

Bagpiper: Solving Open-Ended Audio Tasks via Rich Captions

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Abstract

Current audio foundation models typically rely on rigid, task-specific supervision, addressing isolated factors of audio rather than the whole. In contrast, human intelligence processes audio holistically, seamlessly bridging physical signals with abstract cognitive concepts to execute complex tasks. Grounded in this philosophy, we introduce Bagpiper, an 8B audio foundation model that interprets physical audio via *rich captions*, i.e., comprehensive natural language descriptions that encapsulate the critical cognitive concepts inherent in the signal (e.g., transcription, audio events). By pre-training on a massive corpus of 600B tokens, the model establishes a robust bidirectional mapping between raw audio and this high-level conceptual space. During fine-tuning, Bagpiper adopts a *caption-then-process* workflow, simulating an intermediate cognitive reasoning step to solve diverse tasks without task-specific priors. Experimentally, Bagpiper outperforms Qwen-2.5-Omni on MMAU and AIR-Bench for audio understanding and surpasses CosyVoice3 and TangoFlux in generation quality, capable of synthesizing arbitrary compositions of speech, music, and sound effects. To the best of our knowledge, Bagpiper is among the first works that achieve unified understanding-generation for general audio. Model, data, and code are available at [Bagpiper Home Page](#).

1. Introduction

Current audio foundation models are suboptimal for solving open-ended user requests. These models mainly rely on massive multi-tasking (Goel et al., 2025; Yang et al., 2023; Wang et al., 2024; Abouelenin et al., 2025; Valle et al., 2025;

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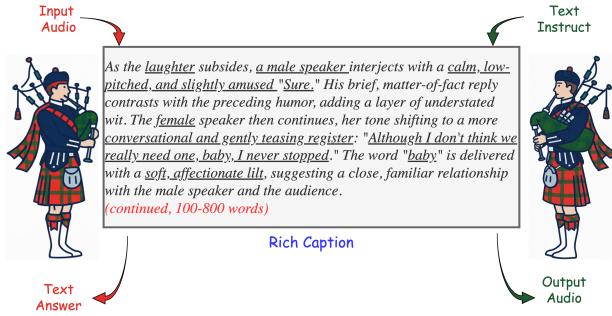


Figure 1. Bagpiper builds *rich caption* as a holistic and semantic medium before materializing responses for **audio understanding** (left) and **audio generation** (right).

Radford et al., 2023; Peng et al., 2024; Maiti et al., 2024), where each task only addresses an isolated aspect of the audio. Additionally, the audio modeling (especially the generation modeling) (Du et al., 2025; Hung et al., 2024; Mousavi et al., 2025; Shi et al., 2024) often has a clear split of speech, music, and sound effects. The lack of a holistic concept at the task- and category-level creates a fundamental bottleneck for scalability: addressing the wide spectrum of audio tasks via exhaustive, domain-specific engineering is unsustainable. More importantly, it generalizes poorly to the user requests that are usually compositional, flexible, and are not likely to fall within the boundaries of the predefined task or category. Thus, we argue for a paradigm shift toward a universal modeling philosophy that unifies all audio tasks and types within a single modeling paradigm.

Human intelligence perceives (understands) and produces (generates) audio in a holistic, open-ended, and multi-perspective manner, seamlessly bridging distinct categories like speech, music, and sound effects (Bregman, 1990; Patel, 2008). We propose that audio in this context is fundamentally twofold, defined by both the physical audio signals and the cognitive concepts they evoke in the human mind, such as text transcription, emotion, prosody, sound events, and music genres. Human intelligence processes audio by bridging these two planes: it converts audio signals into cognitive concepts to understand the world and, conversely, formulates responses derived from these concepts (O’Callaghan, 2009). In this work, we identify the *rich caption* (Ma et al.,

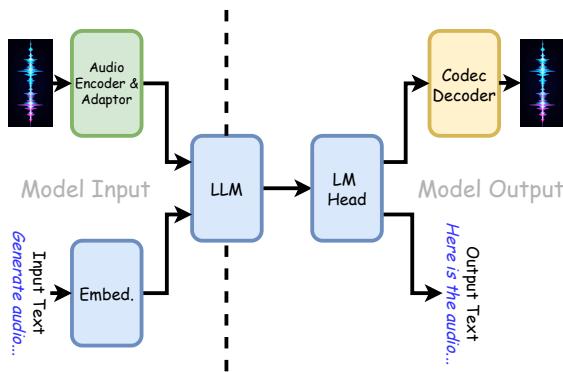


Figure 2. Bagpiper architecture

2025; Tang et al., 2025; Fiscus et al., 2006) as an ideal proxy for this wide range of human cognitive concepts. As illustrated in Figure 1 and Appendix A, rich captions provide lengthy, comprehensive natural language descriptions that cover the critical cognitive concepts inherent in an audio signal, offering sufficient information to support diverse downstream open-ended task solving. Guided by this philosophy, the core objective of our audio foundation model, Bagpiper, is to uniformly solve audio tasks by establishing and leveraging a broad, holistic, and robust bidirectional mapping between physical audio signals and these cognitive concepts. In implementation, we build this mapping during pre-training using a massive, curated dataset of 600B tokens, comprising audio-text pairs that span speech, music, and sound effects. We then proceed to a fine-tuning stage where we simulate diverse open-ended request-response pairs with thinking traces, teaching the model how to infer appropriate answers from predicted cognitive concepts (understanding) and how to translate user requests into cognitive concept blueprints before physically producing audio (generation). Throughout this development pipeline, we incorporate no prior knowledge of specific audio tasks or types; nonetheless, the model demonstrates the capability to solve a diverse array of open-ended audio tasks.

Experimentally, we first validate the efficacy of our pre-training Bagpiper-Base, demonstrating that physical audio and rich captions can be translated bidirectionally with high fidelity across a suite of probing tasks. In terms of open-ended understanding, the fine-tuned Bagpiper surpasses the capabilities of its 7B competitor Qwen-2.5-Omni (Xu et al., 2025), achieving superior performance on both AIR-Bench (Yang et al., 2024) and AudioBench (Wang et al., 2025). Regarding generative tasks, Bagpiper significantly outperforms prior state-of-the-art text-to-audio models, TangoFlux (Hung et al., 2024) and AudioLDM2-Large (Liu et al., 2024), in an extensive A/B testing on complex generation prompts. Beyond these quantitative metrics, we observe emergent model behaviors that transcend the scope of current evaluation protocols; we invite readers to explore

these qualitative examples on [Bagpiper Home Page](#). To facilitate reproducibility and future research, we commit to releasing our code, data, and trained models.

2. Bagpiper

We firstly introduce the unified model architecture of our Bagpiper in §2.1. We then describe the pre-training stage in §2.2, where we establish the bidirectional mapping between audio signals and cognitive concepts (rich captions). Finally, in §2.3, we discuss the supervised fine-tuning strategy that equips the model with open-ended task-solving capabilities.

2.1. Architecture

Like Tian et al. (2025b), our Bagpiper is designed to process any interleaved audio and text sequences within a unified framework. As shown in Figure 2, the backbone is initialized with the decoder-only LLM, i.e., Qwen3-8B-Base (Yang et al., 2025). We adopt the established *Encoder-Adaptor-LLM* architecture (Liu et al., 2023; Goel et al., 2025) for audio input, which connects a pre-trained acoustic encoder to the LLM backbone via an MLP layer. For audio output, the model auto-regressively predicts multi-stream audio codec tokens, which are then detokenized into audio waveforms.¹ This design enables the consistent and seamless processing of multimodal inputs and outputs.

For all training stages, we apply standard next-token prediction loss on target tokens only. During inference, we have separate inference configurations for text and audio generation. We additionally apply classifier-free guidance (Ho & Salimans, 2022; Hussain et al., 2025) for all audio generation tasks. No noticeable performance change is observed by varying the inference configurations. Detailed configurations are in the tables 9 and 10.

2.2. Pre-Training

The central premise of Bagpiper pre-training is that physical audio signals and cognitive concepts (i.e., rich captions) can be mutually translated with high fidelity. To realize this, our pre-training is to construct a robust bidirectional mapping between audio signals and rich captions via massive-scale learning. Additionally, it also requires preserving the text processing capabilities of the underlying LLM to support downstream complex task solving.

¹The audio encoder and codec model are adopted from Qwen3-Omni-30B-A3B (Team, 2025) and X-Codec (Ye et al., 2025), respectively. Each audio is represented by 8 tokens, and the audio token sequences are delay-interleaved (Copet et al., 2024).

2.2.1. DATA CURATION

Collection and Labeling. To ensure universal audio processing capabilities, we aggregate a massive collection of publicly available audio data covering speech, music, and sound effects (full list in Appendix C.1). Notably, this mixture features diverse in-the-wild distributions, naturally encompassing complex compositions such as speech with background noise or musical accompaniment. We segment all audio into clips of up to 30 seconds. As in Fig.3, we generate a rich caption for every clip using the Qwen3-Omni-30B-A3B-Captioner (Team, 2025). This process yields a total of 422M raw audio-caption pairs.

Audio Taxonomy Classification. As distinct audio categories (speech, music, and sound effects) exhibit divergent quality distributions and severe data imbalances, a stratified processing approach is used to keep a rough balance in the curated pre-training mixture.² While automatic classification directly from raw audio has been rarely addressed before, we find it is readily achievable by leveraging the semantic information in rich captions. We explicitly categorize all audio clips into speech, music, or sound effects by prompting Qwen3-32B to analyze their rich descriptions. This text-based strategy proves highly effective, achieving a 93% accuracy on the MMAU dataset (Sakshi et al., 2024) when benchmarked against the original ground-truth category labels.

Stratified Data Filtering. For each audio category, we score the audio-text pairs along three dimensions: (1) Audio-Only: We use UTMOS (Saeki et al., 2022; Shi et al., 2025) for speech and audiobox-aesthetics (Tjandra et al., 2025) for music and sound effects. (2) Text-Only: We apply heuristic filters combined with an LLM-as-a-judge approach (Zheng et al., 2023), evaluating three specific rubrics (Peng et al., 2025a). (3) Audio-text alignment: We compute the semantic similarity between the audio and caption using a CLAP-based model (Wu* et al., 2023).³ To unify these diverse metrics, we compute the percentile rank of each sample for every dimension within its specific category and average these percentiles to form a final quality score. Next, to maintain data diversity while removing low-quality outliers, we employ a Gumbel Top- k resampling trick (Kool et al., 2019) to perform a soft truncation of the tail distribution. Finally, we perform the text-based de-duplication by MinHush (Broder, 1997) using a setup as in Li et al. (2024). We observed that the generated rich captions possessed high natural diversity, resulting in the removal of only 1M pairs during de-duplication. Further details are

²For example, we observe the average aesthetic score of *music* is much higher than *sound effects* on average.

³As the CLAP model has a limited text context window, we summarize them into short captions in advance.

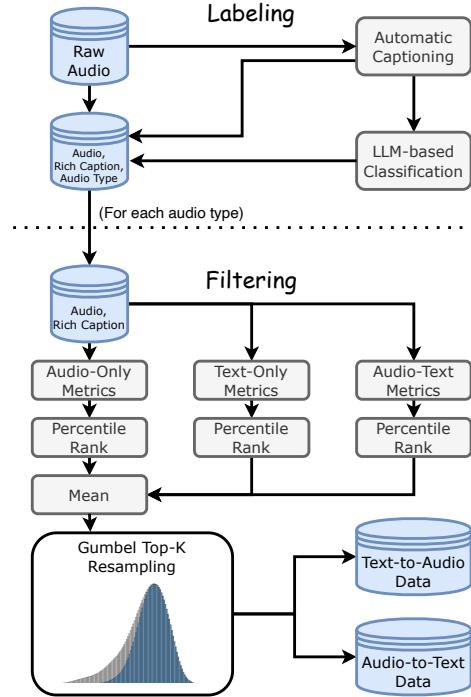


Figure 3. Pre-training data labeling and filtering workflow.

provided in Appendix C.2.

Text-Only Corpus. To preserve the text capability of the base LLM, we incorporate high-quality text-only corpora into the pre-training mixture. We specifically utilize datasets from (Bercovich et al., 2025) and the mid-training data of (Olmo et al., 2025), totaling 150B tokens. These datasets are yielded from harsh curation in prior works, so we skip further curation on text-only data.

Training Budget and Scheduling. Like in (Maiti et al., 2024; Olmo et al., 2025), we first allocate a total training budget of 600B tokens.⁴ Following empirical observations from Tian et al. (2025b), we adopt a data ratio of 300B (Text-to-Audio) : 150B (Audio-to-Text) : 150B (Text-only). This distribution serves two purposes: first, Tian et al. (2025b) finds that audio generation (Text-to-Audio) typically requires a longer training horizon to converge than understanding; second, it perfectly balances the output modalities, ensuring a 1:1 ratio between text-output and audio-output supervision. Within the text-to-audio and audio-to-text tasks, we evenly split the budget across speech, music, and sound effects, which effectively up-samples the music and sound effects data by a factor of 3–4× to counteract the natural scarcity of these domains compared to speech.

⁴A token represents either a text subword or an audio frame.

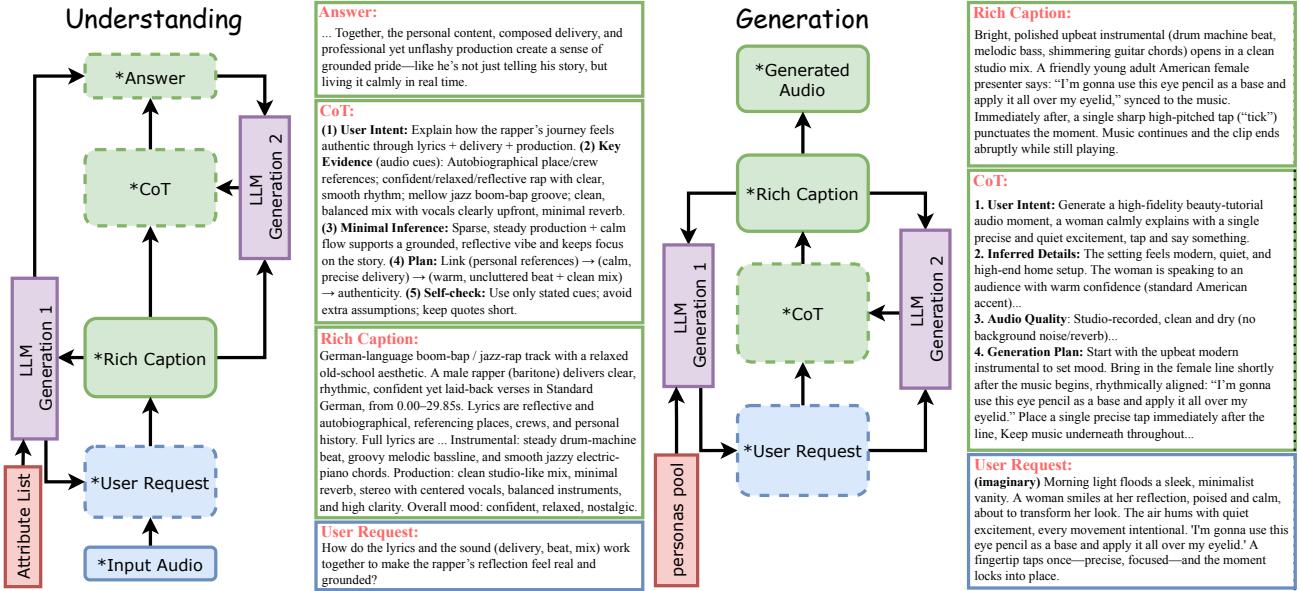


Figure 4. SFT data simulation pipeline §2.3.2 for open-ended audio task solving. Blue means model input; green means model output. Dashed boxes are simulated by prompting LLMs. Components with * are included in training sequences.

2.2.2. TRAINING STRATEGY

We implement a two-stage training protocol following (Wu et al., 2025). Stage 1 begins with an adapter and embedding warm-up stage (2k steps), where the audio encoder and LLM backbone are frozen; only the embeddings and the adaptor are optimized. During this stage, we employ a substantially larger batch size and learning rate compared to the subsequent stage to rapidly align the modalities. Following this, stage 2 launches the full pre-training stage. Here, we unfreeze the relevant parameters and apply a linear learning rate warm-up followed by cosine decay. The loss of audio tokens is observed to be much higher than that of text tokens on average. Consequently, we use sequence packing (Krell et al., 2021) that carefully fuses samples from both sides to reduce the training loss fluctuation. Detailed training hyperparameters are provided in Appendix 9. We refer to the resulting model as Bagpiper-Base.

2.3. Supervised Fine-Tuning (SFT)

In this SFT stage, we evolve Bagpiper-Base into a generalist problem solver. Consistent with our goal of overcoming the limitations of isolated supervision, we deliberately eschew traditional categorical labels during data simulation. Instead, we condition Bagpiper to treat rich captions as a universal semantic interface. By grounding the model’s reasoning process entirely in these natural language descriptions, we enable it to handle the boundless variety of open-ended tasks described in our introduction.

2.3.1. DATA COLLECTION AND GEMINI CAPTIONING

We curate diverse and high-quality audio-caption pairs for both audio understanding and generation. For audio understanding, we sample $\approx 271k$ examples from a series of open datasets. We use our manual prompt to query Gemini-3-Flash/Gemini-2.5-Pro to obtain the rich caption (detailed distributions can be referred to Appendix C.1). For audio generation, we continue our strategy of Gumbel Top- k sampling, but with a much lower temperature to select the highest quality data in our pre-training. We end up with 1M samples. Our audio generation data relies on the pre-training captions rather than Gemini-generated ones, preventing data leakage as Gemini is later employed as the evaluator in §3.2.2.

2.3.2. FINE-TUNING DATA CONSTRUCTION

Pipeline: Caption-then-Process. Our data simulation always starts from audio-caption pairs, and uniformly enforces an explicit “thinking” pattern. For **audio understanding**, we adopt the template: *[Audio, User Request, Rich Caption, CoT, Answer]*. As shown on the left of Figure 4, we prompt a strong text LLM to first synthesize a valid (*User Request, Answer*) pair given the ground-truth rich caption, and subsequently generate a *Chain-of-Thought (CoT)* trace (Wei et al., 2022) that reasons from cognitive concepts (i.e., rich captions) to the expected answer. For **audio generation**, we adopt the template: *[User Request, CoT, Rich Caption, Audio]*. As shown in the right of Figure 4, the simulation process is similar: the LLM generates a creative *User Request* based on the rich caption, followed by a *CoT* trace

that plans the audio content before outputting the caption.

Diversification. To cover more diversity of user requests, we employ targeted prompting strategies using strong open-source text LLMs.⁵ For **understanding**, we sample from an attribute list of 108 attributes⁶ to construct complex, multi-faceted inquiries. The LLMs are instructed to generate complex but reasonable requests with self-selected attributes. Our simulation also includes the cases where multiple related attributes are queried together to form compositional requests (Acuna et al., 2025). For **generation**, we adopt a “Persona-based” prompting strategy, selecting from 12 distinct user personas (Ge et al., 2024) to generate varying generation requests. Besides the user requests that explicitly mention the exact audio events and details, we also generate the imaginary user requests that describe a feeling, an atmosphere, or a scene, which potentially boost the model’s creativity in audio generation (Tian et al., 2025b).

Automatic Quality Assurance. To ensure high data quality, we implement a rigorous filtering pipeline utilizing the LLM-as-judge framework (Zheng et al., 2023). We employ Qwen3-235B-A22B-Instruct-2507-FP8 to evaluate each sample on a 5-point scale, assessing five key dimensions: user request diversity, request-response alignment, thinking trace coherence, rich caption quality, and overall training value. By retaining only those samples with an average score exceeding 3, we distill our simulated data into a final set of 845k understanding samples and 1.47M generation samples. Note that multiple requests will be generated for each audio-caption pair before this filtering.

3. Experiments

3.1. Pre-Training

3.1.1. EVALUATION SETUP

The Bagpiper-Base is not for real task-solving. Instead, our evaluation design for this pre-trained model is to quantify how much critical cognitive concepts are preserved in the rich captions that can support downstream task solving. We mainly rely on LibriSpeech Test-Clean (Panayotov et al., 2015) for local, phonetic-level capability and MMAU-Mini (Sakshi et al., 2024) for other audio-related capability in general, which covers speech, music, and sound effects.

Audio Understanding (Information Retention).

Following Ma et al. (2025), to quantify how much cognitive concepts are preserved for downstream understanding, we feed the generated caption into Gemini-3-Flash and request it to perform audio tasks solely based on the text,

⁵Specifically Qwen3-235B-A22B-Instruct-2507-FP8 and GPT-OSS-120B.

⁶We randomly sample 10k pre-training captions, ask Gemini-3-Pro to analyze them, and obtain this attribute list.

without access to the original audio. We report the Word Error Rate (WER) on LibriSpeech Test-Clean and question-answering accuracy on MMAU-Mini. High performance here indicates that the captions generated from audio successfully encapsulate the essential semantics of the audio clips for understanding.

Audio Generation (Reconstruction Fidelity). We evaluate whether the pre-trained model can physically produce the audio waveform with the audio caption generated by the original captioner (Team, 2025). We generate audio conditioned solely on the rich captions and compare the output to the ground truth audio. We report WER on LibriSpeech Test-Clean to assess phonetic preservation.⁷ For general audio, we employ a model-based metric on MMAU-Mini: We use Shi et al. (2025) to compute the FAD (Kilgour et al., 2018) and audio-audio CLAP similarity (Wu* et al., 2023) between the reference and generated audio, and average the number across all three categories.

Cycle Consistency. Given the unified understanding-generation nature of our model, isolated evaluation is often insufficient. We therefore follow Hori et al. (2019) to conduct a cycle consistency test to verify the robustness of the bidirectional mapping, which is similar to evaluating an auto-encoder. We perform consecutive *Audio → Rich Caption → Audio* (reconstruction) and *Rich Caption → Audio → Rich Caption* (grounding) loops using Bagpiper-Base. We measure the cosine similarity between the input and the final output using Qwen3-Embedding-8B (Yang et al., 2025) for the text domain (*Text Sim.*) and the CLAP audio encoder (Wu* et al., 2023) for the audio domain (*Audio Sim.*). High similarity confirms minimal information loss through mutual translation between the physical audio signals and cognitive concepts.

Text Capability Preservation. To verify that incorporating audio objectives does not degrade language reasoning, we evaluate Bagpiper-Base on standard text benchmarks: MMLU-Redux (world knowledge) (Gema et al., 2025), GPQA-Diamond (general reasoning) (Rein et al., 2024), and GSM8K (mathematical reasoning) (Cobbe et al., 2021).

3.1.2. RESULTS AND ANALYSIS

Robust Bidirectional Mapping. In audio understanding, our objective is to match the performance of our teacher model. As shown in Table 1, Bagpiper-Base (8B) achieves performance parity with the Qwen3-Captioner (30B) topline (Team, 2025). This result validates the effectiveness of our distillation efforts from the captioner, demonstrating that our 8B backbone successfully learns to extract comprehensive cognitive details comparable to much larger

⁷We only test the examples whose rich captions contain the fully correct text transcriptions, which is around 60% of the volume of the whole test set.

models. Also, we find that both models show considerable hallucination on the ASR task (5.5% and 5.0%). After manually checking, the hallucination is almost all from the captioner models, not the probing LLM. This is further discussed in table 5. Overall, these probing results conclude that physical audio signals can be effectively compressed into cognitive concepts by Bagpiper-Base.

Table 1. Understanding probing results for Bagpiper-Base. Both models are NOT for real task solving; the task is solved by an external LLM using the generated rich captions.

Model	Param.	WER (↓)	MMAU-Mini (↑)
Qwen3-Captioner	30B-A3B	5.5	71.1
Bagpiper-Base (ours)	8B	5.0	69.0

For audio generation, to the best of our knowledge, there are no rich caption-to-audio baselines to compare with. Thus, we compare our Bagpiper-Base with specialized state-of-the-art baselines in speech (TTS) and sound/music (TTA), respectively. Note that these baselines are limited to their standard input format (transcripts for TTS; short captions for TTA), whereas Bagpiper-Base utilizes the full rich captions. Table 2 shows that Bagpiper-Base achieves WER comparable to dedicated TTS systems and outperforms TTA baselines in fidelity. This suggests that cognitive concepts in rich captions can be accurately grounded back into physical audio signals with Bagpiper-Base.

Table 2. Generation probing results for Bagpiper-Base. Our model is prompted by rich captions, while others are prompted by text transcriptions or short captions.

Model	Param.	Text-to-Speech	Text-to-Audio	
		WER (↓)	FAD (↓)	CLAP (↑)
OpusLM (TTS)	8B	4.0	-	-
CosyVoice3 (TTS)	0.5B	2.9	-	-
TangoFlux (TTA)	0.5B	-	5.15	0.50
AudioLDM2-L (TTA)	1.5B	-	3.79	0.48
Bagpiper-Base (ours)	8B	1.8	2.98	0.55

Subsequently, on the cycle consistency test (Table 3), we compare Bagpiper-Base against pipelined combinations of different understanding (Team, 2025; Goel et al., 2025) and generation models (Hung et al., 2024; Liu et al., 2024). Since baseline generation models cannot process the lengthy rich captions, we summarize captions to fit their context windows. Bagpiper-Base significantly outperforms these composite pipelines in both audio and text similarity, confirming that a unified model establishes a far more coherent bidirectional mapping than loosely coupled systems.

As demonstrated in Table 4, Bagpiper-Base maintains close performance to its initialization checkpoint (Qwen3-8B-Base) across knowledge, general reasoning, and math benchmarks. Preserving this strong textual foundation is not merely for maintenance; it directly powers our open-ended task solving during downstream fine-tuning.

Table 3. Cycle consistency probing results for pre-training

Audio-to-Text	Text-to-Audio	Audio-Sim. (↑)	Text-Sim. (↑)
Qwen3-Omni	AudioLDM2-L	0.445	0.465
Qwen3-Omni	TangoFlux	0.361	0.486
AudioFlamingo3	AudioLDM2-L	0.457	0.515
AudioFlamingo3	TangoFlux	0.471	0.570
Bagpiper-Base (ours)		0.502	0.840

By retaining the model’s inherent logic and world knowledge, Bagpiper can leverage complex text-based reasoning (e.g., Chain-of-Thought) to decompose and solve flexible audio instructions within the text domain and reflect it back to the audio modality.

Table 4. Text capability probing results for pre-training

	MMLU-Redux (↑)	GPQA-Diamond (↑)	GSM8K (↑)
Qwen3-8B-Base	76.1	39.3	89.8
Bagpiper-Base (ours)	74.3	41.9	88.2

3.2. SFT Evaluation

Unlike prior probing tests in §3.1, this SFT evaluation is to validate the fine-tuned Bagpiper’s efficacy in addressing real audio tasks through a unified, open-ended interface.

3.2.1. AUDIO UNDERSTANDING

We benchmark Bagpiper against leading multi-task and understanding-oriented models (Goel et al., 2025; Xu et al., 2025) to validate its unified processing capabilities. First, we assess Automatic Speech Recognition (ASR) performance on the Librispeech Test-Clean set. By leveraging high-fidelity captions (from Gemini) to minimize hallucination, Bagpiper achieves a significant reduction in Word Error Rate (WER) compared to the baseline reported in Table 1.

Beyond transcription, we evaluate the model’s reasoning and general understanding. Incorporating Chain-of-Thought (CoT) reasoning via thinking traces, like Goel et al. (2025), achieves substantial gains on MMAU-Mini, boosting the score to 74.5. This performance notably exceeds the upper bound observed during the pre-training stage in Table 1 (69.0).

Finally, we evaluate open-ended capabilities using the chat subset of AIR-Bench (covering speech, music, and sound effects) (Yang et al., 2024) and 5 open-ended question-answering subsets of AudioBench (Wang et al., 2025).⁸ On AIR-Bench, GPT-4o-based evaluations confirm that Bagpiper outperforms its direct competitor of 7B, Qwen-2.5-Omni, while achieving parity with AudioFlamingo3. Similarly, on the AudioBench open-ended QA subsets, Bagpiper maintains competitive performance against strong baselines.

⁸Specifically: CN-College-Listen, DREAM-TTS, Public-SG-SpeechQA, WavCaps-QA, and AudioCaps-QA.

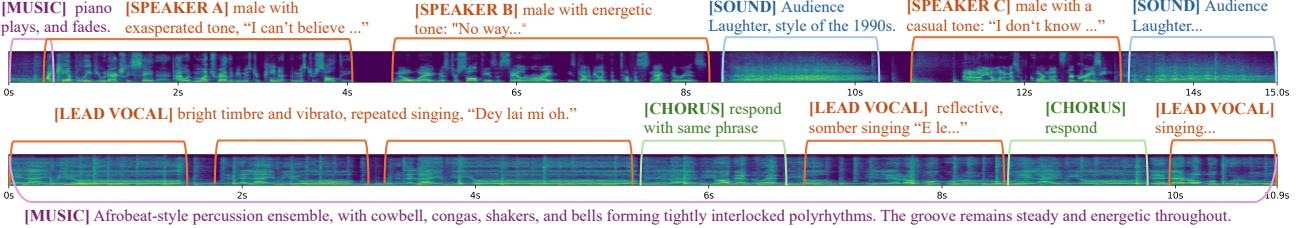


Figure 5. Spectrum of audio samples generated by Bagpiper. Our model is capable of generating multi-speaker dialogue with sound and music (upper) and singing voice with accompaniment (downer).

These results demonstrate that Bagpiper, despite being a unified understanding-generation model, delivers understanding performance comparable to specialized, state-of-the-art systems.

Table 5. Audio understanding results after fine-tuning. Our Bagpiper is a unified understanding-generation model, while the others are specialized understanding models.

Param.	ASR WER	MMAU -Mini	Open-Ended	
			AIR-Bench-chat	AudioBench
AudioFlamingo3	8B	1.6	73.3	6.80
Qwen2.5-Omni	7B	1.6	71.5	6.30
Bagpiper	8B	2.4	74.5	6.42
				70.23

3.2.2. AUDIO GENERATION

We first examine our model on the classical text-to-speech (TTS) task on Librispeech Test-Clean. As our model is pre-trained for a general purpose, we prompt the model to generate with *a calm, neutral voice*, plus the text transcription. As in the table 6, our generalist Bagpiper outperforms the dedicated TTS model on the WER, even though it has never been tuned for this specific task.

Table 6. Text-to-speech results after fine-tuning.

Model	WER
CosyVoice3	2.9
Bagpiper (ours)	2.7

We subsequently evaluate the model’s capability for general audio generation, specifically its ability to synthesize arbitrary combinations of diverse audio types. To assess performance on complex instructions, we query Gemini-3-Flash to generate detailed prompts for each audio sample in MMAU-Mini, yielding a total of 1,000 evaluation samples.

We compare Bagpiper against state-of-the-art baselines, including TangoFlux (Hung et al., 2024) and AudioLDM2-Large (Liu et al., 2024). To ensure a fair comparison (standard text-to-audio models may struggle with lengthy instructions), we also evaluate the baselines using condensed 15-word summaries of the original prompts (denoted as *summary*). We conduct a side-by-side preference evaluation

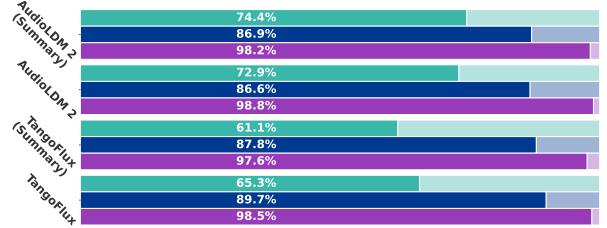


Figure 6. Comparison of model performance across three categories with Gemini-3-Pro as the judge. Categories are color-coded as: **Sound**, **Music**, and **Speech**. For each bar, the darker region represents the **Win Rate** of our Bagpiper, while the corresponding lighter region indicates the loss rate.

using Gemini-3-Pro as the judge. As shown in the left of Fig. 6, our model significantly outperforms all competitors, achieving a remarkably high win rate. This advantage is particularly pronounced in the *speech* subset, where Bagpiper successfully synthesizes intelligible speech integrated with complex sound events or music, a capability largely absent in prior text-to-audio models.

3.3. Qualitative Observation

As an open-ended task solver, Bagpiper exhibits several attractive behaviors that extend beyond the scope of current evaluation protocols, particularly in the domain of audio generation. We highlight key observations below and refer readers to our [Bagpiper Project Page](#) for comprehensive demonstrations.

Compositional Audio Synthesis. As demonstrated in Fig.5, our model is capable of generating complex audio sequences that simultaneously incorporate speech, environment sounds, and music, within a single clip. Notably, this includes conversational features such as multi-speaker dialogue with sound effects.

Instruction Following. Leveraging its reasoning capabilities, the model processes instructions that extend beyond simple acoustic descriptions to include logic-based constraints. For instance, when prompted to “*sing ‘Merry Christmas’ twice*”, the model correctly produces the repetition: “*Merry Christmas, Merry Christmas*”.

World Knowledge Utilization. The model effectively leverages world knowledge derived from its textual pre-training to ground audio generation in specific contexts. For example, when prompted to “Imagine walking through Disneyland”, the model generates contextually appropriate audio, such as marching bands and fireworks, without needing explicit acoustic descriptions of those elements.

4. Related Work

Open-Ended Task Solving. The paradigm of open-ended task solving has matured significantly in the text domain (Hurst et al., 2024; Yang et al., 2025; Olmo et al., 2025; Grattafiori et al., 2024), where generalization is initially achieved through massive multi-task supervision. As the milestone, text foundational models like FLAN-T5 (Chung et al., 2024) enumerate over 1,800 distinct text tasks to facilitate zero-shot generalization on unseen user requests. However, replicating this “task scaling” strategy in the audio domain is prohibitively expensive and practically infeasible due to the massive human labor and scarcity of well-defined, diverse enough audio tasks. Consequently, existing audio language models that attempt naive multi-tasking (Abouelenin et al., 2025; Wang et al., 2024; Yang et al., 2023; Tang et al., 2023) still struggle with flexible, compositional instructions that fall outside their training distribution, as in §3.2.2. In contrast, Bagpiper bypasses the need for massive task enumeration. By establishing rich captions as a universal semantic proxy, we effectively offload the burden of open-ended reasoning to the text capabilities of the LLM, enabling the solution of complex audio tasks without explicit audio-domain task supervision.

Rich Captions as a Modal Interface. The utilization of automated, detailed captions has gained traction in recent research. Emerging works have demonstrated that descriptive captions can significantly enhance specific downstream capabilities, such as in music understanding (Ghosh et al., 2025), text-to-speech (Diwan et al., 2025), and text-to-audio/music generation (Zhu et al., 2025; Chen et al., 2025a; Sun et al., 2024), with the research scope narrowed to task-specific objectives, relatively small scale, and unidirectional. To our knowledge, Bagpiper is among the first frameworks to establish a universal mapping between natural language and all audio categories, and subsequently becomes a firm foundation for downstream open-ended processing.

Universal Audio Processing. While the pursuit of universal audio understanding has yielded significant progress (Abouelenin et al., 2025; Tang et al., 2023; Goel et al., 2025), the landscape of audio generation remains largely fragmented. Current state-of-the-art generation models are typically confined to specialized verticals, optimizing exclusively for speech (Peng et al., 2025b; Ju et al., 2024;

Eskimez et al., 2024; Chen et al., 2025b), environmental sound (gil Lee et al., 2025; Hung et al., 2024; Huang et al., 2023), or music (Copet et al., 2024). Even hybrid domains like singing voice synthesis, which inherently blend vocals and accompaniment (Yuan et al., 2025; Lam et al., 2025), remain restricted to their specific modality. Although pioneering works like (Yang et al., 2023) have attempted to cover the full auditory spectrum, they rely on rigid and pre-defined control tokens. In contrast, Bagpiper is capable of synthesizing integrated acoustic scenes containing arbitrary, overlapping combinations of speech, music, and sound events within a single clip. Furthermore, while recent efforts have sought partial unification using text transcripts for speech (Tian et al., 2025a) or short captions for non-speech audio (Tian et al., 2025b), Bagpiper demonstrates that rich captions serve as a superior, all-encompassing semantic interface. Anonymous (2026b) and Anonymous (2026a) also consider the inclusion of rich captions, where Anonymous (2026b) focuses on universal reasoning for audio understanding while Anonymous (2026a) works on diffusion models for speech editing. Anonymous (2026c) pursues universal audio processing by streaming on-the-fly retrieval.

5. Limitation on the Descriptive Bias

The explicit generation of rich captions and the associated reasoning process impose a computational overhead, resulting in higher inference latency compared to prior works. Additionally, while Bagpiper demonstrates strong generalization across a diverse array of open-ended requests, it exhibits limitations when handling highly compositional prompts; specifically, the model struggles to simultaneously satisfy multiple conflicting or complex constraints within a single instruction.

6. Conclusion

In this work, we presented Bagpiper, an 8B audio foundation model that unifies understanding and generation by using rich captions as a universal semantic proxy. By establishing a robust bidirectional mapping between raw physical signals and high-level cognitive concepts via pre-training on 600B tokens, Bagpiper achieves superior performance over state-of-the-art baselines like Qwen-2.5-Omni and TangoFlux. Beyond quantitative benchmarks, the model demonstrates emergent behaviors such as precise temporal controllability and the integration of world knowledge to ground complex audio synthesis. By reformulating audio processing as a scalable text-reasoning problem, Bagpiper represents a significant advancement toward flexible and truly general-purpose audio intelligence.

Impact Statement

This paper presents Bagpiper, an audio foundation model that uses a rich-caption (concept-level) intermediate representation to support open-ended audio understanding and generation. When developed and deployed responsibly, such capabilities may improve accessibility (e.g., detailed audio descriptions and natural-language audio interaction), support education and simulation, and accelerate creative workflows for producing or editing sound.

However, here are some potential societal consequences of our work, which we feel must be specifically highlighted here. General-purpose audio generation can be misused for deception, harassment, and disinformation, and it may raise copyright and ownership concerns. For understanding tasks, performance disparities across accents, demographics, and acoustic conditions could lead to biased outcomes. Large-scale training also carries environmental and data-governance risks, including potential exposure to sensitive content if data are not curated carefully.

To mitigate these risks, any release or deployment should incorporate strong data governance and licensing checks, evaluations and transparent reporting across diverse conditions, safeguards such as access control and abuse monitoring, and provenance measures where applicable.

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A. Rich caption examples

Rich Caption Example for Music

The audio clip begins abruptly, launching into a high-energy, distorted electric guitar riff characteristic of heavy metal or hard rock, immediately accompanied by a powerful, driving drum beat. The guitar, panned hard left and treated with heavy distortion and reverb, delivers a rapid, repetitive motif that anchors the track's intensity. The drums, centered in the mix, feature a punchy kick and snare with a prominent crash cymbal, while the bass guitar sits low and centered, reinforcing the riff's rhythmic foundation. The overall sound is dense, loud, and saturated with analog-style distortion, suggesting a vintage or intentionally lo-fi production style. At the three-second mark, a male vocalist-delivering a strained, aggressive, and raspy performance-shouts, "Sold my car!" in a non-rhotic accent reminiscent of British or Australian English. His voice, heavily processed with reverb and distortion, is panned slightly to the right and stands out against the thick instrumental backdrop. The shout is forceful and emotionally charged, with the final syllable ("car") trailing off and blending into the reverberant mix. No other vocals, harmonies, or spoken words are present. Immediately following the vocal line, the instruments maintain their relentless energy, with the guitar and drums continuing their unyielding rhythm. The audio ends abruptly, cutting off mid-beat without any fade-out or resolution, leaving the listener with a sense of unresolved intensity.

This audio clip features a raw, high-energy rock/metal excerpt with a distorted guitar riff, driving drums, and a shouted male vocal line. The production is intentionally lo-fi, evoking the sound of 1980s underground or DIY recordings, and the lyrics "Sold my car!" are delivered with aggressive emotion. The clip is likely an excerpt from a demo or independent release, designed to convey urgency, rebellion, and personal upheaval, and is devoid of additional spoken content or environmental noise."

Rich Caption Example for Sound Effects

The audio begins with the immersive, high-fidelity sound of a steady stream of water cascading over rocks in a natural outdoor setting. The water's movement is characterized by a continuous, low-frequency gurgle interwoven with midrange bubbling and a lively, high-frequency hiss, all centered in the stereo field and closely miked. This creates a richly detailed and enveloping sonic texture, evoking the presence of a small stream or brook flowing through a rocky bed, with no extraneous environmental sounds or human activity. The recording remains uninterrupted, maintaining its clarity and presence throughout, until it is abruptly and completely cut off at the end with no residual noise or fade-out.

This audio presents a pure, uninterrupted sample of natural water sounds, captured with professional equipment in a pristine outdoor environment. The absence of speech, music, or any cultural or geographic markers, along with the sudden termination, suggests a utilitarian purpose—likely as a sound effect for media production, relaxation, or ambient use. The high-quality, immersive recording is designed to evoke tranquility and natural serenity, serving as a versatile and context-free sonic backdrop.

Rich Caption Example for Speech

The audio begins in a large, open urban environment, likely a city street or plaza in the Netherlands, characterized by a persistent low-frequency rumble from traffic and a faint, high-frequency hiss typical of a mobile recording device. Immediately, a sharp, metallic two-tone car horn sounds nearby, lasting about a second. The horn's clarity and proximity suggest the microphone is close to the source, and the lack of reverberation confirms an outdoor, non-enclosed setting.

As the horn fades, a female voice emerges in the background, speaking Dutch with a clear, neutral tone. She says, "Nee, maar ik ben..." ("No, but I am..."), her words partially obscured by the ongoing traffic noise. The male speaker, positioned closer to the microphone, responds succinctly with "Ja" ("Yes"), his voice calm and matter-of-fact. Both voices are slightly muffled and distant, indicating their location within the larger ambient soundscape.

The female speaker continues with a casual remark: "Laat maar even zien hoe het is dan." ("Just let me see how it is then."), delivered in a friendly, conversational manner. The male speaker replies in a relaxed, explanatory tone, "Ik vind het leuk om geluiden op te nemen." ("I like to record sounds."), directly addressing the recording's purpose. Their interaction is informal and natural, reflecting an everyday exchange in a Dutch urban context.

Throughout the clip, the background remains dominated by traffic, with no evidence of additional people, music, or environmental sounds. The conversation is unhurried and the speakers' voices are neither urgent nor emotional, indicating a casual, unscripted moment. The audio concludes abruptly, with the recording ending mid-phrase, suggesting intentional capture or editing.

In summary, this recording presents a slice of urban Dutch life: a brief, friendly exchange between two individuals, set against the ambient noise of city traffic. The male speaker explains his interest in capturing sounds, while the female speaker engages in casual conversation. The audio's technical quality, conversational flow, and environmental context reflect a spontaneous, everyday interaction in a public urban space, with no music or extraneous events present.

B. Supervised Fine-Tuning (SFT) Examples

SYSTEM PROMPT: You are a helpful audio understanding assistant. When given an audio and a question about it, first think through what you hear in the audio and how it relates to the question, then provide a clear and accurate answer.



I'm trying to understand how the rapper's personal journey comes through not just in his words, but in the way everything around him sounds—like the music and the recording itself. How does the combination of what he says and how it's presented make his reflection feel authentic and grounded?

Caption of the audio: This audio clip features a German-language hip-hop track characterized by a relaxed, old-school, boom-bap aesthetic. The piece is driven by a male rapper whose delivery is clear, confident, and rhythmically precise. He flows smoothly over a mellow, jazz-infused instrumental, creating a laid-back yet articulate and engaging atmosphere. The content of the lyrics appears to be reflective and autobiographical, referencing places, crews, and personal history within the hip-hop scene.

The instrumental backing consists of a steady, classic drum machine beat, a prominent and melodic bassline that provides a strong groovy foundation, and smooth, jazzy electric piano chords that add harmonic color. The production is clean and well-balanced, with the vocals sitting clearly in the forefront of the mix without overpowering the beat. This balance suggests a professional studio recording.

The overall mood is cool, confident, and slightly nostalgic. The rapper's consistent tone and the repetitive, hypnotic nature of the beat create a cohesive and immersive listening experience. The recording quality is high, with no discernible background noise, distortion, or audio artifacts, allowing the musical and lyrical elements to be heard with clarity.

S1 speaks from 0.00s to 29.85s.

Rapping and instrumental music begin at 0.00s and continue uninterrupted throughout the entire clip.

The overall duration of the audio is 29.85s.

In the emotion semantic wise, the audio shows confident/relaxed/nostalgic from 0.00s to 29.85s.

The VAD result shows that the audio has speech from 0.00s to 29.85s.

There is no backtracking found in the audio. There are no interruptions found in the audio. There is no overlapped speech found in the audio. The speech transcription of the audio is: "Mir geht es gut. Jahrelang habe ich mich konzentriert auf den richtigen Groove. Von Ihlill City bis WDR, Mala Hierba. Für dieses Ding pumpe ich meinen Herzschlag. Und bald steht mein Name auf dem Cover und im Nachhinein könnte ich sagen, alles war so locker. Ich denk zurück an A-Town, die Set Crew, die TCS, ja ihr seid noch heute back von der Old School. An das Extrakt, die Typen vom Tower mit der südlichen Power zwischen all den typischen Bauer", and its corresponding phonetic transcription is not available.

The speaker attribute of the audio is:

speaker S1 is an aged Adult (~20s-30s) Male speaker with Baritone, clear timbre, rhythmic and smooth delivery (rapping), speaking in Confident, Relaxed, Reflective emotion. None for speech disfluency patterns. Clear and precise enunciation. For articulatory. Speaking in Standard German (Hochdeutsch) dialect, with Standard German accent and None code-switching. Speaking at Moderate rap tempo pace. None apparent Disease.

There is no noise found in the audio. The reverb of the audio is Minimal, consistent with a professional studio recording environment.

The perception quality of the audio is Excellent.

There is no recording quality audio distortion found in the audio. The audio is recorded in a Studio recording. The volume of the audio is Consistent, moderate volume. There is no audio events found in the audio.

There is no detailed description of each audio event found in the audio. The spatial information of the audio is Stereo mix with vocals centered and instruments balanced across the stereo field.

The instrument sound texture of the audio is Drum machine, bass guitar, and electric piano (or similar keyboard). The genre style of the audio is Hip-Hop / Rap (Boom Bap, Jazz Rap). The rhythm tempo of the audio is Approximately 90 BPM, 4/4 time. The mood expression of the audio is Relaxed, Confident, Groovy, Nostalgic. The lyrics of the audio are Mir geht es gut. Jahrelang habe ich mich konzentriert auf den richtigen Groove. Von Ihlill City bis WDR, Mala Hierba. Für dieses Ding pumpe ich meinen Herzschlag. Und bald steht mein Name auf dem Cover und im Nachhinein könnte ich sagen, alles war so locker. Ich denk zurück an A-Town, die Set Crew, die TCS, ja ihr seid noch heute back von der Old School. An das Extrakt, die Typen vom Tower mit der südlichen Power zwischen all den typischen Bauer. The harmony chords of the audio are Simple, repetitive jazzy chord progression. The melody of the audio is The primary melody is carried by the bassline and the jazzy keyboard chords. The music structure segmentation of the audio is Verse. The timbre descriptors of the audio are Smooth electric piano, deep bass, crisp drums.

There is no backchannel frequency in the audio. There is no interruption frequency in the audio. There is no overlap rate in the audio.

- User Intent: The user wants to understand how the rapper's personal journey is conveyed not just through lyrical content but also through the sonic and production elements of the track, particularly how these elements contribute to a sense of authenticity and groundedness.

- Evidence & Salient Audio Cues: The lyrics include autobiographical references such as 'Ich denk zurück an A-Town, die Set Crew, die TCS' and 'Von Ihlill City bis WDR, Mala Hierba', indicating personal history. The rapper's delivery is described as 'confident, relaxed, reflective with clear timbre and rhythmic and smooth delivery'. The instrumental features a 'mellow, jazz-infused boom-bap beat', 'steady groove at ~90 BPM', 'smooth electric piano', 'deep bass', and 'crisp drums'. The production is 'clean and well-balanced', with 'minimal reverb', 'vocals centered', and 'professional studio recording' quality. The mood is consistently 'relaxed, confident, nostalgic'.

- Inferred Details (Assumptions): The calm, uncluttered production suggests intentionally in highlighting the lyrics (assumption: minimal effects = focus on authenticity). The steady, unhurried tempo and smooth flow reflect emotional composure (assumption: musical pacing mirrors personal acceptance). The nostalgic mood supports the reflective lyrical content (assumption: sonic atmosphere reinforces emotional tone).

- Answering Plan: Connect lyrical content (personal references) with vocal delivery (calm confidence) and production (clean, groove-based jazz-infused beat) to show how they jointly create authenticity. Emphasize that the lack of audio distortion, centered vocals, and consistent mix enhance intimacy and sincerity. Link the claim 'bald steht mein Name auf dem Cover' with the understated musical backdrop to illustrate earned pride.

- Self-Check: All claims are directly supported by the caption. No invented details. Quotes are short and used as evidence. The reasoning traces how sound and speech jointly convey authenticity without overinterpretation.

The rapper's autobiographical reflections, such as 'Ich denk zurück an A-Town, die Set Crew, die TCS' and 'Von Ihlill City bis WDR, Mala Hierba', gain authenticity because they're delivered in a calm, confident tone over a smooth, jazz-infused boom-bap beat with a steady groove. The clean studio recording, minimal reverb, and balanced mix keep the focus on his voice and lyrics, making it feel intimate and sincere. Rather than sounding boastful, his claim 'bald steht mein Name auf dem Cover' feels earned, supported by the relaxed musical backdrop and his unhurried flow. Together, the personal content, composed delivery, and professional yet unflashy production create a sense of grounded pride—like he's not just telling his story, but living it calmly in real time.

Figure 7. SFT example (audio-to-text). Representative audio understanding samples synthesized by our Caption-then-Process pipeline ([Audio, User Request, Rich Caption, CoT, Answer]).

SYSTEM PROMPT: You are a helpful audio understanding assistant. When given an audio and a question about it, first think through what you hear in the audio and how it relates to the question, then provide a clear and accurate answer.



Morning light floods a sleek, minimalist vanity. A woman smiles at her reflection, poised and calm, about to transform her look. The air hums with quiet excitement, every movement intentional. 'I'm gonna use this eye pencil as a base and apply it all over my eyelid.' A fingertip taps once—precise, focused—and the moment locks into place.

1. User Intent: The user requests an audio generation that captures a specific moment in a morning beauty routine—focused on a woman using an eye pencil as a base—set in a sleek, minimalist environment. The scene conveys calm intentionality and quiet excitement, with spoken instruction and a precise physical gesture (a tap) emphasized as key elements.

2. Inferred Details: The setting is a modern, quiet, and acoustically controlled space—likely a professional or high-end home studio—given the emphasis on minimalism and focus. The woman is a presenter in a beauty tutorial, speaking directly to an audience. Her tone should reflect confidence and warmth, fitting a relatable yet polished persona. The tap is not casual but demonstrative, meant to draw attention, suggesting it should be clearly audible and distinct. The atmosphere of "quiet excitement" implies energetic but not overwhelming background music that enhances mood without overshadowing speech.

3. Audio Quality: The audio is high-fidelity, studio-recorded, with no background noise or reverb, indicating professional production. The music is modern, upbeat, and polished—featuring a steady electronic beat, melodic bass, and shimmering guitar chords in a clean stereo mix. The female voice is clear, close-miked, with a bright but natural timbre, delivered in a standard American accent. The tap sound is sharp, transient, and isolated, recorded with precision to stand out momentarily against the music. All elements are tightly edited for synchronization, typical of social media content optimized for engagement.

4. Generation Plan: Begin with the instrumental track—upbeat, modern, and rhythmically steady—to establish tone. Introduce the female speaker shortly after the music begins, aligning her vocal delivery with the music's tempo. Record her line with clarity and warmth, ensuring no ambient noise. Insert the tap sound immediately after her speech, using a high-frequency transient effect to mimic a fingertip on hard surface. Maintain the music throughout, ending the clip abruptly mid-phrase to preserve the dynamic energy, consistent with short-form tutorial formats. Ensure seamless integration of voice, music, and sound effect in a tightly edited, broadcast-quality mix.

The audio begins with a bright, professionally produced instrumental track characterized by a steady drum machine beat, a melodic electric bassline, and shimmering electric guitar chords. The music is modern, upbeat, and polished, with a clean stereo mix and no ambient noise or environmental sounds, creating an inviting and energetic backdrop. Shortly after the music starts, a young adult female speaker with a clear, high-pitched, and friendly voice enters, her tone warm and approachable. She speaks in a standard American accent without regional markers, and her delivery is confident and encouraging, typical of a makeup tutorial. She states, "I'm gonna use this eye pencil as a base and apply it all over my eyelid," her words closely synchronized with the rhythm of the background music, indicating careful editing for a tutorial format. Throughout her speech, there are no extraneous sounds such as makeup application noises, reinforcing the controlled studio setting.

Immediately following her instruction, the music continues seamlessly, maintaining its tempo and style. At a distinct point, a sharp, high-pitched "tick" sound interrupts the music, likely produced by a fingernail or makeup tool tapping a hard surface such as plastic or glass. This sound is brief, clean, and isolated, suggesting a deliberate demonstration to accompany the spoken instruction. The musical track persists until the end of the clip, which concludes abruptly while the music is still playing.

In summary, the audio is a concise, high-fidelity excerpt from a modern American beauty tutorial, featuring a friendly female presenter who explains and demonstrates the use of an eye pencil as a base for eyelid makeup. The segment is marked by upbeat, professionally produced music, clear and encouraging narration, and a single, purposeful sound effect that underscores the instructional content. The overall style, production quality, and presentation are consistent with social media beauty content, designed to engage and educate viewers in a visually and aurally appealing manner.

Figure 8. SFT example (text-to-audio). Representative audio generation samples synthesized by our simulation pipeline ([User Request, CoT, Rich Caption, Audio]).

C. Implementation Details

C.1. Data Collection

Warm-up and Pre-training Stage: we jointly train on a mixture of audio–text paired datasets and text-only datasets. The audio-text paired datasets include: *OWSM v4 captions*⁹, *LAION-Audio-300M*¹⁰, *Clotho-AQA*¹¹, *clotho*, *Emilia*¹², *LAION captioned AI music snippets*¹³, *LAION in-the-wild sound events*¹⁴, *AudioCaps*¹⁵, *AudioSet*¹⁶, *WavCaps*¹⁷, *FMA*¹⁸, *YouTube-8M*¹⁹, *LAION-DISCO-12M*²⁰ *YODAS*²¹. For text-only data, we use a broad *Dolma3 ingredientI*²² mixture (domain-balanced CommonCrawl high-quality subsets, plus code/math/reasoning/STEM-centric subsets) together with dialogue-style instruction corpora (*llama-nemotron*²³, *Olmo3*²⁴).

Supervised Fine-tuning Stage: we supervise multi-turn user requests using dialogue-style instruction data that contains both audio-to-text understanding and text-to-audio generation samples (examples are shown in App. B).

The audio-to-text understanding datasets include: *OWSM v4 (200k subset)*, *Librispeech (train-clean-100)*, *Common Voice Corpus 15*, *IEMOCAP*, *MELD*, *SLUE (SQA, NEL, DAC)*, *VocCeleb1*, *Fake-or-Real*, *Free Music Archive (FMA)*, *MUSIC-AVQA*, *MusicCaps*, *NSynth*, *AudioCaps*, *AudioGrounding*, *AVQA*, *Clotho-AQA*, *CochlScene*, *2025 DCASE AudioQA*, and *SoundDescs*, *TUT-acoustic-scenes-2017*, and *VocalSound*. We construct the SFT training set by excluding all test splits from our evaluation benchmarks. The overall training split is formed by randomly sampling all valid samples. The resulting data composition is summarized in Table 7, showing broad coverage across speech, music, and general sound domains. The distribution of three domains is also presented in Figure 9.

To standardize input length, when a source corpus contains clips longer than 30 seconds, we extract a 30-second segment by truncating from a uniformly random start time within the clip. In contrast, for multimodal datasets such as AVQA, where audio is tightly aligned with video content, random truncation may break semantic coherence. We therefore discard videos longer than 30 seconds and retain only those shorter than 30 seconds long. After this filtering, 50 AVQA videos remain; applying our per-corpus random sampling then yields 7 AVQA samples in the final SFT dataset. Besides, in our SLUE dataset, we only include the training set in SQA, NEL and DAC splits, since all audios in the TED split are all longer than 30 seconds.

For text-to-audio generation data, we use a subset of all the pre-training data. Specifically, we use Gumbel Top-k sampling to sample 1M samples from the pre-training distribution, with the temperature of 0.03.

⁹https://huggingface.co/datasets/espnet/yodas_owsmv4

¹⁰<https://huggingface.co/datasets/laion/LAION-Audio-300M>

¹¹<https://huggingface.co/datasets/lmms-lab/ClothoAQA>

¹²<https://huggingface.co/datasets/amphion/Emilia-Dataset>

¹³<https://huggingface.co/datasets/laion/captioned-ai-music-snippets>

¹⁴<https://huggingface.co/datasets/laion/in-the-wild-sound-events>

¹⁵<https://huggingface.co/datasets/d0rj/audiocaps>

¹⁶<https://huggingface.co/datasets/agkphysics/AudioSet>

¹⁷<https://huggingface.co/datasets/cvssp/WavCaps>

¹⁸<https://huggingface.co/datasets/benjamin-paine/free-music-archive-full>

¹⁹<https://huggingface.co/datasets/leee99/yt8m-h264>

²⁰<https://huggingface.co/datasets/laion/LAION-DISCO-12M>

²¹<https://huggingface.co/datasets/espnet/yodas>

²²https://huggingface.co/datasets/allenai/dolma3_pool

²³<https://huggingface.co/datasets/nvidia/Llama-Nemotron-Post-Training-Dataset>

²⁴<https://huggingface.co/collections/allenai/olmo-3>

Table 7. Dataset distribution for the SFT stage captioned by Gemini_2.5_Pro and Gemini_3_Flash, grouped by domain. “–” indicates the dataset is not present for that model.

Domain	Dataset	Gemini_2.5_Pro	Gemini_3_Flash	All sample number
Speech	Common Voice Corpus 15	9996	23775	33771
	IEMOCAP	7869	–	7869
	LibriSpeech (train-clean-100)	10000	4368	14368
	MELD	9984	–	9984
	SLUE	–	12779	12779
	VoxCeleb1	10000	81144	91144
	Fake-or-Real	9994	–	9994
Speech subtotal		57843	122066	179909
Music	FMA	1813	–	1813
	MUSIC-AVQA	50	–	50
	MusicCaps	2644	–	2644
	NSynth	9993	10045	20038
Music subtotal		14500	10045	24545
Sounds	AudioCaps	10000	8793	18793
	AudioGrounding	3528	–	3528
	AVQA	–	7	7
	Clotho-AQA	1169	–	1169
	CochlScene	9993	–	9993
	2025_DCASE_AudioQA	9314	–	9314
	SoundDescs	5629	–	5629
	TUT-acoustic-scenes-2017	3508	–	3508
Sounds subtotal		53137	13282	66419
Sum		125480	145393	270873

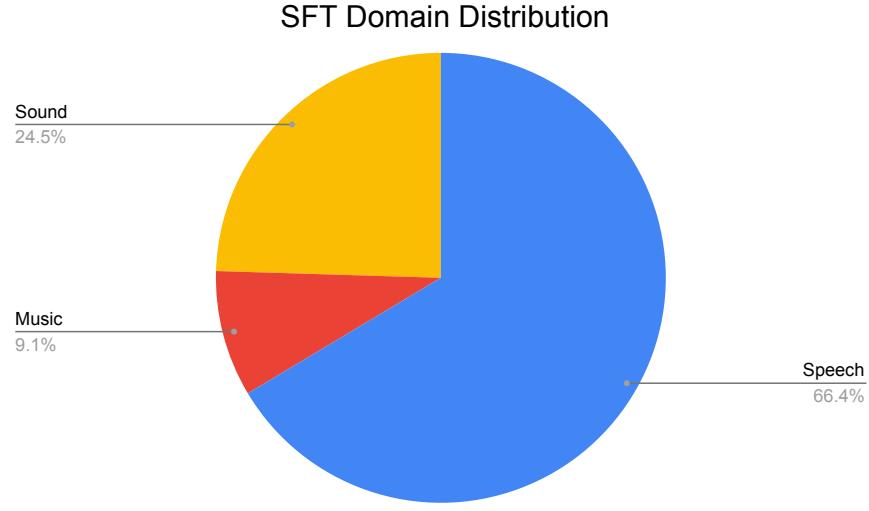


Figure 9. SFT domain distribution for speech, sound and music.

C.2. Data Curation

We provide additional details for data curation, as mentioned in §2.2.

Audio. For perceptual quality, we use UTMOS for speech and the AudioBox aesthetic score for non-speech audio.

text. We have rule-based filtering that excludes: (1) labeled incomplete in rich captioner captioning; (2) contain non-Latin characters; (3) character repetition for 5 times or above; (4) word repetition for 3 times or above; (5) 5-gram repetition for 10% and above; (6) unique word ratio for 30% or below; (7) average word length lower than 2 or larger than 15; (8) number of tokens larger than 800 or smaller than 200.

We additionally prompt the Qwen3-32B to: (1) find the audio type, a.k.a., speech, music, sound effects; (2) find if the text is purely in English, and exclude it if not; (3) find the text is centralized to audio content, and exclude it if not; (4) score the audio intelligibility, with a scale of 1–5; (5) score the audio complexity, with a scale of 1–5; (6) score the audio diversity, with a scale of 1–5;

Audio-Text Alignment. We use CLAP model to test the audio-text alignment. As the CLAP model would only accept text up to 77 tokens, we use Qwen3-32B to summarize it into short captions.

Gumbel Top-K sampling. For audio understanding, we use a temperature of 0.3/0.3/0.3 and discard 20%/20%/42% examples for sound effects/music/speech. For audio generation, we use a temperature of 0.1/0.1/0.1 and discard 20%/20%/28% examples for sound effects/music/speech.

C.3. Model Details

The model details discussed in Sec.2.1, are shown in Table 8

Table 8. Bagpiper Model configuration.

Component	Model Configuration
Text backbone	Qwen/Qwen3-8B-Base
Discrete audio tokenizer	X-Code (hubert-general)
Continuous audio encoder	Qwen/Qwen3-Omni-30B-A3B-Instruct-Encoder

C.4. Training Details (3-stages)

We train the model in three stages: (1) warmup, (2) large-scale pretraining, and (3) supervised fine-tuning (SFT). Across all stages, we use packed batching (`batchfy_method=pack`), mixed-modality data, and DeepSpeed for distributed optimization. All stages use `dtype=bfloat16` with activation checkpointing enabled. The pre-training is complete on 80 NVIVIDA GH200 GPUs.

Table 9. Training configuration across the three stages. The pipeline progresses from connector alignment to full backbone pre-training, concluding with supervised fine-tuning (SFT).

	Warmup	Pre-train	SFT
Frozen Modules	Audio Encoder, Transformer Body	Audio Encoder	Audio Encoder
Batch Size	4.8M	1.2M	1.2M
Optimizer	AdamW	AdamW	AdamW
LR Schedule	Constant	Cosine Decay	Constant
Warmup Steps	200	5k	-
Steps	2k	480k	12.5k
Peak LR	5×10^{-4}	1×10^{-4}	1×10^{-5}

C.5. Inference Configuration

We employ modality-specific decoding with *bfloat16* precision and a greedy search ($N = 1$), other details shown in Fig.10.

Table 10. Inference configuration with modality-specific decoding hyper-parameters.

Item	Temperature	Top- k	Classifier-Free Guidance (CFG)	max-decode-steps
Text decoding	0.6	20	-	2048
Audio decoding	0.8	20	3	2048

D. Acknowledgments

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