Listen Again and Choose the Right Answer: A New Paradigm for Automatic Speech Recognition with Large Language Models

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Abstract

Recent advances in large language models (LLMs) have promoted generative error correction (GER) for automatic speech recognition (ASR), which aims to predict the ground-truth transcription from the decoded N-best hypotheses. Thanks to the strong language generation ability of LLMs and rich information in the N-best list, GER shows great effectiveness in enhancing ASR results. However, it still suffers from two limitations: 1) LLMs are unaware of the source speech during GER, which may lead to results that are grammatically correct but violate the source speech content, 2) N-best hypotheses usually only vary in a few tokens, making it redundant to send all of them for GER, which could confuse LLM about which tokens to focus on and thus lead to increased miscorrection. In this paper, we propose ClozeGER, a new paradigm for ASR generative error correction. First, we introduce a multimodal LLM (*i.e.*, SpeechGPT) to receive source speech as extra input to improve the fidelity of correction output. Then, we reformat GER as a cloze test with logits calibration to remove the input information redundancy and simplify GER with clear instructions. Experiments show that ClozeGER achieves a new breakthrough over vanilla GER on 9 popular ASR datasets.

1 Introduction

Recent advances in large language models (LLMs) have attracted a surge of research interest thanks to their remarkable language generation and reasoning ability (OpenAI, 2022, 2023; Touvron et al., 2023a,b), which achieve a wide range of success on natural language processing (NLP) tasks (Brown et al., 2020; Wei et al., 2022; Ouyang et al., 2022). Powered by LLMs, latest work (Chen et al., 2023a) proposes a generative error correction (Yang et al., 2023) (GER) benchmark[1] for automatic speech recognition (ASR), and they release a HyPoradise dataset[2] that contains over 332K pairs of decoded N-best hypotheses and ground-truth transcription in various ASR domains. It has shown great effectiveness in learning the mapping from hypotheses to transcription by parameter-efficient LLM fine-tuning (Hu et al., 2021), which significantly enhances the ASR result and outperforms typical LM rescoring methods (Mikolov et al., 2010).

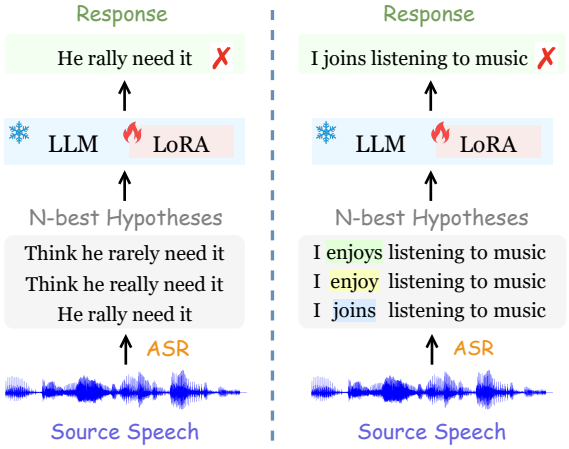

Figure 1: Two limitations of generative error correction (Chen et al., 2023a). **Left: violate source speech**, LLM removes the word "Think" in first two hypotheses as it rarely appears at the beginning of a sentence and followed by a subject according to grammar, but this actually happens in the source speech. **Right: information redundancy in N-best hypotheses input**, there is only one difference between N-best candidates, making it redundant to send all of them for GER, which confuses LLM about which tokens to focus on for correction.

However, GER paradigm is also observed to suffer from two limitations. First, LLMs are unaware of the source speech during GER process, which could lead to results that do not match the source speech content. For example, as shown in Fig. 1 (left), the source speech reads the word "Think" at

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[1]https://github.com/Hypotheses-Paradise/Hypo2Trans
[2]https://huggingface.co/datasets/PeacefulData/HP-v0

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the beginning and followed by "he", which is correctly recognized by the 1-best hypothesis. Then during the GER process, LLM removes the word "Think", as this structure of verb plus noun at the beginning of a sentence is not rigorous according to grammar. However, this is not expected as it violates the source speech content. Second, we observe that N-best hypotheses usually only vary in a few tokens. For example, as shown in Fig. 1 (right), all the tokens in candidates are the same except "enjoys"/"enjoy"/"joins". In this case, it would be information redundant to leverage all of the hypotheses for predicting the ground-truth transcription, which could confuse the LLMs about which tokens to focus on for correction and thus lead to sub-optimal GER performance.

Motivated by the above observations, we propose ClozeGER, a new paradigm for ASR generative error correction. First, we introduce a popular multimodal LLM, SpeechGPT (Zhang et al., 2023a), to receive source speech as an extra input to the GER paradigm. With the powerful cross-modal ability of SpeechGPT, we can now constrain GER to comply with the source speech while correcting the errors in decoded hypotheses. Then, in order to remove the input information redundancy, we reformat it as a cloze test (*i.e.*, a special multiple-choice question) with logits calibration (Kumar, 2022; Wang et al., 2023), where the identical parts across N-best hypotheses are set as the context and the varying parts are set as blanks (each with several options provided). With such clear instructions for error correction, it would be easier for LLMs to perform context reasoning and choose the right answer for each blank rather than predicting the entire sentence from redundant N-best inputs[3]. Finally, we add a simple post-processing stage to correct the errors in cloze context (*i.e.*, identical parts across N-best list) to further improve the correction result.

Our contributions are summarized as follows:

- We propose ClozeGER, a new paradigm based on multimodal LLM for ASR generative error correction, which receives both source speech and the decoded N-best hypotheses as input to predict the ground-truth transcription.
- We further reformat the generative error correction as a cloze test with logits calibration to remove the information redundancy in N-best hypotheses input and simplify the GER paradigm with clear instructions.
- Experiment evidence shows that our proposed ClozeGER achieves a new breakthrough over vanilla GER on 9 popular ASR datasets.

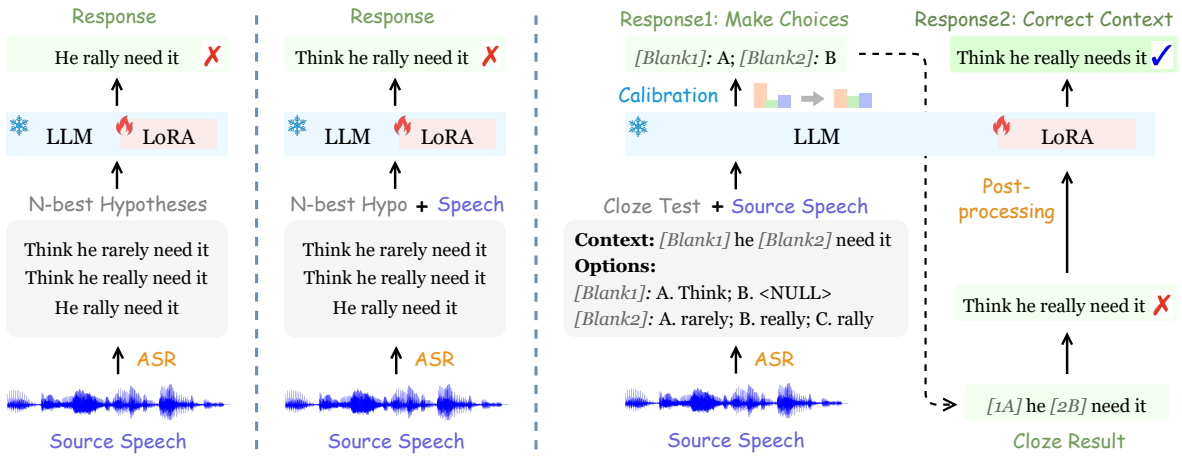
[3]Think if we humans are asked to do GER, which option is easier and efficient, cloze or entire sentence prediction?

2 Related Work

Large Language Models. There is recently a surge of research interests in Transformer-based LLMs, such as ChatGPT (OpenAI, 2022), GPT-4 (OpenAI, 2023) and LLaMA (Touvron et al., 2023a,b). Benefiting from the huge model size and abundant training data, LLMs can well understand the linguistic structures and semantic meanings behind textual data, which shows remarkable performance on a wide range of NLP tasks (Brown et al., 2020; Wei et al., 2022; Ouyang et al., 2022). More recently, researchers have started to explore the potential of LLMs on multimodal tasks by incorporating other modalities into LLMs (Liu et al., 2023; Li et al., 2023; Chen et al., 2023b; Zhang et al., 2023b,c; Gao et al., 2023; Fathullah et al., 2023). Among them, SpeechGPT (Zhang et al., 2023a) is one of the most popular multimodal LLMs that represent speech and text using a unified tokenizer, which enables us to add source speech into the original N-best hypotheses input of the GER paradigm.

LM Rescoring and ASR Generative Error Correction. LM rescoring has been widely used in ASR decoding to rerank the N-best hypotheses and yield better 1-best recognition result (Arisoy et al., 2015; Shin et al., 2019; Mikolov et al., 2010). Furthermore, to make full use of all candidatures, recent works employ the entire N-best list for error correction (Leng et al., 2021; Ma et al., 2023). Powered by LLMs, latest work proposes a generative error correction (GER) benchmark (Chen et al., 2023a) to predict the ground-truth transcription from ASR N-best hypotheses and achieves remarkable performance. This work serves as an extension of GER to resolve the existing limitations.

Cloze Test with LLMs. As a special format of multiple-choice questions (MCQ), the cloze test provides a context with some blanks, where each blank is provided with several options for selection. Recently, cloze test and MCQ are widely adopted in LLM-centric scenarios (Chiang et al., 2023; Zheng et al., 2023b), as well as numerous LM benchmarks including MMLU (Hendrycks et al., 2020), AGIEval (Zhong et al., 2023), and C-Eval (Huang et al., 2023). However, recent works



(a) Vanilla GER (b) GER w/ Source Speech (c) ClozeGER (ours)

Figure 2: Frameworks of (a) vanilla GER that employs N-best hypotheses to predict ground-truth transcription, (b) GER with source speech as extra input to improve the fidelity of correction output, (c) our ClozeGER that reformats GER as a cloze test with logits calibration, followed by a post-processing stage to further correct the cloze context.

observe that LLMs-based cloze test is vulnerable to option position changes due to their inherent "selection bias" (Kumar, 2022; Wang et al., 2023; Pezeshkpour and Hruschka, 2023). In this work, we reformat the GER paradigm as a cloze test for simplification, as well as introduce a logits calibration method to remove the existing selection bias and make LLM a robust cloze solver.

3 Methodology

In this section, we present our proposed ClozeGER paradigm in detail. We first introduce the preliminary knowledge of GER in §3.1, and then we investigate to introduce source speech to GER paradigm with multimodal LLM (§3.2). Finally, we present the new task format of ClozeGER in §3.3.

3.1 Preliminary: Generative Error Correction

We follow the original generative error correction benchmark (Chen et al., 2023a) as shown in Fig. 2 (a). Given an input speech X, the pre-trained ASR model first transcribe it into N-best hypotheses $\mathcal{Y}_N = \{Y_1, Y_2, \cdots, Y_N\}$ by beam search decoding. The goal of GER is to learn a hypotheses-to-transcription (H2T) mapping $\mathcal{M}_{\text{H2T}}$ that predicts the transcription Y based on N-best list $\mathcal{Y}_N$:

$$Y = \mathcal{M}_{\text{H2T}}(\mathcal{Y}_N), \tag{1}$$

Given the ground-truth transcription Y^*, we can finetune the LLM to learn $\mathcal{M}_{\text{H2T}}$ in an auto-regressive manner, where the cross-entropy loss $\mathcal{L}_{\text{H2T}}$ is formulated as:

$$\mathcal{L}_{\text{H2T}} = \sum_{t=1}^{T} -\log \mathcal{P}_\theta(y_t^* | y_{t-1}^*, \cdots, y_1^*, \mathcal{Y}_N), \tag{2}$$

where y_t^* is the t-th token of Y^*, and θ denotes the learnable parameters in LLM (*i.e.*, LoRA).

3.2 GER with Source Speech

In order to prevent GER from violating the content of source speech, we incorporate it as an extra input into LLM to improve output fidelity as shown in Fig. 2 (b). So that Eq.(1) should be rewritten as:

$$Y = \mathcal{M}_{\text{H2T}}(\mathcal{Y}_N, X), \tag{3}$$

where the N-best hypotheses and source speech are concatenated using the following instructions:

"Below is a speech and its candidate transcriptions from a speech recognition system. Please listen to the speech and revise the candidate transcriptions to generate better final recognition results. ### Speech:{speech units}. ### Candidates:{N-best hypotheses}. ### Response: "

To jointly process text and speech, we leverage the popular multimodal LLM, SpeechGPT[4] (Zhang et al., 2023a), to replace the LLaMA in original GER benchmark. Notably, SpeechGPT is developed by discretizing speech into 1,000 HuBERT units and adding them to LLaMA-7b[5] tokenizer, and it then finetunes LLaMA-7b to learn cross-modality mapping. With such multimodal ability, we can enable GER to comply with source speech.

[4] https://huggingface.co/fnlp/SpeechGPT-7B-cm
[5] https://huggingface.co/yahma/llama-7b-hf

3.3 ClozeGER

3.3.1 Cloze Format

Since N-best hypotheses usually only vary in a few tokens, it would be information redundant to send all of them for GER, which could confuse the LLM about which tokens to focus on and thus lead to increased miscorrection. To this end, we simplify the GER paradigm as a cloze test as shown in Fig. 2 (c). Specifically, we set the identical parts across N-best hypotheses as the context and the varying parts as blanks, where each blank is provided with several options. In addition, we also insert a null token '<NULL>' to align the N-best candidates. We design an instruction-following cloze template:

"Below is a speech and its candidate transcriptions from a speech recognition system. The candidates are formatted as a cloze test, where the blanks to fill are indicated by '[Blank1]', '[Blank2]', etc. Each blank is provided with several options indicated by ID letters 'A', 'B', 'C', etc., where '<NULL>' denotes the null token. To generate a better final recognition result, please listen to the speech and write an answer choice for each blank. ### Speech:{speech units}. ### Cloze test: [Blank1] he [Blank2] need it. ### Options: [Blank1]: A. Think; B. <NULL>. [Blank2]: A. rarely; B. really; C. rally. ### Answer choices: "

With such clear instructions for error correction, it would be easier for LLM to perform context reasoning and choose the right answer for each blank than to predict the entire sentence from redundant N-best inputs. In addition, the strong speech understanding ability of SpeechGPT enables ClozeGER to refer to source speech to make better choices.

3.3.2 Logits Calibration with Prior Estimate

Despite the promising performance, most recent works find that LLMs-based cloze test is vulnerable to option position changes due to their inherent "selection bias" (Kumar, 2022; Wang et al., 2023; Pezeshkpour and Hruschka, 2023; He et al., 2023). Similarly, in our experiments, we have observed a strong "selection bias" towards option 'A', especially in the cases where ClozeGER makes mistakes. One reason is that most ground-truth options are 'A' in the training data[6] as the 1-best hypothesis usually enjoys the best quality. As a result, during inference when LLM find it hard to decide the answer choice, it tends to select 'A' that can at least guarantee no performance drop, *i.e.*, option 'A' comes from 1-best hypothesis (baseline). Inspired by prior works on permutation-based debiasing (Wang et al., 2023; Zheng et al., 2023b,a), we propose a logits calibration approach with prior estimation to alleviate this bias during inference.

Formally, we denote the question context as c, the n option IDs (*e.g.*, A/B/C) for one blank as d, and the default option contents (*i.e.*, follow the order of N-best hypotheses) as x. Take the second blank in Fig. 2 (c) as an example, we have $c =$ "*[Blank1]* he *[Blank2]* need it", $d =$ [A, B, C], $n = 3$, $x =$ [rarely, really, rally]. The concatenation of default option IDs and contents is denoted as o.

Then, we use I to denote a permutation of $\{1, 2, \cdots, n\}$, and $\mathcal{I}$ to denote the set of all possible Is. For better formulation, we denote o^I as the concatenation of option IDs and I-permuted option contents, and $r_I(i)$ denotes the position of ID i in I. Take the above example to illustrate, assume $I = [2, 3, 1]$, then $o^I =$ {A: really, B : rally, C : rarely} and $r_I(1) = 3, r_I(2) = 1, r_I(3) = 2$. In order to alleviate the selection bias of LLMs towards the option IDs, we have to first formulate it mathematically. One feasible solution (Wang et al., 2023; Zheng et al., 2023b) is to enumerate all permutations of the option contents and average their output distributions for debiasing:

$$\mathcal{P}_{\text{real}}(x_i|c, o) = \frac{1}{|\mathcal{I}|} \sum_{I \in \mathcal{I}} \mathcal{P}_{\text{llm}}(d_{r_I(i)}|c, o^I), \quad (4)$$

where $i \in \{1, 2, \cdots, n\}$, and $\mathcal{P}_{\text{real}}(x_i|c, o)$ denotes the debiased (*i.e.*, real) probability of i-th option content in x. After such enumeration of all possible permutations of option contents, the "selection bias" towards option IDs could be well resolved.

Furthermore, considering calculating full permutations is prohibitively expensive ($\times n!$ costs), we leverage the cyclic permutation as an alternative, *i.e.*, $I = \{(i, i+1, \cdots, n, 1, 2, \cdots, i-1)\}_{i=1}^{n}$. Take the previous example, we have $I = \{(1, 2, 3), (2, 3, 1), (3, 1, 2)\}$. It reduces the computational cost from $\times n!$ to $\times n$ and guarantees one pairing between each option ID and content. However, the inference cost of $\times n$ is still much too high especially in practical scenarios.

Inspired by recent work on MCQ debiasing (Zheng et al., 2023a), it is a promising idea to disentangle the distribution bias of option IDs from the original predictions from LLMs. The insight behind is that the option ID itself is inherently unrelated to the option contents, the option orders,

[6] Ablation study on debiased training is in Table 4.

and the context. Therefore, the LLM predicted distribution over d_i can be disentangled as a prior distribution of the option ID d_i and the debiased (*i.e.*, real) distribution of option content of d_i:

$$\mathcal{P}_{\text{llm}}(d_i|c,o) \propto \mathcal{P}_{\text{prior}}(d_i|c)\mathcal{P}_{\text{real}}(x_i|c,o), \quad (5)$$

where we omit I as only the default order of options needs to be considered during formal inference. The prior distribution $\mathcal{P}_{\text{prior}}(d_i|c)$ indicates the LLM's selection bias towards option ID d_i, and the debiased distribution $\mathcal{P}_{\text{real}}(x_i|c,o)$ indicates the LLM's real confidence of option content x_i.

Inspired by recent work (Zheng et al., 2023a), we calculate the averaged prior distribution $\hat{\mathcal{P}}_{\text{prior}}(d_i)$ on validation set $\mathcal{D}_v$ to estimate $\mathcal{P}_{\text{prior}}(d_i|c)$. In particular, we perform cyclic permutation $\mathcal{I}_c$ for each sample in $\mathcal{D}_v$ and send all of them for inference, and then we average their output distributions to obtain the prior distribution of option ID d_i:

$$\hat{\mathcal{P}}_{\text{prior}}(d_i) = \frac{1}{|\mathcal{D}_v|} \sum_{\{c,o\}\in\mathcal{D}_v} \mathcal{P}_{\text{prior}}(d_i|c),$$

$$\mathcal{P}_{\text{prior}}(d_i|c) = \text{sm}\left(\frac{1}{|\mathcal{I}|}\sum_{I\in\mathcal{I}} \log \mathcal{P}_{\text{llm}}(d_i|c,o^I)\right), \quad (6)$$

where "sm" denotes softmax operation. With the estimated prior distribution, we can perform logits calibration during the inference stage:

$$\hat{\mathcal{P}}_{\text{real}}(x_i|c,o) \propto \mathcal{P}_{\text{llm}}(d_i|c,o)/\hat{\mathcal{P}}_{\text{prior}}(d_i), \quad (7)$$

In case of the small size of $\mathcal{D}_v$, this logits calibration method would be efficient during inference.

3.3.3 Post-processing

After cloze test with logits calibration, many ASR errors captured by the blanks (*i.e.*, varying tokens between N-best hypotheses) are corrected, but what about those remaining in the question context? For example, as shown in Fig. 2 (c), the ASR model fails to recognize the word "needs", where all N-best hypotheses produce "need". In this case, we need a simple post-processing stage to further correct them, with the following instructions:

"Below is a speech and its candidate transcription from a speech recognition system. Please listen to the speech and correct the candidate transcription. ### Speech:{speech units}. ### Candidate:{cloze result}. ### Response: "

Similar to GER, here we also use SpeechGPT with LoRA finetuning for post-processing. This stage is necessary especially when ASR model does not perform well on current speech domains.

4 Experiments

4.1 Setup

Dataset. We utilize the HyPoradise (HP) dataset from the original GER benchmark (Chen et al., 2023a) for our experiments, which contains over 332K hypotheses-transcription pairs collected from multiple mainstream ASR corpora. Specifically, each transcription is paired with 5-best hypotheses transcribed from Whisper-Large model (Radford et al., 2023) with beam search decoding. In this work, we select 9 popular ASR corpora from HyPoradise to evaluate the proposed ClozeGER, including WSJ (Paul and Baker, 1992), CommonVoice (Ardila et al., 2019), TED-LIUM3 (Hernandez et al., 2018), SwitchBoard (Godfrey et al., 1992), LibriSpeech (Panayotov et al., 2015), CHiME-4 (Vincent et al., 2016), LRS2 (Chung et al., 2017), ATIS (Hemphill et al., 1990), and CORAAL (Kendall and Farrington, 2021). Since HyPoradise provides 5-best hypotheses for each sample, we follow it to set 5 options for each cloze blank. More statistical details are in Appendix A.

Models. As introduced before, we use SpeechGPT as the LLM in our main experiments, and later on we also try LLaMA-2-7b[7] (Touvron et al., 2023b) to verify the effectiveness of ClozeGER paradigm in case of no source speech input. For efficient LLM finetuning, we employ the popular low-rank adapter (LoRA) tuning strategy (Hu et al., 2021), where the rank r is set to 8 and the LoRA is added in the query, key, value, and output layers in each Transformer block (Vaswani et al., 2017). As a result, the number of trainable parameters is only 8.39 M, accounting for only 0.12% of the LLM.

Training and Inference. During finetuning, we employ Adam optimizer (Kingma and Ba, 2014) with a learning rate set to $2e^{-4}$ and warmup steps set to 100. The number of training epochs is set to 5, the batch size is set to 256. The maximum input sequence length is set to 1024. For inference, we adopt top-k and top-p sampling strategies at the same time, where $k = 40$ and $p = 0.75$. The temperature is set to 0.1, and beam size is set to 4.

4.2 Main Results

Table 1 presents the WER results of ClozeGER with SpeechGPT and LoRA tuning. First, we can observe that vanilla GER achieves significant im-

[7] https://huggingface.co/meta-llama/Llama-2-7b-hf

Test Set	Baseline	*w/o Source Speech*	*w/ Source Speech*				Oracle	
		GER (2023a)	GER	ClozeGER (ours)	+ Calibration	+ Post-processing	o_{nb}	o_{cp}
WSJ	4.2	$2.9_{-31.0\%}$	$2.7_{-35.7\%}$	$3.8_{-9.5\%}$	$3.3_{-21.4\%}$	$\mathbf{2.4_{-42.9\%}}$	2.7	1.0
CommonVoice	14.4	$11.4_{-20.8\%}$	$10.1_{-29.9\%}$	$13.7_{-4.9\%}$	$12.4_{-13.9\%}$	$\mathbf{8.5_{-41.0\%}}$	10.5	7.5
TED-LIUM3	6.8	$5.8_{-14.7\%}$	$5.4_{-20.6\%}$	$6.1_{-10.3\%}$	$5.1_{-25.0\%}$	$\mathbf{4.8_{-29.4\%}}$	4.4	1.6
SwitchBoard	16.4	$14.8_{-9.8\%}$	$14.3_{-12.8\%}$	$15.8_{-3.7\%}$	$15.0_{-8.5\%}$	$\mathbf{13.3_{-18.9\%}}$	13.3	4.6
LibriSpeech	2.7	$2.7_{-0.0\%}$	$2.6_{-3.7\%}$	$2.7_{-0.0\%}$	$2.5_{-7.4\%}$	$\mathbf{2.5_{-7.4\%}}$	1.9	1.1
CHiME-4	9.4	$7.4_{-21.3\%}$	$7.9_{-16.0\%}$	$8.7_{-7.4\%}$	$7.6_{-19.1\%}$	$\mathbf{7.1_{-24.5\%}}$	5.9	2.7
LRS2	12.3	$10.7_{-13.0\%}$	$9.5_{-22.8\%}$	$10.7_{-13.0\%}$	$9.3_{-24.3\%}$	$\mathbf{7.6_{-38.2\%}}$	7.5	2.8
ATIS	7.3	$2.9_{-60.3\%}$	$2.4_{-67.1\%}$	$7.1_{-2.7\%}$	$6.5_{-11.0\%}$	$\mathbf{2.1_{-71.2\%}}$	4.1	1.0
CORAAL	29.2	$27.9_{-4.5\%}$	$27.6_{-5.5\%}$	$29.1_{-0.3\%}$	$28.1_{-3.8\%}$	$\mathbf{26.7_{-8.6\%}}$	27.9	10.9

Table 1: WER (%) results of ClozeGER with SpeechGPT and LoRA. "+ Calibration" denotes adding logits calibration on ClozeGER to remove the selection bias, and "+ Post-processing" denotes further adding the post-processing stage to correct the context. o_{nb} denotes the N-best oracle that refers to word error rate (WER) of the "best candidate" in the N-best list, and o_{cp} denotes the compositional oracle that is the best achievable WER using all the tokens in N-best hypotheses. They indicate the upper-bounds of LM rescoring and GER (with occurred tokens), respectively. The subscript percentage denotes the relative WER reduction over ASR baseline.

Test Set	Baseline	*w/o Source Speech*				Oracle	
		GER (2023a)	ClozeGER (ours)	+ Calibration	+ Post-processing	o_{nb}	o_{cp}
WSJ	4.2	$2.8_{-33.3\%}$	$3.7_{-11.9\%}$	$3.3_{-21.4\%}$	$\mathbf{2.5_{-40.5\%}}$	2.7	1.0
CommonVoice	14.4	$10.8_{-25.0\%}$	$13.1_{-9.0\%}$	$12.4_{-13.9\%}$	$\mathbf{8.6_{-40.3\%}}$	10.5	7.5
TED-LIUM3	6.8	$5.3_{-22.1\%}$	$6.0_{-11.8\%}$	$5.0_{-26.5\%}$	$\mathbf{4.7_{-30.9\%}}$	4.4	1.6
SwitchBoard	16.4	$14.6_{-11.0\%}$	$15.6_{-4.9\%}$	$14.5_{-11.6\%}$	$\mathbf{12.9_{-21.3\%}}$	13.3	4.6
LibriSpeech	2.7	$2.7_{-0.0\%}$	$2.6_{-3.7\%}$	$2.4_{-11.1\%}$	$\mathbf{2.4_{-11.1\%}}$	1.9	1.1
CHiME-4	9.4	$7.3_{-22.3\%}$	$7.9_{-16.0\%}$	$7.2_{-23.4\%}$	$\mathbf{7.0_{-25.5\%}}$	5.9	2.7
LRS2	12.3	$10.5_{-14.6\%}$	$10.5_{-14.6\%}$	$9.0_{-26.8\%}$	$\mathbf{7.4_{-39.8\%}}$	7.5	2.8
ATIS	7.3	$2.4_{-67.1\%}$	$6.3_{-13.7\%}$	$5.8_{-20.5\%}$	$\mathbf{2.1_{-71.2\%}}$	4.1	1.0
CORAAL	29.2	$27.4_{-6.2\%}$	$29.1_{-0.3\%}$	$27.9_{-4.5\%}$	$\mathbf{26.8_{-8.2\%}}$	27.9	10.9

Table 2: WER (%) results of ClozeGER with LLaMA-2-7b and LoRA. This study investigates the performance of our ClozeGER in case of no source speech input. o_{nb} and o_{cp} follow the same definitions as those in Table 1.

provements over Whisper ASR baseline, and introducing source speech as extra input further enhances the performance. In comparison, our proposed ClozeGER also improves the baseline but underperforms the GER approach. There are two reasons, the cloze test suffers from selection bias and cannot yield satisfactory results, and on the other hand, there are many errors exist in the cloze context due to imperfect N-best list quality (*i.e.*, Whisper is a general ASR model and may not perform well in every specific domain). To this end, we first propose a logits calibration approach to alleviate the selection bias, which results in considerable WER reductions. Furthermore, we add a post-processing stage to correct the errors in cloze context, which moves one step forward and outperforms the GER approach with source speech input, where some results even surpass the N-best oracle.

Table 2 reports the WER results of ClozeGER using LLaMA-2 as a backbone in case of no source speech as input, where we observe similar gains of performance of the proposed ClozeGER over GER baseline. It demonstrates the general effectiveness of ClozeGER paradigm, as well as the proposed logits calibration and post-processing techniques.

4.3 Ablation Study and Analysis

Why we need logits calibration?

We note that ClozeGER only produces limited improvement and even underperforms the GER baseline, where one key reason is the "selection bias" towards option IDs. Take the WSJ dataset as an example, we visualize the distribution of predicted option IDs in Fig. 3, where over 80% of predictions fall on option 'A'. This phenomenon can be explained by the imbalanced training label distribution[8] and its resulted "selection bias" as shown in Table 3. As a result, the proposed ClozeGER yields poor predicting accuracy on options 'B' to 'E', which limits its final WER performance.

How does logits calibration work?

To alleviate this limitation, we propose to estimate a prior distribution to represent the selection bias

[8]Because top-1 hypothesis enjoys the best quality and is most likely to be the ground-truth choice.

Label Dist. / Prior (%)	A	B	C	D	E
WSJ	75.51 / 95.68	10.27 / 2.92	6.84 / 0.63	4.16 / 0.42	3.22 / 0.35
CommonVoice	80.32 / 95.94	8.33 / 2.54	5.47 / 0.59	3.34 / 0.57	2.54 / 0.36
TED-LIUM3	75.22 / 98.13	10.34 / 1.63	6.89 / 0.17	4.30 / 0.03	3.25 / 0.04
SwitchBoard	77.93 / 96.70	9.18 / 2.78	6.07 / 0.30	3.85 / 0.09	2.98 / 0.13
LibriSpeech	73.80 / 98.08	11.51 / 1.50	7.63 / 0.28	4.01 / 0.08	3.05 / 0.06
CHiME-4	77.56 / 84.17	8.83 / 9.13	6.89 / 4.54	3.98 / 1.33	2.73 / 0.83
LRS2	77.21 / 95.85	9.81 / 3.63	6.58 / 0.31	3.54 / 0.15	2.86 / 0.07
ATIS	78.43 / 82.78	10.08 / 8.67	5.63 / 4.27	3.08 / 2.28	2.78 / 2.00
CORAAL	77.58 / 83.08	8.85 / 7.86	6.21 / 3.78	3.95 / 2.73	3.40 / 2.54

Table 3: Training label distribution (%) and the estimated prior distribution (%) over 5 option IDs (*i.e.*, 'A', 'B', 'C', 'D', and 'E') of different datasets. The training label distribution refers to the proportions of each option ID in the labels of cloze training data, and the estimated prior distribution is illustrated in Eq.(6) as $\hat{\mathcal{P}}_{\text{prior}}(d_i)$.

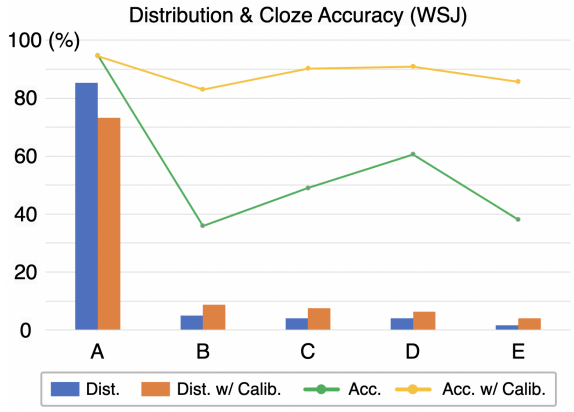


Figure 3: Distribution and cloze accuracy of five options with logits calibration on WSJ dataset. "Dist." denotes the distribution of five options in the predictions, "Acc." denotes the predicting accuracy of each ground-truth option, and "w/ Calib." denotes with logits calibration.

Test Set	ClozeGER		ClozeGER *w/ Calib.*	
	Acc (%)	WER (%)	Acc (%)	WER(%)
WSJ	84.7	3.8	92.6	3.3
CommonVoice	82.6	13.7	91.5	12.4
TED-LIUM3	76.0	6.1	91.3	5.1
SwitchBoard	78.7	15.8	86.8	15.0
LibriSpeech	80.3	2.7	95.3	2.5
CHiME-4	74.4	8.7	87.5	7.6
LRS2	83.9	10.7	91.7	9.3
ATIS	78.9	7.1	84.5	6.5
CORAAL	78.9	29.1	87.3	28.1

Table 4: Effect of the logits calibration approach in proposed ClozeGER framework, in terms of the cloze test accuracy and final WER performance.

and then remove it from the output logits during inference stage to conduct calibration. As illustrated by the orange bars and yellow lines in Fig. 3, our proposed calibration approach mitigates the imbalance of predicted options and effectively improves their cloze accuracy. As a result, the overall cloze accuracy is significantly improved on various ASR datasets in Table 4, which thus produces better WER performance in the final. More visualization on other datasets is in the Appendix Fig. 5.

Why not do calibration during training stage?

One may raise concerns about why we conduct the calibration during inference instead of training stage, where simply shuffling the options seems able to mitigate the selection bias. To this end, we present an ablation study in Table 5 to explore calibration in different stages, where we observe that shuffled training can indeed achieve some improvement over ClozeGER but still lag behind the proposed logits calibration approach. When further adding the post-processing stage, our calibration also produces better performance, indicating that it is more beneficial to remove selection bias during the inference stage rather than training stage.

This observation may suggest that within our specific framework, the model's acquisition of selection bias during training is *somehow advantageous*, as the strategy of arbitrarily selecting 'A' would at worst regress to the baseline (top-1 hypothesis) without deterioration. As a result, the task difficulty of ClozeGER is naturally reduced, because it can rely on the heuristic of selecting 'A' when feeling uncertain and hard to make the choice. Thereafter, the logits calibration during inference removes such bias by diversifying some of the 'A' choices to other options to improve the accuracy.

Why we need post-processing?

Table 6 further investigates the role of the post-processing stage in ClozeGER paradigm. We observe that such post-processing is necessary to further correct the errors in cloze context, which results in promising gains of performance. On the other hand, this phenomenon also reflects the sub-optimal quality of N-best hypotheses, according to

Test Set	Baseline	GER	ClozeGER	Train stage		Infer stage		Oracle	
				+ Shuf.	+ Post.	+ Calib.	+ Post.	o_{nb}	o_{cp}
WSJ	4.2	2.7	3.8	3.5	2.7	3.3	**2.4**$_{-42.9\%}$	2.7	1.0
CommonVoice	14.4	10.1	13.7	12.9	9.2	12.4	**8.5**$_{-41.0\%}$	10.5	7.5
TED-LIUM3	6.8	5.4	6.1	5.7	5.1	5.1	**4.8**$_{-29.4\%}$	4.4	1.6
SwitchBoard	16.4	14.3	15.8	15.3	13.8	15.0	**13.3**$_{-18.9\%}$	13.3	4.6
LibriSpeech	2.7	2.6	2.7	2.6	2.5	2.5	**2.5**$_{-7.4\%}$	1.9	1.1
CHiME-4	9.4	7.9	8.7	8.0	7.3	7.6	**7.1**$_{-24.5\%}$	5.9	2.7
LRS2	12.3	9.5	10.7	9.8	7.9	9.3	**7.6**$_{-38.2\%}$	7.5	2.8
ATIS	7.3	2.4	7.1	6.9	2.4	6.5	**2.1**$_{-71.2\%}$	4.1	1.0
CORAAL	29.2	27.6	29.1	28.4	27.2	28.1	**26.7**$_{-8.6\%}$	27.9	10.9

Table 5: Effect of calibration during different stages, *i.e.*, training and inference. "+ Shuf." denotes shuffling the option contents during training stage (keep the order of option IDs as "A, B, C, D, E"), "+ Calib." denotes using logits calibration during inference stage, "+ Post." denotes adding pre-processing on top of shuffling or calibration.

Test Set	Baseline	GER		ClozeGER *w/ Calib.*		Oracle	
		Original	+ Post-processing	Original	+ Post-processing	o_{nb}	o_{cp}
WSJ	4.2	2.7$_{-35.7\%}$	2.6$_{-38.1\%}$	3.3$_{-21.4\%}$	**2.4**$_{-42.9\%}$	2.7	1.0
CommonVoice	14.4	10.1$_{-29.9\%}$	9.6$_{-33.3\%}$	12.4$_{-13.9\%}$	**8.5**$_{-41.0\%}$	10.5	7.5
TED-LIUM3	6.8	5.4$_{-20.6\%}$	5.2$_{-23.5\%}$	5.1$_{-25.0\%}$	**4.8**$_{-29.4\%}$	4.4	1.6
SwitchBoard	16.4	14.3$_{-12.8\%}$	14.0$_{-14.6\%}$	15.0$_{-8.5\%}$	**13.3**$_{-18.9\%}$	13.3	4.6
LibriSpeech	2.7	2.6$_{-3.7\%}$	2.6$_{-3.7\%}$	2.5$_{-7.4\%}$	**2.5**$_{-7.4\%}$	1.9	1.1
CHiME-4	9.4	7.9$_{-16.0\%}$	7.8$_{-17.0\%}$	7.6$_{-19.1\%}$	**7.1**$_{-24.5\%}$	5.9	2.7
LRS2	12.3	9.5$_{-22.8\%}$	9.0$_{-26.8\%}$	9.3$_{-24.3\%}$	**7.6**$_{-38.2\%}$	7.5	2.8
ATIS	7.3	2.4$_{-67.1\%}$	2.3$_{-68.5\%}$	6.5$_{-11.0\%}$	**2.1**$_{-71.2\%}$	4.1	1.0
CORAAL	29.2	27.6$_{-5.5\%}$	27.3$_{-6.5\%}$	28.1$_{-3.8\%}$	**26.7**$_{-8.6\%}$	27.9	10.9

Table 6: Effect of the post-processing stage on GER and our proposed ClozeGER frameworks (with SpeechGPT as LLM). "Calib." denotes the logits calibration approach. o_{nb} and o_{cp} follow the same definitions as those in Table 1.

the errors in cloze context (see Fig. 2 (c)), as Whisper is a general ASR model that may not generalize well to some specific domains like accents.

The role of ClozeGER and post-processing.

One may raise concerns on whether the effectiveness of our approach is all attributed to post-processing. To this end, we add it onto the GER baseline, which also shows some improvement but still underperforms our ClozeGER, indicating that our proposed ClozeGER paradigm and logits calibration raises the upper-bound performance of GER by correcting errors in a targeted manner. Based on that, the post-processing aims to further correct the errors in cloze context that cannot be resolved by the cloze-test paradigm.

Case study.

We illustrate a case study in Fig. 2 to interpret the motivation of our approach. First, we introduce source speech as extra input to improve output fidelity, *i.e.*, avoid removing the word "Think". Second, we reformat GER as a cloze test to reduce the task difficulty with clear instructions, *i.e.*, explicitly prompt the LLM to select a word from ["rarely", "really", "rally"], which results in an effective correction. Finally, we note that there still exist some errors in the cloze context, *e.g.*, "need", which cannot be corrected by the cloze-test paradigm. To this end, we design a post-processing stage to further remove them and improve the final output.

5 Conclusion

In this paper, we propose ClozeGER, a new paradigm for ASR generative error correction. First, we introduce a multimodal LLM (*i.e.*, SpeechGPT) to receive source speech as extra input to improve the fidelity of correction output. Then, we reformat GER as a cloze test with logits calibration to remove the input information redundancy and simplify GER with clear instructions. Experimental evidence shows that ClozeGER achieves a new breakthrough over vanilla GER on 9 popular ASR datasets. Further analysis verifies the effectiveness of different modules in our framework.

Limitations

This work introduces an extra input of source speech to improve the output fidelity, which achieves some improvements but is somewhat limited since we only employ a new prompt for LLMs to exploit the source speech. In future, we may investigate more advanced multimodal prompting techniques for it and also combine them with our proposed cloze-test paradigm for further improvements. In addition, we believe it should also be beneficial to further investigate the reasons for the sub-optimal performance of cloze-test paradigm, as well as integrate the calibration and post-processing stages as an end-to-end pipeline in future work.

Ethics Statement

This work does not pose any ethical issues. All the data used in this paper are publicly available and under the following licenses: the Creative Commons BY-NC-ND 3.0 License, Creative Commons BY-NC-ND 4.0 License, Creative Commons BY-NC-SA 4.0 License, Creative Commons Attribution 4.0 International License, Creative Commons (CC0) License, the LDC User Agreement for Non-Members, the TED Terms of Use, the YouTube's Terms of Service, and the BBC's Terms of Use.

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References

Rosana Ardila, Megan Branson, Kelly Davis, Michael Henretty, Michael Kohler, Josh Meyer, Reuben Morais, Lindsay Saunders, Francis M Tyers, and Gregor Weber. 2019. Common voice: A massively-multilingual speech corpus. *arXiv preprint arXiv:1912.06670*.

Ebru Arisoy, Abhinav Sethy, Bhuvana Ramabhadran, and Stanley Chen. 2015. Bidirectional recurrent neural network language models for automatic speech recognition. In *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 5421–5425. IEEE.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.

Chen Chen, Yuchen Hu, Chao-Han Huck Yang, Sabato Marco Siniscalchi, Pin-Yu Chen, and Ensiong Chng. 2023a. Hyporadise: An open baseline for generative speech recognition with large language models. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.

Feilong Chen, Minglun Han, Haozhi Zhao, Qingyang Zhang, Jing Shi, Shuang Xu, and Bo Xu. 2023b. X-llm: Bootstrapping advanced large language models by treating multi-modalities as foreign languages. *arXiv preprint arXiv:2305.04160*.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E Gonzalez, et al. 2023. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality. *See https://vicuna. lmsys. org (accessed 14 April 2023)*.

Joon Son Chung, Andrew Senior, Oriol Vinyals, and Andrew Zisserman. 2017. Lip reading sentences in the wild. In *2017 IEEE conference on computer vision and pattern recognition (CVPR)*, pages 3444–3453. IEEE.

Yassir Fathullah, Chunyang Wu, Egor Lakomkin, Junteng Jia, Yuan Shangguan, Ke Li, Jinxi Guo, Wenhan Xiong, Jay Mahadeokar, Ozlem Kalinli, et al. 2023. Prompting large language models with speech recognition abilities. *arXiv preprint arXiv:2307.11795*.

Peng Gao, Jiaming Han, Renrui Zhang, Ziyi Lin, Shijie Geng, Aojun Zhou, Wei Zhang, Pan Lu, Conghui He, Xiangyu Yue, et al. 2023. Llama-adapter v2: Parameter-efficient visual instruction model. *arXiv preprint arXiv:2304.15010*.

John J Godfrey, Edward C Holliman, and Jane McDaniel. 1992. Switchboard: Telephone speech corpus for research and development. In *Acoustics, Speech, and Signal Processing, IEEE International Conference on*, volume 1, pages 517–520. IEEE Computer Society.

Guande He, Peng Cui, Jianfei Chen, Wenbo Hu, and Jun Zhu. 2023. Investigating uncertainty calibration of aligned language models under the multiple-choice setting. *arXiv preprint arXiv:2310.11732*.

Charles T Hemphill, John J Godfrey, and George R Doddington. 1990. The atis spoken language systems pilot corpus. In *Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27, 1990*.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. In *International Conference on Learning Representations*.

François Hernandez, Vincent Nguyen, Sahar Ghannay, Natalia Tomashenko, and Yannick Esteve. 2018. Tedlium 3: Twice as much data and corpus repartition for experiments on speaker adaptation. In *Speech and Computer: 20th International Conference, SPECOM 2018, Leipzig, Germany, September 18–22, 2018, Proceedings 20*, pages 198–208. Springer.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*.

Yuzhen Huang, Yuzhuo Bai, Zhihao Zhu, Junlei Zhang, Jinghan Zhang, Tangjun Su, Junteng Liu, Chuancheng Lv, Yikai Zhang, Jiayi Lei, et al. 2023. C-eval: A multi-level multi-discipline chinese evaluation suite for foundation models. *arXiv preprint arXiv:2305.08322*.

Tyler Kendall and Charlie Farrington. 2021. The corpus of regional african american language. version 2021.07. eugene, or: The online resources for african american language project.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Sawan Kumar. 2022. Answer-level calibration for free-form multiple choice question answering. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 665–679.

Yichong Leng, Xu Tan, Rui Wang, Linchen Zhu, Jin Xu, Wenjie Liu, Linquan Liu, Tao Qin, Xiang-Yang Li, Edward Lin, et al. 2021. Fastcorrect 2: Fast error correction on multiple candidates for automatic speech recognition. *arXiv preprint arXiv:2109.14420*.

Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. 2023. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *arXiv preprint arXiv:2301.12597*.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. 2023. Visual instruction tuning. *arXiv preprint arXiv:2304.08485*.

Rao Ma, Mark JF Gales, Kate Knill, and Mengjie Qian. 2023. N-best t5: Robust asr error correction using multiple input hypotheses and constrained decoding space. *arXiv preprint arXiv:2303.00456*.

Tomas Mikolov, Martin Karafiát, Lukas Burget, Jan Cernockỳ, and Sanjeev Khudanpur. 2010. Recurrent neural network based language model. In *Interspeech*, volume 2, pages 1045–1048. Makuhari.

OpenAI. 2022. Introducing chatgpt. *OpenAI Blog*.

OpenAI. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744.

Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur. 2015. Librispeech: an asr corpus based on public domain audio books. In *2015 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 5206–5210. IEEE.

Douglas B Paul and Janet Baker. 1992. The design for the wall street journal-based csr corpus. In *Speech and Natural Language: Proceedings of a Workshop Held at Harriman, New York, February 23-26, 1992*.

Pouya Pezeshkpour and Estevam Hruschka. 2023. Large language models sensitivity to the order of options in multiple-choice questions. *arXiv preprint arXiv:2308.11483*.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. 2023. Robust speech recognition via large-scale weak supervision. In *International Conference on Machine Learning*, pages 28492–28518. PMLR.

Joonbo Shin, Yoonhyung Lee, and Kyomin Jung. 2019. Effective sentence scoring method using bert for speech recognition. In *Asian Conference on Machine Learning*, pages 1081–1093. PMLR.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023a. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023b. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems*, 30.

Emmanuel Vincent, Shinji Watanabe, Jon Barker, and Ricard Marxer. 2016. The 4th chime speech separation and recognition challenge. *URL: http://spandh. dcs. shef. ac. uk/chime_challenge/(last accessed on 1 August, 2018)*.

Peiyi Wang, Lei Li, Liang Chen, Dawei Zhu, Binghuai Lin, Yunbo Cao, Qi Liu, Tianyu Liu, and Zhifang Sui. 2023. Large language models are not fair evaluators. *arXiv preprint arXiv:2305.17926*.

Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Emergent abilities of large language models. *arXiv preprint arXiv:2206.07682*.

Wen Wu, Chao Zhang, and Philip C Woodland. 2021. Emotion recognition by fusing time synchronous and time asynchronous representations. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6269–6273. IEEE.

Chao-Han Huck Yang, Yile Gu, Yi-Chieh Liu, Shalini Ghosh, Ivan Bulyko, and Andreas Stolcke. 2023. Generative speech recognition error correction with large language models and task-activating prompting. *arXiv preprint arXiv:2309.15649*.

Dong Zhang, Shimin Li, Xin Zhang, Jun Zhan, Pengyu Wang, Yaqian Zhou, and Xipeng Qiu. 2023a. Speechgpt: Empowering large language models with intrinsic cross-modal conversational abilities. *arXiv preprint arXiv:2305.11000*.

Hang Zhang, Xin Li, and Lidong Bing. 2023b. Video-llama: An instruction-tuned audio-visual language model for video understanding. *arXiv preprint arXiv:2306.02858*.

Renrui Zhang, Jiaming Han, Aojun Zhou, Xiangfei Hu, Shilin Yan, Pan Lu, Hongsheng Li, Peng Gao, and Yu Qiao. 2023c. Llama-adapter: Efficient fine-tuning of language models with zero-init attention. *arXiv preprint arXiv:2303.16199*.

Chujie Zheng, Hao Zhou, Fandong Meng, Jie Zhou, and Minlie Huang. 2023a. Large language models are not robust multiple choice selectors. *arXiv preprint arXiv:2309.03882*.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. 2023b. Judging llm-as-a-judge with mt-bench and chatbot arena. *arXiv preprint arXiv:2306.05685*.

Wanjun Zhong, Ruixiang Cui, Yiduo Guo, Yaobo Liang, Shuai Lu, Yanlin Wang, Amin Saied, Weizhu Chen, and Nan Duan. 2023. Agieval: A human-centric benchmark for evaluating foundation models. *arXiv preprint arXiv:2304.06364*.

A HyPoradise Dataset Details

A.1 Hypotheses Generation

We employ the HyPoradise (HP) dataset[9] from original GER benchmark (Chen et al., 2023a), which contains over 332K pairs of N-best hypotheses and ground-truth transcription. The hypotheses are generated using Whisper-Large (Radford et al., 2023) beam search decoding, where the beam size is set to 50. After removing repetitive utterances, the top-5 hypotheses with the highest probabilities are selected as the final N-best list. The HyPoradise dataset is built by carrying out this decoding strategy on multiple popular ASR datasets as introduced in §A.2. As a result, the detailed statistics of HyPoradise dataset is illustrated in Table 7.

[9] https://huggingface.co/datasets/PeacefulData/HP-v0

A.2 ASR Corpora Selection

For ASR corpora selection, we follow original benchmark (Chen et al., 2023a) to cover common ASR scenarios, *e.g.*, noise and accents. Consequently, the following corpora with evident domain characteristics are collected to build the HP dataset.

WSJ (Paul and Baker, 1992): The Wall Street Journal (WSJ) is a widely-used benchmark for speech recognition. It includes read speech from speakers in a controlled environment, with a focus on business news and financial data. The *train-si284* split (37,514 samples) is utilized to generate HP training set. The *dev93* (503 samples) and *eval92* (333 samples) splits are combined to build test set.

CommonVoice (Ardila et al., 2019): CommonVoice 5.1 is a publicly available dataset for automatic speech recognition. It contains speech recordings from diverse speakers in over 60 languages. To generate HP dataset, they randomly select 51,758 samples from its *train-en* split with various accent labels, including African, Australian, Indian, and Singaporean. Then, it is separated into two parts to build training (with 49,758 samples) and test (with 2,000 samples) sets respectively.

TED-LIUM3 (Hernandez et al., 2018): TED-LIUM3 is a speech dataset recorded from TED talks. It contains a diverse range of background noise, speaker accents, and speech topics. Considering its large size, they randomly select 50,000 samples from its *train* split for HP dataset generation, which is then separated into training (47,500 samples) and test (2,500 samples) sets.

SwitchBoard (Godfrey et al., 1992): The SwitchBoard corpus is a telephone speech dataset collected from conversations. It focuses on North American English and involves over 2,400 conversations from around 200 speakers. They randomly select 36,539 samples from its *train* split to generate HP training set, as well as 2,000 samples from the *eval2000* split to generate HP test set.

LibriSpeech (Panayotov et al., 2015): LibriSpeech is a public corpus of read speech from audiobooks,

Domain		Training Set	# Pairs	Length	Test Set	# Pairs	Length
Source	Category						
WSJ	Business News	*train-si284*	37,514	17.5	*dev93 & eval92*	836	16.9
CommonVoice	Speaker Accents	*train-accent*	49,758	10.5	*test-accent*	2,000	10.5
TED-LIUM3	TED Talks	*train*	47,500	12.6	*test*	2,500	12.6
SwitchBoard	Telephone	*train*	36,539	11.8	*eval2000*	2,000	11.8
LibriSpeech	Audiobooks	*train-960*	88,200	33.7	*test-clean*	2,620	20.1
CHiME4	Background Noise	*tr05-real-noisy*	9,600	17.0	*test-real*	1,320	16.4
LRS2	BBC Television	*train*	42,940	7.6	*test*	2,259	7.6
ATIS	Airline Info.	*train*	3,964	12.4	*test*	809	11.3
CORAAL	Interview	*train*	1,728	24.2	*test*	100	24.0
Total		*train*	317,743	18.1	*test*	14,444	13.4

Table 7: HyPoradise dataset statistics in terms of different ASR domains (*i.e.*, including speech and text domains), the number of hypotheses-transcription pairs, and the average utterance length of each dataset.

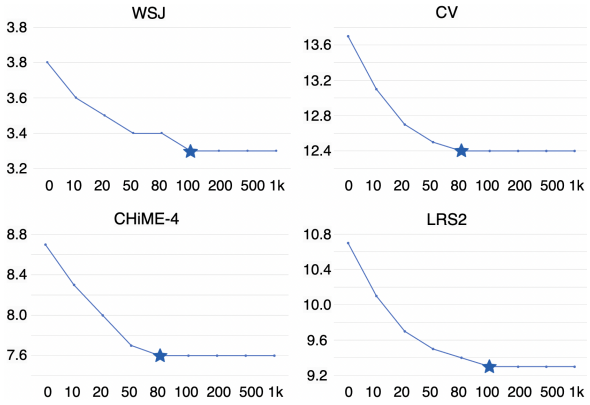

Figure 4: WER (%) results of utilizing different numbers of validation samples for prior estimation. The minimum required amount to obtain the best performance is highlighted in the star mark.

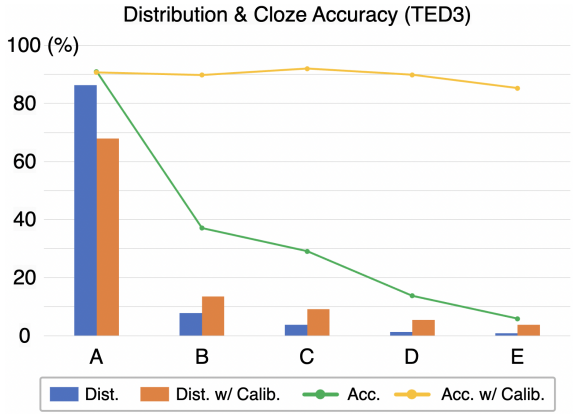

Figure 5: Distribution and cloze accuracy of five options with and without logits calibration on TED-LIUM 3 dataset. The remarks follow that in Fig. 3.

including 1,000 hours of labeled speech data from diverse speakers, genders, and accents. To generate HP training data, they exclude some simple utterances from its *train-960* split that yield 0% WER, which results in 88,200 training samples. The *test-clean* split (2,620 samples) is used for HP test data.

CHiME-4 (Vincent et al., 2016): CHiME-4 is a dataset for far-field noisy speech recognition. It includes real and simulated noisy recordings in four noisy environments, *i.e.*, bus, cafe, pedestrian area, and street junction. Its *tr05-real-noisy* (9,600 samples) and *test-real* (1,320 samples) splits are used to generate HP training and test data, respectively.

LRS2 (Chung et al., 2017): Lip Reading Sentences 2 (LRS2) is a large-scale publicly available audio-visual dataset, consisting of 224 hours of video clips from BBC programs. They randomly select 42,940 samples from its *train* split as training set, and the rest of 2,259 samples are used for test set.

ATIS (Hemphill et al., 1990): Airline Travel Information System (ATIS) is a dataset comprising spoken queries for air travel information, including flight times, prices, and availability. It contains 4,773 utterances recorded from over 500 speakers, which are separated into two parts to build training (3,964 samples) and test (809 samples) sets.

CORAAL (Kendall and Farrington, 2021): The Corpus of Regional African American Language (CORAAL) is the first public corpus of AAL speech data. It contains audio recordings along with the time-aligned orthographic transcriptions from over 150 sociolinguistic interviews. To generate HyPoradise dataset, they select 1,728 samples as training set and 100 samples as test set.

A.3 Validation Set Selection

As mentioned in §3.3.2, our logits calibration method requires a validation set to calculate the

prior distribution $\hat{\mathcal{P}}_{\text{prior}}(d_i)$. To this end, we reserve a small portion of training samples to build the validation set. To save the computation cost and time, we randomly select 100 samples from each ASR corpus in Table 7 for prior estimation (Wu et al., 2021). Relevant ablation study is illustrated in Fig. 4, where we observe that around 100 validation samples are sufficient to estimate a reliable prior distribution for logits calibration on most datasets.

B Examples of Cloze test

Table 8 presents several examples of cloze test built from CHiME-4 *test-real* set, where each example contains the context and several options.

Table 8: Examples of cloze test built from CHiME-4 *test-real* set.

Example ID	F06_443C0212_CAF
Cloze Context	yesterday is losers included *[Blank1]*
Options	*[Blank1]*: A. automobiles B. all of you C. automobile D. all the ideas E. automakers
Answer	A
Example ID	F06_446C0204_BUS
Cloze Context	the consensus was that a new piece of paper is not required *[Blank1]* one u s *[Blank2]*
Options	*[Blank1]*: A. except B. said C. to be sent D. to set E. to send *[Blank2]*: A. dollar B. diplomat C. dollar D. standard E. tip to them
Answer	B B
Example ID	M05_440C020W_STR
Cloze Context	durable goods *[Blank1]* frequently are highly volatile from month to month
Options	*[Blank1]*: A. and goods B. <NULL> C. and fluids D. and foods E. or goods
Answer	A
Example ID	M05_443C020R_STR
Cloze Context	as part of the marketing plan the company will begin airing television commercials during *[Blank1]* on election night next tuesday
Options	*[Blank1]*: A. the prime time B. the fine time C. prime time D. fine time E. primetime
Answer	C