Qwen2-Audio Technical Report

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Code & Demo & Models: https://github.com/QwenLM/Qwen2-Audio

Abstract

We introduce the latest progress of Qwen-Audio, a large-scale audio-language model called Qwen2-Audio, which is capable of accepting various audio signal inputs and performing audio analysis or direct textual responses with regard to speech instructions. In contrast to complex hierarchical tags, we have simplified the pre-training process by utilizing natural language prompts for different data and tasks, and have further expanded the data volume. We have boosted the instruction-following capability of Qwen2-Audio and implemented two distinct audio interaction modes for voice chat and audio analysis. In the voice chat mode, users can freely engage in voice interactions with Qwen2-Audio without text input. In the audio analysis mode, users could provide audio and text instructions for analysis during the interaction. Note that we do not use any system prompts to switch between voice chat and audio analysis modes. Qwen2-Audio is capable of intelligently comprehending the content within audio and following voice commands to respond appropriately. For instance, in an audio segment that simultaneously contains sounds, multi-speaker conversations, and a voice command, Qwen2-Audio can directly understand the command and provide an interpretation and response to the audio. Additionally, DPO has optimized the model's performance in terms of factuality and adherence to desired behavior. According to the evaluation results from AIR-Bench, Qwen2-Audio outperformed previous SOTAs, such as Gemini-1.5-pro, in tests focused on audio-centric instruction-following capabilities. Qwen2-Audio is open-sourced with the aim of fostering the advancement of the multi-modal language community.

1 Introduction

Audio serves as a crucial medium for interaction and communication among humans and other living beings, carrying rich information content. A comprehensive understanding of various forms of audio signals is paramount to achieving Artificial General Intelligence (AGI). Recently, significant advancements have been made in the development of large audio-language models (LALMs) (Chu et al., 2023; Das et al., 2024; Kong et al., 2024; Tang et al., 2024; OpenAI, 2024), demonstrating remarkable achievements in comprehending diverse speech signals, performing speech signal analysis, and complex reasoning.

In this report, we develop Qwen2-Audio, with a primary focus on enhancing its instruction-following capabilities. Qwen2-Audio is a Large Audio-Language Model (LALM) designed to process both audio and text inputs to generate textual outputs. Compared to previous models, Qwen2-Audio significantly scales up the training dataset. To reduce the gap between pre-training and post-training stages, we simplify the

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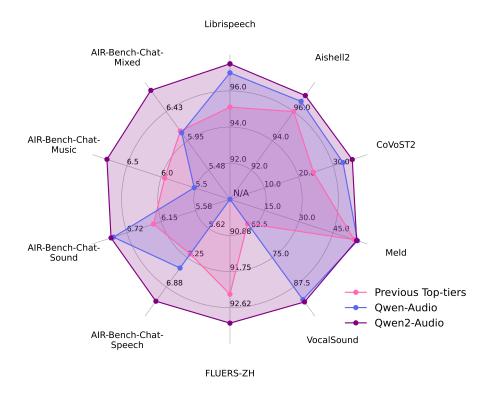


Figure 1: Performance of Qwen2-Audio, Qwen-Audio and previous top-tiers from LALMs such as SpeechT5 (Ao et al., 2021), SpeechNet (Chen et al., 2021), SpeechLLaMA (Wu et al., 2023a), SALMONN (Tang et al., 2024), Whisper (Radford et al., 2023) Pengi (Deshmukh et al., 2023), and SpeechVerse (Das et al., 2024). We demonstrate the test set results across the 10 datasets covering Automatic Speech Recognition (ASR), Speech-to-Text Translation (S2TT), Speech Emotion Recognition (SER), Vocal Sound Classification (VSC), and instruction-following benchmark (Yang et al., 2024). The results of ASR datasets, such as Librispeech and Aishell2 refer to 1 - WER%. The results of CoVoST2 is the average BLEU score of seven translation directions (en-de, de-en, en-zh, zh-en, es-en, fr-en and it-en). The results of the AIR-Bench chat benchmark encompass four dimensions: speech, sound, music, and mixed. Scores for each dimension are automatically assessed by GPT-4, with values ranging from 0 to 10. Qwen2-Audio achieves remarkable performance without requiring any task-specific fine-tuning, surpassing its counterparts.

pre-training process by directly using natural language prompts for various data and tasks, as illustrated in figure 2. Following the practices in Large Language Models (LLMs) (OpenAI, 2023; Qwen, 2023), we further conduct instruction tuning and direct preference optimization to align the model's outputs with human preferences.

Qwen2-Audio operates in two distinct modes: Audio Analysis and Voice Chat. These two modes are differentiated by their functionality, but there is no need for users to distinguish between them during use. In the audio analysis mode, users can leverage Qwen2-Audio to analyze a diverse range of audio types, including speech, sound, music, or various mixed audio forms. Commands can be issued either through audio or text, and Qwen2-Audio will autonomously discern the command segments within the audio. Conversely, in voice chat mode, users can interact with Qwen2-Audio as if it were a conversational agent, engaging in unrestricted dialogue. Audio interaction is available, and users can switch to text interaction at any moment they choose. For instance, if a user inputs an audio clip where the initial part is the sound of typing on a keyboard, followed by the user asking "What is this sound?" in spoken language, Qwen2-Audio is expected to respond directly with "This is the sound of a keyboard."

As shown in Figure 1, extensive evaluation demonstrates that Qwen2-Audio, without any task-specific fine-tuning, outperforms previous LALMs across a diverse range of tasks. Among them, Qwen2-Audio

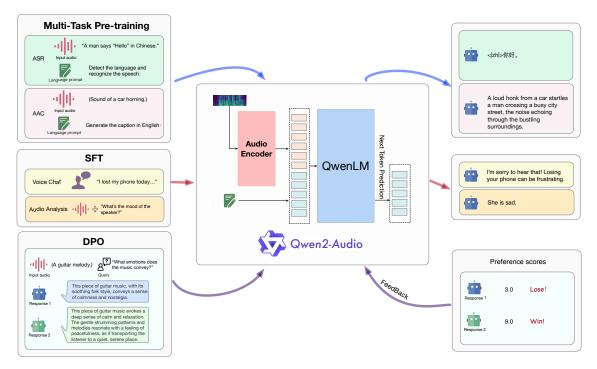


Figure 2: The overview of three-stage training process of Qwen2-Audio.

achieves state-of-the-art performance on the test set of Aishell2, FLUERS-zh, VocalSound and AIR-Bench chat benchmark.

2 Methodology

Model Architecture The training process of Qwen2-Audio is depicted in Figure 2, which contains an audio encoder and a large language model. Given the paired data (a, x), where the *a* and *x* denote the audio sequences and text sequences, the training objective is to maximize the next text token probability as

$$\mathcal{P}_{\theta}(x_t | \boldsymbol{x}_{< t}, \operatorname{Encoder}_{\phi}(\boldsymbol{a})), \tag{1}$$

conditioning on audio representations and previous text sequences $x_{<t}$, where θ and ϕ denote the trainable parameters of the LLM and audio encoder respectively.

Different from Qwen-Audio, the initialization of the audio encoder of Qwen2-Audio is based on the Whisperlarge-v3 model (Radford et al., 2023). To preprocess the audio data, we resamples it to a frequency of 16kHz and converts the raw waveform into 128-channel mel-spectrogram using a window size of 25ms and a hop size of 10ms. Additionally, a pooling layer with a stride of two is incorporated to reduce the length of the audio representation. As a result, each frame of the encoder output approximately corresponds to a 40ms segment of the original audio signal. Qwen2-Audio still incorporates the large language model Qwen-7B (Bai et al., 2023) as its foundational component. The total parameters of Qwen2-Audio is 8.2B parameters.

Pre-training At the pre-training stage, we replace the hierarchical tags (Chu et al., 2023) with the natural language prompts. As shown in Figure 2. We find that using language prompts can improve better generalization ability and better instruction following ability.

Supervised Fine-tuning The thorough pretraining of Qwen2-Audio has equipped the model with a comprehensive understanding of audio content. Building upon this, we employ instruction-based fine-tuning

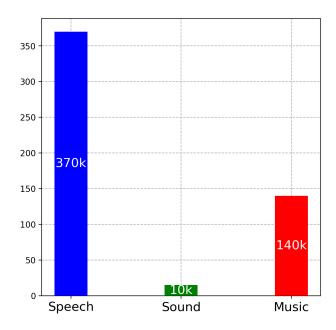


Figure 3: Statistics (hours) of pre-training dataset.

techniques to improve the ability of the model to align with human intent, resulting in an interactive chat model. Our prelimilary study emphasizes the critical influence of the quality and complexity of SFT data on the model's performance. Accordingly, a meticulously curated set of high-quality SFT data was collected, with rigorous quality control procedures implemented.

We consider two distinct modes for human interactions:

• Audio Analysis: In the audio analysis mode, users are afforded the flexibility to have Qwen2-Audio analyze a diverse array of audio. User instructions can be given either through audio or text.

This mode is often used for offline analysis of audio files.

• Voice Chat: In the voice chat mode, users are encouraged to engage in voice conversations with Qwen2-Audio, asking a wide range of questions. Please feel free to consider it your voice chat assistant. This mode is often used for online interaction with LALMs.

For consistency and model uniformity, both interaction modes were jointly trained, thus users will not experience mode differentiation during use, nor is it necessary to switch between different modes using separate system prompts. The two modes are seamlessly integrated in actual use.

Direct Preference Optimization We employ DPO (Rafailov et al., 2024) to further optimize models to follow human preferences. By obtaining the dataset \mathcal{D} with the triplet data (x, y_w, y_l) , where x is the input sequence with input audio, and y_w and y_l are the human-annotated good and bad responses respectively, we optimize the model \mathcal{P}_{θ} as follows:

$$\mathcal{L}_{\text{DPO}}(\mathcal{P}_{\theta}; \mathcal{P}_{\text{ref}}) = -\mathbb{E}_{(\boldsymbol{x}, \boldsymbol{y}_{\boldsymbol{w}}, \boldsymbol{y}_{\boldsymbol{l}}) \sim \mathcal{D}} \left[\log \sigma \left(\beta \log \frac{\mathcal{P}_{\theta}(\boldsymbol{y}_{\boldsymbol{w}} \mid \boldsymbol{x})}{\mathcal{P}_{\text{ref}}(\boldsymbol{y}_{\boldsymbol{w}} \mid \boldsymbol{x})} - \beta \log \frac{\mathcal{P}_{\theta}(\boldsymbol{y}_{\boldsymbol{l}} \mid \boldsymbol{x})}{\mathcal{P}_{\text{ref}}(\boldsymbol{y}_{\boldsymbol{l}} \mid \boldsymbol{x})} \right) \right],$$
(2)

where \mathcal{P}_{ref} denotes the reference model initialized with \mathcal{P}_{θ} , σ represents sigmoid function and β is a hyperparameter. Figure 2 illustrates the three-stage training process of Qwen2-Audio.

¹https://github.com/mjpost/sacrebleu

| Task | Description | Dataset | Split | Metric |
|----------------------------------|------------------------------|---|--|---|
| ASR | Automatic Speech Recognition | Fleurs (Conneau et al., 2022) Aishell2 (Du et al., 2018) Librispeech (Panayotov et al., 2015) Common Voice (Ardila et al., 2020) | dev test test dev test dev test | WER |
| S2TT | Speech-to-Text Translation | CoVoST2 (Wang et al., 2020) | test | BLEU ¹ (Papineni et al., 2002) |
| SER | Speech Emotion Recognition | Meld (Poria et al., 2019) | test | ACC |
| VSC | Vocal Sound Classification | VocalSound (Gong et al., 2022) | test | ACC |
| AIR-Bench (Yang et al., 2024) | Chat-Benchmark-Speech | Fisher (Cieri et al., 2004) SpokenWOZ (Si et al., 2023) IEMOCAP (Si et al., 2023) Common voice (Ardila et al., 2020) | dev test | GPT-4 Eval |
| | Chat-Benchmark-Sound | Clotho (Drossos et al., 2020) | dev test | GPT-4 Eval |
| | Chat-Benchmark-Music | MusicCaps (Agostinelli et al., 2023) | dev test | GPT-4 Eval |
| | Chat-Benchmark-Mixed-Audio | Common voice (Ardila et al., 2020) AudioCaps (Kim et al., 2019) MusicCaps (Agostinelli et al., 2023) | dev test | GPT-4 Eval |

Table 1: Summary of Evaluation Benchmarks for Qwen2-Audio.

3 Experiments

3.1 Evaluation

In practice, we have found that many previous test datasets are highly limited and cannot adequately reflect performance in real-world scenarios, such as some SLU (Spoken Language Understanding) and SER (Speech Emotion Recognition) datasets. Therefore, we mainly evaluated performance directly on AIR-Bench. We discovered that the scores from AIR-Bench align more closely with the actual user interaction experience. Meanwhile, in order to assess the universal understanding capabilities of Qwen2-Audio, as shown in Table 1, we still perform a comprehensive evaluation that encompasses various tasks, namely Automatic Speech Recognition (ASR), Speech-to-Text Translation (S2TT), Speech Emotion Recognition (SER), Vocal Sound Classification (VSC). The evaluation is conducted across 13 datasets. The evaluation datasets are rigorously excluded from the training data to avoid data leakage. The models we compare include open-source models and callable APIs, such as Gemini.

3.2 Main Results

In this section, we present a comprehensive evaluation of the Qwen2-Audio model, assessing its performance across various tasks without any task-specific fine-tuning. We begin by examining its English Automatic Speech Recognition (ASR) results, as depicted in Table 2, where Qwen2-Audio exhibits superior performance compared to previous multi-task learning models. Specifically, it achieves a 1.6% and 3.6% WER on the librispeech test-clean and test-other datasets, respectively. Compared with Whisper-large-v3 on Fleurs zh subset, we achieve better results than Whisper-large-v3. One point to note is that Qwen2-Audio is not evaluated in a zero-shot manner on the Common Voice 15 dataset, whereas Whisper's results are obtained in a zero-shot fashion. However, on the Fleurs dataset, both Qwen2-Audio and Whisper are evaluated in a zero-shot manner. Furthermore, we evaluate Qwen2-Audio's speech translation performance on the CoVoST2 dataset. The results reveal that Qwen2-Audio outperforms the baselines by a substantial margin across all seven translation directions. For sound, we analyze the performance of Qwen2-Audio on SER, and VSC, as summarized in Table 2. Across these tasks, Qwen2-Audio consistently outperforms the baselines by a significant margin.

Lastly, to objectively evaluate the chat capabilities of Qwen2-Audio, we measured its performance on the

| Task | Dataset | Model | Performance | |
|----------------------------------|--|---|------------------|--|
| | | | Metrics | Results |
| | Librispeech dev-clean dev-other test-clean test-other | SpeechT5 (Ao et al., 2021) SpeechNet (Chen et al., 2021) SLM-FT (Wang et al., 2023b) SALMONN (Tang et al., 2024) SpeechVerse (Das et al., 2024) Qwen-Audio (Chu et al., 2023) Qwen2-Audio | WER↓ | 2.1 5.5 2.4 5.8 - - 30.7 - - - 2.6 5.0 - - 2.1 4.9 - - 2.1 4.4 1.8 4.0 2.0 4.2 1.3 3.4 1.6 3.6 |
| ASR | Common Voice 15 <i>en</i> <i>zh</i> <i>yue</i> <i>fr</i> | Whisper-large-v3 (Radford et al., 2023) Qwen2-Audio | WER \downarrow | 9.3 12.8 10.9 10.8 8.6 6.9 5.9 9.6 |
| | Fleurs zh | Whisper-large-v3 (Radford et al., 2023) Qwen2-Audio | WER \downarrow | 7.7 7.5 |
| | Aishell2 Mic iOS Android | MMSpeech-base (Zhou et al., 2022) Paraformer-large (Gao et al., 2023) Qwen-Audio (Chu et al., 2023) Qwen2-Audio | WER \downarrow | 4.5 3.9 4.0 - 2.9 - 3.3 3.1 3.3 3.0 3.0 2.9 |
| S2TT | CoVoST2 en-de de-en en-zh zh-en | SALMONN (Tang et al., 2024) SpeechLLaMA (Wu et al., 2023a) BLSP (Wang et al., 2023a) Qwen-Audio (Chu et al., 2023) Qwen2-Audio | BLEU ↑ | 18.6 - 33.1 - - 27.1 - 12.3 14.1 - - - 25.1 33.9 41.5 15.7 29.9 35.2 45.2 24.4 |
| | CoVoST2 es-en fr-en it-en | SpeechLLaMA (Wu et al., 2023a) Qwen-Audio (Chu et al., 2023) Qwen2-Audio | BLEU ↑ | 27.9 25.2 25.9 39.7 38.5 36.0 40.0 38.5 36.3 |
| SER | Meld | WavLM-large (Chen et al., 2022) Qwen-Audio (Chu et al., 2023) Qwen2-Audio | ACC ↑ | 0.542 0.557 0.553 |
| VSC | VocalSound | CLAP (Elizalde et al., 2022) Pengi (Deshmukh et al., 2023) Qwen-Audio (Chu et al., 2023) Qwen2-Audio | ACC ↑ | 0.4945 0.6035 0.9289 0.9392 |
| AIR-Bench (Yang et al., 2024) | Chat Benchmark Speech Sound Music Mixed-Audio | SALMONN (Tang et al., 2024) BLSP (Wang et al., 2023a) Pandagpt (Su et al., 2023) Macaw-LLM (Lyu et al., 2023) SpeechGPT (Zhang et al., 2023) Next-gpt (Wu et al., 2023b) Qwen-Audio (Chu et al., 2023) Gemini-1.5-pro (Reid et al., 2024) Qwen2-Audio | GPT-4↑ | $\begin{array}{c} 6.16 \mid 6.28 \mid 5.95 \mid 6.08\\ 6.17 \mid 5.55 \mid 5.08 \mid 5.33\\ 3.58 \mid 5.46 \mid 5.06 \mid 4.25\\ 0.97 \mid 1.01 \mid 0.91 \mid 1.01\\ 1.57 \mid 0.95 \mid 0.95 \mid 4.13\\ 3.86 \mid 4.76 \mid 4.18 \mid 4.13\\ 6.47 \mid 6.95 \mid 5.52 \mid 6.08\\ 6.97 \mid 5.49 \mid 5.06 \mid 5.27\\ \textbf{7.18 \mid 6.99 \mid 6.79 \mid 6.77} \end{array}$ |

Table 2: The results of Automatic Speech Recognition (ASR), Speech-to-Text Translation (S2TT), Speech Emotion Recognition (SER), Vocal Sound Classification (VSC), and AIR-Bench chat benchmark. Note that for Qwen2-Audio, the results for Fleurs are zero-shot, whereas the results for Common Voice are not zero-shot.

chat benchmark of the AIR-Bench (Yang et al., 2024). Note that since Gemini-1.5 (Reid et al., 2024)² cannot correctly return some test samples due to its SAFETY reasons during testing, the number of samples of Gemini-1.5 on AIR-Bench-chat has been reduced by about 1/5. As shown in table 2, Qwen2-Audio demonstrates state-of-the-art (SOTA) instruction-following capabilities across speech, sound music and mixed-Audio subsets. It shows substantial improvements compared to Qwen-Audio and significantly outperforms other LALMs.

 $^{^{2} \}tt https://console.cloud.google.com/vertex-ai/generative/multimodal/create$

4 Cases

Here, we present a part of cases to illustrate Qwen2-Audio's audio-based interaction capabilities. For more impressive examples, please refer to https://github.com/Qwen1M/Qwen2-Audio.

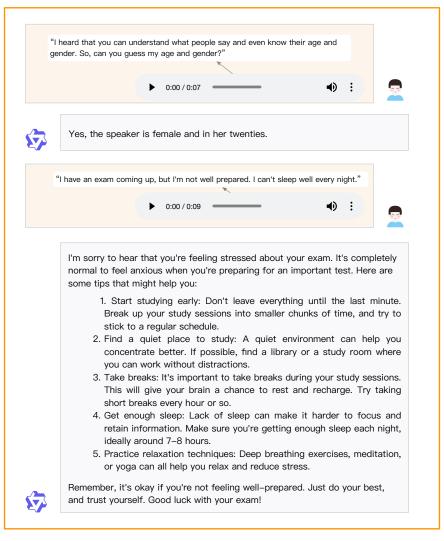


Figure 4: Example showing Qwen2-Audio's capability in free chat around speech.

5 Conclusion

In this paper, we present Qwen2-Audio, which builds upon Qwen-Audio's capability to analyze various types of audio while also being endowed with voice interaction abilities. During the pre-training stage, we utilized natural language prompts for different data and tasks and have further expanded the data volume. In the SFT phase, we enhanced Qwen2-Audio's alignment with human interaction by increasing the quantity, quality, and complexity of SFT data, thereby enabling seamless voice and text interactions. Additionally, we improved Qwen2-Audio's response quality through the DPO stage. Objective metrics tested on diverse benchmarks demonstrate Qwen2-Audio's proficiency in audio understanding and dialogue capabilities. The cases presented within the paper also illustrate Qwen2-Audio's fluent and flexible voice interaction capability.



Figure 5: Example showing Qwen2-Audio's capability in free chat around speech.



Figure 6: Example showing Qwen2-Audio's capability in free chat around speech and nature sound.

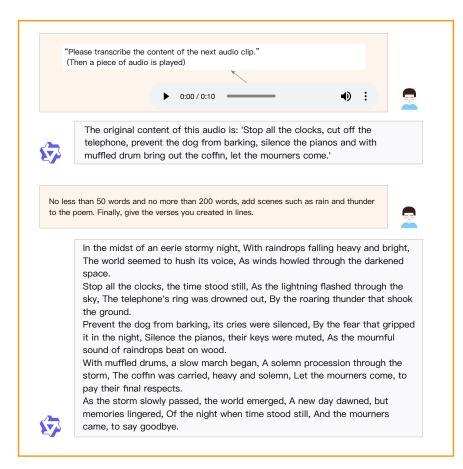


Figure 7: Example showing Qwen2-Audio's capability in speech analysis.

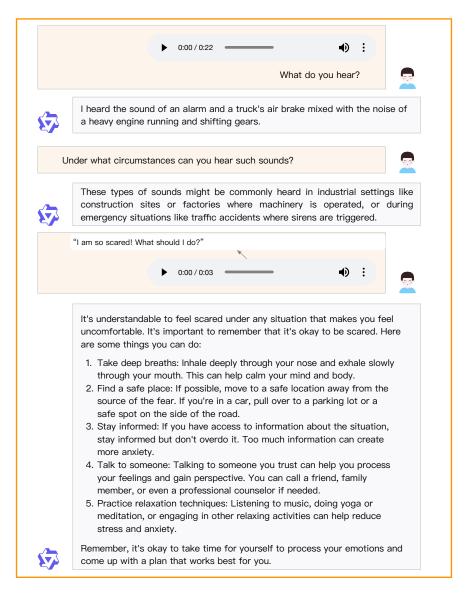


Figure 8: Example showing Qwen2-Audio's capability in sound analysis.

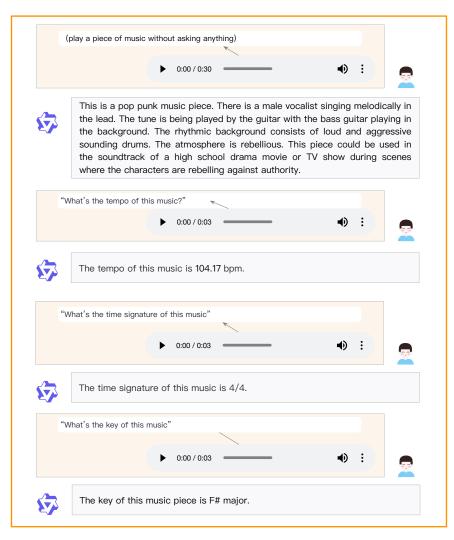


Figure 9: Example showing Qwen2-Audio's capability in music analysis.



Figure 10: Example showing Qwen2-Audio's robustness in mixed audio analysis.

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