地球的自然环境。 Translation: We changed our earth, so we need to protect the earth's natural.
Over Correction	Input: 比如说是生活方式,吃的东西都会有区别。 Translation: For example is, lifestyle and what you eat will be different. Output: 比如说生活方式和饮食习惯都会有区别。 Translation: For example, lifestyle and eating habits will be different. Correct: 比如说生活方式,吃的东西都会有区别。 Translation: For example, lifestyle and what you eat will be different.
Missing Component	Input: 还有公众利益方面来说,社会上还有不吸烟的人。最近他们的声音越来越大,因为他们虽然不吸烟可是受到吸烟人的影响,他们叫被吸烟者。 Translation: Also, in terms public interest, there are still non-smokers in society. Recently their voices have become louder because although they do not smoke but are influenced by smokers, they called passive smokers.  Output: 还有公众利益方面来说,社会上还有不吸烟的人。最近他们的声音越来越大,因为他们虽然不吸烟,但受到吸烟人的影响,他们被称为被动吸烟者。 Translation: Also, in terms public interest, there are still non-smokers in society. Recently their voices have become louder because although they do not smoke but are influenced by smokers, they are called passive smokers.  Correct: 还有从公众利益方面来说,社会上还有不吸烟的人。最近他们的声音越来越大,因为他们虽然不吸烟可是还是受到了吸烟人的影响,他们叫做被吸烟者。 Translation: Also, in terms of public interest, there are still non-smokers in society. Recently their voices have become louder because although they do not smoke but are influenced by smokers, they are called passive smokers.
Improper Logicality	Input: 在房间时砂能打伞,不然个子长不高。 Translation: Sand can open an umbrella in the room, or you will not be tall. Output: 在房间里炒子能打伞,不然个子长不高。 Translation: Sand can open an umbrella in the room, or you will not be tall. Correct: 在房间时不能打伞,不然个子长不高。 Translation: You cannot open an umbrella in the room, or you will not be tall.
Under Correction	Input: 我也想 <mark>强烈的</mark> 父母或者花心的爱人不是好的家庭。 Translation: I don't think intense parents or philandering lovers are a good family. Output: 我认为 <mark>强烈的</mark> 父母或者花心的爱人并不构成一个好的家庭。 Translation: I don't think intense parents or philandering lovers make a good family. Correct: 我也认为有性格强势的父母或者花心的爱人不能组成好的家庭。 Translation: I don't think aggressive parents or philandering lovers make a good family.

Table 10: Cases from the MuCGEC test set. The "Output" is from gpt-3.5-turbo 2 shot. We categorized the types of model errors into the following categories: **Improper Collocation**, **Over Correction**, **Missing Component**, **Improper Logicality** and **Under Correction**. We mark the wrong/correct characters.

addition to Chinese, English Grammar Error Correction (EGEC) is also widely concerned. There have been several works (Wu et al., 2023; Fang et al., 2023; Coyne et al., 2023) to evaluate Chat-GPT on the EGEC task. Because the linguistic characteristics of Chinese and English are essentially different, unlike previous work, our work focuses on Chinese and aims to explore the Chinese correction capabilities of ChatGPT and promote the development and progress of Chinese Text Correction in the era of large language models.

#### 5 Conclusion

In this paper, we analyze the correction ability of the existing LLMs from OpenAI, specifically text-davinci-003 and gpt-3.5-turbo. We find that the text correction ability of the LLMs still has some gaps with the previous state-of-the-art fine-tuned models. Through human evaluation, we discover that the LLMs demonstrate greater resilience in addressing issues of fluency in the text. Additionally, we observe that as the difficulty increases, the performance of LLMs tends to decline more significantly compared to the fine-tuned small models. It is evident that the Chinese text correction capability of LLMs has not yet been fully adapted to the current production environment, necessitating

increased attention and resources in this area.

In addition, the research content of this work is still being iterated and updated. Especially after the release of ChatGPT, the LLMs family has added many new models. It is also very meaningful to evaluate the performance of the new LLMs on the Chinese Text Correction task.

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## A Appendix A

Dataset	Model	1	Detection		C	orrection	
		P	R	F	P	R	F
	text-davinci-003	21.2	36.8	26.9	15.4	26.6	19.
	- 1 shot	24.0	40.1	30.0	16.9	28.3	21.
	- 2 shot	24.2	39.2	29.9	17.4	28.1	21.
	- 2 shot ♠	26.3	40.1	31.8	18.7	28.5	22.
	- 5 shot	24.7	40.3	30.6	17.9	29.2	22.
SIGHAN15	- 5 shot ♠	26.7	41.6	32.5	19.1	29.8	23.
DIGILI: (IE	gpt-3.5-turbo	17.2	30.1	21.9	14.3	25.1	18.
	- 1 shot	29.7	38.4	33.5	25.3	32.7	28.
	- 2 shot	29.9	40.1	34.3	24.9	33.5	28.
	- 2 shot ♠	32.2	40.9	36.0	27.2	34.6	30
	- 5 shot	29.4	40.1	33.9	25.4	34.8	29
	- 5 shot ♠	32.0	41.2	36.0	27.3	35.1	30
	text-davinci-003	27.8	42.0	33.4	23.6	35.7	28
	- 1 shot	34.3	50.6	40.9	26.9	39.6	32
	- 2 shot	35.8	51.4	42.2	28.7	41.2	33
	- 2 shot ♠	40.8	52.9	46.1	33.2	43.1	37
	- 5 shot	40.5	54.5	46.5	34.1	45.9	39
LAW	- 5 shot ♠	43.9	56.1	49.2	35.9	45.9	40
	gpt-3.5-turbo	42.0	43.5	42.8	33.7	34.9	34
	- 1 shot	43.5	43.5	43.5	34.9	34.9	34
	- 2 shot	40.9	42.4	41.6	34.8	36.1	35
	- 2 shot ♠	41.3	42.7	42.0	34.8	36.1	35
	- 5 shot	39.1	43.5	41.2	32.7	36.5	34
	- 5 shot ♠	38.8	45.5	41.9	33.4	39.2	36
	text-davinci-003	14.8	27.4	19.2	11.2	20.8	14
	- 1 shot	19.1	34.5	24.6	14.0	25.2	18
	- 2 shot	21.1	36.7	26.8	14.0	24.3	17
	- 2 shot ♠	23.2	38.1	28.8	16.4	27.0	20
	- 5 shot	23.2	39.4	29.2	17.2	29.2	21
MED	- 5 shot ♠	22.9	38.1	28.6	16.2	27.0	20
	gpt-3.5-turbo	30.5	42.0	35.4	23.5	32.3	27
	- 1 shot	32.1	44.7	37.3	27.6	38.4	32
	- 2 shot	29.0	40.7	33.9	24.6	34.5	28
	- 2 shot ♠	30.5	42.0	35.4	25.7	35.4	29
	- 5 shot - 5 shot ♠	30.2 30.5	41.2 40.7	34.8 34.8	26.9 25.2	36.7 33.6	31 28
		<u>'</u>			'		
	text-davinci-003	38.0	50.8	43.5	30.9	41.2	35
	- 1 shot - 2 shot	36.5 38.4	49.6 51.9	42.1 44.2	30.3 32.8	41.2 44.3	35 37
	- 2 shot - 2 shot ♠	41.6	52.3	46.4	34.7	44.3	38
	- 2 shot	39.6	53.1	45.4	34.7	46.2	39
ODW	- 5 shot ♠	40.7	50.8	45.2	33.6	42.0	37
JUII	gpt-3.5-turbo	63.8	54.6	58.8	52.2	44.7	48
	- 1 shot	60.0	58.4	59.2	50.6	49.2	49
	- 1 shot - 2 shot	65.9	63.4	64.6	53.2	51.1	52
	- 2 shot ♠	60.1	58.0	59.0	49.8	48.1	48
	- 2 shot	59.8	59.5	59.7	52.5	52.3	52
	- 5 shot ♠	61.3	59.2	60.2	53.0	51.1	52
	text-davinci-003	23.9	36.4	28.8	12.5	19.0	15
	- 1 shot	24.1	37.6	29.4	12.3	19.0	15
	- 2 shot	24.4	37.6	29.6	13.9	21.4	16
	- 2 shot ♠	29.2	41.0	34.1	15.8	22.2	18
	- 5 shot	27.4	42.8	33.4	15.0	23.4	18
MCSCSet	- 5 shot ♠	31.0	44.4	36.5	16.5	23.6	19
	gpt-3.5-turbo	36.0	36.2	36.1	25.0	25.1	25
	- 1 shot	33.3	35.2	34.3	25.7	27.1	26
	- 2 shot	32.5	34.1	33.2	24.2	25.3	24
	- 2 shot ♠	32.5	34.1	33.2	24.2	25.3	24
	- 5 shot - 5 shot	37.8 38.4	38.2 41.2	38.0 39.8	30.4 29.4	30.7 31.5	30 30

Table 11: The performance of the LLMs and all baselines in CSC. ♠ stands for with **Select correct and erroneous samples** in-context learning strategy.

Dataset	Model		Detection		C	orrection	
		P	R	F	P	R	F
	text-davinci-003	21.2	36.8	26.9	15.4	26.6	19.5
	- 1 shot 🐥	23.2	39.0	29.1	17.8	29.9	22.3
	- 2 shot 🐥	28.7	43.6	34.7	20.6	31.2	24.8
SIGHAN15	- 5 shot ♣	31.6	44.9	37.1	24.2	34.4	28.4
	gpt-3.5-turbo	17.2	30.1	21.9	14.3	25.1	18.2
	- 1 shot 🚓	29.2	37.5	32.8	24.1	31.1	27.2
	- 2 shot 🐥	28.2	37.5	32.2	24.3	32.3	27.8
	- 5 shot 🐥	29.1	39.0	33.3	25.2	33.8	28.9
	text-davinci-003	27.8	42.0	33.4	23.6	35.7	28.
	- 1 shot 🚓	37.9	51.8	43.8	30.2	41.2	34.8
	- 2 shot 🐥	42.3	52.5	46.9	35.0	43.5	38.8
LAW	- 5 shot ♣	46.7	58.8	52.1	38.0	47.8	42.4
	gpt-3.5-turbo	42.0	43.5	42.8	33.7	34.9	34
	- 1 shot 🚓	40.5	42.7	41.6	35.7	37.6	36.6
	- 2 shot 🐥	39.2	43.5	41.3	32.5	36.1	34.2
	- 5 shot 🐥	35.7	42.0	38.6	30.3	35.7	32.
	text-davinci-003	14.8	27.4	19.2	11.2	20.8	14.
	- 1 shot 🐥	17.2	30.5	22.0	12.2	21.7	15.0
	- 2 shot 🐥	22.3	36.3	27.7	14.7	23.9	18.2
MED	- 5 shot ♣	22.9	36.3	28.1	15.9	25.2	19.5
	gpt-3.5-turbo	30.5	42.0	35.4	23.5	32.3	27.
	- 1 shot 🐥	30.6	40.7	34.9	26.9	35.8	30.
	- 2 shot 🚣	28.9	39.4	33.3	24.0	32.7	27.
	- 5 shot 🐥	29.6	40.7	34.3	26.0	35.8	30.
	text-davinci-003	38.0	50.8	43.5	30.9	41.2	35.
	- 1 shot 🐥	45.5	56.1	50.3	39.6	48.9	43.
	- 2 shot 🐥	48.4	58.8	53.1	43.4	52.7	47.0
ODW	- 5 shot ♣	51.8	60.3	55.7	44.3	51.5	47.
	gpt-3.5-turbo	63.8	54.6	58.8	52.2	44.7	48.
	- 1 shot 🐥	59.1	53.1	55.9	51.5	46.2	48.
	- 2 shot 🚣	59.1	58.4	58.7	52.1	51.5	51.
	- 5 shot 🚓	55.5	55.7	55.6	48.3	48.5	48.
	text-davinci-003	23.9	36.4	28.8	12.5	19.0	15.0
	- 1 shot 🐥	28.0	41.8	33.5	14.7	22.0	17.0
	- 2 shot 🐥	31.7	45.3	37.3	16.6	23.8	19.
MCSCSet	- 5 shot ♣	32.5	45.1	37.8	18.8	26.1	21.9
	gpt-3.5-turbo	36.0	36.2	36.1	25.0	25.1	25.
	- 1 shot 🐥	31.6	34.3	32.9	23.9	25.9	24.
	- 2 shot 🐥	34.2	37.2	35.6	27.5	29.9	28.
	- 5 shot 🐥	35.3	38.8	37.0	27.7	30.5	29.

Table 12: The performance of the LLMs and all baselines in CSC. A stands for with **Select hard erroneous** samples in-context learning strategy.

MODEL	NLPCC			MuCGEC			NaCGEC		
	P	R	$\mathbf{F}$	P	R	F	P	R	F
text-davinci-003	19.6	23.1	20.2	29.3	26.0	28.6	6.7	10.7	7.21
- 1 shot	20.3	22.4	20.7	29.7	24.0	28.3	5.9	8.2	6.2
- 1 shot 🐥	21.7	23.0	21.9	34.9	26.6	32.9	6.8	9.6	7.2
- 2 shot	22.3	23.0	22.5	31.3	24.6	29.7	6.2	8.0	6.5
- 2 shot 🏟	24.7	21.9	24.1	34.3	22.9	31.2	7.0	6.9	7.0
- 2 shot 🐥	22.4	22.6	22.4	37.4	28.2	35.1	6.7	8.3	7.0
- 5 shot	22.0	23.6	22.3	31.3	24.9	29.8	5.5	7.1	5.7
- 5 shot 🌲	25.0	22.4	24.4	34.4	22.8	31.3	8.7	8.0	8.5
- 5 shot ૈ	23.2	23.7	23.3	38.4	28.6	35.9	7.2	9.1	7.5
gpt-3.5-turbo	14.4	27.2	15.9	20.4	32.4	22.0	5.6	11.7	6.3
- 1 shot	15.2	26.3	16.6	21.0	31.4	22.5	5.2	7.9	5.6
- 1 shot 🐥	15.4	28.4	17.0	26.1	33.2	27.2	5.6	9.6	6.1
- 2 shot	15.3	25.4	16.5	22.1	31.6	23.5	6.1	7.3	6.3
- 2 shot 🌲	16.8	27.5	18.2	22.3	32.2	23.8	6.4	10.0	6.9
- 2 shot 🐥	15.5	28.1	17.0	28.5	34.1	29.4	4.9	8.0	5.3
- 5 shot	15.9	26.1	17.2	22.4	31.3	23.7	6.1	7.1	6.2
- 5 shot 🌲	17.6	29.0	19.1	23.6	31.8	24.8	6.2	10.0	6.7
- 5 shot 🕏	16.0	28.9	17.6	30.8	35.0	31.6	5.9	9.4	6.4

Table 13: The performance of the LLMs and all baselines in CGEC. ♠ stands for with **Select correct and erroneous samples** in-context learning strategy. ♣ stands for with **Select hard erroneous samples** in-context learning strategy.