

Thinking With Videos: Multimodal Tool-Augmented Reinforcement Learning for Long Video Reasoning

Haoji Zhang^{1*} Xin Gu^{2*} Jiawen Li³ Chixiang Ma³ Sule Bai¹ Chubin Zhang¹
 Bowen Zhang³ Zhichao Zhou³ Dongliang He³ Yansong Tang^{1†}

¹Tsinghua Shenzhen International Graduate School, Tsinghua University

²University of Chinese Academy of Sciences ³Bytedance Intelligent Creation

Abstract

The video reasoning ability of multimodal large language models (MLLMs) is crucial for downstream tasks like video question answering and temporal grounding. While recent approaches have explored text-based chain-of-thought (CoT) reasoning for MLLMs, these methods often suffer from limited cross-modal interaction and increased hallucination, especially with longer videos or reasoning chains. To address these challenges, we propose **Video Intelligence via Tool-Augmented Learning (VITAL)**, a novel end-to-end agentic video reasoning framework. With a visual toolbox, the model can densely sample new video frames on demand and generate multimodal CoT for precise long video reasoning. We observe that temporal grounding and question answering are mutually beneficial for video understanding tasks. Therefore, we construct two high-quality multi-task video reasoning datasets MTVR-CoT-72k for supervised fine-tuning and MTVR-RL-110k for reinforcement learning. Moreover, we propose a Difficulty-aware Group Relative Policy Optimization algorithm (DGRPO) to mitigate difficulty imbalance in multi-task reinforcement learning. Extensive experiments on 11 challenging video understanding benchmarks demonstrate the advanced reasoning ability of VITAL, outperforming existing methods in video question answering and temporal grounding tasks, especially in long video scenarios. All code, data and model weight will be made publicly available.

1 Introduction

Video understanding is a fundamental challenge in artificial intelligence, with wide-ranging applications such as recommendation [27, 33], smart surveillance [4, 65], generation [10, 44], visual navigation [21, 42], and autonomous driving [70, 82]. Recent advances in multimodal large language models (MLLMs) [1, 9, 28, 34, 62] have significantly improved the ability to jointly process visual and textual information, opening new opportunities for complex video reasoning tasks.

Video reasoning refers to inferring objects, relationships, events and causality from video content, often requiring multi-step and temporal understanding [86, 95]. This capability is fundamental for downstream tasks like video question answering [14], temporal grounding [17], spatial-

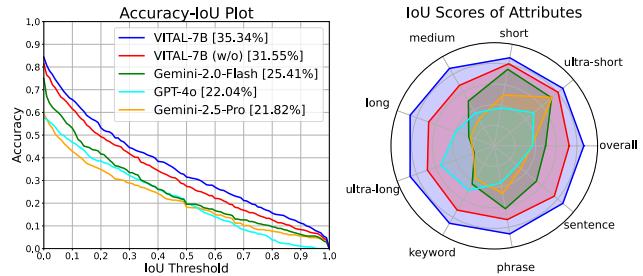


Figure 1: Performance on long video temporal grounding benchmark VUE-TR. VITAL-7B (w/o) denotes VITAL-7B without toolbox. VITAL-7B achieves state-of-the-art.

temporal grounding [19] and captioning [3, 55], where accurate reasoning over dynamic scenes enables more precise and informative results. Inspired by the success of DeepSeek-R1 [20] in enhancing the reasoning ability of LLMs through reinforcement learning (RL), some works apply Group Relative Policy Optimization (GRPO) post-training to improve MLLMs’ reasoning ability on images [2, 47, 54] and videos [13, 39].

Despite these advances, most existing MLLMs only rely on **text-based chain-of-thought** (CoT) reasoning for video understanding [11, 13, 39, 57]. While effective in some scenarios, such approaches often suffer from two major limitations: (1) insufficient cross-modal interaction, which restricts the model’s ability to fully leverage visual information during reasoning, and (2) increased hallucination, especially when handling long videos or long reasoning chains. Thus, a key question arises: *How can we enable MLLMs to perform effective reasoning over long videos, with strong cross-modal interaction and minimal hallucination?*

To address these challenges, we propose to evolve from text-based CoT to **multimodal CoT** reasoning, where the model can explicitly incorporate visual tools and dynamically attend to relevant video content throughout the reasoning process (Fig. 2). This improved paradigm enables more accurate and interpretable video understanding, as shown in Fig. 1, which highlight the effectiveness of our approach and confirm that integrating multimodal CoT is a key factor in advancing long video understanding.

Motivated by this insight, we propose **Video Intelligence**

*These authors contributed equally.

†Corresponding author.

Question: Please find the visual event described by a sentence in the video, determining its starting and ending times. The sentence: **Gregs Microscope book discussion**.

Ground Truth: From 297.00 to 339.00 seconds.

Thinking without tools: From 260.94 to 335.93 seconds. IoU = 49.9% Fail!

Thinking with tools: From 296.00 to 336.00 seconds. IoU = 90.7% Success!



Thinking without tools

```
<think>The user wants the start and end times for the “Gregs Microscope book discussion”. At frame `296.75s`, the man is holding a book titled “ANN CAN FLY” and appears to be finishing his thoughts on that topic. At 297.75s, the man turns to a new book, “GREGS MICROSCOPE”. This seems like the start. Now I need to find when this discussion ends. The man continues to hold and discuss the “Gregs Microscope” book throughout the latter part of the video. At frame `329.93s`, he is flipping through the pages of the book. At frame `331.43s`, he is putting the book back on the shelf. Thus, the event of discussing the “Gregs Microscope” book spans from when he starts talking about it around 297.00s until just after he finishes around 330.93s. Re-checking earlier frames, I see at 260.75s he is already holding “GREGS MICROSCOPE” and introducing it. This means the actual start is much earlier. I’ll revise the start time to 260.94s. Now, to find the end, I’ll scan towards the end of the video. At 330.93s, he closes the book, and by 331.43s, he is putting it back. This indicates the discussion concludes as he puts the book away. Thus, the event spans from when he starts talking about it around 260.94s until he finishes around 335.93s. </think>
<answer>The event happens from 260.94 to 335.93 seconds
</answer>
```

Thinking with tools

```
Get_video_clip(start=290, end=336)
```

```
<think>Okay, I need to find the start and end times for the “Gregs Microscope” discussion. I’ll scan for the book’s appearance. I see him pull out a yellow-covered book around 297.94s. This must be it. He starts flipping through it at 300.94s and puts it down around 315.93s. So, my initial guess is the discussion is roughly from 297.94s to 315.93s. Let’s refine this. He gestures towards the book as early as 296.94s, so I’ll adjust the start time to 296.00s. For the end, he’s still talking about it after putting it down at 315.93s. I’ll extend the end time to 320.00s. My refined range is 296.00s to 320.00s.</think>
<tool_call>{"name": "get_video_clip_frame", "arguments": {"start_time": 290.00, "end_time": 336.00}}</tool_call>
```



```
<think>Okay, let’s re-evaluate with the clip from 290s to 336s. The book appears around 297s, and he discusses it until he puts it down around 320s. However, he continues talking about it and related items even after that. Considering this, the discussion really begins when he introduces the book around 296s and continues until he completely moves on to the next topic at 336s. Therefore, I’ll set the final range from 296.00s to 336.00s to cover the entire segment dedicated to the book and its related context.</think>
<answer>The event happens from 296.00 to 336.00 seconds.</answer>
```

Figure 2: Comparison between text-based CoT (left) and multimodal CoT (right) on temporal grounding task. Green text denotes correct inference and orange text denotes wrong inference. “Thinking with tools” reduces hallucination in the reasoning process by integrating relevant, densely sampled video clip frames into multimodal CoT, resulting in more accurate grounding.

via Tool-Augmented Learning (**VITAL**), a novel end-to-end agentic framework for video multimodal (CoT) reasoning. It enables efficient multi-round multimodal tool-augmented training and evaluation. As shown in Fig. 3, VITAL consists of a MLLM and a visual toolbox, which allows the model to actively sample new frames and extract relevant multimodal information on demand during reasoning. This enables the model to focus its attention on critical temporal segments, effectively bridging the gap between textual reasoning and visual evidence and thus reducing hallucination. To enhance the model’s multimodal reasoning abilities for efficient tool calling, we first conduct a cold-start phase, followed by reinforcement learning. In both phases, the model is jointly optimized on temporal grounding, video question answering, and grounded question answering tasks. To support this training paradigm, we construct two large-scale, high-quality training datasets tailored for multi-task video reasoning: **MTVR-CoT-72k** for supervised fine-tuning (SFT) and **MTVR-RL-110k** for reinforcement learning (RL), as shown in Fig. 5. Moreover, we propose a novel Difficulty-aware Group Relative Policy Optimization (**DGRPO**) algorithm to mitigate the difficulty imbalance in multi-task reinforcement learning. By adjusting the reward scale based on task difficulty and sample difficulty, DGRPO ensures adaptive difficulty balancing, leading to more stable training and improved generalization ability. Our contributions include:

- We design a tool-augmented learning framework that allows MLLMs to sample frames on demand with a visual

toolbox and generate multimodal CoTs, which enables efficient training and evaluation.

- We construct two large-scale, high-quality multi-task video reasoning datasets: MTVR-CoT-72k and MTVR-RL-110k for comprehensive video reasoning learning.
- We introduce a Difficulty-aware Group Relative Policy Optimization algorithm to address difficulty imbalance in multi-task reinforcement learning.
- Extensive experiments on 11 benchmarks and ablation studies demonstrate that VITAL achieves superior performance in long video understanding, video question answering and temporal grounding tasks.

2 Related Works

2.1 Reasoning-Enhanced MLLMs

Recently, OpenAI-o1 [29] and DeepSeek-R1 [20] demonstrate that RL-based post-training can further enhance the reasoning abilities of LLMs. Following the rule-based outcome reward modeling and Group Relative Policy Optimization (GRPO) of DeepSeek-R1, some works apply similar post-training paradigms to MLLMs to enhance multimodal reasoning ability in many tasks like: mathematical and scientific image VQA [26, 53]; image segmentation and grounding [2, 46, 47, 54, 66, 67, 85]; video reasoning VQA [8, 13, 38, 68]; video spatial or temporal grounding [18, 39, 52, 72]. **Different from** prior works that rely on

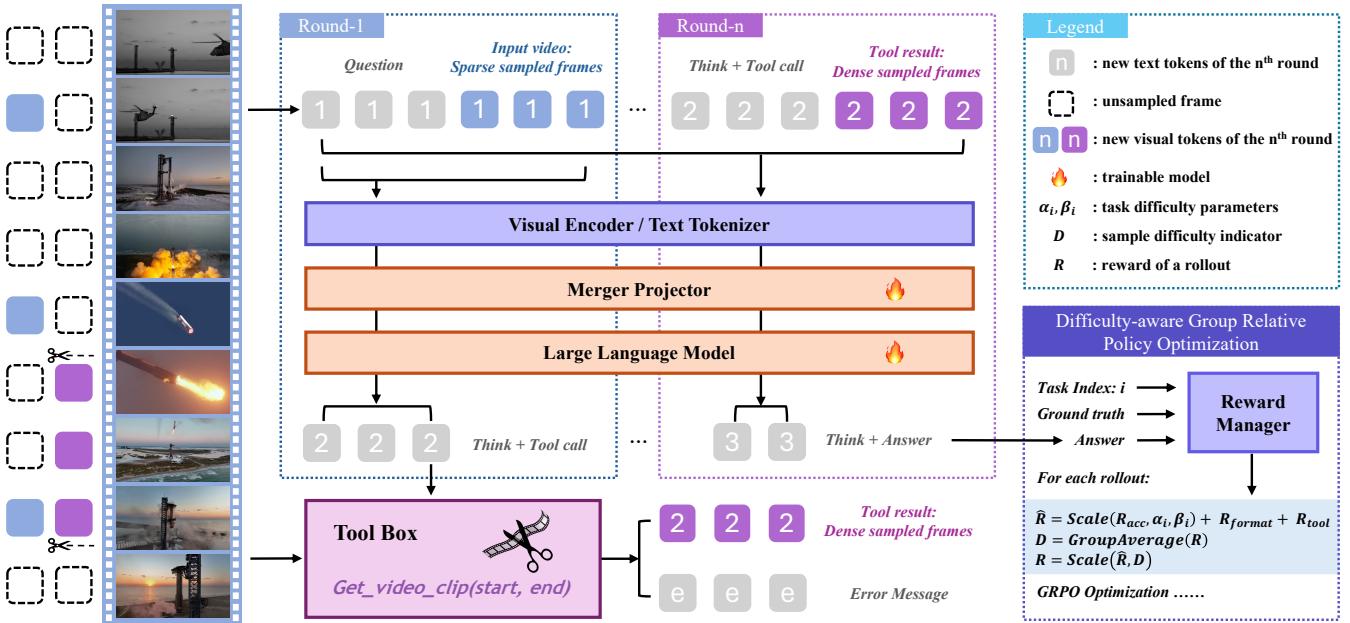


Figure 3: Overview of the Video Intelligence Tool-Augmented Learning (VITAL) framework. In the multi-round generation process, the model can attend to video tools adaptively and integrate the tool result to form a multimodal CoT. The model is optimized with Difficulty-aware Group Relative Policy Optimization (DGRPO).

text-based CoT reasoning, we leverage multimodal CoT reasoning to effectively improve the video understanding ability of MLLMs.

2.2 Tool-Augmented LLMs

Recent advances in large language models (LLMs) [61, 81] have shown that equipping models with external tools can enhance their capabilities beyond pure text understanding and generation, and learn to interact with the world. For example, using visual tools can introduce vision ability to LLMs [75, 84]. Based on DeepSeek-R1 [20] style post-training, many works explore using code execution tools for mathematical and coding tasks [12, 36, 40, 69]. Some works leverage search engines as tools for deep search [30] and deep research [93]. In the multimodal domain, several works apply visual foundation models [45], image editing tools [15, 25], or spatial grounding tools [37, 73, 77] to enhance visual reasoning ability. FAST [60] and MVoT [35] incorporate visual evidence in the reasoning process to form a multimodal CoT for image tasks. Inspired by DeepSeek-R1 [20] and OpenAI-o3 [51], recent works DeepEyes [94] and OpenThinkImg [59] explore “thinking with images” capability by integrating image zoom-in, sketching, detection and segmentation tools to MLLMs for image reasoning tasks. **Different from** existing methods, we focus on enhancing “thinking with videos” capability for long video reasoning by leveraging video grounding and clipping tools.

2.3 Long Video Understanding

Understanding long videos poses significant challenges for MLLMs due to the high computational complexity. Earlier

works focus on object-centric feature extraction [76, 91]. MIST [16] and SEVILA [87] introduce iterative temporal selection and answering models for long video VQA tasks. Some MLLM works [23, 49, 58, 74], LLaMA-VID [41] and Flash-VStream [89] propose MLLM visual token compression techniques for long videos. LongVA [90] and LongVILA [7] propose long context extension finetuning, which enables training with thousands of frames per video. However, these approaches tend to be computationally intensive. Recent works [22, 50, 71] explore the coarse-to-fine dynamic frame sampling strategy for efficient long video understanding. **Different from** previous works, we propose a multimodal tool-augmented RL framework for efficient and accurate long video reasoning.

3 Method

Overview. We propose VITAL, an end-to-end agentic video reasoning framework that enables “thinking with videos” by generating multimodal chain-of-thought (CoT) using a visual toolbox. As depicted in Fig. 3, VITAL follows the Visual Encoder-LLM architecture commonly used in MLLMs, and integrates a tool-augmented multi-round learning process with the Difficulty-aware GRPO algorithm. In the following subsections, we first introduce the tool-augmented learning framework of VITAL (Sec. 3.1), then discuss the preparation of the multi-task video reasoning training data (Sec. 3.2), and finally present the Difficulty-aware GRPO algorithm (Sec. 3.3), which is employed to optimize the proposed framework with the constructed training data.

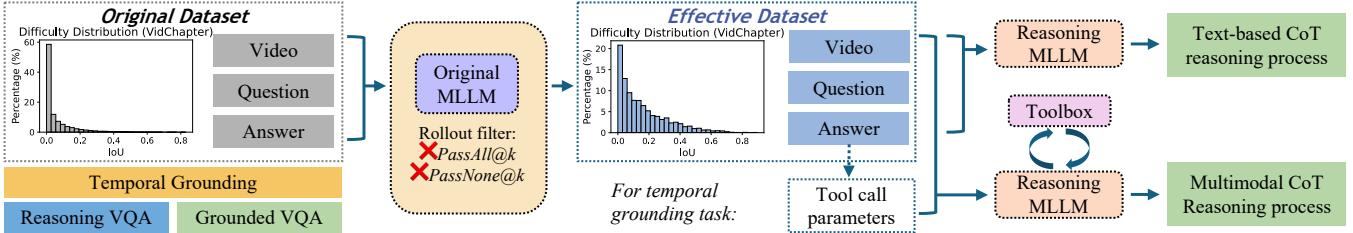


Figure 4: Data generation pipeline of MTVR training dataset. A rollout filter is applied to improve data quality.

3.1 Tool-Augmented Learning Framework

The tool-augmented learning framework operates through a multi-round generation process. In each round, the MLLM determines whether to invoke a tool from the visual toolbox. **Multi-round Generation.** Given a user question \mathcal{T}_0 and a video \mathcal{V}_0 as input, the VITAL model learns to reason and dynamically decide whether to call a visual tool or directly output an answer. If a tool is called, the next round begins after tool execution, forming a multimodal CoT. At round-k, the model generates:

$$\mathcal{O}_k = f_{\text{MLLM}}(\{\mathcal{T}_i, \mathcal{C}_i, \mathcal{V}_i\}_{i=0}^k) \quad (1)$$

After round-k generation, the parser extracts the thinking step and tool call $\mathcal{T}_{k+1}, \mathcal{C}_{k+1} = p(\mathcal{O}_k)$ or error message \mathcal{E}_k^p . Here, \mathcal{T}_{k+1} is the text reasoning step and \mathcal{C}_{k+1} denotes the tool call request. ($\mathcal{C}_0 = \emptyset$ is empty.) If a tool call is made, the visual toolbox executes it and returns a new video result $\mathcal{V}_{k+1} = g_{\text{tool}}(\mathcal{C}_{k+1})$ or error message \mathcal{E}_k^g . f_{MLLM} denotes the MLLM backbone and g_{tool} denotes the visual toolbox (e.g., video clipping tools). Specifically, when $\mathcal{C}_{k+1} == \mathcal{A}_{k+1}$, no further tool calls are made and the process terminates with the final answer. This procedure results in a multimodal CoT trajectory $\tau = \{\mathcal{T}_1, \mathcal{C}_1, \mathcal{V}_1, \mathcal{T}_2, \mathcal{C}_2, \mathcal{V}_2, \dots, \mathcal{T}_n, \mathcal{A}_n\}$.

Visual Toolbox. We test several video tools in Tab. 6 and identify the “video clipping” tool as the most effective for video temporal grounding and reasoning tasks. As shown in Fig. 3, “video clipping” tool receives two time range parameters and returns a densely sampled frame sequence of the requested range. The video clipping tool operates as:

$$\mathcal{V}_{k+1} = g_{\text{clip}}(\mathcal{V}_0, t_{\text{start}}, t_{\text{end}}) \quad (2)$$

3.2 Multi-Task Video Reasoning Training Data

To enhance tool calling and multimodal reasoning, we construct two high-quality multi-task video reasoning datasets: MTVR-CoT-72k for SFT cold start and MRVR-RL-110k for RL. These datasets cover temporal grounding, video question answering (VQA), and grounded VQA, where temporal grounding serves as the basis for question-guided video clipping, and VQA tasks evaluate general reasoning capabilities. Grounded VQA further requires the model to predict relevant time ranges and answers simultaneously. The original data are collected from Charades-STA [17], ActivityNet-MR [31], VidChapters-7M [80], Video-R1 [13], LongVideo-Reason [6], ReXTIME [5] and NEXT-GQA [79].

As shown in Fig. 4, our data generation pipeline employs a rollout filtering process to improve post-training efficiency.

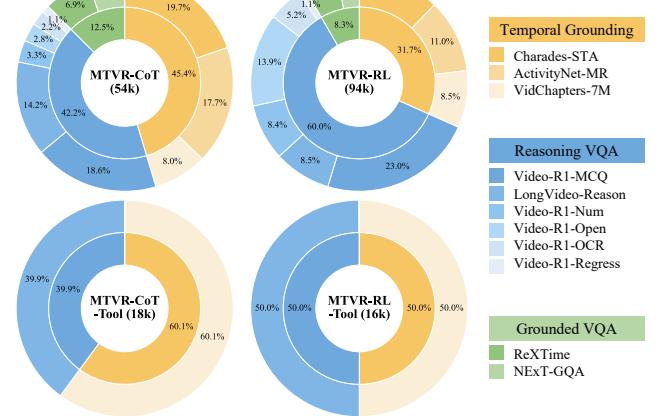


Figure 5: Task distribution of MTVR training dataset.

For each sample, we use MLLM [1] to generate k rollouts with a high temperature to encourage diversity. We then retain samples with moderate difficulty, filtering out those where all rollouts pass (*PassAll@k*, too easy) or none pass (*PassNone@k*, too hard). This results in a curated dataset with balanced difficulty. After filtering out extreme data, we leverage a strong reasoning MLLM (e.g., Gemini 2.5 [9]) to roll out the text-based CoT for all data and multimodal CoT for long video data. For long video temporal grounding, we predefine visual tool parameters by adding 20% noise to the ground truth time range. For long video QA, the reasoning MLLM autonomously selects tool parameters. We use $k = 8$ and temperature = 1.0 for both rollout generation and RL training. Filtering criterion for different tasks and CoT generation prompts are detailed in the supplementary material.

Ultimately, we construct four data subsets for multi-stage training: **MTVR-CoT** (54k) and **MTVR-RL** (94k) for basic video reasoning, and **MTVR-CoT-Tool** (18k) and **MTVR-RL-Tool** (16k) for multi-round tool-augmented long video reasoning. Task and data source distributions are in Fig. 5.

3.3 Difficulty-aware GRPO Training

To address the challenges of multi-task RL training, this section introduces our reward design and difficulty balancing strategies, which ensure stable optimization.

Reward Design. To enable multi-task RL training, we adopt a multi-task accuracy reward $\mathcal{R}_{\text{acc}}(\tau)$ follow-

Algorithm 1: Difficulty-aware Reward Calculation						
Require: Trajectories in a batch $\{\tau_{i,j}^k\}$, parameters α_i, β_i						
1: for each task i do						
2: for each sample j do						
3: for each rollout $k = 1, \dots, G$ do						
4: Compute $\mathcal{R}_{\text{acc}}(\tau_{i,j}^k), \mathcal{R}_{\text{format}}(\tau_{i,j}^k), \mathcal{R}_{\text{tool}}(\tau_{i,j}^k)$						
5: if task i is temporal grounding then						
6: $S_1 \leftarrow \text{clamp}\left(\frac{\mathcal{R}_{\text{IoU}}(\tau_{i,j}^k) - \alpha_i}{\beta_i - \alpha_i}, 0, 1\right)$						
7: else						
8: $S_1 \leftarrow \mathcal{R}_{\text{acc}}(\tau_{i,j}^k)$						
9: end if						
10: $\widehat{\mathcal{R}}(\tau_{i,j}^k) \leftarrow S_1 + \mathcal{R}_{\text{format}}(\tau_{i,j}^k) + \mathcal{R}_{\text{tool}}(\tau_{i,j}^k)$						
11: end for						
12: $D_{i,j} \leftarrow \frac{1}{G} \sum_{k=1}^G \widehat{\mathcal{R}}(\tau_{i,j}^k)$						
13: for each rollout $k = 1, \dots, G$ do						
14: $w_{i,j}^k \leftarrow \text{clamp}(2 - D_{i,j}, 0, 1) \times 0.5 + 0.5$						
15: $\mathcal{R}(\tau_{i,j}^k) \leftarrow \widehat{\mathcal{R}}(\tau_{i,j}^k) \cdot w_{i,j}^k$						
16: end for						
17: end for						
18: end for						
19: return $\mathcal{R}(\tau_{i,j}^k)$ for all $\tau_{i,j}^k$						

ing [13]. To keep stable thinking and tool calling, we prompt the model to format its rollout output as: <think>... </think><tool_call>{“name”: ..., “arguments”: ...}</tool_call><think>... </think>... <answer>... </answer> and a strict rule-based *format reward* $\mathcal{R}_{\text{format}}(\tau)$ is applied. In order to encourage the model to attend to the toolbox for new visual information, we add another *tool reward* $\mathcal{R}_{\text{tool}}(\tau)$ to a rollout if it calls at least one tool successfully.

Difficulty Balancing. In our initial explorations, we supervised fine-tuned the model on MTVR-CoT and conducted GRPO training on MTVR-RL with a multi-task objective. However, we noticed there is a phenomenon of difficulty imbalance during GRPO training. For short video datasets and some easy tasks like multiple-choice questions, the reward increases quickly. However, for harder tasks like long video temporal grounding, the IoU reward increases more slowly, which forms *task-wise difficulty imbalance*. We attribute it to the lack of discrimination for continuous IoU function. Another observation is that as the RL training goes on, the proportion of easy samples becomes higher and that of hard samples becomes lower, as discussed in [2], then the optimization soon meets a bottleneck and could not make further breakthrough, which forms *sample-wise difficulty imbalance*. Therefore, we propose a Difficulty-aware GRPO algorithm to address these problems.

Specifically, to mitigate task-wise imbalance, after getting $\mathcal{R}_{\text{acc}}(\tau), \mathcal{R}_{\text{format}}(\tau)$ and $\mathcal{R}_{\text{tool}}(\tau)$ reward of a rollout τ , the accuracy reward (IoU) is scaled conditioned on the difficulty of task- i when the task is temporal grounding (otherwise not scaled), as shown in Alg. 1. Here, α_i, β_i are difficulty parameters of task i . To reduce the sample-wise imbalance, we propose to calculate sample difficulty of task- i , sample- j $D_{i,j}$ by averaging the reward of all G rollouts. Then we ap-

Train Stage	Style	LVR	VCh	MMMU	Cha	Avg
		Acc	IoU	Acc	IoU	
① Qwen2.5-VL	Not think	60.1	0.5	47.4	43.6	37.9
② SFT	Not think	62.0	10.8	49.9	46.0	42.2
③ SFT+GRPO	Not think	63.3	23.5	50.2	56.2	48.3
④ SFT	Think	62.8	15.6	50.5	46.8	43.9
⑤ SFT+GRPO	Think	66.0	25.8	52.0	57.2	50.3
⑥ SFT+DGRPO	Think	70.2	28.8	52.1	57.1	52.1
⑦ SFT+DGRPO*	Think+Tool	79.3	35.0	54.2	59.9	57.1

Table 1: Ablation study on training stages. Experiments show that tool-augmented DGRPO is effective for long video reasoning and temporal grounding. * notes this experiment repeats SFT + DGRPO for two times (four stages).

ply a soft linear scaling to $D_{i,j}$ to get the difficulty weight of sample- j (ranging from 0.5 to 1).

After this difficulty-aware reward balancing, we apply the GRPO algorithm based on rollout reward $\mathcal{R}(\tau_{i,j}^k)$ to optimize toward this objective:

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}_{q \sim P(Q), \{\tau_k\}_{k=1}^G \sim \pi_{\theta_{\text{old}}}(\tau|q)} \left[\frac{1}{G} \sum_{k=1}^G \frac{\pi_{\theta}(\tau_k|q)}{\pi_{\theta_{\text{old}}}(\tau_k|q)} A_k - \beta \mathbb{D}_{\text{KL}}(\pi_{\theta} \| \pi_{\text{ref}}) \right] \quad (3)$$

$$\mathbb{D}_{\text{KL}}(\pi_{\theta} \| \pi_{\text{ref}}) = \frac{\pi_{\text{ref}}(\tau_k|q)}{\pi_{\theta}(\tau_k|q)} - \log \frac{\pi_{\text{ref}}(\tau_k|q)}{\pi_{\theta}(\tau_k|q)} - 1 \quad (4)$$

Here $q = \{\mathcal{T}_0, \mathcal{V}_0\}$ denotes the question and input video. As presented in Tab. 1, the DGRPO training is more stable than GRPO and achieves better performance on challenging long video benchmarks LongVideo-Reason (LVR), VidChapters-7M (VidCh), while reserving good accuracy on Video-MMMU and Charades-STA (Cha). Implementation details of DGRPO are included in the supplementary.

4 Experiments

4.1 Experimental Setup

Implementation Details. The VITAL-7B model is implemented with a visual encoder, a merger projector and a large language model pretrained from Qwen2.5-VL-7B [1]. The training framework extends the functionalities of verl [56, 88] and vLLM [32], providing additional support for multimodal tool-augmented multi-round training and evaluation.

Training Settings. VITAL is trained with the AdamW optimizer [48] and a cosine lr scheduler. The weight decay is 1e-2. The learning rate is 1e-5 for SFT and 1e-6 for RL. The batch size is 256 for SFT and 64 for RL. The number of rollouts is 8 for DGRPO. We train the VITAL-7B model for one epoch at each of the four stages, totaling 640 GPU hours.

Evaluation Settings. We evaluated our model on long video question answering benchmark Video-MME [14], long video reasoning benchmark LongVideo-Reason (LVR) [6], long video temporal grounding benchmarks VidChapters-7M (VidCh) [80] and VUE-TR [63]. We report the results on VUE-TR-Vision to test visual ability of models.

To evaluate the basic video reasoning and temporal grounding ability of our model, we further compare it with

Model	Video-MME		LVR	Vid-Chapters-7M			VUE-TR-Vision			
	Acc	Long	Acc	R@0.3	R@0.5	R@0.7	P	R	IoU	
GPT-4o	71.9	65.3	60.7	VTimeLLM-7B	10.6	4.1	1.6			
Gemini-1.5-Pro	75.0	67.4	67.3	CLIP	10.7	5.2	2.3			
Video-R1-7B	59.3	—	62.7	M-DETR	37.4	27.3	17.6			
LongVILA-R1-7B	62.4	53.3	67.9	ReVisionLLM	33.8	27.4	21.8			
Qwen2.5-VL-7B	62.9	51.0	60.1	Qwen2.5-VL-7B	0.8	0.3	0.1			
VITAL-7B (w/o)	62.5	51.2	70.2	VITAL-7B (w/o)	35.2	25.8	19.5			
VITAL-7B	64.1	54.0	79.3	VITAL-7B	45.4	34.7	24.3			
ΔToolbox	+1.6	+2.8	+9.1	ΔToolbox	+10.2	+8.9	+4.8			

(a) Long video question answering

(b) Long video temporal grounding

(c) Long video temporal grounding

Table 2: Performance on long video question answering and long video temporal grounding benchmarks. Here $\mathbf{R}@x$ denotes recall at an IoU threshold of x . $\overline{\mathbf{P}}$, $\overline{\mathbf{R}}$, and $\overline{\text{IoU}}$ denote Area Under Curve (AUC) values of precision, recall and Intersection over Union (IoU). Gray rows denote models not open-sourced. VITAL-7B (w/o) denotes VITAL-7B without toolbox.

Model	Temporal Grounding							Grounded VQA			
	Charades-STA			ActivityNet-MR			NExT-GQA		ReXTime		
	R@0.3	R@0.5	R@0.7	mIoU	R@0.3	R@0.5	R@0.7	mIoU	Acc	mIoU	Acc
VTimeLLM-7B	51.0	27.5	11.4	31.2	44.0	27.8	14.3	30.4	28.8	17.4	20.1
TimeChat-7B	46.7	32.2	15.7	32.2	30.2	16.9	8.2	21.8	14.4	7.6	11.6
Momentor-7B	42.9	23.0	12.4	29.3	42.6	26.6	11.6	28.5	—	—	—
VTG-LLM-7B	52.0	33.8	15.7	—	—	8.3	3.7	12.0	—	—	—
TRACE-7B	—	61.7	41.4	41.4	54.0	37.7	24.0	39.0	—	—	—
TimeMarker-8B	73.5	51.9	26.9	48.4	67.4	50.7	33.0	49.5	—	—	—
TimeZero-7B	78.1	60.8	35.3	58.1	58.6	39.0	21.4	40.5	—	—	—
VideoChat-R1-7B	82.1	71.7	50.2	60.8	51.8	33.4	17.7	36.6	32.4	70.6	—
TimeSearch-7B	73.6	52.4	24.5	48.6	61.0	43.0	26.1	43.9	—	—	36.7
Temporal-RLT-7B	79.6	67.9	44.1	57.0	56.9	38.4	20.2	39.0	37.3	78.7	—
DeepVideo-R1-7B	—	71.7	50.6	61.2	—	33.9	18.0	36.9	36.8	72.5	—
Qwen2.5-VL-7B	67.9	50.3	24.3	43.6	28.3	15.8	7.5	21.1	15.4	59.5	27.5
VITAL-7B (w/o)	81.1	68.1	41.3	57.1	68.5	47.1	26.0	46.6	37.2	77.5	40.9
VITAL-7B	83.1	72.0	46.7	59.9	70.9	50.8	31.6	49.8	43.0	78.7	47.6
ΔToolbox	+2.0	+3.9	+5.4	+2.8	+2.4	+3.7	+5.6	+3.2	+5.8	+1.2	+6.7

Table 3: Comparison of models on video temporal grounding and grounded VQA benchmarks. VITAL-7B (w/o) denotes VITAL-7B without toolbox. Best results are bold-faced.

previous works on three complex video reasoning benchmarks: VSI-Bench [83], Video-MMMU (MMMU) [24], MMVU [92]; two video temporal grounding benchmarks: Charades-STA (Cha) [17], ActivityNet-MR [31], and two grounded VQA benchmarks: NExT-GQA [79], ReXTime [5]. We report accuracy (Acc) for VQA tasks, mean Intersection over Union (mIoU) and recalls for temporal grounding tasks. More evaluation details are included in the supplementary materials.

4.2 Main Results

Long Video Understanding. As shown in Tab. 2, VITAL-7B achieves state-of-the-art performance on long video question answering and long video temporal grounding benchmarks. VITAL-7B outperforms previous best open-source models by a large margin on LongVideo-Reason benchmark (Acc: 79.3% vs. 67.9%) and VidChapters-7M (R@0.5: 34.7% vs. 27.4%). The improvement is particularly pronounced in long video scenarios, demonstrating the effectiveness of tool-augmented multimodal CoT reasoning.

Complex Video Reasoning. On challenging multi-step rea-

soning benchmarks such as VSI-Bench, Video-MMMU, and MMVU, VITAL-7B consistently outperforms strong baselines (Tab. 4), confirming its advanced reasoning capability across diverse video reasoning tasks like spatial reasoning and multi-discipline knowledge learning. For clearer judgement, we test models on MMVU multiple-choice split following previous work [13, 38].

Video Temporal Grounding and Grounded VQA. As shown in Tab. 3, VITAL-7B excels in short video temporal grounding benchmarks (Charades-STA and ActivityNet-MR), indicating that the proposed model has strong basic temporal grounding capability. On grounded VQA benchmarks (NExT-GQA and ReXTime), VITAL-7B also sets new state-of-the-art performance, demonstrating the multi-modal CoT design facilitates the integration of accurate temporal grounding and deep video reasoning, leading to more reliable video understanding MLLMs.

4.3 Ablation Study

Effectiveness of DGRPO. We conduct an ablation study on training stages and training styles, e.g., with or with-

Model	VSI-Bench	Video-MMMU	MMVU (mc)
	Acc	Acc	Acc
LongVA-7B	29.2	23.9	—
VILA-1.5-8B	28.9	20.8	—
LLaVA-OV-7B	32.4	33.8	49.2
AoTD-7B	28.8	—	—
Video-R1-7B	37.1	52.4	64.2
VideoRFT-7B	36.8	51.1	68.5
Temporal-RLT-7B	—	—	65.0
Qwen2.5-VL-7B	31.8	47.4	61.3
VITAL-7B (w/o)	37.5	52.1	62.6
VITAL-7B	41.8	54.2	68.7
ΔToolbox	+4.3	+2.1	+6.1

Table 4: Comparison of models on complex video reasoning question answering benchmarks. VITAL-7B (w/o) denotes VITAL-7B without toolbox.

Training Data	Size	LVR	VidCh	MMMU	Cha	Avg
		Acc	mIoU	Acc	mIoU	
① None	0	60.1	0.5	47.4	43.6	37.9
TG	73k	59.5	24.8	44.5	52.8	45.4
RQA	95k	76.5	4.7	48.9	37.9	42.0
TG+RQA	168k	78.3	33.8	52.3	57.6	55.5
⑦ TG+RQA+GQA	182k	79.3	35.0	54.2	59.9	57.1

Table 5: Analysis of training data composition. Combining temporal grounding, reasoning VQA and grounded VQA brings the best result. Experiments in line 2-5 conduct the same four stages training as Exp. ⑦.

out thinking. As shown in row 5 and row 6 of Tab. 1, the introduction of DGRPO improves difficult long video understanding tasks by a large margin while keeping the same short video perception ability, increasing the average score from 50.3 to 52.1. This demonstrates that difficulty-aware reward balancing in DGRPO helps the model better handle diverse task complexities and improves overall robustness.

Analysis of Tool-Augmented Reinforcement Learning. Comparing rows 6 and 7 of Tab. 1, we observe that introducing tool-augmented RL improves long video perception capability, and leads to substantial improvements across all benchmarks. The delta results Δ Toolbox in the last row of Tabs. 2 to 4 further highlight the consistent benefits of tool integration across diverse video reasoning tasks.

Analysis of Training Dataset Composition. We categorize MTVR-CoT-72k and MTVR-RL-110k by task type, and train VITAL-7B on different task combinations, each for four stages. As shown in Tab. 5, combining temporal grounding (TG), reasoning VQA (RQA), and grounded VQA (GQA) data yields the best overall performance, with the average score improving from 37.9% (without training data) to 57.1%. This result highlights that multi-task training with all three data types provides strong synergy and is crucial for robust video reasoning and temporal grounding.

Analysis of Visual Tools. Tab. 6 compares the impact of different visual tools on temporal grounding task. We adopt two strong reasoning MLLMs GPT and Gemini. We observe that adding clip caption or clip QA tools does not improve results

Style	Tool	Vid-Chapters-7M*		Charades-STA*	
		mIoU	GPT	mIoU	Gemini
Not think	—	26.3	28.1	31.5	32.1
Think	—	28.4	29.8	30.1	33.0
Think	Clip caption	2.0	8.0	30.8	27.8
Think	Clip QA	2.0	10.4	25.5	28.1
Think	Video clip	25.5	26.3	28.8	31.7

Table 6: Ablation study on different visual tools. We test the zero-shot temporal grounding ability of GPT-4.1 and Gemini-2.5-Pro with different visual tools. * denotes using a 3k subset of the benchmark to reduce computational cost.

and even leads to significant drops in mIoU. Video clipping empirically reduces hallucination compared to other tools. We notice all these tools could not improve the performance of GPT or Gemini. We suggest this is due to the zero-shot setting and the models are not optimized with visual tools. Thus, we adopt video clipping tool by default and conduct 4-stage training to enhance tool calling ability. Tool implementation details are in supplementary.

4.4 Qualitative Analysis

Fig. 2 presents a qualitative comparison between text-based CoT and multimodal CoT on the temporal grounding task. The former relies solely on textual reasoning, which leads to inaccurate self-reflection and a lower IoU score due to error accumulation and hallucination. In contrast, the multimodal CoT leverages visual evidence during reasoning, which allows the model to more precisely determine the temporal boundaries of the target event. More qualitative case analyses are provided in the supplementary material.

5 Conclusion

In this work, we introduce VITAL, a novel tool-augmented framework that empowers MLLMs with advanced long video reasoning capabilities, which effectively mitigates hallucination and enhances cross-modal interaction. We further construct two high-quality multi-task video reasoning datasets and propose the DGRPO algorithm to address difficulty imbalance in multi-task reinforcement learning. Our results highlight the importance of tool-augmented multimodal reasoning and provide valuable insights for future research in long video understanding.

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Supplementary Material

To facilitate a deeper understanding and reproducibility of our work, this supplementary material provides additional details on the implementation of the proposed VITAL framework, including **method** details (Sec. A), **experiment** details (Sec. B), and **dataset** construction (Sec. C). We further present extended **ablation studies** (Sec. D) and additional **case analyses** (Sec. E) to comprehensively evaluate the effectiveness and robustness of our approach. Finally, we discuss the **limitations** of our current work and outline potential directions for **future work** (Sec. F). For reference and reproducibility, we also provide the experimental **code** along with detailed documentation.

A Method Implementation Details

This section describes the methodology details of the proposed VITAL framework in Sec. 3. We first illustrate the implementation details of toolbox g_{tool} and then demonstrate the details of Difficulty-aware Group Relative Policy Optimization (DGRPO).

A.1 Tool Implementation Details

In order to enhance the video reasoning ability of MLLMs by incorporating new evidences related to the user query, we implement three visual tools in the visual toolbox:

- Video clip captioning tool:** This tool takes the start and end timestamps of a video clip as input, and generates a descriptive caption for the specified segment.
- Video clip QA tool:** This tool receives the start and end timestamps of a video clip, together with a natural language question, as input. It outputs an answer to the given question based on the visual content of the specified clip.
- Video clipping tool:** This tool takes the start and end timestamps as input and outputs the visual content (represented as visual tokens) corresponding to the selected video segment.

Tab. 7 summarizes the input and output formats of these visual tools.

Tool Name	Inputs	Outputs
Clip Captioning	start, end	caption of the clip
Clip QA	start, end, question	answer to the question
Video Clipping	start, end	video clip visual tokens

Table 7: Inputs and outputs of visual tools

For all tools, the model parses and extracts tool call parameters following the Hermes-style protocol [1, 64]. Each tool call is formatted as a JSON string, enclosed within the `<tool_call>` and `</tool_call>` tags. After tool execution, the tool response is returned as a JSON string; if the tool outputs video tokens, the response includes a corresponding video token sequence. In cases where tool execution fails—due to incorrect parameter formatting or other unexpected errors—an error message is returned in the form of a JSON dictionary string.

```

def get_video_clip_caption(start_time: float, end_time: float)
-> str:
"""
Retrieve the text caption associated with a specified
video segment.

Args:
    start_time (float): The start time (in seconds) of
        the video segment, keeping two decimal places.
    end_time (float): The end time (in seconds) of the
        video segment, keeping two decimal places.

Returns:
    str: The caption string describing the video segment.
"""

pass

def ask_video_clip_question(start_time: float, end_time: float,
                            question: str) -> str:
"""
Answer a question about the content of a specified video
segment.

Args:
    start_time (float): The start time (in seconds) of
        the video segment, keeping two decimal places.
    end_time (float): The end time (in seconds) of the
        video segment, keeping two decimal places.
    question (str): The question about the content of the
        video segment.

Returns:
    str: The answer to the given question.
"""

pass

def get_video_clip_frame(start_time: float, end_time: float)
-> List[Image]:
"""
Get frames of a video segment from start_time to end_time.

Args:
    start_time (float): The start time (in seconds) of
        the video segment, keeping two decimal places.
    end_time (float): The end time (in seconds) of the
        video segment, keeping two decimal places.

Returns:
    List[Image]: A list of frame images of the segment.
"""

pass

```

Figure 6: Python-style pseudo code for the three video reasoning tools, showing input parameters, output types, and function descriptions.

The system prompt includes tool schemas derived from pseudo code in Fig. 6.

A.2 DGRPO Algorithm Details

We propose Difficulty-aware GRPO to mitigate the task-wise difficulty imbalance and sample-wise difficulty imbalance, as discussed in Sec. 3.3 and Alg. 1. In this subsection, we present the hyper-parameters used in our approach and provide the rationale behind their selection.

Reward design. In DGRPO reinforcement learning, we adopt three rewards: the accuracy reward, the format reward and the tool reward, as shown in Tab. 8.

For the accuracy reward, we adopt following rewards for each sub-task following [13]:

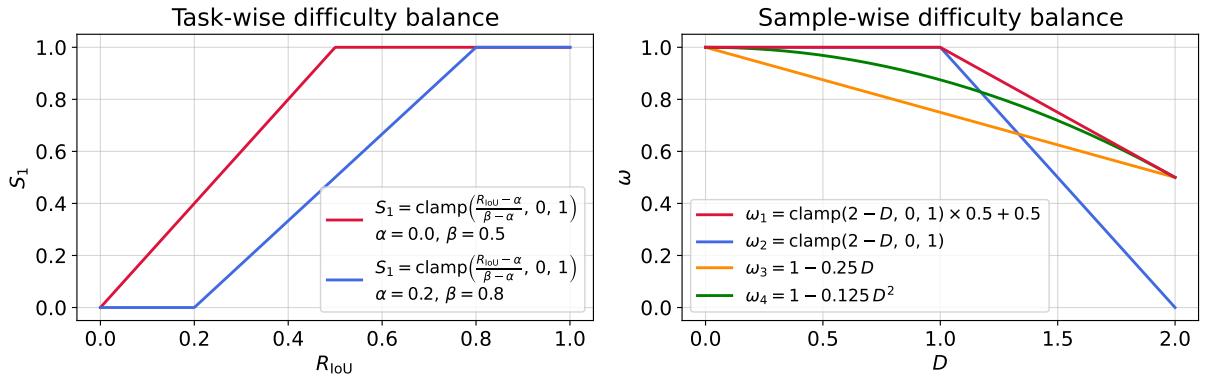


Figure 7: DGRPO clamped difficulty balance functions. Left: task-wise difficulty balance functions. Here we adopt two hyper-parameter settings for short video temporal grounding and long video temporal grounding tasks. Right: sample-wise difficulty balance functions. Here we adopt ω_1 for simplicity and effectiveness.

Task	Sub-task	Accuracy Reward	Max Value		
			Acc	Format	Tool
Reasoning VQA	Temporal Grounding	IoU	1	0.5	0.5
	MCQ	EM	1	0.5	0.5
	Number	EM	1	0.5	0.5
	Open-ended	Rouge	1	0.5	0.5
	OCR	WER	1	0.5	0.5
	Regression	L1	1	0.5	0.5
Grounded VQA	MCQ	(IoU + EM)/2	1	0.5	0.5
	Open-ended	(IoU + Rouge)/2	1	0.5	0.5

Table 8: Reward design of DGRPO with tools. For DGRPO without tools, tool reward is removed and the format reward ranges from 0 to 1.

- **IoU**: the Intersection over Union value of predicted time range and ground truth time range.
- **EM**: Exact Match reward, is equal to 1 when the prediction matches ground truth answer exactly.
- **Rouge**: Recall-Oriented Understudy for Gisting Evaluation [43], calculated as an average of Rouge-1, Rouge-2 and Rouge-L between the prediction and the ground truth answer.
- **WER**: Word Error Rate, measuring the edit distance between the prediction and the ground truth answer.
- **L1**: calculated as $\text{clamp}(1 - |\hat{y} - y|/|y|, 0, 1)$, where, \hat{y} is the predicted number and y is the ground truth number.

The format reward is equal to 0.5 only when the model response τ matches this format exactly: <think>...</think><tool_call>...</tool_call><think>...</think><answer>...</answer>, or <think>...</think><answer>...</answer>. If the response does not match any of these formats, the format reward is set to 0.

Similarly, the tool reward is equal to 0.5 only when the model successfully performs a tool call, otherwise it is 0. For the second stage DGRPO without tools, the tool reward is removed and the format reward ranges from 0 to 1.

Task	Data source	α	β
Temporal Grounding	Charades-STA	0.2	0.8
	ActivityNet-MR	0.2	0.8
	VidChapters-7M	0.0	0.5
Reasoning VQA	All	—	—
Grounded VQA	ReXTime	0.2	0.8
	NExT-GQA	0.2	0.8

Table 9: DGRPO hyper-parameters α and β for each task and data source of MTVR-RL-110k training dataset.

Task-wise difficulty balance. DGRPO algorithm uses clamped linear transformations for task-wise difficulty balance. As shown in Tab. 9 and in the left of Fig. 7, we adopt two hyper-parameter settings for short video temporal grounding and long video temporal grounding tasks based on their difficulty distributions. For multiple-choice question VQA tasks, we do nothing about task-wise difficulty balance as their reward metric is originally discrete (0 or 1). For Grounded VQA tasks, we transform the IoU value for balancing before adding it with EM or Rouge value.

Sample-wise difficulty balance. As presented in the right of Fig. 7, we apply sample-wise difficulty balance with another clamped linear transformation ω_1 , which results in a updating weight w based on sample difficulty D . The sample difficulty D is estimated by averaging all rollout rewards \hat{R} of the sample. We adopt the piecewise linear function ω_1 with the motivation to provide *soft penalty to easier samples* regardless of the format reward and the tool reward. (format reward + tool reward ≤ 1 , and they always converge to a constant value after several training steps) We also compare other transformation functions in Sec. D.1.

Configuration	Stage-1	Stage-2	Stage-3	Stage-4
method	SFT	DGRPO	SFT	DGRPO
using_tools	False	False	True	True
freeze_visual_encoder		True		
learning_rate	1e-5	1e-6	1e-5	1e-6
kl_loss_coeff (β)	0	1e-2	0	1e-2
optimizer		AdamW (0.9, 0.999)		
AdamW_betas		1e-2		
weight_decay				
warmup_ratio	0.1	0	0.1	0
lr_scheduler		cosine		
group_size	–	8	–	8
batch_size	256	64	256	64
mini_batch_size	256	64	256	64
micro_batch_size_per_device	4	2	4	2
number_of_samples	54k	94k	18k	16k
number_of_epochs	1	1	1	1
max_num_turns	0	0	2	2
max_total_pixels		64×224×224		3×64×224×224
max_sequence_length	4096	4096	10240	10240
max_response_length	0	1024	0	1024
training throughput (/gpu/h)	1408.0	142.9	1429.3	32.7
sample speed (s)	2.6	25.2	2.5	110.3

Table 10: Training configurations. Here group_size is the number of rollouts, and num_turns is the number of tool call rounds.

B Experimental Details

In this section, we provide more details about the four-stage training procedure, the evaluation settings and metrics. For image samples in the training dataset, we set max_pixels = 448×448. For video samples in the training dataset and evaluation datasets, we first sample them at FPS = 2 and then bound the number of frames and frame pixels according to the video length. We adopt the number prompt technique [78] during training and evaluation to print absolute timestamps on frames, providing additional temporal information for MLLMs for accurate temporal perception.

B.1 Training Details

The training configurations are listed in Tab. 10. Generally, we split the training procedure into two phases, post-training without tools and post-training with tools, each of which contains a cold-start SFT stage and a RL stage. For the 3rd and the 4th stage training with tools, we only train the model on long video datasets since our motivation is to enhance long video understanding with visual tools. We also tried training with tools from the pretrained MLLM directly, but found this paradigm is inefficient and the model is optimized slowly, since tool-augmented RL takes longer time than text-based RL because it contains multi-round generation, as shown in Tab. 10.

In each training stage, we sample short videos with max_frames = 64 and max_pixels = 224×224, while sampling long videos (e.g., LongVideo-Reason or Vid-Chapters-7M) with max_frames = 256 and max_pixels = 112×112 for the initial input video. For densely sampled video clip, i.e., the tool results, we set max_frames = 64 and max_pixels = 224×224 for all videos. For DGRPO rollout generation, we set temperature = 1.0, top_p = 1.0, group_size = 8.

B.2 Evaluation Details

We evaluate the VITAL-7B model on eleven challenging benchmarks. The evaluation details are illustrated in table Tab. 11. In all evaluation experiments, we keep temperature = 0.01 and top_p = 0.001, with max_response_length = 1024 and max_num_turns = 2, which guarantees stable and reproducible results.

Dataset	Max frames	Max pixels
Video-MME [14]	1024	224*224
LongVideo-Reason [6]	1024	224*224
Vid-Chapter-7M [80]	1024	224*224
VUE-TR-Vision [63]	1024	224*224
Charades-STA [17]	256	384*384
ActivityNet-MR [31]	256	384*384
NExT-GQA [79]	256	384*384
ReXTime [5]	256	384*384
VSI-Bench [83]	256	384*384
Video-MMMU [24]	256	384*384
MMVU (mc) [92]	256	384*384

Table 11: Evaluation configurations for each dataset.

C Dataset Construction Details

C.1 Dataset Statistics

We present comprehensive statistics of the MTVR dataset in Figs. 8 and 9. The dataset comprises four subsets: MTVR-CoT (54k), MTVR-RL (94), MTVR-CoT-Tool (18k), and MTVR-RL-Tool (16k). Fig. 8 illustrates the distributions of video duration and token length across all subsets. Notably, the video durations vary significantly in each subset, reflecting the diversity of video sources and categories. The token

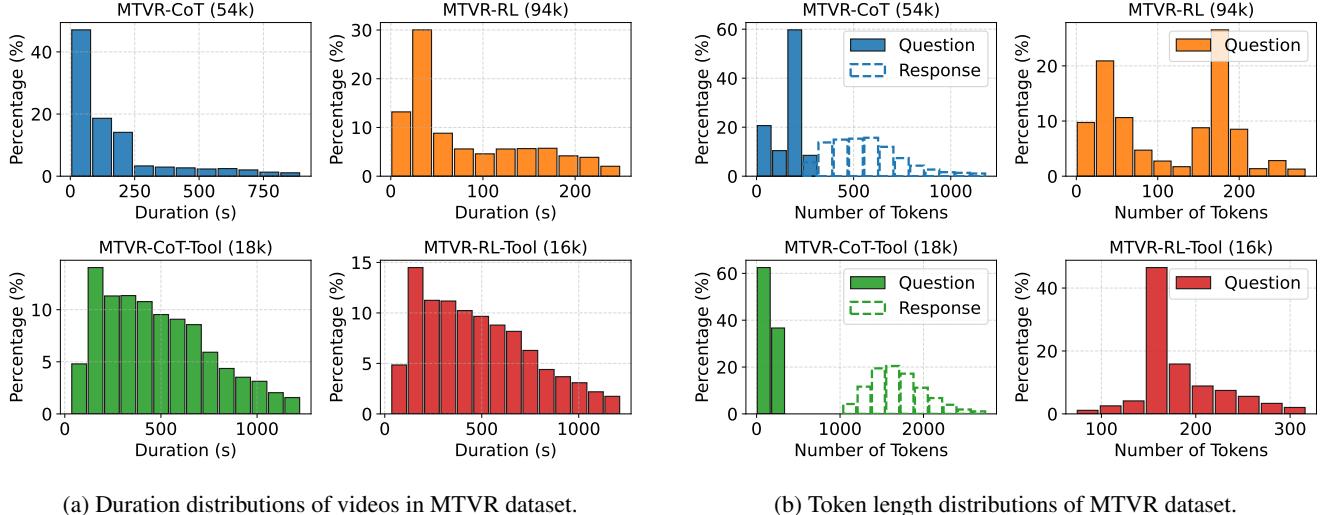


Figure 8: Distributions of video duration and token length of the MTVR dataset.

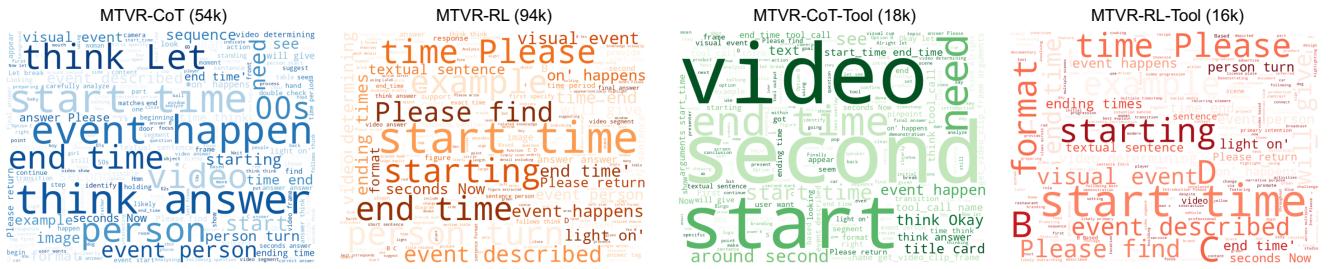


Figure 9: Word cloud of each subset of the MTVR dataset.

length distributions for both questions and responses are also reported, providing insights into the complexity and richness of the textual data. Furthermore, Fig. 9 visualizes the most frequent words in each subset using word clouds, highlighting the prevalent concepts and linguistic patterns.

C.2 Data Filtering Criterion

As described in Sec. 3.2, we propose a rollout filtering process to enhance data quality for DGRPO training. Overly easy or overly hard samples are not beneficial for post-training, as all rollouts for such samples will result in predictions that are either consistently successful or consistently failed. To address this, we design a criterion to filter out these uninformative samples. Specifically, for a sample j of sub-task i , the initial MLLM backbone, i.e., Qwen2.5-VL-7B [1], generates 8 rollouts. The k -th rollout has a task-specific reward $\mathcal{R}_{i,j}^k$ according to Tab. 8. We then compute the reward range for each sample as $\Delta\mathcal{R}_{i,j} = \max\{\mathcal{R}_{i,j}^k\}_{k=1}^8 - \min\{\mathcal{R}_{i,j}^k\}_{k=1}^8$. Samples with range $\Delta\mathcal{R}_{i,j} \leq 0.05$ are discarded, as they provide limited learning signals for the model during DGRPO process. The samples that pass the filtering criterion are considered informative and are therefore selected for the MTVR-RL dataset and the next annotation step of the MTVR-CoT dataset.

C.3 Data Generation Prompts

During the data generation pipeline, we annotate the text-based CoT reasoning process with the prompts in Fig. 10, and annotate the multimodal CoT reasoning process with the prompts in Fig. 11 with three round conversations. In the first round, the reasoning MLLM, e.g., Gemini 2.5 Pro [9] is prompted to generate a thinking process. In the second round, it generates the tool call. In the third round, it generates the reflection thinking process and the concluded answer.

Notably, in the second round, the model receives a pre-defined **tool parameter suggestion** for the video temporal rounding task, in order to improve the quality of reasoning. Specifically, for a sample with video \mathcal{V} , question \mathcal{Q} and ground truth answer $\mathcal{A} = [s, e]$, the suggested video tool range is calculated as:

$$s' = \text{clamp}(s - \lambda \cdot |s| \cdot \text{rand}(), 0, L) \quad (5)$$

$$e' = \text{clamp}(e + \lambda \cdot |L - e| \cdot \text{rand}(), 0, L) \quad (6)$$

Here L denotes the duration of the input video, $\text{rand}()$ is a random float number between 0 and 1. λ is a randomness parameter, which is set to 0.2 by default. The clamp function ensures that the resulting values remain within the valid range $[0, L]$. For other tasks like video question answering,

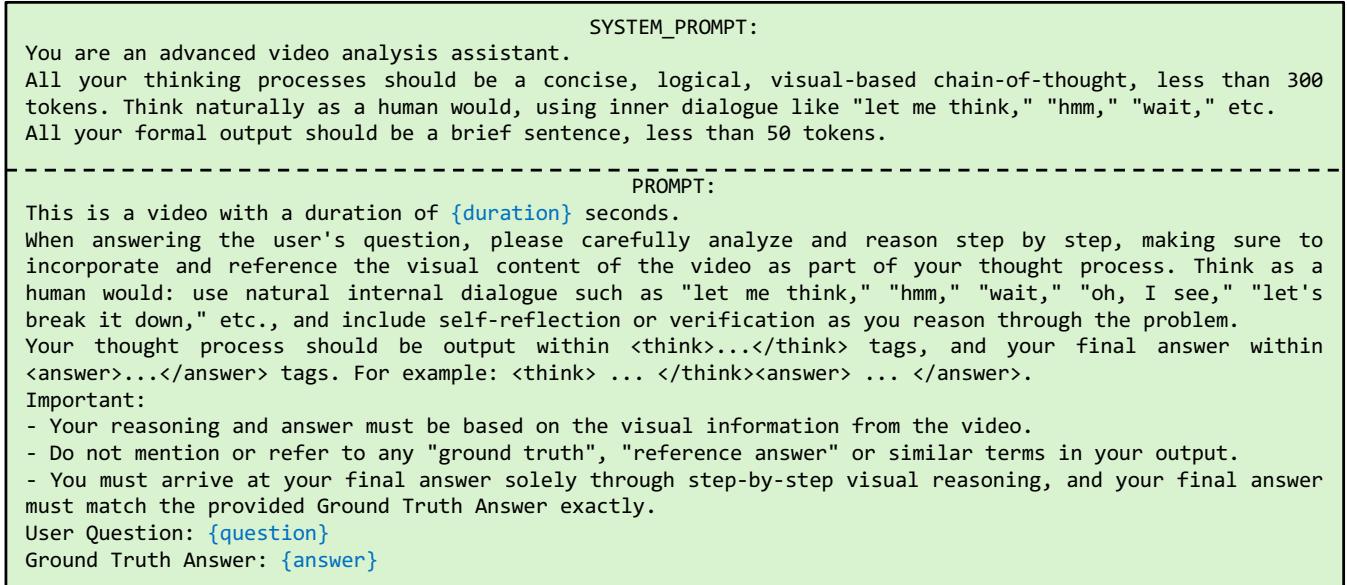


Figure 10: Prompts for text-based CoT generation.

	Function	LVR Acc	VidCh mIoU	MMMU Acc	Cha mIoU	Avg
⑥	$\omega_1(D)$	70.2	28.8	52.1	57.1	52.1
	$\omega_2(D)$	58.3	22.6	39.9	44.2	41.3
	$\omega_3(D)$	65.0	26.7	47.3	51.0	47.5
	$\omega_4(D)$	68.9	27.9	49.5	54.6	50.2

Table 12: Ablation study on DGRPO transformations. Each experiment contains training for the first two stages, i.e., SFT and DGRPO without tools.

we do not use the tool parameter suggestion and remove the corresponding sentences in the prompts in Fig. 11. We turn on the thinking mode of reasoning MLLM in round 1 and 3.

C.4 Data Post-Process

After generating chain-of-thoughts automatically, we perform a rule-based post-processing to control the data quality. A sample is excluded from the training dataset if it meets any of the following criteria:

1. The chain-of-thought is incomplete or does not reach a final answer.
2. The generated answer does not match the ground truth.
3. The sample contains irrelevant or off-topic content, e.g., direct description of "ground truth" or "suggestion".

After data post-processing, we obtain the final **MTVR-CoT-72k** dataset, which consists of high-quality and well-formatted samples suitable for cold-start supervised fine-tuning. The dataset consists of two subsets, **MTVR-CoT (54k)** for training stage-1 and **MTVR-CoT-Tool (18k)** for training stage-3, as illustrated in Fig. 5 in the main paper.

D More Ablation Studies

D.1 Ablation Study on DGRPO Transformations

We conducted ablation studies on the selection of transformation functions for Sample-wise Difficulty Balance of DGRPO. As presented in Sec. A.2 and Fig. 7, we design four transformation functions:

$$\omega_1(D) = \text{clamp}(2 - D, 0, 1) \times 0.5 + 0.5 \quad (7)$$

$$\omega_2(D) = \text{clamp}(2 - D, 0, 1) \quad (8)$$

$$\omega_3(D) = 1 - 0.25D \quad (9)$$

$$\omega_4(D) = 1 - 0.125D^2 \quad (10)$$

Tab. 12 shows the experimental results of using these functions to train for the first two stages. Comparing $\omega_1(D)$ and $\omega_2(D)$, we observe the importance of soft penalty. $\omega_2(D)$ style hard penalty will totally remove the contribution of easy samples, which is harmful for training. $\omega_1(D)$ also outperforms continuous functions $\omega_3(D)$ and $\omega_4(D)$. We attribute it to the phenomenon that the format reward + tool reward is always equal to 1 after tens of training steps. After that, the reward will vary from 1.0 to 2.0 in most situations. Therefore, $\omega_1(D)$ maximizes the range of sample-wise difficulty coefficient, resulting in better performance.

D.2 Ablation Study on Cold Start

Tab. 13 presents an ablation study on cold start SFT. The first two rows serve as baselines without tool usage, where adding cold start SFT shows few performance improvements. Introducing additional training with tools (row 3 and row 4) leads to notable improvements. Comparison between row 3 and row 4 demonstrates that cold start SFT (row 4) is beneficial for tool-augmented reinforcement learning, while directly applying tool-augmented DGRPO after two-stage training (row 3) impedes the model from learning to reason with tool calls.

```

SYSTEM_PROMPT:
You are an advanced video analysis assistant.
All your thinking processes should be a concise, logical, visual-based chain-of-thought, less than 300 tokens. Think naturally as a human would, using inner dialogue like "let me think," "hmm," "wait," etc.
All your formal output should be a brief sentence, less than 50 tokens.

PROMPT_ROUND_1:
This is a video with a duration of {duration} seconds.
Step 1: Think.
Analyze the user's question based on the entire visual content of the video step-by-step. You may start by analyzing each key event in the video, including self-reflection or verification in your reasoning.
---
User Question: {question}
Suggested Range: {suggestion}
---
Your just need to think and analyze. Your thinking should be ended around the Suggested Range, but you MUST NOT mention "suggest" or similar words in thinking or output.
Finally, you will think about calling the get_video_clip_frame tool with the Suggested Range as parameters, but you MUST NOT really call the tool.
You MUST NOT directly answer the user question, since your answer may be incorrect and you need tool results for further analysis.

PROMPT_ROUND_2:
Step 2: Act.
Based on the reasoning process you just formulated, call the appropriate tool to analyze the most relevant video segment.
Your output must be ONLY the tool call.
---
User Question: {question}
Suggested Range: {suggestion}
---
Your output for this step must be exactly one tool call. The tool call parameters must be exactly the Suggested Range.

PROMPT_ROUND_3:
You have received the tool output for the video clip from {start_time:.2f} to {end_time:.2f} seconds.
Step 3: Answer.
Integrate your initial reasoning with the new visual evidence from the tool. Think step-by-step again and provide the final answer.
---
User Question: {question}
Ground Truth Answer: {answer}
---
Your final answer must exactly match the provided Ground Truth Answer, but you MUST NOT mention or refer to any "ground truth", "reference answer", or similar terms in thinking or output.

```

Figure 11: Prompts of each round for multimodal CoT generation.

D.3 Fair Ablation of Tool Calling

We conduct an ablation study on whether using tools in Tab. 1 in the main paper (Exp. ⑥ vs Exp. ⑦). However, this may be due to the different number of video tokens during the final training stage of them, as presented in Tab. 10 (Stage-2 and Stage-4).

Therefore, for a fairer comparison, we conduct an additional two-stage experiment, shown in row 5 of Tab. 13, which matches the experimental setting of row 2 except for the increased video resolution. In the experiment shown in row 5, we set max_total_pixels to $2 \times 64 \times 224 \times 224$. This setting ensures that the video token budget is comparable to that of Exp. ⑦, as the average number of tool calls in Exp.

⑦ is less than 1. As shown in the last two rows of Tab. 13, VITAL-7B with tools (row 4) still significantly outperforms the improved baseline (row 5) by a large margin.

D.4 Ablation Study on Data Size

We provide evaluation results at different steps during the last training stage, DGRPO with tools. As shown in Tab. 14, although some metric fluctuations occur during training, the overall performance on both long and short video understanding benchmarks consistently improves as the training data size increases.

Train Stage	LVR Acc	VidCh mIoU	MMMU Acc	Cha mIoU	Avg	#Tools
DGRPO	70.1	28.5	50.9	57.5	51.8	0
⑥ SFT+DGRPO	70.2	28.8	52.1	57.1	52.1	0
+DGRPO*	70.5	30.1	51.3	57.3	52.3	0
⑦ +SFT+DGRPO*	79.3	35.0	54.2	59.9	57.1	0.87
SFT+DGRPO [†]	73.7	30.9	51.3	58.9	53.7	0

Table 13: Ablation study on cold start and video resolution. The first two rows present results without using tools. * in rows 3 and row 4 indicates further training with tools following row 2 (Exp. ⑥). [†] denotes experiments trained with double the max_total_pixels. #Tools is the average number of successful tool calls.

Data Size	LVR Acc	VidCh mIoU	MMMU Acc	Cha mIoU	Avg
0	68.7	18.9	45.2	52.3	46.3
4k	73.8	27.0	50.6	55.8	51.8
8k	76.1	31.5	51.8	58.3	54.4
12k	75.8	29.5	52.7	58.6	54.1
⑦ 16k	79.3	35.0	54.2	59.9	57.1

Table 14: Ablation study on different data sizes. Data size denotes the data already used during stage-4 DGRPO training.

E More Case Analyses

E.1 Data Quality Analysis

High-quality training data is the foundation of robust model performance. In this subsection, we examine representative samples from our MTVR dataset to illustrate the diversity and complexity of the video-question pairs. As shown in Figs. 12 to 15, the MTVR training set features precise temporal annotations, detailed event descriptions, and a wide range of real-world scenarios. These examples demonstrate the dataset’s ability to capture fine-grained actions and support complex reasoning, ensuring comprehensive coverage for both short and long video understanding tasks. Such high-quality, diverse samples provide a strong foundation for training models capable of robust and generalizable video-language reasoning, e.g., text-based CoT or tool-augmented multimodal CoT.

E.2 Reasoning Quality Analysis

Understanding the model’s reasoning process is crucial for evaluating its effectiveness in complex video understanding tasks. We present several case studies that compare multimodal CoT reasoning chains generated by VITAL-7B with text-based CoT generated by VITAL-7B (w/o). As shown in Figs. 16 and 17, the results demonstrate that tool-augmented multimodal CoT enables VITAL-7B to perform more accurate and fine-grained reasoning compared to text-only CoT. By leveraging both visual and textual modalities, as well as external tools for temporal grounding and evidence extraction, the model can systematically integrate multimodal cues, leading to more precise event localization and deeper

narrative understanding. These case studies highlight the substantial advantages of multimodal, tool-augmented reasoning chains for challenging long video video question answering and temporal reasoning tasks.

F Limitations and Future Work

Limitations. While VITAL achieves strong results in long video reasoning, our current framework only provides tools for temporal grounding and question answering, limiting its ability to address other tasks such as spatial grounding. Furthermore, our approach mainly focuses on visual features and ignores audio information, which may restrict the model’s overall understanding. Expanding the toolbox and incorporating multimodal features like audio could further enhance the model’s comprehension of videos.

Future Work. In the future, we plan to expand the variety of tools within our framework and enable multimodal chain-of-thought reasoning across more modalities, such as integrating both visual and audio cues. This will allow our method to support a broader spectrum of video understanding tasks, including spatio-temporal video grounding, semantic segmentation, and analysis of videos in complex scenarios. Furthermore, we aim to develop more adaptive tool selection strategies to enhance the robustness and versatility of multimodal reasoning in open-ended video understanding.

Question: Please find the visual event described by a sentence in the video, determining its starting and ending times. The sentence: **person talking on the phone**.

Ground Truth: From 4.00 to 16.80 seconds.

Data Source: MTVR-CoT (54k), Charades-STA

Task Type: Temporal Grounding



Thinking without tools

<think>Let me carefully analyze the sequence of images to determine when the person starts and stops talking on the phone.

First, I need to identify when the person begins talking on the phone. In the early frames (0.00s to about 4.00s), the person is holding a phone and a glass, but not yet talking on the phone. At 4.97s, the phone is brought up to the ear, and by 5.47s, the person is clearly holding the phone to their ear, which is a typical gesture for talking on the phone.

Now, I need to find when this action ends. The person continues to hold the phone to their ear while moving into the kitchen, up until around 16.80s. At 16.89s, the phone is no longer at the ear, and the person is now using both hands for other tasks, indicating the phone conversation has ended.

So, the event "person talking on the phone" starts at 4.00s (when the phone is first brought to the ear) and ends at 16.80s (just before the phone is lowered).

Let me double-check:

- **At 4.00s, the phone is being raised.**
- At 4.97s and after, the phone is at the ear.
- At 16.80s, the phone is still at the ear.
- **At 16.89s, the phone is no longer at the ear.**

This confirms the event duration. </think>

<answer>The event 'person talking on the phone' happens in the 4.00 - 16.80 seconds.</answer>

Figure 12: This case study highlights the high data quality of the MTVR-CoT (54k) dataset for temporal grounding tasks. The precise frame-by-frame annotations enable accurate identification of the event boundaries—here, the action "person talking on the phone" is reliably localized between 4.00s and 16.80s. Such detailed and consistent text-based CoT reasoning label supports robust event understanding and temporal modeling in complex video scenarios.

Question: Based on the content of the video, answer the following question: **How does she style her hair to give it more volume?** In the <answer> </answer> tag, first specify the exact time period in seconds of the video segment that support your answer, then, provide your final answer with a short sentence.

Ground Truth: From 72.58 to 157.25, she blow dries her hair with a white blower, sections her hair, brushes her hair with a roller brush while blow drying it at the same time, and rolls the brush downwards and upwards.

Data Source: MTVR-RL (94k), ReXTime (ActivityNet)

Task Type: Grounded VQA (Open-ended)



Figure 13: This case study demonstrates the high-quality annotations in the MTVR-RL (94k) dataset for grounded video question answering. The dataset provides precise temporal grounding for open-ended questions, as shown by the accurate localization of the hair styling process between 72.58s and 157.25s. The annotations are collected from original data source.

Question: What is the primary goal of the person in the video, as inferred from the interaction dynamics, textual cues, and video composition?

- A. To demonstrate proper handling techniques for various reptiles.
- B. To advocate for adopting reptiles as pets by showcasing their docile nature.
- C. To promote a YouTube channel focused on reptile care through direct calls to action.
- D. To document a personal hobby of collecting exotic lizards and geckos.

Ground Truth: C

Data Source: MTVR-CoT-Tool (18k), LongVideo-Reason

Task Type: Long Video Reasoning VQA



Thinking with tools

<think>Alright, here's my take on this video's purpose, distilled as if it were my own internal monologue. Okay, so I need to figure out the main objective of this video based on its content. The person's got a crested gecko, and they're holding it, so maybe it's about reptile handling or showing how docile they are. But the shirt, "I'D RATHER BE AT HOME WITH MY LIZARD," suggests this goes deeper. Let's break it down.

The video jumps around, showing other reptiles: a tortoise, bearded dragons, snakes. Seems like a collection, so maybe it's about their hobby. But then there are those text overlays, asking questions. "Will you get a bearded dragon?" "Will you get a snake?" That's a classic YouTube format. And the answers are shown with the actual reptiles, keeping viewers hooked.

The "Subscribe" button appearing and getting clicked, then the end screen with the subscribe prompts, links to other videos, and social media? That's a dead giveaway. **This isn't just a video about reptiles; it's designed to grow a YouTube channel. It's the core strategy of the content.**

The reptile content is the vehicle.

Sure, they are showing off the reptiles. They are likely documenting their personal hobby, and maybe even showcasing their nature. They are definitely trying to engage their audience. But, when you get down to it, the main push is about growing that channel.</think>

<tool_call>{"name": "get_video_clip_frame", "arguments": {"start_time": 359.00, "end_time": 394.00}}</tool_call>



<think>Okay, here's how I'm thinking about this, based on the tool's output and my expertise.

Alright, so I need to pick the best answer to this multiple-choice question, and it's all about the video's primary purpose. My initial read was that this video is *specifically* designed to promote a YouTube channel. My reasoning was based on a few things, the Q&A format, which can be a way YouTubers interact with viewers. But the strongest clues were the calls to action I expected, and the elements I thought I would find in a YouTube end screen.

Now, let's see if the tool backs up my initial reasoning. Looking at the clip from the tool (between 359 and 394 seconds), my hypothesis has been *completely* validated. I mean, it's practically a checklist of what I expected to see.

- At the very start of the clip, at 359.55s, we get the classic "Subscribe" button animation - with a click!
- At 360.64s we see "Subscribed".

• Then, the tool identified a YouTube notification prompt at 362.83s.

• Finally, at 393.45s, the end screen appears. This is the really telling part. I'm seeing a "SUBSCRIBE TO THIS CHANNEL" bar, a comments section,

more video recommendations, and calls to "FOLLOW THE GECKOS" with links.

So, this is undeniable proof. The video is using very deliberate, very YouTube-specific elements.

Here's how I'm synthesizing all of this to pick the correct answer:

- The Q&A format isn't *just* about answering questions. It's a proven engagement tactic for YouTubers.
- Yeah, the video *does* feature reptiles, but it's not an instructional video. It's not designed to teach specific handling techniques - it's more of a personal, and very casual look at keeping reptiles. That would mean rule out Option A.
- The video does document someone's hobby, so I could see how option D seems possible, but again it's not the main purpose.
- And yes, the video *may* encourage reptile adoption indirectly, but that's not the video's central thrust, so rule out Option B.
- The *really* crucial part here is the explicit use of those on-screen subscribe buttons, notification prompts, and the dedicated end screen. Those aren't incidental features; they are the core of the video's structure and purpose. They're there to grow a YouTube channel and drive viewer engagement.

Therefore, **the only logical conclusion is C. To promote a YouTube channel focused on reptile care through direct calls to action.** The evidence is absolutely clear.</think>

<answer>C</answer>

Figure 14: This case study illustrates the depth and reliability of the MTVR-CoT-Tool (18k) dataset for long video reasoning tasks. By combining multimodal cues—including video structure, on-screen text, and explicit calls to action—the dataset enables nuanced analysis of the video’s primary goal. The detailed annotation and step-by-step reasoning process allow for accurate identification of the intent: promoting a YouTube channel focused on reptile care through direct viewer engagement. This demonstrates the dataset’s capacity to support complex, high-level, tool-augmented reasoning for long videos.

Question: Please find the visual event described by the sentence in the video, determining its starting and ending times. The sentence: First Views of Fairmont Chateau Lake

Ground Truth: From 91.0 to 163.0 seconds

Data Source: MTVR-RL-Tool (16k), Vid-Chapters-7M

Task Type: Long Video Temporal Grounding



Figure 15: This case study highlights the precise temporal localization enabled by the MTVR-RL-Tool (16k) dataset for long video understanding. By providing accurate annotations for complex events, such as identifying the exact segment (91.0s to 163.0s) for "First Views of Fairmont Chateau Lake," the dataset supports fine-grained reasoning and comprehensive analysis in complex, extended, multi-scene, long video content. The annotations are collected from original data source.

Question: Please find the visual event described by a sentence in the video, determining its starting and ending times. The sentence: **Regional management approaches should be adopted, as demonstrated by the herring project.**

Ground Truth: From 1682.00 to 1813.00 seconds.

Thinking without tools: From 1300.77 to 1379.73 seconds. IoU = 0.0% Fail!

Thinking with tools: From 1699.00 to 1808.00 seconds. IoU = 83.2% Success!



Get_video_clip(start=900, end=1990)

Thinking without tools

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<think>
The user wants to find the start and end times for the event where "Regional management approaches should be adopted, as demonstrated by the herring project" is discussed.
1. I will scan through the provided video frames to locate any mention of the herring project or regional management approaches.
2. At frame 1206.72s, a slide titled "The Bristol Channel Herring Project" appears. This marks the beginning of the discussion on this specific project.
3. At frame 1210.73s, the slide changes to "Next phase: Identify and map spawning". This confirms that the herring project is still the focus.
4. At frame 1239.93s, a new slide titled "Regional Approaches to Fisheries Management" appears. This slide outlines four steps for adopting regional management approaches. This is a strong indicator that the discussion about adopting regional management approaches has begun.
5. At frame 1250.73s, the slide "Regional Approaches to Fisheries Management" is fully visible and the speaker is presenting it.
6. At frame 1279.94s, the slide "Fisheries Research and Management Plans" appears, which is part of the regional management approach outlined in the previous slide.
7. At frame 1309.15s, the slide "What needs to be done" appears, summarizing the need for improvements in local governance and co-management.
8. At frame 1320.16s, the speaker is finishing his point on the need for co-management.
9. At frame 1321.16s, a new slide titled "How might we achieve 'leaving the environment in a better state'" appears. This clearly marks the end of the discussion on the herring project and the beginning of a new section.
Based on this analysis, the event starts when the herring project is introduced at 1206.72s and ends right after the speaker finishes discussing the need for co-management at 1321.16s. Therefore, the event spans from approximately 1206.72 seconds to 1321.16 seconds.</think>
<answer>The event happens in the 1300.77 - 1379.73 seconds </answer>
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Thinking with tools

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<think>Okay, let's pinpoint those timestamps. I'm looking for the exact moment this specific text appears on screen. First, I'll scan through the video, focusing on the slides. Ah, here we go! At around 1261.26s, the slide titled "Regional Approaches to Fisheries Management" pops up. That's our starting point. Now, I need to find when the specific phrase "Regional management approaches should be adopted, as demonstrated by the herring project" actually appears on the screen. Let's see... at 1261.26s, the slide is there, but not the full text. It's building up. Okay, at 1262.72s, the complete text is fully visible. Perfect. Now, I need to determine when it disappears. Scanning forward, it's still there at 1264.18s. But at 1265.64s, it's gone. So, the text is fully displayed between approximately 1262.72s and 1264.18s. To be precise, I'll use the start time of 1262.72s and end time of 1264.18s. Let's check it. </think>
<tool_call> {"name": "get_video_clip_frame", "arguments": {"start_time": 900.00, "end_time": 1990.00}} </tool_call>
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<think>Okay, let's break this down. I'm tasked with pinpointing the start and end times for the appearance of the phrase "Regional management approaches should be adopted, as demonstrated by the herring project."
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First, I did a quick scan of the entire video. I saw the phrase "Regional management approaches should be adopted..." pop up on a slide, specifically under the "Regional Approaches to Fisheries Management" section. My initial guess was somewhere between 1262.72 and 1264.18 seconds, based on a quick look at the full video. Next, I zeroed in on the relevant section using the tool. I found the phrase "Regional management approaches should be adopted..." on a slide, and it appeared around 1703.99 seconds. The slide also mentioned the Bristol Channel Herring Project. This is promising! Now, I need to refine my search. I'm looking for the first time the phrase appears. I went back and reviewed the frames leading up to 1703.99 seconds. At 1699.00 seconds, the previous slide was still present. Then, at 1703.99 seconds, the target slide appeared. So, the start time is definitely around 1703.99 seconds. I also need to determine the last time the phrase is visible. I went through the subsequent slides. The phrase remained on screen until about 1803.15 seconds. Then, at 1808.31 seconds, the next slide appeared. Therefore, the end time is approximately 1803.15 seconds.

Finally, I want to make sure I have the right context. The phrase is part of a larger discussion about regional approaches. The slide also mentions the Bristol Channel Herring Project. This confirms that the phrase is indeed the key focus.

So, the phrase "Regional management approaches should be adopted, as demonstrated by the herring project" first appears on screen at approximately 1703.99 seconds and disappears around 1803.15 seconds. I'm confident in these timestamps. </think>

<answer>The event happens in the 1699.00 - 1808.00 seconds.</answer>

Figure 16: This example demonstrates the effectiveness of the VITAL-7B model's multimodal chain-of-thought (CoT) reasoning for temporal grounding tasks, which leverages tool-augmented analysis to integrate visual and textual information. By systematically using external tools to extract and interpret relevant video segments, the model accurately locates where "regional management approaches should be adopted, as demonstrated by the herring project" is discussed. This tool-augmented multimodal CoT enables robust, step-by-step reasoning and significantly enhances temporal localization in complex, real-world video tasks.

Question: Based on the narrative progression and environmental details, what is the most likely connection between the framed photo of another man on the desk (0:00:20-0:00:30) and the later appearance of the robot in the office (0:05:30-0:05:40)?

- A. The man in the photo is a rival executive who sent the robot to sabotage the protagonist.
- B. The photo depicts a younger version of the protagonist, hinting at a time-travel plot involving the robot.
- C. The photo shows the inventor of the robot, who died before completing the project the protagonist is reacting to.
- D. The robot is an AI replica of the man in the photo, created to fulfill a corporate strategy revealed in the documents.

Ground Truth: C
Thinking without tools: D Fail!
Thinking with tools: C Success!



Get_video_clip(start=20, end=30)

Thinking without tools

<think>The reasoning begins by analyzing the framed photo of another man on the desk. The man in the photo is dressed in a suit and tie, suggesting he holds a position of authority or importance. This detail establishes him as a key figure in the narrative. Next, the robot appears in the office, shown interacting with a computer and displaying a "CODE" screen. This scene indicates the robot is designed to execute specific tasks, likely tied to corporate objectives. The robot's presence in the office suggests it is intended to assist or automate certain functions, implying a connection to the man in the photo.

Further analysis of the video reveals a document titled "CODE KEN-2" dated 1987, which outlines a plan to "build a robot to do all the work." This document directly links the robot to a corporate strategy aimed at automating tasks. The robot's appearance in the office aligns with this plan, reinforcing its role as a tool for corporate efficiency.

The man in the photo could be the inventor of the robot, who died before completing the project. However, the robot's advanced features and its ability to interact with the computer suggest it is more than just a physical creation. It is likely an AI replica of the man in the photo, designed to fulfill his corporate vision and execute the plan outlined in the document.

In conclusion, the most logical explanation is that the robot is an AI replica of the man in the photo, created to fulfill a corporate strategy revealed in the documents.</think>

<answer>D</answer>

Thinking with tools

<think>Alright, let's dissect this. I'm looking at a video, and the task is to figure out how a picture of a guy on a desk relates to a robot in the scene. My initial thought is, "Okay, let's see... what's the connection here?" First, I note the picture. It's a guy, bald, in a suit. He's smiling, and he's got a serious look on his face. Then, the video cuts to a robot, a large, blue, mechanical thing. It's in a lab, and it's talking. The timestamps are key here; the picture appears around 20 seconds, and the robot shows up much later, around 330 seconds. The robot is clearly a character in the story, and the picture is just a piece of background detail. Now, I have to consider the options. Option A, a rival executive? No, the robot isn't attacking anyone. Option B, a time-travel plot? Possible, but not the strongest link. Option C, the inventor? Maybe, but the robot is talking, so it's probably not the inventor. Option D, an AI replica? That's interesting. The robot is talking, and it's acting like a person. It's also in a lab, which suggests it might be a creation. The documents at the end seem to confirm this. So, I'm leaning towards option D. The robot is an AI, and it's designed to act like the man in the picture. The documents at the end will probably explain how this works. The picture is just a visual cue, a way to introduce the character. The robot is the AI version of the man. This makes the most sense given the context.</think>

<tool_call> {"name": "get_video_clip_frame", "arguments": {"start_time": 20.00, "end_time": 30.00}}</tool_call>



<think>Let's analyze the narrative and environmental cues between 0:00:20 and 0:00:30. In these frames, a framed photo of another man is clearly visible on the desk beside the protagonist. The setting is a professional office, and the photo is placed prominently, suggesting the man in the photo holds significance to the protagonist or the company. The protagonist is holding documents, indicating business or project matters are central to the plot. Later, a robot appears in the office (0:05:30-0:05:40). Given the office environment and the visible documents, it's reasonable to infer the robot is linked to a corporate or technological project. The placement of the photo-clearly visible and not just background decor-implies a narrative connection.

Option A (rival executive) doesn't fit: there's no evidence of sabotage or rivalry. Option B (time-travel) is unlikely; the photo shows a different man, not a younger version of the protagonist. Option D (AI replica) would require more explicit hints that the robot is modeled after the man in the photo, but nothing in the scene suggests this.

Option C stands out: the photo is likely of the robot's inventor, someone important to the project but no longer present. The protagonist's reaction to the robot and the documents further support the idea that the inventor died before the project's completion, and the robot's appearance is a direct continuation of that legacy. The narrative progression—from the photo, to the protagonist's focus on documents, to the robot's arrival—suggests the photo serves as a memorial and narrative anchor for the robot's origin. **Therefore, the most logical answer is C:** The photo shows the inventor of the robot, who died before completing the project the protagonist is reacting to.</think>

<answer>C</answer>

Figure 17: This example highlights the VITAL-7B model's ability to perform tool-augmented multimodal chain-of-thought inference for reasoning VQA tasks. By combining visual scene analysis with textual evidence and leveraging external tools for precise temporal grounding, the model systematically interprets narrative context to infer the relationship between the framed photo and the robot. This approach enables explainable, context-aware decision-making in complex, story-driven video understanding tasks.