WavLLM: Towards Robust and Adaptive Speech Large Language Model

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Abstract

The recent advancements in large language models (LLMs) have revolutionized the field of natural language processing (NLP), progressively broadening their scope to multimodal perception and generation. However, effectively integrating listening capabilities into LLMs poses significant challenges, particularly with respect to generalizing across varied contexts and executing complex auditory tasks. In this work, we introduce WavLLM, a robust and adaptive speech large language model with dual encoders, and a prompt-aware LoRA weight adapter, optimized by a two-stage curriculum learning approach. Leveraging dual encoders, we decouple different types of speech information, utilizing a Whisper encoder to process the semantic content of speech, and a WavLM encoder to capture the unique characteristics of the speaker's identity. Within the curriculum learning framework, WayLLM first builds its foundational capabilities by optimizing on mixed elementary single tasks, including automatic speech recognition (ASR), speech translation (ST), speaker verification (SV), emotion recognition (ER), instruction tuning (IT) and speech question answering (SQA), followed by advanced multi-task training on more complex tasks such as combinations of the elementary tasks. To enhance the flexibility and adherence to different tasks and instructions, a prompt-aware LoRA weight adapter is introduced in the second advanced multi-task training stage. We validate the proposed model on universal speech benchmarks including tasks such as ASR, ST, SV, ER, and also apply it to specialized datasets like Gaokao English listening comprehension set for SQA, and speech Chain-of-Thought (CoT) evaluation set. Experiments demonstrate that the proposed model achieves state-of-the-art performance across a range of speech tasks on the same model size, exhibiting robust generalization capabilities in executing complex tasks using CoT approach. Furthermore, our model successfully completes Gaokao English listening comprehension tasks without specialized training. The codes, models, audio samples, and Gaokao evaluation set can be accessed at aka.ms/wavllm.

1 Introduction

Large language models (LLMs) have witnessed a meteoric rise in advancement within the last couple of years, reaching or even exceeding the proficiency of humans in a myriad of natural language processing (NLP) tasks [OpenAI, 2023, Touvron et al., 2023, Anil et al., 2023]. These impressive capabilities are attributable to the large-scale training of vast training datasets and a substantial number of model parameters, combined with advanced training methodologies, like instruction-following protocols and Reinforcement Learning from Human Feedback (RLHF) algorithms [Ouyang et al., 2022]. With large language models attaining substantial breakthroughs, the focus is increasingly

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shifting towards the capabilities and advancements of multi-modal large language models (MLLMs), which possess the ability to listen [Tang et al., 2023, Deshmukh et al., 2023], speak [Rubenstein et al., 2023, Hao et al., 2023], see [Huang et al., 2023, OpenAI, 2023], and create content [Pan et al., 2023, Brooks et al., 2024].

Amidst the broadening scope of abilities, speech stands out as a crucial form of human communication, prompting extensive research to equip large language models (LLMs) with speech perception capabilities [Shu et al., 2023, Wu et al., 2023, Tang et al., 2023, Chu et al., 2023]. Typically, LLMs are augmented with an auxiliary audio encoder designed to preprocess audio signals, transforming them into the same input space as that of the LLMs, enabling them to achieve various speech tasks, such as automatic speech recognition (ASR), speech question answering (SQA), and so on. However, previous research has yet to overcome significant challenges in achieving effective generalization due to two main issues: (1) specialized tasks are highly sensitive to prompt design, resulting in performance degradation when confronted with unseen or complex instructions; (2) there is an absence of speech Chain-of-Thought (CoT) capability, which is essential for addressing complex tasks.

In this work, we propose a robust and adaptive speech large language model, WavLLM, aiming at enhancing the generalization capabilies, following speech instruction effectively, and processing the given speech in accordance with provided textual prompts, as well as supporting multi-round dialog. Specifically, to distinguish various types of speech information, we utilize a Whisper [Radford et al., 2023] encoder to encode the semantic content of the speech, and a WavLM [Chen et al., 2022] encoder to capture the acoustic information, like unique characteristics of the speaker's identity. During the model training phase, we develop a curriculum learning method that progressively fine-tune LLMs to follow instructions for understanding and processing speech, starting from simple tasks and advancing towards more complex ones. In the initial mixed single-task training stage, we leverage a substantial dataset of synthesized spoken question-answering content generated by GPT-4 and tailored to various speech-centric tasks such as automatic speech recognition (ASR), speech-to-text translation (ST), emotion recognition (ER), speaker verification (SV), and so on, to fine-tune the WavLLM with Low Rank Adaptation (LoRA) techniques [Hu et al., 2021]. Our preliminary experiments indicate that incorporating speech modality into LLMs by efficient fine-tuning technique, e.g., LoRA, may result in over-fitting on the training tasks, particularly on ASR task, and leading to subpar generalization on the unseen or complex instructions. To this end, we introduce a novel prompt-aware LoRA weight adapter in the advanced multi-task training stage. This adapter, trained on a specially constructed prompt-aware multi-task dataset, such as combinations of the elementary tasks, can adaptively adjust the LoRA weights in response to the different prompts, with the goal of enhancing the generalization ability of the initial model.

We evaluate the proposed model on 1) single tasks, including a) universal speech benchmark, for speech recognition, speaker verification, emotion recognition and speech translation; b) spoken-query-based question answering and English Listening Comprehension test in Chinese National College Entrance Examination (Gaokao), which presents a spoken dialogue between various speakers, and requires to answer text-based single-answer multiple-choice questions related to the conversation, and 2) multiple tasks, consisting of c) instruction-independent multi-tasks dataset that combines multiple independent prompts within a single instruction; d) speech CoT evaluation set that decomposes a complex task into multiple sub-tasks for effective assessment. Extensive evaluations demonstrate that our proposed model exhibits robust generalization and CoT capabilities, consistently surpassing strong baselines across a broad spectrum of speech-related tasks.

In summary, the contributions of this paper can be categorized as follows:

- Equipped with a prompt-aware LoRA weight adapter, we introduce a curriculum learningbased training approach that progressively fine-tunes large language models to follow instructions with strong speech processing and comprehension capabilities, starting from simple tasks and advancing to more complex ones.
- Our model decouples speech information into semantic and acoustic components, employing the Whisper encoder and the WavLM encoder to model them separately, which enhances the speech representation and yields benefits for downstream tasks.
- WavLLM demonstrates exceptional generalization capabilities when responding to diverse prompts and completing complex tasks. It exhibits impressive capabilities in zero-shot

SQA such as Gaokao English listening comprehension, and shows strong proficiency in CoT-based tasks, delivering performance gains over non-CoT tasks.

2 Related Work

The exploration of multi-modal large language models involves the integration of diverse data types including text, images, video, speech, audio, and more. This represents a natural progression from text-based large language models, designed to enable the perception of the world and the creation of content through the integration of various forms of input beyond text [OpenAI, 2023, Huang et al., 2023, Hao et al., 2023]. For instance, Kosmos-1 [Huang et al., 2023] and GPT-4V [OpenAI, 2023] are able to perceive general modalities beyond text, and follow instruction provided by users to process and analyze image inputs. Another research direction focuses on improving the multi-modal generative abilities of language models, enabling them to produce visual content like images or videos, as exemplified by MiniGPT-5 [Zheng et al., 2023] and Sora [Brooks et al., 2024]. Related research to this work focuses on speech-enhanced large language models that aim to endow LLMs with the capability to perceive and process speech signal [Zhang et al., 2023, Shu et al., 2023, Wu et al., 2023, Tang et al., 2023, Chu et al., 2023].

Among these studies, SpeechGPT [Zhang et al., 2023] empowers large language models with cross-modal conversational abilities by three-stage training stages, using hidden units as the discrete representation of speech. It constructs a speech-text cross-modal instruction-following dataset based on ASR data and textual SFT data. LLaSM [Shu et al., 2023] builds a large Chinese/English speech-language model that can understand and follow instructions, through pre-training stage and cross-modal instruction fine-tuning stage. SALMONN [Tang et al., 2023], named from a speech audio language music open neural network, boosts large language models with generic hearing abilities with a activation tuning stage by playing with the LoRA scaling factor. Qwen-audio [Chu et al., 2023] scales up audio-language pre-training to cover over 30 tasks and various audio types, including human speech, natural sounds, music, and songs. Despite achieving impressive results on specific speech tasks and being capable of following instructions to complete tasks, they continue to encounter challenges with regard to their weak generalization capabilities to complex tasks.

Motivation Previous research on Speech Large Language Models (Speech LLMs) has primarily concentrated on executing a single speech task in response to a given instruction, while the feasibility of using a single instruction to simultaneously complete multiple and complex speech tasks has remained unexplored. The employment of multi-task instructions allows for the efficient completion of several tasks at once and improves performance by dividing complex tasks into logical, related sub-tasks, such as CoT tasks.

Our initial experiments indicate that (1) prior open-source speech LLMs underperformed in multitask scenarios, demonstrating these models' limited ability to generalize to complex instructions; (2) reducing the LoRA scaling factor can be beneficial for multi-task instructions, but leads to a substantial degradation of the results of training tasks [Tang et al., 2023], which suggests that single and multiple tasks might benefit from distinct LoRA scaling factors; (3) there is a notable decline in performance when the model encounters unseen or diverse prompts as opposed to seen prompts (3.5% vs. 2.1%, see Section 4.4), when employing various prompts to evaluate the ASR performance of the open-source model. Consequently, we introduce a curriculum learning approach that progresses from simple to complex instruction tasks, propose a prompt-aware LoRA weight adapter which dynamically adjusts the amplitude of the LoRA output according to the instruction, and further enhance the generalization by utilizing a diverse array of prompts generated by GPT-4 across all training tasks.

3 Method

In this section, we will first introduce the model architecture of the proposed framework (See subsection 3.1), consisting of dual speech encoders with modality adapters, and LLM with prompt-aware LoRA weight adapter. In subsection 3.2, we outline the training stages based on curriculum learning, which initially equip the LLM with strong speech processing and comprehension capabilities. Subsequently, in the second advanced multi-task training stage, the model is augmented with the capacity to generalize across complex multi-task instructions, achieving this without compromising

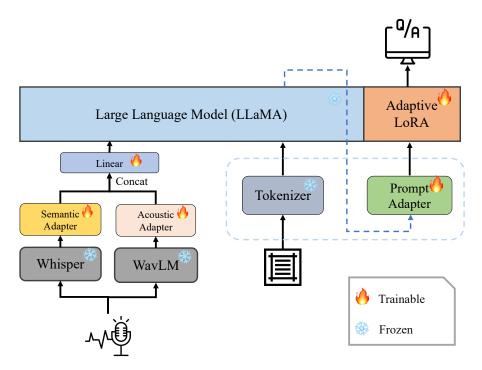


Figure 1: Overview of the proposed WavLLM. Two speech encoders and adapters with different focuses are utilized, where Whisper and the corresponding adapter is used for extracting semantic information, and WavLM for extracting acoustic information. Before being fed to the LLM, these two representations are concatenated together and linearly transformed. Adaptive LoRA approach is used for cross-modal efficient fine-tuning with online adaptation, where the prompt adapter is able to generate prompt-dependent parameters to adjust the amplitude of LoRA in the second advanced multi-task training stage.

its performance on single speech tasks. The WavLLM is optimized by maximizing the following probability:

$$p(\boldsymbol{Y}|[\boldsymbol{X},\boldsymbol{T}];\boldsymbol{\Theta}) = \prod_{t=0}^{T_Y} p(\boldsymbol{y}_t|[\boldsymbol{X},\boldsymbol{T},\boldsymbol{Y}_{< t}];\boldsymbol{\Theta})$$
 (1)

where X and T are the speech input and text prompt respectively. $Y = [y_1, y_2, ..., y_{T_Y}]$ is the target text output. Θ denotes the parameters of WavLLM. The detailed template of WavLLM's training data can be found in Appendix D.

3.1 Model Architecture

The model architecture of our framework is shown in Figure 1, which consists of speech encoders (i.e., Whisper [Radford et al., 2023] and WavLM [Chen et al., 2022]) as well as modality adapters, a large language model (i.e., LLaMA [Touvron et al., 2023]) and a proposed prompt adapter.

Speech Encoders and Modality Adapters In order to extract both the semantic and acoustic information in the speech, we utilize two state-of-the-art speech encoders, namely Whisper and WavLM. Whisper is trained for ASR and ST tasks in a weakly supervised fashion on a massive 680k-hour speech corpus recorded in diverse conditions, making it well suited for encoding semantic information in speech. WavLM is a predictive based self-supervised learning (SSL) pre-trained model. During its pre-training stage, WavLM mixes each utterance with signals from multiple speakers in the same batch, yet selectively predicts only the targets associated with the utterance's original speaker. Such training method allows WavLM to better extract speaker-related acoustic information. In our work, the 32-layer transformer-based encoder of Whisper-large-v2 and WavLM-base are utilized. Both modality adapters have three components, including two 1-D convolution layers to down-sample and align the output of both encoders within the temporal domain, a down-up bottleneck adapter

[Houlsby et al., 2019], and a final linear projector. The semantic adapter receives its input from the Whisper encoder's output, while the acoustic adapter takes a weighted sum of the hidden states from all layers of WavLM, where the weights are learnable. The outputs of both adapters are concatenated together before feedforwarding into the linear projector.

LLM, LoRA and Prompt Adapter Our framework utilizes the LLaMA-2-7B-chat as the LLM backbone, featuring a 32-layer Transformer decoder with an attention dimension of 4096, specifically optimized for dialogue-related use cases. To integrate the speech modality within the LLM, we employ the parameter-efficient fine-tuning method known as LoRA, which is specifically applied to the key, query, value, and output weight matrices within the attention module of the LLaMA.

To enable adaptive LoRA scaling factors for different single-task and multiple-task instructions, inspired by adapter layer in Houlsby et al. [2019], we design an online adaptation strategy by introducing a down-up prompt-aware LoRA weight adapter (aka. prompt adapter) with attention weights, designed to modulate the effect of LoRA on LLaMA, as shown in Figure 1. This is achieved by producing D-dim tailored parameters in response to the provided instruction, prior to LoRA's interaction with LLaMA, where D is the dimension of the LoRA representations. As shown in Figure 1, given the text-based prompts T with length M, we can get the representation $t \in \mathbb{R}^{D \times M}$ with LLAMA, $t = f(T; \Theta_{\text{LLaMA}})$, and this representation is fed into the prompt adapter to get the LoRA scaling factors, $t \in \mathbb{R}^{D \times 1}$:

$$r = g(t; \Theta_{\text{prompt_adapter}})$$
 (2)

$$= \operatorname{Softmax}(I_D(W_A o)) \odot o I_M \tag{3}$$

$$o = P^u \text{GeLU}(P^d t)$$
 (4)

where $\boldsymbol{W}_A \in \mathbb{R}^{1 \times D}$ is the matrix of attention weights, $\boldsymbol{I}_D(\boldsymbol{W}_A \boldsymbol{o}) \in \mathbb{R}^{D \times M}$ is unnormalized weights for the hidden states $\boldsymbol{o} \in \mathbb{R}^{D \times M}$. $\boldsymbol{I}_D \in \mathbb{R}^{D \times 1}$ and $\boldsymbol{I}_M \in \mathbb{R}^{M \times 1}$ are the all-ones vectors. $\boldsymbol{P}^u \in \mathbb{R}^{D \times K}$ and $\boldsymbol{P}^d \in \mathbb{R}^{K \times D}$ are up-linear projection and down-linear projection layers respectively, and GeLU is the GeLU activation function. The hidden states of an attention layer equipped with adaptive LoRA are expressed by:

$$h = W_0 x + (BAx) \odot (r I_{M+N}^T)$$
(5)

where $\boldsymbol{x} \in \mathbb{R}^{D \times (N+M)}$ is the input of the attention layer from the speech input \boldsymbol{X} with the length N and text prompt \boldsymbol{T} . $\boldsymbol{B} \in \mathbb{R}^{D \times R}$ and $\boldsymbol{A} \in \mathbb{R}^{R \times D}$ are the LoRA parameters, $\boldsymbol{W_0} \in \mathbb{R}^{D \times D}$ is a weight matrix in the attention layer. $\boldsymbol{I}_{M+N} \in \mathbb{R}^{(M+N) \times 1}$ is the all-ones vector.

3.2 Curriculum Learning

In this section, we present the two-stage curriculum-learning (CL) based training method, which facilitates a progression from learning simple data to understanding complex data, thereby enhancing the model's capacity for generalization.

3.2.1 Mixed Single-Task Training Stage

In the first stage, various single-task, cross-modal, speech-text pairing datasets or text-only datasets are utilized to endow the LLM with robust capabilities in speech processing and comprehension. We freeze the parameters of LLM, WavLM, and Whisper encoder, and optimize the modality adapters, a linear layer and LoRA components within the large language model.

Data Construction The first mixed single-task training stage involves various speech tasks, including automatic speech recognition (ASR), speech-to-text translation (ST), speaker verification (SV), emotion recognition (ER), spoken-based instruction tuning and text-based instruction tuning (IT) tasks, as well as a large mount of GPT-generated speech question answering (SQA). There are various questions within the SQA tasks, including those related to the speaker and gender, as well as continuation and summary tasks. Concurrently, these tasks draw upon multiple datasets, including LibriSpeech [Panayotov et al., 2015] with English reading speech, AMI [Carletta et al., 2005] with multi-talker meeting recordings, as well as Fisher [Cieri et al., 2004] and Switchboard [Godfrey et al., 1992] corpora with 2-channel English telephony conversations. Examples of the training data and prompts used to generate data with GPT-4 can be found in the Appendix A.1 and A.3 respectively.

Table 1: Training data used in the first stage and second stage. For all tasks, the instructions are diverse. "#Hours" refers to the duration of speech data for each task, not the total number of hours of the data source. The targets of SQA tasks are generated using GPT3.5, GPT-4 or LLAMA-2-chat.

Task	Description	Data Source	#Hours
	automatic speech recognition (ASR)	LibriSpeech [Panayotov et al., 2015] LibriHeavy medium [Kang et al., 2023]	960 1800
	speech-to-text translation (ST), including English to German (En2De), English to Japanese (En2Ja), and English to Chinese (En2Zh)	CoVoST2 [Wang et al., 2020] MuST-C [Di Gangi et al., 2019]	440 280
	speaker verification (SV)	VoxCeleb [Nagrani et al., 2017]	1290
Single	emotion recognition (ER)	IEMOCAP Session 1-4 [Busso et al., 2008]	5
-task	speech question answering (SQA),	LibriSpeech	520
tuore	including gender and speaker-related questions,	AMI [Carletta et al., 2005]	50
	and multi-round QA	Fisher [Cieri et al., 2004]	710
		Switchboard [Godfrey et al., 1992]	230
	speech question answering (SQA), continue writing tasks	LibriSpeech	960
	speech question answering (SQA), summary tasks	LibriSpeech	410
	instruction tuning (IT), including spoken based and text based tasks	Alpaca [Taori et al., 2023]	90
	ER + text based IT	IEMOCAP Session 1-4, Alpaca	71
	ASR + text based IT	LibriSpeech, Alpaca	274
	ST + text based IT	CoVoST2, MuST-C, Alpaca	343
Multi	SV + text based IT	VoxCeleb, Alpaca	243
-task	SQA + text based IT	AMI, Fisher, Switchboard, Alpaca	773
-task	ASR + ST	LibriSpeech	74
	ASR + SQA	LibriSpeech	43
	ASR + ST + text-based IT	CoVoST2, Alpaca	5
	ASR + SQA + text-based IT	LibriSpeech, Alpaca	1066

The speech audio clips of spoken-based instruction tuning task are generated by using Microsoft Azure text-to-speech API¹. In Table 1, we list the detailed task information about description, data source, and data hours.

3.2.2 Advanced Multi-Task Training Stage

Owing to the incongruity between textual and spoken modalities, extensively fine-tuning the model using the LoRA method on a large amount of prompt-repetitive speech-text data, such as ASR and ST tasks, may cause the model to overfit on specific speech tasks, thereby compromising the LLM's powerful instruction-following capabilities. For instance, the model exhibits subpar performance when handling multi-task instructions, often only managing to accomplish a fraction of the tasks assigned. Specifically, if ASR is included in the tasks, the model might complete only the ASR portion while failing to address the remaining instructions.

To this end, we construct a more complex prompt-aware multi-task dataset in the second stage, by integrating various single-task instructions. Multi-task and single-task datasets are utilized together in this training stage. Besides, we noted that simply incorporating more challenging training data may slightly diminish the performance of single-task instructions, such as ASR, when compared to results of the first training phase. Hence we introduce a prompt adapter, as illustrated in Section 3.1, to produce adaptive LoRA scaling factors for different instructions and tasks, and serve as an effective approach to concurrently enhance the model's generalization capabilities.

Data Construction Given a speech audio clip, we combine different task prompts for this audio segment as well as text-based instruction tuning tasks in the first mixed single-task training stage together as instructions, and then the training target is designed to complete the tasks sequentially and to repeat key parts of each prompt prior to delivering a response. For example, for an utterance in LibriSpeech, ASR, SQA and text-based IT (t-IT) tasks can be combined into multi-task dataset. Please refer to Appendix A.2 for specific examples. In our work, a total of 2.9K hours of various multitask data are used, including ER+t-IT, ASR+t-IT, ST+t-IT, SV+t-IT, SQA+t-IT, ASR+ST, ASR+SQA, ASR+ST+t-IT and ASR+SQA+t-IT combined tasks, which are summarized in Table 1.

4 Experiments

4.1 Implementation Details

As mentioned above, the semantic and acoustic speech encoders are the encoder of Whisper-large-v2² and WavLM-base³, the backbone LLM is LLaMA-2-chat-7b⁴, and all of their parameters are frozen. The outputs of both modality adapters have a time stride of 80 ms and a dimension of 2048, and the rank (R) of LoRA is set as 32. In the first mixed single-task training stage, the total number of parameters in our model is 7.55 billion, of which 76.6 million are trainable. In the advanced training phase, the bottleneck dimension (K) of the prompt adapter is set as 1024. The 4096-dimensional prompt-dependent parameters produced by prompt adapter are element-wise multiplied with the outputs of the LoRA. Our models are trained with the two-stage curriculum-learning method on 32 V100 GPUs using the Adam optimizer, set with hyperparameters $\beta_1 = 0.9$, $\beta_2 = 0.98$ and batch size equivalent to 30 seconds per GPU, where the first stage consisted of 400K steps and the subsequent stage involved an additional 150K steps. Additionally, we employed a maximum learning rate of 1×10^{-4} , incorporating a warm-up phase for the first 10% of steps. The two-stage training data are presented in data construction part of Section 3.2.

4.2 Evaluation Setup

Corresponding to the training methods, two primary levels of testing tasks were conducted, namely, single-task evaluation and multi-task evaluation. The detailed information of the two types of task evaluations are privided in the Table 2. Single-task evaluation consists of ASR, ST, SV, ER, SQA, and spoken-query-based question answering (SQQA). The key difference between SQQA and SQA is that in SQQA, the audio contains the question, usually about general knowledge, and the model must directly answer the question asked in the speech; whereas, SQA involves speech that ofen takes the form of a conversation or statement, and the model must understand the content of the speech and then integrate with given instructions to answer the question within instructions. In our work, the single-answer multiple-choice questions of English Listening Comprehension examination (Gaokao) in China are used as the zero-shot SQA task, which gives a short dialogue, a question, and three options, the model is required to choose the correct one from the three options. The performance of SQA is not only a measure of the comprehension of the cross-modal speech and textual content, but also serves as an indicator of the model's generalization capabilities with respect to a diverse array of instructions.

In the multi-task evaluation, two distinct types of tasks are presented, both of which are given a speech audio clip: the tasks that consist of independent instructions (II-Task) and the tasks that feature sequentially progressive instructions, which are also known as CoT tasks. Examples of these two tasks can be found in the Appendix B. For tasks with independent instructions, our focus lies on not only the ability to follow instructions, i.e. instruction following rate (IFR), but also the correct completion of each instruction. Whereas for CoT tasks, our primary concern is the performance of the final instruction, which will be compared to the performance of one-shot non-CoT based instructions. The audio for zero-shot II-task is from the SQA task (Gaokao), the multitasking instruction includes ASR, SQA, ST and the general knowledge question task. The audio for zero-shot CoT task is generated from the Gigaword [Graff et al., 2003] dataset using Microsoft Azure text-to-speech API, and the target German texts are translated from English summaries of Gigaword dataset⁵ by utilizing GPT-4. The CoT task requires the Speech LLM complete the ASR, summary and translation tasks in turn. In contract, the instructions of one-shot non-CoT based tasks require the cross-lingual summarization directly. For open-ended or target-lack test sets, GPT-4 is utilized to score the outputs, including the accuracy of SQQA and II-task, which is conducted three times and then take the average to minimize the randomness introduced by GPT-4. In addition, the IFR of SQQA is scored manually on 10% of the test utterances.

¹https://azure.microsoft.com/en-us/products/ai-services/text-to-speech

²https://huggingface.co/openai/whisper-large-v2

³https://huggingface.co/microsoft/wavlm-base

⁴https://huggingface.co/meta-llama/Llama-2-7b-chat-hf

⁵Translation directions of ASR+SQA+ST tasks in second advanced training stage are all English to Chinese.

Table 2: Single-task and multi-task evaluation benchmarks, including tasks, datasets, and metrics.

Task	(Dataset	Split	Metric	
	ASR	LibriSpeech	test-clean test-others	WER (%)	
	ST	CoVoST2 MUSTC	En2De	BLEU	
Single-task	SV	VoxCeleb1	test set	Accuracy (%)	
Single-task	ER	IEMOCAP	Session 5	Accuracy (%)	
	SQQA	WikiQA [Yang et al., 2015]	test set	Accuracy (%)	
	SQA	MuTual [Cui et al., 2020]	test set of English listening comprehension exams	Accuracy (%)	
	II-Task	In-house, based on MuTual	-	Accuracy, IFR (%)	
Multi-task	СоТ	In-house, based on Gigaword [Graff et al., 2003]	-	R-1, R-2, R-L, BERTScore [Zhang et al., 2019]	
		In-house, based on story generated by GPT-4	-		

4.3 Main Results

Single-task Evaluation Table 3 shows the main results of our WavLLM on various single-task instructions compared to other open source speech LLMs and baseline system that combines Whisper large-v2 with LLaMA-2-7b-chat in a cascaded fashion. For the ASR task, our chat model achieves state-of-the-art WERs of 2.0% and 4.8% on test-clean and test-other sets of LibriSpeech corpus, surpassing other open-source chat models on the same size (7B), including SALMONN [Tang et al., 2023] and Qwen-Audio-Chat [Chu et al., 2023]. Comparable patterns of superior performance are observed in speech-to-text translation, speaker verification, emotion recognition and spoken-query-based question answering tasks.

The SQA task in our paper is the zero-shot English listening comprehension tests in China, which requires the model to be able to accurately understand and follow the prompt, as well as comprehend the content of speech. Two criteria are evaluated: the first requires that the correct choice must be explicitly given to be considered correct, while the second accepts answers that are semantically equivalent to the correct option, and is scored by utilizing the GPT-4 (The score instruction can be found in Appendix C.1). As shown in column "SQA" of Table 3, the first number is the accuracy based on the given option, and the second number is the accuracy scored by GPT-4. The larger the both accuracy, the better the model's comprehension and generalization capacity, while the smaller the difference between the both accuracy, the better the model's ability to follow instructions. From the results, we can observe that our WavLLM model consistently surpasses the cascaded Whisper + LLaMA baseline, and other open source speech large language models. Additionally, our WavLLM model supports multiple dialogue scenario, with a representative instance detailed in Appendix E.

Table 3: Single-task instruction performance of our WavLLM model compared to other open-source speech large language models and cascaded Whisper+LLM baseline model. "*" stands for the results from public paper.

	ASR		ST (Er	ST (En2De)		ER	SOOA	SOA	
Models	test-clean	test-other	CoVoST2	MUSTC	SV	LK	SQQA	SQA	
	WER↓		BLEU [↑]		Acc. [↑]	Acc. [↑]	Acc. [↑]	Acc. [↑]	
Whisper + LLM	2.7*	5.2*	18.2	11.5	-	-	0.78	59.30% (63.50%)	
SALMONN-7B	2.4	5.4	17.1	12.5	0.86	-	-	39.95% (40.00%)	
SALMONN-13B	2.1*	4.9*	18.6*	19.5	0.94*	0.69*	0.41*	43.35% (43.35%)	
Qwen-Audio-Chat 7B	2.2	5.1	23.2	18.4	0.50	-	0.38	25.50% (54.25%)	
Our WavLLM 7B	2.0	4.8	23.6	21.7	0.91	0.72	0.57	67.55% (67.55%)	

Multi-task Evaluation Table 4 shows the results of our WavLLM model on zero-shot independent instructions tasks (II-task) and CoT-task instructions compared to other open source speech large language models. Despite the optimization of SALMONN through activation tuning, and the fact that Qwen-Audio-Chat conducts fine-tuning only on audio encoder without impacting LLM by LoRA weights, their performance in following multitasking instructions remains significantly suboptimal.

Our final chat model demonstrates a markedly higher instruction-following rate for the II-Task compared to open-source models like SALMONN and Qwen-Audio-Chat (92.50% vs. 24.25%-57.75%), which highlights the necessity and effectiveness of our advanced multi-task training stage with prompt adapter. From the accuracy based on the GPT-4, which focuses not only on whether instructions are followed, but also on whether they are completed correctly, similar trend can be observed (62.44% vs. 19.58%-37.99%). The score instruction can be found the Appendix C.2.

When the model possesses the capability to handle multi-task instructions, we aspire to enhance its performance through the employment of Chain of Thought (CoT) methodology. Specifically, the CoT based prompt is excepted to give a better performance than one-shot non-CoT based instructions which require the cross-lingual summarization directly. We list the examples of these two types of prompts in the Appendix B.2. From the results in Table 4, we can draw two conclusions: 1) Our WavLLM model produces the best performance on the CoT-task instructions; 2) Compared with the performance given one-shot non-CoT instructions, our model produces consistent performance improvements on all metrics.

Table 4: Multi-task instruction performance of our WavLLM model compared to other open-source speech large language models.

Models	II-tasks		CoT (ASR+SUMM+En2De, gigaword)				w/o CoT (De_SUMM, gigaword)			
Wiodels	Acc. [↑]	IFR↑	R-1 [↑]	R-2 [↑]	R-L [↑]	BERTScore [↑]	R-1 [↑]	R-2 [↑]	R-L [↑]	BERTScore [↑]
SALMONN-7B	22.49	34.50	11.9	2.4	10.7	66.46	15.0	3.3	13.5	69.50
SALMONN-13B	19.58	24.25	10.9	2.1	9.8	68.12	14.0	2.9	12.6	69.11
Qwen-Audio-Chat 7B	37.99	57.75	5.9	0.9	5.7	67.62	5.8	0.9	5.3	65.84
Our WavLLM 7B	62.44	92.50	16.5	4.1	14.7	70.60	15.4	3.8	13.9	70.37

4.4 Analysis

The Effect of Advanced Training Table 5 and 6 show the results of our models after first mixed single-task training stage and second advanced multi-task training stage. As discussed earlier, the model with only mixed training is incapable of generalizing to multi-task instructions, and the poor performance of II-tasks confirms this. After advanced training, our model produces comparable or even better performance on single-task prompts compared to the first-stage model. For zero-shot II-tasks, significant enhancement of generalization ability is obtained after advanced training, as evidenced not only by the increased adherence to instructions (92.50% vs. 26.25%) but also by the higher accuracy of each executed instruction (62.44% vs. 22.92%). For cross-lingual summary tasks using CoT based instructions, our model after the second advanced multi-task training stage consistently outperforms the first stage model. In addition, we found that the first stage model mainly accomplished the ST task and did not perform the summarization task. To better demonstrate the effectiveness of the second stage, we crafted a long story-based CoT task by GPT-4 where the audio contains a 100-word story, and the target is a 20-word summary in German. In this task, if the model solely focuses on completing the translation, there will be a noticeable discrepancy in length between its output and the desired target. From the results of this task in Table 6, the second advanced multi-task training stage model significantly outperforms the first stage model. Similar results are obtained when utilizing SALMONN-7B to conduct story-based CoT task instructions, which produces 10.6, 1.3, 7.8 and 63.90 on R-1, R-2, R-L and BERTScore respectively.

Table 5: Performance of model with or without advanced training on single-task instructions. *mixed training* means the first mixed single-task training stage, and *advanced training* means the second advanced multi-task training stage.

	A	SR	ST (Er	2De)	SV	ER	SQQA	SQA
Models	test-clean	test-other	CoVoST2	MUSTC	3 4	LIX	зуул	
	WER↓		BLEU [↑]		Acc. [↑]	Acc. [↑]	Acc. [↑]	Acc. [↑]
mixed training	2.0	4.8	23.9	21.9	0.91	0.72	0.55	67.30%
+ advanced training	2.0	4.8	23.6	21.7	0.91	0.72	0.57	67.55%

Table 6: Performance of model with or without advanced training on multi-task instructions. II-tasks and CoT tasks refer to independent instruction and chain-of-thought tasks, as detailed in section 4.2.

Models	II-tasks		CoT (ASR+SUMM+En2De, gigaword)				CoT (ASR+SUMM+En2De, story)			
Wiodels	Acc. [↑]	IFR↑	R-1 [↑]	R-2 [↑]	R-L [↑]	BERTScore [↑]	R-1 [↑]	R-2 [↑]	R-L [↑]	BERTScore [↑]
mixed training	22.92	26.25	14.7	3.3	13.2	69.71	18.0	2.9	13.7	68.61
+ advanced training	62.44	92.50	16.5	4.1	14.7	70.60	24.5	4.8	19.0	72.52

The Effect of Prompt Adapter Despite the fact that data-level curricular learning benefits the performance on complex cross-modal tasks, we have observed that the method of sharing LoRA parameters between single-task and multi-task instructions can diminish the performance on single-task prompts. Concurrently, we believe that this approach may also constrain the performance on multi-task instructions. A prompt-aware LoRA weight adapter (prompt adapter) is proposed to address this issue. Comparative experiments are conducted to analyze the effect of prompt adapter during the second advanced multi-task training stage. Additionally, we build a one-stage model trained by combining all data, including both single-task and multi-task data.⁶

From the results of Table 7 and 8, the following conclusions can be drawn. Firstly, the results of two-stage model without a prompt adapter against one-stage model further demonstrate that the two-stage curriculum learning based training is effective as evidenced by 1) the comparable performance of single-task instructions; 2) consistent performance improvements on zero-shot II-task and CoT-task prompts. Secondly, incorporating the proposed prompt adapter consistently outperforms the baseline two-stage model without such module on all single-task and multi-task instructions.

Table 7: Performance of the model across training stages with and without a prompt adapter on single-task instructions. *one-stage* denotes the model is trained by utilizing all single-task and multi-task data simultaneously. *two-stage* (*LoRA*) stands for two-stage training method with only LoRA technique.

	A:	SR	ST (Er	SV	ER	SOOA	SOA	
Models	test-clean	test-other	CoVoST2	MUSTC	31	LK	SQQA	SQA
	WER↓		BLEU↑		Acc. [↑]	Acc. [↑]	Acc. [↑]	Acc. [↑]
one-stage	2.1	5.0	22.7	21.0	0.88	0.71	0.51	65.35%
two-stage (LoRA)	2.1	5.1	23.3	21.2	0.89	0.71	0.54	63.70%
+ Prompt Adapter	2.0	4.9	23.6	21.6	0.90	0.72	0.57	65.00%

Table 8: Performance of the model across training stages with and without a prompt adapter on multi-task instructions.

Models	II-ta	asks	CoT (ASR+SUMM+En2De, gigaword)				
IVIOUCIS	Acc. [↑]	IFR↑	R-1 [↑]	R-2 [↑]	R-L [↑]	BERTScore [↑]	
one-stage	59.34	85.50	14.8	3.4	13.2	69.64	
two-stage (LoRA)	61.15	90.25	15.8	3.8	14.5	70.42	
+ Prompt Adapter	63.05	92.75	16.5	4.0	14.8	70.75	

The Effect of WavLM WavLM model has been widely used for speech processing as a foundation model, especially for speaker information extraction. Table 9 shows the single-task instruction performance on models with or without WavLM encoder after the first mixed single-task training stage. Incorporating WavLM-base encoder not only brings performance improvements to speaker verification task but also enhances other tasks such as ASR (relative WER reductions of 13.04% and 11.11% on test-clean and test-other) and ST tasks.

⁶Due to the computing resource constraints, only a portion of the single-task dataset are utilized during the second advanced multi-task training stage in this section.

Table 9: Single-task instruction performance of models with or without WavLM encoder after the mixed training.

	AS	SR	ST (Er	n2De)	SV	ER	SOOA	SQA
Models	test-clean	test-other	CoVoST2	MUSTC	3 4	LK	SQQA	
	WER↓		BLEU↑		Acc. [↑]	Acc. [↑]	Acc. [↑]	Acc. [↑]
WavLLM	2.0	4.8	23.9	21.9	0.91	0.72	0.55	67.30%
WavLLM w/o WavLM	2.3	5.4	23.4	21.0	0.89	0.73	0.55	68.55%

Robustness Analysis In this subsection, the robustness of the speech LLMs is evaluated by comparing the performance between the seen/single and the unseen/diverse prompts on our WavLLM model and SALMONN model. From the results in Table 10, compared to the SALMONN model, which experienced a decline in performance with unseen or diverse prompts, our WavLLM model does not exhibit any performance degradation with unseen prompts on ASR tasks and even produces performance improvement on the ST task, demonstrating our model's powerful robustness.

Table 10: Performance of models using seen (or single) or unseen (or diverse) prompts on WavLLM and SALMONN.

		AS	SR		ST-CoVoST2		
Models		WE	ER↓		BLEU↑		
Wiodels	tes	t-clean	tes	t-other	En2De		
	seen/single	unseen/diverse	seen/single	unseen/diverse	seen/single	unseen/diverse	
SALMONN-7B	2.4	81.8	5.4	85.5	17.1	15.9	
SALMONN-13B	2.1	3.5	4.9	8.8	18.6	18.2	
Our WavLLM 7B	2.0	2.0	4.8	4.8	23.4	23.6	

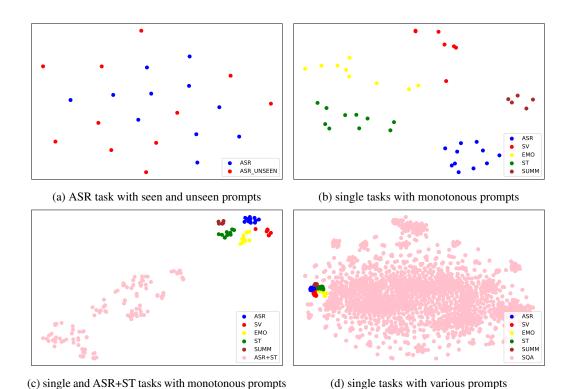


Figure 2: TSNE visualization of the proposed prompt adapter's outputs in our final WavLLM model. Each point corresponds to a prompt.

⁷For our WavLLM model, the training prompts are used as the seen prompts, while for SALMONN, the prompts in Fig.4 and 5 in the paper [Tang et al., 2023] are used as the single prompt. Various prompts generated by GPT-4 are used as unseen prompts for our model and diverse prompts for SALMONN.

Visualization of LoRA Weights In this subsection, TSNE [Van der Maaten and Hinton, 2008] based visualization of the proposed prompt adapter's output is given in Figure 2. Several trends can be observed: 1) The overlap between two clusters of the seen ASR prompts and unseen ASR prompts implies the generalization of the proposed prompt adapter; 2) the clear discrimination among single-task prompts suggests that the proposed prompt adapter is capable of discerning various single-task instructions and assigning disparate weights to each; 3) Similar strong discrimination between single-task and multi-task instructions is obtained which validates our motivation; 4) The wide distribution of the SQA task with various prompts, illustrates that the prompt adapter can accommodate diverse prompts.

5 Conclusion and Future Work

In this paper, we propose WavLLM, a robust and adaptive speech large language model, which uses LLaMA-2-chat as foundational LLM backbone, and extracts semantic and acoustic information from speech audio utilizing Whisper and WavLM encoders. Utilizing a curriculum learning approach, the proposed WavLLM commences with single-task instruction training in the initial mixed training phase and subsequently expanding our training to encompass additional multi-task prompts in the second advanced phase with the integration of the proposed prompt adapter. Massive experiments demonstrate that our WavLLM model delivers state-of-the-art performance on various speech-related tasks and robust generalization abilities on single-task and multi-task instructions, enhanced by a CoT processing ability that greatly improves its effectiveness in tackling intricate tasks. For future work, we are interested in advancing the capability to autonomously decompose complex one-shot instruction tasks into CoT based tasks, and equipping our model with the speech synthesis ability.

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A Some Examples of Training Data

A.1 SQA Task

speech transcript	instructions	targets	source
the nautilus would still have nothing to fear	What animal would still have	The nautilus.	LibriSpeech
from their attacks	nothing to fear from attacks?		
as gelatinous or glutinous matters impress	What is the gender of the	The speaker is fe-	LibriSpeech
the sense of touch i have spoken both of	speaker? And what is the	male. And she is talk-	
sound and of voice i mean to say that the	speaker talking about?	ing about sound and	
sound was one of distinct of even wonder-		voice being distinct.	
fully thrillingly distinct			
A: so how do you feel about it; B: uh i	What is the second speaker's	The second speaker	Switchboard
don't see any problem with with random-	opinion on random drug test-	doesn't see any	
testing for random drugs; A: yeah i myself	ing?	problem with random	
almost um am in favor of it uh; A: i work at	_	drug testing.	
Honeywell and i went through a a pretty i			
don't know i went through a standard drug			
testing thing before i was brought on; B:			
um-hum			

A.2 Multi-task Instruction Datasets

speech transcript	instructions	targets	source
the nautilus would still have	Initially, Analyze the speech	The audio transcription is: the nau-	LibriSpeech,
nothing to fear from their at-	in the given audio clip and	tilus would still have nothing to fear	Alpaca
tacks	provide a complete textual	from their attacks \n For the ques-	
	transcription; Then, answer	tion "What animal would still have	
	the question: What animal	nothing to fear from attacks?", the	
	would still have nothing to	response is: The nautilus. \n The	
	fear from attacks?; Thirdly,	response to "Come up with 5 activi-	
	ignore the audio clip, Come	ties for a birthday party for a 5-year-	
	up with 5 activities for a	old. " is: 1. Play a game of freeze	
	birthday party for a 5-year-	dance \n 2. Make balloon animals	
	old.	\n 3. Have a color scavenger hunt \n	
		4. Bake cupcakes \n 5. Make a craft	
		project together	

A.3 The Prompts for Generating SQA Data by GPT-4

You are asked to generate **only one** questions, and their corresponding answers, according to some conversational sentences given below. These sentences have been transcribed from conversational speech data with one or multiple speakers who are taking to each other. "Speaker A" and "Speaker B" in the senteces are labeled by human and your response must not contain human-marked information, namely "Speaker A" and "Speaker B". Here are the requirements: 1. Your response should strictly follow the format below: "Question": "xxx", "Answer": "xxx"; 2. Please ignore "Speaker A" and "Speaker B" in the given sentences. Your response should strictly not include the phrase "Speaker A" and "Speaker B"; 3. Your question should be highly related to the conversation, and your answer must be **correct**, and should be simple and clear. Besides, you question should be designed as your answer has to be reasoned from the conversation; 4. For example, a sentence "Speaker A: It is a good day; Speaker B: Yes, but I have to go to hospital" means that speaker A first say it is a good day and speaker B then say that Yes, but I have to go to hospital. 5. **Very Importance**: Your questions and answers **can not** contain the word "Speaker A" and "Speaker B", because "Speaker A" and "Speaker B" in the sentences are additional labels for transcripts, and they are different people. For example, the question "What is Speaker B's opinion?" **does not** meet the requirements because it contains word "Speaker B". Namely, you can not use "Speaker A" and "Speaker B" to represent they in questions and answers, maybe you can use the first or second speaker to denote "Speaker A" or "Speaker B"; 6. The type of response should be diverse. The respone **must contain** double quotation marks for each part. Here are the sentences: transcript

B Some Examples of Evaluation Data

B.1 Examples of II-task Instruction

speech transcript	instructions	targets	source
Women: "How much time	To begin, What will the man do next? A. Start to take	-	MuTual
do you usually spend exercis-	exercise; B. Do as he always does; C. Change his working		
ing daily?" Man: "Frankly	time.; Next, Create a French transcript for this English		
speaking, I'm an awfully	audio clip; Furthermore, Recognize the speech and give		
lazy man. I know it's time	me the transcription; Last step, setting aside the audio,		
to change."	Who wrote "The Adventures of Sherlock Holmes"?		

B.2 Examples of CoT-task and Non-CoT-task Instruction

speech transcript	instructions	targets	source
three films from Asia-Pacific are in the	First of all, transcribe the audio recording	Drei Film	ne gigaword
running for the coveted golden palms	into text, capturing every spoken word; Ad-	aus de	m
at this years Cannes film festival, com-	ditionally given this audio clip and text, can	asiatisch-	
peting in a field dominated by Euro-	you condense it into a clear, concise sum-	pazifischen	
pean productions, organizers announced	mary, no more than 20 words?; Lastly dis-	Raum i	m
Monday.	regarding the sound, translate this English	Rennen	in
•	summary into German.	Cannes	
three films from Asia-Pacific are in the	Please summarize the content of the audio	Drei Film	ne gigaword
running for the coveted golden palms	clip in German, no more than 20 words.	aus de	m
at this years Cannes film festival, com-	_	asiatisch-	
peting in a field dominated by Euro-		pazifischen	
pean productions, organizers announced		Raum i	m
Monday.		Rennen	in
·		Cannes	
			<u> </u>

C The Prompt for Scoring using GPT-4

C.1 SQA Scoring

Next, I will give you a multiple-choice question along with its correct answer, as well as a generated answer that needs to be evaluated for correctness. You will need to determine whether the given answer is correct based on the question and the correct answer, and give a simple reason. The answer must explicitly give the correct option to be considered correct and not by implication or indirect response. Your response should strictly follow the format:{"result": "xx", "reason": "xx"}, if the given answer is correct, then your response should be {"result": "True", "reason": "xx"}. Here is the question: {"What will the man do next? A. Start to take exercise; B. Do as he always does; C. Change his working time."}, and the correct answer is {"A"}, the answer that needs to be judged is {"B. Do as he always does"}.

C.2 II-task Scoring

Next i will give you an audio transcription, instructions related or unrelated to the audio, and the corresponding responses. You need to use the given information to figure out how many instructions were completed correctly in the given responses and how many were left unanswered or answered incorrectly, then give the simple and clear reason why each question was completed or not, Finally, you need to do the self-examination to ensure responses you give must be correct and without inconsistencies.

You must adhere to the following **rules**: 1. instructions are only answered sequentially, and one answer must only correspond to one instruction; 2. For choice questions, the answer must be in **English** and only **one** of the three options, multiple options or none of the options are considered incomplete, e.g. the answer is "A. xx; B. xx; C. xx." (note that options may appear across sentences or lines); 3. All instructions must be completed in **English**, except translation tasks; 4. The translation task is not a translation of instructions, but a translation of the content of the given audio speech 5. If the response is a repetition of the instruction, then it is considered not completed. Your response should strictly follow the format: {"instructions completed": "xx", "instructions incompleted": "xx", "Reasons for each instructions": ["instruction_1: xx", "instruction_2: xx", "instruction_3: xx", "instruction_4: xx"]}.

You need to refer to **this example**: the transcription of the audio: "So James What are you going to do for your birthday? Well, I was hoping to have a party but most of my friends are busy so I have accepted my sisters offer to take me to a film. At least it is better than going out for a meal with my parents."; the instructions are "To begin, ignore the audio clip, Who is known for developing the theory of relativity?; Then, What will the man do on his birthday? A. Have a party; B. See a movie; C. Go out for a meal.; Moreover, Convert the spoken words in this audio file into a textual format; Last step, Translate this English speech into Japanese";

and the respones are "1. エイトリングの理論を発展した人物は誰ですか?; 2. What will the man do on his birthday? A. Have a party; B. See a movie; C. Go out for a meal.; 3. この音声>ファイルをテキスト形式に変換してください。; 4. この英語のスピーチを日本語に翻訳してください。".

And your output should be {"instructions completed": "0", "instructions incompleted": "4", "Reasons for each instructions": ["instruction_1: incompleted, the answer is the Japanese translation of the instruction. Q&A task should be completed in English.", "instruction_2: incompleted, the answer is the a repetition of the instruction. More than one options were given", "instruction_3: incompleted, the answer is the Japanese translation of the instruction", "instruction_4: incompleted, the answer is the Japanese translation of the instruction"]}.

Be sure to carefully follow the rules and refer to the examples for responses.

Here is the transcription of the audio: {"I really want to go to the concert, but I haven't got a ticket yet leave it to me, I'll organize that we can go together really that's wonderful."},

the instructions are {"To begin, disregarding the sound, How many elements are on the periodic table?; Then, Translate this English speech into Japanese; Additionally, How will the speaker get a ticket to the concert? A. The man will go to buy the ticket; B. The woman will get the ticket; C. The man will have someone buy the ticket.; Lastly, Transcribe the given audio clip into text"},

the responses is {"Addressing the prompt 'How many elements are on the periodic table?", the answer is: There are currently 118 elements on the periodic table. From the audio, we have the following translations: コンサートに行きたいけどまだチケットがないのどうするんだ? For the question "How will the speaker get a ticket to the concert? A. The man will go to buy the ticket; B. The woman will get the ticket; C. The man will have someone buy the ticket.", the response is: B; The audio transcription is: i really want to go to the concert but i haven't got a ticket yet b leave it to me i'll organize that we can go together r really that's wonderful }

D Prompt Template for WavLLM

The template of our WavLLM containing a speech audio clip, text instructions and targets are constructed as follows:

<bos>[INST]«SYS»\n As a helpful language and speech assistant, you are able to understand the speech content provided by the user, and assist the user with a variety of tasks using natural language. \n«/SYS»\n\n <SPEECH>"speech" </SPEECH>"instruction" [/INST]" target "<eos>

where "speech" will be replaced by the 4096-dim speech features extracted from speech encoders and modality adapters, while "instruction" and "target" are the specific task prompts and outputs. The input to the WavLLM is this template with the <eos> removed, while the target is this template without the <bos>. During training, only the "target" part is involved in the loss calculation.

E Example of Multi-round Dialog



Women: How much time do you usually spend exercising daily? Man: Frankly, speaking, I'm an awfully lazy man I know it's time to change.



What will the man do next? A. Start to take exercise; B. Do as he always does; C. Change his working time.



The answer is A.



Why the answer is not B?



Because the man himself acknowledges that he is a lazy person and is willing to change.

Figure 3: An example of multi-round dialog based on Gaokao task