Large Audio-Language Models and Applications

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Outline

- **Introduction**
- **Large audio models & large language models**
- **Large audio-language models**
  - Motivation
  - Example models & datasets
  - Open challenges
  - Integration of audio and language models
- **Applications of LALMs to various cross-modal generation tasks**
  - Audio captioning (e.g. audio to text generation)
  - Audio question answering and reasoning
  - Text to audio generation & composition & storytelling
  - Language guided audio source separation
  - LLMs for controllable audio editing
  - Neural audio coding
- **Conclusions and future works**

Research Interest: Audio Signal Processing & AI

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Tasks:

- Audio source separation
- Audio source localisation/tracking
- Audio event detection/localisation
- Audio scene classification
- Audio tagging
- Audio search and retrieval
- Audio rendering
- Audio recognition
- …

Models:

- Physics-based models
- Perceptually motivated models
- Data-driven models
- Hybrid models
- ….

Data:

- Audio-only
- Multimodal (audio, visual, texts, EEG, etc)

(Large) Audio Models

Learning **general/universal audio representations** from large scale audio data shows promising performance in downstream tasks (classification, separation, retrieval, etc):

- **PANNs** (Kong, et al, 2020): large scale CNN-based audio model
- Audio2Vec (Tagliasacchi et al, 2020): sequence to sequence unsupervised model
- CLAR (Al-Tahan and Mohsenzadeh, 2021): self-supervised model
- COLA (Saeed et al, 2021): self supervised model
- BOYL-A (Niizumi et al, 2021): self supervised model
- AST (Gong et al, 2021): large scale transformer-based audio model
- ATST (Li and Li, 2022): transformer-based model
- MAE-AST (Baade et al, 2022): self-supervised model
- SSAST (Gong et al, 2022): self-supervised AST model
- Audio-MAE (Huang et al, 2022): self-supervised model
- BEATs (Chen et al, 2023): audio pre-training with acoustic tokenizers
- **ASiT** (Atito et al, 2024): self-supervised models for general audio representation
- SSLAM (Alex et al, 2025): self-supervised learning from audio mixtures

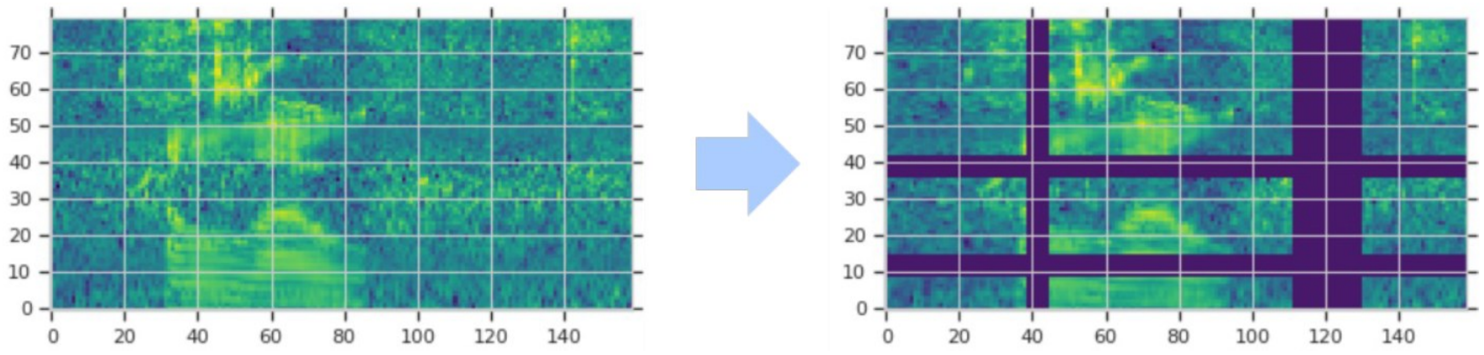
mean Average Precision (mAP) on AudioSet: **31.4** (2017) -> **55.8** (2025)

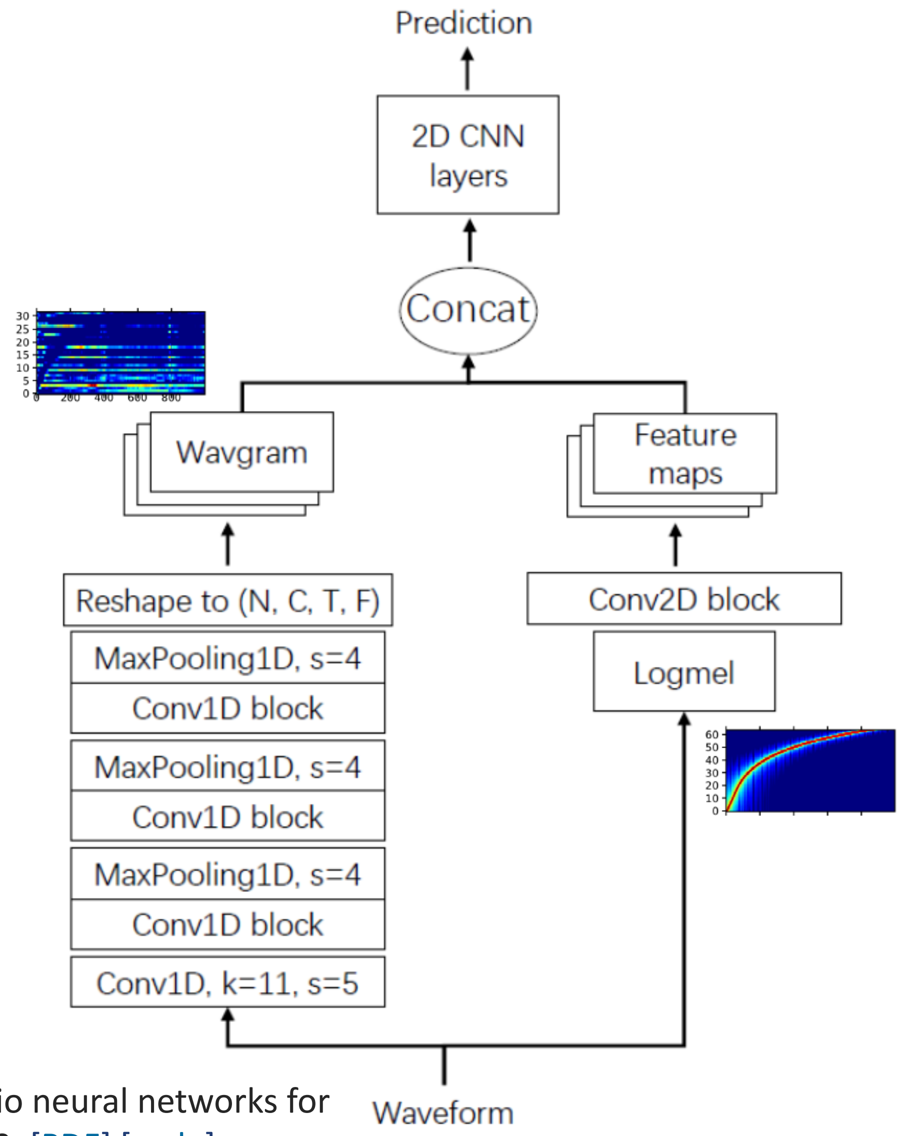
PANNs: Large-Scale Pre-trained Audio Neural Networks

Wavegram-Logmel-CNN for AudioSet tagging

- Time-domain (“Wavegram”), plus
- Log mel spectrogram

Data augmentation, e.g. use SpecAugment: randomly mask time and frequency stripes of log mel spectrogram



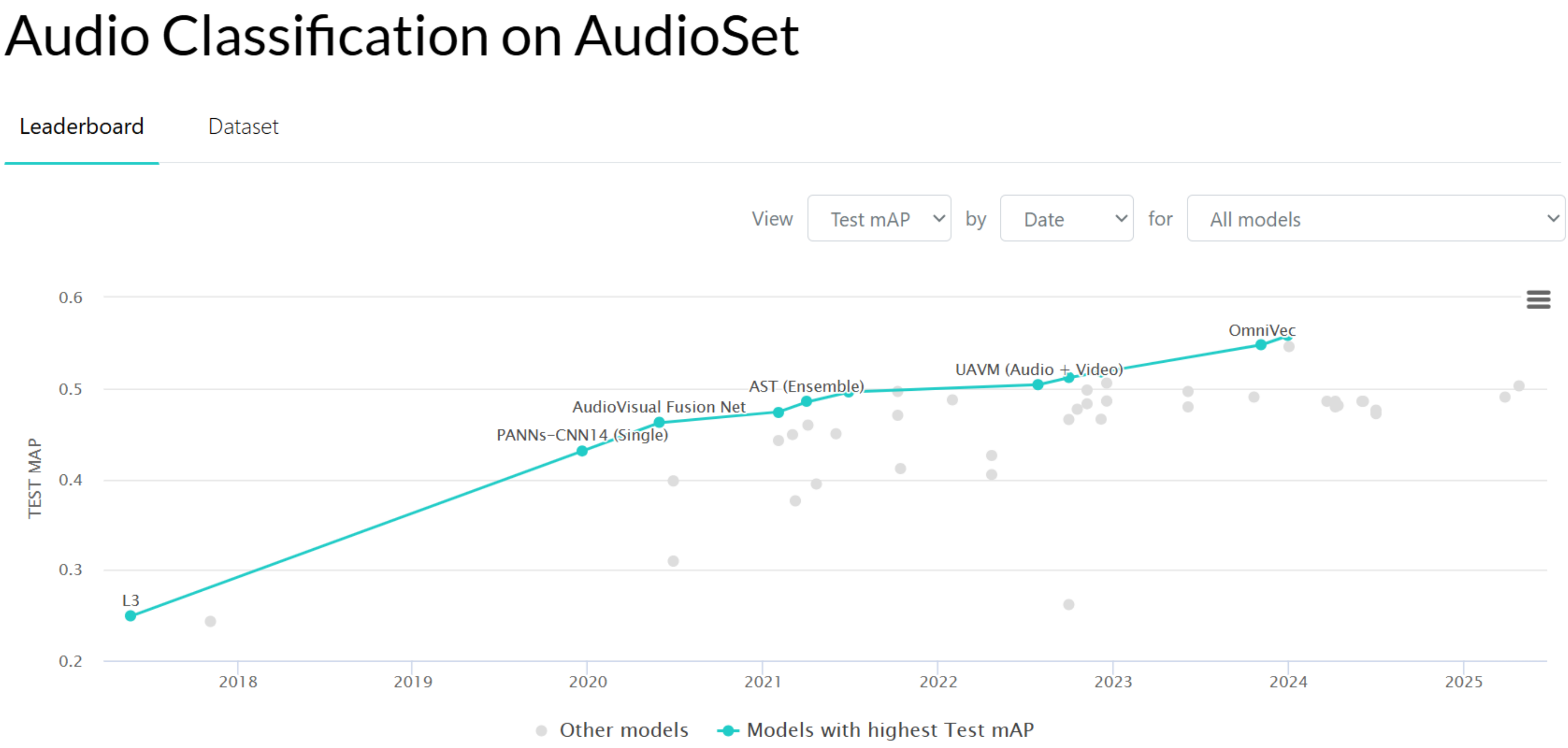


Q. Kong, Y. Cao, T. Iqbal, Y. Wang, W. Wang, and M. D. Plumbley, "PANNs: large-scale pretrained audio neural networks for audio pattern recognition", *IEEE/ACM Transactions on Audio Speech and Language Processing*, 2020. [PDF] [code]

PANNs: Demo

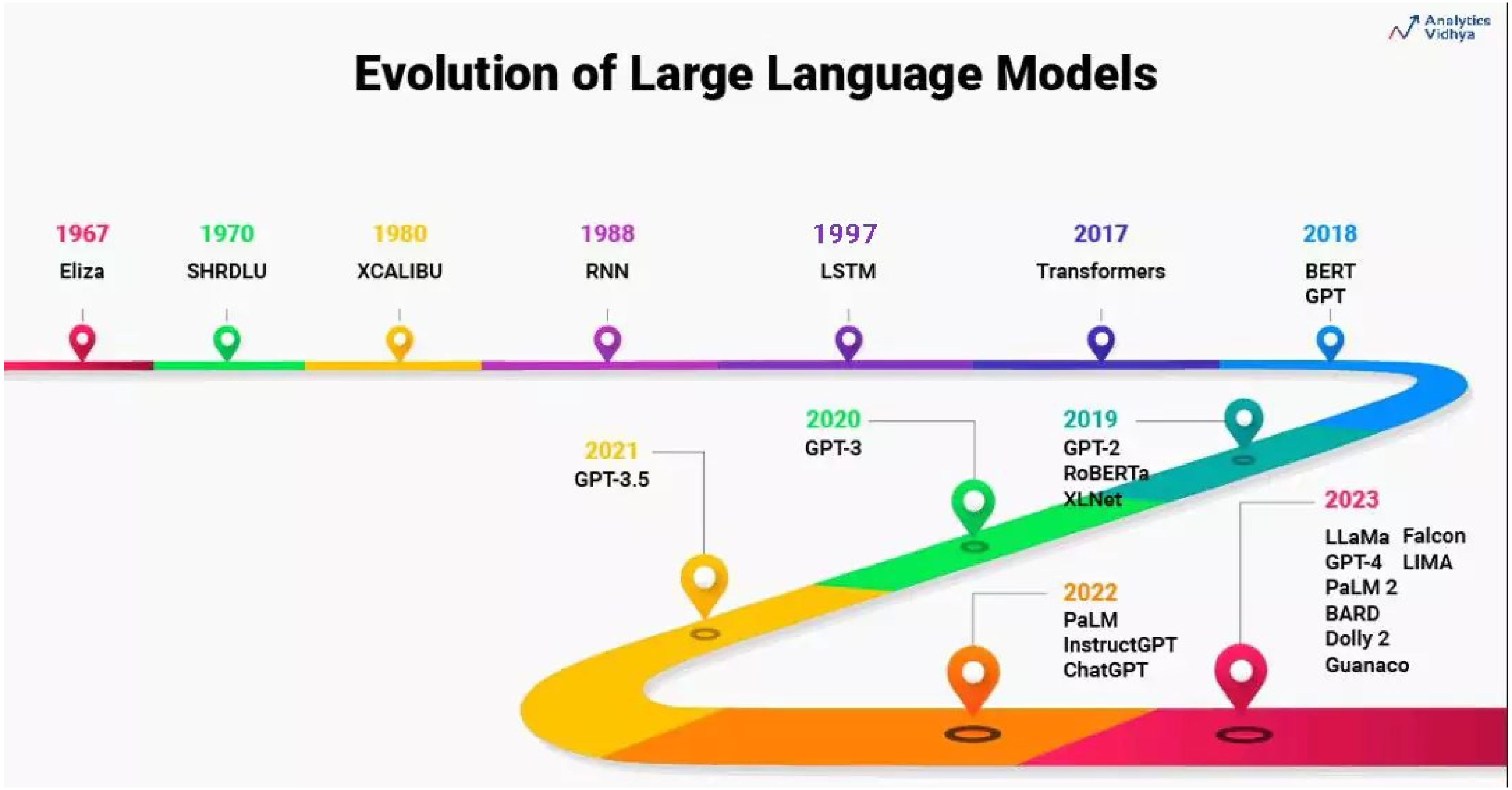
Music: 0.661
Speech: 0.039
Singing: 0.036
Inside: 0.011
Jingle bell: 0.007

(Large) Audio Models



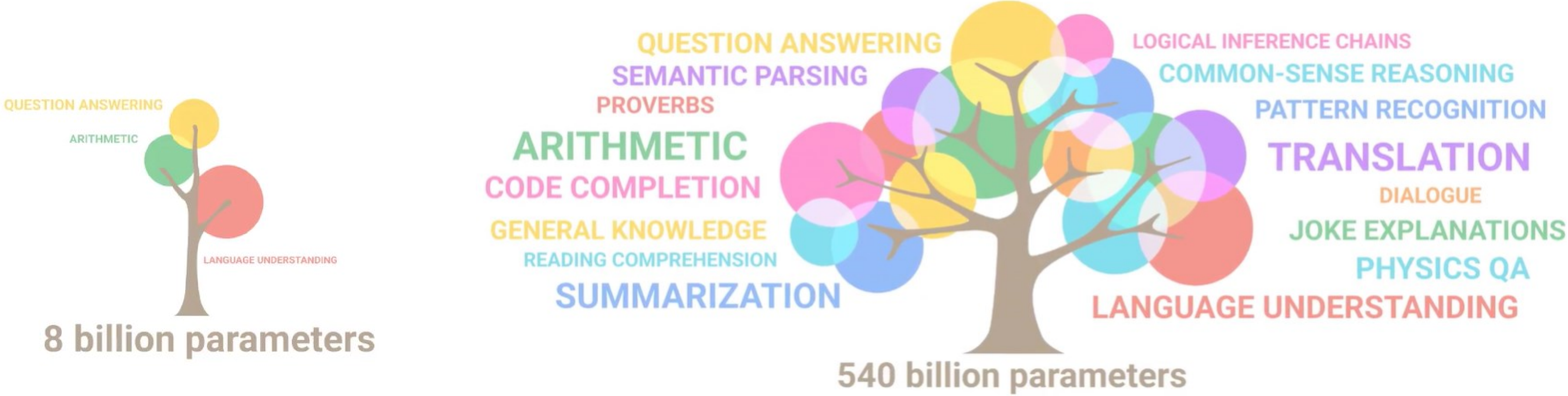
Leaderboard:
https://paperswithcode.com/sota/audio-classification-on-audioset
https://www.codesota.com/audio/classification

Large Language Models (LLMs)



Courtesy to Aravind Pai: https://www.analyticsvidhya.com/blog/2023/07/beginners-guide-to-build-large-language-models-from-scratch/

Large Language Models (LLMs)



Figures from Ryan O'Connor: https://www.assemblyai.com/blog/emergent-abilities-of-large-language-models/

Wei et al, “Emergent abilities of large language models,” *Transactions on Machine Learning Research*, 2022.

Large Audio-Language Models: Why?

- Leverage knowledge within LLMs to address the limitations of audio models
  - Zero-shot or few-shot classification
- Explore homogeneity across tasks with LLMs
  - Use LLMs as an agent to solve multi-task problems
- Extend the capabilities of audio models for new tasks
  - Extending from audio classification to audio captioning/question answering & reasoning
  - Extending from audio generation to storytelling & controllable editing
  - Extending from audio source separation to language queried audio source separation

Large Audio Language Models - Examples

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Whisper: automatic speech recognition (ASR)
Wav2Vec 2.0: speech to text (STT)
DeepSpeech: open-source ASR
Coqui AI: speech synthesis and TTS
Jasper and QuartzNet: ASR
GPT-3 with Whisper: ASR + LLMs
Sonix.ai: speech transcription and analysis
SpeechBrain: platform for speech models
OpenSTT: ASR
Gemini: text/image/speech
WavLLM: speech LLMs
MuseNet: music instrumental composition & style transfer
MusicVAE: melody generation, remixing, and style interpolation
JukeBox: raw music with vocals and lyrics
Riffusion: text to music generation
MusicLM: text to music generation
REMI: symbolic music generation (e.g. MIDI)
DeepBach: classic music composition
AIVA: music generation assistant

Wav2CLIP: audio and language mapping
AudioCLIP: audio-text-image alignment
CLAP: audio-text alignment
CLAP-LAION: audio-text alignment
Pengi: audio classification & AQA
Qwen-Audio: speech, music, general audio
AudioLM: Speech/music generation
LTU: audio QA and reasoning
SALMONN: speech-audio-music LLMs
ImageBind: image, text, audio, depth
ONE-PEACE: audio-text-image
AudioGPT: Speech, Music, Talking Head
UniAudio: speech/sound/music/singing

AudioLDM: text to audio generation
AudioLDM 2: text to audio generation
Re-AudioLDM: text to audio generation
T-CLAP: audio-text alignment
WavCraft: text prompted audio editing
APT-LLM: LLM based AQA and reasoning

(Large) Audio-Language Datasets

- AudioCaps (Kim et al, 2019)
- Clotho (Drossos et al, 2020)
- SoundDescs (Koepke et al, 2021)
- LAION-Audio-630K (Wu et al, 2023)
- Auto-ACD (Xu et al, 2024)
- Audio-FLAN (Xue et al, 2025)
- SeaBench-Audio (Liu et al, 2025)
- MusicSem (Salganik et al, 2026)

- **WavCaps (Mei et al, 2023)**
- **Sound-VECaps (Yuan et al, 2024)**
- **AudioSetCaps (Bai et al, 2025)**

- CLEAR (Abdelnour et al, 2018)
- DAQA (Fayek and Johnson, 2019)
- Clotho-AQA (Lipping et al, 2022)
- MUSIC-AVQA (Li et al, 2022)
- mClothoAQA (Behera et al, 2023)
- OpenAQA-5M (Gong et al, 2023)
- AudioMCQ (He et al, 2025)
- Audio Flamingo 3 (Goel et al, 2025)
- Jamendo-MT-QA (Koh et al, 2026)

Large Audio-Language Models- Recent Progress

Leaderboard: MMAU-v05.15.25

Open-Source | Open-Access | Proprietary | Fine-tuned

		Sound		Music		Speech		Avg	
Name	Size	Test-mini	Test	Test-mini	Test	Test-mini	Test	Test-mini	Test
Audio-Thinker 🥇	8.4B	81.98	78.8	74.25	73.8	76.88	75.16	77.7	75.98
Nova 2 Omni 🥈	-	81.08	77.87	70.36	66.37	81.98	81.82	77.8	75.28
Step-Audio-2 🥉	-	84.04	80.60	73.56	68.23	75.15	72.75	77.58	73.86
MiMo-Audio	7B	81.68	77.2	74.25	69.73	68.17	70.77	74.7	72.59
Audio Flamingo 3	8.2B	79.58	75.83	73.95	74.47	66.37	66.97	73.30	72.42
Qwen2.5-Omni	8.2B	78.10	76.77	65.90	67.33	70.60	68.90	71.50	71.00
Step-Audio-2-mini	8.3B	79.30	75.57	68.44	66.85	68.16	66.49	72.73	70.23
Gemini 2.5 Pro	-	75.08	70.63	68.26	64.77	71.47	72.67	71.60	69.36
Gemini 2.5 Flash	-	73.27	69.50	65.57	69.40	76.58	68.27	71.80	67.39
Gemini 2.0 Flash	-	71.17	68.93	65.27	59.30	75.08	72.87	70.50	67.03
DeSTA2.5-Audio	8B	70.27	66.83	56.29	57.10	71.47	71.94	66.00	65.21
Kimi-Audio	8.2B	75.68	70.70	66.77	65.93	62.16	56.57	68.20	64.40
Audio Reasoner	8.2B	67.87	67.27	69.16	61.53	66.07	62.53	67.70	63.78

https://sakshi113.github.io/mmau_homepage/#leaderboard-v15-parsed

Trends and Open Questions in LLAMs

Open challenges:

- **Fusion of audio and language models**: aligning/fusing audio-text data
- **Applications to audio tasks**: addressing existing challenges in audio tasks
- **Extending to multi-modality**: text, audio, visual, or more modalities
- **Data scarcity**: audio-language dataset shortage for building audio-language models
- **Extending to multi-tasks**: exploring in new tasks & solving multi-task problems
- **Multi-lingual models and datasets**: lacking multi-lingual models and datasets
- **Real-time streaming**: demands for real-time processing for applications in live captioning, gaming, and customer service
- **Low-resource language support**: growing interest in training models for underrepresented languages for inclusiveness
- **Safety issues**: growing concerns about toxicity and privacy issues
- **Explaining models**: explaining and interpreting different choices and decisions made by the model
- **Object hallucination**: struggling in answering discriminative questions related to the identification of specific object sounds within an audio clip
- **Performance evaluations**: lack of common evaluation protocols, tools and benchmarks

Applications:

- Accessibility, voice assistants, content creation, and human-computer interaction

Typical Methods for Fusing Audio and Language

- Aligning audio-texts with contrastive pretraining
  - Examples: CLAP, CLAP-LAION, AudioCLIP, Wav2CLIP, T-CLAP, etc.
- Tokenizing audio and texts, then followed by LLMs
  - Examples: Moshi, VITA, LSLM, Voicebox, FunAudioLLM, LauraGPT, etc.
- Fusing embeddings with cross-attention
  - Examples: Q-former
- Cascading acoustic models with LLMs
  - Examples: naive ASR+LLM+TTS
- Combination of the above schemes
  - Examples: SPIRIT-LM, Spectron, etc.

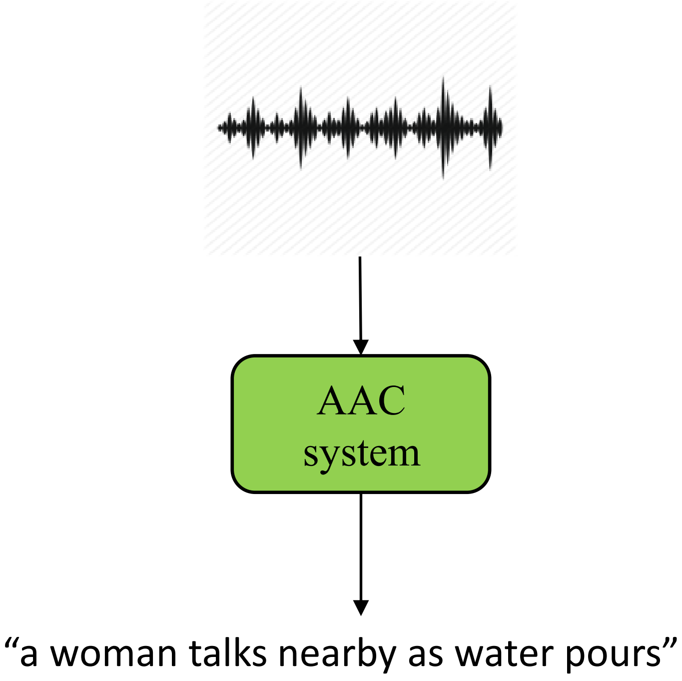
Task 1: Audio to Text Generation

- **Automated audio captioning** (AAC) is a cross-modal translation task which aims at generating a natural language description given an audio clip.

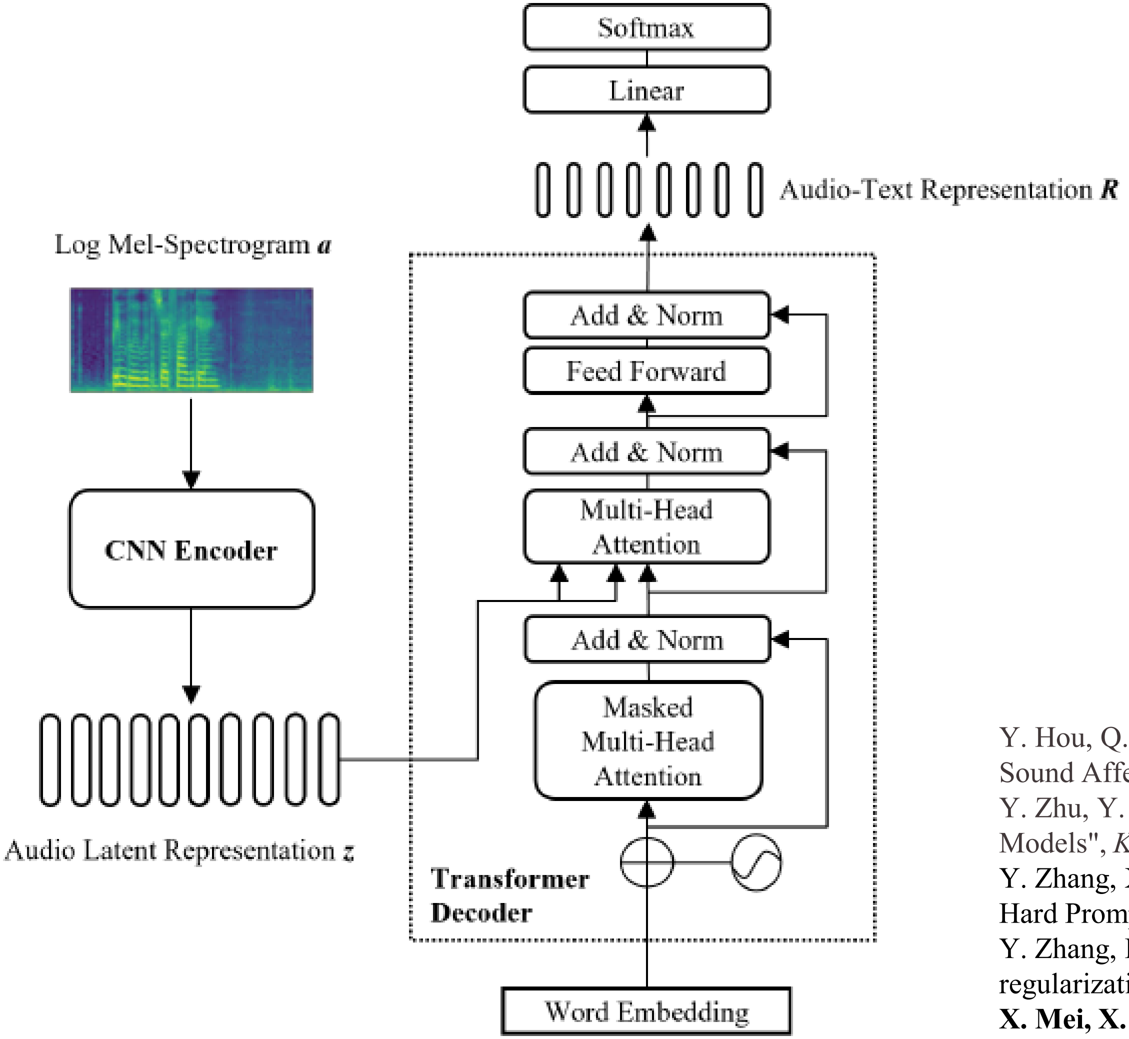
- This task requires detecting the audio events and their spatial-temporal relationships and describing these information using natural language.

- Applications
  - Audio retrieval
  - Assist hearing-impared to understand environmental sounds
  - Subtitle for sounds in TV programs

- AAC started in 2017, and has received increasing attention in recent three years with freely available datasets released and being held as a task in DCASE Challenges 2020-2022.



An Example: CNN-Transformer Encoder-Decoder

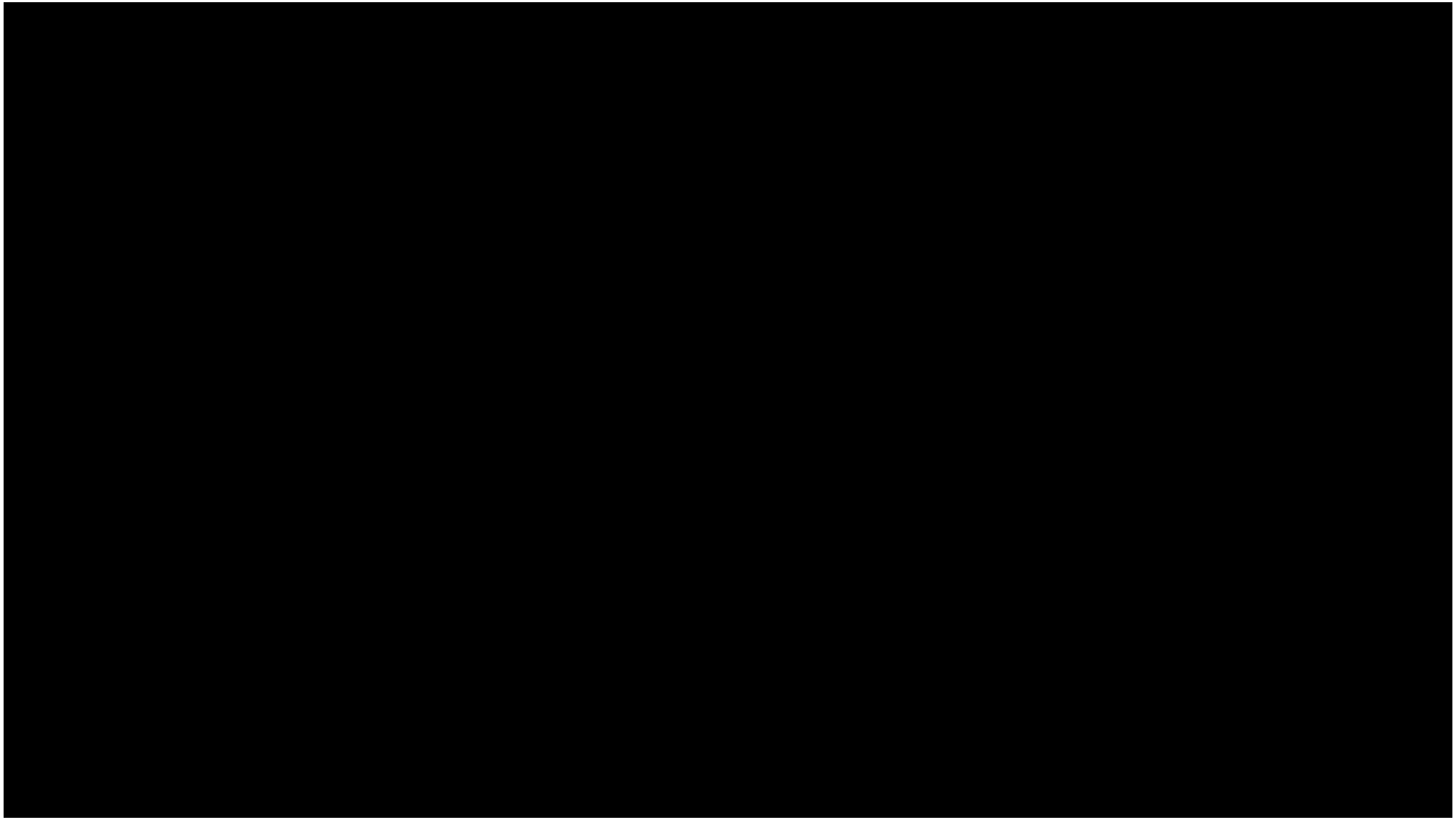


Common challenges in automated audio captioning:

- Data scarcity
- Representations of audio, text and audio-text
- Diversity of captions
- Multi-lingual captioning
- Interactions with other modalities (e.g. vision)
- ....

Y. Hou, Q. Ren, A. Mitchell, W. Wang, J. Kang, T. Belpaeme, and D. Botteldooren, "Soundscape Captioning using Sound Affective Quality Network and Large Language Model," *IEEE Transactions on Multimedia*, 2026.
Y. Zhu, Y. Zhang, L. Xiao, W. Wang, and A. Men, "Zero-shot Diverse Audio Captioning with Diffusion Models", *Knowledge Based Systems*, 2026.
Y. Zhang, X. Xu, R. Du, H. Liu, Y. Dong, Z.-H. Tan, W. Wang, and Z. Ma, "Zero-Shot Audio Captioning Using Soft and Hard Prompts," *IEEE Transactions on Audio Speech and Language Processing,* vol. 33, pp. 2045 - 2058, May 2025.
Y. Zhang, H. Yu, R. Du, Z.-H. Tan, W. Wang, Z. Ma, Y. Dong, "ACTUAL: audio captioning with caption feature space regularization," *IEEE/ACM Transactions on Audio Speech and Language Processing*, vol. 31, pp. 2643 - 2657, 2023.
X. Mei, X. Liu, M. Plumbley, and W. Wang, "Automated audio captioning: an overview of recent progress and new challenges", *EURASIP Journal on Audio Speech and Music Processing*, 2022.
F. Xiao, J. Guan, H. Lan, Q. Zhu, and W. Wang, "Local information assisted attention-free decoder for audio captioning," *IEEE Signal Processing Letters*, vol. 29, pp. 1604-1608, 2022.

Audio Captioning Demos



Task 2: Audio Question Answering & Reasoning

Acoustic Prompt Tuning (APT): an adapter extending LLMs/VLMs to the audio domain using an improved soft-prompting approach

Motivation:

- **Existing works** on LALMs used pretrained audio embeddings as soft prompt and adjust the LLM with Parameter-Efficient Fine-Tuning (PEFT).
- However, they **cannot generalize to multi-modal setting**, e.g., audio-visual language models.
- **Can we extend the off-the-shelf language models to the audio domain rather than training a dedicated LLM (~7B to 70B)?**

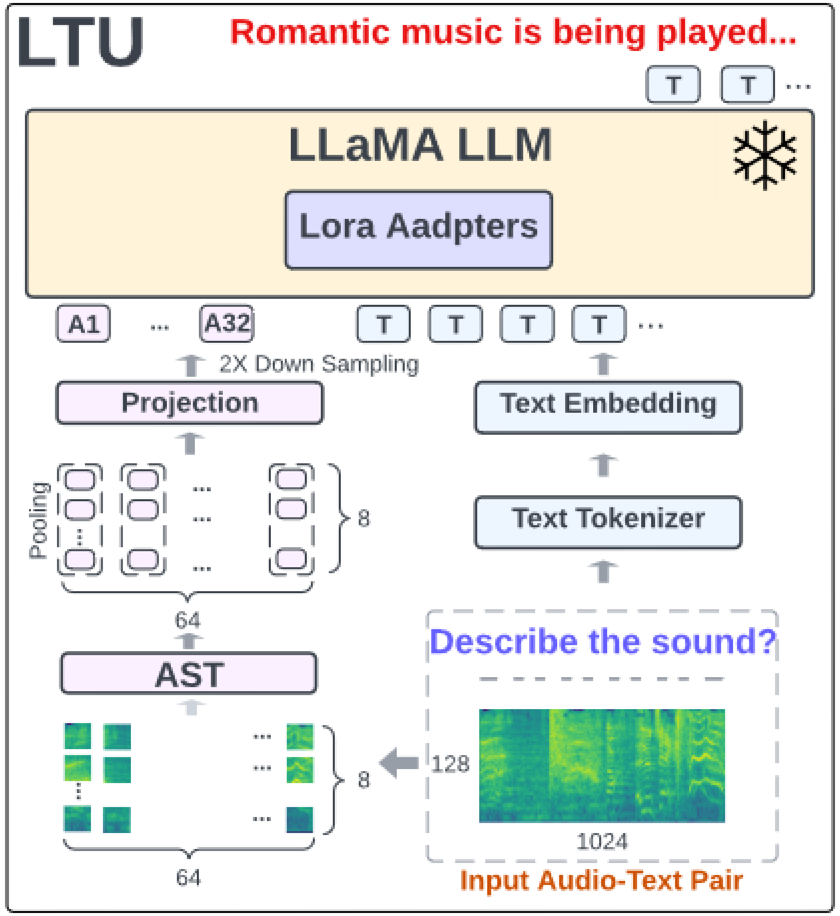
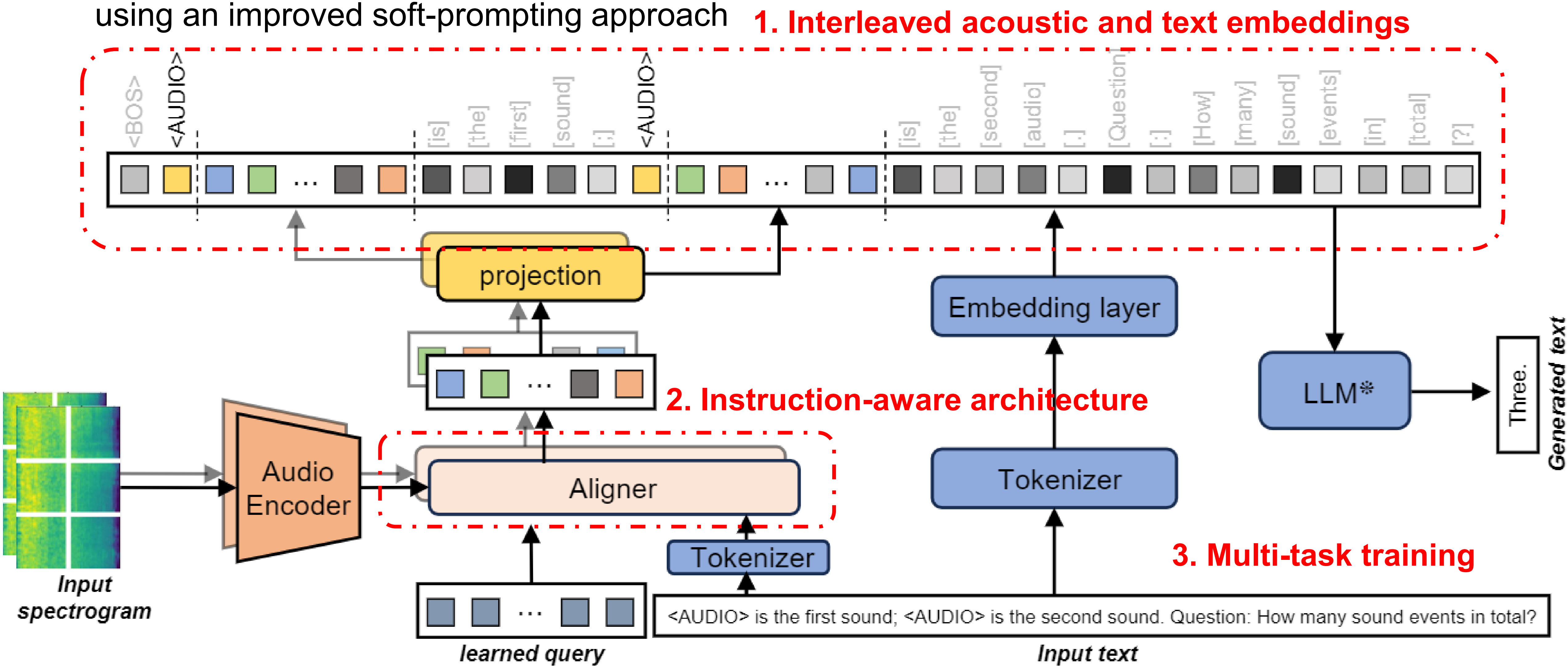


Fig. An example of an audio LLM structure (LTU (Gong et al, 2023)).

J. Liang, X. Liu, W. Wang, M. D. Plumbley, H. Phan, E. Benetos, "Acoustic Prompt Tuning: Empowering Large Language Models with Audition Capabilities", *IEEE Transactions on Audio Speech and Language Processing*, vol. 33, 949 - 961, 2025. arXiv:2312.00249

Task: Audio Reasoning – **APT**

Acoustic Prompt Tuning (APT): an adapter extending LLMs/VLMs to the audio domain using an improved soft-prompting approach



APT – Experimental Results

Table 3: Zero-shot performance comparison with audio language models. We group the methods in terms of their training strategy. “#Params.” denotes the number of trainable parameters and “#Pairs” represents the number of audio-text pairs. ↑ indicates the higher number, the better performance.

Model	#Params.	#Pairs	AudioSet (mAP↑)	AudioCaps (SPICE↑)	Clotho (SPICE↑)
Audio-language models trained with the contrastive loss					
AudioCLIP (Guzhov et al., 2022)	30M	2M	25.9	-	-
CLAP (Elizalde et al., 2023)	190M	128k	5.8	-	-
One-for-all models for various audio tasks					
LTU (Gong et al., 2023)	96M	5.7M	18.5	17.0	11.9
Pengi (Deshmukh et al., 2023)	>191M	3.4M	-	18.2	12.6
APT-LLM	101M	2.6M	14.7	17.1	11.6

Table 4: Performance comparison in audio captioning tasks. ↑ indicates the higher number, the better performance.

Model	AudioCaps		Clotho	
	SPICE ↑	SPIDEr ↑	SPICE ↑	SPIDEr ↑
Specialised systems trained with task-specific examples				
PANNs-BART (Xu et al., 2021)	0.153	0.183	0.083	0.127
CNN-GPT2 (Kim et al., 2023)	0.167	**0.438**	0.111	0.215
WSAC+PD (Kouzelis & Katsouros, 2023)	0.173	0.403	0.123	0.247
One-for-all models for various audio tasks				
APT-LLM	**0.191**	0.402	**0.132**	**0.248**

Table 5: Accuracy (%) of various methods on ESC-50 in the few-shot settings.

	Accuracy↑	
	5-way	12-way
Specialised systems trained with task-specific examples		
ProtoNet (Snell et al., 2017)	88.2	77.7
MatchNet (Vinyals et al., 2016)	86.8	71.8
HPN (Liang et al., 2022)	88.7	78.7
Audio language models trained with constractive learning		
TIP-adapter (Zhang et al., 2022)	97.5	95.6
Treff adapter (Liang et al., 2023)	98.5	96.3
One-for-all models for various audio tasks		
APT-LLM	91.0	54.2

Table 3: Benchmarking APT on the natural language audio reasoning task.

Model	Accuracy↑ (%)
the baseline	29.9
APT-Vicuna v1.1	62.9
APT-Vicuna v1.5	**63.8**

APT-LLM has a promising result on common audio tasks without fine-tuning on task-specific data. After fine-tuning for two epochs, APT-LLM achieves the best performance on downstream tasks.

APT – Demos

"first_recording": "Creaking pier.wav"

"second_recording": "Machetes sliding 2.wav"

"first_recording": "Rain and Storm.wav"

"second_recording": "Car vs. Freight Train.wav"

"first_recording": "Creaking pier.wav",
"second_recording": "Machetes sliding 2.wav",
"**question**": "In which recording are the sound events more evenly distributed?",
"**answer**": "second“

"first_recording": "Rain and Storm.wav",
"second_recording": "Car vs. Freight Train.wav",
"**question**": "Does the second recording have a calming effect like the first recording?",
"**answer**": "yes"

Code: https://github.com/JinhuaLiang/APT
Paper: https://arxiv.org/abs/2312.00249

Task 3: Text to Audio Generation

Potential Applications:

Computational “foley artist”:
- Game developer: e.g., A ghost is haunting a house.
- Audio producer: e.g., high heels hitting metal ground.
- Movie producer: e.g., the laser sound from a laser gun.
- …

Automatic content creation
- Endless music
- Audiobook with ambient noises
- White noise for meditation
- …

Data Augmentations

Related Works:

Label-to-Audio Generation

- Acoustic Scene (Kong et al., 2019), Sound event (Liu et al., 2019), FootStep (Comunit et al. 2019), …

Text-to-Audio Generation

- DiffSound (Yang et al., 2022), AudioGen (Kreuk et al., 2022), Make-an-Audio (Huang et al., 2023)

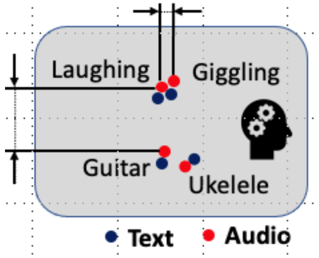
Text-to-Music Generation

- MusicLM (Andrea et al., 2023)
- Moûsai (Flavio et al., 2023)
- Noise2Music (Huang et al., 2023)

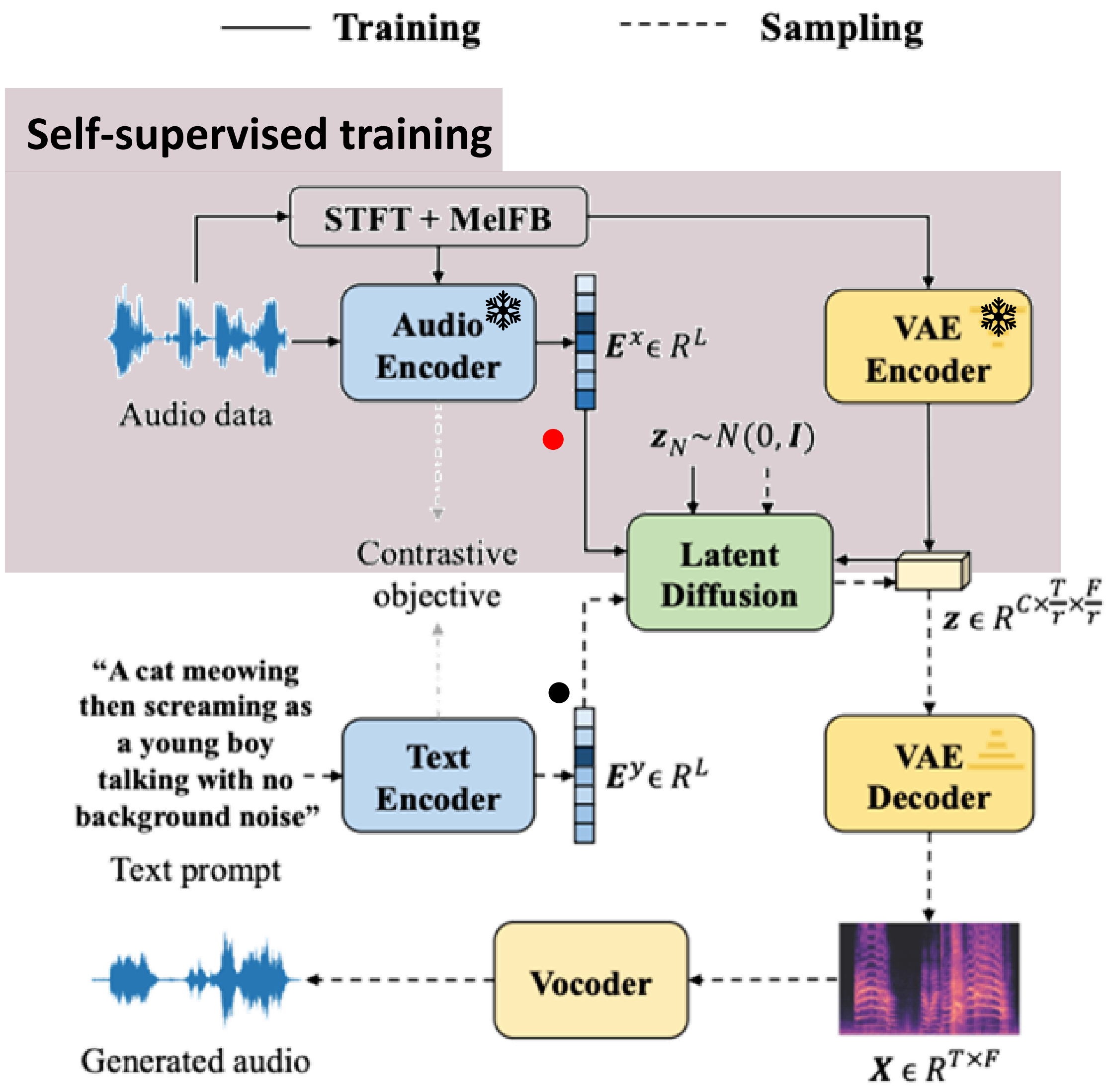
Others

- JukeBox (Dhariwal et al., 2020), AudioLM (Borsos et al., 2022), SingSong (Donahue et al., 2023),…

AudioLDM



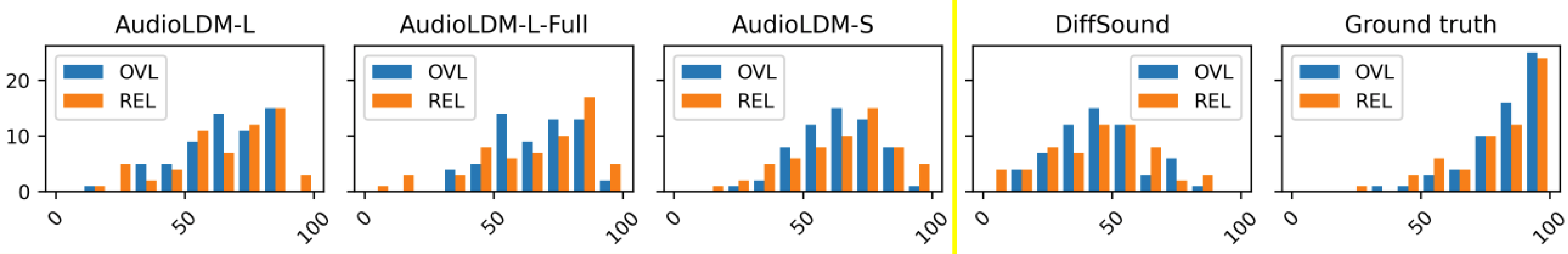
1. **Contrastive Language-Audio Learning (CLAP) Encoders**
   - Align audio and text in one space.
2. **Latent Diffusion Models**
   - Learn to generate VAE latent conditioned on CLAP embedding
3. **Mel-spectrogram Autoencoder**
   - Learn latent representations.
4. **Mel-to-Waveform Vocoder**
   - Reverse Mel back to waveform



H. Liu, Z. Chen, Y. Yuan, X. Mei, X. Liu, D. Mandic, W. Wang, M. D. Plumbley, "AudioLDM: text-to-audio generation with latent diffusion models," in *Proc. IEEE International Conference on Machine Learning* (ICML 2023), Hawaii, USA, 23-29 July, 2023.

AudioLDM – Experimental Results

Model	Datasets	Text	Params	FD ↓	IS ↑	KL ↓	FAD ↓	OVL ↑	REL ↑
Ground truth	-	-	-	-	-	-	-	83.61	80.11
DiffSound† (Yang et al., 2022)	AS+AC	✓	400M	47.68	4.01	2.52	7.75	45.00	43.83
AudioGen† (Kreuk et al., 2022)	AS+AC+8 others	✓	285M	-	-	2.09	3.13	-	-
AudioLDM-S	AC	✗	181M	29.48	6.90	1.97	2.43	63.41	64.83
AudioLDM-L	AC	✗	739M	27.12	7.51	1.86	2.08	64.30	64.72
AudioLDM-L-Full	AS+AC+2 others	✗	739M	**23.31**	**8.13**	**1.59**	**1.96**	**65.91**	**65.97**



Trained on a single 3090 or A100 GPU!

AudioLDM 2 – LLM+LDM

Auto-regressive modeling:

- ✅ Explicit modeling of temporal dependencies.
- ✅ Enjoy the advance of recent LLM development.
- ✅ Good in-context learning performance.
- ❌ Long generation sequence/ lack of parallelism
- ❌ Long range dependencies
- ❌ Error propagation

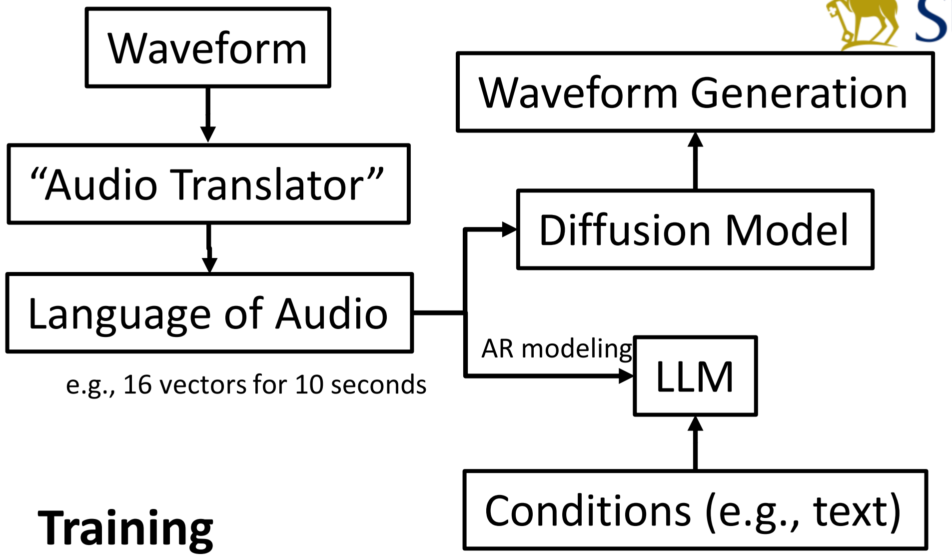
Diffusion-based approach:

- ✅ Stable
- ✅ State-of-the-art generation quality
- ✅ Flexible formulation for manipulation, interpolation, etc.
- ❌ Do not explicitly model temporal dependencies
- ❌ Less flexible on duration

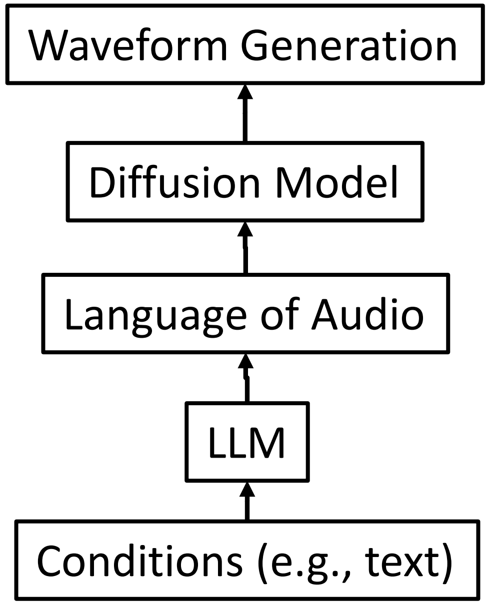
Can we utilize both advantages from LLM and Diffusion?

Code: https://github.com/haoheliu/audioldm2

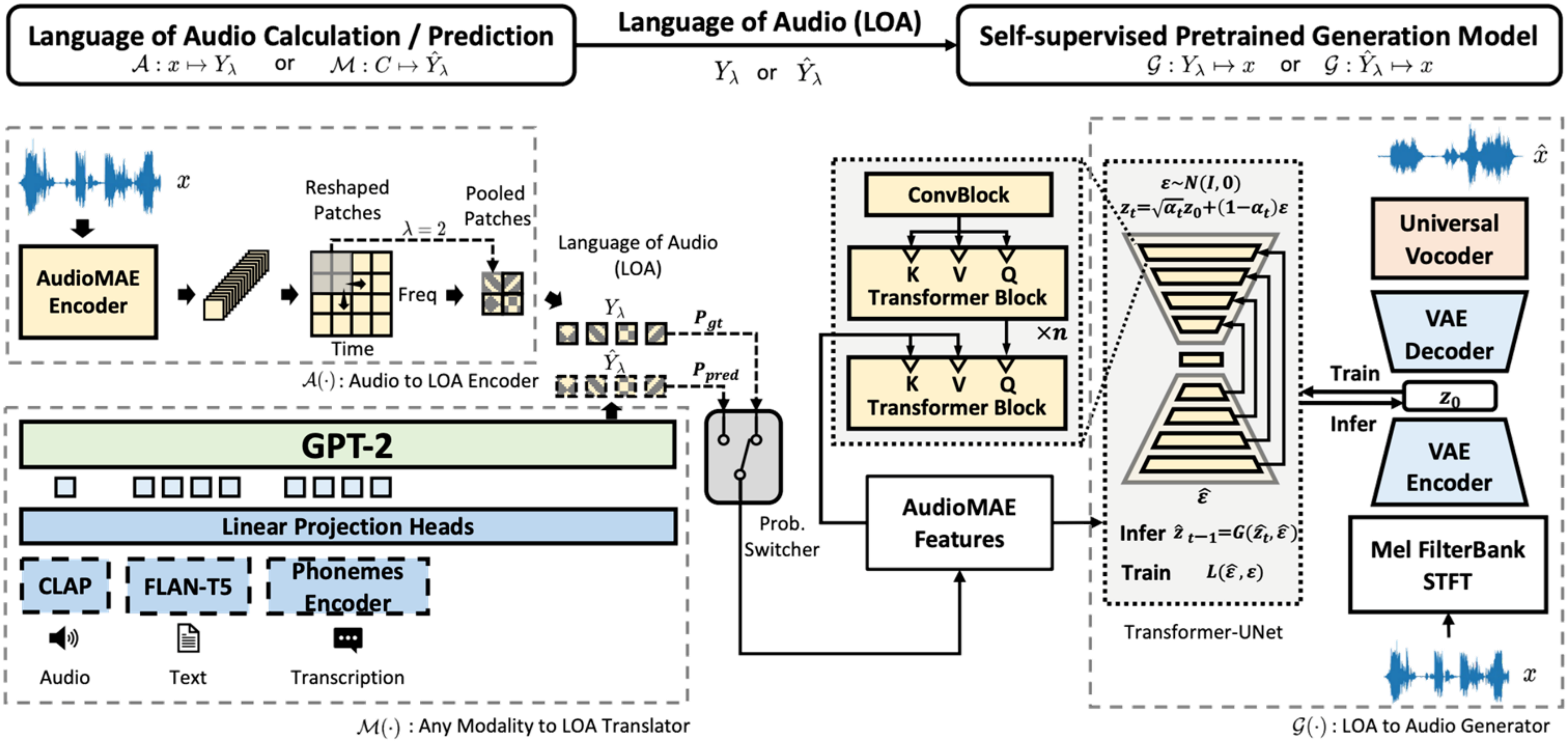
Training



Inference



AudioLDM 2 - Architecture



H. Liu , Y. Yuan , X. Liu , X. Mei , Q. Kong , Q. Tian , Y. Wang , W. Wang, Y. Wang , M. D. Plumbley, "AudioLDM 2: Learning holistic audio generation with self-supervised pretraining," *IEEE/ACM Transactions on Audio Speech and Language Processing*, vol. 32, pp. 2871-2883, 2024. [PDF] [code]

AudioLDM 2 - Performance

SoTA performance on Text-to-Audio/Music/Speech Generation Tasks

Text-to-Music Generation on MusicCaps

Model	FAD↓	KL↓	CLAP (%)↑	OVL↑	REL↑
GroundTruth	-	-	25.3	3.82	4.26
Riffusion	14.80	2.06	19.0	-	-
Mousai	7.50	1.59	-	-	-
MeLoDy	5.41	-	-	-	-
MusicLM	4.00	-	-	-	-
MusicGen-Medium	3.4	1.23	32.0	-	-
MusicGen-Medium†	4.89	1.35	29.1	3.37	3.38
AudioLDM-M†	3.20	1.29	**36.0**	3.03	3.25
AudioLDM 2-MSD	4.47	1.32	29.4	**3.41**	3.30
AudioLDM 2-Full	**3.13**	**1.20**	30.1	3.34	**3.54**

Text-to-Audio Generation on AudioCaps

Model	Duration (h)	Param	FAD↓	KL↓	CLAP (%)↑	OVL ↑	REL ↑
GroundTruth	-	-	-	-	25.1	4.04	4.08
AudioGen-Large	6824	1 B	1.82	1.69	-	-	-
Make-an-Audio	3000	453 M	2.66	1.61	-	-	-
AudioLDM-Large-FT	9031	739 M	1.96	1.59	-	-	-
AudioLDM-M	9031	416 M	4.53	1.99	14.1	3.61	3.55
Make-an-Audio 2	3700	937 M	2.05	1.27	17.3	3.68	3.62
TANGO	145	866 M	1.73	1.27	17.6	3.75	3.72
AudioLDM 2-AC	145	346 M	1.67	1.01	**24.9**	3.88	**3.90**
AudioLDM 2-AC-Large	145	712 M	**1.42**	**0.98**	24.3	**3.89**	3.87

Text-to-Speech Generation on LJSpeech

Model	Mean Opinion Score↑
GroundTruth	4.63 ± 0.08
GT-AudioMAE	4.14 ± 0.13
FastSpeech2	3.78 ± 0.15
AudioLDM 2-LJS	3.65 ± 0.21
AudioLDM 2-LJS-Pretrained	4.00 ± 0.13

AudioLDM 2 - Demo

We generated a total of 350 audio files with prompts (generated by ChatGPT) without cherry-picking.

Codes and more demos: https://audioldm.github.io/audioldm2/

Audio Storytelling - **WavJourney**

UNIVERSITY OF SURREY

WavJourney - Compositional Audio Creation with LLMs

Open Challenges:

- **Contextual comprehension and design**
  - Understand text instructions
  - Design storytelling with speech/music/SFX
- **Audio production and composition**
  - Dynamic spatial-temporal relationship
- **Interpretable and interactive creation**

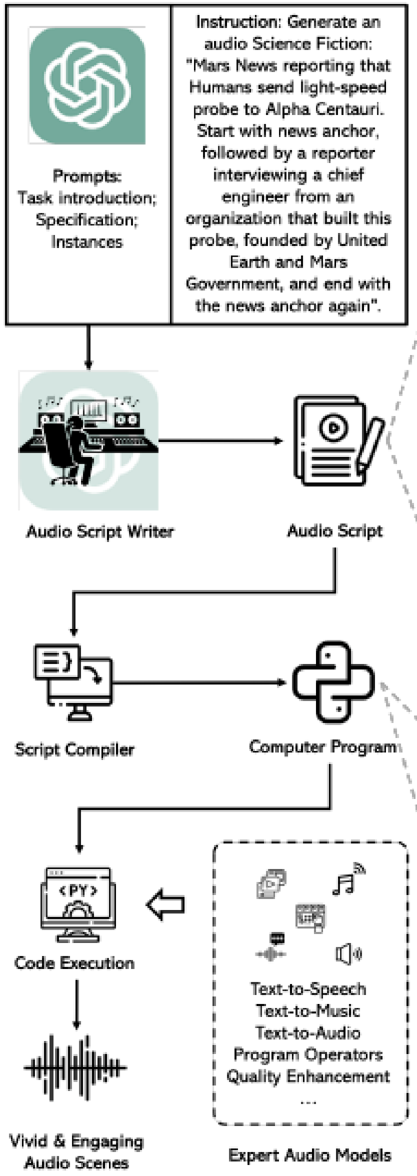
Advantages offered by WavJourney:

- Create audio storytelling with:
  - Personalized **speakers**
  - Lifelike **speech**
  - Immersive **music**
  - Impactful **sound effects**

All simply from texts!

Paper: https://arxiv.org/abs/2307.14335
Code: https://github.com/Audio-AGI/WavJourney
Demo: https://huggingface.co/spaces/Audio-AGI/WavJourney

WavJourney – Overall Architecture



Audio Type	Layout	ID	Character	Volume	Action	Content Description	Duration
Music	Background	1	N/A	-30	Begin	Dramatic orchestral news theme.	Auto
Speech	Foreground	N/A	Host	-15	N/A	Welcome to Mars News ...	Auto
Music	Background	1	N/A	N/A	End	N/A	Auto
Speech	Foreground	N/A	Host	-15	N/A	Now let's connect with our on-site reporter ...	Auto
Sound effect	Foreground	N/A	N/A	-35	N/A	Transition swoosh.	1
Sound effect	Background	2	N/A	-30	Begin	Background noise of busy engineering office.	Auto
Speech	Foreground	N/A	Reporter	-15	N/A	We're here at the headquarters of ...	Auto
Speech	Foreground	N/A	Director	-15	N/A	Thank you, so it's a fantastic ...	Auto
Speech	Foreground	N/A	Reporter	-15	N/A	This is truly an impressive feat ...	Auto
Speech	Foreground	N/A	Director	-15	N/A	The primary goal is to explore ...	Auto
Speech	Foreground	N/A	Reporter	-15	N/A	Thanks director, so the above ...	Auto
Sound effect	Background	2	N/A	-30	End	N/A	Auto
Sound effect	Foreground	N/A	N/A	-35	N/A	Transition swoosh.	1
Speech	Foreground	N/A	Host	-15	N/A	Back to the studio, as humanity ...	Auto
Music	Foreground	N/A	N/A	-25	N/A	Orchestral news outro music.	10

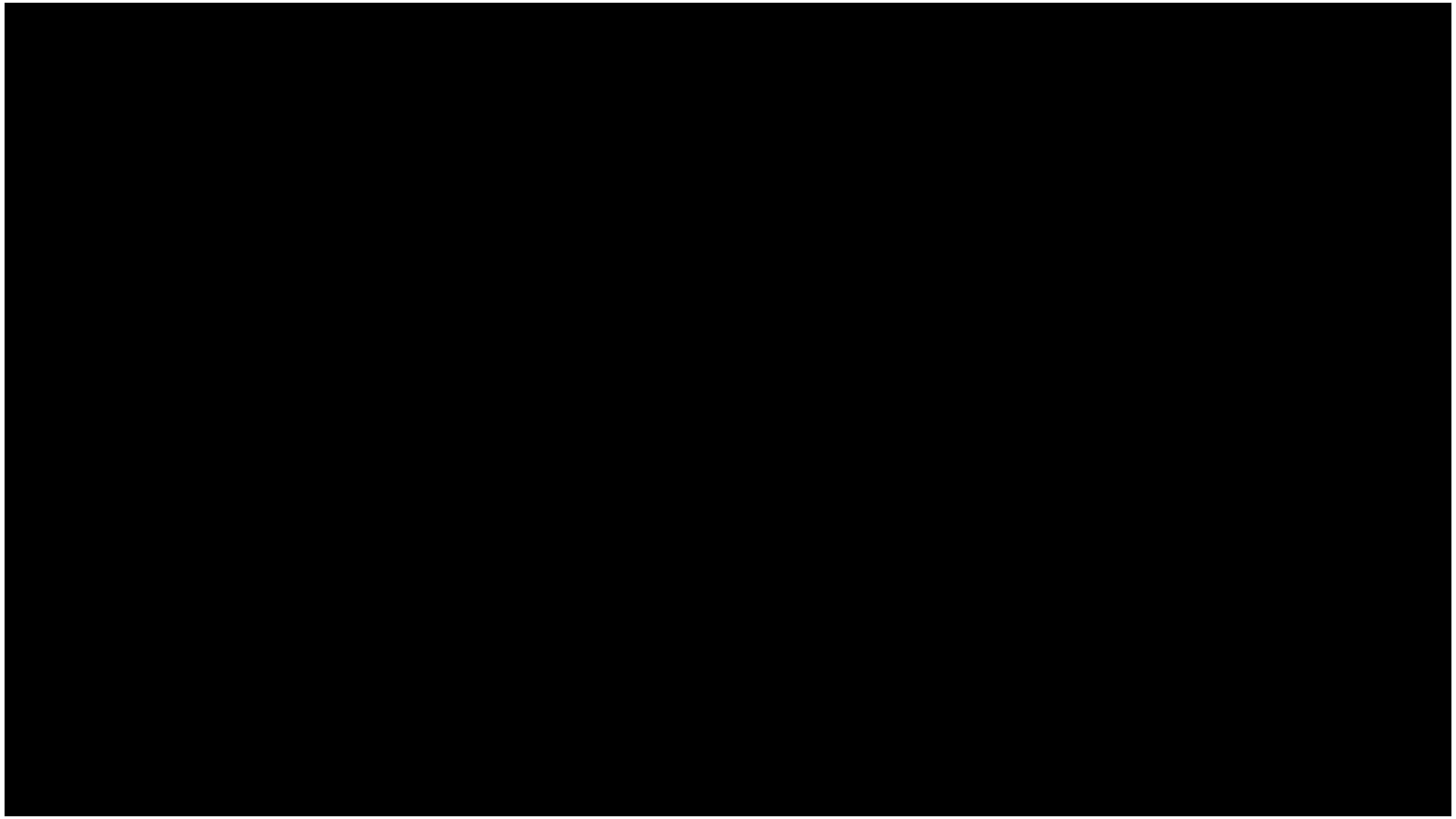
Audio script as a list of acoustic elements with attributes

```
Import relevant APIs (TTM, TTS, TTA, MIX, CAT)
Define the script text and sound effects for the audio generation
For each line in the script
    Generate the foreground speech with TTS (Text-to-Speech)
    Save the audio file and compute its length
Generate additional foreground sound effects using TTA (Text-to-Audio)
Combine all the foreground audio files with CAT (Concatenate audio)
Determine the background audio lengths and offsets based on the foreground audio lengths
Generate background music using TTM (Text-to-Music)
Generate background sound effects using TTA (Text-to-Audio)
Combine all the background audio files and the foreground audio file with MIX (Mix audio)
Save the final composed audio file
```

Script Compiler output (simplified pseudo code)

WavJourney – Sound Demo for Science Fiction Storytelling

UNIVERSITY OF SURREY



Paper: https://arxiv.org/abs/2307.14335

Code: https://github.com/Audio-AGI/WavJourney

Demo: https://huggingface.co/spaces/Audio-AGI/WavJourney

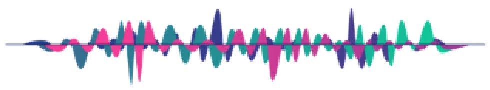
Music to Dance Generation

Focus only on hand-crafted musical features.

No genre information.

Based on 24-Joint dataset. Lack of hand motion.

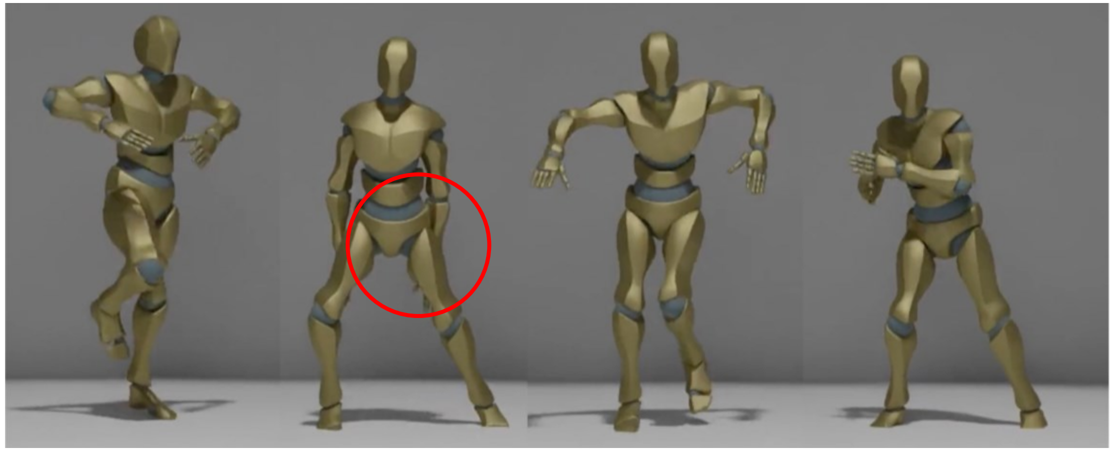
Input Music Audio



MFCC | Chroma | Beat | Envelop

Music Condition

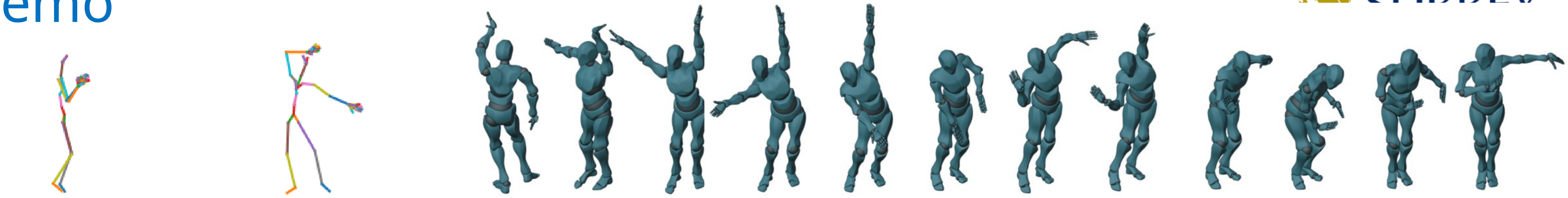
Generative Model



Generated Dance Segment

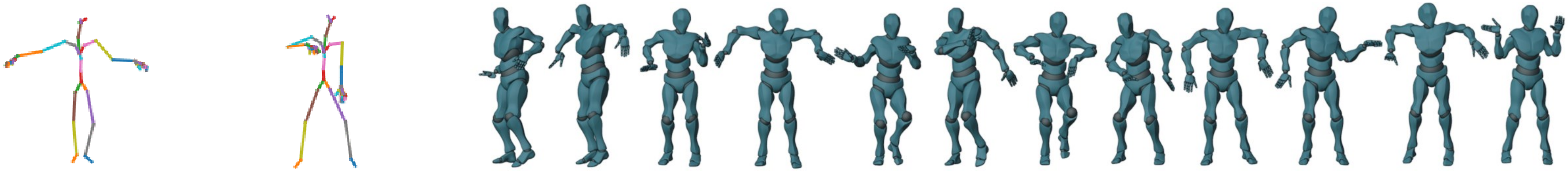
X. Liu, Z. Feng, D. Kanojia, W. Wang, "DGFM: Full Body Dance Generation Driven by Music Foundation Models", *NeurIPS 2024 Workshop on Audio Imagination*, 2024.

Demo



This is a "HanTang" type of music.

This is a "Dai" type of music.



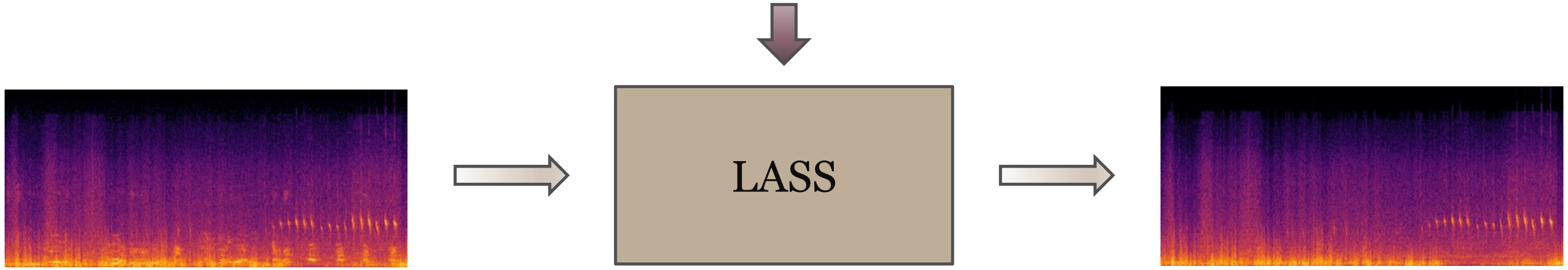
This is a "Hiphop" type of music.

X. Liu, X. Dong, S. Qian, D. Kanojia, W. Wang, and Z. Feng, "GCDance: Genre-Controlled Music-Driven 3D Full Body Dance Generation," *IEEE Transactions on Multimedia*, 2026. [arXiv] [PDF] [code, data, & demo]

Task 4: Language-Queried Audio Source Separation

- LASS – Separate a **target source** from an audio mixture based on the **natural language descriptions** of the target source
- First attempt bridging audio source separation and natural language processing
- Support input arbitrary text to separate desired sound sources

Language Query: A bird is chirping under the thunder storm

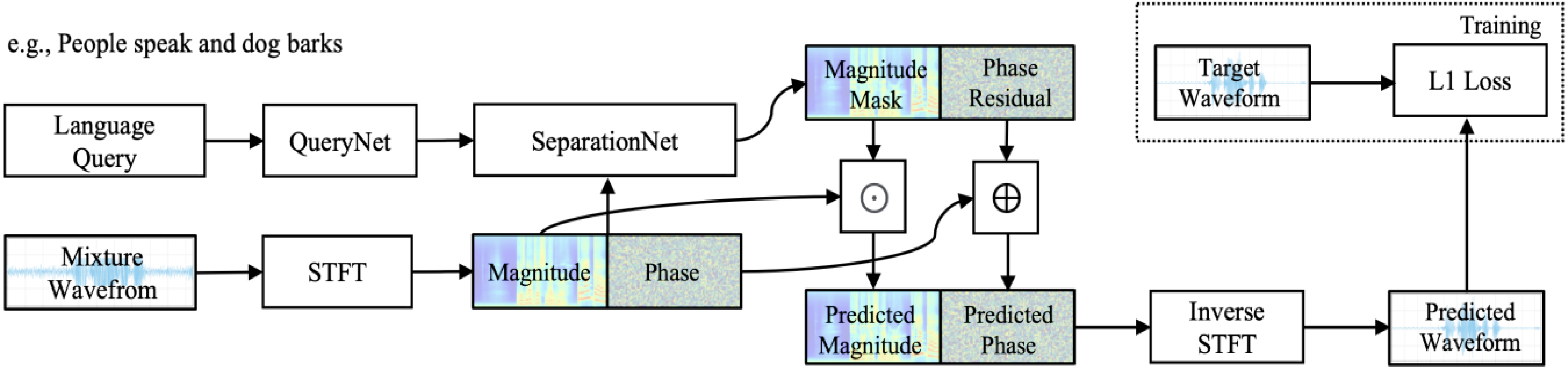


- **Existing methods**
  - LASS-Net (Liu et al 2022): first LASS model
  - SoundFilter (Kilgour 2022): exploiting audio supervision
  - CLIPSep (Dong et al. 2023): exploiting visual supervision
- **Challenges**
  - Small scale of data available for training
  - Open-domain source separation with texts
  - Overlapping sound events
  - Processing artefacts and incomplete separation

X. Liu, H. Liu, Q. Kong, X. Mei, J. Zhao, Q. Huang, M.D. Plumbley, and W. Wang,"Separate What You Describe: Language-Queried Audio Source Separation," in *Proc. 23rd Interspeech Conference* (INTERSPEECH 2022), 18-22 September, 2022, Incheon, Korea.

Task 4: **AudioSep** - Architecture

- CLAP/CLIP + ResUNet, trained with **14,000** hours of multimodal data
- A foundation model for open-domain sound separation with texts
- Impressive zero-shot performance in separating speech, music, sounds



X. Liu, Q. Kong, Y. Zhao, H. Liu, Y. Yuan, Y. Liu, R. Xia, Y. Wang, M. D. Plumbley, and W. Wang, "Separate anything you describe," *IEEE Transactions on Audio Speech and Language Processing*, vol. 33, 458--471, 2025. [PDF] [code]

Demo: https://huggingface.co/spaces/Audio-AGI/AudioSep

Task 4: **AudioSep** - Results

- AudioSep achieved the **state-of-the-art** results on multiple datasets.
- Impressive zero-shot separation performance on MUSIC and ESC-50.

AUDIOSEP TRAINING DATASETS.

	Caption	Label	Video	Num. clips	Hours
AudioSet	×	✓	✓	2 063 839	5800
VGGSound	×	✓	✓	183 727	550
AudioCaps	✓	✓	✓	49 768	145
Clotho v2	✓	×	×	4884	37
WavCaps	✓	×	×	403 050	7568

BENCHAMRK EVALUATION RESULTS OF AUDIOSEP AND COMPARISON WITH BASELINE SYSTEMS.

	AudioSet		**VGGSound**		**AudioCaps**		**Clotho**		**MUSIC**		**ESC-50**		**Voicebank-DEMAND**	
	SI-SDR	SDRi	SI-SDR	SDRi	SI-SDR	SDRi	SI-SDR	SDRi	SI-SDR	SDRi	SI-SDR	SDRi	PESQ	SSNR
USS-ResUNet30 [15]	-	5.57	-	-	-	-	-	-	-	-	-	-	2.18	9.00
USS-ResUNet60 [15]	-	5.70	-	-	-	-	-	-	-	-	-	-	2.40	**9.35**
LASSNet [3]	-3.64	1.47	-4.50	1.17	-0.96	3.32	-3.42	2.24	-13.55	0.13	-2.11	3.69	1.39	0.98
CLIPSep [23]	-0.19	2.55	1.22	3.18	-0.09	2.95	-1.48	2.36	-0.37	2.50	-0.68	2.64	2.13	1.56
AudioSep-CLIP	**6.60**	**7.37**	7.24	7.50	5.95	7.45	4.54	6.28	**9.14**	**10.45**	8.90	10.03	2.40	8.09
AudioSep-CLAP	6.58	7.30	**7.38**	**7.55**	**6.45**	**7.68**	**4.84**	**6.51**	8.45	9.75	**9.16**	**10.24**	**2.41**	8.95

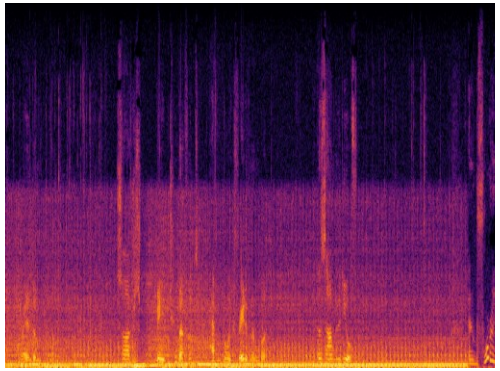
X. Liu, Q. Kong, Y. Zhao, H. Liu, Y. Yuan, Y. Liu, R. Xia, Y. Wang, M.D. Plumbley, and W. Wang,“Separate Anything You Describe" in *IEEE/ACM Transactions on Audio Speech and Language Processing,* vol. 33, 458--471, 2025.

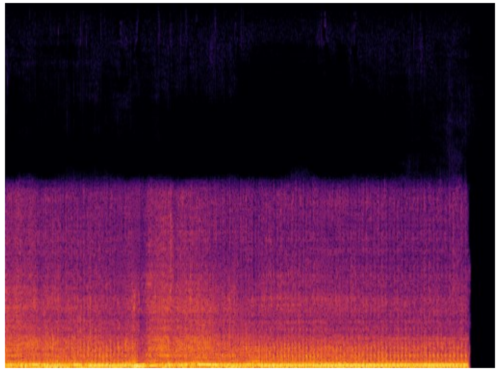
Task 4: AudioSep - Demo

Human query: “The engine sound of a vehicle”

Mix

Separated

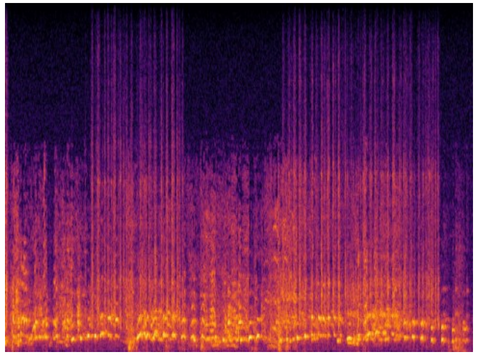


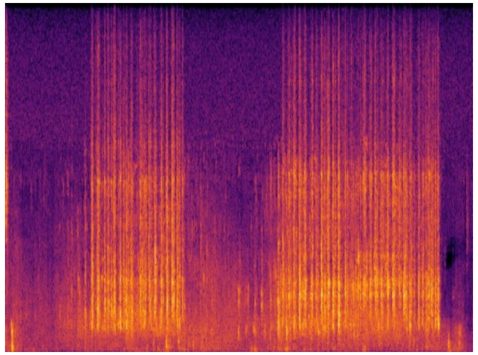


Human query: “The sound of hitting the keyboard”

Mix

Separated





Task 4: **FlowSep** - Motivation

Existing Ideas:

- Discriminative approaches.
- Time-frequency masking on spectrogram to remove the noise sound sources.

Challenges:

- Challenging with overlapping sound events.
- Excessive and insufficient masking leads to **artifacts**, including spectral holes and incomplete separation.

A “New” Idea:

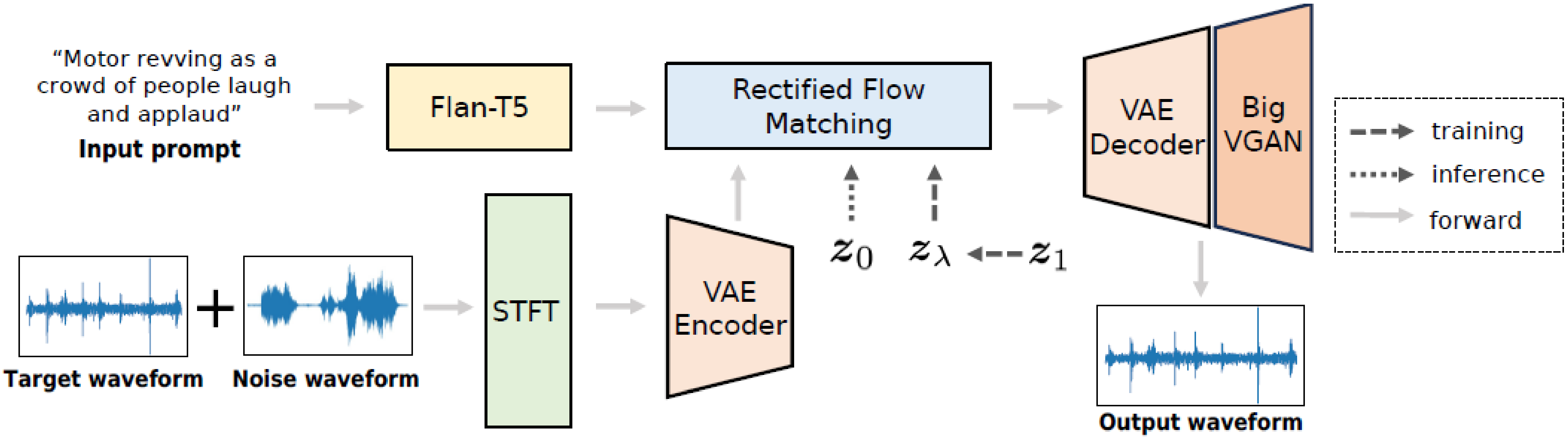
Using the generative approaches.

Diffusion-based generation framework with rectified flow matching.

Separation system by generating new audio samples with the noisy clips and text prompts as a condition.

Task 4: **FlowSep** - Architecture

- Text-to-audio generation model as the backbone, Rectified Flow Matching for feature generation.
- Extended VAE latent space to integrate the noise audio feature.
- Flan-T5 text encoder, VAE latent decoder and BigVGAN vocoder.



Y. Yuan, X. Liu, H. Liu, M.D. Plumbley, and W. Wang,"FlowSep: Language-Quried Sound Separation with Rectified Flow Matching" in *ICASSP 2025*.

Task 4: FlowSep

Training data:

A total of 1,680 hours of audio from various datasets for training. When creating the mixture audio samples, every two audio clips are not sharing any overlapping sound source classes. All the segments are padded or cropped to 10 seconds with 16kHz sampling rate, and we mix two waveforms with a random SNR between -15 and 15 dB.

- AudioCaps: One of the largest publicly available audio captioning dataset, containing 49837 10-second audio clips with human annotated captions.
- VGGSound: Audio dataset with 200,000 audio clips. Each sample has a duration of 10 seconds and annotated with labels.
- WavCaps: Large-scale audio dataset with weakly-labelled captions generated with LLM. We only use the samples less than 10 seconds and collected a total of 400,000 clips.

Testing data:

- VGGSound: 2000 mixtures generated from a group of 200 clean and distinct audio samples, mixed with random LUFS loudness between -35 and -25 dB.
- ESC-50: 2000 mixtures with a SNR at 0 dB.
- AudioCaps: 928 samples by mixing the audio from testing set under random SNR between -15 and 15 dB.
- DCASE2024 Task 8: DCASE-Synth includes 3000 mixtures from 1000 selected audio clips under an SNR between -15 and 15 dB. DCASE-Real consists of 100 audio clips from read-world scenarios.

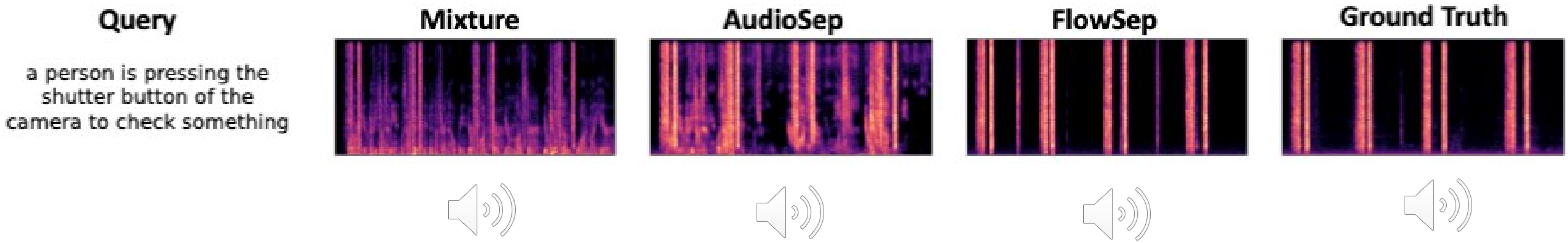
Task 4: FlowSep - Results

- Unlike discriminative network that modify the original audio clips, generated results do not strictly align with the target audio sample in the temporal dimension.
- Hence, traditional objective metrics are not suitable for evaluating generative models based separation methods.
- We apply FAD, CLAPScore and CLAPScoreA from generative tasks to evaluate the performance.

TABLE I
OBJECTIVE EVALUATION ON LASS, WHERE AC, VGG AND ESC ARE SHORT FOR AUDIOCAPS, VGGSOUND AND ESC50 RESPECTIVELY.

Model	FAD ↓				CLAPScore ↑					CLAPScore_A ↑			
	AC	DE-S	VGG	ESC	AC	DE-S	DE-R	VGG	ESC	AC	DE-S	VGG	ESC
Unprocessed	59.8	40.5	42.5	48.1	11.9	23.2	22.7	13.6	19.1	64.9	71.3	66.7	71.3
LASS-Net	5.09	1.83	3.09	3.28	14.4	24.4	25.3	17.4	20.5	70.2	76.6	69.5	79.6
AudioSep	4.38	1.21	2.30	1.93	13.6	26.1	29.7	19.0	21.2	69.6	78.9	72.4	80.5
FlowSep	**2.86**	**0.90**	**2.06**	**1.49**	**21.9**	**26.9**	**31.3**	**19.5**	**22.7**	**81.7**	**80.1**	**73.2**	**80.7**

Task 4: FlowSep - Demo

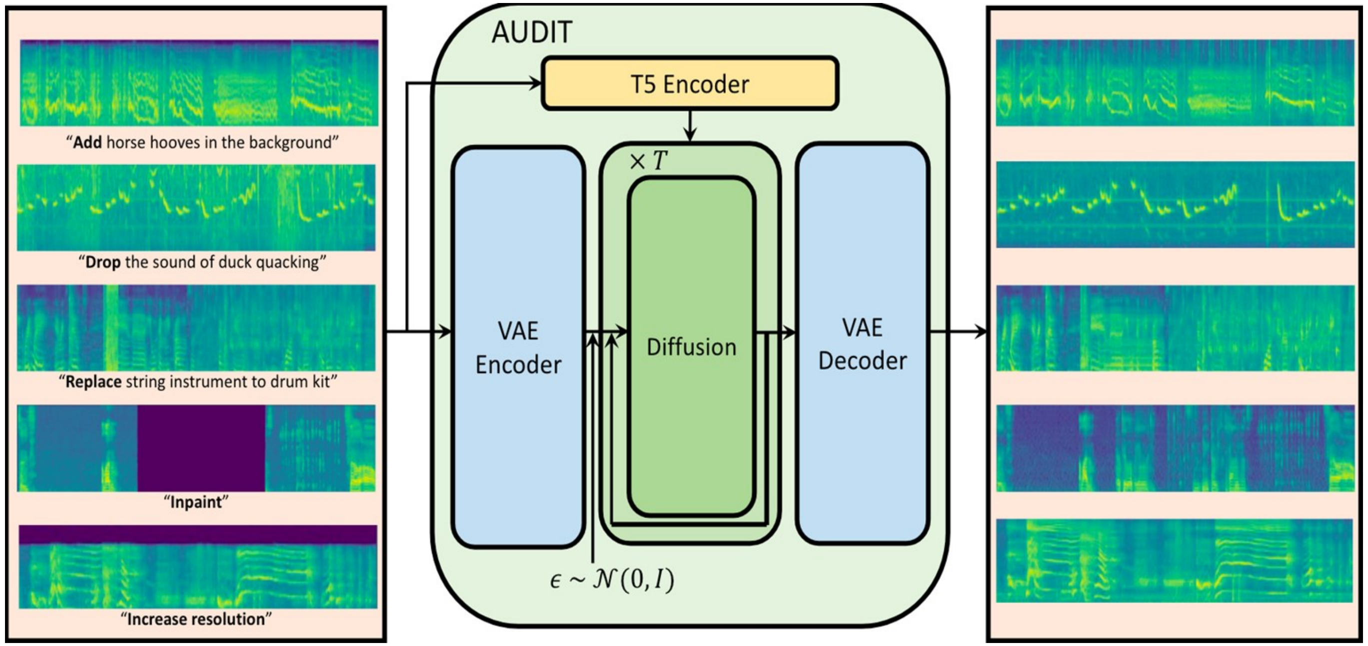


- Baseline models show incomplete separation with noticeable spectral gaps.
- FlowSep demonstrates promising capabilities in such situations.
- More demos please refer to https://audio-agi.github.io/FlowSep_demo/.

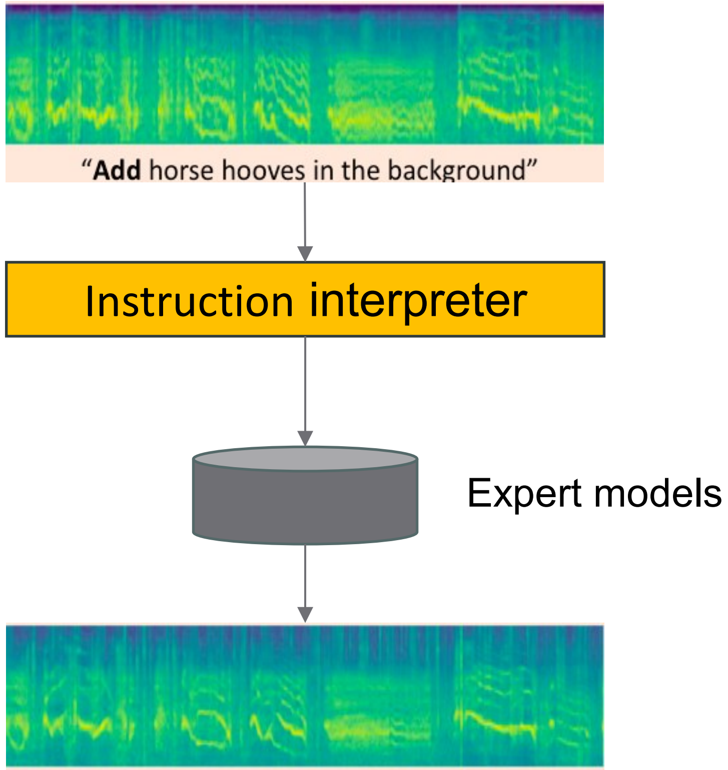
Y. Yuan, X. Liu, H. Liu, M.D. Plumbley, and W. Wang, “FlowSep: Language-Quried Sound Separation with Rectified Flow Matching" in *ICASSP 2025*.

Task 5: LLMs for Controllable Audio Editing

Audio editing is to change the content of audio by following the instruction precisely.
This work introduces an audio agent that understands the user instruction, decomposes the instruction into several tasks, and allocates different tasks to the proper models.

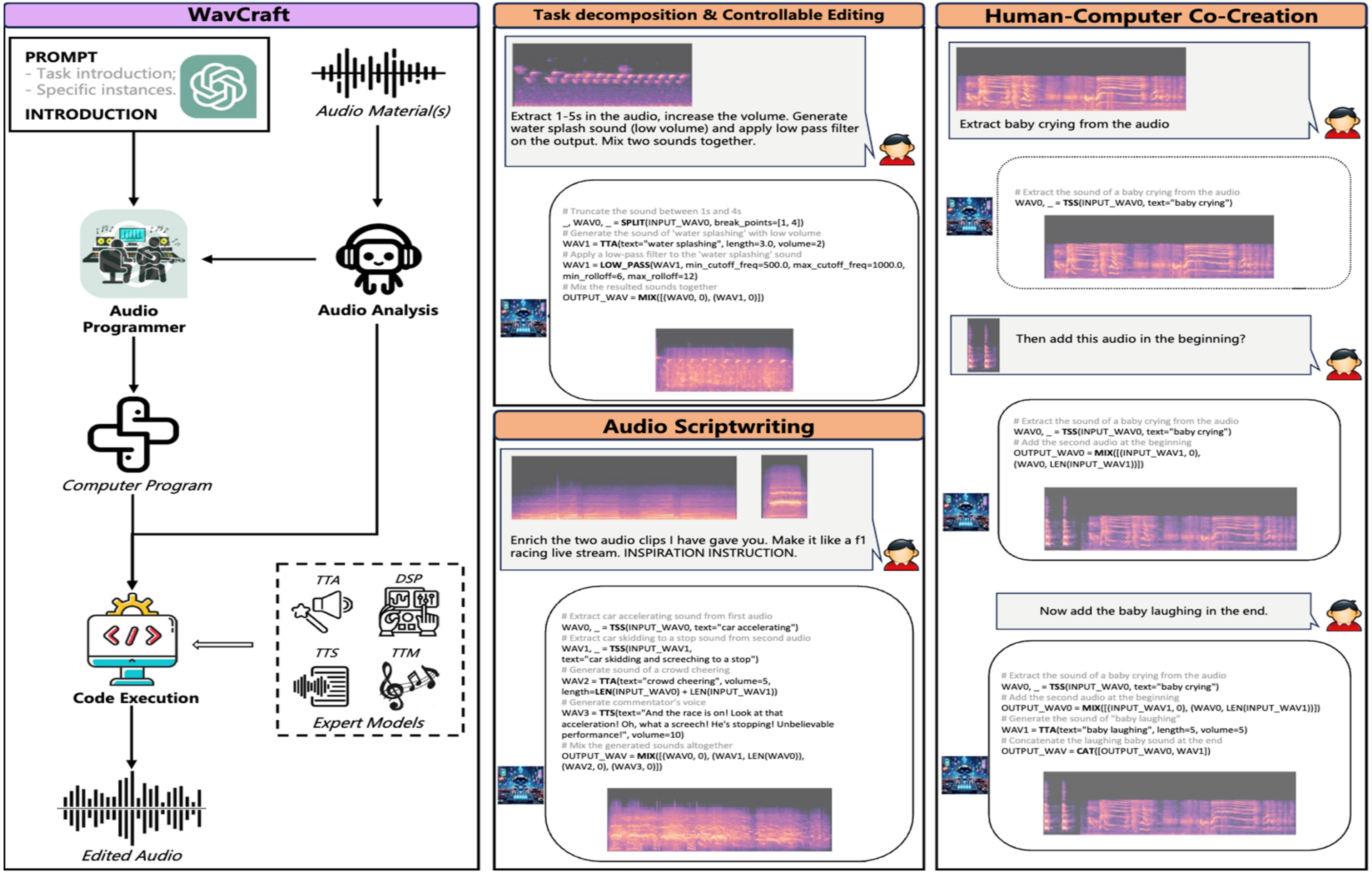


An example of end-to-end audio editing system: AUDIT

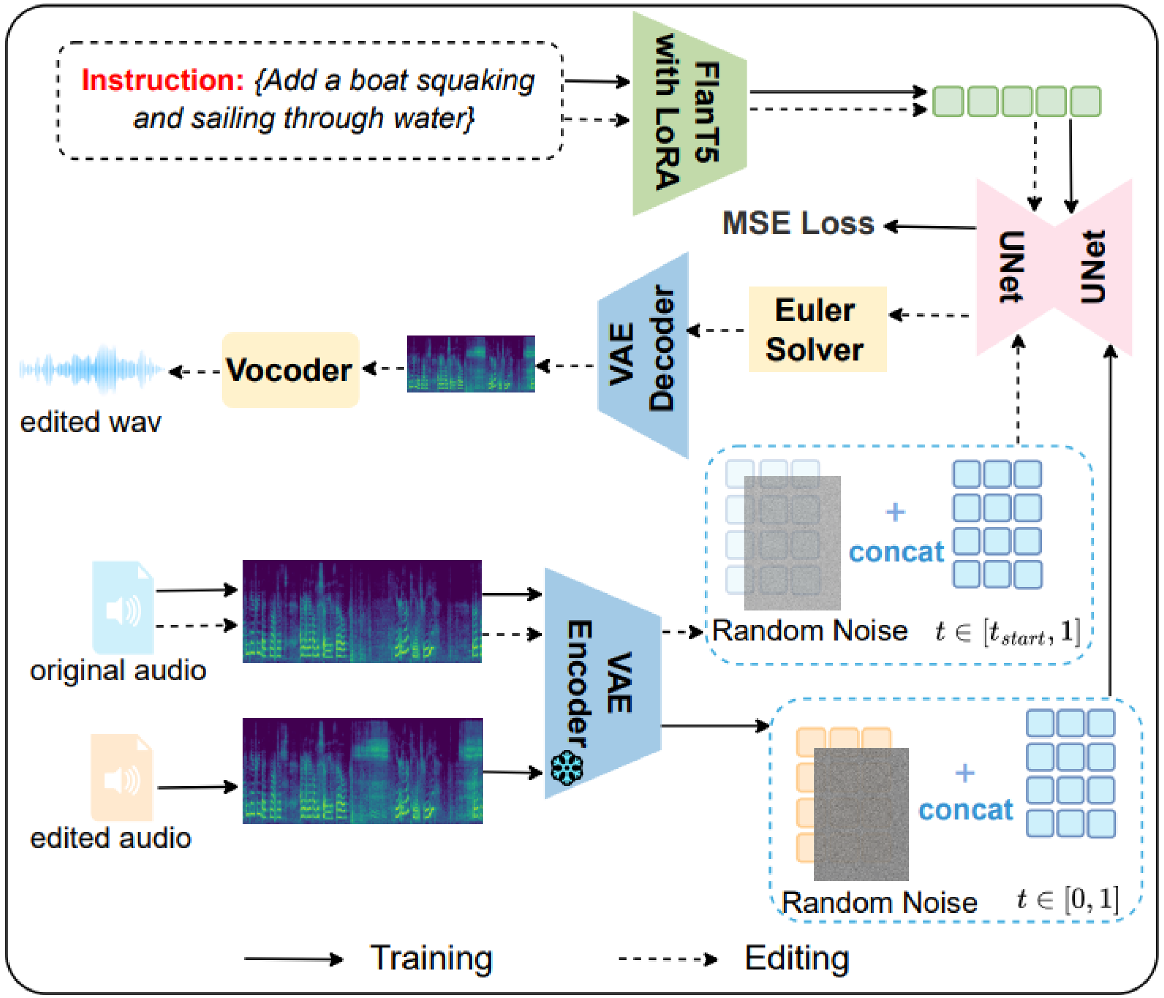


J. Liang, H. Zhang, H. Liu, Y. Cao, Q. Kong, X. Liu, W. Wang, M. Plumbley, and E. Benetos, "WavCraft: Audio Editing and Generation with Large Language Models", in *ICLR 2024 Workshop on Large Language Model (LLM) Agents*, 2024.

WavCraft – Overall Architecture



RFM-EDITING



Demos here:
https://katelin-glt.github.io/RFM-Editing-Demo/

Remove continuous frying noises:

Original:

Edited:

Replace someone suddenly sneezes out loud with several pigeons cooing:

Original:

Edited:

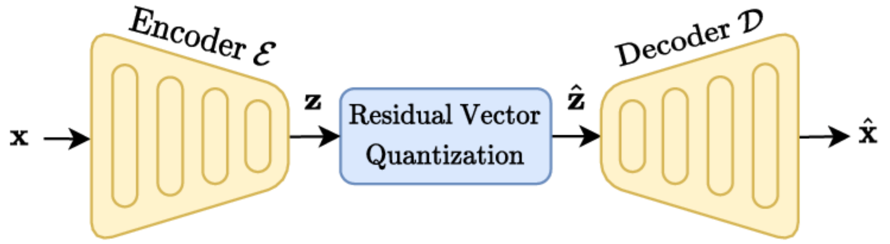
L. Gao, Y. Yuan, Y. Chen, Y. Cheng, Z. Li, J. Wen, S. Zhang, and W. Wang, "RFM-EDITING: Rectified Flow Matching for Text-Guided Audio Editing," in *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing* (ICASSP 2026), Barcelona, Spain, May 4-8, 2026. [PDF]

Task 6: Neural Audio Codec

Audio Codec:

- A device or software that encodes or decodes digital audio data for transmission, storage, or playback.
- **Co**mpressor-**dec**ompressor → "Codec"
- MP3, FLAC, AAC, Vorbis, etc.

Neural Audio Codec:



SoundStream (Zeghidour et al. 2021)

Encodec (Défossez et al. 2021)

Descript (Kumar et al. 2023)

HiFi-Codec (Yang et al. 2023)

SpeechTokenizer (Zhang et al, 2023)

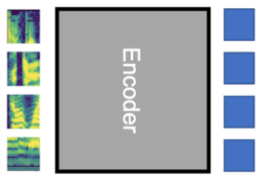
Codec Superb Benchmark (Wu et al. 2024)

- https://github.com/voidful/Codec-SUPERB

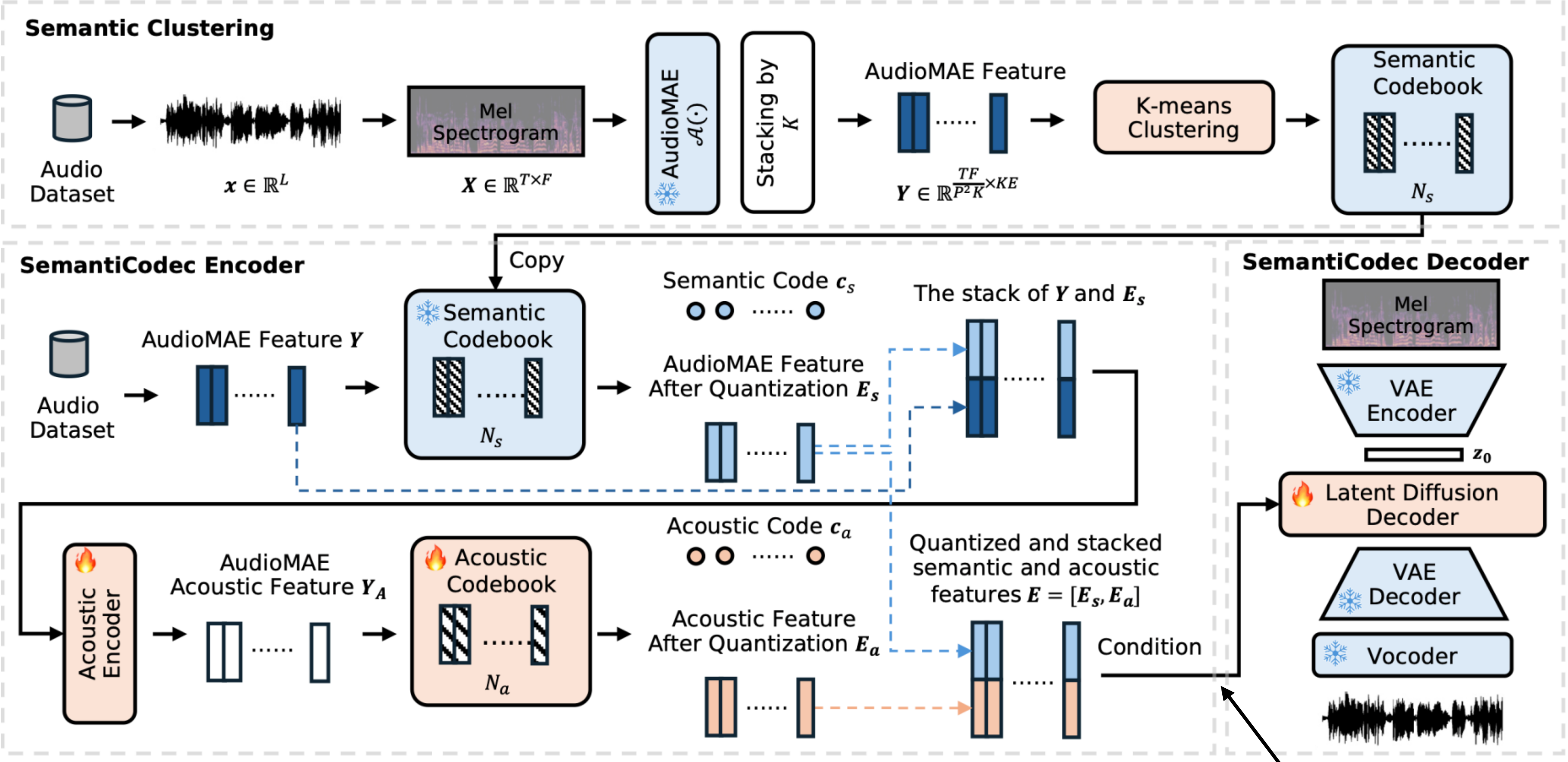
Task 6: **SemantiCodec**

Large scale k-means is challenging
AudioSet + Million Song Dataset + GigaSpeech
https://github.com/haoheliu/kmeans_pytorch

- Ultra-low bit rate (0.31 kbps ~1.40 kbps, token rate 25, 50, or 100 per second) & Strong semantics in the token & Variable vocabulary sizes



AudioMAE Encoder



CrossAtten

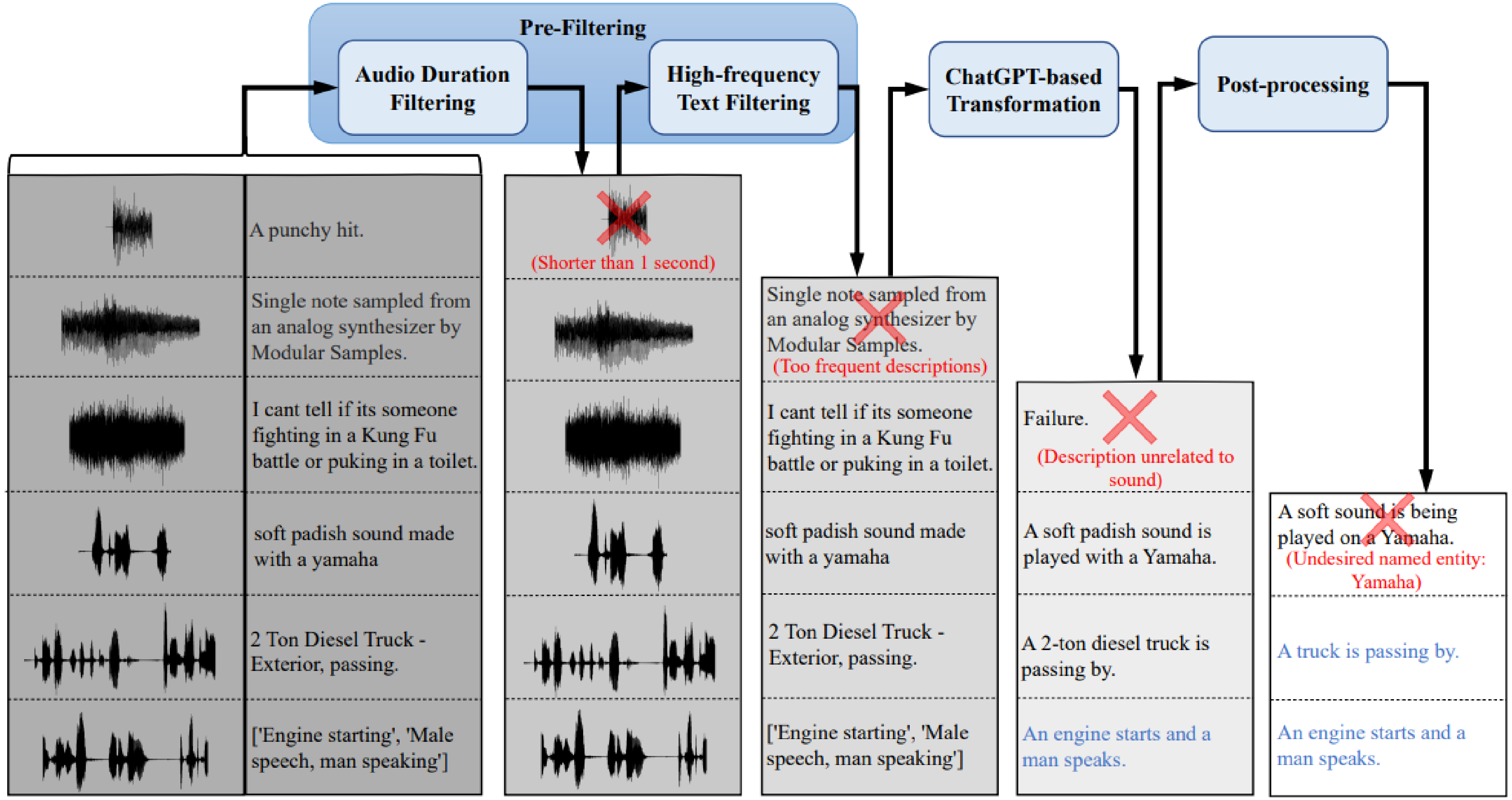
https://haoheliu.github.io/SemantiCodec/

Task 6: SemantiCodec - Demos

	Original	HiFi-Codec (2.0 kbps)	Encodec (1.5 kbps)	DAC (1.41 kbps)	SemantiCodec (1.43 kbps)	DAC (0.47 kbps)	SemantiCodec (0.35 kbps)
Music (MUSDB18)							
General Audio (AudioSet)							
Speech (Libri)							

More sound demos: https://haoheliu.github.io/SemantiCodec/

Dataset: **WavCaps**



X. Mei, C. Meng, H. Liu, Q. Kong, T. Ko, C. Zhao, M. D. Plumbley, Y. Zou, and W. Wang, "WavCaps: A ChatGPT-Assisted Weakly-Labelled Audio Captioning Dataset for Audio-Language Multimodal Research," *IEEE/ACM Transactions on Audio Speech and Language Processing*, vol. 32, pp. 3339--3354, 2024. [PDF] [arXiv] [code] (https://github.com/XinhaoMei/WavCaps)

WavCaps – Statistics

TABLE I
EXAMPLE PROMPTS TO CHATGPT FOR FREESOUND AND AUDIOSET STRONGLY-LABELLED SUBSET. TRANSFORMATION EXAMPLES ARE ARE IGNORED. 'SL' REFERS TO 'STRONGLY-LABELLED'.

Data sources	Prompts
FreeSound BBC Sound Effects SoundBible	I will give you a list of descriptions of sounds. Process each individually. Extract the type of the sound and generate an audio caption describing the sound events. The audio caption should be less than 20 words. Delete the author of the sound. Delete locations, city names, country names. Delete the time. Delete device names. Delete the proper noun modifiers, number modifiers, and unit modifiers. Summarize each output into one sentence. Replace all named entities with their hypernyms. Replace people names with "someone". Do not write introductions or explanations. Only describe the sound events and do not use "heard", "recorded". Start each output sentence with its index. Make sure you are using grammatical subject-verb-object sentences. Output "Failure." if the description is not related to sound.
AudioSet SL	I will give you a number of lists containing sound events occurred sequentially in time. Process each individually. Write an one-sentence audio caption to describe these sounds. Make sure you are using grammatical subject-verb-object sentences. Directly describe the sounds and avoid using the word "heard". The caption should be less than 20 words.

TABLE II
EXAMPLES OF RAW DESCRIPTIONS AND CHATGPT'S OUTPUTS.

Data sources	raw descriptions	ChatGPT's output
FreeSound	This sound is of a book falling down the staircase in the Stanford University library west stacks.	A book is falling down a staircase.
	After 2h and 15min. Excerpt.	Failure.
BBC Sound Effects	Timber & Wood - Rip saw, carpenters' workshop.	Someone is using a rip saw in a carpenter's workshop.
	Motor Car: Ford Ecsort 1300 (Automatic) - Ford Escort 1300, exterior, passing with horn. (1300cc engine, automatic transmission.)	A car is passing with its horn.
SoundBible	Tasmanian Devil growling screaming hissing. Warning sounds from a Tasmanian Devil in Zoo.	An animal is growling, screaming, and hissing.
	Large Tibetan Bells ringing in a temple. Could also use for Monastery or Monks.	Bells are ringing.
AudioSet SL	['Accelerating, revving, vroom', 'Race car, auto racing']	A race car is accelerating and revving.
	['Female speech, woman speaking', 'Whoosh, swoosh, swish']	A woman is speaking while something whooshes.

TABLE IV
COMPARATIVE OVERVIEW OF MAIN AUDIO-LANGUAGE DATASETS BETWEEN OUR PROPOSED WAVCAPS DATASET.

Dataset	Num. audios	Duration (h)	Text source
AudioCaps [38]	52904	144.94	Human
Clotho [43]	5929	37.00	Human
MACS [44]	3537	9.83	Human
WavText5K [50]	4072	23.20	Online raw-data
SoundDescs [8]	32979	1060.4	Online raw-data
LAION-Audio-630K [51]	633526	4325.39	Online raw-data
WavCaps	403050	7567.92	ChatGPT

Sound-VECaps

➢ Challenge

- Existing audio generation models struggle with complex and detailed prompts, leading to potential performance degradation.
- Captions of current audio datasets are too simple to provide detail information.

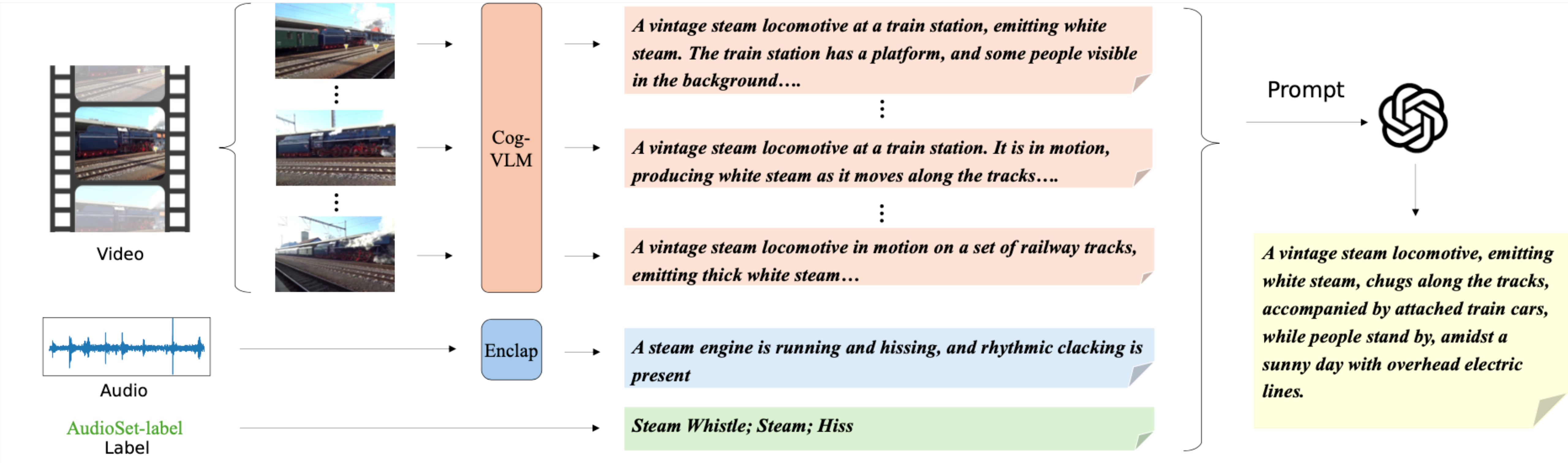
➢ Sound-VECaps

- 1.66M high-quality audio-caption pairs with enriched details including audio event orders, occurred places and environment information.

Dataset	Number	Avg. Len	Loc. Inf	Env. Inf
AudioSet	2.1M	3	Label	Label
Clotho	5K	11	1.2K	0.9K
AudioCaps	46K	9	4K	3K
WavCaps	400K	8	51K	37K
Auto-ACD	1.9M	18	1.23M	69K
Sound-VECaps$_A$	1.66M	31	1.44M	1.36M
Sound-VECaps$_F$	1.66M	40	1.46M	1.38M

The analysis of audio-caption datasets, Loc and Env are the number of captions that include the location and environment information.

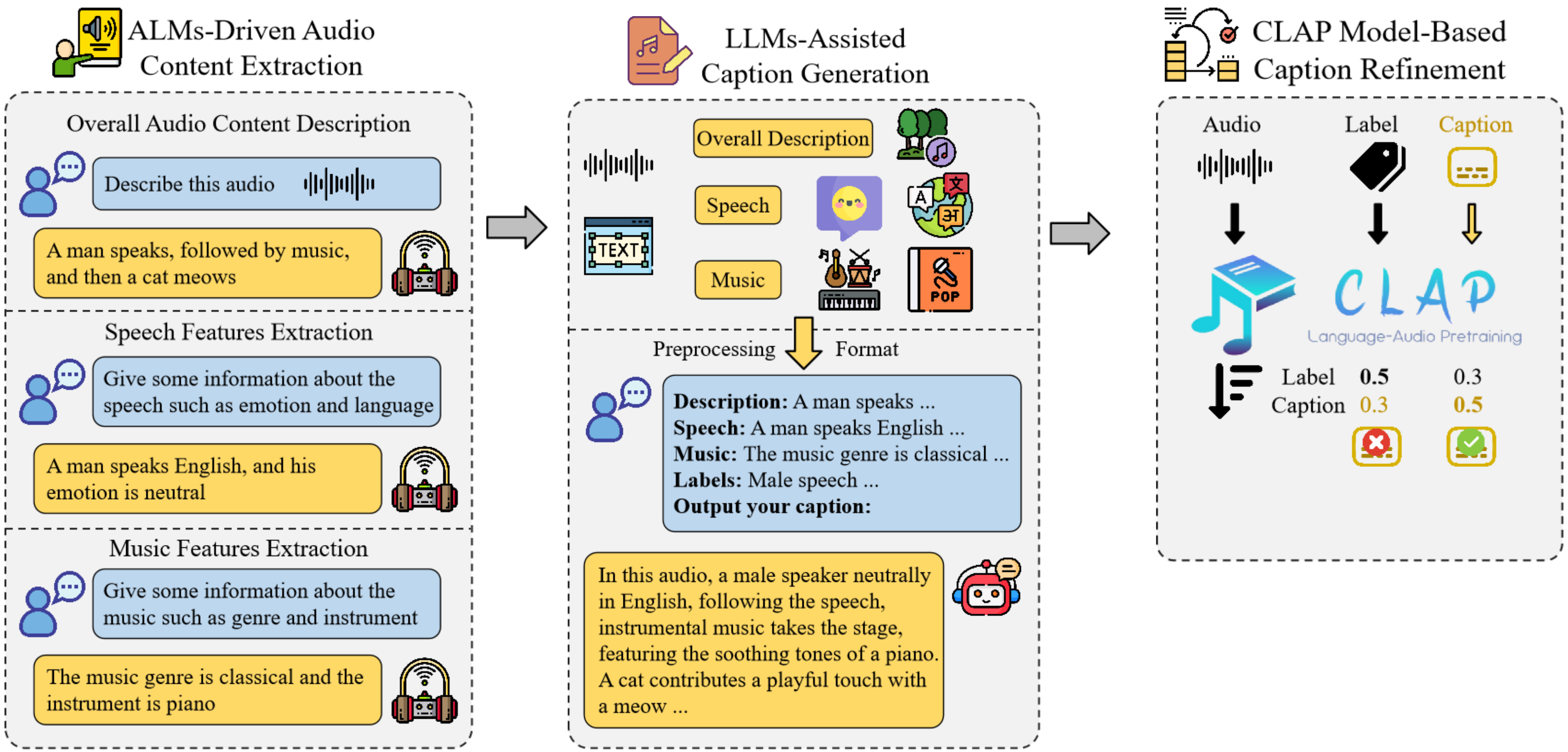
Sound-VECaps – Processing Pipeline



Y. Yuan, D. Jia, X. Zhuang, Y. Chen, Z. Chen, Y. Wang, Y. Wang, X. Liu, X. Kang, M.D. Plumbley, and W. Wang, "Sound-VECaps: Improving Audio Generation With Visual Enhanced Captions," in *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing* (ICASSP 2025), Hyderabad, India, April 6-11, 2025. [PDF]

Paper, data & code: https://yyua8222.github.io/Sound-VECaps-demo

Dataset: **AudioSetCaps**



J. Bai, H. Liu, M. Wang, D. Shi, **W. Wang**, M. D. Plumbley, W.-S. Gan, and J. Chen, "AudioSetCaps: An Enriched Audio-Caption Dataset using Automated Generation Pipeline with Large Audio and Language Models," *IEEE Transactions on Audio Speech and Language Processing*, vol. 33, pp. 2817 - 2829, June 2025. [arXiv][code]

AudioSetCaps – Statistics

Table 1: The statistics comparison with popular audio-language datasets. Caption source: H (human), A (audio models), V (visual models), L (language models).

Dataset	Quantity	Ave-Length	Vocabulary	Caption Source
Clotho	30K	11	4K	H
AutoCaps	57K	9	5K	H
LAION-Audio-630K	630K	7	311K	L
WavCaps	400K	8	24K	L
Auto-ACD	1.5M	18	20K	L+A+V
Sound-VECaps	1.6M	40	50K	L+A+V
AudioSetCaps	1.9M	28	21K	L+A

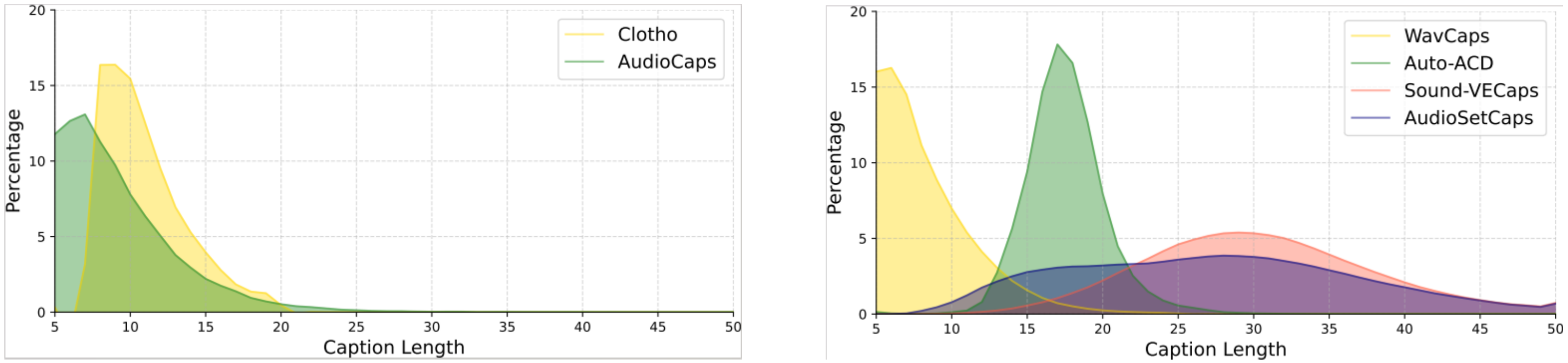


Figure 2: Distribution of caption lengths across several popular audio caption datasets. (Left) Caption length distributions of human-labeled datasets. (Right) Caption length distributions of LLMs-assisted datasets.

AudioSetCaps – An Example

ID: Y0qH8FmqGI2U

Dataset-Caption	Mean Subjective Score
Label: Female speech, Woman speaking, Background noise, Generic impact sounds, Surface contact, Babbling, Tick, Human voice, Breathing, Baby laughter	4
AudioCaps: A human baby laughs and gurgles as a female sings gently	4
WavCaps: People are talking and babbling with a baby laughing and surface contact.	4.2
Auto-ACD: The sound of a laughing baby and women chatting and giggling can be heard at a busy spa.	4
AudioSetCaps: A joyful interaction between a woman and a baby, as the infant giggles and the woman responds with a happy and upbeat tone.	**4.4**

Conclusion & Future Works

- **Summary**
  - Large language-audio models are promising - offering new opportunities to solve problems in conventional audio tasks and newly emerging audio tasks
  - These models often provide SOTA performance in many downstream tasks and may offer new capabilities that were not available in previous audio models.
- **Future Works**
  - Developing unified models for multi-tasks (e.g. understanding and generation) and multi-modal data (audio, visual, language)
  - Improving controllability/personalization/customisation of LALMs in various downstream tasks (e.g. generation and captioning)
  - Developing LALMs for long form audio activity understanding, reasoning
  - Developing LALMs for spatial audio generation and reasoning
  - Leveraging physics-based model + data driven models

Paper, Codes, Demos, and More, …

AudioLDM:
Paper: https://arxiv.org/abs/2301.12503
Project Page: https://audioldm.github.io/
Github:
- Pretrained model: https://github.com/haoheliu/AudioLDM
- Evaluation tools: https://github.com/haoheliu/audioldm_eval

YouTube: https://www.youtube.com/watch?v=_0VTltNYhao

SemantiCodec:
Paper/code/demos at project page:
https://haoheliu.github.io/SemantiCodec/

AudioSep:
Code: https://github.com/Audio-AGI/AudioSep

RFM-EDITING:
https://katelin-glt.github.io/RFM-Editing-Demo/

WavCaps:
Paper: https://arxiv.org/abs/2303.17395
Code: https://github.com/xinhaomei/wavcaps

More code about other works avaliable at:
https://github.com/XinhaoMei/DCASE2021_task6_v2
https://github.com/XinhaoMei/ACT
https://github.com/liuxubo717/cl4ac

AudioLDM2:
Project Page: https://audioldm.github.io/audioldm2/

APT:
Code: https://github.com/JinhuaLiang/APT

WavCraft:
Code: https://github.com/JinhuaLiang/WavCraft

WavJourney:
Paper: https://arxiv.org/abs/2307.14335
Code: https://github.com/Audio-AGI/WavJourney
Demo: https://huggingface.co/spaces/Audio-AGI/WavJourney

AudioSetCaps:
Data and code: https://github.com/JishengBai/AudioSetCaps
https://huggingface.co/datasets/baijs/AudioSetCaps

Sound-VECaps: paper, data & code:
https://yyua8222.github.io/Sound-VECaps-demo

GCDance: paper, data & code:
https://xinranliu7715.github.io/gcdance/

Thank you for listening!

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