LREC 2026 Palma

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Multilingual and Multimodal LLMs in the Wild: Building for Low-Resource Languages

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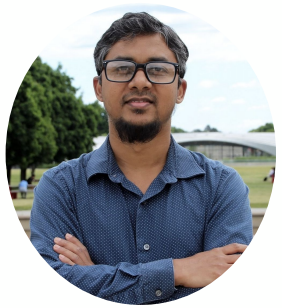
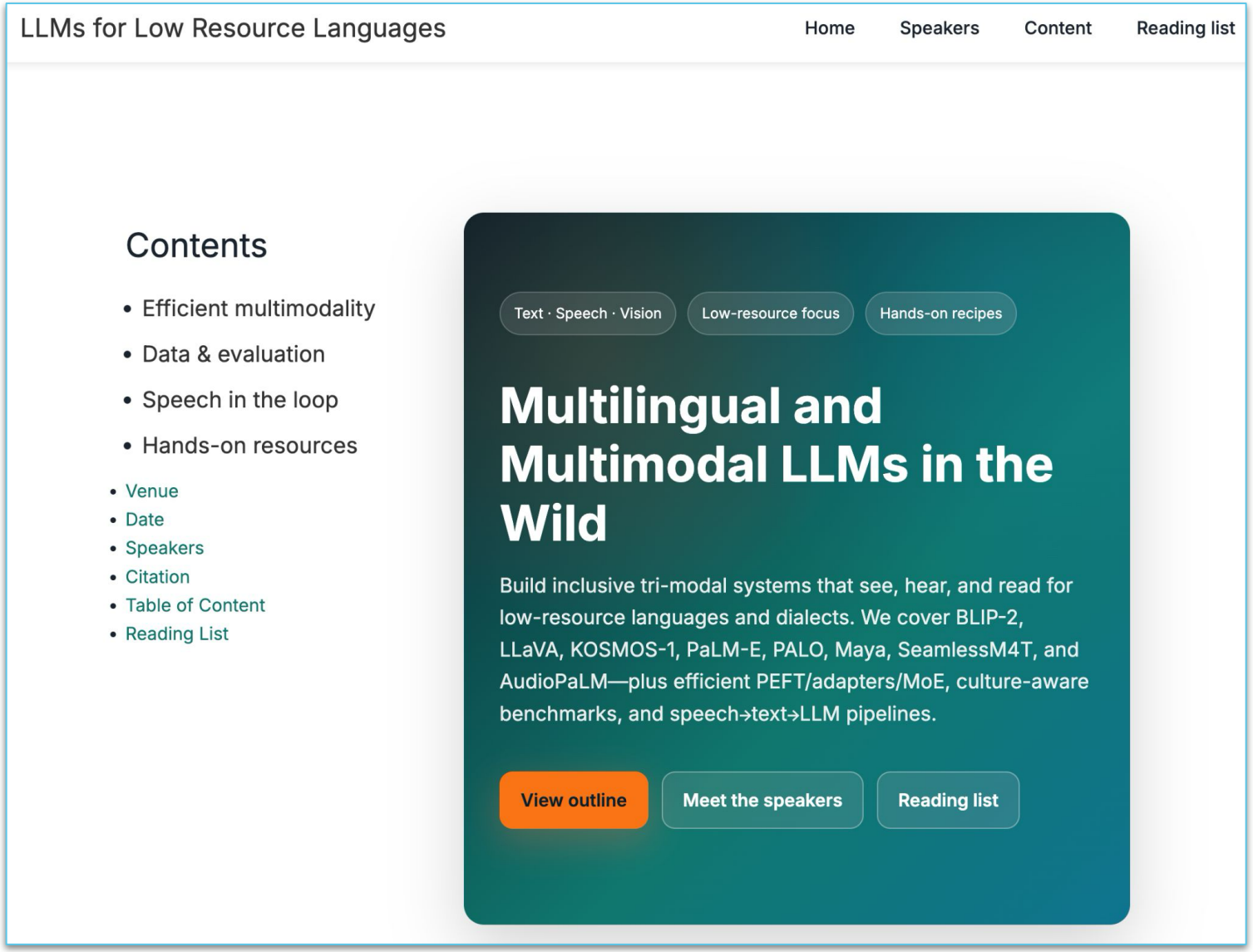


Enamul Hoque Prince
Associate Professor,
York University

LREC 2026, 12th May, 2026

Tutorial Resources



https://mm-llms-in-the-wild.github.io

Tutorial Outlines

Introduction
(low-resource and challenges)

Multilingual and Multimodal Models
(Capabilities for low-resource languages)

Multilingual & Multimodal Resource Development
(Low-cost pipeline, training, and benchmarking datasets)

Architectures and Efficient Training
(Adapter-based and parameter-efficient methods)

Speech-centric LLMs
(State-of-the-art models and curated resources)

Evaluation, Benchmarking Tools, Analysis
(Evolution of Evaluation metrics, benchmarking tools and resources)

Speech-Centric Multimodality

Shammur Chowdhury
Scientist, QCRI

Why Audio LLMs Matter

- Speech is the primary interface for many communities
  - Text-only systems less inclusive: Low literacy, dialectal variation

- Spoken interaction lowers the barrier to using AI.
- Speech carries meaning beyond words
- Text-centric LLMs miss real-world language variation
- AudioLLMs can learn directly from spoken input and enable practical applications

Audio Modalities Types

Speech

Spoken language with semantic content - words, phrases, and meaning conveyed through voice

Non-speech

Crying, laughter, silence, and ambient noise - human sounds beyond words

Sound Events

Door slams, footsteps, machinery, and nature - the sounds of the physical world

Music

Melodies, chords, and instrument timbre - structured auditory art

Challenges

Continuous Waveforms

Unlike text tokens, audio is a dense, unstructured signal requiring aggressive downsampling.

Long Context

A 1-hour meeting is ~200M samples; transformer attention becomes intractable without compression.

Noise & Variation

Real speech is accented, emotional, noisy; models must abstract over immense surface variation.

Multilevel Semantics

Meaning lives at phoneme, word, utterance, and turn-taking levels simultaneously.

Timing-Sensitive

Absolute timing (latency, prosody, rhythm) matters; 'what was said' ≠ 'how it was said'.

Why Speech/Audio Is Low-Resource

Data Scarcity

Only ~1% of the world's 7,000+ languages have **significant speech datasets (labeled)**. **Text corpora are 100-1000x larger** than paired speech-text data.

Annotation Cost

Transcribing speech requires real-time human listening - 1 hour of audio takes 4-10 hours to label. Per-hour costs are 10-50x higher than text.

Domain Fragmentation

Models trained on read speech fail on spontaneous conversation or noisy environments. Each domain needs dedicated data.

Speech models require 10-100x more compute per token of useful supervision than text LLMs

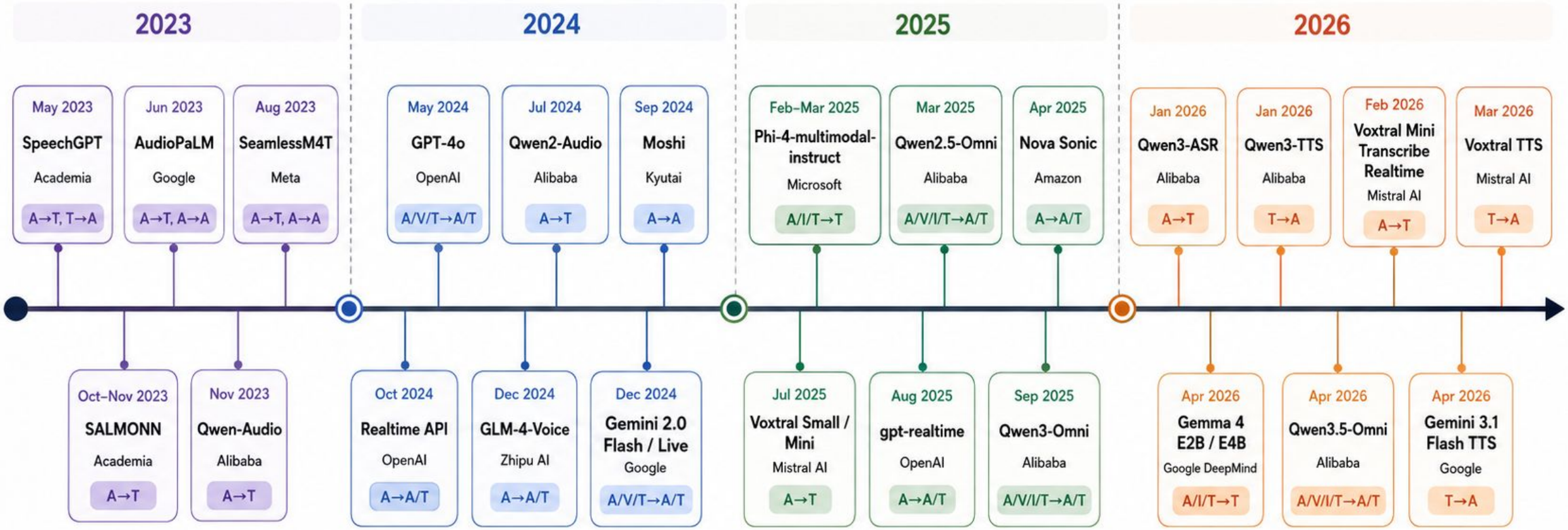
Cascade Pipeline

Pipeline: Traditional speech-to-speech systems chain three separate models in sequence, introducing latency and compounding errors.

Challenges

- High Latency
- Error Propagation
- Loss of Paralinguistic Information

AudioLLM/LALM Timeline



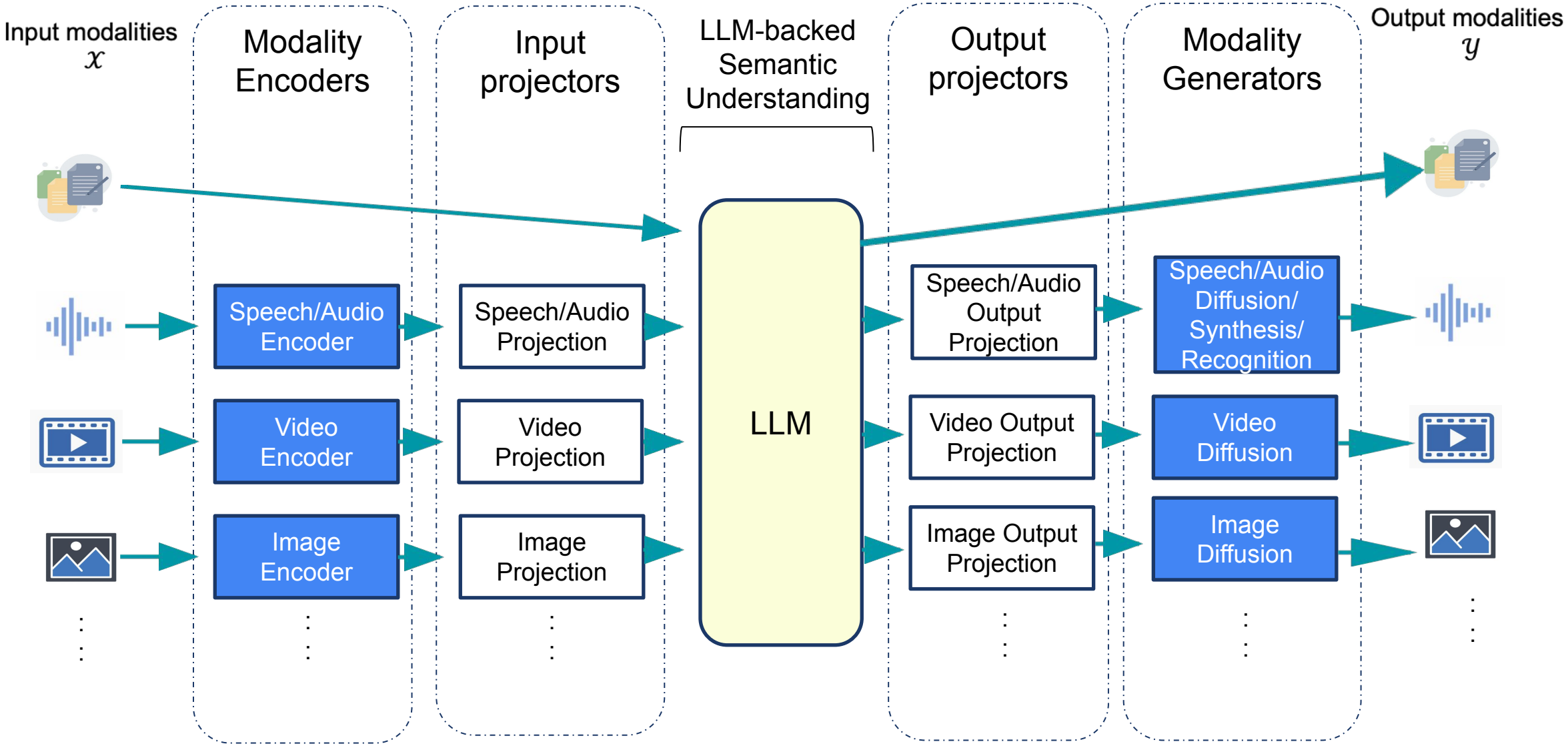
Audio Capable multimodal and real-time speech capabilities

Recent breakthroughs shows Speech I/O is now practical

A→T	speech/audio input to text
A→A/T	speech/audio input to speech or text
T→A	text to speech

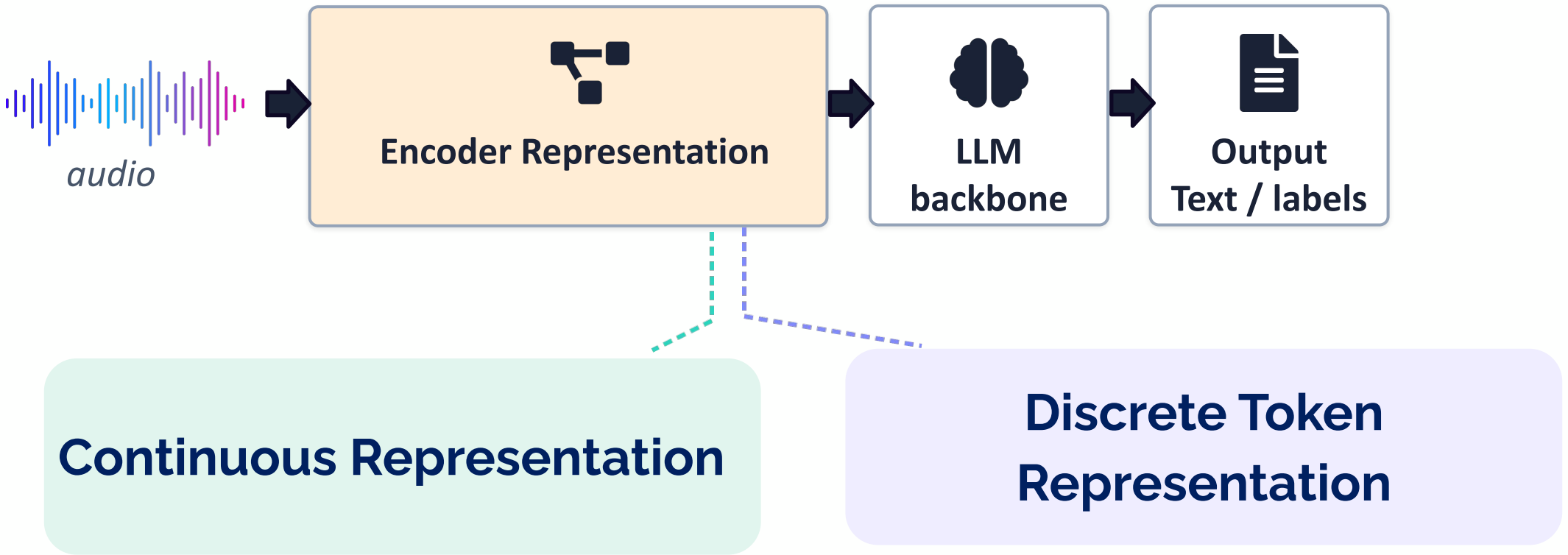
MMLLM Architectures

General Overview

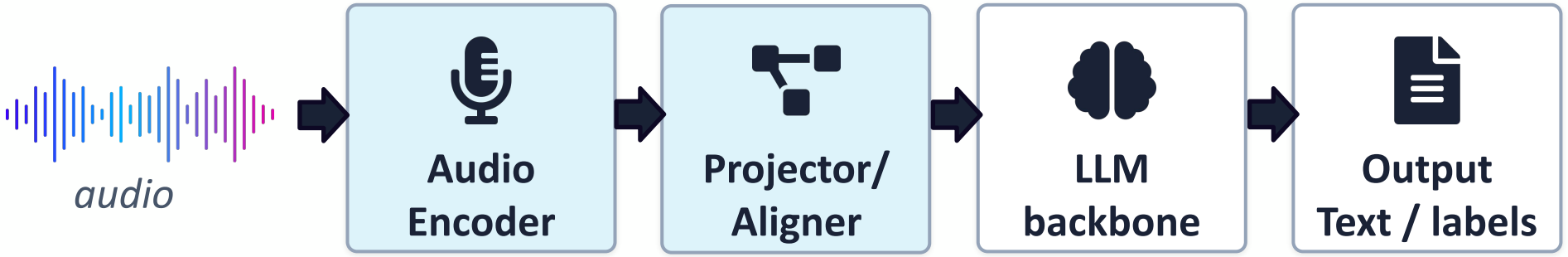


Zhang, Duzhen, et al., MM-LLMs: Recent advances in multimodal large language models, 2024

Simplified Architecture



Continuous Representation



Fast Inference • Preserve Paralinguistic Information

• Depends on the Projector Alignment

Speech Encoder Architectures

SSL models

Wav2Vec 2.0, HuBERT, XLS-R, mHuBERT

- Self-supervised learning from raw audio
- No labels required for pretraining
- Discrete units vs. continuous features

Whisper-style

Qwen-Audio, Qwen2-Audio, Qwen2.5 Omni (whisper-L-v3)

- Encoder-Decoder Architecture
- **Trained on ≈5 M h**
- Large weakly-supervised pretrain
- **99-language coverage**
- Off-the-shelf, easy to plug in

AuT (Audio Transformer)

Qwen3-Omni

- Attention-based Encoder-Decoder
- **Trained on ≈20M h audio (v2: 40M)**
- Block-wise streaming
- Stronger audio reps
- ASR and AU tasks
- 80% Chinese and English, 10% ASR other languages, and 10% AU. (8 to 10 lang)

USM-based

Gemma 3n, Gemma 4

- Conformer-based
- Best-RQ: Unsupervised pre-training
- **12M hours** of unlabeled audio and 28B sentences.
- **300+ language**
- Multi-Objective training
- Spacial-Awareness (v2)

Speech-to-LLM Alignment Architectures

Linear Projectors

Simplest form of alignment using a single Linear layer or MLP to map encoder hidden states to LLM embedding space dim.

Used in: Early Audio-LLMs, LLaVA-Audio variants, Low-resource models.

Low Latency

Q-Former / Perceiver

Uses a fixed set of learnable query tokens to cross-attend to encoder features. Significantly reduces sequence length.

Used in: BLIP-2 style adaptations, SALMONN.

Context Efficient

Convolutional Downsamplers

1D Strided Convolutions to shrink the temporal resolution of audio features before LLM injection.

Used in: Qwen2-Audio, Gemini (variants).

Local Modeling

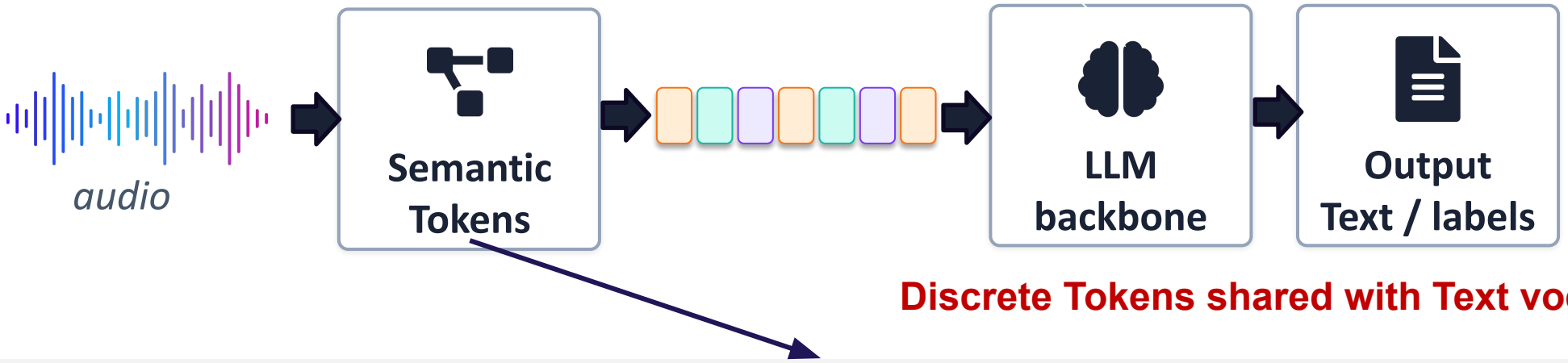
Pooling

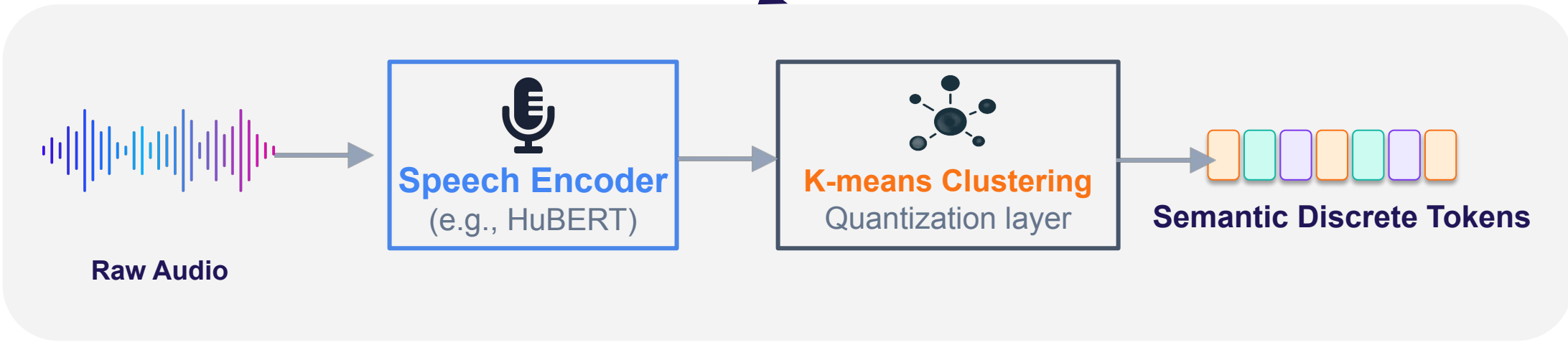
Abstracts acoustic features into high-level semantic units via attention-based pooling or clustering.

Used in: LTU.

Semantic Rich

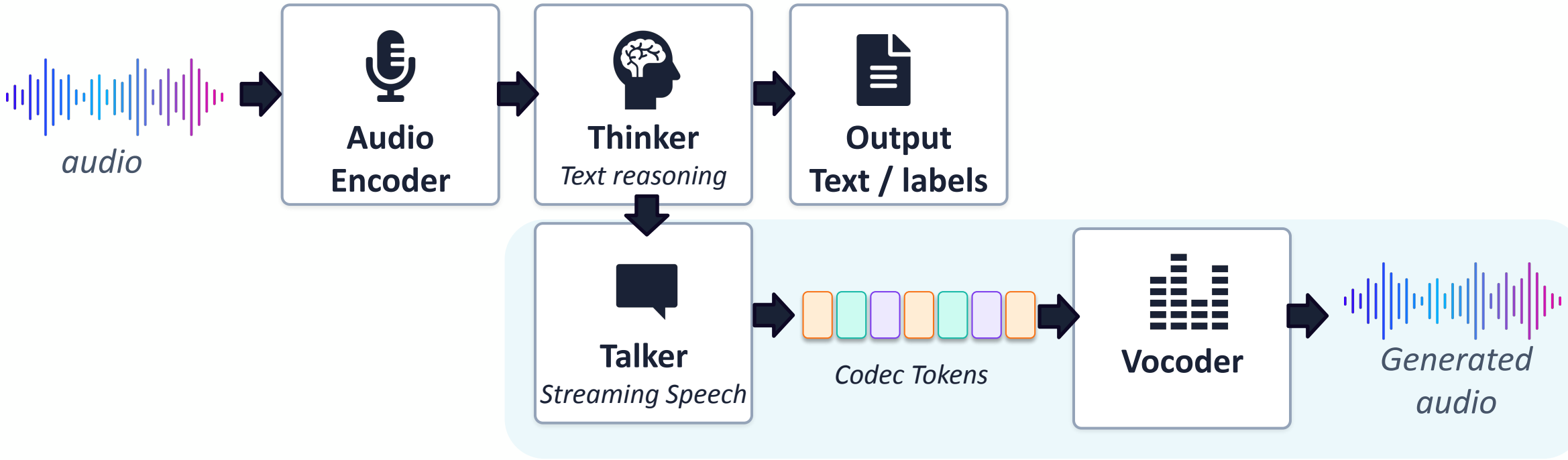
Discrete Audio Tokens





- Codec Quality Bottleneck
- Higher Token Overhead

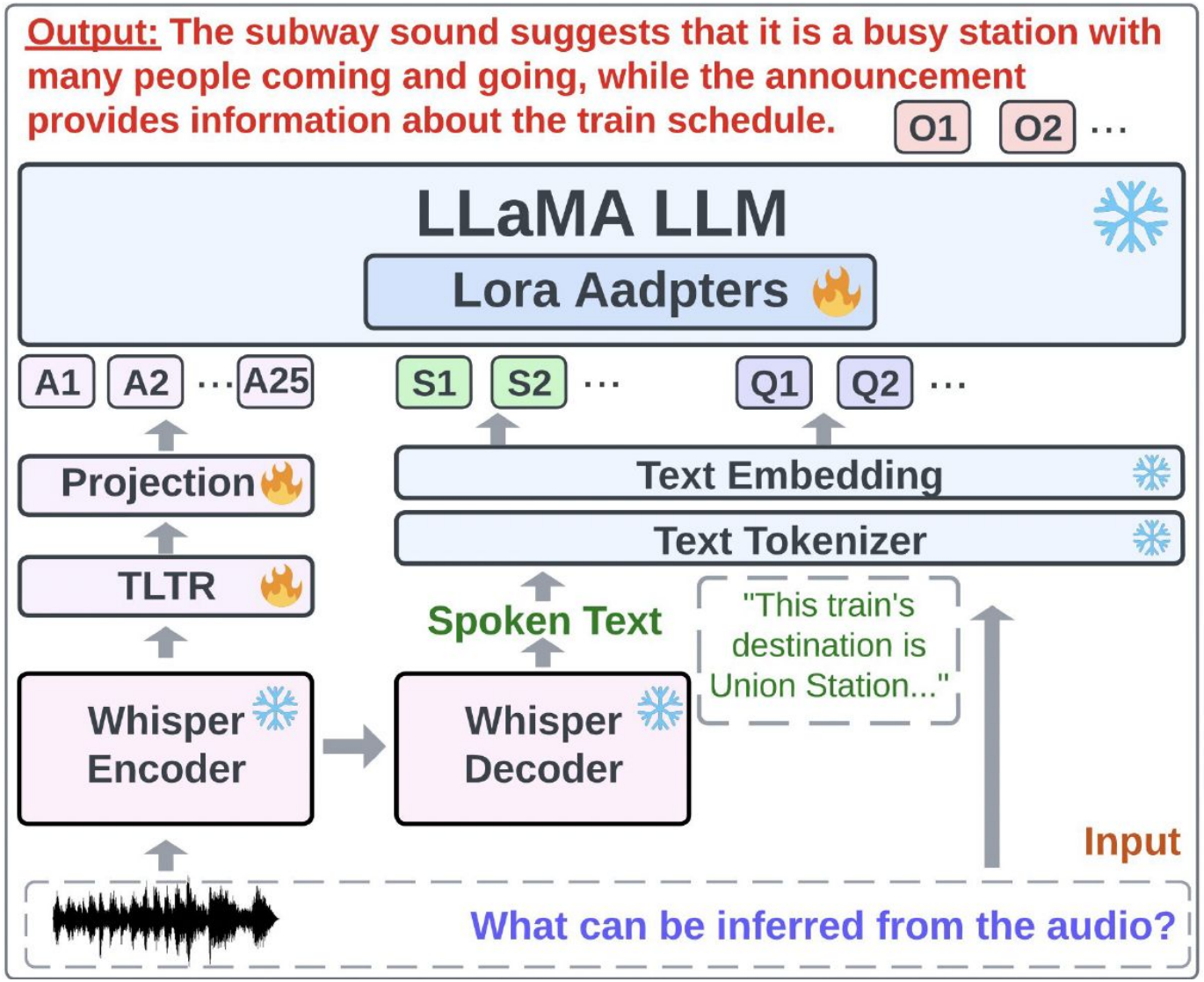
Omni-Model (Thinker-Talker)



• Low Latency • Expressive • Reduce Error Propagation

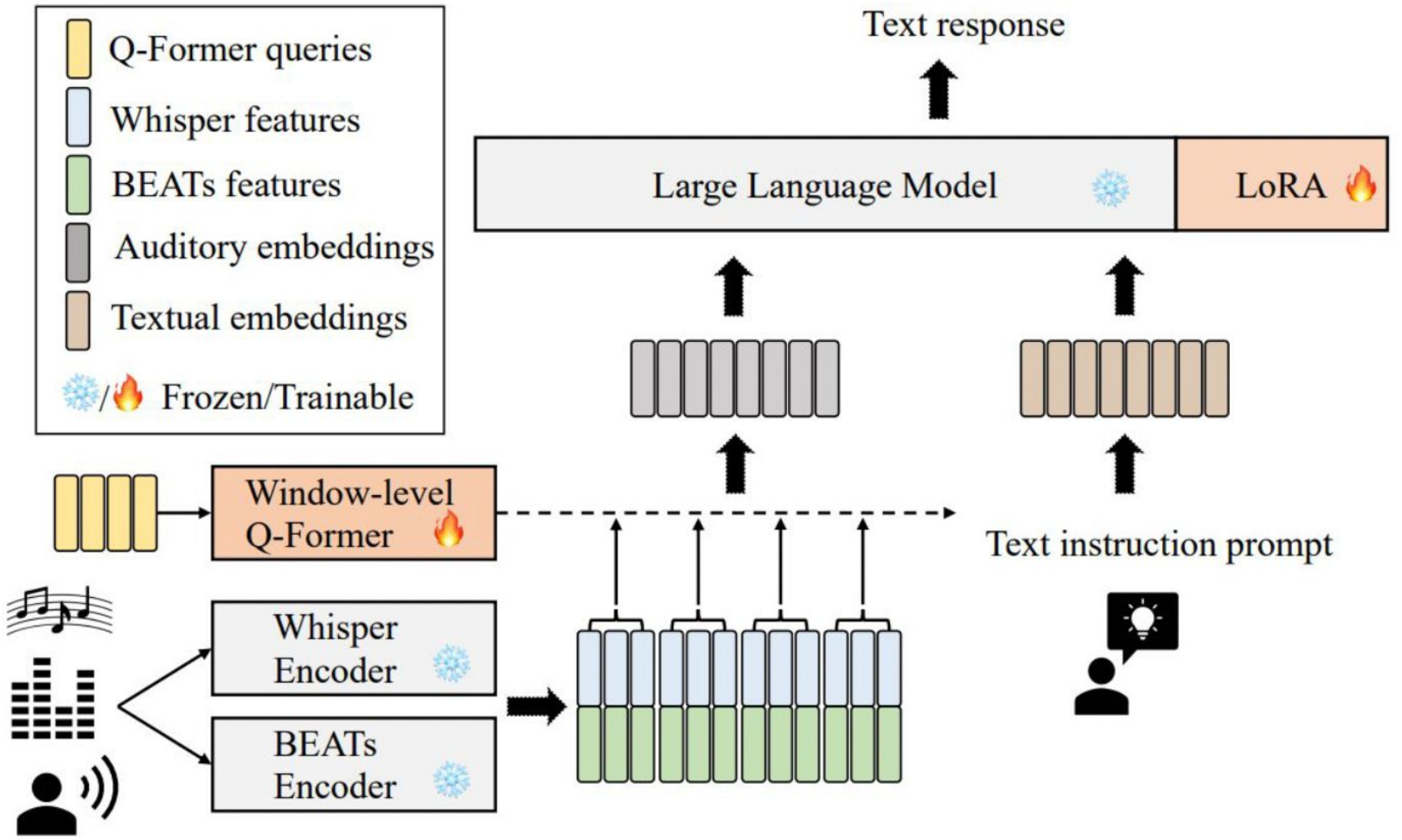
• Higher Token Overhead • Need High Resource • Hard to debug

LTU: Listen, Think and Understand



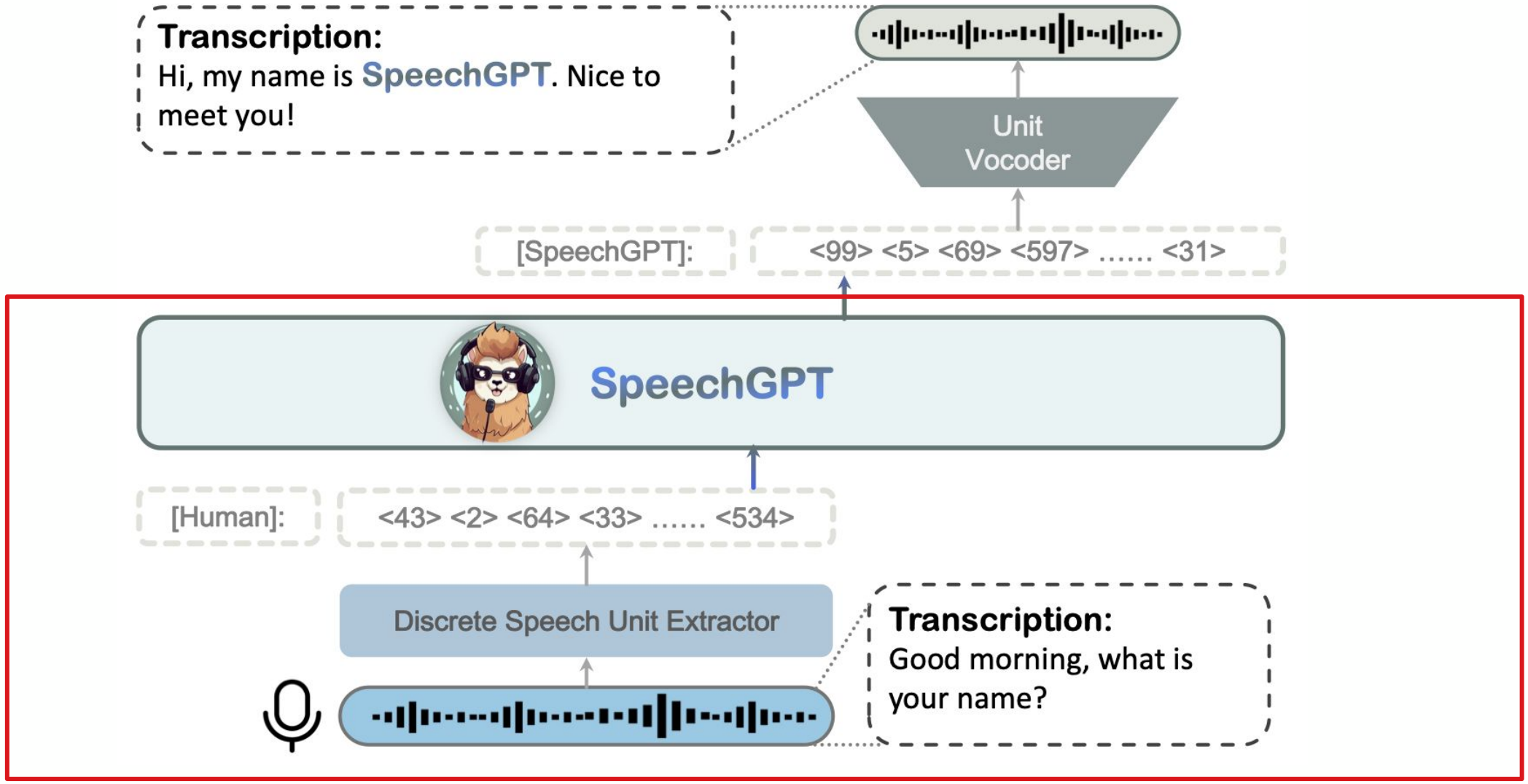
Gong et al., Listen, think, and understand, ICLR 2024

SALMONN



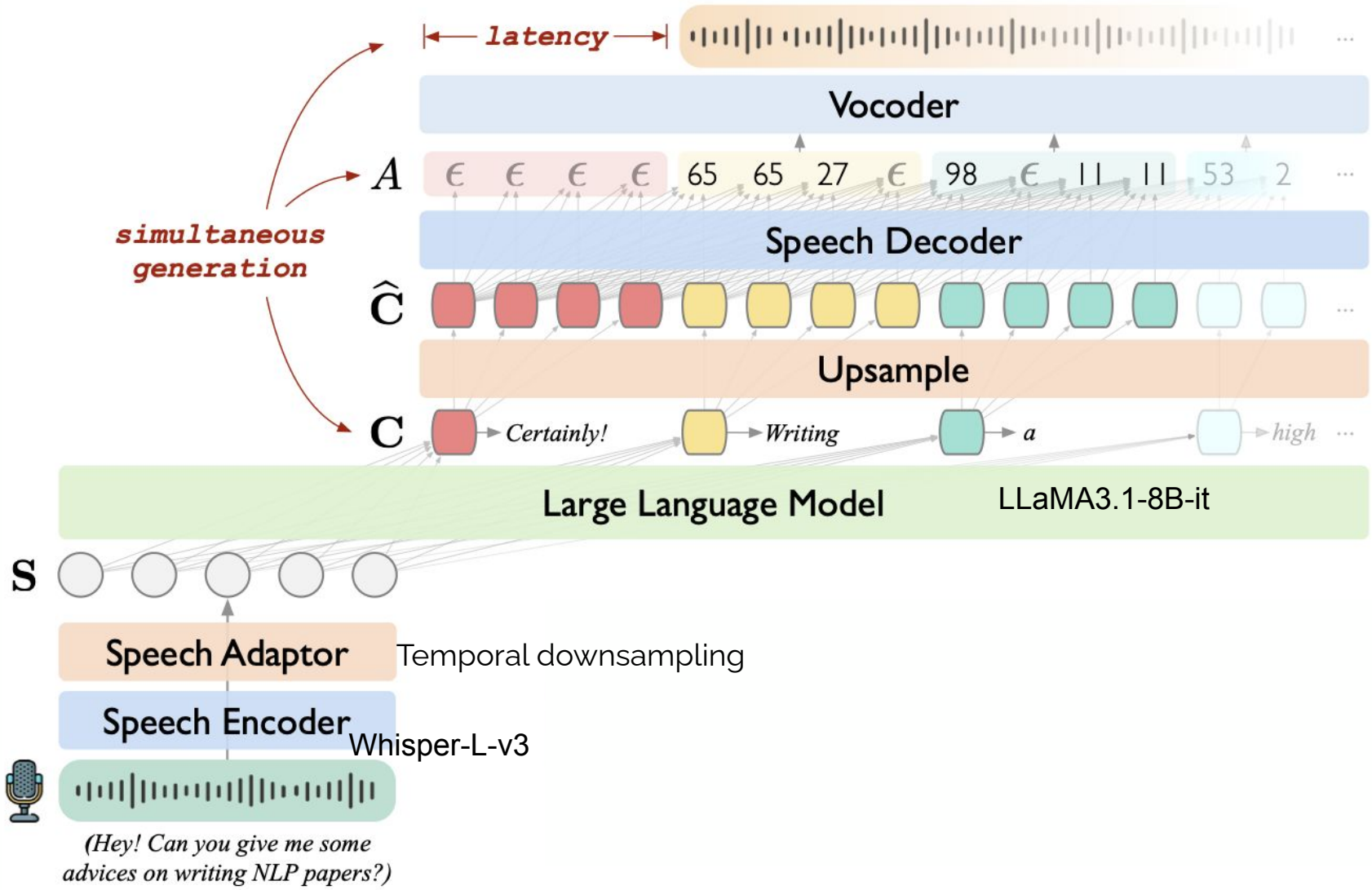
Tang et al., SALMONN: Towards Generic Hearing Abilities for Large Language Models. ICLR 2024

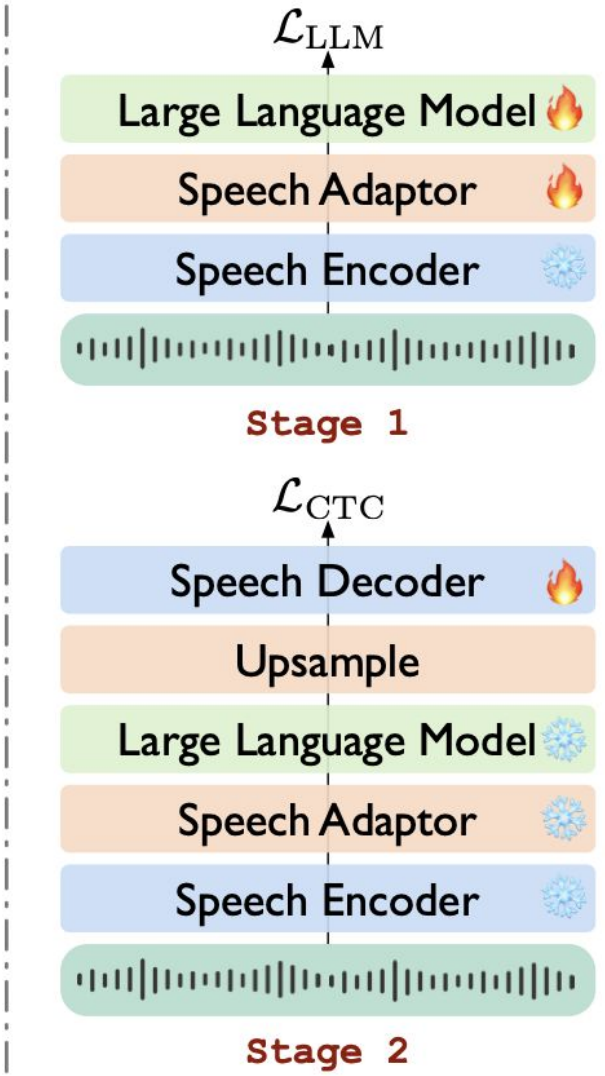
SpeechGPT



Tang et al., SALMONN: Towards Generic Hearing Abilities for Large Language Models. ICLR 2024

LLaMA-Omni

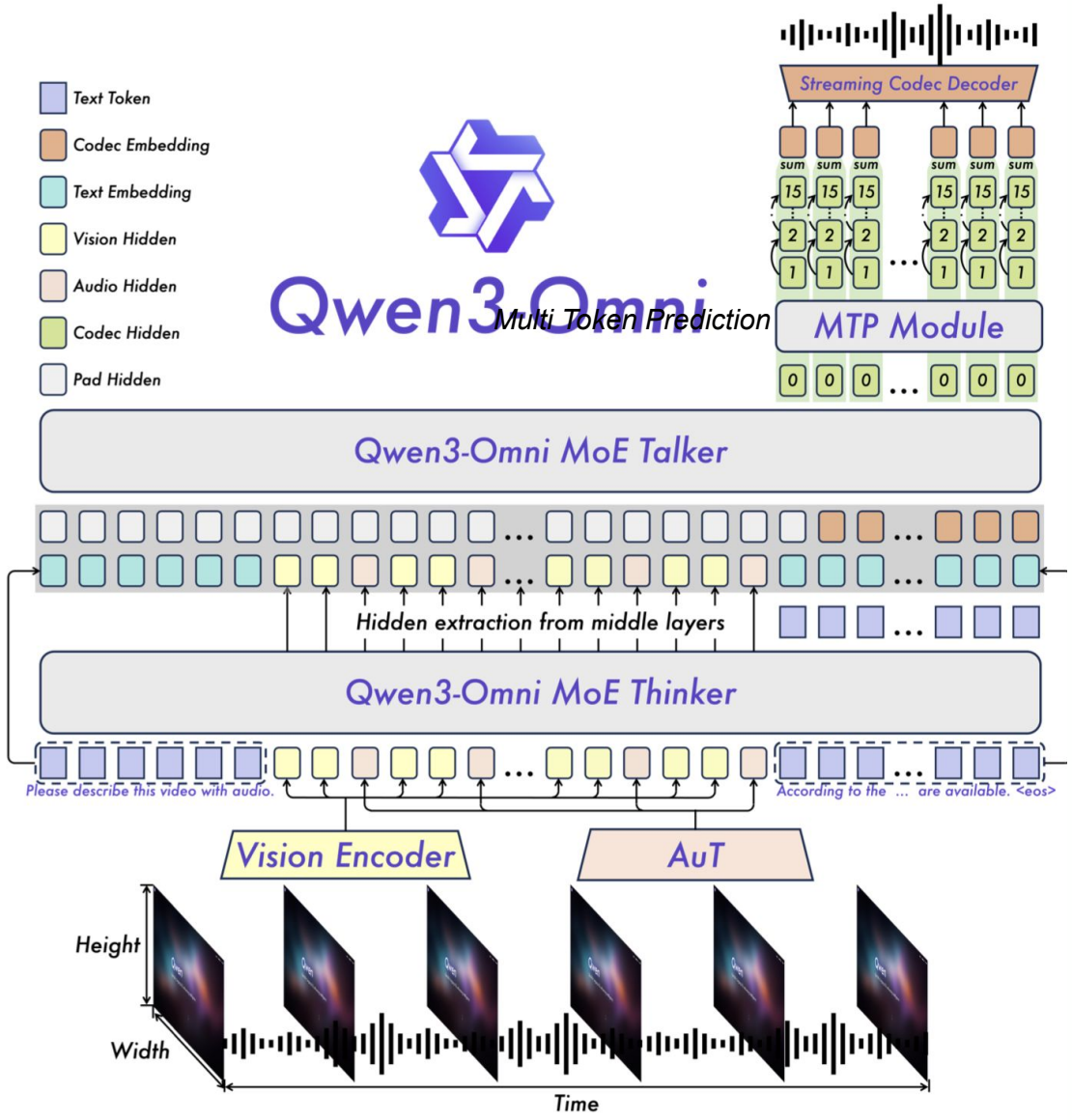

latency
Vocoder
A
Speech Decoder
simultaneous generation
Ĉ
Upsample
C
Certainly!
Writing
a
high
Large Language Model
LLaMA3.1-8B-it
S
Speech Adaptor
Temporal downsampling
Speech Encoder
Whisper-L-v3
(Hey! Can you give me some advices on writing NLP papers?)


$\mathcal{L}_{\text{LLM}}$
Large Language Model
Speech Adaptor
Speech Encoder
Stage 1
$\mathcal{L}_{\text{CTC}}$
Speech Decoder
Upsample
Large Language Model
Speech Adaptor
Speech Encoder
Stage 2

Qwen3-Omni

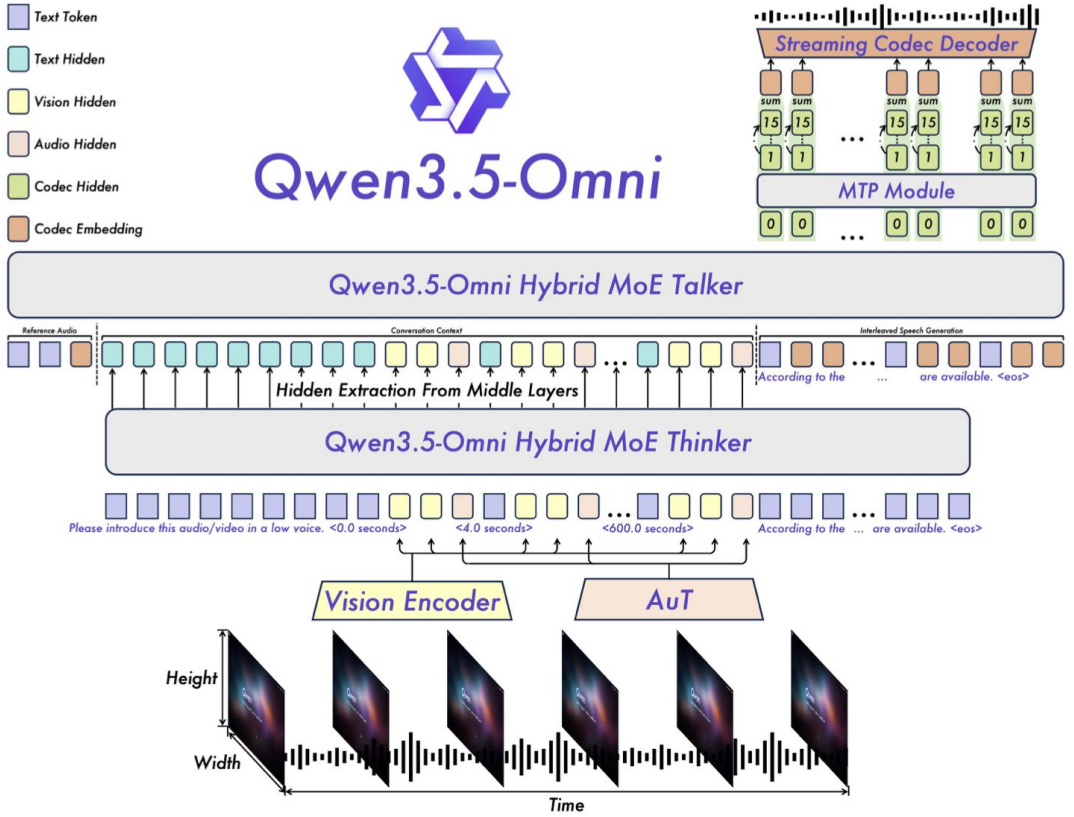
Stages

1. **Encoder alignment:** AuT, vision encoder, modality adapters (Thinker frozen).
2. **Full multimodal pretraining:** Full.
3. **Audio-text / audio-video instruction tuning:** Full. Focus: ASR, speech translation, audio QA, audio-video reasoning.
4. **Talker speech generation training:** Talker, speech codec prediction heads, MTP modules (Thinker frozen). Generate expressive multi-codebook speech tokens.
5. **Code2Wav training:** Lightweight causal ConvNet vocoder (Talker/Thinker frozen).
6. **RL / post-training**: Talker and/or policy heads for better speech stability



Qwen-3.5

1. **AuT encoder pretraining:** 20M → 40M. Build stronger multilingual audio representations.
2. **Full omnimodal pretraining:** Full.
3. **Thinker post-training:** Train the **Thinker** and related modality modules. Use specialist distillation, on-policy audio distillation, and instruction tuning. To improve audio-conditioned reasoning and interaction quality.
4. **Talker general training:** Use multilingual speech data with multimodal context. Generate expressive and context-aware speech.
5. **Talker long-context training:** Extend speech generation context and improve grounding.
6. **Preference / RL alignment:** Use multilingual preference pairs. Goal to improve speech naturalness, stability, and user preference.
7. **Speaker fine-tuning:** Fine-tune lightweight speaker-specific components. Improve voice cloning, speaker similarity, and expressive control.



Instruction Datasets · English Speech & Dialog SFT

Dataset	Languages	Hours	# Examples	Use
SpeechInstruct (SpeechGPT)	English	≈9k h speech	≈2M cross-modal instructions	HuBERT-unit instr SFT
InstructS2S-200K (LLaMA-Omni)	English	≈250 h synthetic	200k spoken-instr → response	TTS-synthesised SFT
LibriSQA	English	≈960 h (LibriSpeech)	107k Part I · 214k total	Free-form spoken QA
AudioChatLlama	English	—	speech-dialog SFT (proprietary)	End-to-end speech chat
SALMONN training mix	English (mostly)	re-uses encoders	600k SQA/AQA + 50k storytelling	Generic-hearing SFT
Distil-Whisper Voice Assistant SFT	English	re-uses Whisper data	≈100k voice-dialog turns	Distilled voice-assistant SFT
VoiceBench train slices	English	synthetic + real	8 task slices · 10s of k prompts	Voice-assistant SFT (incl. safety)

Instruction Datasets · Audio QA & Captioning

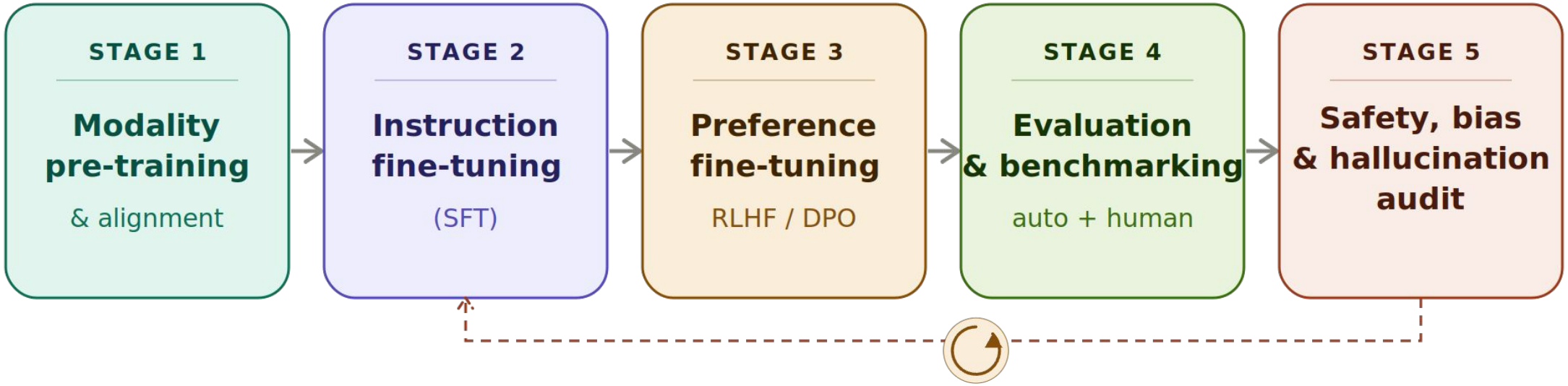
Dataset	Languages	Hours	# Examples	Use
OpenAQA-5M (LTU / LTU-AS)	English	≈5.8k → 9k h	5.6M → 9M (audio,Q,A)	Open + closed audio QA
Audio-FLAN	EN-heavy (multi-domain)	multi-source	100M+ instances · 80 tasks	Unified speech / sound / music
WavCaps	English	≈7,568 h	≈403k clip-caption pairs	Weak captions, ChatGPT-filtered
AudioCaps	English	≈128 h	≈46k clip-caption pairs	Human captions for AudioSet
Clotho	English	≈37 h	5,929 × 5 = 29.6k captions	Human-authored, retrieval
AudioSetCaps	English	≈5.8k h	≈1.9M enriched captions	LLM-assisted refinement
MMAU / MMAU-Pro	English	≈28 h	10k QA · 27 tasks	Reasoning eval (+ train mirrors)
BAT (Spatial Audio QA)	English	synth multi-channel	≈30k spatial-audio QA	Listen · spatialise · reason
Audio-Reasoner data	English	multi-source	1.2M structured CoT samples	Audio chain-of-thought
DCASE-2025 AQA	English	small subsets	Bioacoustics + Temporal + Complex	Challenge benchmark

Instruction Datasets · Multilingual

Dataset	Languages	Hours	# Examples	Use
Qwen-Audio / Qwen2-Audio mix	8+ langs (EN · ZH · JA · FR · DE · ES · IT · Cantonese)	proprietary; large	30+ tasks, NL prompts + DPO	Multitask + preference
Audio Flamingo Next (NVIDIA, 2026)	Multilingual	≈1M h audio	≈108M samples	Long-form, multi-talker, safety
Step-Audio 2 mix	Multilingual	proprietary	raw-audio in + reasoning-RL data	End-to-end audio LLM
SIFT-50M (Speech-Instruction FT)	5 langs (EN · ZH · DE · FR · ES)	≈14k h	50M instruction examples	Open multilingual SFT corpus
MLC-SLM 2025 challenge	11 langs (incl. EN · ZH · DE · FR · ES · JA · KO · RU · etc.)	≈1,604 h	real-world conversational dialogues	Multilingual conversational LLM
Emilia	6 langs (EN · ZH · DE · FR · JA · KO)	≈101k h	wild-style speech	Speech generation pretrain · gen SFT
WenetSpeech	Chinese Mandarin	22,400 h (10k labeled)	multi-domain YouTube + podcast	Mandarin ASR / instr backbone
AISHELL-1 · 2 · 3 · 4	Chinese Mandarin	170 + 1k + 85 + 120 h	multi-condition, multi-speaker	Mandarin ASR + speaker mixing
WenetSpeech-Yue	Cantonese (yue)	1k+ h	labelled + weakly-labelled	Cantonese AudioLLM training
KsponSpeech	Korean	969 h	≈2 000 speakers spontaneous	Korean SFT backbone

Recipes: Low-resource Speech Models

Recipes For Low-Resource



Singapore-Centric
Languages: English • Chinese • Malay • Tamil • Vietnamese • Indonesian • Thai • Filipino • Khmer • Lao • Burmese • Javanese • Sundanese

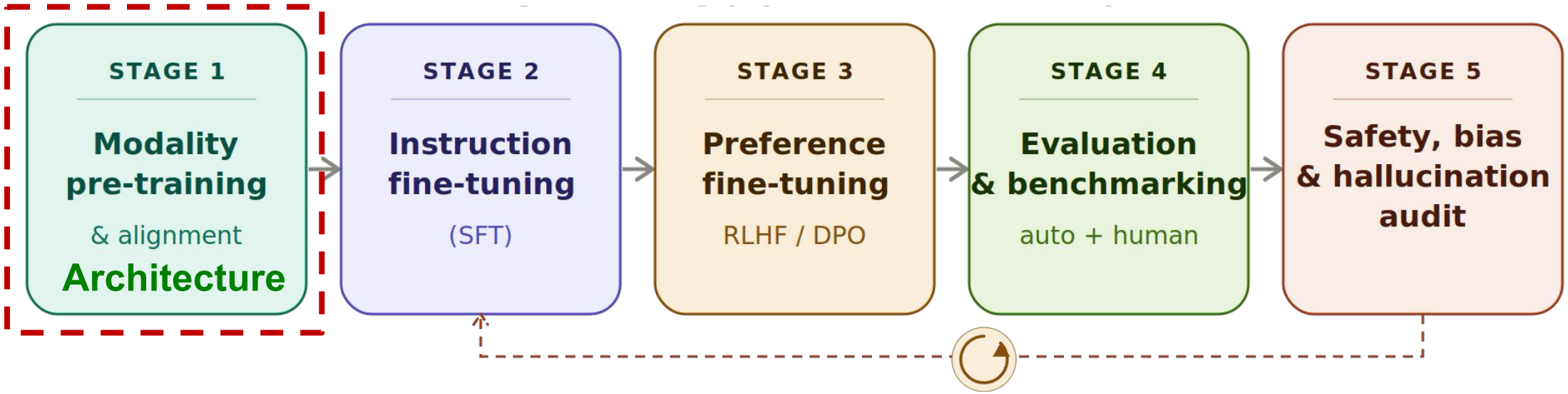
Arabic-Centric
Languages: Modern Standard Arabic (MSA), English
Dialects: Egyptian, Gulf, Levantine, North African

Tibetan (Ti-Audio)
Dialects: Amdo • Ü-Tsang • Kham

Thai-Centric
Languages: Thai (primary) + English (bilingual)

Typhoon 2: A Family of Open Text and Multimodal Thai Large Language Models (2024)
MERaLiON-AudioLLM: Bridging Audio and Language with Large Language Models (2025)
TI-AUDIO: THE FIRST MULTI-DIALECTAL END-TO-END SPEECH LLM FOR TIBETAN. (2026)
Multi-Task Instruction Tuning via Data Scheduling for Low-Resource Arabic AudioLLMs. (2026)

Recipes For Low-Resource



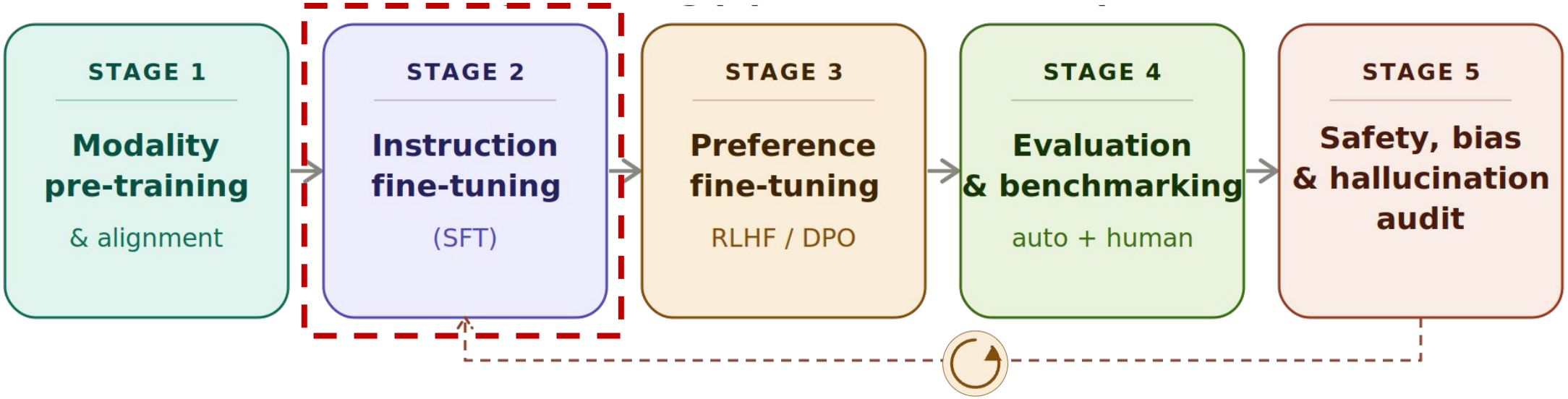
A Multilingual Base

Start from a multilingual foundation model. Speech Encoder (Whisper, MMS, XLS-R, Seamless, AuT) and LLMs.

B Language Alignment

[Optional] Fine-tuned the model to the target language distribution. Data Source: ASR, Audio Caption etc.

Recipes For Low-Resource



FT: Instruction Data • Strategies for FT • Balancing Imbalanced class/tasks/labels

Instruction Data Generation Pipelines

LLM-Based Metadata

- **Task Prompting:** Use LLMs to generate text instructions
- **Transcription:** Auto-generate "transcribe the audio" tasks
- **Translation:** Cross-lingual alignment prompts

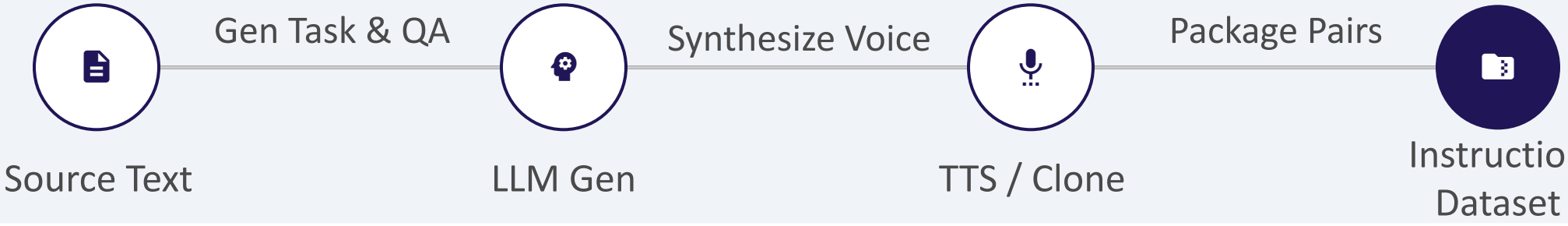
QA Generation

- **Contextual QA:** LLMs generate Q&A pairs from source text
- **Dialogue:** Simulating multi-turn spoken interactions

Synthetic Speech

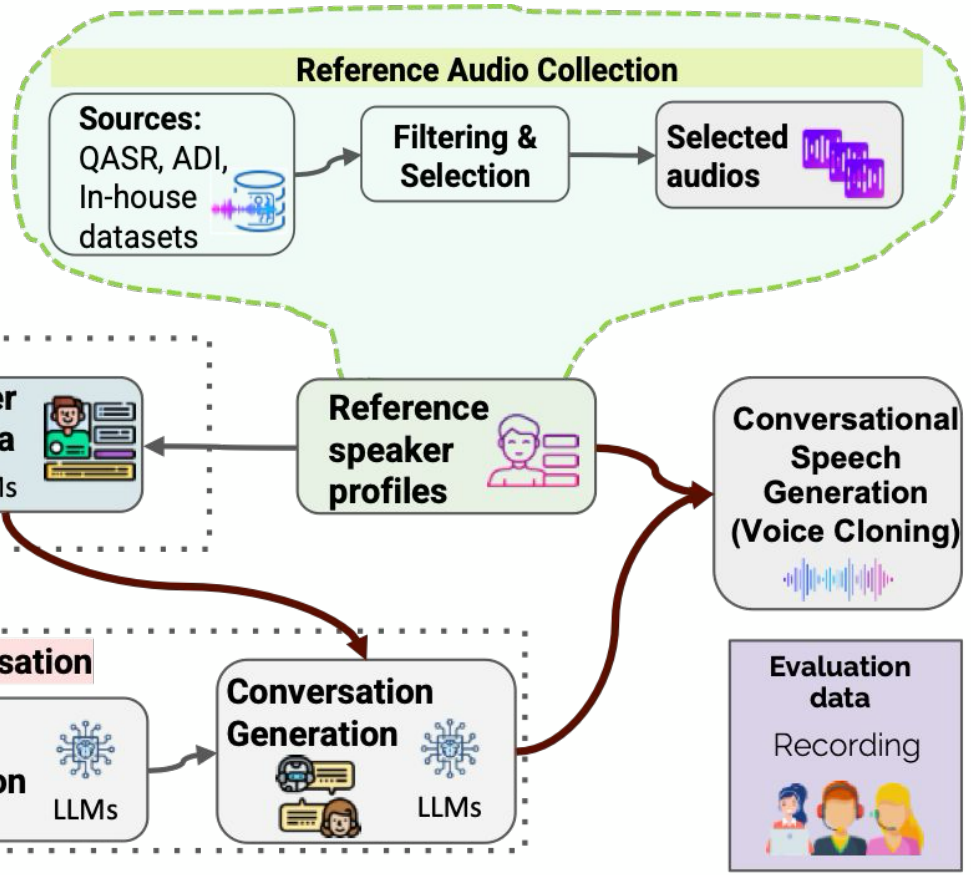
- **TTS Synthesis:** Converting generated QA into audio
- **Voice Cloning:** Using few-shot cloning for diverse speaker profiles

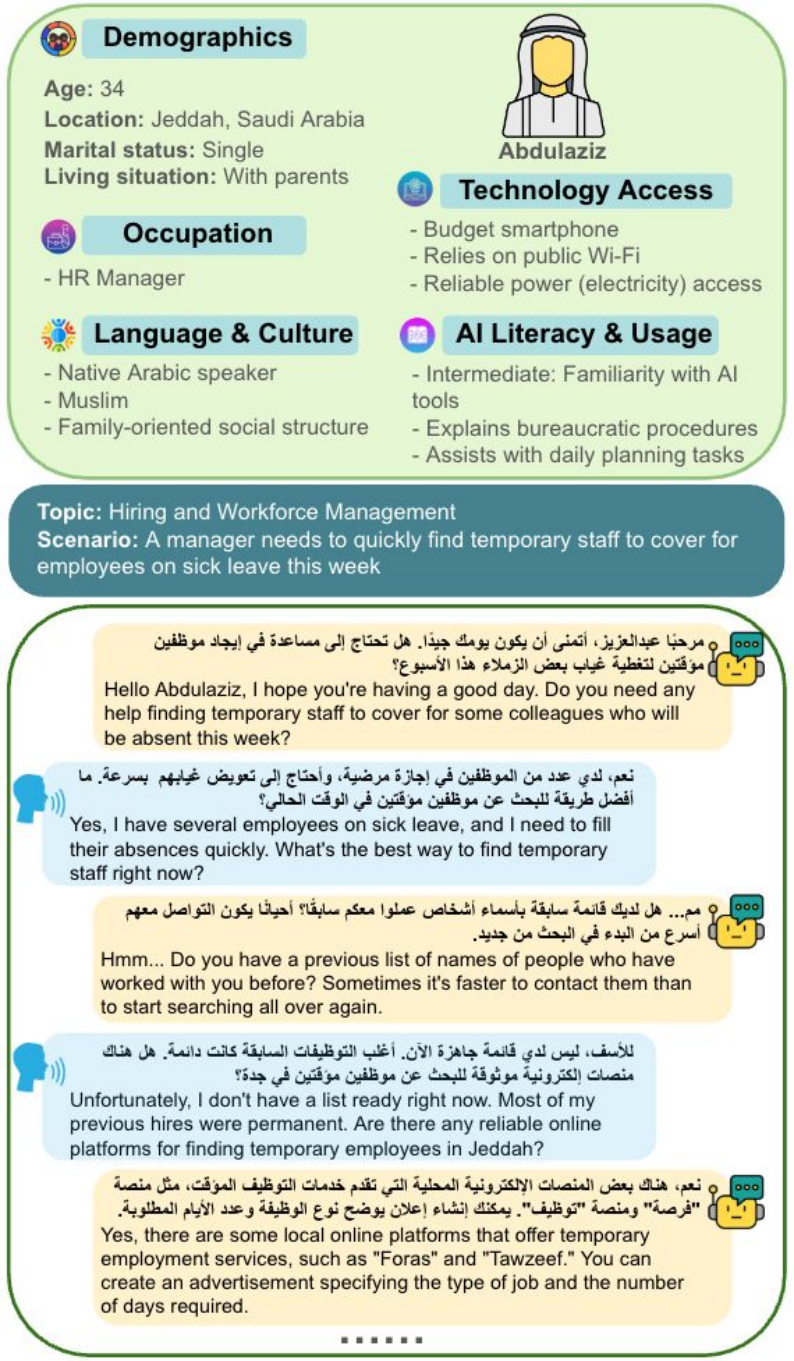
Workflow Diagram



Speech Instruction Data

MENA Speech Bank





17,641	124	18	417K	5K
utterances	unique speakers	countries	conversations	taxonomy driven scenarios

https://huggingface.co/datasets/QCRI/MenaSpeechBank

Ali et al. MENASpeechBank: A Reference Voice Bank with Persona-Conditioned Multi-Turn Conversations for AudioLLMs, 2026

Speech Instruction Data

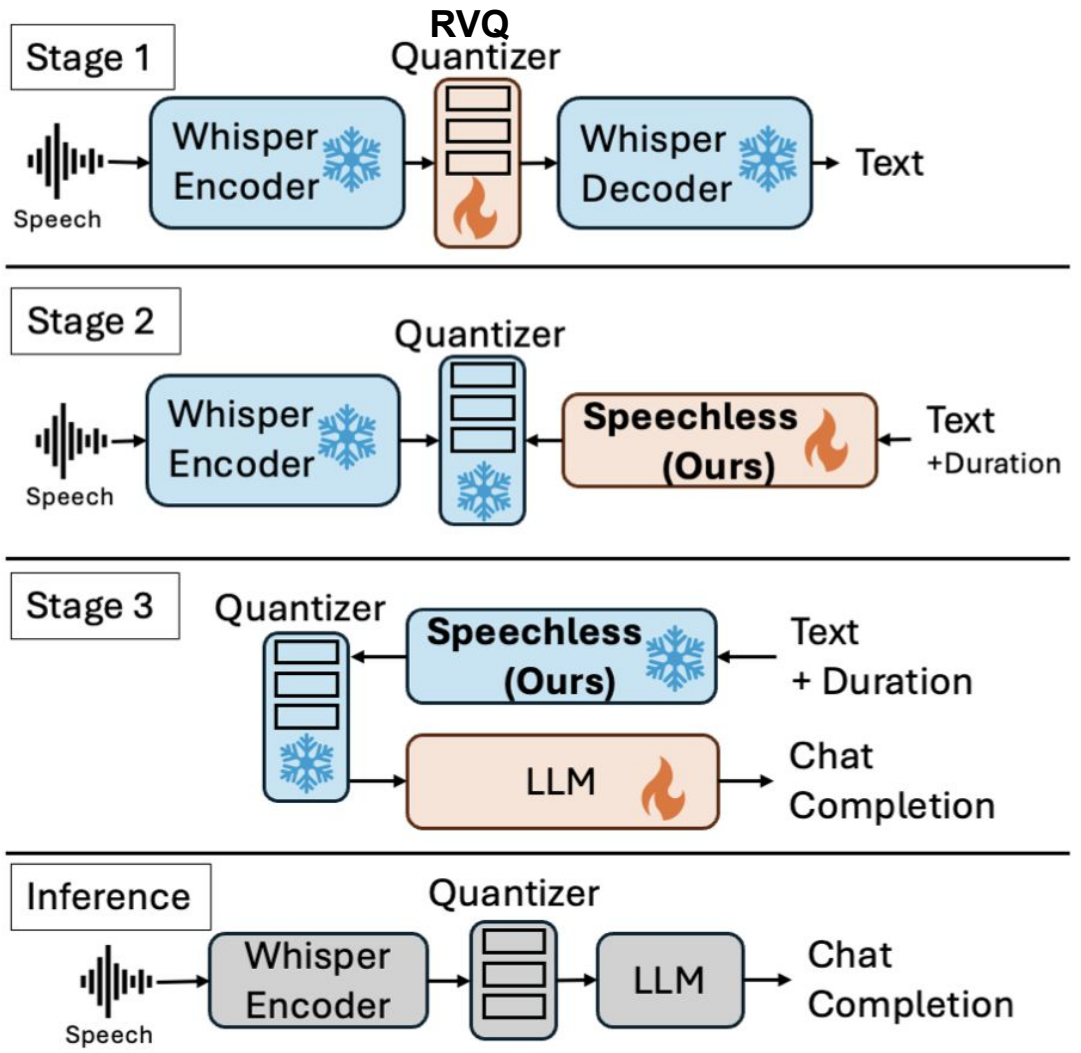
- Trained using: 330k multiturn (Avg. 5 turn/conversation)
- Human Test: 200 Conversation (recorded)
- **Average Rubric Score (ARS)**, computed as the mean pass rate across rubric checks, and
- **Average Pass Rate (APR)**, computed as the fraction of turns that satisfy the required rubric checks jointly (i.e., an over all pass).

Models	Synthetic				Human			
	Conversation		*Turn*		*Conversation*		*Turn*	
	APR	ARS	APR	ARS	APR	ARS	APR	ARS
Large Closed Models								
Gemini-2.5 pro	0.155	0.288	0.391	0.814	0.044	0.399	0.274	0.691
GPT-audio	0.214	0.449	0.423	0.893	0.005	0.314	0.247	0.681
GPT-audio (STT) + GPT-5.2-chat	0.694	0.302	0.573	0.928	0.680	0.288	0.548	0.930
Open and Fine-tuned Models								
Qwen2.5-Omni-7B	0.010	0.099	0.048	0.503	0.005	0.100	0.046	0.490
Qwen2.5-Omni-7B FT	0.000	0.252	0.137	0.599	0.015	0.271	0.128	0.589
Arabic-centric Models (ASR + LLM)								
Fanar (Aura) + ALLaM-7B	0.053	0.332	0.305	0.812	0.024	0.310	0.291	0.801
Fanar (Aura) + Fanar-C-1-8.7B	0.393	0.664	0.576	0.878	0.388	0.674	0.564	0.883
Fanar (Aura) + Fanar-C-2-27B	0.408	0.707	0.607	0.900	0.415	0.694	0.594	0.892

Ali et al. MENASpeechBank: A Reference Voice Bank with Persona-Conditioned Multi-Turn Conversations for AudioLLMs, 2026

Speech Instruction Data

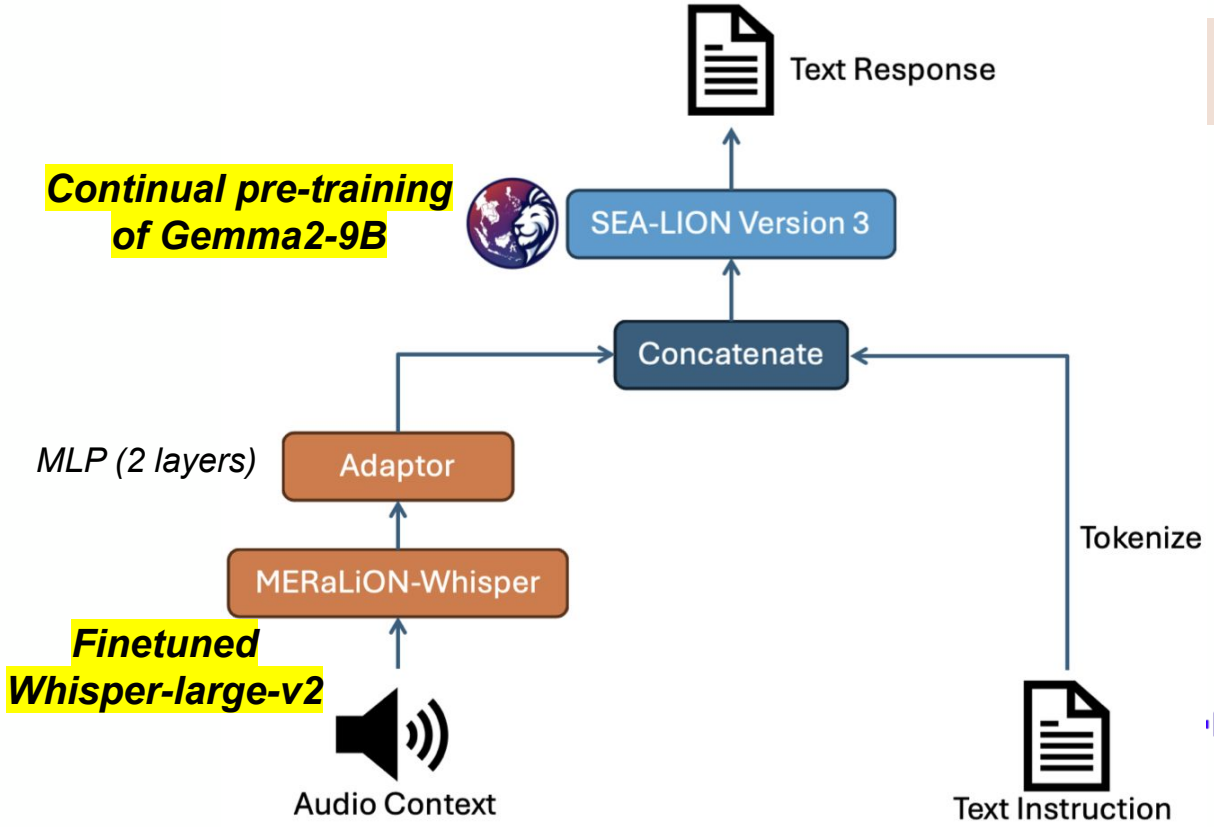
- TTS is a luxury for low-resource.
- **Core Idea is to simulate speech-representation instead of having the speech instruction itself !**



Speechless: Speech Instruction Training Without Speech for Low Resource Languages. 2025

MERaLiON-AudioLLM

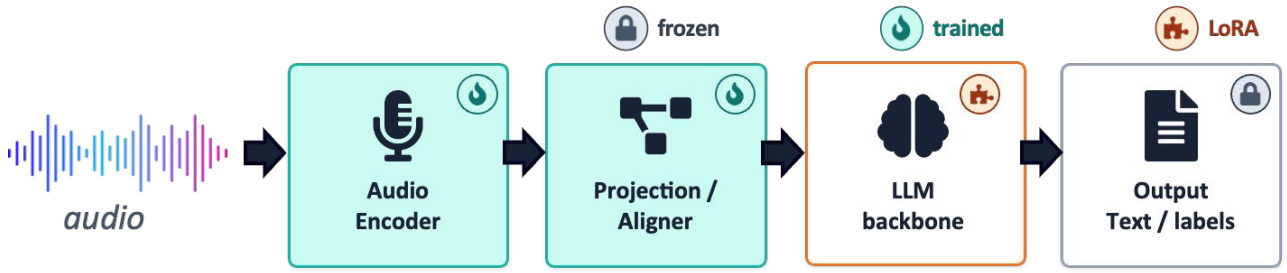
Languages: English • Chinese • Malay • Tamil • Vietnamese • Indonesian • Thai • Filipino • Khmer • Lao • Burmese • Javanese • Sundanese



260K hrs

Speech-text instruction pairs
Public + synthesised + curated data

1. **Local speech encoder adaptation**
2. **Multimodal Instruction Fine-tuning**



MERaLiON Instruction Data Overview

260K hrs
Speech-text instruction pairs
Public + synthesised + curated data

13+ langs
Coverage

6 Tasks: ASR, ST, SQA, SDS, Para (Gender/Emotion/..)
Instruction Types

National Speech Corpus (NSC) — 10,600 hrs

Part 1-2 6,500 hrs	Prompted readings — people, food, brands
Part 3 900 hrs	Conversational data — daily life, games
Part 4 900 hrs	Code-switching — Singlish + Mother Tongue
Part 5 1,000 hrs	Scripted recordings across domains
Part 6 1,300 hrs	Simulated phone calls — hotel, bank, govt

Speaker metadata (gender, age, ethnicity, L1) used for paralinguistics tasks. Verified + filtered for label accuracy.

Public Datasets

GigaSpeech	10K hrs English multi-domain ASR
GigaSpeech 2	SEA languages — Thai, Indonesian, Vietnamese
Common Voice	Massively multilingual crowd-sourced speech
AudioCaps	Audio event captioning with descriptions
VoiceAssistant-400K	400K instruction-following pairs
YODAS2	Large-scale diverse audio data

Synthesised + Augmented

SDS	Spoken Dialogue Summarization
SQA	Speech Question Answering
GR	Gender Recognition from speech

MERaLiON-AudioLLM

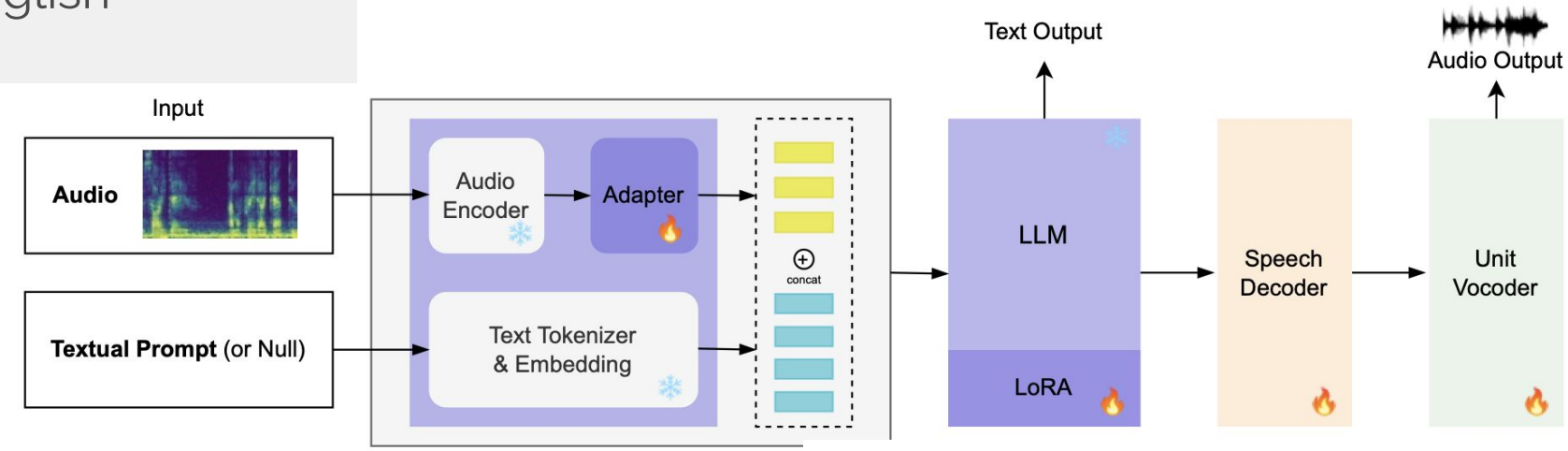
- **Local speech adaptation plus multitask instruction tuning (even synthetic) improves speech-language understanding for Singapore-centric audio tasks.**

- **Key lesson: regional AudioLLMs need local speech, accents, and task mixtures, not only generic multilingual models**

Typhoon2-Audio

2.46M total training examples (1.82M pre-train + 640K SFT)

Languages: Thai (primary) + English (bilingual)



Audio Understanding:

1. Pre-training: Trains Q-Former + MLP adapter for audio-to-LLM alignment (ASR, AC)
2. SFT: Adapter + LoRA

Component	Initialization
Whisper Encoder	Thonburian Whisper
BEATs	BEATs pre-trained weights
Q-Former	Randomly Initialized
Linear Layers	Randomly Initialized
LLM	Typhoon2-8B (Llama-3.1-based)
Speech Decoder	Randomly Initialized
Vocoder	Randomly Initialized

Speech decoder training:

1. Train decoder to predict discrete speech units from LLM hidden states.
   - Use CTC loss.
2. Vocoder training: Train HiFi-GAN-style unit vocoder.

Experiment	#Ex	ASR*↓	Th2En↑	SpokenQA↑	SpeechIF↑	ComplexIF†↑
Pre-trained	-	**13.52**	0.00	28.33	1.12	1.41
100% English SFT	600K	80.86	6.01	36.88	1.48	6.35
Our SFT recipe	640K	16.89	**24.14**	**64.60**	**6.11**	**7.54**

Typhoon2-Audio

Pre-training Data (1.82M examples)

ASR-EN	LibriSpeech + GigaSpeech (English read/web speech)
ASR-TH	CommonVoice 17 + GigaSpeech 2 (Thai spontaneous)
AC-EN	AudioCaps + Clotho (English audio descriptions)
AC-TH	AudioCaps + Clotho translated to Thai
NOTE	Adapter-only training; encoder frozen throughout

No Thai audio captioning exists natively; all translated via Typhoon LLM.

SFT Data (640K examples)

ASR	English + Thai transcription with diverse prompts
ST	Speech translation (TH→EN, EN→TH, CoVoST2)
QA	Audio document QA from SALMONN + LTU data
AC	Audio captioning with GPT-4o generated prompts
SIF	Speech instruction following (TTS-synthesised Thai)
GC	Gender classification from FLEURS (EN + TH)

Strategy

TTS	TTS-synthesised Thai speech instructions (no native data exists)
MIX	90/10 EN/TH ratio in SFT; 10% prompt translation to Thai

Typhoon2-Audio

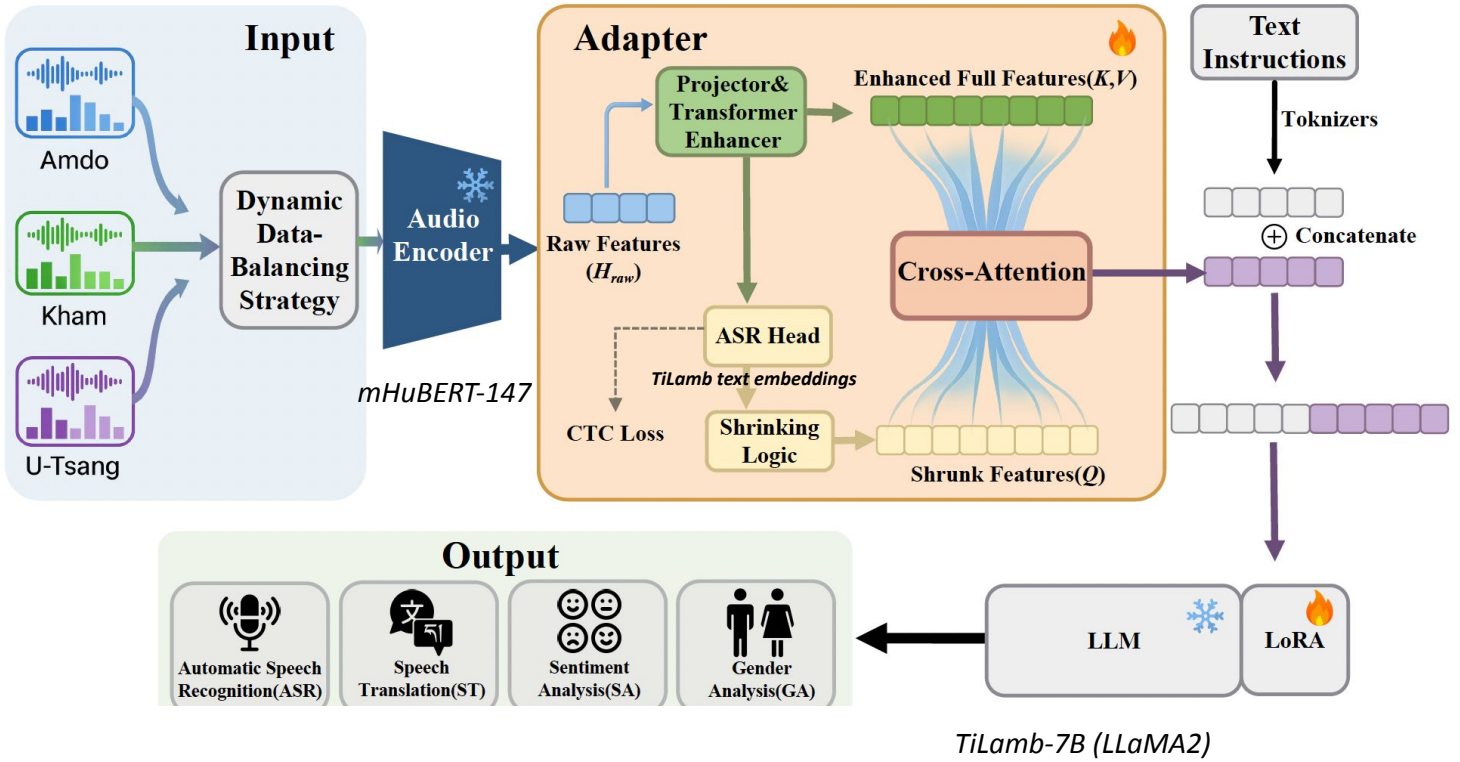
- **Thai-specific adaptation (adapter + LoRA-LLM) improves Thai audio performance while preserving broader English/multimodal capabilities.**

- **Key lesson:** low-resource AudioLLMs benefit from language-specialized encoders, adapter training, and efficient LoRA-based SFT. Synthesized data is also a key!

Ti-Audio

499 hrs Total audio from 6 Tibetan speech datasets, 319K+ samples

Dialects: Amdo (26.9%) • Ü-Tsang (46.9%) • Kham (24.9%)



TiLamb-7B (LLaMA2)

1. **Computes sampling probability using temperature-aware sampling**
   - Uses dialect-task pair size and a temperature hyperparameter
   - Upsamples low-resource combinations
   - Prevents overfitting to mainstream dialects
2. **Train Dynamic Q-Former Adapter for speech–LLM alignment.**
   - Use CTC loss (peaks) to guide informative frame selection.
3. **Apply LoRA to adapt the Tibetan LLM.**
   - Jointly optimize generation loss + CTC loss.

Key Results

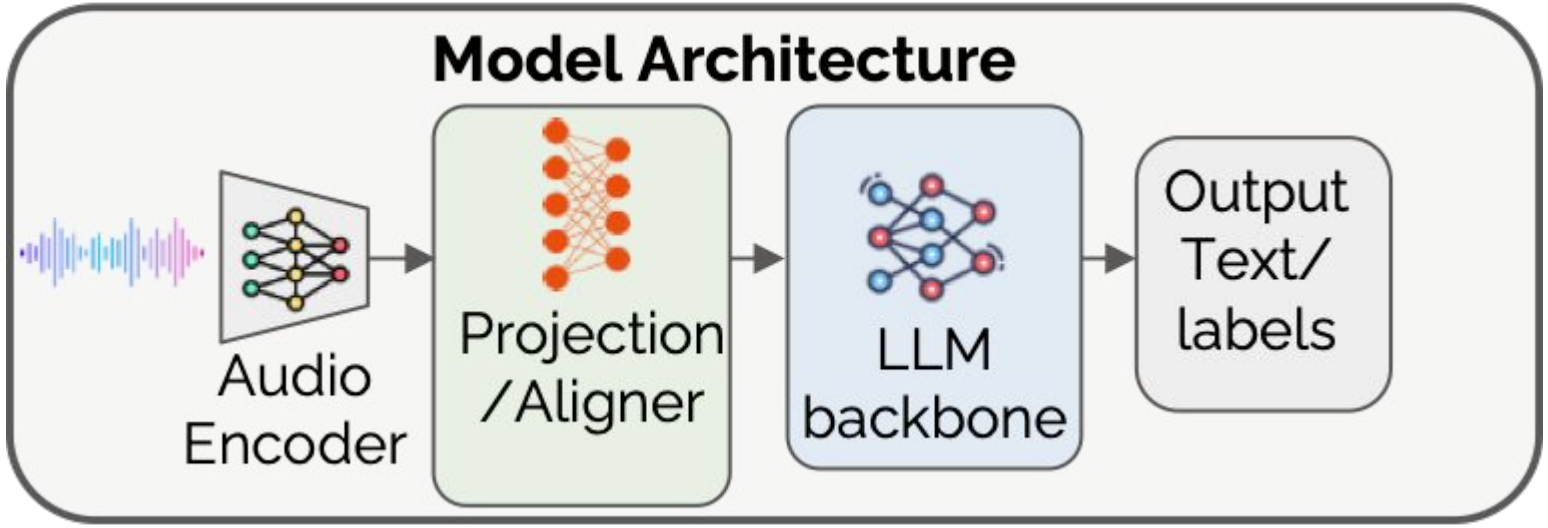
E2E	Outperforms cascaded mHuBERT+LLM and Meta Omnilingual (WER 73%)
DIAL	Cross-dialect training improves all 3 dialects consistently
12%	WER reduction over baselines via Dynamic Q-Former Adapter

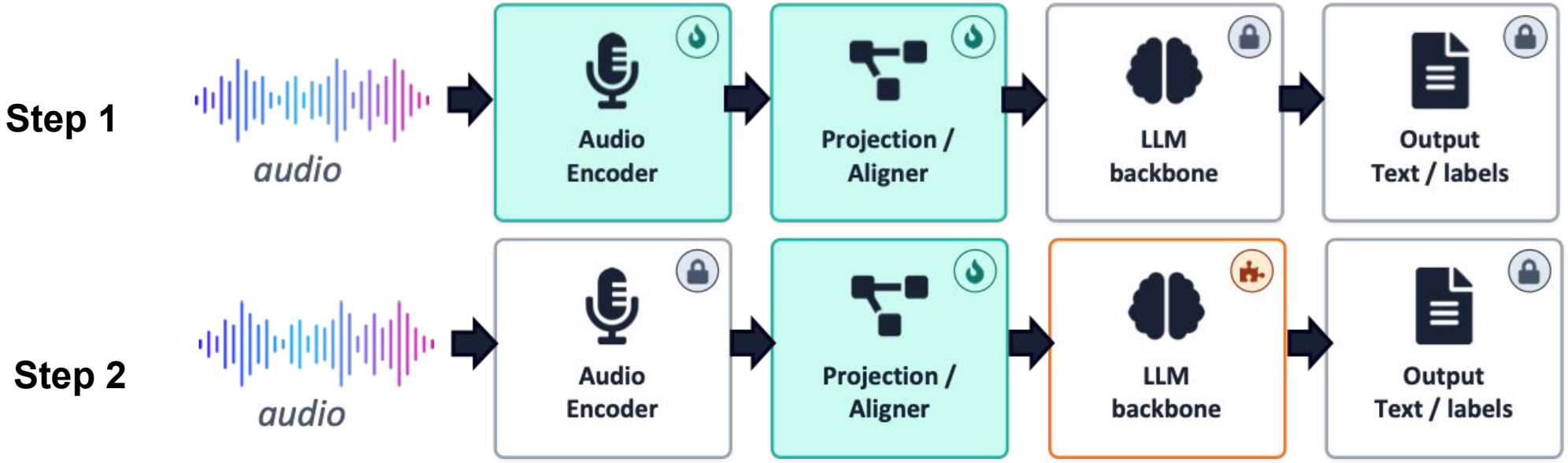
Ti-Audio

- **Cross-dialect joint training outperforms isolated dialect training and achieves state-of-the-art results on Tibetan ASR and speech translation benchmarks.**

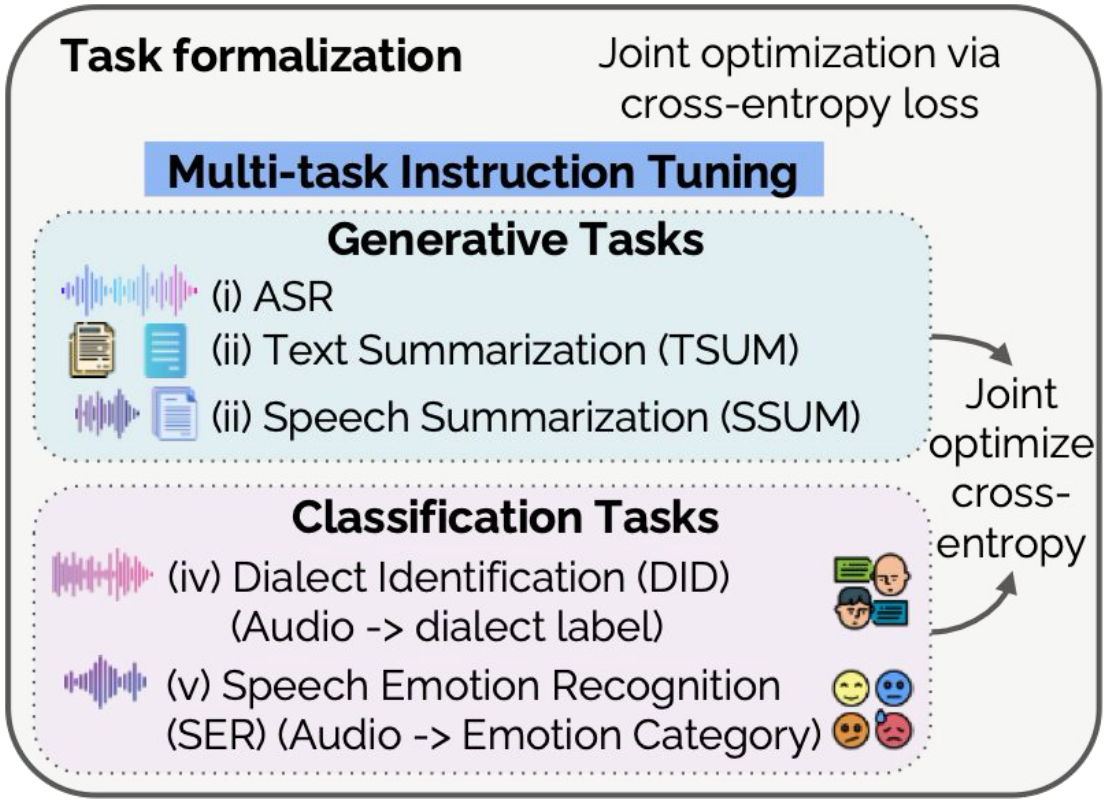
- **Key lesson:** Related dialects can help each other when sampling is balanced and alignment is data-efficient.

Arabic AudioLLM

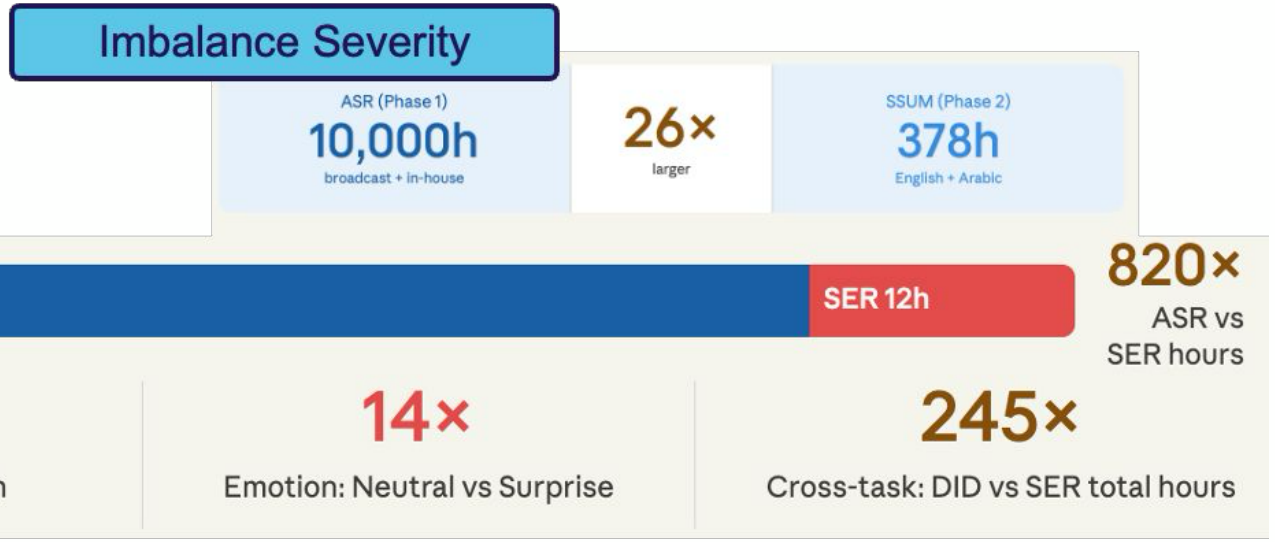




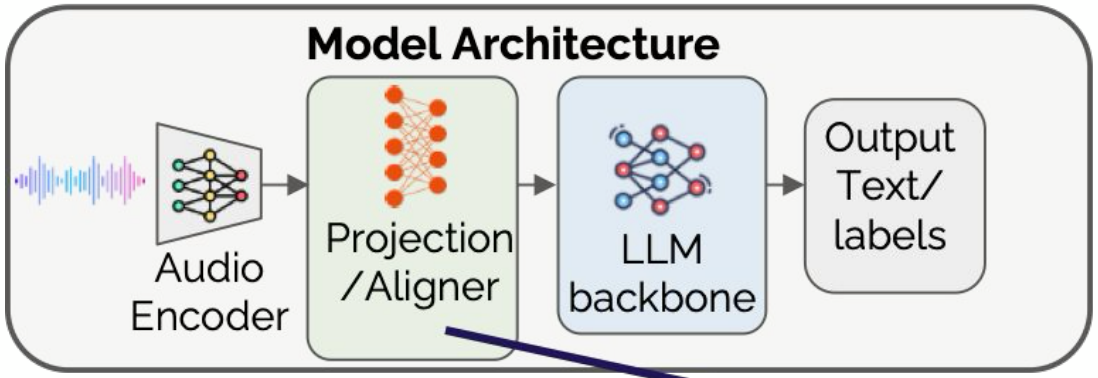
Arabic AudioLLM

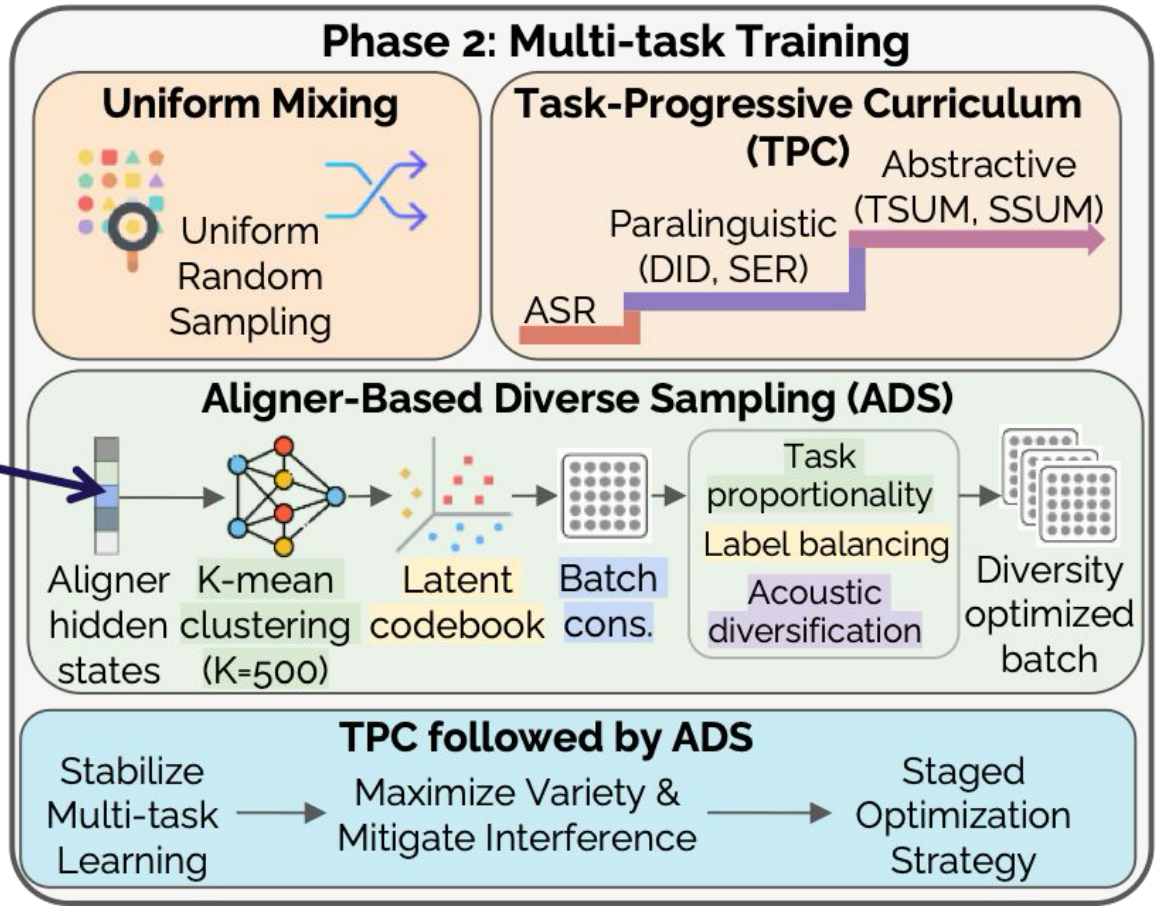


Phase 2: Multi-task Training			
Gen.	ASR	20% subset of Phase 1	≈1,740h
Gen.	SSUM	MegaSSUM (Matsuura et al., 2024) + AraMega-SSum (ours)	378h
Gen.	TSUM	MegaSSUM (Matsuura et al., 2024) + AraMega-SSum (ours)	101,242#
Disc.	DID	ADI-17 (Shon et al., 2020) + ADI-5 (MSA only) (Ali et al., 2017b)	≈2,983h
Disc.	Emo.	ANAD (Klaylat et al., 2018) + EAED (Safwat et al., 2023) + KEDAS (Belhadj et al., 2022) + KSU (Meftah et al., 2021) + BAVED (Aouf, 2020) + YSED (Derhem et al., 2025)	12.17h
Total			**5,113h + 101,242#**



Arabic AudioLLM





Findings

01 — Curriculum ordering improves ASR, weakens paralinguistics

02 — ADS accelerates paralinguistic learning, trades off generative quality

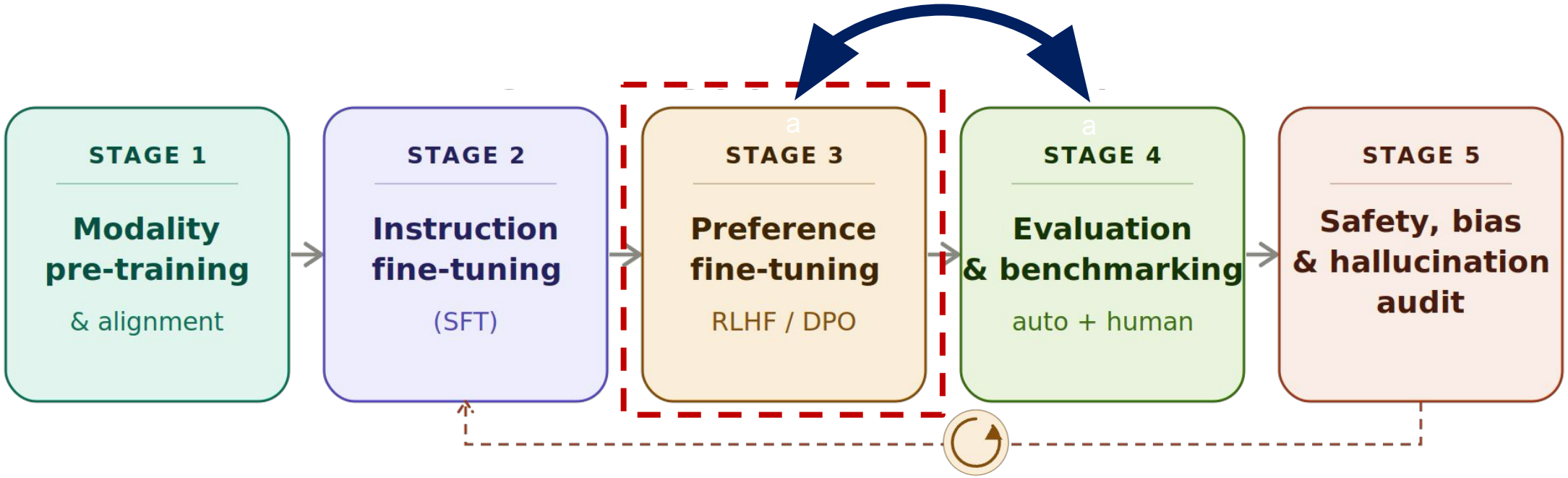
03 — TPC→ADS hybrid gives the most balanced performance

Bhatti et al., Multi-Task Instruction Tuning via Data Scheduling for Low-Resource Arabic AudioLLMs, 2026

Instruction Datasets · Low-Resource & Dialectal

Dataset	Languages	Hours	# Examples	Use
MENASpeechBank	Arabic (MSA · Egyptian · Maghrebi · Gulf · Levantine) + EN	26.4 h ref + synthetic	18k utt · 124 spk · ≈417k dialogues	Persona-conditioned MENA dialog SFT
MERaLiON-AudioLLM	Singlish · EN · Malay · Tamil · Mandarin	≈260k h	62M multimodal instructions	Dialect-aware Southeast Asia
Typhoon-Audio SFT	Thai + English	re-uses public	1.82M PT · 640k SFT	Low-resource Thai instruction
BhasaAnuvaad	13 Indian langs (Hi · Ta · Bn · Te · Mr · Gu · Ka · Ml · Pa · Or · As · Ne · Ur)	≈44,400 h	17M text seg · S2T	Indic AST training
IndicVoices-R	22 Indic langs (multi-dialect, multi-domain)	≈1,600+ h	speaker- and dialect-balanced	Open Indic multilingual SFT
IndicST	8 Indian langs ↔ EN	smaller, matched	translation pairs	Indian Speech LLM AST
Indic-TEDST	9 Indian langs	≈203 h	EN⟶Indic TED talks	Indic ST eval/train
Inkuba Instruct (text)	5 African langs (Hausa · Swahili · Zulu · Yoruba · Xhosa)	— (text only)	MT · NER · QA · classification	Text instruction ⟶ audio adapt
African ASR pseudo-labels	Kinyarwanda · Luganda · Swahili · Amharic · Yoruba	≈3,800 + 1,700 + 1,100 h	ASR corpora used for SFT bootstrap	African low-resource AudioLLM
Ti-Audio Tibetan dialect mix	Tibetan dialects (Lhasa · Kham · Amdo)	small — pooled across dialects	dialect-balanced QA + ASR	Multi-dialect Tibetan SpeechLLM

Recipes For Low-Resource



Most pre-2024 AudioLLMs skip Preference training entirely.

Voice-dialog systems and reasoning-heavy models add it on top of SFT.

Preference Data

Work	Task	Preference data	Learning method	Main finding
SpeechAlign	TTS / codec LM	Gold codec tokens preferred over synthetic tokens; human verification	DPO / PPO iterative alignment	Bridges train–inference distribution gap; improves speech generation
Speechworthy ITLM	Text response for speech delivery	20K response pairs from Dolly prompts with listened judgments	Reward model + preference tuning	Models learn more speakable, concise responses
IPO	Audio captioning + speech translation	Few hundred human referee labels over beam hypotheses	Imbalanced Preference Optimization	Weak and strong models improve from limited feedback
BPO-AVASR	Audiovisual ASR	Simulated audio/vision corruptions and transcript rewrites	Bifocal Preference Optimization	Improves real-world video ASR by emphasizing correct vs. error pairs
Spoken dialogue	Full-duplex S2S dialogue	>150K preference pairs from raw multi-turn conversations with AI feedback	Offline alignment	Covers linguistic content plus timing, interruption, and turn context

Mainly focus on the Generation Part!

Research Trends 2025–2026

Real-time omni	**GPT-4o · Qwen2.5-Omni · Step-Audio 2** — streaming, low-latency conversation.
Audio reasoning	**Audio-Reasoner · Step-Audio-R1 · ART** — beyond transcription, into multi-hop reasoning.
Preference alignment	**FPO · INTP · DPO-SE** — DPO and reward modelling for TTS and audio enhancement.
Low-resource LLMs	**Speechless · Ti-Audio · MERaLiON** — cross-lingual adaptation and in-the-wild benchmarking.
Long-context audio	Lectures · meetings · field recordings — **New benchmarks** emerging for long-form understanding.

QA