MixingBuddy: A Multimodal LLM for Audio Mix Critique and Advice

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Fall 2025 Project Proposal

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Brief Introduction

overview

- **Music mixing** requires **expertise** and a **complex, relational understanding** of multiple audio tracks.
- This research develops a **multimodal** system that equips a **pre-trained LLM** with the ability to analyze **raw audio**, allowing it to provide actionable feedback on **flawed mixes**.
- As a starting point, we focus on generating advice for **gain-balancing** only.

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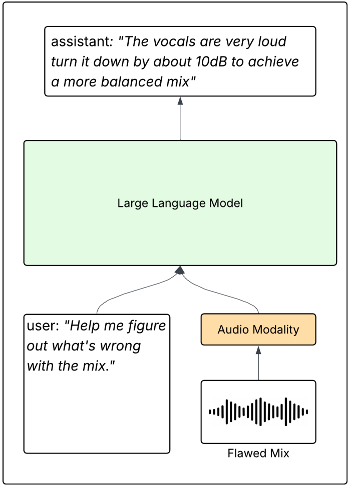
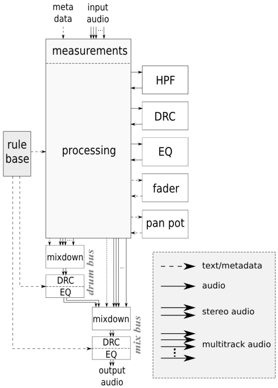


Automatic Mixing Review

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

- Wave-U-Net autoencoders for automatic mixing [3]
- Differentiable mixing console with neural effects [4]

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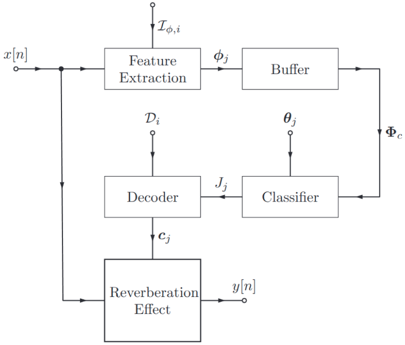

Fig. 1. Reverb application.

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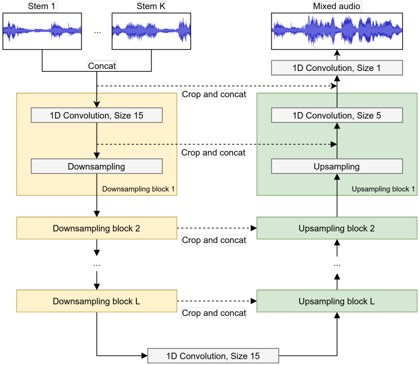

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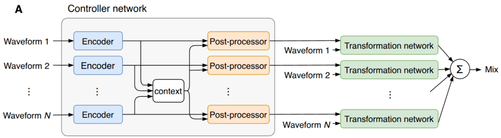
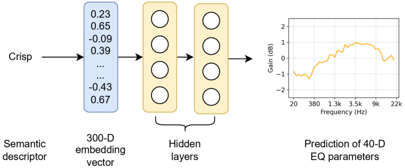


Automatic Mixing Review
Semantic Approaches

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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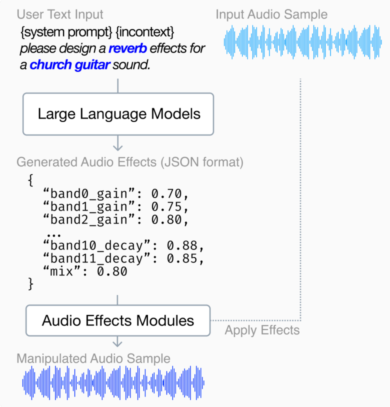
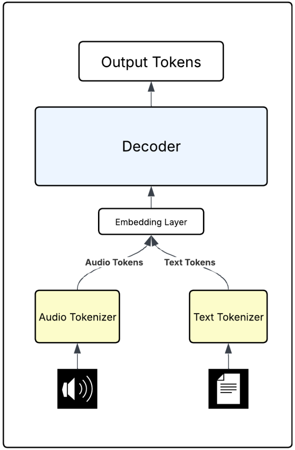


Automatic Mixing Review

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., LTU) [14], [15].



Unified Approach

Automatic Mixing Review

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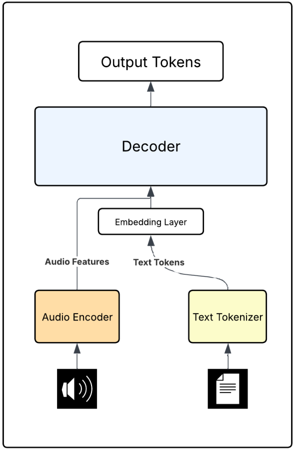

Cascade Approach

Research Questions

primary

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Primary Research Question

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

Research Questions

secondary

Secondary Questions

- **Model Understanding**: What model architecture best represents and reasons about the input mix for learning relative gain relationships?
- **Mixing Conventions**: To what extent does the model's advice reflect established mixing conventions?
- **Communication**: How effectively does the model communicate its advice in a way that is clear, actionable, and "correct"?
- **Usefulness**: How do audio engineers and producers evaluate the effectiveness, musicality, and real-world usefulness of the advice?

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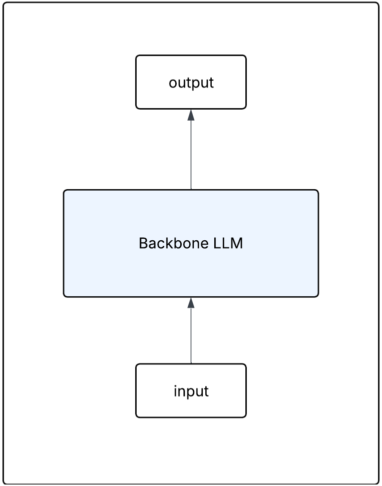
Proposed Method

Overview

- **LLM as backbone**: A pretrained LLM such as Qwen2 [16] as the backbone.
- **Input**: A Flawed mix and a text prompt.
- **Output**: A structured response containing advice pointing out the flaws and suggesting solutions.
- **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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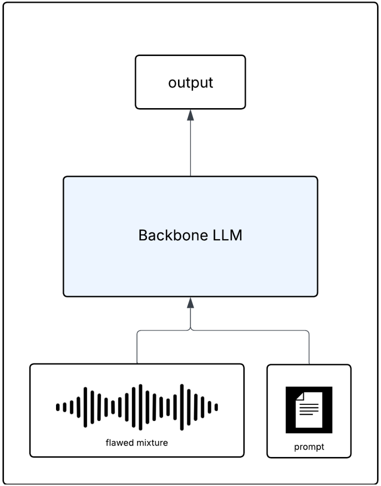

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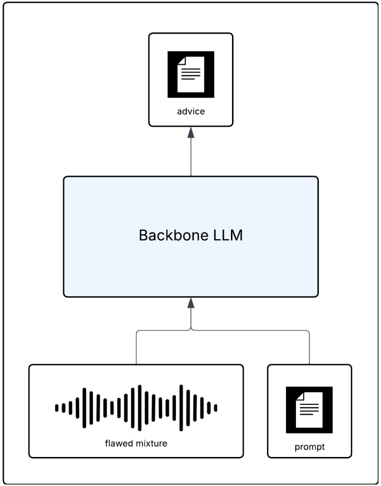

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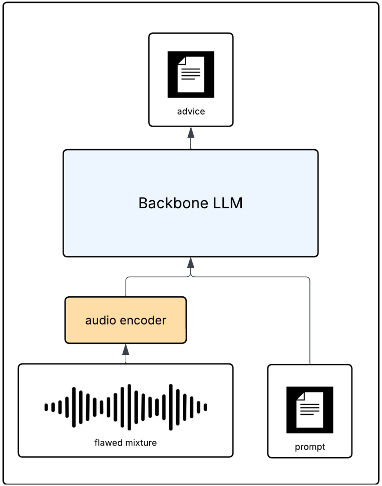

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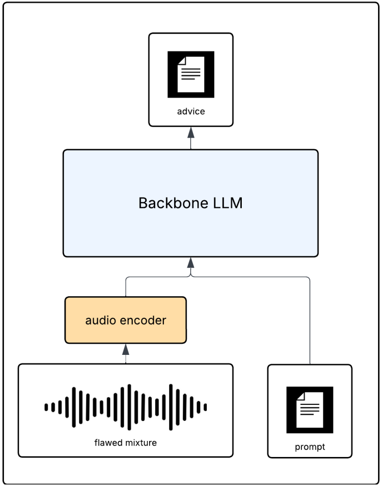

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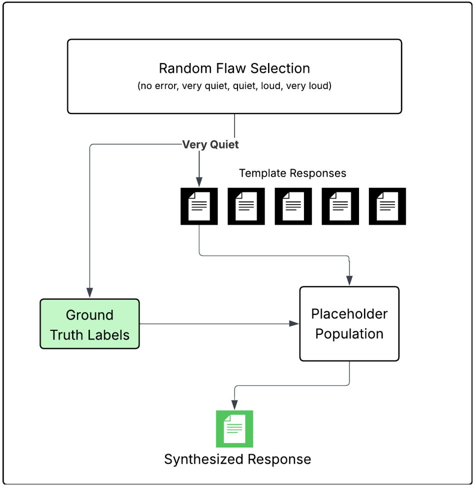
Dataset Synthesis

- **Audio-Driven Prompt Generation**: For this milestone, user instructions are implicit or generic, focusing the model purely on audio input to identify mixing flaws.
- **Flaw-Driven Templating**: a "Flaw Category" is identified, dictating the structure and content of the response.
- **Dynamic Population**: Template variables such as **stem names** and **suggested gain values** are automatically populated.



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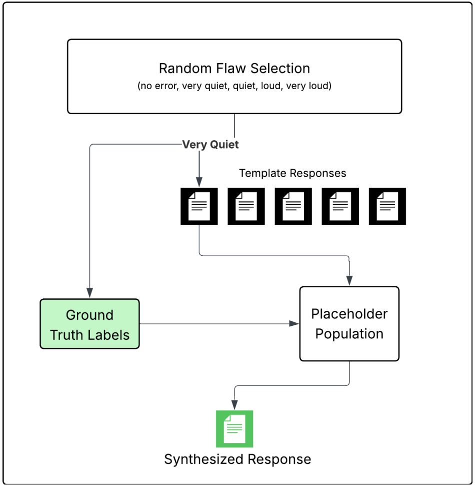

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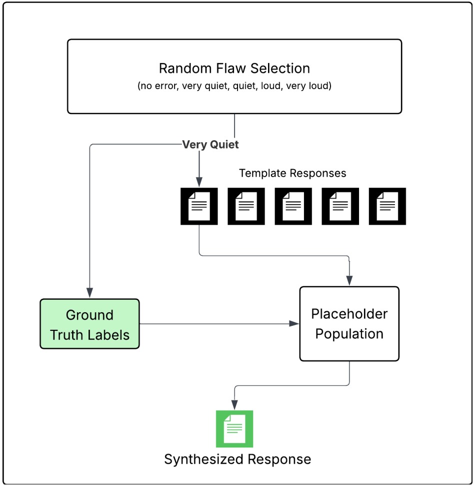

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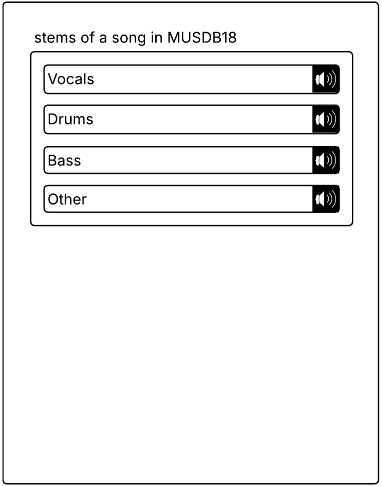
Key Mixing Flaw Categories for Synthesis:

- **No Error**: *"The mix sounds balanced."*
- **Quiet**: *"The vocal is too quiet."*
- **Very Quiet**: *"The vocal is much too quiet."*
- **Loud**: *"The bass is too loud."*
- **Very Loud**: *"The bass is much too loud."*

Proposed Method

Flawed Mix Input

- **Dataset**: A multitrack dataset like MUSDB18 [19].
- Chunk a song into 10-second segments.
- Inject an error of $\pm n$ dB on a non-anchor track based on Flaw Categories.
- Sum the stems to get the flawed mix.



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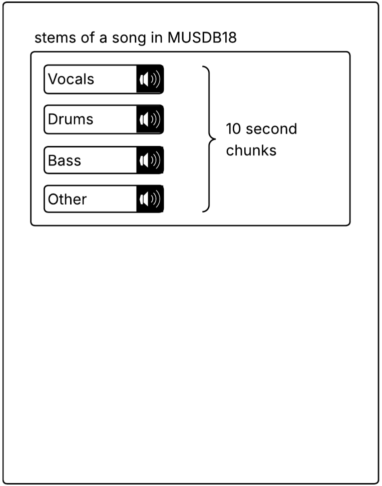

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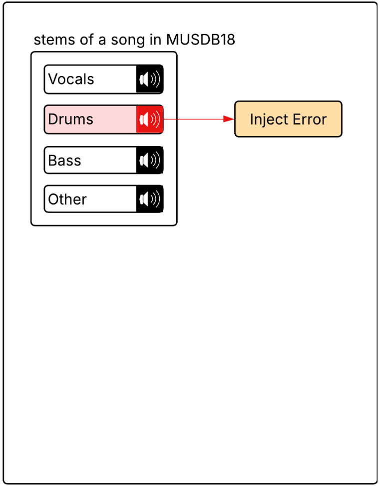

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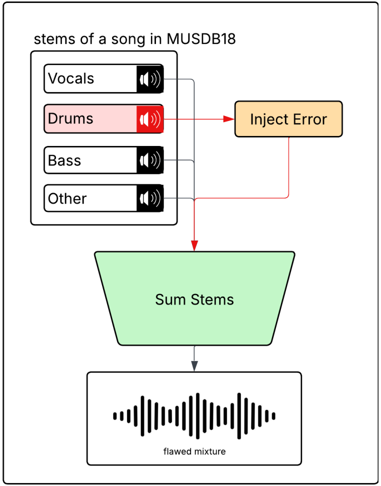

Evaluation Framework

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?
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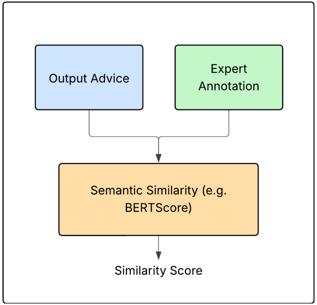
Compares generated advice to expert annotations for relevance.



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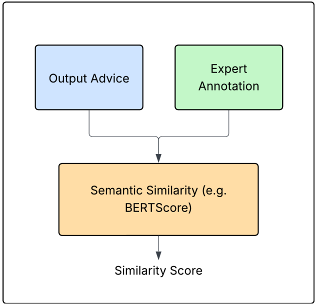

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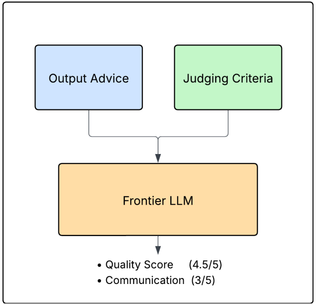

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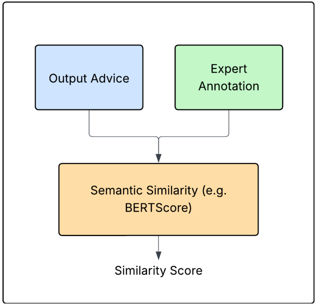

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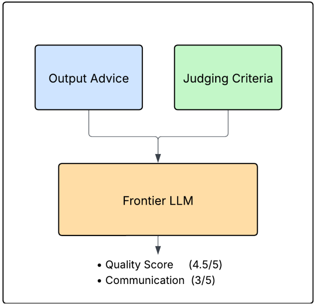
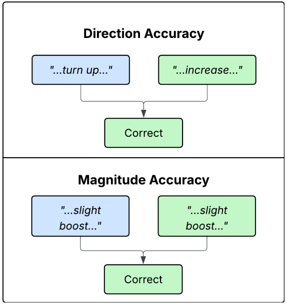


3. Gain Advice Accuracy

Compares suggested adjustments to ground truth.



Limitations

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- **Advisory, Not Prescriptive**: Evaluation focuses on the usefulness of the textual advice, not the numeric accuracy of specific gain predictions.
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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.

references

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