AURELIA: Test-time Reasoning Distillation in Audio-Visual LLMs

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https://schowdhury671.github.io/aurelia_project/

Abstract

Recent advancements in reasoning optimization have greatly enhanced the performance of large language models (LLMs). However, existing work fails to address the complexities of audio-visual scenarios, underscoring the need for further research. In this paper, we introduce AURELIA*, a novel actor-critic based audio-visual (AV) reasoning framework that distils structured, step-by-step reasoning into AVLLMs at test time, improving their ability to process complex multi-modal inputs without additional training or fine-tuning. To further advance AVLLM reasoning skills, we present AVReasonBench, a challenging benchmark comprising 4500 audio-visual questions, each paired with detailed step-by-step reasoning. Our benchmark spans six distinct tasks, including AV-GeoIQ, which evaluates AV reasoning combined with geographical and cultural knowledge. Evaluating 18 AVLLMs on AVReasonBench reveals significant limitations in their multi-modal reasoning capabilities. Using* AURELIA*, we achieve up to a 100% relative improvement, demonstrating its effectiveness. This performance gain highlights the potential of reasoning-enhanced data generation for advancing AVLLMs in real-world applications.*

1. Introduction

Multi-agent AI systems powered by LLMs have excelled in structured reasoning tasks, including mathematical problem-solving [63, 74, 84, 86], coding assistance [95], and drug discovery [64]. These systems often employ systematic problem decomposition, as in chain-of-thought (CoT) reasoning [78]. More advanced approaches optimize reasoning through outcome reward models [87, 93], which refine solutions based on final results, and process reward models [39, 47, 91], which assess and improve intermediate steps.

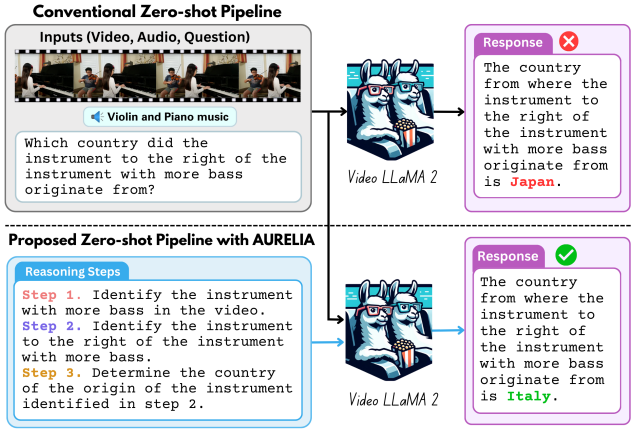

Figure 1. **Effect of injecting reasoning steps.** AURELIA enhances the ZS capabilities of audio-visual models (e.g., VideoLLaMA2). The conventional pipeline struggles in audio-visual comprehension, leading to incorrect responses. In contrast, AURELIA systematically breaks down the problem into intermediate reasoning steps, guiding the model toward more accurate and interpretable answers.

Real-world reasoning extends beyond structured text-based tasks, often requiring multimodal integration, especially in audio-visual (AV) environments. Identifying a music performance's origin, for instance, involves both visual cues (e.g., attire, instruments) and audio cues (e.g., melody, language). AV reasoning is crucial for capturing abstract nuances that text or images alone cannot convey. Despite advancements in multimodal LLMs [9, 40, 60, 65, 66, 68, 75, 94], most benchmarks remain image-text focused, overlooking audio's role and its interplay with visual signals. AV reasoning presents unique challenges. Firstly, unlike static images, AV data unfolds over time, requiring models to track events, infer temporal relationships, and integrate multi-frame context. Secondly, audio often lacks direct textual mappings, making structured interpretation harder. For example, a roaring crowd may signal excitement at a concert

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or unrest at a protest—context is essential for disambiguation. Current models often struggle with AV reasoning, relying on biases rather than deep cross-modal comprehension.

Moreover, current AVLLMs are susceptible to cultural, contextual, and perceptual biases embedded in their training data. As illustrated in Fig. 1, an AVLLM might incorrectly associate a musical instrument with Japan due to the presence of East Asian musicians and a Japanese track, even when the actual answer is Italy. This highlights the models' tendency to depend on dominant visual or auditory cues rather than true reasoning. While recent advances in test-time reasoning [33, 78, 97] have significantly improved text-based LLMs, these techniques remain largely unexplored for AV models.

To address these shortcomings, we introduce **AURELIA**, a test-time multi-agent reasoning distillation framework for addressing challenges in audio-visual cross-modal comprehension by mitigating visual and auditory biases without the need for additional training. Specifically, AURELIA employs an interactive LLM-based multi-agent framework that harnesses the reasoning capabilities of LLMs to iteratively generate high-quality reasoning data required for multimodal audio-video understanding. By leveraging the reasoning data, our approach distills structured reasoning into AVLLMs, enhancing their capabilities in multimodal audio-video commonsense reasoning, geographical understanding, music comprehension, and humor understanding.

To rigorously assess AVLLMs' reasoning capabilities, we further introduce **AVReasonBench**, a comprehensive benchmark comprising 4500 audio-visual questions, each paired with detailed step-by-step reasoning solutions generated through our pipeline. Our benchmark suite spans six distinct tasks, including the novel **AV-GeoIQ** task for geographical and cultural reasoning. Evaluating 18 existing AVLLMs on AVReasonBench reveals significant deficiencies in their ability to process dynamic audio-video content. However, incorporating AURELIA-generated reasoning solutions significantly enhances AVLLMs' performance, highlighting the impact of structured test-time reasoning. We summarize our contributions below:

- We present AURELIA, *a scalable and automated pipeline* for generating high-quality Audio-Visual reasoning data, serving as both an evaluation resource and to the best of our knowledge, the *first training-free reasoning distillation framework* for Audio Visual LLMs.
- Leveraging our proposed reasoning data generation pipeline, we introduce *AVReasonBench*, a comprehensive AV benchmark featuring 4500 audio-visual samples with detailed step-by-step reasoning solutions across six diverse tasks, encompassing multimodal commonsense reasoning, music comprehension, and humor detection. Additionally, as a part of our benchmark, we introduce a novel task *AV-GeoIQ* for geographical understanding and curate 1,000 AV-Compositional and 100 AV-Meme understanding samples through careful manual inspection.
- Leveraging our curated reasoning dataset, we demonstrate *up to 100% relative improvement* in AVLLM performance through zero-shot reasoning distillation, demonstrating the effectiveness of our approach in enhancing the reasoning capabilities of AV models.

2. Related Work

Reasoning in Multimodal LLMs. Researchers have been optimizing CoT reasoning for MLLMs to tackle complex tasks. Most studies focus on extracting graphical [15, 22, 30, 71], logical [16, 32, 76, 81, 96], or textual [3, 8, 83] information from images to solve mathematical problems. LLaVA-CoT [83] explores improved algorithms for reasoning paths, while Virgo [17] examines fine-tuning data and text-to-image reasoning transferability. MAmmoTH-VL [25] developed a large multimodal instruction-tuning dataset for enhanced question-answering. In contrast, our approach specifically targets general video understanding, where various AV information aspects are continuously referenced during reasoning.

Benchmarks for Audio-Visual LLMs. The rapid advancement of MLLMs [28, 42, 55, 57, 58, 67, 98] has driven the development of increasingly challenging video understanding benchmarks, shifting the focus from basic video description and perceptual abilities [5, 7, 11, 34, 49, 52, 59] to reasoning capabilities [13, 18, 20, 37, 38, 43]. Specifically, NExT-QA [80] emphasizes causal reasoning while Video-MME [20] features questions that necessitate integrating both audio and visual cues for effective reasoning. Our proposed AVReasonBench presents more challenging questions that demand deeper reasoning, extensive world knowledge, and a more seamless integration of AV information.

Reasoning Benchmarks While text-based benchmarks like GSM8K [14] and MMLU [31] assess logical and commonsense reasoning, multimodal benchmarks are still developing. Recent efforts such as MathVista [46] and VideoQA datasets [19, 36, 77, 82] introduce vision-based tasks, but focus more on perception than deeper reasoning. Existing benchmarks also lack comprehensive challenges requiring integration of multiple modalities, such as audio, video, and world knowledge. Some works propose assessing reasoning quality in LLMs, like logical consistency checks [23, 45, 70] and adversarial reasoning tasks [13, 50], but mainly measure static performance rather than adaptive reasoning. Although multi-agent systems [26, 29, 51, 89] and collaborative reasoning frameworks [4, 62, 72] show potential, their evaluations remain fragmented across different domains.

Our work addresses these gaps by introducing a comprehensive benchmark to evaluate multimodal reasoning skills in LLMs, integrating text, vision, audio, and external knowledge. Unlike purely visual tasks, audio-visual reasoning poses unique challenges such as temporal synchronization

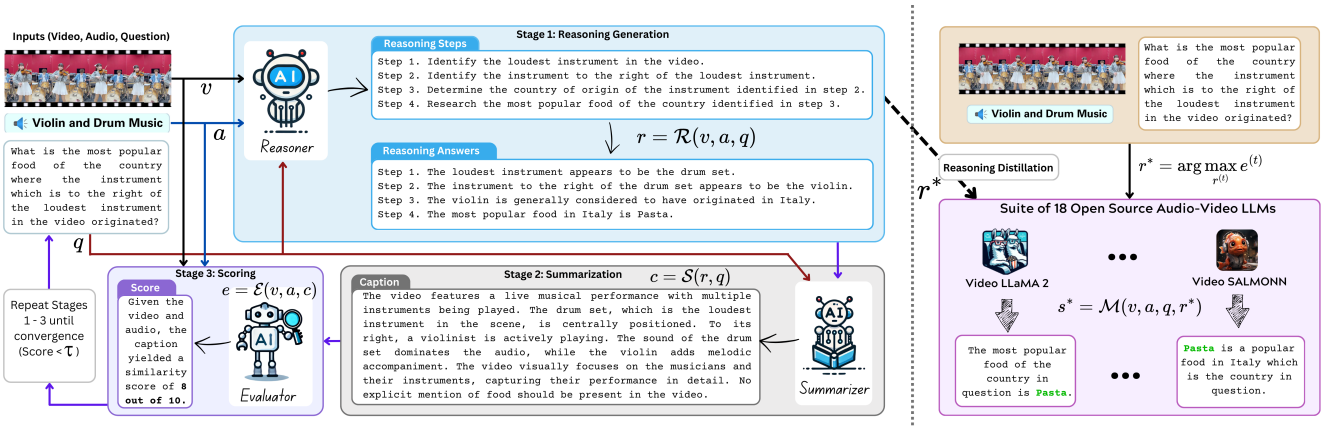

Figure 2. **Overview of AURELIA:** Our proposed AURELIA consists of a multi-agent interactive framework that functions in sync and generates reasoning steps that are then distilled inside the target model. The input set consisting of the audio, video, and question is first fed into the reasoning generator agent, which generates an initial set of reasoning steps that provide a structured pathway to reach the final answer. These reasoning steps are synthesized into a detailed caption by a Summarizer agent. The Evaluator agent then outputs a score that measures the relevance of the caption with the input audio and video. A feedback mechanism then provides supervision to the Reasoning generator based on the evaluation score, which adjusts its output to maximize the evaluation score. This actor-critique framework continues until the evaluation score exceeds a specific threshold or the number of iterations are exhausted.

of cues, ambiguity in auditory semantics, and the need for deeper cross-modal understanding.

3. Method

In this section, we will first provide an overview of audio-video multi-modal agents in Sec. 3.1, followed by a detailed description and working of AURELIA in Sec. 3.2.

3.1 Audio-Video Multi-Agent System

Our interactive audio-video multi-agent system is structured as a tuple $\langle \mathcal{R}, \mathcal{S}, \mathcal{E}, \mathcal{F} \rangle$, where multiple LLM-based agents collaboratively operate on the dataset comprising of video, audio and textual query, represented as $\langle \mathcal{V}, \mathcal{A}, \mathcal{Q} \rangle$, to enhance the performance of the target model $\mathcal{M}$. As shown in Fig. 2, the reasoning generator agent $\mathcal{R}$ processes the input video $v \in V$ and audio $a \in A$ and produces a sequence of reasoning steps r necessary for answering the given question $q \in Q$. Leveraging this information, the summarizer agent $\mathcal{S}$ extracts key cues and synthesizes them into a concise caption s that encapsulates the core content of both the video $v \in \mathcal{V}$ and the audio $a \in \mathcal{A}$. The relevance of the reasoning steps generated by $\mathcal{R}$ is assessed by the quality of the caption produced by $\mathcal{S}$. This assessment is conducted by the evaluation agent $\mathcal{E}$, a multi-modal model that takes $\{v, a, c\}$ as input and assigns a score quantifying the correctness and coherence of the reasoning steps. Based on this evaluation, a feedback mechanism ($\mathcal{F}$) iteratively refines the reasoning process by guiding $\mathcal{R}$ toward more effective reasoning paths. This interaction functions as an actor-critic framework, continuously optimizing until a satisfactory evaluation score is achieved. Ultimately, the refined reasoning steps, along with the original inputs $\langle v, a, q, r \rangle$, are fed into the target model $\mathcal{M}$. This process enhances the model's internal reasoning mechanism, leading to improved overall performance. We further present AURELIA mathematically in Algorithm 1.

3.2 AURELIA

Our proposed AURELIA enhances the performance of AVLLMS through a combination of multi-modal agents that interact with each other and generate a set of reasoning steps which distills the knowledge into the model in a training-free manner. Below, we describe the different components of AURELIA and their working in detail.

Reasoning Generator. The first component of AURELIA is a multi-modal reasoning generation agent, denoted as $\mathcal{R}$. Since our proposed method operates in a zero-shot setting, let $(x, y) \in \mathcal{D}^{test}$ represent samples from the test set, where each input x in $\mathcal{D}^{test}$ is a tuple $\langle v, a, q \rangle$, comprising a video v, an audio a, and a question q. The agent $\mathcal{R}$ processes this input tuple and produces three key outputs: a sequence of reasoning steps, a justification for these steps, and the final answer to the question. Formally,

$$r = \{r_1, r_2, r_3\} = \mathcal{R}(v, a, q), \tag{1}$$

where r_1 represents the reasoning steps, r_2 provides their justification, r_3 is the final answer to the question q.

Summarizer. The summarizer agent, denoted as $\mathcal{S}$, processes the reasoning information r generated in the previous stage along with the question q and synthesizes them into a caption c such that $c = \mathcal{S}(r, q)$. This caption provides a comprehensive summary of the video and its corresponding audio, encapsulating key details in a concise manner. The accuracy and relevance of the generated caption c depend on both the reliability of reasoning steps and the final answer produced by the reasoning generator agent. To ensure con-

sistency and correctness, we introduce an evaluation agent $\mathcal{E}$ that assesses caption in relation to given audio and video.

Evaluator. The reliability of the reasoning steps and the generated answer directly impact the summarizer agent, which synthesizes the content into a detailed caption. Consequently, the quality of the caption is inherently tied to the correctness of the reasoning process. We hypothesize that an accurate caption aligns closely with well-formed reasoning steps, ultimately leading to a correct final answer.

To assess this alignment, we introduce a multi-modal evaluation agent $\mathcal{E}$ that serves as a judge. This agent receives the video v, audio a, and the corresponding caption c as input and assigns an evaluation score e based on their coherence. The score ranges from 1 to 10, where 1 indicates minimal alignment between the caption and the input data, while 10 signifies a perfect match.

$$e = \mathcal{E}(v, a, c), \tag{2}$$

where $e \in [1, 10]$ quantifies the relevance of the caption to the input signals and, by extension, evaluates the effectiveness of the reasoning steps in deriving the final answer.

Feedback Mechanism. Based on the evaluation score obtained in the previous step, we follow an Actor-Critic framework that facilitates iterative agent improvement through a feedback loop. In this case, the Actor is the Reasoning generating agent $\mathcal{R}$ which is evaluated by another agent $\mathcal{E}$ acting as a judge and based on the evaluation score, the Critic agent provides feedback to guide the Actor Agent in regenerating improved solutions. Let $\mathcal{F}$ be the feedback mechanism facilitating the interaction between the Actor and Critic, then the goal of the feedback mechanism is to maximize the evaluation score e such that e is above a certain threshold τ.

$$r^* = \arg\max_{r^{(t)}} \quad e^{(t)}, \quad \text{s.t} \quad e^{(t)} \geq \tau, \quad t \leq T. \tag{3}$$

If $e^{(t)} \geq \beta$ at any iteration t, the process terminates and returns the corresponding reasoning steps r^*. Otherwise, the system continues iterating, refining $r^{(t)}$ through $\mathcal{F}$ until T iterations are exhausted.

Reasoning Distillation. The optimal reasoning steps r^*, obtained through the multi-agent interaction process, serve as a structured sequence of logical inferences and contextual cues that can enhance the target model ($\mathcal{M}$) response. These steps encapsulate the essential knowledge relationships and transformations necessary to bridge the input modalities to derive an accurate and well-grounded solution. In other words, the knowledge inside the reasoning information is distilled in a training-free manner inside the target model $\mathcal{M}$ which now receives a refined and enriched input containing reasoning steps, in addition to the raw audio, video and the question, that highlight key features, intermediate conclusions, and decision pathways. By conditioning the target model $\mathcal{M}$ on the distilled reasoning steps r^*, we facilitate a more structured decision-making process, reducing ambiguity and improving model interpretability. The optimal solution s^* is formulates as,

$$s^* = \mathcal{M}(v, a, q, r^*) \tag{4}$$

- **AURELIA** is the first multi-agent framework capable of reasoning distillation in Audio Visual LLMs through an iterative actor-critique mechanism.
- **AURELIA** systematically mitigates visual and auditory biases by enforcing a structured reasoning process, leading to more objective and reliable cross-modal comprehension.
- **AURELIA** can scale and generalize to diverse audio-visual reasoning tasks due to zero-shot nature, where fine-tuning methods often fail due to training biases.

4. AVReasonBench: Audio-Visual Reasoning Benchmark

4.1 Why Designing AV Reasoning Tasks are Difficult?

Limitations in Forming Question-Answer Pairs for AV Setup. In vision-language tasks, the formation of question-answer pairs is relatively simple since objects have visible attributes (e.g., "What color is the book?"). However, in audio-visual reasoning, many objects do not make an inherent sound, making it harder to design meaningful QA pairs. For instance, "What does the book sound like?" lacks relevance unless an action (e.g., flipping pages) is involved. This necessitates carefully crafting interactions where both audio and visual cues contribute meaningfully.

Ambiguity in Audio-Visual Associations. Interpreting emotional tone in audio-visual tasks is challenging because the same visual cue, such as laughter, can convey different meanings depending on the accompanying audio. Cheerful music may indicate joy, while eerie background sounds might suggest nervousness or fear. Unlike vision-language tasks, where textual cues explicitly define emotions, AV models must infer meaning from the interplay of sound and visuals, requiring deeper multi-modal understanding. To encompass these scenarios we incorporate AV compositional understanding, meme understanding and dance matching tasks.

Cultural and Contextual Understanding. Object recognition and language understanding can often be generalised across cultures. If an image contains sushi, the model can easily label it as "sushi" using object detection and language mapping. However, AV tasks require deeper cultural and contextual awareness. For example, in music-dance matching, Flamenco music should pair with Flamenco dance rather than Hip-Hop. Similarly, laughter in a scene could indicate humour, but it could also indicate nervousness, depending on the visual cues. To address this gap we introduce AV-GeoIQ.

Audio-visual tasks pose additional challenges compared to only language or vision-language tasks due to the need for temporal synchronization [12], ambiguity resolution, noise handling, and cultural grounding. These challenges demand

Algorithm 1 AURELIA

Input: Data: D^{test}, Reasoning generator $\mathcal{R}$, Summarizer $\mathcal{S}$, Evaluator $\mathcal{E}$, Iterations T, Threshold τ
Output: Optimized Reasoning Steps r^*
Sample data: $\langle$Audio a, Video v, Question $q\rangle \subseteq \mathcal{D}^{test}$
Set iteration counter, $t = 1$
while $e \leq \tau$ **and** $t \leq T$ **do**
    Generate Reasoning Steps, $r^{(t)} = \mathcal{R}(v, a, q)$
    Generate Caption, $c^{(t)} = \mathcal{S}(r^{(t)}, q)$
    Evaluate Generated Caption, $e^{(t)} = \mathcal{E}(v, a, c^{(t)})$
    Feedback (Repeat Steps 6-8), $\mathcal{F}(v, a, q, e^{(t)})$
    Update $t \leftarrow t + 1$
Select Optimal Reasoning, $r^* = \arg\max_{r^{(t)}} e^{(t)}$
return r^*

more sophisticated models that can process and align multimodal inputs dynamically over time, making AV reasoning a significantly harder problem than L/VL reasoning.

4.2 Task Overview

Audio-Visual Question Answering. Audio-visual question answering (AVQA) focuses on responding to questions that require both auditory and visual understanding. To construct our dataset, we gather question-answer pairs from AVSD [1] and MusicAVQA [35] enhancing them with detailed reasoning steps. We carefully curate samples which require strong audio-visual comprehension in terms of their interplay, association, dependency, etc.

Audio-Visual Captioning. This task involves generating detailed textual descriptions based on audio-visual inputs. Unlike image- or audio-only captioning methods, it demands robust multimodal understanding and advanced reasoning capabilities. We obtain samples from VALOR [6] for this task and augment them with reasoning annotations.

Audio-Visual Compositional Attribute Understanding. Inspired by [13], in this task we ensure each AV pair contains two separate events which are associated with two different attributes. For example, 'a cow is mooing' and a 'sheep is bleating'. Here the answer choices contain the same words but in a different sequence ('cow is bleating' and 'sheep is mooing'). An AVLLM must have a strong AV and linguistic understanding to comprehend the constituent modalities and semantically align them with the correct attributes.

AV-GeoIQ. We introduce AV-GeoIQ, a *novel* audio-visual reasoning task that integrates commonsense understanding with geographical and country-specific knowledge. This task challenges models to process and reason over multimodal inputs, requiring the alignment of audio cues, visual elements, and world knowledge. Unlike standard audio-visual question-answering tasks, AV-GeoIQ extends beyond perceptual understanding by incorporating reasoning over cultural and geographic attributes. For example, a question like *"What is the most famous drink of the country where the instrument to the left of the louder sounding instrument originates?"* necessitates multiple reasoning steps: identifying the loudest instrument, determining the relative position of another instrument, recognizing its country of origin, and retrieving cultural knowledge about that country's famous drinks—leading to the answer *Sangria*. Such questions require deep multimodal comprehension, contextual association, and factual world knowledge. AV-GeoIQ (Fig. 1) serves as a benchmark to evaluate the reasoning capabilities of AVLLMs in handling complex, real-world scenarios that go beyond direct perception.

AV Meme Understanding. Inspired by AV-Odyssey Bench [24], we include AV-Meme a task that challenges models to interpret humour, sarcasm, and the context in multimodal memes by analyzing visual elements, audio cues, and text. Unlike traditional meme analysis, AV-Meme requires grasping subtle relationships between sound effects, expressions, and captions. For example, dramatic music over an ordinary event or mismatched audio-visual pairings creates irony, demanding nuanced cultural awareness. This task serves as a benchmark for evaluating AVLLMs in recognizing implicit meanings and internet humour.

Dance and Music Matching. We also include Dance-Music Matching (DM-Match) [24], a task that evaluates a model's ability to align dance movements with appropriate musical styles by analyzing audio-visual correlations. Unlike standard motion or music classification, DM-Match requires understanding rhythm, tempo, and movement patterns to determine whether a given dance sequence matches the accompanying music. For instance, a ballet performance set to fast-paced electronic music may indicate a mismatch, while a tango paired with traditional tango music would be correct. This task serves as a benchmark for assessing AVLLMs in capturing temporal synchronization, genre compatibility, and expressive coherence between dance and music.

4.3 AVReasonBench Size

We carefully curate 1000 samples each from Music-AVQA, AVSD, and VALOR which are suitable for AV reasoning. For the AV compositional understanding task, we collect 1000 samples from the web through careful manual inspection. For AV-GeoIQ we again tailor-make 200 samples which require strong AV reasoning capabilities. We augment more videos to the original AV-meme set to make a total of 100 test samples while we adapt 200 samples of DM-Match to make the total size of our reasoning benchmark, AVReasonBench to 4500. We add further details in the supplementary.

4.4 Reasoning Data Generation

For each test sample comprising an audio, a video, and a question, we supplement the input with reasoning informa-

Models	AV-QA		AV-Captioning	AV-Compositional	AV-GeoIQ	AV-Meme	DM-Match
	Music-AVQA	AVSD					
Closed-Source Models							
Gemini 1.5 Pro	70.6 / 68.9	74.7 / 72.5	84.9 / 82.7	38.9 / 36.8	71.2 / 68.0	52.0 / 49.0	43.4 / 41.5
Reka Core	67.9 / 64.3	74.5 / 69.5	83.2 / 80.4	38.6 / 35.3	45.7 / 42.5	24.0 / 19.0	35.8 / 32.5
Open-Source Models in ZS							
PandaGPT (13B)	35.8 / 33.7	29.1 / 26.1	67.8 / 64.7	28.8 / 24.1	17.2 / 12.5	25.0 / 21.0	30.2 / 27.0
Macaw-LLM (7B)	34.7 / 31.8	38.4 / 34.3	67.7 / 65.9	26.1 / 24.3	17.2 / 14.0	18.0 / 14.0	24.5 / 20.0
VideoLLaMA (7B)	39.1 /36.6	40.0 / 36.7	68.4 / 66.2	28.8 / 25.8	19.3 / 16.5	18.0 / 16.0	26.6 / 23.0
ImageBind-LLM	44.2 / 43.9	42.7 / 39.2	69.0 / 66.9	28.8 / 25.4	18.0 / 13.0	17.7 / 15.0	26.2 / 22.5
X-InstructBLIP (13B)	47.8 / 44.5	43.9 / 40.1	69.5 / 66.1	27.5 / 25.9	27.6 / 14.5	18.7 / 15.0	27.3 / 24.5
AV-LLM (13B)	48.2 / 45.2	55.4 / 52.6	70.1 / 67.6	29.6 / 26.1	18.0 / 14.5	24.4 / 20.0	29.4 / 27.0
OneLLM (7B)	49.9 / 47.6	52.3 / 49.8	71.6 / 68.1	29.7 / 26.3	20.9 / 17.0	24.5 / 18.0	28.8 / 26.5
AVicuna (7B)	51.6 / 49.6	56.2 / 53.1	71.2 / 67.9	29.6 / 26.6	19.7 / 16.5	28.4 / 23.0	29.6 / 27.0
CREMA (4B)	56.8 / 52.6	62.3 / 58.6	73.8 / 68.4	31.6 / 27.0	23.8 / 19.0	29.0 / 26.0	31.5 / 28.5
VideoLLaMA2 (7B)	-	-	70.4 / 68.3	29.7 / 26.8	25.7 / 22.0	27.5 / 23.0	28.4 / 25.5
AnyGPT (7B)	53.7 / 50.7	59.2 / 56.9	72.5 / 68.1	28.8 / 26.2	25.7 / 22.5	24.0 / 19.0	28.9 / 25.5
NExT-GPT (7B)	53.5 / 50.9	58.4 / 56.3	68.7 / 67.9	28.0 / 26.4	23.8 / 22.0	19.5 / 16.0	32.3 / 28.0
Unified-IO-2 L (6.8B)	58.3 / 55.1	60.0 / 57.9	73.8 / 70.1	31.8 / 27.2	25.6 / 21.5	26.5 / 22.0	29.3 / 27.5
Unified-IO-2 XL	61.3 / 57.2	59.7 / 58.6	73.7 / 71.8	30.0 / 28.5	24.7 / 22.5	29.0 / 26.0	29.6 / 27.0
Bay-CAT (7B)	55.6 / 53.8	58.3 / 56.5	71.9 / 69.5	31.9 / 28.2	24.4 / 20.5	22.0 / 18.0	29.8 / 27.5
Video-SALMONN (7B)	56.8 / 54.9	58.7 / 57.2	71.1 / 70.2	29.8 / 27.5	24.7 / 22.0	21.0 / 17.0	27.5 / 26.5
VITA (7B)	59.0 / 58.6	61.2 / 60.1	73.8 / 72.9	30.1 / 29.2	26.7 / 25.5	44.0 / 41.0	29.2 / 27.5
Open-Source Models with AURELIA							
PandaGPT (13B)	41.9$^{+24.33\%}$	32.7$^{+25.28\%}$	72.9$^{+12.67\%}$	28.6$^{+18.67\%}$	25.0$^{+100\%}$	25.0$^{+19.04\%}$	31.0$^{+14.81\%}$
Macaw-LLM (7B)	41.6$^{+30.81\%}$	38.1$^{+11.07\%}$	73.5$^{+11.53\%}$	29.3$^{+20.57\%}$	25.5$^{+82.14\%}$	24.0$^{+71.42\%}$	28.5$^{+42.5\%}$
VideoLLaMA (7B)	45.8$^{+25.13\%}$	41.5$^{+13.07\%}$	74.2$^{+12.08\%}$	29.6$^{+14.72\%}$	28.5$^{+72.72\%}$	28.0$^{+75.0\%}$	29.0$^{+26.08\%}$
ImageBind-LLM	49.7$^{+13.21\%}$	44.2$^{+12.75\%}$	72.8$^{+8.81\%}$	30.1$^{+18.50\%}$	28.0$^{+100\%}$	23.0$^{+53.33\%}$	31.0$^{+37.77\%}$
X-InstructBLIP (13B)	52.3$^{+17.52\%}$	46.9$^{+16.95\%}$	72.6$^{+9.83\%}$	29.8$^{+15.05\%}$	29.0$^{+100\%}$	27.0$^{+80.0\%}$	30.0$^{+22.45\%}$
AV-LLM (13B)	52.7$^{+16.59\%}$	57.9$^{+10.07\%}$	73.4$^{+8.57\%}$	31.1$^{+19.15\%}$	28.5$^{+83.87\%}$	29.0$^{+45.0\%}$	34.0$^{+25.92\%}$
OneLLM (7B)	54.1$^{+13.65\%}$	55.3$^{+11.04\%}$	73.9$^{+8.51\%}$	30.7$^{+16.73\%}$	29.0$^{+70.58\%}$	29.0$^{+61.11\%}$	33.5$^{+26.41\%}$
AVicuna (7B)	55.3$^{+11.49\%}$	57.8$^{+8.85\%}$	73.1$^{+7.65\%}$	30.4$^{+14.28\%}$	29.5$^{+79.09\%}$	34.0$^{+47.80\%}$	34.5$^{+27.78\%}$
CREMA (4B)	59.8$^{+13.68\%}$	67.2$^{+14.67\%}$	74.2$^{+8.47\%}$	31.9$^{+18.14\%}$	32.5$^{+71.05\%}$	40.0$^{+53.84\%}$	34.0$^{+19.29\%}$
VideoLLaMA2 (7B)	-	-	74.7$^{+9.37\%}$	31.6$^{+17.91\%}$	38.0$^{+72.72\%}$	35.0$^{+40.0\%}$	34.5$^{+35.29\%}$
AnyGPT (7B)	56.2$^{+10.84\%}$	62.5$^{+9.84\%}$	73.3$^{+7.63\%}$	31.4$^{+19.84\%}$	35.5$^{+57.77\%}$	33.0$^{+73.68\%}$	33.0$^{+29.41\%}$
NExT-GPT (7B)	57.8$^{+13.55\%}$	60.8$^{+7.99\%}$	73.5$^{+8.25\%}$	31.8$^{+20.45\%}$	36.0$^{+63.63\%}$	32.0$^{+100\%}$	33.5$^{+19.64\%}$
Unified-IO-2 L (6.8B)	61.9$^{+12.34\%}$	62.0$^{+7.08\%}$	74.6$^{+6.41\%}$	32.4$^{+19.11\%}$	36.5$^{+69.76\%}$	35.0$^{+59.09\%}$	33.5$^{+21.81\%}$
Unified-IO-2 XL (6.8B)	62.3$^{+8.91\%}$	62.8$^{+7.16\%}$	75.6$^{+5.29\%}$	33.6$^{+17.89\%}$	38.5$^{+71.11\%}$	40.0$^{+53.84\%}$	34.0$^{+25.92\%}$
Bay-CAT (7B)	58.5$^{+8.73\%}$	61.1$^{+8.14\%}$	75.0$^{+7.91\%}$	32.7$^{+15.95\%}$	34.0$^{+65.85\%}$	35.0$^{+94.40\%}$	32.5$^{+18.18\%}$
Video-SALMONN (7B)	59.8$^{+8.92\%}$	61.7$^{+7.86\%}$	75.2$^{+7.12\%}$	32.5$^{+18.18\%}$	37.5$^{+70.45\%}$	32.0$^{+88.23\%}$	33.0$^{+24.52\%}$
VITA (7B)	62.6$^{+6.82\%}$	66.5$^{+10.64\%}$	78.8$^{+8.09\%}$	33.8$^{+15.75\%}$	39.0$^{+52.94\%}$	50.0$^{+21.95\%}$	35.0$^{+27.27\%}$

Table 1. **Performance comparison of various models across multiple tasks in AVReasonBench**. The lower section highlights the performance improvement using AURELIA. The numbers in teal denotes relative gains over ZS results. Video-LLamA2 zero-shot is not reported because the publicly available model is already fine-tuned on the dataset. For ZS evaluation *A/B* represents best/mean of 3 runs evaluation. AV-Captioning values denote CIDEr scores.

Model	AV-Captioning		
	BLEU@4 ↑	METEOR ↑	ROUGE ↑
Zero-shot			
AVLLM	10.2	18.1	34.6
OneLLM	11.3	19.7	36.1
AVicuna	10.6	19.1	35.4
CREMA	11.5	20.1	36.9
VITA	12.9	22.8	40.3
Zero-shot with AURELIA			
AVLLM	12.8	21.9	40.7
OneLLM	14.1	24.3	42.1
AVicuna	12.8	23.7	41.8
CREMA	13.8	24.9	43.3
VITA	14.5	26.0	46.4

Table 2. **Evaluation results of five models on the AV-Captioning**. The top section indicates ZS inference results of models. The bottom section indicates results after reasoning distillation with AURELIA. Clearly, the quality of the captions improves with our reasoning pipeline.

Subset	Modality	Category						
		Knowledge	*Film & Television*	*Sports Competition*	*Artistic Performance*	*Life Record*	*Multilingual*	Overall
Short	ZS	81.4	87.5	78.7	86.7	85.6	86.7	84.4
	+ AURELIA	85.6	91.3	81.2	88.0	88.9	89.4	**87.4**
Medium	ZS	80.2	83.9	72.1	84.3	76.8	100.0	82.8
	+ AURELIA	83.3	86.5	75.9	87.1	78.2	100.0	**85.16**
Long	ZS	81.1	73.2	72.6	63.3	66.7	83.3	73.3
	+ AURELIA	85.5	77.4	75.7	67.1	69.9	86.3	**76.98**
Overall	ZS	80.9	82.4	74.6	78.8	78.0	89.7	80.7
	+ AURELIA	83.4	85.3	77.8	81.0	82.3	92.6	**83.73**

Table 3. **Performance of VITA across Video-MME**. Table shows the performance of VITA on 6 major categories of Video-MME. The evaluation is done on audio-visual inputs.

tion at inference time before feeding it into the target model through a structured multi-agent pipeline. This ensures that model decisions are grounded in logical deductions rather than implicit associations, enhancing both accuracy and interpretability. For instance, in Fig. 2, the video showcases people playing musical instruments, accompanied by audio, and the question to identify the *most popular food of the country* through a complex audio-visual referral. To answer this, the model must first *identify the loudest instrument* via audio analysis followed by determining spatial relationships to *locate the musical instrument*. Once the instrument is located, the model must infer the instrument's origin, and finally retrieve the corresponding cuisine. This structured reasoning provided by our AURELIA enforces logical progression, reducing errors and hallucinations while enhancing interpretability. We defer more details to supplementary.

Reason Gen.	Summ.	Eval.	AV-GeoIQ	AV-Comp	DM-Match
Gemini	Gemini	Gemini	36.5	30.2	33.0
Gemini	GPT-4o	Gemini	38.0	31.6	34.5

Table 4. **Effect of using a combination of agents.** Using a combination of different closed-source LLMs as agents proves beneficial compared to using a single type of LLM.

Iteration (T)	AV-Cap	AV-Meme	AV-GeoIQ	AV-Comp	DM-Match	Time
1	68.8	25.0	27.5	27.3	26.5	16.28
3	73.2	30.0	34.0	32.0	31.5	45.66
5	74.7	35.0	38.0	31.6	34.5	74.01

Table 5. **Effect of number of iterations.** The results improve as the number of feedback iterations increase. Time: time required to generate reasoning steps per sample

Threshold (τ)	AV-Cap	AV-Meme	AV-GeoIQ	AV-Comp	DM-Match	Time
4	69.6	26.5	28.5	27.9	28.5	23.90
6	72.2	30.0	32.5	29.7	32.0	47.15
8	74.7	35.0	38.0	31.6	34.5	61.28
10	74.8	35.0	38.0	31.4	34.5	65.81

Table 6. **Effect of Threshold Value.** A larger threshold for the evaluation score shows positive trend on the performance.

5. Experiments and Results

5.1 Baselines

We extensively evaluate VideoLLaMA [92], VideoLLaMA2 [10], Reka Core [69], Gemini 1.5 Pro [56], Unified-IO-2 [44], X-InstructBLIP [53], PandaGPT [58], OneLLM [27], AnyGPT [90], NExT-GPT [79], VITA [21], VideoSALMONN [61], ImagebindLLM [28], MacawLLM [48], CAT [85], AVicuna [67], CREMA [88]. AVLLM [57] on AVReasonBench.

5.2 Metrics

For AV-QA, AV-Comp, AV-GeoIQ, AV-Meme, and DM-Match, we report the Top-1 accuracy as the metric by extracting the model outputs using a choice extraction strategy outlined in the supplementary. We report the performance of AV captioning tasks on several established metrics, including BLUE@4 [54], METEOR [2], ROGUE [41], and CIDEr [73]. We employ GPT-based evaluation for AV-GeoIQ and AVSD which has open-ended answers.

5.3 Main Results

We extensively compare the performance of the baseline AVLLMs in Tab. 1 across all 6 AV tasks of our AVReasonBench benchmark. The experimental results reveal that closed-source models consistently outperform open-source ones in every reasoning task. Specifically, among the two closed-source models, we observe that Gemini 1.5 Pro surpasses Reka Core, likely due to its superior audio comprehension capabilities. This suggests that our AVReasonBench benchmark presents challenging scenarios that require strong audio-visual joint understanding. By leveraging the zero-shot reasoning distillation through AURELIA, we observe consistent boost in the performance of all the AVLLMs as seen from the experimental results with relative improvements up to 100% for X-InstructBLIP. Furthermore, for more challenging tasks such as AV-GeoIQ, AV-Meme, and DM-Match, we observe substantial improvements highlighting the importance of AURELIA's step by step reasoning distillation in deriving answers to complex AV queries.

We further note that recent approaches such as Unified-IO-2 XL and VITA demonstrate improved reasoning abilities over the other methods due to their stronger LLM backbone, which is capable of capturing finer multimodal information. Models with more robust audio encoders, such as AVicuna and Video-SALMONN, outperform alternatives like PandaGPT and Macaw-LLM. This highlights the critical role of the audio modality in leveraging the strengths of AVReasonBench.

Tab. 2 presents the AV-captioning results for five AVLLMs across three additional captioning metrics. As shown in the table, all models exhibit consistent improvements, highlighting the effectiveness of our reasoning-enhanced data in the dense captioning task.

Results on other benchmarks. Tab. 3 results demonstrate that our reasoning pipeline is generalizable across other benchmarks. We select VideoMME [20] as an alternative benchmark due to its tasks, which demand advanced reasoning abilities. Notably, the greatest improvements are observed in the long video *Knowledge* assessment categories, further emphasizing the generalizability of AURELIA.

5.4 Ablation Study

Combination of Agents. The multi-agent framework of AURELIA offers the flexibility to integrate various existing multi-modal LLMs as specialized agents. To assess the impact of different LLMs on reasoning generation, summarization, and evaluation, we conduct an analysis on three datasets across target model VideoLLaMA-2 (Tab. 4). Our findings indicate that leveraging a combination of models, specifically GPT-4o alongside Gemini yields superior performance compared to employing Gemini alone for all three agents roles as is evident from the higher accuracy scores in case of combination of agents. This suggests that while Gemini excels in processing multi-modal inputs such as video and audio, GPT-4o demonstrates stronger capabilities in textual comprehension and reasoning. The synergy between these models enhances the overall effectiveness of AURELIA, underscoring the advantages of a diversified agent selection.

Number of Generation Attempts. Our analysis reveals that the choice of T significantly influences overall performance. To evaluate this impact, we conduct an ablation study on five datasets across VideoLLaMA-2 model, as presented in Tab. 5. With just a single iteration, the obtained scores are notably low, whereas increasing the iterations to five yields substantial improvements across most datasets. This suggests that additional iterations allow AURELIA to progressively enhance its reasoning quality. However, considering computational efficiency and latency constraints, we cap the number of iterations at five for the final evaluation. AV-Cap values are CIDEr scores.

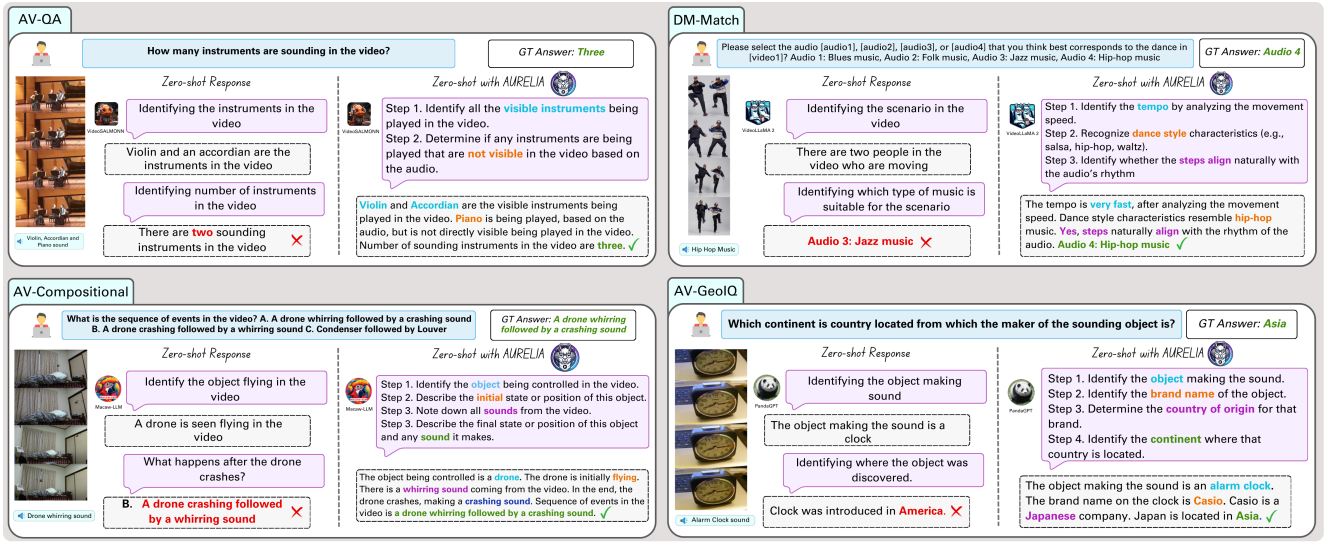

Figure 3. **Qualitative Visualizations.** Figure shows the qualitative visualizations of effect of AURELIA's reasoning distillation on the final answer across four tasks. Compared to vanilla zero-shot inference, AURELIA augments the target model with reasoning capabilities, leading to the improved answers.

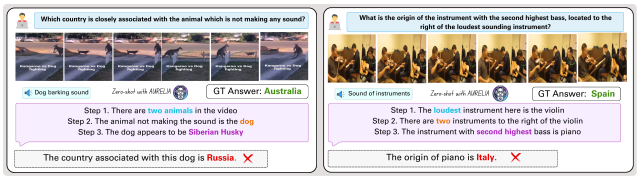

Figure 4. **Examples of Failure Cases. (Left)** AURELIA fails to comprehend audio, focus on single modality i.e. video, leading to incorrect reasoning chain. **(Right)** AURELIA fails to comprehend the dynamics of the video.

Threshold Value. Evaluation score (τ) quantifies the consistency of the reasoning steps with multimodal input. To empirically analyze the impact of the threshold (τ), we present results in Tab. 6 on five datasets across VideoLLaMA-2 model. As expected, a higher threshold value indicates stronger alignment, leading to superior model performance. However, we observe that a threshold of 8 yields performance comparable to the highest value, suggesting that setting the threshold at 8 or above ensures optimal reasoning quality. The increasing value of time required to generate the samples indicates to obtain improved reasoning steps we need more iterations. AV-Cap report CIDEr values.

5.5 Qualitative Results

To visualize the effect of AURELIA's reasoning distillation, refer to Fig. 3. We compare the performance of various AVLLMs on 4 tasks. We notice that in the absence of reasoning distillation, the target model faces difficulties in figuring out answers to the given queries. For example, in the AV-Captioning task, due to the step-wise guidance to the AVLLM, the generated caption is dense and rick of contextual information compared to ZS response. Similarly, for AV-GeoIQ, powered by the sequence of prompts, the AVLLM is able to correctly respond to the query whereas the response in ZS is wrong. Empirical studies reveal, with the addition of reasoning information, the decision-making capability of model improves by structuring its response in accordance with the reasoning steps, thereby leading to correct answers. We add more qualitative results in the supplementary.

5.6 Failure Cases

Fig. 4 illustrates a few failure cases in our reasoning generation pipeline. In the first example, an error in interpreting the animal sounds leads to the assumption that the *dog* is silent. This assumption propagates through the reasoning steps, producing an incorrect response. In the second example, the pipeline fails to spot the *instrument with the second highest bass*, resulting in an erroneous conclusion. We believe that fine-grained AV comprehension and refining understanding of language instructions can help mitigate these issues.

6. Conclusion

In this work, we introduce AURELIA, a novel test-time framework designed to enhance the reasoning capabilities of AVLLMs through interactive multi-agent system which distills structured, step-by-step reasoning into AVLLMs without any training. To further advance the AVLLMs' reasoning abilities, we also present AVReasonBench, a comprehensive benchmark consisting of six diverse tasks including the novel AV-GeoIQ for geo-cultural knowledge reasoning. The samples in each task are paired with step-by-step reasoning data, generated using AURELIA, which facilitates both the evaluation and enhancement of existing AVLLMs. AURELIA serves as an essential step toward more robust, context-aware, and reasoning-driven multimodal AI, enabling future advancements in artificial audio-visual intelligence.

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