

Finetuning Audio-Language Models for Multi-Track Gain Balancing Mixing Advice

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Fall 2025 Project Proposal



Georgia Tech · College of Design

Center for
Music Technology

Brief Introduction

overview

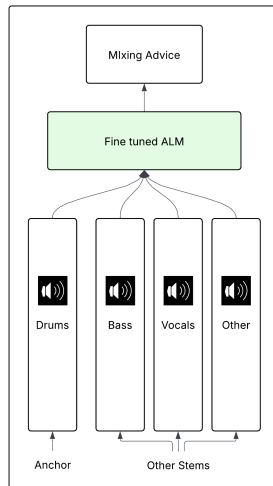
- **Music mixing** requires a complex, relational understanding of multiple audio tracks, and collaboration.
- This research investigates a framework to fine-tune an **Audio-Language Model (ALM)** to generate actionable mixing advice.
- As a starting point, we condition the model on an "**anchor track**" (e.g., bass) to teach it how to balance the levels of other instruments relative to that **stable reference point**.



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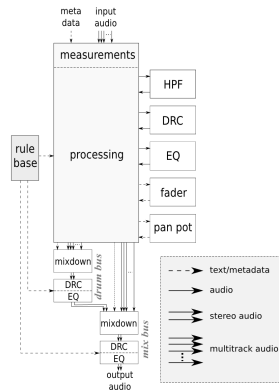
Rule-Based & Deep Learning Approaches

Rule-Based and Traditional Machine Learning Systems

- Knowledge-engineered autonomous mixing [1]
- A machine-learning approach for instrument-specific application of artificial reverberation. [2]

Deep Learning Architectures

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- Differentiable mixing console with neural effects [4]



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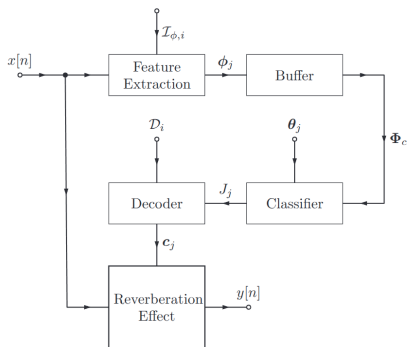


Fig. 1. Reverb application.

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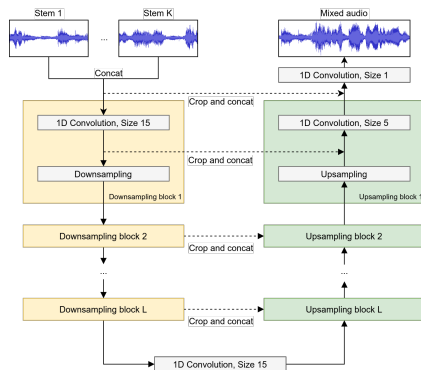
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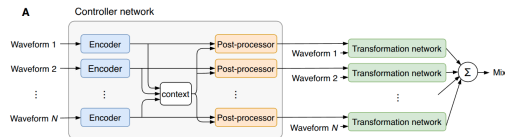
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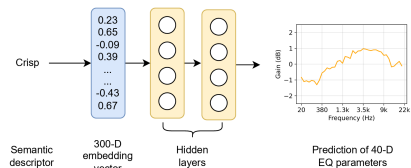


Automatic Mixing Review

Semantic Approaches

Language-Audio Integration

- Word-embedding approaches linking audio and language for effects/EQ recommendations [5], [6], [7]
- Text-driven interfaces mapping natural language to effect parameters and mix actions [8], [9], [10]

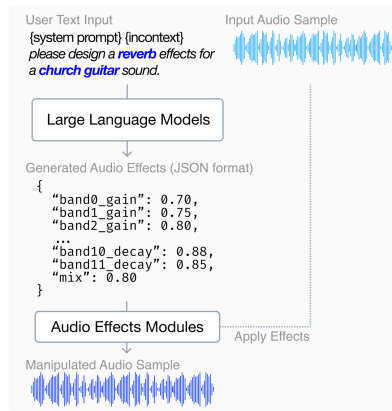


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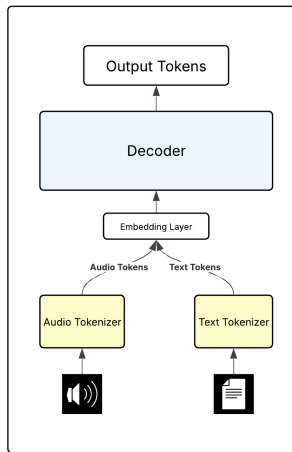
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Automatic Mixing Review

Architectural Approaches for Audio-Language Models

- **Direct Tokenization (Unified Approach):**
converts raw audio into discrete tokens via audio codecs; tokens are flattened into a 1D sequence as LLM input; the LLM vocabulary is extended to include audio tokens [11], [12], [13].
- **Feature Extraction (Cascade Approach):**
uses audio-specific encoders/decoders with the LLM as a central backbone; high-level features are passed between modules (e.g., M²UGen) [14], [15].

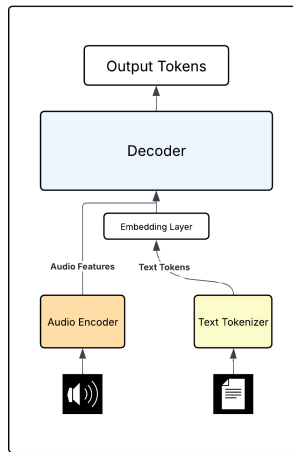


Unified Approach

Automatic Mixing Review

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Cascade Approach

Research Questions

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- To what extent can an **Audio-Language Model**, conditioned on an **anchor track**, learn the **relative gain** relationships among multitrack stems and generate musically effective gain-balancing **advice**?

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Secondary Questions

- **Model Understanding:** What model architecture best represents and reasons about multitrack stems and anchor tracks for learning relative gain relationships?
- **Mixing Conventions:** To what extent does the model's advice reflect established mixing conventions?
- **Communication & Actionability:** How effectively does the model communicate its advice in a way that is clear, actionable, and distinct from simply being "correct"?
- **Human Evaluation & Usefulness:** How do audio engineers and producers evaluate the effectiveness, musicality, and real-world usefulness of the advice in their workflows?

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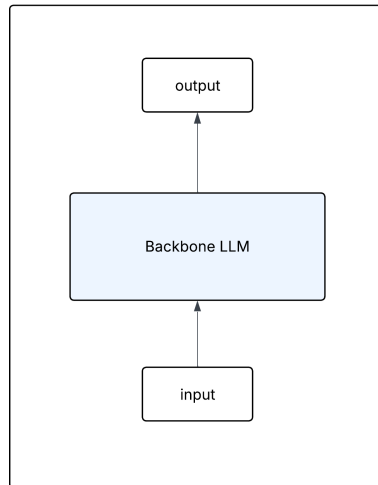
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Proposed Method

Overview

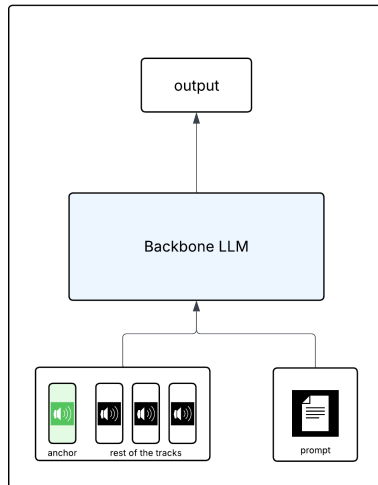
- **Base Model:** A pretrained Audio LLM like Qwen-Audio [16] as the backbone.
- **Input:** Anchor track and the rest of the tracks and a text prompt.
- **Output:** A structured response containing advice for the user to balance the levels of the tracks.
- **Architecture:** Cascade approach, with the LLM as the backbone.
- **Training strategy:** Supervised fine-tuning using PEFT (Parameter-Efficient Fine-Tuning), specifically LoRA [17] or QLoRA [18].



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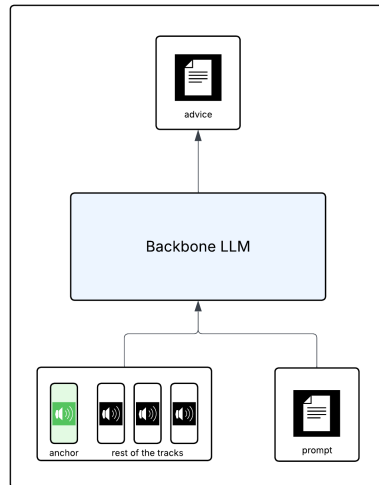
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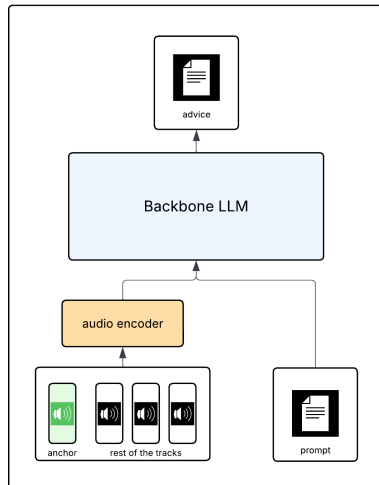
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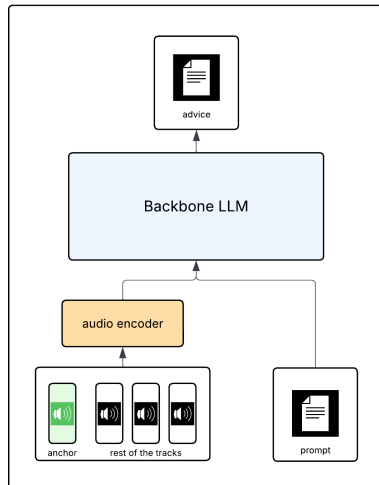
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Dataset Synthesis

- **Prompt:** Create per-sample prompts in addition to the constant system prompt.
- **Multitrack Input:**
 - **Dataset:** A multitrack dataset like MUSDB18 [19].
 - Chunk the song into 10-second segments.
 - Inject an error of $\pm n$ dB on the non-anchor track.
- **Response Formulation:** We will programmitically create structured responses.
 - Pick a template based on the prompt, containing both description and solution placeholders.
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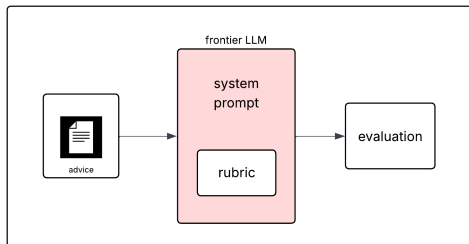
Human Evaluation

- **Participants:** Semi-professional audio engineers and producers
- **Evaluation Criteria:**
 - **Effectiveness:** How well does the advice address the mixing challenge?
 - **Actionability:** How clear and implementable is the advice?
 - **Adherence to Conventions:** How well does the advice follow established mixing practices?
- **Methodology:** Rating scales and qualitative feedback collection

Evaluation Framework

Automated Evaluation

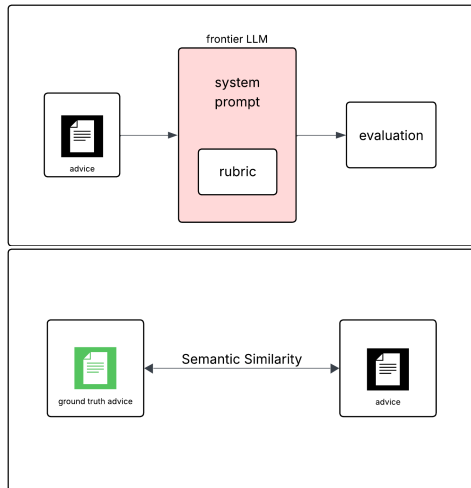
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- **Semantic Similarity:** Compare advice to expert annotations
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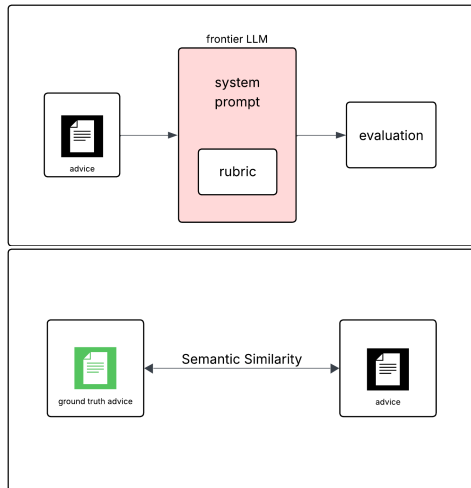
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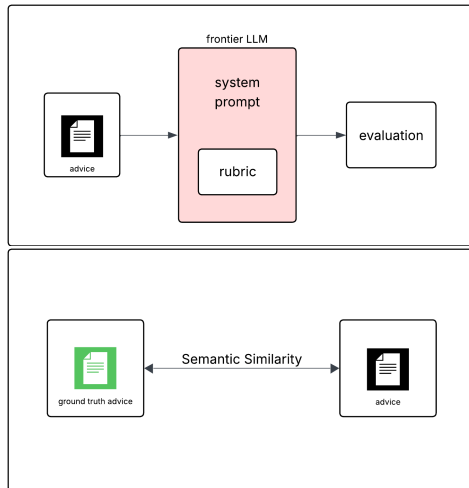
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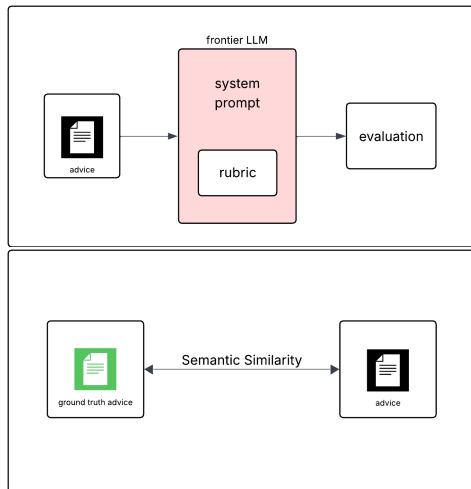
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Limitations

- **Focus on Gain Only:** The model's scope is limited to gain-balancing advice; it does not address other effects like EQ, compression, or spatial effects.
- **Advisory, Not Prescriptive:** Evaluation focuses on the usefulness of the textual advice, not the numeric accuracy of specific gain predictions.
- **Dataset Dependency:** The project relies on the MUSDB18 dataset for valid “ground truth” for professional mixes.

Timeline

Tasks Leading to Nov. 28th Submission

- ~~Dataset preprocessing and JSONL format conversion.~~
- ~~Initial codebase and data loading pipeline setup.~~
- ~~Partial fine-tuning pilot experiments and architecture testing.~~
- Finalize architecture and execute all remaining experiments.
- Submit and obtain IRB approval for human studies.
- Conduct the human evaluation study with audio professionals.
- Complete the final paper, web interface, and Hugging Face deployment.

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