

General Audio Processing

Perception, Understanding, and Generation

Yuan Gong / MIT 6.8620/HST.728 / Spring 2024

Outline

Part 1

Listen

General audio events
recognition

Part 2

Understand

Audio large language model

Part 3

Generation

Music
General Audio



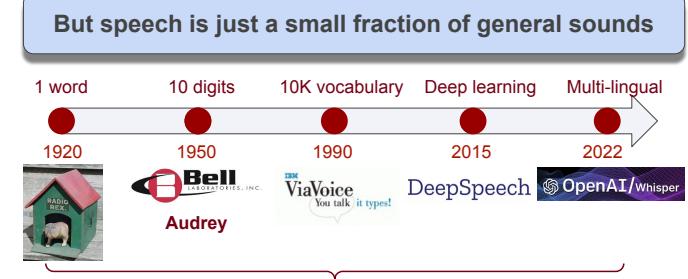
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History of machine listening



3

History of machine listening



4

Sample



What did you hear?

You **hear** the sound of an emergency vehicle before seeing it

**Crucial Information but
not in speech**

Applications of general sound recognition

Further Boost Accessibility



Embodied AI with Audio Capability



Music Recognition



Sound-Based Surveillance



Smart Alerts - Glass break sounds

History of machine listening

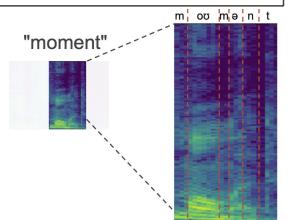


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Speech is composed of a finite number of elementary units

- Speech**
- composed of elementary units: phonemes
 - ~40 phonemes for English

- Vowels:** [i], [ə], [u]
- Consonants:**
 - Plosives:** [p], [t], [k]
 - Fricatives:** [f], [s], [ʃ]
 - Nasals:** [m], [n], [ŋ]
- Semivowels:** [j], [w]



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There are unlimited number of general sounds

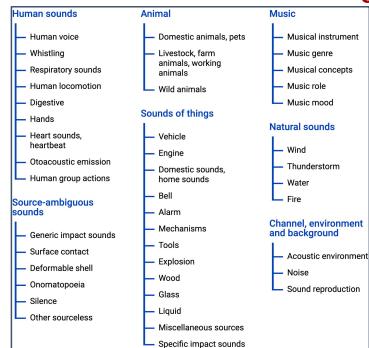
Speech

- composed of elementary units: phonemes
 - ~40 phonemes for English

General audio

- no** elementary units
- unlimited number** of sound classes
 - 527 classes in AudioSet

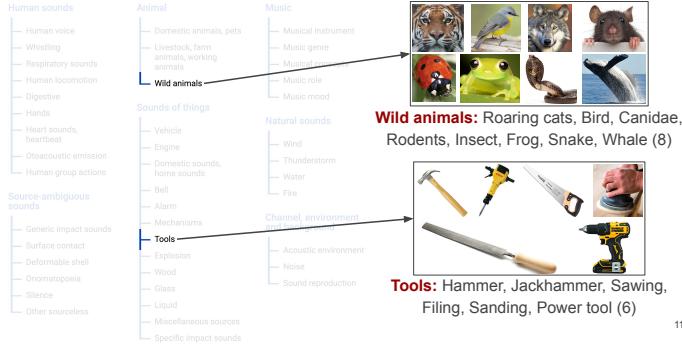
There are unlimited number of general sounds



AudioSet ontology (top-level)
527 classes in total

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There are unlimited number of general sounds



AudioSet is already the largest dataset

Dataset	# Recordings	Avg Duration	Total Duration	# Sound Events	Label	Annotation
ESC-50	2,000	5s	2.8h	50	Single	Manual
UrbanSound	1,302	75s	27.0h	10	Single	Manual
DCASE 2017	52,762	10s	146.6h	17	Single	Manual
AudioSet (Strong Label)	120K	10s	~330h	456	Multiple	Automatic Suggestion and Manual Verification
AudioSet (Weak Label)	2.1 M	10s	5,800h ~ 8 months	527	Multiple	

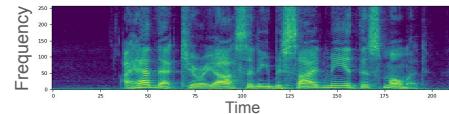
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	Speech	General Audio
Elementary units	Phonemes	N/A
# Classes	~40 for English	Unlimited 527 for AudioSet

General audio classification has a larger search space

Speech has structured spectrogram patterns

Transcript: I had that curiosity beside me at this moment



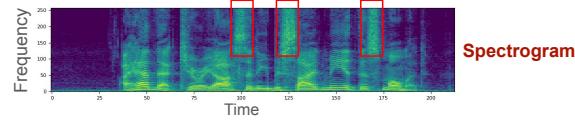
Spectrogram

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Speech has structured spectrogram patterns

Transcript: I had that curios**i**ty besi**d**e me at thi**s** moment



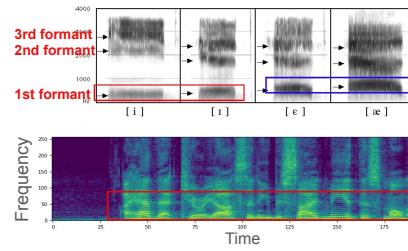
Spectrogram

Fricatives exhibit high-frequency turbulence

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Speech has structured spectrogram patterns

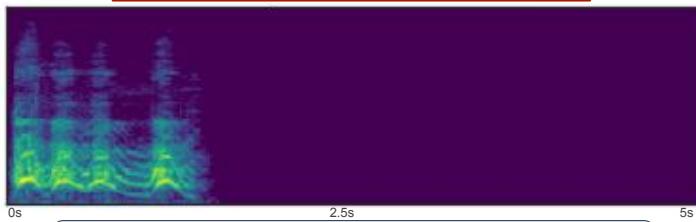


Spectrogram

- Each vowel has relatively fixed formant patterns
- The duration of each phone is typically < 300ms

General audios have more diverse patterns

Class name: dog - 5-231762-A-0.wav



- No elementary units (e.g., phonemes)
- Can be transient-, harmonic-, and noise-like
- Duration can be up to a few seconds

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Differences between speech and general audio recognition

	Speech	General Audio
Elementary units	Phonemes	N/A
# Classes	~40 for English	Unlimited 527 for AudioSet
Duration	Typically < 300ms	Up to a few seconds
Pattern	Structured	Diverse & Complex
Task	Single-label Classification	Multi-label Classification

Data-driven method

Differences between speech and general audio recognition

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Capture long-range context

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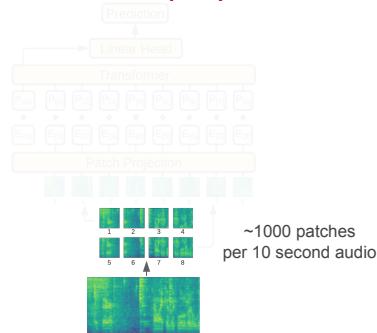
Differences between speech and general audio recognition

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Attend to multiple sounds

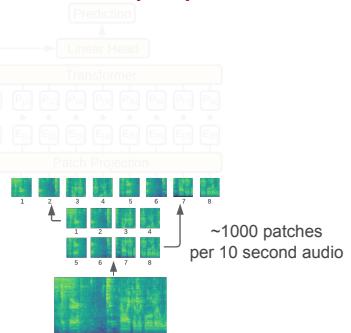
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Audio spectrogram transformer (AST)



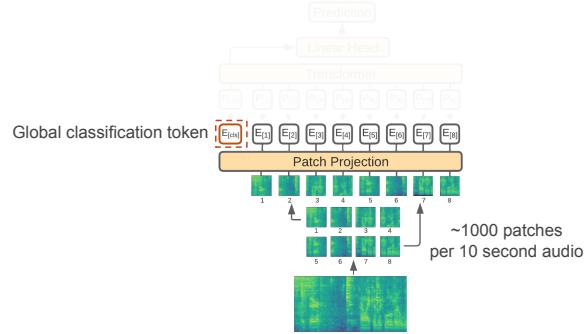
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Audio spectrogram transformer (AST)



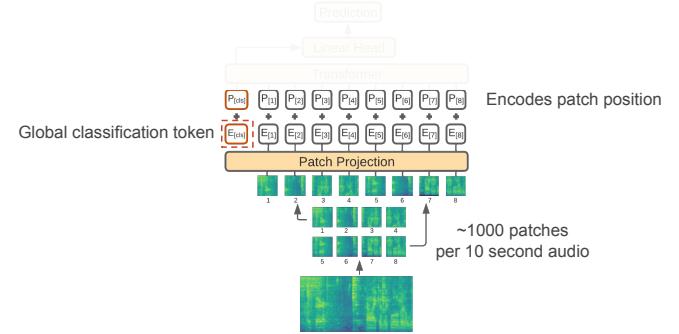
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Audio spectrogram transformer (AST)



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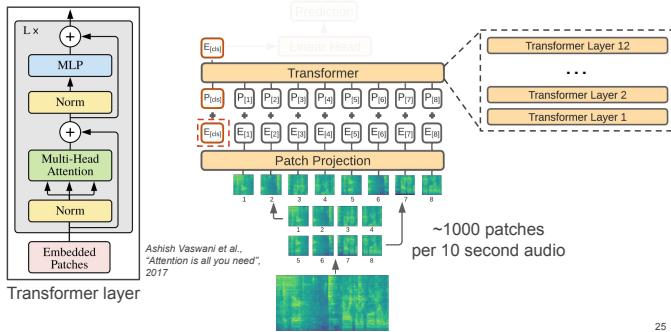
Audio spectrogram transformer (AST)



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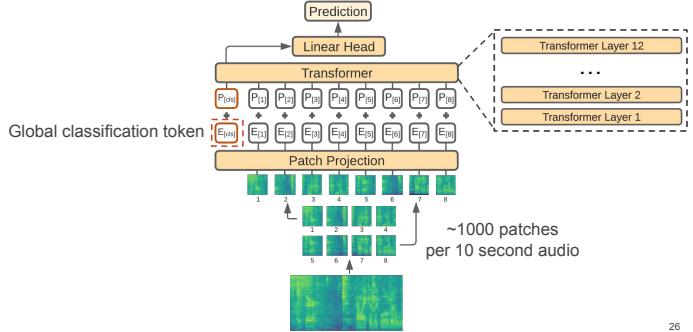
Yuan Gong et al., Audio Spectrogram Transformers, 2021

Audio spectrogram transformer (AST)



Yuan Gong et al., Audio Spectrogram Transformers, 2021

Audio spectrogram transformer (AST)



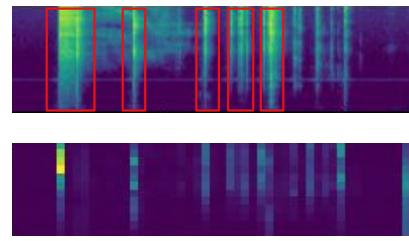
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Advantage of AST: long-range dependencies

	Speech	General Audio
Elementary units	Phonemes	N/A
# Classes	~40 for English	Unlimited 527 for AudioSet
Duration	Typically < 300ms	Up to a few seconds
Pattern	Structured	Diverse & Complex
Task	Single-label Classification	Multi-label Classification

Capture long-range context

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Advantage of AST: dynamic attention

	Speech	General Audio
Elementary units	Phonemes	N/A
# Classes	~40 for English	Unlimited 527 for AudioSet
Duration	Typically < 300ms	Up to a few seconds
Pattern	Structured	Diverse & Complex
Task	Single-label Classification	Multi-label Classification

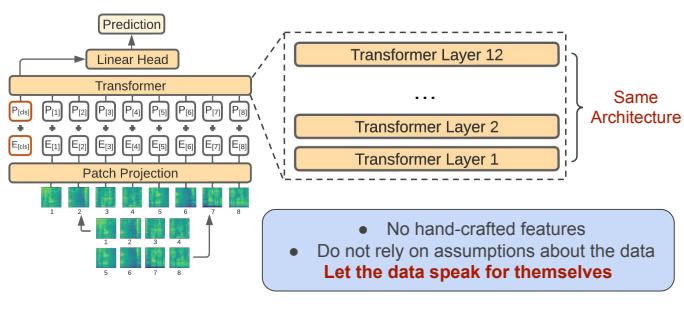
Attend to multiple sounds

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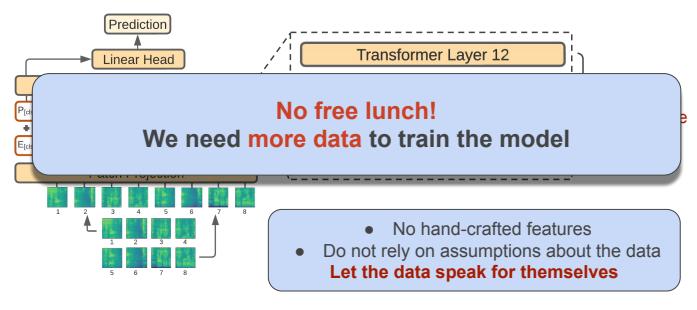


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AST is a data-driven model

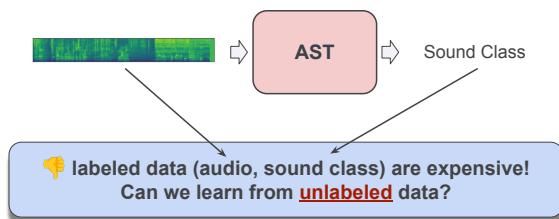


AST is a data-driven model



The data issue

Conventional supervised learning



Audio self-supervised learning

Stage 1: Self-supervised pretraining

Large-scale unlabeled data



Random masking, no human annotation required

Audio self-supervised learning

Start

Why this work?

If the model can perfectly complete this task, what does it mean?



Self-supervised learning task (proxy task):
Predict the original spectrogram from the masked spectrogram

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Audio self-supervised learning



This sound features rise and fall in pitch

The model learns the **spectrogram pattern**
The model does not associate the pattern with sound class

This sound features repetitive, high-frequency tones



This sound features wide-band noise

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Audio self-supervised learning

Stage 1: Self-supervised pretraining



At this point, the model cannot do classification

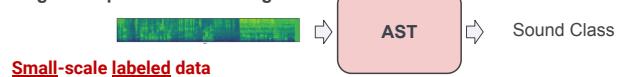
Audio self-supervised learning

Stage 1: Self-supervised pretraining



Weight Inheritance

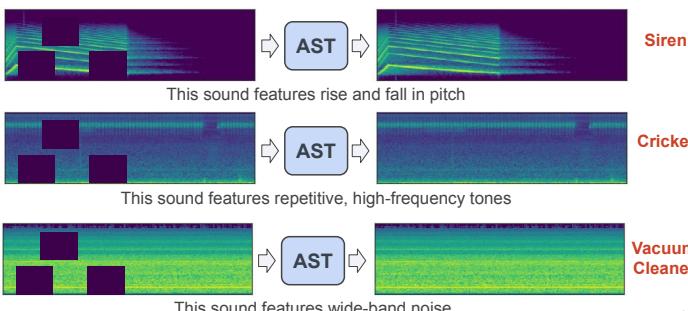
Stage 2: Supervised finetuning



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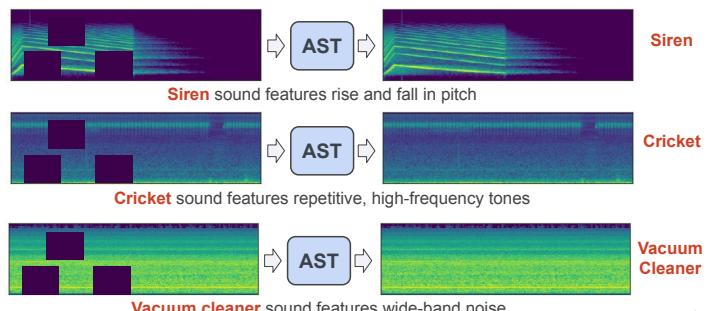
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Audio self-supervised learning



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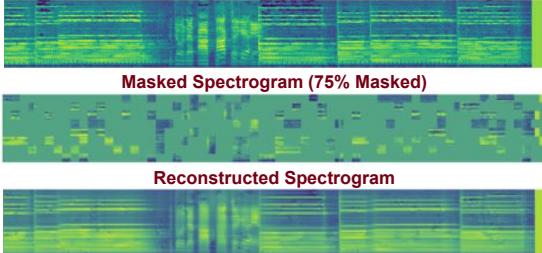
Audio self-supervised learning



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Surprisingly strong reconstruction ability

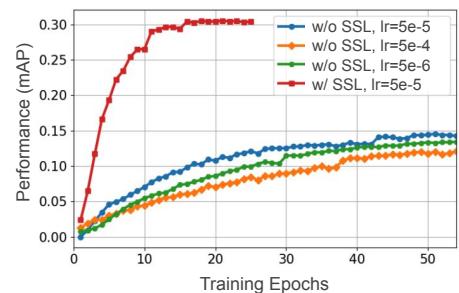
Original Spectrogram



Reconstruction ability serves merely as a sanity check
Ultimately, we care about the performance in sound classification

Improvement led by self-supervised learning (SSL)

SSL pretrain data:
2M unlabeled audios
Fine-tuning data:
20K (1%) labeled audios



Yuan Gong et al., Self-supervised Audio Spectrogram Transformers, 2022

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Unified speech and non-speech recognition



Yuan Gong et al., Whisper-AT: Noise-Robust Automatic Speech Recognizers are Also Strong Audio Event Taggers, 2023.

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Impact of AST

Task	Dataset	Model	Metric Name	Metric Value	Global Rank	Uses Extra Training Data	Result	Benchmark
Audio Tagging	AudioSet	Audio Spectrogram Transformer	mean average precision	0.485	# 1	✓	Compare	
Audio Classification	AudioSet	Audio Spectrogram Transformer	Test mAP	0.485	# 1	✓	Compare	
Audio Classification	ESC-50	Audio Spectrogram Transformer	Top-1 Accuracy	95.7	# 1	✓	Compare	
			PRE-TRAINING DATASET	AudioSet, ImageNet	# 1	✓	Compare	
			Accuracy (5-fold)	95.7	# 1	✓	Compare	
Keyword Spotting	Google Speech Commands	Audio Spectrogram Transformer	Google Speech Commands V2 35	98.11	# 1	✓	Compare	

<https://paperswithcode.com/paper/ast-audio-spectrogram-transformer>, as of 7/14/2021

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MIT / [ast-finetuned-audioset-10-10-0.4593](#) like

Audio Classification Transformers PyTorch Safetensors

audio-spectrogram-transformer Inference Endpoints arxiv:2104.01778 Li

Train Deploy Use in Transformers

Model card Files Community 10

Edit model card

Downloads last month 2,226,298

>2 million model downloads per month when AST is 3 years old

<https://huggingface.co/MIT/ast-finetuned-audioset-10-10-0.4593>, as of 3/31/2024

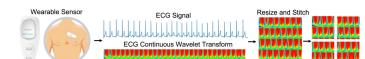
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Impact of AST

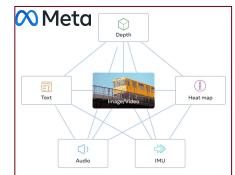
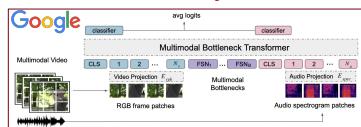
Wildlife Conservation



Bioelectrical Signal Classification



Multi-modal Systems



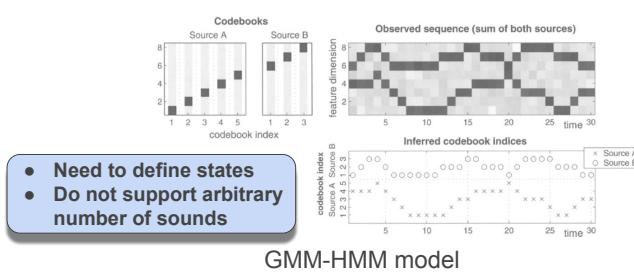
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Limitations of AST

- Cannot predict onset and offset timestamps
- Not "true" self-supervised learning
 - Data is the unlabeled version of labeled data
- Computationally expensive
 - $O(n^2)$ w.r.t the audio length

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Old methods for general audio recognition



Daniel Ellis, Model-based scene analysis, 2006

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Old methods for general audio recognition

VGGish [1]	CNN6	CNN10	CNN14
Log-mel spectrogram 96 frames × 64 mel bins		Log-mel spectrogram 1000 frames × 64 mel bins	
$3 \times 3 @ 64$	$5 \times 5 @ 64$	$(3 \times 3 @ 64) \times 2$	$(3 \times 3 @ 64) \times 2$
BN, ReLU	BN, ReLU	(BN, ReLU) × 2	(BN, ReLU) × 2
MP 2 × 2		Pooling 2 × 2	
$3 \times 3 @ 128$	$5 \times 5 @ 128$	$(3 \times 3 @ 128) \times 2$	$(3 \times 3 @ 128) \times 2$
ReLU	BN, ReLU	(BN, ReLU) × 2	(BN, ReLU) × 2
MP 2 × 2		Pooling 2 × 2	
$(3 \times 3 @ 256) \times 2$	$5 \times 5 @ 256$	$(3 \times 3 @ 256) \times 2$	$(3 \times 3 @ 256) \times 2$
ReLU	BN, ReLU	(BN, ReLU) × 2	(BN, ReLU) × 2
MP 2 × 2		Pooling 2 × 2	
$(3 \times 3 @ 512) \times 2$	$5 \times 5 @ 512$	$(3 \times 3 @ 512) \times 2$	$(3 \times 3 @ 512) \times 2$
ReLU	BN, ReLU	(BN, ReLU) × 2	(BN, ReLU) × 2
MP 2 × 2		Global pooling	
Flatten		Pooling 2 × 2	
FC 4096 × 2	FC 512, ReLU	$(3 \times 3 @ 1024) \times 2$	
ReLU		(BN, ReLU) × 2	
FC 527, Sigmoid	FC 527, Sigmoid	Global pooling	
		FC 2048, ReLU	
		FC 527, Sigmoid	

- More complex design

Convolutional neural networks

Guoliang Kong et al., PANNs: Large-Scale Pretrained Audio Neural Networks for Audio Pattern Recognition, 2020

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Outline

Part 1

Listen

Part 2

Understand

Part 3

Generation

General audio events
recognition

Audio large language model

Music
General Audio



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There is one thing missing...



No **thinking** and **understanding** ability!

We only modeled **listening** ability

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Human cognitive ability

[Listen] High-frequency crackling noises, intermittent low-frequency pops.



perceive

understand

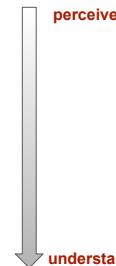
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Human cognitive ability

[Listen] High-frequency crackling noises, intermittent low-frequency pops.



[Think] Could be some burning or frying or arcing sound.



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Human cognitive ability

[Listen] High-frequency crackling noises, intermittent low-frequency pops.



perceive

[Think] Could be some burning or frying or arcing sound.

[Think] Combined with the speech, it is a cooking sizzling sound.

understand

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Human cognitive ability



[Listen] High-frequency crackling noises, intermittent low-frequency pops. perceive

[Think] Could be some burning or frying or arcing sound.

[Think] Combined with the speech, it is a cooking sizzling sound.

[Understand] A hands-on cooking class. understand

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Human cognitive ability



[Listen] High-frequency crackling noises, intermittent low-frequency pops. perceive

[Think] Could be some burning or frying or arcing sound.

[Think] Combined with the speech, it is a cooking sizzling sound.

[Understand] A hands-on cooking class.

[Emotion, Action] Hungry, what should I eat for lunch? understand

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Human cognitive ability

[Listen] High-frequency crackling noises, intermittent perceive

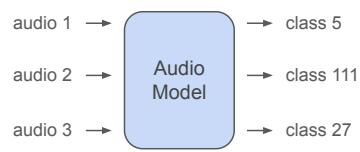
- We do more than just listen; we also comprehend sounds.
- Our comprehension integrates speech and non-speech sounds.

Can we make AI having a similar understanding ability?

[Emotion, Action] Hungry, what should I eat for lunch? understand

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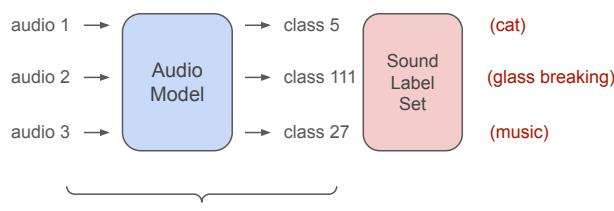
Conventional training won't work



"Listening" model only knows class indices, not sounds

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Conventional training won't work



"Listening" model only knows class indices, not sounds

Conventional training won't work

"cat's meow is soft" knowledge about sound



"Listening" model only knows class indices, not sounds

what we need to model additionally

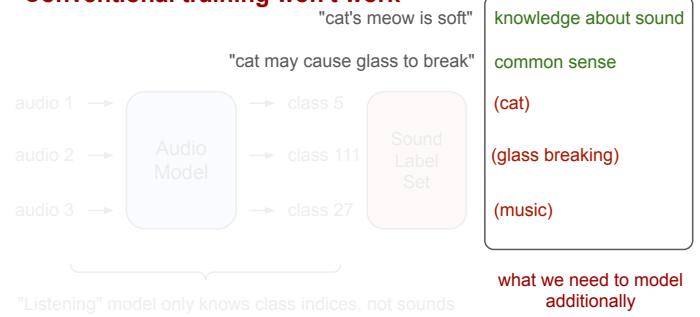
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Conventional training won't work

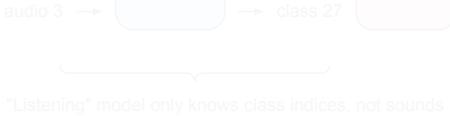


Conventional training won't work



Conventional training won't work

Text-based large language models can model these



Pure language LLMs already have knowledge about sounds

YU What is the acoustic feature of dog barking?

The acoustic features of dog barking vary by breed, individual dog, context, and emotion conveyed. However, several common acoustic features can be identified in dog barks:

- Frequency:** Dog barks can range widely in frequency. Small breeds tend to have higher-pitched barks, while larger breeds generally produce lower-pitched barks. The fundamental frequency (or pitch) of a dog's bark can range from as low as 160 Hz for large dogs to as high as 2362 Hz for small dogs.
- Duration:** The duration of individual barks can vary, but a typical single bark lasts between 0.1 to 1 second.
- Harmonic Structure:** Like human voices, dog barks contain harmonics or overtones. The relationship and amplitude of these harmonics compared to the fundamental frequency can contribute to the unique sound of each bark.

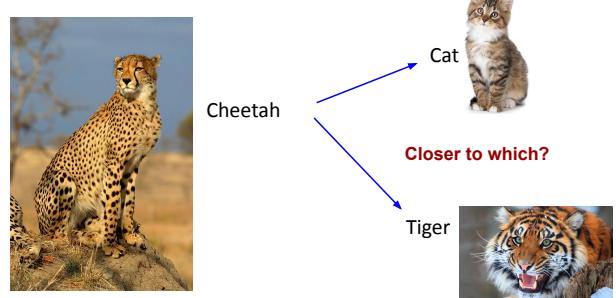
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Pure language LLMs already have knowledge about sounds

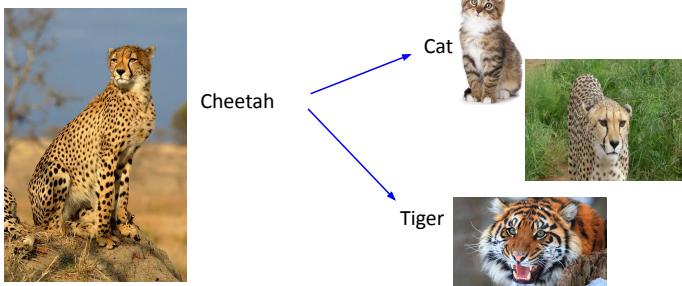
- Temporal Pattern:** Dogs can vary the rate and pattern of their barks. Rapid barking might indicate alarm or urgency, while sporadic barking might be more investigatory or attention-seeking.
- Amplitude (Loudness):** The loudness of a bark can convey different emotions or intents. A loud bark might be used for warnings or threats, while softer barks might be more inquisitive or playful.
- Tonal Quality:** Some barks are more tonal (having a clear pitch), while others might be more noisy or harsh. This can also contribute to the emotional content of the bark.
- Modulation:** Barks can have variations in pitch and volume. A bark that rises in pitch might convey a question or be more attention-seeking, while one that falls might be more commanding or assertive.
- Context-specific Characteristics:** Dogs can produce different barks in different contexts. For instance, a bark at a stranger might be different in quality and pattern from a bark when the dog is left alone or hears a peculiar noise.

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Pure language LLMs already have knowledge about sounds

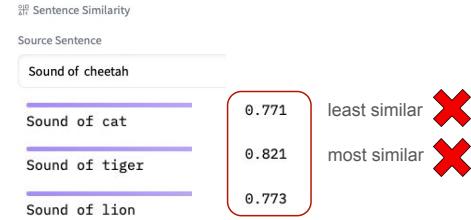


Pure language LLMs already have knowledge about sounds



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"Small" language model (LaBSE) gives wrong answer



Understandable, this needs complex reasoning:

"Roaring cats (lions, tigers, jaguars, and leopards) have an incompletely ossified hyoid, which in theory allows them to roar but not to purr. Cheetahs belong to the purring cats subfamily and as such do not roar."

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Pure language LLMs already have knowledge about sounds

YU Is Cheetah sound more closer to cat sound or tiger sound? Why?

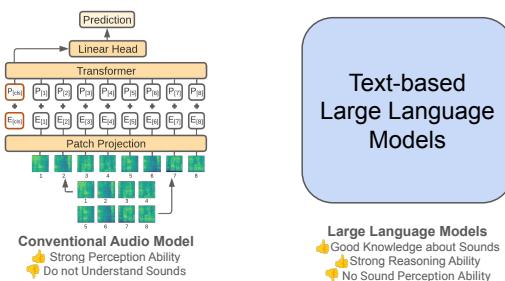
When comparing the sounds of cheetahs to those of domestic cats and tigers, the vocalizations of cheetahs are more akin to domestic cats. Here's a breakdown:

1. Purring:

- **Cheetah:** Cheetahs are one of the few big cats that purr in a manner similar to domestic cats. Their purring is continuous, occurring during both inhalation and exhalation.
- **Domestic Cat:** Domestic cats purr in much the same way, during both inhalation and exhalation.
- **Tiger:** While tigers can produce a purring sound, it's different from the continuous purr of cheetahs and domestic cats. It's generally not as sustained and tends to occur mainly during the exhalation.

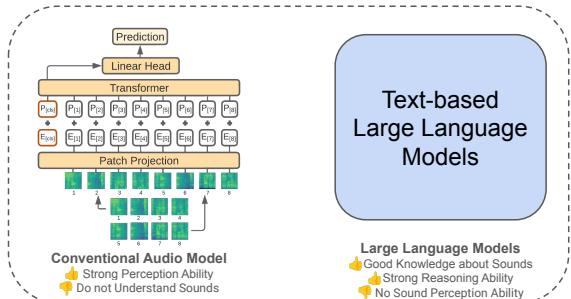
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Bridging sound perception and understanding



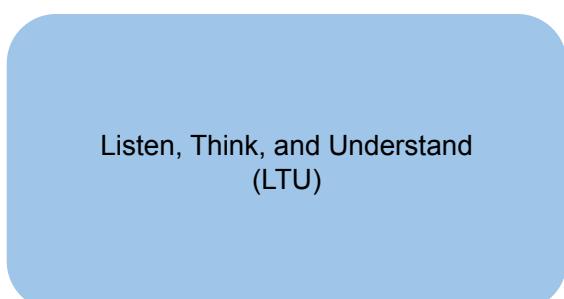
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Bridging sound perception and understanding



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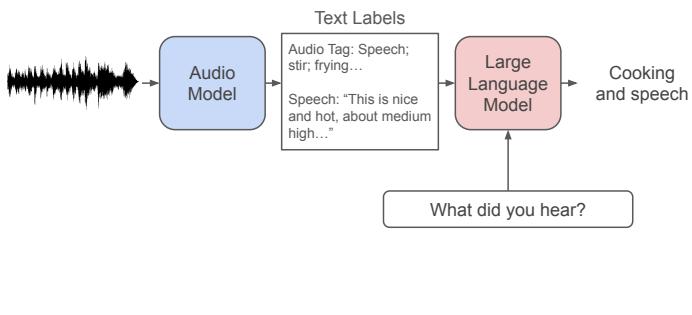
Bridging sound perception and understanding



Yuan Gong et al., Listen, Think, and Understand, 2024
Yuan Gong et al., Joint Audio and Speech Understanding, 2023

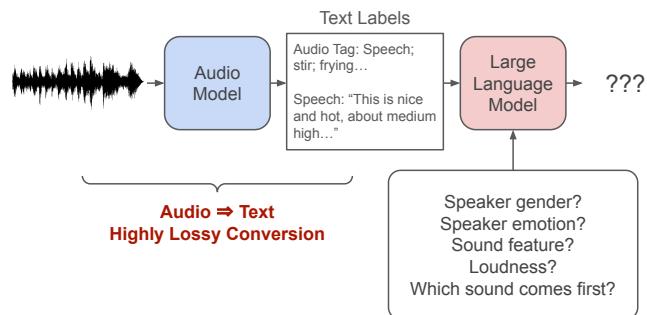
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Can we just concatenate an audio model and an LLM?



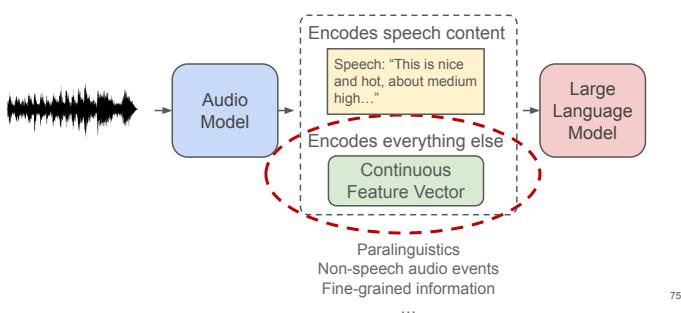
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Can we just concatenate an audio model and an LLM?



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Continuous acoustic features are needed



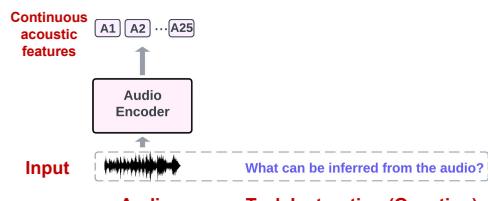
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LTU model architecture



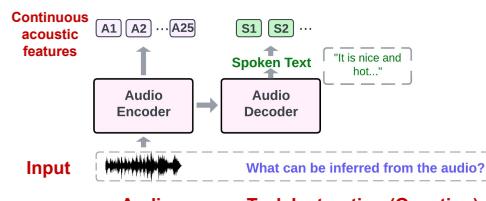
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LTU model architecture



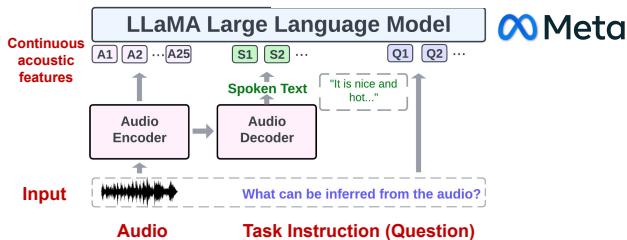
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LTU model architecture



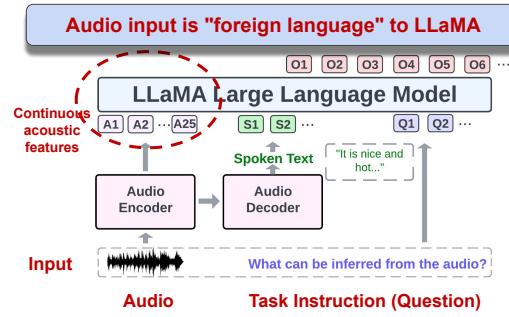
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LTU model architecture



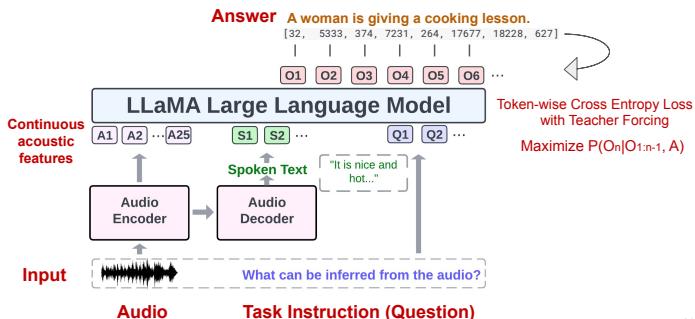
79

LTU model architecture



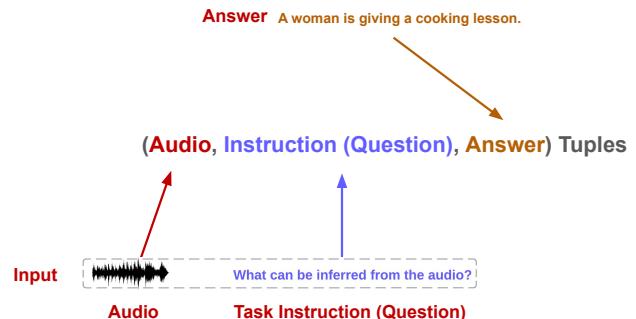
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LTU training objective



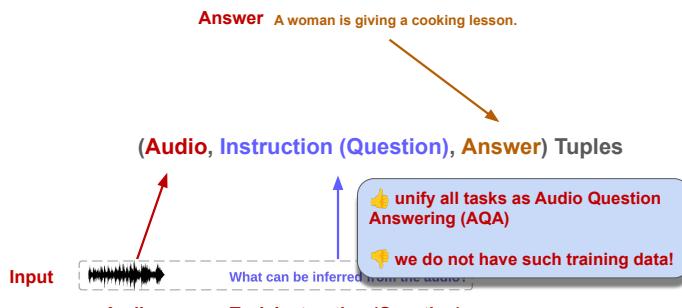
81

LTU training data



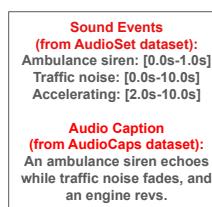
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LTU training data



83

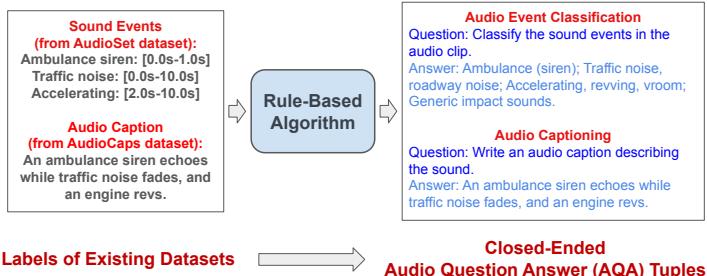
Closed-ended AQAs are easy to generate



Labels of Existing Datasets

84

Closed-ended AQAs are easy to generate



85

If we train LTU with only closed-ended AQAs



On Seen Tasks:

Audio Event Classification 
Question: Classify the sound events in the audio clip.
Answer: Female speech, woman speaking; Stir; Cutlery, silverware; Dishes, pots, and

Audio Captioning
Question: Write an audio caption.
Answer: A woman speaks while frying food in a pan with background noise from a kitchen or dining room.

Looks Good!

86

If we train LTU with only closed-ended AQAs



On Seen Tasks:

Audio Event Classification
Question: Classify the sound events in the audio clip.
Answer: Female speech, woman speaking; Stir; Cutlery, silverware; Dishes, pots, and pans; Breathing

Audio Captioning
Question: Write an audio caption.
Answer: A woman speaks while frying food in a pan with background noise from a kitchen or dining room.

Looks Good!

But on unseen tasks:

Question: Describe the acoustic features you heard.

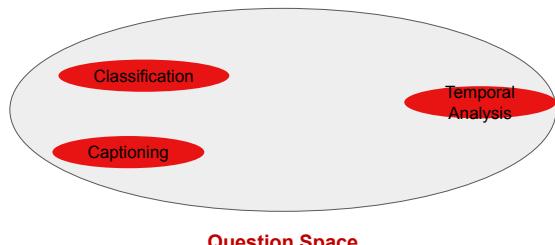
Answer: Female speech, woman speaking; Stir; Cutlery, silverware; Dishes, pots, and pans; Breathing

Question: What is the gender of the speaker?
Answer: A woman speaks while frying food in a pan with background noise from a kitchen or dining room.

... The model cannot generalize!

87

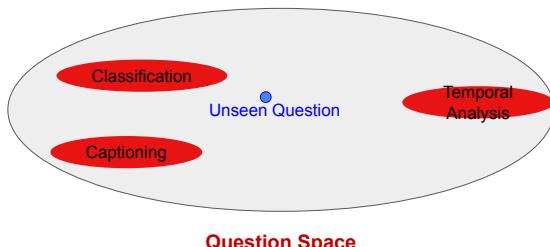
Closed-ended AQAs cannot train a generalized model



Question Space

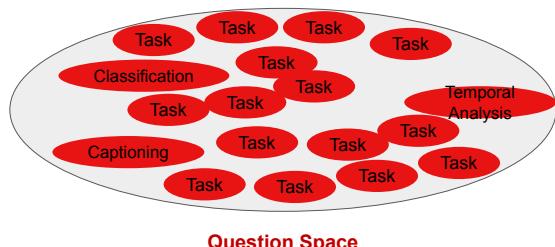
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Closed-ended AQAs cannot train a generalized model



85

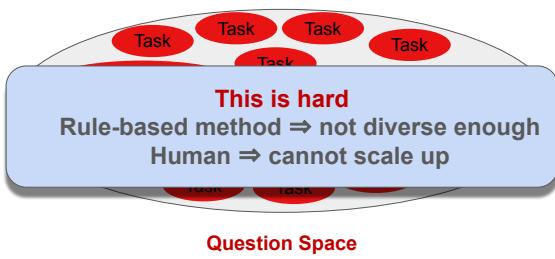
Ideally...



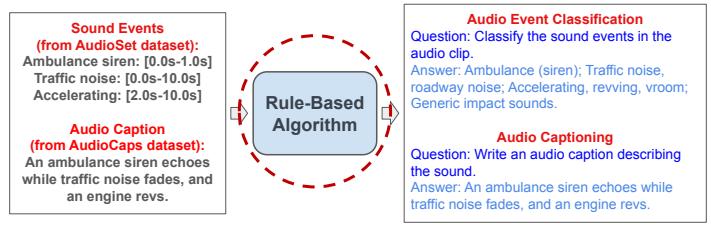
Question Space

90

Ideally...



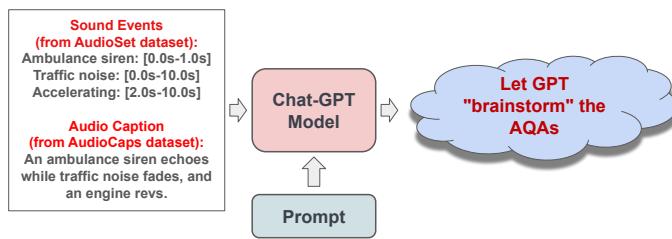
Rule-based algorithm cannot generate open-ended AQAs



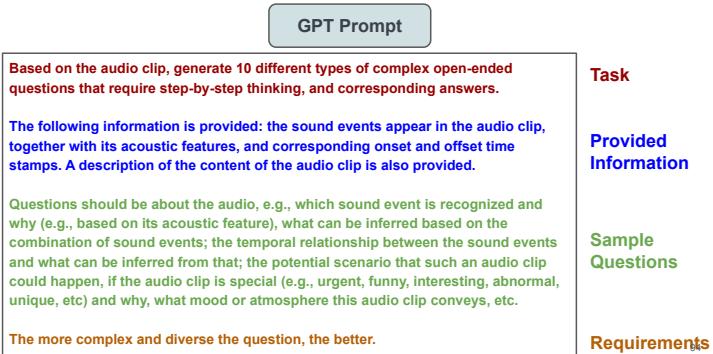
91

92

Audio instruction generation with GPT assistant

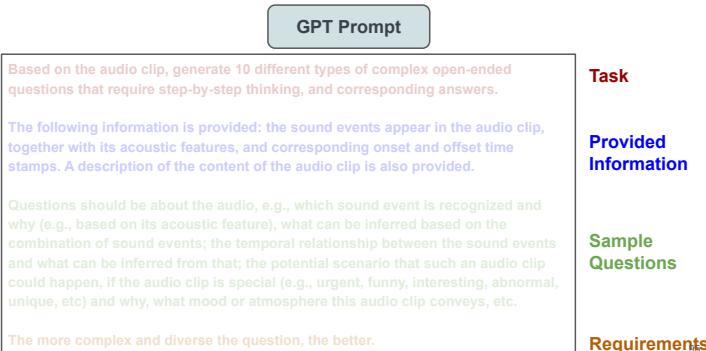


A closer look at the GPT prompt

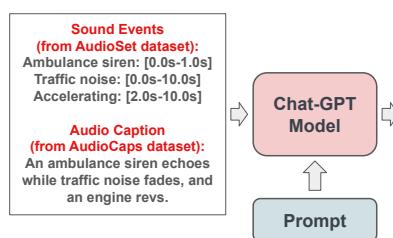


93

A closer look at the GPT prompt

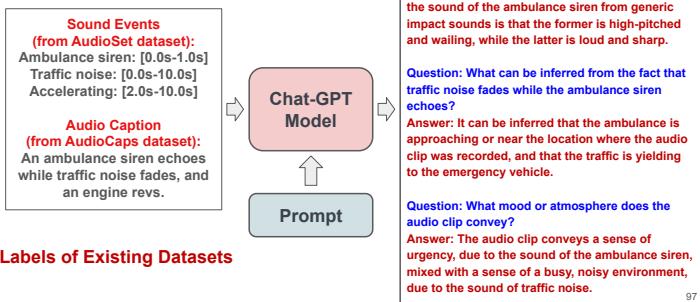


Audio instruction generation

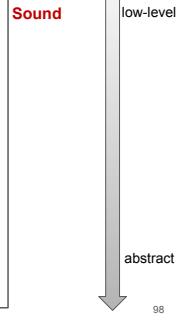


96

Audio instruction generation

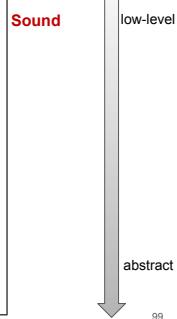


Question: What is the acoustic feature that distinguishes the sound of the ambulance siren from the generic impact sounds?
Answer: The acoustic feature that distinguishes the sound of the ambulance siren from generic impact sounds is that the former is high-pitched and wailing, while the latter is loud and sharp.



Question: What is the acoustic feature that distinguishes the sound of the ambulance siren from the generic impact sounds?
Answer: The acoustic feature that distinguishes the sound of the ambulance siren from generic impact sounds is that the former is **high-pitched and wailing**, while the latter is **loud and sharp**.

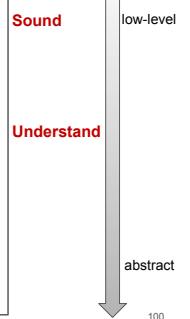
Not in original label
Generated based on ChatGPT's knowledge



Question: What is the acoustic feature that distinguishes the sound of the ambulance siren from the generic impact sounds?
Answer: The acoustic feature that distinguishes the sound of the ambulance siren from generic impact sounds is that the former is high-pitched and wailing, while the latter is loud and sharp.

Question: What can be inferred from the fact that traffic noise fades while the ambulance siren echoes?
Answer: It can be inferred that the ambulance is approaching or near the location where the audio clip was recorded, and that the **traffic is yielding to the emergency vehicle**.

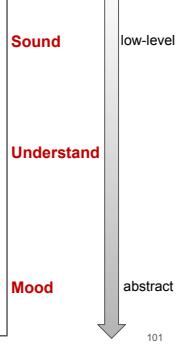
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Generated based on ChatGPT's common sense



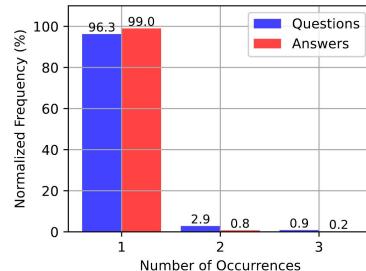
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Question: What can be inferred from the fact that traffic noise fades while the ambulance siren echoes?
Answer: It can be inferred that the ambulance is approaching or near the location where the audio clip was recorded, and that the traffic is yielding to the emergency vehicle.

Question: What mood or atmosphere does the audio clip convey?
Answer: The audio clip conveys a sense of urgency, due to the sound of the ambulance siren, mixed with a sense of a busy, noisy environment, due to the sound of traffic noise.

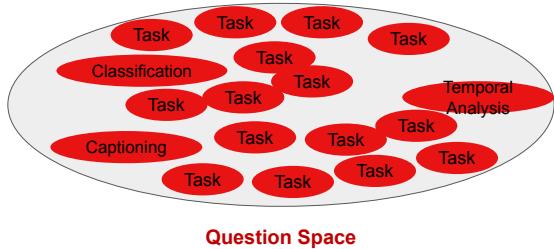


Generated open-ended questions are diverse



96.3% questions and 99.0% answers appears only once

Ideally...



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Dataset	Audio Event	Audio Caption	Spoken Text*	Speaker Gender	Speaker Age	Speech Style	Speaker Emotion	Music Genre	# Audio Clips	# Closed-Ended QAs	# Open-Ended QAs
<i>Audio Datasets (OpenQA) [5]</i>											
AS-Strong [30]	X	X	X	X	-	-	-	-	102k	683k	901k
AudioSet [31]	X	-	X	X	-	-	-	-	500k	536k	184k
VGGSound	-	-	-	-	-	-	-	-	-	-	403k
PSD50K	-	-	-	-	-	-	-	-	-	-	473k
AudioSet	-	-	-	-	-	-	-	-	-	-	791k
FriXion	-	-	-	-	-	-	-	-	-	-	89k
ClothesF	-	-	-	-	-	-	-	-	-	-	10k
SoundP	-	-	-	-	-	-	-	-	-	-	3,763k
Sum	-	-	-	-	-	-	-	-	-	-	-
<i>Speech</i>											
HEMOCT	-	-	-	-	-	-	-	-	-	-	83k
LibriTTS	-	-	-	-	-	-	-	-	-	-	418k
VoxCeleb	-	-	-	-	-	-	-	-	-	-	926k
MOSI	-	-	-	-	-	-	-	-	-	-	355k
Sum	-	-	-	-	-	-	-	-	-	-	1,784k
<i>Joint</i>											
AudioSet [31]	-	-	-	-	-	-	-	-	-	-	72k
FMA [29]	-	-	-	-	-	-	-	-	-	-	396k
Sum	-	-	-	-	-	-	-	-	-	-	1,143k
Total	-	-	-	-	-	-	-	-	-	-	6,690k
(9,641k Question Answer Pairs)											

9.6 million AQAs in total

- **3.0 million** closed-ended AQAs generated by rule-based method
- **6.6 million** open-ended AQAs generated by GPT-assisted method
- Using **13** existing datasets
- **1 million** audio clips

Revisit the cooking demo



Question: What is the gender of the speaker? Why?

105

Revisit the cooking demo



Question: What is the gender of the speaker? Why?
Answer: The speaker is female because her voice has a higher pitch than most male voices.

106

Revisit the cooking demo



Question: What is the gender of the speaker? Why?
Answer: The speaker is female because her voice has a higher pitch than most male voices.
Question: Describe the acoustic features you heard.

107

Revisit the cooking demo



Question: What is the gender of the speaker? Why?
Answer: The speaker is female because her voice has a higher pitch than most male voices.
Question: Describe the acoustic features you heard.
Answer: The audio clip contains the sound of frying food in a small room with high reverberation and low frequency sounds.

108

Revisit the cooking demo



Question: What is the gender of the speaker? Why?
Answer: The speaker is female because her voice has a higher pitch than most male voices.

Question: Describe the acoustic features you heard.
Answer: The audio clip contains the sound of frying food in a small room with high reverberation and low frequency sounds.

Question: What do you feel when you hear this?

109

Revisit the cooking demo



Question: What is the gender of the speaker? Why?
Answer: The speaker is female because her voice has a higher pitch than most male voices.

Question: Describe the acoustic features you heard.
Answer: The audio clip contains the sound of frying food in a small room with high reverberation and low frequency sounds.

Question: What do you feel when you hear this?
Answer: The sound of frying food can evoke hunger or nostalgia for some people, while others may find it unpleasant or annoying.

110

Demo of environment understanding



Question: What is the weather?

111

Demo of environment understanding



Question: What is the weather?

Answer: It is likely to be windy or rainy due to the sound of the wind and rain falling.

112

Demo of environment understanding



Question: What is the weather?

Answer: It is likely to be windy or rainy due to the sound of the wind and rain falling.

Question: Where could this audio be recorded?

113

Demo of environment understanding



Question: What is the weather?

Answer: It is likely to be windy or rainy due to the sound of the wind and rain falling.

Question: Where could this audio be recorded?

Answer: This audio could be recorded in a busy urban area.

114

Demo of environment understanding



Question: What is the weather?

Answer: It is likely to be windy or rainy due to the sound of the wind and rain falling.

Question: Where could this audio be recorded?

Answer: This audio could be recorded in a busy urban area.

Question: What should I do when I hear this, why?

115

Demo of environment understanding



Question: What is the weather?

Answer: It is likely to be windy or rainy due to the sound of the wind and rain falling.

Question: Where could this audio be recorded?

Answer: This audio could be recorded in a busy urban area.

Question: What should I do when I hear this, why?

Answer: When you hear this, you should move to the side of the road and stay there until the emergency vehicle has passed. This is because the sound of an emergency vehicle is a warning signal that something is happening and you should stay out of the way to avoid accidents or injuries.

116

Demo of emotion recognition



Question: What is the emotion of the speaker? Why?

117

Demo of emotion recognition



Question: What is the emotion of the speaker? Why?

Answer: Based on the speech content, the speaker seems to express anxiety or nervousness about public speaking. The high pitch and fast speed suggest excitement or tension as well. Therefore, the emotion of the speaker can be inferred as nervousness or anxiety.

118

Demo of emotion recognition



Question: What is the emotion of the speaker? Why?

Answer: Based on the speech content, the speaker seems to express anxiety or nervousness about public speaking. The high pitch and fast speed suggest excitement or tension as well. Therefore, the emotion of the speaker can be inferred as nervousness or anxiety.

Speech content

Acoustic feature

119

Demo of emotion recognition



Question: What is the emotion of the speaker? Why?

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Question: Provide the speaker 5 suggestions.

120

Demo of emotion recognition

Question: What is the emotion of the speaker? Why?

Answer: Based on the speech content, the speaker seems to express anxiety or nervousness about public speaking. The high pitch and fast speed suggest excitement or tension as well. Therefore, the emotion of the speaker can be inferred as nervousness or anxiety.



Question: Provide the speaker 5 suggestions.

Answer: 1. Take a deep breath before speaking. 2. Practice public speaking regularly. 3. Use humor or lightheartedness to ease nerves. 4. Focus on the audience rather than yourself during speeches. 5. Seek feedback from others to improve your delivery.

121

Demo of music understanding

Question: What did you hear? Answer: Music, punk rock.

Question: Why the music is rock? Consider both lyrics and sounds.

Answer: The music has a strong beat, distorted guitar riffs, and aggressive vocals that are typical characteristics of rock music. The lyrics also contain themes of rebellion and defiance which align with the genre's cultural significance.



122

Demo of music understanding

Question: What did you hear? Answer: Music, punk rock.

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Answer: The music has a strong beat, distorted guitar riffs, and aggressive vocals that are typical characteristics of rock music. The lyrics also contain themes of rebellion and defiance which align with the genre's cultural significance.



Question: Is this music appropriate to play in a primary school?

Answer: No, the lyrics and overall tone are not suitable for children.

123

Demo of music understanding

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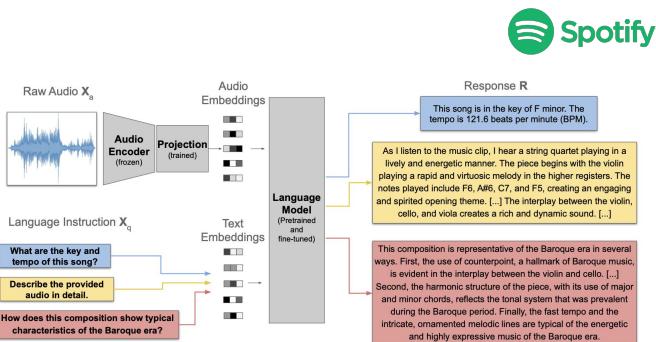
Question: Is this music appropriate to play in a primary school?

Answer: No, the lyrics and overall tone are not suitable for children.

Question: What mood does this music convey?

Answer: The music conveys a rebellious and energetic mood with its fast-paced tempo and aggressive guitar riffs. The lyrics also add to the sense of rebellion.

124



125

Demo of information extraction

Question: What did you hear?

Answer: Subway, metro, underground.

Question: What spoken text is heard?

Answer: The spoken text is "This is the transfer point for the Metro Purple Line to Wilshire Western. Boarding platform is located downstairs..."

Question: Which line does this station transfer to?

Answer: The transfer point is to the Metro Purple Line.

Question: What should I do if I hear this?

Answer: You should board the next train and proceed to your destination.

126

Demo of unseen language

Question: 你听到了什么？(What did you hear?) [Instruction in unseen language]
Answer: A train is moving and a man is speaking.

Question: Can you translate the spoken text into Chinese? [Unseen task]
Answer: The spoken text is 'Transfer point for the Metropolitan Purple Line to Busselton West. Boarding platform is located downstairs. This train's destination is Union Station. Please proceed to the boarding platform and present your ticket at the fare gate when boarding.' The translation would be '替换站点为大都市绿色线到布塞尔东。车站位于下层。这次列车的目的地是联邦站。请在购票门前准备出票并进入车站。'

Question: 这班车的终点站在哪里？用中文作答。(What is the destination?
Answer in Chinese) [Unseen task and language]
Answer: This train's final destination station is in Union Station. 这班车的终点站在 Union Station.

Quick Demo of Listen, Think, and Understand (LTU)
LTU is a new audio model that bridges audio perception and advanced reasoning. It can answer any open-ended question about the given audio. [Paper] [GitHub]
LTU is authored by Yuan Gong, Hongxin Liu, Alexander H. Liu, Leonid Klimonyuk, and James Glass (MIT & MIT IBM Watson AI Lab).
Note LTU is not an ASR and has limited ability to recognize the speech content, it focuses on general audio perception and understanding.
Input an audio and ask questions! Audio will be converted to 16kHz and padded or trim to 20 seconds. Don't have an audio sample on hand? Try some samples from AudioSet evaluation set: [/sample_audios_from_audioset_evaluation_set/](#)



Drop Audio Here
or -
Click to Upload

question
Why this audio is fun?

Audio Meta Information
Original input audio length: 10.03 seconds, number of channels: 1, sampling rate: 16000.

LTU Output
aaa instruction:
Why this audio is fun?
aaa Response:
The audio is fun because it contains laughter and splashing sounds, which are associated with joy, happiness, and relaxation.

Flag

128

Formal evaluation

Closed-Ended Tasks

Evaluated on 15 major benchmarks

- 23.6% improvement over previous SOTA
- First generative model

Open-Ended Tasks

Subjective Evaluation (Amazon Mechanical Turk)

- 476 independent human evaluators
- 82.9% correct rate
- 74.9% of human evaluators rate LTU answers are better than human-crafted answers.

Please listen to the given 10-second audio and answer the questions. All answers needs to be in English.

▶ 0:00 / 10

Audio ID: MhDzvQHfM

Question: What are the main events in the audio clip? (Please describe the main events in the audio clip correctly.)

Answer: The sound events in the audio clip convey a new and completely different scenario, with the explosion and gunfire suggesting potential danger.

Did this answer directly address the question? (Indicates if whether the answer is correct or not.)

Yes, the answer directly addresses the question (regarding whether the answer is correct or not). No, the answer is not related to the question if answer 'No', please explain.

If select "Totally correct" or "Wrong", please explain which part is wrong.

Is this answer totally correct?

Correct Partially Correct Wrong

Please compare the following two answers.

Question: What are the main events in the audio clip? (Please describe the main events in the audio clip correctly.)

Answer 1: The sound events in the audio clip convey a tense and extremely dangerous atmosphere, with the explosion and gunfire suggesting potential danger.

Answer 2: The audio clip conveys a tense and dramatic mood due to the combination of narration, noise, speech, explosive sounds, and artillery fire.

Which answer is better?

Answer 1 is better Answer 2 is better

Please answer the question based on the audio by yourself (at least 4 words).

Add a new question based on the audio and provide the corresponding answer:

Question (at least 4 words):

Answer (at least 4 words):

129

Formal evaluation

Closed-Ended Tasks

Evaluated on 15 major benchmarks

- 23.6% improvement over previous SOTA
- First generative model

Open-Ended Tasks

Subjective Evaluation (Amazon Mechanical Turk)

- 476 independent human evaluators
- 82.9% correct rate
- 74.9% of human evaluators rate LTU answers are better than human-crafted answers.

Q: "What type of sound is it?"

LTU Answer: "The audio clip contains the sounds of a train, clickety-clack, and steam whistle blowing at a high pitch."

Human Answer: "It was train moving sound."

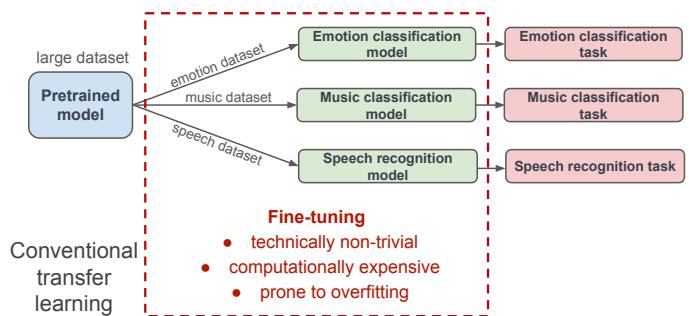
130

Advantage of LTU - 1/ understanding

LTU jointly understands
spoken text
speech paralinguistics (e.g., emotion)
non-speech audio events

almost **everything** in audio

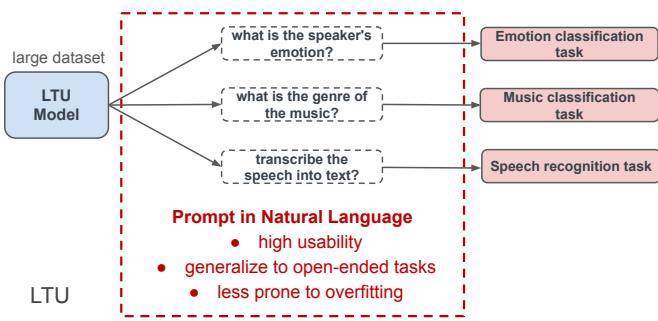
Advantage of LTU - 2/ broader capacity



131

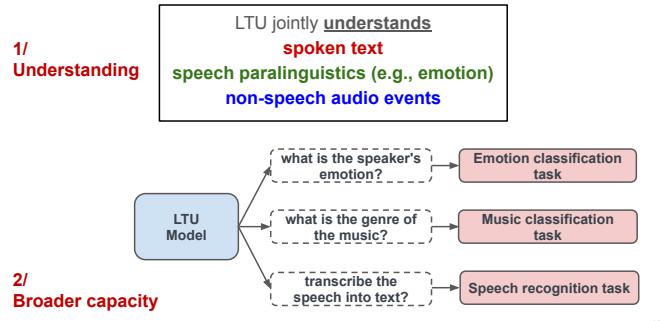
132

Advantage of LTU - 2/ broader capacity



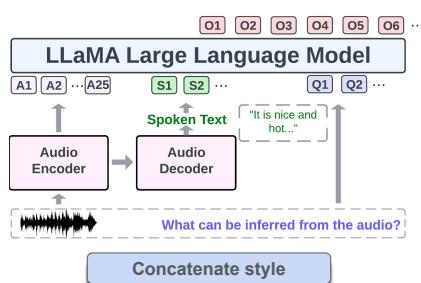
LTU

LTU is a step closer to artificial general intelligence (AGI)



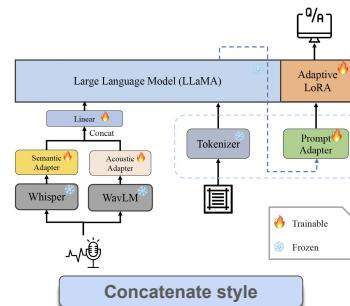
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Other types of audio large language models



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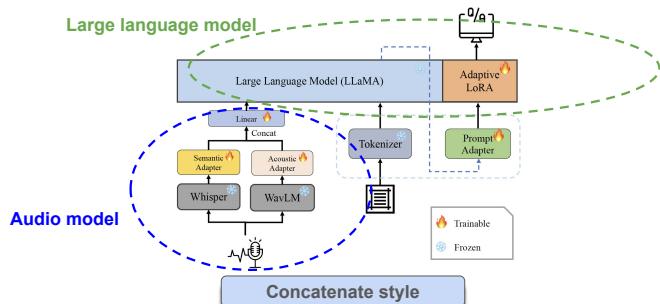
Other types of audio large language models



Shujie Hu et al., WavLM: Towards Robust and Adaptive Speech Large Language Model, 2024

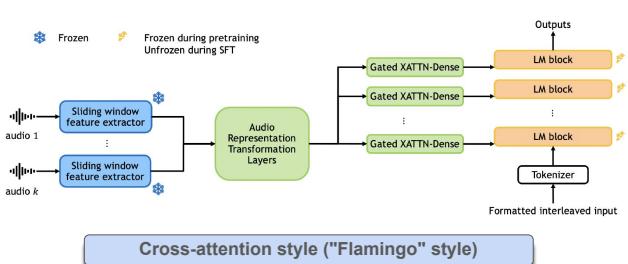
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Other types of audio large language models



Shujie Hu et al., WavLM: Towards Robust and Adaptive Speech Large Language Model, 2024

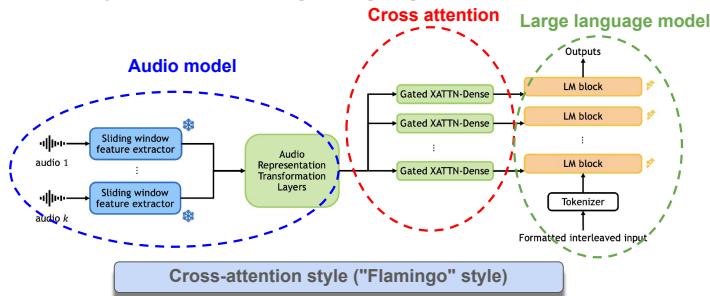
Other types of audio large language models



Zhifeng Kong et al., Audio Flamingo: A Novel Audio Language Model with Few-Shot Learning and Dialogue Abilities, 2024

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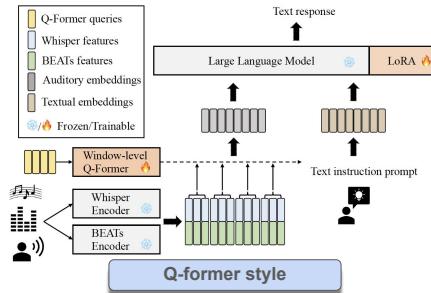
Other types of audio large language models



Zhilong Kong et al., Audio Flamingo: A Novel Audio Language Model with Few-Shot Learning and Dialogue Abilities, 2024

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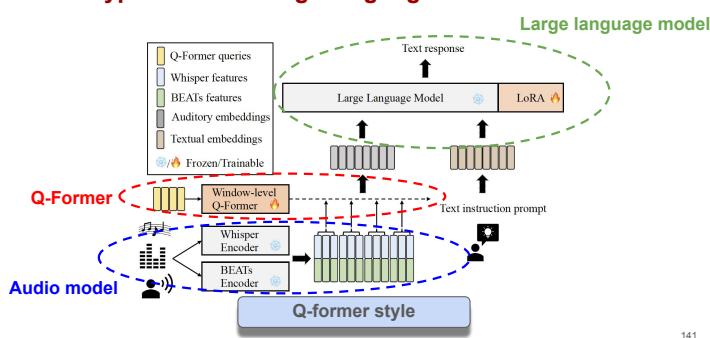
Other types of audio large language models



Changli Tang et al., SALMONN: Towards Generic Hearing Abilities For Large Language Models, 2023

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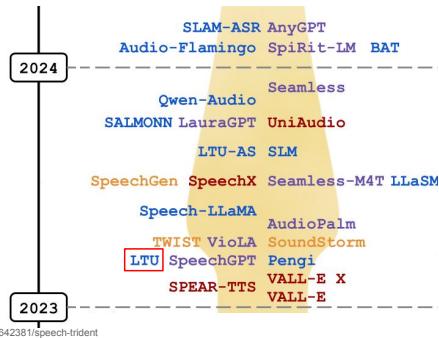
Other types of audio large language models



Changli Tang et al., SALMONN: Towards Generic Hearing Abilities For Large Language Models, 2023

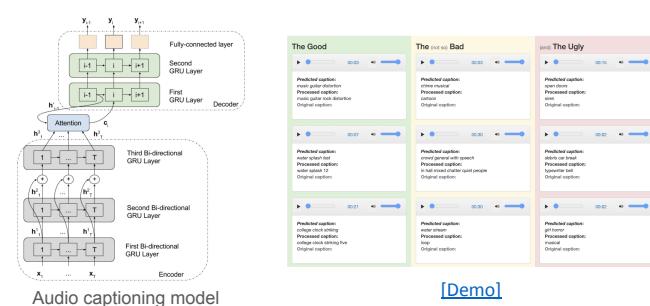
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A list of audio large language models



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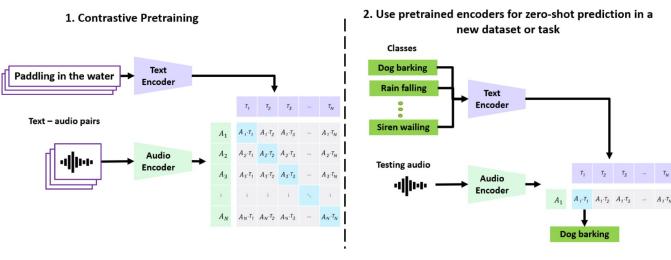
Other audio-text models



Konstantinos Drossos et al., Automated audio captioning with recurrent neural networks, 2017

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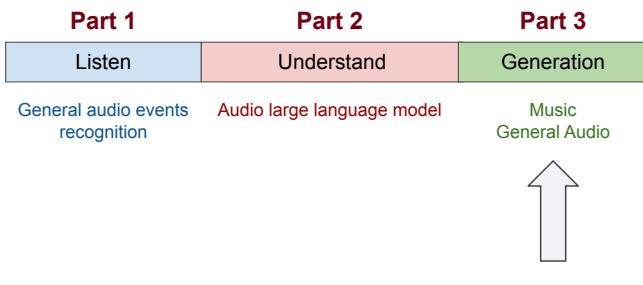
Other audio-text models



Benjamin Elizalde et al., CLAP: Learning Audio Concepts From Natural Language Supervision, 2022

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Outline



Audio generation



We modeled *listening and understanding*

Audio generation

Categorized by generation targets:

- Speech synthesis
 - [NaturalSpeech \(v1, v2, v3\)](#)
 - [Vall-E](#)
- Music generation
 - [Suno](#)
 - [MusicLM](#)
- Unified generation model
 - [AudioLM \(v1, v2\)](#)
 - [Make-An-Audio](#)

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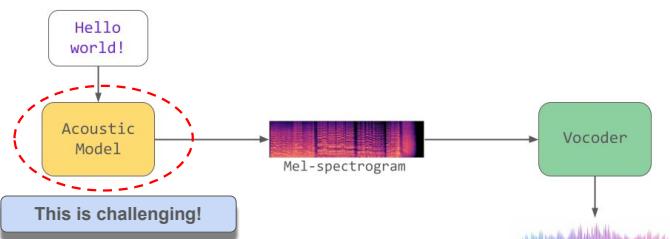
Audio generation

Categorized by generation methods:

- Diffusion-based models
- Audio codec-based models

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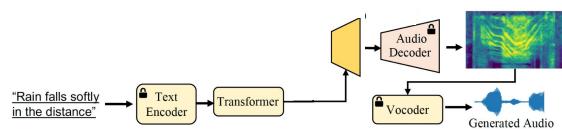
Diffusion-based models



<https://www.assemblyai.com/blog/recent-developments-in-generative-ai-for-audio>

Diffusion-based models

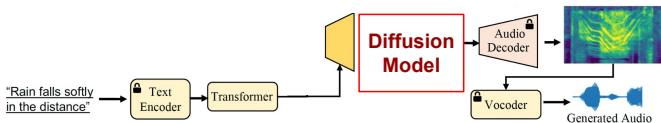
Make-An-Audio Model



Rongjie Huang et al., Make-An-Audio: Text-To-Audio Generation with Prompt-Enhanced Diffusion Models, 2024

Diffusion-based models

Make-An-Audio Model

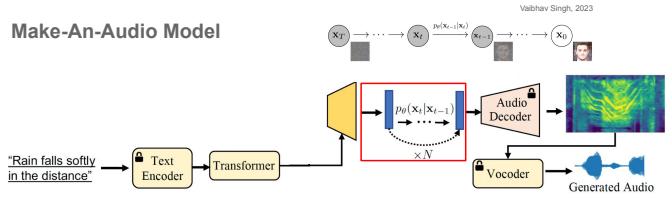


Rongjie Huang et al., Make-An-Audio: Text-To-Audio Generation with Prompt-Enhanced Diffusion Models, 2024

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Diffusion-based models

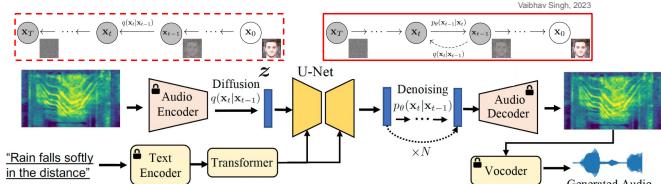
Make-An-Audio Model



Rongjie Huang et al., Make-An-Audio: Text-To-Audio Generation with Prompt-Enhanced Diffusion Models, 2024

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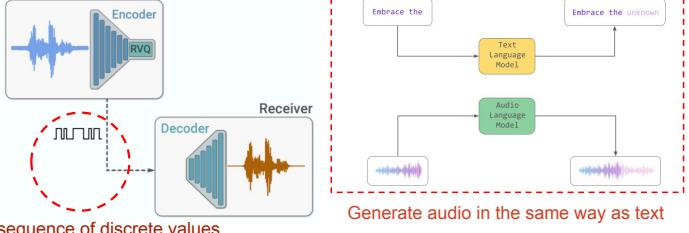
Diffusion-based models



Rongjie Huang et al., Make-An-Audio: Text-To-Audio Generation with Prompt-Enhanced Diffusion Models, 2024

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Audio codec based models



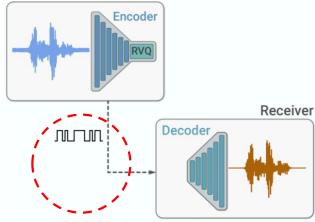
A sequence of discrete values

- Original designed for compression
- Later found ideal as generation units

Neil Zeghidour et al., SoundStream: An End-to-End Neural Audio Codec 2021

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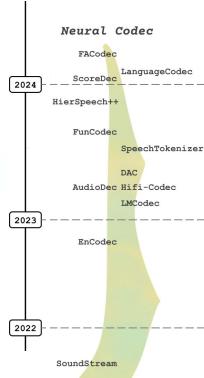
Audio codec based models



A sequence of discrete values

- Original designed for compression
- Later found ideal as generation units

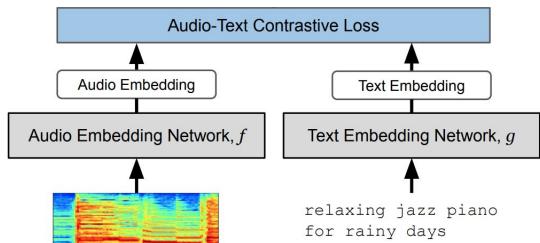
<https://github.com/ga642381/speech-trident>



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Audio codec based models

MuLan (Music-text embedding model)

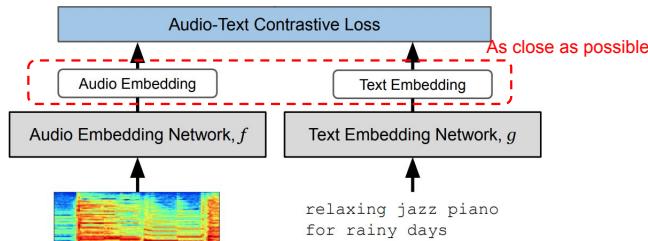


Qingding Huang et al., MuLan: A Joint Embedding of Music Audio and Natural Language, 2022

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Audio codec based models

MuLan (Music-text embedding model)



Qingqing Huang et al., MuLan: A Joint Embedding of Music Audio and Natural Language, 2022

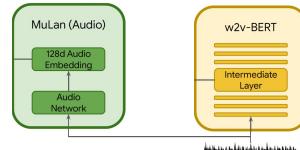
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Audio codec based models

MusicLM

Step 1. Convert audio to representations

- An audio-text representation MA
 - MuLan embedding, aligned with text
- An audio representation S to model coarse semantics (e.g., melody)
 - w2v-BERT embedding



Andrea Agostinelli et al., MusicLM: Generating Music From Text, 2023

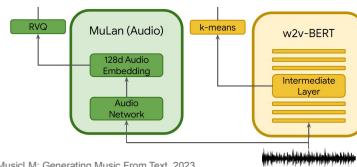
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Audio codec based models

MusicLM

Step 2. Quantize representations to discrete values

- Residual vector quantization (RVQ) for MuLan embeddings M^A
- K-means for w2v-BERT embeddings S



Andrea Agostinelli et al., MusicLM: Generating Music From Text, 2023

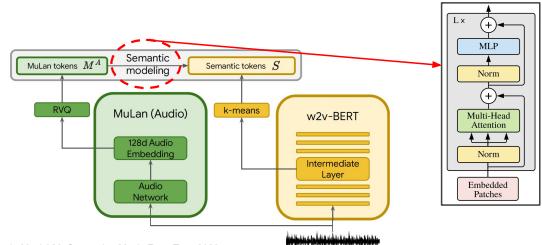
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Audio codec based models

MusicLM

Step 3. Predict semantic tokens S from audio-text tokens MA

- Modeled by a Transformer



Andrea Agostinelli et al., MusicLM: Generating Music From Text, 2023

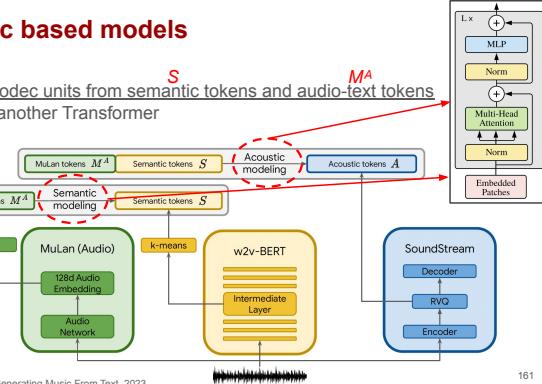
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Audio codec based models

MusicLM

Step 4. Predict codec units from semantic tokens and audio-text tokens

- Modeled by another Transformer



Andrea Agostinelli et al., MusicLM: Generating Music From Text, 2023

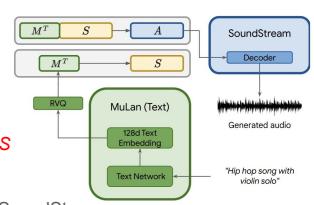
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Audio codec based models

MusicLM

Inference

- Input text description
- Get MuLan embedding MT ($\sim MA$)
- Predict S conditioned on MT
 - Use learned Transformer 1
- Predict codec A conditioned on MT and S
 - Use learned Transformer 2
- Convert A to **waveform**
 - Use pretrained audio codec model SoundStream



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Responsible audio AI

AP News https://apnews.com › article › new-hampshire-primary-bl... :

Fake Biden robocall being investigated in New Hampshire

Jan 22, 2024 — New Hampshire officials are investigating reports of an apparent robocall that used AI to mimic President Biden's voice before the primary ...



- Audio watermarking
- Deepfake detection
- Policies for responsible use of audio AI

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Responsible audio AI

Fairness

- Existing models are mostly English-centric
- Models may bias against minority groups

Trustworthiness

- Hallucination
- Not good at tasks requiring high reliability

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Revisit this sample

Question: 你听到了什么? (What did you hear?) [Instruction in unseen language]
Answer: A train is moving and a man is speaking.

Question: Can you translate the spoken text into Chinese? [Unseen task]
Answer: The spoken text is 'Transfer point for the Metropolitan Purple Line to Busselton West. Boarding platform is located downstairs. This train's destination is Union Station. Please proceed to the boarding platform and present your ticket at the fare gate when boarding.' The translation would be '替换站点为大都市绿色线到布塞尔东。车站位于下层。这次列车的目的地是联邦站。请在购票门前准备出票并进入车站。'

Question: 这班车的终点站在哪里? 用中文作答。 (What is the destination?
Answer in Chinese) [Unseen task and language]
Answer: This train's final destination station is in Union Station. 这班车的终点站在 Union Station.

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Revisit this sample

Question: 你听到了什么? (What did you hear?) [Instruction in unseen language]
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Question: Can you translate the spoken text into Chinese? [Unseen task]
Answer: The spoken text is 'Transfer point for the Metropolitan Purple Line to Busselton West. Boarding platform is located downstairs. This train's destination

Problem:
The model is a strong preference to speak English

Question: 这班车的终点站在哪里? 用中文作答。 (What is the destination?
Answer in Chinese) [Unseen task and language]
Answer: This train's final destination station is in Union Station. 这班车的终点站在 Union Station.

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Responsible audio AI

Fairness

- Existing models are mostly English-centric
- Models may bias against minority groups

- Mainly due to training data, but hard to be solved by collecting multi-lingual data.
- Need a deep integration with translation systems

• Not good at tasks requiring high reliability

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Revisit this sample

Question: 你听到了什么? (What did you hear?) [Instruction in unseen language]
Answer: A train is moving and a man is speaking.

Question: Can you translate the spoken text into Chinese? [Unseen task]
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Problem:
Purple Line is mistranslated as "绿色线" (Green Line)

Responsible audio AI

- Hard to be completely solved by pure neural-based methods
 - Require neural-symbolic methods

Trustworthiness

- Hallucination
- Not good at tasks requiring high reliability

References

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