



# VideoMind: A Chain-of-LoRA Agent for Long Video Reasoning

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<https://videomind.github.io/>

## Abstract

Videos, with their unique temporal dimension, demand precise grounded understanding, where answers are directly linked to visual, interpretable evidence. Despite significant breakthroughs in reasoning capabilities within Large Language Models, multi-modal reasoning – especially for videos – remains unexplored. In this work, we introduce **VideoMind**, a novel video-language agent designed for temporal-grounded video understanding. VideoMind incorporates two key innovations: (i) We identify essential capabilities for video temporal reasoning and develop a role-based agentic workflow, including a planner for coordinating different roles, a grounder for temporal localization, a verifier to assess temporal interval accuracy, and an answerer for question-answering. (ii) To efficiently integrate these diverse roles, we propose a novel **Chain-of-LoRA** strategy, enabling seamless role-switching via lightweight LoRA adaptors while avoiding the overhead of multiple models, thus balancing efficiency and flexibility. Extensive experiments on 14 public benchmarks, including 3 on grounded video question-answering (Grounded VideoQA), 6 on video temporal grounding (VTC), and 5 on general video question-answering (VideoQA), verify that our agent achieves state-of-the-art performance on diverse video understanding tasks, underscoring its effectiveness in advancing video agent and long-form temporal reasoning.

## 1. Introduction

Recent advancements in Large Language Models (LLMs) have demonstrated remarkable effectiveness in reasoning tasks, such as Chain-of-Thought (CoT) [65, 85, 95], significantly improving both accuracy and interpretability in complex problem-solving scenarios [96]. Inspired by these achievements, researchers are now working to extend these reasoning capabilities to multi-modal domains [64, 69, 94] such as visual math understanding [73, 89, 106].

Among multi-modal inputs, videos present a unique

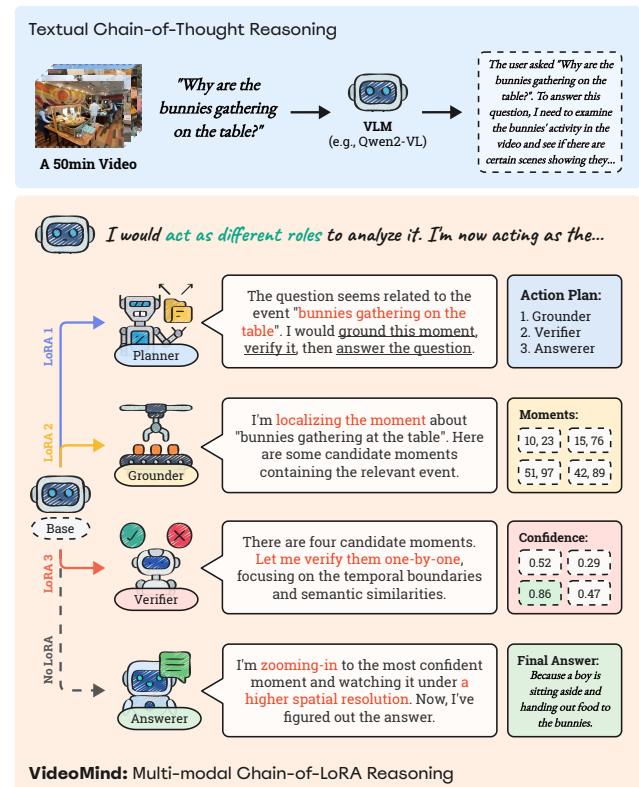


Figure 1. An illustration of **VideoMind’s Chain-of-LoRA reasoning strategy** applied to a complex question for a 50-min long video. The problem is decomposed by Planner and distributed to Grounder, Verifier, and Answerer to systematically localize, verify, and interpret the relevant video moments. Such a role-based pipeline enables more human-like video reasoning compared with the pure textual CoT process.

challenge due to their temporal dimension, which introduces complexities not found in static images or text. Effective video reasoning requires not only recognizing appearance but also understanding their dynamic interactions over time (*i.e.*, temporal-grounded understanding) [6, 7, 88]. While recent visual CoT methods [73, 89, 106] excel at generating detailed thoughts for static visual inputs, they struggle with videos because they cannot explicitly localize

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or revisit earlier parts of the sequence, as demonstrated in Fig. 1. Humans, by contrast, approach video understanding with ease: they break down complex problems, identify relevant moments, revisit them to confirm details, and synthesize their observations into coherent answers. This natural proficiency inspires the development of an AI assistant capable of replicating this process, adeptly managing multiple abilities to achieve advanced video reasoning.

In this work, we introduce VideoMind, a novel video-language agent with enhanced video temporal reasoning. **(i)** To meet the demands of diverse tasks, we first identify several key roles essential for understanding long videos: a **Grounder** for precise moment retrieval, a **Verifier** for validating information accuracy, an **Answerer** for generating query-aware responses, and a **Planner** to flexibly coordinate these roles. Each role has been carefully designed to deliver strong performance, *e.g.*, Grounder is equipped with a timestamp-decoder to ensure strong temporal grounding ability. **(ii)** To enable efficient collaboration among these roles, we propose a novel **Chain-of-LoRA** strategy, built upon a single base MLLM (*i.e.*, Qwen2-VL [77]). This approach embodies a minimalist yet flexible design philosophy, facilitating seamless transitions and interactions between roles without the computational burden of multiple full models. Therefore, VideoMind achieves both efficiency and adaptability, offering a practical and flexible solution for diverse video tasks.

To evaluate the effectiveness of VideoMind, we conducted extensive experiments across 14 benchmarks, including **Grounded Video Question-Answering** (CG-Bench [6], ReXTime [8], NExT-GQA [88]), **Video Temporal Grounding** (Charades-STA [17], ActivityNet-Captions [27], QVHighlights [30], TACoS [60], Ego4D-NLQ [18], ActivityNet-RTL [23]), and **General Video Question-Answering** (Video-MME [13], MLVU [108], LVBench [79], MVBench [34], LongVideoBench [86]). VideoMind demonstrates its capability to progressively process complex reasoning tasks by jointly providing temporal-grounded evidence and delivering accurate answers. Notably, our model demonstrates significant performance improvements even at the smaller 2B size, achieving a substantial increase in accuracy on long videos (27 minutes) in CG-Bench, even surpassing top-performing models such as GPT-4o [56]. Moreover, it demonstrates strong performance on sub-settings including video temporal grounding and general video question-answering. Ablation studies reveal the essential contributions of our design choices, particularly the Chain-of-LoRA mechanism, which enhances performance while achieving remarkable computational efficiency compared to traditional fine-tuning methods. Overall, our contributions are threefold:

1. We propose VideoMind, a multi-modal agent framework that enhances video reasoning by emulating human-like

processes, such as breaking down tasks, localizing and verifying moments, and synthesizing answers. This approach addresses the unique challenges of temporal-grounded reasoning in a progressive strategy.

2. We introduce Chain-of-LoRA, a minimalist strategy built on one vision-language model, allowing seamless collaboration among multiple roles. This method ensures VideoMind adapts flexibly to diverse tasks without the overhead of multiple models.
3. VideoMind achieves state-of-the-art results across three settings: Grounded VideoQA, Video Temporal Grounding, and General VideoQA. Notably, on the long video benchmarks [6, 79, 108], our 2B model outperforms GPT-4o on grounded QA tasks. Extensive ablations further confirm its effectiveness and efficiency.

## 2. Related Work

### 2.1. Temporal-grounded Video Understanding

Significant advances in video understanding have propelled tasks such as video captioning [41, 107], video question answering [87, 99], and video-text retrieval [39, 53], which emphasize instance-level understanding, yet these models often lack *visual-grounded correspondence* and interpretability, particularly for long-form video streams. The task of Video Temporal Grounding [17, 27] tackles this by requiring precise temporal localization for diverse queries, though regression-based models [46, 47] excel at localization but fall short in providing textual interpretability. Recent benchmarks (such as Grounded Question Answering) [6, 88] intensify this challenge, demanding both reasoning for complex questions and fine-grained temporal correspondence. Previous baselines for these tasks typically rely on multi-task objectives or modular agents composed of distinct components [11, 82, 97, 99], often yielding suboptimal performance (*e.g.*, LLM-based approaches for temporal grounding) or overly complex systems, which constrain their efficiency and flexibility. In this work, our proposed VideoMind introduces an agentic workflow built upon a unified backbone, seamlessly integrating multiple functionalities while enhancing localization and interpretability, thus surpassing the limitations of prior methods.

### 2.2. Multi-modal Reasoning

Large Multimodal Models [44], trained with supervised instruction-tuning (SFT), exhibit generalized capabilities such as free-form dialogue and question answering; however, they fall short in addressing complex challenges that often require the reasoning abilities of LLMs [85]. **(i)** One approach to overcome this is to develop **agent-based interfaces** [26, 99], which integrates textual outputs from multiple visual tools to enable language reasoning via LLMs. Advanced methods [16, 69, 94] leverage strategies like

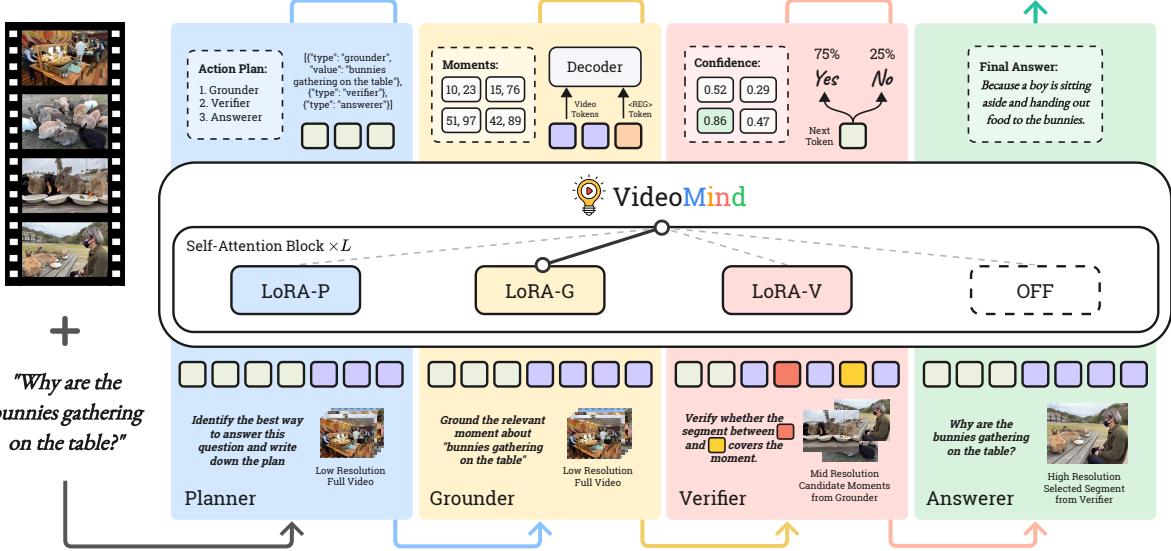


Figure 2. **The overall workflow of VideoMind.** Given a video and a query, VideoMind adaptively activates different roles (Planner → Grounder → Verifier → Answerer in this case) and perform step-by-step reasoning by calling individual modules.

Codex or ReAct [96] to invoke visual APIs (*e.g.*, detectors, captioners) through progressive execution and reasoning. (ii) Alternatively, **pure text-based reasoning** [2, 19] has been a dominant paradigm in LLMs [85, 99], exemplified by training with long CoT processes using Reinforcement Learning, which provides detailed, step-by-step readable reasoning, with some works [89, 106] extending this to the visual domain for complex mathematical or scientific problems. Despite these advances, extending reasoning to videos across temporal dimensions remains an open challenge. Given the long-context nature of informative videos, we think that *a video-centric CoT* should incorporate a human-like re-watch strategy and self-validation of intermediate observations, leading us to introduce a novel Chain-of-LoRA framework for video reasoning.

### 2.3. Inference-time Searching

Inference-time searching has emerged as a critical technique for tackling complex reasoning and planning challenges in domains like robotics [20, 80], games [67], and navigation [72], distinct from training-time strategies as it optimizes model behavior during inference rather than model parameters during training. The advent of OpenAI-o1 has advanced these inference-time techniques within LLMs by integrating sampling strategies such as controlled decoding [5, 91], Best-of-N sampling [32, 36], and Monte Carlo Tree Search (MCTS) [74, 76, 81, 100], allowing LLMs to iteratively refine outputs and achieve superior performance without altering their underlying weights. However, the potential of inference-time searching remains largely untapped in video understanding, where temporal reasoning introduces unique challenges. In our framework,

we explore how MCTS can be tailored for video temporal reasoning, observing that models are highly sensitive to the selection of temporal segments, often producing unreliable predictions when segment choices are suboptimal. To address this, we propose a video moment-level MCTS approach where a Grounder generates multiple segment candidates, followed by a Verifier that evaluates and determines the correct correspondence, validating that this strategy significantly enhances temporal localization accuracy and robustness across diverse video contexts.

## 3. VideoMind

**Overview.** Fig. 2 provides an overview of VideoMind. Our model derives from the widely adopted Qwen2-VL [77] architecture, which consists of an LLM backbone and a ViT-based visual encoder that natively supports dynamic resolution inputs. Given a video input  $\mathcal{V}$  and a text query  $\mathcal{Q}$ , the model adaptively activates different roles and performs step-by-step reasoning by calling individual modules: (i) **Planner:** Dynamically coordinates the following roles based on the query. (ii) **Grounder:** Identifies and localizes relevant video moments. (iii) **Verifier:** Evaluates the validity of the moments identified by Grounder, refining them through a zoom-in process with boolean outputs. (iv) **Answerer:** Generates the final response in natural language. This mechanism enables the models to revisit the videos several times (with varying temporal segments & spatial resolutions) to derive the final response.

**Chain-of-LoRA.** To meet the diverse demands of different roles, we introduce a novel Chain-of-LoRA strategy. The model dynamically activates role-specific LoRA adapters

[21] during inference via self-calling, ensuring both efficiency and adaptability. Next, we describe how we optimize each design and detail the curation of their SFT data.

### 3.1. Planner

In practice, an agent should be flexible enough to meet various demands and determine efficiently which function to call next. To this end, we introduce the **Planner** role, which dynamically coordinates all other roles for each query. The key idea is that the planner should decide the sequence of function calls based on the visual context.

We formulate each function call as a JSON-style object `{"type":<role>, "value":<argument>}`. Thus, a sequence of roles can be succinctly represented as a list of such objects. We define three plans illustrated in Fig. 3.

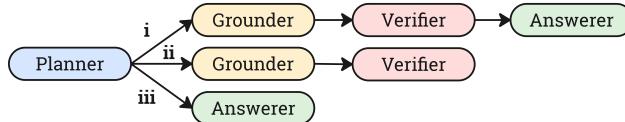


Figure 3. The Planner coordinates other roles based on the query, providing three modes and rephrasing tailored for different needs.

**(i) Grounding & Answering:** This plan requires the agent to generate both a response and a temporal moment. Such as “*What is the boy doing when the baby is crying?*” in grounded question-answering tasks [87], the agent must not only answer the question but also pinpoint the relevant moment. We enable this planning capability by repurposing the “temporal” questions from NExT-QA [87].

**(ii) Grounding Only:** Designed for tasks such as moment retrieval like “*When does the woman go downstairs?*”, this plan focuses solely on grounding, as the grounded timestamps are already the answer. We apply templates to sampled queries from QVHighlights [30] to train this setting.

**(iii) Answering Only:** When the question is straightforward (e.g., “*Summarize this video*”), the model may not need to localize moments. Instead, it can watch the entire video and answer the question directly, thereby avoiding an extra grounding call. We utilize the “causal” and “descriptive” questions in NExT-QA [87] for training this plan.

**Query Rephrasing:** Moreover, when the user query lacks sufficient detail for accurate localization, the planner is allowed to **rephrase** the question into a more descriptive version. For instance, the original query “*What is the person sitting on the bed doing as the baby plays?*” might confuse the grounder as it contains multiple instances (person and baby) in query. It can be rephrased to “*the baby is playing*” for a clear query. We train this rephrasing ability by using GPT-4o mini [56] to generate question-query pairs.

### 3.2. Grounder

The purpose of the grounder is to localize relevant moments (*i.e.*, start and end timestamps) based on text queries,

thereby supporting the reasoning process by identifying visual cues. This requirement calls for the development of an LMM with robust temporal grounding capabilities.

**Timestamp Decoder.** Rather than directly predicting textual timestamps through language modeling [63] or special tokens [22, 48], we develop a timestamp decoder head built upon the LMM. We introduce a special token `<REG>` to facilitate the timestamp decoding process. When this token is generated, the last-layer hidden states of `<REG>` and all the visual tokens will be sent into the decoder for timestamp prediction, obtaining an array (*i.e.*,  $[t_{start}, t_{end}]$ ) representing the normalized start and end timestamps.

As shown in Fig. 4, the decoder accepts hidden states of the visual tokens  $\mathbf{h}_v \in \mathbb{R}^{(T \times H \times W) \times D_L}$  and the `<REG>` token  $\mathbf{h}_r \in \mathbb{R}^{1 \times D_L}$  as inputs, where  $T, H, W, D_L$  are the down-sampled number of frames, width, height, and hidden dimensions of the LLM, respectively. We apply a 1D average pooling with kernel size and stride equal to  $H \times W$  to compress the visual tokens to one token per frame.

$$\mathbf{h}'_v = \text{AvgPool}(\mathbf{h}_v) \in \mathbb{R}^{T \times D_L} \quad (1)$$

Then,  $\mathbf{h}'_v$  and  $\mathbf{h}_r$  are projected by two linear layers  $E_v$  and  $E_r$  to reduce the hidden dimension to  $D$ .

$$\mathbf{e}_v = E_v(\mathbf{h}'_v) \in \mathbb{R}^{T \times D}, \quad \mathbf{e}_r = E_r(\mathbf{h}_r) \in \mathbb{R}^{1 \times D} \quad (2)$$

The resulting  $\mathbf{e}_v$  and  $\mathbf{e}_r$  serve as consolidated representations of the video frames and the query<sup>1</sup>, respectively. To effectively integrate their information, we add them with learnable modality embeddings, concatenate them along the sequence dimension, and encode them with a transformer.

$$[\mathbf{e}'_v; \mathbf{e}'_r] = \text{Transformer}([\mathbf{e}_v + \mathbf{m}_v + \mathbf{e}_p; \mathbf{h}_r + \mathbf{m}_r]) \quad (3)$$

Here,  $\mathbf{m}_v \in \mathbb{R}^{1 \times D}$  and  $\mathbf{m}_r \in \mathbb{R}^{1 \times D}$  are randomly initialized learnable embeddings as modality indicators. Notably,  $\mathbf{m}_v$  is expanded to  $T \times D$  before being added to  $\mathbf{e}_v$ .  $\mathbf{e}_p$  is a normalized sinusoidal positional encoding [75] for preserving temporal awareness. The output sequence is split into  $\mathbf{e}'_v$  and  $\mathbf{e}'_r$ , indicating the contextualized frame and query embeddings, respectively.

**Temporal Feature Pyramid.** To enhance adaptability to varying lengths of videos and moments, we map  $\mathbf{e}'_v$  into a four-level temporal feature pyramid with multiple temporal resolutions. This is achieved by applying a varying number of Conv1D → LayerNorm → SiLU blocks for each pyramid level, where the Conv1D employs a kernel size and stride of 2 (down-sampling the sequence by 1/2 along the temporal dimension). In practice, the four levels retain 1, 1/2, 1/4, and 1/8 of the original sequence length, respectively. They can be denoted as  $\mathbf{p}_v^n \in \mathbb{R}^{(T/n^2) \times D}$  where

<sup>1</sup>We use the term “query” to denote the features of `<REG>` token, aligning with common notations in temporal grounding literature.

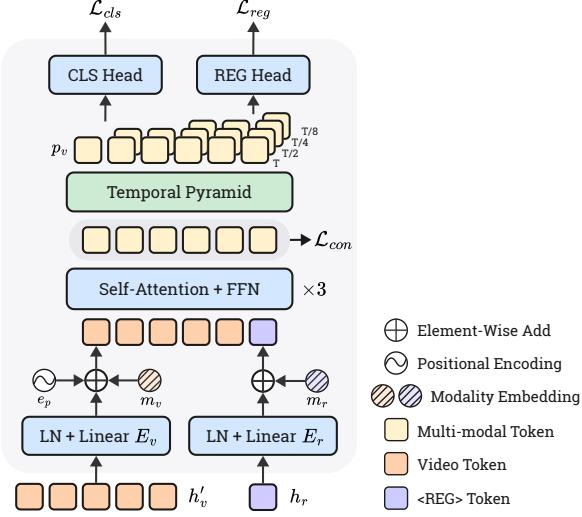


Figure 4. **Detailed architecture of the timestamp decoder.** This module accepts hidden states of both the frame tokens and the <REG> token, decoding them into the start and end timestamps.

$n \in [1, 4]$  is the index of the pyramid level. To accelerate the prediction process, we concatenate the sequences from all pyramid levels along the temporal dimension into  $p_v$  with length  $L = T + T/2 + T/4 + T/8$ , such that the prediction can be made in parallel.

**Training Objectives.** To model the continuous timestamps, we adopt two dense prediction heads [40, 47]: (i) a **classification head** is adopted for frame-level foreground-background classification. This is instantiated by a two-layer Conv1D module (kernel size=3, padding=1) followed by a Sigmoid activation. The outputs are frame-level confidence scores  $\{\hat{c}_i\}_{i=0}^L$  indicating whether each frame falls inside the desired moment. A binary focal loss [42] is leveraged to optimize this process.

$$\mathcal{L}_{cls} = -\lambda_{cls}\alpha(1 - \hat{c}_i)^\gamma \log(\hat{c}_i) \quad (4)$$

Here,  $\alpha = 0.9$  and  $\gamma = 2.0$  are hyperparameters of the focal loss, and  $\lambda_{cls}$  is a term balancing different losses. (ii) a **boundary regression head** is utilized to predict the 1d-offset with the temporal boundaries  $\{[\hat{b}_i^s, \hat{b}_i^e]\}_{i=0}^L$  for each frame. This is a two-layer convolution block, with an output dimension of 2 and an exponential function as the final activation. The outputs corresponding to different pyramid levels are further scaled by different learnable scalar factors. This head is supervised by an  $L1$  loss.

$$\mathcal{L}_{reg} = \lambda_{reg}(|b_i^s - \hat{b}_i^s| + |b_i^e - \hat{b}_i^e|) \quad (5)$$

In order to realize better alignment between  $e_v$  and  $e_r$ , we incorporate an additional contrastive loss to encourage learning more discriminative representations. Specifically, we calculate the cosine similarities among all frame-query

Role	#Samples	Pretraining Datasets
Planner	39K	NeXT-QA-Plan (34K), QVHighlights-Plan (5K)
Grounder	210K	QVHighlights (5K), DiDeMo (33K), TACoS (9K), QuerYD (19K), HiREST <sub>mr</sub> (8K), HiREST <sub>step</sub> (4K), CosMo-Cap (87K), InternVid-VTime (54K)
Verifier	232K	DiDeMo-Verify (165K), TACoS-Verify (43K), QVHighlights-Verify (24K)

Table 1. **Supervised fine-tuning datasets for VideoMind.** The planning dataset is repurposed from NeXT-QA [87] and QVHighlights [30]. Verify datasets are generated from the pre-trained Grounder’s predictions. *mr* and *step* denote the moment retrieval and step localization subsets of HiREST [98], respectively.

pairs (denoted as  $\{s_i\}_{i=0}^L$ ), then sample a positive frame (falling within the ground truth boundary) and apply the following optimization objective:

$$\mathcal{L}_{con} = -\lambda_{con} \log \frac{\exp(s_p/\tau)}{\exp(s_p/\tau) + \sum_{i \in \Theta} \exp(s_i/\tau)} \quad (6)$$

Here,  $\Theta$  contains the frame indices with  $s_p > s_i$ , and  $\tau = 0.07$  is a temperature. The final loss for the timestamp decoder is the sum of these losses at all layers with  $\lambda_{cls}=5.0$ ,  $\lambda_{reg}=1.0$ , and  $\lambda_{con}=0.05$ .

We pre-train the grounder on a large variety of temporal grounding datasets as shown in Tab. 1. During training, we optimize the timestamp decoder and introduce LoRA adapters on the LLM.

### 3.3. Verifier

A key moment is crucial for providing visual cues, yet it may be imprecise due to its sensitivity. Thus, further confirmation is necessary. We let the grounder generate top- $N$  predictions ( $N = 5$ ), which are then verified by the verifier to select the most reliable one, illustrated in Fig. 5.

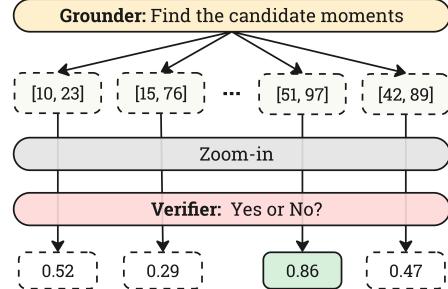


Figure 5. The grounder generates multiple candidate moments, which are then refined by applying a **zoom-in** strategy and evaluated by **Verifier** to select the best moment.

**Recap by Zoom-in:** For each candidate moment, we apply a zoom-in strategy by expanding the boundaries by 50% on both sides, cropping, and enlarging the resolution. The resulting video segment, together with the original text query, is then sent to the verifier to assess whether

Method	Size	long-acc.	mIoU	R@IoU	A@IoU
GPT-4o [56]	–	<b>45.2</b>	5.62	8.30	4.38
GPT-4o-mini [56]	–	33.4	3.75	5.18	2.21
Gemini-1.5-Pro [61]	–	37.2	3.95	5.81	2.53
Gemini-1.5-Flash [61]	–	32.3	3.67	5.44	2.45
Claude-3.5-Sonnet	–	40.5	3.99	5.67	2.79
Video-LLaVA [37]	7B	16.2	1.13	1.96	0.59
VideoLLaMA [102]	7B	18.4	1.21	1.87	0.84
Videochat2 [34]	7B	19.3	1.28	1.98	0.94
Qwen-VL-Chat [4]	7B	21.6	0.89	1.19	0.42
ST-LLM [45]	7B	23.8	2.23	2.86	1.13
ShareGPT4Video [9]	16B	26.7	1.85	2.65	1.01
Chat-UniVi-v1.5 [25]	13B	25.9	2.07	2.53	1.21
ViLA [38]	8B	28.7	1.56	2.89	1.35
MiniCPM-v2.6 [71]	8B	30.1	2.35	2.61	1.04
LongVA [104]	7B	28.7	2.94	3.86	1.78
LLaVA-OV [31]	7B	31.1	1.63	1.78	1.08
Video-CCAM [12]	14B	29.7	2.63	3.48	1.83
Kangaroo [43]	8B	30.2	2.56	2.81	1.94
VITA [14]	8×7B	33.3	3.06	3.53	2.06
Qwen2-VL [78]	72B	41.3	3.58	5.32	3.31
InternVL2 [10]	78B	42.2	3.91	5.05	2.64
<b>VideoMind</b> (Ours)	2B	31.0	5.94	8.50	4.02
<b>VideoMind</b> (Ours)	7B	38.4	<b>7.10</b>	<b>9.93</b>	<b>4.67</b>

R@IoU – rec. @IoU, A@IoU – acc. @IoU

Table 2. **Grounded VideoQA on CG-Bench [6]** Despite its smaller size, VideoMind surpasses GPT-4o and open-source baselines on this challenging long video benchmark (avg. dur: 27 min).

the queried event occurs within the segment. To enhance boundary awareness, we introduce two special tokens, `<SEG_START>` and `<SEG_END>`, to explicitly mark the beginning and end of the moment. These tokens are inserted among the visual tokens at the corresponding frames, effectively guiding the model in recognizing boundaries.

**Boolean Judgement:** The verifier’s responses are designed to be binary – either ‘Yes’ or ‘No’. To train the verifier, we sample predictions from the grounder on its training datasets and assign binary labels based on an IoU threshold of 0.5. The model is then fine-tuned via SFT to predict these labels. During inference, for each candidate moment, we employ teacher forcing to obtain the likelihoods of the `<Yes>` and `<No>` tokens, denoted as  $L_y$  and  $L_n$ , respectively. The confidence score for a moment is defined as  $\text{Sigmoid}(L_y - L_n)$ . Finally, we re-rank the moments based on their confidence scores to yield the best one.

### 3.4. Answerer

The answerer is responsible for answering the given question based on either the cropped video segment (when the grounder is used) or the entire video (if the planner opts for a direct answer). Since the objective of this role is strictly aligned with existing LMMs (*i.e.*, Qwen2-VL [77] in our case), we employ the pre-trained model directly *without any fine-tuning or architectural modifications*.

All our modules (Planner, Grounder, Verifier, and An-

Method	Size	FT	R@0.3	R@0.5	mIoU	Acc	Acc@IoU
VTimeLLM [22]	7B		28.84	17.41	20.14	36.16	–
TimeChat [62]	7B		14.42	7.61	11.65	40.04	–
LITA [23]	13B		29.49	16.29	21.49	34.44	–
VTimeLLM [22]	7B	✓	43.69	26.13	29.92	57.58	17.13
TimeChat [62]	7B	✓	40.13	21.42	26.29	49.46	10.92
<b>VideoMind</b> (Ours)	2B		34.31	22.69	24.83	69.06	17.26
<b>VideoMind</b> (Ours)	7B		<b>38.22</b>	<b>25.52</b>	<b>27.61</b>	<b>74.59</b>	<b>20.20</b>

Table 3. **Grounded VideoQA on ReXTime [8]**. FT indicates whether fine-tuned on the downstream training set. VideoMind demonstrates strong generalization; its zero-shot scores outperforms all zero-shot baseline and surpasses fine-tuned variants.

swerer) are built on top of the same backbone LMM and augmented with **additional LoRA adapters** and a lightweight timestamp decoder (for Grounder). Different LoRA adapters are switched for each role, allowing us to maximize role-specific capabilities while minimizing modifications to the model architecture.

## 4. Experiments

We conduct extensive experiments across various benchmarks to evaluate our VideoMind. Specifically, we study the following research questions.

- Q1.** Whether VideoMind is flexible and effective on different video temporal reasoning tasks compared to baselines with task-specific designs?
- Q2.** What effects does each individual role contribute?
- Q3.** Compared with training a single agent on multiple tasks, what advantages does Chain-of-LoRA offer?

Experiments on more datasets and further ablation studies can be found in the supplementary.

### 4.1. Benchmarks and Settings

We extensively design experiments across 14 diverse benchmarks. The tasks include (i) **Grounded Video Question-Answering**, (ii) **Video Temporal Grounding**, and (iii) **General Video Question-Answering**. We present the results on CG-Bench [6], ReXTime [8], NExT-GQA [88], Charades-STA [17], ActivityNet-Captions [27], Video-MME [13], MLVU [108], and LVBench [79] here. More experiments and details are in the supplementary.

### 4.2. Q1: Comparison with State-of-the-Arts

**Grounded Video Question-Answering.** In Tab. 2, we report results on CG-Bench [6], a challenging benchmark with an average duration of 27 minutes. In grounding metrics, our lightweight 2B model outperforms all compared models (including InternVL2-78B [10] and most closed-source models such as Claude-3.5-Sonnet), with the exception of GPT-4o [56], while our 7B model surpasses it and achieves competitive overall performance.

Method	Size	IoU			IoP			Acc@ GQA
		R@0.3	R@0.5	mIoU	R@0.3	R@0.5	mIoP	
FrozenBiLM NG+ [93]	890M	13.5	6.1	9.6	28.5	23.7	24.2	17.5
VIOLETv2 [15]	—	4.3	1.3	3.1	25.1	23.3	23.6	12.8
SeViLA [97]	4B	29.2	13.8	21.7	34.7	22.9	29.5	16.6
LangRepo [26]	8×7B	—	12.2	18.5	—	28.7	31.3	17.1
VideoStreaming [58]	8.3B	—	13.3	19.3	—	31.0	32.2	17.8
LLoVi [99]	1.8T	—	15.3	20.0	—	36.9	37.3	24.3
HawkEye [83]	7B	37.0	19.5	25.7	—	—	—	—
VideoChat-TPO [92]	7B	41.2	23.4	27.7	47.5	32.8	35.6	25.5
<b>VideoMind (Ours)</b>	2B	45.2	23.2	28.6	51.3	32.6	36.4	25.2
<b>VideoMind (Ours)</b>	7B	<b>50.2</b>	<b>25.8</b>	<b>31.4</b>	<b>56.0</b>	<b>35.3</b>	<b>39.0</b>	<b>28.2</b>

Table 4. **Grounded VideoQA on NExT-GQA [88].** VideoMind beats both agent-based solutions [99] and end-to-end methods [92] trained with large-scale data. Notably, our 2B model is comparable with 7B counterparts.

Method	Size	FT	R@0.3	R@0.5	R@0.7	mIoU
Moment-DETR [30]	—	✓	65.8	52.1	30.6	45.5
UniVTG [40]	—	✓	70.8	58.1	35.6	50.1
R <sup>2</sup> -Tuning [47]	—	✓	70.9	59.8	37.0	50.9
VTImeLLM [22]	13B		55.3	34.3	14.7	34.6
TimeChat [63]	7B		51.5	32.2	13.4	—
Momentor [57]	7B		42.6	26.6	11.6	28.5
HawkEye [83]	7B		50.6	31.4	14.5	33.7
ChatVTG [59]	7B		52.7	33.0	15.9	34.9
VideoChat-TPO [92]	7B		58.3	40.2	18.4	38.1
E.T. Chat [48]	4B		65.7	45.9	20.0	42.3
<b>VideoMind (Ours)</b>	2B		67.6	51.1	26.0	45.2
<b>VideoMind (Ours)</b>	7B		<b>73.5</b>	<b>59.1</b>	<b>31.2</b>	<b>50.2</b>

Table 6. **Zero-shot Video Temporal Grounding on Charades-STA [17].** VideoMind significantly surpasses counterparts.

In Tab. 3, we show the results on ReXTime [8]. Despite the challenge posed by the temporal and causal event relationships, our model successfully identifies the correct event and zooms in on the relevant moment. Notably, our zero-shot model outperforms all zero-shot baselines by a significant margin and yield comparable performance to several fine-tuned variants in grounding, while also achieving higher accuracy. This demonstrates the strong generalization capability of our method.

We further present results on NExT-GQA [88] in Tab. 4. Compared to text-rich, agent-based solutions such as LLoVi [99] and LangRepo [26] – which leverage additional tools and chain-of-thought, and SeViLA [97] – a self-chained video agent with a similar design, our 2B model matches the performance of state-of-the-art 7B models across both agent-based and end-to-end approaches. Moreover, our 7B model significantly outperforms all other models.

**Video Temporal Grounding.** Since the performance of Grounder and Verifier is essential for VideoMind, we evaluate these modules on temporal grounding datasets. In Tab. 6

Method	Size	Video-MME		MLVU	LBench
		All	Long	M-Avg	Overall
Gemini-1.5-Pro [70]	—	75.0	67.4	—	33.1
GPT-4o [56]	—	71.9	65.3	54.5	30.8
Video-LLaVA [37]	7B	41.1	37.8	29.3	—
TimeChat [63]	7B	34.3	32.1	30.9	22.3
MovieChat [68]	7B	38.2	33.4	25.8	22.5
PLLaVA [90]	34B	40.0	34.7	53.6	26.1
VideoChat-TPO [92]	7B	48.8	41.0	54.7	—
LongVA [103]	7B	52.6	46.2	56.3	—
<b>VideoMind (Ours)</b>	2B	53.6	45.4	58.7	35.4
<b>VideoMind (Ours)</b>	7B	<b>58.2</b>	<b>49.2</b>	<b>64.4</b>	<b>40.8</b>

Table 5. **VideoQA on Video-MME [13] (~15min), MLVU [108] (~15min), and LBench [79] (~1.1h).** VideoMind shows superior performance on long videos.

Method	Size	FT	R@0.3	R@0.5	R@0.7	mIoU
2D-TAN [105]	—	✓	60.4	43.4	25.0	42.5
MMN [84]	—	✓	64.5	48.2	29.4	46.6
VDI [49]	—	✓	—	48.1	28.8	—
VideoChat [33]	7B		8.8	3.7	1.5	7.2
Video-LLaMA [102]	7B		6.9	2.1	0.8	6.5
Video-ChatGPT [51]	7B		26.4	13.6	6.1	18.9
Valley [50]	7B		30.6	13.7	8.1	21.9
ChatVTG [59]	7B		40.7	22.5	9.4	27.2
Momentor [57]	7B		42.9	23.0	12.4	29.3
E.T. Chat [48]	4B		24.1	12.8	6.1	18.9
<b>VideoMind (Ours)</b>	2B		44.0	26.5	12.6	30.1
<b>VideoMind (Ours)</b>	7B		<b>48.4</b>	<b>30.3</b>	<b>15.7</b>	<b>33.3</b>

Table 7. **Zero-shot Video Temporal Grounding on ActivityNet-Captions [27].** VideoMind outperforms LLM-based methods.

and Tab. 7, we validate the zero-shot grounding capabilities of VideoMind. Benefiting from (i) the timestamp decoder design of Grounder, and (ii) a verifier that refines the results by focusing on critical segments, our model achieves significant zero-shot performance – surpassing all LLM-based temporal grounding methods and yielding competitive results compared to fine-tuned temporal grounding experts.

**General Video Question-Answering.** We are also interested in whether our temporal-augmented design can improve general video QA tasks. In Tab. 5, we evaluate our model on three widely used benchmarks to determine if the Chain-of-LoRA design generalizes to common settings. Notably, Video-MME (Long) [13], MLVU [108], and LBench [?] features long videos, where grounding and verifying are critical. Our designs effectively help the model localize cue segments before answering the question.

### 4.3. Ablation Studies

**Q2: Effect of Individual Roles.** To study the contribution of each individual role, we conduct ablation studies (Tab. 8).

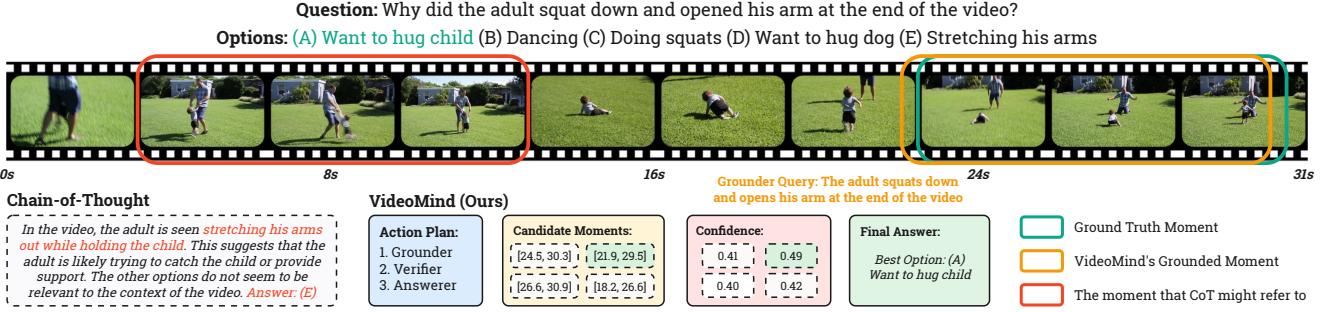


Figure 6. **Visualization of the VideoMind workflow.** The Planner first determines the need for function calls and generates several candidate moments using the Grounder. It then applies the Verifier to select the most relevant video segment (highlighted in yellow). After zooming in, the segment is passed to the Answerer. By chaining the Grounder, Verifier, and Answerer roles, VideoMind accurately localizes the critical moment and selects the correct answer, thereby avoiding confusion from an incorrect segment (red box).

VideoMind Roles			ReXTime		Charades-STA				
Ans.	Gnd.	Ver.	Pla.	G%	mIoU	Acc	R@0.5	R@0.7	mIoU
✓				0%	—	68.0	—	—	—
✓	✓			100%	24.5	68.8	—	—	—
✓	✓	✓		100%	24.8	69.1	—	—	—
✓	✓	✓	✓	100%	24.7	69.2	—	—	—
✓	✓	✓	✓	40%	<b>26.7</b>	<b>70.0</b>	—	—	—
	✓				—	—	47.2	21.7	42.0
	✓	✓			—	—	<b>51.1</b>	<b>26.0</b>	<b>45.2</b>

Ans. – Answerer, Gnd. – Grounder, Ver. – Verifier, Pla. – Planner

Table 8. **Key ablations to study the effects of individual roles.** The top half evaluates the full system on Grounded VideoQA, while the bottom half details the impact of the Grounder and Verifier on Video Temporal Grounding. G% indicates the percentage of samples processed with the Grounder module.

Our observations are as follows: **(i) Grounder:** By identifying visual cues, the grounder can slightly improve QA acc., indicating that the grounder is especially effective on long videos. **(ii) Verifier:** Selecting the best candidate with the verifier improves grounded moments, yielding a consistent gain of 3.2 mIoU on the pure grounding metrics for Charades-STA. **(iii) Planner:** Coordinating roles via the Planner – even when performing grounding on only 40% samples (with the remaining 60% are processed by watching the whole video) – boosts the accuracy from 69.2 to 70.0. This highlights the dynamic benefits of Planner under different visual and textual context.

**Q3: Effect of the Chain-of-LoRA strategy.** Tab. 9 investigates the impact of integrating different modules. First, naive CoT does not improve the base model, highlighting the need for a visual-centric, test-time search strategy. Second, while multi-task co-training enhances the baseline overall, it fails to optimize individual capabilities (*e.g.*, grounding performance remains poor at around 3% mIoU on Charades-STA). Although the all-distributed approach achieves the best performance, it requires multiple copies

Method	Mem.	NExT-GQA		Charades-STA		Video-MME	
		mIoU	Acc	R@0.5	mIoU	All	Long
Qwen2-VL-2B	4.1G	—	69.6	—	—	49.7	43.1
+ CoT [85]	4.1G	—	69.7	—	—	49.6	43.2
+ All-in-One	4.2G	28.0	70.5	47.8	42.1	52.8	44.6
+ All-Distributed	16.6G	28.6	71.4	51.1	45.2	53.6	45.4
<b>+ Chain-of-LoRA</b>	<b>4.2G</b>	<b>28.6</b>	<b>71.4</b>	<b>51.1</b>	<b>45.2</b>	<b>53.6</b>	<b>45.4</b>

Table 9. **Key ablations to study the test-time strategy with different role integrations**, including the base model, a version using textual CoT, and three implementations that integrate multiple roles. **Mem.** indicates GPU memory usage. Notably, Chain-of-LoRA achieves the best performance with minimal memory cost.

(4×) of the model weights. In contrast, Chain-of-LoRA maintains top performance in the most efficient manner.

#### 4.4. Qualitative Analysis

In Fig. 6, we illustrate how VideoMind applies all roles to progressively derive the correct answer while avoiding potential mistakes or confusion.

### 5. Conclusion and Limitations

We introduced **VideoMind**, a novel video-language agent designed for temporal grounded video reasoning. Our approach employs an agentic workflow consisting of a Planner, Grounder, Verifier, and Answerer, along with a **Chain-of-LoRA** strategy to efficiently switch among these roles. Extensive experiments in grounded video question-answering, video temporal grounding, and general video question-answering demonstrate the effectiveness and significance of VideoMind, particularly in long-form video reasoning tasks by providing precise, evidence-based answers. We acknowledge that our model requires huge optimization of individual designs and preparing training data. We hope this work inspires future advancements in multimodal video agents and reasoning.

## Appendix

In this document, we provide more descriptions of the model, implementation details, and benchmarks to complement the main paper. Additional experiments and prompt templates are also incorporated.

## A. Model Details

### A.1. Inference Pipeline

The formulation of VideoMind’s inference pipeline is illustrated in Algorithm 1. Given a video and a question, Planner dynamically calls different roles on demand to analyze the problem and generate the answer.

**Algorithm 1** VideoMind’s Chain-of-LoRA Pipeline

```

1: Input: a video  $\mathcal{V}$  with a query  $\mathcal{Q}$ 
2: Output: an answer  $\mathcal{A}$  with temporal moment  $\mathcal{T} = [t_s, t_e]$ 
3: Plan  $\mathcal{P} \leftarrow \text{Planner}(\mathcal{V}, \mathcal{Q})$ 
4: if Grounder  $\in \mathcal{P}$  then
5:    $\{[t_s^i, t_e^i]\}_i \leftarrow \text{Grounder}(\mathcal{V}, \mathcal{Q})$ 
6:   for all  $i$  do
7:      $\tilde{\mathcal{V}}_i \leftarrow \text{ZoomIn}(\mathcal{V}, [t_s^i, t_e^i])$ 
8:      $Score_i \leftarrow \text{Verifier}(\tilde{\mathcal{V}}_i, \mathcal{Q})$ 
9:   end for
10:   $i \leftarrow \arg \max s_i(Score_i)$ 
11: end if
12: if Answerer  $\in \mathcal{P}$  then
13:    $\mathcal{A} \leftarrow \text{Answerer}(\tilde{\mathcal{V}}_i, \mathcal{Q})$ 
14: end if
15: return  $(\mathcal{A}, \mathcal{T})$ 
```

### A.2. Implementation Details

We leverage the 2B and 7B versions of Qwen2-VL [77] as our base model, and apply LoRA adapters with rank 64 and alpha 64 to Planner, Grounder, and Verifier. The hidden size of the timestamp decoder in Grounder is 256. The maximum number of tokens per frame and maximum number of frames for Planner, Grounder, Verifier, and Answerer are set as [64, 100], [64, 150], [64, 64], and [256, 32], respectively. The video frames are sampled as 2 FPS except Grounder, which uses 1 FPS since more frames are used. We train different roles separately on different datasets, and load them together by setting different names for LoRA adapters, such that the model can efficiently switch roles via actively setting different LoRAs. During training, we set the global batch size as 32, and utilize AdamW optimizer with learning rate 2e-5, 1e-4, and 5e-5 for Planner, Grounder, and Verifier, respectively. All the roles were trained for 1 epoch on their specific datasets, with a linear warmup in the first 3% steps. During inference, we apply NMS with IoU threshold 0.75 to reduce duplicated moments from Grounder.

Dataset	Duration	Domain	Main Metrics
<i>Grounded Video Question-Answering (Grounding + QA)</i>			
CG-Bench [6]	1624.4s	Diverse	rec.@IoU, acc.@IoU
ReXTime [8]	141.1s	Mixed*	mIoU, Acc (IoU $\geq 0.5$ )
NEXT-GQA [88]	39.5s	Reasoning	mIoP, Acc@GQA
<i>Video Temporal Grounding (Grounding only)</i>			
Charades-STA [66]	30.1s	Indoor	R@{0.3 ~ 0.7}, mIoU
ANet-Captions [27]	111.4s	Activity	R@{0.3 ~ 0.7}, mIoU
QVHighlights [30]	150s	Mixed*	R@{0.5, 0.7}, mAP
TACoS [60]	358.2s	Cooking	R@{0.3 ~ 0.7}, mIoU
Ego4D-NLQ [18]	379.0s	Egocentric	R@{0.3 ~ 0.7}, mIoU
ANet-RTL [23]	111.4s	Reasoning	P@0.5, mIoU
<i>General Video Question-Answering (QA only)</i>			
Video-MME [13]	1017.9s	Diverse	Acc (w/o subs)
MLVU [108]	930s	Diverse	Acc
LVBench [79]	4101s	Diverse	Acc
MVBench [34]	15s	Diverse	Acc
LongVideoBench [86]	473s	Diverse	Acc

\* Vlog, News, and Activity

**Table 10. Statistics of Evaluation Datasets.** The datasets encompass three representative tasks – Grounded VideoQA, Video Temporal Grounding, and General VideoQA, with video durations ranging from less than 1 minute to more than 1 hour.

Method	Size	R1		mAP		
		@0.5	@0.7	@0.5	@0.75	Avg.
<i>Non-LLM-based Specialists</i>						
XML [29]	–	41.83	30.35	44.63	31.73	32.14
XML+ [30]	–	46.69	33.46	47.89	34.67	34.90
Moment-DETR [30]	–	59.78	40.33	60.51	35.36	36.14
UMT [46]	–	60.83	43.26	57.33	39.12	38.08
MomentDiff [35]	–	58.21	41.48	54.57	37.21	36.84
QD-DETR [54]	–	62.40	44.98	62.52	39.88	39.86
UniVTG [40]	–	65.43	50.06	64.06	45.02	43.63
R <sup>2</sup> -Tuning [47]	–	68.03	49.35	69.04	47.56	46.17
<i>LLM-based Models</i>						
<b>VideoMind</b> (Ours)	2B	75.42	59.35	74.11	55.15	51.6

**Table 11. Fine-tuned Video Temporal Grounding on QVHighlights [30].** VideoMind achieves state-of-the-art performance.

## B. Experimental Details

### B.1. Benchmarks

The statistics of evaluation benchmarks we used are listed in Tab. 10. We mainly evaluate VideoMind on grounded VideoQA and video temporal grounding scenarios, and also study its generalizability on general long VideoQA benchmarks. The information about major benchmarks are introduced below.

**CG-Bench** [6] is designed for long video grounded question-answering, featuring a diverse domain and various evaluation metrics. It includes 1.2K manually curated

Method	Size	FT	R@0.3	R@0.5	R@0.7	mIoU
<i>Non-LLM-based Specialists</i>						
2D-TAN [105]	-	✓	40.0	28.0	12.9	27.2
VSLNet [101]	-	✓	35.5	23.5	13.1	25.0
Moment-DETR [30]	-	✓	38.0	24.7	12.0	25.5
UniVTG [40]	-	✓	51.4	35.0	17.4	33.6
R <sup>2</sup> -Tuning [47]	-	✓	49.7	38.7	25.1	35.9
<i>LLM-based Models</i>						
<b>VideoMind</b> (Ours)	2B	✓	38.6	26.9	15.5	27.4
<b>VideoMind</b> (Ours)	7B	✓	<b>49.5</b>	<b>36.2</b>	<b>21.4</b>	<b>34.4</b>

Table 12. **Video Temporal Grounding on TACoS [60].** VideoMind’s pretraining dataset already contains TACoS, and we did not apply any further fine-tuning on it. The performance is comparable to task-specific experts trained for multiple epochs.

Method	Size	FT	R@0.3	R@0.5	R@0.7	mIoU
<i>Non-LLM-based Specialists</i>						
2D-TAN [105]	-	✓	4.3	1.8	0.6	3.4
VSLNet [101]	-	✓	4.5	2.4	1.0	3.5
Moment-DETR [30]	-	✓	4.3	1.8	0.7	3.5
UniVTG [40]	-	✓	7.3	4.0	1.3	4.9
R <sup>2</sup> -Tuning [47]	-	✓	7.2	4.5	2.1	4.9
UniVTG [40]	-		6.5	3.5	1.2	4.6
<i>LLM-based Models</i>						
<b>VideoMind</b> (Ours)	2B		5.9	2.9	1.2	4.7
<b>VideoMind</b> (Ours)	7B		<b>7.2</b>	<b>3.7</b>	<b>1.7</b>	<b>5.4</b>

Table 13. **Zero-shot Video Temporal Grounding on Ego4D-NLQ [18].** VideoMind is comparable with fine-tuned experts.

Method	Size	FT	P@0.5	mIoU
LITA [23]	7B	✓	21.2	24.1
LITA [23]	13B	✓	25.9	28.6
<b>VideoMind</b> (Ours)	2B		20.1	22.7
<b>VideoMind</b> (Ours)	7B		<b>28.0</b>	<b>31.3</b>

Table 14. **Zero-shot Reasoning Temporal Localization on ActivityNet-RTL [23].** Our zero-shot method even performs better than fine-tuned baselines.

videos, ranging from 10 to 80 minutes, with a total of 12K QA pairs. The dataset is categorized into perception, reasoning, and hallucination question types, and introduces clue-based evaluation methods like white box and black box assessments to ensure models provide answers based on accurate video reasoning.

**ReXTIME** [8] tests models on complex temporal reasoning, using an automated pipeline for QA pair generation, significantly reducing manual effort. It includes 921 validation and 2,1K test samples, each manually curated for accuracy, and highlights a 14.3% accuracy gap between SoTA models and human performance. This benchmark is crucial for

Method	Charades-STA			
	R@0.3	R@0.5	R@0.7	mIoU
VideoMind-Grounder	63.55	47.23	21.69	42.02
w/o ADL	62.52	46.90	20.88	40.43

Table 15. **Effect of the auxiliary decoding loss (ADL).**

#Pyramid Levels	Charades-STA			
	R@0.3	R@0.5	R@0.7	mIoU
1	60.55	44.57	15.82	38.13
2	61.51	46.90	19.36	40.43
3	62.62	47.02	20.08	41.27
4	63.55	47.23	21.69	42.02

Table 16. **Effect of the temporal feature pyramid.**

Verifier Type	Charades-STA			
	R@0.3	R@0.5	R@0.7	mIoU
Direct	60.42	45.28	19.32	39.84
Expand	65.10	48.70	23.15	43.57
Textual	65.24	49.33	23.89	44.01
Special Token	67.63	51.05	25.99	45.22

Table 17. **Effect of different Verifier styles.**

evaluating models on cause-and-effect relationships across video segments, driving advancements in video understanding research.

**NEXT-GQA** [88] aims to challenge models to reason about causal and temporal actions, supporting both multi-choice and open-ended tasks. It is an extension of NExT-QA [87] and comprises 10.5K manually videos QA pairs with temporal segments. The samples in this benchmark are categorized into “causal” and “temporal” questions, while the “descriptive” questions from NExT-QA are discarded.

**Charades-STA** [17] contains 10K in-door videos, averaging 30.1 seconds each, with 16K temporal annotations spanning daily activity, alongside free-text descriptions. These rich annotations make Charades-STA particularly suitable for evaluating temporal grounding models under indoor environments.

**ActivityNet-Captions** [27] is a large-scale benchmark with 20K untrimmed YouTube videos totaling 849 hours, covering diverse activities from personal care to sports. This dataset contains high-quality dense video captioning annotations (3.65 temporally localized sentences per video), which we use as queries for video temporal grounding. Each query has an average length of 13.48 words.

## B.2. More Comparisons with State-of-the-Arts

**More Video Temporal Grounding benchmarks.** We additionally compare VideoMind with representative meth-

Model	Size	AS	AP	AA	FA	UA	OE	OI	OS	MD	AL	ST	AC	MC	MA	SC	FP	CO	EN	ER	CI	Avg.
GPT-4V [1]	–	55.5	63.5	72.0	46.5	73.5	18.5	59.0	29.5	12.0	40.5	83.5	39.0	12.0	22.5	45.0	47.5	52.0	31.0	<b>59.0</b>	11.0	43.5
Video-ChatGPT [51]	7B	23.5	26.0	62.0	22.5	26.5	54.0	28.0	40.0	23.0	20.0	31.0	30.5	25.5	39.5	48.5	29.0	33.0	29.5	26.0	35.5	32.7
Video-LLaMA [102]	7B	27.5	25.5	51.0	29.0	39.0	48.0	40.5	38.0	22.5	22.5	43.0	34.0	22.5	32.5	45.5	32.5	40.0	30.0	21.0	37.0	34.1
VideoChat [33]	7B	33.5	26.5	56.0	33.5	40.5	53.0	40.5	30.0	25.5	27.0	48.5	35.0	20.5	42.5	46.0	26.5	41.0	23.5	23.5	36.0	35.5
Video-LLaVA [37]	7B	46.0	42.5	56.5	39.0	53.5	53.0	48.0	41.0	29.0	31.5	82.5	45.0	26.0	53.0	41.5	33.5	41.5	27.5	38.5	31.5	43.0
TimeChat [63]	7B	40.5	36.0	61.0	32.5	53.0	53.5	41.5	29.0	19.5	26.5	66.5	34.0	20.0	43.5	42.0	36.5	36.0	29.0	35.0	35.0	38.5
PLLaVA [90]	7B	58.0	49.0	55.5	41.0	61.0	56.0	61.0	36.0	23.5	26.0	82.0	39.5	42.0	52.0	45.0	42.0	53.5	30.5	48.0	31.0	46.6
ShareGPT4Video [9]	7B	49.5	39.5	79.5	40.0	54.5	82.5	54.5	32.5	50.5	41.5	84.5	35.5	62.5	75.0	51.0	25.5	46.5	28.5	39.0	51.5	51.2
ST-LLM [45]	7B	66.0	53.5	<b>84.0</b>	44.0	58.5	80.5	73.5	38.5	42.5	31.0	86.5	36.5	56.5	78.5	43.0	44.5	46.5	34.5	41.5	58.5	54.9
VideoGPT+ [52]	3.8B	69.0	60.0	83.0	48.5	66.5	85.5	75.5	36.0	44.0	34.0	89.5	39.5	71.0	90.5	45.0	53.0	50.0	29.5	44.0	60.0	58.7
VideoChat2 [34]	7B	75.5	58.0	83.5	<b>50.5</b>	60.5	87.5	74.5	<b>45.0</b>	47.5	44.0	82.5	37.0	64.5	87.5	<b>51.0</b>	<b>66.5</b>	47.0	35.0	37.0	72.5	60.4
<b>VideoMind (Ours)</b>	2B	<b>77.0</b>	<b>78.0</b>	77.0	46.5	70.5	87.0	71.5	33.0	48.0	39.5	<b>91.0</b>	<b>53.0</b>	78.0	89.0	43.5	53.5	61.5	37.5	49.5	53.0	61.9
<b>VideoMind (Ours)</b>	7B	74.0	71.5	81.0	50.0	<b>77.0</b>	<b>93.0</b>	<b>75.0</b>	38.0	<b>48.5</b>	<b>46.0</b>	<b>91.0</b>	39.0	<b>80.0</b>	<b>94.5</b>	49.5	55.5	<b>70.0</b>	<b>40.5</b>	57.0	<b>61.0</b>	<b>64.6</b>

Table 18. General Video Question-Answering on MVBench [34]. VideoMind can also achieve comparable performance on short (average duration is around 15s) video understanding, demonstrating strong generalization abilities.

Method	Size	Acc	Acc @ Duration Groups				
			A	B	C	D	
GPT-4o [56]	–	66.7	71.4	76.7	69.1	60.9	
GPT-4 Turbo [55]	–	59.0	65.2	68.2	62.4	50.5	
Gemini-1.5-Pro [70]	–	64.0	67.4	75.1	65.3	58.6	
Gemini-1.5-Flash [70]	–	61.6	68.3	76.2	62.6	54.0	
Idefics2 [28]	8B	49.7	<b>59.8</b>	<b>65.7</b>	47.8	42.7	
Phi-3-Vision [3]	4B	49.6	59.3	61.6	46.8	44.7	
Mantis-Idefics2 [24]	8B	47.0	56.6	55.8	45.6	42.2	
Mantis-BakLLaVA [24]	7B	43.7	53.4	57.6	40.3	38.7	
<b>VideoMind (Ours)</b>	2B	48.8	59.3	59.3	49.3	41.7	
<b>VideoMind (Ours)</b>	7B	<b>56.3</b>	<b>67.7</b>	<b>67.4</b>	<b>56.8</b>	<b>48.6</b>	

A: (8, 15] B: (15, 60] C: (180, 600] D: (900, 3600]

Table 19. Video Question-Answering on LongVideoBench [86] **val split**. VideoMind is superior on all duration groups.

ods on the challenging QVHighlights [30], TACoS [60] and Ego4D-NLQ [18] datasets in Tab. 11, Tab. 12 and Tab. 13, respectively. To our best knowledge, VideoMind is the first LLM-based grounding model that supports multi-moment outputs, thereby being able to evaluated on QVHighlights. Compared with task-specific experts, our 2B VideoMind significantly performs better under all metrics. Our model also performs better than UniVTG [40] on TACoS but slightly worse on Ego4D-NLQ because UniVTG was originally pre-trained on egocentric videos. Even without egocentric pre-training, VideoMind can still produce comparable results on Ego4D-NLQ.

**Results on Reasoning Temporal Localization.** We also evaluate the generalization ability of Grounder and Verifier on the more challenging reasoning temporal localization [23] task, which is similar to video temporal grounding but the queries are not directly describing the moment. The models are required to infer the actual event using its world knowledge. The results in Tab. 14 show that VideoMind

can successfully generalize its strong zero-shot grounding capability from referring to reasoning scenarios.

**More General VideoQA benchmarks.** Tab. 18 presents the evaluation results of VideoMind on MVBench [34] which is a VideoQA benchmark with very short videos. Although this is out of our main scope, our model can still achieve good performance on such short video scenarios. For long VideoQA, we also provide evaluations on LongVideoBench [86] in Tab. 19, which further verifies the effectiveness of VideoMind on long videos.

### B.3. Further Ablation Studies

**Effect of auxiliary decoding loss.** Tab. 15 compares the difference in performance whether the auxiliary decoding loss is added or not. When removing this auxiliary loss, the performance of VideoMind-Grounder degrades by about 1.5 mIoU, suggesting the effectiveness of this loss term.

**Effect of the temporal feature pyramid.** Tab. 16 studies the effectiveness of the temporal feature pyramid. Our baseline model directly makes predictions on the last-layer transformer outputs. When adding more pyramid levels, the performance of video temporal grounding consistently improves under all metrics on the Charades-STA [17] dataset under zero-shot setting, suggesting the effectiveness of the improving robustness of the model when facing moments with different lengths.

**Design choices of Verifier.** In Table 17, we examine various design choices for the Verifier. The term ‘‘Direct’’ refers to the method where the grounded moment is directly sent into the model without any expansion. ‘‘Expand’’ denotes expanding the temporal boundaries by 50%, while ‘‘Textual’’ involves adding supplementary textual information to indicate the length of the target event. ‘‘Special Token’’ represents our final approach, utilizing special tokens to denote the grounded start and end timestamps. The comparison re-

sults demonstrate that expanding the temporal boundaries effectively broadens the Verifier’s perceptual range, and the use of special tokens enhances the model’s understanding of the precise moment boundaries.

## C. Prompt Templates

We present the prompts used in this work, including the input prompts for each role of VideoMind and the prompt for GPT-4o mini [56] for data annotation.

### Prompt for Planner:

You are acting as the planner now. Given a question about the video, your task is to analyze the question and identify the best way to answer this question. You have access to the following tools:

Grounder: Accepts a text query and localizes the relevant video segment according to the query.

Verifier: A tool supporting grounder by verifying the reliability of its outputs.

Answerer: Answer a given question directly based on the whole video or a cropped video segment.

Your response must be a list in JSON format. A valid plan for reasoning could be “grounder, verifier, answer”, “grounder, verifier”, or “answerer”, depending on the given question. Please see an example of the format below.

```
[{"type": "grounder", "value": "text query"}, {"type": "verifier"}, {"type": "answerer"}]
```

Note that only the grounder can accept an argument called “value”, which is the text query used for grounding. Now I give you the question: ‘{question}’. Please think carefully and respond with your plan in JSON directly.

### Prompt for Grounder:

You are acting as the grounder now. Given a video and a text query, your goal is to temporally localize the video moment described by the query. If the query is directly describing a moment, simply localize it according to its content. Otherwise, if the moment is described as ‘before/after a pivotal event’, you need to determine the actual event it refers to. The localized moment should only cover the target event. Now I give you the query: ‘{query}’. Please think carefully and provide your response.

### Prompt for Verifier:

You are acting as the verifier now. You will be presented a text query describing a moment that potentially happens in the given video. Your task is to identify whether the video segment between <SEG\_START> and <SEG-END> perfectly covers the moment. If the described moment can be seen in the video, please focus on verifying whether the moment starts at <SEG.START> and ends at <SEG.END>. Respond with ‘Yes’ if you think the moment boundaries are correct, otherwise ‘No’. If the described moment cannot be seen in the video, respond with ‘No’ directly. Now I give you the query: ‘{query}’. Please think carefully and respond with ‘Yes’ or ‘No’ directly.

**Prompt for Answerer:** When subtitles are considered, we use only the first 100 lines as context.

You are given a video with {duration} seconds long.

Subtitles: {subtitles}

{question}

Options:

- (A) {option 1}
- (B) {option 2}
- (C) {option 3}
- (D) {option 4}

Please only give the best option.

### Prompt for query rephrasing data generation:

You are an expert in rewriting questions into queries. I will give you a question that requires to be answered based on a specific moment in a video. Your task is to analyze the question and rewrite it into a declarative sentence, which could be used as a text query to search for the relevant video moment. The query should be concise, describing the key event or key scene that the question asks for.

Here are some examples:

Question: How does the male cyclist react when he sees the steep path?

Query: The male cyclist sees the steep path.

Question: What did the girl do at the end of the video?

Query: The end of the video.

Question: What did the lady do as she was cycling off?

Query: The lady is cycling off.

Question: What is the person with red shirt doing on the yacht?

Query: The person with red shirt stays on the yacht.

Now I give you the question: ‘{question}’. Please think carefully and respond with the query directly.

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