TreeReasoner: Reinforcing Tool-Augmented Tree-of-Videos Reasoning

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Abstract

We present TreeReasoner, a tool-augmented, tree-structured reasoning framework that recasts long-video understanding as an active hypothesis-verification problem over a vast visual search space. By maintaining multiple parallel reasoning paths, the model systematically explores the temporal dimension and, guided by intermediate hypotheses, invokes frame-level tools such as temporal zooming, temporal jumping, and sliding to incrementally search a minimal yet sufficient chain of evidence. The entire framework is trained end-to-end with Tree-of-Tool Relative Policy Optimization (ToT-RPO) following a supervised fine-tuning warmup, achieving superior video-understanding accuracy while decoding far fewer frames than existing methods and exhibiting interpretable temporal localization and causal-verification behaviors. Experiments on six long-video reasoning benchmarks show that TreeReasoner consistently outperforms both standard IO and naive tool-calling baselines. Transferability experiments on hallucination further confirm its generalization and reduced hallucination tendencies. These experiments validate the stability and efficiency of TreeReasoner in complex temporal scenarios.

1. Introduction

Previous progress in multimodal large language models (MLLMs) [1, 14, 15, 30, 34, 40, 41, 46, 48, 50, 61] has driven significant advancements in the ability of models to understand videos. However, long-video understanding remains an unresolved and open challenge. Unlike image understanding or short video understanding, long-video understanding requires processing visual contextual information spanning several hours or even longer. Due to constraints in computation and memory, it is impractical to conduct a comprehensive analysis of the entire visual content.

Mainstream end-to-end long-video understanding solutions typically employ uniform frame sampling at fixed intervals or with a fixed number of frames. They alleviate computational burdens through visual compression [9, 21, 24, 35] or by expanding the context length of MLLMs [59, 68], aiming to incorporate as many frames as possible for understanding. For most long-video understanding tasks, completing the task does not actually require accessing information from the entire video. Consequently, a growing body of research has begun exploring more efficient video sampling strategies [2, 47, 51, 53, 64, 65]. These approaches leverage vision-language models to select frames that are most relevant to the specific task, thereby significantly reducing the computational overhead of long-video understanding (*Fig. 1*) . Nevertheless, since frame sampling and the model's frame understanding process often cannot be optimized in an end-to-end manner, these methods, which are analogous to agent workflows, have clearly imposed limitations on performance of long-video understanding systems (*Fig. 2*) .

Recently, OpenAI o3 [29] has presented an alternative perspective on visual understanding and reasoning: visual

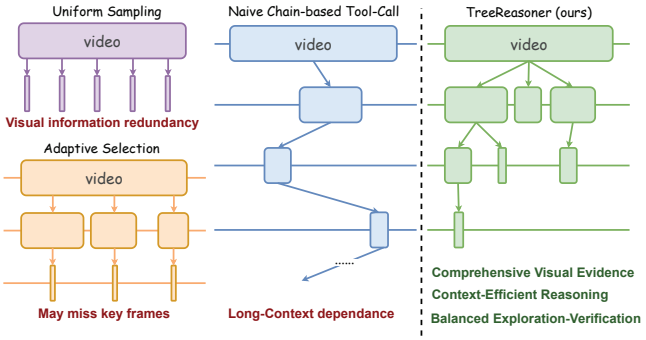

Figure 1. **Schematic illustrating different approaches for long-video understanding.** Left: Traditional sampling methods. *Uniform Sampling* (top) suffers from visual information redundancy, while *Adaptive Selection* (bottom) may miss key frames. Middle: A *Naive Chain-based Tool-Call* approach, which relies on a single reasoning path and can suffer from long-context dependence. Right (Ours): The *TreeReasoner* framework, which uses a parallel, tree-structured search to achieve comprehensive visual evidence, context-efficient reasoning, and balanced exploration-verification.

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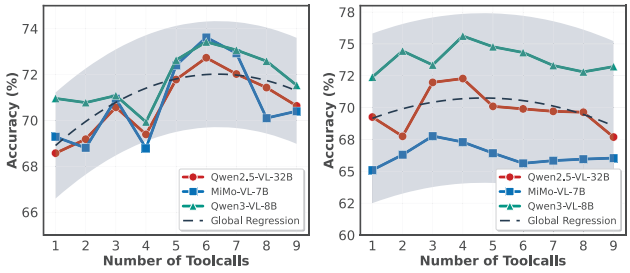


(a) VideoMME (b) EgoSchema

Figure 2. **Tool-call Scaling.** Empirical analysis on VideoMME (a) and EgoSchema (b) showing how performance varies under different fixed tool-call times.

perception can be treated as a tool for invocation, enabling the model to autonomously learn how to identify critical visual cues. This insight inspires us to develop an end-to-end optimization framework, which empowers the model to strategically explore the vast visual search space of long videos. The goal is to identify the minimal chain of evidence required to answer specific questions, thereby achieving efficient resolution of long-video understanding tasks.

In this work, we introduce TreeReasoner, a novel framework that reformulates video understanding as an active search problem through tool-augmented tree-of-thought reasoning. Our key insight is that effective video comprehension mirrors human cognitive processes: we don't passively observe entire videos but actively seek specific temporal evidence through hypothesis-driven exploration. TreeReasoner achieves this by maintaining multiple reasoning trajectories in a tree structure, where each path represents a distinct hypothesis about the temporal location and relationship of relevant events. Crucially, this tree-based exploration is intrinsically coupled with tool utilization—the model employs frame extraction, temporal navigation, and region focusing tools to gather evidence, with each tool-call guided by the current reasoning state and contributing to trajectory expansion.

The synergy between tree-structured reasoning and tool augmentation addresses the fundamental challenges of video understanding. The tree structure enables systematic exploration of multiple temporal hypotheses in parallel, preventing premature commitment to potentially incorrect temporal interpretations. Meanwhile, tool augmentation transforms each reasoning step from passive prediction to active verification, allowing the model to adaptively zoom into specific temporal regions, extract key frames based on intermediate hypotheses, and incrementally build minimal evidence chains. This bidirectional relationship—where tree exploration guides tool selection and tool outputs inform trajectory prioritization—creates an efficient search mechanism through the vast temporal space.

We train *TreeReasoner* using Tree-of-Tool Relative Policy Optimization (*ToT-RPO*), which learns to balance exploration of diverse reasoning paths with exploitation of promising trajectories. Through reinforcement learning, the model develops sophisticated temporal search strategies, learning when to extract frames, how to navigate temporal neighborhoods, and which visual details require verification. Our experiments demonstrate that TreeReasoner significantly outperforms existing methods on challenging video understanding benchmarks, achieving superior accuracy while requiring substantially fewer processed frames. The emergent search behaviors reveal interpretable reasoning patterns, including temporal bracketing, causal chain verification, and adaptive temporal resolution adjustment.

2. Related Work

2.1. Visual Agentic Reasoning

Reinforcement Learning from Verifiable Rewards (RLVR) has achieved remarkable success in the domain of Large Language Models [8, 39, 60]. Models trained with algorithms such as GRPO/PPO demonstrate strong performance across a wide range of complex reasoning and agentic tasks. Inspired by these advances, recent efforts have extended RLVR-inspired paradigms to Vision-Language Models (VLMs), yielding promising results. One line of research enhances native visual reasoning through supervised fine-tuning (SFT) or reinforcement learning (RL), encouraging models to reason truly over visual inputs rather than relying solely on the text-based reasoning capabilities inherited from their LLM backbones [12, 18, 20, 22, 31, 36, 45, 52, 55, 57, 58, 63, 67]. Another complementary approach equips VLMs with external tools (e.g., zoom-in/search/crop/coding api, etc) and employs end-to-end RL to further strengthen their practical agentic capabilities [19, 25, 27, 42, 43, 69, 71]. In contrast to these works, this paper focuses on naive long-video agentic reasoning and proposes a tree-based reasoning framework that generalizes beyond simple chain-of-thought (CoT) processes.

2.2. Long-Video Understanding and Reasoning

Existing end-to-end long-video Multimodal Large Language Models (MLLMs) primarily fall into two categories. First, given the visual redundancy inherent in long videos, numerous studies [9, 16, 21, 24, 35, 50, 61] have attempted to design visual compression algorithms to reduce the number of video tokens, thereby enabling long-video understanding with acceptable computational overhead. The second research direction [14, 59, 68] draws on techniques from long-context large language models, leveraging context extension to increase the input sequence length. Additionally, a substantial body of work has focused on developing complex Agent systems for long-video understanding [2, 47, 51, 53, 64, 65], their core design involves algorithms that select key frames from long videos for understanding and reasoning. However, due to the difficulty of

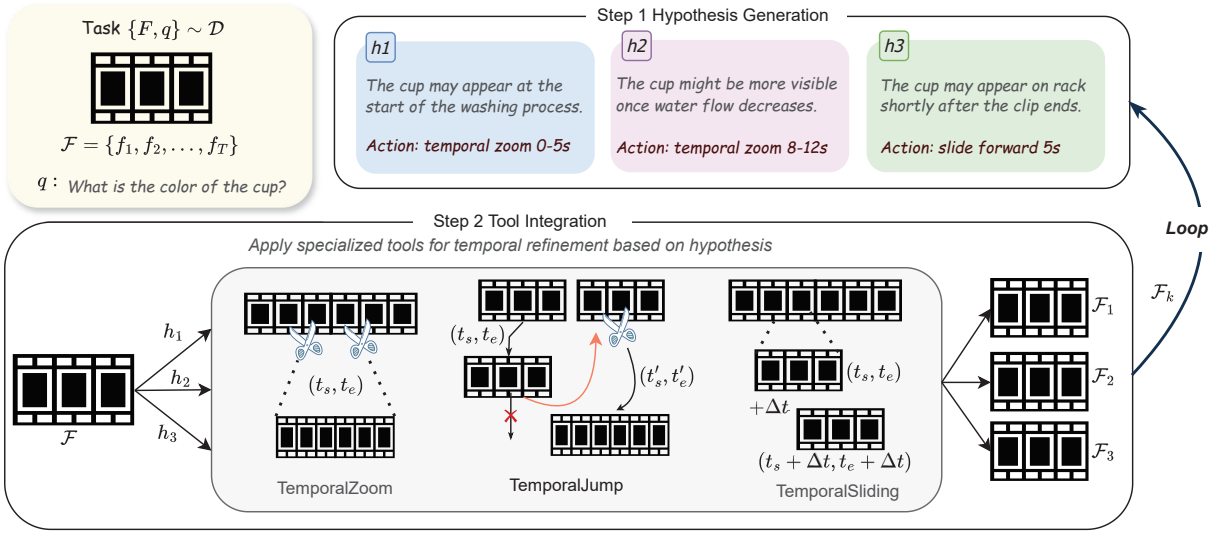


Figure 3. **Overview of TreeReasoner.** Given a question and a long video, the model first generates n parallel hypotheses about where and when relevant evidence might occur. For each hypothesis it invokes a specialized, frame-level tool—zoom, jump, or slide—to extract a short, task-specific clip. Every tool-call spawns a new child node, and the process is repeated breadth-first until an answer is reached or the budget is exhausted, yielding a minimal yet sufficient chain of evidence.

implementing end-to-end optimization, such methods struggle to further push the boundaries of performance. Recently, there have been many efforts [3, 5, 7, 10, 13, 23, 44] to enhance video reasoning capabilities using RL, yet these still fail to address the issue of excessive overhead during long-video understanding and reasoning. Unlike previous approaches, this paper proposes a solution that supports end-to-end optimization and enables efficient long-video understanding through temporal processing.

3. Methodology

In this section, we introduce our tool-augmented video reasoning as an active search and critic over temporal hypotheses under partial observability with tree-based expansion policy. Specifically, in section 3.1, we formulate our theoretical framework on learning objectives and constraints. Then in section 3.2, we dive into details of our reasoning process end-to-end. Finally, in section 3.3 we introduce the reward formulation and training strategy based on our proposed Tree-of-Tool Relative Policy Optimization (ToT-RPO) algorithm for tree-based video reasoning.

3.1. Problem Formulation

We formulate video reasoning process as an active search and criticism over temporal hypotheses under partial observability via the guidance of a tree-based policy. Given a video sequence $\mathcal{F} = \{f_1, f_2, \ldots, f_T\}$ with T total frames and a language query q, our reasoning objective is to discover or search an optimal evidence set $\mathcal{E}^* \subseteq \mathcal{F}$ that maximizes accuracy while minimizing computational cost. This constitutes a multi-objective optimization problem:

$$\mathcal{E}^*, \tau^* = \arg\max_{\mathcal{E},\tau} \mathbb{P}(y^* \mid q, \mathcal{E}, \tau) \quad \textbf{s.t.} \quad C(\mathcal{E}, \tau) \leq C_{\text{budget}}.$$

Here y^* denotes the ground truth answer, τ represents the reasoning trajectory, $C(\mathcal{E}, \tau)$ measures computational cost, which contains both the number of reasoning trajectories and the computational complexity of each trajectory. C_{budget} means the controlled reasoning budget. The fundamental challenge emerges from the exponential search space $|\mathcal{P}(\mathcal{F})| = 2^T$ over the frame sequences and the partial observability constraint that limits frame access at any given time step. We model partial observability through a state-dependent visibility function $\mathcal{V}_t : \mathcal{S} \times \mathcal{A} \to 2^T$ that determines which video segments become observable after taking action a in state s. This formulation captures the realistic constraint that video understanding models cannot process entire video frames simultaneously due to memory and computational limitations. Additionally, we impose temporal coherence constraints on searched evidence frame chains through conditional dependencies:

$$\begin{aligned} &\forall \mathcal{E} = \{f_{i_1}, \ldots, f_{i_k}\}, i_1 < \cdots < i_k : \\ &\mathbb{P}(f_{i_{j+1}} | f_{i_1}, \ldots, f_{i_j}, q) > \mathbb{P}(f_{i_{j+1}} | q), \end{aligned} \tag{1}$$

thus ensuring that evidence frames form meaningful temporal narratives rather than disconnected visual elements.

3.2. Tree-of-video Reasoning

Our approach models the reasoning process as a directed tree $\mathcal{T} = (\mathcal{N}, \mathcal{E}_{\text{tree}})$ where nodes represent reasoning states and edges encode tool-augmented state transitions. Given the challenge of searching through massive frame sequences in long-video understanding, chain-like reasoning methods (e.g., Chain-of-Thought) may fail to accurately localize relevant clips from the outset. Their depth-first expansion tends to trap the policy model in irrelevant frame

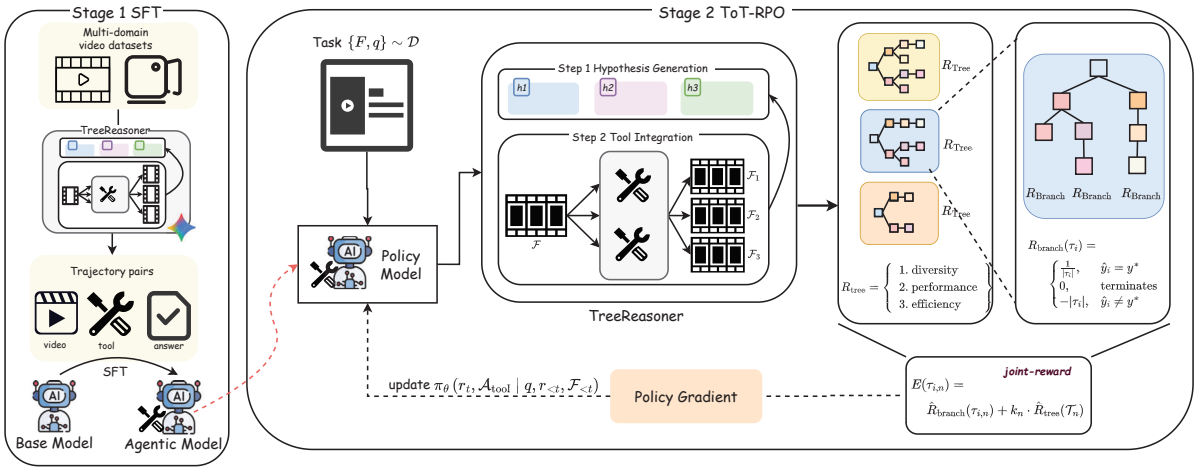


Figure 4. **Training paradigm of TreeReasoner.** *Stage 1*: the agent is warmed up with SFT on multi-turn, tool-augmented reasoning trajectories distilled from a teacher model. *Stage 2*: we continue with *ToT-RPO*, sampling entire reasoning trees per video–question pair and optimizing a composite reward that balances answer accuracy, search efficiency, tool utility, and inter-branch diversity. The whole pipeline is end-to-end and produces a single policy that jointly learns when to reason, which tool to call, and where to look next.

regions, with limited ability to recover or escape. Moreover, current RL algorithms face significant convergence difficulties in multi-turn tool-use settings. To address these issues, we adopt a breadth-first tree search strategy, enabling parallel exploration of multiple key frame intervals while progressively refining clip localization via tool interaction. This leads to earlier correct answer retrieval or timely early stopping, substantially improving reasoning efficiency.

3.2.1. Reasoning Process Representation

In our work, the reasoning state$s_t \in \mathcal{S}$ of each node $n_t \in \mathcal{N}$ is comprehensively characterized by a multi-modal tuple:

$$s_t = \langle q, \mathcal{H}_t, \mathcal{O}_t, \mathcal{R}_t, \mathcal{A}_t \rangle, \tag{2}$$

where q represents the input query. $\mathcal{H}_t = \{h_1, \ldots, h_t\}$ denotes the sequence of hidden representations encoding temporal hypotheses. $\mathcal{O}_t = \{(o_i, t_i, b_i)\}$ contains observed visual elements o_i with their temporal locations t_i and spatial bounding boxes b_i. $\mathcal{R}_t$ maintains the textual reasoning trace. $\mathcal{A}_t = \{a_1, \ldots, a_{t-1}\}$ represents the history of actions taken up to the current state.

The state transition function $\delta : \mathcal{S} \times \mathcal{A} \to \mathcal{S}$ governs how states evolve through actions. For tool-based actions, the transition incorporates environmental feedback:

$$s_{t+1} = \delta(s_t, a_t) = \begin{cases} \delta_{\text{tool}}(s_t, a_t, \text{Env}(a_t, s_t)) & \text{if } a_t \in \mathcal{A}_{\text{tool}} \\ \delta_{\text{answer}}(s_t, a_t) & \text{if } a_t \in \mathcal{A}_{\text{answer}} \\ \delta_{\text{terminal}}(s_t, a_t) & \text{if } a_t \in \mathcal{A}_{\text{terminal}} \end{cases} \tag{3}$$

where $\text{Env}(a_t, s_t)$ executes the tool action with parameters $\boldsymbol{\theta}_a$ in the video environment and returns observations.

3.2.2. Tool Integration

The action space $\mathcal{A} = \mathcal{A}_{\text{tool}} \cup \mathcal{A}_{\text{answer}} \cup \mathcal{A}_{\text{terminal}}$ encompasses three distinct categories of operations. Answer actions $\mathcal{A}_{\text{answer}}$ involve generating the final response directly to the query based on the reasoning trace and collected visual evidence. Tool actions $\mathcal{A}_{\text{tool}}$ enable active video exploration with potential environmental interaction through parameterized functions. Inspired by natural human behaviors when watching videos, we design the following concrete tools:

- **TemporalZoom**(t_s, t_e) performs temporal zooming within the current clip, extracting frames at higher temporal resolution r from time interval $[t_s, t_e]$
- **TemporalJump**(t'_s, t'_e) jumps out of the current clip to extract frames from a different temporal interval $[t'_s, t'_e]$ in the global video, avoiding trapping in a local loop.
- **Sliding**$(t_s, t_e, \Delta t)$ slides a temporal window starting from interval $[t_s, t_e]$ with stride Δt, progressively exploring adjacent temporal segments.

These tool actions are practically useful as they mirror natural human video-watching behaviors: carefully examining details within interesting segments (zooming), jumping to other parts of the video to seek relevant evidence (jumping), and smoothly browsing continuous video content (sliding). Each tool action is parameterized by a continuous parameter vector $\boldsymbol{\theta}_a \in \mathbb{R}^{d_a}$ learned through the policy network. This parameterization allows the policy model to learn optimal tool usage strategies through RL rather than relying on hand-crafted heuristics.

3.2.3. Hierarchical Tree Expansion

Tree expansion follows a principled hierarchical search strategy that balances exploration breadth with computational efficiency. At each state s_t, the policy network π_θ generates a probability distribution $\pi_\theta(a_t|s_t)$ over actions conditioned on the current state, where the policy network π_θ employs a transformer architecture with specialized attention mechanisms for processing temporal hypotheses, visual observations, and textual reasoning traces. First from a

high-level perspective, the search process maintains k parallel trajectories with diversity regularization. For each trajectory i, we sample actions at timestep t according to the constrained policy distribution:

$$a_t^{(i)} \sim \pi_\theta(\cdot|s_t^{(i)}) \quad \text{s.t.} \quad \sum_{j=1}^{k} \mathrm{KL}[\pi(\cdot|s_t^{(i)})\|\pi(\cdot|s_t^{(j)})] \geq \beta_{\text{div}}, \tag{4}$$

where the diversity constraint β_{div} prevents trajectory collapse and encourages exploration of alternative reasoning paths. This constraint is enforced through a diversity-augmented sampling procedure that rejects actions leading to excessive similarity with existing trajectories.

Then, dive into the internal trajectory, the hierarchical expansion strategy operates across multiple temporal scales through a coarse-to-fine refinement process. Initially, the search explores broad temporal regions using low temporal resolution sampling: $\mathcal{L}_{\text{coarse}}(t_s, t_e) = \{t_s + k \cdot \Delta_{\text{coarse}} : k \in \mathbb{Z}, t_s \leq t_s + k \cdot \Delta_{\text{coarse}} \leq t_e\}$ where Δ_{coarse} represents the coarse temporal resolution. Promising regions identified during coarse search are subsequently refined using higher temporal resolution: $\mathcal{L}_{\text{fine}}(t_s, t_e) = \{t_s + k \cdot \Delta_{\text{fine}} : k \in \mathbb{Z}, t_s \leq t_s + k \cdot \Delta_{\text{fine}} \leq t_e\}$ with $\Delta_{\text{fine}} \ll \Delta_{\text{coarse}}$. Note that this tree-structured, frame-granular enhancement expansion strategy can enable the policy model to concurrently focus on key frame intervals, allowing it to rapidly identify important clues or terminate search early—avoiding wasted computation on irrelevant frames or iterative trial-and-error over incorrect frame parts (as in deep tool-call chain), thereby significantly reducing inference time.

3.3. Learn to Tree-of-video Reasoning

3.3.1. Warmup SFT

To enable model to learn how to reason with tool use based on external execution feedback, we first generate multi-round multimodal reasoning data using Gemini2.5-Pro API within our agent data workflow. For an input video query q, the Gemini2.5 model generates l rounds of reasoning output R_{query}, we filter the output with wrong answers and finally construct a SFT dataset $\mathcal{D}$. This dataset is used to train the model to predict correct tool-use action $(r_t, \mathcal{A}_{\text{tool}})$ on input query q, previously selected video frame sequence $\mathcal{F}_{<t}$ and reasoning result $r_{<t}$. The SFT objective is to unlock the policy's reasoning ability with specific tool use. Formally, we minimize following negative log-likelihood loss:

$$\mathcal{L}_{\text{SFT}} = -\mathbb{E}_{(q,r,\mathcal{A}_{\text{tool}},\mathcal{F})\sim\mathcal{D}} \left[\sum_{t=1}^{T} \log \pi_\theta \left(r_t, \mathcal{A}_{\text{tool}} \mid q, r_{<t}, \mathcal{F}_{<t} \right) \right]. \tag{5}$$

3.3.2. Reinforcement Learning Via ToT-RPO

Although SFT enables the model to imitate tool-augmented reasoning trajectories, it cannot optimize long-term decision outcomes or balance exploration and efficiency. To address these limitations, we further refine TreeReasoner with *Tree-of-Tool Relative Policy Optimization (*ToT-RPO*)* [8], which extends GRPO to structured reasoning trees for end-to-end optimization over multi-branch trajectories. After the SFT stage, the model is trained via *ToT-RPO* by sampling a group of tree-based trajectories for each video–query pair (Sec 3.2) and optimizing composite rewards that integrate accuracy, reasoning efficiency, tool utility, and exploration diversity, enabling adaptive and cost-aware reasoning across tree-structured trajectories.

Algorithm 1 *ToT-RPO* Rollout

Require: An array of video-query pairs $Q = \{(q_1, \mathcal{F}_{1,0}), (q_2, \mathcal{F}_{2,0}), \ldots, (q_n, \mathcal{F}_{n,0})\}$
Ensure: Rollout responses T of tree for all $(q, v) \in Q$.

```
P ← Q                                              ▷ Init root node of tree
while P ≠ ∅ do
    S ← INFERENCE(P)                               ▷ Reason with action
    p^last ← P
    P ← ∅                                          ▷ Clean up the node queue
    for s_k in S do                                ▷ Recongize node states
        if a_k ∈ A_terminal or a_k ∈ A_answer then
            T ← T ⊕ {p_k^last ⊕ s_k}               ▷ Build tree
        else
            for a_{k,l} in s_k do                  ▷ Expand child node
                s'_{k,l} ← EXECUTE(a_{k,l}, s_k)   ▷ Execute tool
                P ← P ∪ {s'_{k,l}}
            end for
        end if
    end for
end while
return T                                           ▷ Return the final responses of tree
```

Tree-structured Rollout Process. In TreeReasoner, each reasoning episode can be viewed as a stochastic tree-search process, where the policy π_θ governs both reasoning and tool-usage actions across the tree nodes. Given a video–query pair (v, q), the model generates a reasoning tree $\mathcal{T} = \{\tau_1, \tau_2, \ldots, \tau_{|\mathcal{T}|}\}$ consisting of $|\mathcal{T}|$ branch trajectories $\tau_i = \{(s_t, a_t)\}_{t=1}^{T_i}$, each representing a distinct hypothesis exploration path ending with either an answer or early termination signal. Unlike linear chain rollouts, *ToT-RPO* treats these trajectories collectively during optimization, leveraging their structural interdependence. To operationalize this process, the reasoning tree is constructed through breadth-first expansion: starting at the root node N_0, a queue P is maintained to manage nodes at each depth level, and for every node in P, the model proactively generates reasoning analysis along with an associated action. These actions encompass tool-calling actions,

Table 1. **Performance of our TreeReasoner on video understanding benchmarks.** We compare our **TreeReasoner** against baseline models (IO), chain-based **Tool-call** method, and other SOTA models on 6 datasets. The 🔥 denotes models trained with both SFT and RL.

Model	Method	VideoMME	LongVideoBench	EgoSchema	MLVU	VSIBench	TOMATO	Average
OpenAI GPT-4o [17]	IO	71.9	66.7	72.2	64.6	34.0	37.7	57.9
Gemini2.5-Flash-Lite [6]	IO	65.0	60.2	–	69.3	27.0	–	–
Qwen2.5-VL-7B [1]	IO	65.1	56.0	65.0	70.2	34.2	27.6	53.0
Qwen2.5-VL-72B [1]	IO	73.3	60.7	76.2	74.6	37.2	31.2	58.9
Llama3.2-11B-Inst[28]	IO	46.0	45.5	54.3	44.4	20.6	21.5	38.7
Gemma3-12B-IT[38]	IO	58.2	51.5	56.9	52.3	32.4	28.6	46.7
MiMo-VL 7B [37]	IO	70.3	60.4	67.4	71.3	40.8	36.1	57.7
	Tool-call	72.3	63.1	69.2	74.1	45.1	38.4	60.4
	Tool-call 🔥	75.1	65.2	71.0	78.2	47.8	40.3	62.9
	TreeReasoner	73.2	63.3	69.6	77.1	46.7	38.5	61.4
	TreeReasoner 🔥	75.9	67.8	73.7	81.8	49.6	41.5	65.0
Qwen3-VL 8B [60]	IO	71.4	58.4	73.2	78.1	59.4	34.9	62.5
	Tool-call	73.3	61.5	75.6	80.8	61.8	37.3	65.1
	Tool-call 🔥	76.2	64.8	77.8	84.3	63.1	40.5	67.8
	TreeReasoner	73.7	62.2	76.4	81.5	62.6	37.8	65.7
	TreeReasoner 🔥	77.2	65.9	80.0	85.5	64.6	41.5	69.1
Qwen2.5-VL 32B [1]	IO	70.4	57.8	69.2	71.3	37.1	29.8	55.9
	Tool-call	72.3	59.1	71.8	75.4	43.7	31.5	59.0
	Tool-call 🔥	74.8	62.1	74.6	79.8	46.1	35.2	62.1
	TreeReasoner	72.5	60.2	73.0	76.4	44.7	33.2	60.0
	TreeReasoner 🔥	76.4	62.9	77.6	80.4	47.6	37.5	63.7

answer-generation actions, and early-stopping actions (see Sec. 3.2.1). When a tool-calling action is correctly produced, the corresponding tool is executed and its feedback is appended to the next-layer nodes, which are then added to P; otherwise, that branch halts. Each node can expand into at most W child nodes, and the overall depth of the tree is capped at D, ensuring a controlled yet expressive exploratory reasoning structure.

Hierarchical Reward Design. During *ToT-RPO* training, the rollout process naturally produces a structured reasoning tree rather than a single linear trajectory. This structural property prevents direct application of conventional trajectory-level policy gradient updates. To address this, we employ a hierarchical reward formulation that evaluates both local branch trajectories and the global reasoning tree, enabling stable and efficient optimization.

At the branch-trajectory level, we define a reward function that jointly captures prediction correctness and search efficiency:

$$\mathcal{R}_{\text{branch}}(\tau_i) = \begin{cases} \frac{1}{|\tau_i|}, & \text{if } \hat{y}_i = y^*, \\ 0, & \text{if the branch terminates,} \\ -|\tau_i|, & \text{if } \hat{y}_i \neq y^*, \end{cases} \tag{6}$$

where $|\tau_i|$ denotes the number of nodes in the branch trajectory and $\hat{y}_i$ is the predicted answer. This formulation encourages the discovery of correct answers with minimal reasoning depth while heavily penalizing long yet incorrect exploration paths.

Beyond branch evaluation, we introduce a tree-level reward to assess the overall quality of the reasoning tree $\mathcal{T}_j$. This reward integrates three complementary aspects: (1) *diversity*, encouraging exploration of distinct reasoning hypotheses through average branch dissimilarity; (2) *performance*, measured by the success rate of branch trajectories arriving at correct answers; and (3) *efficiency*, reflected by the depth of the reasoning tree. Together, these components ensure that the model learns to balance explorative breadth and computational economy.

To stabilize optimization, both branch-trajectory rewards and tree-level rewards are standardized across the batch. The combined advantage $E(\tau_{i,j})$ is defined as

$$E(\tau_{i,j}) = \hat{R}_{\text{branch}}(\tau_{i,j}) + k_j \cdot \hat{R}_{\text{tree}}(\mathcal{T}_j), \tag{7}$$

where

$$\begin{cases} \hat{\mathcal{R}}_{\text{branch}}(\tau_{i,j}) = \dfrac{\mathcal{R}_{\text{branch}}(\tau_{i,j}) - \mu(\mathcal{R}_{\text{branch}}(\cdot,j))}{\sigma(\mathcal{R}_{\text{branch}}(\cdot,j))}, \\ \hat{\mathcal{R}}_{\text{tree}}(\mathcal{T}_j) = \dfrac{\mathcal{R}_{\text{tree}}(\mathcal{T}_j) - \mu(\mathcal{R}_{\text{tree}})}{\sigma(\mathcal{R}_{\text{tree}})}. \end{cases} \tag{8}$$

Here, $\mu(\cdot)$ and $\sigma(\cdot)$ denote the empirical mean and standard deviation, respectively, computed over the collection of values indicated within the parentheses.

The optimization objective follows the standard GRPO framework:

$$\mathcal{L}_{\text{ToT-RPO}} = -\mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{k=1}^{K} A_{\text{group}}(\tau)\,\log\pi_\theta(a_k|s_k) - \lambda_{\text{KL}}\,D_{\text{KL}}(\pi_\theta\|\pi_{\text{ref}})\right]. \tag{9}$$

The group-normalized advantage is computed as

$$A_{\text{group}}(\tau) = E(\tau)\cdot\text{clip}\left(\frac{\pi_\theta(\tau)}{\pi_{\text{old}}(\tau)},\,1-\delta,\,1+\delta\right) \tag{10}$$

where the clipping operation prevents excessively large updates and contributes to training robustness.

4. Experiments

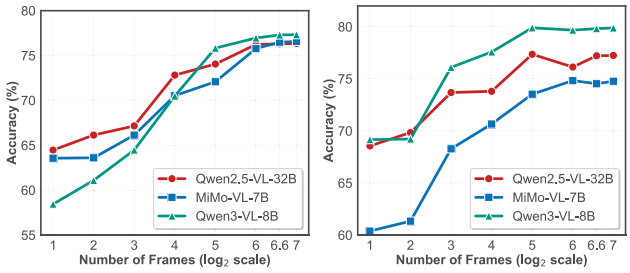
4.1. Settings

Models and baselines. We select three representative families of SOTA open-source VLMs, including Qwen2.5-VL [1], Qwen3-VL [60], and MiMo-VL [37] to evaluate our TreeReasoner framework. For each selected model family, we first assess its baseline performance, then enhance its reasoning capabilities through both standard chain-based tool-calling and our proposed TreeReasoner paradigm, with and without SFT and end-to-end RL. Additionally, we include several strong closed-source models and other competitive open-source models in our comparison directly to comprehensively demonstrate the effectiveness and robustness of our approach.

Benchmarks. We evaluate on several challenging video understanding and reasoning benchmarks, including one general video understanding task (VideoMME [11]), three long-video understanding tasks (MLVU [72], LongVideoBench [54], EgoSchema [26]) and two complex video reasoning tasks (TOMATO [33], VSIBench [62]).

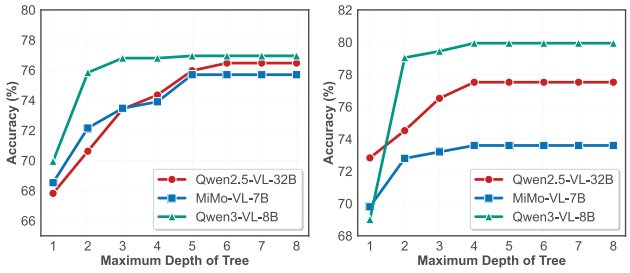
4.2. Performances of TreeReasoner

Table 1 shows the main performance of different baselines and our proposed TreeReasoner methods. Compared with the IO and naive Tool-Call baselines, TreeReasoner delivers consistent and substantial performance improvements across all six datasets. This demonstrates that TreeReasoner's parallel hypothesis exploration and early evidence verification provide immediate benefits over linear Tool-call or single-pass inference. When equipped with SFT and RL training, the TreeReasoner framework yields additional performance gains and enables multiple backbone models to reach state-of-the-art results across several benchmarks. Case study for interpretability of TreeReasoner can be found in the appendix.



(a) VideoMME (b) EgoSchema

Figure 5. **Ablation of Frame Numbers.** (a) Accuracy with various Frame Numbers on VideoMME . (b) Accuracy with various Frame Numbers on EgoSchema .



(a) VideoMME (b) EgoSchema

Figure 6. **Ablation of Max Tree Depth of TreeReasoner.** (a) Accuracy with various tree depth budgets on VideoMME. (b) Accuracy with various tree depth budgets on EgoSchema.

4.3. Analysis

Ablation on training stages. Both SFT and RL are compatible with the proposed TreeReasoner framework. To elucidate the impact of different training stages on final performance, we conducted an ablation study comparing various training configurations of TreeReasoner. As shown in Table 2, we can find that incorporating the RL stage consistently improves performance across various base models and benchmarks. These results indicate that TreeReasoner's RL process effectively refines temporal reasoning and cross-frame consistency, providing stable performance boosts regardless of model scale.

Ablation on limit of exploring depth and frame numbers for each node. Tree depth and the number of frames per node are two critical hyperparameters in our TreeReasoner reasoning framework, playing a pivotal role in balancing inference accuracy and computational efficiency. We conduct comprehensive ablation studies on these key parameters to identify the optimal configuration and to demonstrate their adaptability and robustness across diverse tasks. As shown in Fig. 5, increasing the number of sampled frames per node improves performance until saturation. Similarly, Fig. 6 shows that increasing the maximum tree depth yields consistent gains before convergence. These results indi-

Table 2. **Ablation Study on Training Stages with Different Base Models.** Accuracy(%) comparison across six video benchmarks for comparison with different base models at both SFT stage and the combined SFT with RL (SFT+RL) stage.

Base Model	Stage	VideoMME	LongVideoBench	EgoSchema	MLVU	VSIBench	TOMATO	Average
MiMo-VL 7B	SFT	73.9	65.6	71.6	79.7	47.6	39.6	63.0
	SFT+RL	75.9	67.8	73.7	81.8	49.6	41.5	65.0
Qwen3-VL 8B	SFT	75.2	63.9	78.2	83.4	63.2	39.4	67.3
	SFT+RL	77.2	65.9	80.0	85.5	64.6	41.5	69.1
Qwen2.5-VL 32B	SFT	74.4	61.0	75.4	78.4	45.7	35.6	61.8
	SFT+RL	76.4	62.9	77.6	80.4	47.6	37.5	63.7

Table 3. **Hallucination.** Accuracy(%) on Hallucer benchmark.

Model	Method	Basic	Hallucinated	Overall
MiMo-VL 7B	IO	82.8	66.8	57.6
	Tool-call	84.0	67.6	58.6
	TreeReasoner	84.3	69.7	60.7
	Tool-call 🔥	87.7	72.6	65.2
	TreeReasoner 🔥	89.9	75.9	69.1
Qwen3-VL 8B	IO	79.4	78.2	61.8
	Tool-call	81.1	81.2	64.6
	TreeReasoner	83.5	83.0	66.5
	Tool-call 🔥	84.5	85.1	69.8
	TreeReasoner 🔥	86.0	87.1	72.9
Qwen2.5-VL 32B	IO	75.2	80.4	62.0
	Tool-call	76.2	81.8	62.8
	TreeReasoner	77.9	82.3	64.6
	Tool-call 🔥	79.4	87.0	67.5
	TreeReasoner 🔥	82.6	88.7	71.8

cate that enriching frame-level visual diversity enables more comprehensive evidence aggregation and strengthens the model's structured visual reasoning process, while redundant frames offer limited additional benefit.

Transferability on Hallucination. A key challenge in the reasoning process of MLLM lies in their propensity to hallucinate—particularly when reasoning chains become overly long or complex. As attention distributions become sparse, the model may drift away from visual grounding, resulting in unfaithful or fabricated content. To assess the robustness and transferability of our reasoning framework under such conditions, we evaluate models on the Hallucer benchmark [49]. Each sample in Hallucer consists of a Basic question (testing factual understanding) and a Hallucinated counterpart (containing unverifiable or false premises). A point is awarded only when the model correctly answers both questions in a pair, ensuring that robustness against hallucination is jointly assessed with factual consistency. Experimental results show that our proposed TreeReasoner framework achieves substantially lower hallucination rates compared to standard IO and naive Tool-call, demonstrating its stronger transferability and robustness in mitigating hallucination. As shown in Table 3, TreeReasoner consistently mitigates hallucination across various backbone models and configurations.

Table 4. **Efficiency.** Efficiency analysis on LongVideoBench.

Method	Output/Input tokens	Accuracy
IO (best of 6)	9.1k / 21.1k	63.5
Tool call (best of 6) 🔥	13.2k / 49k	67.4
TreeReasoner 🔥	13.6k / 36.2k	67.8

Efficiency. To evaluate the computational efficiency of our approach, we conduct a comprehensive comparison between TreeReasoner and naive chain-based Tool Call on the LongVideoBench under the Pass@K setting, where K denotes the ratio of token consumption relative to the naive Tool Call baseline. As shown in Table 4, TreeReasoner achieves superior performance while maintaining comparable token consumption to naive Tool Call Pass@K, demonstrating its efficiency advantage. This improvement stems from TreeReasoner's ability to effectively explore multiple "local-global" video understanding paths in parallel, thereby circumventing the accumulated errors and global misjudgments that often arise from naive Tool Call's sequential, single-path exploration strategy.

5. Conclusion

In this work, we present TreeReasoner, a novel framework that recasts long-video understanding as an active search problem over temporal hypotheses. By maintaining multiple parallel reasoning trajectories in a tree structure and strategically invoking frame-level tools—temporal zooming, jumping, and sliding—our approach efficiently discovers minimal evidence chains without exhaustive frame processing. Trained end-to-end via *ToT-RPO*, TreeReasoner achieves state-of-the-art performance across six challenging benchmarks while requiring substantially fewer frames than existing methods. Using MiMo-VL 7B as example, our experiments demonstrate consistent improvements of 7.3% over corresponding standard IO version and 2.1% over naive chain-based tool-calling approaches with training, validating that tree-structured exploration with tool augmentation provides a principled and efficient solution for long-video understanding. The interpretable emergent behaviors—including temporal bracketing and adaptive resolution adjustment—further confirm that our framework learns sophisticated temporal reasoning strategies that mirror human video comprehension processes.

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