AIR-Bench: Benchmarking Large Audio-Language Models via Generative Comprehension

Anonymous ACL submission

Abstract

Recently, instruction-following audio-language models have received broad attention for human-audio interaction. However, the absence of benchmarks capable of evaluating audio-centric interaction capabilities has impeded advancements in this field. Previous models primarily focus on assessing different fundamental tasks, such as Automatic Speech Recognition (ASR), and lack an assessment of the open-ended generative capabilities centered around audio. Thus, it is challenging to track the progression in the Large Audio-Language Models (LALMs) domain and to provide guidance for future improvement. In this paper, we introduce AIR-Bench (**A**udio **I**nst**R**uction **Bench**mark), the first benchmark designed to evaluate the ability of LALMs to understand various types of audio signals (including human speech, natural sounds, and music), and furthermore, to interact with humans in the textual format. AIR-Bench encompasses two dimensions: *foundation* and *chat* benchmarks. The former consists of 19 tasks with approximately 19k single-choice questions, intending to inspect the basic single-task ability of LALMs. The latter one contains 2k instances of open-ended question-and-answer data, directly assessing the comprehension of the model on complex audio and its capacity to follow instructions. Both benchmarks require the model to generate hypotheses directly. We design a unified framework that leverages advanced language models, such as GPT-4, to evaluate the scores of generated hypotheses given the meta-information of the audio. Experimental results demonstrate a high level of consistency between GPT-4-based evaluation and human evaluation. By revealing the limitations of existing LALMs through evaluation results, AIR-Bench can provide insights into the direction of future research.

1 Introduction

Recent advancements in artificial general intelligence have been significantly driven by the emergence of large language models (LLMs) (Brown et al., 2020; OpenAI, 2022, 2023; Chowdhery et al., 2022; Anil et al., 2023; Touvron et al., 2023a,b; Bai et al., 2023a). These models exhibit remarkable abilities in retaining knowledge, engaging in intricate reasoning, and solving problems following human intents. Motivated by the striking progress in large language models (LLMs), the domain of large audio-language models (LALMs) has undergone a revolutionary transformation. To perceive and comprehend rich audio signals and further generate textual responses following human instructions, many works have been proposed, such as SALMONN (Tang et al., 2023a), BLSP (Wang et al., 2023a), Speech-LLaMA (Wu et al., 2023a), and Qwen-Audio (Chu et al., 2023), showcasing promising capabilities for audio-central dialogues.

However, previous LALMs (Tang et al., 2023a; Wang et al., 2023a; Wu et al., 2023a; Chu et al., 2023; Huang et al., 2023b; Shen et al., 2023; Gong et al., 2023; Wang et al., 2023b) have predominantly concentrated on evaluation in specific fundamental tasks. The absence of a standardized benchmark for assessing the generative instruction-following abilities of these models has resulted in a reliance on showcasing examples or releasing the chat models for public experimentation to demonstrate their conversational skills. This approach poses significant challenges for conducting fair and objective comparisons across different research endeavors. Moreover, it tends to obscure the models' existing limitations, impeding the ability to monitor advancements within the domain of LALMs.

For evaluation in audio domains, the majority of research efforts have concentrated on the creation of benchmarks tailored to individual tasks such as LibriSpeech (Panayotov et al., 2015) and Common Voice benchmark (Ardila et al., 2019) for ASR. Beyond task-specific ones, benchmarks like SUPERB (Yang et al., 2021a) and HEAR (Turian et al., 2021) have been designed to test the versatility of

self-supervised learning models in a wide variety of tasks. Regarding the assessment of LALMs' ability to follow instructions, to the best of our knowledge, Dynamic-SUPERB (Huang et al., 2023a) is the only benchmark devoted to this aspect. Nevertheless, Dynamic-SUPERB only focuses on human speech processing and does not extend to the assessment of models' capabilities in producing open-ended generations such as dialogues.

In this paper, we present AIR-Bench (**A**udio **I**nst**R**uction **Bench**mark), a novel benchmark designed to evaluate the ability of LALMs to comprehend various audio signals and to interact following instructions. AIR-Bench is characterized by three primary features: 1) **Comprehensive audio signals coverage**. AIR-Bench offers comprehensive coverage of audio signals, including human speech, natural sounds, and music, ensuring a comprehensive evaluation of LALMs' capabilities. 2) **Hierarchical Benchmark Structure**. The benchmark consists of *foundation* and *chat* benchmarks. The foundation benchmark comprises 19 distinct audio tasks with over 19,000 single-choice questions, with each question focusing only on a specific foundational ability. GPT-4 (OpenAI, 2023) extends the questions and candidate choices using dedicated designed prompts. The chat component consists of over 2,000 audio-prompted open-ended questions. To enhance the complexity of the audio and achieve a closer resemblance to the intricate audio encountered in real-life situations, we propose a novel audio mixing strategy that incorporates loudness control and temporal dislocation. Specifically, we adjust the loudness and introduce different temporal offsets during the mixing process of two audio clips. The resulting variations in relative loudness and temporal location are then recorded as additional meta-information, contributing to a more comprehensive textual representation of the audio. The quality of data is upheld through automated filtering by GPT-4, followed by manual verification. 3) **Unified, objective, and reproducible evaluation framework**. Models are required to generate hypothesis sequences directly across both benchmarks to align more accurately with practical scenarios. Then, we employ GPT-4 to generate reference answers given meta-information through carefully constructed prompts. Given references and hypotheses, following Liu et al. (2023b); Bai et al. (2023b), we use GPT-4 (OpenAI, 2023) to judge whether the choice is correct for the foundation benchmark or score hypotheses for the chat benchmark. We further perform a second scoring by swapping their positions to eliminate the position bias. Based on comprehensive experiments on 9 LALMs, we observe that existing LALMs either have limited audio understanding or instruction-following capabilities, leaving significant room for improvement in this field.

Our contribution is summarized below:

- AIR-Bench is the first generative evaluation benchmark for large audio-language models, encompassing a wide array of audio such as speech, natural sounds, and music. AIR-Bench is a large and hierarchical benchmark, consisting of the foundation benchmark with 19 audio tasks and over 19k single-choice questions, alongside a chat benchmark with over 2k meticulously curated open-ended audio questions for comprehensive evaluation.

- We propose a novel audio mixing strategy with loudness control and temporal dislocation to enhance the complexity of the audio.

- A unified, objective, and reproducible evaluation framework has been developed to assess the quality of generative hypotheses.

- We conducted a thorough evaluation of 9 models for the purpose of benchmarking. The evaluation code, datasets, and an open leaderboard will be made publicly available soon.

2 Related Work

Benchmarks for Audio Processing. Previous studies have primarily focused on evaluating the specific fundamental capabilities of models. In the field of speech processing, automatic speech recognition is one of the most popular tasks, with representative benchmarks including Librispeech (Panayotov et al., 2015), Common Voice (Ardila et al., 2019), and FLEURS (Conneau et al., 2022). Additionally, there are various benchmarks available for different speech processing tasks such as speech-to-text translation (Wang et al., 2020a,b; Jia et al., 2022) and emotion recognition (Cao et al., 2014; Livingstone and Russo, 2018). In the field of sound processing, several benchmarks have emerged such as Clotho (Drossos et al., 2020) and Audiocaps (Kim et al., 2019a) for automatic audio captioning, and AVQA (Yang et al., 2022) for sound question answering. In the domain of music processing, numerous datasets are

available, including MusicCaps (Agostinelli et al., 2023) for automatic music captioning, and MUSIC-AVQA (Li et al., 2022) for music question answering. Note that most existing question-answering benchmarks, such as Clotho-AQA, AVQA, and MUSIC-AVQA, have highly constrained answer formats for ease of close-ended evaluation or conversion into classification tasks, rather than supporting open-ended generation.

Besides the aforementioned datasets that focus on specific tasks, there are benchmarks like SUPERB (Yang et al., 2021b) and HEAR (Turian et al., 2022) for comprehensive evaluation of self-supervised learning models. When it comes to assessing the ability of LALMs to follow instructions, Dynamic-SUPERB is the only benchmark dedicated to this aspect. However, Dynamic-SUPERB focuses on human speech processing and does not cover open-ended dialogue generation. In contrast, AIR-Bench is the first large-scale generative evaluation benchmark for large audio-language models, encompassing various audio types such as speech, natural sounds, and music.

Large Audio-Language Models following Human Instruction Recently, there has been significant interest in instruction-following end-to-end audio-language models. Several models have emerged, each focusing on different audio domains. For instance, there are models specifically focusing on speech processing, such as SpeechGPT (Zhang et al., 2023), BLSP (Wang et al., 2023a), and LLaSM (Shu et al., 2023). Similarly, there are models tailored for sound processing, like LTU (Gong et al., 2023), and for music processing, such as LLark (Gardner et al., 2023). In contrast, SALMONN (Tang et al., 2023b) and Qwen-Audio (Chu et al., 2023) are trained using various audio types, showcasing strong universal audio understanding abilities. However, these models are evaluated on different fundamental tasks, making it difficult to conduct a fair comparison. Furthermore, these models rely on showcasing examples or public demos to demonstrate their conversational skills and do not perform rigorous experiments to evaluate their instruction-following abilities. To address these issues, this paper introduces AIR-Bench, which proposes two benchmarks - the foundation benchmark and the chat benchmark, enabling a fair comparison of the models' foundational abilities and their high-level instruction-following capabilities respectively.

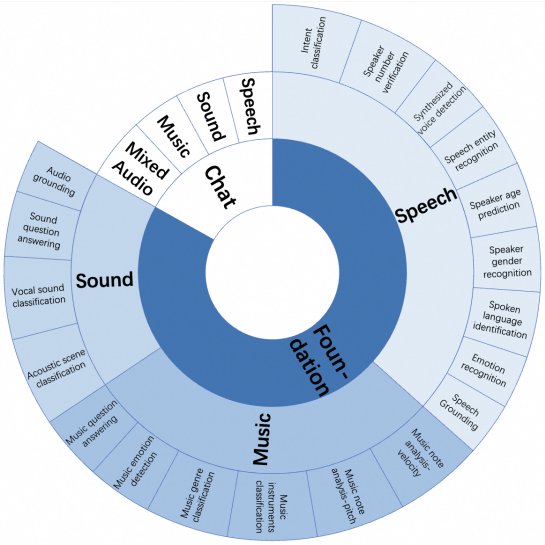


Figure 1: The overview of AIR-Bench. AIR-Bench includes a range of ability dimensions, namely the *foundation* and *chat* abilities, which cater to various audio types such as speech, sound, and music. The foundational dimension comprises 19 distinct leaf abilities, each of which is assessed using a single-choice question format. The chat dimension assesses abilities through an open-ended question-and-answer format, incorporating diverse audio sources and mixed audio.

3 AIR-Bench

There exist three unique characteristics that differentiate AIR-Bench from existing benchmarks for audio understanding: i) AIR-Bench is the first work to incorporate task evaluation from all types of audio in a hierarchical taxonomy; ii) AIR-Bench is the first generative evaluation benchmark that handles the free-form output of LALMs; iii) AIR-Bench adopts GPT-4-based automatic evaluation yielding trustworthy evaluation results with affordable cost. In Sec. 3.1, we present the hierarchical taxonomy of AIR-Bench and discuss the design philosophy behind it. In Sec. 3.2 and Sec. 3.3, we introduce how we collect the audio-central question-answer pairs for foundation and chat tasks. In Sec. 3.4, we present the evaluation framework.

3.1 Overview

Chat interaction based on audio is a complex task that encompasses a variety of fundamental competencies. For instance, humans are able to respond to sound events due to their capacities for sound perception and common sense reasoning. Similarly, the ability to respond to others' spoken words is predicated on foundational skills such as speech-to-text recognition and emotion recognition. Based on

the motivation, we propose the hierarchical benchmark AIR-Bench by dividing it into *foundation* and *chat* benchmarks. The fundamental one is designed to assess capabilities across individual subtasks, serving to diagnose weaknesses within the model, while the chat benchmark directly evaluates complicated audio-based open-ended questions. The data sample is denoted as (A, Q, R), where A denotes the audio, Q represents the query and R is the reference answer.

- **Foundation benchmark**: The purpose of the benchmark is to evaluate the individual capabilities of foundational tasks. To reduce the task difficulties and enable the evaluation of various models, we utilize the single-choice question-answering format. Specifically, the query Q is formed by concatenating a question q and candidate choices C, denoted as $Q = (q, C)$. We curate a collection of 19 audio tasks that span multiple audio types, such as speech, music, and sound. These tasks include tasks like emotion recognition, acoustic scene classification, and music QA. [1]

- **Chat benchmark**: The benchmark encompasses any form of question and answer pairs that could arise from audio signals, with the aim of reflecting the model's ability to genuinely follow user instructions to perform perceiving, reasoning, and interacting within real-world applications. According to the type of audio, the benchmark is categorized into four dimensions: speech, sound, music, and mixed audio, where mixed audio refers to audio that is a mixture of multiple types of audio, such as human voice with background music.

The overview of AIR-Bench is shown in Fig. 1.

3.2 Foundation Benchmark

Data Source. We collected over 19k data samples for the foundation dimension, encompassing 19 different subtasks. The data source and statistics are provided in Table 1. To ensure a fair and comprehensive evaluation of each capability, we aimed for an even distribution of problems related to different abilities during the data collection process. All audio sources were obtained from the original dev or test subsets to prevent data leakage.

[1]For transcription tasks such as ASR and S2TT, we incorporate them into the chat benchmark since they are not suitable for the single-choice task format.

Types	Task	Dataset-Source	Num
Speech	Speech grounding	Librispeech (Panayotov et al., 2015)	0.9k
	Spoken language identification	Covost2 (Wang et al., 2020b)	1k
	Speaker gender recognition (biologically)	Common voice (Ardila et al., 2019) MELD (Poria et al., 2018)	1k
	Emotion recognition	IEMOCAP (Busso et al., 2008) MELD (Poria et al., 2018)	1k
	Speaker age prediction	Common voice (Ardila et al., 2019)	1k
	Speech entity recognition	SLURP (Bastianelli et al., 2020)	1k
	Intent classification	SLURP (Bastianelli et al., 2020)	1k
	Speaker number verification	VoxCeleb1 (Nagrani et al., 2020)	1k
	Synthesized voice detection	FoR (Reimao and Tzerpos, 2019)	1k
Sound	Audio grounding	AudioGrounding (Xu et al., 2021)	0.9k
	Vocal sound classification	VocalSound (Gong et al., 2022)	1k
	Acoustic scene classification	CochlScene (Jeong and Park, 2022) TUT2017 (Mesaros et al., 2017)	1k
	Sound question answering	Clotho-AQA (Lipping et al., 2022) AVQA (Yang et al., 2022)	1k
Music	Music instruments classification	Nsynth (Engel et al., 2017) MTJ-Jamendo (Bogdanov et al., 2019)	1k
	Music genre classification	FMA (Defferrard et al., 2016) MTJ-Jamendo (Bogdanov et al., 2019)	1k
	Music note analysis-pitch	Nsynth (Engel et al., 2017)	1k
	Music note analysis-velocity	Nsynth (Engel et al., 2017)	1k
	Music question answering	MUSIC-AVQA (Li et al., 2022)	0.8k
	Music emotion detection	MTJ-Jamendo (Bogdanov et al., 2019)	1k

Table 1: The statistics of the foundation benchmark.

Types	Dataset-Source	Num	Question Example
Speech	Fisher (Cieri et al., 2004) SpokenWOZ (Si et al., 2023) IEMOCAP (Busso et al., 2008) Common voice (Ardila et al., 2019)	800	Did the first speaker have any more questions or need further information?
Sound	Clotho (Drossos et al., 2020)	400	What should you do to the cloth according to the voice in the audio?
Music	MusicCaps (Agostinelli et al., 2023)	400	How might the elements of the music in the audio, despite its poor sound quality, musically convey a sense of patriotism and ceremonial grandeur within a 150-word essay?
Mixed Audio	Common voice (Ardila et al., 2019) AudioCaps (Kim et al., 2019b)	200	What sound is heard along with the male speaker in his twenties?
	Common voice (Ardila et al., 2019) MusicCaps (Agostinelli et al., 2023)	200	What type of melody can be heard in the background of the male speaker's audio?

Table 2: The statistics and examples of the chat benchmark.

Single-choice Query and Reference. The query Q is formed by concatenating a question q and candidate choices C. For the question q, we mainly construct questions through GPT-4 (OpenAI, 2023), except for QA tasks since the datasets inherently contain questions and we can directly re-use them. Specifically, we design the prompt for the distinct task and provide three questions as demonstrations. Subsequently, GPT-4 generates additional diverse questions based on these inputs. The generated questions are manually reviewed, and 50 different questions are selected for each task. The variability in question format aims to evaluate the model's ability to follow instructions rather than being overly reliant on specific templates. For each question, we further generate candidate choices C from different sources: 1) For tasks with choices in original datasets like AVQA (Yang et al., 2022), we directly re-use it; 2) For classification tasks, we randomly select options from the predetermined set of categories to serve as candidate choices; 3) For other tasks, we prompt GPT-4 to generate candidate choices directly, consisting of one correct option and three incorrect options. We encourage

these incorrect options to resemble the correct one, making the single-choice task more challenging. The reference answer is the golden correct choice. To avoid position bias, the candidate choices are randomly shuffled. We provide examples of each task in Table 6 of the Appendix.

3.3 Chat Benchmark

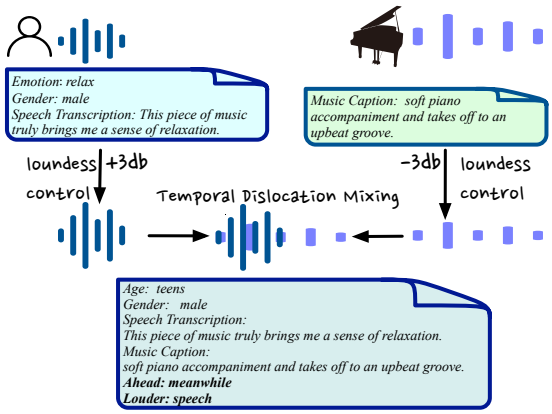


Figure 2: Loudness and temporal location controlled mixing strategy. Loudness control aims to provide *Louder* meta-information, indicating which audio clip exhibits a higher volume. Temporal dislocation mixing aims to provide the *Ahead* meta-information, referring to the temporal relationship between the two audio clips.

Data Source and Audio Mixing Strategy. As shown in Table 2, we have collected more than 2k data samples spanning various audio types including speech, sound, music, and mixed audio. The purpose of introducing mixed audio is to augment the complexity of the audio signals and make it closer to audio from real-world audio scenarios. To achieve this, we propose a novel mixing strategy involving loudness control and temporal dislocation, as illustrated in Fig. 2. Specifically, we can adjust the relative loudness and temporal relationship between two audio clips for mixing. Then, we can create a complex audio signal that combines their meta-information, such as speech transcription accompanied by a background music caption. Furthermore, the meta-information also includes labels indicating which audio clip is louder and which is ahead in the temporal sequence.

Open-ended Query and Reference. To prompt GPT-4 to generate open-ended question-answer pairs for audio, we should interpret the rich information in each audio with texts. We collect all of *meta-information* such as gender, age, emotion, transcription, language for speech, caption for natural sound, and instrument, caption for music from the original dataset. Rather than relying on pre-trained models to extract this meta-information for each audio clip, we adopt the ground truth meta-information to avoid potential errors.

After gathering meta-information about the audio, we manually construct prompts (see Appendix 5 for guiding GPT-4 in generating question-answer pairs that specifically focus on different abilities). These prompts are carefully designed to ensure a comprehensive coverage of chat interactions, taking into consideration the diverse range of audio signals involved. We design the prompts to facilitate the generation of questions related to the perception and reasoning for different types of audio. For the natural sound, the prompts are further tailored to generate questions that involve determining appropriate responses to sound events within a specific scenario. For the music category, prompts are devised to elicit creative writing and story-generation questions based on music composition. To ensure the quality of the generated results, these prompts are designed in a manner that enables GPT-4 to automatically filter out responses that are not directly related to audio. Additionally, we manually reviewed all the question-answer pairs to ensure the quality of the questions and the reliability of the answers. The generated answers from GPT-4 are considered as references.

3.4 Evaluation Strategy

In this paper, we leverage a unified evaluation method, as shown in Fig. 3, by viewing both the single-choice question in the foundation benchmark, and the open-ended question in the chat benchmark, as the generation tasks for the purpose of better alignment with actual use case scenarios of LALMs. That is, given audio and questions, LALMs are required to directly generate the answers as hypotheses, rather than comparing the perplexity on the probability of different reference answers via teacher forcing. Automated and accurate evaluation of open-ended generation is a challenging problem. Traditional automatic metrics such as WER, ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005) have shown a low correlation with human judgments (Liu et al., 2023a). Recently, LLM-based evaluation, such as GPT-4, shows better human preference alignment (Zheng et al., 2023; Liu et al., 2023a). In this work, we adopt reference-based GPT-4 evaluators to judge the generation

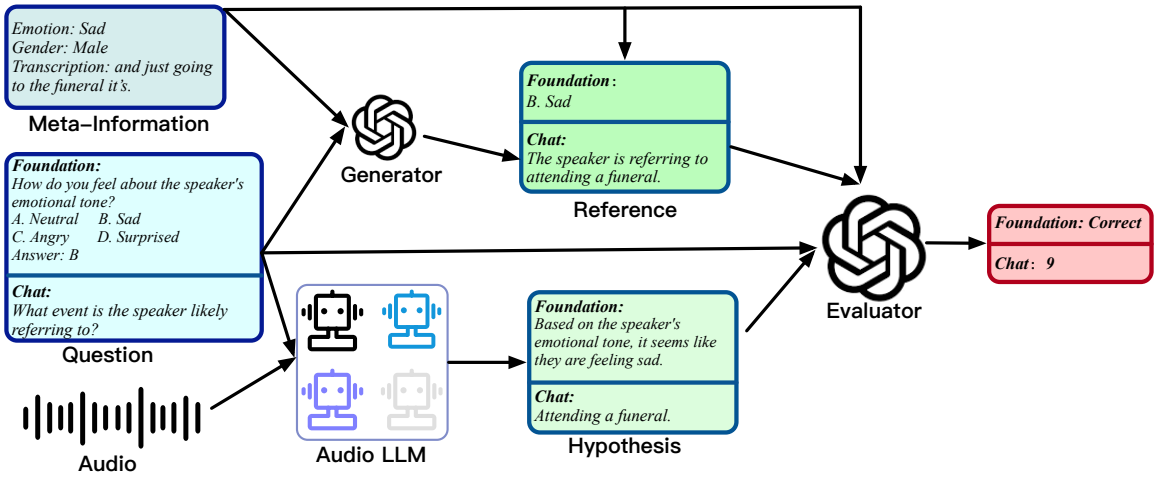


Figure 3: Automated generative evaluation for large audio-language models (LALMs). In the evaluation framework, LALMs are provided with audio input along with a corresponding question, following which they generate a hypothesis. The performance of the hypothesis is then assessed using the GPT evaluator, which compares it against a reference answer by considering the meta-information and the question. For the foundation benchmark, the reference answer is the golden choice extracted from the meta-information, and the evaluation score is binary, with 0 indicating an incorrect answer and 1 representing a correct answer. For the chat benchmark, the reference answer is produced by the GPT-4 generator. The reference answer serves as a reference for scoring, stabilizing the scoring process. The output score for the chat benchmark ranges from 1 to 10, based on the assessment of usefulness, relevance, accuracy, and comprehensiveness of the hypothesis.

quality of LALMs in the audio domain.

However, GPT-4 cannot be directly used as an evaluator since it cannot receive audio inputs. To address this limitation, we offer the GPT-4 model rich meta-information of audio to replace audio input. Subsequently, we present questions and employ GPT-4 to evaluate the hypotheses produced by LALMs. To ensure consistency and fairness for evaluation, each model's answer is compared against the same reference answer for scoring. For the foundation benchmark, the reference answer is the golden choice, and we prompt the evaluator to determine whether the hypothesis is correct or not. For the chat benchmark, the reference answer is generated by GPT-4, and we prompt the evaluator to provide a score ranging from 1 to 10, based on the assessment of usefulness, relevance, accuracy, and comprehensiveness of the hypothesis. The prompts used in the evaluation process can be found in Appendix 5. Note that for the chat benchmark, the role of the reference is not to serve as the ground truth answer, but rather as a reference for scoring by GPT-4, in order to stabilize its scoring. Additionally, to mitigate any potential position bias resulting from the order of hypothesis and reference, following Bai et al. (2023b), we perform a second scoring round by swapping their positions and then compute the average of the two scores. Unless otherwise specified, the GPT-4 evaluator is GPT-4 Turbo, the *gpt-4-0125-preview* version [2].

4 Experiments

4.1 Models

We evaluate the performance of various LALMs with instruction-following capabilities. These models are either open-sourced or accessible through public APIs, such as SpeechGPT (Zhang et al., 2023), BLSP (Wang et al., 2023a), SALMONN (Tang et al., 2023a), Qwen-Audio-Chat (Chu et al., 2023), and Qwen-Audio Turbo [3]. Additionally, we consider large multi-modality models with audio understanding abilities like PandaGPT (Su et al., 2023), Macaw-LLM (Lyu et al., 2023), and NExT-GPT (Wu et al., 2023b). Besides, we also incorporate a sequential approach comprising Whisper-large-v2 (Radford et al., 2023) and GPT-4 Turbo (OpenAI, 2023) for tasks related to speech as a baseline. We evaluate the performance of all these models on both fundamental and chat benchmarks, utilizing their latest publicly available checkpoints. In cases of multiple checkpoints, we select the model with the largest param-

[2] https://platform.openai.com/docs/models/gpt-4-and-gpt-4-turbo

[3] https://help.aliyun.com/zh/dashscope/developer-reference/qwen-audio-api

Benchmark	Foundation				Chat				
Categories	Speech	Sound	Music	Average	Speech	Sound	Music	Mixed Audio	Average
SALMONN	37.8%	33.0%	37.1%	36.0%	6.16	6.28	5.95	**6.08**	6.11
Qwen-Audio-Chat	58.7%	60.2%	44.8%	54.5%	6.47	**6.95**	5.52	5.38	6.08
Qwen-Audio Turbo	**63.4%**	**61.0%**	**48.9%**	**57.8%**	7.04	6.59	**5.98**	5.77	**6.34**
BLSP	36.6%	31.4%	26.1%	31.4%	6.17	5.55	5.08	4.52	5.33
PandaGPT	39.0%	43.6%	38.1%	40.2%	3.58	5.46	5.06	2.93	4.25
Macaw-LLM	32.2%	30.1%	29.7%	30.7%	0.97	1.01	0.91	1.00	1.01
SpeechGPT	34.3%	27.5%	28.1%	30.0%	1.57	0.95	0.95	1.14	1.15
NExT-GPT	33.6%	32.2%	28.9%	31.5%	3.86	4.76	4.18	2.92	4.13
Whisper+GPT-4	53.6%	/	/	/	**7.54**	/	/	/	/

Table 3: The comparison of different LALMs on AIR-Bench.

Model Name	Exact Matching	GPT Align
SALMONN	97.3%	100.0%
Qwen-Audio-Chat	30.7%	100.0%
Qwen-Audio Turbo	48.2%	100.0%
BLSP	100.0%	100.0%
PandaGPT	30.8%	100.0%
Macaw-LLM	0.1%	100.0%
SpeechGPT	0.0%	100.0%
NExT-GPT	98.1%	100.0%

Table 4: The success rate of different strategies of matching hypotheses with the golden choices for the foundation benchmark.

eter size. For all models, we directly follow their default decoding strategies for evaluation.

4.2 Main Results

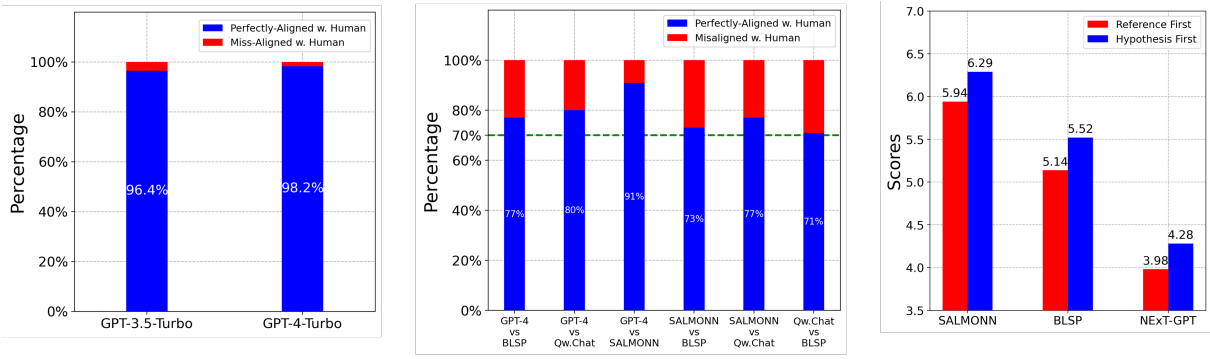
The results of LALMs are presented in Table 3. The detailed results are shown in Table 5. For the foundation benchmark, we also conduct a comparison between the use of an exact matching strategy with our proposed GPT-4 alignment strategy. As an example, we try to match 'B', 'B.', 'B)', *etc.* with LALMs' hypothesis for the exact matching. The results are shown in Table 4. We can find that BLSP and SALMONN have a high success rate in directly generating the choice, showcasing their strong ability to follow single-choice instruction. However, we find that it is challenging to precisely extract the predicted choice from the hypotheses of other models due to significant variations in the output formats of different LALMs. However, with the assistance of GPT-4 as the evaluator, the success rate for all models can be improved to 100%.

According to Table 3, Qwen-Audio-Chat and Qwen-Audio Turbo demonstrate superior performance in the foundation benchmark, surpassing other models in the domains of speech, sound, and music. Second to the two models, PandaGPT and SALMONN also exhibit noteworthy performances. Regarding the chat benchmark, Qwen-Audio Turbo achieves the highest average score, followed by SALMONN and Qwen-Audio-Chat with scores of 6.11 and 6.08, respectively. Among these models, SALMONN outperforms others in terms of mixed audio understanding. Note that the speech dimension in the foundation benchmark includes tasks beyond speech transcriptions, such as speaker gender, age, and emotion prediction, while the speech in the chat benchmark primarily revolves around speech transcriptions. Thus, Whisper plus GPT-4 receives a relatively low score in the foundation benchmark but obtains the highest score in the chat benchmark.

Based on these results, we have several observations: 1) The existing LALMs either have limited audio understanding or instruction-following capabilities. For instance, Qwen-Audio Turbo achieves the highest average score in both foundation and chat benchmarks while the model displays a weak proficiency in following single-choice instructions such as often directly generating a full sentence semantically akin to one of the choices, and thus receives a low success rate for the exact matching; 2) As for chat abilities related only to speech transcription, none of the models surpass the sequential baseline Whisper plus GPT-4.

4.3 Human Evaluation

To evaluate the consistency between the evaluations of GPT-4 and human judgments, we design experiments for both the foundation and chat benchmarks. For the foundation benchmark, we instruct



(a) the foundation benchmark

(b) Human evaluation for the chat benchmark

(c) Positional bias of evaluation

Figure 4: The experiments of human evaluation and the position bias of GPT-4 evaluator. Figure (a) and (b) are the results of consistency between the GPT-4 evaluator and human judgment on the foundation benchmark and chat benchmark, respectively. Figure (c) refers to the result of scores by interchanging the position of the hypothesis and reference during evaluation on the chat benchmark.

the testers to determine which option aligns closest with the hypothesis. We then compare the option selected by human testers with the option chosen by GPT-4 to assess the extent of agreement. For this consistency analysis, we employed Qwen-Audio-Chat as a representative model and randomly selected 400 questions from the benchmark. These questions were then evaluated by three native English speakers. Additionally, we also compared the performance of GPT-4 with GPT-3.5 Turbo. As depicted in Figure 4 (a), GPT-4 Turbo, serving as the evaluator, exhibited a high level of consistency at 98.2% with human judgments. Comparatively, GPT-3.5 Turbo had a slightly lower consistency rate of 96.4%.

Regarding the chat benchmark, obtaining a numerical score on a scale of 1 to 10 directly from testers poses challenges. Therefore, we resort to a pairwise comparison of the models instead. Testers listen to audio and compare the performance of both models based on their usefulness, relevance, accuracy, and comprehensiveness to the given question, indicating their preference as either "A is better", "B is better", or "Both are equal". Subsequently, we convert the GPT-4 scores into the same preference-based rating as the human testers for any two models. We then assess the consistency between the two sets of results. For the chat benchmark, we conduct pairwise comparisons among Qwen-Audio-Chat, SALMONN, BLSP, and GPT-4. We randomly select 200 questions and have them evaluated by three native English speakers. As depicted in Figure 4 (b), the pairwise preference consistency scored above 70%, demonstrating a high level of agreement.

4.4 Ablation Study of Positional Bias

In our evaluation framework, we adopt a strategy of scoring twice by interchanging the positions of the hypothesis and reference and calculating the average of the two scores. This approach helps mitigate the bias that may arise from the positional placement. The outcomes of these two evaluations are presented in Figure 4 (c). We observe that the GPT-4 evaluator exhibits a clear bias in scoring when the hypothesis is placed before the reference. This highlights the importance of conducting a second scoring to account for addressing this bias.

5 Conclusion

In this paper, we present AIR-Bench, the first generative evaluation benchmark designed specifically for audio-language models. AIR-Bench comprises 19 audio tasks with over 19k single-choice questions in the foundation benchmark, as well as over 2k open-ended audio questions in the chat benchmark. Notably, the benchmark covers diverse audio types such as speech, natural sounds, and music. We also propose a novel audio mixing strategy to simulate audio from real-world scenarios more accurately. A standardized, objective, and reproducible evaluation framework is employed to automatically assess the quality of hypotheses generated by LALMs. We conduct a thorough evaluation of 9 prominent open-source LALMs. Additionally, we plan to launch and maintain a leaderboard that will serve as a platform for the community to access and compare model performance consistently over time.

6 Limitations

The objective of AIR-Bench is to develop a large-scale, extensive and generative evaluation framework that encompasses a wide range of audio domains and tasks. However, AIR-Bench currently has several limitations. Firstly, it does not incorporate tasks involving multiple audio comparisons, such as assessing music coherence, for both the foundation and chat benchmark. Besides, AIR-Bench does not encompass the evaluation of multi-turn dialogues that may involve multiple audio inputs. For evaluation, AIR-Bench relies on a powerful and robust evaluator such as GPT-4. However, the availability and accessibility of the GPT-4 API are external factors beyond our control. In the event that GPT-4 transitions to a closed-source model or implements higher pricing standards in the future, alternative evaluators will need to be explored and considered.

7 Ethical Considerations

The AIR-Bench initiative uses publicly available datasets to create a collection of relevant question-and-answer data. It then uses automated methods to evaluate this data, which is a more efficient alternative to manually evaluating it. However, there are challenges with this automated evaluation approach, including the potential for data misuse and the introduction of biases. To prevent data misuse, we follow the licenses and usage guidelines associated with the original open-source materials when generating related data. It's important to point out that the automated evaluation could be biased. These biases may come from the datasets themselves or the scoring algorithms used, causing differences between automated evaluation results and human judgment. Therefore, the outcomes obtained from automated evaluations should be viewed with caution and used as a general benchmark, rather than a definitive measure.

References

Andrea Agostinelli, Timo I Denk, Zalán Borsos, Jesse Engel, Mauro Verzetti, Antoine Caillon, Qingqing Huang, Aren Jansen, Adam Roberts, Marco Tagliasacchi, et al. 2023. Musiclm: Generating music from text. *arXiv preprint arXiv:2301.11325*.

Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. 2023. PaLM 2 technical report. *arXiv:2305.10403*.

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*.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. 2023a. Qwen technical report. *arXiv preprint arXiv:2309.16609*.

Shuai Bai, Shusheng Yang, Jinze Bai, Peng Wang, Xingxuan Zhang, Junyang Lin, Xinggang Wang, Chang Zhou, and Jingren Zhou. 2023b. Touchstone: Evaluating vision-language models by language models. *arXiv preprint arXiv:2308.16890*.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: an automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization@ACL 2005, Ann Arbor, Michigan, USA, June 29, 2005*. Association for Computational Linguistics.

Emanuele Bastianelli, Andrea Vanzo, Pawel Swietojanski, and Verena Rieser. 2020. Slurp: A spoken language understanding resource package. *arXiv preprint arXiv:2011.13205*.

Dmitry Bogdanov, Minz Won, Philip Tovstogan, Alastair Porter, and Xavier Serra. 2019. The mtg-jamendo dataset for automatic music tagging. ICML.

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. *NeurIPS*.

Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N Chang, Sungbok Lee, and Shrikanth S Narayanan. 2008. Iemocap: Interactive emotional dyadic motion capture database. *Language resources and evaluation*, 42:335–359.

Houwei Cao, David G Cooper, Michael K Keutmann, Ruben C Gur, Ani Nenkova, and Ragini Verma. 2014. Crema-d: Crowd-sourced emotional multimodal actors dataset. *IEEE transactions on affective computing*, 5(4):377–390.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. 2022. PaLM: Scaling language modeling with pathways. *arXiv:2204.02311*.

Yunfei Chu, Jin Xu, Xiaohuan Zhou, Qian Yang, Shiliang Zhang, Zhijie Yan, Chang Zhou, and Jingren Zhou. 2023. Qwen-audio: Advancing universal audio understanding via unified large-scale audio-language models. *CoRR*, abs/2311.07919.

Christopher Cieri, David Miller, and Kevin Walker. 2004. The fisher corpus: A resource for the next generations of speech-to-text. In *LREC*, volume 4, pages 69–71.

Alexis Conneau, Min Ma, Simran Khanuja, Yu Zhang, Vera Axelrod, Siddharth Dalmia, Jason Riesa, Clara Rivera, and Ankur Bapna. 2022. FLEURS: few-shot learning evaluation of universal representations of speech. In *IEEE Spoken Language Technology Workshop, SLT 2022, Doha, Qatar, January 9-12, 2023*. IEEE.

Michaël Defferrard, Kirell Benzi, Pierre Vandergheynst, and Xavier Bresson. 2016. Fma: A dataset for music analysis. *arXiv preprint arXiv:1612.01840*.

Konstantinos Drossos, Samuel Lipping, and Tuomas Virtanen. 2020. Clotho: An audio captioning dataset. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 736–740. IEEE.

Jesse Engel, Cinjon Resnick, Adam Roberts, Sander Dieleman, Mohammad Norouzi, Douglas Eck, and Karen Simonyan. 2017. Neural audio synthesis of musical notes with wavenet autoencoders. In *International Conference on Machine Learning*, pages 1068–1077. PMLR.

Josh Gardner, Simon Durand, Daniel Stoller, and Rachel M Bittner. 2023. Llark: A multimodal foundation model for music. *arXiv preprint arXiv:2310.07160*.

Yuan Gong, Hongyin Luo, Alexander H. Liu, Leonid Karlinsky, and James R. Glass. 2023. Listen, think, and understand. *CoRR*, abs/2305.10790.

Yuan Gong, Jin Yu, and James Glass. 2022. Vocalsound: A dataset for improving human vocal sounds recognition. In *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 151–155. IEEE.

Chien-yu Huang, Ke-Han Lu, Shih-Heng Wang, Chi-Yuan Hsiao, Chun-Yi Kuan, Haibin Wu, Siddhant Arora, Kai-Wei Chang, Jiatong Shi, Yifan Peng, Roshan S. Sharma, Shinji Watanabe, Bhiksha Ramakrishnan, Shady Shehata, and Hung-yi Lee. 2023a. Dynamic-superb: Towards A dynamic, collaborative, and comprehensive instruction-tuning benchmark for speech. *CoRR*, abs/2309.09510.

Rongjie Huang, Mingze Li, Dongchao Yang, Jiatong Shi, Xuankai Chang, Zhenhui Ye, Yuning Wu, Zhiqing Hong, Jiawei Huang, Jinglin Liu, Yi Ren, Zhou Zhao, and Shinji Watanabe. 2023b. Audiogpt: Understanding and generating speech, music, sound, and talking head. *CoRR*, abs/2304.12995.

Il-Young Jeong and Jeongsoo Park. 2022. Cochlscene: Acquisition of acoustic scene data using crowdsourcing. In *2022 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, pages 17–21. IEEE.

Ye Jia, Michelle Tadmor Ramanovich, Quan Wang, and Heiga Zen. 2022. CVSS corpus and massively multilingual speech-to-speech translation. In *Proceedings of Language Resources and Evaluation Conference (LREC)*.

Chris Dongjoo Kim, Byeongchang Kim, Hyunmin Lee, and Gunhee Kim. 2019a. Audiocaps: Generating captions for audios in the wild. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*.

Chris Dongjoo Kim, Byeongchang Kim, Hyunmin Lee, and Gunhee Kim. 2019b. Audiocaps: Generating captions for audios in the wild. In *NAACL-HLT*.

Guangyao Li, Yake Wei, Yapeng Tian, Chenliang Xu, Ji-Rong Wen, and Di Hu. 2022. Learning to answer questions in dynamic audio-visual scenarios. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 19108–19118.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81.

Samuel Lipping, Parthasaarathy Sudarsanam, Konstantinos Drossos, and Tuomas Virtanen. 2022. Clotho-aqa: A crowdsourced dataset for audio question answering. In *2022 30th European Signal Processing Conference (EUSIPCO)*, pages 1140–1144. IEEE.

Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. 2023a. Gpteval: Nlg evaluation using gpt-4 with better human alignment. *arXiv preprint arXiv:2303.16634*.

Yuan Liu, Haodong Duan, Yuanhan Zhang, Bo Li, Songyang Zhang, Wangbo Zhao, Yike Yuan, Jiaqi Wang, Conghui He, Ziwei Liu, et al. 2023b. Mmbench: Is your multi-modal model an all-around player? *arXiv preprint arXiv:2307.06281*.

Steven R Livingstone and Frank A Russo. 2018. The ryerson audio-visual database of emotional speech and song (ravdess): A dynamic, multimodal set of facial and vocal expressions in north american english. *PloS one*, 13(5):e0196391.

Chenyang Lyu, Minghao Wu, Longyue Wang, Xinting Huang, Bingshuai Liu, Zefeng Du, Shuming Shi, and Zhaopeng Tu. 2023. Macaw-llm: Multi-modal language modeling with image, audio, video, and text integration. *CoRR*, abs/2306.09093.

Annamaria Mesaros, Toni Heittola, Aleksandr Diment, Benjamin Elizalde, Ankit Shah, Emmanuel Vincent, Bhiksha Raj, and Tuomas Virtanen. 2017. Dcase

2017 challenge setup: Tasks, datasets and baseline system. In *DCASE 2017-Workshop on Detection and Classification of Acoustic Scenes and Events*.

Arsha Nagrani, Joon Son Chung, Weidi Xie, and Andrew Zisserman. 2020. Voxceleb: Large-scale speaker verification in the wild. *Computer Speech & Language*, 60:101027.

OpenAI. 2022. Introducing ChatGPT.

OpenAI. 2023. Gpt-4 technical report.

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.

Soujanya Poria, Devamanyu Hazarika, Navonil Majumder, Gautam Naik, Erik Cambria, and Rada Mihalcea. 2018. Meld: A multimodal multi-party dataset for emotion recognition in conversations. *arXiv preprint arXiv:1810.02508*.

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.

Ricardo Reimao and Vassilios Tzerpos. 2019. For: A dataset for synthetic speech detection. In *2019 International Conference on Speech Technology and Human-Computer Dialogue (SpeD)*, pages 1–10. IEEE.

Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. 2023. Hugginggpt: Solving AI tasks with chatgpt and its friends in huggingface. *CoRR*, abs/2303.17580.

Yu Shu, Siwei Dong, Guangyao Chen, Wenhao Huang, Ruihua Zhang, Daochen Shi, Qiqi Xiang, and Yemin Shi. 2023. Llasm: Large language and speech model. *arXiv:2308.15930*.

Shuzheng Si, Wentao Ma, Yuchuan Wu, Yinpei Dai, Haoyu Gao, Ting-En Lin, Hangyu Li, Rui Yan, Fei Huang, and Yongbin Li. 2023. Spokenwoz: A large-scale speech-text benchmark for spoken task-oriented dialogue in multiple domains. *arXiv preprint arXiv:2305.13040*.

Yixuan Su, Tian Lan, Huayang Li, Jialu Xu, Yan Wang, and Deng Cai. 2023. Pandagpt: One model to instruction-follow them all. *arXiv preprint arXiv:2305.16355*.

Changli Tang, Wenyi Yu, Guangzhi Sun, Xianzhao Chen, Tian Tan, Wei Li, Lu Lu, Zejun Ma, and Chao Zhang. 2023a. SALMONN: towards generic hearing abilities for large language models. *CoRR*, abs/2310.13289.

Changli Tang, Wenyi Yu, Guangzhi Sun, Xianzhao Chen, Tian Tan, Wei Li, Lu Lu, Zejun Ma, and Chao Zhang. 2023b. Salmonn: Towards generic hearing abilities for large language models. *arXiv preprint arXiv:2310.13289*.

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:2302.13971*.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023b. Llama 2: Open foundation and fine-tuned chat models. *CoRR*, abs/2307.09288.

Joseph Turian, Jordie Shier, Humair Raj Khan, Bhiksha Raj, Björn W. Schuller, Christian J. Steinmetz, Colin Malloy, George Tzanetakis, Gissel Velarde, Kirk McNally, Max Henry, Nicolas Pinto, Camille Noufi, Christian Clough, Dorien Herremans, Eduardo Fonseca, Jesse H. Engel, Justin Salamon, Philippe Esling, Pranay Manocha, Shinji Watanabe, Zeyu Jin, and Yonatan Bisk. 2021. HEAR: holistic evaluation of audio representations. In *NeurIPS 2021 Competitions and Demonstrations Track,*, Proceedings of Machine Learning Research.

Joseph Turian, Jordie Shier, Humair Raj Khan, Bhiksha Raj, Björn W Schuller, Christian J Steinmetz, Colin Malloy, George Tzanetakis, Gissel Velarde, Kirk McNally, et al. 2022. Hear: Holistic evaluation of audio representations. In *NeurIPS 2021 Competitions and Demonstrations Track*, pages 125–145. PMLR.

Changhan Wang, Juan Pino, Anne Wu, and Jiatao Gu. 2020a. CoVoST: A diverse multilingual speech-to-text translation corpus. In *Proceedings of The 12th Language Resources and Evaluation Conference*.

Changhan Wang, Anne Wu, and Juan Pino. 2020b. Covost 2 and massively multilingual speech-to-text translation. *arXiv preprint arXiv:2007.10310*.

Chen Wang, Minpeng Liao, Zhongqiang Huang, Jinliang Lu, Junhong Wu, Yuchen Liu, Chengqing

Zong, and Jiajun Zhang. 2023a. Blsp: Bootstrapping language-speech pre-training via behavior alignment of continuation writing. *arXiv preprint arXiv:2309.00916*.

Mingqiu Wang, Wei Han, Izhak Shafran, Zelin Wu, Chung-Cheng Chiu, Yuan Cao, Yongqiang Wang, Nanxin Chen, Yu Zhang, Hagen Soltau, et al. 2023b. Slm: Bridge the thin gap between speech and text foundation models. *arXiv:2310.00230*.

Jian Wu, Yashesh Gaur, Zhuo Chen, Long Zhou, Yimeng Zhu, Tianrui Wang, Jinyu Li, Shujie Liu, Bo Ren, Linquan Liu, and Yu Wu. 2023a. On decoder-only architecture for speech-to-text and large language model integration. abs/2307.03917.

Shengqiong Wu, Hao Fei, Leigang Qu, Wei Ji, and Tat-Seng Chua. 2023b. Next-gpt: Any-to-any multimodal LLM. *CoRR*, abs/2309.05519.

Xuenan Xu, Heinrich Dinkel, Mengyue Wu, and Kai Yu. 2021. Text-to-audio grounding: Building correspondence between captions and sound events. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 606–610. IEEE.

Pinci Yang, Xin Wang, Xuguang Duan, Hong Chen, Runze Hou, Cong Jin, and Wenwu Zhu. 2022. Avqa: A dataset for audio-visual question answering on videos. In *Proceedings of the 30th ACM International Conference on Multimedia*, pages 3480–3491.

Shu-Wen Yang, Po-Han Chi, Yung-Sung Chuang, Cheng-I Jeff Lai, Kushal Lakhotia, Yist Y. Lin, Andy T. Liu, Jiatong Shi, Xuankai Chang, Guan-Ting Lin, Tzu-Hsien Huang, Wei-Cheng Tseng, Ko-tik Lee, Da-Rong Liu, Zili Huang, Shuyan Dong, Shang-Wen Li, Shinji Watanabe, Abdelrahman Mohamed, and Hung-yi Lee. 2021a. SUPERB: speech processing universal performance benchmark. In *Interspeech 2021, 22nd Annual Conference of the International Speech Communication Association*. ISCA.

Shu-wen Yang, Po-Han Chi, Yung-Sung Chuang, Cheng-I Jeff Lai, Kushal Lakhotia, Yist Y Lin, Andy T Liu, Jiatong Shi, Xuankai Chang, Guan-Ting Lin, et al. 2021b. Superb: Speech processing universal performance benchmark. *arXiv preprint arXiv:2105.01051*.

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

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

A Detailed Results of Foundation Benchmark

In Table 5, we delineate the performance assessment for each model across the various tasks on the foundation benchmark. With the exception of Speaker Gender Recognition and Synthesized Voice Detection, which are binary-choice tasks, all other tasks necessitate a selection from four options. As such, a random selection in the Speaker Gender Recognition and Synthesized Voice Detection datasets would theoretically achieve an accuracy of 50%, while the expected accuracy for random choices across the remaining datasets stands at 25%. Consequently, any performance metrics that approximate these random baselines are indicative of an absence of discernible proficiency in the respective tasks.

B GPT Prompts for the Chat benchmark

In Figure 5, we display the carefully crafted prompts that we have developed on our chat benchmark. The figure is divided into two sections, the upper section contains prompts designed specifically for generating question-answer pairs related to reasoning, while the lower section features prompts aimed at assessing the chat performance scores of the models.

When generating questions and reference answers, we guide the process by specifying the type of questions to be elicited, allowing GPT-4 to automatically exclude data that is less amenable to question formulation. For the evaluation of the chat performance scores, we instruct GPT-4 to take a multifaceted approach, scoring both the reference answers and the model responses. This ensures that the reference answers consistently serve as a standard for comparison.

C Examples of the Foundation Benchmark

In Table 6, we present data examples for each task within the foundation benchmark.

D Examples of LALMs' responses

In Figure 6, we illustrate a representative response from various models on the foundation benchmark. The upper portion of the figure displays the question along with the metadata for the corresponding audio. This metadata is not provided as input to the models under evaluation, the models only have

Format of Prompt for Creating QA in Chat Benchmark

[System Prompt]
You are an AI audio assistant capable of analyzing sound. You will create some questions and answers. The questions you pose should simulate what queries might arise when a person hears this sound.

[Question & Answer Requirements]
Here I will give you the detailed requirements for creating questions in the following aspects. (1)Create some relatively difficult questions, and using the audio information I've provided you, ask questions that require reasoning, such as what to do next, and how to react. (2)If you find the sound too simple to generate any complex questions, then output "No QA Pairs." (3)Don't explain your question and answer. (4)Do not generate answers for questions that are uncertain or unknown. (5)Do not include any descriptions of the sound in the question, as this would require the user to first know what the sound is. (6)Your output format is either "No QA Pairs" or several dict containing key "Question" and "Answer" in a list.

[Detailed Audio Description]
The list in the next line provides descriptions of the audio, with each sentence being an annotation of the audio made by different annotators. To reiterate, do not mention any information about this audio clip in the question, use "the sound" as a substitute.

Format of Prompt for Scoring in Chat Benchmark

You are a helpful and precise assistant for checking the quality of the answer.

[Detailed Audio Description]

[Question]

[The Start of Assistant 1s Answer]

[The End of Assistant 1s Answer]
[The Start of Assistant 2s Answer]

[The End of Assistant 2s Answer]
[System]
We would like to request your feedback on the performance of two AI assistants in response to the user question and audio description displayed above. AI assistants are provided with detailed audio descriptions and questions.
Please rate the helpfulness, relevance, accuracy, and comprehensiveness of their responses. Each assistant receives an overall score on a scale of 1 to 10, where a higher score indicates better overall performance. Please first output a single line containing only two values indicating the scores for Assistant 1 and 2, respectively. The two scores are separated by a space. In the subsequent line, please provide a comprehensive explanation of your evaluation, avoiding any potential bias and ensuring that the order in which the responses were presented does not affect your judgment.

Figure 5: GPT prompts for creating QA in the foundation benchmark and scoring in the chat benchmark.

Categories	Qwen-Audio	Qwen-Audio Turbo	SALMONN	BLSP	NExT-GPT	SpeechGPT	PandaGPT	Whisper+GPT-4
Speech grounding	**56.1%**	45.4%	25.3%	25.0%	25.4%	28.8%	23.0%	35.0%
Spoken language identification	92.8%	95.9%	28.1%	30.8%	23.7%	39.6%	34.6%	**96.8%**
Speaker gender recognition	67.2%	**82.5%**	35.5%	33.2%	57.0%	29.2%	66.5%	21.9%
Emotion recognition	43.2%	**60.0%**	29.9%	27.4%	25.7%	37.6%	26.0%	59.5%
Speaker age prediction	36.0%	58.8%	48.7%	51.2%	**62.4%**	20.4%	42.5%	41.1%
Speech entity recognition	**71.2%**	48.1%	51.7%	37.2%	26.1%	35.9%	34.0%	69.8%
Intent classification	77.8%	56.4%	36.7%	46.6%	25.6%	45.8%	28.5%	**87.7%**
Speaker number verification	35.3%	**54.3%**	34.3%	28.1%	25.4%	32.6%	43.2%	30.0%
Synthesized voice detection	48.3%	**69.3%**	50.0%	50.0%	30.8%	39.2%	53.1%	40.5%
Audio grounding	23.9%	41.6%	24.0%	34.6%	**62.2%**	26.1%	38.3%	/
Vocal sound classification	**84.9%**	78.1%	45.3%	29.8%	23.5%	26.2%	31.6%	/
Acoustic scene classification	**67.5%**	61.3%	34.1%	25.2%	24.1%	23.7%	55.7%	/
Sound question answering	**64.6%**	62.8%	28.4%	36.1%	18.8%	33.9%	48.7%	/
Music instruments classification	59.1%	**59.6%**	41.3%	22.8%	24.3%	29.1%	47.7%	/
Music genre classification	71.2%	**77.1%**	45.3%	26.1%	28.1%	29.3%	39.8%	/
Music note analysis-pitch	28.6%	**30.1%**	26.4%	23.5%	25.1%	24.1%	26.4%	/
Music note analysis-velocity	25.4%	25.1%	22.8%	24.9%	23.1%	25.2%	**27.2%**	/
Music question answering	48.2%	**62.5%**	54.6%	31.0%	47.1%	31.3%	50.7%	/
Music emotion detection	36.1%	**39.0%**	32.2%	28.3%	25.4%	29.7%	36.7%	/

Table 5: The accuracy of each model across all tasks in the foundation benchmark.

access to the audio and the question posed. The lower two columns of the figure document the responses from the 9 models being tested. Similarly, an example of responses from various models on the chat benchmark can be seen in Figure 7.

E Details in Human Evaluation

We conducted a pairwise crowd worker evaluation to assess the alignment between the judgments derived from GPT-4 and those of human evaluators for both the foundation and chat benchmarks. Each pair of evaluations was scrutinized by three native English-speaking judges.

- For the foundation benchmark, we randomly selected 400 questions from the pool of model responses. These were accompanied by both GPT-3.5 and GPT-4 alignment results. Evaluators were instructed to ascertain whether the responses provided by GPT-3.5 Turbo and GPT-4 Turbo was accurate. The screenshots of instructions for the foundation benchmark is shown in Figure 8.

- For the chat benchmark, we randomly chose 200 dialogues from the responses generated by Qwen-Audio-Chat, SALMONN, BLSP, and GPT-4, respectively. Evaluators were tasked with determining which model exhibited superior or equivalent performance. The screenshots of instructions for the chat benchmark is shown in Figure 9.

Types	Task	Question Example	Choice Example
Speech	Speech Grounding	Choose when 'hate' is spoken.	A.[7.67, 8.05] B.[1.03, 1.53] C.[3.07, 3.27] D.[7.02, 7.21]
	Spoken language identification	Recognize the language of the speech.	A.en B.ja C.de D.fr
	Speaker gender recognition (biologically)	Detect the gender of the speaker in this audio file.	A.male B.female
	Emotion recognition	What emotion is at the forefront of the speaker's words?	A.angry B.happy C.sad D.neutral
	Speaker age prediction	Which age range do you believe best matches the speaker's voice?	A.teens to twenties B.thirties to forties C.fifties to sixties D.seventies to eighties
	Speech entity recognition	Tell me the first 'transport_type'-connected word in this audio.	A.go B.how C.metro D.train
	Intent classification	What's your opinion on the speaker's goal in this sound clip?	A.audio_volume_up B.news_query C.lists_createoradd D.play_podcasts
	Speaker number verification	The speech features how many speakers?	A.2 B.4 C.3 D.1
	Synthesized voice detection	Based on your assessment, is this speech Real or Fake?	A.fake B.real
Sound	Audio grounding	What are the exact times when 'a woman briefly talks' is present in the clip?	A.[0.44, 2.38] B. [3.85, 4.11] C. [9.01, 10.02] D. [4.15, 7.83]
	Vocal sound classification	What's the provenance of the sound in this clip?	A.Sigh B.Throat clearing C.Cough D.Sneeze
	Acoustic scene classification	What venue are the sounds indicative of?	A.kitchen B.elevator C.street D.crowded indoor
	Sound question answering	What animal makes a sound in the video?	A.cattle B.horse C.cat D.bird
Music	Music instruments classification	Discern the principal instrument in this tune.	A.bass B.string C.brass D.mallet
	Music genre classification	What's the genre identity of this music?	A.Jazz B.Rock C.Country D.Experimental
	Music note analysis-pitch	What is the MIDI pitch level of the note played?	A.midi_pitch_19 B.midi_pitch_29 C.midi_pitch_37 D.midi_pitch_71
	Music note analysis-velocity	What numerical value is the MIDI velocity for this note?	A.midi_velocity_127 B.midi_velocity_50 C.midi_velocity_100 D.midi_velocity_25
	Music question answering	Is the guzheng louder than the piano?	A.yes B.no C.four D.one
	Music emotion detection	What kind of sentiment does this music invoke?	A.meditative B.positive C.trailer D.advertising

Table 6: Examples of questions and choices on the foundation benchmark.

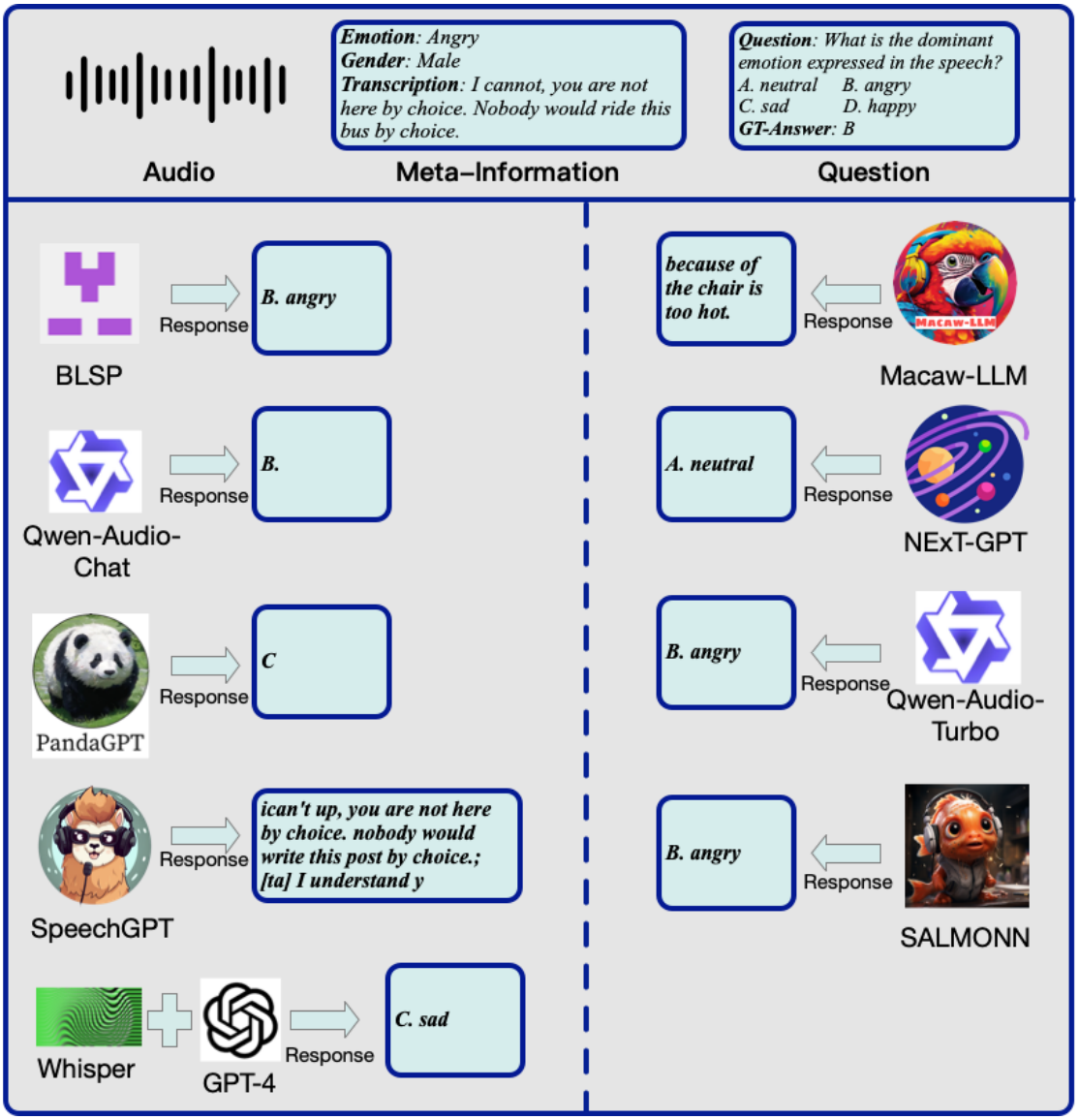


Figure 6: The illustration of the models' responses on the foundation benchmark.

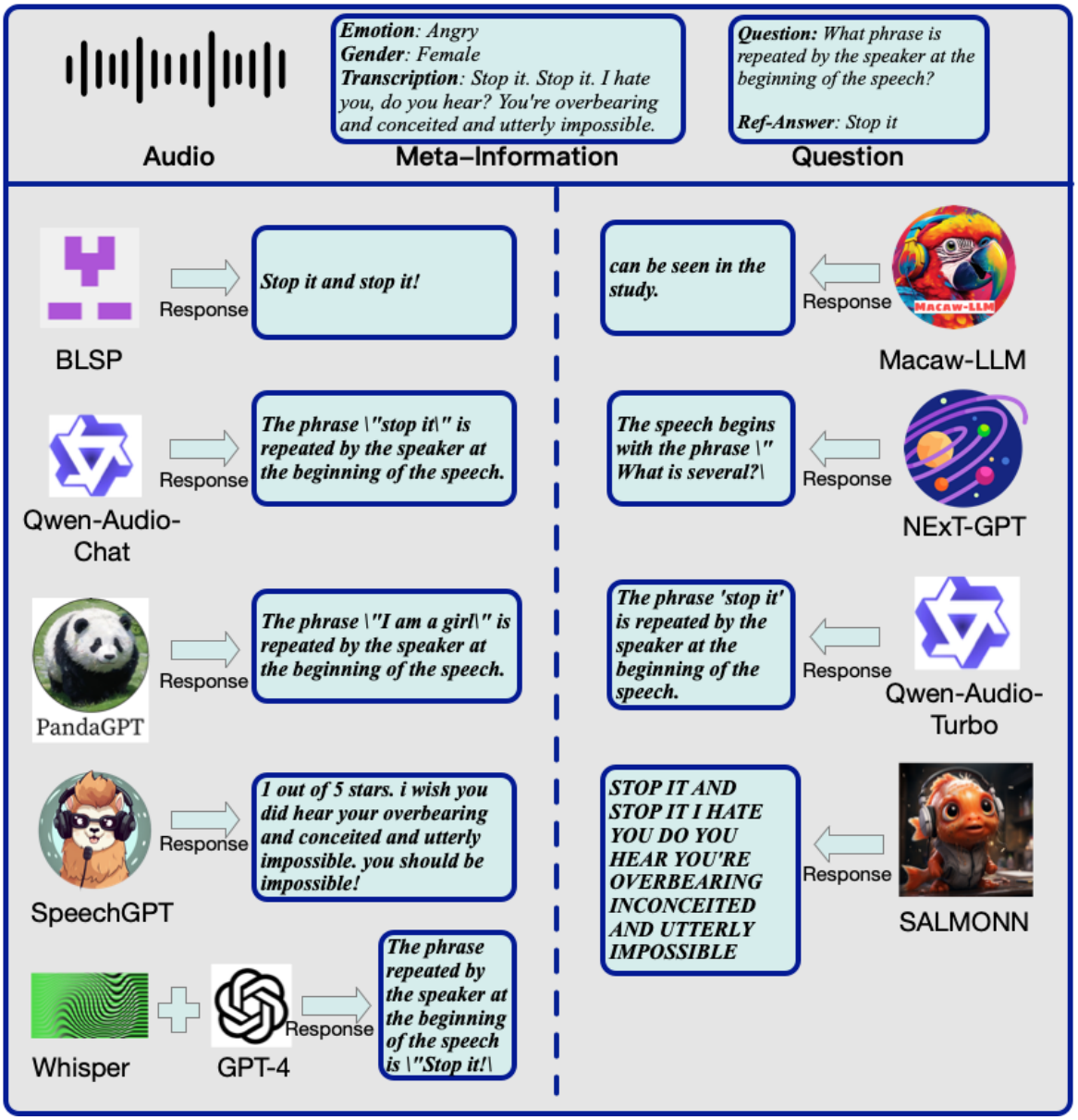


Figure 7: The illustration of the model's responses on the chat benchmark.

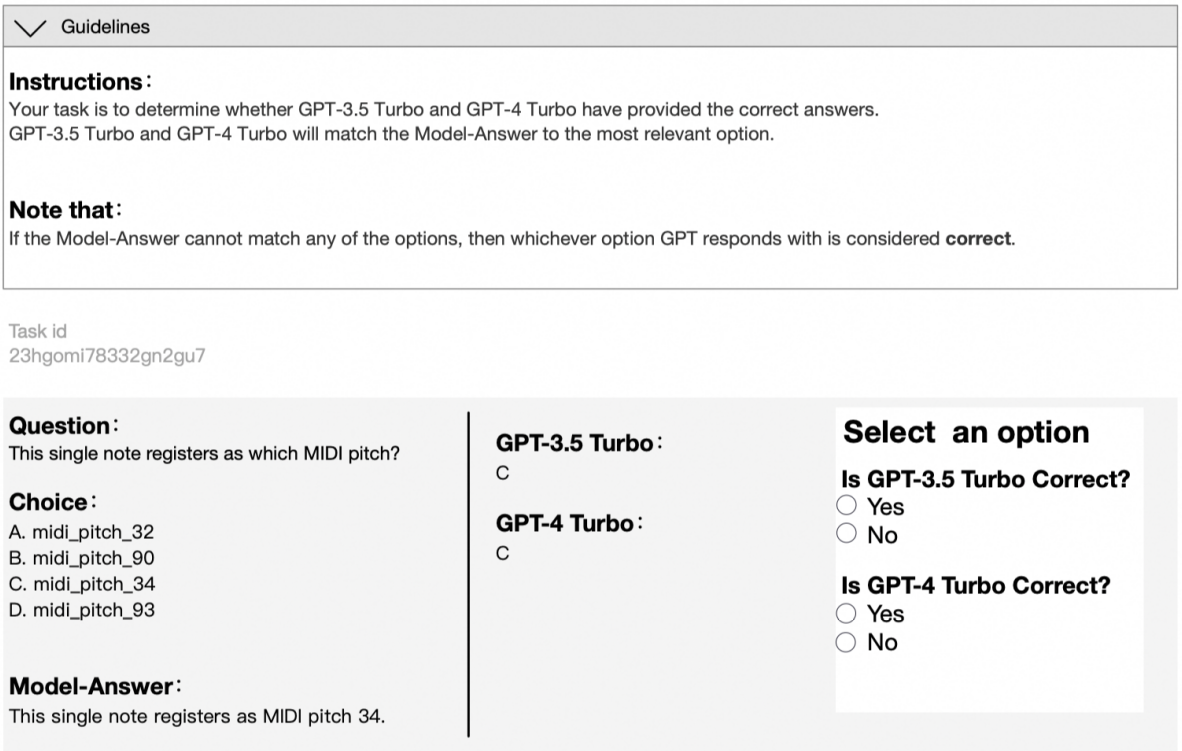


Figure 8: Screenshot of human evaluation for the foundation benchmark.

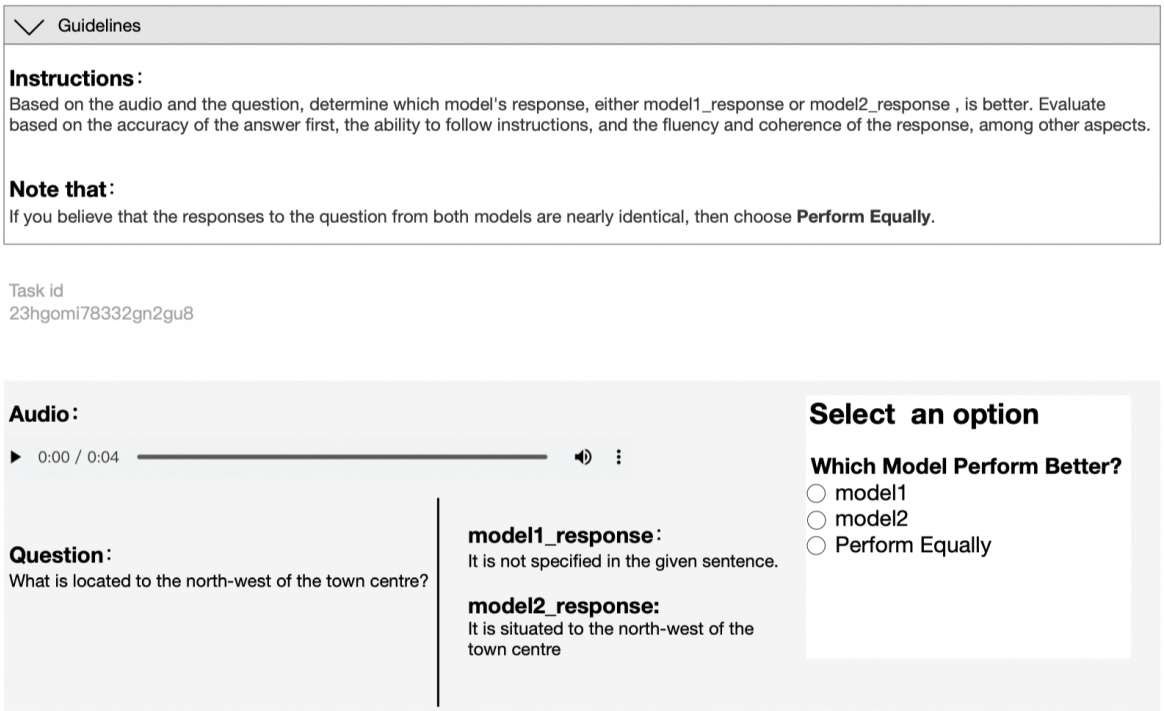


Figure 9: Screenshot of human evaluation for the chat benchmark.